ML 1000 Assignment 2

by Anupama r.k, Queenie Tsang, Crystal (Yunan) Zhu

21/02/2021

To do list:

- **Add Pie charts! - by sub_category, region** # (done)
- **Create a Month variable - to see the change of sales/profits by month?**
- **bar charts of profits/sales by region** #(done)
- **Output the characteristics of the orders with the highest and lowest profits/sales - e.g. what made the order? when? bought what product? in which city/state/region? Any discount?**
- **relationship between discount & sales, discount & profits, sales & profits, and the role of region?**
- **from someone's analysis - there is no significant change between the four discount categories when it comes to Sales**
- **sales/profits by month, rather than by date? color by region?**

Abstract

Anomaly detection or Outlier detection identifies data points, events or observations that deviate from dataset's normal behavior. Anomalous data indicate critical incidents or potential opportunities. In order to take advantage of opportunities or fix costly problems anomaly detection has to be done in real time. Unsupervised machine learning models can be used to automate anomaly detection. Unsupervised anomaly detection algorithms scores data based on intrinsic properties of the dataset. Distances and densities are used to give an estimation what is normal and what is an outlier. Anomaly detection monitor is a tool developed for an online retailer to check product quality issues like profit opportunities and sales glitches. The application is built using R and Shinyapp following CRISP-DM framework.

Business Case

Objective

Detect point anomalies from superstore dataset using K-NN and clustering methods.

Data Understanding

US Superstore dataset is sourced from US uperstore dataset . The dataset have online orders for Superstores in U.S. from 2014-2018. Tableau community is the owner of the dataset. The dataset has 9994 records and 21 attributes.

Import data

```
superstore<- read_excel("US_Superstore_data.xls")
```

```
## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L2236 / R2236C12: '05408'

## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L5276 / R5276C12: '05408'

## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L8800 / R8800C12: '05408'

## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L9148 / R9148C12: '05408'

## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L9149 / R9149C12: '05408'

## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L9150 / R9150C12: '05408'

## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L9388 / R9388C12: '05408'

## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L9389 / R9389C12: '05408'

## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L9390 / R9390C12: '05408'

## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L9391 / R9391C12: '05408'

## Warning in read_fun(path = enc2native(normalizePath(path)), sheet_i = sheet, :
## Coercing text to numeric in L9743 / R9743C12: '05408'
```

```
data_superstore
```

Table 1: Dataset description

Attribute	Data Type	Description
Row ID	numeric	row number
Order ID	character	unique order number
Order Date	numeric	order placed date
Ship Date	numeric	order shipping date
Ship Mode	character	shipping mode of order
Customer ID	character	unique customer id for order

Attribute	Data Type	Description
Customer Name	character	name of customer
Segment	character	section of product
Country	character	country based on order
City	character	city based on order
State	character	state based on order
Postal Code	numeric	pin code
Region	character	region based on order
Product ID	character	product id of product
Category	character	category of product
Sub-Category	character	sub-category of product
Product Name	character	name of product
Sales	numeric	selling price of product
Quantity	numeric	order quantity
Discount	numeric	discount on product
Profit	numeric	profit from product

```
##  [1] "ï..Row.ID-0 missing values"     "Order.ID-0 missing values"
##  [3] "Order.Date-0 missing values"    "Ship.Date-0 missing values"
##  [5] "Ship.Mode-0 missing values"     "Customer.ID-0 missing values"
##  [7] "Customer.Name-0 missing values" "Segment-0 missing values"
##  [9] "Country-0 missing values"       "City-0 missing values"
## [11] "State-0 missing values"         "Postal.Code-0 missing values"
## [13] "Region-0 missing values"        "Product.ID-0 missing values"
## [15] "Category-0 missing values"      "Sub.Category-0 missing values"
## [17] "Product.Name-0 missing values"  "Sales-0 missing values"
## [19] "Quantity-0 missing values"      "Discount-0 missing values"
## [21] "Profit-0 missing values"        "diff_in_days-0 missing values"
```

Get a general idea of the data set.

```
length(unique(data$Customer.ID))
```

```
## [1] 793
```

```
#793 unique customer IDs
length(unique(data$Customer.Name))
```

```
## [1] 793
```

```
#793 unique customer names - drop one of these two vars


length(unique(data$Order.Date))
```

```
## [1] 1237
```

```
#1237 unique order dates
length(unique(data$Ship.Date))
```

```
## [1] 1334
```

```r
#1334 unique ship dates - more unique ship dates than order dates - orders made on the same day were sh
length(unique(data$Segment))
```

```
## [1] 3
```

```r
unique(data$Segment)
```

```
## [1] "Consumer"    "Corporate"   "Home Office"
```

```r
#"Consumer"    "Corporate"   "Home Office"
unique(data$Country)
```

```
## [1] "United States"
```

```r
#all are from US - could drop this variable due to no-variation introduced by it
length(unique(data$City))
```

```
## [1] 531
```

```r
#531 different cities
length(unique(data$State))
```

```
## [1] 49
```

```r
#49 states
length(unique(data$Postal.Code))
```

```
## [1] 631
```

```r
#631 postal code - 793 unique customer IDs - some customers live very close!
unique(data$Region)
```

```
## [1] "South"   "West"    "Central" "East"
```

```r
#only 4 regions
unique(data$Category)
```

```
## [1] "Furniture"       "Office Supplies" "Technology"
```

```r
#only 3 categories - "Furniture" "Office Supplies" "Technology"

length(unique(data$Sub.Category))
```

```
## [1] 17
```

```r
unique(data$Sub.Category)
```

```
##  [1] "Bookcases"   "Chairs"      "Labels"      "Tables"      "Storage"
##  [6] "Furnishings" "Art"         "Phones"      "Binders"     "Appliances"
## [11] "Paper"       "Accessories" "Envelopes"   "Fasteners"   "Supplies"
## [16] "Machines"    "Copiers"
```

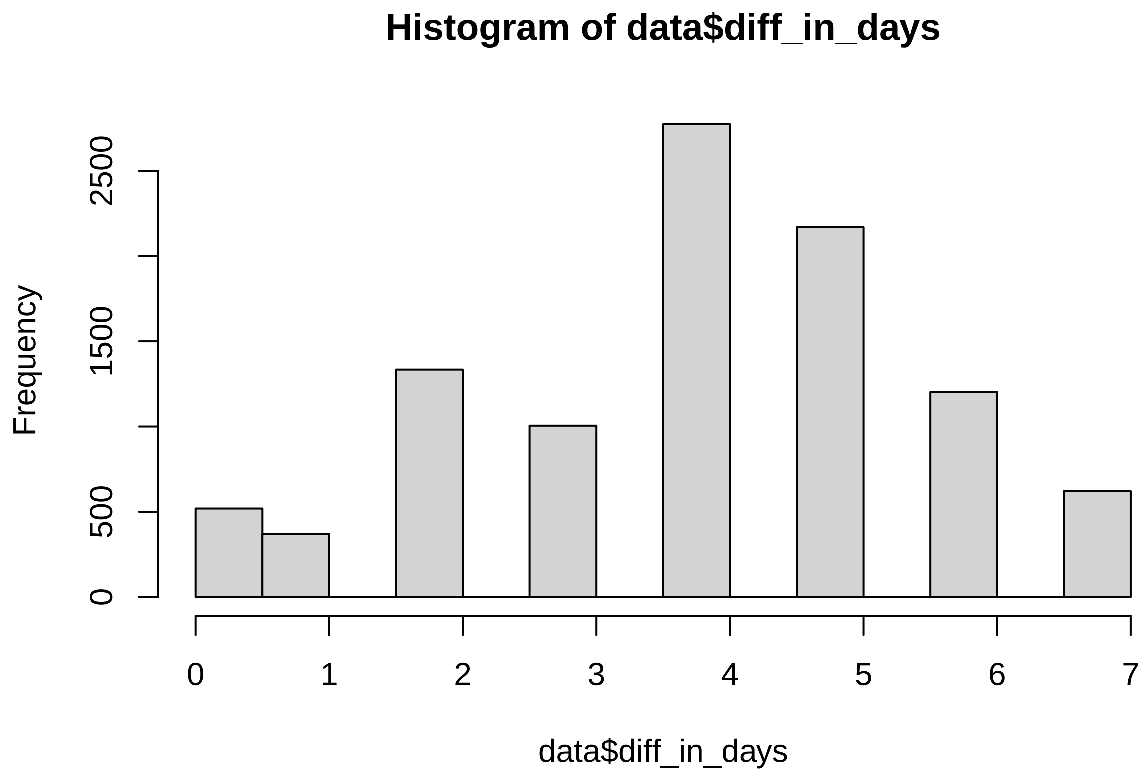
```r
#17 sub-categories

length(unique(data$Product.Name))
```

```
## [1] 1850
```

```r
#1850 product names
length(unique(data$Product.ID))
```

```
## [1] 1862
```

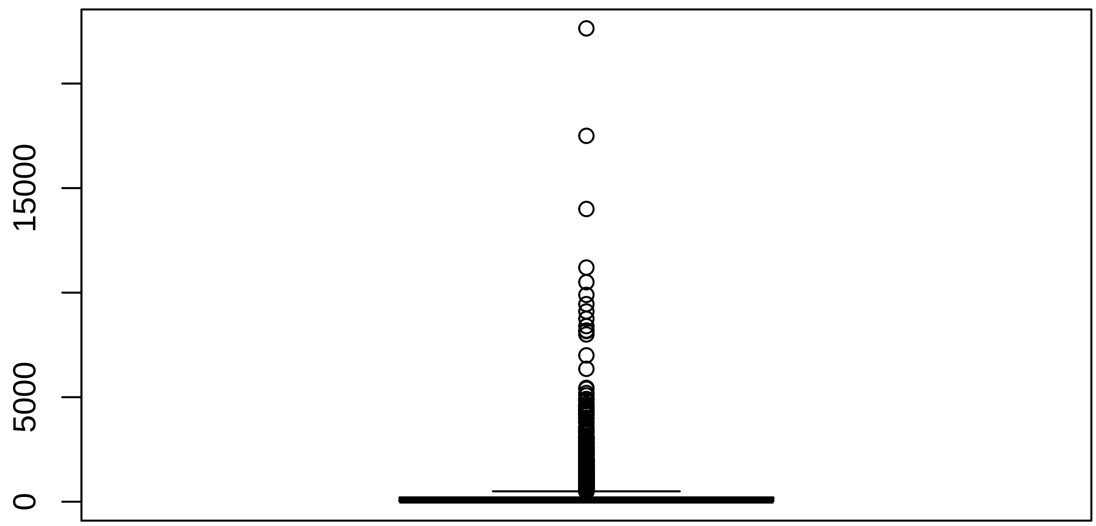
```r
#1862 product IDs - potential redundant variables!

hist(data$diff_in_days)
```



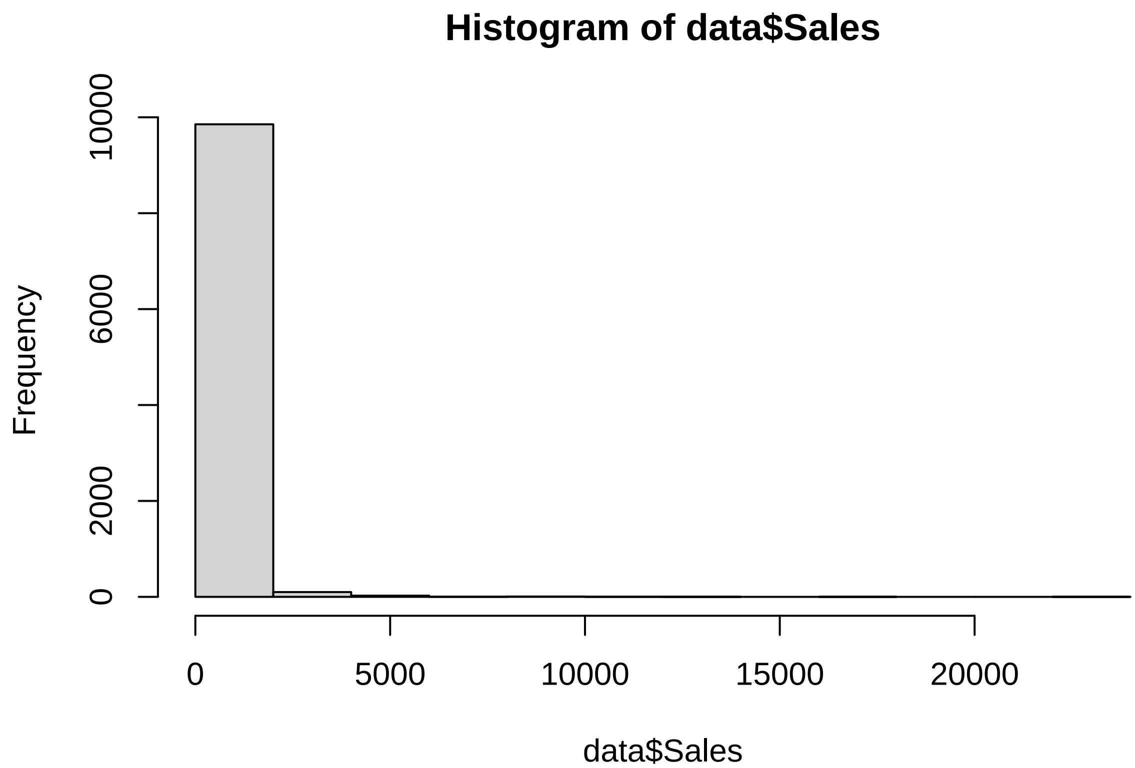

```
#The time difference between order date and ship date typically takes 4 days.

summary(data$Sales)
```

```
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
##     0.444    17.280    54.490   229.858   209.940 22638.480
```

```
boxplot(data$Sales)
```



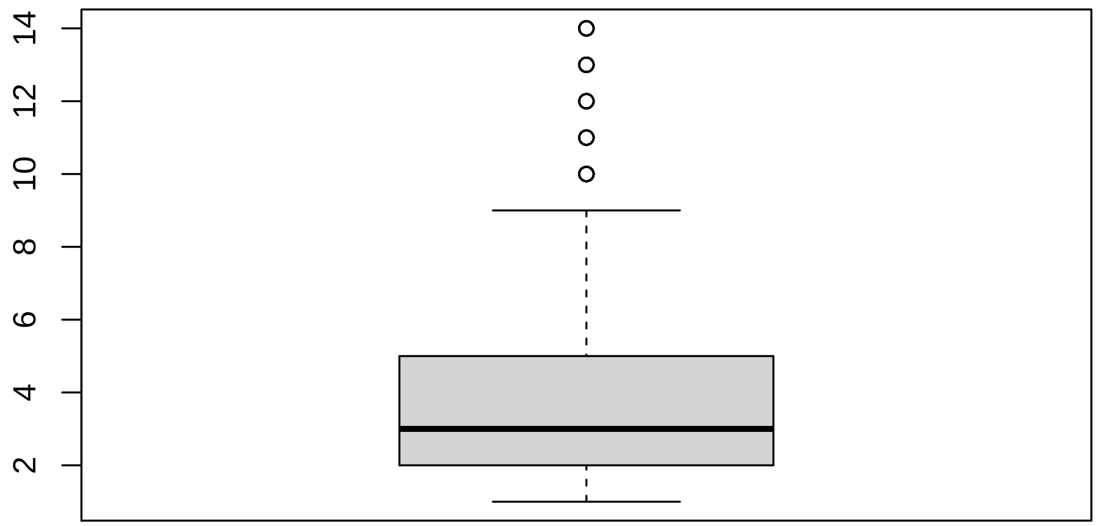

```r
hist(data$Sales)
```



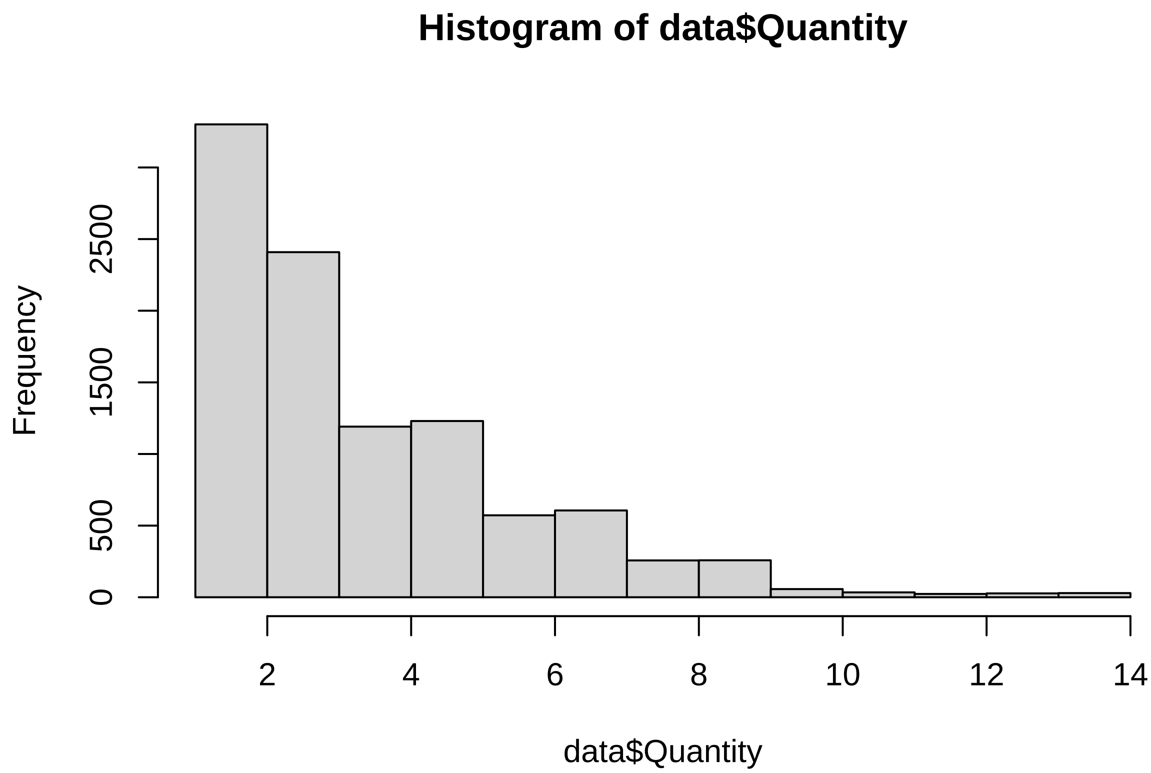

```
#a large amount of orders with very small Sales!

summary(data$Quantity)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00    2.00    3.00    3.79    5.00   14.00
```

```
boxplot(data$Quantity)
```



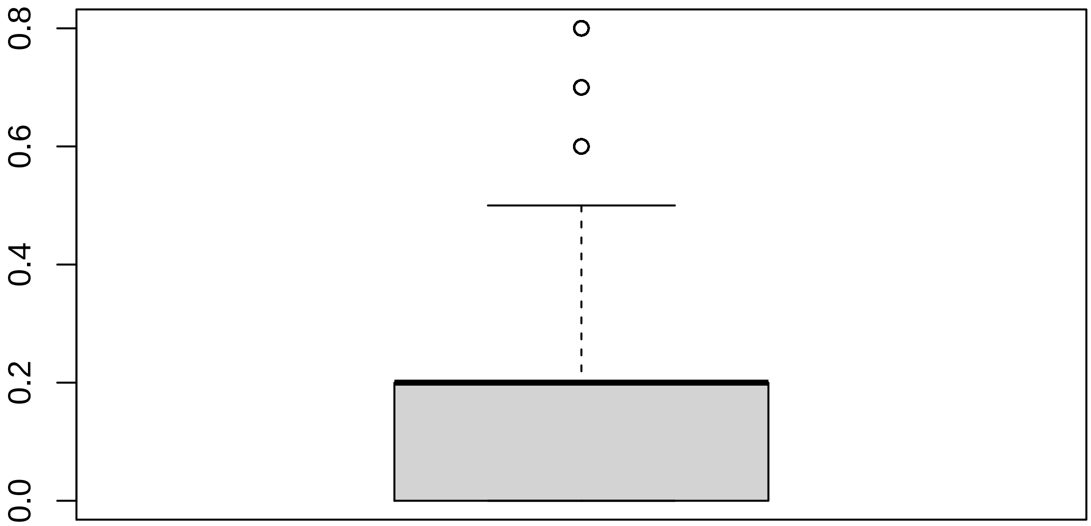

```r
#not many outliers - the #of products in each order is stable?
hist(data$Quantity)
```



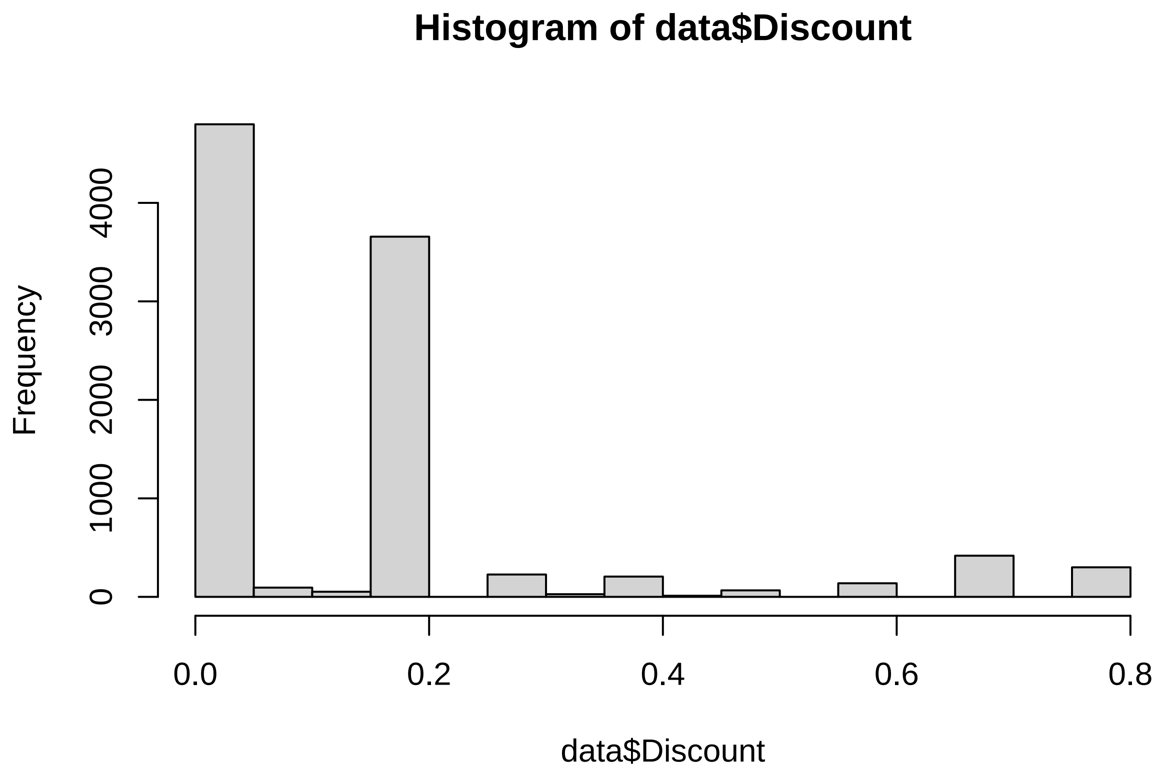

```r
#very skewed distribution - most of the orders have small #of items

summary(data$Discount)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.2000  0.1562  0.2000  0.8000
```

```r
boxplot(data$Discount)
```



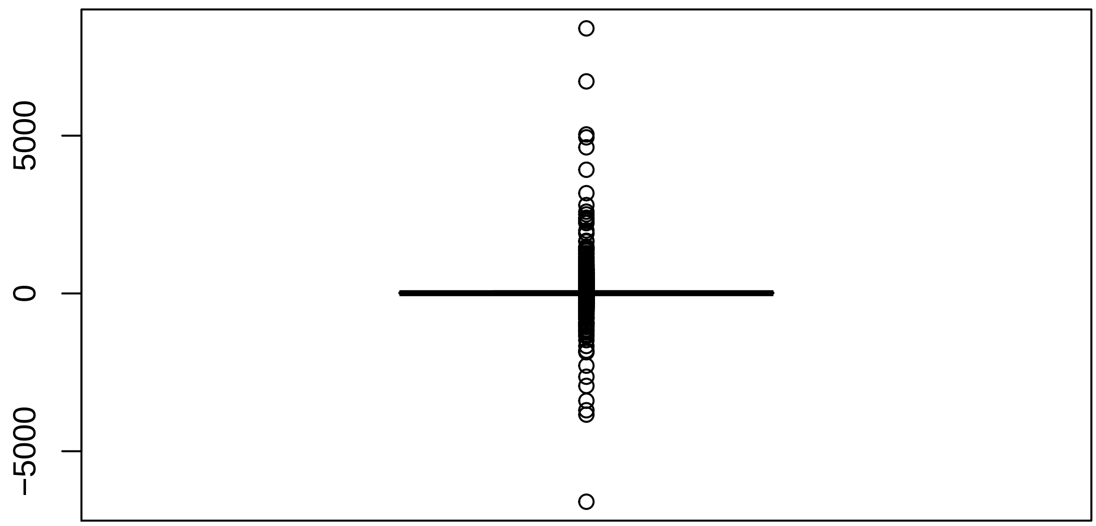

```
#a strange looking box dataplot? - median & 3rd quantile are the same (0.2) - not many orders have high
hist(data$Discount)
```



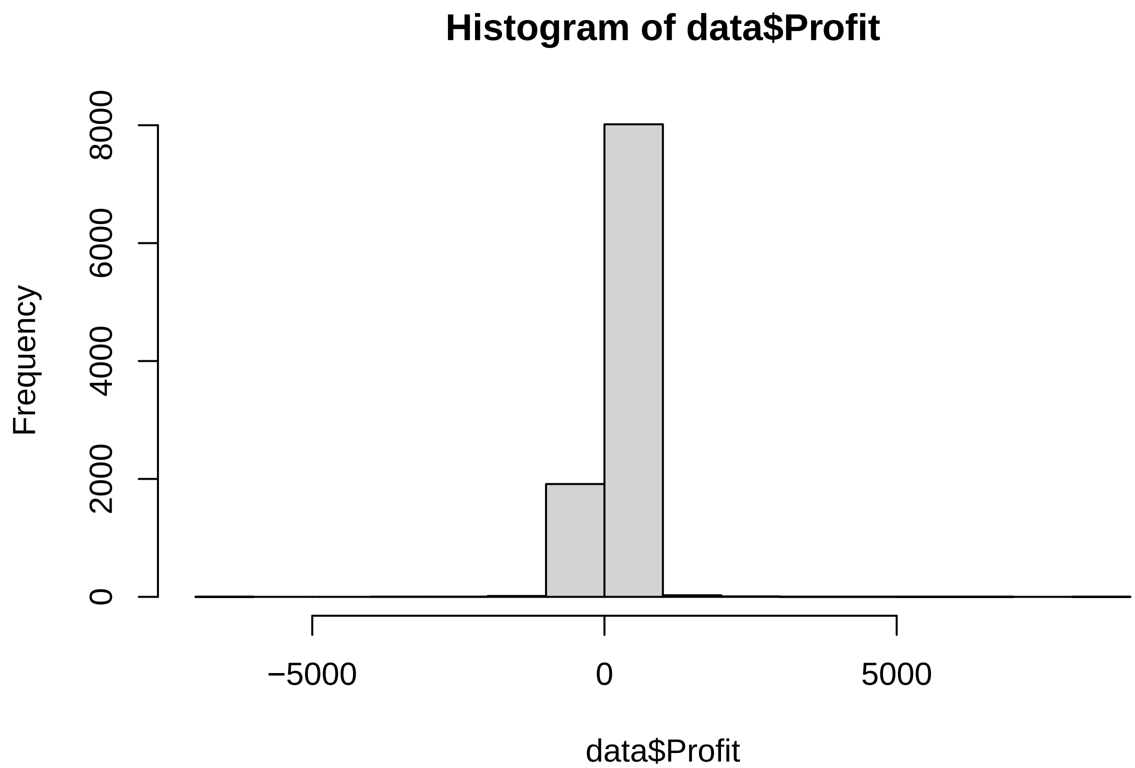

```r
#most of the orders were placed without any discounts or with 20% off

summary(data$Profit)
```

```
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## -6599.978     1.729     8.666    28.657    29.364  8399.976
```

```r
boxplot(data$Profit)
```




```r
#most of the profits are outside of the box - but most of them clustered close to the box(not with so e
hist(data$Profit)
```



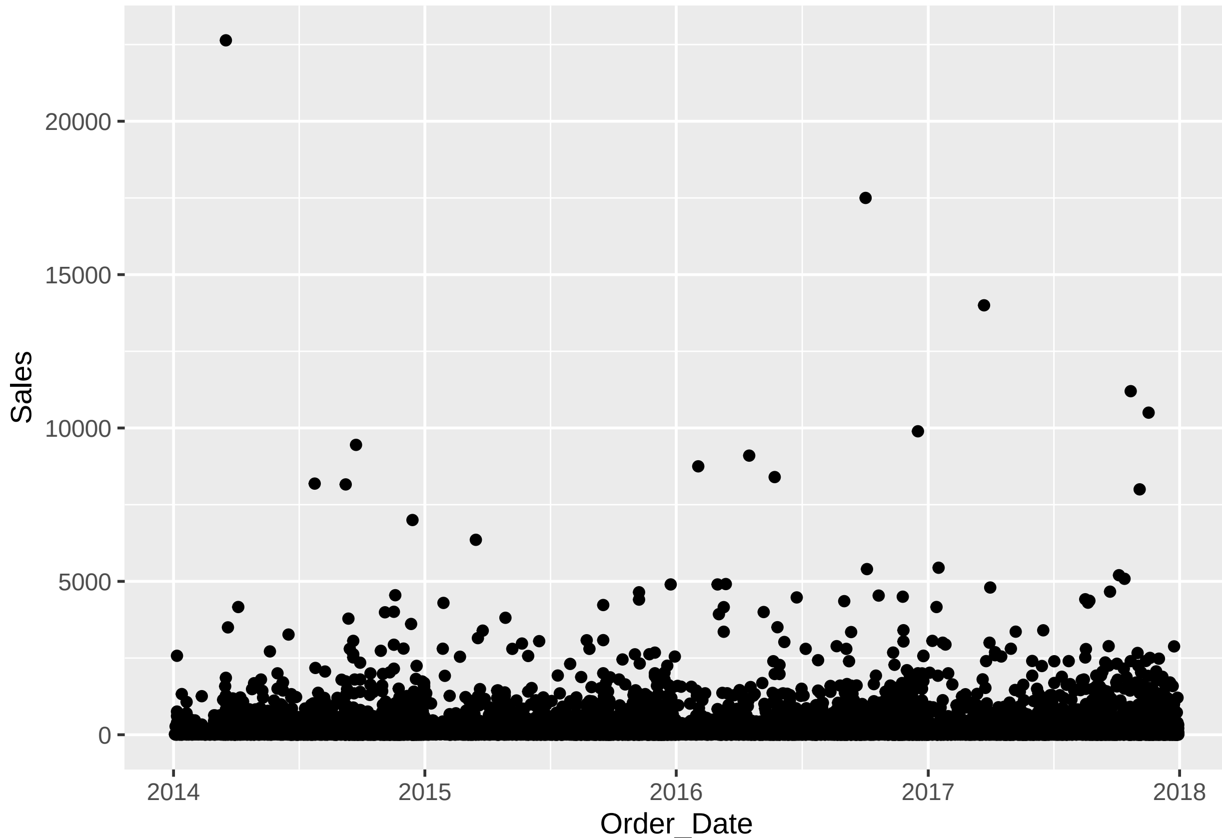

```
#most of the orders have profits ~1000 (or ~800?), and ~ -800
```

Remove the dot in the column names and replace with "_" to make variable names easier to handle:

```
##  [1] "ï__Row_ID"     "Order_ID"      "Order_Date"    "Ship_Date"
##  [5] "Ship_Mode"     "Customer_ID"   "Customer_Name" "Segment"
##  [9] "Country"       "City"          "State"         "Postal_Code"
## [13] "Region"        "Product_ID"    "Category"      "Sub_Category"
## [17] "Product_Name"  "Sales"         "Quantity"      "Discount"
## [21] "Profit"        "diff_in_days"
```

Exploratory Data Analysis

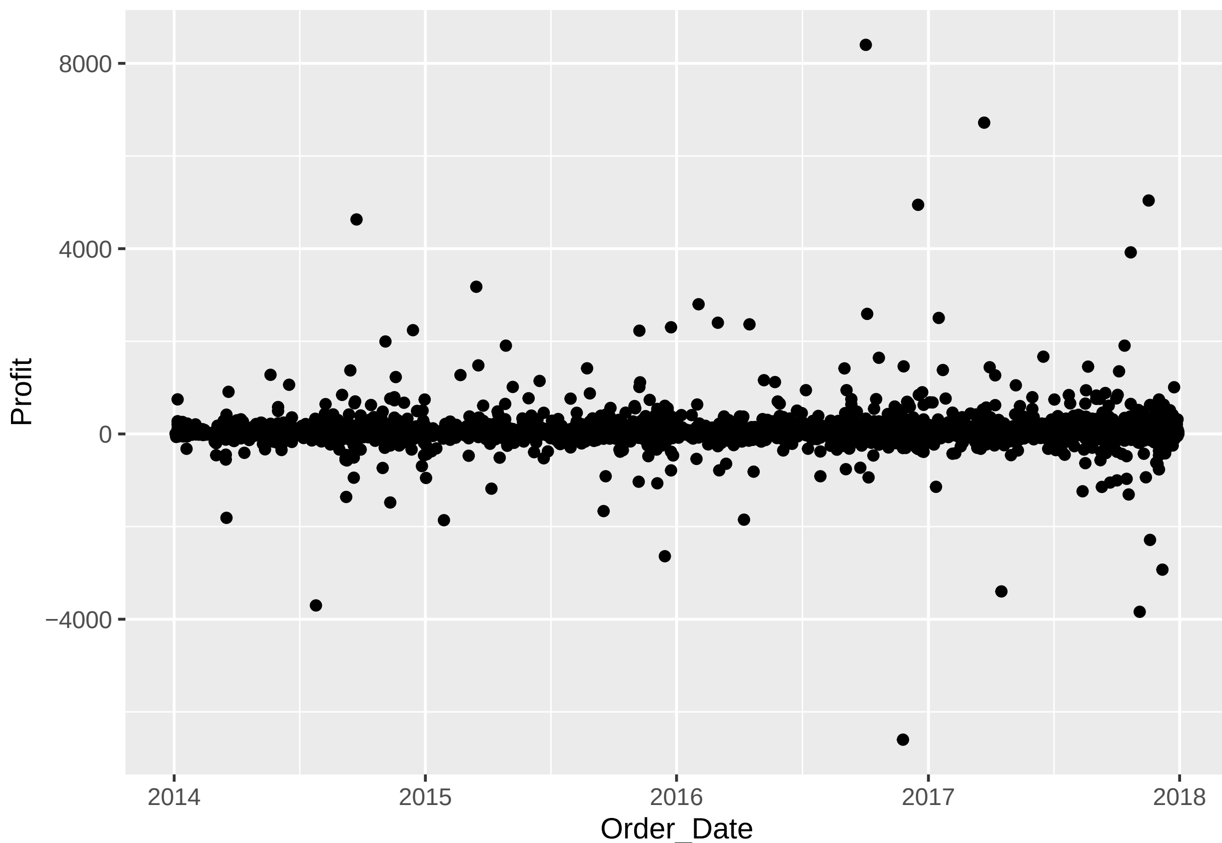
Plot Sales in relation to Order Date:



Plot Profit in relation to Order Date:

```
ggplot(data = data) +
  geom_point(mapping = aes(x = Order_Date, y = Profit), xlab="Order Date", ylab="Profit")
```

```
## Warning: Ignoring unknown parameters: xlab, ylab
```



Some outliers for certain days

```
table(data$`Sub_Category`)
```

```
##
## Accessories  Appliances         Art     Binders   Bookcases      Chairs
##         775         466         796        1523         228         617
##     Copiers   Envelopes   Fasteners Furnishings      Labels    Machines
##          68         254         217         957         364         115
##       Paper      Phones     Storage    Supplies      Tables
##        1370         889         846         190         319
```

look at the time range for these transactions, ie. start date for Order_Date column:

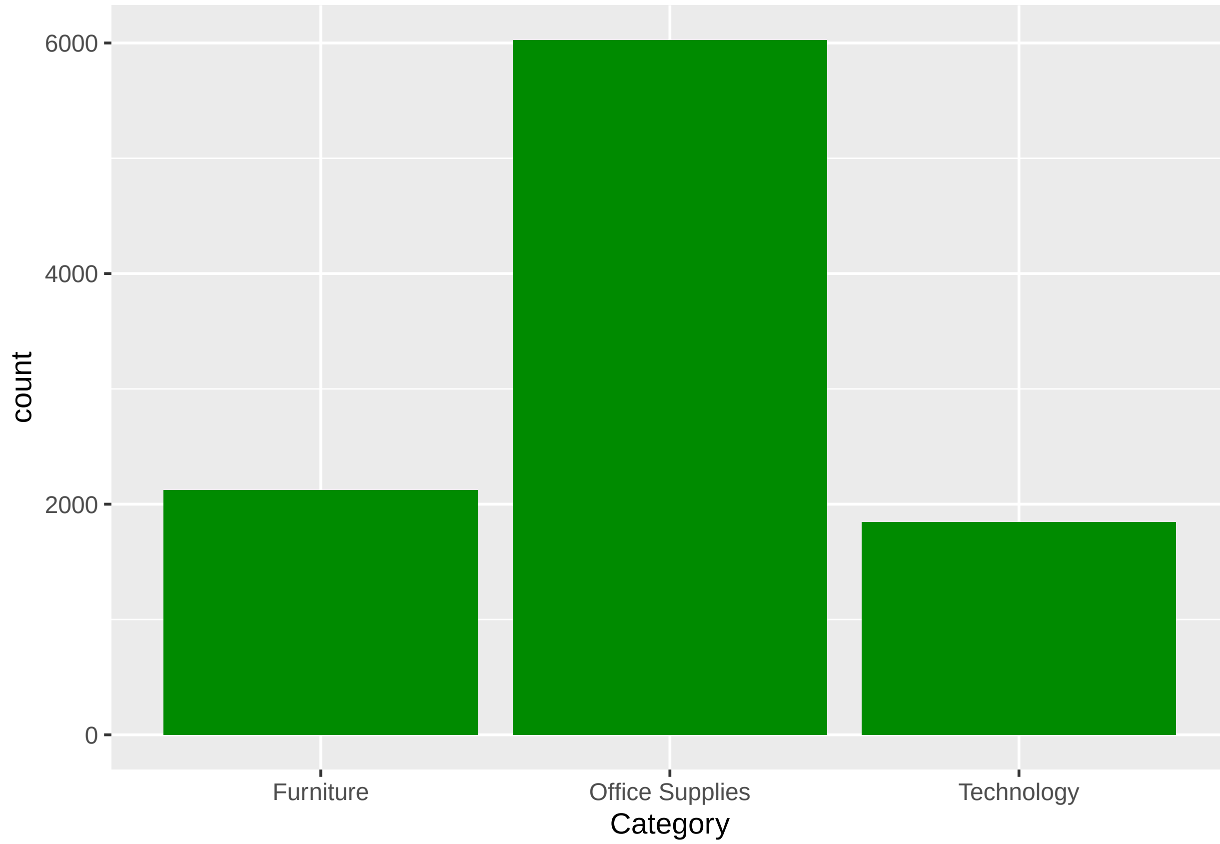
```
summary(data$Order_Date)
```

```
##         Min.      1st Qu.       Median         Mean      3rd Qu.         Max.
## "2014-01-03" "2015-05-23" "2016-06-26" "2016-04-30" "2017-05-14" "2017-12-30"
```

```
#[1] min "2014-01-03", max "2017-12-30"
```

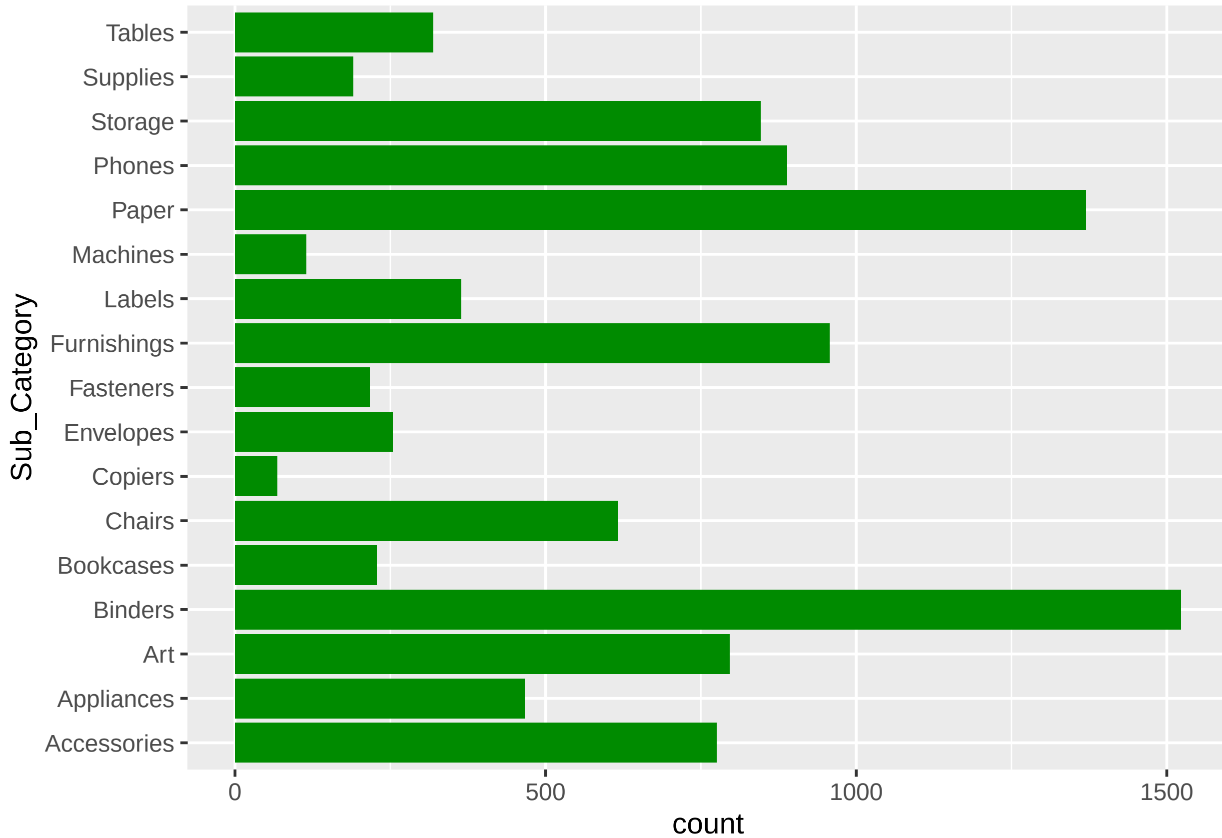
Basically this dataset covers transactions ranging from 2014-01-03 to 2017-12-30.

```r
ggplot(data = data) +
  geom_bar(mapping = aes(x = Category),fill="green4")
```



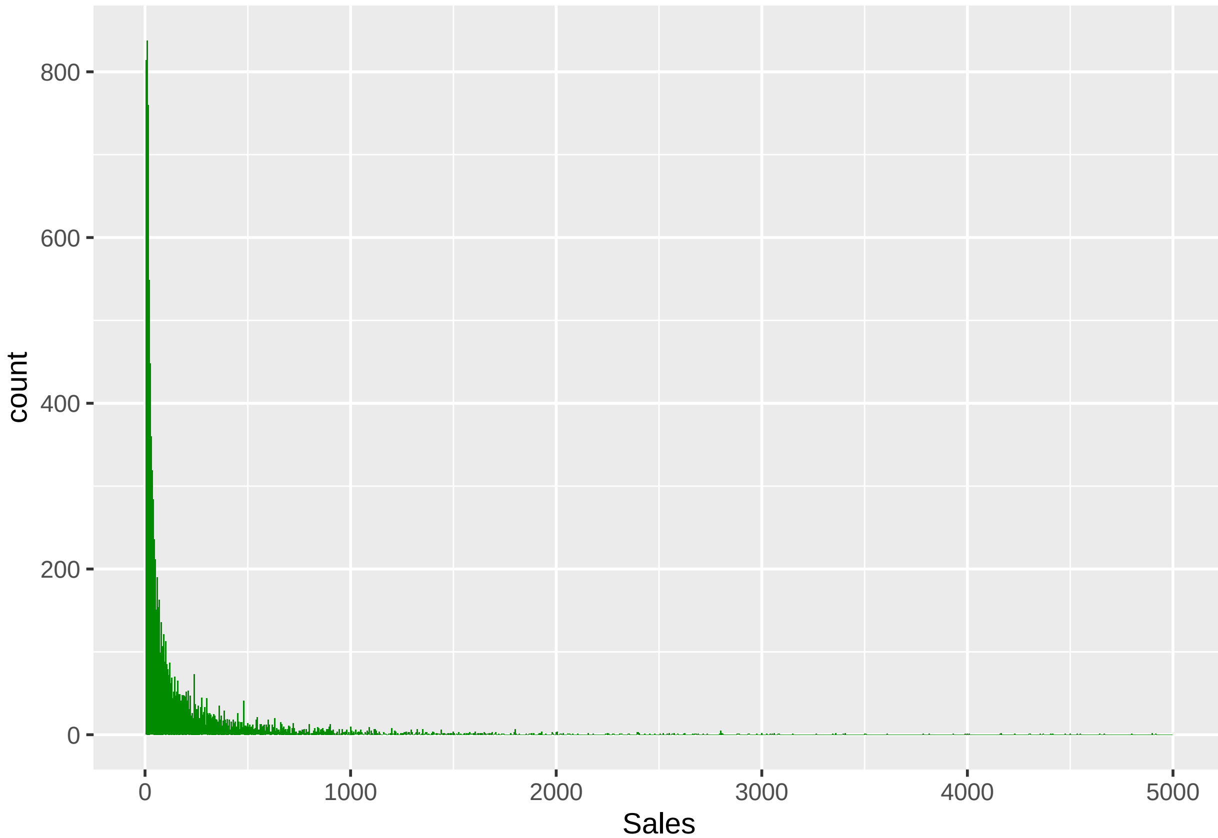
Most type of products sold belong to the Office supplies category.

```r
ggplot(data = data) +
  geom_bar(mapping = aes(y = `Sub_Category`), fill="green4")
```



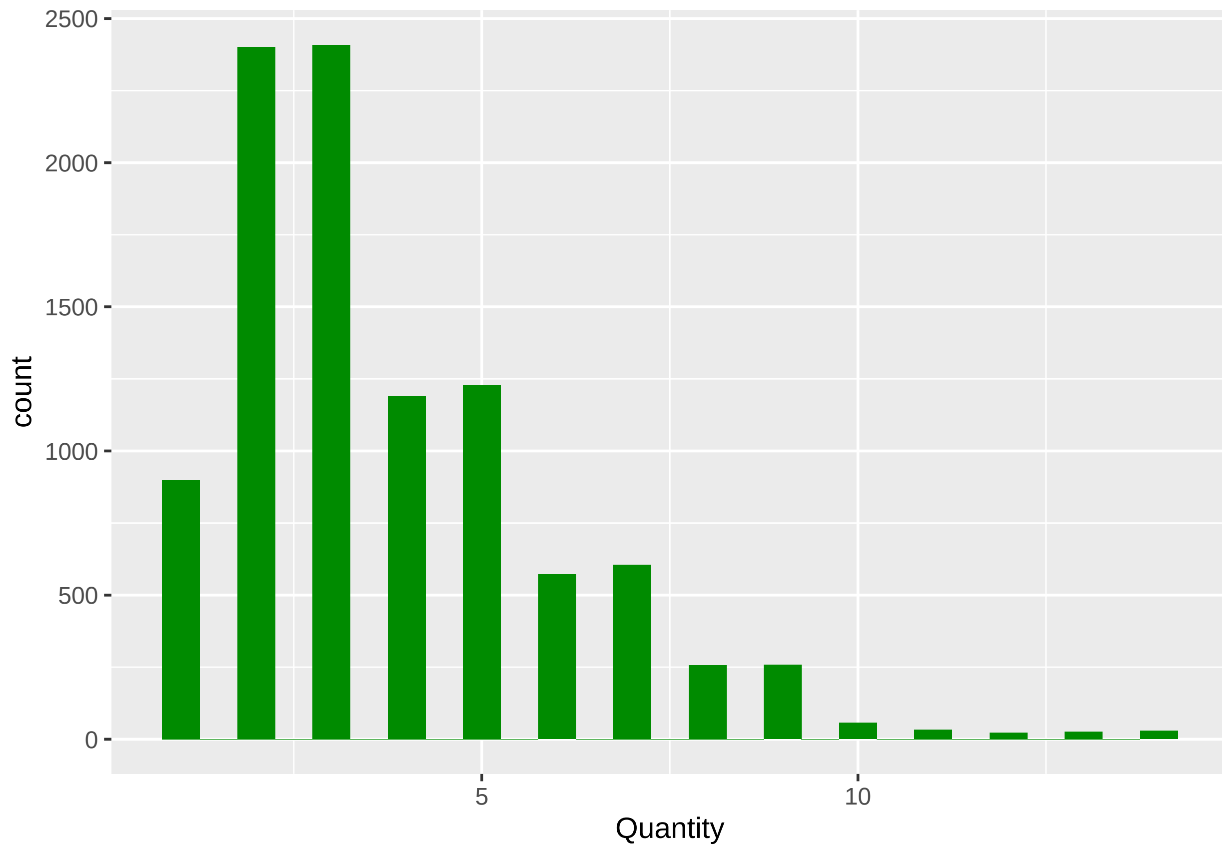

```
ggplot(data = data, mapping = aes(x = Sales)) +
  xlim(0, 5000) +
  geom_histogram(binwidth = 5,fill="green4")
```

```
## Warning: Removed 19 rows containing non-finite values (stat_bin).

## Warning: Removed 2 rows containing missing values (geom_bar).
```



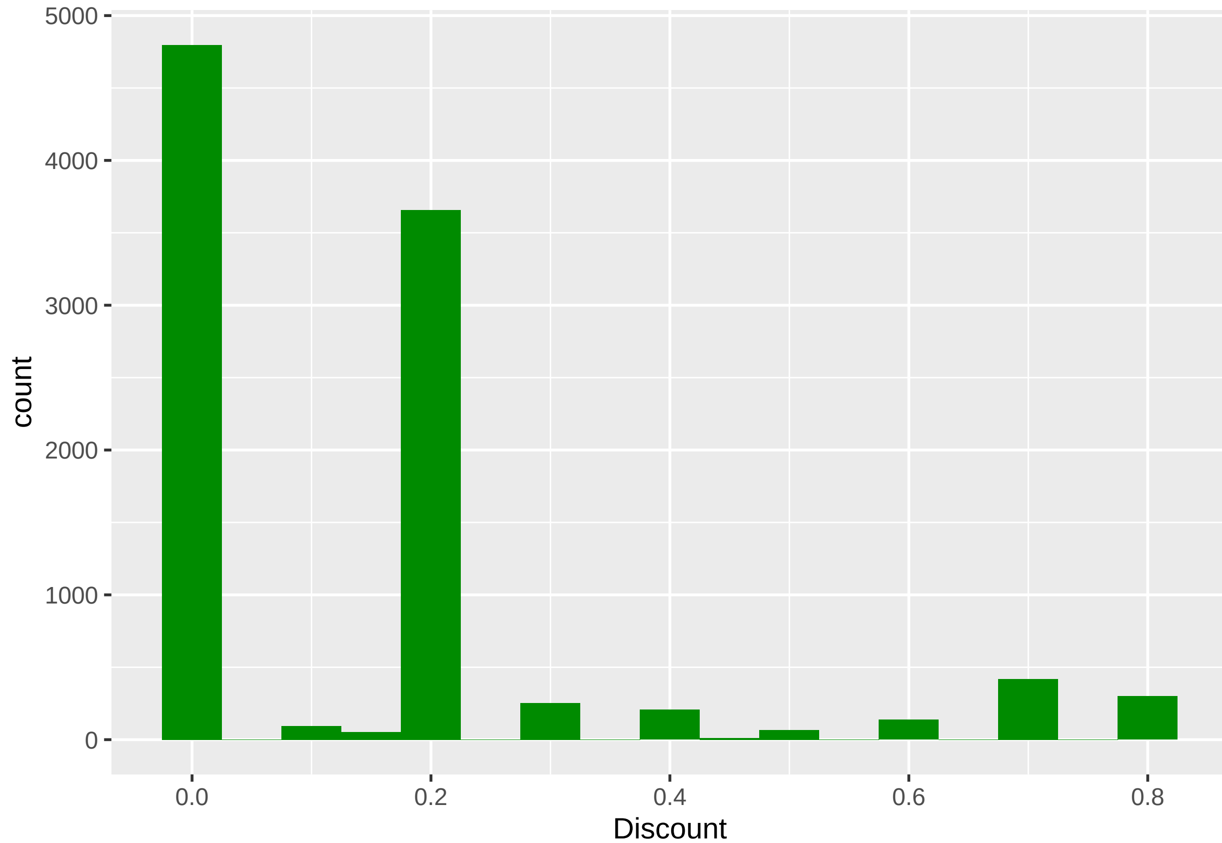
Most sales are very few items (<500).

```
ggplot(data = data, mapping = aes(x = Quantity)) +
  geom_histogram(binwidth = 0.5,fill="green4")
```




```r
ggplot(data = data) +
  geom_histogram(mapping = aes(x = Discount),
                 binwidth = 0.05,
                 xlab="Discount",
                 fill="green4")
```

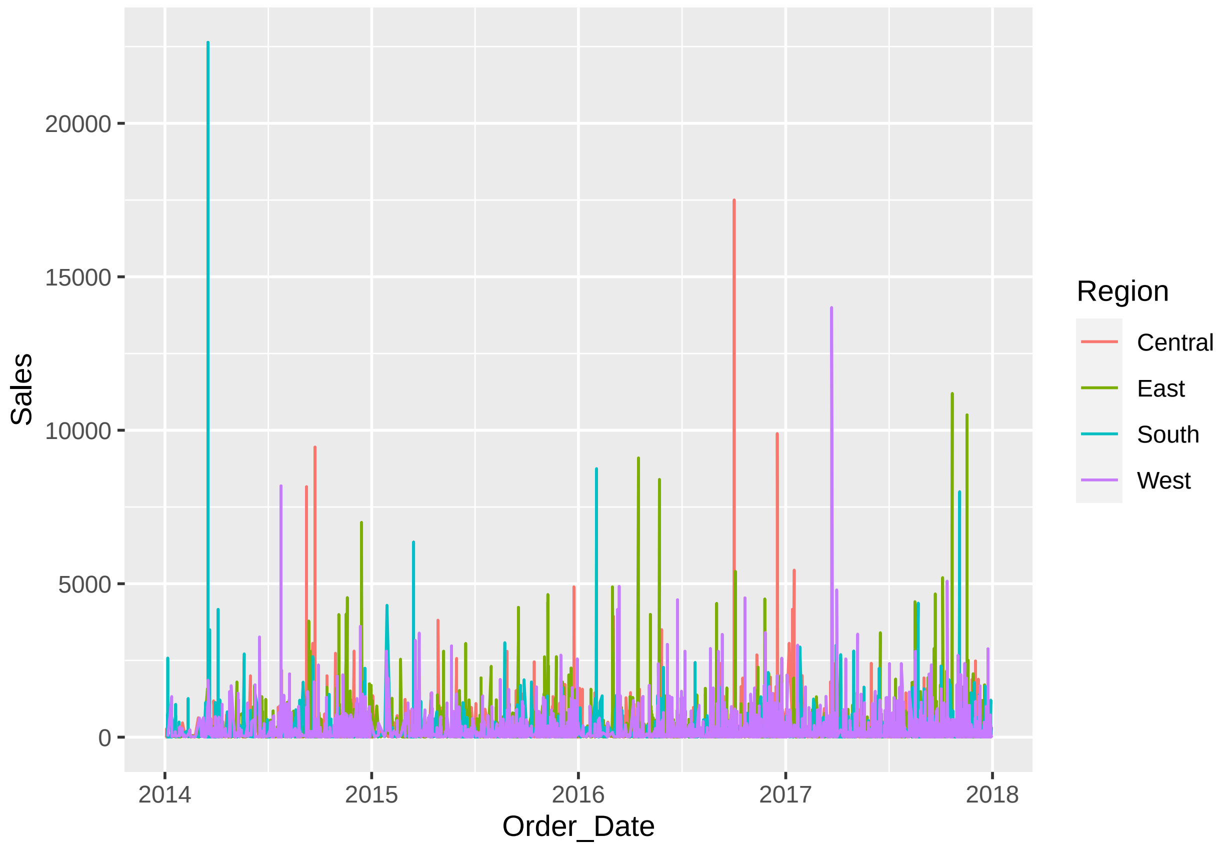
```
## Warning: Ignoring unknown parameters: xlab
```



Sales transactions mostly do not involve discounts.

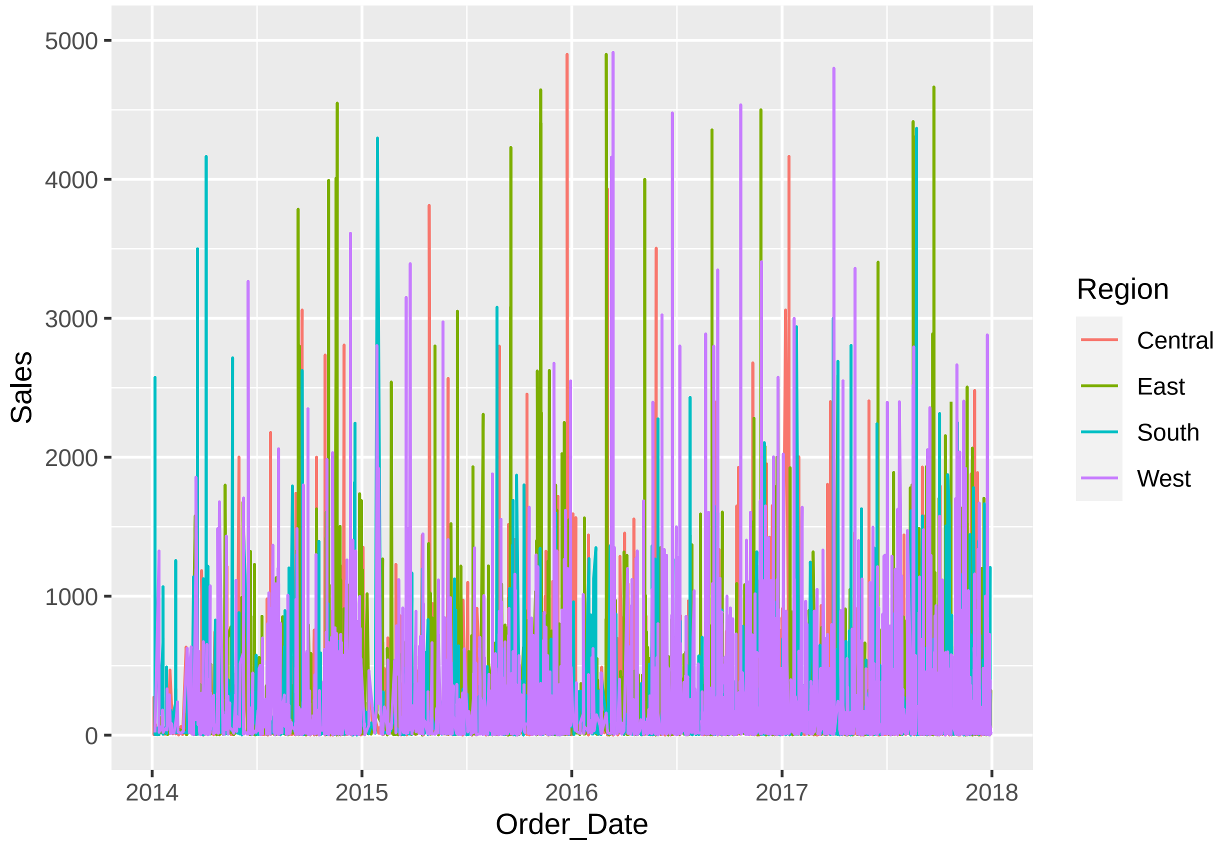
Visualise sales transactions by Region over time (order date).

```
ggplot(data, aes(Order_Date, Sales,color=Region)) +
    geom_line()
```



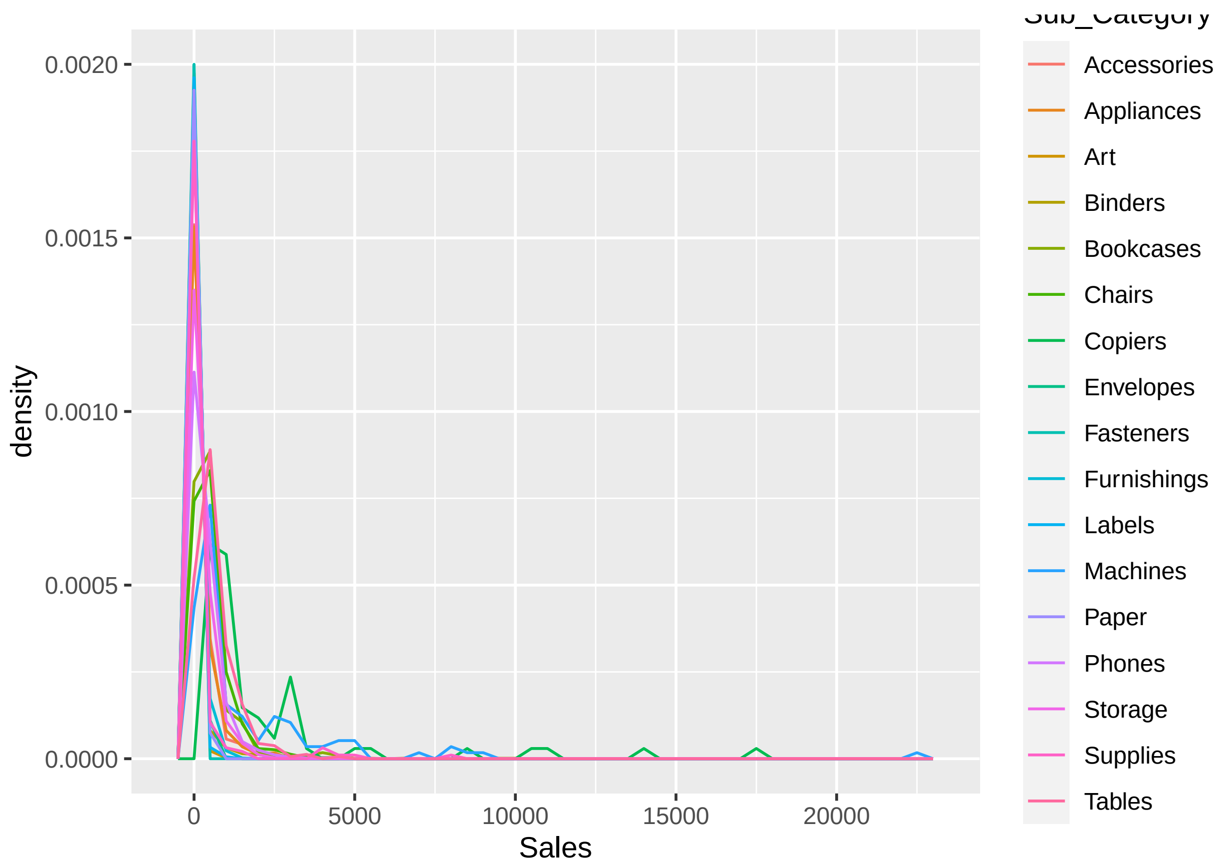
Let's zoom in a little bit - Visualise sales transactions by Region over time (order date).

```
ggplot(data, aes(Order_Date, Sales,color=Region)) +
     geom_line() +
     ylim(0,5000)
```



How does profit change with sub-category?

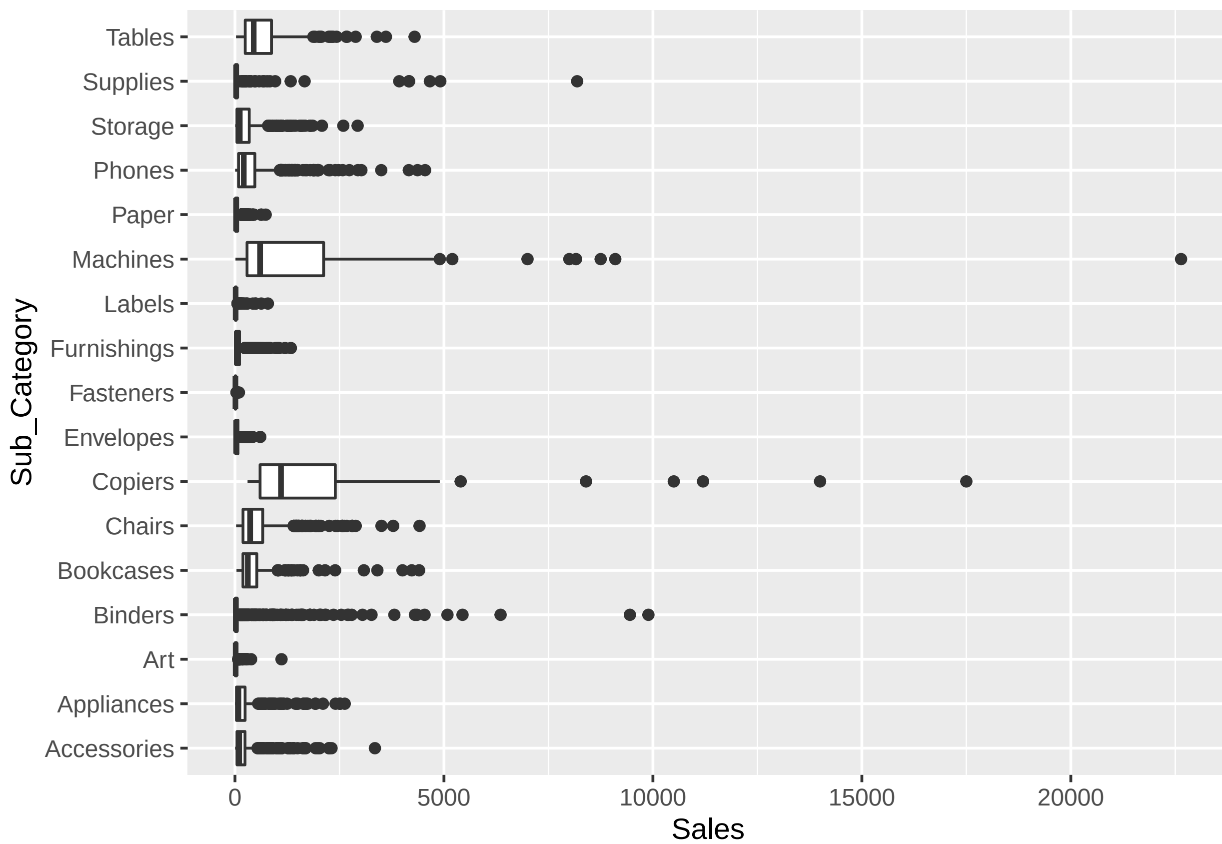
```
#density plot where the count is standardized,area under each frequency is 1
ggplot(data = data, mapping = aes(x = Sales, y = ..density..)) +
  geom_freqpoly(mapping = aes(colour = Sub_Category), binwidth = 500)
```



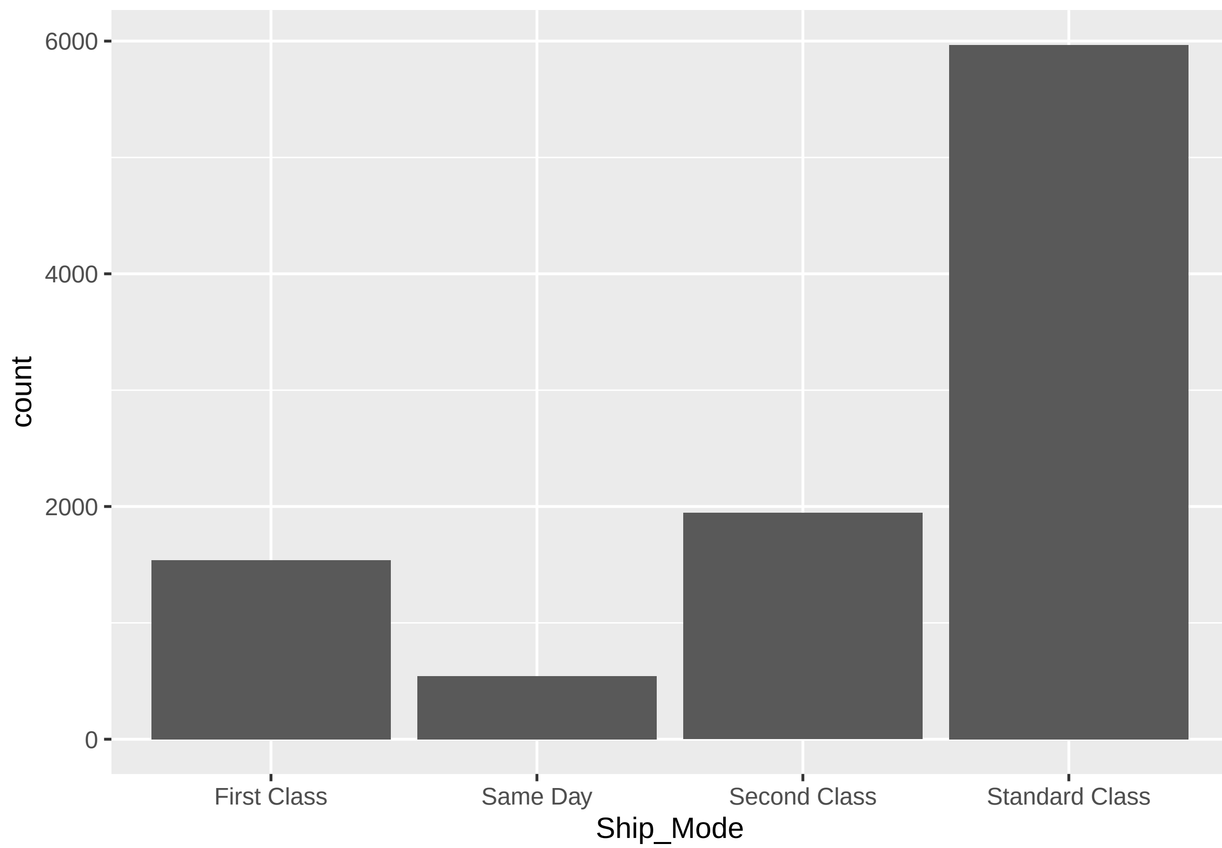
It looks like some categories of items ie. supplies or accessories have negative sales values.

How does sales vary across sub category?

```
ggplot(data = data, mapping = aes(x = Sales, y = `Sub_Category` )) +
  geom_boxplot()
```



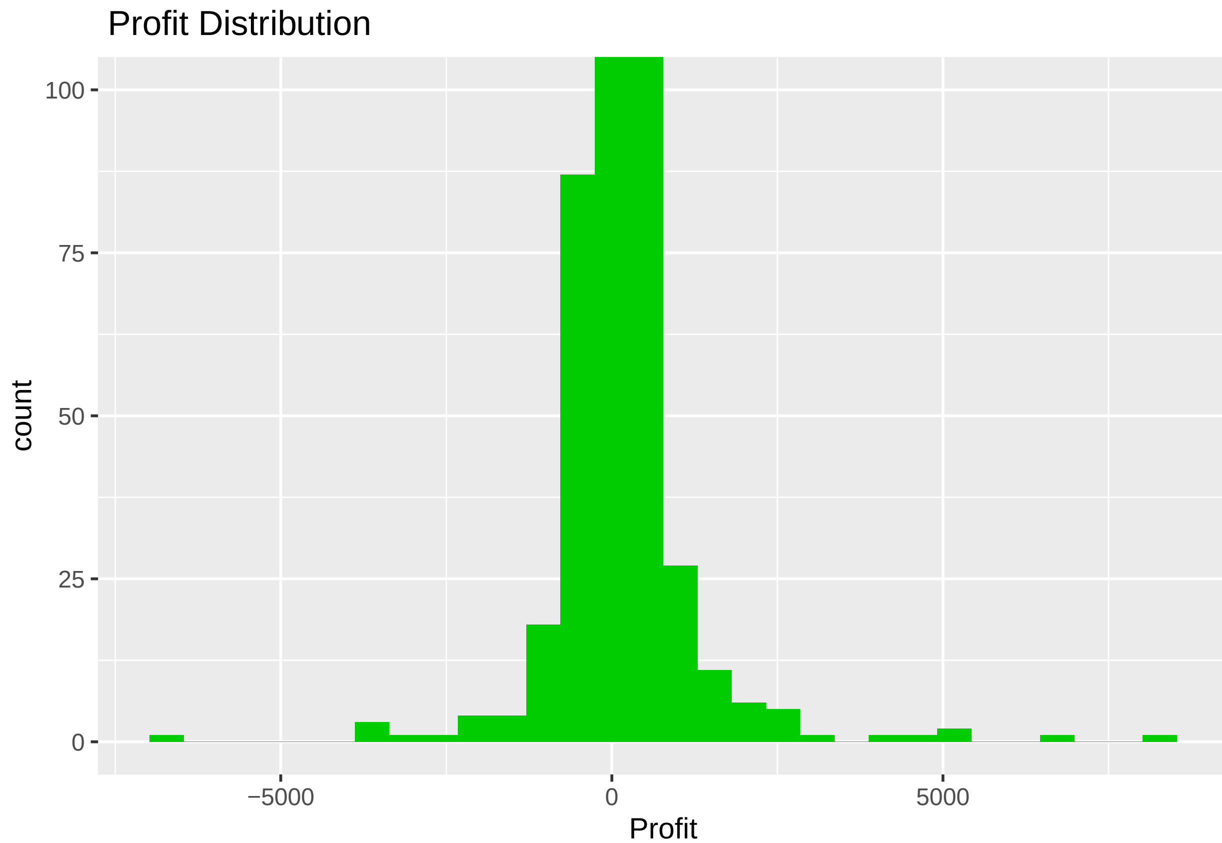

```
ggplot(data =data, mapping = aes(x = Ship_Mode)) +
  geom_bar()
```



Most transactions are shipped via Standard Class method.

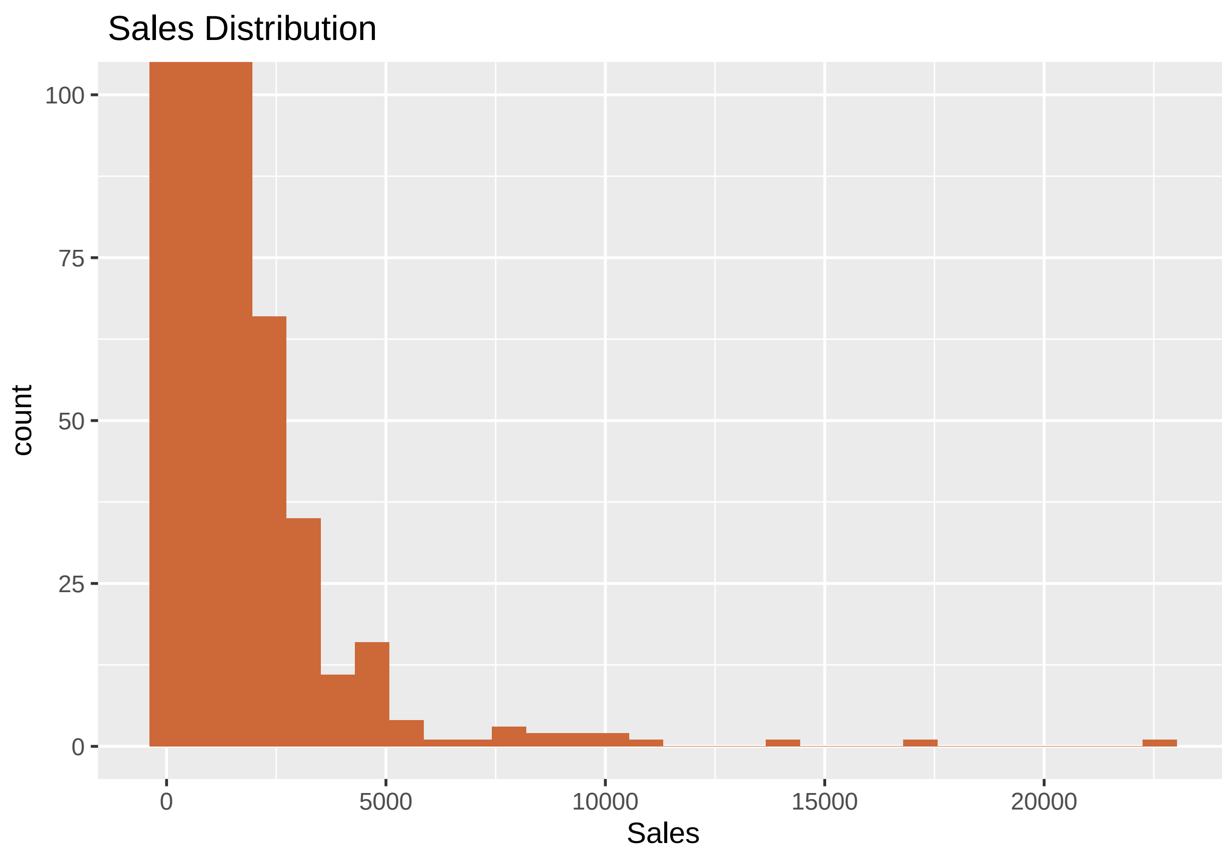
```
ggplot(data)+
geom_histogram(mapping=aes(x=Profit),fill="green3")+
coord_cartesian(ylim = c(0, 100))+
labs(title=" Profit Distribution")
```

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

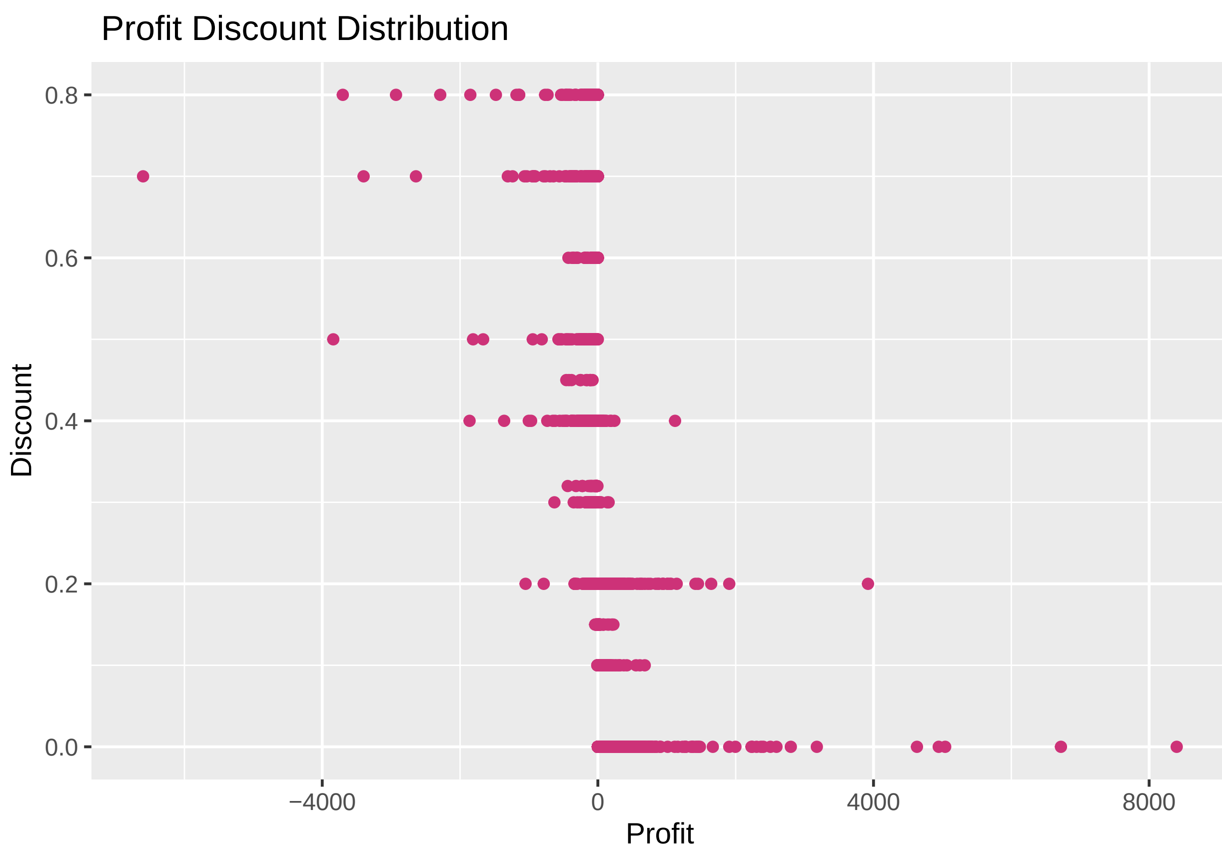



```
ggplot(data)+
geom_histogram(mapping=aes(x=Sales),fill="sienna3")+
coord_cartesian(ylim = c(0, 100))+labs(title=" Sales Distribution")
```

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

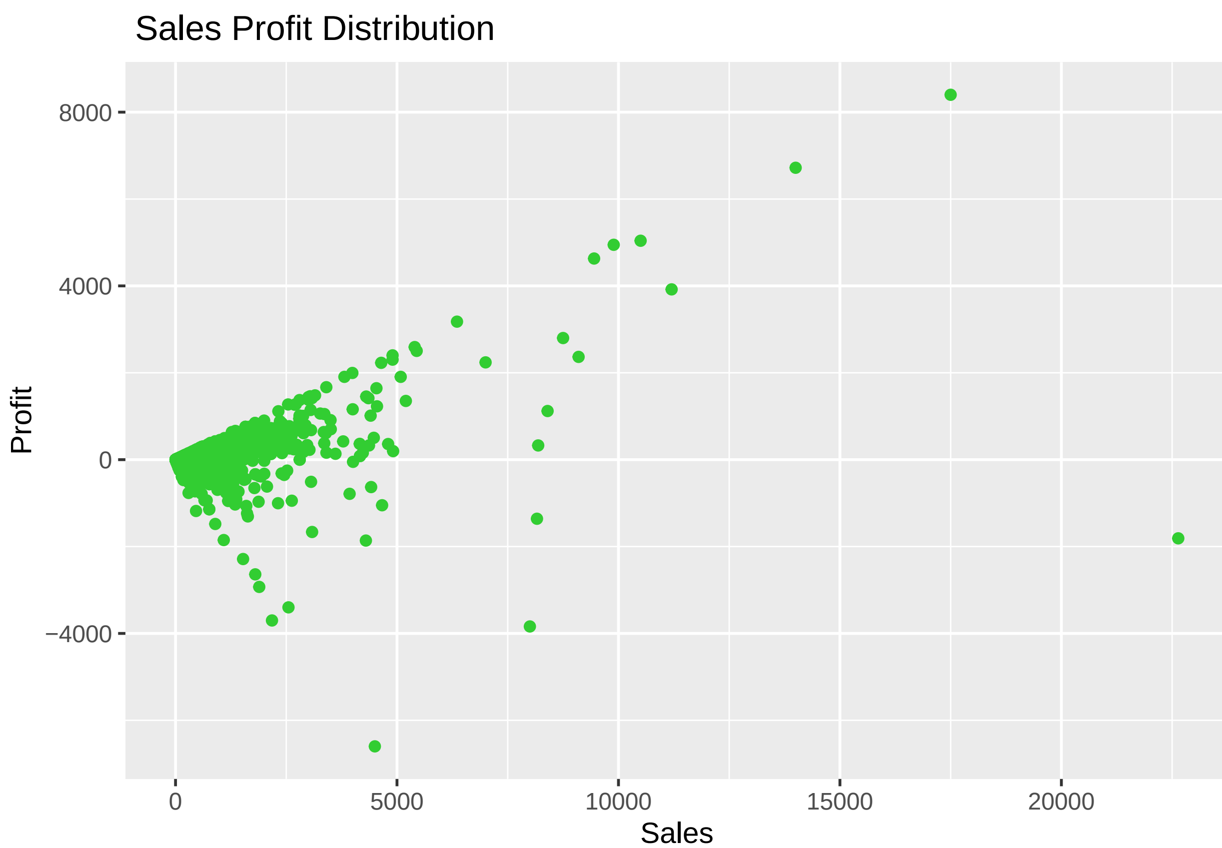



```
ggplot(data) +
geom_point(mapping = aes(x = Profit, y = Discount),colour="violetred3")+
labs(title=" Profit Discount Distribution")
```



Sales Profit

```
ggplot(data) +
geom_point(mapping = aes(x = Sales, y = Profit),colour="limegreen")+
labs(title=" Sales Profit Distribution")
```




```
#product name and product id mismatch
data %>%
  distinct(Product_Name,Product_ID) %>%
  group_by(Product_ID) %>%
  filter(n()>1) %>%
  select(Product_ID)
```

```
## # A tibble: 64 x 1
## # Groups:   Product_ID [32]
##    Product_ID
##    <chr>
##  1 FUR-FU-10004848
##  2 FUR-CH-10001146
##  3 OFF-BI-10004654
##  4 FUR-CH-10001146
##  5 OFF-PA-10002377
##  6 OFF-AR-10001149
##  7 OFF-PA-10000659
##  8 TEC-MA-10001148
##  9 FUR-FU-10004017
## 10 TEC-AC-10003832
## # ... with 54 more rows
```

```
#total category and subcategory
```

```r
count_category<-unique(data$Category)
length(count_category)
```

```
## [1] 3
```

```r
count_subcategory<-unique(data$Sub_Category)
length(count_subcategory)
```

```
## [1] 17
```

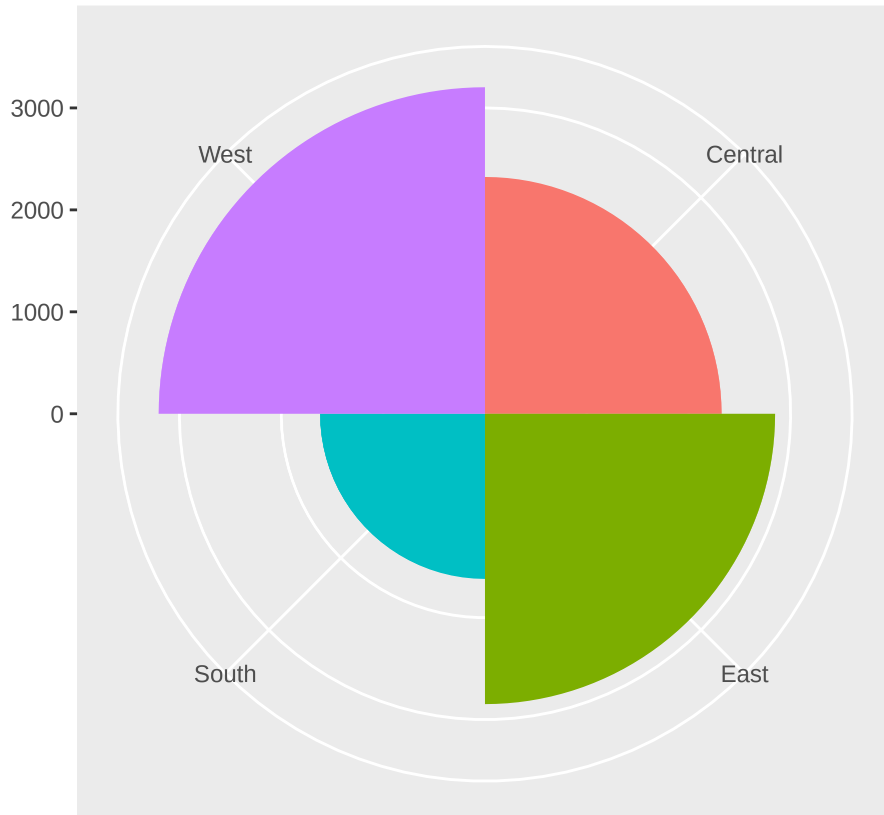
```r
data %>%
  distinct(Category, Sub_Category)
```

```
##           Category Sub_Category
## 1        Furniture    Bookcases
## 2        Furniture       Chairs
## 3  Office Supplies       Labels
## 4        Furniture       Tables
## 5  Office Supplies      Storage
## 6        Furniture  Furnishings
## 7  Office Supplies          Art
## 8       Technology       Phones
## 9  Office Supplies      Binders
## 10 Office Supplies   Appliances
## 11 Office Supplies        Paper
## 12      Technology  Accessories
## 13 Office Supplies    Envelopes
## 14 Office Supplies    Fasteners
## 15 Office Supplies     Supplies
## 16      Technology     Machines
## 17      Technology      Copiers
```

```r
superstore_sales<-data %>%
                  select(Order_Date,Sales)


superstore_sales<-as_tibble(superstore_sales)
```

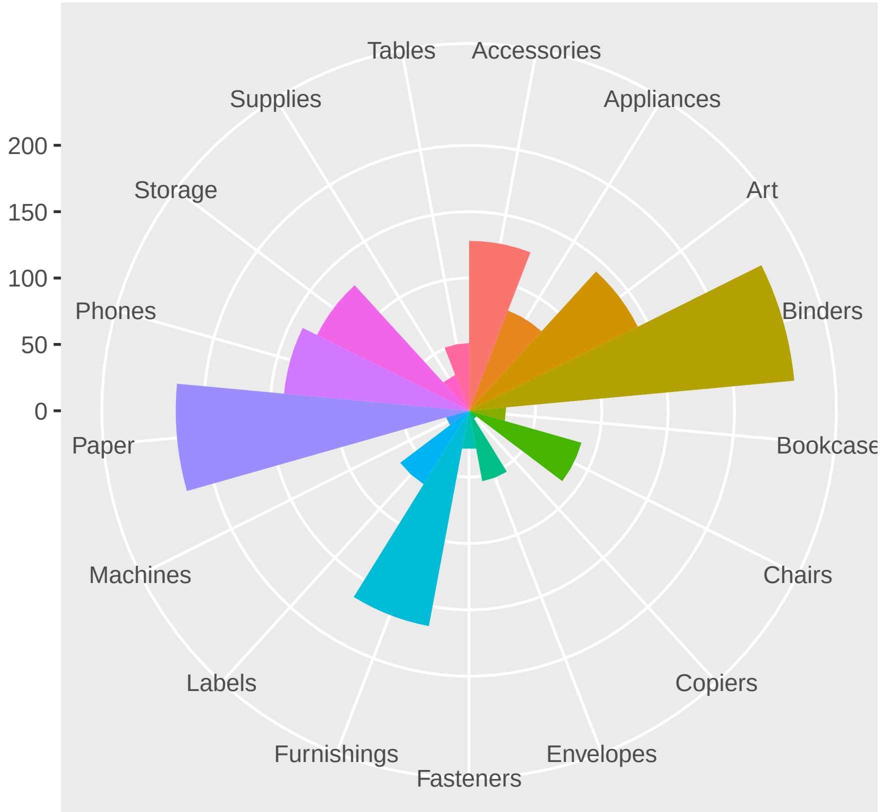
Transactions by region:

```r
bar <- ggplot(data = data) +
  geom_bar(
    mapping = aes(x = Region, fill = Region),
    show.legend = FALSE,
    width = 1
  ) +
  theme(aspect.ratio = 1) +
  labs(x = NULL, y = NULL)

bar + coord_polar()
```



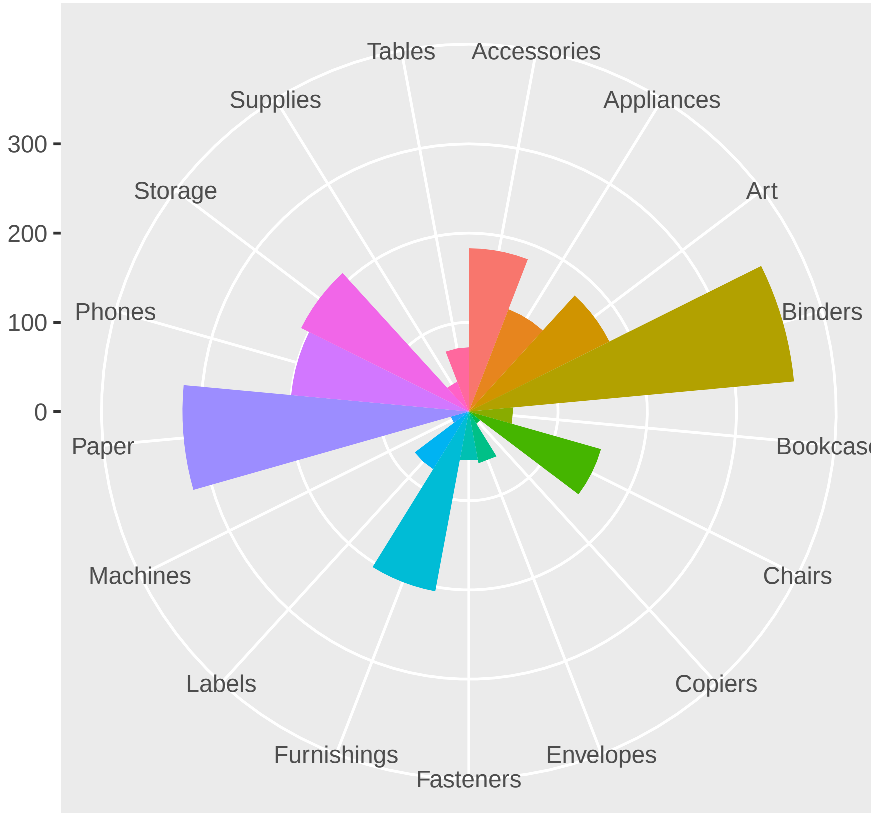
The above chart shows proportions of transactions from the different regions.

```
#Extracting the rows for South region, and sub-categories:
South <- data %>%
  select(Region, Sub_Category) %>%
  filter(Region == "South")

bar <- ggplot(data = South) +
  geom_bar(
    mapping = aes(x = Sub_Category, fill = Sub_Category),
    show.legend = FALSE,
    width = 1
  ) +
  theme(aspect.ratio = 1) +
  labs(x = NULL, y = NULL)

bar + coord_polar()
```

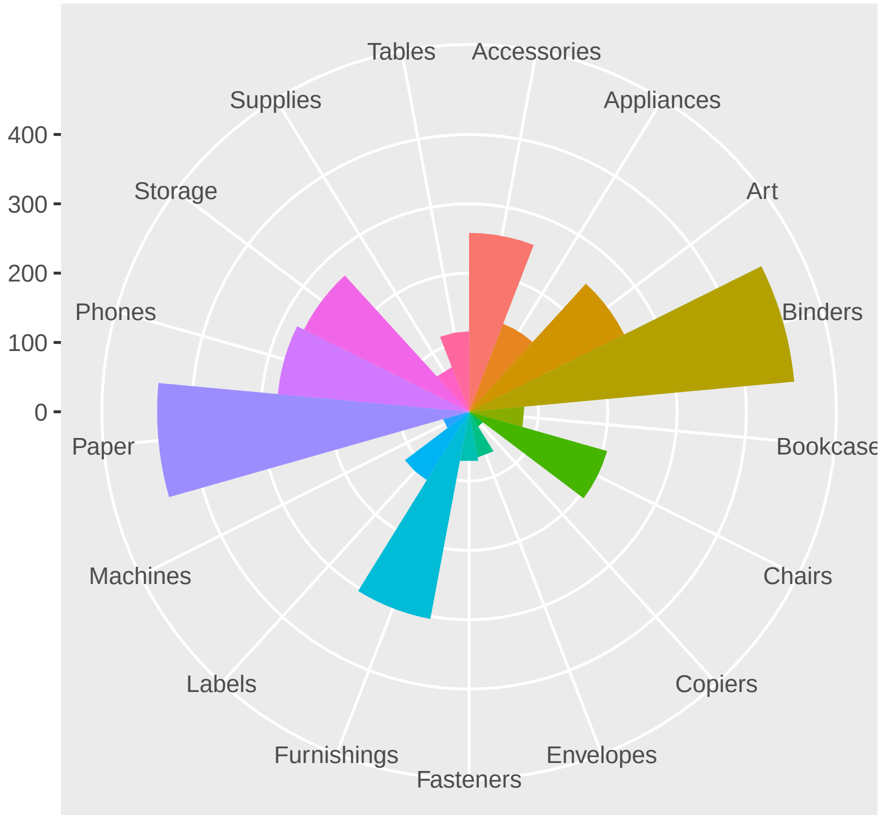


In the South, most transactions are Binders, Paper, or Furnishings.

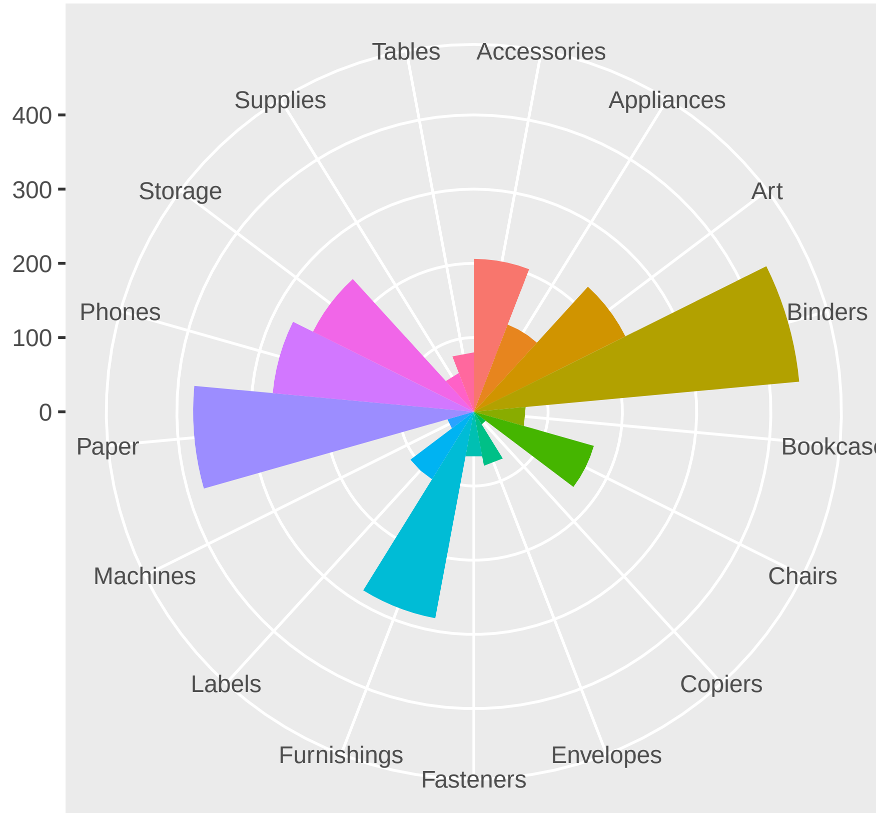
```
#Extracting the rows for Central region, and sub-categories:
Central <- data %>%
  select(Region, Sub_Category) %>%
  filter(Region == "Central")

bar <- ggplot(data = Central) +
  geom_bar(
    mapping = aes(x = Sub_Category, fill = Sub_Category),
    show.legend = FALSE,
    width = 1
  ) +
  theme(aspect.ratio = 1) +
  labs(x = NULL, y = NULL)

bar + coord_polar()
```




```
#Extracting the rows for West region, and sub-categories:
West <- data %>%
  select(Region, Sub_Category) %>%
  filter(Region == "West")

bar <- ggplot(data = West) +
  geom_bar(
    mapping = aes(x = Sub_Category, fill = Sub_Category),
    show.legend = FALSE,
    width = 1
  ) +
  theme(aspect.ratio = 1) +
  labs(x = NULL, y = NULL)

bar + coord_polar()
```

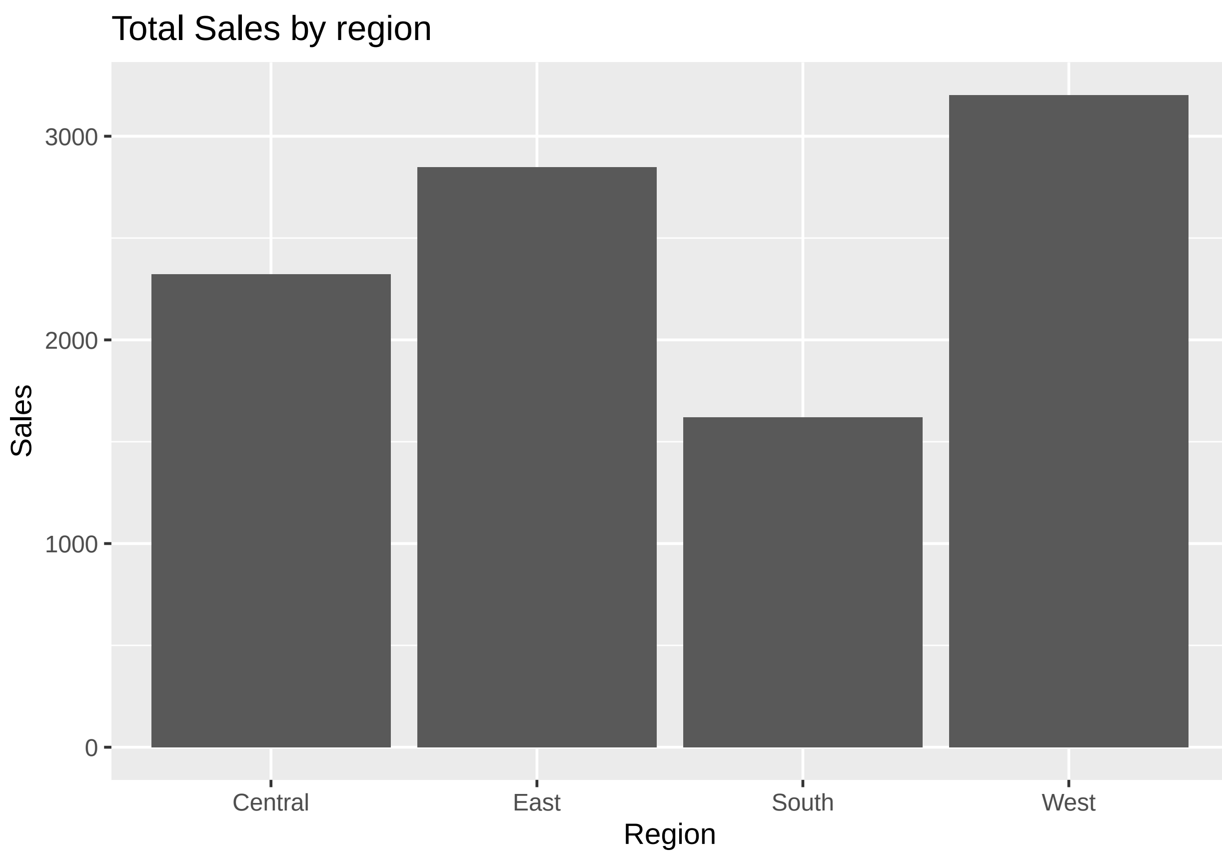



```r
#Extracting the rows for East region, and sub-categories:
East <- data %>%
  select(Region, Sub_Category) %>%
  filter(Region == "East")

bar <- ggplot(data = East) +
  geom_bar(
    mapping = aes(x = Sub_Category, fill = Sub_Category),
    show.legend = FALSE,
    width = 1
  ) +
  theme(aspect.ratio = 1) +
  labs(x = NULL, y = NULL)

bar + coord_polar()
```



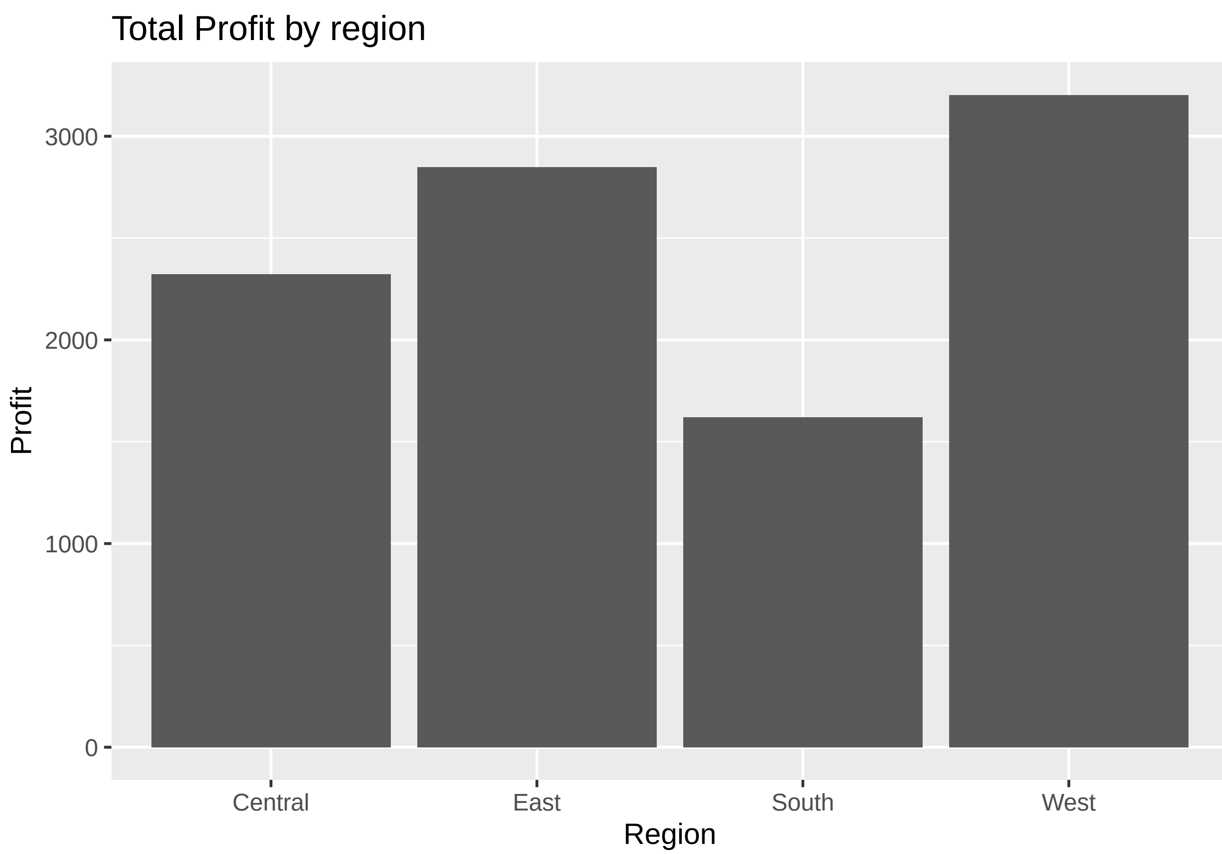
- **bar charts of profits/sales by region**

```
ggplot(data = data) +
  geom_bar(mapping = aes(x = Region, fill = Sales)) +
  ggtitle("Total Sales by region") +
  ylab("Sales")
```



Total sales per region.

```
ggplot(data = data) +
  geom_bar(mapping = aes(x = Region, fill = Profit))+
  ggtitle("Total Profit by region")+
  ylab("Profit")
```



Look at relationship between numeric variables:

```
#subset the numeric variables:
numeric_vars<- c("Sales", "Quantity", "Discount", "Profit", "diff_in_days")
num_data <- data[numeric_vars]
```

We'll use a correlation matrix to look at the relationship between numeric variables:

```
cor(num_data)
```

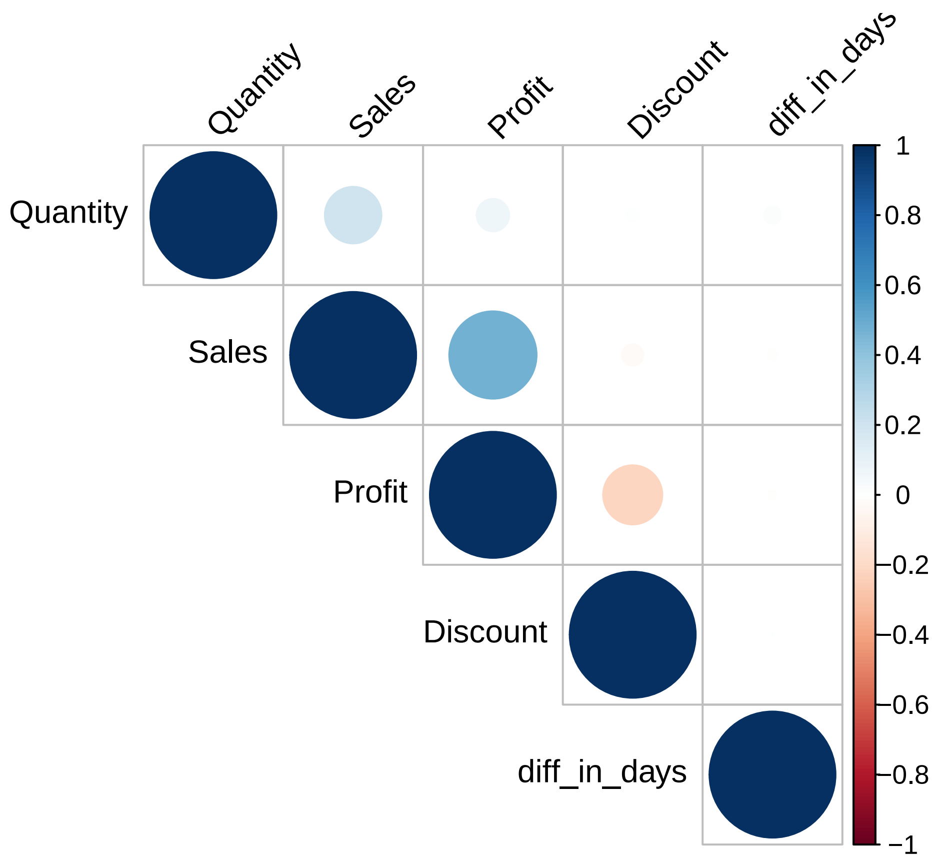
```
##                     Sales   Quantity      Discount       Profit  diff_in_days
## Sales         1.000000000 0.20079477 -0.0281901242  0.479064350 -0.0073535371
## Quantity      0.200794771 1.00000000  0.0086229703  0.066253189  0.0182984399
## Discount     -0.028190124 0.00862297  1.0000000000 -0.219487456  0.0004084856
## Profit        0.479064350 0.06625319 -0.2194874564  1.000000000 -0.0046493531
## diff_in_days -0.007353537 0.01829844  0.0004084856 -0.004649353  1.0000000000
```

```
#correlation matrix with statistical significance
cor_result=rcorr(as.matrix(num_data))

cor_result$r
```

```
##                     Sales   Quantity      Discount       Profit  diff_in_days
## Sales         1.000000000 0.20079477 -0.0281901242  0.479064350 -0.0073535371
## Quantity      0.200794771 1.00000000  0.0086229703  0.066253189  0.0182984399
```

```
## Discount     -0.028190124 0.00862297  1.0000000000 -0.219487456  0.0004084856
## Profit        0.479064350 0.06625319 -0.2194874564  1.000000000 -0.0046493531
## diff_in_days -0.007353537 0.01829844  0.0004084856 -0.004649353  1.0000000000
```

```
corrplot(cor_result$r, type = "upper", order = "hclust", tl.col = "black", tl.srt = 45)  #display only
```



Discount is negatively correlated with profit, whereas sales is positively correlated with profit. The time between order date and ship date (diff_in_days) is not correlated with sales, quantity, discount, or profit.

Since the difference in days between Order date and Ship date has 0 correlation with the other variables, let's drop diff_in_days for the K-means clustering analysis.

Data Preparation

```
#make a copy of the original dataset and copy to data1
data1 <- data
```

drop column Row ID because it is not necessary; it is the row number from the original excel file. The country variable is also not needed because all the values are United states. Customer_Name and Customer_ID give redundant information. So we will drop the Customer_Name column and keep only the Customer_ID column.

```
data1[,c("Row_ID","ï__Row_ID", "Country", "Customer_Name")]<-NULL
```

```r
head(data1)
```

```
##          Order_ID Order_Date  Ship_Date      Ship_Mode Customer_ID   Segment
## 1 CA-2016-152156 2016-11-08 2016-11-11   Second Class    CG-12520  Consumer
## 2 CA-2016-152156 2016-11-08 2016-11-11   Second Class    CG-12520  Consumer
## 3 CA-2016-138688 2016-06-12 2016-06-16   Second Class    DV-13045 Corporate
## 4 US-2015-108966 2015-10-11 2015-10-18 Standard Class    SO-20335  Consumer
## 5 US-2015-108966 2015-10-11 2015-10-18 Standard Class    SO-20335  Consumer
## 6 CA-2014-115812 2014-06-09 2014-06-14 Standard Class    BH-11710  Consumer
##              City      State Postal_Code Region      Product_ID        Category
## 1       Henderson   Kentucky       42420  South FUR-BO-10001798       Furniture
## 2       Henderson   Kentucky       42420  South FUR-CH-10000454       Furniture
## 3     Los Angeles California       90036   West OFF-LA-10000240 Office Supplies
## 4 Fort Lauderdale    Florida       33311  South FUR-TA-10000577       Furniture
## 5 Fort Lauderdale    Florida       33311  South OFF-ST-10000760 Office Supplies
## 6     Los Angeles California       90032   West FUR-FU-10001487       Furniture
##   Sub_Category                                                     Product_Name
## 1    Bookcases                                Bush Somerset Collection Bookcase
## 2       Chairs      Hon Deluxe Fabric Upholstered Stacking Chairs, Rounded Back
## 3       Labels        Self-Adhesive Address Labels for Typewriters by Universal
## 4       Tables                    Bretford CR4500 Series Slim Rectangular Table
## 5      Storage                                   Eldon Fold 'N Roll Cart System
## 6  Furnishings Eldon Expressions Wood and Plastic Desk Accessories, Cherry Wood
##      Sales Quantity Discount    Profit diff_in_days
## 1 261.9600        2     0.00   41.9136            3
## 2 731.9400        3     0.00  219.5820            3
## 3  14.6200        2     0.00    6.8714            4
## 4 957.5775        5     0.45 -383.0310            7
## 5  22.3680        2     0.20    2.5164            7
## 6  48.8600        7     0.00   14.1694            5
```

Model

For this K-means clustering we will use the numeric variables only: which are sales, quantity, discount, profit (columns 15 - 18). K means clustering is affected by the starting assignment points, so we will try with 25 different starting assignments (nstart = 25), and see which ones work the best.

(https://www.datanovia.com/en/blog/k-means-clustering-visualization-in-r-step-by-step-guide/)

```r
#Compute K-means clustering with k=3 (3 initial distinct cluster centres)
set.seed(123)

results_kmeans <- kmeans(scale(data1[,(15:18)]), 3, nstart =25)

#kmeans clusters to show the group of the individuals
results_kmeans$cluster
```

```
##    [1] 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 1
##   [38] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##   [75] 2 1 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2
##  [112] 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [149] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2
```

```
##  [186] 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 1 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 1
##  [223] 2 1 2 2 2 2 2 2 1 1 1 1 2 2 2 2 1 1 2 1 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2
##  [260] 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2
##  [297] 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 1 2 2 2 1 1 1
##  [334] 1 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [371] 2 2 1 2 2 2 2 2 1 2 1 2 2 2 1 2 1 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2
##  [408] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2
##  [445] 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 1 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2
##  [482] 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 1 2 1 2 2 2 2 2 3 2 2 2 2 2 2 2 2
##  [519] 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2
##  [556] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 1 2
##  [593] 2 2 2 2 2 2 2 1 1 2 2 2 1 1 2 1 2 1 2 2 2 1 1 1 2 2 2 2 2 1 2 2 2 2 2 2 2
##  [630] 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 1 2 2 2
##  [667] 2 2 2 1 1 2 2 2 2 2 1 2 1 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2
##  [704] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2
##  [741] 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [778] 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [815] 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [852] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2
##  [889] 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2
##  [926] 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 1 2 2 2 2
##  [963] 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 1 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2
## [1000] 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 1
## [1037] 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 1 2 2 2
## [1074] 1 1 2 2 2 2 2 2 2 1 2 2 3 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 1 2 2 1 1 2 2
## [1111] 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [1148] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2
## [1185] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 1 2
## [1222] 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1
## [1259] 2 2 2 1 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2
## [1296] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 1 2 2 2 2 1 2
## [1333] 1 1 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 1 1 2 2 2 2
## [1370] 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 1 2 2 1
## [1407] 2 2 2 1 2 2 2 2 2 2 2 2 1 2 1 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2
## [1444] 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2
## [1481] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2
## [1518] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2
## [1555] 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2
## [1592] 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [1629] 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2
## [1666] 2 2 2 2 1 2 2 2 2 1 1 2 2 2 1 2 1 2 2 2 1 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2
## [1703] 2 2 1 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2
## [1740] 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 1 2 1 2 2 2 2 2
## [1777] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 1 2 2 2
## [1814] 2 2 2 2 2 1 1 1 2 2 2 1 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2
## [1851] 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2
## [1888] 1 2 1 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 1 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2
## [1925] 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2
## [1962] 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 1 2
## [1999] 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2036] 2 2 2 2 1 1 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
## [2073] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2
## [2110] 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 1 2 1 1 1 2 2 2 1 2 1 2 2
## [2147] 1 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 1 2 1 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2
```

```
## [2184] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2221] 2 1 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2258] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2295] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2332] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 1 2 2 2 2 2
## [2369] 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2406] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 1 1 1 2 2 2 2 2 2 2 1 2 2 2 2
## [2443] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2480] 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 1 1 2 2 3 2 1 2 2 2 2 1 2 2 2
## [2517] 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2554] 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2591] 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 3 2 2 2
## [2628] 2 1 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2665] 1 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 1 1 2 2 1 2 2 2 2 2 1 3 2 2 2
## [2702] 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 1 1 1 2 2 2 2 2 2 2 2 2
## [2739] 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 2 2 2
## [2776] 2 2 2 2 2 2 2 2 1 1 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2813] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2
## [2850] 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2
## [2887] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [2924] 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2
## [2961] 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2
## [2998] 2 2 1 2 1 2 2 2 2 2 2 2 2 1 1 1 1 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [3035] 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [3072] 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 1 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2
## [3109] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 1 2 2 2 2 2 2 2 1 2 2 2 2 1 2 1 2 2 2
## [3146] 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2
## [3183] 2 2 2 1 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2
## [3220] 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2
## [3257] 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2
## [3294] 2 1 2 1 2 2 1 2 1 2 1 2 2 2 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 1 2 2 2 2
## [3331] 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2
## [3368] 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 2 2 2 2 2 1 1
## [3405] 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 1 1 2 2 2
## [3442] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [3479] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2
## [3516] 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2
## [3553] 2 1 2 2 2 2 2 2 2 1 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
## [3590] 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2
## [3627] 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [3664] 2 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2
## [3701] 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2
## [3738] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2
## [3775] 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 1 2 2
## [3812] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [3849] 2 2 2 2 1 2 2 1 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2
## [3886] 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 1 1 2 1 2 2 2 1 2 2 1 2 2 2 2
## [3923] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
## [3960] 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [3997] 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2
## [4034] 2 1 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1
## [4071] 1 2 2 2 2 2 2 2 2 2 2 1 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 1 1 2 2 2 2 1
## [4108] 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2
## [4145] 2 2 2 1 2 2 2 2 2 2 1 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
```

```
## [4182] 2 2 2 2 2 1 1 2 2 3 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [4219] 2 2 2 2 2 2 1 1 2 2 2 1 1 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [4256] 1 1 1 2 2 2 2 2 1 2 1 2 1 2 2 2 2 2 2 2 1 2 3 2 2 2 2 2 2 2 2 2 2 1 2 2 2
## [4293] 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2
## [4330] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 1 2 2 1 2 2 2 2 2 2 2
## [4367] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2
## [4404] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2
## [4441] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2
## [4478] 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
## [4515] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 1 2 2
## [4552] 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [4589] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2
## [4626] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [4663] 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 1 2 2 2 2 2 2 2 2 2
## [4700] 2 2 2 1 1 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2
## [4737] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [4774] 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2 1 1 1 2 2 2 2 2 2
## [4811] 2 2 2 2 2 2 2 2 2 2 1 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 1 2 2 2 2 2
## [4848] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 1 2 2 2 1 2 2 2 2 2
## [4885] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 1 2 2 2 1 1 2 2 2 2 2 2 2 1
## [4922] 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [4959] 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2 1 2 2 2
## [4996] 2 2 1 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5033] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 1 2 2
## [5070] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 1 2 2 2 2 1 1 2 1 1 2 2 2 2 2 2 2 2
## [5107] 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5144] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2
## [5181] 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5218] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2
## [5255] 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2
## [5292] 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2
## [5329] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5366] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2
## [5403] 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2
## [5440] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 1 2 2
## [5477] 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2
## [5514] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 1 1 2 2 2 2 2
## [5551] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 1 2 2 2 2 2 2 2 2 2 2 2
## [5588] 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5625] 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2
## [5662] 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1
## [5699] 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5736] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5773] 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5810] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2
## [5847] 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5884] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5921] 2 2 2 1 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
## [5958] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5995] 2 2 2 1 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [6032] 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2
## [6069] 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [6106] 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2
## [6143] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
```

```
## [6180] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2
## [6217] 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 2
## [6254] 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2
## [6291] 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [6328] 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2
## [6365] 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [6402] 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 3 1 2 1 2 1 1 2 2 2 2 2 2
## [6439] 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [6476] 1 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2
## [6513] 2 2 2 2 2 2 2 2 3 2 2 2 1 1 1 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2 2 2
## [6550] 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [6587] 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [6624] 2 2 2 3 2 2 1 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 1 2 1 2 2 1 2 2 2 2 2 2 2 1
## [6661] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2
## [6698] 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2
## [6735] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2
## [6772] 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1 2 2 2 2 2 2 2
## [6809] 1 1 1 2 1 2 1 2 2 2 1 1 2 1 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2
## [6846] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2
## [6883] 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2
## [6920] 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2
## [6957] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2
## [6994] 2 2 2 1 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [7031] 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [7068] 1 2 2 2 2 2 2 1 2 2 1 2 2 1 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
## [7105] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2
## [7142] 2 2 1 1 1 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1
## [7179] 1 2 2 2 2 2 2 2 2 1 1 2 2 1 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2
## [7216] 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 1 2 2 2 2
## [7253] 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 1 2 2 2 2 2 1
## [7290] 2 2 2 1 2 2 2 2 2 1 1 2 1 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 1 2 2 2 2 2 2 2
## [7327] 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 1 2 2 2 2 2 1 1 2 2 2
## [7364] 1 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2
## [7401] 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 1 2 1 2 1 2 2 2 1 2 2 2 2 2 2 1 2 2 2
## [7438] 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2
## [7475] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2
## [7512] 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 1 2 2 2 2 2 2 1
## [7549] 1 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [7586] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2
## [7623] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 1 2 2 1 2 2 2 2 2 2 2 2 1
## [7660] 2 1 1 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2
## [7697] 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [7734] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [7771] 2 1 1 2 2 2 2 2 2 2 2 1 2 1 2 2 1 2 1 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [7808] 1 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [7845] 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2
## [7882] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 3 2 2 2
## [7919] 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 1 2 2 1 2 2 2 2 2
## [7956] 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 1 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [7993] 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2
## [8030] 2 1 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2
## [8067] 2 2 2 2 1 2 2 1 1 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [8104] 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 1 2 2 1 2 2 2
## [8141] 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
```

```
## [8178] 2 2 1 1 1 1 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 3 2 1 2 1 2 2 1 2 1
## [8215] 2 1 1 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 1 1 1
## [8252] 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 1 2 2
## [8289] 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2
## [8326] 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2 2 1
## [8363] 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
## [8400] 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 1
## [8437] 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2 2 1 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2
## [8474] 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2
## [8511] 2 2 1 2 2 2 2 1 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2
## [8548] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2 2
## [8585] 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [8622] 2 2 1 2 2 2 2 2 1 2 1 1 2 1 2 2 2 2 2 1 1 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2
## [8659] 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2
## [8696] 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2
## [8733] 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 1 1 1 2
## [8770] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [8807] 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [8844] 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 1 2 2 2
## [8881] 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 1
## [8918] 2 1 2 2 2 2 1 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 1 2 2 2 2
## [8955] 2 2 2 1 2 1 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 1 2 1 1 1 1 1 1 2 1 2 2 2 3
## [8992] 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2
## [9029] 2 2 2 2 2 2 1 2 2 2 2 3 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [9066] 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2
## [9103] 2 1 1 2 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 1 1 2 2 1 1 2 2 2 2 2 2 2 1 2
## [9140] 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2
## [9177] 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [9214] 2 2 2 1 2 2 1 2 2 2 1 1 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2
## [9251] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 3 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1
## [9288] 2 2 2 2 2 1 2 2 1 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 1 2
## [9325] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2
## [9362] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [9399] 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [9436] 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2
## [9473] 2 2 2 2 1 1 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [9510] 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2
## [9547] 2 2 1 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 1 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2
## [9584] 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2
## [9621] 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2
## [9658] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2
## [9695] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [9732] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [9769] 2 2 2 2 2 2 1 1 1 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 1 1 2 1 2 2 2 2 2
## [9806] 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 1 1 2 2 2 2 2 2
## [9843] 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 1 1
## [9880] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2
## [9917] 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [9954] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [9991] 2 2 2 2
```

```r
summary(results_kmeans)
```

```
##              Length Class  Mode
```

```
## cluster      9994   -none- numeric
## centers        12   -none- numeric
## totss           1   -none- numeric
## withinss        3   -none- numeric
## tot.withinss    1   -none- numeric
## betweenss       1   -none- numeric
## size            3   -none- numeric
## iter            1   -none- numeric
## ifault          1   -none- numeric
```

```
results_kmeans
```

```
## K-means clustering with 3 clusters of sizes 1136, 8831, 27
##
## Cluster means:
##         Sales     Quantity   Discount     Profit
## 1 -0.05714414  0.045908572  2.3730228 -0.5928228
## 2 -0.02922217 -0.007823215 -0.3039892  0.0425665
## 3 11.96210167  0.627210176 -0.4157497 11.0200717
##
## Clustering vector:
##    [1] 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 1
##   [38] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##   [75] 2 1 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2
##  [112] 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [149] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2
##  [186] 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 1 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 1
##  [223] 2 1 2 2 2 2 2 2 1 1 1 1 2 2 2 2 1 1 2 1 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2
##  [260] 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2
##  [297] 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 1 2 2 2 1 1 1
##  [334] 1 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [371] 2 2 1 2 2 2 2 2 1 2 1 2 2 2 1 2 1 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2
##  [408] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2
##  [445] 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 1 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2
##  [482] 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 1 2 1 2 2 2 2 2 3 2 2 2 2 2 2 2 2
##  [519] 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2
##  [556] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 1 2
##  [593] 2 2 2 2 2 2 2 1 1 2 2 2 1 1 2 1 2 1 2 2 2 1 1 1 2 2 2 2 2 1 2 2 2 2 2 2 2
##  [630] 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 1 2 2 2
##  [667] 2 2 2 1 1 2 2 2 2 2 1 2 1 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2
##  [704] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2
##  [741] 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [778] 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [815] 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [852] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2
##  [889] 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2
##  [926] 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 1 2 2 2 2
##  [963] 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 1 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2
## [1000] 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 1
## [1037] 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 1 2 2 2
## [1074] 1 1 2 2 2 2 2 2 2 1 2 2 3 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 1 2 2 1 1 2 2
## [1111] 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [1148] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2
## [1185] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 1 2
```

```
## [1222] 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1
## [1259] 2 2 2 1 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2
## [1296] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 1 2 2 2 2 1 2
## [1333] 1 1 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 1 1 2 2 2 2
## [1370] 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 1 2 2 1
## [1407] 2 2 2 1 2 2 2 2 2 2 2 2 1 2 1 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2
## [1444] 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2
## [1481] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2
## [1518] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2
## [1555] 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2
## [1592] 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [1629] 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2
## [1666] 2 2 2 2 1 2 2 2 2 1 1 2 2 2 1 2 1 2 2 2 1 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2
## [1703] 2 2 1 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2
## [1740] 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 1 2 1 2 2 2 2 2
## [1777] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 1 2 2 2
## [1814] 2 2 2 2 2 1 1 1 2 2 2 1 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2
## [1851] 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2
## [1888] 1 2 1 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 1 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2
## [1925] 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2
## [1962] 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 1 2
## [1999] 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2036] 2 2 2 2 1 1 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
## [2073] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2
## [2110] 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 1 2 1 1 1 2 2 2 1 2 1 2 2
## [2147] 1 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 1 2 1 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2
## [2184] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2221] 2 1 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2258] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2295] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2332] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 1 2 2 2 2 2
## [2369] 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2406] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 1 1 1 2 2 2 2 2 2 2 1 2 2 2 2
## [2443] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2480] 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 1 1 2 2 3 2 1 2 2 2 2 1 2 2 2
## [2517] 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2554] 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2591] 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 3 2 2 2
## [2628] 2 1 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2665] 1 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 1 1 2 2 1 2 2 2 2 2 1 3 2 2 2
## [2702] 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 1 1 1 2 2 2 2 2 2 2 2 2
## [2739] 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 2 2 2
## [2776] 2 2 2 2 2 2 2 2 1 1 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [2813] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2
## [2850] 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2
## [2887] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [2924] 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2
## [2961] 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2
## [2998] 2 2 1 2 1 2 2 2 2 2 2 2 2 1 1 1 1 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [3035] 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [3072] 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 1 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2
## [3109] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 1 2 1 2 2 2
## [3146] 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2
## [3183] 2 2 2 1 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2
```

```
## [3220] 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2
## [3257] 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2
## [3294] 2 1 2 1 2 2 1 2 1 2 1 2 2 2 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 1 2 2 2 2
## [3331] 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2
## [3368] 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 2 2 2 2 2 1 1
## [3405] 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 1 1 2 2 2
## [3442] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [3479] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2
## [3516] 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2
## [3553] 2 1 2 2 2 2 2 2 2 1 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
## [3590] 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2
## [3627] 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [3664] 2 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2
## [3701] 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2
## [3738] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2
## [3775] 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 1 2 2
## [3812] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [3849] 2 2 2 2 1 2 2 1 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2
## [3886] 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 1 1 2 1 2 2 2 1 2 2 1 2 2 2 2
## [3923] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
## [3960] 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [3997] 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2
## [4034] 2 1 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1
## [4071] 1 2 2 2 2 2 2 2 2 2 2 1 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 1 1 2 2 2 2 1
## [4108] 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2
## [4145] 2 2 2 1 2 2 2 2 2 2 1 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [4182] 2 2 2 2 2 1 1 2 2 3 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [4219] 2 2 2 2 2 2 1 1 2 2 2 1 1 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [4256] 1 1 1 2 2 2 2 2 1 2 1 2 1 2 2 2 2 2 2 2 1 2 3 2 2 2 2 2 2 2 2 2 2 1 2 2 2
## [4293] 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2
## [4330] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 1 2 2 1 2 2 2 2 2 2 2
## [4367] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2
## [4404] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2
## [4441] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2
## [4478] 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
## [4515] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 1 2 2
## [4552] 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [4589] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2
## [4626] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [4663] 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 1 2 2 2 2 2 2 2 2 2 2
## [4700] 2 2 2 1 1 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2
## [4737] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [4774] 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2 1 1 1 2 2 2 2 2 2
## [4811] 2 2 2 2 2 2 2 2 2 2 1 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 1 2 2 2 2 2
## [4848] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 1 2 2 2 1 2 2 2 2 2
## [4885] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 1 2 2 2 1 1 2 2 2 2 2 2 1
## [4922] 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [4959] 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2 1 2 2 2
## [4996] 2 2 1 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5033] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 1 2 2
## [5070] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 1 2 2 2 2 1 1 2 1 1 2 2 2 2 2 2 2 2
## [5107] 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5144] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2
## [5181] 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
```

```
## [5218] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2
## [5255] 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2
## [5292] 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2
## [5329] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5366] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2
## [5403] 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2
## [5440] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 1 2 2
## [5477] 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2
## [5514] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 1 1 2 2 2 2 2
## [5551] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 1 2 2 2 2 2 2 2 2 2 2 2
## [5588] 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5625] 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2
## [5662] 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1
## [5699] 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5736] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5773] 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5810] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2
## [5847] 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5884] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5921] 2 2 2 1 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
## [5958] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [5995] 2 2 2 1 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [6032] 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2
## [6069] 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [6106] 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2
## [6143] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [6180] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2
## [6217] 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 2
## [6254] 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2
## [6291] 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [6328] 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2
## [6365] 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [6402] 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 3 1 2 1 2 1 1 2 2 2 2 2 2
## [6439] 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [6476] 1 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2
## [6513] 2 2 2 2 2 2 2 2 3 2 2 2 1 1 1 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2 2 2
## [6550] 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [6587] 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [6624] 2 2 2 3 2 2 1 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 1 2 1 2 2 1 2 2 2 2 2 2 2 1
## [6661] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2
## [6698] 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2
## [6735] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2
## [6772] 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1 2 2 2 2 2 2 2
## [6809] 1 1 1 2 1 2 1 2 2 2 1 1 2 1 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2
## [6846] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2
## [6883] 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2
## [6920] 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2
## [6957] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2
## [6994] 2 2 2 1 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [7031] 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [7068] 1 2 2 2 2 2 2 1 2 2 1 2 2 1 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
## [7105] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2
## [7142] 2 2 1 1 1 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1
## [7179] 1 2 2 2 2 2 2 2 2 1 1 2 2 1 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2
```

```
## [7216] 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 1 2 2 2 2
## [7253] 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 1 2 2 2 2 2 1
## [7290] 2 2 2 1 2 2 2 2 2 1 1 2 1 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 1 2 2 2 2 2 2 2
## [7327] 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 1 2 2 2 2 2 1 1 2 2 2
## [7364] 1 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2
## [7401] 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 1 2 1 2 1 2 2 2 1 2 2 2 2 2 2 1 2 2 2
## [7438] 2 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2
## [7475] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2
## [7512] 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 1 2 2 2 2 2 2 1
## [7549] 1 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [7586] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2
## [7623] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 1 2 2 1 2 2 2 2 2 2 2 2 1
## [7660] 2 1 1 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2
## [7697] 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [7734] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [7771] 2 1 1 2 2 2 2 2 2 2 2 1 2 1 2 2 1 2 1 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [7808] 1 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [7845] 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2
## [7882] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 3 2 2 2
## [7919] 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 1 2 2 1 2 2 2 2 2
## [7956] 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 1 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [7993] 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2
## [8030] 2 1 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2
## [8067] 2 2 2 2 1 2 2 1 1 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [8104] 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 2 1 2 2 1 2 2 2
## [8141] 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [8178] 2 2 1 1 1 1 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 3 2 1 2 1 2 2 1 2 1
## [8215] 2 1 1 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 1 1 1
## [8252] 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 1 2 2
## [8289] 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2
## [8326] 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2 1
## [8363] 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2
## [8400] 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 1
## [8437] 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2 2 1 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2
## [8474] 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2
## [8511] 2 2 1 2 2 2 2 1 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2
## [8548] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2 2
## [8585] 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [8622] 2 2 1 2 2 2 2 2 1 2 1 1 2 1 2 2 2 2 2 1 1 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2
## [8659] 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2
## [8696] 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2
## [8733] 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 1 1 1 2
## [8770] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [8807] 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [8844] 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 1 2 2 2
## [8881] 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 1
## [8918] 2 1 2 2 2 2 1 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 1 2 2 2 2
## [8955] 2 2 2 1 2 1 2 2 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 1 2 1 1 1 1 1 1 2 1 2 2 2 3
## [8992] 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2
## [9029] 2 2 2 2 2 2 1 2 2 2 2 3 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1
## [9066] 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2
## [9103] 2 1 1 2 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 1 1 2 2 1 1 2 2 2 2 2 2 2 1 2
## [9140] 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2
## [9177] 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
```

```
## [9214] 2 2 2 1 2 2 1 2 2 2 1 1 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2
## [9251] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 3 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1
## [9288] 2 2 2 2 2 1 2 2 1 2 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 1 2
## [9325] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2
## [9362] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [9399] 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [9436] 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2
## [9473] 2 2 2 2 1 1 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [9510] 2 2 1 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2
## [9547] 2 2 1 2 2 2 2 2 2 2 2 1 2 2 2 2 1 2 2 2 1 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2
## [9584] 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2
## [9621] 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2
## [9658] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2
## [9695] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [9732] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [9769] 2 2 2 2 2 2 1 1 1 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 1 1 2 1 2 2 2 2
## [9806] 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2 2 1 1 2 2 2 2 2 2
## [9843] 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 1 1
## [9880] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2
## [9917] 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [9954] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
## [9991] 2 2 2 2
##
## Within cluster sum of squares by cluster:
## [1]  5207.851 16648.669  3315.203
##  (between_SS / total_SS =  37.0 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

```r
# https://towardsdatascience.com/clustering-analysis-in-r-using-k-means-73eca4fb7967

#cluster means are the centroid vectors
#clustering vector is the group that the observation is placed into
#percentage indicates compactness of the clustering or how similar observations are within the same gro
```

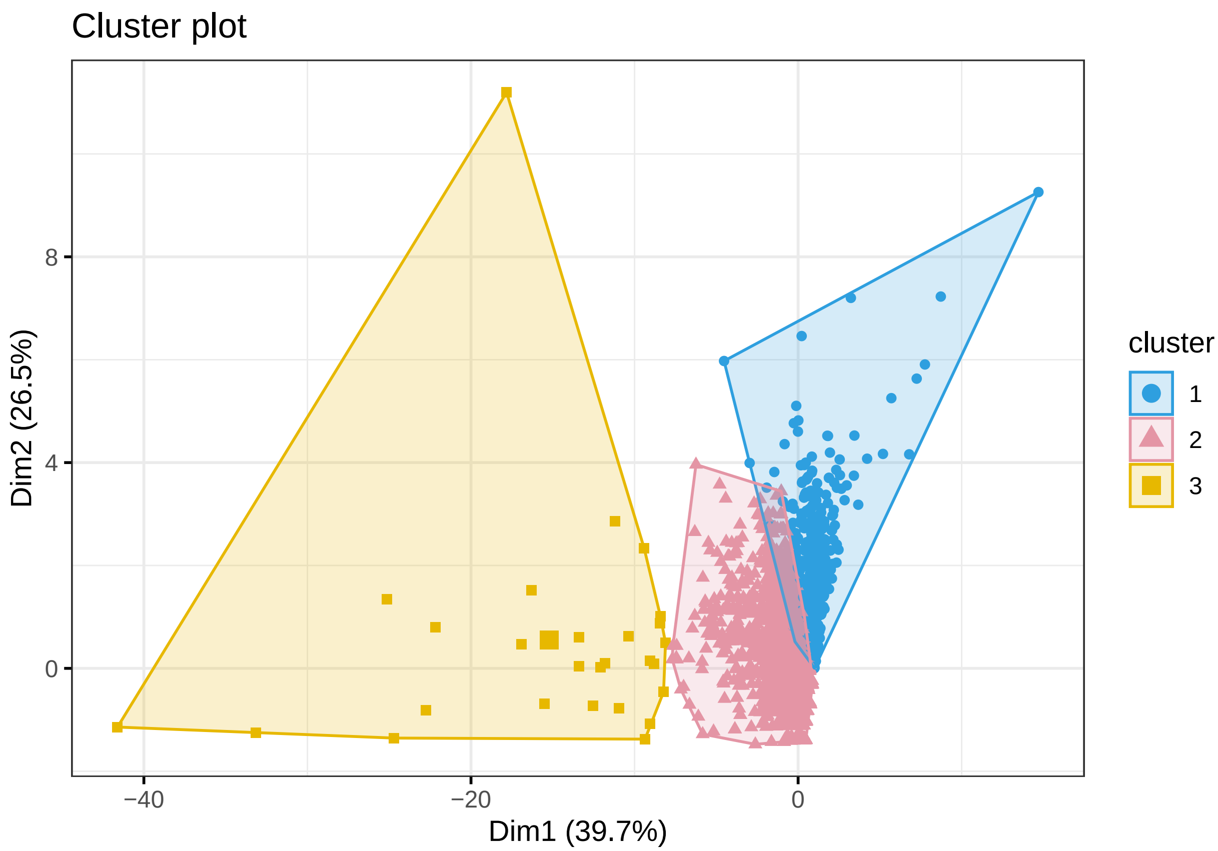
The results of this clustering indicate that the within cluster sum of squares by cluster is 37.0 % which means that the observations within a given group are not very similar to each other.

Plot K-means

The factoextra package contains a function called fviz_cluster() which can be used to visualize kmeans clusters. The input required is the original dataset, and the kmeans results. These are used to produce plots which show points that represent observations.

```r
fviz_cluster(results_kmeans, data = data1[,(15:18)],
             palette = c("#2E9FDF", "#E495A5", "#E7B800"),
             geom = "point",
             ellipse.type = "convex",
```

```
            ggtheme = theme_bw()
            )
```



Reduce dimensions using Principal Component Analysis.

```
results_pca <- prcomp(data1[,(15:19)], scale=TRUE)

#Coordinates of individual observations
indiv_coordinates <- as.data.frame(get_pca_ind(results_pca)$coord)

#Add clusters obtained through the Kmeans algorithm
indiv_coordinates$cluster <- factor(results_kmeans$cluster)

#Add region from the dataset
indiv_coordinates$Region <- data1$Region

#look at the first few rows of individual coordinates
head(indiv_coordinates)
```

```
##         Dim.1       Dim.2      Dim.3         Dim.4       Dim.5 cluster Region
## 1  0.04520418 -1.13666870  0.3612739  0.0807637427  0.30768311       2  South
## 2  1.15718390 -0.84275631  0.4252513  0.1851981706  0.21856052       2  South
## 3 -0.31072375 -1.08484635 -0.2274155 -0.0007838382  0.15040037       2   West
## 4 -0.63620673  2.24187253 -1.2663321  0.5805617103  1.55922466       1  South
## 5 -0.58444157 -0.08714015 -1.6947210  0.7880697439 -0.05040709       2  South
## 6  0.39080002  0.44622564 -0.7312599 -1.4739348647 -0.19665673       2   West
```

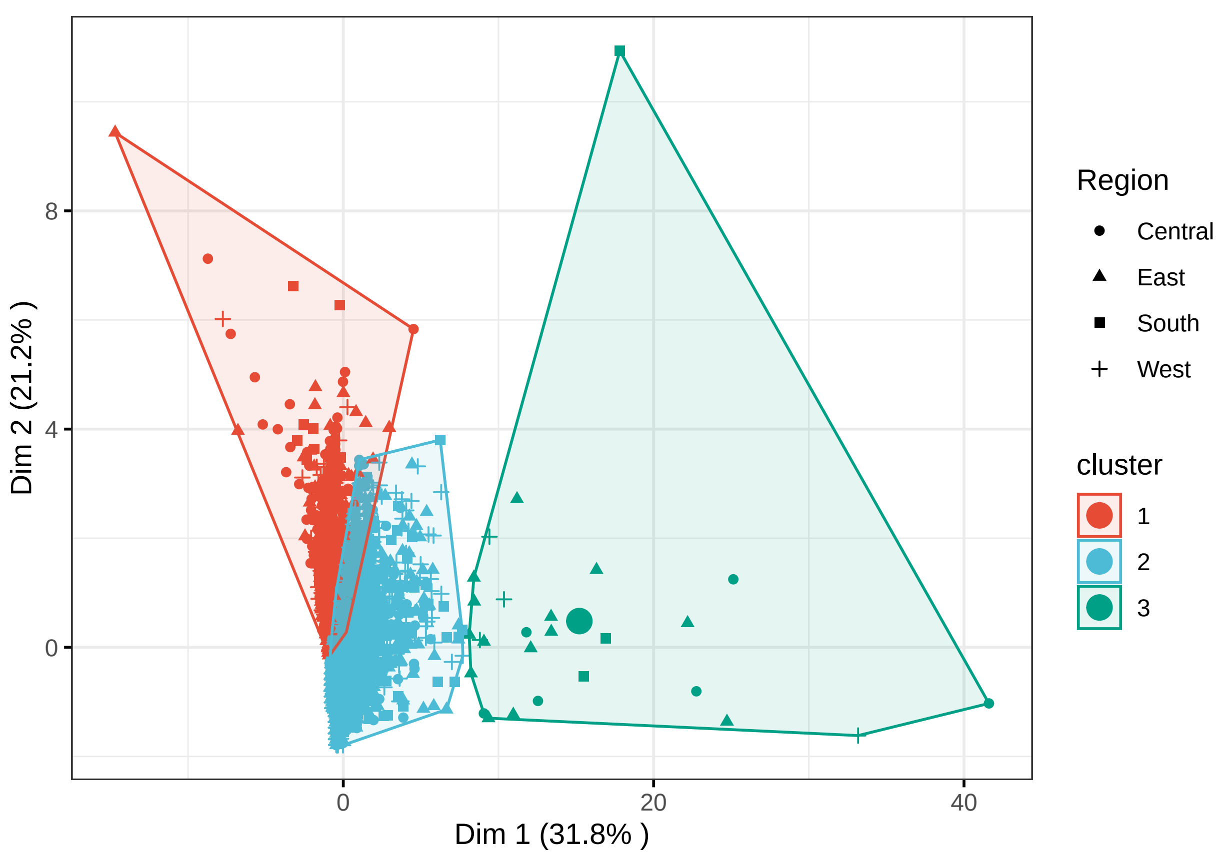
Percentage of variance explained by dimensions.

```
eigenvalue <- round(get_eigenvalue(results_pca), 1)
variance.percent <- eigenvalue$variance.percent
head(eigenvalue)
```

```
##       eigenvalue variance.percent cumulative.variance.percent
## Dim.1        1.6             31.8                        31.8
## Dim.2        1.1             21.2                        53.0
## Dim.3        1.0             20.0                        73.0
## Dim.4        0.9             17.6                        90.6
## Dim.5        0.5              9.4                       100.0
```

Variance of a group indicates how different members of a group are. Higher variance means greater dissimilarity within a group.

```
#To visualize the k-means clusters:

ggscatter(
  indiv_coordinates, x = "Dim.1", y = "Dim.2",
  color = "cluster", palette = "npg", ellipse = TRUE, ellipse.type = "convex",    #adding the concentra
  shape = "Region", size = 1.5,  legend = "right", ggtheme = theme_bw(),
  xlab = paste0("Dim 1 (", variance.percent[1], "% )" ),
  ylab = paste0("Dim 2 (", variance.percent[2], "% )" )
) +
  stat_mean(aes(color = cluster), size = 4)      #stat_mean is used for adding the cluster centroid
```



The clustering plot shows that the groups are very close together, and overlap slightly. The clusters could be further apart with some tuning by changing the number of clusters (k).

Evaluation

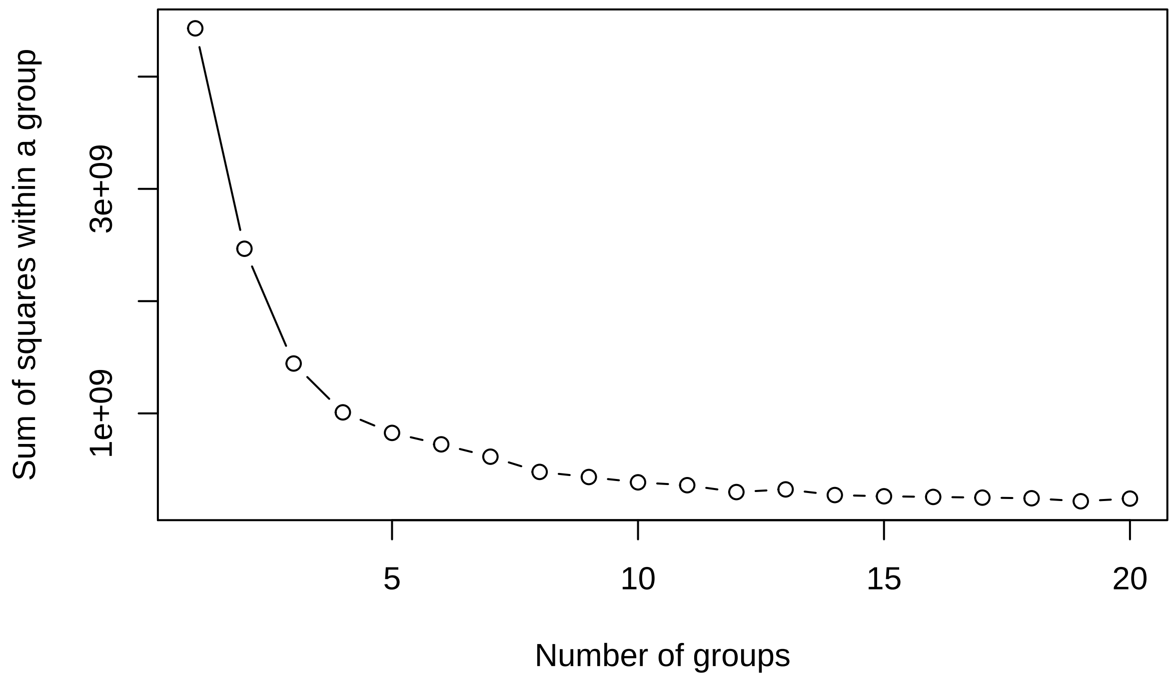
(https://towardsdatascience.com/clustering-analysis-in-r-using-k-means-73eca4fb7967)

The within sum of squares (Withinss) is a value that represents the level of dissimilarity within a group. The higher the withinss, the greater the dissimilarity within the group.

(Foncesca, 2019)

```
#To plot a within sum of squares plot for a range of different number of initial K-means centroids:

#This function is from:  (https://towardsdatascience.com/clustering-analysis-in-r-using-k-means-73eca4f

#data is the input dataset, nc is the maximum number of initial centres

wssplot <- function(data, nc=25, seed=123){
               wss <- (nrow(data)-1)*sum(apply(data,2,var))
               for (i in 2:nc){
                    set.seed(seed)
                    wss[i] <- sum(kmeans(data, centers=i)$withinss)}
                plot(1:nc, wss, type="b", xlab="Number of groups",
                     ylab="Sum of squares within a group")}

wssplot(data1[,(15:18)], nc = 20)
```

```
## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations

## Warning: did not converge in 10 iterations
```



From the Within sum of squares plot, the optimal number of clusters is around 5. when the number of groups (k) initially increases 1 to 6, the error measures (sum of squares within a group) starts to decrease. When the number of groups is 7 or 8, the error measure starts to flatten.

The main purpose is to find a number of initial groups which achieves some fair amount of compactness (or similarity) between observations within a group. When k is too high, each cluster starts to represent individual points, whereas when k is too low, the observations may not be in the right cluster.

We can try re-running the k-means model with the number of groups, k = 4

```
set.seed(123)
clustering_results_4 <- kmeans(scale(data1[,(15:18)]), centers = 4, nstart = 25)
clustering_results_4
```

```
## K-means clustering with 4 clusters of sizes 27, 1044, 2838, 6085
##
## Cluster means:
##        Sales    Quantity   Discount      Profit
## 1 11.9621017  0.62721018 -0.4157497 11.02007172
## 2 -0.1222964  0.02095769  2.4788189 -0.58466503
## 3  0.2856822  1.19688927 -0.2981228  0.17558930
## 4 -0.1653353 -0.56459922 -0.2844025 -0.03048054
##
## Clustering vector:
##    [1] 4 4 4 2 4 3 4 3 4 3 3 3 4 4 2 2 3 4 4 4 4 3 3 4 4 4 4 2 2 4 4 3 2 4 4 3 2
##   [38] 3 4 4 4 4 4 4 4 4 4 4 4 3 3 4 4 3 3 3 3 3 4 4 4 4 4 3 4 4 3 3 4 4 4 4 3 4
##   [75] 4 2 2 4 2 4 4 3 4 3 4 4 4 4 3 4 4 4 4 4 4 2 3 4 3 3 4 2 4 3 4 2 3 4 4 3 4
```

```
##   [112] 4 3 3 4 4 3 4 2 4 4 3 3 3 4 2 2 3 4 4 2 4 3 4 4 4 4 4 3 3 4 4 4 4 4 3 4 3
##   [149] 4 3 3 3 4 3 4 3 4 4 4 3 4 4 3 4 4 3 4 3 3 2 4 4 4 3 2 4 2 3 3 4 4 3 4 3 4
##   [186] 4 3 4 4 3 3 3 4 3 3 4 4 4 2 4 4 2 4 2 3 4 4 4 4 3 4 4 4 2 2 2 4 3 4 4 3 2
##   [223] 4 2 4 4 3 4 4 3 2 2 2 2 4 4 4 3 2 2 4 2 2 4 3 4 3 3 4 4 4 3 3 4 2 4 3 3 4
##   [260] 4 3 2 2 3 4 4 4 3 4 4 3 3 4 4 4 4 4 4 3 4 2 3 3 3 3 3 2 4 3 3 3 4 2 3 4 4
##   [297] 2 4 3 3 4 4 4 2 4 4 4 3 4 4 4 4 4 4 4 4 4 4 1 3 4 4 4 3 4 4 2 4 4 3 2 4 2
##   [334] 2 4 4 4 4 4 4 4 2 3 3 4 4 4 4 4 4 4 4 4 1 3 4 4 3 3 3 4 4 4 4 3 4 4 4 3 3
##   [371] 3 4 2 3 4 3 4 3 2 4 2 3 4 4 2 4 2 4 4 4 4 4 3 2 4 4 4 4 4 3 4 4 4 3 4 3 4
##   [408] 3 3 4 3 4 3 4 3 4 3 3 4 4 4 3 4 4 3 4 3 4 3 2 3 3 4 3 2 3 4 3 3 4 4 4 4 4
##   [445] 4 3 4 4 4 3 4 4 4 2 4 4 4 4 4 4 3 4 3 2 2 4 4 2 4 2 4 4 4 4 3 3 3 3 4 3 3
##   [482] 4 4 4 4 3 3 3 4 4 4 3 4 4 2 4 3 4 4 3 2 2 4 2 4 3 4 4 4 1 4 4 4 4 4 3 4 4
##   [519] 4 4 4 2 4 4 4 3 4 4 4 4 3 4 4 3 3 4 2 4 4 4 3 3 3 4 4 2 3 4 3 2 3 4 4 4 4
##   [556] 4 4 3 3 4 3 3 4 4 4 4 3 3 4 4 3 4 3 4 4 3 4 4 4 2 4 4 4 4 2 4 4 4 4 4 2 4
##   [593] 4 4 4 4 3 3 4 2 2 4 4 4 2 2 4 2 3 4 4 4 4 3 3 2 4 4 3 4 4 2 4 3 4 3 3 4 3
##   [630] 4 4 3 4 4 4 4 2 4 3 4 4 4 3 4 4 4 3 4 4 4 4 3 4 3 4 2 4 4 2 3 3 3 2 3 4 4
##   [667] 4 4 3 2 2 3 3 4 3 4 2 4 2 2 4 4 4 2 4 4 4 4 4 4 4 4 4 3 3 4 3 4 4 2 2 4 4
##   [704] 4 4 3 4 4 3 3 4 4 3 4 4 3 4 4 4 3 4 4 4 3 3 4 4 3 2 4 4 4 4 4 3 4 4 3 4 4
##   [741] 4 2 3 4 4 4 3 4 4 4 3 3 4 4 4 2 4 4 4 4 3 4 2 4 4 3 4 3 4 4 4 4 3 4 4 3 3
##   [778] 4 4 4 4 2 4 2 4 4 4 4 4 4 3 4 3 4 4 3 3 4 3 3 4 4 3 4 4 4 3 4 4 4 3 4 4 4
##   [815] 3 3 4 3 2 3 2 4 4 4 4 4 3 4 4 4 4 4 4 4 2 2 4 4 4 4 4 4 4 4 3 4 4 3 4
##   [852] 3 3 4 4 4 3 4 4 4 4 4 3 4 4 4 4 4 2 2 2 4 4 3 3 4 4 4 2 4 3 4 4 3 4 4 3 3
##   [889] 3 3 4 4 4 3 3 4 4 3 3 2 3 2 4 4 4 4 4 3 4 3 3 4 3 4 3 4 4 2 4 4 4 4 4 3 4
##   [926] 4 3 4 4 4 4 4 4 3 2 4 4 4 4 4 4 4 3 3 4 3 2 3 3 3 4 3 4 4 4 3 4 2 4 4 4 4
##   [963] 4 4 4 4 4 4 4 4 3 2 2 4 3 4 2 3 2 4 3 4 4 3 4 4 4 2 3 4 3 4 4 3 3 4 4 4 3
##  [1000] 3 4 3 3 4 4 4 4 2 3 4 4 4 4 3 4 3 4 4 3 3 4 4 3 4 4 4 4 4 3 4 4 3 3 4 2 2
##  [1037] 4 4 3 4 3 4 4 3 2 3 3 4 3 4 4 4 3 4 4 4 4 4 4 4 4 4 3 4 2 4 2 4 4 2 3 4 4
##  [1074] 2 2 4 3 4 4 4 4 3 3 4 4 1 4 4 4 4 4 3 4 3 4 3 2 3 4 4 4 4 2 2 4 3 2 2 3 4
##  [1111] 3 4 2 4 4 4 4 3 3 4 4 3 3 4 4 4 4 4 3 4 4 3 4 4 4 4 3 4 4 3 4 4 4 4 4 4 4
##  [1148] 4 4 4 4 3 4 3 4 3 4 4 4 4 4 4 4 4 3 4 3 4 4 4 4 4 3 2 3 4 4 4 4 4 3 4 4 3
##  [1185] 3 3 4 4 4 3 4 4 4 4 4 4 4 3 4 2 4 2 4 4 4 3 4 4 3 3 4 4 4 2 2 4 4 4 4 3 3
##  [1222] 3 4 4 4 4 4 4 4 4 4 4 4 4 4 2 4 4 4 4 4 4 4 4 3 3 3 4 3 3 3 4 3 4 2 4 4 2
##  [1259] 4 3 4 2 4 4 3 4 4 3 4 4 4 2 2 4 3 4 4 4 4 4 4 4 2 4 2 3 4 4 4 4 4 3 4 3 4
##  [1296] 3 4 4 3 4 3 4 4 4 4 3 3 4 4 4 4 4 4 3 3 3 4 4 2 2 4 3 4 4 2 3 4 4 4 4 4
##  [1333] 2 2 3 4 4 4 4 3 2 2 2 4 3 4 3 3 3 3 4 4 3 4 4 4 3 4 2 4 3 4 2 3 2 3 4 4 3
##  [1370] 2 4 4 4 4 3 4 3 3 3 3 4 2 4 3 3 4 4 4 4 4 4 4 3 4 2 2 4 4 4 4 4 4 4 3 4 2
##  [1407] 4 4 4 2 4 4 4 3 4 4 3 4 2 4 2 4 2 3 3 4 4 3 3 3 3 3 4 3 3 3 4 4 3 3 4 4 4
##  [1444] 4 3 4 3 4 2 4 2 3 4 3 3 4 4 3 4 4 4 4 4 3 4 4 4 4 4 4 4 4 4 2 3 4 3 3 4 4
##  [1481] 3 4 4 4 4 4 3 4 4 4 4 4 3 4 4 3 4 3 3 4 3 4 4 4 4 3 4 4 4 4 3 3 4 2 2 4 3
##  [1518] 4 4 3 3 3 3 3 3 3 4 4 3 4 4 4 4 3 4 4 4 4 4 4 3 3 3 4 4 3 4 2 4 4 2 4 3 3
##  [1555] 4 4 4 3 4 3 3 4 2 4 3 4 4 2 4 4 3 4 4 4 4 3 4 4 4 4 3 4 4 4 4 3 4 4 4 4 3
##  [1592] 3 4 4 4 4 3 4 4 4 2 4 4 3 3 4 3 4 4 4 4 4 4 3 4 4 4 4 4 4 4 3 4 4 3 4 3 3
##  [1629] 3 2 4 4 4 4 4 4 3 4 4 4 4 4 4 4 3 4 4 4 2 4 4 4 3 4 4 4 4 3 4 4 4 2 2 3 4
##  [1666] 4 4 4 4 2 4 4 4 4 2 2 4 4 4 2 4 2 4 4 4 2 2 4 4 2 3 3 3 4 4 4 4 4 3 3 4 3
##  [1703] 4 3 2 2 3 4 4 4 3 3 3 2 4 4 3 3 4 3 4 4 4 4 4 4 4 3 4 4 3 4 4 4 4 3 4 4 4
##  [1740] 3 3 4 4 4 3 4 2 4 4 4 4 4 3 4 4 3 3 2 4 4 4 3 4 4 4 3 4 2 2 4 2 4 3 4 3 4
##  [1777] 4 3 3 4 4 4 4 4 3 3 4 4 4 3 4 3 4 4 4 3 4 3 3 4 4 4 2 3 4 3 3 3 3 2 4 3 3
##  [1814] 4 4 4 4 4 2 2 2 4 4 4 2 4 4 4 3 2 3 4 4 2 3 3 3 4 4 4 4 4 4 2 4 3 4 4 4 4
##  [1851] 3 3 3 4 3 4 3 2 4 4 4 4 4 2 4 2 3 3 4 4 3 4 4 4 4 4 4 4 4 2 4 3 4 3 4 4 4
##  [1888] 2 4 2 4 4 4 4 4 4 4 4 2 2 3 4 4 4 4 3 2 2 4 4 4 3 4 3 4 4 4 3 4 3 4 4 3 4
##  [1925] 4 4 4 4 4 4 4 4 4 3 3 3 4 2 3 2 4 4 4 2 4 4 4 4 4 4 3 4 3 3 4 4 4 4 4 4 3
##  [1962] 3 4 3 4 4 4 3 4 4 4 3 2 4 4 4 3 3 4 3 4 4 4 3 4 4 3 4 3 4 4 2 3 4 4 2 2 4
##  [1999] 4 3 3 3 4 3 2 3 3 4 4 4 4 4 4 4 4 3 4 4 4 3 3 4 4 3 3 4 4 4 4 3 4 4 4 4 4
##  [2036] 4 4 4 4 2 2 3 3 3 4 4 4 4 3 2 2 3 3 3 4 3 3 4 4 4 3 4 3 4 4 4 3 4 4 4 2 3
##  [2073] 4 4 3 4 3 3 3 3 4 4 3 4 4 3 3 4 4 4 4 4 3 4 3 3 4 4 4 3 4 4 4 4 4 4 2 4 4
```

```
## [2110] 4 3 4 4 3 4 4 4 3 4 3 2 4 4 3 3 3 4 4 4 4 3 3 4 2 3 2 2 2 4 3 4 2 3 4 3 4
## [2147] 2 3 4 3 4 3 4 4 2 3 4 4 4 2 4 4 4 4 4 2 4 2 4 4 2 4 4 2 4 4 3 3 3 3 4 4 3
## [2184] 3 3 4 4 3 4 3 4 4 4 4 4 3 4 4 4 4 3 3 4 4 4 4 2 4 4 3 3 3 4 4 3 4 4 4 4 4
## [2221] 3 2 3 4 4 2 4 4 4 4 4 3 3 4 3 4 3 3 2 4 3 2 4 4 4 4 4 4 3 3 3 4 4 4 4 4 4
## [2258] 3 4 4 4 4 4 4 4 4 4 4 4 4 3 3 3 4 4 4 3 4 4 4 3 4 3 4 3 4 4 3 3 4 4 3 4 4
## [2295] 4 4 3 4 3 4 4 4 4 3 4 4 4 3 4 4 3 4 4 4 4 3 4 3 4 4 3 4 4 3 3 4 4 4 4 4 4
## [2332] 3 3 4 3 4 3 4 4 4 3 3 4 4 3 3 2 3 3 4 4 4 3 3 3 4 4 3 2 2 3 4 2 4 4 4 4 4
## [2369] 3 4 4 2 4 3 4 4 2 4 3 4 4 3 4 3 4 4 4 4 4 4 3 3 4 4 4 4 3 4 3 3 3 3 3 3 3
## [2406] 3 3 3 4 3 4 3 4 4 3 4 3 4 3 4 4 4 4 3 2 2 3 2 2 2 3 4 3 4 4 4 3 2 4 4 3 4
## [2443] 3 3 3 4 4 3 4 3 3 3 4 4 3 3 4 3 4 4 4 4 3 4 4 4 4 4 3 4 3 4 4 4 3 3 3 4 4
## [2480] 4 4 3 4 3 3 4 4 4 4 3 4 3 1 3 3 3 4 4 4 4 4 2 2 4 4 1 3 2 4 3 3 3 2 4 4 4
## [2517] 3 4 3 3 4 4 4 4 3 4 2 2 4 4 3 4 3 4 3 4 4 2 4 3 4 3 4 4 4 4 4 4 3 3 4 3 4
## [2554] 4 3 4 2 4 3 3 4 4 4 4 4 4 3 3 3 4 4 4 3 3 4 3 4 4 4 3 4 4 3 4 4 4 3 4 4 4
## [2591] 2 2 4 3 4 4 4 4 4 4 3 4 4 4 4 2 4 4 4 3 4 4 2 4 4 3 4 3 4 4 4 3 4 1 3 3 4
## [2628] 4 2 2 4 4 4 4 4 2 4 4 4 4 3 4 3 4 3 4 4 4 3 4 3 4 4 4 4 4 4 3 4 3 3 4 4 4
## [2665] 2 2 4 4 4 4 4 3 4 3 4 3 4 2 2 3 3 4 4 4 3 4 2 2 3 4 2 4 4 3 4 4 2 1 4 4 4
## [2702] 4 4 4 3 4 4 4 3 3 2 4 3 4 3 4 4 4 4 2 4 3 3 3 4 2 2 2 3 4 3 4 4 4 4 4 3 4
## [2739] 4 4 4 3 4 3 4 4 4 4 2 4 3 4 4 4 3 3 4 4 4 4 3 4 3 2 2 4 4 3 2 3 4 3 4 4 4
## [2776] 4 3 4 3 4 4 3 4 4 2 4 4 2 3 2 4 4 4 3 4 3 4 4 4 3 3 4 4 4 3 4 4 4 3 4 3 3
## [2813] 4 3 4 3 4 4 3 3 4 4 4 4 3 4 2 4 3 3 4 3 4 3 4 4 4 3 2 4 3 3 4 4 3 4 2 3 3
## [2850] 2 4 4 4 4 4 3 3 4 4 4 3 3 4 4 3 4 4 3 4 4 4 4 4 3 4 4 3 4 4 4 3 4 2 4 4 3
## [2887] 4 4 3 3 4 4 4 3 3 4 3 3 4 4 4 3 3 3 4 4 4 3 4 4 4 3 4 4 4 4 4 4 3 4 3 4 2
## [2924] 4 4 4 4 4 2 4 4 4 4 4 4 4 3 3 3 4 4 3 4 3 4 3 4 3 3 4 3 4 4 4 4 4 4 2 4 4
## [2961] 4 3 4 4 3 4 2 4 4 3 2 4 4 3 4 4 3 4 3 4 4 4 4 4 2 4 4 3 4 4 3 3 4 3 4 3 4
## [2998] 4 4 2 4 2 3 4 4 4 3 4 4 3 2 2 2 2 4 2 3 2 3 4 4 4 3 4 3 4 4 4 3 4 4 4 4 4
## [3035] 3 3 4 3 4 4 3 4 4 3 2 3 4 3 4 4 4 4 4 4 4 3 4 3 4 4 4 3 4 4 3 3 3 3 3 4 3
## [3072] 4 3 4 4 4 2 4 3 4 4 4 4 4 2 4 2 2 3 3 3 3 4 4 4 3 2 4 4 4 4 3 4 2 3 4 3 4
## [3109] 4 4 3 4 4 3 3 3 3 4 3 4 4 4 2 2 4 4 4 4 4 4 3 4 4 4 2 4 4 4 4 2 4 2 3 3 3
## [3146] 3 4 3 3 4 3 2 4 3 4 4 2 4 3 4 2 4 3 4 3 4 4 3 3 3 3 2 3 4 3 2 4 4 4 4 3 4
## [3183] 4 3 4 2 4 3 4 4 4 4 2 2 3 4 4 2 4 3 4 4 3 4 4 3 3 3 3 3 4 2 3 4 4 3 4 4 4
## [3220] 3 4 4 4 4 4 3 4 4 4 4 3 2 2 4 4 4 4 4 3 3 2 3 2 3 4 4 3 4 4 4 3 4 4 4 4 4
## [3257] 4 2 2 2 4 4 3 4 4 4 4 4 4 4 4 3 3 3 4 3 3 4 4 3 3 4 4 4 2 4 4 4 3 3 4 4 4
## [3294] 4 2 3 2 4 3 2 4 3 4 2 4 4 4 2 4 3 3 3 3 4 4 4 2 3 4 3 4 3 4 4 2 2 4 3 3 4
## [3331] 4 4 4 2 4 4 4 4 3 4 3 4 4 4 3 4 3 3 2 4 4 4 4 4 4 4 4 3 2 4 4 4 4 4 2 4 4
## [3368] 4 4 4 3 3 4 4 3 4 4 3 2 4 3 4 4 3 3 4 4 4 2 2 4 3 4 2 3 4 4 4 4 3 4 4 2 2
## [3405] 4 4 4 2 4 4 3 4 4 4 4 4 4 3 4 4 4 3 3 4 4 4 3 4 2 3 4 4 3 4 3 2 2 2 4 3 4
## [3442] 3 4 3 4 3 4 4 4 3 4 4 4 4 4 4 4 4 2 2 4 4 3 4 4 4 4 3 3 4 4 4 4 4 4 3 3 3
## [3479] 4 3 3 4 3 4 4 4 4 4 4 3 3 4 4 4 3 4 4 3 3 4 4 3 4 4 3 4 2 4 4 4 2 3 3 4 4
## [3516] 4 3 4 4 2 4 3 4 3 3 4 4 3 4 4 3 3 4 4 3 4 4 4 4 3 3 4 4 4 3 2 3 4 4 3 4 3
## [3553] 3 2 4 3 3 4 4 4 4 2 2 4 4 4 3 2 4 3 3 4 4 4 3 4 4 4 4 3 3 4 4 4 4 4 4 2 4
## [3590] 4 3 4 4 2 3 4 4 3 4 4 3 4 3 3 4 4 4 4 4 4 4 4 4 3 4 2 4 4 3 4 3 3 4 3 4
## [3627] 4 4 3 4 3 4 3 4 3 4 4 4 3 4 3 2 4 4 4 3 4 4 2 3 3 3 4 4 3 4 4 4 4 4 3 4 3
## [3664] 4 3 2 4 3 3 3 4 4 4 2 4 4 4 4 4 4 4 4 4 3 3 3 4 2 3 3 2 4 3 4 3 3 4 4 3 4
## [3701] 4 4 3 4 4 3 4 2 2 3 4 3 4 4 4 3 3 4 3 3 4 4 3 2 4 4 4 4 4 4 3 4 3 4 4 4 4
## [3738] 4 4 4 4 4 3 4 4 3 4 4 4 4 3 4 4 4 3 3 3 3 4 4 4 3 4 4 2 4 4 3 3 4 3 4 4 4
## [3775] 4 4 3 3 4 4 4 4 4 4 4 2 3 4 4 3 3 2 3 4 4 4 4 4 2 3 4 4 4 4 4 4 3 2 2 3 4
## [3812] 4 4 3 3 4 4 4 3 4 4 4 3 3 4 3 3 3 4 4 4 4 4 2 4 4 4 4 4 3 4 4 4 4 4 3 3 4
## [3849] 3 3 3 4 2 4 3 2 3 4 3 2 4 4 4 4 2 4 3 3 4 3 4 4 4 4 2 4 4 2 4 4 4 4 3 4 4
## [3886] 2 4 4 4 4 4 3 3 3 2 3 4 4 4 4 4 4 3 3 4 2 4 2 4 4 2 4 4 4 2 4 4 2 4 4 4 4
## [3923] 3 3 4 4 4 3 3 4 3 4 4 3 3 4 4 4 4 3 4 4 3 3 4 4 4 4 4 4 3 4 4 4 4 4 4 2 4
## [3960] 4 3 3 4 4 4 4 4 2 2 3 3 4 4 3 3 3 4 4 4 4 4 4 4 3 4 4 3 3 3 4 4 4 4 3 4 3
## [3997] 3 4 3 3 3 3 4 2 4 4 4 3 4 3 4 4 4 4 4 3 3 4 3 4 4 2 3 3 4 4 3 4 2 4 4 3 3
## [4034] 4 2 3 4 3 4 3 4 4 3 3 3 2 2 4 3 4 4 4 2 3 4 3 4 3 3 4 4 4 4 3 4 3 4 3 3 2
## [4071] 2 4 4 3 4 4 4 4 4 4 3 2 2 4 2 4 4 4 3 4 4 4 4 3 4 4 3 3 1 4 2 2 3 4 3 4 2
```

```
## [4108] 4 2 4 4 4 4 4 4 3 4 4 3 3 4 3 4 4 4 4 3 3 2 4 2 4 4 3 4 3 3 3 2 4 3 4 3 3
## [4145] 4 4 4 2 4 4 4 3 4 4 2 2 4 2 4 4 4 4 4 4 3 3 4 4 4 3 4 3 4 4 4 4 3 4 3 3 2
## [4182] 4 4 4 4 3 2 2 4 4 1 3 4 4 4 3 4 4 2 4 4 3 3 3 4 4 4 4 3 4 4 4 4 4 4 4 4 3
## [4219] 3 4 3 3 4 4 2 2 4 4 4 2 2 4 3 2 4 3 2 3 4 4 4 4 4 4 4 4 3 3 3 3 3 3 4 4 4
## [4256] 2 2 2 4 4 3 4 4 2 3 2 3 2 3 3 3 4 3 4 4 2 4 1 4 3 4 4 4 4 4 4 4 4 2 4 4 3
## [4293] 4 2 2 4 4 3 4 3 4 3 4 3 4 3 4 4 3 4 4 4 4 4 4 4 4 4 4 3 4 4 2 2 2 4 4 3 3
## [4330] 4 3 4 3 3 4 4 4 4 4 4 4 4 3 3 4 4 4 4 2 3 4 4 4 4 2 2 4 4 2 4 4 4 4 4 3 4
## [4367] 3 4 3 3 4 3 4 3 3 3 4 3 4 4 4 4 2 4 4 3 4 4 3 4 4 4 4 3 4 2 4 4 4 3 4 3 4
## [4404] 4 4 4 4 4 4 4 3 4 4 4 4 4 3 3 4 2 3 4 4 4 3 3 4 4 3 4 4 4 3 4 4 2 3 2 4 4
## [4441] 4 3 3 3 3 3 4 3 4 4 4 3 4 3 4 4 4 3 4 4 4 4 2 4 4 4 3 4 4 4 4 4 4 2 4 4 4
## [4478] 4 4 3 3 4 3 4 4 4 4 2 3 2 4 4 4 3 3 3 3 2 4 4 3 3 3 3 4 4 4 4 4 4 4 4 2 4
## [4515] 4 4 3 3 4 3 4 4 4 3 3 4 3 4 4 2 4 4 4 4 4 4 4 4 4 4 4 3 2 4 3 4 3 2 4 2 4 4
## [4552] 4 4 4 4 4 4 2 4 4 4 4 3 4 3 4 2 4 2 4 4 4 4 3 4 3 4 4 4 3 3 4 3 4 3 3 3 4
## [4589] 4 3 4 4 4 4 4 4 3 4 3 4 3 4 4 4 4 3 4 4 4 3 3 4 4 3 2 3 4 4 4 3 4 3 4 4 4
## [4626] 4 3 4 3 4 4 3 4 3 4 4 4 4 4 3 4 2 4 4 4 4 4 4 4 3 3 3 4 4 3 4 4 4 4 4 3 4 3
## [4663] 4 4 2 4 4 4 2 3 3 4 4 4 4 4 4 4 3 4 4 3 3 2 2 2 3 3 2 4 4 4 3 4 4 4 4 3 4
## [4700] 4 4 4 2 2 3 4 4 3 4 4 4 2 3 2 4 4 4 4 3 3 4 2 4 4 2 4 3 4 3 4 3 4 4 4 4 4
## [4737] 4 4 4 4 4 4 4 4 4 4 4 4 4 3 4 4 4 4 2 4 2 2 3 4 4 4 4 4 4 4 3 4 4 4 4 3 2
## [4774] 3 4 4 4 4 3 4 4 2 3 3 3 2 4 4 3 3 2 4 4 4 4 4 2 3 4 3 4 2 2 4 3 4 3 4 4 4
## [4811] 4 4 3 4 4 4 4 4 4 4 2 3 2 2 4 4 4 4 4 4 3 4 4 4 3 4 4 2 3 2 4 2 3 4 4 4 3
## [4848] 3 4 4 3 3 3 4 4 4 4 4 3 3 4 3 4 4 4 3 3 4 4 4 3 4 2 4 2 3 4 4 2 4 3 3 4 3
## [4885] 4 3 4 3 4 3 4 4 4 4 4 4 3 4 4 2 4 4 3 4 4 4 3 2 4 4 3 4 2 2 4 4 3 4 4 4 2
## [4922] 4 4 3 4 4 2 4 4 3 4 4 4 2 4 4 3 3 4 3 3 4 4 4 4 4 4 4 3 4 4 4 4 4 3 4 4 2
## [4959] 3 4 4 4 4 4 2 4 4 4 4 4 4 4 4 4 4 3 3 4 3 4 2 4 4 4 3 3 4 3 2 4 4 2 3 3 3
## [4996] 4 4 2 4 3 4 3 4 4 4 3 3 4 2 3 2 2 2 3 3 3 2 4 4 4 4 4 4 4 4 4 4 4 4 4 4 3
## [5033] 4 4 3 4 4 3 4 4 3 4 4 3 3 3 4 3 2 4 4 4 4 3 4 3 3 3 2 4 3 4 4 4 4 4 2 3 4
## [5070] 4 4 3 4 4 4 3 3 4 4 4 4 4 4 4 2 3 4 2 4 4 4 4 2 2 4 2 2 4 4 4 4 4 4 3 4 4
## [5107] 4 3 3 3 3 4 2 4 4 4 4 4 3 3 3 4 4 4 3 3 3 4 4 4 3 3 4 3 4 3 4 4 4 4 3 4 3 3
## [5144] 4 4 4 4 4 4 4 4 3 4 4 4 4 4 4 2 4 4 3 4 4 4 4 4 4 4 4 3 4 4 4 2 4 4 4 4 4
## [5181] 4 3 4 4 3 3 3 4 3 3 4 4 3 3 4 4 4 3 3 4 4 3 3 4 4 4 4 4 3 4 4 4 4 4 3 3 4
## [5218] 4 3 3 4 3 3 3 4 3 3 4 4 4 3 4 3 3 4 4 4 4 4 4 4 4 2 4 4 4 4 2 4 4 3 4 4 4
## [5255] 4 4 4 3 3 4 4 2 4 4 4 4 4 4 4 4 3 4 3 2 4 4 3 3 4 4 4 4 4 4 4 3 2 2 4 4 3
## [5292] 3 4 4 3 4 4 3 4 4 3 3 3 4 2 3 4 4 4 3 2 4 4 4 4 3 4 4 4 2 2 2 4 4 3 3 4 4
## [5329] 4 4 4 3 4 4 4 4 4 3 3 3 4 3 4 3 4 3 4 4 4 3 3 4 4 3 3 4 3 4 4 4 3 3 3 4 4
## [5366] 4 4 4 4 4 4 4 4 3 4 3 4 3 4 4 3 3 3 4 4 3 3 4 4 4 4 3 4 3 3 3 3 3 2 3 4 4
## [5403] 4 4 3 4 4 4 4 4 4 3 4 3 2 4 4 4 3 4 2 4 4 3 4 3 3 3 4 4 4 4 2 4 3 4 4 2 4
## [5440] 4 4 4 4 3 4 4 3 3 4 3 4 4 3 3 4 4 3 4 3 3 4 4 2 4 3 2 4 4 4 4 3 3 4 2 4 4
## [5477] 3 4 4 2 4 4 4 4 4 4 2 4 4 4 4 4 4 4 4 2 4 4 4 4 3 4 4 4 4 2 4 4 3 4 4 4 4
## [5514] 4 4 4 3 3 4 4 3 4 3 4 3 4 4 4 3 4 3 3 4 4 4 4 4 4 4 4 2 4 2 2 2 3 4 4 4 3
## [5551] 4 3 4 3 4 4 4 4 4 3 4 4 3 4 4 4 3 4 4 4 4 4 2 4 4 4 3 4 4 3 3 4 3 4 4 4 4
## [5588] 3 4 4 4 4 4 2 4 4 4 4 4 4 3 4 4 3 3 4 4 3 4 4 4 4 3 4 3 3 3 4 4 3 4 4 3 4
## [5625] 4 4 3 3 4 3 4 3 4 3 3 3 4 4 3 4 3 4 4 4 3 3 3 4 3 3 4 3 4 4 2 4 4 4 2 4 4
## [5662] 4 3 4 2 4 4 4 3 4 4 4 4 4 4 3 4 2 3 4 4 4 4 3 3 4 3 3 3 4 3 3 4 3 4 4 2 2
## [5699] 4 3 4 3 4 4 4 4 4 4 4 4 4 3 4 4 4 3 3 4 3 4 3 3 4 4 4 4 3 3 4 4 4 4 4 3 4 4
## [5736] 4 4 4 4 4 4 4 4 4 3 3 4 4 4 3 2 4 3 3 4 2 3 4 2 4 4 4 4 3 3 4 3 3 4 4 4 3
## [5773] 4 4 3 4 4 4 4 4 4 4 4 4 2 3 2 3 3 2 3 4 4 4 4 3 4 4 4 4 4 4 4 4 4 4 4 4 4
## [5810] 4 4 4 4 4 4 4 4 4 3 4 4 4 3 4 4 4 4 4 4 4 4 4 4 3 2 2 3 4 3 3 4 4 3 4 3 3
## [5847] 4 4 4 4 4 4 4 4 3 4 2 2 4 4 4 4 4 4 4 4 3 4 2 3 3 4 4 3 4 4 3 4 3 4 4 3 3
## [5884] 4 3 4 4 4 4 4 4 4 4 4 4 4 3 4 4 4 3 4 4 4 3 4 4 4 4 4 4 4 4 3 3 4 4 3 3 4
## [5921] 4 4 4 2 3 3 3 4 4 2 4 2 4 4 4 3 4 4 4 4 3 4 4 4 3 4 4 3 4 4 4 3 4 3 4 2 3
## [5958] 3 4 4 4 3 4 4 4 3 4 4 4 4 4 4 4 4 3 4 4 3 3 4 4 4 4 3 3 4 4 3 4 3 3 3 4 3
## [5995] 4 3 4 2 4 4 4 4 2 2 4 4 4 4 4 4 3 4 4 3 3 4 3 4 4 3 4 4 4 4 3 4 3 3 4 4 4
## [6032] 4 3 4 2 2 4 3 4 4 4 4 4 4 3 4 4 2 2 3 3 3 4 4 2 2 3 4 3 4 4 4 3 4 4 3 3 3
## [6069] 4 4 4 4 4 4 4 4 3 4 4 4 3 2 2 3 4 4 2 4 4 2 4 4 3 4 4 4 4 4 4 3 4 3 4 4 2
```

```
## [6106] 4 2 3 4 2 3 4 3 3 4 3 3 4 4 4 3 2 4 4 3 4 4 3 4 4 4 3 3 4 4 4 2 3 4 4 3 4
## [6143] 4 3 4 4 4 4 4 3 3 3 4 4 4 4 4 4 3 3 4 4 4 2 4 4 4 4 4 4 4 4 3 4 4 3 3 4 4
## [6180] 4 3 4 4 3 3 3 4 3 3 4 3 4 3 2 3 2 4 3 4 4 3 4 3 3 4 3 4 4 4 3 3 4 4 4 4 4
## [6217] 3 4 3 4 3 3 4 3 4 2 4 4 2 4 4 4 4 3 3 3 4 4 4 4 4 3 2 4 3 4 4 4 4 4 4 2 3
## [6254] 4 3 4 2 4 4 4 4 4 2 4 3 4 3 4 3 4 3 3 3 3 4 4 3 3 4 4 4 4 4 4 3 3 2 4 4 3 3
## [6291] 3 4 4 4 4 3 3 4 4 4 2 4 3 4 4 3 4 4 4 3 4 4 4 4 4 4 4 4 3 3 4 4 4 4 3 4 4
## [6328] 4 3 4 4 4 4 3 4 3 4 3 4 4 1 4 4 4 4 4 3 4 4 4 2 4 2 4 4 3 3 4 4 3 4 3 3 4
## [6365] 3 4 4 4 3 2 4 4 4 4 4 3 4 4 4 3 3 2 2 2 4 3 2 4 4 3 4 4 4 3 4 4 4 4 3 3 3
## [6402] 4 4 4 4 4 3 3 3 4 4 4 4 3 2 4 2 4 4 4 4 4 3 3 4 1 2 4 2 4 2 2 4 3 3 4 3 4
## [6439] 4 3 3 4 4 3 4 3 2 4 4 4 4 4 4 4 4 3 4 3 4 3 3 4 4 3 4 3 3 3 3 3 4 3 3 4 2
## [6476] 2 4 4 4 3 3 4 4 2 3 4 3 2 3 3 4 4 3 4 4 4 4 4 3 3 3 3 3 2 4 4 4 4 3 4 4 3
## [6513] 4 3 4 4 3 3 4 4 1 4 3 4 4 2 2 3 4 4 2 3 4 3 3 3 2 4 4 3 3 4 4 4 2 4 4 3 4
## [6550] 3 4 4 3 4 4 4 2 4 3 3 4 2 4 4 4 3 2 3 4 4 4 4 4 4 3 3 4 3 3 4 4 4 4 3 4 3
## [6587] 3 4 4 4 4 4 3 4 3 2 4 2 4 4 4 3 3 4 4 3 4 3 4 3 4 4 4 3 4 4 3 4 3 3 3 4 3
## [6624] 3 4 4 1 4 3 2 4 3 4 4 2 4 3 4 3 2 3 4 3 4 3 4 2 4 2 4 3 2 4 3 4 4 4 3 4 2
## [6661] 4 4 3 3 3 3 3 4 4 3 4 4 3 4 3 4 3 4 3 4 4 4 4 3 4 2 3 3 4 3 4 3 3 4 4 4 4
## [6698] 4 4 4 4 4 2 4 4 4 3 4 3 4 3 4 2 2 4 3 3 4 4 4 3 4 4 3 4 4 4 3 3 2 4 4 4 4
## [6735] 4 4 4 3 4 4 4 4 4 3 3 3 3 4 4 4 4 4 4 4 4 3 4 3 4 4 4 4 3 4 4 4 4 2 3 3 3
## [6772] 2 4 4 3 4 4 3 4 4 4 3 4 4 4 3 4 4 3 4 3 4 4 4 4 2 2 2 2 2 2 4 4 4 4 4 4 4
## [6809] 2 2 2 4 2 3 2 4 3 3 2 2 4 2 3 3 4 4 1 4 3 4 4 4 4 4 4 3 4 4 3 3 2 4 4 3 3
## [6846] 4 4 4 4 4 3 3 4 4 4 4 4 4 4 3 3 3 4 4 4 3 4 4 3 4 3 4 4 2 4 4 3 2 4 3 3 3
## [6883] 4 3 3 4 4 4 4 3 3 4 4 4 4 4 3 2 3 2 3 3 4 2 3 4 4 4 4 2 4 4 4 4 4 2 4 3 4
## [6920] 2 3 4 3 4 3 3 4 4 4 3 4 4 4 4 4 4 2 4 4 4 3 3 4 3 4 3 4 4 4 3 2 4 4 4 3 4
## [6957] 3 4 4 4 4 4 3 4 3 4 4 3 4 3 4 4 4 2 4 4 4 4 3 3 4 4 3 4 4 4 4 3 3 2 4 3 4
## [6994] 3 3 4 2 4 4 4 4 4 3 4 4 4 2 2 4 4 3 4 4 4 4 4 4 4 3 4 4 4 3 3 3 3 4 4 3 4
## [7031] 4 4 4 4 4 4 4 4 4 4 4 4 3 4 4 4 4 4 4 4 3 4 4 4 3 4 3 3 4 4 4 4 4 4 4 3 3
## [7068] 2 3 4 4 4 4 3 2 4 3 2 3 4 2 4 2 4 3 2 4 4 4 4 4 4 4 3 3 3 4 3 3 3 4 4 2 4
## [7105] 3 4 3 4 4 4 4 4 3 4 3 4 4 4 4 4 2 3 4 4 4 4 4 3 4 4 3 4 3 4 4 4 2 4 2 4 4
## [7142] 3 3 2 2 2 4 4 4 4 4 2 4 2 3 3 4 4 4 4 4 4 3 3 4 4 4 4 3 4 4 4 3 3 4 2 4 2
## [7179] 2 4 4 4 3 3 4 4 4 2 2 4 4 2 3 3 4 4 3 4 4 4 4 2 3 2 4 4 3 4 4 4 4 3 4 4 3
## [7216] 4 4 4 4 4 2 4 4 4 3 4 3 3 3 4 4 4 4 3 4 4 4 2 3 3 3 3 4 3 3 3 4 2 3 4 4 4
## [7253] 4 4 3 4 4 3 3 3 4 3 2 4 3 4 2 4 4 3 4 4 4 2 3 3 3 4 4 3 3 2 2 3 4 4 4 4 2
## [7290] 3 4 3 2 3 4 4 3 3 2 2 3 2 3 4 4 4 4 4 4 4 3 2 2 3 4 4 4 4 2 3 3 4 4 4 4 3
## [7327] 4 4 3 3 2 4 2 4 4 4 4 4 4 4 4 3 4 3 2 4 4 4 2 3 3 3 3 3 3 3 4 4 3 2 4 4 4
## [7364] 2 3 2 4 3 2 4 4 3 4 3 4 4 4 3 4 4 3 3 4 4 4 4 3 3 4 4 3 4 3 4 3 2 4 3 3 4
## [7401] 4 3 4 3 4 4 4 3 3 4 4 4 4 4 4 3 2 3 2 3 2 4 2 4 4 4 2 4 4 4 4 4 4 2 4 3 3
## [7438] 3 3 3 4 4 4 4 4 4 2 3 3 4 3 2 3 4 4 4 4 4 3 3 3 4 3 4 3 4 3 4 4 4 2 4 3 4
## [7475] 3 4 4 4 3 4 4 4 4 3 4 3 3 3 3 4 3 3 4 3 2 4 4 4 4 4 4 4 4 4 4 2 4 4 4 3 3
## [7512] 3 3 3 4 3 4 3 4 4 4 2 2 4 3 3 3 4 3 4 4 4 4 4 3 4 2 4 4 2 2 4 3 3 3 3 3 2
## [7549] 2 2 4 3 4 4 2 3 3 4 4 4 3 4 4 4 4 4 4 4 3 4 4 3 4 4 4 4 4 4 4 3 4 4 4 3 3
## [7586] 4 4 4 4 3 3 4 4 4 3 4 4 4 4 3 2 3 3 4 2 2 3 4 4 3 4 4 4 4 4 2 4 3 4 3 3 4
## [7623] 4 4 3 3 3 4 3 3 3 3 3 4 4 4 4 4 3 4 3 2 2 2 3 4 2 4 3 3 4 4 4 4 4 4 4 4 2
## [7660] 3 2 2 3 3 4 4 1 4 3 4 4 4 4 3 4 4 4 4 4 3 4 3 4 1 3 4 3 4 3 4 4 4 3 4 3 3
## [7697] 2 4 4 4 3 4 4 4 4 4 4 4 4 2 3 4 4 4 3 4 3 2 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4
## [7734] 4 4 4 4 3 3 4 4 4 4 4 4 4 4 3 4 4 4 4 4 4 4 3 3 4 4 4 4 4 4 3 4 3 3 4 3 4
## [7771] 4 2 2 4 4 4 4 4 4 4 4 2 4 3 4 4 2 4 2 3 2 2 4 3 4 4 3 4 4 4 4 4 4 4 4 4 2
## [7808] 2 4 4 4 4 4 3 4 4 4 3 1 3 3 3 4 4 3 4 4 4 4 4 4 4 4 3 4 4 4 4 4 4 3 4 4 3
## [7845] 4 3 3 2 4 4 4 4 2 4 4 4 4 3 4 4 2 4 4 4 4 4 2 4 4 4 4 4 3 4 4 3 4 4 2 2 3
## [7882] 3 3 4 3 4 3 4 3 3 4 3 4 4 3 4 3 3 2 3 4 4 3 4 4 4 2 4 4 3 4 4 2 4 1 4 4 4
## [7919] 4 4 4 4 3 2 4 3 4 4 4 3 4 4 3 4 4 4 4 3 4 3 4 3 2 3 4 2 2 3 3 2 4 4 3 4 4
## [7956] 4 3 4 3 4 4 3 2 4 4 3 4 2 4 4 2 4 4 2 4 2 4 4 4 4 4 4 3 3 4 3 3 4 4 4 4 2
## [7993] 4 2 2 2 3 3 3 4 4 3 3 4 4 4 3 4 4 3 3 3 3 3 4 4 3 3 4 3 4 2 3 3 2 4 4 4 3
## [8030] 3 2 3 4 2 2 4 3 4 4 3 3 4 4 4 3 3 2 4 3 2 4 3 4 2 3 4 3 3 4 4 3 4 4 4 4 4
## [8067] 4 4 3 3 2 4 4 2 2 2 4 4 4 3 3 4 3 2 3 3 4 4 4 3 3 4 3 4 4 4 3 3 4 4 3 4 3
```

```
## [8104] 3 3 4 3 4 4 3 4 3 2 4 3 4 4 3 4 4 4 3 4 3 4 2 4 4 2 4 4 4 4 2 4 3 2 3 3 3
## [8141] 4 4 4 4 4 3 4 4 3 4 4 4 4 1 4 4 4 3 4 3 4 3 4 3 3 4 4 3 3 4 4 3 4 3 4 4 3
## [8178] 3 4 2 3 2 2 2 4 4 4 3 4 4 3 4 2 4 4 4 4 3 4 2 4 3 4 4 1 4 2 4 2 4 4 2 4 2
## [8215] 4 2 2 4 2 4 2 4 4 3 4 3 4 4 4 4 4 3 3 4 4 2 3 4 4 4 4 4 4 3 4 4 2 4 2 2 2
## [8252] 2 4 4 4 3 4 3 3 3 4 4 4 2 4 3 4 2 4 3 4 3 4 4 3 3 2 2 4 4 4 4 4 4 3 2 3 3
## [8289] 3 3 4 4 2 4 4 3 4 4 4 4 4 3 4 4 4 3 3 4 3 4 4 4 3 4 4 3 4 4 3 4 4 2 4 3 3
## [8326] 4 2 2 4 4 4 4 3 4 4 3 4 4 3 3 3 4 3 3 4 4 3 4 3 3 4 4 2 2 2 4 4 3 4 3 4 2
## [8363] 3 4 4 4 4 4 3 4 4 2 4 4 3 3 4 4 4 3 4 4 4 4 4 4 4 3 4 3 4 4 4 3 4 4 3 2 4
## [8400] 4 3 4 4 4 4 3 4 3 3 4 2 3 4 3 4 4 3 4 4 4 4 4 3 4 3 2 4 4 3 3 4 3 4 4 2 2
## [8437] 3 4 4 4 4 4 2 2 2 4 4 4 4 3 4 3 4 4 2 4 4 2 2 2 3 4 4 4 4 4 4 4 3 4 4 4 4
## [8474] 4 2 4 4 3 4 4 4 4 4 3 3 4 4 4 1 3 3 4 3 4 2 4 4 4 4 3 4 4 4 4 4 2 3 4 3 4
## [8511] 4 4 2 4 4 3 4 2 4 4 4 3 4 3 4 3 2 4 4 4 4 4 3 4 4 4 2 3 4 4 3 4 3 4 4 4 4
## [8548] 4 4 4 4 4 4 3 3 3 3 4 3 4 4 2 3 2 3 4 4 3 3 3 4 4 2 4 4 4 4 4 4 4 2 4 4 3
## [8585] 4 2 3 3 4 4 4 4 4 4 4 4 4 4 4 4 4 4 3 4 4 3 4 4 4 4 4 3 4 4 4 4 4 4 3 4 2
## [8622] 4 4 2 3 4 4 3 4 2 4 2 2 4 2 3 3 3 3 4 2 2 3 4 2 4 4 4 3 2 3 4 4 4 4 4 4 4
## [8659] 2 3 3 2 3 3 3 3 3 4 4 4 4 4 4 4 4 3 2 3 2 3 3 3 4 4 3 3 4 3 4 4 4 4 3 3 4
## [8696] 4 4 4 4 3 3 4 3 4 3 4 4 4 4 4 4 4 4 4 3 3 2 2 2 3 4 4 3 2 3 3 4 4 4 4 3 4
## [8733] 4 4 3 4 4 2 4 4 3 4 4 4 4 4 4 4 4 4 3 4 4 4 3 2 2 4 3 4 4 4 3 4 4 4 2 2 2 4
## [8770] 4 4 3 4 3 4 4 3 3 4 4 4 3 4 4 4 3 4 4 4 4 3 3 4 3 3 4 4 4 3 3 4 4 4 4 4 4
## [8807] 4 2 2 3 4 4 3 4 4 3 4 4 3 4 4 2 4 4 4 4 3 3 4 4 3 4 4 4 4 4 4 3 4 4 4 4 4
## [8844] 3 2 4 3 4 4 3 2 4 4 3 4 4 3 4 1 4 4 4 4 4 3 4 3 4 4 3 3 4 2 2 2 4 2 4 4 3
## [8881] 4 3 4 4 2 2 2 4 3 4 3 4 3 4 4 4 4 4 4 4 2 4 4 4 4 4 3 3 3 4 4 3 2 4 3 2 2
## [8918] 4 2 4 4 4 4 2 3 2 2 3 4 4 4 3 4 4 4 3 3 4 3 4 4 2 2 4 4 4 4 3 4 2 4 4 3 3
## [8955] 4 4 4 2 3 2 3 4 4 4 3 2 4 3 4 3 4 4 4 3 3 4 4 2 4 2 2 2 2 2 2 4 2 4 4 4 1
## [8992] 3 4 2 3 3 4 4 3 3 2 4 4 3 3 3 4 4 4 4 4 4 3 3 3 4 4 4 4 4 3 2 4 4 4 4 4 4
## [9029] 4 4 4 4 4 4 2 4 4 4 4 1 2 4 4 4 4 3 3 3 4 4 4 4 4 4 4 4 3 3 4 3 4 4 3 3 2
## [9066] 4 4 4 4 4 4 4 4 3 3 2 4 4 4 4 3 4 4 4 3 4 2 3 4 3 3 4 2 4 3 4 3 3 3 4 4 4
## [9103] 4 2 2 4 2 4 3 4 3 4 4 4 3 2 4 4 4 3 3 3 4 2 2 2 4 4 2 2 4 4 4 3 4 4 4 2 3
## [9140] 3 4 4 4 3 3 2 4 3 3 4 3 4 4 3 4 3 4 3 3 2 2 3 4 4 2 3 4 4 3 4 4 4 4 4 4 4
## [9177] 2 4 4 4 4 4 4 4 4 4 4 3 4 4 3 2 4 2 4 3 4 4 3 3 4 4 4 4 3 3 4 3 4 4 4 4 4
## [9214] 4 3 3 2 4 3 2 4 3 4 2 2 2 4 3 4 4 3 2 3 4 3 3 4 4 4 3 2 4 3 4 4 3 4 4 4 3
## [9251] 3 4 3 4 4 4 4 4 4 4 4 4 4 3 2 3 4 4 4 3 1 4 3 3 3 3 4 4 2 4 4 3 4 4 4 4 2
## [9288] 4 3 4 4 4 2 3 4 2 4 4 4 2 4 4 4 4 2 3 4 4 4 3 3 4 4 3 4 2 4 4 4 4 4 2 2 3
## [9325] 4 4 4 4 4 4 4 4 4 4 4 4 3 4 3 4 3 4 3 2 2 4 4 3 3 4 4 4 4 4 4 4 4 3 2 4 3
## [9362] 3 3 4 4 4 4 3 4 4 4 4 3 3 3 4 4 4 4 4 4 4 4 3 4 3 4 4 4 4 3 4 3 3 4 4 3 4
## [9399] 3 3 4 4 4 3 3 4 4 3 4 2 3 4 3 2 4 4 4 4 4 2 2 3 3 4 4 3 3 3 3 3 4 4 4 3 4
## [9436] 4 2 4 2 4 4 3 4 4 4 4 3 3 4 4 3 4 3 4 4 2 4 2 4 4 4 3 4 4 3 4 3 4 4 4 4 4
## [9473] 4 3 4 3 2 2 3 2 2 4 4 3 3 3 4 4 4 3 3 4 3 3 4 3 4 4 4 3 4 4 3 4 3 4 4 3 4
## [9510] 3 3 2 4 3 3 3 2 4 4 4 4 4 4 4 3 3 4 3 4 4 4 4 3 3 4 4 2 4 3 4 3 4 2 4 4 4
## [9547] 4 4 2 4 4 3 4 3 3 4 3 2 3 3 4 4 2 4 4 3 2 4 4 2 4 4 4 3 4 4 2 3 4 4 3 3 3
## [9584] 4 4 4 3 4 4 4 2 2 2 4 4 4 4 4 4 4 3 3 3 2 4 4 4 3 4 4 3 4 4 4 3 4 4 4 4 3
## [9621] 3 4 4 2 4 4 4 4 3 2 4 3 3 4 3 3 4 4 4 3 3 3 3 4 3 4 2 4 4 3 3 4 3 4 2 4 4
## [9658] 4 4 3 3 4 4 4 4 4 4 3 4 4 3 3 4 2 4 4 3 4 4 4 3 4 3 3 4 4 3 2 3 4 4 4 3 3
## [9695] 4 4 3 4 4 4 4 4 4 3 4 4 4 4 4 4 4 2 3 3 4 4 4 3 3 4 4 4 4 3 4 4 3 3 4 4 3
## [9732] 3 3 4 4 4 4 4 3 3 4 3 3 4 4 4 4 2 4 4 4 4 4 4 4 4 4 3 4 3 4 4 4 4 3 4 4 3
## [9769] 3 3 4 4 3 4 2 2 2 3 2 2 4 4 3 4 4 4 3 3 4 4 4 3 4 4 2 2 4 4 2 4 2 3 4 4 4
## [9806] 4 2 4 2 3 4 4 4 3 3 3 4 3 4 4 3 2 4 4 4 4 4 4 4 4 4 2 4 3 2 2 3 4 4 4 3 4
## [9843] 4 4 2 4 3 3 3 4 4 4 4 3 4 4 3 3 3 4 4 4 4 4 4 4 3 4 4 2 2 4 4 4 4 4 4 2 2
## [9880] 3 4 4 3 4 4 4 4 4 4 4 4 3 3 4 3 3 4 4 4 4 4 4 4 2 4 3 4 4 3 4 4 3 4 4 4 3
## [9917] 4 4 4 3 2 2 4 4 4 3 4 4 4 3 4 4 3 4 4 4 4 4 3 4 3 3 3 3 4 4 4 3 3 4 4 4 4
## [9954] 4 4 4 3 4 4 4 4 4 4 4 4 3 3 4 3 4 3 4 3 3 4 4 3 4 3 4 3 3 4 3 4 4 4 3 4
## [9991] 4 4 4 4
##
## Within cluster sum of squares by cluster:
```

```
## [1] 3315.203 4284.643 7571.058 3614.724
##  (between_SS / total_SS =  53.0 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

The within cluster sum of squares by cluster value is now 53.0%. This represents the compactness of the clustering, or how similar observations are to other observations within the same group.

We can try re-running the k-means model with the number of groups, k = 7

```
set.seed(123)
clustering_results_7 <- kmeans(scale(data1[,(15:18)]), centers = 7, nstart = 25)
clustering_results_7
```

```
## K-means clustering with 7 clusters of sizes 3317, 200, 12, 914, 2574, 9, 2968
##
## Cluster means:
##         Sales    Quantity   Discount       Profit
## 1 -0.17099202 -0.55401551 -0.7476979   0.01999970
## 2  3.70037129  1.13047292 -0.4332859   2.62598142
## 3  8.36049519  1.14320638  2.0689103 -11.91366497
## 4 -0.21824012  0.05129912  2.6451425  -0.46197164
## 5  0.04223395  1.22666437 -0.2946436   0.03793345
## 6 16.87915324  0.84359568 -0.6489669  19.79865024
## 7 -0.11265862 -0.54381990  0.2993725  -0.10180518
##
## Clustering vector:
##    [1] 1 1 1 4 7 5 1 5 7 5 5 7 7 7 4 4 5 1 1 7 7 5 5 7 1 7 1 3 4 7 7 5 4 7 7 5 4
##   [38] 5 7 7 7 7 1 7 1 1 1 1 1 5 5 1 1 5 5 5 5 5 1 1 7 1 1 5 1 1 7 5 7 1 7 1 5 7
##   [75] 7 4 4 7 4 1 1 5 1 5 7 1 1 1 5 1 7 1 1 1 1 4 5 7 5 5 7 4 1 5 7 4 5 7 7 5 1
##  [112] 1 5 5 7 7 5 1 4 1 1 5 5 5 7 4 4 5 7 1 7 7 5 1 1 1 1 7 5 5 7 1 1 1 1 5 7 5
##  [149] 1 2 5 5 7 5 1 5 1 7 1 5 1 7 5 7 7 3 7 5 5 4 7 1 1 5 4 7 4 5 5 1 7 5 1 5 1
##  [186] 1 5 7 7 7 5 5 7 5 5 7 7 1 4 7 7 4 7 4 5 7 1 1 1 5 1 7 7 4 7 4 7 5 7 7 5 4
##  [223] 7 4 7 1 5 1 7 5 4 7 4 4 7 7 1 5 4 4 7 4 4 7 2 1 5 2 1 7 1 2 5 1 4 7 5 5 1
##  [260] 1 5 4 7 5 7 1 7 5 7 7 1 5 1 7 1 1 7 7 5 7 4 5 5 5 5 5 4 7 5 5 5 7 4 5 7 7
##  [297] 4 7 5 5 1 1 1 4 1 1 1 5 1 7 7 7 7 1 7 7 7 1 2 5 1 1 1 5 1 7 7 7 7 5 4 7 4
##  [334] 4 7 7 7 7 7 1 7 4 5 5 7 7 1 1 1 1 1 7 1 2 5 1 1 5 5 5 1 1 1 1 5 1 1 1 5 1
##  [371] 5 7 4 5 7 5 7 5 4 7 4 5 7 1 7 7 4 7 7 7 1 7 2 4 7 1 1 1 7 7 7 7 7 5 1 5 7
##  [408] 5 5 1 5 1 5 7 5 7 5 5 1 1 1 5 1 1 1 1 5 1 5 4 5 5 7 5 4 5 7 5 5 1 1 1 1 1
##  [445] 1 5 1 1 1 5 1 1 1 7 7 1 7 7 7 1 5 7 5 4 4 7 7 4 7 4 1 1 7 7 5 5 5 5 1 5 5
##  [482] 1 1 1 1 5 5 2 7 7 7 5 1 1 7 1 5 1 7 5 4 4 7 4 7 5 1 1 1 6 1 1 7 1 1 2 1 1
##  [519] 1 7 7 4 1 7 1 5 7 7 7 7 5 7 1 5 5 7 4 7 1 1 5 5 5 7 7 4 5 1 5 4 5 7 7 7 1
##  [556] 7 1 7 5 1 5 5 7 1 1 7 5 5 1 7 5 1 5 1 1 5 1 1 7 4 1 7 7 7 4 7 1 1 7 7 4 7
##  [593] 7 7 1 7 5 5 7 7 7 7 7 7 4 4 7 4 5 7 7 7 7 5 5 4 1 1 5 1 1 4 1 5 1 5 5 1 5
##  [630] 1 7 5 7 7 7 1 4 7 5 7 1 1 5 1 1 1 5 7 1 7 1 5 1 5 7 4 7 7 4 5 5 5 4 5 1 7
##  [667] 7 7 5 4 7 5 5 1 5 1 4 7 4 4 7 1 1 3 7 1 1 1 7 1 1 1 1 5 5 7 5 7 7 4 4 7 1
##  [704] 7 7 5 7 1 5 5 1 7 5 1 1 5 1 7 7 5 1 1 1 5 5 7 7 5 7 1 1 1 1 1 5 7 1 5 1 7
##  [741] 7 4 5 7 7 7 5 1 7 1 5 5 1 7 1 4 1 1 7 1 5 1 7 1 1 5 1 5 7 1 1 1 5 1 1 5 5
##  [778] 7 1 1 1 4 7 7 7 1 7 7 1 1 5 1 5 1 1 5 5 1 5 5 1 7 5 1 1 7 2 1 1 1 5 1 1 1
##  [815] 2 5 7 5 4 5 4 7 1 1 1 1 5 1 1 1 1 1 1 7 7 7 4 7 7 1 1 7 7 7 1 1 5 1 7 5 1
##  [852] 5 5 1 1 1 5 1 1 1 1 1 5 7 7 1 1 7 4 4 7 1 1 5 5 1 1 1 4 7 5 1 1 5 1 7 5 5
```

```
##  [889] 5 5 7 1 1 5 5 7 7 5 5 4 5 4 7 1 1 1 7 5 7 1 2 1 5 1 5 7 7 4 7 7 1 1 1 5 7
##  [926] 7 5 1 1 7 7 7 7 5 4 7 7 1 1 1 1 7 7 5 1 5 4 5 5 5 7 5 7 7 7 5 7 4 7 1 7 1
##  [963] 1 7 1 1 1 1 1 1 5 7 4 7 5 7 4 2 4 1 5 7 7 5 7 7 7 4 5 1 5 7 1 5 2 1 1 1 5
## [1000] 5 1 2 5 1 1 7 7 4 5 7 1 1 1 2 1 5 1 1 5 5 1 1 2 7 7 7 7 7 5 1 1 5 5 7 4 4
## [1037] 1 7 5 7 1 1 7 5 4 5 5 7 5 1 7 7 5 1 1 7 7 7 7 7 7 7 5 7 7 7 4 7 7 4 5 7 7
## [1074] 4 4 7 5 1 1 7 1 5 5 1 1 2 1 7 1 7 7 5 7 5 1 5 4 5 1 1 1 1 4 4 1 5 4 4 5 7
## [1111] 5 7 4 7 7 1 1 5 5 1 1 5 5 1 1 1 1 1 5 1 1 5 1 7 7 7 5 1 1 5 1 1 1 1 7 1 1
## [1148] 1 1 1 1 5 1 5 1 2 1 1 7 1 1 1 1 7 5 1 5 1 1 1 1 1 5 4 5 1 1 1 1 7 5 1 7 5
## [1185] 5 5 1 1 1 5 7 1 1 7 7 7 7 5 7 4 7 4 7 7 7 5 1 7 5 5 7 7 7 4 4 7 7 7 7 5 5
## [1222] 5 1 1 7 1 1 1 1 1 1 1 1 7 7 4 7 7 1 1 1 1 7 1 5 5 2 7 5 5 2 1 1 7 7 7 7 4
## [1259] 7 5 7 4 7 1 5 1 1 5 7 1 7 4 4 7 7 7 7 7 1 1 1 7 4 7 4 5 1 1 7 1 7 5 1 5 1
## [1296] 5 7 7 5 1 5 1 1 1 1 5 5 7 1 1 7 1 1 7 5 5 5 7 7 4 4 7 5 7 1 4 5 1 1 1 7 7
## [1333] 4 4 5 1 1 1 1 5 4 4 4 1 5 1 5 5 5 5 7 1 5 1 7 7 5 1 4 7 5 7 7 5 4 5 7 7 5
## [1370] 4 7 1 1 7 5 1 5 5 5 5 7 4 1 5 5 1 1 1 1 1 1 1 1 5 7 4 4 7 1 1 1 1 1 7 5 7 7
## [1407] 7 1 1 4 7 1 1 5 1 1 5 7 4 7 4 7 4 5 5 7 7 5 5 5 5 5 1 2 5 5 7 7 5 5 1 7 1
## [1444] 7 2 7 5 7 4 7 4 5 1 5 2 1 1 5 7 1 7 7 7 5 1 7 7 7 1 1 1 7 1 4 5 7 5 5 7 1
## [1481] 5 1 7 7 1 1 5 1 1 7 1 1 5 1 1 5 7 5 5 7 5 7 7 1 1 5 7 1 1 1 5 5 7 4 4 7 1
## [1518] 7 7 5 5 5 5 5 5 5 7 7 5 1 7 7 7 5 7 1 1 1 1 1 5 5 5 7 1 5 7 4 7 7 4 1 5 5
## [1555] 1 1 7 5 1 5 5 1 4 7 5 7 7 4 1 1 5 1 1 7 7 5 7 1 1 1 5 1 7 1 1 5 1 1 1 1 5
## [1592] 5 7 1 7 7 5 7 7 7 4 1 7 5 5 1 5 7 1 7 7 7 7 5 7 1 1 1 1 1 1 5 7 1 5 2 5 5
## [1629] 5 4 7 7 7 7 7 7 5 7 1 1 1 1 7 1 2 1 7 7 4 7 1 1 5 1 1 7 1 5 7 7 7 7 4 5 7
## [1666] 7 7 7 7 7 7 1 7 1 4 4 1 1 7 7 7 4 1 1 7 4 4 7 7 5 5 5 5 7 1 1 1 1 5 5 7 2
## [1703] 1 5 4 4 5 7 1 7 5 2 5 4 7 7 5 5 1 5 7 7 7 7 7 7 7 7 7 1 1 5 7 7 7 7 5 7 1 1
## [1740] 5 5 7 7 7 5 1 4 7 7 7 7 1 5 1 1 5 5 4 7 7 7 5 7 1 1 5 1 4 4 7 4 7 5 1 5 1
## [1777] 1 5 5 1 1 1 1 1 5 5 1 1 1 5 1 2 1 7 1 5 1 5 5 7 7 1 4 3 7 2 5 5 5 4 7 5 5
## [1814] 7 7 1 1 1 4 4 4 7 7 7 4 7 7 7 5 7 2 1 7 7 5 5 5 7 7 7 7 7 1 7 4 1 5 1 7 7 1
## [1851] 5 5 5 1 5 1 5 4 1 1 7 1 7 4 7 7 5 5 7 1 5 7 7 1 7 7 7 7 7 7 4 1 5 1 5 7 1 7
## [1888] 4 7 7 1 1 7 7 1 7 2 7 4 7 5 1 7 7 7 5 4 4 1 1 1 5 7 5 7 7 7 5 1 5 1 7 5 7
## [1925] 1 1 7 7 1 1 7 7 1 5 5 5 1 4 5 4 7 7 7 4 7 7 1 1 7 1 5 1 5 5 1 1 1 1 1 1 5
## [1962] 5 1 5 1 1 1 5 1 1 7 5 4 7 7 1 2 5 7 7 7 1 1 5 1 1 7 1 5 1 1 4 5 7 7 4 4 1
## [1999] 1 5 5 5 1 5 4 5 5 7 7 7 7 7 7 1 1 1 7 1 1 5 2 1 1 1 5 1 7 7 1 5 1 1 7 7 1
## [2036] 1 1 1 7 4 4 5 5 5 7 1 1 1 5 4 4 5 5 5 1 5 2 1 1 1 5 7 5 7 1 7 5 1 1 7 4 5
## [2073] 7 1 5 1 5 5 5 5 7 7 5 7 1 5 5 1 1 1 1 7 5 1 5 5 1 1 7 5 7 7 7 1 1 7 4 1 7
## [2110] 1 5 7 1 7 1 7 7 5 1 5 4 7 1 5 5 5 7 7 7 1 5 5 1 4 5 7 4 4 1 5 1 7 5 7 5 7
## [2147] 4 5 1 5 7 5 1 7 4 5 1 1 7 4 7 1 1 7 7 4 7 4 7 7 7 7 7 4 7 1 5 5 5 5 1 1 2
## [2184] 5 5 7 1 5 1 2 1 7 1 1 1 5 7 1 7 7 5 5 7 1 7 7 4 7 1 5 5 5 1 7 5 1 7 7 7 1
## [2221] 7 7 5 7 7 4 7 7 7 7 1 5 5 7 5 1 5 5 4 7 5 7 1 1 1 1 7 1 5 5 5 1 1 1 1 1 1
## [2258] 5 1 1 1 1 1 1 1 1 7 1 1 7 5 5 5 7 7 7 5 1 1 7 5 1 5 1 5 7 1 5 5 1 1 5 1 1
## [2295] 1 1 5 1 2 1 1 1 1 1 1 7 7 5 7 7 5 7 7 1 1 5 1 5 1 1 5 1 1 5 5 7 7 1 7 7 1
## [2332] 5 5 1 5 1 5 1 1 7 5 5 1 7 5 5 4 5 5 7 1 1 5 5 5 1 7 5 4 7 5 1 4 1 1 1 7 1
## [2369] 5 7 1 4 7 5 7 1 4 7 5 7 7 5 1 5 7 7 7 1 7 1 5 5 1 1 1 1 5 1 5 5 5 5 5 5 5
## [2406] 5 5 5 7 5 7 5 1 7 5 1 5 7 2 1 1 7 7 5 4 7 5 4 4 4 5 1 5 7 1 1 5 4 7 7 5 7
## [2443] 1 5 5 1 1 7 1 5 5 5 7 1 5 5 1 5 1 1 1 7 5 7 1 1 1 1 1 5 1 5 7 7 7 5 5 1 7 1
## [2480] 7 7 5 7 5 5 1 1 1 1 1 1 5 2 7 5 5 1 1 7 7 7 4 4 1 1 2 5 4 7 5 1 5 4 7 7 7
## [2517] 5 1 5 5 1 1 1 1 5 7 4 4 7 7 5 1 5 1 5 1 7 7 7 5 7 5 7 1 1 1 7 7 2 5 7 5 1
## [2554] 1 5 1 4 7 5 5 1 7 7 1 1 1 5 2 5 7 7 7 5 5 1 5 1 1 1 5 1 1 5 1 1 7 5 1 1 7
## [2591] 4 4 1 5 1 1 1 1 1 1 5 1 1 7 1 4 1 7 7 5 7 7 4 7 7 5 1 5 1 7 1 5 1 6 2 5 1
## [2628] 7 4 4 1 1 7 7 7 4 1 1 7 1 1 1 5 7 5 1 1 1 5 1 5 7 7 1 1 7 1 5 1 7 2 1 1 7
## [2665] 7 4 7 7 7 1 1 5 1 5 1 5 7 4 4 5 5 1 1 1 5 7 4 4 5 7 4 7 7 5 7 7 4 3 7 7 7
## [2702] 7 7 1 5 1 1 1 5 2 4 7 5 7 5 1 1 1 1 4 7 5 5 5 7 7 7 4 5 1 1 1 1 1 1 1 5 1
## [2739] 1 1 1 5 1 5 7 7 7 7 4 7 5 7 1 1 5 2 1 1 1 1 5 1 5 4 4 7 7 2 4 5 7 5 7 1 7
## [2776] 1 5 7 5 7 1 5 1 7 7 7 1 4 5 4 1 1 1 5 7 5 7 1 1 5 5 7 1 1 5 7 1 1 5 7 5 5
## [2813] 1 1 1 5 1 1 5 5 7 7 7 7 5 7 4 7 5 5 7 5 7 5 1 1 1 5 4 1 1 5 7 7 5 1 4 5 2
## [2850] 4 7 1 1 1 1 5 7 7 1 1 2 5 7 1 5 1 1 5 7 7 7 7 1 5 1 7 5 1 1 1 5 1 4 1 7 5
```

```
## [2887] 1 1 5 5 1 1 1 5 5 1 5 7 7 7 1 5 5 5 7 1 1 5 1 1 7 5 1 7 1 1 1 7 5 7 5 1 4
## [2924] 1 1 1 1 1 4 1 7 7 7 7 7 1 5 5 5 7 1 2 1 5 1 5 1 5 5 7 5 7 7 7 7 1 1 4 7 1
## [2961] 1 5 7 7 5 1 4 7 7 5 4 7 7 5 7 7 5 1 5 7 7 7 7 7 4 1 1 5 1 7 5 5 1 1 7 5 7
## [2998] 7 7 4 7 4 5 7 1 1 5 7 1 5 4 3 4 4 7 7 5 4 5 1 1 1 5 7 5 1 7 7 5 7 1 1 7 7
## [3035] 5 5 1 5 1 7 5 1 1 2 7 5 1 5 1 1 1 1 1 1 1 2 1 5 1 7 7 5 1 1 5 5 5 5 5 7 2
## [3072] 1 5 1 7 7 4 7 5 1 7 1 1 7 4 7 4 4 5 5 5 5 1 7 7 5 4 7 7 7 7 5 1 4 5 7 5 1
## [3109] 1 1 5 1 7 5 5 5 5 1 5 7 7 7 4 4 7 7 7 1 1 7 5 7 1 7 4 7 7 7 7 4 1 4 5 5 5
## [3146] 7 7 5 5 1 2 3 7 5 1 7 7 1 5 7 4 1 5 1 5 7 1 5 5 5 5 4 5 7 5 4 7 1 1 1 5 1
## [3183] 1 2 1 4 7 5 1 7 7 1 4 4 5 1 1 4 7 5 7 7 5 1 1 5 5 5 5 5 7 4 5 7 7 5 1 7 1
## [3220] 5 1 1 7 7 7 5 7 7 7 1 5 4 4 7 7 7 1 7 7 5 4 5 4 5 7 1 5 1 7 7 5 7 7 7 7 7
## [3257] 7 7 4 4 7 1 5 1 7 7 7 1 1 1 1 5 5 2 1 5 5 1 1 5 2 7 7 1 4 1 1 7 5 5 1 1 1
## [3294] 1 4 2 4 7 2 4 7 5 7 4 7 7 7 4 7 5 5 5 5 1 1 7 4 5 1 5 7 5 1 1 4 4 7 5 5 7
## [3331] 7 7 7 4 1 7 1 7 5 1 5 1 7 1 5 1 5 5 4 7 1 7 7 1 7 1 1 5 4 7 1 1 1 1 4 7 7
## [3368] 7 1 7 5 5 1 1 5 1 1 5 4 7 5 7 1 5 2 7 7 7 4 7 7 7 7 4 5 1 1 1 1 5 1 1 4 4
## [3405] 1 7 7 4 7 7 5 7 1 1 7 1 1 5 7 1 1 5 5 7 7 1 2 7 7 5 1 1 5 7 5 4 4 4 7 5 7
## [3442] 5 1 2 7 5 1 1 7 5 1 1 7 1 7 7 7 7 4 4 7 7 5 7 7 1 1 5 5 7 1 7 7 1 1 5 5 5
## [3479] 1 5 5 1 5 1 1 1 7 7 7 5 5 7 7 1 5 1 7 5 5 1 1 5 7 7 1 7 4 7 7 7 7 5 5 7 7
## [3516] 1 5 7 7 4 7 5 1 5 5 1 1 5 7 7 5 5 7 1 5 1 1 1 1 5 5 7 7 7 5 4 5 1 1 5 7 5
## [3553] 5 4 1 5 5 7 7 1 7 4 4 7 1 1 2 4 1 2 2 7 7 1 5 7 7 1 1 5 2 1 1 1 1 1 1 7 1
## [3590] 1 2 7 1 4 5 7 7 5 7 7 5 7 7 5 1 1 1 7 7 7 7 7 7 7 5 7 4 7 7 5 7 5 5 1 5 1
## [3627] 1 1 2 7 5 1 5 7 5 7 7 7 5 7 5 4 7 1 1 5 1 1 4 5 5 5 1 1 5 7 7 7 7 7 5 1 5
## [3664] 1 5 4 7 5 5 5 7 7 7 4 7 7 1 1 1 1 1 1 1 5 5 5 1 4 5 5 4 7 5 7 5 5 1 1 5 1
## [3701] 1 7 5 1 1 5 7 4 4 5 7 5 1 1 1 5 5 1 5 5 1 1 5 4 7 7 1 1 1 1 5 1 5 1 1 1 1
## [3738] 1 1 1 1 1 5 7 1 5 1 1 1 7 5 7 1 7 5 5 7 5 1 1 1 5 1 1 4 7 7 5 5 7 5 7 1 7
## [3775] 7 7 5 5 7 1 1 7 7 7 7 4 5 7 7 5 5 4 5 1 1 7 1 7 7 5 7 7 7 7 7 7 7 5 4 4 5 7
## [3812] 7 1 5 5 7 1 1 5 7 7 1 5 5 7 5 5 2 1 1 1 1 1 1 7 7 7 7 7 7 5 1 7 7 1 1 5 5 1
## [3849] 1 5 5 1 4 1 5 4 5 7 5 4 7 7 7 1 4 1 5 5 7 5 1 1 7 7 4 7 7 4 7 7 7 7 5 7 7
## [3886] 4 1 1 1 1 1 2 5 5 4 5 7 7 7 7 7 7 5 5 7 4 7 7 7 7 4 7 1 1 4 7 7 4 7 1 1 7
## [3923] 5 5 1 1 1 5 7 7 5 7 7 5 5 7 7 7 7 2 1 7 5 5 1 7 7 7 7 7 5 7 7 1 1 1 1 4 7
## [3960] 7 5 5 1 1 7 7 1 4 4 5 5 1 1 5 5 5 1 1 7 7 1 1 7 2 1 7 2 5 5 1 7 7 7 5 1 5
## [3997] 5 1 5 5 5 5 7 7 7 1 1 5 7 5 7 7 1 1 1 5 5 1 5 1 7 7 5 5 7 7 5 7 4 1 1 5 5
## [4034] 1 4 5 7 5 1 5 7 7 5 5 5 4 4 1 5 1 1 7 7 5 7 5 7 5 5 7 7 7 7 5 7 5 7 5 5 4
## [4071] 4 7 1 5 7 7 1 1 1 7 5 4 4 7 4 7 7 7 5 1 1 7 7 2 1 1 5 5 6 1 4 4 5 1 5 7 4
## [4108] 1 7 1 1 1 1 7 7 5 7 1 5 5 7 5 1 7 1 7 5 5 4 1 4 7 7 5 1 5 5 5 4 7 5 1 5 5
## [4145] 1 7 1 4 7 7 7 5 7 7 4 4 7 4 7 1 1 1 1 1 5 5 1 1 7 5 7 5 1 1 1 1 5 1 5 5 4
## [4182] 1 1 1 1 5 4 4 7 1 6 5 1 7 1 5 1 7 4 1 7 5 5 5 1 1 1 1 2 7 7 1 1 1 1 1 1 5
## [4219] 2 1 5 5 1 1 4 4 1 7 1 4 4 7 5 4 7 5 4 5 1 1 1 7 1 1 1 1 5 5 5 1 5 5 7 7 7
## [4256] 4 4 4 7 1 5 1 1 4 5 4 5 4 5 1 5 1 5 1 7 4 1 6 1 5 1 1 1 1 1 7 7 7 7 4 7 1 5
## [4293] 1 7 4 1 1 2 7 5 7 5 7 5 1 5 7 7 5 7 7 1 7 1 1 7 1 1 5 7 1 4 7 4 7 7 1 5 5
## [4330] 7 5 1 5 5 7 7 7 1 1 7 1 1 5 5 1 1 1 1 4 5 7 7 7 1 4 4 7 7 4 7 1 1 1 1 1 1
## [4367] 5 7 5 5 1 5 1 5 5 5 1 5 1 1 1 7 4 7 7 5 1 7 5 7 1 1 7 5 7 4 7 7 7 5 1 5 7
## [4404] 1 7 7 1 1 1 1 5 1 1 1 1 7 5 5 7 4 5 7 1 1 5 5 1 1 2 1 1 1 5 1 1 4 5 4 7 7
## [4441] 1 5 5 5 5 5 1 5 1 1 1 5 1 5 1 7 7 5 7 7 7 7 4 7 7 7 5 1 7 1 7 7 7 7 7 7 7
## [4478] 1 1 5 5 1 5 1 7 1 1 4 5 4 7 7 7 5 5 5 5 4 1 1 5 5 5 5 1 1 7 1 1 7 1 1 4 7
## [4515] 1 1 5 5 1 5 1 1 7 5 5 1 5 1 7 4 1 1 7 1 1 1 7 1 1 1 5 4 1 5 7 5 4 7 4 7 1
## [4552] 7 7 1 1 1 1 4 7 7 1 7 5 7 5 7 4 7 4 1 1 1 7 5 1 5 1 7 1 5 5 7 5 1 5 5 5 1
## [4589] 1 5 1 7 7 1 7 1 5 1 5 1 5 1 7 7 7 5 1 1 7 5 5 1 7 5 4 5 7 1 1 2 7 5 7 7 7
## [4626] 7 5 1 5 1 1 5 1 5 1 1 1 1 1 2 1 4 7 7 7 1 1 1 5 5 5 1 1 5 1 7 7 7 7 5 7 5
## [4663] 7 7 4 7 1 1 4 5 5 1 1 1 1 7 7 1 5 1 7 5 5 7 4 4 5 5 4 7 7 7 5 7 1 1 1 5 1
## [4700] 7 7 7 4 4 5 1 1 5 1 1 1 4 5 4 7 7 1 1 5 5 1 4 1 1 4 7 1 7 5 7 5 1 1 1 1 1
## [4737] 1 1 1 7 1 1 1 1 1 1 1 1 1 5 7 7 7 7 4 7 4 4 1 7 7 7 7 1 1 1 5 7 7 7 1 5 4
## [4774] 5 7 1 1 1 5 1 7 4 5 5 5 4 7 7 5 5 4 7 7 1 1 1 4 5 7 5 7 4 4 7 5 1 5 1 7 1
## [4811] 1 7 7 7 1 7 7 7 7 1 4 5 4 4 7 7 7 1 1 7 5 1 1 1 5 1 7 4 5 7 1 4 5 1 7 7 5
## [4848] 5 7 1 5 5 5 1 1 1 7 1 5 5 2 5 7 7 1 2 5 1 1 7 5 7 4 7 4 5 7 7 4 1 1 2 1 5
```

```
## [4885] 1 5 1 5 1 5 1 1 1 1 1 1 1 7 7 4 1 1 5 1 7 1 5 4 7 7 5 7 4 4 1 7 5 7 1 1 4
## [4922] 1 1 5 1 1 7 1 1 5 1 1 7 4 7 7 5 5 7 5 5 1 1 1 1 7 1 1 5 1 1 1 1 1 5 1 1 4
## [4959] 5 7 1 7 1 1 4 7 1 1 1 1 7 7 7 7 1 5 5 7 5 7 4 7 1 1 5 5 7 5 4 7 7 3 5 5 5
## [4996] 7 7 4 7 5 1 5 1 1 1 5 2 1 4 5 4 4 4 5 5 5 7 1 1 1 1 1 1 1 1 1 1 1 7 1 1 5
## [5033] 1 1 5 1 1 5 7 1 5 1 1 5 5 1 7 5 4 7 1 7 1 5 7 5 5 5 4 1 5 1 1 1 1 7 5 5 1
## [5070] 1 1 5 1 1 7 5 5 7 1 7 1 7 7 7 1 4 5 7 4 7 7 7 1 4 4 7 4 4 7 7 7 7 7 5 7 7
## [5107] 1 5 5 5 5 7 4 7 7 7 1 1 5 5 5 1 1 1 5 5 2 1 1 1 5 5 7 5 7 5 7 1 1 5 1 5 5
## [5144] 7 1 1 1 7 7 1 1 5 7 1 1 1 7 7 4 7 7 5 1 7 1 1 1 1 1 1 1 2 1 1 7 4 7 7 7 1 7
## [5181] 1 5 1 1 5 5 5 1 2 5 7 1 5 5 1 1 1 5 2 7 7 5 5 1 1 1 1 1 5 1 1 1 1 1 5 5 1
## [5218] 1 5 5 1 5 5 5 1 5 5 7 1 7 5 1 5 5 7 1 1 1 1 1 1 7 1 4 1 7 7 7 4 1 7 5 1 1 7
## [5255] 7 7 1 5 5 7 7 4 7 7 7 1 1 1 1 1 5 1 5 4 1 1 5 5 1 1 1 1 1 1 1 5 4 4 1 7 5
## [5292] 5 7 7 5 7 1 5 1 1 2 2 5 7 4 5 1 1 7 5 3 7 7 1 1 5 7 7 7 4 4 4 7 1 5 5 1 1
## [5329] 7 7 1 5 1 1 1 1 7 5 5 5 1 5 7 5 1 1 7 7 1 5 5 7 7 5 5 1 5 1 1 1 5 5 5 1 7
## [5366] 7 7 1 1 7 1 1 7 5 7 5 1 5 7 1 5 5 5 7 7 5 5 7 1 1 7 5 1 5 5 5 5 5 4 5 1 1
## [5403] 7 7 5 1 1 1 7 7 1 5 1 5 4 7 7 1 5 7 7 7 7 7 5 1 2 5 5 1 7 7 7 4 7 2 1 7 4 7
## [5440] 7 7 7 1 5 1 7 5 5 1 5 1 1 5 5 7 7 5 1 5 5 7 1 4 7 5 4 7 7 7 1 5 5 7 4 1 1
## [5477] 5 1 1 4 7 1 1 1 7 7 4 7 7 7 7 7 1 1 7 4 7 1 1 1 5 1 7 7 7 7 1 1 5 7 7 7 7
## [5514] 1 1 1 2 5 7 7 5 7 5 1 5 1 1 1 5 7 2 5 1 1 1 1 1 1 1 7 4 7 4 4 4 5 1 7 1 5
## [5551] 7 5 7 5 7 1 1 1 1 5 1 1 2 1 7 7 5 7 7 7 7 7 4 7 7 7 5 1 1 5 5 1 5 1 1 1 1
## [5588] 5 7 1 1 1 1 4 1 1 1 1 1 7 5 7 7 5 5 7 7 5 1 1 7 1 5 1 5 5 5 7 1 5 1 1 5 1
## [5625] 1 1 2 5 7 5 1 5 1 5 5 5 1 1 5 7 5 1 1 1 5 5 5 1 5 5 1 5 1 1 4 7 7 7 4 7 7
## [5662] 7 5 7 4 7 7 1 5 1 1 7 7 7 1 5 1 4 5 1 1 1 1 5 5 7 5 5 5 7 5 5 1 5 1 7 4 4
## [5699] 7 5 7 5 7 7 7 1 7 1 1 1 2 1 7 1 5 5 1 5 1 5 5 7 7 1 7 5 5 1 1 1 1 1 5 1 1
## [5736] 7 1 1 7 1 1 7 1 1 5 5 7 7 7 5 4 1 5 1 1 4 2 7 4 1 7 1 1 5 5 7 5 5 1 1 1 1
## [5773] 1 7 5 7 7 1 1 7 7 1 1 1 4 5 4 5 5 4 5 7 1 1 7 2 1 1 1 7 7 7 7 7 7 7 7 7 7
## [5810] 7 1 1 7 1 7 1 7 7 5 1 1 1 5 7 7 1 1 1 1 1 1 1 1 7 5 4 4 5 7 5 5 1 7 5 1 5 5
## [5847] 7 1 1 1 1 1 1 1 5 7 4 4 7 1 7 1 1 1 1 1 1 5 7 4 7 5 1 1 5 1 7 5 1 5 1 7 5 5
## [5884] 1 2 7 1 1 1 1 7 7 7 1 1 1 5 1 1 1 5 1 1 1 5 1 1 7 1 1 7 1 1 5 5 1 1 2 5 1
## [5921] 1 1 1 7 5 5 5 1 1 4 7 7 7 7 7 5 7 7 7 7 5 1 7 1 5 1 1 5 1 1 1 5 7 5 7 4 5
## [5958] 5 1 7 1 5 1 1 1 5 7 1 1 7 1 1 7 1 5 1 1 5 5 1 1 1 1 5 5 1 1 5 1 5 2 5 7 5
## [5995] 7 7 7 7 7 1 1 7 4 4 1 1 1 1 1 1 2 1 7 5 2 1 5 1 1 5 1 1 7 1 5 7 5 5 7 1 7
## [6032] 1 5 1 4 4 1 5 1 1 7 7 7 7 5 7 1 4 4 5 5 5 7 7 4 4 5 1 5 7 1 1 5 1 1 5 5 5
## [6069] 1 7 7 7 7 7 7 1 5 1 1 1 5 4 4 5 7 7 4 1 1 4 1 1 5 1 1 1 1 7 1 2 1 2 1 1 7
## [6106] 7 4 5 7 4 5 7 5 5 7 5 2 1 7 7 5 4 7 7 5 1 7 5 7 1 1 5 5 7 1 7 4 5 7 1 5 1
## [6143] 1 5 1 1 1 7 7 5 5 5 1 7 7 7 7 1 5 1 7 7 7 4 7 7 7 7 1 1 7 1 5 1 1 2 5 1 1
## [6180] 1 5 1 1 5 5 5 1 5 5 7 5 1 5 4 5 7 7 5 1 1 2 7 5 5 7 5 7 7 7 2 5 1 1 1 1 1
## [6217] 5 1 5 1 5 5 7 5 7 4 7 7 7 7 1 7 1 5 2 5 7 7 1 1 7 5 4 1 5 1 1 1 1 1 1 4 5
## [6254] 1 5 7 4 7 1 1 7 1 4 1 5 7 5 1 5 7 5 5 5 1 1 5 5 1 7 7 7 7 7 5 5 7 7 7 5 7
## [6291] 5 1 7 1 7 2 5 1 7 1 4 7 5 7 1 5 7 7 7 5 7 1 1 1 1 1 1 1 1 5 5 7 7 1 1 5 1 1
## [6328] 1 5 1 1 1 1 5 1 5 1 5 1 1 2 7 1 1 1 1 5 7 1 1 4 7 4 1 1 5 5 1 1 5 1 5 5 7
## [6365] 5 1 1 1 5 4 7 1 1 1 7 5 7 1 1 5 5 4 7 4 7 5 4 1 1 5 1 1 1 5 1 1 7 7 5 5 5
## [6402] 1 1 1 7 7 5 5 5 7 7 7 1 5 4 7 7 7 1 1 1 1 5 5 1 2 4 7 7 7 5 4 7 5 5 1 5 7
## [6439] 7 5 5 1 1 5 1 5 4 7 7 1 1 1 7 7 1 5 1 5 1 5 5 1 1 5 1 5 5 2 5 5 1 5 5 7 4
## [6476] 4 7 7 7 5 5 7 7 7 5 1 7 4 5 5 7 7 5 7 7 7 7 1 5 5 5 5 5 4 1 7 7 7 5 7 1 5
## [6513] 1 5 7 7 5 5 1 7 2 1 5 7 7 4 4 2 1 7 4 5 1 5 2 2 7 7 1 5 5 1 7 1 4 7 7 5 7
## [6550] 5 1 1 5 7 7 7 4 7 5 5 1 4 1 7 1 1 4 5 7 7 7 7 1 1 5 5 7 5 5 1 1 1 1 5 1 5
## [6587] 5 1 1 1 7 1 5 7 5 4 7 4 7 1 1 5 5 7 1 5 7 5 7 5 7 1 1 5 1 7 5 1 5 5 2 1 5
## [6624] 5 7 7 2 1 5 4 7 2 1 1 4 7 5 1 5 5 5 1 5 7 5 7 4 7 4 7 5 4 7 7 7 7 7 5 7 5
## [6661] 1 1 5 5 5 5 5 1 1 5 1 7 5 1 5 1 5 1 5 1 1 1 1 5 7 4 5 1 1 5 1 5 5 1 1 7 7
## [6698] 1 1 7 7 7 4 7 1 7 5 1 7 7 5 7 4 4 7 5 5 1 1 7 5 1 1 5 1 1 7 5 5 4 7 7 7 7
## [6735] 7 1 1 5 7 7 7 7 7 5 5 5 5 7 1 1 1 1 1 1 1 1 5 1 5 1 7 1 1 5 7 7 7 7 4 5 5 5
## [6772] 4 7 7 5 1 7 5 1 1 1 5 7 7 7 5 7 1 5 7 5 1 1 7 7 4 4 4 4 7 4 7 7 7 1 1 7 7
## [6809] 4 4 4 7 4 5 4 1 5 2 4 4 7 4 5 5 1 1 6 1 5 1 1 1 7 7 1 5 1 1 2 5 4 1 1 5 1
## [6846] 7 1 7 7 1 2 5 1 1 1 1 1 1 1 5 5 5 7 7 7 5 1 7 2 1 5 7 1 4 7 1 2 4 7 2 5 2
```

```
## [6883] 1 5 2 7 7 1 7 5 5 1 1 1 1 1 5 4 5 4 5 2 7 4 5 1 1 7 1 4 1 1 1 7 7 4 7 5 1
## [6920] 4 5 1 5 1 5 5 1 1 1 5 1 7 7 7 7 7 4 7 1 7 5 1 1 5 1 5 1 7 7 5 7 7 7 7 5 1
## [6957] 5 1 1 1 1 1 5 1 5 1 1 5 1 5 7 7 7 4 7 7 7 1 5 5 1 1 5 1 1 1 1 5 5 4 1 5 1
## [6994] 5 5 1 4 7 1 1 1 7 5 7 7 1 4 4 7 7 5 1 1 7 1 1 1 1 5 7 7 7 5 5 5 5 7 1 5 1
## [7031] 1 1 1 7 7 7 7 1 1 1 7 1 7 7 7 7 7 1 7 7 5 1 1 1 5 7 5 5 1 1 7 7 7 7 1 5 5
## [7068] 4 5 1 7 7 7 5 4 7 5 4 5 7 7 7 4 1 5 4 7 1 1 7 1 1 1 5 5 5 7 5 5 5 7 7 4 1
## [7105] 5 7 5 1 1 1 1 1 5 7 2 7 1 7 1 7 4 5 1 1 1 1 1 5 1 7 5 1 2 1 1 1 4 7 4 7 1
## [7142] 5 5 7 4 7 7 1 1 7 1 4 7 4 5 5 1 1 1 7 7 1 5 5 7 1 1 7 5 7 1 1 5 2 7 4 7 4
## [7179] 4 1 1 7 5 5 7 7 7 4 4 7 7 4 5 5 1 1 5 1 1 1 7 5 5 4 1 1 5 7 7 7 1 5 7 1 5
## [7216] 1 1 7 1 7 4 1 7 7 5 1 5 5 5 1 1 1 1 5 1 7 1 4 5 5 5 5 1 2 5 5 7 4 5 1 1 7
## [7253] 1 1 5 1 1 5 5 5 1 5 7 7 5 7 4 7 7 5 7 1 7 4 5 5 5 7 1 5 2 4 4 5 7 1 1 1 7
## [7290] 5 7 5 4 5 1 7 5 5 4 4 5 4 5 7 7 7 1 7 1 1 5 4 4 5 7 1 7 7 4 5 5 7 7 1 1 5
## [7327] 7 1 2 2 4 7 4 7 7 1 7 1 1 1 1 5 1 5 4 7 7 7 4 5 5 5 5 5 5 5 7 7 5 7 1 7 7
## [7364] 7 5 4 7 5 4 7 1 5 1 5 1 7 7 5 7 1 5 5 1 1 1 1 5 5 1 7 5 7 5 1 5 7 1 5 5 7
## [7401] 1 5 1 5 1 7 7 5 5 7 1 7 7 7 7 5 7 5 4 5 4 7 4 7 7 7 4 1 1 1 1 1 1 7 4 7 5 5
## [7438] 5 5 5 7 1 7 7 7 7 4 5 5 7 7 4 5 7 7 7 1 1 5 5 7 1 5 1 5 1 5 1 1 1 4 7 2 7
## [7475] 2 1 1 1 1 1 1 1 7 5 1 5 5 2 7 1 5 5 7 7 4 7 1 1 1 1 1 1 7 1 7 1 4 7 1 7 5 5
## [7512] 5 5 5 1 5 1 5 1 1 2 4 4 7 5 5 5 1 5 7 7 7 7 7 5 1 4 1 7 4 4 7 5 5 5 5 5 4
## [7549] 4 4 1 5 7 1 4 5 5 1 1 1 5 7 7 7 7 1 7 7 5 1 1 5 1 1 1 1 1 7 1 2 1 7 1 2 5
## [7586] 1 1 1 1 5 5 7 7 7 5 1 7 7 7 5 4 5 5 1 4 4 5 7 1 5 1 1 1 1 1 4 1 5 7 5 5 7
## [7623] 1 1 5 5 5 7 5 5 5 5 5 1 1 1 1 1 5 1 5 4 4 4 5 7 4 7 7 5 7 7 7 1 1 1 1 1 4
## [7660] 5 4 4 5 5 1 1 2 1 5 1 1 1 1 5 7 1 7 1 1 2 1 5 1 2 5 1 2 1 5 1 1 1 5 7 5 5
## [7697] 4 1 1 1 5 7 1 1 1 1 1 1 7 4 5 7 7 7 5 7 5 4 1 1 1 7 1 7 7 7 7 1 7 7 7 7 7
## [7734] 7 1 1 7 5 5 1 1 7 1 1 1 1 7 5 1 1 1 1 1 1 7 7 5 5 1 1 7 7 7 7 5 1 2 5 7 5 7
## [7771] 1 4 3 7 1 1 1 1 7 1 1 4 7 5 7 1 4 7 4 5 4 4 7 5 1 7 5 1 1 1 7 1 7 7 7 7 4
## [7808] 4 7 7 1 1 7 5 7 7 1 5 2 5 5 5 1 1 5 1 7 7 7 1 7 7 7 5 7 7 7 1 1 1 1 1 1 5
## [7845] 7 5 2 4 7 7 7 7 4 1 1 1 7 5 1 1 4 1 1 7 7 7 4 1 1 7 7 1 7 1 1 5 7 7 4 7 5
## [7882] 5 5 7 5 7 5 7 5 5 1 5 1 7 5 1 5 5 4 5 7 7 5 7 7 7 4 1 7 5 1 7 4 7 2 1 7 7
## [7919] 7 1 1 1 5 4 1 5 1 1 1 5 1 7 5 1 7 1 7 2 1 5 7 5 4 5 7 4 4 5 5 4 7 7 1 1 1
## [7956] 7 5 1 5 7 7 5 4 7 7 5 1 4 7 7 7 7 7 4 7 4 7 1 1 7 7 1 5 5 7 5 5 1 1 1 1 4
## [7993] 7 4 4 4 5 5 5 1 1 5 5 1 1 1 5 1 1 2 5 5 5 5 1 1 5 5 7 5 1 4 5 7 4 1 1 1 1
## [8030] 5 4 5 7 4 4 7 5 1 7 5 5 1 1 1 5 5 4 7 5 4 7 5 1 4 5 7 5 5 7 1 5 7 1 1 1 1
## [8067] 7 1 5 5 4 7 7 4 4 4 1 1 1 5 5 7 5 4 5 5 7 7 7 5 5 1 5 1 1 1 5 5 1 1 2 1 2
## [8104] 5 5 7 5 7 7 5 7 7 4 7 5 1 1 5 7 1 7 5 7 7 7 4 7 7 4 1 1 1 1 4 1 5 4 5 5 5
## [8141] 7 1 1 7 7 5 1 1 5 1 1 1 1 6 1 1 7 5 7 5 1 5 1 5 5 7 7 5 2 7 1 5 1 5 1 7 5
## [8178] 5 1 4 5 7 4 4 7 7 7 5 1 1 5 1 4 7 7 1 7 5 7 4 7 5 1 1 2 1 7 7 4 7 7 4 7 4
## [8215] 7 4 4 7 4 7 4 7 7 5 1 5 1 1 1 1 1 5 5 1 7 4 2 7 7 7 7 7 7 1 5 1 1 4 7 7 4 4
## [8252] 4 7 1 1 5 1 5 5 5 1 1 1 4 1 5 1 7 7 2 7 2 7 7 5 5 4 4 7 1 7 7 7 7 7 5 4 5 5
## [8289] 5 5 7 7 4 7 1 5 1 7 7 1 1 2 7 7 7 5 5 1 5 7 7 1 2 7 7 5 7 7 5 1 7 4 1 5 5
## [8326] 7 4 4 1 1 1 1 5 1 1 5 1 1 5 5 5 1 5 5 7 7 5 1 5 5 1 7 4 7 4 7 1 5 7 5 7 4
## [8363] 5 7 7 7 1 1 5 7 7 4 1 1 5 5 7 7 7 5 7 7 7 1 1 7 1 5 1 5 1 1 1 5 1 7 5 4 7
## [8400] 7 5 1 1 1 1 5 1 5 5 7 7 5 7 5 7 1 5 1 1 1 1 1 1 5 1 2 4 7 1 5 5 1 5 7 7 4 4
## [8437] 5 7 7 7 7 7 7 4 7 7 1 1 7 5 1 5 7 7 4 7 7 4 4 4 5 1 1 7 7 1 1 7 2 7 7 7 7
## [8474] 7 4 7 7 1 1 1 1 7 1 5 5 1 1 1 6 5 5 1 5 7 4 7 1 1 1 5 1 7 7 1 7 4 5 7 5 1
## [8511] 1 7 4 7 1 5 1 4 1 1 1 5 1 5 7 5 4 7 7 7 1 1 5 1 1 1 4 5 7 7 5 7 5 1 1 1 1
## [8548] 1 1 7 7 7 7 5 5 5 5 7 5 7 7 4 2 4 5 7 7 5 5 5 7 7 7 1 1 7 1 1 1 1 4 7 7 5
## [8585] 7 4 5 5 7 7 1 7 7 7 7 1 1 7 7 1 1 7 5 7 7 5 1 1 1 7 1 5 1 1 1 7 1 7 5 1 4
## [8622] 7 7 4 5 7 1 5 7 7 1 4 4 7 4 5 5 5 5 1 4 4 5 7 4 7 7 7 5 4 5 1 1 1 1 1 1 1
## [8659] 4 5 5 4 5 5 5 5 5 7 7 1 7 7 7 7 7 5 4 7 4 5 2 5 1 1 5 5 1 5 1 7 7 7 5 5 1
## [8696] 7 7 7 7 2 5 7 5 7 5 1 1 1 7 7 1 7 7 5 5 4 4 4 5 7 7 5 4 5 5 1 7 7 7 7 5 1
## [8733] 1 1 5 1 1 4 7 7 5 1 7 7 1 1 1 7 7 2 1 7 7 5 4 4 1 5 1 1 2 5 1 1 7 4 4 4 7
## [8770] 7 7 7 7 5 7 7 5 5 7 7 7 5 7 1 7 5 7 7 7 7 5 5 1 5 5 7 1 1 5 2 7 1 1 1 1 7
## [8807] 1 4 7 5 1 1 5 7 1 5 1 1 5 7 7 4 7 7 7 7 5 5 1 1 5 1 7 1 1 1 1 5 1 7 1 1 1
## [8844] 5 4 7 5 7 7 5 4 7 1 5 7 7 5 7 2 7 1 1 1 1 5 1 7 7 7 5 5 1 4 4 4 7 4 1 1 5
```

```
## [8881] 1 5 7 7 4 4 4 1 5 1 2 1 2 7 1 1 7 1 1 1 4 7 7 7 1 1 5 5 5 1 7 5 4 7 5 4 4
## [8918] 7 4 1 1 7 7 4 7 4 4 5 7 7 7 5 1 1 7 5 5 7 5 7 7 4 4 7 1 1 1 5 1 5 7 7 5 5
## [8955] 7 1 7 4 5 4 5 7 1 1 5 4 7 5 7 5 7 1 7 5 5 7 7 4 1 4 4 4 4 4 4 7 4 7 7 1 2
## [8992] 5 7 4 5 5 7 7 5 7 4 1 1 5 5 5 1 1 1 7 1 7 5 5 5 7 7 1 7 1 5 4 7 1 1 1 1 1
## [9029] 1 7 1 1 1 2 4 7 1 1 7 6 7 7 1 1 7 5 5 5 1 1 1 1 7 7 1 1 2 5 7 5 7 1 5 5 4
## [9066] 7 1 1 7 1 7 1 1 5 5 4 7 1 1 1 5 1 1 1 5 7 4 7 7 5 5 7 4 1 5 1 5 5 5 7 7 7
## [9103] 7 4 4 7 7 7 5 7 5 1 1 1 5 7 7 7 7 5 5 5 1 4 4 4 1 7 4 4 7 1 1 5 7 7 7 4 5
## [9140] 5 1 1 7 5 5 4 1 5 2 1 5 7 7 5 7 5 1 5 5 4 4 5 1 7 4 2 1 1 5 1 1 1 1 1 7 1
## [9177] 4 1 1 7 7 7 1 1 1 7 2 7 7 5 4 7 4 7 5 7 1 5 5 7 1 1 7 5 5 1 5 7 1 1 1 1 1
## [9214] 1 5 5 4 1 5 4 1 2 1 4 4 4 7 5 1 7 5 4 5 1 7 5 7 7 7 5 4 7 5 7 1 5 1 1 7 5
## [9251] 5 7 5 1 1 1 1 1 1 1 1 7 1 5 4 5 1 1 1 5 2 1 1 2 5 5 7 7 4 7 1 5 7 7 1 7 4
## [9288] 7 5 1 1 1 4 5 7 4 7 7 7 4 7 7 7 7 4 5 1 1 1 5 5 7 7 5 1 7 7 7 1 1 1 4 4 5
## [9325] 7 7 1 7 1 1 1 7 1 1 7 7 5 7 5 1 5 7 5 7 4 7 7 5 5 1 7 7 7 7 1 1 1 5 7 1 5
## [9362] 5 5 1 1 1 7 5 1 1 7 7 5 5 5 1 1 1 7 7 7 7 7 5 1 5 1 1 1 1 5 7 5 5 1 7 5 1
## [9399] 2 5 1 7 7 2 5 7 7 5 1 4 5 7 2 4 7 1 1 7 7 4 4 5 5 7 1 2 5 5 5 5 7 7 7 5 7
## [9436] 7 4 1 7 7 1 5 7 7 7 1 5 5 1 7 5 1 5 1 7 7 7 4 1 7 1 5 1 7 5 1 5 7 1 1 1 7
## [9473] 1 5 7 5 4 4 5 4 4 7 7 5 5 5 7 1 7 5 2 1 5 2 1 5 1 1 1 5 1 1 5 1 5 1 1 5 1
## [9510] 5 5 4 7 2 5 5 7 7 7 1 1 7 7 7 5 5 7 5 7 7 1 7 5 5 1 7 4 7 5 1 5 7 4 7 7 1
## [9547] 1 7 4 7 7 5 1 5 5 7 5 4 5 5 7 7 4 7 1 5 4 7 1 4 7 7 7 5 1 7 7 7 1 1 5 5 5
## [9584] 7 1 7 5 7 7 7 4 4 4 1 1 1 7 7 1 7 5 5 5 7 1 7 7 5 1 1 5 1 7 1 5 2 1 7 7 5
## [9621] 5 7 7 4 7 7 7 1 5 4 7 5 5 1 5 2 1 1 1 3 5 5 5 7 5 7 4 1 1 2 5 1 5 7 4 1 7
## [9658] 1 1 5 2 1 7 1 1 1 1 5 1 1 5 5 7 4 7 1 5 1 1 1 5 1 5 5 1 1 5 4 5 1 1 7 5 5
## [9695] 1 7 5 7 1 1 7 1 1 5 1 7 7 1 1 1 7 4 5 5 7 7 7 5 5 7 1 1 1 5 7 1 5 5 1 7 5
## [9732] 5 5 1 1 7 1 1 5 5 1 2 5 1 7 7 7 4 7 1 7 7 7 1 1 1 1 5 1 5 1 1 1 1 5 1 1 5
## [9769] 5 5 7 7 5 1 3 4 4 5 4 4 1 7 5 1 1 1 5 5 7 7 7 5 7 7 4 4 7 7 7 7 7 5 7 1 1
## [9806] 7 4 7 4 5 7 1 1 5 5 5 7 5 7 7 5 4 1 1 7 7 7 1 7 7 7 4 7 5 4 4 5 1 1 7 5 1
## [9843] 7 7 4 7 5 5 5 1 1 7 1 5 1 1 5 2 5 1 1 1 1 1 1 1 5 1 7 4 4 7 7 1 7 1 7 4 7
## [9880] 5 7 1 5 1 1 1 1 1 1 1 1 5 5 1 5 5 7 7 7 7 7 7 7 4 7 5 7 7 5 1 1 5 7 1 1 5
## [9917] 1 1 1 7 4 4 7 7 1 5 1 1 1 2 7 7 5 1 7 7 1 7 5 1 5 5 5 5 1 7 7 2 2 1 1 1 7
## [9954] 1 7 7 5 1 1 7 1 7 7 7 1 1 5 5 1 5 1 5 7 5 5 1 7 5 7 5 1 5 5 1 5 1 1 1 5 7
## [9991] 1 7 1 1
##
## Within cluster sum of squares by cluster:
## [1] 1131.9138 1960.3599 1460.2766 1749.2333 3515.6513  778.7336 1329.8103
##  (between_SS / total_SS =  70.2 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

Re-running k-means with k = 8:

```r
set.seed(123)
clustering_results_8 <- kmeans(scale(data1[,(15:18)]), centers = 8, nstart = 25)
clustering_results_8
```

```
## K-means clustering with 8 clusters of sizes 912, 2114, 2923, 12, 9, 182, 3263, 579
##
## Cluster means:
##         Sales    Quantity   Discount        Profit
## 1 -0.21598994  0.03592803  2.6411836  -0.463442556
## 2  0.06144353  0.84777662 -0.3020867   0.051473515
```

```
## 3 -0.12740261 -0.55718427  0.2964566  -0.102300730
## 4  8.36049519  1.14320638  2.0689103 -11.913664966
## 5 16.87915324  0.84359568 -0.6489669  19.798650239
## 6  3.85740734  0.99833967 -0.4172776   2.749990730
## 7 -0.18963127 -0.56474906 -0.7485896   0.008899425
## 8  0.17956725  2.49300690 -0.2367609   0.083089163
##
## Clustering vector:
##    [1] 7 7 7 1 3 2 7 2 3 2 8 2 3 3 1 1 2 7 7 3 3 2 2 3 7 3 7 4 1 3 3 2 1 3 3 2 1
##   [38] 8 3 3 3 3 7 3 7 7 7 7 7 2 2 7 7 2 2 2 2 2 7 7 3 7 7 2 7 7 2 8 3 7 3 7 8 3
##   [75] 3 1 1 3 1 7 7 2 7 2 3 7 7 7 2 7 3 7 7 7 7 1 2 3 2 2 3 1 7 2 3 1 8 3 3 2 7
##  [112] 7 2 8 3 3 2 7 1 7 7 2 8 2 3 1 1 2 3 7 3 3 8 7 7 7 7 3 2 8 3 7 7 7 7 2 3 8
##  [149] 7 6 2 2 3 2 7 2 7 3 7 2 7 3 2 3 3 4 3 8 2 1 3 7 7 2 1 3 1 2 2 7 3 2 7 2 7
##  [186] 7 8 3 3 2 2 8 3 2 2 3 3 7 1 3 3 1 3 1 2 3 7 7 7 8 7 3 3 1 3 1 3 2 3 3 2 1
##  [223] 3 1 3 7 2 7 3 8 1 3 1 1 3 3 7 2 1 1 3 1 1 3 6 7 2 6 7 3 7 6 2 7 1 3 2 2 7
##  [260] 7 2 1 3 8 3 7 3 2 3 3 2 2 7 3 7 7 3 3 2 3 1 2 2 2 2 2 1 3 2 2 8 3 1 8 3 3
##  [297] 1 3 2 8 7 7 7 1 7 7 7 2 7 3 3 3 3 7 3 3 3 7 6 2 7 7 7 2 7 3 3 3 3 8 1 3 1
##  [334] 1 3 3 3 3 3 7 3 1 8 8 3 3 7 7 7 7 7 3 7 6 2 7 7 2 2 8 7 7 7 7 8 7 7 7 2 2
##  [371] 2 3 1 8 3 8 3 2 1 3 1 2 3 7 3 3 1 3 3 3 7 3 6 1 3 7 7 7 3 3 3 3 3 2 7 2 3
##  [408] 2 2 7 8 7 8 3 2 3 8 2 7 7 7 2 7 7 2 7 8 7 2 1 2 2 3 2 1 2 3 2 8 7 7 7 7 7
##  [445] 7 2 7 7 7 2 7 7 7 3 3 7 3 3 3 7 8 3 2 1 1 3 3 1 3 1 7 7 3 3 2 2 2 2 7 2 2
##  [482] 7 7 7 7 2 2 6 3 3 3 2 7 7 3 7 8 7 3 8 1 1 3 1 3 2 7 7 7 5 7 7 3 7 7 6 7 7
##  [519] 7 3 3 1 7 3 7 2 3 3 3 3 2 3 7 2 2 3 1 3 7 7 2 8 8 3 3 1 2 7 8 1 2 3 3 3 7
##  [556] 3 7 3 2 7 2 2 3 7 7 3 8 2 7 3 2 7 2 7 7 8 7 7 3 1 7 3 3 3 1 3 7 7 3 3 1 3
##  [593] 3 3 7 3 2 8 3 3 3 3 3 3 1 1 3 1 8 3 3 3 3 8 8 1 7 7 8 7 7 1 7 2 7 8 2 7 2
##  [630] 7 3 2 3 3 3 7 1 3 2 3 7 7 2 7 7 7 2 3 7 3 7 8 7 8 3 1 3 3 1 2 8 2 1 2 7 3
##  [667] 3 3 2 1 3 8 2 7 2 7 1 3 1 1 3 7 7 4 3 7 7 7 3 7 7 7 7 2 8 3 2 3 3 1 1 3 7
##  [704] 3 3 2 3 7 2 8 7 3 2 7 7 2 7 3 3 2 7 7 7 2 2 3 3 8 3 7 7 7 7 7 2 3 7 2 7 3
##  [741] 3 1 2 3 3 3 8 7 3 7 8 2 7 3 7 1 7 7 3 7 8 7 3 7 7 2 7 2 3 7 7 7 2 7 7 2 2
##  [778] 3 7 7 7 1 3 3 3 7 3 3 7 7 8 7 2 7 7 2 2 7 2 2 7 3 8 7 7 3 6 7 7 7 2 7 7 7
##  [815] 6 8 3 8 1 2 1 3 7 7 7 7 2 7 7 7 7 7 7 3 3 3 1 3 3 7 7 3 3 3 7 7 2 7 3 2 7
##  [852] 2 2 7 7 7 8 7 7 7 7 7 2 3 3 7 7 3 1 1 3 7 7 2 2 7 7 7 1 3 2 7 7 2 7 3 8 2
##  [889] 2 2 3 7 7 8 2 3 3 2 8 1 2 1 3 7 7 7 3 2 3 2 6 7 2 7 8 3 3 1 3 3 7 7 7 2 3
##  [926] 3 2 7 7 3 3 3 3 8 1 3 3 7 7 7 7 3 2 2 7 2 1 2 2 8 3 2 3 3 3 2 3 1 3 7 3 7
##  [963] 7 3 7 7 7 7 7 7 2 3 1 3 2 3 1 6 1 7 2 3 3 2 3 3 3 1 2 7 2 3 7 2 6 7 7 7 2
## [1000] 2 7 6 2 7 7 3 3 1 2 3 7 7 7 8 7 2 7 7 2 2 7 7 6 3 3 3 3 3 2 7 7 8 2 3 1 1
## [1037] 7 3 2 3 2 7 3 2 1 8 2 3 8 7 3 3 8 7 7 3 3 3 3 3 3 3 2 3 3 3 1 3 3 1 2 3 3
## [1074] 1 1 3 2 7 7 3 7 8 8 7 7 6 7 3 7 3 3 8 3 2 7 2 1 2 7 7 7 7 1 1 7 2 1 1 8 3
## [1111] 2 3 1 3 3 7 7 2 2 7 7 2 2 7 7 7 7 7 2 7 7 2 7 3 3 3 8 7 7 2 7 7 7 7 3 7 7
## [1148] 7 7 7 7 2 7 2 7 6 7 7 3 7 7 7 7 3 2 7 8 7 7 7 7 7 2 1 2 7 7 7 7 3 2 7 3 2
## [1185] 2 2 7 7 7 8 3 7 7 3 3 3 3 8 3 1 3 1 3 3 3 2 7 3 2 2 3 3 3 1 1 3 3 3 3 2 8
## [1222] 8 7 7 3 7 7 7 7 7 7 7 7 3 3 1 3 3 7 7 7 7 3 7 8 2 6 3 2 8 8 7 2 3 3 3 3 1
## [1259] 3 8 3 1 3 7 2 7 7 2 3 7 3 1 1 3 2 3 3 3 7 7 7 3 1 3 1 2 7 7 3 7 3 2 7 2 7
## [1296] 8 3 3 2 7 2 7 7 7 7 2 2 3 7 7 3 7 7 3 2 8 2 3 3 1 1 3 2 3 7 1 2 7 7 7 3 3
## [1333] 1 1 8 7 7 7 7 8 1 1 1 7 2 7 2 2 8 2 3 7 2 7 3 3 8 7 1 3 2 3 3 8 1 2 3 3 2
## [1370] 1 3 7 7 3 2 7 8 2 2 2 3 1 7 8 2 7 7 7 7 7 7 7 2 3 1 1 3 7 7 7 7 7 3 2 3 3
## [1407] 3 7 7 1 3 7 7 2 7 7 2 3 1 3 1 3 1 2 2 3 3 2 2 8 8 2 7 8 2 2 3 3 2 2 7 3 7
## [1444] 3 8 3 2 3 1 3 1 2 7 2 6 7 7 8 3 7 3 3 3 2 7 3 3 3 7 7 7 3 7 1 2 3 2 2 3 7
## [1481] 2 7 3 3 7 7 2 7 7 3 7 7 2 7 7 2 3 2 2 3 8 3 3 7 7 2 3 7 7 7 8 8 3 1 1 3 2
## [1518] 3 3 2 2 2 2 8 2 2 3 3 2 7 3 3 3 2 3 7 7 7 7 7 2 2 2 3 7 2 3 1 3 3 1 7 2 2
## [1555] 7 7 3 2 7 8 2 7 1 3 2 3 3 1 7 7 2 7 7 3 3 2 3 7 7 7 8 7 3 7 7 2 7 7 7 7 2
## [1592] 2 3 7 3 3 8 3 3 3 1 7 3 2 2 7 2 3 7 3 3 3 3 2 3 7 7 7 7 7 7 8 3 7 2 6 2 2
## [1629] 2 1 3 3 3 3 3 3 2 3 7 7 7 7 3 7 6 7 3 3 1 3 7 7 2 7 7 3 7 2 3 3 3 3 1 2 3
## [1666] 3 3 3 3 3 3 7 3 7 1 1 7 7 3 3 3 1 7 7 3 1 1 3 3 2 2 2 2 3 7 7 7 7 2 2 3 6
```

```
## [1703] 7 2 1 1 2 3 7 3 2 8 2 1 3 3 2 2 7 8 3 3 3 3 3 3 3 2 7 7 8 3 3 3 3 2 3 7 7
## [1740] 2 8 3 3 3 2 7 1 3 3 3 3 7 8 7 7 8 2 1 3 3 3 2 3 7 7 8 7 1 1 3 1 3 2 7 8 7
## [1777] 7 8 2 7 7 7 7 7 2 8 7 7 7 2 7 6 7 3 7 8 7 2 2 3 3 7 1 4 3 6 2 2 2 1 3 2 2
## [1814] 3 3 7 7 7 1 1 1 3 3 3 1 3 3 3 2 3 8 7 3 3 2 2 2 3 3 3 3 7 3 1 7 2 7 3 3 7
## [1851] 2 2 2 7 2 7 2 1 7 7 3 7 3 1 3 3 2 2 3 7 2 3 3 7 3 3 3 3 3 1 7 2 7 2 3 7 3
## [1888] 1 3 3 7 7 3 3 7 3 6 3 1 3 2 7 3 3 3 8 1 1 7 7 7 2 3 2 3 3 3 2 7 2 7 3 8 3
## [1925] 7 7 3 3 7 7 3 3 7 2 2 8 7 1 2 1 3 3 3 1 3 3 7 7 3 7 8 7 2 2 7 7 7 7 7 7 2
## [1962] 2 7 2 7 7 7 2 7 7 3 2 1 3 3 7 2 2 3 2 3 7 7 2 7 7 3 7 2 7 7 1 2 3 3 1 1 7
## [1999] 7 2 2 2 7 2 1 2 2 3 3 3 3 3 3 7 7 2 3 7 7 2 6 7 7 2 2 7 3 3 7 2 7 7 3 3 7
## [2036] 7 7 7 3 1 1 2 2 2 3 7 7 7 2 1 1 8 2 2 7 2 6 7 7 7 2 3 8 3 7 3 8 7 7 3 1 2
## [2073] 3 7 2 7 2 2 2 2 3 3 2 3 7 2 2 7 7 7 7 3 2 7 2 8 7 7 3 2 3 3 3 7 7 3 1 7 3
## [2110] 7 2 3 7 2 7 3 3 2 7 2 1 3 7 8 2 2 3 3 3 7 8 2 7 1 2 3 1 1 7 8 7 3 2 3 2 3
## [2147] 1 2 7 2 3 2 7 3 1 2 7 7 3 1 3 7 7 3 3 1 3 1 3 3 3 3 3 1 3 7 8 2 8 2 7 2 6
## [2184] 2 8 3 7 2 7 8 7 3 7 7 7 2 3 7 3 3 2 2 3 7 3 3 1 3 7 2 8 2 7 3 8 7 3 3 3 7
## [2221] 2 3 8 3 3 1 3 3 3 3 7 2 2 3 2 7 8 2 1 3 2 3 7 7 7 7 3 7 2 2 2 7 7 7 7 7 7
## [2258] 2 7 7 7 7 7 7 7 7 3 7 7 3 2 2 2 3 3 3 2 7 7 3 8 7 2 7 2 3 7 2 2 7 7 2 7 7
## [2295] 7 7 2 7 6 7 7 7 7 2 7 3 3 2 3 3 2 3 3 7 7 2 7 2 7 7 2 7 7 2 8 3 3 7 3 3 7
## [2332] 2 2 7 2 7 2 7 7 3 2 2 7 3 8 2 1 2 2 3 7 7 2 2 2 7 3 2 1 3 2 7 1 7 7 7 3 7
## [2369] 2 3 7 1 3 8 3 7 1 3 2 3 3 2 7 8 3 3 3 7 3 7 2 8 7 7 7 7 2 7 2 2 2 2 2 2 8
## [2406] 2 8 2 3 8 3 2 7 3 2 7 2 3 6 7 7 3 3 2 1 3 8 1 1 1 8 7 2 3 7 7 8 1 3 3 2 3
## [2443] 2 2 2 7 7 2 7 2 2 2 3 7 8 8 7 2 7 7 7 3 2 3 7 7 7 2 2 7 8 3 3 3 2 2 2 3 7
## [2480] 3 3 2 3 2 2 7 7 7 7 2 7 2 6 2 2 8 7 7 3 3 3 1 1 7 7 6 8 1 3 2 2 2 1 3 3 3
## [2517] 8 7 2 2 7 7 7 7 8 3 1 1 3 3 2 7 2 7 2 7 3 3 3 2 3 2 3 7 7 7 3 3 6 8 3 2 7
## [2554] 7 2 7 1 3 2 2 7 3 3 7 7 7 2 6 8 3 3 3 2 2 7 2 7 7 7 8 7 7 8 7 7 3 2 7 7 3
## [2591] 1 1 7 8 7 7 7 7 7 7 2 7 7 3 7 1 7 3 3 2 3 3 1 3 3 2 7 8 7 3 7 2 7 5 6 2 7
## [2628] 3 1 1 7 7 3 3 3 1 7 7 3 7 2 7 2 3 8 7 7 7 2 7 2 3 3 7 7 3 7 2 7 2 6 7 7 3
## [2665] 3 1 3 3 3 7 7 2 7 2 7 2 3 1 1 2 2 7 7 7 8 3 1 1 2 3 1 3 3 2 3 3 1 4 3 3 3
## [2702] 3 3 7 2 7 7 7 2 6 1 3 8 3 2 7 7 7 7 1 3 2 2 2 3 3 3 1 2 7 2 7 7 7 7 7 2 7
## [2739] 7 7 7 2 7 2 3 3 3 3 1 3 8 3 7 7 2 6 7 7 7 7 2 7 2 1 1 3 3 6 1 2 3 2 3 7 3
## [2776] 7 2 3 8 3 7 8 7 3 3 3 7 1 2 1 7 7 7 8 3 2 3 7 7 2 2 3 7 7 2 3 7 7 2 3 8 2
## [2813] 7 2 7 2 7 7 2 2 3 3 3 3 8 3 1 3 2 2 3 2 3 2 7 7 7 2 1 7 2 2 3 3 8 7 1 2 6
## [2850] 1 3 7 7 7 7 2 2 3 7 7 6 2 3 7 2 7 7 2 3 3 3 3 7 8 7 3 2 7 7 7 2 7 1 7 3 2
## [2887] 7 7 2 2 7 7 7 2 8 7 2 2 3 3 7 2 2 2 3 7 7 2 7 7 3 2 7 3 7 7 7 3 2 3 2 7 1
## [2924] 7 7 7 7 7 1 7 3 3 3 3 3 7 2 2 2 3 7 6 7 8 7 2 7 8 2 3 2 3 3 3 3 7 7 1 3 7
## [2961] 7 8 3 3 2 7 1 3 3 2 1 3 3 2 3 3 2 7 2 3 3 3 3 3 1 7 7 8 7 3 2 2 7 2 3 2 3
## [2998] 3 3 1 3 1 2 3 7 7 2 3 7 2 1 4 1 1 3 3 8 1 2 7 7 7 2 3 8 7 3 3 2 3 7 7 3 3
## [3035] 2 2 7 2 7 3 2 7 7 6 1 2 7 2 7 7 7 7 7 7 7 6 7 8 7 3 3 8 7 7 8 8 2 2 2 3 6
## [3072] 7 2 7 3 3 1 3 8 7 3 7 7 3 1 3 1 1 2 2 2 2 7 3 3 8 1 3 3 3 3 2 7 1 2 3 2 7
## [3109] 7 7 8 7 3 2 2 2 2 7 2 3 3 3 1 1 3 3 3 7 7 3 2 3 7 3 1 3 3 3 3 1 7 1 2 2 2
## [3146] 2 3 2 2 7 6 4 3 2 7 3 3 7 2 3 1 7 2 7 8 3 7 2 8 8 2 1 2 3 2 1 3 7 7 7 2 7
## [3183] 7 6 7 1 3 2 7 3 3 7 1 1 2 7 7 1 3 2 3 3 8 7 7 8 2 8 2 8 3 1 8 3 3 2 7 3 7
## [3220] 2 7 7 3 3 3 2 3 3 3 7 2 1 1 3 3 3 7 3 2 2 1 2 8 2 3 7 2 7 3 3 2 3 3 3 3 3
## [3257] 3 3 1 1 3 7 2 7 3 3 3 7 7 7 7 8 2 6 7 2 2 7 7 2 6 3 3 7 1 7 7 3 2 2 7 7 7
## [3294] 7 1 6 1 3 6 1 3 2 3 1 3 3 3 1 3 2 2 2 2 7 7 3 1 8 7 2 3 2 7 7 1 1 3 2 8 3
## [3331] 3 3 3 1 7 3 7 3 8 7 2 7 3 7 8 7 2 2 1 3 7 3 3 7 3 7 7 8 1 3 7 7 7 7 1 3 3
## [3368] 3 7 3 2 2 7 7 2 7 7 8 1 3 8 3 7 2 6 3 3 3 1 3 3 2 3 1 2 7 7 7 7 2 7 7 1 1
## [3405] 7 3 3 1 3 3 8 3 7 7 3 7 7 2 3 7 7 8 2 3 3 7 8 3 3 2 7 7 8 3 2 1 1 1 3 2 3
## [3442] 8 7 6 3 2 7 7 3 2 7 7 3 7 3 3 3 3 1 1 3 3 2 3 3 7 7 8 2 3 7 3 3 7 7 2 2 8
## [3479] 7 2 2 7 2 7 7 7 3 3 3 2 2 3 3 7 2 2 3 2 2 7 7 8 3 3 2 3 1 3 3 3 3 2 8 3 3
## [3516] 7 8 3 3 1 3 2 7 8 2 7 7 8 3 3 2 2 3 7 2 7 7 7 7 2 2 3 3 3 8 1 2 7 7 8 3 2
## [3553] 8 1 7 2 2 3 3 7 3 1 1 3 7 7 6 1 7 6 6 3 3 7 8 3 3 7 7 2 6 7 7 7 7 7 7 3 7
## [3590] 7 8 3 7 1 2 3 3 2 3 3 8 3 2 2 7 7 7 3 3 3 3 3 3 3 2 3 1 3 3 2 3 8 2 7 8 7
## [3627] 7 7 6 3 2 7 8 3 2 3 3 3 2 3 2 1 3 7 7 2 7 7 1 2 2 2 7 7 8 3 3 3 3 3 2 7 8
## [3664] 7 2 1 3 2 8 2 3 3 3 1 3 3 7 7 7 7 7 7 7 8 2 2 7 1 2 2 1 3 2 3 2 2 7 7 2 7
```

```
## [3701] 7 3 2 7 7 2 3 1 1 2 3 2 7 7 7 2 2 7 2 2 7 7 8 1 3 3 7 7 7 7 2 7 2 7 7 7 7
## [3738] 7 7 7 7 7 8 3 7 2 7 7 7 3 2 3 7 3 2 2 2 2 7 7 7 2 7 7 1 3 3 2 8 3 2 3 7 3
## [3775] 3 3 2 2 3 7 7 3 3 3 3 1 2 3 3 2 2 1 2 7 7 3 7 3 3 2 3 3 3 3 3 3 2 1 1 2 3
## [3812] 3 7 2 2 3 7 7 2 3 3 7 2 2 3 8 8 6 7 7 7 7 7 7 3 3 3 3 3 3 8 7 3 3 7 7 2 2 7
## [3849] 2 2 2 7 1 7 2 1 2 3 2 1 3 3 3 7 1 7 2 8 3 2 7 7 3 3 1 3 3 1 3 3 3 3 2 3 3
## [3886] 1 7 7 7 7 7 2 8 2 1 2 3 3 3 3 3 3 8 2 3 1 3 3 3 3 1 3 7 7 1 3 3 1 3 7 7 3
## [3923] 2 2 7 7 7 2 2 3 2 3 3 2 2 3 3 3 3 2 7 3 2 2 7 3 3 3 3 3 2 3 3 7 7 7 7 1 3
## [3960] 3 2 2 7 7 3 3 7 1 1 8 8 7 7 2 8 2 7 7 3 3 7 7 3 6 7 3 6 2 2 7 3 3 3 2 7 2
## [3997] 2 7 2 2 8 2 3 3 3 7 7 2 3 8 3 3 7 7 7 2 2 7 8 7 3 3 2 2 3 3 2 3 1 7 7 2 2
## [4034] 7 1 2 3 2 7 2 3 3 8 2 2 1 1 7 8 7 7 3 3 8 3 2 3 2 2 3 3 3 3 8 3 2 3 8 8 1
## [4071] 1 3 7 2 3 3 7 7 7 3 8 1 1 3 1 3 3 3 8 7 7 3 3 6 7 7 2 2 5 7 1 1 8 7 2 3 1
## [4108] 7 3 7 7 7 7 3 3 2 3 7 2 8 3 2 7 3 7 3 2 2 1 7 1 3 3 8 7 2 2 2 1 3 2 7 8 2
## [4145] 7 3 7 1 3 3 3 2 3 3 1 1 3 1 3 7 7 7 7 7 2 8 7 7 3 2 3 2 7 7 7 7 2 7 2 8 1
## [4182] 7 7 7 7 2 1 1 3 7 5 2 7 3 7 2 7 3 1 7 3 2 2 2 7 7 7 7 6 3 3 7 7 7 7 7 7 8
## [4219] 6 7 2 2 7 7 1 1 7 3 7 1 1 3 2 1 3 8 1 2 7 7 7 3 7 7 7 7 2 2 2 2 2 2 3 3 3
## [4256] 1 1 1 3 7 2 7 7 1 8 1 2 1 2 2 8 7 8 7 3 1 7 5 7 2 7 7 7 7 3 3 3 3 1 3 7 8
## [4293] 7 3 1 7 7 6 3 2 3 2 3 2 7 2 3 3 2 3 3 7 3 7 7 3 7 7 2 3 7 1 3 1 3 3 7 2 8
## [4330] 3 2 7 2 2 3 3 3 7 7 3 7 7 2 2 7 7 7 7 1 8 3 3 3 7 1 1 3 3 1 3 7 7 7 7 2 7
## [4367] 8 3 2 2 7 2 7 2 2 2 7 2 7 7 7 3 1 3 3 2 7 3 2 3 7 7 3 2 3 1 3 3 3 2 7 2 3
## [4404] 7 3 3 7 7 7 7 2 7 7 7 7 3 2 8 3 1 2 3 7 7 2 2 7 7 6 7 7 7 2 7 7 1 2 1 3 3
## [4441] 7 2 2 2 2 2 7 2 7 7 7 2 7 2 7 3 3 2 3 3 3 3 1 3 3 3 8 7 3 7 3 3 3 3 3 3 3
## [4478] 7 7 2 2 7 8 7 3 7 7 1 8 1 3 3 3 2 2 8 2 1 7 7 2 2 2 2 7 7 3 7 7 3 7 7 1 3
## [4515] 7 7 2 2 7 8 7 7 3 2 2 7 2 7 3 1 7 7 3 7 7 7 3 7 7 7 2 1 7 8 3 2 1 3 1 3 7
## [4552] 3 3 7 7 7 7 1 3 3 7 3 2 3 2 3 1 3 1 7 7 7 3 2 7 2 7 3 7 8 2 3 8 7 2 2 2 7
## [4589] 7 2 7 3 3 7 3 7 8 7 2 7 8 7 3 3 3 2 7 7 3 2 8 7 3 2 1 8 3 7 7 6 3 2 3 3 3
## [4626] 3 2 7 2 7 7 2 7 2 7 7 7 7 7 6 7 1 3 3 3 7 7 7 8 2 2 7 7 2 7 3 3 3 3 2 3 2
## [4663] 3 3 1 3 7 7 1 2 2 2 2 7 7 3 3 7 8 7 3 8 8 3 1 1 2 8 1 3 3 3 2 3 7 7 7 8 7
## [4700] 3 3 3 1 1 2 7 7 2 7 7 7 1 2 1 3 3 7 7 2 2 7 1 7 7 1 3 2 3 2 3 2 7 7 7 7 7
## [4737] 7 7 7 3 7 7 7 7 7 7 7 7 7 2 3 3 3 3 1 3 1 1 2 3 3 3 3 7 7 7 2 3 3 3 7 8 1
## [4774] 2 3 7 7 7 2 7 3 1 2 2 2 1 3 3 8 2 1 3 3 7 7 7 1 2 3 2 3 1 1 3 8 7 8 7 3 7
## [4811] 7 3 3 3 7 3 3 3 3 7 1 2 1 1 3 3 3 7 7 3 2 7 7 7 2 7 3 1 2 3 7 1 2 7 3 3 2
## [4848] 8 3 7 2 8 2 7 7 7 3 7 8 2 6 2 3 3 7 6 8 7 7 3 2 3 1 3 1 2 3 3 1 7 2 6 7 2
## [4885] 7 2 7 2 7 2 7 7 7 7 7 7 7 2 3 3 1 7 7 2 7 3 7 2 1 3 3 2 3 1 1 7 3 2 3 7 7 1
## [4922] 7 7 2 7 7 3 7 7 2 7 7 3 1 3 3 2 2 3 2 8 7 7 7 7 3 7 7 2 7 7 7 7 7 2 7 7 1
## [4959] 8 3 7 3 7 7 1 3 7 7 7 7 3 3 3 3 7 8 2 3 2 3 1 3 7 7 2 2 3 2 1 3 3 4 8 8 2
## [4996] 3 3 1 3 2 7 2 7 7 7 2 6 7 1 2 1 1 1 2 2 2 3 7 7 7 7 7 7 7 7 7 7 7 3 7 7 8
## [5033] 7 7 2 7 7 2 3 7 2 7 7 8 2 2 3 2 1 3 7 3 7 2 3 8 2 2 1 7 8 7 7 7 7 3 2 2 7
## [5070] 7 7 2 7 7 3 2 2 3 7 3 7 3 3 3 7 1 2 3 1 3 3 3 7 1 1 3 1 1 3 3 3 3 3 2 3 3
## [5107] 7 8 2 2 2 3 1 3 3 3 7 7 2 8 2 7 7 7 8 2 6 7 7 7 8 8 3 2 3 2 3 7 7 2 7 2 8
## [5144] 3 7 7 7 3 3 7 7 2 3 7 7 7 3 3 1 3 3 8 7 3 7 7 7 7 7 7 6 7 7 3 1 3 3 3 7 3
## [5181] 7 2 7 7 2 2 8 7 6 2 3 7 2 2 7 7 7 2 6 3 3 2 2 7 7 7 7 7 2 7 7 7 7 7 2 2 7
## [5218] 7 2 2 7 2 2 2 7 2 2 3 7 3 2 7 2 2 3 7 7 7 7 7 3 7 1 7 3 3 3 1 7 3 2 7 7 3
## [5255] 3 3 7 2 2 3 3 1 3 3 3 7 7 7 7 7 2 7 2 1 7 7 2 2 7 7 7 7 7 7 7 8 1 1 7 3 2
## [5292] 2 3 3 8 3 7 8 7 7 6 6 2 3 1 2 7 7 3 2 4 3 3 7 7 8 3 3 3 1 1 1 3 7 2 2 7 7
## [5329] 3 3 7 2 7 7 7 7 3 2 2 2 7 2 3 2 7 2 3 3 7 2 8 3 3 8 2 7 2 7 7 7 8 2 2 7 3
## [5366] 3 3 7 7 3 7 7 3 2 3 2 7 2 3 7 2 2 8 3 3 8 8 3 7 7 3 2 7 2 2 2 2 8 1 2 7 7
## [5403] 3 3 2 7 7 7 3 3 7 2 7 2 1 3 3 7 2 3 3 3 3 2 7 6 2 2 7 3 3 3 1 3 6 7 3 1 3
## [5440] 3 3 3 7 8 7 3 2 2 7 2 7 7 2 2 3 3 2 7 2 8 3 7 1 3 2 1 3 3 3 7 2 2 3 1 7 7
## [5477] 2 7 7 1 3 7 7 7 3 3 1 3 3 3 3 3 7 7 3 1 3 7 7 7 2 7 3 3 3 3 7 7 2 3 3 3 3
## [5514] 7 7 7 6 8 3 3 2 3 2 7 8 7 7 7 2 3 6 2 7 7 7 7 7 7 7 3 1 3 1 1 1 2 7 3 7 2
## [5551] 3 2 3 2 3 7 7 7 7 2 7 7 6 7 3 3 2 3 3 3 3 3 1 3 3 3 2 7 7 2 8 7 2 7 7 7 7
## [5588] 2 3 7 7 7 7 1 7 7 7 7 7 3 2 3 3 2 2 3 3 2 7 7 3 7 8 7 2 2 2 3 7 2 7 7 8 7
## [5625] 7 7 6 2 3 8 7 2 7 2 2 2 7 7 2 3 8 7 7 7 2 2 8 7 2 2 7 2 7 7 1 3 3 3 1 3 3
## [5662] 3 8 3 1 3 3 7 8 7 7 3 3 3 7 2 7 1 2 7 7 7 7 2 2 3 2 2 2 3 8 2 7 2 7 3 1 1
```

```
## [5699] 3 2 3 2 3 3 3 7 3 7 7 7 6 7 3 7 2 2 7 2 7 2 2 3 3 7 3 8 2 7 7 7 7 7 8 7 7
## [5736] 3 7 7 3 7 7 3 7 7 2 2 3 3 3 2 1 7 2 2 7 1 6 3 1 7 3 7 7 8 2 3 2 2 7 7 7 2
## [5773] 7 3 2 3 3 7 7 3 3 7 7 7 1 2 1 2 2 1 2 3 7 7 3 8 7 7 7 3 3 3 3 3 3 3 3 3 3
## [5810] 3 7 7 3 7 3 7 3 3 8 7 7 7 2 3 3 7 7 7 7 7 7 7 7 3 2 1 1 2 3 2 2 7 3 2 7 2 2
## [5847] 3 7 7 7 7 7 7 7 2 3 1 1 3 7 3 7 7 7 7 7 2 3 1 2 2 7 7 2 7 3 2 7 2 7 3 8 8
## [5884] 7 6 3 7 7 7 7 3 3 3 7 7 7 2 7 7 7 8 7 7 7 2 7 7 3 7 7 3 7 7 2 2 7 7 6 2 7
## [5921] 7 7 7 3 2 8 8 7 7 1 3 3 3 3 3 2 3 3 3 3 8 7 3 7 2 7 7 2 7 7 7 2 3 2 3 1 2
## [5958] 2 7 3 7 8 7 7 7 2 3 7 7 3 7 7 3 7 2 7 7 8 2 7 7 7 7 2 2 7 7 2 7 2 6 2 3 2
## [5995] 3 2 3 3 3 7 7 3 1 1 7 7 7 7 7 7 6 7 3 2 6 7 2 7 7 2 7 7 3 7 8 3 2 2 3 7 3
## [6032] 7 2 7 1 1 7 2 7 7 3 3 3 3 3 2 3 7 1 1 2 2 2 3 3 1 1 8 7 2 3 7 7 2 7 7 2 8 8
## [6069] 7 3 3 3 3 3 3 7 2 7 7 7 8 1 1 8 3 3 1 7 7 1 7 7 8 7 7 7 7 3 7 6 7 6 7 7 3
## [6106] 3 1 2 3 1 2 3 2 8 3 2 6 7 3 3 8 1 3 3 2 7 3 2 3 7 7 8 2 3 7 3 1 2 3 7 2 7
## [6143] 7 2 7 7 7 3 3 2 2 8 7 3 3 3 3 7 8 2 3 3 3 1 3 3 3 3 7 7 3 7 2 7 7 6 2 7 7
## [6180] 7 2 7 7 8 2 8 7 2 2 3 8 7 2 1 2 3 3 2 7 7 6 3 2 8 3 2 3 3 3 6 2 7 7 7 7 7
## [6217] 8 7 2 7 2 8 3 2 3 1 3 3 3 3 7 3 7 8 6 2 3 3 7 7 3 8 1 7 2 7 7 7 7 7 7 1 8
## [6254] 7 8 3 1 3 7 7 3 7 1 7 2 3 8 7 2 3 8 2 2 7 7 2 2 7 3 3 3 3 3 2 2 3 3 3 2 2
## [6291] 8 7 3 7 3 6 2 7 3 7 1 3 2 3 7 2 3 3 3 8 3 7 7 7 7 7 7 7 2 2 3 3 7 7 2 7 7
## [6328] 7 2 2 7 7 7 2 7 2 7 2 7 7 6 3 7 7 7 7 2 3 7 7 1 3 1 7 7 2 2 7 7 2 7 2 2 3
## [6365] 8 7 7 7 2 1 3 7 7 7 3 2 3 7 7 2 8 1 3 1 3 8 1 7 7 2 7 7 7 2 7 7 3 3 2 8 2
## [6402] 7 7 7 3 3 2 2 2 3 3 3 7 2 1 3 3 3 7 7 7 7 2 8 7 6 1 3 3 3 2 1 3 2 2 7 2 3
## [6439] 3 2 2 7 7 2 7 2 1 3 3 7 7 7 3 3 7 2 7 2 7 2 2 7 7 2 7 2 2 6 2 2 7 2 8 3 1
## [6476] 1 3 3 3 2 2 3 3 3 2 7 2 1 8 2 3 3 2 3 3 3 3 7 8 8 2 2 2 1 7 3 3 3 2 3 7 2
## [6513] 7 2 3 3 2 8 7 3 6 7 2 3 3 1 1 6 7 3 1 2 7 2 6 6 3 3 7 2 2 7 3 7 1 3 3 2 3
## [6550] 2 2 7 2 3 3 3 1 3 8 2 7 1 7 3 7 2 1 2 3 3 3 3 7 7 8 8 3 2 2 7 7 7 7 2 7 2
## [6587] 2 7 7 7 3 7 2 3 2 1 3 1 3 7 7 8 2 3 7 2 3 2 3 2 3 7 7 2 7 3 2 7 2 2 6 7 2
## [6624] 8 3 3 6 7 8 1 3 6 7 7 8 3 2 7 2 8 2 7 8 3 2 3 1 3 1 3 2 1 3 2 3 3 3 2 3 8
## [6661] 7 7 2 2 2 2 2 7 7 2 7 3 2 7 2 7 2 7 2 7 7 7 7 2 3 1 2 2 7 2 7 2 8 7 7 3 3
## [6698] 7 7 3 3 3 1 3 7 3 2 7 2 3 8 3 1 1 3 2 2 7 7 3 2 7 7 2 7 7 3 2 2 1 3 3 3 3
## [6735] 3 7 7 8 3 3 3 3 3 2 2 2 2 3 7 7 7 7 7 7 7 2 7 2 7 3 7 7 2 3 3 3 3 1 2 2 2
## [6772] 1 3 3 2 7 3 8 7 7 7 8 3 3 3 2 3 7 2 3 2 7 7 3 3 1 1 1 1 3 1 3 3 3 7 7 3 3
## [6809] 1 1 1 3 1 8 1 7 2 6 1 1 3 1 2 8 7 7 5 7 2 7 7 7 3 3 7 2 7 7 6 2 1 7 7 2 2
## [6846] 3 7 3 3 7 6 2 7 7 7 7 7 7 7 2 8 8 3 3 3 2 7 3 6 7 8 3 7 1 3 7 6 1 3 6 2 6
## [6883] 7 2 6 3 3 7 3 8 2 7 7 7 7 7 2 1 2 1 2 6 3 1 2 7 7 3 7 1 7 7 7 3 3 1 3 2 7
## [6920] 1 2 7 2 7 2 8 7 7 7 2 7 3 3 3 3 3 1 3 7 3 2 2 7 2 7 2 7 3 3 2 3 3 3 3 2 7
## [6957] 2 7 7 7 7 7 2 7 2 7 7 8 7 2 3 3 3 1 3 3 3 7 8 2 7 7 2 7 2 7 7 2 2 1 7 2 7
## [6994] 2 2 7 1 3 7 7 7 3 2 3 3 7 1 1 3 3 2 7 7 3 7 7 7 7 2 3 3 3 8 2 8 2 3 7 2 7
## [7031] 7 7 7 3 3 3 3 7 7 7 3 7 2 3 3 3 3 7 3 3 2 7 7 7 2 3 8 2 7 7 3 3 3 3 7 2 2
## [7068] 1 8 7 3 3 3 2 1 3 2 1 8 3 3 3 1 7 8 1 3 7 7 3 7 7 7 2 2 2 3 2 8 2 3 3 1 7
## [7105] 2 3 8 7 7 7 7 7 2 3 6 3 7 3 7 3 1 2 7 7 7 7 7 7 2 7 3 2 7 6 7 7 7 1 3 1 3 7
## [7142] 2 2 3 1 3 3 7 7 3 7 1 3 1 2 2 7 7 7 3 3 7 2 8 3 7 7 3 8 3 7 7 2 6 3 1 3 1
## [7179] 1 7 7 3 2 8 3 3 3 1 1 3 3 1 8 2 7 7 2 7 7 7 3 1 2 1 7 7 8 3 3 3 7 8 3 7 2
## [7216] 7 7 3 7 3 1 7 3 3 2 7 2 2 2 7 7 7 7 8 7 3 7 1 2 2 2 2 7 6 2 2 3 1 8 7 7 3
## [7253] 7 7 2 7 7 2 2 2 7 2 3 3 2 3 1 3 3 8 3 7 3 1 2 2 8 3 7 2 6 1 1 2 3 7 7 7 3
## [7290] 8 3 8 1 2 7 3 2 2 1 1 2 1 2 3 3 3 7 3 7 7 2 1 1 8 3 7 3 3 1 2 2 3 3 7 7 2
## [7327] 3 7 2 6 1 3 1 3 3 7 3 7 7 7 7 8 7 2 1 3 3 3 1 2 2 2 8 2 2 8 3 3 2 3 7 3 3
## [7364] 3 8 1 3 2 1 3 7 8 7 2 7 3 3 2 3 7 2 2 7 7 7 7 2 8 7 3 2 3 2 7 2 3 7 2 8 3
## [7401] 7 2 7 2 7 3 3 2 8 3 7 3 3 3 3 2 3 2 1 2 1 3 1 3 3 3 1 7 7 7 7 7 3 1 3 2 2
## [7438] 2 2 2 3 7 3 3 3 3 1 2 2 3 2 1 2 3 3 3 7 7 2 8 2 7 8 7 8 7 8 7 7 7 1 3 6 3
## [7475] 6 7 7 7 2 7 7 7 3 2 7 2 2 6 3 7 2 2 3 2 1 3 7 7 7 7 7 3 7 3 7 1 3 7 3 8 2
## [7512] 2 2 2 7 2 7 2 7 7 6 1 1 3 2 2 2 7 2 3 3 3 3 3 2 7 1 7 3 1 1 3 2 2 2 2 2 1
## [7549] 1 1 7 2 3 7 1 2 2 7 7 7 2 3 3 3 3 7 3 3 8 7 7 2 2 7 7 7 7 3 7 6 7 3 7 6 2
## [7586] 7 7 7 7 2 8 3 3 3 2 7 3 3 3 2 1 2 8 7 1 1 8 3 7 2 7 7 7 7 7 1 7 2 3 2 2 3
## [7623] 7 7 2 8 2 3 2 2 2 2 8 7 7 7 7 7 2 7 2 1 1 1 2 3 1 3 2 8 3 3 3 7 7 7 7 7 1
## [7660] 2 1 1 2 2 7 7 6 7 2 7 7 7 7 2 3 7 3 7 7 6 7 2 7 6 8 7 8 7 8 7 7 7 2 3 2 2
```

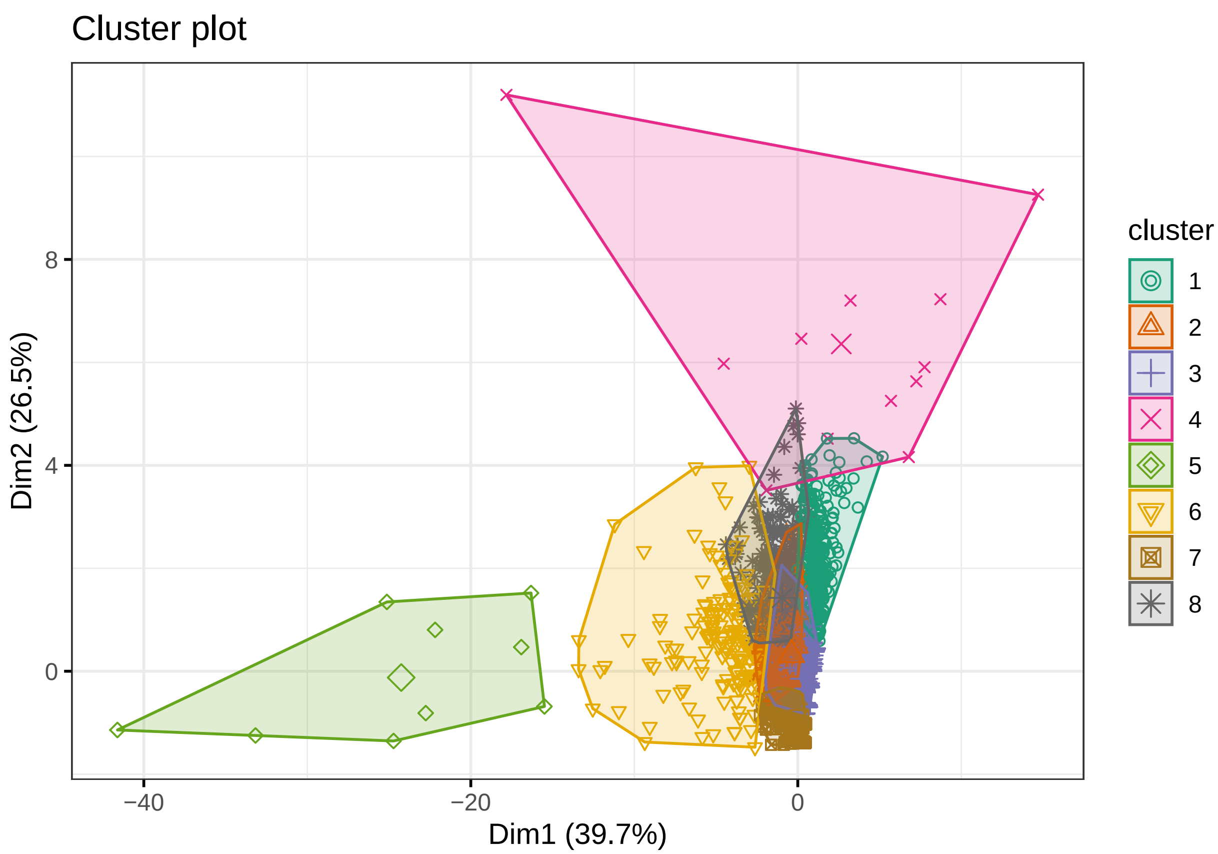
```
## [7697] 1 7 7 7 2 3 7 7 7 7 7 7 3 1 2 3 3 3 2 3 2 1 7 7 7 3 7 3 3 3 3 7 3 3 3 3 3
## [7734] 3 7 7 3 8 2 7 7 3 7 7 7 7 3 2 7 7 7 7 7 3 3 2 2 7 7 3 3 3 3 8 7 6 2 3 2 3
## [7771] 7 1 4 3 7 7 7 7 3 7 7 1 3 8 3 7 1 3 1 8 1 1 3 2 7 3 2 7 7 7 3 7 3 3 3 3 1
## [7808] 1 3 3 7 7 3 2 3 3 7 2 6 8 2 8 7 7 2 7 3 3 3 7 3 3 3 2 3 3 3 7 7 7 2 7 7 8
## [7845] 3 2 6 1 3 3 3 3 1 7 7 7 3 2 7 7 1 7 7 3 3 3 1 7 7 3 3 7 2 7 7 2 3 3 1 3 2
## [7882] 2 8 3 2 3 2 3 2 8 7 2 7 3 2 7 8 2 1 2 3 3 2 3 3 3 1 7 3 8 7 3 1 3 6 7 3 3
## [7919] 3 7 7 7 2 1 7 2 7 7 7 2 7 3 2 7 3 7 3 6 7 8 3 8 1 2 3 1 1 2 2 1 3 3 2 7 7
## [7956] 3 2 7 2 3 3 2 1 3 3 8 7 1 3 3 3 3 3 1 3 1 3 7 7 3 3 7 2 2 3 2 2 7 7 7 7 1
## [7993] 3 1 1 1 2 8 2 7 7 2 2 7 7 7 8 7 7 2 2 2 2 8 7 7 2 8 3 8 7 1 2 2 1 7 7 7 2
## [8030] 2 1 2 3 1 1 3 2 7 3 2 2 7 7 7 8 2 1 3 2 1 3 2 7 1 2 3 8 2 3 7 2 3 7 7 7 7
## [8067] 3 7 2 2 1 3 3 1 8 1 7 7 7 8 2 3 2 1 8 2 3 3 3 8 2 7 2 7 7 7 2 2 7 7 6 7 6
## [8104] 2 2 3 2 3 3 2 3 2 1 3 2 7 7 2 3 7 3 8 3 3 3 1 3 3 1 7 7 7 7 1 7 2 1 8 8 8
## [8141] 3 7 7 3 3 2 7 7 2 7 7 7 7 5 7 7 3 2 3 2 7 2 7 2 2 3 3 2 6 3 7 2 7 2 7 3 2
## [8178] 2 7 1 8 3 1 1 3 3 3 8 7 7 2 7 1 3 3 7 3 2 3 1 3 2 7 7 6 7 3 3 1 3 3 1 3 1
## [8215] 3 1 1 3 1 3 1 3 3 2 7 8 7 7 7 7 7 2 2 7 3 1 6 3 3 3 3 3 7 8 7 7 1 3 3 1 1
## [8252] 1 3 7 7 8 7 2 2 8 7 7 7 1 7 2 7 3 3 6 3 6 3 3 2 8 1 1 3 7 3 3 3 3 8 1 2 2
## [8289] 2 2 3 3 1 3 7 8 7 3 3 7 7 6 3 3 3 2 2 7 8 3 3 7 6 3 3 2 3 3 8 7 3 1 7 2 2
## [8326] 3 1 1 7 7 7 7 2 7 7 8 7 7 2 2 2 7 2 2 3 3 2 7 8 2 7 3 1 3 1 3 7 2 3 2 3 1
## [8363] 2 3 3 3 7 7 2 3 3 1 7 7 2 2 3 3 3 2 3 3 3 7 7 3 7 2 7 2 7 7 7 2 7 3 2 1 3
## [8400] 3 2 7 7 7 7 2 7 2 2 3 3 2 3 8 3 7 2 7 7 7 7 7 2 7 6 1 3 7 2 2 7 8 3 3 1 1
## [8437] 8 3 3 3 3 3 3 1 3 3 7 7 3 8 7 2 3 3 1 3 3 1 1 1 2 7 7 3 3 7 7 3 6 3 3 3 3
## [8474] 3 1 3 3 2 7 7 7 3 7 2 8 7 7 7 5 8 2 7 8 3 1 3 7 7 7 2 7 3 3 7 3 1 2 3 8 7
## [8511] 7 3 1 3 7 8 7 1 7 7 7 8 7 2 3 2 1 3 3 3 7 7 2 7 7 7 1 2 3 3 2 3 2 7 7 7 7
## [8548] 7 7 3 3 3 3 8 2 2 8 3 8 3 3 1 6 1 2 3 3 2 2 8 3 3 3 7 7 3 7 7 7 7 1 3 3 2
## [8585] 3 1 2 2 3 3 7 3 3 3 3 7 7 3 3 7 7 3 2 3 3 2 7 7 7 3 7 2 7 7 7 3 7 3 2 7 1
## [8622] 3 3 1 2 3 7 2 3 3 7 1 1 3 1 2 2 2 2 7 1 1 8 3 1 3 3 3 2 1 2 7 7 7 7 7 7 7
## [8659] 1 2 2 1 2 2 2 2 2 3 3 7 3 3 3 3 3 2 1 2 1 2 6 2 7 7 2 2 7 2 7 3 3 3 2 2 7
## [8696] 3 3 3 3 6 8 3 2 3 8 7 7 7 3 3 7 3 3 2 2 1 1 1 8 3 3 8 1 2 2 7 3 3 3 3 2 7
## [8733] 7 7 2 7 7 1 3 3 2 7 3 3 7 7 7 3 3 6 7 3 3 2 1 1 7 8 7 7 6 8 7 7 3 1 1 1 3
## [8770] 3 3 2 3 2 3 3 2 8 3 3 3 2 3 7 3 2 3 3 3 3 8 2 7 2 2 3 7 7 2 6 3 7 7 7 7 3
## [8807] 7 1 3 2 7 7 2 3 7 2 7 7 2 3 3 1 3 3 3 3 2 2 7 7 8 7 3 7 7 7 7 2 7 3 7 7 7
## [8844] 2 1 3 2 3 3 8 1 3 7 2 3 3 2 3 6 3 7 7 7 7 2 7 2 3 3 2 8 7 1 1 1 3 1 7 7 8
## [8881] 7 2 3 3 1 1 1 7 8 7 6 7 6 3 7 7 3 7 7 7 1 3 3 3 7 7 8 2 8 7 3 8 1 3 2 1 1
## [8918] 3 1 7 7 3 3 1 2 1 1 2 3 3 3 2 7 7 3 8 2 3 2 3 3 1 1 3 7 7 7 2 7 2 3 3 2 2
## [8955] 3 7 3 1 2 1 2 3 7 7 2 1 3 2 3 8 3 7 3 2 2 3 3 1 7 1 1 1 1 1 1 3 1 3 3 7 6
## [8992] 2 3 1 2 2 3 3 2 2 1 7 7 2 8 2 7 7 7 3 7 3 2 2 2 3 3 7 3 7 2 8 3 7 7 7 7 7
## [9029] 7 3 7 7 7 6 1 3 7 7 3 5 3 3 7 7 3 2 2 2 7 7 7 7 3 3 7 7 6 2 3 2 3 7 2 8 1
## [9066] 3 7 7 3 7 3 7 7 2 2 1 3 7 7 7 2 7 7 7 2 3 1 2 3 2 8 3 1 7 2 7 2 2 2 3 3 3
## [9103] 3 1 1 3 3 3 2 3 2 7 7 7 2 3 3 3 3 2 2 2 7 1 1 1 7 3 1 1 3 7 7 2 3 3 3 1 2
## [9140] 2 7 7 3 8 2 1 7 2 8 7 2 3 3 2 3 2 7 8 8 1 1 2 7 3 1 6 7 7 8 7 7 7 7 7 3 7
## [9177] 1 7 7 3 3 3 7 7 7 3 6 3 3 2 1 3 1 3 2 3 7 2 2 3 7 7 3 2 8 7 8 3 7 7 7 7 7
## [9214] 7 2 2 1 7 2 1 7 6 7 1 1 1 3 2 7 3 8 1 8 7 2 2 3 3 3 2 1 3 2 3 7 2 7 7 3 2
## [9251] 8 3 2 7 7 7 7 7 7 7 7 3 7 2 1 2 7 7 7 2 6 7 2 6 2 2 3 3 1 3 7 2 3 3 7 3 1
## [9288] 3 2 7 7 7 1 2 3 1 3 3 3 1 3 3 3 3 1 2 7 7 7 2 8 3 3 2 7 3 3 3 7 7 7 1 1 8
## [9325] 3 3 7 3 7 7 7 3 7 7 3 3 2 3 2 7 2 3 2 3 1 3 3 2 8 7 3 3 3 3 7 7 7 2 3 7 2
## [9362] 2 2 7 7 7 3 2 7 7 3 3 2 2 2 7 7 7 3 3 3 3 3 2 7 8 7 7 7 7 2 3 8 2 7 3 2 7
## [9399] 6 2 7 3 3 6 2 3 3 8 7 1 2 3 6 1 3 7 7 3 3 1 1 2 2 3 7 6 2 2 8 2 3 3 3 2 3
## [9436] 3 1 7 3 3 7 2 3 3 3 7 2 2 7 3 8 7 2 7 3 3 3 1 7 3 7 2 7 3 2 7 2 3 7 7 7 3
## [9473] 7 2 3 2 1 1 2 1 1 3 3 2 8 8 3 7 3 2 6 7 8 6 7 2 7 7 7 8 7 7 8 7 2 7 7 2 7
## [9510] 2 8 1 3 6 2 8 3 3 3 7 7 3 3 3 2 2 3 2 3 3 7 3 8 2 7 3 1 3 2 7 2 3 1 3 3 7
## [9547] 7 3 1 3 3 2 7 2 2 3 2 1 2 2 3 3 1 3 7 2 1 3 7 1 3 3 3 2 7 3 3 2 7 7 2 2 2
## [9584] 3 7 3 2 3 3 3 1 1 1 7 7 7 3 3 7 3 8 2 2 3 7 3 3 2 7 7 8 7 3 7 2 6 7 3 3 2
## [9621] 2 3 3 1 3 3 3 7 2 1 3 2 8 7 2 8 7 2 7 4 2 2 2 3 2 3 1 7 7 6 8 7 2 3 1 7 3
## [9658] 7 2 2 6 7 3 7 7 7 7 2 7 7 2 2 3 1 3 7 2 7 7 7 8 7 2 8 7 7 2 1 2 7 7 3 8 2
```

```
## [9695] 7 3 2 3 7 7 3 7 7 2 7 3 3 7 7 7 3 1 2 2 3 3 3 2 2 3 7 7 7 8 3 7 2 2 7 3 2
## [9732] 8 8 7 7 3 7 7 2 2 7 6 2 7 3 3 3 1 3 7 3 3 3 7 7 7 7 2 7 2 7 7 7 7 2 7 7 2
## [9769] 2 2 3 3 2 7 4 1 1 8 1 1 7 3 2 7 7 7 2 2 3 3 3 2 3 3 1 1 3 3 3 3 3 2 3 7 7
## [9806] 3 1 3 1 2 3 7 7 2 2 2 3 2 3 3 8 1 7 7 3 3 3 7 3 3 3 1 3 2 1 1 2 7 7 3 8 7
## [9843] 3 3 1 3 2 2 2 7 7 3 7 2 7 7 2 6 2 7 7 7 7 7 7 7 7 2 7 3 1 1 3 3 7 3 7 3 1 3
## [9880] 2 3 7 8 7 7 7 7 7 7 7 7 2 2 7 2 8 3 3 3 3 3 3 3 1 3 2 3 3 2 7 7 2 3 7 7 2
## [9917] 7 7 7 2 1 1 3 3 7 8 7 7 7 6 3 2 2 7 3 3 7 3 2 7 2 8 8 2 7 3 3 6 6 7 7 7 3
## [9954] 7 3 3 2 7 7 3 7 3 3 3 7 7 2 2 7 2 7 2 3 2 2 7 3 2 3 8 7 2 2 7 8 7 7 7 2 3
## [9991] 7 3 7 7
##
## Within cluster sum of squares by cluster:
## [1] 1692.9327 1850.0638 1220.0787 1460.2766  778.7336 1798.3840  994.1753
## [8]  958.1986
##  (between_SS / total_SS =  73.1 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

The within cluster sum of squares by cluster value is 73.1% for k= 8, which is not very different from the Within cluster sum of square by cluster value for k = 7 (70.2%).

Let's plot the K-means clusters

```r
library(RColorBrewer)
fviz_cluster(clustering_results_8, data = data1[,(15:18)],
             palette = brewer.pal(n = 8, name = "Dark2"),
             geom = "point",
             ellipse.type = "convex",
             ggtheme = theme_bw()
             )
```



There are still some overlaps between cluster groups.

Compute PCA and extract individual components and extract individual components.

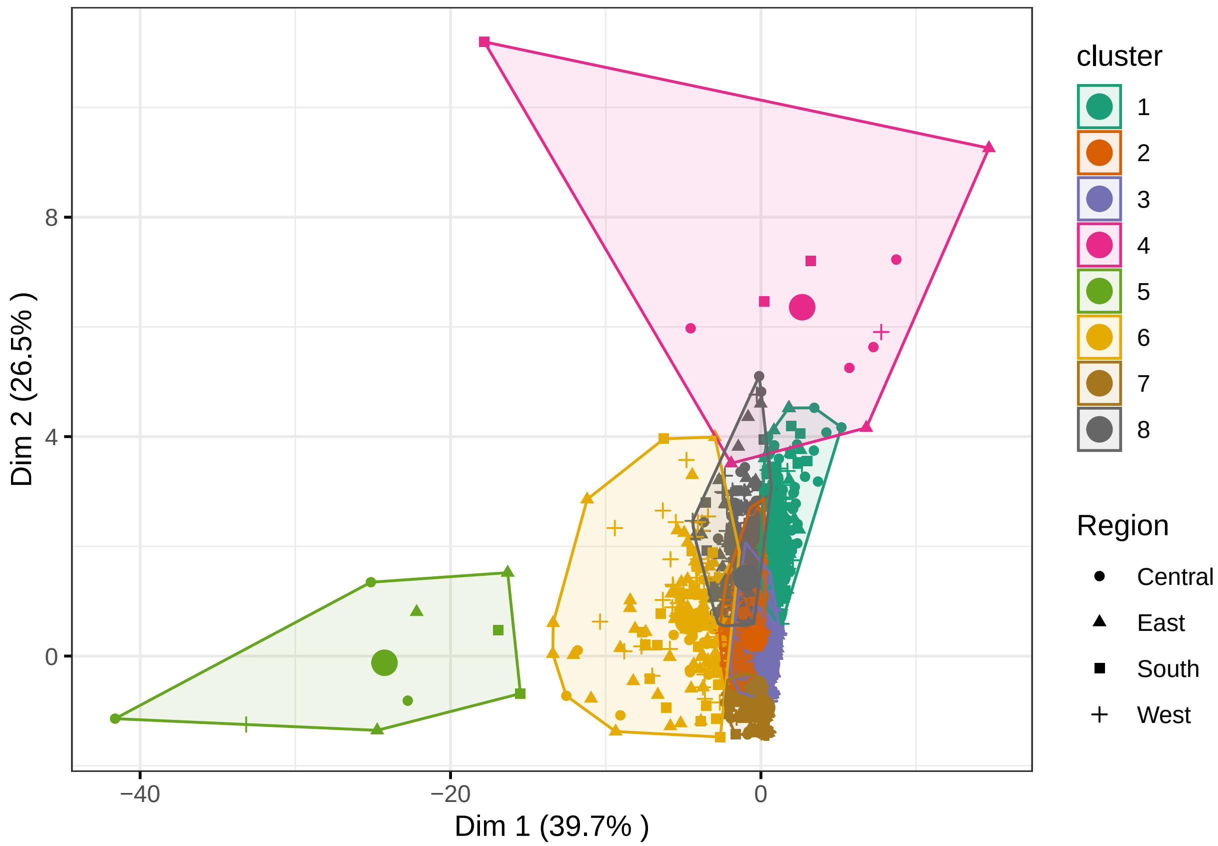
```
# Dimension reduction using PCA
results_pca_8 <- prcomp(data1[,(15:18)],  scale = TRUE)

# Coordinates of individuals
ind.coord <- as.data.frame(get_pca_ind(results_pca_8)$coord)

# Add clusters obtained using the K-means algorithm
ind.coord$cluster <- factor(clustering_results_8$cluster)

# Add Region groups from the original data sett
ind.coord$Region <- data1$Region

#look at the first few rows to double check
head(ind.coord)
```

```
##        Dim.1      Dim.2       Dim.3       Dim.4 cluster Region
## 1 -0.0426607 -1.0508481  0.14635987  0.31244832       7  South
## 2 -1.1546701 -0.7511273  0.25351937  0.22331213       7  South
## 3  0.3107253 -1.1081474 -0.01276717  0.15000936       7   West
## 4  0.6283963  1.9637213  0.37261495  1.54367992       1  South
## 5  0.5768386 -0.4056909  0.55980463 -0.06649362       3  South
## 6 -0.3936310  0.3152509 -1.56442060 -0.20148637       2   West
```

```
# Percentage of variance explained by dimensions
eigenvalue <- round(get_eigenvalue(results_pca_8), 1)
variance.percent <- eigenvalue$variance.percent
head(eigenvalue)
```

```
##       eigenvalue variance.percent cumulative.variance.percent
## Dim.1        1.6             39.7                        39.7
## Dim.2        1.1             26.5                        66.2
## Dim.3        0.9             22.0                        88.3
## Dim.4        0.5             11.7                       100.0
```

```
ggscatter(
  ind.coord, x = "Dim.1", y = "Dim.2",
  color = "cluster", palette = brewer.pal(n = 8, name = "Dark2"), ellipse = TRUE, ellipse.type = "conve
  shape = "Region", size = 1.5,  legend = "right", ggtheme = theme_bw(),            #change point s
  xlab = paste0("Dim 1 (", variance.percent[1], "% )" ),
  ylab = paste0("Dim 2 (", variance.percent[2], "% )" )
) +
  stat_mean(aes(color = cluster), size = 4)      #add cluster centroid using stat_mean()
```



Clustering Validation

(https://towardsdatascience.com/clustering-analysis-in-r-using-k-means-73eca4fb7967)

Silhouette coefficient can be used to evaluate the goodness of the clustering. First, for each observation i, it calculates the dissimilarity between i and all the other points within the same cluster. This value is called average dissimilarity Di.

Then calculate the dissimilarity between i and all the other clusters and get the lowest value among them. Find the dissimilarity between i and the next closest cluster, called Ci.

Next find the silhouette width which is the difference between Ci and Di, divided by the maximum difference between Ci and Di. Si = (Ci - Di)/max(Di, Ci)

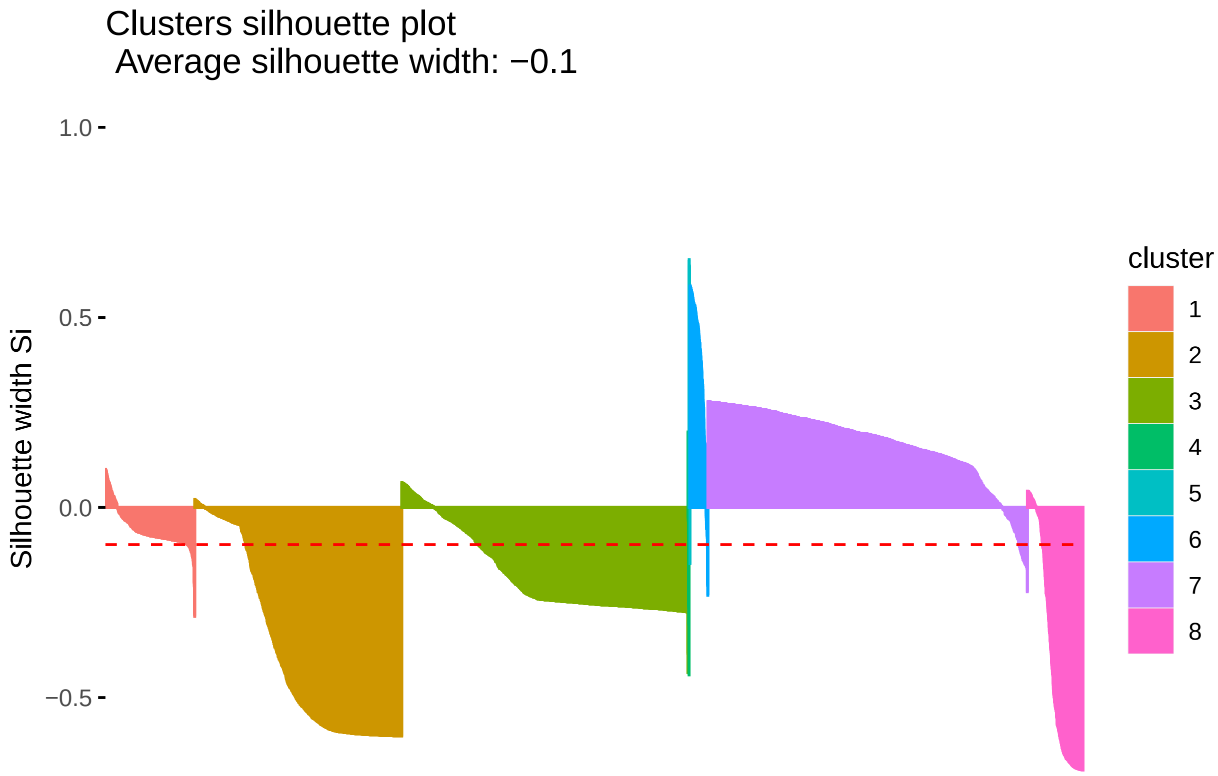
Si>0 means the observation is well clustered. The closer it is to 1 the better it is clustered.

Si <0 means the observation is wrongly clustered.

Si = 0 means the observation is between 2 clusters.

```
library(cluster)
library(factoextra)

sil <- silhouette(clustering_results_8$cluster, dist(data1[,(15:18)]))
fviz_silhouette(sil)
```

```
##   cluster size ave.sil.width
## 1       1  912         -0.06
## 2       2 2114         -0.38
## 3       3 2923         -0.18
## 4       4   12         -0.17
## 5       5    9          0.48
## 6       6  182          0.37
## 7       7 3263          0.17
## 8       8  579         -0.40
```



From the table, 5 of the 8 clusters have a negative silhouette width which means that some observations may be in the wrong cluster, so the clustering is not very good.

Method 2: K-medoids

Following this tutorial: https://towardsdatascience.com/clustering-on-mixed-type-data-8bbd0a2569c3

K-means algorithm is limited in that it can only work with numerical data, whereas our dataset contains both numeric and categorical data.

We will now try the PAM clustering algorithm (Partitioning across medoids). K-medoids is more robust to outliers and noise than K-means. This algorithm uses Gower distance to measure the partial dissimilarity across individuals, and ranges in [0 1]. Standardization is first applied to the features, and the distance between individuals represents the average of all feature specific distances.

Partial dissimilarity is different depending on the type of variable: numeric or categorical.

Numeric features - partial dissimilarity is dependent on absolute difference between 2 observations (x_i and x_j), and the maximum range observed from all individuals. d_ij^f = |x_i - x_j|/|max_N(x) - min_N(x))| where N is the number of individuals in a dataset.

Categorical/Qualitative features - feature dissimilarity is equal to 1 if y_i and y_j do not have the same values, otherwise it is 0.

One method to determine the number of clusters is by using the Silhouette coefficient.

Data Preparation

For this K-medoids analysis we will omit the Region variable because there are only 4 values and the information is too broad.

We will try to cluster transactions according to the following features:

```
data2 <- data1 %>%
              select(Ship_Mode, Segment, City, State, Sub_Category, diff_in_days, Sales, Quantity, Disc

#convert all character data type to factor:
data2[sapply(data2, is.character)] <- lapply(data2[sapply(data2, is.character)],
                                        as.factor)
```

Compute Gower distance

```
gower_dist <- daisy(data2, metric = "gower")

gower_mat <- as.matrix(gower_dist)
```

```
#Print most similar transactions
data2[which(gower_mat == min(gower_mat[gower_mat != min(gower_mat)]), arr.ind = TRUE)[1, ], ]
```

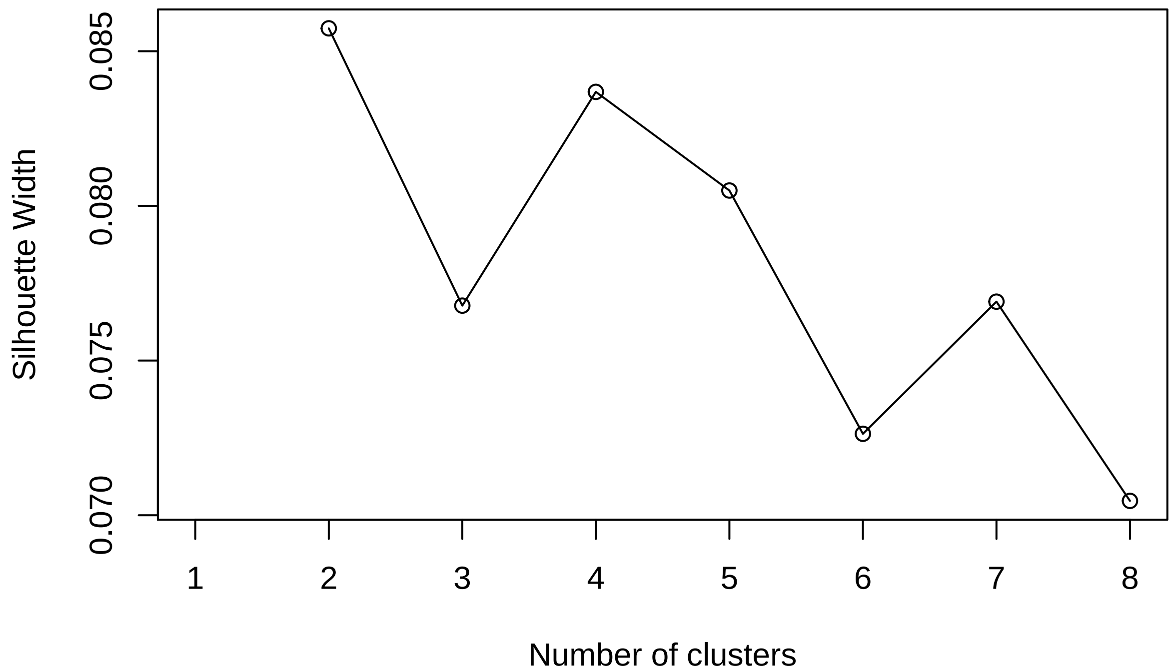
```
##           Ship_Mode  Segment    City State Sub_Category diff_in_days Sales
## 4875 Standard Class Consumer Houston Texas      Binders            4 1.188
## 3326 Standard Class Consumer Houston Texas      Binders            4 1.234
##      Quantity Discount  Profit
## 4875        1      0.8 -1.9602
## 3326        1      0.8 -1.9744
```

```
#Print most dissimilar transactions
data2[which(gower_mat == max(gower_mat[gower_mat != max(gower_mat)]), arr.ind = TRUE)[1, ], ]
```

```
##           Ship_Mode   Segment      City   State Sub_Category diff_in_days
## 6827 Standard Class Corporate Lafayette Indiana      Copiers            7
## 6798       Same Day  Consumer   Houston   Texas      Binders            0
##          Sales Quantity Discount    Profit
## 6827 17499.950        5      0.0 8399.9760
## 6798     3.798        1      0.8   -6.0768
```

Try to figure out the number of clusters to use by using the silhouette coefficient. Typically the number of clusters used is between 2 and 8.

```
sil_width <- c(NA)
for (i in 2:8){
  pam_fit <- pam(gower_dist, diss = TRUE, k = i )
  sil_width[i] <- pam_fit$silinfo$avg.width
}

plot(1:8, sil_width,
     xlab = "Number of clusters",
     ylab = "Silhouette Width")
lines(1:8, sil_width)
```



2 clusters has the highest silhouette width, while 4 has the second highest. 2 Clusters may be too simple, so We will pick k = 4.

To look at a summary of each of the clusters:

```
k <- 4
pam_fit_4 <- pam(gower_dist, diss = TRUE, k)
pam_results_4 <- data2 %>%
  mutate(cluster = pam_fit_4$clustering) %>%
  group_by(cluster) %>%
  do(the_summary = summary(.))
pam_results_4$the_summary
```

```
## [[1]]
##           Ship_Mode           Segment                  City              State
##  First Class    : 528   Consumer    :1586   San Francisco: 279   California:638
##  Same Day       : 284   Corporate   : 386   Seattle      : 113   Texas     :195
##  Second Class   :1262   Home Office: 200   Los Angeles  : 100   Washington:142
##  Standard Class:  98                        Houston      :  85   Ohio      :127
##                                             Chicago      :  66   Illinois  : 95
##                                             Columbus     :  53   New York  : 90
##                                             (Other)      :1476   (Other)   :885
##       Sub_Category   diff_in_days       Sales            Quantity
##  Furnishings:407   Min.   :0.000   Min.   :    0.99   Min.   : 1.000
##  Paper      :260   1st Qu.:2.000   1st Qu.:   18.58   1st Qu.: 2.000
##  Accessories:196   Median :2.000   Median :   54.79   Median : 3.000
##  Storage    :193   Mean   :2.358   Mean   :  216.38   Mean   : 3.699
```

```
##  Art        :188   3rd Qu.:3.000   3rd Qu.:  197.91   3rd Qu.: 5.000
##  Phones     :168   Max.   :7.000   Max.   :13999.96   Max.   :14.000
##  (Other)    :760
##     Discount          Profit            cluster
##  Min.   :0.0000   Min.   :-1862.312   Min.   :1
##  1st Qu.:0.0000   1st Qu.:    2.936   1st Qu.:1
##  Median :0.0000   Median :    9.752   Median :1
##  Mean   :0.1113   Mean   :   32.005   Mean   :1
##  3rd Qu.:0.2000   3rd Qu.:   31.693   3rd Qu.:1
##  Max.   :0.8000   Max.   : 6719.981   Max.   :1
##
##
## [[2]]
##           Ship_Mode           Segment                City
##  First Class   : 309   Consumer   :2746   Los Angeles  : 615
##  Same Day      :  69   Corporate  : 475   San Francisco: 165
##  Second Class  : 159   Home Office: 237   Houston      : 152
##  Standard Class:2921                      Chicago      : 136
##                                           Seattle      : 135
##                                           San Diego    : 100
##                                           (Other)      :2155
##         State          Sub_Category   diff_in_days       Sales
##  California:1142   Binders    :1063   Min.   :0.000   Min.   :    0.444
##  Texas     : 408   Phones     : 312   1st Qu.:4.000   1st Qu.:   14.943
##  Illinois  : 221   Art        : 263   Median :5.000   Median :   49.564
##  Washington: 164   Storage    : 263   Mean   :4.711   Mean   :  225.913
##  Ohio      : 161   Accessories: 231   3rd Qu.:6.000   3rd Qu.:  217.584
##  Florida   : 135   Chairs     : 213   Max.   :7.000   Max.   :10499.970
##  (Other)   :1227   (Other)    :1113
##     Quantity         Discount          Profit             cluster
##  Min.   : 1.000   Min.   :0.0000   Min.   :-6599.978   Min.   :2
##  1st Qu.: 2.000   1st Qu.:0.0000   1st Qu.:   -0.936   1st Qu.:2
##  Median : 3.000   Median :0.2000   Median :    6.774   Median :2
##  Mean   : 3.846   Mean   :0.2148   Mean   :   19.673   Mean   :2
##  3rd Qu.: 5.000   3rd Qu.:0.2000   3rd Qu.:   25.192   3rd Qu.:2
##  Max.   :14.000   Max.   :0.8000   Max.   : 5039.986   Max.   :2
##
##
## [[3]]
##           Ship_Mode           Segment                City               State
##  First Class   : 281   Consumer   : 295   Philadelphia:506   Pennsylvania:537
##  Same Day      :  83   Corporate  : 190   Seattle     : 79   Texas       :147
##  Second Class  : 204   Home Office:1188   Houston     : 66   Illinois    : 90
##  Standard Class:1105                      Chicago     : 55   Washington  : 89
##                                           Columbus    : 34   Ohio        : 85
##                                           Springfield : 31   California  : 72
##                                           (Other)     :902   (Other)     :653
##       Sub_Category  diff_in_days       Sales              Quantity
##  Paper      :322   Min.   :0.000   Min.   :    0.852   Min.   : 1.000
##  Binders    :187   1st Qu.:3.000   1st Qu.:   15.552   1st Qu.: 2.000
##  Phones     :163   Median :4.000   Median :   47.984   Median : 3.000
##  Storage    :141   Mean   :4.014   Mean   :  216.941   Mean   : 3.727
##  Accessories:137   3rd Qu.:5.000   3rd Qu.:  203.976   3rd Qu.: 5.000
##  Furnishings:133   Max.   :7.000   Max.   :22638.480   Max.   :14.000
```

```
## (Other)    :590
##    Discount          Profit            cluster
## Min.   :0.0000   Min.   :-3399.980   Min.   :3
## 1st Qu.:0.0000   1st Qu.:   -2.131   1st Qu.:3
## Median :0.2000   Median :    5.443   Median :3
## Mean   :0.2065   Mean   :   10.078   Mean   :3
## 3rd Qu.:0.2000   3rd Qu.:   20.539   3rd Qu.:3
## Max.   :0.8000   Max.   : 2591.957   Max.   :3
##
##
## [[4]]
##          Ship_Mode          Segment                City
## First Class   : 420   Consumer   : 564   New York City: 789
## Same Day      : 107   Corporate  :1969   Seattle      : 101
## Second Class  : 320   Home Office: 158   Houston      :  74
## Standard Class:1844                      Columbus     :  70
##                                          Springfield  :  59
##                                          Chicago      :  57
##                                          (Other)      :1541
##        State          Sub_Category  diff_in_days       Sales
## New York  : 925   Paper      :600   Min.   :0.000   Min.   :    1.24
## Texas     : 235   Storage    :249   1st Qu.:4.000   1st Qu.:   20.34
## California: 149   Phones     :246   Median :4.000   Median :   62.28
## Washington: 111   Art        :215   Mean   :4.248   Mean   :  253.84
## Ohio      :  96   Accessories:211   3rd Qu.:5.000   3rd Qu.:  219.10
## Florida   :  94   Furnishings:205   Max.   :7.000   Max.   :17499.95
## (Other)   :1081   (Other)    :965
##    Quantity         Discount           Profit            cluster
## Min.   : 1.000   Min.   :0.00000   Min.   :-3839.990   Min.   :4
## 1st Qu.: 2.000   1st Qu.:0.00000   1st Qu.:    3.972   1st Qu.:4
## Median : 3.000   Median :0.00000   Median :   12.118   Median :4
## Mean   : 3.828   Mean   :0.08585   Mean   :   49.049   Mean   :4
## 3rd Qu.: 5.000   3rd Qu.:0.20000   3rd Qu.:   39.660   3rd Qu.:4
## Max.   :14.000   Max.   :0.80000   Max.   : 8399.976   Max.   :4
##
```

The first cluster has the majority values: ship mode is Second Class , segment is Consumer , City is San Francisco/other, State is California/other, sub category is furnishings. The mean difference in days between order date and ship date is 2.358 days, the mean value for Sales is $216.38, the mean quantity is 3.699, the discount mean is $0.1113, profit mean is $32.

cluster 1 is made of second class shippping, Consumer segment x San Franciso x California x furnishings.

For cluster 2, the ship mode is mostly standard class, segment is mostly consumer, city is mostly Los Angeles/other, State is mostly California/Other, subcategory is mostly Binders/other. The mean difference in days between order date and ship date is 4.7 days, the mean sales $225.91, mean quantity is 3.48, discount is 0.2148, and profit mean is $19.67.

Cluster 2 is made of standard class shipping x consumer segment x Los Angeles x California x Binders.

For cluster 3, the main ship mode is First class, the segment is mostly Home Office, the most common city is Philadelphia/Other, the most common State is Pennsylvania/Other, and the most common subcategory is paper/other. For numeric variables, the mean difference in days between order date and ship date is 4.04 days, the mean sales $216.94, mean quantity is 3.72, mean discount is 0.2065, and mean profit is $10.08.

Cluster 3 is First class shipping x Home Office segment x Philadelphia x Pennsylvania x Paper. Cluster 3 has the lowest mean profit of the 4 clusters.

For cluster 4, the main ship mode is First class, the most common segment is Corporate, New York City/Other is the most common city, New York State/Other is the most common state, and the most common subcategory is paper. For the numeric features, the mean difference in days between order date and ship date is 4.25 days, the mean sales is $253.84, and mean quantity is 3.83, mean discount is 0.086, mean profit is $49.05.

Cluster 4 is made of First Class shipping x Corporate segment x New York City x New York State x Paper. Cluster 4 has the highest mean sales amount and mean profit, with lowest mean discount.

We can now visualise the clusters in lower dimensional space with tSNE (t-Distributed Stochastic Neighbor Embedding) which can be used for dimensionality reduction.

```
#summary(pam_fit_4)
```

Medoids: ID
[1,] 560 560 [2,] 9 9 [3,] 951 951 [4,] 6943 6943

Objective function: build swap 0.3215923 0.3208374

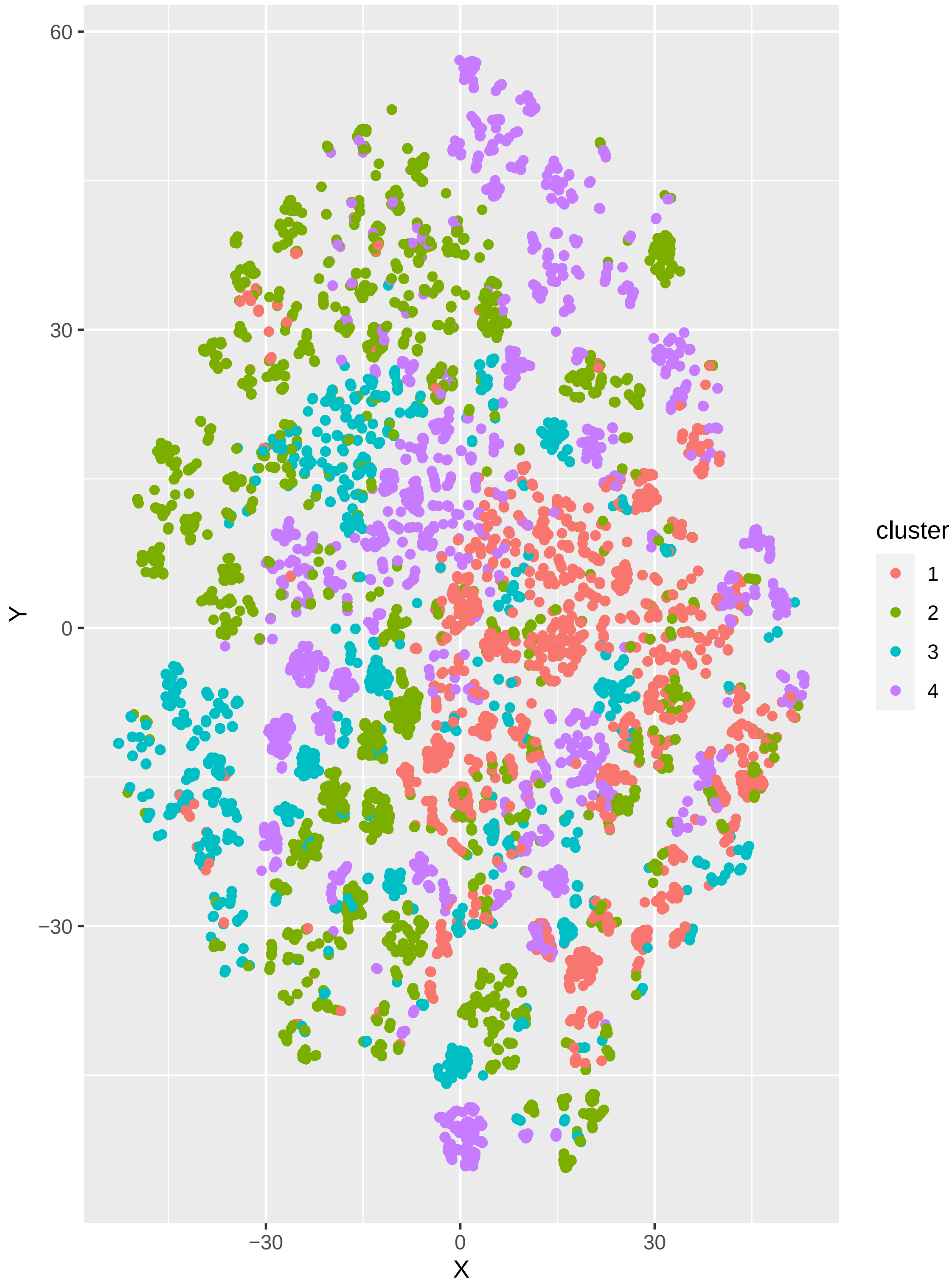
Numerical information per cluster: size max_diss av_diss diameter separation [1,] 2172 0.5369861 0.3495248 0.7527143 0.0004132536 [2,] 3458 0.6045552 0.3040315 0.8092413 0.0142857143 [3,] 1673 0.5553794 0.3280627 0.7789958 0.0142857143 [4,] 2691 0.5881813 0.3147869 0.8127438 0.0004132536

Isolated clusters: L-clusters: character(0) L*-clusters: character(0)

Average silhouette width per cluster: [1] 0.07665593 0.11233789 0.05559724 0.07000398 Average silhouette width of total data set: [1] 0.08368581

Available components: [1] "medoids" "id.med" "clustering" "objective" "isolation" "clusinfo" "silinfo" "diss" "call"

```
tsne_obj <- Rtsne(gower_dist, is_distance = TRUE)

tsne_data <- tsne_obj$Y %>%
  data.frame() %>%
  setNames(c("X", "Y")) %>%
  mutate(cluster = factor(pam_fit_4$clustering))

ggplot(aes(x = X, y = Y), data = tsne_data) +
  geom_point(aes(color = cluster))
```




```
input_data <- data2
```

Let's try using k=3:

```r
gower_dist_3 = daisy(input_data, metric = "gower", type = list(logratio = 3))
                  gower_mat = as.matrix(gower_dist_3)
                  pam_fit_3 = pam(gower_mat, k=3, diss=TRUE)
```

```r
#summary(pam_fit_3)
```

some information from the summary of pam fit for k=3:

Medoids: ID
[1,] "399" "399" [2,] "9" "9"
[3,] "7119" "7119"

Numerical information per cluster: size max_diss av_diss diameter separation [1,] 2361 0.6204122 0.3754422 0.7803200 0.01490751 [2,] 4281 0.6045552 0.3173436 0.8092413 0.01524512 [3,] 3352 0.5882532 0.3311972 0.8127438 0.01490751

Isolated clusters: L-clusters: character(0) L*-clusters: character(0)

Average silhouette width per cluster: [1] 0.06840880 0.09434220 0.06023282 Average silhouette width of total data set: [1] 0.07677532

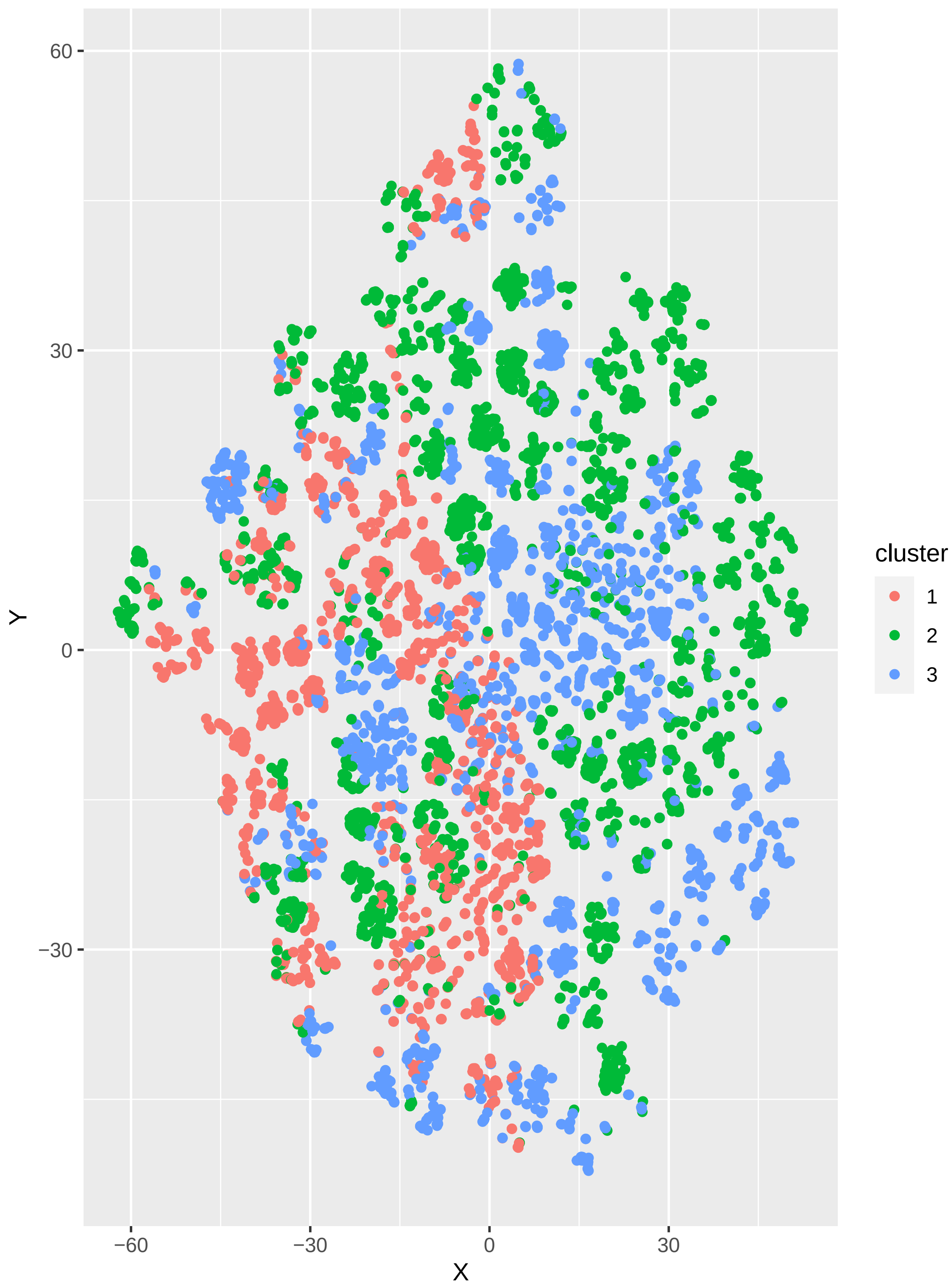
Available components: [1] "medoids" "id.med" "clustering" "objective" "isolation" "clusinfo" "silinfo" "diss" "call"

```r
pam_results_3 <- data2 %>%
  mutate(cluster = pam_fit_3$clustering) %>%
  group_by(cluster) %>%
  do(the_summary = summary(.))
pam_results_3$the_summary
```

```
## [[1]]
##           Ship_Mode          Segment                City     
##  First Class   : 650   Consumer   :1593   Houston      : 286  
##  Same Day      : 276   Corporate  : 342   Philadelphia : 137  
##  Second Class  :1277   Home Office: 426   Seattle      : 135  
##  Standard Class: 158                      Chicago      :  90  
##                                           Dallas       :  64  
##                                           San Francisco:  63  
##                                           (Other)      :1586  
##           State           Sub_Category  diff_in_days       Sales         
##  Texas       : 528   Storage    :340   Min.   :0.000   Min.   :    0.444  
##  Ohio        : 171   Furnishings:251   1st Qu.:2.000   1st Qu.:   19.152  
##  Washington  : 162   Paper      :251   Median :2.000   Median :   67.000  
##  California  : 152   Phones     :238   Mean   :2.524   Mean   :  239.150  
##  Pennsylvania: 150   Accessories:222   3rd Qu.:3.000   3rd Qu.:  239.980  
##  Illinois    : 140   Art        :203   Max.   :7.000   Max.   :13999.960  
##  (Other)     :1058   (Other)    :856                                     
##     Quantity         Discount          Profit              cluster 
##  Min.   : 1.000   Min.   :0.0000   Min.   :-2639.991   Min.   :1  
##  1st Qu.: 2.000   1st Qu.:0.0000   1st Qu.:    0.691   1st Qu.:1  
##  Median : 3.000   Median :0.2000   Median :    6.871   Median :1  
##  Mean   : 3.713   Mean   :0.1758   Mean   :   20.726   Mean   :1  
##  3rd Qu.: 5.000   3rd Qu.:0.2000   3rd Qu.:   28.310   3rd Qu.:1  
##  Max.   :14.000   Max.   :0.8000   Max.   : 6719.981   Max.   :1  
## 
```

```
##
## [[2]]
##          Ship_Mode          Segment               City
##  First Class   : 391   Consumer   :3015   Los Angeles  : 710
##  Same Day      : 138   Corporate  : 549   San Francisco: 335
##  Second Class  : 292   Home Office: 717   Philadelphia : 257
##  Standard Class:3460                      Chicago      : 154
##                                           Seattle      : 154
##                                           San Diego    : 133
##                                           (Other)      :2538
##          State          Sub_Category   diff_in_days       Sales
##  California  :1583   Binders    :1217   Min.   :0.000   Min.   :    0.836
##  Texas       : 283   Phones     : 376   1st Qu.:4.000   1st Qu.:   14.910
##  Pennsylvania: 282   Furnishings: 354   Median :5.000   Median :   47.976
##  Illinois    : 253   Art        : 317   Mean   :4.497   Mean   :  224.406
##  Ohio        : 185   Accessories: 299   3rd Qu.:5.000   3rd Qu.:  206.962
##  Washington  : 184   Paper      : 285   Max.   :7.000   Max.   :22638.480
##  (Other)     :1511   (Other)    :1433
##     Quantity         Discount          Profit             cluster
##  Min.   : 1.000   Min.   :0.0000   Min.   :-6599.978   Min.   :2
##  1st Qu.: 2.000   1st Qu.:0.0000   1st Qu.:    0.000   1st Qu.:2
##  Median : 3.000   Median :0.2000   Median :    6.888   Median :2
##  Mean   : 3.815   Mean   :0.2051   Mean   :   19.091   Mean   :2
##  3rd Qu.: 5.000   3rd Qu.:0.2000   3rd Qu.:   24.858   3rd Qu.:2
##  Max.   :14.000   Max.   :0.8000   Max.   : 5039.986   Max.   :2
##
##
## [[3]]
##          Ship_Mode          Segment               City
##  First Class   : 497   Consumer   : 583   New York City: 796
##  Same Day      : 129   Corporate  :2129   Philadelphia : 143
##  Second Class  : 376   Home Office: 640   Seattle      : 139
##  Standard Class:2350                      San Francisco: 112
##                                           Columbus     :  87
##                                           Chicago      :  70
##                                           (Other)      :2005
##          State          Sub_Category   diff_in_days      Sales
##  New York    : 935   Paper      : 834   Min.   :0.00   Min.   :    1.24
##  California  : 266   Furnishings: 352   1st Qu.:4.00   1st Qu.:   18.96
##  Texas       : 174   Art        : 276   Median :4.00   Median :   53.28
##  Washington  : 160   Phones     : 275   Mean   :4.28   Mean   :  230.28
##  Pennsylvania: 155   Accessories: 254   3rd Qu.:5.00   3rd Qu.:  197.18
##  Ohio        : 113   Storage    : 237   Max.   :7.00   Max.   :17499.95
##  (Other)     :1549   (Other)    :1124
##     Quantity         Discount           Profit             cluster
##  Min.   : 1.000   Min.   :0.00000   Min.   :-3839.99   Min.   :3
##  1st Qu.: 2.000   1st Qu.:0.00000   1st Qu.:    4.02   1st Qu.:3
##  Median : 3.000   Median :0.00000   Median :   11.65   Median :3
##  Mean   : 3.811   Mean   :0.07989   Mean   :   46.46   Mean   :3
##  3rd Qu.: 5.000   3rd Qu.:0.20000   3rd Qu.:   37.14   3rd Qu.:3
##  Max.   :14.000   Max.   :0.80000   Max.   : 8399.98   Max.   :3
##
```

```r
tsne_obj <- Rtsne(gower_dist_3, is_distance = TRUE)

tsne_data <- tsne_obj$Y %>%
  data.frame() %>%
  setNames(c("X", "Y")) %>%
  mutate(cluster = factor(pam_fit_3$clustering))

ggplot(aes(x = X, y = Y), data = tsne_data) +
  geom_point(aes(color = cluster))
```



Let's try using k=5:

```
gower_dist_5 = daisy(input_data, metric = "gower", type = list(logratio = 3))
                  gower_mat = as.matrix(gower_dist_5)
                  pam_fit_5 = pam(gower_mat, k=5, diss=TRUE)
```

```r
pam_results_5 <- data2 %>%
  mutate(cluster = pam_fit_5$clustering) %>%
  group_by(cluster) %>%
  do(the_summary = summary(.))
pam_results_5$the_summary
```

```
## [[1]]
##          Ship_Mode             Segment                 City              State
##  First Class   : 155   Consumer   :997   Houston      :284   Texas     :519
##  Same Day      : 143   Corporate  :334   Seattle      : 62   Ohio      :106
##  Second Class  :1026   Home Office:146   Dallas       : 60   Illinois  : 88
##  Standard Class: 153                     Chicago      : 56   Florida   : 80
##                                          Columbus     : 43   Washington: 78
##                                          New York City: 38   New York  : 68
##                                          (Other)      :934   (Other)   :538
##       Sub_Category  diff_in_days       Sales             Quantity
##  Storage    :258   Min.   :0.000   Min.   :   0.444   Min.   : 1.000
##  Phones     :147   1st Qu.:2.000   1st Qu.:  18.240   1st Qu.: 2.000
##  Binders    :141   Median :2.000   Median :  63.920   Median : 3.000
##  Accessories:132   Mean   :2.747   Mean   : 230.215   Mean   : 3.744
##  Art        :129   3rd Qu.:4.000   3rd Qu.: 243.384   3rd Qu.: 5.000
##  Furnishings:121   Max.   :7.000   Max.   :8749.950   Max.   :14.000
##  (Other)    :549
##     Discount          Profit             cluster
##  Min.   :0.0000   Min.   :-2287.782   Min.   :1
##  1st Qu.:0.0000   1st Qu.:   -1.829   1st Qu.:1
##  Median :0.2000   Median :    5.490   Median :1
##  Mean   :0.2094   Mean   :   16.073   Mean   :1
##  3rd Qu.:0.2000   3rd Qu.:   22.653   3rd Qu.:1
##  Max.   :0.8000   Max.   : 2799.984   Max.   :1
##
##
## [[2]]
##          Ship_Mode             Segment                  City
##  First Class   :  50   Consumer   :2446   Los Angeles  : 596
##  Same Day      :  62   Corporate  : 443   San Francisco: 160
##  Second Class  : 224   Home Office: 238   Seattle      : 127
##  Standard Class:2791                      Chicago      : 125
##                                           San Diego    : 100
##                                           New York City:  70
##                                           (Other)      :1949
##         State           Sub_Category  diff_in_days       Sales
##  California:1125   Binders    : 937   Min.   :0.000   Min.   :    0.836
##  Texas     : 235   Phones     : 286   1st Qu.:4.000   1st Qu.:   15.534
##  Illinois  : 201   Art        : 242   Median :5.000   Median :   51.900
##  Washington: 155   Storage    : 217   Mean   :4.876   Mean   :  228.879
##  Ohio      : 132   Accessories: 215   3rd Qu.:6.000   3rd Qu.:  220.408
##  Florida   : 126   Chairs     : 200   Max.   :7.000   Max.   :10499.970
##  (Other)   :1153   (Other)    :1030
##     Quantity          Discount          Profit              cluster
##  Min.   : 1.000   Min.   :0.000   Min.   :-6599.978   Min.   :2
##  1st Qu.: 2.000   1st Qu.:0.000   1st Qu.:    0.995   1st Qu.:2
##  Median : 3.000   Median :0.200   Median :    7.822   Median :2
```

```
##  Mean   : 3.873   Mean   :0.197   Mean   :   24.238   Mean   :2
##  3rd Qu.: 5.000   3rd Qu.:0.200   3rd Qu.:   28.140   3rd Qu.:2
##  Max.   :14.000   Max.   :0.800   Max.   : 5039.986   Max.   :2
##
##
## [[3]]
##           Ship_Mode           Segment              City              State
##  First Class   : 117   Consumer   :265   Philadelphia:472   Pennsylvania:503
##  Same Day      :  68   Corporate  :257   Seattle     : 68   Illinois    :100
##  Second Class  : 166   Home Office:943   Chicago     : 64   Texas       : 98
##  Standard Class:1114                     Columbus    : 30   Washington  : 77
##                                          Houston     : 30   Ohio        : 75
##                                          Springfield : 28   Florida     : 71
##                                          (Other)     :773   (Other)     :541
##       Sub_Category  diff_in_days       Sales             Quantity
##  Furnishings:331   Min.   :0.000   Min.   :    0.852   Min.   : 1.000
##  Binders    :147   1st Qu.:4.000   1st Qu.:   15.936   1st Qu.: 2.000
##  Phones     :144   Median :4.000   Median :   49.080   Median : 3.000
##  Accessories:115   Mean   :4.285   Mean   :  222.880   Mean   : 3.695
##  Art        :109   3rd Qu.:5.000   3rd Qu.:  212.940   3rd Qu.: 5.000
##  Storage    :109   Max.   :7.000   Max.   :22638.480   Max.   :14.000
##  (Other)    :510
##     Discount          Profit             cluster
##  Min.   :0.0000   Min.   :-3399.980   Min.   :3
##  1st Qu.:0.0000   1st Qu.:   -4.196   1st Qu.:3
##  Median :0.2000   Median :    4.115   Median :3
##  Mean   :0.2238   Mean   :    5.651   Mean   :3
##  3rd Qu.:0.2000   3rd Qu.:   16.795   3rd Qu.:3
##  Max.   :0.8000   Max.   : 2591.957   Max.   :3
##
##
## [[4]]
##           Ship_Mode           Segment               City             State
##  First Class   :1133   Consumer   :985   San Francisco:287   California:628
##  Same Day      : 181   Corporate  :409   Los Angeles  :119   New York  :101
##  Second Class  : 224   Home Office:224   Seattle      : 81   Washington: 93
##  Standard Class:  80                     New York City: 71   Ohio      : 80
##                                          San Diego    : 48   Virginia  : 57
##                                          Philadelphia : 37   Illinois  : 48
##                                          (Other)      :975   (Other)   :611
##       Sub_Category  diff_in_days       Sales            Quantity
##  Paper      :393   Min.   :0.000   Min.   :    0.99   Min.   : 1.000
##  Binders    :149   1st Qu.:1.000   1st Qu.:   17.43   1st Qu.: 2.000
##  Furnishings:147   Median :2.000   Median :   50.86   Median : 3.000
##  Accessories:138   Mean   :2.101   Mean   :  208.15   Mean   : 3.666
##  Art        :119   3rd Qu.:3.000   3rd Qu.:  179.94   3rd Qu.: 5.000
##  Phones     :116   Max.   :7.000   Max.   :13999.96   Max.   :14.000
##  (Other)    :556
##     Discount           Profit            cluster
##  Min.   :0.00000   Min.   :-2639.99   Min.   :4
##  1st Qu.:0.00000   1st Qu.:    3.63   1st Qu.:4
##  Median :0.00000   Median :   11.24   Median :4
##  Mean   :0.09589   Mean   :   35.76   Mean   :4
##  3rd Qu.:0.20000   3rd Qu.:   34.20   3rd Qu.:4
```

```
##  Max.   :0.80000   Max.   : 6719.98   Max.   :4
##
##
## [[5]]
##            Ship_Mode            Segment                City                State
##  First Class   :  83   Consumer   : 498   New York City: 736   New York   :861
##  Same Day      :  89   Corporate  :1577   Seattle      :  90   California:157
##  Second Class  : 305   Home Office: 232   Columbus     :  62   Texas      :118
##  Standard Class:1830                      San Francisco:  53   Washington:103
##                                           Springfield  :  44   Michigan  : 77
##                                           Chicago      :  41   Ohio      : 76
##                                           (Other)      :1281   (Other)   :915
##       Sub_Category  diff_in_days      Sales            Quantity
##  Paper      :576   Min.   :0.000   Min.   :    1.24   Min.   : 1.000
##  Art        :197   1st Qu.:4.000   1st Qu.:   19.44   1st Qu.: 2.000
##  Phones     :196   Median :5.000   Median :   57.96   Median : 3.000
##  Accessories:175   Mean   :4.585   Mean   :  250.62   Mean   : 3.853
##  Furnishings:175   3rd Qu.:5.000   3rd Qu.:  209.32   3rd Qu.: 5.000
##  Storage    :172   Max.   :7.000   Max.   :17499.95   Max.   :14.000
##  (Other)    :816
##     Discount            Profit            cluster
##  Min.   :0.00000   Min.   :-3839.990   Min.   :5
##  1st Qu.:0.00000   1st Qu.:    4.584   1st Qu.:5
##  Median :0.00000   Median :   12.672   Median :5
##  Mean   :0.06621   Mean   :   52.335   Mean   :5
##  3rd Qu.:0.20000   3rd Qu.:   40.422   3rd Qu.:5
##  Max.   :0.80000   Max.   : 8399.976   Max.   :5
##
```

```
#summary(pam_fit_5)
```

Medoids: ID
[1,] "399" "399" [2,] "9" "9"
[3,] "3027" "3027" [4,] "7230" "7230" [5,] "7554" "7554"

```
build      swap
```

0.3108903 0.3097443

Numerical information per cluster: size max_diss av_diss diameter separation [1,] 1477 0.5268858 0.3377785 0.7446928 0.001792861 [2,] 3127 0.5648233 0.2947558 0.7741892 0.014292276 [3,] 1465 0.5496150 0.3155812 0.7789958 0.001792861 [4,] 1618 0.5867120 0.3260236 0.7515684 0.014292276 [5,] 2307 0.5948357 0.2969881 0.8127438 0.014472373

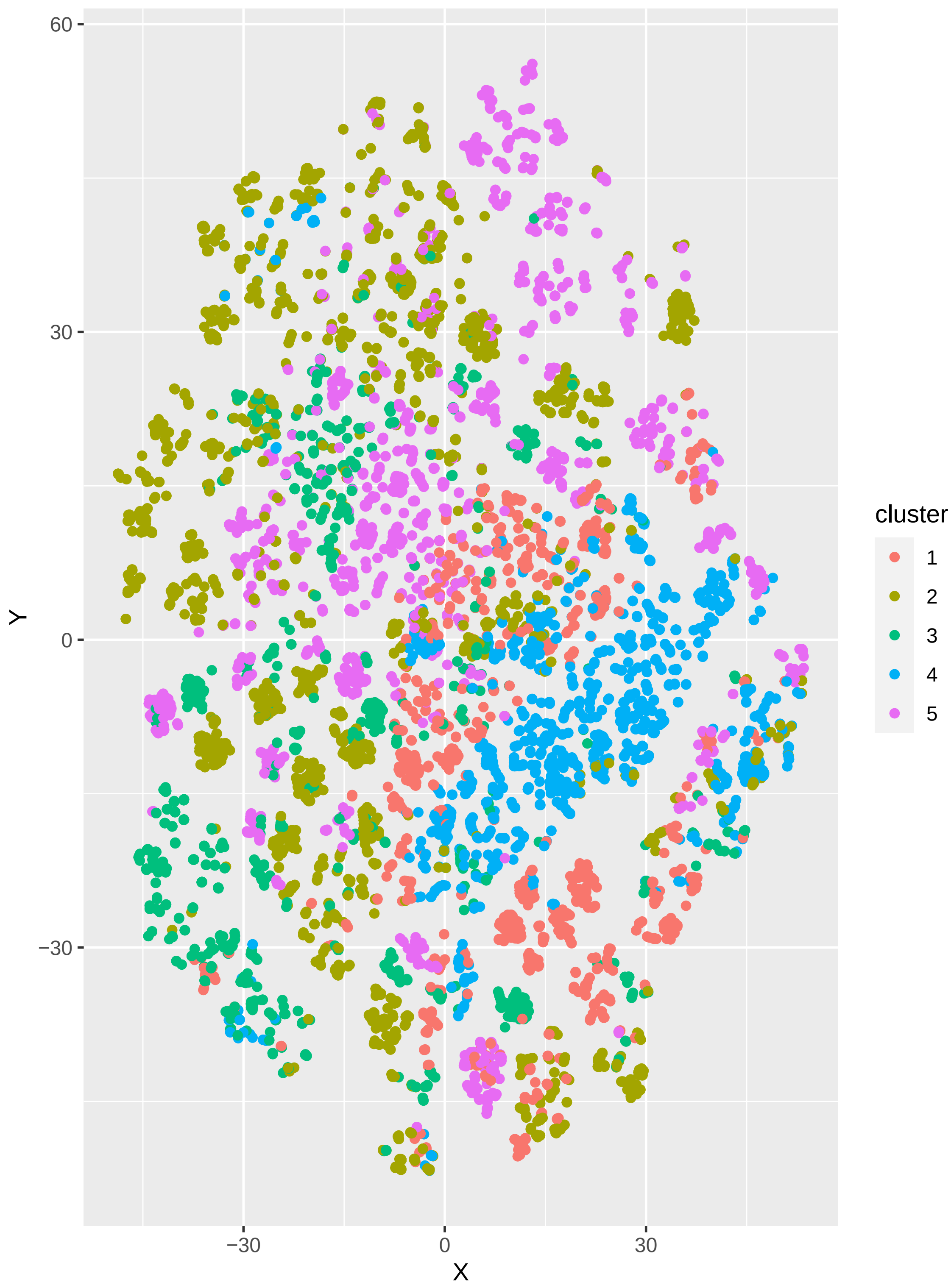
Isolated clusters: L-clusters: character(0) L*-clusters: character(0)

"'Average silhouette width per cluster: [1] 0.05349182 0.10906323 0.04114758 0.08911682 0.07800729 Average silhouette width of total data set: [1] 0.08049662

Available components: [1] "medoids" "id.med" "clustering" "objective" "isolation" "clusinfo" "silinfo" "diss" [9] "call"

```
tsne_obj <- Rtsne(gower_dist_5, is_distance = TRUE)

tsne_data <- tsne_obj$Y %>%
```

```r
  data.frame() %>%
  setNames(c("X", "Y")) %>%
  mutate(cluster = factor(pam_fit_5$clustering))

ggplot(aes(x = X, y = Y), data = tsne_data) +
  geom_point(aes(color = cluster))
```



Evaluating the consistency within Clusters of Data

Silhouette coefficient can be used to compare the average distance to observations within the same cluster, to the average distance to observations in other clusters.

High silhouette coefficient means that the observation is well clustered, while a low silhouette coefficient may indicate outliers.

Deployment

Responsible ML Framework

Conclusion

References

https://www.datanovia.com/en/blog/k-means-clustering-visualization-in-r-step-by-step-guide/

https://www.tidymodels.org/learn/statistics/k-means/

https://towardsdatascience.com/clustering-analysis-in-r-using-k-means-73eca4fb7967

https://towardsdatascience.com/clustering-evaluation-strategies-98a4006fcfc

https://www.analyticsvidhya.com/blog/2020/12/a-case-study-to-detect-anomalies-in-time-series-using-anomalize-package-in-r/

https://www.datanovia.com/en/lessons/k-medoids-in-r-algorithm-and-practical-examples/