K-means & K-medoid clustering in product segmentation: ASDS 6303 Final Project

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Loading the dataset

```
product_data = read_excel('./dataset/sku_data.xlsx')
kable(head(product_data),
      booktabs = TRUE,
      format = "latex",
      caption = "Dataset head") %>% kable_styling(latex_options = "hold_position")
```

Table 1: Dataset head

ID	Unitprice	Expire date	Outbound number	Total outbound	Pal grossweight	Pal height	Units per pal
1	0.058	547	9	2441	105.60	1.56	1920
2	0.954	547	0	0	207.68	1.00	384
3	2.385	547	12	23	165.78	1.02	108
4	5.100	547	0	0	221.04	1.05	72
5	0.000	547	0	0	0.00	0.00	0
6	1.110	547	1	1	207.68	1.00	384

```
summary(product_data)
```

```
##        ID           Unitprice        Expire date    Outbound number
##  Min.   :   1.0   Min.   :  0.000   Min.   :  0.0   Min.   :   0
##  1st Qu.: 570.5   1st Qu.:  0.000   1st Qu.:365.0   1st Qu.:   0
##  Median :1140.0   Median :  1.294   Median :547.0   Median :   1
##  Mean   :1140.0   Mean   :  4.269   Mean   :410.4   Mean   : 236
##  3rd Qu.:1709.5   3rd Qu.:  4.545   3rd Qu.:547.0   3rd Qu.:  45
##  Max.   :2279.0   Max.   :518.592   Max.   :734.0   Max.   :6325
##  Total outbound    Pal grossweight   Pal height     Units per pal
##  Min.   :    0.0   Min.   :  0.0   Min.   :0.0000   Min.   :     0.0
##  1st Qu.:    0.0   1st Qu.: 60.0   1st Qu.:0.0000   1st Qu.:    32.0
##  Median :    3.0   Median :167.7   Median :0.8400   Median :   108.0
##  Mean   :  731.7   Mean   :192.9   Mean   :0.6728   Mean   :   755.6
##  3rd Qu.:  419.5   3rd Qu.:277.6   3rd Qu.:1.0200   3rd Qu.:   384.0
##  Max.   :26411.0   Max.   :907.2   Max.   :2.1600   Max.   :200000.0
```

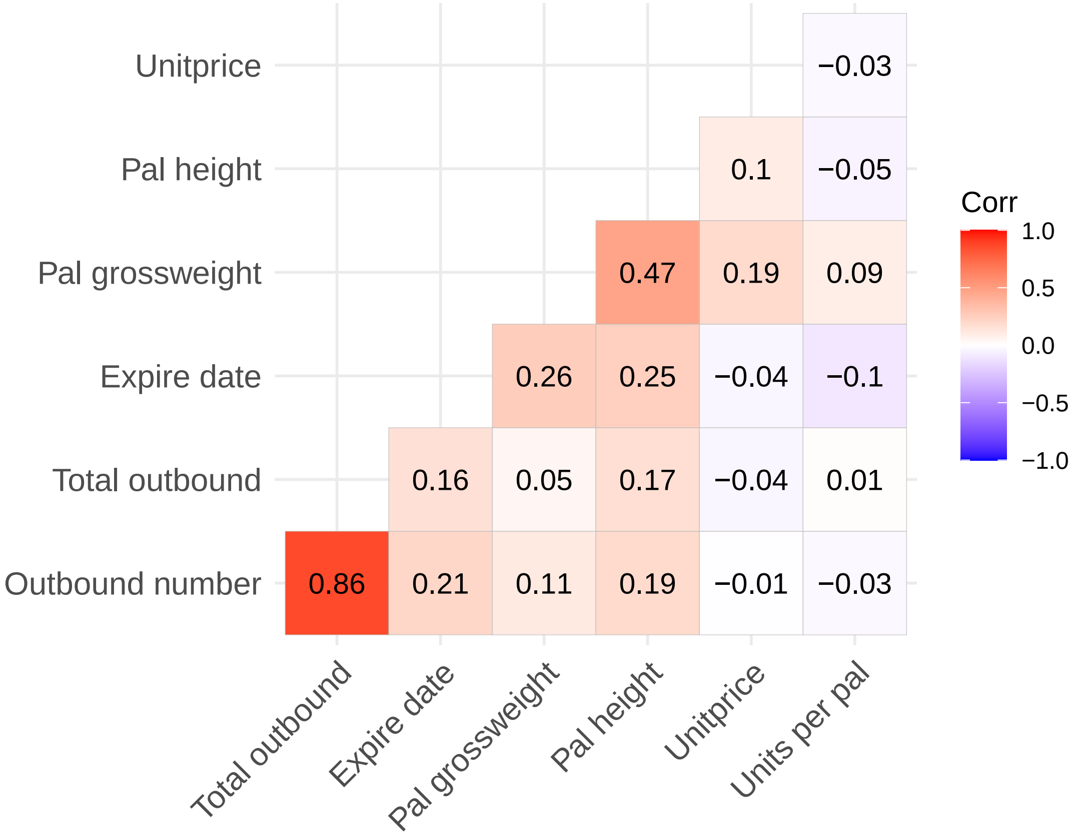
```r
product_data <- select(product_data, -c("ID"))
```

Checking correlation

```r
library(ggcorrplot)
```

```
## Warning: package 'ggcorrplot' was built under R version 4.3.2
```

```r
correlation = cor(product_data)
ggcorrplot(correlation, hc.order = TRUE, type = "lower",
   lab = TRUE)
```



Let's only consider the `Outbound number` and `Total outbound` features in our dataset to perform the clustering, due to high correlation.

```r
product_subset <- select(product_data, c("Outbound number", "Total outbound"))
```

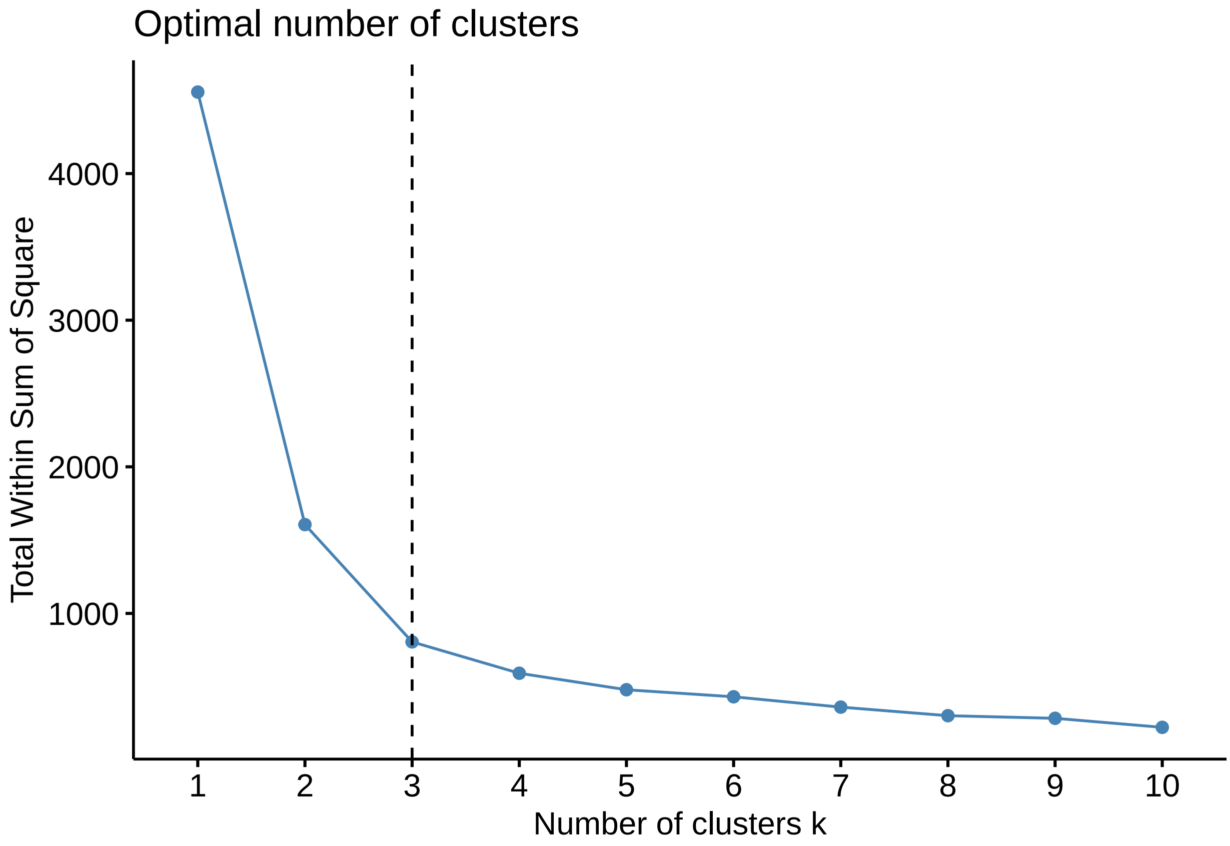
Scaling data

```r
product_subset_scaled = scale(product_subset)
```

K-means clustering

Checking a scree-plot for the ideal number of clusters, we see:

```r
fviz_nbclust(product_subset_scaled, kmeans, method = "wss") +
geom_vline(xintercept = 3, linetype = 2)
```



```r
set.seed(8093)
model.kmeans <- kmeans(product_subset_scaled, nstart = 20, centers = 3)
print(model.kmeans)
```

```
## K-means clustering with 3 clusters of sizes 34, 173, 2072
##
## Cluster means:
##   Outbound number Total outbound
## 1        5.679717      6.3389854
## 2        1.971275      1.4644906
## 3       -0.257790     -0.2262946
##
## Clustering vector:
##    [1] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##   [38] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##   [75] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [112] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [149] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [186] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [223] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [260] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [297] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [334] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [371] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [408] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [445] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [482] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [519] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [556] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [593] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [630] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [667] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [704] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [741] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [778] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [815] 3 3 3 3 3 3 3 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [852] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [889] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [926] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##  [963] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [1000] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [1037] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [1074] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [1111] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [1148] 3 3 3 3 3 3 3 3 3 3 3 3 3 1 2 3 3 3 1 3 2 3 2 3 3 3 2 3 3 3 3 3 3 1 2 2 2
## [1185] 2 1 2 2 2 1 1 2 1 1 1 1 1 2 3 2 2 2 1 1 1 2 3 2 1 3 2 1 2 2 1 2 3 2 2 3 3
## [1222] 3 3 3 3 3 2 3 3 2 2 3 3 3 3 2 3 2 3 2 3 3 3 2 3 3 3 3 2 3 3 3 3 3 3 2 3 2
## [1259] 3 3 3 3 3 3 3 3 3 3 3 3 1 2 3 3 2 3 3 3 3 2 1 2 3 3 3 3 3 3 2 2 3 3 3 3 3
## [1296] 3 3 3 3 3 3 1 3 3 3 3 3 3 1 3 2 2 3 3 3 1 2 2 2 3 1 2 3 3 3 3 3 3 3 3 3 3
## [1333] 3 3 3 3 3 3 2 2 3 3 2 3 2 3 3 3 3 2 3 1 2 1 2 2 3 2 2 2 2 3 2 2 2 1 2 2 2
## [1370] 3 3 3 3 3 3 3 3 3 3 3 3 3 2 3 3 3 3 3 3 2 3 2 3 3 3 2 3 3 2 3 3 2 1 2 2 2
## [1407] 2 2 2 3 3 3 3 2 3 2 3 3 3 2 2 3 3 3 2 3 3 3 3 2 2 1 2 2 3 2 2 3 3 3 2 2 3
## [1444] 3 3 3 2 3 2 2 3 3 3 3 3 3 3 3 3 3 3 3 2 3 3 2 3 3 3 3 2 3 3 3 2 2 3 2 2 3
## [1481] 3 3 2 1 3 3 3 3 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 2 3 3 3 2 3 3 3 3 3
## [1518] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [1555] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 2 2 2 3 3 3 3 3 2 2
## [1592] 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 2 2 3 1 2 2
## [1629] 3 2 2 2 2 2 2 2 1 2 3 3 2 2 3 2 2 2 2 3 3 2 2 2 1 1 2 2 2 2 3 2 3 2 2 3 3
## [1666] 3 3 3 3 3 3 3 3 3 2 2 3 3 3 3 3 2 3 3 3 3 2 3 3 3 3 3 3 3 3 3 2 3 3 3 3 3
## [1703] 3 3 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [1740] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 2 3 3 3 3 3 3 3 2 3 3 3 3 3 3 3
## [1777] 3 3 3 3 3 3 3 3 3 2 3 3 2 3 2 3 3 3 3 3 3 3 3 3 3 3 2 3 2 3 3 3 3 2 3 3 3
## [1814] 3 3 3 2 3 3 2 3 3 3 3 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 2 2 3 3 3 3 3
## [1851] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 2 3 3 3 3 3 3 3 3 3 1 3 3 3 2 3 3 3 3
## [1888] 3 3 3 3 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [1925] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [1962] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 2 2 3 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [1999] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 2 3 3 2 3 3 3 3 3 3 2 2 3 2 3 3 3
## [2036] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3 2 3 3 3 3 3 3 3 3 3
## [2073] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [2110] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [2147] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [2184] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [2221] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
## [2258] 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
##
## Within cluster sum of squares by cluster:
```

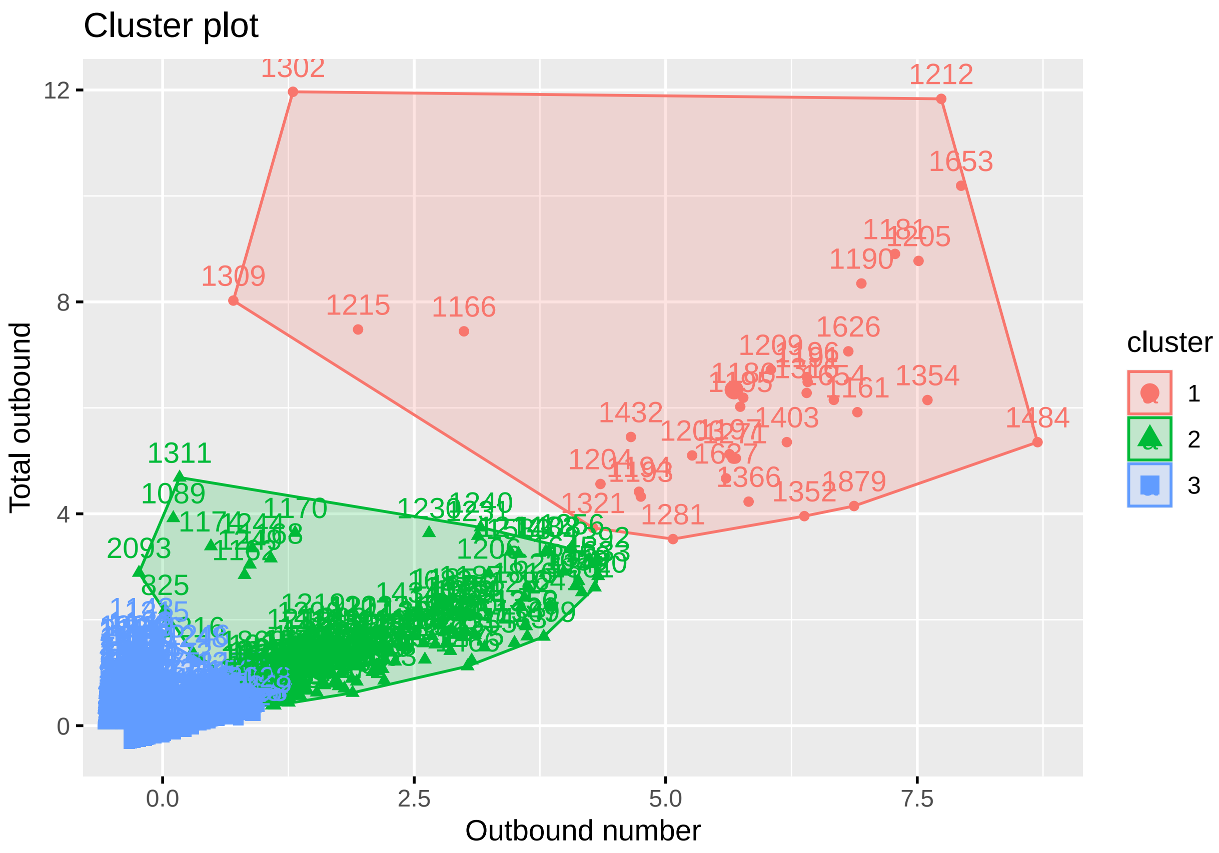
cluster	Unitprice	Expire date	Outbound number	Total outbound	Pal grossweight	Pal height	Units per pal
1	1.903088	568.5882	4213.0882	14335.3529	207.2529	0.9700000	310.3529
2	3.590896	561.8902	1616.3237	3874.5416	248.1189	1.0087283	250.9480
3	4.364883	395.1245	55.4638	246.0661	188.0976	0.6398726	805.0014

```
## [1] 260.0769 306.0841 239.7081
##  (between_SS / total_SS =  82.3 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

Aggregating cluster characteristics

```
kable(aggregate(product_data, by=list(cluster=model.kmeans$cluster), mean),
      format = "latex",
      booktabs = TRUE) %>% kable_styling(position="center")
```

```
fviz_cluster(model.kmeans, product_subset_scaled)
```



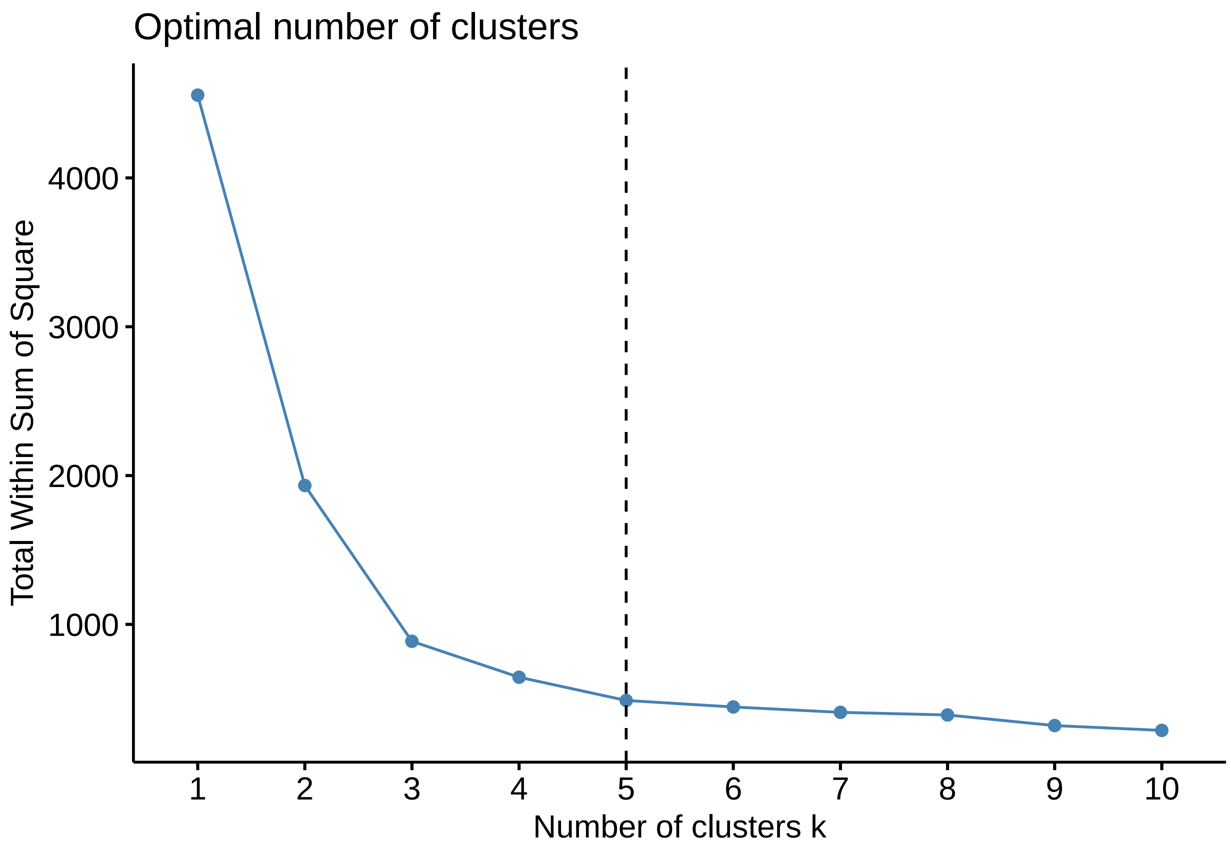
Silhouette scores

[TODO]

K-medoid clustering

Visualizing the ideal number of clusters for `pam` (k-medoid clustering) using `fvz_nbclust`:

```
fviz_nbclust(product_subset_scaled, pam, method = "wss") +
  geom_vline(xintercept = 5, linetype = 2)
```



It appears that k-medoid clustering for the same product-data does best with 5 clusters. Performing clustering with 5 clusters:

```
set.seed(8093)
model.kmedoid <- pam(product_subset_scaled, k = 5)
model.kmedoid
```

```
## Medoids:
##        ID Outbound number Total outbound
## [1,] 1325       0.1499844      0.1320107
## [2,]    2      -0.3369980     -0.3409557
## [3,] 1980       1.2710435      0.7722628
## [4,] 1195       5.7409990      6.0210248
## [5,] 1364       3.0133265      2.0867832
## Clustering vector:
##     [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 2 2 2 2 2 2 2
##    [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 1 2 2 2 2 2 2 2 2 2 2 2 2
##    [75] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##   [112] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 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 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
##   [186] 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 2 2 2 2 2 2 2 2
##  [223] 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
##  [260] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [297] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [334] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [371] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 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 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [445] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 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 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [519] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 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 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [593] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [630] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [667] 2 2 2 1 2 2 2 1 1 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 1 2
##  [704] 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 2
##  [741] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
##  [778] 2 2 2 2 2 2 2 2 2 2 2 2 2 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 1 2 2 2 2 2 1 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 2
##  [852] 2 2 2 2 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 2 2 2 2 2 2 2
##  [889] 2 2 2 2 2 2 2 1 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
##  [926] 2 2 2 2 1 2 2 1 1 1 2 2 2 2 2 1 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 1 1 1 2 2 2
##  [963] 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 2 2 2
## [1000] 1 2 2 2 2 2 1 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 2
## [1037] 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 2 2
## [1074] 2 2 2 2 1 1 2 2 1 2 2 2 1 1 2 3 2 1 2 1 1 2 2 1 2 2 2 2 1 2 2 2 2 2 1 2 1
## [1111] 2 1 1 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 2 2 2 1 1 2 1 2 1 1 2 2 1 2 1 2 1 1 2
## [1148] 1 2 2 2 2 1 2 1 2 2 2 2 1 4 3 2 2 2 4 2 5 1 5 2 1 1 3 1 2 2 1 2 2 4 5 3 3
## [1185] 5 4 5 5 3 4 4 5 4 4 4 4 4 3 3 3 3 5 4 4 4 5 1 3 4 3 5 4 5 5 4 3 2 3 3 2 3
## [1222] 3 2 2 1 1 3 1 1 5 5 1 1 2 1 3 1 3 1 5 2 2 1 5 2 3 2 3 3 2 2 2 1 2 2 5 2 3
## [1259] 1 1 2 3 2 1 2 2 2 1 2 1 4 5 2 2 3 2 2 2 2 5 5 5 2 1 2 2 1 1 3 3 1 2 2 2 2
## [1296] 2 2 2 1 2 2 4 1 2 1 1 2 1 4 2 5 3 2 2 1 4 3 3 5 2 5 5 2 2 1 2 2 2 2 2 2 1
## [1333] 2 2 2 2 2 2 3 3 2 2 3 2 3 2 2 2 2 3 3 4 5 4 5 5 1 3 5 5 5 2 3 5 3 4 5 3 5
## [1370] 2 2 1 1 2 1 2 2 2 2 1 2 1 3 2 2 2 2 2 2 5 2 5 1 3 1 3 1 3 5 2 1 3 4 3 3 3
## [1407] 3 5 3 3 2 1 1 3 2 3 1 2 1 5 5 2 2 2 3 3 2 2 2 3 3 4 3 5 2 3 3 2 1 1 3 3 1
## [1444] 1 1 1 3 1 3 3 2 2 1 1 1 1 1 2 2 2 2 2 3 2 1 5 2 2 2 1 3 1 1 2 5 3 2 3 5 1
## [1481] 1 2 5 4 1 1 2 2 2 2 1 3 2 2 2 2 2 2 2 1 2 2 1 2 2 2 1 3 2 3 2 3 1 1 2 2 2
## [1518] 2 2 2 2 1 2 2 2 2 2 1 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 2 2 2
## [1555] 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 2 2 3 2 3 5 3 1 1 2 2 2 3 3
## [1592] 3 2 1 2 2 2 2 2 1 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 5 3 1 4 3 3
## [1629] 1 3 3 3 5 5 5 5 4 5 1 1 5 3 1 3 5 3 3 2 2 5 3 3 4 4 5 5 3 3 1 3 2 3 3 2 3
## [1666] 2 3 2 1 1 2 2 2 1 5 5 1 1 2 2 1 5 2 2 2 2 3 1 1 2 2 2 2 2 2 2 3 1 2 2 1 2
## [1703] 2 1 1 2 2 3 2 2 1 2 3 2 2 1 1 2 2 2 2 1 2 3 1 2 2 2 2 2 2 2 1 2 1 2 2 2 2
## [1740] 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 1 3 2 1 1 2 2 1 1 3 2 1 1 2 2 1 1
## [1777] 2 2 2 2 2 1 3 1 2 3 2 2 3 1 3 2 2 3 1 1 3 1 1 2 2 1 3 1 3 2 1 2 3 5 2 2 1
## [1814] 1 2 2 3 1 2 3 2 1 2 2 1 2 2 5 2 1 2 2 1 2 2 2 2 2 2 2 2 2 1 3 3 2 1 2 2 2
## [1851] 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 1 3 2 1 2 2 2 2 2 2 1 4 1 2 1 3 2 2 1 2
## [1888] 1 1 2 2 1 2 2 3 1 2 1 2 1 1 1 2 1 1 1 1 2 2 2 1 1 1 2 2 1 2 2 2 2 2 2 1 2
## [1925] 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 2 1 1 2
## [1962] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 5 5 2 3 1 1 1 2 2 2 2 2 1 2 2 2 2 2 1 2 2 2
## [1999] 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 1 2 5 2 2 2 2 1 3 3 5 1 3 2 1 2
## [2036] 2 1 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 3 1 2 2 2 1 2 1 2 2
## [2073] 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 3 2 2 1 2 1 2 2 2 2 2 2 2 2 2 2 2
## [2110] 2 2 2 1 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 2 2 2 2 2 2 2 2
## [2147] 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 2 2 2 2
## [2184] 1 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 2 2
```

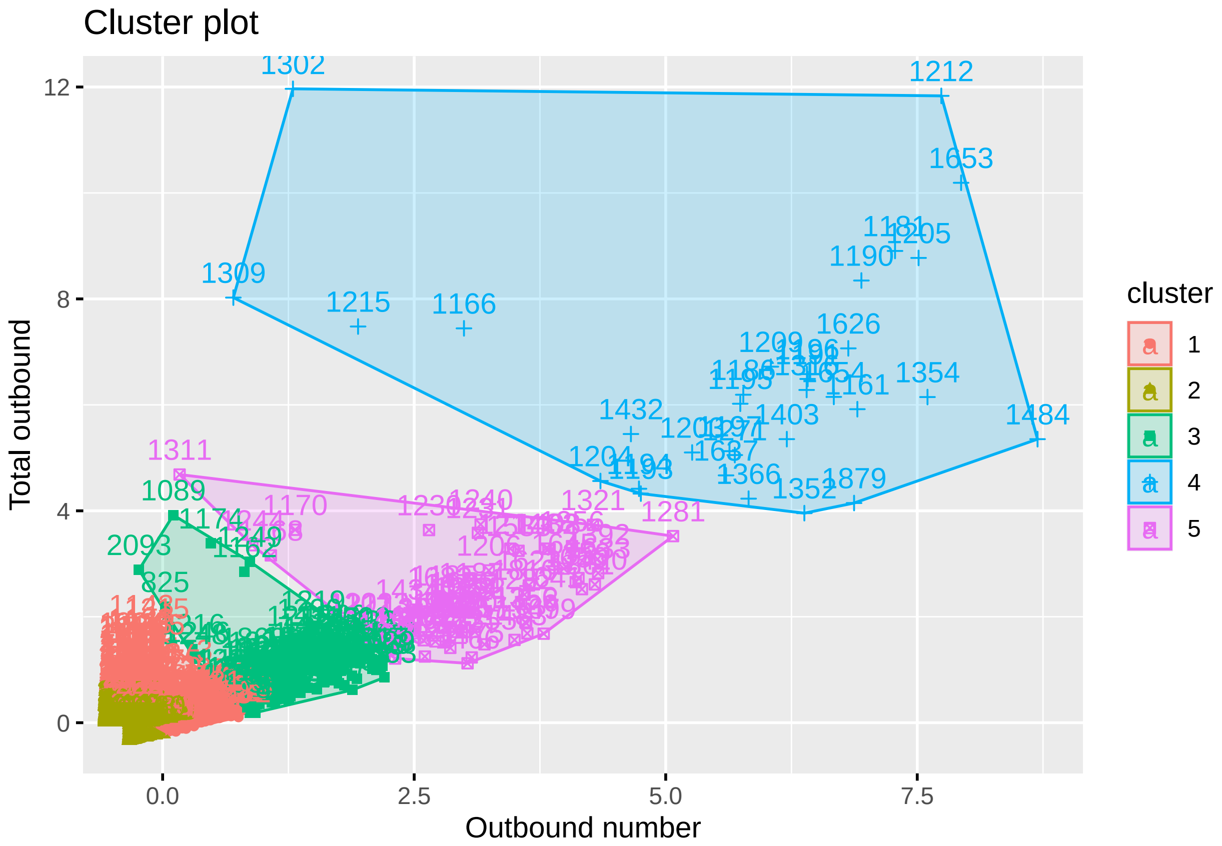
cluster	Unitprice	Expire date	Outbound number	Total outbound	Pal grossweight	Pal height	Units per pal
1	4.079924	468.8511	273.70922	1317.3794	228.9536	0.9068972	1633.4681
2	4.402425	381.2756	11.01358	55.2077	180.2633	0.5913531	680.7040
3	4.216886	552.6591	1129.59091	2706.6818	258.6896	1.0346970	237.7652
4	1.944063	569.9375	4257.06250	14698.8750	209.1037	0.9628125	312.1250
5	2.750076	577.5455	2360.77273	5618.9045	239.1029	0.9886364	259.3030

```
## [2221] 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 2 2 2 1 2 1 1 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 1
## Objective function:
##     build      swap
## 0.1805800 0.1718847
##
## Available components:
##  [1] "medoids"    "id.med"     "clustering" "objective"  "isolation"
##  [6] "clusinfo"   "silinfo"    "diss"       "call"       "data"
```

Aggregating cluster characteristics

```r
kable(aggregate(product_data, by=list(cluster=model.kmedoid$cluster), mean),
      format = "latex",
      booktabs = TRUE) %>% kable_styling(position="center")
```

```r
fviz_cluster(model.kmedoid, product_subset_scaled)
```


Cluster plot
Total outbound
Outbound number
cluster