

Estimating the Demand

A) The available dataset has 1000 sales records of previously sold items. Besides the percentage of sales in each hour and the total sold items, there are 2 categorical features which are department's name of the item and the part of the event's day. In this assignment, you should determine the demand for all available items in the dataset.

B) If the categorical features had more than 2 categories, would it be possible to use k-means clustering? Discuss your answer.

Answer A) From the 'Assignment6_Data.csv' dataset, there are 1,000 obs. of 29 variables. At first, we have imported the data and then converted the categorical data into numerical data.

```
> str(A$6data)
'data.frame': 1000 obs. of 29 variables:
 $ 1..Item.      : num  1 2 3 4 5 6 7 8 9 10 ...
 $ Department    : num  1 1 1 2 1 1 1 1 1 1 ...
 $ Event.Part.of.the.day: num  2 2 1 2 1 2 2 2 1 2 ...
 $ hour.1        : num  0.14 0.14 0.3 0.26 0.22 0.34 0.32 0.21 0.52 0.38 ...
 $ hour.2        : num  0.18 0.13 0.16 0.12 0.11 0.09 0.17 0.14 0.16 0.15 ...
 $ hour.3        : num  0.15 0.07 0.06 0.07 0 0.13 0.11 0.06 0 0.11 ...
 $ hour.4        : num  0.07 0.06 0.1 0.04 0.08 0.03 0.08 0.09 0.11 0.05 ...
 $ hour.5        : num  0 0.11 0.05 0.04 0 0.06 0.05 0.04 0.06 0.06 ...
 $ hour.6        : num  0 0.1 0.02 0.04 0.05 0.03 0.03 0.1 0 0.04 ...
 $ hour.7        : num  0.15 0.08 0.02 0.03 0 0.01 0.03 0.02 0 0.02 ...
 $ hour.8        : num  0.09 0 0.02 0.04 0.05 0.05 0.02 0.03 0.03 0 ...
 $ hour.9        : num  0.03 0 0.02 0.03 0 0.03 0.01 0.02 0.07 0.04 ...
 $ hour.10       : num  0.03 0.08 0.03 0 0.02 0.06 0.05 0.03 0.01 0.09 ...
 $ hour.11       : num  0.06 0 0.04 0.04 0.04 0.03 0.01 0.02 0 0 ...
 $ hour.12       : num  0 0.01 0 0.01 0.02 0 0.03 0.04 0.01 0 ...
 $ hour.13       : num  0.04 0.05 0.01 0.04 0.04 0.01 0.03 0 0 0.03 ...
 $ hour.14       : num  0.02 0.07 0.02 0.03 0 0.01 0 0.02 0 0 ...
 $ hour.15       : num  0 0 0 0.01 0.02 0.01 0 0 0 0 ...
 $ hour.16       : num  0 0 0 0.01 0 0.01 0 0 0 0 ...
 $ hour.17       : num  0 0 0 0 0.01 0.01 0.02 0 0 ...
 $ hour.18       : num  0 0 0 0 0 0 0 0 0.03 ...
 $ hour.19       : num  0 0 0 0 0 0 0 0 0 ...
 $ hour.20       : num  0 0.01 0 0 0 0 0 0 0 ...
 $ hour.21       : num  0.01 0 0 0 0 0 0 0 0 ...
 $ hour.22       : num  0.01 0 0.02 0.01 0 0 0 0 0 ...
 $ hour.23       : num  0 0 0.01 0 0 0 0 0 0 ...
 $ hour.24       : num  0 0.02 0.02 0 0 0.03 0 0 ...
 $ Total.sales   : num  91.80 91.17 85.88 51.63 71.98 ...
 $ Total        : num  91.8 80.8 91.6 171.6 85.4 ...
```

```
> summary(A$6data)
1..Item.      Department      Event.Part.of.the.day      hour.1      hour.2      hour.3      hour.4
Min.   : 1.0      Min.   :1.000      Min.   :1.000      Min.   :0.1100      Min.   :0.0400      Min.   :0.00000      Min.   :0.00000
1st Qu.: 250.8    1st Qu.:1.000      1st Qu.:1.000      1st Qu.:0.2100      1st Qu.:0.1200      1st Qu.:0.05000      1st Qu.:0.05000
Median : 500.5    Median :1.000      Median :2.000      Median :0.2800      Median :0.1400      Median :0.08000      Median :0.07000
Mean   : 500.5    Mean   :1.396      Mean   :1.537      Mean   :0.2676      Mean   :0.1396      Mean   :0.07228      Mean   :0.07237
3rd Qu.: 750.2    3rd Qu.:2.000      3rd Qu.:2.000      3rd Qu.:0.3100      3rd Qu.:0.1600      3rd Qu.:0.09000      3rd Qu.:0.08250
Max.   :1000.0    Max.   :2.000      Max.   :2.000      Max.   :0.5200      Max.   :0.2200      Max.   :0.15000      Max.   :0.17000

hour.5      hour.6      hour.7      hour.8      hour.9      hour.10      hour.11
Min.   :0.00000      Min.   :0.00000      Min.   :0.00000      Min.   :0.00000      Min.   :0.00000      Min.   :0.00000      Min.   :0.00000
1st Qu.:0.04000      1st Qu.:0.02000      1st Qu.:0.02000      1st Qu.:0.02000      1st Qu.:0.02000      1st Qu.:0.01000      1st Qu.:0.01000
Median :0.06000      Median :0.04000      Median :0.03000      Median :0.03000      Median :0.03000      Median :0.03000      Median :0.03000
Mean   :0.05479      Mean   :0.04038      Mean   :0.0421      Mean   :0.04409      Mean   :0.02778      Mean   :0.02744      Mean   :0.02637
3rd Qu.:0.07000      3rd Qu.:0.05000      3rd Qu.:0.05000      3rd Qu.:0.06000      3rd Qu.:0.03000      3rd Qu.:0.03000      3rd Qu.:0.04000
Max.   :0.13000      Max.   :0.12000      Max.   :0.1500      Max.   :0.23000      Max.   :0.07000      Max.   :0.09000      Max.   :0.06000

hour.12      hour.13      hour.14      hour.15      hour.16      hour.17      hour.18
Min.   :0.00000      Min.   :0.00000      Min.   :0.00000      Min.   :0.00000      Min.   :0.00000      Min.   :0.00000      Min.   :0.00000
1st Qu.:0.01000      1st Qu.:0.01000      1st Qu.:0.00000      1st Qu.:0.00000      1st Qu.:0.00000      1st Qu.:0.00000      1st Qu.:0.00000
Median :0.03000      Median :0.03000      Median :0.01000      Median :0.01000      Median :0.01000      Median :0.00000      Median :0.00000
Mean   :0.02186      Mean   :0.02113      Mean   :0.01375      Mean   :0.00959      Mean   :0.01023      Mean   :0.00605      Mean   :0.00446
3rd Qu.:0.04000      3rd Qu.:0.03000      3rd Qu.:0.02000      3rd Qu.:0.01000      3rd Qu.:0.01000      3rd Qu.:0.01000      3rd Qu.:0.00000
Max.   :0.07000      Max.   :0.05000      Max.   :0.07000      Max.   :0.03000      Max.   :0.09000      Max.   :0.05000      Max.   :0.05000

hour.19      hour.20      hour.21      hour.22      hour.23      hour.24      Total.sales
Min.   :0.00000      Min.   :0.00000      Min.   :0.00000      Min.   :0.00000      Min.   :0.00000      Min.   :0.00000      Min.   : 51.00
1st Qu.:0.00000      1st Qu.:0.00000      1st Qu.:0.00000      1st Qu.:0.00000      1st Qu.:0.00000      1st Qu.:0.00000      1st Qu.: 64.00
Median :0.00000      Median :0.00000      Median :0.00000      Median :0.00000      Median :0.00000      Median :0.00000      Median : 79.00
Mean   :0.00466      Mean   :0.00513      Mean   :0.00862      Mean   :0.00679      Mean   :0.00324      Mean   :0.00495      Mean   : 89.62
3rd Qu.:0.00000      3rd Qu.:0.01000      3rd Qu.:0.01000      3rd Qu.:0.01000      3rd Qu.:0.00000      3rd Qu.:0.00000      3rd Qu.:103.00
Max.   :0.06000      Max.   :0.08000      Max.   :0.05000      Max.   :0.05000      Max.   :0.03000      Max.   :0.05000      Max.   :488.00

Total
Min.   : 51.63
1st Qu.: 64.63
Median : 79.59
Mean   : 90.29
3rd Qu.:103.67
Max.   :488.72
```

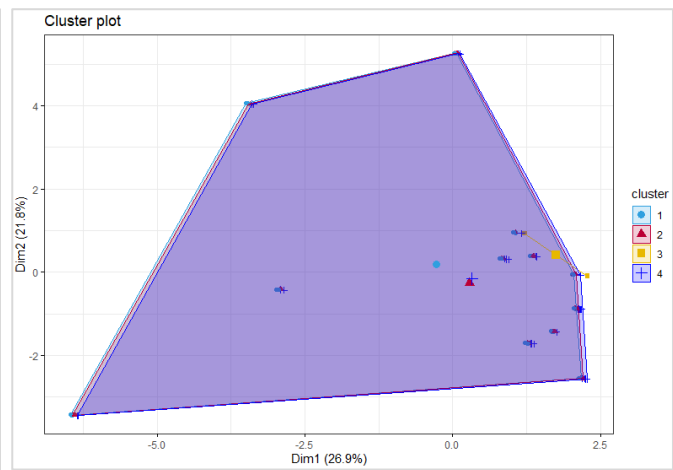
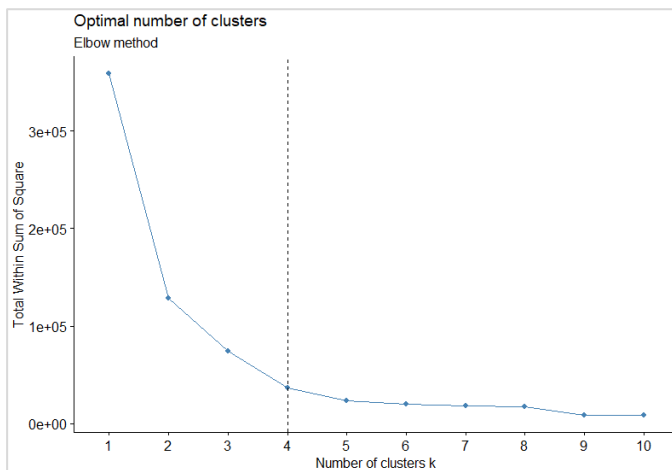
Here are the 2 categorical features which are department's name of the item and the part of the event's day. Please refer to the R code as determined the demand for all available items in the dataset.

```
true_demand
stockouts=cbind(stockouts,true_demand)
View(stockouts)
colnames(stockouts)
colnames(not_stockouts)
View(stockouts[,c(2,31)])
```

Output:

```
> colnames(stockouts)
[1] "f..Item." "Department" "Event.Part.of.the.day" "hour.1" "hour.2"
[6] "hour.3" "hour.4" "hour.5" "hour.6" "hour.7"
[11] "hour.8" "hour.9" "hour.10" "hour.11" "hour.12"
[16] "hour.13" "hour.14" "hour.15" "hour.16" "hour.17"
[21] "hour.18" "hour.19" "hour.20" "hour.21" "hour.22"
[26] "hour.23" "hour.24" "Total.sales" "Total" "stockout_time"
[31] "true_demand"
```

```
> #K-means Clustering
> clusters <- kmeans(not_stockouts[,3:28],4, nstart = 20)
> not_stockouts=cbind(not_stockouts,clusters$cluster)
> centroids=clusters$center
> centroids[4,]
Event.Part.of.the.day hour.1 hour.2 hour.3 hour.4
1.677419e+00 2.664516e-01 1.441935e-01 7.290323e-02 6.032258e-02
hour.5 hour.6 hour.7 hour.8 hour.9
4.677419e-02 3.838710e-02 4.032258e-02 3.000000e-02 2.258065e-02
hour.10 hour.11 hour.12 hour.13 hour.14
2.290323e-02 2.709677e-02 2.064516e-02 2.225806e-02 1.290323e-02
hour.15 hour.16 hour.17 hour.18 hour.19
7.419355e-03 1.032258e-02 5.161290e-03 5.806452e-03 3.870968e-03
hour.20 hour.21 hour.22 hour.23 hour.24
4.193548e-03 8.387097e-03 7.419355e-03 6.774194e-03 2.322581e-02
Total.sales
1.614839e+02
```



Answer B) It is simply not possible to use the k-means clustering over categorical data because we need a distance between elements and that is not clear with categorical data as it is with the numerical part of our data. So, the best solution that comes to my mind is that we construct somehow a similarity matrix (or dissimilarity/ distance matrix) between our categories to complement it with the distances for our numerical data (for which we can use simply an euclidean or manhattan distance). Then use the K-medoid algorithm, which can accept a dissimilarity matrix as input and using R with the "cluster" package that includes the pam() function.

If there is a logical order of the categories (i.e. category A is more similar to category B than to category C due to some features of the categories) we can apply weighted values to categories. But this is a typical "false" category feature (because it can be decomposed in a vector of numerical features). If the problem is related to real categorical features each category has the same distance to each other. You can set a fixed distance for any category feature depending on the logic importance (weight) of this category for clustering.

Example: if you have two category features A and B by the knowledge of the clustering problem, we can set that a mismatch in the category.

Bibliographic Reference:

(Anonymous, 2021) *Colors in R* Retrieved from
<http://www.sthda.com/english/wiki/colors-in-r>

Shendre S. April 29, 2020 *Clustering datasets having both numerical and categorical variables* Retrieved from <https://towardsdatascience.com/clustering-datasets-having-both-numerical-and-categorical-variables-ed91cdca0677>

Marchese L. and Ramirez-Flandes S. July 21, 2021 *RESEARCH-GATE* Retrieved from <https://www.researchgate.net/post/What-is-the-best-way-for-cluster-analysis-when-you-have-mixed-type-of-data-categorical-and-scale>