Social media market segmentation

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Problem statement

Twitter tweets from the followers of a consumer brand were analyzed. Every tweet has been classified as belonging to a category like sports, cooking, beauty, fitness etc. by annotators.

These tweets can help in market segmentation i.e., to classify social market into segments to help understand the customer base better in terms of their interests, preferences, social media activity etc. This can help in targeted advertisement campaigns, better reach to customers, tweak promotional offers according to customers etc., in effect helping the business to grow.

Our task here to is to identify these segments based on intuition and sound data analysis and interpret them in a coherent manner.

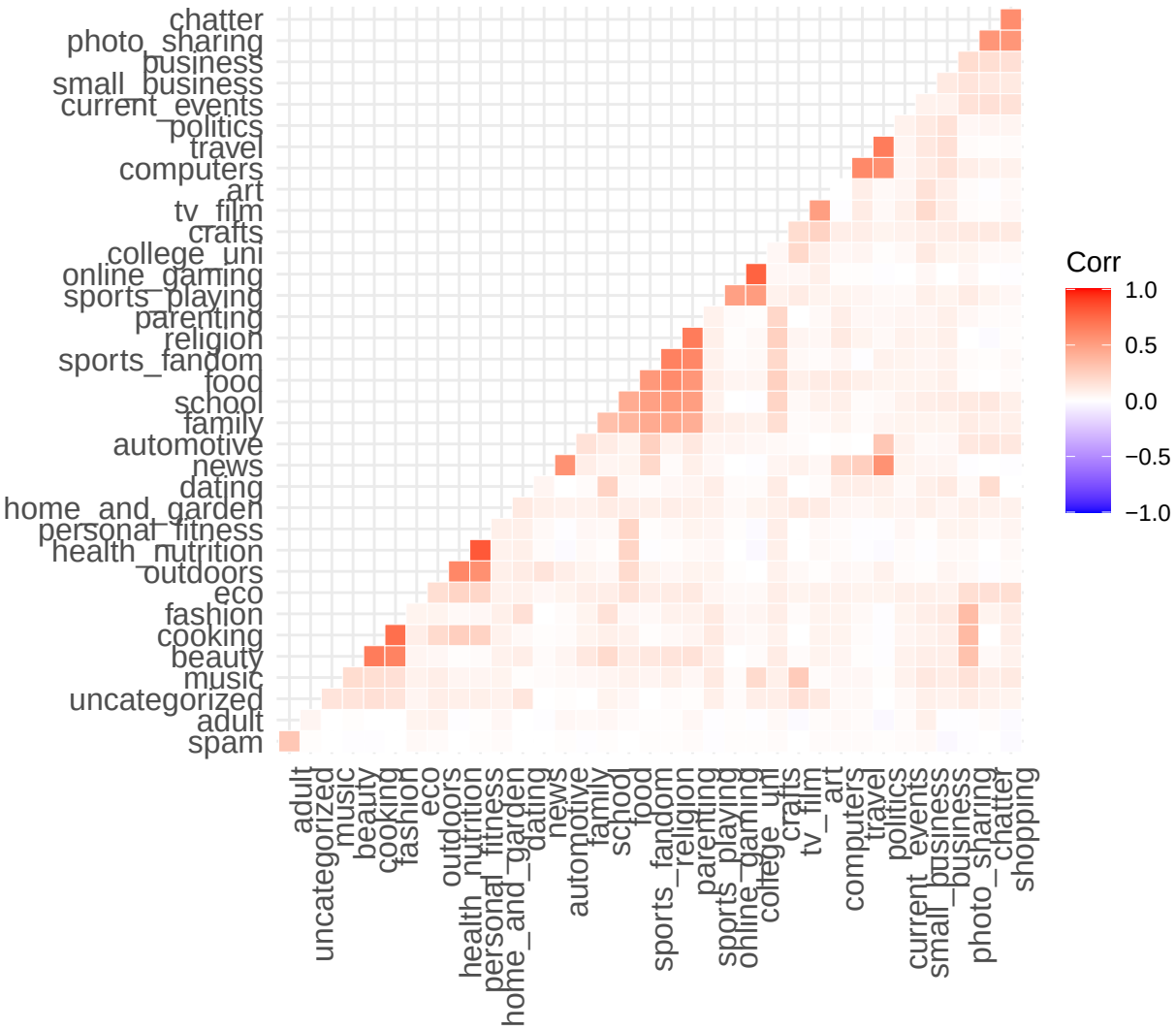
Steps

The broad outline of the approach we took to carry out this task as follows:

1. Exploratory data analysis

We find out that the data has 36 features available for each user. These 36 features specify the number of tweets in each category (like online_gaming, politics, cooking etc.) by that user. It is intuitive to first check for correlation between these features as that can help us in finding out correlated features. Since correlation is not sensitive to scaling, we just run plot correlation for the raw data.

```
sm_data <- read.csv("social_marketing.csv")
#summary(sm_data)
#head(sm_data, 10)

sm_feat_raw <- sm_data[,2:length(sm_data)]



# Creating a correlation plot

cormat <- round(cor(sm_feat_raw), 2)
#head(cormat[, 1:6])
ggcorrplot(cormat, hc.order = TRUE,
           type = "lower",
           outline.color = "white") + theme( axis.text.x = element_text(angle=90, hjust=1))
```



Correlation plot reveals some interesting and intutitive correlations between features. Some very strong +ve correlations can be seen, like between health nutrition and personal fitness, cooking and fashion, online_gaming and college_uni. These are intuitive like people who are interested in health_nutrition also are likely to tweet about personal fitness. A rather peculiar one is between sports_fandom and religion which doesn't seem so intuitive. (Maybe if you are a fan of God, you are likely to be a fan of sports team :)).

2. Segmentation using clustering approach

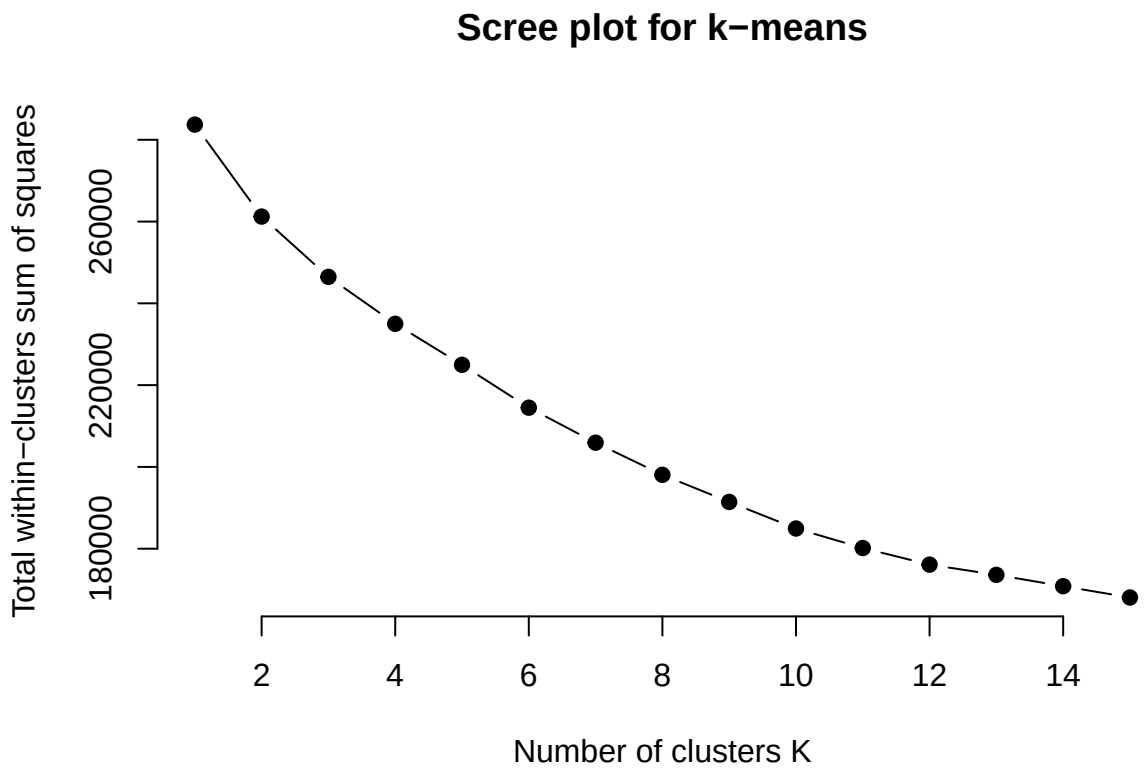
In order to see if these features and correlation can help to identify some interesting groups of users with shared features, we decide to try the clustering approach to help identify some number of clusters. We decide to go for the KMeans++ clustering approach. The first step in this clustering is to scale the data to zero mean and unit variance of the columns. This will even out the intrinsic variations in the features data and help us in clustering.

```
sm_user <- sm_data[, 1]

# Scaling and centering data
sm_sca = scale(sm_feat_raw, center=TRUE, scale=TRUE)
```

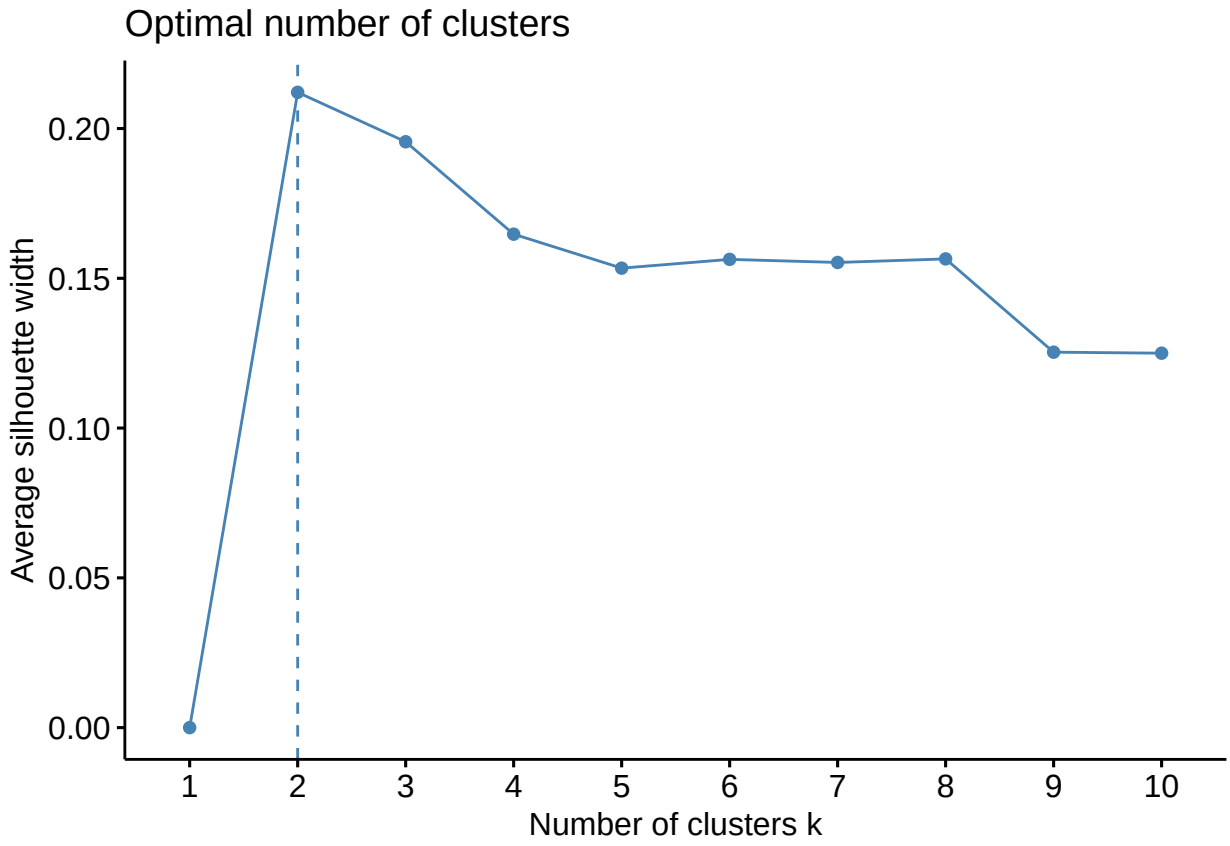
2.1 Finding an optimal number of clusters: Scree analysis, silhouette method, gap statistic

For kmeans++ clustering, we need to give the number of clusters beforehand. So we do a scree analysis, silhouette analysis and gap statistic analysis to see if that gives meaningful number of clusters.

```
set.seed(100)

# function to compute total within-cluster sum of square
wss <- function(k) {
  kmeans(sm_sca, k, nstart = 10 )$tot.withinss
}

# Compute and plot wss for k = 1 to k = 15
k.values <- 1:15

# extract wss for 2-15 clusters
wss_values <- map_dbl(k.values, wss)

scree = plot(k.values, wss_values,
     type="b", pch = 19, frame = FALSE,
     xlab="Number of clusters K",
     ylab="Total within-clusters sum of squares",
     main = "Scree plot for k-means")
```




```
sil = fviz_nbclust(sm_sca, kmeans, method = "silhouette")
plot(sil, main = "Silhouette analysis for k-means")
```




```
#  set.seed(123)
#  gap_stat <- clusGap(sm_sca, FUN = kmeans, nstart = 10,
#                      K.max = 18, B = 10)
#
# gap = fviz_gap_stat(gap_stat)
```

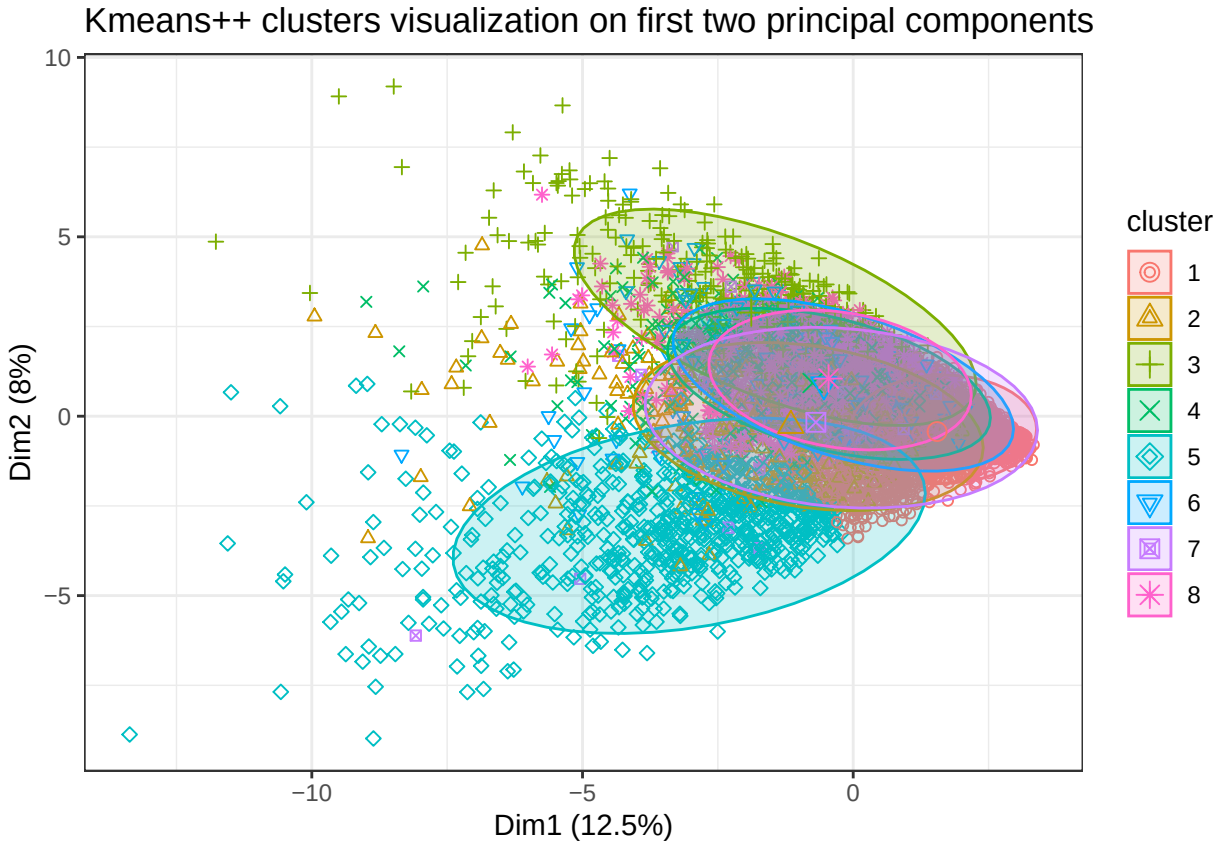
Inference on number of clusters: Scree plot doesn't have any elbow to conclude anything meaningful about number of clusters. Since within cluster sum of squares keeps on decreasing, it rather suggests higher the better. The silhouette method tells the optimum number of clusters to be 2, it is too low for any meaningful analysis. So we tried a reasonable numbers like 6 and 8 which are feasible enough for market segmentation point of view and see if we can interpret the clusters. ***Here we present the results from k=8 clustering which we found more interesting and revealing.***

2.2 Kmeans++ clustering with k=8

We do the clustering with k=8 with a fixed seed to enable the same results to be produced again. The visalization of clusters on first two principal components is a popular visualization to see the variation in clusters. While some clusters are well separated and differently aligned as indicated by the ellipses, this visualization doesn't necessarily capture the distinction between the clusters fully. This is because the two principal components only capture 12.5% and 8% of the total variance of the data as indicated on the axes of the plot. We will come to this point later.

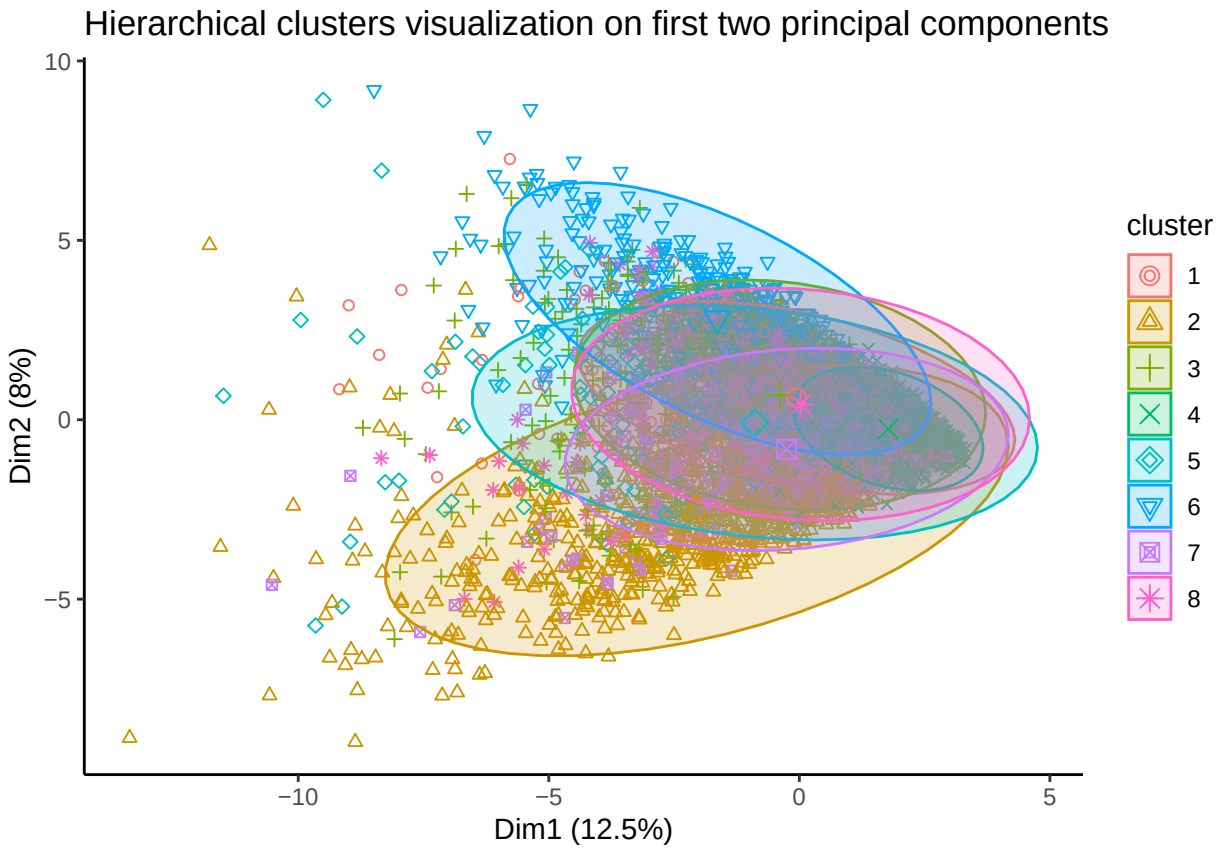
```
set.seed(100)

# Run k-means with 8 clusters and 25 starts
clust1 = kmeanspp(sm_sca, 8, nstart=25)

#visualization of clusters on first two pincipal components
```

```
fviz_cluster(clust1, data = sm_sca,  stand = FALSE,
             ellipse.type = "t", geom=c("point"),
             main="Kmeans++ clusters visualization on first two principal components") +
  theme_bw()
```



We also take a sneak peek into hierarchical clustering to see if there is any significant difference between kmeans and hclust on this data.

```
#Hierarchical clustering 8 clusters cutoff.
hclust1 <- hcut(sm_sca, 8, hc_method ="ward" , hc_metric="euclidian" )

#visualization in first 2 PCs for quick look if they are different
fviz_cluster(hclust1, data = sm_sca, stand = FALSE,
                        ellipse.type = "norm", geom=c("point"),
             main="Hierarchical clusters visualization on first two principal components") +
   theme_classic()
```

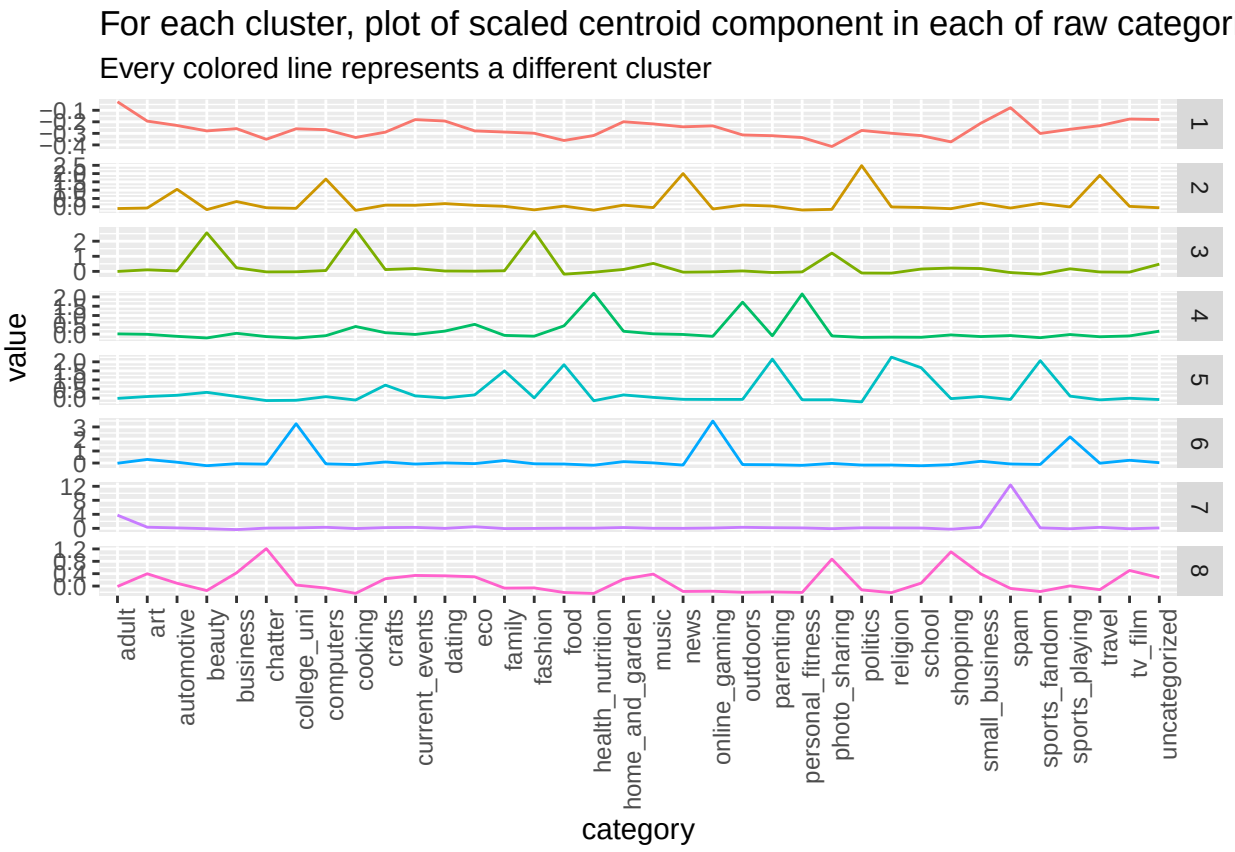


As we can see this, plot looks very similar to the one we obtained using kmeans++ and hence, gives us more confidence in our clustering.

3. Interpreting the clusters

The important analysis is here to correctly interpret the clusters and see if they make any sensible market segment. For this purpose, we visualize the scaled centroid of each cluster to see if which features(columns) in raw data dominate if any for each of the cluster. From this information we maybe able to infer some interesting information about these clusters.

```
rs      <- as.data.frame(t(clust1$center))
rs$category <- rownames(rs)
rs      <- melt(rs, id.vars=c("category"), variable.name = "cluster")



ggplot(rs, aes(x = category, y = value),
       main="Centroid coordinate in each category for each cluster") +
  geom_line(aes(color = cluster, group=cluster)) +
  facet_grid(cluster ~ ., scales = "free_y") +
  theme(legend.position = "none", axis.text.x = element_text(angle=90, hjust=1)) +
  labs(title = "For each cluster, plot of scaled centroid component in each of raw categories",
              subtitle = "Every colored line represents a different cluster")
```



4. Market segments

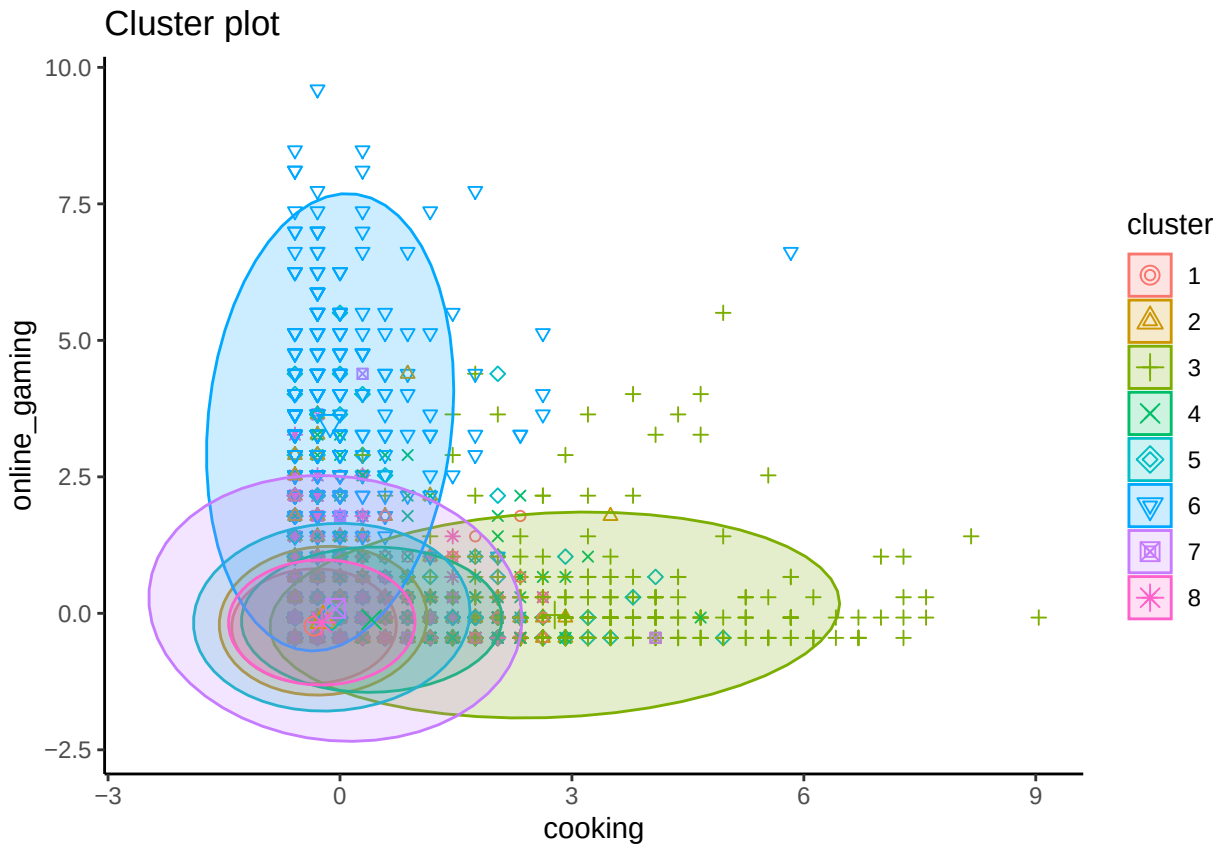
From this plot it is easy to see what each cluster represents.

Market Segments:

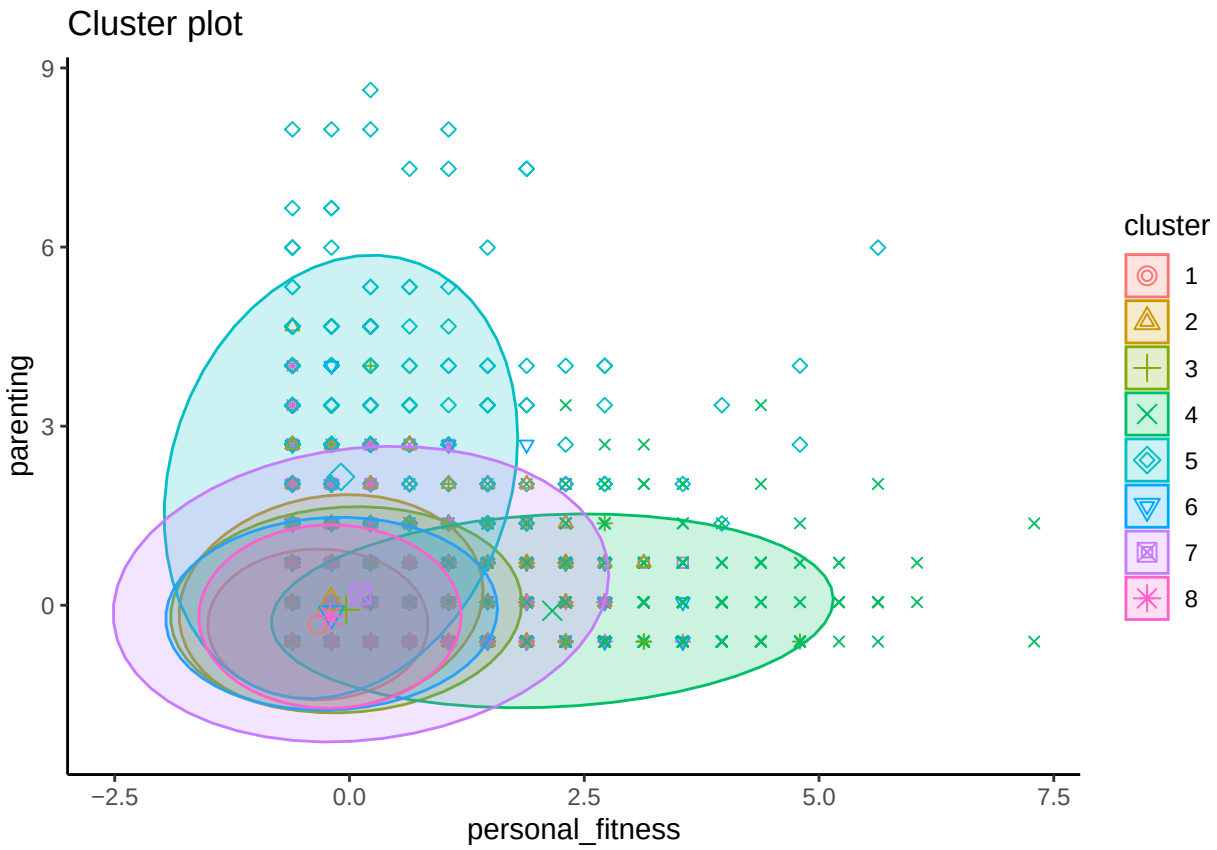
1. ***Tech oriented aware people (Cluster 2)***: The major dominating features of this cluster are computers, automotives, news and politics. This group is likely to be highly educated.
2. ***Fashionistas (Cluster 3)***: This cluster's dominating features lie in fashion, beauty, photosharing.
3. ***Fitness enthusiasts (Cluster 4)***: Health nutrition, outdoors and personal fitness dominates the features indicating a high interest in outdoor activity, nutrition to be fit.
4. ***Social and family minded people(Cluster 5)***: These people are likely to be talking about social strucutres like family, parenting and religion.
5. ***Sports and games enthusiasts (Cluster 6)***: Major features are online_gaming and sports_playing. They also are likely to be in college or university.
6. ***Spammers (Cluster 7)***: This cluster scores overwhelmingly high on two features: spam and adult content. BOT ALERT!!!
7. ***Social media birds (Cluster 8)***: They are likely to be sharing photos and engaging in general chatter.
8. ***General (Cluster 1)***: No interpretation. This cluster doesn't seem to have any dominating features, it probably represents ones who don't have any specific interest.

As we have seen, the two principal components may not reveal the relevance of these clusters. So we plot some these in plane of raw features to show how these clusters can be visualized. Given below is a visualization of clusters on the axes of online_gaming vs cooking.

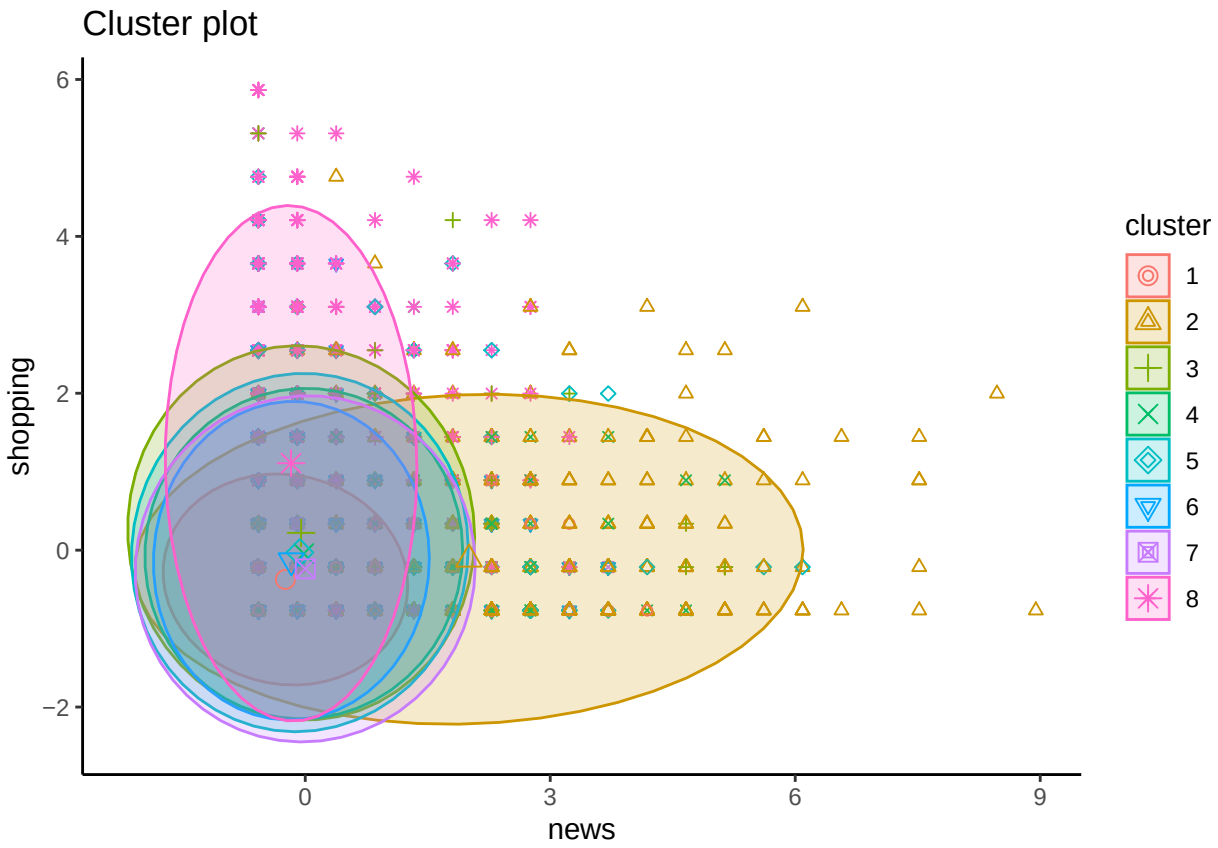
```
fviz_cluster(clust1, data = sm_sca, choose.vars = c("cooking", "online_gaming"), stand = FALSE,
             ellipse.type = "norm", geom=c("point")) + theme_classic()
```




```
fviz_cluster(clust1, data = sm_sca, choose.vars = c("personal_fitness", "parenting"), stand = FALSE,
             ellipse.type = "norm", geom=c("point")) + theme_classic()
```




```
fviz_cluster(clust1, data = sm_sca, choose.vars = c("news", "shopping"), stand = FALSE,
             ellipse.type = "norm", geom=c("point")) + theme_classic()
```



We can see from this visualization how cluster 3 extends in the cooking space while cluster 6 extends in the online_gaming space. Cluster 4 extends in the personal_fitness space and cluster 5 in contrats just extends in parenting space. Cluster 8 has prominence in shopping space while cluster 2 is more prominent in politics space. This makes more clear that indeed our clustering is relevant and is clearly demonstrated in these plots.