

# Free Classification: Clustering Project

## Clustering

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### Data

We have data in wide format. Each row is a talker type and each col is a participant.

```
df <- read_csv("data/class_wide_1.csv")

## Parsed with column specification:
## cols(
##   .default = col_double(),
##   speaker = col_character(),
##   `54` = col_character()
## )

## See spec(...) for full column specifications.
```

### Clustering

#### Introduction

In this task, individuals heard spoken speech tokens and freely classified them into groups. Using hierarchical clustering we aimed to see what clusters or groups appear as a result of the free classification task.

45 speech samples were selected from The Speech Accent Archive. The talkers included three American English regional dialects, three international English dialects, and nine nonnative accents. The nonnative accents were split into three accents from East Asia, three accents from South Asia, and three accents from Southeast Asia. The American English dialects included the New England dialect, the Southern dialect, and the Midland dialect. The international English dialects included British English, Australian English, and Afrikaans. The native languages of the nonnative-accented talkers were Mandarin, Korean, and Japanese from East Asia, Bengali, Gujarati, and Urdu from South Asia, and Indonesian, Tagalog, and Thai from Southeast Asia.

```
# For reproducibility
set.seed(666)

library(here)
library(tidyverse) # data manipulation
library(cluster)   # clustering algorithms
library(factoextra) # clustering visualization
library(dendextend) # for comparing two dendrograms
```

## Data Preparation

1. Rows are observations (individuals) and columns are variables
2. Any missing value in the data must be removed or estimated.
3. The data must be standardized (i.e., scaled) to make variables comparable if they are not on the same scale (I do not do it here).

## Read in the data

```
clust_data <- read_csv(here("data", "class_wide_1.csv")) # read in data

## Warning: Missing column names filled in: 'X1' [1]
## Parsed with column specification:
## cols(
##   .default = col_double(),
##   speaker = col_character(),
##   `54` = col_character()
## )
## See spec(...) for full column specifications.

clust_data <- select(clust_data, -X1, -`54`) # remove extra col sub 54 has weird formatting

clust_data <- as.data.frame(clust_data) # turn into df

rownames(clust_data) <- clust_data$speaker # make row names speaker

clust_data <- select(clust_data, -speaker) # remove extra col sub 54 has weird formatting

head(clust_data) # show first couple rows
```

	8	7	1	10	11	12	14	15	16	17	18	19	2	20	23	25	26	27	28	29	3	30	31	32	33	34	35	36	38	4	40	
## bengali_9	1	5	5	1	11	2	1	8	4	2	2	1	9	7	4	5	1	1	1	11	5	1	7	7	9	8	10	8	1	3	1	
## bengali_13	6	5	5	7	14	4	2	7	4	2	6	3	9	1	4	5	4	2	3	11	12	1	8	11	9	8	10	11	1	4	12	
## bengali_16	1	5	5	7	7	4	3	6	2	8	3	3	3	1	3	4	6	1	3	10	2	1	7	8	9	8	10	11	6	3	8	
## gujarati_5	4	5	5	1	14	4	1	7	4	9	9	1	9	4	3	5	4	2	4	8	9	1	7	9	9	6	10	8	1	2	8	
## gujarati_13	1	5	5	1	15	4	2	8	4	2	6	1	9	4	5	5	6	2	4	8	5	1	7	9	9	8	10	2	1	2	12	
## gujarati_14	5	5	5	1	7	4	1	8	4	9	9	3	9	5	7	5	4	4	6	1	5	1	6	9	9	6	10	9	1	4	13	
##	5	50	51	52	53	55	56	58	59	6	78	87	90	91	96	105	110	111	115	121	123	125	132	133	135	148						
## bengali_9	1	3	7	1	8	9	1	1	5	9	1	11	1	11	1	6	11	1	2	1	9	1	3	1	1	1						
## bengali_13	5	4	7	3	8	9	1	8	11	7	1	11	1	11	1	6	11	7	8	6	9	1	6	2	3	6						
## bengali_16	5	4	7	3	8	9	8	1	6	7	5	11	2	6	1	6	10	6	8	6	10	10	4	2	3	1						
## gujarati_5	10	3	7	11	8	9	7	3	11	7	1	11	2	10	1	1	11	6	8	6	9	10	4	3	2	3						
## gujarati_13	2	4	7	1	8	9	7	10	5	7	1	11	2	11	1	6	11	2	8	6	9	10	4	2	1	1						
## gujarati_14	3	3	7	15	8	8	8	6	5	6	2	11	8	11	1	6	11	6	9	6	9	8	4	2	1	2						
##	159	160	161	162	163	164	165	166	167	168	169																					

```
## bengali_9      1  5  1  7  4  1  5  1  7  1  2
## bengali_13     2  1 14  7  6  4  5  1  4  2  4
## bengali_16     2  3 14  7  7  1  5  1  7  4  4
## gujarati_5      1  3 14  7  5  6  6  1  4  2  5
## gujarati_13     1  4 14  7  5  6  5  1  7  3  6
## gujarati_14     8  4  5  3  7  6  7  6  7  5  1
```

## Agglomerative Hierarchical Clustering

I am going to cluster the data using average link clustering. Average link clustering computes all pairwise dissimilarities between the elements, and considers the average of these dissimilarities as the distance between clusters.

First, we calculate the dissimilarity matrix using euclidean distance.

Second, we compute the clustering with average link.

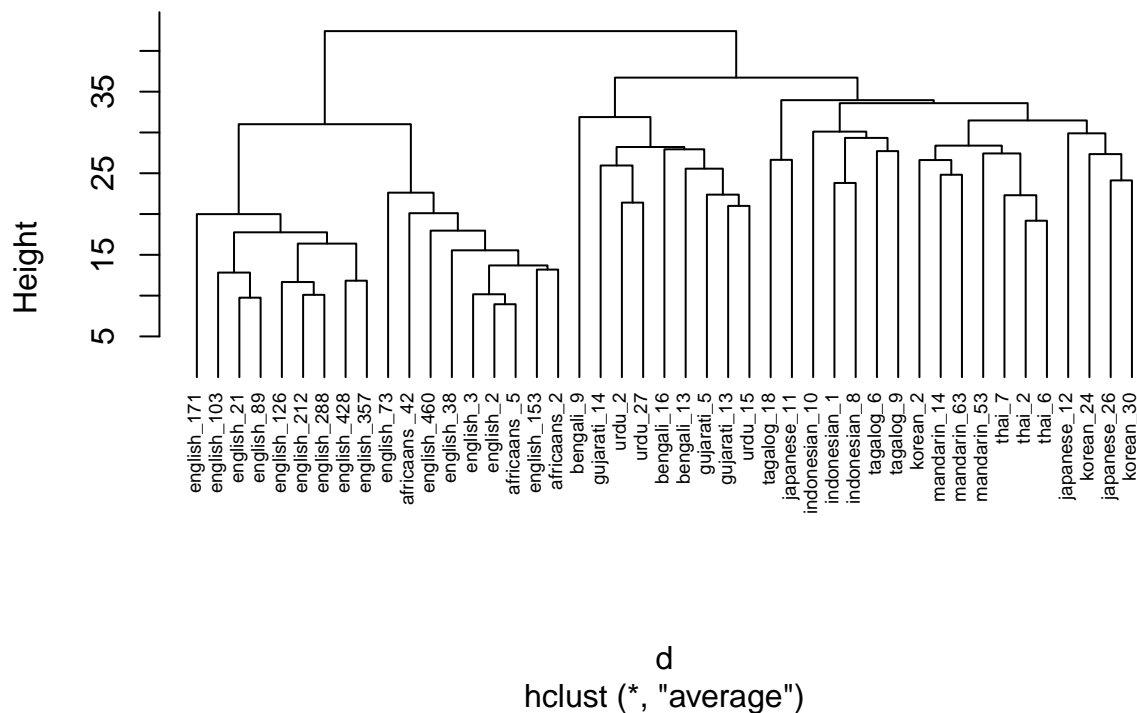
Third, we plot the cluster solution

```
# Dissimilarity matrix
d <- dist(clust_data, method = "euclidean")

# Hierarchical clustering using Average Linkage
hc1 <- hclust(d, method = "average" )

# Plot the obtained dendrogram
plot(hc1, cex = 0.6, hang = -1)
```

## Cluster Dendrogram



In the dendrogram displayed above, each leaf corresponds to one observation. As we move up the tree,

observations that are similar to each other are combined into branches, which are themselves fused at a higher height.

The height of the fusion, provided on the vertical axis, indicates the (dis)similarity between two observations. The higher the height of the fusion, the less similar the observations are. Note that, conclusions about the proximity of two observations can be drawn only based on the height where branches containing those two observations first are fused. We cannot use the proximity of two observations along the horizontal axis as a criteria of their similarity.

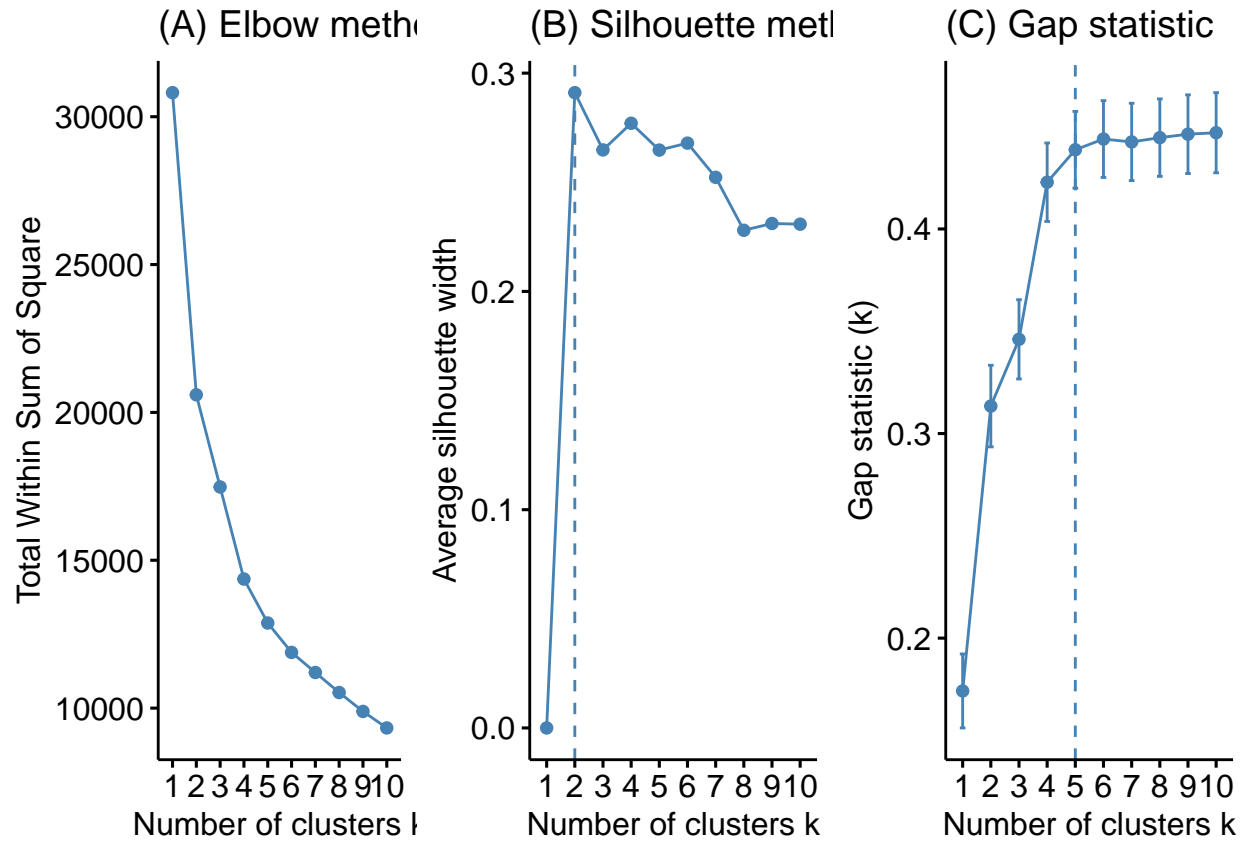
The height of the cut to the dendrogram controls the number of clusters obtained. It plays the same role as the  $k$  in  $k$ -means clustering. In order to identify sub-groups (i.e. clusters), we can cut the dendrogram with `cutree` `###` How many?

Although hierarchical clustering provides a fully connected dendrogram representing the cluster relationships, you may still need to choose the preferred number of clusters to extract. Fortunately we can execute approaches similar to those discussed for  $k$ -means clustering (Section 20.6). The following compares results provided by the elbow, silhouette, and gap statistic methods. There is no definitively clear optimal number of clusters in this case; although, the silhouette method and Elbow method suggest 2-5 clusters.

```
# Plot cluster results
p1 <- fviz_nbclust(clust_data, FUN = hcut, method = "wss",
                  k.max = 10) +
  ggtitle("(A) Elbow method")
p2 <- fviz_nbclust(clust_data, FUN = hcut, method = "silhouette",
                  k.max = 10) +
  ggtitle("(B) Silhouette method")
p3 <- fviz_nbclust(clust_data, FUN = hcut, method = "gap_stat",
                  k.max = 10) +
  ggtitle("(C) Gap statistic")

## Clustering k = 1,2,..., K.max (= 10): .. done
## Bootstrapping, b = 1,2,..., B (= 100) [one "." per sample]:
## ..... 50
## ..... 100

# Display plots side by side
gridExtra::grid.arrange(p1, p2, p3, nrow = 1)
```



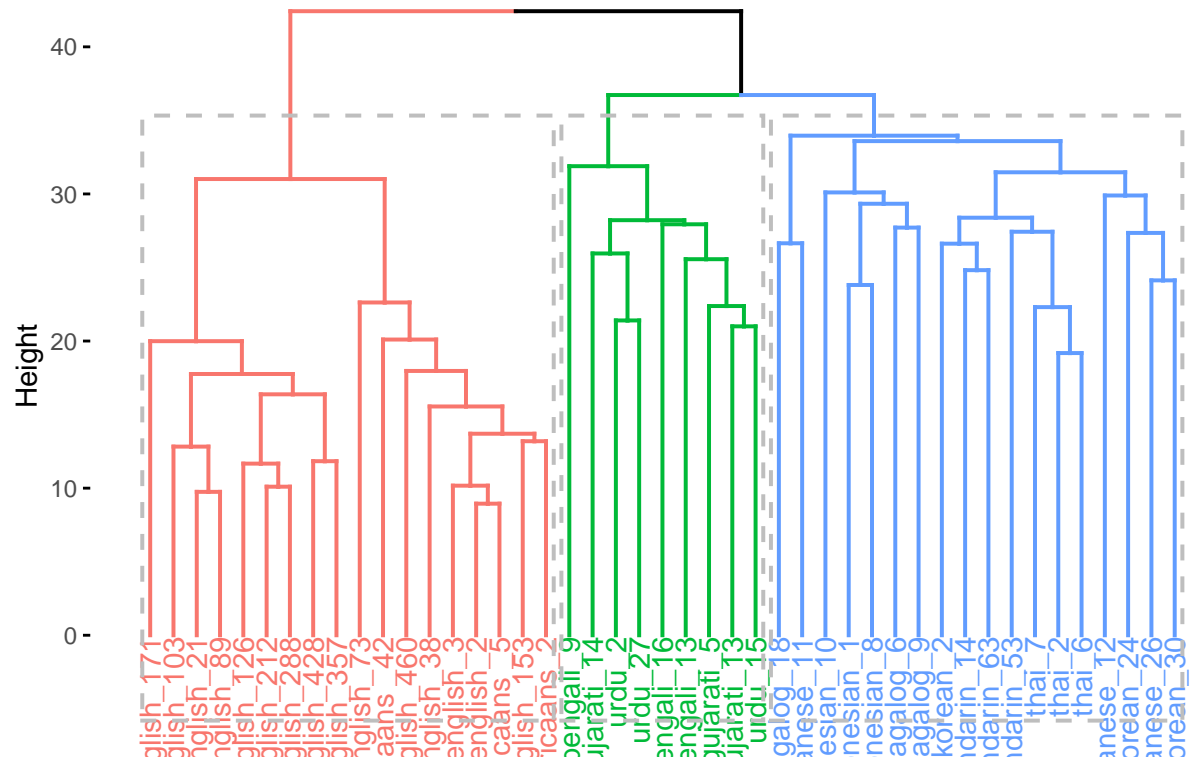
**Dendrogram** Although it is a bit ambiguous I would say 3 clusters are the most interpretable. I could be wrong.

From this, we glean that 3 clusters appear to be adequate. Generally participants grouped speakers into 3 clusters/groups:

- English/African: Clust 1
- Indo/European: Clust 2
- Asian: Clust 3

```
hc.cut <- hcut(clust_data, k = 3, hc_method = "average")
fviz_dend(hc.cut, show_labels = TRUE, rect = TRUE)
```

## Cluster Dendrogram



## Visualize Clusters

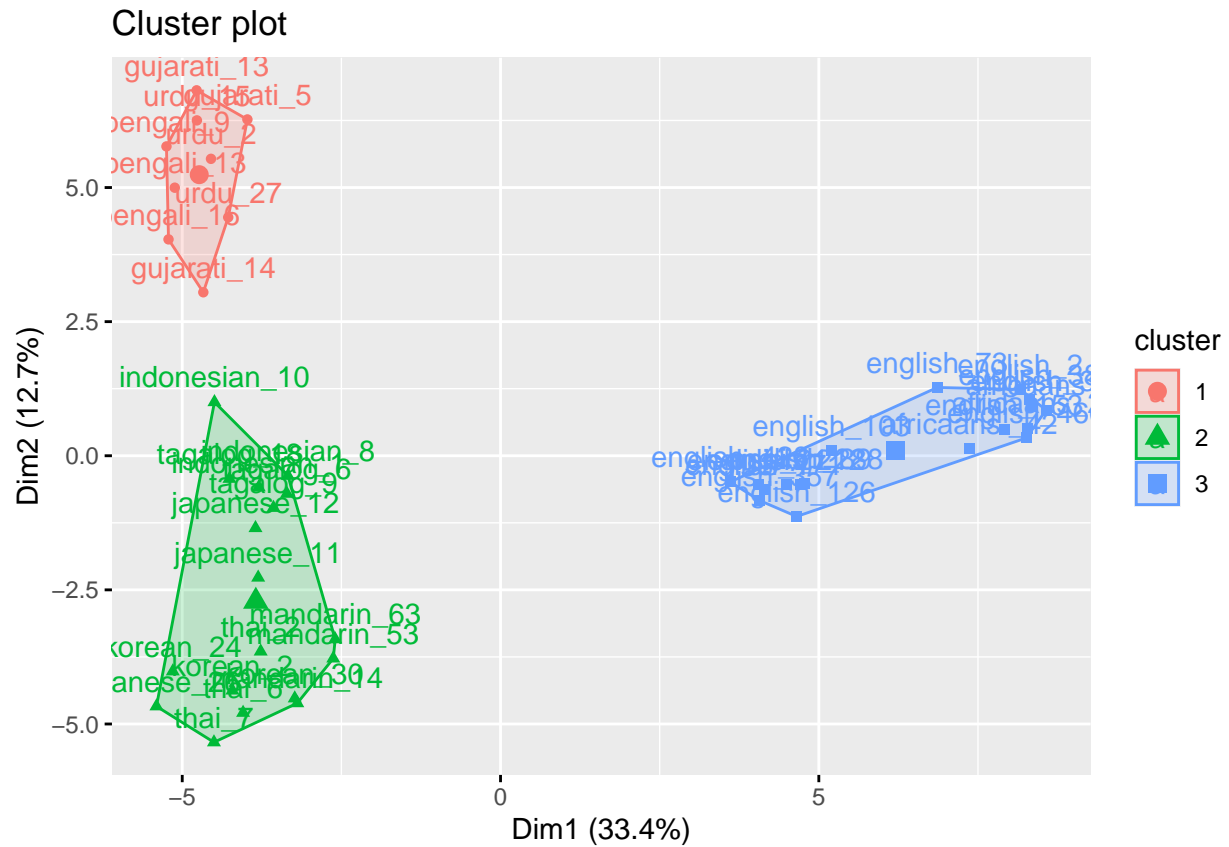
```
# Cut tree into 3 groups
sub_grp <- cutree(hc.cut, k = 3)

# Number of members in each cluster
table(sub_grp)
```

### 3 Clusters

```
## sub_grp
## 1 2 3
## 9 18 18

fviz_cluster(list(data = clust_data, cluster = sub_grp))
```



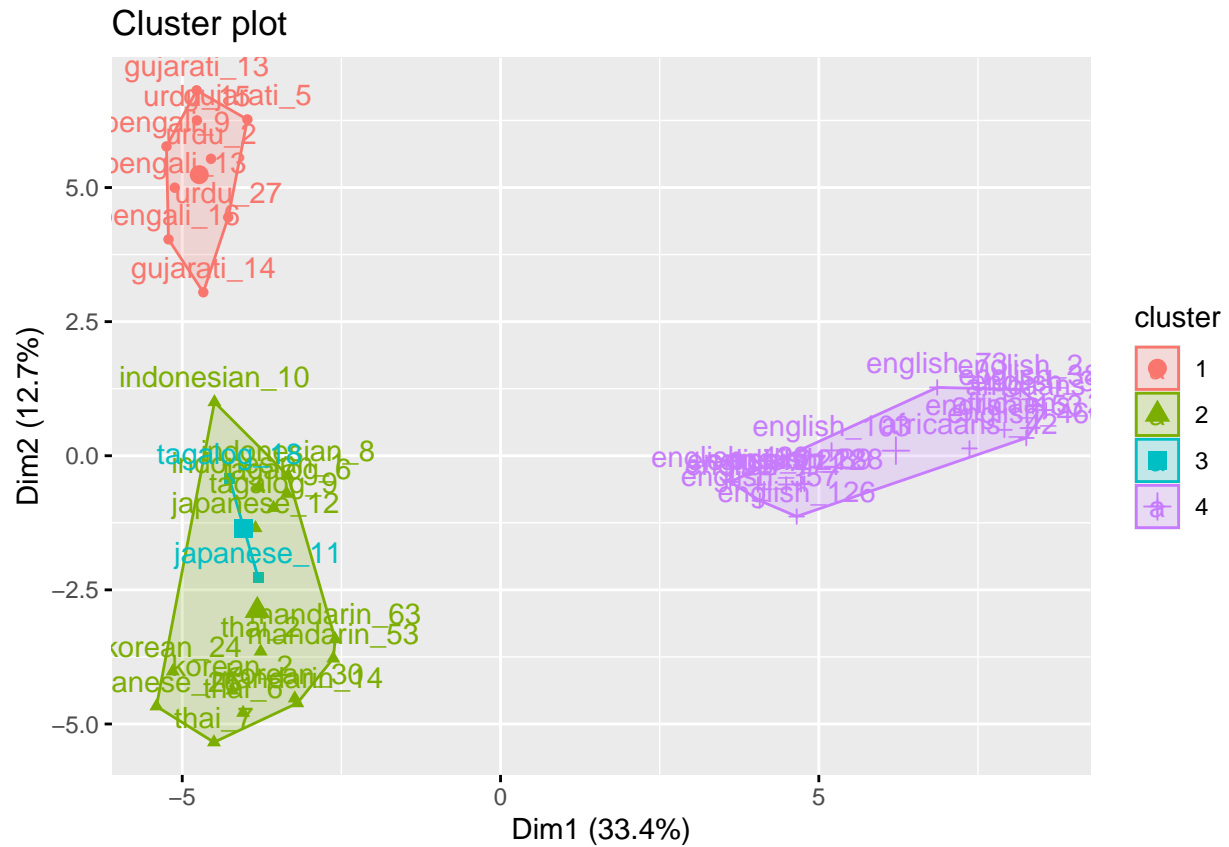
```
# Cut tree into 3 groups
sub_grp <- cutree(hc.cut, k = 4)

# Number of members in each cluster
table(sub_grp)
```

4 clusters

```
## sub_grp
## 1 2 3 4
## 9 16 2 18
```

```
fviz_cluster(list(data = clust_data, cluster = sub_grp))
```



```
# Cut tree into 3 groups
sub_grp <- cutree(hc.cut, k = 5)

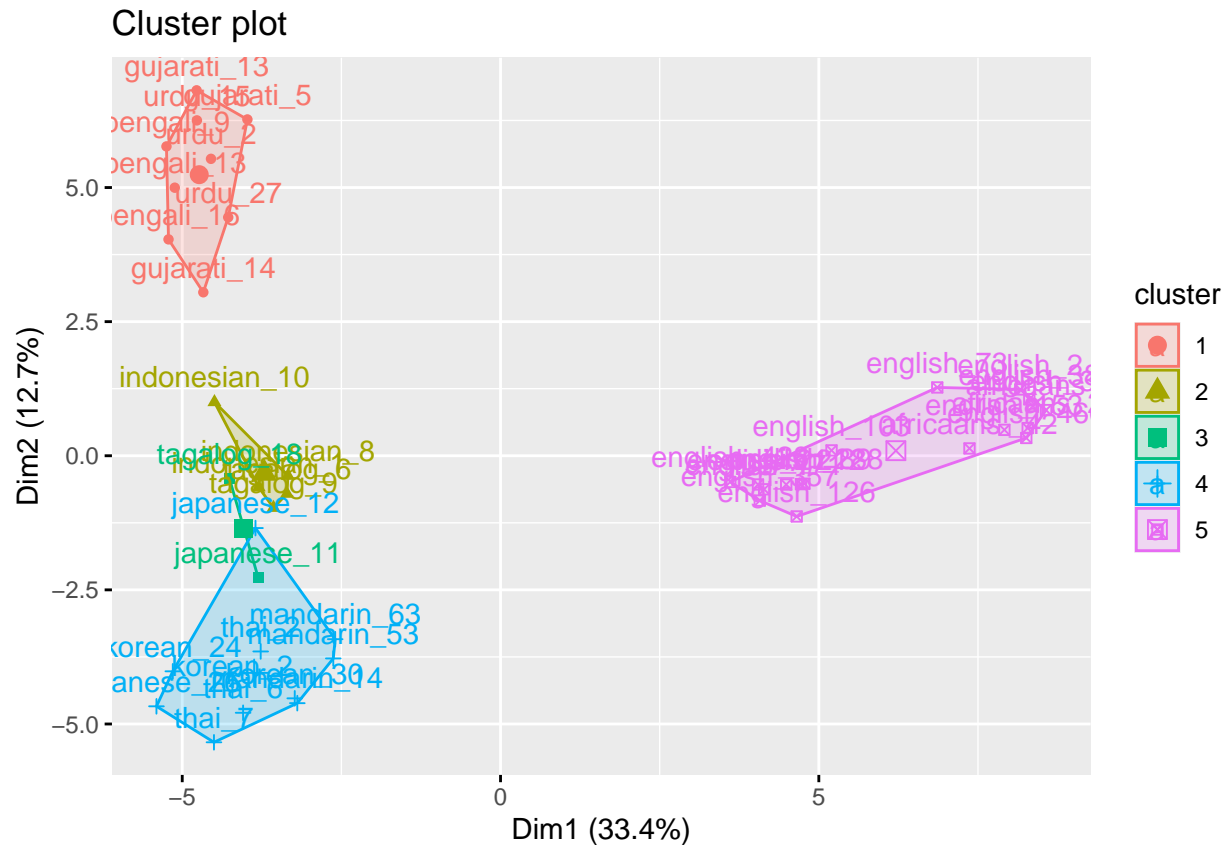
# Number of members in each cluster
table(sub_grp)
```

5 clusters

```
## sub_grp
## 1 2 3 4 5
## 9 5 2 11 18
```

```
fviz_cluster(list(data = clust_data, cluster = sub_grp))
```





## Conclusion

I ran a hierarchical clustering analysis using the average link method to classify talkers in a free classification task. I made the decision that 3 clusters looks good. This is a subjective decision. You might think that 4 or 5 clusters makes more sense. You should refer to the elbow, shilotte, and gap plots above.

## Full Code

The full script of executive code contained in this document is reproduced here.

```
df <- read_csv("data/class_wide_1.csv")
# For reproducibility
set.seed(666)
library(here)
library(tidyverse) # data manipulation
library(cluster)   # clustering algorithms
library(factoextra) # clustering visualization
library(dendextend) # for comparing two dendrograms

clust_data <- read_csv(here("data", "class_wide_1.csv")) # read in data

clust_data <- select(clust_data, -X1, -`54`) # remove extra col sub 54 has weird formatting

clust_data <- as.data.frame(clust_data) # turn into df
```

```

rownames(clust_data) <- clust_data$speaker # make row names speaker

clust_data <- select(clust_data,-speaker) # remove extra col sub 54 has weird formatting

head(clust_data)# show first couple rows

# Dissimilarity matrix
d <- dist(clust_data, method = "euclidean")

# Hierarchical clustering using Average Linkage
hc1 <- hclust(d, method = "average" )

# Plot the obtained dendrogram
plot(hc1, cex = 0.6, hang = -1)

# Plot cluster results
p1 <- fviz_nbclust(clust_data, FUN = hcut, method = "wss",
                  k.max = 10) +
  ggtitle("(A) Elbow method")
p2 <- fviz_nbclust(clust_data, FUN = hcut, method = "silhouette",
                  k.max = 10) +
  ggtitle("(B) Silhouette method")
p3 <- fviz_nbclust(clust_data, FUN = hcut, method = "gap_stat",
                  k.max = 10) +
  ggtitle("(C) Gap statistic")

# Display plots side by side
gridExtra::grid.arrange(p1, p2, p3, nrow = 1)

hc.cut <- hcut(clust_data, k = 3, hc_method = "average")

fviz_dend(hc.cut, show_labels = TRUE, rect = TRUE)

# Cut tree into 3 groups
sub_grp <- cutree(hc.cut, k = 3)

# Number of members in each cluster
table(sub_grp)

fviz_cluster(list(data = clust_data, cluster = sub_grp))
# Cut tree into 3 groups
sub_grp <- cutree(hc.cut, k = 4)

# Number of members in each cluster
table(sub_grp)

fviz_cluster(list(data = clust_data, cluster = sub_grp))
# Cut tree into 3 groups
sub_grp <- cutree(hc.cut, k = 5)

# Number of members in each cluster
table(sub_grp)

```

```
fviz_cluster(list(data = clust_data, cluster = sub_grp))
```

## References