Mini Project IV
Clustering Texts

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Introduction

Recent interest in identifying authorship of written text by analytical analysis has opened the doors to some interesting research in this arena. In this study, we compare categorical clusterings of texts by genre to unsupervised clusterings. These unsupervised clusterings are created through summary statistics that summarize writer styles. We have 18 indicators of style, including how much an author writes in first person, the motion or spacing of the text, and others. Jeff Collins [1] study on textual analysis contains a more complete listing of the variables used and how they are quantified.

We have 1000 texts with 15 common genres for which these texts fall under. We wish to analyze how natural groupings compare to the way the texts are currently classified, as well as compare how 5 clusters grouped naturally compare to 5 ”super genres” comprising the following: Press, Non-press Nonfiction, Biography, Scholarship and Official Documents, Fiction.

How well do authors styles within a genre categorize texts? Do Authors writing styles stick to genre or is there significant overlap? This analysis will help uncover some statistics governing these phenomenon.

Clustering the Texts

We begin by clustering the texts into groups of 3,4,5,6, and 7. That is, we create 3 clusters of the 1000 texts, then a separate 4 clusters, and so on to 7. The clusters are initially created using Ward’s Linkage, then bettered using an iterative algorithm called k-means.

Ward’s Linkage

There are a variety of ways to create clusters. One reasonable method to get clusters is using Ward’s Linkage. This method begins by clustering the two points nearest in Eulidean distance. The algorithm then considers the next two closets points, treating the centroid of the pair just created as a point. So if the two nearest points

[1] https://tofu.byu.edu/stat666/assignments/DissertationOn18RhetoricalCategories.pdf

of the data (including the pair made in the last step) is the centroid of the couplet just created and another point, the cluster created in the first step becomes a triplet. Otherwise, another couplet is formed, and the centroid is treated as a "point" when creating the next cluster. This process is iterated until a predetermined number of clusters are created.

K-means

Another way to calculate clusters is using the k-means method. K-means creates clusters by moving observations across groups until the sums of squares of Euclidean distances for each observation to its group mean. The process begins by selecting an initial set of clusters. Observations are then moved to the group with the nearest centroid (using the Euclidean distance metric). Centroids are recalculated, and the process repeats until none of the observations move to different clusters.

A criticism of this method is that initial starting groups need to be selected, and different starting groups don't necessarily converge to the same final groups. To utilize this idea of maximizing distance between groups, some propose beginning with multiple sets of random starts then choosing the best set of final groups. We instead use Ward's Linkage to get a reasonable starting set of groupings, and better the classification of observations into groups by using the k-means algorithm.

Selecting the Best Set of Clusters

Now we have a best set of clusters for k=3,4,5,6, and 7 clusters. Choosing how many clusters we should use is a somewhat subjective procedure. We first conduct a MANOVA test of the following form:

H_0: There is no difference of means: $\mu_{\mathbf{1}} = \mu_{\mathbf{2}} = ... = \mu_{\mathbf{k}}$ Vs.

H_0: At least one $\mu_{\mathbf{j}}$ is different from the others: $\mu_{\mathbf{j}} \neq \mu_{\mathbf{i}}$ for some $i \neq j$

where k is the number of clusters, $\mu_{\mathbf{j}}$ is the cluster mean for the j^{th} cluster, and i, $j \in$ 1,...,k.

However, in each case the null hypothesis is rejected with $p < .0001$. This is expected as we hope the clustering are statistically different. As a second selection method, we look at misclassification rates for each set of clusters. This is done by calculating the best clusters, then (using the same calculating procedure) recalculating clusters holding out one observation.

Once new clusters are obtained, we then see if the hold-out observation is predicted back into the same group it was originally a part of, i.e. is the observation still closest to the mean of the original cluster it was in. If this is not the case, we say this point has been misclassified. This method demonstrates the stability of the clusters. We repeat this process for all 1000 data points and calculate the percentage misclassified for each of the clusters of 3,4,5,6, and 7. The results are included in the following table.

Table 1: Error Rates

	k=3	k=4	k=5	k=6	k=7
Error.Rate	0.01	0.23	0.24	0.31	0.33

Cluster 3 has the lowest misclassification rate. We would expect grouping to be more distinct for smaller sets of groups, and in fact we see that misclassification rates increase with number of clusters. This procedure is again somewhat objective, but group 3 seems to have a much lower misclassification rate than other groups, so we choose $k = 3$.

Attributes of Clusters

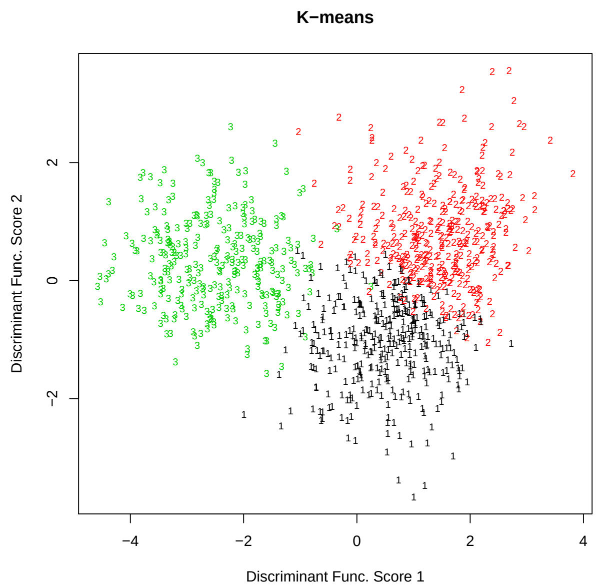
Our clusters live in $s - space$ defined by $min(p, k - 1)$ where p is the number of variables in each observation (18) and k is the number of clusters (3). So $s = 2$. This implies there is a plane that spans the space of best separation for the group means, unless their means are somewhat collinear in which case the plane that best separates the means can be collapsed to essentially a line. The non-zero eigenvalues of $E^{-1}H$ are 4.028 and 1.119.

This implies λ_1 and the corresponding eigenvector contains 78.25 percent of the variation of the plane in one direction. This certainly means there is more separation in one direction than in the perpendicular direction defined by λ_2 and the corresponding eigenvector. But we need this 2-D plane to span the space of best separation.

	1	2
FirstPerson	-0.55	0.19
InnerThinking	0.08	0.30
ThinkPositive	0.01	-0.12
ThinkNegative	0.07	0.16
ThinkAhead	-0.02	0.08
ThinkBack	-0.31	0.15
Reasoning	0.05	0.44
Share Social Ties	0.22	0.50
Direct Activity	0.05	0.06
Interacting	-0.25	0.22
Notifying	0.15	0.18
LinearGuidance	-0.38	0.22
WordPicture	-0.08	-0.09
SpaceInterval	-0.36	0.33
Motion	-0.12	-0.10
PastEvents	-0.38	0.13
TimeInterval	0.05	0.08
ShiftingEvents	-0.01	-0.28

More extreme measurements of the variables measured corresponding to the bolded components for each eigenvector are going to best separate texts in each direction of the plane respectively.

Groups are best separated by the plane created in the two orthogonal directions as the eigenvectors listed above. This is graphically is illustrated by the following plot.



Note the table below that shows which proportion of the 15 genre's were put into each of the 3 groups.

	Cluster 1	Cluster 2	Cluster 3
Press: Reporting	**0.86**	0.11	0.02
Press: Editorial	0.17	0.80	0.04
Press: Reviews	**0.79**	0.18	0.03
Religion	0.09	0.88	0.03
Skills and Hobbies	**0.67**	0.29	0.04
Popular Lore	0.42	0.49	0.09
Biography	0.33	0.51	0.16
Official Communications	0.53	0.47	0.00
Learned	0.40	0.59	0.01
General Fiction	0.02	0.02	0.97
Mystery	0.02	0.00	0.98
Science Fiction	0.00	0.08	0.92
Adventure	0.03	0.00	0.97
Romance	0.02	0.02	0.97
Humor	0.06	0.06	0.89

Notice that texts for some of the genre's fall predominately into one cluster. In some sense, our natural clusters have classified some genre's primarily into one cluster, and further, similar genre's have been grouped together. Cluster 3 seems to be the fiction genre, while clusters 1 and 2 seem to make up the other genres. Perhaps clusters 2 contains more objective non-fiction, and cluster 1 the somewhat subjective non-fiction.

Comparing Super Genres

We now want to see how the 5 super genres compare to the 5 natural clusters created above. A comparison of misclassification rates for each grouping, (the super genres and natural clusters for k=5), as well as some intuition into how these genres in general are being grouped will be outlined.

Super Genres have a higher misclassification rate (.36) than that of the natural clusters (.24) for k=5 (see Table 2). A MANOVA reveals that the centroids of super genres and natural clusters are both significant, but the natural centroids are more distinct than the super genre centroids. The F-statistics are 83.6 and 35.3 respectively (see Table 3). From a heat map of the proportions of super genres to natural clusters, it appears that the fourth & fifth clusters combine to form the Fiction genre. And Clusters 1 to 3 make up the non-fiction genre.

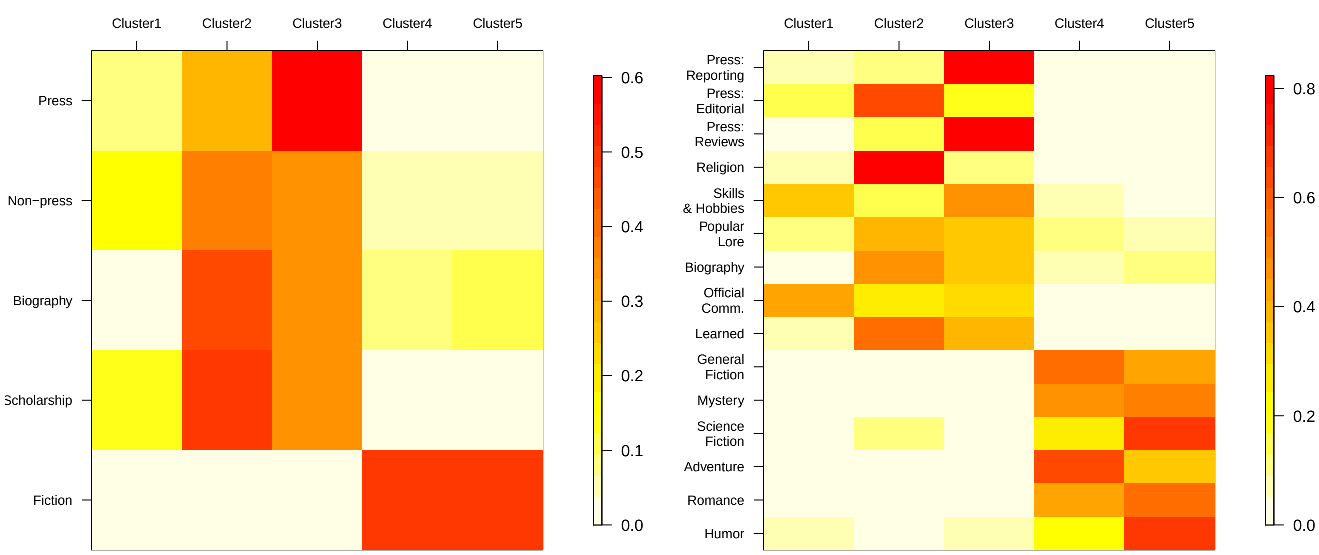
Table 2: Error Rates of Super Genres and Natural Clusters (k=5)

	Super.Genres	Natural,k=5
Error Rate	0.36	0.24

Table 3: MANOVA for Super Genres and Natural Clusters (k=5)

	F.stat	df1	df2	p.val
Natural, k=5:	83.58	72.00	3848.11	0.00
Super Genres:	35.28	72.00	3848.11	0.00

Proportions of Genres Vs. Natural Clusters



Conclusion

We determined the ward linkage performs the best for separating our data into different clusters. The optimal number of clusters, is 3. That is, separating our data into three clusters yields the lowest misclassification rate. Natural cluster means and super genre means are significantly different. It appears that there are 2 main clusters - fiction and non-fiction. The non-fiction genres can also be subdivided into subjective and non-subjective writing. Subjective writing includes religion and editorials; non-subjective writing includes reporting and reviews.