International Journal of Research
Available at https://edupediapublications.org/journals

p-ISSN: 2348-6848
e-ISSN: 2348-795X
Volume 04 Issue 06
May 2017

A Study of Comparison between Different Types of Document Clustering Techniques in Data Mining

G Venkanna[1]

Asst.Proffesor

Syed Thayyab Hussain[2]

Asst.Proffesor

[1,2]*Netaji Institute of Engineering & Technology*

Abstract:- *This paper displays the aftereffects of a trial investigation of some basic document clustering methods. Specifically, we contrast the two primary methodologies with document grouping, agglomerative Hierarchical clustering and K-means. (For K-means we utilized a "standard" K-means calculation and a variation of K-means, "bisecting" K-means.) Hierarchical grouping is regularly depicted as the better quality clustering approach, yet is constrained due to its quadratic time multifaceted nature. Conversely, K-means and its variations have a period multifaceted nature which is straight in the quantity of documents, however are thought to create mediocre clusters. Now and then K-means and agglomerative Hierarchical methodologies are joined in order to "defeat both universes." In any case, our outcomes show that the bisecting K-means system is superior to anything the standard K-means approach and in the same class as or superior to anything the progressive methodologies that we tried for an assortment of group assessment measurements. We propose a clarification for these outcomes that depends on an examination of the specifics of the clustering calculations and the way of document information.*

Keywords:-Clustering, K-means, bisecting K-means, Hierarchical clustering

INTRODUCTION

Clustering is a programmed learning procedure gone for gathering an arrangement of items into subsets or clusters. The objective is to make clusters that are sound inside, yet generously not quite the same as each other. In plain words, questions in a similar cluster ought to be as comparable as could be expected under the circumstances, while protests in one group ought to be as disparate as conceivable from items in alternate clusters . Programmed document clustering has assumed an essential part in many fields like data recovery, information mining, and so forth. The point of this proposal is to enhance the proficiency and exactness of document clustering. We talk about two clustering calculations and the fields where these perform superior to the known standard clustering calculations. The principal approach is a change of the chart parceling strategies utilized for document clustering. In this we preprocess the chart utilizing a heuristic and afterward apply the standard diagram dividing calculations. This enhances the nature of groups all things considered.

The second approach is a totally extraordinary approach in which the words are grouped first and afterward the word cluster is utilized to cluster the documents. This lessens the commotion in information and consequently enhances the nature of the clusters. In both these methodologies there are parameters which can be changed by the dataset in order to enhance the quality and effectiveness.

Document clustering is the demonstration of gathering comparable documents into canisters, where similitude is some capacity on a document. The clustering calculations executed for LEMUR are depicted in "A Correlation of Document Clustering Methods", Michael Steinbach, George Karypis and Vipin Kumar. TextMining Workshop. KDD. 2000. Except for Probabilistic Inert Semantic Examination (PLSA), all utilization cosine similitude in the vector space display as their metric.

The LEMUR clustering support gives two guideline APIs, the Group Programming interface, which characterizes the clusters themselves, and the ClusterDB Programming interface, which characterizes how Clusters are tenaciously put away. Comparability is scored by means of a SimilarityMethod protest. At present

there is a solitary SimilarityMethod,
CosSim, characterized.

Clustering Methods

1. K-Means

K-means is the most important flat clustering algorithm. The objective function of K-means is to minimize the average squared distance of objects from their cluster centers, where a cluster center is defined as the mean or centroid μ of the objects in a cluster C:

$$^{1}\sum x \mid C \mid_{x\in C}$$

The ideal cluster in K-means is a sphere with the centroid as its center of gravity. Ideally, the clusters should not overlap. A measure of how well the centroids represent the members of their clusters is the Residual Sum of Squares (RSS), the squared distance of each vector from its centroid summed over all vectors

$$\mathrm{RSS}_i = \sum_{x\in C_i} \| x - \mu(C_i) \|^2$$

$$\mathrm{RSS} = \sum_{i=1}^{K} RSS_i$$

K-means can start with selecting as initial clusters centers K randomly chosen objects, namely the seeds. It then moves the cluster centers around in space in order to minimize RSS. This is done iteratively by repeating two steps until a stopping criterion is met

1. reassigning objects to the cluster with closest centroid
2. recomputing each centroid based on the current members of its cluster.

We can use one of the following termination conditions as stopping criterion

- A fixed number of iterations I has been completed.
- Centroids μ_i do not change between iterations.
- Terminate when RSS falls below a pre-estabilished

threshold. Algorithm for K-Means

```
1.  procedure KMEANS(X,K)
2.        {s1, s2, · · · , sk}  SelectRandomSeeds(K,X)
3.        for i ←1,K do
4.            μ(Ci) ← si
5.        end for
6.      repeat
7.          mink~xn−~μ(Ck)k Ck = Ck [ {~xn}
8.          for all Ck do
9.              μ(Ck) = 1
10.         end for
11.     until stopping criterion is met
12. end procedure
```

Hierarchical Clustering

Hierarchical Clustering clustering approaches endeavor to make a progressive disintegration of the given document accumulation consequently accomplishing a progressive structure. Hierarchical techniques are normally arranged into Agglomerative and Divisive strategies relying upon how the progressive system is developed.

Agglomerative strategies begin with an underlying clustering of the term space, where all documents are considered speaking to a different group. The nearest clusters utilizing a given between group similitude measure are then consolidated persistently until just 1 cluster or a predefined number of groups remain.

Straightforward Agglomerative Clustering Calculation:

1. Compute the likeness between all sets of groups i.e. ascertain a likeness lattice whose ijth passage gives the closeness between the ith and jth clusters.

2. Merge the most comparable (nearest) two groups.

3. Update the likeness network to mirror the pairwise closeness between the new cluster and the first groups.

4. Repeat stages 2 and 3 until just a solitary group remains.

Divisive clustering calculations begin with a solitary group containing all documents. It then constantly partitions clusters until all documents are contained in their own particular group or a predefined number of clusters are found.

Agglomerative calculations are typically ordered by the between cluster similitude measure they utilize. The most prevalent of these are single-connection, finish connection and gathering normal. In the single connection technique, the separation between groups is the base separation between any match of components drawn from these clusters (one from each), in the entire connection it is the most extreme separation and in the normal connection it is correspondingly a normal separation

The Vector Space Model and Document Clustering

Many issues specific to documents are discussed more fully in information retrieval texts [Rij79, Kow97]. We briefly review a few essential topics to provide a sufficient background for understanding document clustering.

For our clustering algorithms documents are represented using the vector-space model. In this model, each document, *d*, is considered to be a vector, ***d***, in the term-space (set of document "words"). In its simplest form, each document is represented by the (*TF*) vector,

$$\mathbf{d}_{tf} = (tf_1, tf_2, \ldots, tf_n),$$

where tf_i is the frequency of the i^{th} term in the document. (Normally very common words are stripped out completely and different forms of a word are reduced to one canonical form.) In addition, we use the version of this model that weights each term based on its *inverse document frequency* (IDF) in the document collection. (This discounts frequent words with little discriminating power.) Finally, in order to account for documents of different lengths, each document vector is normalized so that it is of unit length.

The similarity between two

documents must be measured in some way if a clustering algorithm is to be used. There are a number of possible measures for computing the similarity between documents, but the most common one is the cosine measure, which is defined as

$cosine(\, \mathbf{d_1}, \mathbf{d_2}\,) = (\mathbf{d_1} \bullet \mathbf{d_2}) / \|\mathbf{d_1}\|\ \|\mathbf{d_2}\|$,
where • indicates the vector dot product and $\|\mathbf{d}\|$ is the length of vector ***d***.

Given a set, *S*, of documents and their corresponding vector representations, we define the ***centroid*** vector ***c*** to be which is nothing more than the vector obtained by averaging the weights of the various terms present in the documents of *S*. Analogously to documents, the similarity between two centroid vectors and between a document and a centroid vector are computed using the cosine measure, i.e.,

$cosine(\, \mathbf{d}, \mathbf{c}\,) = (\mathbf{d} \bullet \mathbf{c}) / \|\mathbf{d}\|\ \|\mathbf{c}\| = (\mathbf{d} \bullet \mathbf{c}) / \|\mathbf{c}\|$ $cosine(\, \mathbf{c_1}, \mathbf{c_2}) = (\mathbf{c_1} \bullet \mathbf{c_2}) / \|\mathbf{c_1}\|\ \|\mathbf{c_2}\|$

Note that even though the document vectors are of length one, the centroid vectors will not necessarily be of unit length. (We use these two definitions in defining two of our agglomerative hierarchical techniques in Section 7, the "intra-cluster similarity and "centroid similarity" techniques, respectively.)

For K-means clustering, the cosine measure is used to compute which document centroid is closest to a given document. While a median is sometimes used as the centroid for K-means clustering, we follow the common practice of using the mean. The mean is easier to calculate than the median and has a number of nice mathematical properties.

For example, calculating the dot product between a document and a cluster centroid is equivalent to calculating the average similarity between that document and all the documents that comprise the cluster the centroid represents. (This observation is the basis of the "intra-cluster similarity" agglomerative hierarchical clustering technique in section 7.) Mathematically,

Also the square of the length of the centroid vector is just the average pairwise similarity between all points in the cluster. (This includes the similarity of each point with itself, which is just 1.) In the following section, we will use this average pairwise similarity as the basis for one of the measures for quantifying the goodness of a clustering algorithm.

Bisecting k-Means Algorithm

Like any calculation, there are negatives to the k-Means for Clustering. To start with, there are settled Circles, which means it's a quadratic calculation in the most pessimistic scenario for the Enormous Goodness Calculation, which means the execution on vast informational collections is not the best. Besides, separate metric utilized inside the settled Circle is done genuinely, in this manner making for what may be tractability worries for the calculation.

Finally, however in particular however, is that the calculation has been known to be [1] tend to fall on neighborhood minima rather than worldwide minima because of poor instatement in all likelihood in light of the introduction of the K number of centroids to their separate focuses. All things considered, how can one know what point a given centroid ought to be appointed to? Moreover, no doubt surmises irregular focuses for every centroid (in the most pessimistic scenario) could likewise reason for an execution punishment if the arbitrarily relegated focuses are far away from where the centroids really wind up being. A potential solution for this, is to do a post-preparing of the made Clustered Demonstrate, where the Group to be part is singled out which Group has the most astounding SSE (Aggregate of Squared Mistakes).

Total of Squared Blunders: SSE is: Σ

(i =1..N) ((y (anticipated esteem) - y (genuine esteem)) squared

This will ideally yield for a SSE between the two resultant youngster clusters that is not as much as the SSE for their parent group. Truth be told, this is reason for the calculation known as the Bisecting K-Means calculation which is appeared as underneath.

Summed up Bisecting k-Means Calculation

- Beginning Conditions
- Begin with the greater part of the focuses in one centroid (i.e. Cluster)
- Be that as it may, at present choose the aggregate number of groups fancied
- Circle: until the halting condition for the quantity of Clusters has been come to
- Circle: for ever cluster
- Measure the aggregate mistake for the parent cluster in this current circle's cycle
- Apply the K-Means Calculation to the cluster with k= 2
- Measure the aggregate SSE mistake of the youngsters groups contrasted with their parent cluster
- Picked the group split that gives the most minimal blunder and submit this split
- End Circle
- End Circle

Not at all like with the K-Means Calculation, you require not introduce a K Number of centroids before the calculation begins since we begin with one group; recall that, it is the arbitrary instatement of centroids to focuses for each cluster before the primary calculation of the K-Means calculation begins that can help for falling on nearby minima rather than worldwide minima. Like with the K-Means Calculation, a foreordained number of groups still should be settled on before the primary calculation is begun, which fills in as the ceasing condition for the calculation. As a side note, it ought to be considered how does a client suspect what number of clusters there ought to be early? Perhaps a conceivable metric to utilize would base on the rate (subordinate) of what amount the SSE is diminishing as parts are being finished?

Be that as it may, back to the fundamental impulse for Bisecting K-means, is that the group whose split is to be conferred, is that parent cluster which when part, brings about the two kids groups that have the most reduced aggregate SSE contrasted with it, when contrasted with all other relative SSE contrasts of other parent/youngster cluster parts. This would propose that it can't be expected that the Cluster with the most astounding SSE is the one that will bring about the least accumulated SSE among its youngsters groups. Every single other split are disposed of.

In conclusion, take note of that the cluster split is finished with the great old k-Means calculation recorded above, aside from that k is set equivalent to 2 (k=2). The fundamental point however, is that Bisecting K-Means calculation has been appeared to bring about better group task for information focuses, joining to worldwide minima as than that of stalling out in nearby minima as K-Means does.

Comparison of Agglomerative Hierarchical Techniques

In this section we compare three different agglomerative hierarchical schemes against one another. We will then compare the "best" of these algorithms against our K-means and bisecting K-means algorithms.

Before describing the results, we briefly describe the different hierarchical clustering algorithms that we used. As mentioned before, the only real difference between the different hierarchical schemes is how they choose which clusters to merge, i.e., how they choose to define cluster similarity.

Techniques

Intra-Cluster Similarity Technique (IST): This hierarchical technique looks at the similarity of all the documents in a cluster to their cluster centroid and is defined by Sim(X)

$= \sum_{d \in X} cosine(\mathbf{d}, \mathbf{c})$, where d is a document in cluster, X, and $\mathbf{c}$ is the centroid of cluster X. The choice of which pair of clusters to merge is made by determining which pair of clusters will lead to smallest decrease in similarity. Thus, if cluster Z is formed by merging clusters X and Y, then we select X and Y so as to maximize Sim(Z) – (Sim(X) + Sim(Y)). Note that Sim(Z) – (Sim(X) + Sim(Y)) is non-positive.

Centroid Similarity Technique (CST): This hierarchical technique defines the similarity of two clusters to be the cosine similarity between the centroids of the two clusters.

UPGMA: This is the UPGMA scheme as described in [DJ88, KR90]. It defines the cluster similarity as follows,

$$similarity(cluster1, cluster2) = \frac{\sum_{\substack{d_1 \in cluster1 \\ d_2 \in cluster2}} cosine(\mathbf{d}_1, \mathbf{d}_2)}{size(cluster1) * size(cluster2)}$$

where d_1 and d_2 are, documents, respectively, in cluster1 and cluster2.

Results

The F-measure results are shown in table 8 – larger is better. UPGMA is the best, although the two other techniques are often not much worse.

Data Set	UPGMA	Centroid Similarity	Cluster Similarity
re0	**0.5859**	0.5028	0.5392
re1	**0.6855**	0.5963	0.5509
wap	**0.6434**	0.4977	0.5633
tr31	**0.8693**	0.7431	0.7989
tr45	**0.8528**	0.7105	0.8054

Fbis	**0.6717**	0.6470	0.6233
la1	**0.6963**	0.4557	0.5977
la2	**0.7168**	0.4531	0.5817

Table 2: Comparison of the F-measure for Different Clustering Algorithms

The entropy results are shown in figures 1 - 8. Notice that UPGMA and IST are the best, with similar behavior with respect to entropy. CST does poorly. Figures 1, 5, and 6 indicate that CST does about as well with respect to entropy as do IST and UPGMA in the initial phases of agglomeration, but, at some point, starts “making mistakes” as to which clusters to merge, and its performance diverges from the other schemes from then on. In the cases represented by the other figures, this divergence happens earlier. UPGMA shows similar behavior, but only when the number of clusters is very small.

Overall, UPGMA is the best performing hierarchical technique that we investigated and we compare it to K-means and bisecting K-means in the next section

Comparison of K-means, Bisecting K-means and UPGMA

Here we provide some brief details of how we performed the runs that produced the results we are about to discuss.

For these experiments we equalized the number of runs for bisecting K-means versus customary K-means. In the event that ITER is the quantity of trial bisections for each period of bisecting K-means and K is the quantity of groups looked for, then a bisecting K-means run is identical to log2 (K) * ITER customary K-means runs. (There are what might as well be called ITER K-means keeps running for the entire arrangement of documents for each of the log2 (K) levels in the separation procedure.) For the bisecting K-means, we set ITER = 5. We did 10 keeps running of the bisecting K-means and for each keep running of the bisecting K-means we performed log2 (K) * ITER keeps running of a standard K-means. Since Hierarchical clustering produces a similar outcome without fail, there was no compelling reason to lead numerous keeps running for UPGMA.

There is additionally another issue that must be specified. Both bisecting K-means and Hierarchical clustering produce clustering comes about that can be further "refined" by utilizing the K-means calculation. That is, if the centroids of the groups delivered by these two methods are utilized as the underlying centroids for a K-means clustering calculation, then the K-means calculation will change these underlying centroids and rearrange the clusters. The key question here is whether such refinement will enhance the nature of the clusterings created.

We likewise say that progressive clustering with a K-means refinement is basically a Hierarchical K-mean half breed that is like procedures that other individuals have attempted. Specifically, the Disseminate/Assemble framework [CKTP92] utilizes Hierarchical clustering to create "seeds" for a last K-means stage.

Tables 3 - 5 demonstrate the entropy aftereffects of these runs, while tables 6 - 9 demonstrate the general likeness comes about. Figure 10 additionally indicates entropy comes about and is simply Figure 1 with the entropy comes about for bisecting K-means included. Table 8 demonstrates the examination between F values for bisecting K-means and UPGMA. We express the three principle comes about concisely.

- Bisecting K-means, with or without refinement is superior to anything standard K-means and UPGMA, with or without refinement, as a rule. Indeed, even in situations where different plans are better, bisecting K-means is just marginally more terrible.

- Refinement fundamentally enhances the execution of UPGMA for both the general comparability and the entropy measures.

- Regular K-means, albeit more terrible than bisecting K-means, is by and large superior to anything UPGMA, even after refinement.

We make a couple brief remarks on the way that we did different keeps running of K-means and bisecting K-means. For bisecting K-means, this did not enhance the outcomes much as this calculation tends to create generally predictable outcomes. For standard K-means, the outcomes do change a lot starting with one run then onto the next. In this way, one keep running of customary K-means may create comes about that are not in the same class as those delivered by UPGMA, even without refinement.

In any case, even many keeps running of K-means or bisecting K-means are altogether speedier than a solitary keep running of a hierarchal clustering calculation, especially if the informational collections are vast. For instance, for the informational collection, la1, with

3204 documents and 31,472 terms, a solitary progressive clustering run takes well in overabundance of a hour on a cutting edge Pentium framework. By correlation, a solitary bisecting K-means rush to discover 32 groups takes not as much as a moment on a similar machine.

Data Set	K	Bisecting K-means	Bisecting K-means with refinement	Regular K-means	Hierarchical (UPGMA)	Hierarchical (UPGMA) with refinement
re0	16	1.3305	**1.1811**	1.3839	1.9838	1.4811
re1	16	**1.6315**	1.7111	1.6896	2.0058	1.7361
wap	16	**1.5494**	1.5601	1.8557	2.0584	1.8028
tr31	16	**0.4713**	**0.4722**	0.5228	0.8107	0.5711
tr45	16	**0.6909**	**0.6927**	0.7426	1.1955	0.8665
fbis	16	1.3708	1.4053	**1.3198**	1.8594	1.3832
la1	16	0.9570	**0.9511**	1.0710	2.4046	1.2390
la2	16	0.9799	**0.9445**	0.9673	1.5955	1.1392

Table 3: Comparison of the Entropy for Different Clustering Algorithms for K = 16

Data Set	K	Bisecting K-means	Bisecting K-means with refinement	Regular K-means	Hierarchical (UPGMA)	Hierarchical (UPGMA) with refinement
re0	32	**1.0884**	1.1085	1.2064	1.5850	1.3969
re1	32	1.4229	1.3148	1.4290	1.5360	**1.2138**
wap	32	1.3314	**1.2482**	1.4422	1.7201	1.5252
tr31	32	**0.2940**	0.3327	0.4281	0.5123	0.4641
tr45	32	0.5676	0.4991	0.5293	0.7312	**0.4730**
fbis	32	**1.1872**	1.2060	1.2618	1.4538	1.2841
la1	32	**0.8659**	0.9149	1.0626	1.5375	1.0111
la2	32	0.8969	**0.8463**	0.9659	1.3568	0.9623

Table 4: Comparison of the Entropy for Different Clustering Algorithms for K = 32

Data Set	K	Bisecting K-means	Bisecting K-means with refinement	Regular K-means	Hierarchical (UPGMA)	Hierarchical (UPGMA) with refinement
re0	64	1.0662	**0.9428**	0.9664	1.3215	1.1764
re1	64	1.0249	**0.9869**	1.1177	1.1655	**0.9826**
wap	64	1.1066	**1.0783**	1.2807	1.3742	1.2825
tr31	64	0.3182	**0.2743**	0.3520	0.3985	0.3855
tr45	64	0.4613	0.4199	0.4308	0.4668	**0.3913**
fbis	64	**1.0456**	1.0876	1.0504	1.2346	1.1430
la1	64	**0.8698**	0.8748	1.0084	1.3082	1.0066
la2	64	0.7514	**0.7291**	0.9204	1.1082	0.9138

Table 5: Comparison of the Entropy for Different Clustering Algorithms for K = 64

Data Set	K	Bisecting K-means	Bisecting K-means with refinement	Regular K-means	Hierarchical (UPGMA)	Hierarchical (UPGMA) with refinement
re0	16	0.4125	0.4137	**0.4158**	0.3157	0.3784
re1	16	0.3325	**0.3341**	0.3317	0.2703	0.3084
wap	16	0.2763	**0.2771**	0.2703	0.2440	0.2533
tr31	16	0.4212	**0.4231**	0.4204	0.3560	0.3619
tr45	16	0.4182	**0.4204**	0.4190	0.3561	0.3739
fbis	16	0.4464	0.4496	**0.4514**	0.3657	0.4189
la1	16	0.2228	**0.2244**	0.2198	0.1420	0.1995
la2	16	0.2282	**0.2299**	0.2276	0.1694	0.2019

Table 6: Comparison of the Overall Similarity for K = 16

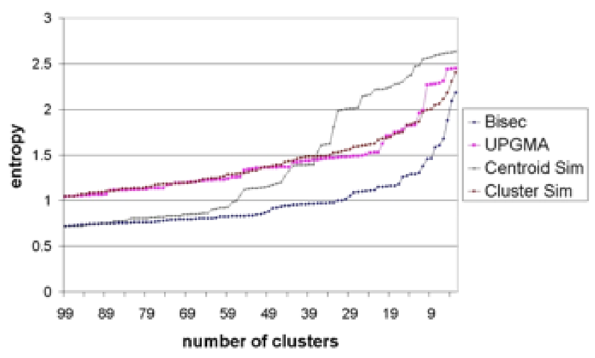
Data Set	K	Bisecting K-means	Bisecting K-means with refinement	Regular K-means	Hierarchical (UPGMA)	Hierarchical (UPGMA) with refinement
re0	32	0.4677	**0.4788**	0.4778	0.4136	0.4421
re1	32	0.3957	**0.4009**	**0.4009**	0.3369	0.3690
wap	32	0.3226	**0.3258**	0.3235	0.2786	0.2876
tr31	32	0.4802	**0.4866**	0.4795	0.4373	0.4441
tr45	32	0.4786	**0.4827**	0.4763	0.4299	0.4382
fbis	32	0.4989	0.5071	**0.5110**	0.4435	0.4827
la1	32	0.2606	**0.2640**	0.2596	0.1922	0.2247
la2	32	0.2675	**0.2738**	0.2655	0.2018	0.2437

Table 7: Comparison of Overall Similarity for K = 32

Data Set	K	Bisecting K-means	Bisecting K-means with refinement	Regular K-means	Hierarchical (UPGMA)	Hierarchical (UPGMA) with refinement
re0	64	0.5327	**0.5541**	0.5521	0.4983	0.5258
re1	64	0.4671	**0.4758**	0.4742	0.4270	0.4422
wap	64	0.3842	**0.3914**	0.3850	0.3478	0.3567
tr31	64	0.5483	**0.5536**	0.5501	0.5214	0.5232
tr45	64	0.5502	**0.5563**	0.5481	0.5168	0.5204
fbis	64	0.5495	**0.5648**	0.5627	0.5032	0.5387
la1	64	0.3047	**0.3129**	0.3080	0.2446	0.2648
la2	64	0.3177	**0.3267**	0.3212	0.2575	0.2842

Table 8: Comparison of Overall Similarity for K = 64

Figure 9: re0 entropy



Data Set	Bisecting K-means	UPGMA
re0	**0.5863**	**0.5859**
re1	**0.7067**	0.6855
wap	**0.6750**	0.6434
tr31	**0.8869**	0.8693
tr45	0.8080	**0.8528**
Fbis	**0.6814**	0.6717
la1	**0.7856**	0.6963
la2	**0.7882**	0.7168

Table 9: Comparison of the F-measure for Bisecting K-means and UPGMA

CONCLUSION

This paper introduced the consequences of a test investigation of some basic document clustering procedures. Specifically, we contrasted the two principle approaches with document clustering, agglomerative Hierarchical clustering and K-means. For K-means we utilized a standard K-means and a variation of K-means, bisecting K-means. Our outcomes show that the bisecting K-means procedure is superior to anything the standard K-means approach and as great or superior to anything the Hierarchical approaches that we tried. All the more particularly, the bisecting K-means approach creates altogether better clustering arrangements reliably as indicated by the entropy and general similitude measures of cluster quality. Besides, bisecting K-means appears to be reliably to improve at creating document progressive systems (as measured by the F measure) than the best of the Hierarchical methods, UPGMA. What's more, the run time of bisecting K-means is exceptionally appealing when contrasted with that of agglomerative Hierarchical clustering procedures - O(n) versus O(n2).

The reason that our relative positioning of K-means and Hierarchical calculations contrasts from those of different scientists could be because of many elements. To begin with we utilized many keeps running of the customary K-means calculation. In the event that agglomerative Hierarchical clustering methods, for example, UPGMA are contrasted with a solitary keep running of K-means, then the correlation would be a great deal more good for the progressive procedures. Besides, we utilized incremental refreshing of centroids, which likewise enhances K-means. Obviously, we additionally utilized the bisecting K-means calculation, which, as far as anyone is concerned, has not been already utilized for document clustering. While there are numerous agglomerative Hierarchical strategies that we didn't attempt, we tried a few different methods which we didn't report here. The outcomes were similar– bisecting K-means executed also or

better then the progressive systems that we tried. At last, take note of that Hierarchical clustering with a K-means refinement is basically a half breed progressive K-means plot like other such plans that have been utilized before [CKPT92]. What's more, this plan was superior to any of the Hierarchical procedures that we attempted, which gives us extra trust in the generally great execution of bisecting K-means opposite progressive methodologies.

We alert that the primary point our paper is not an announcement that bisecting K-means is "predominant" to any conceivable varieties of agglomerative Hierarchical clustering or conceivable half breed blends with K-means. Nonetheless, given the direct run-time execution of bisecting K-means and the reliably great nature of the clusterings that it produces, bisecting K-means is a fantastic calculation for clustering a substantial number of documents.

We contended that agglomerative Hierarchical clustering does not do well due to the way of documents, i.e., closest neighbors of documents frequently have a place with various classes. This makes agglomerative Hierarchical clustering methods commit errors that can't be settled by the progressive plan. Both the K-means and the bisecting K-means calculations depend on a more worldwide approach, which viably sums to taking a gander at the closeness of focuses in a group concerning every single other point in the cluster. This view likewise clarifies why a K-means refinement enhances the entropy of a Hierarchical clustering arrangement.

At long last, we set forward the possibility that the better execution of bisecting K-means versus general K-means is because of certainty that it creates moderately consistently measured clusters rather than groups of broadly differing sizes.

REFERENCES

[1.] Steinbach, M., Karypis, G., & Kumar, V. (2000, August). A comparison of document clustering techniques. In KDD workshop on text mining (Vol. 400, No. 1, pp. 525-526).

[2.] Jain, A. K. (2010). Data clustering: 50 years beyond K-means. Pattern recognition letters, 31(8), 651-666.

[3.] Fung, B. C., Wang, K., & Ester, M. (2003, May). Hierarchical document clustering using frequent itemsets. In Proceedings of the 2003 SIAM International Conference on Data Mining (pp. 59-70). Society for Industrial and Applied Mathematics.

[4.] Jing, L., Ng, M. K., & Huang, J. Z. (2007). An entropy weighting k-means algorithm for subspace clustering of high-dimensional sparse data. IEEE Transactions on knowledge and data engineering, 19(8).

[5.] Kanungo, T., Mount, D. M., Netanyahu, N. S., Piatko, C. D., Silverman, R., & Wu, A. Y. (2002). An efficient k-means clustering algorithm: Analysis and implementation. IEEE transactions on pattern analysis and machine intelligence, 24(7), 881-892.

[6.] Beil, F., Ester, M., & Xu, X. (2002, July). Frequent term-based text clustering. In Proceedings of the eighth ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 436-442). ACM.

[7.] Zhao, Y., & Karypis, G. (2002, November). Evaluation of hierarchical clustering algorithms for document datasets. In Proceedings of the eleventh international conference on Information and knowledge management (pp. 515-524). ACM.

[8.] Zhao, Y., Karypis, G., & Fayyad, U. (2005). Hierarchical clustering algorithms for document datasets. Data mining and knowledge discovery, 10(2), 141-168.

[9.] Pantel, P., & Lin, D. (2002, August). Document clustering with committees. In Proceedings of the 25th annual international ACM SIGIR conference on Research and development in information retrieval (pp. 199-206). ACM.

[10.] Pantel, P., & Lin, D. (2002, July). Discovering word senses from text. In Proceedings of the eighth ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 613-619). ACM.

[11.] Boley, D., Gini, M., Gross, R., Han, E. H. S., Hastings, K., Karypis, G., ... & Moore, J. (1999). Partitioning-based clustering for web document categorization. Decision Support Systems, 27(3), 329-341.

[12.] Hassan-Montero, Y., & Herrero-Solana, V. (2006, October). Improving tag-clouds as visual information retrieval interfaces. In International conference on multidisciplinary information sciences and technologies (pp. 25-28).

[13.] Berkhin, P. (2006). A survey of clustering data mining techniques. In Grouping multidimensional data (pp. 25-71). Springer Berlin Heidelberg.

[14.] Archetti, F., Campanelli, P., Fersini, E., & Messina, E. (2006, June). A hierarchical document clustering environment based on the induced bisecting k-means. In

International Conference on Flexible Query Answering Systems (pp. 257-269). Springer Berlin Heidelberg.

G Venkanna
Assistant Professor
Netaji Institute of Engineering & Technology

Syed Thayyab Hussain
Assistant Professor
Netaji Institute of Engineering & Technology