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Analysis of Clustering Techniques in Data Analytics

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ABSTRACT

Cluster investigation partitions information into important or valuable bunches (clusters). If significant clusters are the objective, at that point the coming about clusters ought to capture the "natural" structure of the information. For case, cluster examination has been utilized to gather related archives for browsing, to discover qualities and proteins that have comparative usefulness, and to give a gathering of spatial areas inclined to earthquakes

Keywords: Clustering, apportioning, information mining, progressive clustering, k-means, density-based, grid-based

INTRODUCTION

Clustering is the handle of gathering a collection of objects (more often than not spoken to as focuses in a multidimensional space) into classes of comparable objects. Cluster investigation is a exceptionally imperative apparatus in information investigation. It is a set of strategies for programmed classification of a collection of designs into clusters based on similitude. Instinctively, designs inside the same cluster are more comparative to each other than designs having a place to a distinctive cluster. It is critical to get it the distinction between clustering (unsupervised classification) and administered classification. Cluster examination has wide applications in information mining, data recovery, science, pharmaceutical, showcasing, and picture division. With the offer assistance of clustering calculations, a client is able to get it characteristic clusters or structures fundamental a information set. For illustration, clustering can offer assistance marketers find particular bunches and characterize client bunches based on acquiring designs in commerce. In science, it can be utilized to infer plant and creature scientific categorizations, categorize qualities with comparable usefulness, and pick up knowledge into structures inborn in populations.

LITERATURE REVIEW

Table 1. Literature review on Clustering analysis

Author	Topic	Result	Goal	Clustering Technique	KeyPoints
Smith etal. (2010)	Healthcare Information Analysis	Improved Understanding Grouping	Enhance Restorative conclusion and Treatment	K-means	- Utilized quiet electronic well being records (EHRs) for clustering based on Restorative history and demographics.
Johnson &Lee(2009)		Identification of Showcase Segments	Optimize venture Strategies	Hierarchical Clustering	- Analyzed stock advertise info to distinguish bunches of stocks

					with comparative cost movements.
Wang &Chen(2015)	Social Media Mining	Community Detection	Understand Client Behavior and Interaction Patterns	DBSCAN	Connected DBSCAN calculation to recognize clusters of clients with comparable interface or behavior designs in social networks.
Liu et al. (2013)	Image Processing	Object Recognition	Enhance picture Classification and Retrieval	Gaussian Blend Models (GMM)	-Developed a framework for question discovery in pictures using GMM to demonstrate the conveyance of pixel power in diverse objects.
Garcia-Hernandez (2013)	Environmental Science	Ecological Zone Mapping	Conservation and Management	Self-organizing Maps (SOM)	organizing Maps (SOM) - Utilized SOM to classify diverse biological zones based on natural factors such as temperature, precipitation, and vegetation cover.
Patel &Sharma(2016)	Customer Segmentation	Enhanced Showcasing Strategies	Improve Client Fulfillment and Retention	Affinity Propagation	-Conducted client division based on obtaining behavior and statistic information to tailor promoting campaigns and services.

CLUSTERING ALGORITHMS

A. Partitioning methods:

This clustering strategy classifies the data into numerous bunches based on the characteristics and similitude of the information. It's the information investigators to indicate the number of clusters that has to be produced for the clustering strategies. In the apportioning strategy when database(D) that contains multiple(N) objects at that point the dividing strategy develops user-specified(K) segments of the information in which each parcel speaks to a cluster and a specific locale. There are numerous calculations that come beneath apportioning strategy a few of the well-known ones are K-Mean, PAM(K-Medoids), CLARA calculation (Clustering Huge Applications) etc. The primary thought of K Implies is summarized in the taking after steps:

- Self-assertively select k objects to be the starting cluster centers/centroids;
- Dole out each question to the cluster related with the closest centroid;
- Compute the unused position of each centroid by the cruel esteem of the objects in a cluster

• Rehash Steps 2 and 3 until the implies are settled. Fig. 1 presents an illustration of the prepare of K-means clustering algorithm.

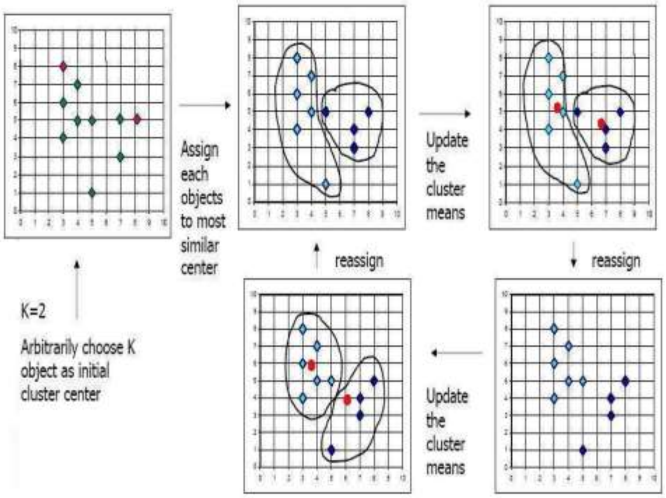
Assign each objects to most similar center
Update the cluster means
reassign
reassign
K=2
Arbitrarily choose K object as initial cluster center
Update the cluster means

Figure.1 Ancase of clustering of K-means.

However, K-means calculation is exceptionally touchy to the determination of the starting centroids, in other words, the diverse centroids may deliver critical contrasts of clustering comes about. Another downside of K-means is that, there is no common hypothetical arrangement to discover the ideal number of clusters for any given information set. A basic arrangement would be to compare the comes about of different runs with distinctive k numbers and select the best one agreeing to a given model, but when the information measure is expansive, it would be exceptionally time devouring to have numerous runs of K-means and the comparison of clustering comes about after each run. Instep of utilizing the cruel esteem of information objects in a cluster as the center of the cluster, a variety of K-means, K-medoids calculates the medoid of the objects in each cluster. The prepare of K-medoids calculation is very comparable as K-means. While, K-medoids clustering calculation is exceptionally delicate to exceptions. Exceptions may truly impact clustering comes about. To fathom this issue, a few endeavors have been made based on K medoids, for case PAM (Apportioning Around Medoids) was proposed by Kaufman and Rousseau. PAM acquires the highlights of K-medoids clustering algorithm.

B. Hierarchical methods:

Hierarchical clustering calculations dole out objects in tree organized clusters, i.e., a cluster can have information focuses or agents of low-level clusters [7]. Various leveled clustering calculations can be classified into categories agreeing their clustering handle: agglomerative and divisive. The handle of agglomerative and divisive clustering is displayed**.**

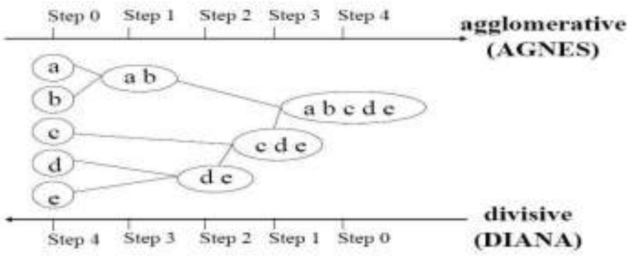

Fig.2 AnCase of clustering of K-means.

A hierarchical clustering method works by combining information objects into a tree of clusters. Progressive clustering calculations are either top-down or bottom-up. The quality of an bona fide progressive clustering strategy breaks down from its failure to actualize alteration once a consolidate or part choice is completed.

The blending of clusters is based on the remove among clusters. The broadly utilized measures for the separate between clusters are as takes after, where mi is the cruel for cluster Ci, ni is the number of focuses in Ci, and |p – p'| is the remove among two focuses p and p'.

Types of Hierarchical Clustering Methods

There are two types of hierarchical clustering methods which are as follows −

Agglomerative Hierarchical Clustering (AHC) −It is a bottom-up clustering strategy where clusters have sub-clusters, which in turn have sub-clusters, etc. It starts by finding each question in its cluster and at that point combines these nuclear clusters into bigger and bigger clusters until all the objects are in a single cluster or until it fulfils particular end condition. Most various levelled clustering strategies are connected to this sort. They are unmistakable as it were in their definition of between-cluster similarity.

Divisive methods are not generally accessible and rarely have been used because of the difficulty of creating the right decision of dividing at a high level. DIANA (Divisi Analysis) is one example of the divisive hierarchical clustering method. It works in the opposite order. Thus, the cluster is divided according to some principle, including splitting the clusters according to the maximum Euclidean distance among the closest neighbouring objects in the cluster

A. Density-based methods:

Density-based strategies the essential thought of density-based strategies is that for each point of a cluster the neighborhood of a given unit separate contains at slightest a least number of focuses, i.e. the thickness in the neighborhood ought to reach a few edges Be that as it may, this thought is based on the suspicion of that the clusters are in the circular or normal shapes. DBSCAN (Density-Based Spatial Clustering of Applications with Commotion) was proposed to receive.

Density-reach ability and thickness network for dealing with the self-assertively molded clusters and clamor. But DBSCAN is exceptionally touchy to the parameter Eps (unit remove or span) and Mints (edge thickness), since some time recently doing cluster investigation, the client is anticipated to assess Eps and Mints. DENCLUE (Density-based Clustering) is a distribution-based calculation, which performs well on clustering expansive datasets with tall clamor. Too, it is altogether quicker than existing density-based calculations, but DENCLUE needs a huge number of parameters. OPTICS is great at examining the subjectively molded clusters, but its non-linear complexity frequently makes it as it were appropriate to little or medium datasets.

B. **Grid-based methods**:

The thought of grid-based clustering strategies is based on the clustering situated inquiry replying in multilevel lattice structures. The upper level stores the rundown of the data of its another level, hence the frameworks make cells between the associated levels, as outlined.

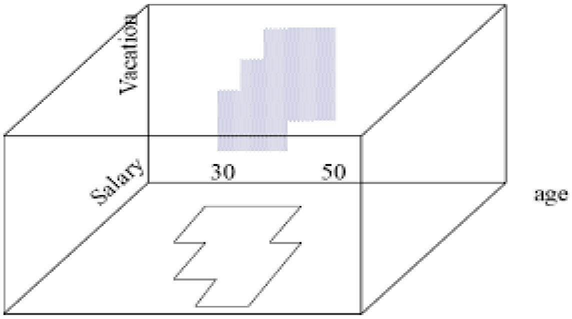

Fig.3 The gird-based clustering strategies

E. Model-based clustering methods:

Model-based clustering strategies are based on the suspicion that information are created by a blend of fundamental likelihood conveyances, and they optimize the fit between the information and a few numerical show, for illustration measurable approach, neural arrange approach and other AI approaches. When confronting an obscure information dissemination, choosing a appropriate one from the demonstrate based candidates is still a major challenge. On the other hand, clustering based on likelihood endures from tall computational fetched, particularly when the scale of information is exceptionally huge.

Based on the over survey, we can conclude that, the application of clustering calculations to identify gathering data in genuine world applications in information mining is still a challenge, basically due to the wastefulness of most existing clustering calculations on adapting with self-assertively formed dissemination of information of amazingly expansive and tall dimensional datasets. Broad overview papers on clustering strategies can be found in the literature.

CLUSTER VALIDATION

A expansive number of clustering calculations have been created to bargain with particular applications. A few questions emerge: which clustering calculation is best appropriate for the application at hand? How numerous clusters are there in the considered information? Is there a superior cluster plot? These questions are related with assessing the quality of clustering comes about, that is, cluster approval. Cluster approval is a method of surveying the quality of clustering comes about and finding a fit cluster methodology for a particular application. It points at finding the ideal cluster conspire and deciphering the cluster designs. Cluster approval is a vital prepare of cluster investigation, since no clustering calculation can ensure the disclosure of honest to goodness clusters from genuine datasets and that distinctive clustering calculations frequently force distinctive cluster structures on a information set indeed if there is no cluster structure show in it. Cluster approval is required in information mining to fathom the taking after issues:

- To degree a segment of a genuine information set created by a clustering calculation.
- To distinguish the veritable clusters from the parcel.
- To translate the clusters.

For the most part talking, cluster approval approaches are classified into the taking after three categories Inner approaches, Relative approaches and Outside approaches.

We provide a brief presentation of cluster approval strategies as follows.

A. Internal approaches:

Internal cluster approval is a strategy of assessing the quality of clusters when insights are formulated to capture the quality of the actuated clusters utilizing the accessible information objects as it were. In other words, inside cluster approval prohibits any data past the clustering information, and as it were centers on surveying clusters' quality based on the clustering information themselves. The measurable strategies of quality appraisal are utilized in inside criteria, for case, root-mean-square standard deviation (RMSSTD) is utilized for compactness of clusters. R-squared (RS) for disparity between clusters; and S_Dbw for compound assessment of compactness and difference The equations of RMSSTD, RS and S_Dbw are appeared below

$$RMSSTD = \sqrt{\frac{\sum_{\substack{i=1\ldots nc \\ j=1\ldots d}} \sum_{k=1}^{n_{ij}} \left(x_k - \overline{x_j} \right)^2}{\sum_{\substack{i=1\ldots nc \\ j=1\ldots d}} \left(n_{ij} - 1 \right)}} \qquad (1.1)$$

Where, xj is the anticipated esteem in the jth measurement; nij is the number of components in the ith cluster jth measurement; nj is the number of components in the jth measurement in the entire information set; nc is the number of clusters.

$$RS = \frac{SS_t - SS_w}{SS_t}.$$

(1.2)

where,

$$SS_t = \sum_{j=1}^{d}\sum_{k=1}^{n_j}\left(x_k - \overline{x_j}\right)^2,\ SS_w = \sum_{\substack{i=1\dots nc\\ j=1\dots d}}\sum_{k=1}^{n_{ij}}\left(x_k - \overline{x_j}\right)^2$$

(1.3)

The formula of S_Dbw is given as:
S_Dbw = Scat(c) + Dens_bw(c)

The esteem of Scat(c) is the degree of the information focuses scattered inside clusters. It reflects the compactness of clusters. The term is the change of a information set; and the term is the change of cluster ci. (c) demonstrates the normal number of focuses between the c clusters (i.e., an sign of inter-cluster thickness) in connection with thickness inside clusters. The equation of Dens_bw is given as:

$$Dens\_bw = \frac{1}{n_c(n_c-1)}\sum_{i=1}^{n_c}\left(\sum_{\substack{j=1,\\ i\neq j}}^{n_c}\frac{density(u_{ij})}{\max\{density(v_i), density(v_j)\}}\right)$$

Where uij is the center point of the remove between the centers of the clusters vi and vj. The thickness work of a point is characterized as the number of focuses around a particular point inside the given span.

B. **Relative approaches**:

Relative evaluation compares two structures and measures their relative justify. The thought is to run the clustering calculation for a conceivable number of parameters (e.g., for each conceivable number of clusters) and distinguish the clustering conspire that best fits the dataset, i.e., they survey the clustering comes about by applying an calculation with distinctive parameters on a information set and finding the ideal arrangement. In hone, relative criteria strategies too utilize RMSSTD, RS and S_Dbw to discover the best cluster conspire in terms of compactness and difference from all the clustering comes about. Relative cluster legitimacy is moreover called cluster stability.

C. External approaches:

The comes about of a clustering calculation are assessed based on a pre-specified structure, which reflects the user's instinct almost the clustering structure of the information set. As a fundamental postprocessing step, outside cluster approval is a method of speculation test, i.e., given a set of course names delivered by a cluster conspire, and compare it with the clustering comes about by applying the same cluster conspire to the other allotments of a database.

CLUSTERING MEASURING METRICS

Adjusted rand index:

ARI (Balanced Rand File) [40] is regularly utilized in cluster approval. The ARI computes closeness between found communities and "ground-truth" communities. Balanced Rand List, spoken to as ARI (X, Y), is characterized as follows:

$$ARIXY = \frac{\sum_{ij}\binom{n_{x_iy_j}}{2} - \sum_i\binom{n_{x_i}}{2}\sum_j\binom{n_{y_j}}{2}/\binom{n}{2}}{\frac{1}{2}\sum_i\binom{n_{x_i}}{2} + \sum_j\binom{n_{y_j}}{2} - \sum_i\binom{n_{x_i}}{2}\sum_j\binom{n_{y_j}}{2}/\binom{n}{2}}$$

where, X = {x1, x2, …, xi} speaks to set of recognized communities, Y = {y1, y2, …, yj} speaks to set of "ground-truth" communities, n speaks to add up to number of hubs, nxi = | xi |, and nxiyj = | xi ∩ yi |.

ARI is a symmetric degree that ranges from − 1 to + 1. When both the communities are completely distinctive at that point the esteem of ARI is − 1 and when both the communities are totally comparable at that point the esteem of ARI is + 1.

Mutual information:

Common data measures the sum of data that two irregular factors give almost each other. Our uncertainty around Y when we do not know X is H(Y). If we are told X, our uncertainty around Y diminishes to H(Y|X). The contrast between our equivocalness around Y when we know X and when we do not know it is the sum of data that X gives approximately Y. The common data between X and Y is in this manner characterized as
I(X ;Y)d= efH(Y)−H(Y|X)
It can be appeared that
IX; Y=IY; X,
namely, the sum of data that X gives almost Y breaks even with that which Y gives around X, advocating the title shared information.
Inequality (4) infers that

IX; Y≥0

with correspondence iff X and Y are free, appearing that free arbitrary factors do not give data almost each other, but all other factors do. Since H(X|Y) and H(Y|X) are nonnegative, we have

IX; Y ≤ min HX, HY

Homogeneity score:

The homogeneity score is calculated based on the conveyance of lesson names inside each cluster. It measures how well the clusters reflect the genuine lesson structure of the information. A higher homogeneity score shows that the clusters are more homogenous in terms of lesson membership.

Mathematically, the homogeneity score H for a set of clusters C with regard to genuine lesson names y is characterized as:

H=1−H(C,y)/H(y)

Where:
H(C,y) is the conditional entropy of the cluster assignments given the true class labels.
H(y) is the entropy of the true class labels.

The conditional entropy measures the instability in the cluster assignments given the genuine lesson names, whereas the entropy of the genuine lesson names measures the vulnerability in the course conveyance itself. By calculating the contrast between the two entropies and normalizing it, the homogeneity score measures the degree to which the clusters capture the lesson structure of the data.

A homogeneity score of 1 demonstrates culminate homogeneity, meaning each cluster contains as it were information focuses from a single course. A score closer to 0 proposes that the clusters are less homogenous with regard to course membership. Completeness **Score** completeness score is a metric used to evaluate the completeness of clusters produced by a clustering algorithm. Completeness refers to the extent to which all data points that are members of a given class or category are assigned to the same cluster.

The completeness score measures how well each true class is represented within a single cluster. A higher completeness score indicates that each cluster contains a high proportion of data points from a single class, leading to a more complete representation of the class structure of the data.
Mathematically, the completeness score C for a set of clusters C with respect to true class labels y is defined as:

$C=1-H(C, y)/H(y)$

Where:
H (C, y) is the conditional entropy of the true class labels given the cluster assignments.
H(y) is the entropy of the true class labels.

Measure score:

The V-Measure score, too known as the V-measure or V-ratio, is a metric utilized to assess the quality of clustering comes about in information mining. It is a consonant cruel of homogeneity and completeness, two common measures of cluster quality.

Homogeneity measures the degree to which clusters contain as it were information focuses from a single genuine lesson or category, whereas completeness measures the degree to which all information focuses of a genuine lesson are allotted to the same cluster. The V-measure combines these two perspectives to give a single degree of clustering execution that accounts for both the immaculateness and completeness of clusters.

Mathematically, the V-Measure V is characterized as:

$V= 2\times (h\times c)/ h+ c$

Where:
h is the homogeneity score
c is the completeness score

The V-measure ranges from 0 to 1, where a score of 1 demonstrates culminate clustering assention with the genuine lesson names, and lower scores show less agreement.

The V-Measure score is invaluable since it gives a adjusted assessment of clustering execution, taking into account both homogeneity and completeness. It is especially valuable when the ground truth lesson names are accessible and important in the setting of the clustering assignment.

Gramm

Silhouette Coefficient:

The Outline Coefficient is a broadly utilized metric in information mining and clustering examination to assess the quality of clusters created by clustering calculations. It measures the degree of partition between clusters and the compactness of information focuses inside clusters.

The Outline Coefficient S for a single information point i is calculated as follows:

$S(i)= b(i)-a(i)/ \max\{a(i), b(i)\}$

Where:

a(i) is the normal remove from i to all other information focuses inside the same cluster (intra-cluster distance).
b(i) is the littlest normal remove from i to all information focuses in any other cluster, minimized over clusters (inter-cluster distance).

The Outline Coefficient for the whole dataset is at that point computed as the cruel of the Outline Coefficients for all information points.
The Outline Coefficient ranges from -1 to 1:

- A coefficient near to +1 demonstrates that the information point is well- clustered and lies distant absent from neighboring clusters.
- A coefficient near to 0 demonstrates that the information point is near to the choice boundary between two clusters.

- A coefficient near to -1 shows that the information point may have been doled out to the off-base cluster.
- The by and large Outline Coefficient of a clustering arrangement can give bits of knowledge into the by and large quality of the clustering:
- A tall generally Outline Coefficient shows that the clustering arrangement has thick, well-separated clusters.
- A moo generally Outline Coefficient proposes that the clusters are covering or ineffectively defined.

The Outline Coefficient is especially valuable when the genuine lesson names are not known and gives a quantitative degree of cluster cohesion and division without depending on outside approval. It is frequently utilized nearby other clustering assessment measurements to survey the viability of clustering calculations and parameter settings.
Grammar

Calinski-Harabasz Index (CHI):

The Calinski-Harabasz List (CHI), moreover known as the Change Proportion Measure, is a metric utilized to assess the quality of clustering in information mining. It measures both the partition between clusters and the compactness of clusters. The higher the CHI esteem, the superior the clustering result.

The CHI is calculated based on the proportion of the between-cluster scattering to the within-cluster scattering. It points to maximize the proportion, demonstrating well-separated and compact clusters. The equation for the CHI is as follows:

$CHI= B(k)/W(k)\times N-k/ k-1$

Where:
$B(k)$ is the between-cluster scattering (too known as the between-cluster whole of squares).

$W(k)$ is the within-cluster scattering (moreover known as the within-cluster entirety of squares).

N is the add up to number of information points.
k is the number of clusters.

The between-cluster scattering measures the change between cluster centres, whereas the within-cluster scattering measures the fluctuation inside each cluster. The proportion of between-cluster scattering to within-cluster scattering speaks to the degree of division between clusters relative to the compactness of clusters.

A higher CHI esteem shows way better clustering, with well-separated and compact clusters. Be that as it may, it's imperative to note that the translation of CHI values may shift depending on the dataset and the clustering calculation utilized. Furthermore, CHI ought to be utilized in conjunction with other clustering assessment measurements to give a comprehensive appraisal of clustering quality.

Visualization for clustering approaches:

Scatter Plots (for low dimensional data):A fundamental but valuable strategy for visualizing clusters in two or three measurements. Each information point is spoken to by a marker, and focuses having a place to the same cluster are coloured essentially. This makes a difference to distinguish outwardly particular groupings in the data.

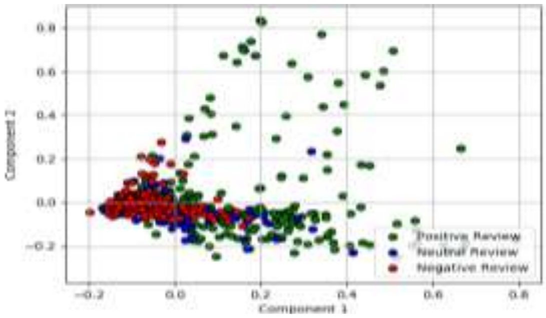

Figure 4. Data distribution in 2D Scatter Plot

Heatmaps (for high dimensional data): Valuable for visualizing connections between information focuses in higher measurements. Each information point is spoken to by a little square on the network, and the colour concentrated encodes the esteem of a specific highlight. Heatmaps can be utilized to investigate how information focuses inside a cluster share comparative highlight values. Figure of Heatmap.

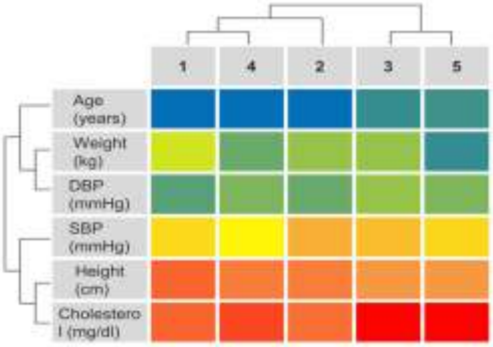

Figure 5. Heat Map Data Visualizations Presentation

Dendrograms (for Hierarchical Clustering): Representation for various levelled clustering calculations. It takes after a tree structure, where each department speaks to a cluster and the remove between branches shows the closeness between the clusters they speak to. Dendrograms offer assistance to visualize the progressive connections between clusters and recognize the fitting level of granularity for the clustering.Figur of Dendrograms.

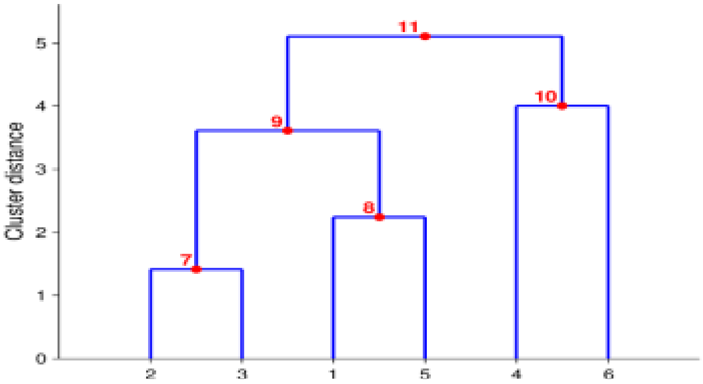

Figure 6. Data sample numbers of Dendrograms

Parallel Coordinates Plots: Useful for visualizing tall dimensional information, where each measurement is mapped to a vertical pivot. Lines are drawn through the tomahawks for each information point, permitting you to outwardly distinguish clusters based on how their lines navigate the parallel axes.

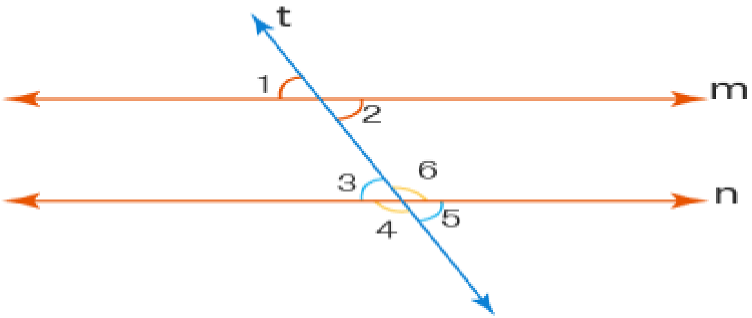

Figure 7Dendrograms Parallel Coordinates Plots

Tsne and UMAP(for dimensionality reduction): These are progressed dimensionality diminishment strategies that venture tall dimensional information focuses into a two or three-dimensional space whereas protecting the connections between the focuses. This permits you to visualize clusters in lower measurements, indeed for complex datasets.

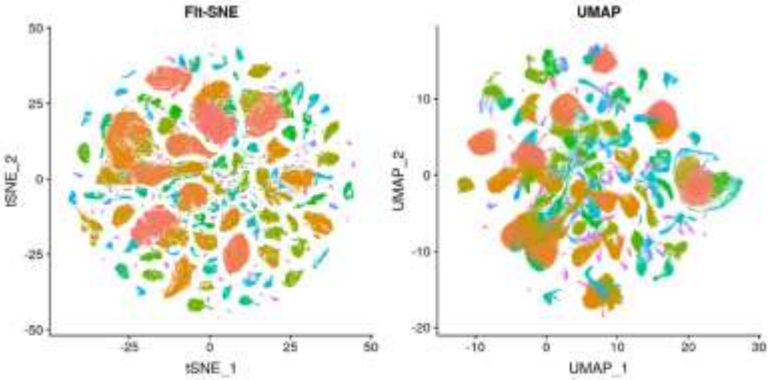

Figure 8. tSNE vs. UMAP: Global Structure

THE PROBLEMS OF CLUSTER ANALYSIS

By the study of cluster examination over, it is clear that there are two major disadvantages that impact the achievability of cluster examination in genuine world applications in information mining. The to begin with one is the shortcoming of most existing mechanized clustering calculations on managing with self-assertively formed information dispersion of the datasets. The moment issue is that, the assessment of the quality of clustering comes about by statistics-based strategies is time devouring when the database is huge, basically due to the disadvantage of exceptionally tall computational taken a toll of statistics-based strategies for surveying the consistency of cluster structure between the inspecting subsets. The execution of statistics-based cluster approval strategies does not scale well in exceptionally expansive datasets. On the other hand, subjectively molded clusters moreover make the conventional measurable cluster legitimacy lists incapable, which clears out it troublesome to decide the ideal cluster structure In expansion, the wastefulness of clustering calculations on dealing with self-assertively molded clusters in amazingly expansive datasets specifically impacts the impact of cluster approval, since cluster approval is based on the investigation of clustering comes about delivered by clustering calculations. Additionally, most of the existing clustering calculations tend to bargain with the whole clustering handle naturally, i.e., once the client sets the parameters of calculations, the clustering result is created with no intrusion, which avoids the client until the conclusion. As a result, it is exceptionally difficult to consolidate client space information into the clustering prepare. Cluster investigation is a different runs iterative handle, without any client space information, it would be wasteful and unintuitive to fulfill particular necessities of application assignments in clustering.

CONCLUSIONS

Clustering lies at the heart of information investigation and information mining applications. The capacity to find exceedingly connected districts of objects when their number gets to be exceptionally expansive is exceedingly alluring, as information sets develop and their properties and information interrelationships alter. At the same time, it is eminent that any clustering "is a division of the objects into bunches based on a set of rules – it is not one or the other genuine or false". A few would contend that the wide run of subject matter, estimate and sort of information, and varying client objectives makes this inescapable, and that cluster examination is truly a collection of distinctive issues that require a assortment of methods for their arrangement. The connections between the diverse sorts of issues and arrangements are regularly not clear. Each article that presents a unused clustering strategy appears its predominance to other strategies, it is difficult to judge how well the method will truly do. In this paper we depicted the handle of clustering from the information mining point of see. We gave the properties of a "good" clustering procedure and the strategies utilized to discover significant partitioning.

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