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Review Article

Review of Literatures on E – Learning Assessment with Clustering Method

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Abstract: E-learning has become a reality which it is impossible to ignore now, especially in this break out of worldwide pandemic. The need to know about its concerns, related concepts, types, algorithms, skills, tools, implementation, deployment and evaluation have motivated many researchers. it also seems reasonable to expect that researchers will rate the computer as the greatest invention in human history in terms of facilitating global communication. E-learning assessment is process of assessing teaching and learning activities in the e-learning system. This paper hovers around the review of literatures on e – learning assessment with clustering method. Assessment is one of the integral parts of the educational system all over the world and it plays a vital role in students' learning progress. This is achieved through different means of assessments which will be added together to achieve effective results in student learning progress. However, it has been observed that students who have undergone e-learning programme just read for grade at the end of the semester thereby lacking learning progress monitoring during the course of study. Most under-graduate and post-graduate modules are fully online but only few numbers of continuous assessment tests (cats) are delivered online. E-learning assessment is a means of assessing students' learning outcomes in e-learning system and most existing systems are based on summative assessment which assess students only at the end of the semester but this assessment system uses clustering method of data mining and formative assessment mechanism, this will significantly improve students' learning experiences and achievements. This constructive criticism and insight can be used to create an action plan that moves forward the ability to modify learning behaviors and achieve their learning goals.
Keywords: Learning Assessment, Clustering Method.

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INTRODUCTION

According to Abdulaziz, (2008), E-learning is the learning system where students learn by themselves. It can be done anywhere at any time and also write examination at the appropriate time. E-learning is general term relating to all learning that is delivered with the assistance of computer through Compact Disc (CD), the internet or shared files on a network (Abdulaziz, 2008). In essence, e-learning is a computer based educational tool or system that enables you to learn anywhere, any time and on your own pace. Today e-learning is mostly delivered though the internet, although in the past it was delivered using a blend of computer-based methods like Compact Disk Read Only Memory (CD-ROM).

According to Horton (2005) e-learning can be defined as the use of internet and digital technologies to create experiences that educate persons. Technology has advanced so much that the geographical gap is bridged with the use of tools that resemble classroom.

Van (2006) described the e-learning approach as centered on the learner as well as its design as involving a system that is interactive, repetitious, self-paced, and customizable.

Wentling *et al.* (2000) also defined e-learning as the use of computer network technology through the internet, to provide information and instruction to individuals. E-learning offers the ability to share material in all kinds of formats such as videos, slideshows, word documents and portable document

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formats (PDFs), conducting webinars (live online classes) and communicating with professors through chat options available to users.

TYPES OF E-LEARNING

There are diverse ways of classifying the types of e-learning. According to Algahtani (2011), there have been some classifications based on the extent of their engagement in education. Some classifications are also based on the timing of interaction. Algahtani (2011) divided e-learning into two basic types, consisting of computer-based and the internet based e-learning. He stated that the computer-based e-learning comprises the use of full range of hardware and software generally that are available for the use of Information and Communication Technology and also each component can be used in either of two ways: computer managed instruction and computer-assisted-learning. In computer assisted- learning, to him, computers are used instead of the traditional methods by providing interactive software as a support tool within the class or as a tool for self-learning outside the class. In the computer-managed instruction, however, computers are employed for the purpose of storing and retrieving information to aid in the management of education.

The internet-based learning according to Almosa (2001) is a further improvement of the computer-based learning, and it makes the content available on the internet, with the readiness of links to related knowledge sources. For examples e-mail services and references which could be used by learners at any time and place as well as the availability or absence of teachers or instructors (Almosa, 2001).

Zeitoun (2008) classified this by the extent of such features use in education, mixed or blended more, assistant mode, and completely online mode. The assistant mode supplements the traditional method as needed. Mixed or blended mode offers a short-term degree for a partly traditional method. The completely online mode, which is the most complete improvement, involves the exclusive use of the network for learning (Zeitoun, 2008).

Algahtani (2011) described the completely online mode as “synchronous” or “asynchronous” by the application of applying optional timing of interaction. The synchronous timing comprises alternate on-line access between teachers or instructors and learners, or between learners, and the asynchronous, to him allows all participants to post communications to any other participant over the internet. The synchronous type allows learners to discuss with the instructors and also among themselves via the internet at the same time with the use of tools such as the videoconference and chat rooms. This type according to Almosa and Almubarak (2005) offers the advantage of instantaneous feedback. The asynchronous mode also allows learners to discuss with the instructors or teachers as well as among themselves over the internet at different times. It is therefore not interaction at the same moment but later, with the use of tools such as thread discussion and emails, with an advantage that learners are able to learn at a time that suits them whilst a disadvantage is that the learners will not be able to receive instant feedback from instructors as well as their colleague learners.

LEARNING ASSESSMENT

E-learning assessment is process of assessing teaching and learning activities in the e-learning system. There are different types of assessment namely (Airasian and Miranda (2002); Al-Smadi&Gütl (2010); Madrid *et al.*, (2012); Buzzetto and Alade (2006).

i. Diagnostics Assessment (as Pre-Assessment),
ii. Formative Assessment,
iii. Summative Assessment,
iv. Norm-Referenced Assessment,
v. Criterion-Referenced Assessment and
vi. Interim Assessment

i. Diagnostic Assessment (as Pre-Assessment)

Diagnostic Assessment is a learning assessment procedure which uses wide variety of methods to conduct the evaluation of student comprehension, learning needs, and academic progress at the beginning of the school year term, semester, a lesson, unit or course. One way to think about it: Assesses a student’s strengths, weaknesses, knowledge, and skills prior to instruction.

ii. Formative Assessment

Formative assessment is a learning assessment procedure which uses wide variety of methods to conduct the evaluation of student comprehension, learning needs, and academic progress during a lesson, unit or course. Formative assessment is the assessment that is conducting when teaching and learning is going on. Assesses a student’s performance during instruction, and usually occurs regularly throughout the instruction process. The primary purpose of formative assessment is to offer learners feedback they can use to improve their e-learning experience, rather than simply giving grade. Formative assessment can be used to identify areas that students may need to improve and pinpoint their strengths during the e-learning course, in contrast to summative assessment which is used to determine whether or not a learner achieved the learning objectives and reached the desired level of proficiency at the end of an e-learning course. In Tselios *et al, 2011* research work; they spelled out Six (6) types of formative assessment, which are;

a. Goal checks: here learners are provided with a goal or objective at the beginning of the E-learning lesson. Upon completion they are given an assessment to determine whether they achieved the goal or how far they have progressed. Additional “milestone “goals can also be set for the rest of the lesson or e-learning course.

b. One-on-one discussion: The instructor meets with a learner to discuss expectations and assess their current knowledge based and skill sets. Typically, the facilitator will ask each learner a pre-determined set of questions to identify areas of improvement. This can be carried out face-to-face via an online chat.
c. Instructor observation: The instructor observe learners as they are completing online activities and assesses the proficiency and skill level of each individual. This usually involves note taking and possibly a follow-up online face-to-face meeting between the instructor and learner.
d. Personal online learning logs: Learners are asked to create a personal online learning log or journal that details what they are learning , their thoughts and feelings about the topics and the core ideas or concepts of online lesson. The instructor can then use this log to track the learner's progress.
e. Group presentations: Learners work together or independently to create an online presentation that must be presented to their peers. The learners are provided with criteria beforehand, which clarify expectations and specify which skills and information must be used throughout the e-learning project.
f. Self-assessment: Learners are encourage to reflect upon their own e-learning experiences and determine their level of proficiency or knowledge mastery. They may also be evaluated by their peers who give them feedback and insight into their works. This form of online assessment is usually paired with another e-learning activity, such as personal online learning log.

iii. Summative Assessment

Summative assessment refers to assessment of students where the focus is on the outcome of a program. It gauges knowledge mastery after the e-learning course on how to track learners' progress in between a course. It measures a student's achievement at the end of instruction; it is like talking to someone about a movie after the movie is over. By using measurements of student performance, summative assessments can be useful for teachers to improve units and lessons year over year because they are, in a way, as much of a reflection on the quality of the units and lessons themselves as they are the students.

iv. Norm-Referenced Assessment

Norm-Referenced Assessment refers to assessment of students where the focus is on comparing a student's performance against other students. It is also called demographic assessment. Many standardized tests are used as norm-referenced assessments. These kinds of assessments are useful over time in student profiles or for placement in national-level programs.

v. Criterion-Referenced Assessment

Criterion-Referenced Assessment refers to assessment of students where the focus is on the measurement a student's performance against a goal, specific objective, or standard. It is a bar to measure all students against goal, specific objective, or standard. This can be a kind of formative assessment and can be integrated throughout teaching curriculum to guide the adjustment of teaching over time.

vi. Interim Assessment

Interim Assessment refers to assessment of students where the focus is on the evaluation of students' performance at periodic intervals, frequently at the end of a grading period. **It is also called Benchmark.** This can predict student performance on end-of-the-year summative assessments. It is bar graph or chart growth throughout a year, often against specific 'benchmarks'.

E-learning assessment tools

Learning evaluation is the technique of assessing the achievement of the learner after the teaching and learning process takes place either in the classroom or the internet (Keppell, 2006). It consists of questions that will cover the objectives of the content of the lesson covered within a specific period. According to Chan *et al*, 2003, there are Six assessment tools and strategies that will help teachers promote a 21st century learning achievement in their classrooms, they are as follows:

i. Rubrics,
ii. Performance-based assessments (PBAs),
iii. Portfolios,
iv. Student self-assessment,
v. Peer-assessment,
vi. Student response systems (SRS).

Although the list does not include all innovative assessment strategies, it includes most common strategies, and ones that may be particularly relevant to the educational context of developing countries (Drillon*et al*, 2005). Many of the assessment strategies currently in use fit under one or more of the categories above. Furthermore, it is important to note that these strategies also overlap in a variety of ways.

i. Rubrics

Rubrics are both a tool to measure students' knowledge and ability as well as an assessment strategy. A rubric allows teachers to measure certain skills and abilities not measurable by standardized testing systems that assess discrete knowledge at a fixed moment in time (Reeves and Hedberg, 2003). Rubrics are frequently used as part of other assessment strategies (portfolios, performances, projects, peer-review and self-assessment). The rubric is not only utilized in conjunction with summative assessments; it is a tool that can enhance the entire learning process from beginning to end by serving a number of purposes including communication expectations for an assignment, providing focused feedback on a project still in process. One of the major strengths of the rubric as an assessment method is that it functions as a teaching tool as well as an evaluative tool (Phillips, 2002).

ii. Performance-based Assessments

Performance-based assessments (PBA), also known as project-based or authentic assessments, are generally used as a summative evaluation strategy to capture not only what students know about a topic, but if they have the skills to apply that knowledge in a "real-world" situation. By asking them to create an end product, PBA pushes students to synthesize their knowledge and apply their skills to a potentially unfamiliar set of circumstances that is likely to occur beyond the confines of a controlled classroom setting (Penny and Coe, 2004).

iii. Portfolio Assessment

Portfolios are collection of student work gathered over time that is primarily used as a summative evaluation method. The most salient characteristic of the portfolio assessment is that rather than being a snapshot of a student's knowledge at one point in time (like a single standardized test), it highlights student effort, development, and achievement over a period of time; portfolios measure a student's ability to apply knowledge rather than simply regurgitate it. They are considered both student-centered and authentic assessments of learning (Keller and Cernerud, 2002). Portfolios are one of the most flexible forms of assessment because they can be effectively adapted across subject areas, grade levels and administrative contexts (i.e. to report individual student progress, to compare achievement across classroom or schools and to increase parent involvement in student learning) National Research Council, 2009). One of the strengths of the portfolio as an assessment tool is that it can be smoothly integrated into classroom instruction (as opposed to be an add-on style of the standardized summative test).

iv. Self-assessment

The previous assessment tools and strategies listed above generally function as summative approaches while self-assessment is generally viewed as a formative strategy, rather than one used to determine a student's final grade. Its main purpose is for students to identify their own strengths and weakness and to work to make improvements to meet specific criteria (Yaghoubi *et al.,* 2009). According to Mandinach, (2005), "self-assessment occurs when students judge their own work to improve performance as they identify discrepancies between current and desired performance". In this way, self-assessment aligns well with standards-based education because it provides clear targets and specific criteria against which students or teachers can measure learning. Self-assessment is used to promote self-regulation, to help students reflect on their progress and to inform revisions and improvements on a project or paper. Ross *et al*, (2006) argue that in order for self-assessment to be truly effective four conditions must be in place:

a. The self-assessment criteria is negotiated between teachers and students,
b. Students are taught how to apply the criteria,
c. Students receive feedback on their self-assessments and
d. Teachers help students to use assessment data in order to develop an action plan.

A number of studies point to the positive effects self-assessment can have on achievement, motivation, self-perception, communication, and behavior. An additional strength of self-assessment as a formative assessment tool is that it allows every student to get feedback on his or her work. Few classrooms allow teachers the luxury of regularly responding to each individual student, so when students are trained in self-assessment it makes them less reliant on teachers to advance their learning (Yaghoubi *et al.,* 2009). While the focus is self-evaluation, the process can also be enhanced through peer and teacher based assessments that offer alternative interpretation and additional evidence to support a student's understanding of their own learning (Yaghoubi *et al.,* 2009).

v. Peer Assessment

Peer assessment, much like self-assessment, is a formative assessment strategy that gives students a key role in learning evaluation (Watkins, 2005). Peer assessment approaches can vary greatly but, essentially, it is a process for learners to consider and give feedback to other learners about the quality or value of their work. Peer assessments can be used for variety of products like papers, presentations, projects, or other skilled behaviors. Peer assessment is understood as a grading procedure and is also envisioned as teaching strategy since engaging in the process develops both the assessor and assessees' skills and knowledge (Watkins, 2005). Feedback that students are asked to provide can confirm existing information, identify or correct errors, provide feedback on process, problem solutions or clarity of communication. The primary goal for using peer assessment is to provide feedback to learners. This strategy may be particularly relevant in classrooms with many students per teacher since student time will always be more plentiful than teacher time.

vi. Student Response Systems

Student response system (SRS), also known as classroom response system (CRS), audience response system (ARS) or colloquially as "clickers," is a general term that refers to a variety of technology-based formative assessment tools that can be used to gather student-level data instantly in the classroom(Yaghoubi *et al.,*2009). Through the combination of hardware (hand held clickers, receiver, PC, internet connection, projector and screen) and software, teachers can ask students a wide range of questions (both closed and open-ended), students can respond quickly and anonymously, and the teacher can display the data immediately and graphically. The value of SRS comes from teachers analyzing information quickly and then devising real-time pedagogical solutions to maximize student learning (Yaghoubi *et al.*, 2009). The effectiveness of the SRS tool is closely linked to the type, quality, quantity, speed and sequence of the questions being asked.

DATA MINING AND ITS OBJECTIVES

Data Mining is the process of applying intelligent methods to extract data patterns. It is a powerful analytical tool that enables educational institutions to better allocate resources and staff, manage student feedback (Grzymala-Busse and Grzymala-Busse, 2010). Applying data mining techniques to educational data for knowledge discovery is significant to educational organizations as well as students.

Data mining has two objectives which are prediction and description objectives (Castro and Vellido, 2007). It canpredict unknown or future values of the attributes of interest using other attributes in the databases, while describingthe data in a manner understandable and interpretable to humans. Predicting the sale amounts of a new product based on advertising expenditure, or predicting wind velocities as a function of temperature, humidity and air pressure are examples of tasks with a predictive goal in data mining. Describing the different terrain groupings that emerge in a sampling of satellite imagery is an example of a descriptive goal for a data mining task. The relative importance of description and prediction can vary between different applications. According to Di Marco and Navigli, (2013), the two data mining objectives have their dedicated tasks, for Predictive objective, the tasks are:

i. Classification
ii. Regression
iii. Deviation Detection

i. Classification– to segregate items into several predefined classes. Given a collection of training samples, this type of task can be designed to find a model for class attributes as a function of the values of other attributes.
ii. Regression– to predict a value of a given continuously valued variable based on the values of other variables, assuming either a linear or nonlinear model of dependency. These tasks are studied in statistics and neural network fields.
iii. Deviation Detection– to discover the most significant changes in data from previously measured or normative values. Explicit information outside the data, like integrity constraints or predefined patterns, is used for deviation detection.

For Descriptive objective, the tasks are

i. Clustering
ii. Summarization
iii. Dependencymodeling

I. Clustering– to identify a set of categories, or clusters that describe the data.
II. Summarization– to find a concise description for a subset of data. Tabulating the mean and standard deviations for all fields is a simple example of summarization. There are more sophisticated techniques for summarization and they are usually applied to facilitate automated report generation and interactive data analysis.
III. Dependencymodeling– to find a model that describes significant dependencies between variables. For example, probabilistic dependency networks use conditional independence to specify the structural level of the model and probabilities or correlation to specify the strengths (quantitative level) of dependencies.

The aim of this research study is to provide an integrated framework for implementing e-learning assessment system using clustering method of data mining. All the focus will be on the clustering method which is under the descriptive objective.

DATA CLUSTERING METHOD

Data clustering is a sub-field of data mining dedicated to incorporating techniques for finding similar groups within a large database. Dataclusteringis a tool for exploring data and finding a valid and appropriate structure for grouping and classifying the data (Witten *et al*, 2011). A clusterindicates a number of similar objects, such that the members inside a cluster are as similar as possible (homogeneity), while at the same time the objects within different clusters are as dissimilar as possible (heterogeneity). The property of homogeneity is similar to the cohesion attribute between objects of a class in software engineering, while heterogeneity is similar to the coupling attribute between the objects of different classes. Unlike data classification, data clustering does not require category labels or predefined group information. Thus, clustering has been studied in the field of machine learning as a type of unsupervisedlearning, because it relies on "learning from observation" instead of "learning from examples." The pattern proximity matrix could be measured by a distance function defined on any pairs of patterns (Beck and Woolf, 2000). Beck and Woolf, (2000) classified clustering as:

i. Hard clustering
ii. Soft clustering
iii. Strict partitioning clustering
iv. Strict partitioning clustering with outliers
v. Overlapping clustering

vi. Hierarchical clustering
vii. Subspace clustering

i. Hard clustering: hard clustering occurs when all the objects in the data set belong to a cluster or none of them is in a cluster.
ii. Soft clustering: this is also called fuzzy clustering, this occurs when all the objects in the data set belongs to each cluster to a certain degree, a likelihood of belonging to the cluster.
iii. Strict partitioning clustering: this occurs when each object in the data set belongs to exactly one cluster.
iv. Strict partitioning clustering with outliers: this occurs when all the objects in the data set belong to no cluster, and are considered outliers
v. Overlapping clustering : this is also called alternative clustering or multi-view clustering, this occurs when all the objects in the data set belongs to more than one cluster, usually involving hard clusters.
vi. Hierarchical clustering: this occurs when all the objects in the data set belong to a child cluster that belongs to the parent cluster.
vii. Subspace clustering: this occurs when all the objects in the data set belong to an overlapping cluster within a uniquely defined subspace.

CLUSTERING ANALYSIS ALGORITHMS

There is no objectively "correct" clustering algorithm, but as it was noted, "clustering is in the eye of the beholder (Karin *et al*., (2004). The most appropriate clustering algorithm for a particular problem often needs to be chosen experimentally, unless there is a mathematical reason to prefer one cluster model over another. An algorithm that is designed for one kind of model will generally fail on a data set that contains a radically different kind of model. For example, k-means cannot find non-convex clusters. There is so many Clustering Analysis Algorithms presently in existence but for this research work, we will consider eight Clustering Analysis Algorithms, which are;

i. Fuzzy k-means clustering Analysis Algorithms
ii. Hierarchical clustering Analysis Algorithms
iii. Constraint-based (Supervised Clustering) clustering Analysis Algorithms
iv. Centroid Based clustering Analysis Algorithms
v. The BIRCH (Balanced Iterative Reducing and Clustering) clustering Analysis Algorithms
vi. CURE (Clustering Using REpresentatives) clustering Analysis Algorithms
vii. Distribution-based clustering Analysis Algorithms
viii. Density-based clusteringAnalysis Algorithms

i. Fuzzy k-means clusteringAnalysis Algorithms, In this algorithm, each data point is allowed to be in exactly one cluster (Pfitzner, *et al.*, 2009). In the fuzzy clustering algorithm we relax this condition and assume that each pattern has some “fuzzy” membership in a cluster. That is, each object is permitted to belong to more than one cluster with a graded membership. Fuzzy clustering has three main advantages (Pfitzner, *et al.*, 2009):

a. It maps numeric values into more abstract measures (fuzzification),
b. Student features may overlap multiple abstract measures, and there may be a need to find a way to cluster under such circumstances; and
c. Most real-world classes are fuzzy rather than crisp.

Therefore, it is natural to consider the fuzzy set theory as a useful tool to deal with the classification problem (Dumitrescu *et al*., 2000). The general idea about clustering revolves around assigning data-points to mutually exclusive clusters, meaning, a data-point always resides uniquely inside a cluster and it cannot belong to more than one cluster. Fuzzy clustering methods change this paradigm by assigning a data-point to multiple clusters with a quantified degree of belongingness metric. The data-points that are in proximity to the center of a cluster may also belong in the cluster that is at a higher degree than points in the edge of a cluster. The possibility of which an element belongs to a given cluster is measured by membership coefficient that varies from 0 to 1.Fuzzy clustering can be used with datasets where the variables have a high level of overlap. It is a strongly preferred algorithm for Image Segmentation, especially in bioinformatics where identifying overlapping gene codes makes it difficult for generic clustering algorithms to differentiate between the image’s pixels and they fail to perform a proper clustering. When the number of clusters is fixed to *k*, *k*-means clustering gives a formal definition as an optimization problem: find the *k* cluster centers and assign the objects to the nearest cluster center, such that the squared distances from the cluster are minimized. The optimization problem itself is known to be NP-hard, and thus the common approach is to search only for approximate solutions. A particularly well known approximate method is Lloyd's algorithm, (Pfitzner, *et al.*, 2009) often just referred to as "*k-means algorithm*". It does however only find a local optimum, and is commonly run multiple times with different random initializations. Variations of *k*-means often include such optimizations as choosing the best of multiple runs, but also restricting the centroids to members of the data set (*k*-medoids), choosing medians (*k*-medians clustering), choosing the initial centers less randomly (*k*-means++) or allowing a fuzzy cluster assignment (fuzzy c-means).Most *k*-means-type algorithms require the number of clusters – *k* – to be specified in advance, which is considered to be one of the biggest drawbacks of these algorithms. Furthermore, the algorithms prefer clusters of approximately similar size, as they will always assign an object to the nearest centroid. This often leads to incorrectly cut borders of clusters.

According to Färber, *et al.*, 2010K-means has a number of interesting theoretical properties as shown in figure 2 and figure 3. First, it partitions the data space into a structure known as a Voronoi diagram. Second, it is conceptually close to nearest neighbor classification, and as such is popular in machine learning. Third, it can be seen as a variation of model based clustering, and Lloyd's algorithm as a variation of the Expectation-maximization algorithm for this model discussed below.

k-means clustering examples.

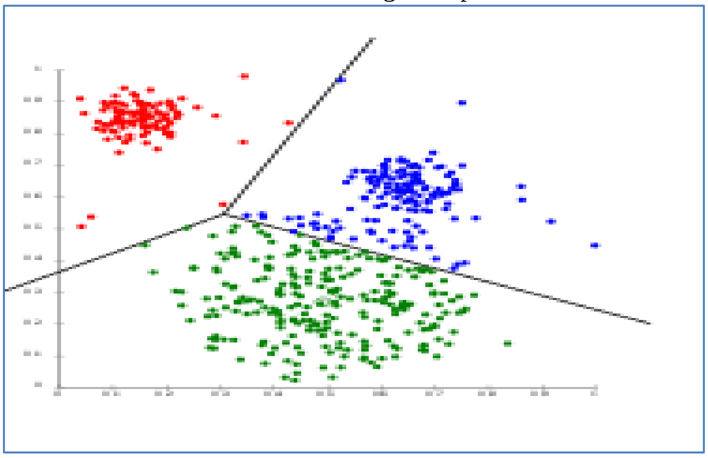

Fig-2: Voronoi cells partitioned by k-means algorithm (Färber, *et al.*, 2010)

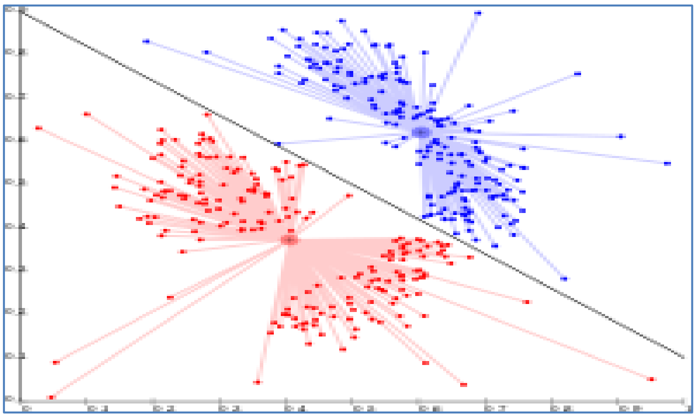

Fig-3: Nearest neighbor classification by k-means algorithm (Färber, *et al.*, 2010)

ii. Hierarchical Methods Analysis Algorithms: this is also called Connectivity-based clustering Analysis Algorithmsis based on the core idea of objects being more related to nearby objects than to objects farther away (Aggarwal and Reddy, 2005). These algorithms connect "objects" to form "clusters" based on their distance. A cluster can be described largely by the maximum distance needed to connect parts of the cluster.

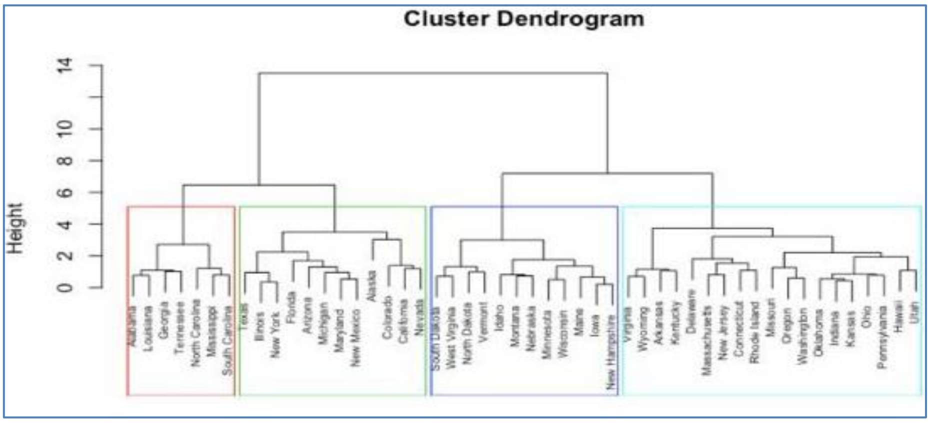

Fig-4: Cluster Dendrogram (Aggarwaland Reddy, 2005)

At different distances, different clusters will form, which can be represented using a dendrogram as shown in figure 4, which explains where the common name "hierarchical clustering" comes from: these algorithms do not provide a single partitioning of the data set, but instead provide an extensive hierarchy of clusters that merge with each other at certain distances. In a dendrogram, the y-axis marks the distance at which the clusters merge, while the objects are placed along the x-axis such that the clusters don't mix. According to Agrawal*et al*, 2005, Connectivity-based clustering is whole families of methods that differ by the way distances are computed. Apart from the usual choice of distance functions, the user also needs to decide on the linkage criterion to use which can be:

a. Single-linkage clustering (SLINK)-the minimum of object distances as shown in figure 5a and 5b,
b. Complete linkage clustering (CLINK)-the maximum of object distances, and
c. UPGMA or WPGMA ("Unweighted or Weighted Pair Group Method with Arithmetic Mean", also known as average linkage clustering (ALINK)).

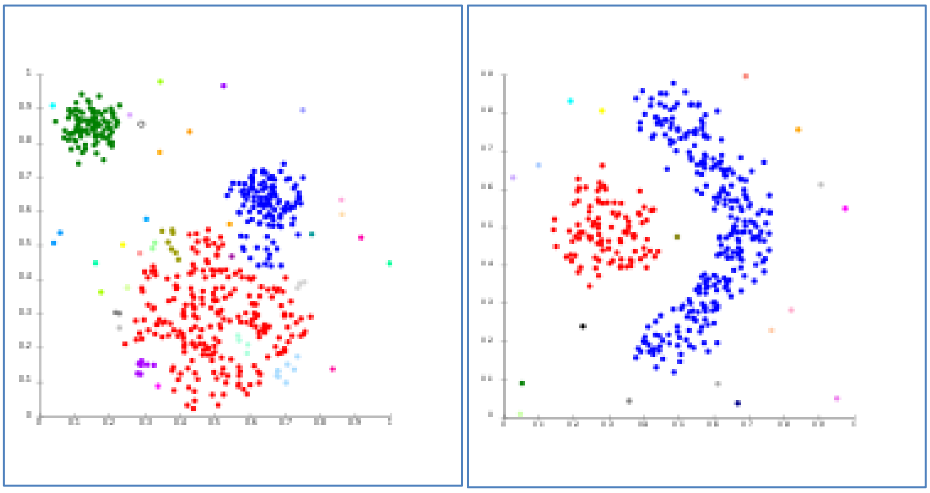

Fig-5a and 5b: single-linkage clustering (SLINK) Agrawal *et al.*, 2005

Hierarchical methods decompose the given set of data items forming a tree, which is called dendrogram as mentioned above. A dendrogram splits the dataset recursively into smaller subsets. A dendrogram can be formed in two ways (Agrawal *et al.*, 2005):

a. The *Bottom-up* approach, also referred to as the *agglomerative* approach, starts with each object forming a distinct group (see figure 6). It successively merges the groups according to some measure, such as the distance between the centers of the groups, which continues until all of the groups are merged into one – the top most level of hierarchy. Agglomerative is quite contrary to Divisive, where all the "N" data points are considered to be a single member of "N" clusters that the data is comprised into as in figure 6. We iteratively combine these numerous "N" clusters to fewer number of clusters, let's say "k" clusters and hence assign the data points to each of these clusters accordingly. This approach is a bottom-up one, and also uses termination logic in combining the clusters. This logic can be a number based criterion (no more clusters beyond this point) or a distance criterion (clusters should not be too far apart to be merged) or variance criterion (increase in the variance of the cluster being merged should not exceed a threshold, Ward Method)
b. The *Top-down* approach, also referred to as the *divisive* approach, starts with all the objects in the same cluster. In every successive iteration, a cluster is split into smaller groups according to some measure until each object is eventually in one cluster, or until a termination condition is met.

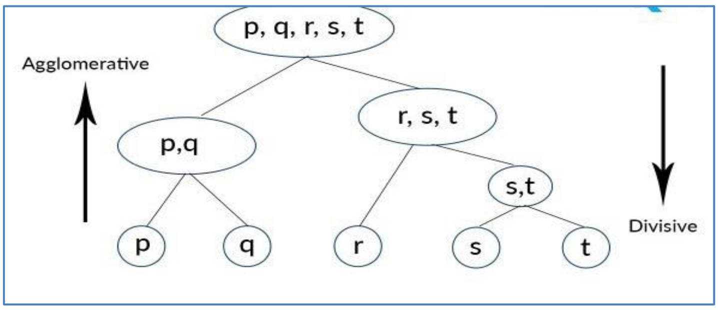

Fig-6: Dendrogram formation arrangement (Agrawal *et al.*, 2005)

Hierarchical methods are popular in biological, social and behavioral systems, which often need to construct taxonomies. Due to rapidly increasing data densities, dendrograms are impractical when the number of patterns exceeds a few hundred (Yaghoubi *et al.,* 2009). As a result, partitioned techniques are more appropriate in the case of large data sets.

iii. Constraint-based (Supervised Clustering): The clustering process, in general, is based on the approach that the data can be divided into an optimal number of “unknown” groups (Achtert, *et al.*, 2007). The underlying stages of all the clustering algorithms to find those hidden patterns and similarities, without any intervention or predefined conditions. However, in certain business scenarios, we might be required to partition the data based on certain constraints. Here is where a supervised version of clustering machine learning techniques come into play.

A constraint is defined as the desired properties of the clustering results, or a user’s expectation on the clusters so formed – this can be in terms of a fixed number of clusters, or, the cluster size, or, important dimensions (variables) that are required for the clustering process as shown in figure 7.

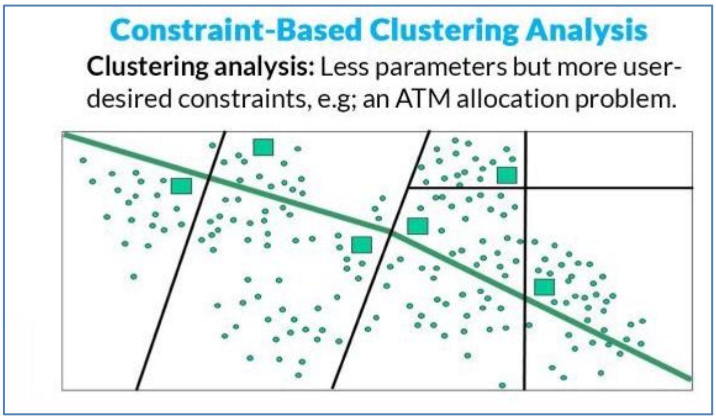

Fig-7: Constraint-based (Supervised Clustering) (Achtert, *et al.*, 2007)

Usually, tree-based, Classification machine learning algorithms like Decision Trees, Random Forest, and Gradient Boosting, etc. made use of attain constraint-based clustering. A tree is constructed by splitting without the interference of the constraints or clustering labels. Then, the leaf nodes of the tree are combined together to form the clusters while incorporating the constraints and using suitable algorithms.

iv. Centroid Based clustering Analysis Algorithms

Centroid based clustering is considered as one of the most simplest clustering algorithms, yet the most effective way of creating clusters and assigning data points to it. The intuition behind centroid based clustering is that a cluster is characterized and represented by a central vector and data points that are in close proximity to these vectors are assigned to the respective clusters (Pourrajabi, *et al.*, 2014).These groups of clustering methods iteratively measure the distance between the clusters and the characteristic centroids using various distance metrics. These are either of Euclidian distance, Manhattan Distance or Minkowski Distance.

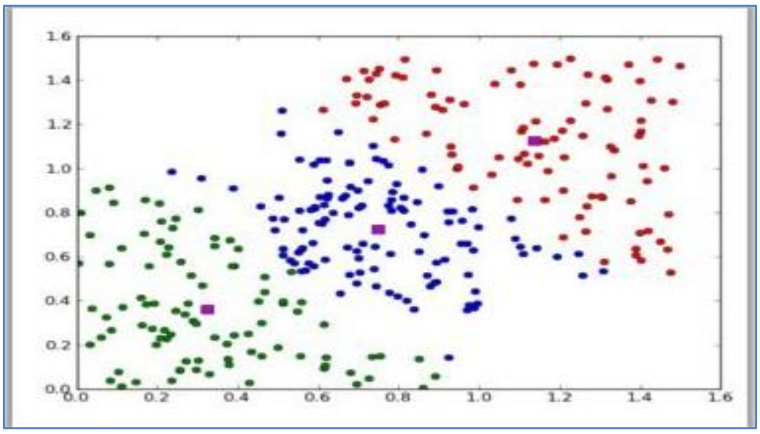

Fig-8: Centroid based clustering Analysis Algorithms (Pourrajabi, *et al.*, 2014).

Despite the flaws, Centroid based clustering has proven its worth over Hierarchical clustering when working with large datasets. Also, owing to its simplicity in implementation and also interpretation, these algorithms have wide application areas viz., market segmentation, customer segmentation, text topic retrieval, image segmentation.

v. The BIRCH (Balanced Iterative Reducing and Clustering) clustering Analysis

Algorithms: BIRCH. The BIRCH (Balanced Iterative Reducing and Clustering) algorithm (Zhang *et al*., 1996) uses a hierarchical data structure, which is referred to as a CF-tree (Clustering Feature-Tree) for incremental and dynamic clustering of data objects. The BIRICH algorithm represents data points as many small CF-trees and then performs clustering with these CF-trees as the objects. A CF is a triplet summarizing information about the sub-cluster in the CF-tree;

CF = (N, LS, SS) where N denotes the number of objects in the sub-cluster, LS is the linear sum of squares of the data points, and SS is the sum of squares of the data points.

Taken together, these three statistical measurements become the object for further pair-wise computation between any two sub-clusters (CF-trees). CF-trees are height-balanced trees that can be treated as sub-clusters. The BIRCH algorithm calls for two input factors to construct the CF-tree:

a. the branching input factor B and
b. Threshold T.

The branching parameter, B, determines the maximum number of child nodes for each CF node. The threshold, T, verifies the maximum diameter of the sub cluster kept in the node (Di Marco and Navigli, 2013). A CF tree is constructed as the data is scanned. Each point is inserted into a CF node that is most similar to it. If a node has more than B data points or its diameter exceeds the threshold T, BIRCH splits the CF nodes into two. After doing this split, if the parent node contains more than the branching factor B, then the parent node is rebuilt as well. The step of generating sub-clusters stored in the CF-trees can be viewed as a pre-clustering stage that reduces the total number of data to a size that fits in the main memory. The BIRCH algorithm performs a known clustering algorithm on the sub-cluster stored in the CF-tree. If N is the number of data points, then the computational complexity of the BIRCH algorithm would be O (N) because it only requires one scan of the data set – making it a computationally less expensive clustering method than hierarchical methods. Experiments have shown good clustering results for the BIRCH algorithm (Di Marco and Navigli, 2013*)*. However, similar to many partitional algorithms it does not perform well when the clusters are not spherical in shape and also when the clusters have different sizes. This is due the fact that this algorithm employs the notion of diameter as a control parameter (Di Marco and Navigli, 2013*)*. Clearly, one needs to consider both computational cost and geometrical constraints when selecting a clustering algorithm, even though real data sets are often difficult to visualize when first encountered.

vi. CURE (Clustering Using REpresentatives) algorithm (Guha *et al*., 1998) integrates

Different partitioned and hierarchical clusters to construct an approach which can handle large data sets and overcome the problem of clusters with non-spherical shape and non-uniform size. The CURE algorithm is similar to the BIRCH algorithm and summarizes the data points into sub-clusters, then merges the sub-clusters that are most similar in a bottom-up (agglomerative) style. Instead of using one centroid to represent each cluster, the CURE algorithm selects a fixed number of well-scattered data points to represent each cluster (Filipovych*et al*., 2011). Once the representative points are selected, they are shrunk towards the gravity centers by a shrinking factor α which ranges between 0 and 1. This helps eliminate the effects of outliers, which are often far away from the centers and thus usually shrink more. After the shrinking step, this algorithm uses an agglomerative hierarchical method to perform the actual clustering. The distance between two clusters is the minimum distance between any representative points. Therefore, if α = 1, then this algorithm will be a single link algorithm, and if α = 0, then it would be equivalent to a centroid-based hierarchical algorithm (Filipovych*et al*., 2011). The algorithm can be summarized as follows:

a. Draw a random sample s from the data set.
b. Partition the sample, s, into p partitions (each of size $|s| / p$).
c. Using the hierarchical clustering method, cluster the objects in each sub-cluster (group) into $|s| / pq$clusters, where q is a positive input parameter.
d. Eliminate outliers; if a cluster grows too slowly, and then eliminate it.
e. Shrink multiple cluster representatives toward the gravity center by a fraction of the shrinking factor α
f. Assign each point to its nearest cluster to find a final clustering.

This algorithm requires one scan of the entire data set. The complexity of the algorithm would be O (N) where N is the number of data points. However, the clustering result depends on the input parameters $|s|$, p, and α. Tuning these parameters can be difficult and requires some expertise, making this algorithm difficult to recommend (Filipovych*et al*., 2011).

vii. Distribution-based clustering; The clustering model most closely related to statistics is based on distribution models (Hartuv and

Shamir, 2000). Most clustering techniques are based on proximity (similarity/distance) or composition (density). There is a family of clustering algorithms that take a totally different metric into consideration – probability. Distribution-based clustering creates and group data points based on their likely hood of belonging to the same probability distribution in the data. The Clusters can then easily be defined as objects belonging most likely to the same distribution. A convenient property of this approach is that this closely resembles the way artificial data sets are generated: by sampling random objects from a distribution. While the theoretical foundation of these methods is excellent, they suffer from one key problem known as over fitting, unless constraints are put on the model complexity. A more complex model will usually be able to explain the data better, which makes choosing the appropriate model complexity inherently difficult.

One prominent method of Distribution-based clustering is known as Gaussian mixture models (using the expectation-maximization algorithm) (Hartuv and Shamir, 2000). Here, the data set is usually modeled with a fixed number of Gaussian distributions that are initialized randomly and whose parameters are iteratively optimized to better fit the data set as shown in figure 9. This will converge to a local optimum, so multiple runs may produce different results. In order to obtain a hard clustering, objects are often then assigned to the Gaussian distribution they most likely belong to. Distribution-based clustering produces complex models for clusters that can capture correlation and dependence between attributes.

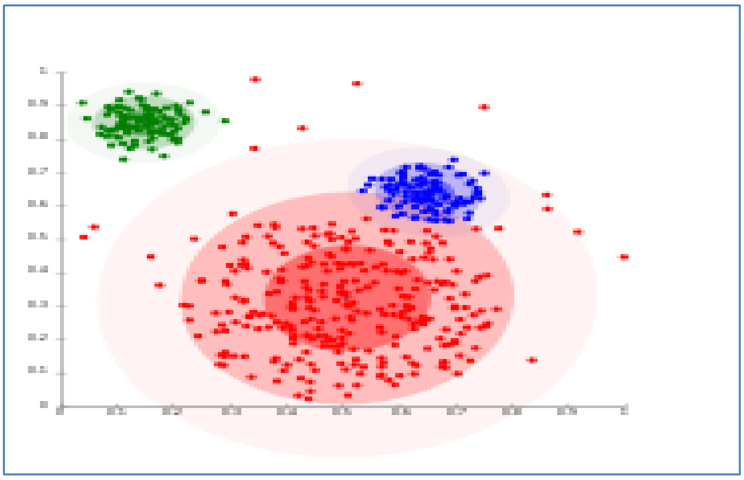

Fig-9: Gaussian mixture model clustering(Hartuv and Shamir, 2000)

The distribution models of clustering are most closely related to statistics as it very closely relates to the way how datasets are generated and arranged using random sampling principles i.e., to fetch data points from one form of distribution. Clusters can then be easily be defined as objects that are most likely to belong to the same distribution.

Distribution based clustering has a vivid advantage over the proximity and centroid based clustering methods in terms of flexibility, correctness and shape of the clusters formed. The major problem however is that these clustering methods work well only with synthetic or simulated data or with data where most of the data points most certainly belong to a predefined distribution, if not, the results will over fit.

viii. Density-based clustering; In density-based clustering, clusters are defined as areas of higher density than the remainder of the data set(Goebel, 2014). They are also considered as the densest region in a data space, which is separated by regions of lower object density and it is defined as a maximal-set of connected points. Objects in sparse areas - that are required to separate clusters - are usually considered to be noise and border points. Density-based Clustering is also called Model-based clustering Methods. Looking into the previous methods that we discussed, one would observe that most of them are dependent on distance (similarity/proximity) metric. Density-based clustering methods take density into consideration instead of distances (Goebel, 2014) as shown in figure 10. When performing most of the clustering, we take two major assumptions, one, the data is devoid of any noise and two, the shape of the cluster so formed is purely geometrical (circular or elliptical). The fact is, data always has some extent of inconsistency (noise) which cannot be ignored. Added to that, we must not limit ourselves to a fixed attribute shape, it is desirable to have arbitrary shapes so as to not to ignore any data points. Density-based algorithms have clusters with arbitrary shapes, clusters without any limitation in cluster sizes, clusters that contain the maximum level of homogeneity by ensuring the same levels of density within it, and also these clusters are inclusive of outliers or the noisy data.

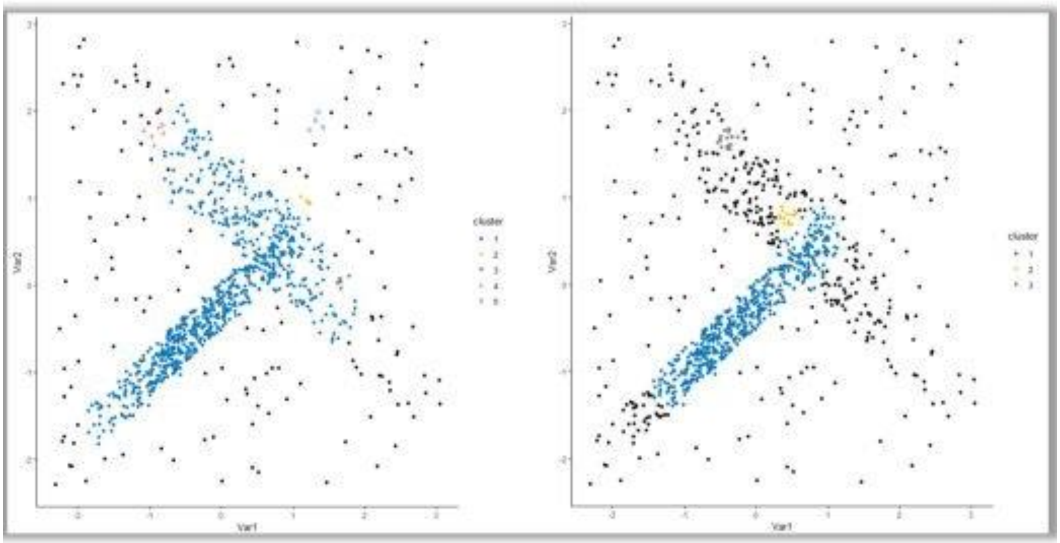

Fig-10: Density-based clustering (Weiss, *et al.*, 2005)

The most popular density based clustering method is DBSCAN (Weiss, *et al.*, 2005) (shown in figure 10). In contrast to many newer methods, it features a well-defined cluster model called "density-reachability". Similar to linkage based clustering; it is based on connecting points within certain distance thresholds.

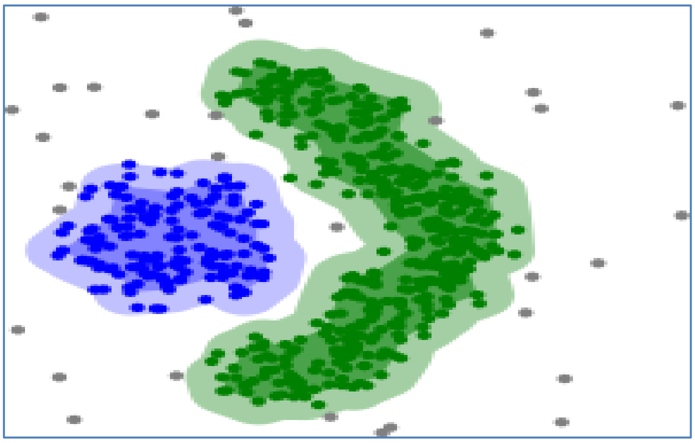

Fig-11: Density-based clustering with DBSCAN (Goebel, 2014).

However, it only connects points that satisfy a density criterion, in the original variant defined as a minimum number of other objects within this radius. A cluster consists of all density-connected objects (which can form a cluster of an arbitrary shape, in contrast to many other methods) plus all objects that are within these objects' range. Another interesting property of DBSCAN is that its complexity is fairly low – it requires a linear number of range queries on the database – and that it will discover essentially the same results (it is deterministic for core and noise points, but not for border points) in each run, therefore there is no need to run it multiple times.

OPTICS (see figure 11) is another class of Density-based clustering that removes the need to choose an appropriate value for the range parameter {\displaystyle\varepsilon} (Weiss, *et al.*, 2005), and produces a hierarchical result related to that of linkage clustering. DeLi-Clu, Density-Link-Clustering combines ideas from single-linkage clustering, DBSCAN and OPTICS, in order to eliminating the {\displaystyle\varepsilon} parameter entirely and offering performance improvements over OPTICS by using an R-tree index.

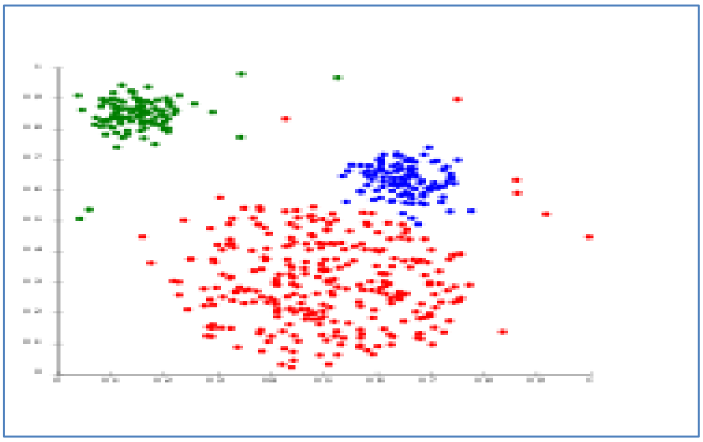

Fig-11: Density-based clustering with OPTICS (Weiss, *et al.*, 2005)

The key drawback of DBSCAN and OPTICS is that they expect some kind of density drop to detect cluster borders. On data sets with, for example, overlapping Gaussian distributions – a common use case in artificial data – the cluster borders produced by these algorithms will often look arbitrary, because the cluster density decreases continuously. On a data set consisting of mixtures of Gaussians, these algorithms are nearly always outperformed by methods such as EM clustering that are able to precisely model this kind of data.

SUMMARY OF THE LITERATURE

Table-1: Summary of the related literature

S/N	NAME OF AUTHORS	RESEARCH OBJECTIVES	METHODOLOGY
1.	Ryder, M. and Wilson, B. (1996*)*	The derivation of performance prediction indicators to develop deploying a simple student performance assessment and monitoring system within a teaching and Learning environment.	Prediction Algorithm and diagnostic assessment
2.	Urdan T.A. and Weggen C.C. (2000)	Reveal the high potential of Data Mining application for university learning management	Decision tree (To predict the student university performance based on the collection of attributes providing information about the student pre-university characteristics) with summative assessment.
3.	Dube and Ma (2010)	The classification task is used to predict the final grade of students and as there are many approaches that are used for data classification	Decision tree, ID3 Algorithm with formative assessment
4	Silva and Restivo (2008)	Prediction of final year student mark based on collected students information	Apriori algorithm with criterion reference assessment
5.	Abdulaziz, H. (2008)	Higher education institution is to provide quality education to its students	Clustering techniques, classification, Association, prediction and decision tree with norm-referenced assessment.
6.	Airasian and Miranda (2002)	Predicting to analyse the student performance	SVM Classification algorithm like Decision tree, Naïve Bayes and support vector machine with diagnostic

			assessment.
7.	Al-Smadi&Gütl (2010)	To predict Students academic success	Classification and prediction(Decision tree algorithm) Unsupervised Algorithm with summative assessment.
8.	*Cashin, W. E., & Downey, R. G. (1999)*	The student information analysis system, which effectively improves the efficency of data mining	Association and Clustering analysis
9.	K Dharmarajan, K Abirami and KkBalasree, 2019	The main objective is to provide quality education to its students. To provide an overview on the data mining techniques that have been used to predict student's e-learning performance improvement using web data mining.	Fuzzy C Means Algorithm and Trajectory Algorithm with summative assessment.
10.	F. Castro, A. Vellido, À. Newbolt, 2007	All the correlated information should be conveyed to the class advisor before the conduction of final exam	Clustering technique, and K-Means with diagnostic assessment

RESEARCH GAPS AND RESEARCH CONTRIBUTIONS

From the summary in table one; we noticed that there are a lot of lapses on the existing e-assessment especially in the assessment mode of operation, this gap calls for need to integrate formative assessment in e-learning of many benefits of formative assessment which are:

i. Provide immediate feedback:- The entire premise behind formative assessment in e-learning is to give your learner the feedback they need to correct unfavourable learning behavior and strengthen desirable behaviours. To do this, your learners must get the feedback the need immediately after they make an error or carry out the negative behavior, so that they can link the constructive criticism to the e-learning event in question. If you notice that learner is not fully grasping the concept or is unable to apply the knowledge they have learned, then you should pause, discuss and offer them the required feedback and guidance as soon as possible.

ii. Student progress dictates the direction of your course:- One of the most notable benefits of using formative assessment in e-learning is that you can quickly modify your e-learning strategy to meet the individual needs of the learner. If you find that they are struggling with a particular topic or skill, you are able to see this right away. You can then customize the e-learning activities, assessment and curriculum to improve their comprehension and knowledge absorption rather than testing at the end, when it may be too late to modify incorrect learning behavior, you have the opportunity to remedy the issue during the learning process.

iii. Identify measureable strengths and weaknesses:- In order to get the most out of your formative assessment strategy you will need to have quantifiable data that you can actually track. Skills may be difficult to put into numbers and percentages, but you can give your learners online assessment periodically to track their mastery of certain skill sets. Have them complete a specific online scenario at different points throughout the e-learning course and keep track of their progress or give them a pop quiz that monitors how they are improving before you even began the e-learning course, encourage them to identify their strengths and weaknesses so that you know their learning gaps. Then you work with them to address their specific needs and pin point areas of improvement.

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