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A Survey on Clustering Techniques of Webinars to Support E-Learning Using Data Mining

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Abstract- This paper performs a detailed discussion about the clustering techniques being proposed by different researchers on Webinars in such a way to support E-Learning Methods. The growth of information technology has lead the learning methods towards webinar where the learner need not go to the place of the tutor or the institution. In providing efficient learning methods and to provide exact information to the learner, clustering the webinar's become more important. To solve the problem of clustering webinar's there are different approaches has been discussed from content based, context based, text based, Speech analysis based, and Ontology based. Each of the approach has their own merits and demerits. Also in the clustering, there are approaches like supervised and unsupervised and hierarchical clustering has been discussed. We explore each of them in detail and perform the analysis of each technique according to their performance in supporting E-Learning. The paper also discusses about different data miningtechniques could be adapted for E-Learning in detail.

Keywords-Learning, Clustering, Data Mining, Webinar, Semantic Ontology.

I. Introduction

The growth of internet technology and information technology has influenced different Sectors of human life like medical industries, manufacturing industries and many more. Similar to that, the information technology has more impact in educational sectors also. Earlier in this decade people uses, internet technology to read and learn about many things. Human peoples spend their most time in this decade to learn or knew about something with the internet. The development from this learning method has been adapted by different an educational organization that allows their students to learn through internet web technology. The process of learning through the internet technology has been known as E-Learning and the

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related webinars can be grouped according to many factors. Similarly, they can be represented based on their semantic meaning. The webinars can be grouped based on their semantic meaning and the semantic ontology. A classic example of learning method based on internet technology is video conferencing where the tutor takes the lesion from somewhere in the world but the student may be located in different geographic region of the world. The problem with this kind of learning is, the people have to be located in one location or in multiple locations. The educational organization may be providing number of courses in different domain like engineering, arts, and many more. Also they can be categorized into many courses into multiple levels. Now a day the universities allow the student to login in to their web page and learn by viewing the webinars. The question here is how good a learner or student has been understood about the seminar provided by any tutor. Here we need to think about the understanding factor about thewebinar being presented by any tutor. Also, there may be number of lessons, subjects presented by different authors or tutors. Theymust be organized in such a way that they could be fetched ineasy andefficient manner to provide more informatics webinars to the students of the educational organization. To provide such results, the webinars has to be grouped into number of classes or categories based on any factor. The process of grouping the webinars based on particular measure or factors is named as clustering. In this paper, we perform detailed analysis of clustering methods has been proposed by many authors and researchers in clustering the webinars to improve the quality of E-Learning.

A. Data Mining Techniques to support E-Learning:

The data mining techniques can be applied to support E-Learning and the clustering and classification processes of data mining can be used to improve the performance of the E-Learning. There are many clustering techniques has been proposed earlier in the literature to improve the performance of E-learning. We discuss about the general clustering techniques proposed earlier in this decade.

Context Based Clustering

In this kind of clustering, the webinars are clustered according to the context. The clustering algorithm maintains set of context and the webinar is identified below a specific context and grouped under the identified one.

Content Based Clustering

The content based clustering approach extract the features of the webinar and according to the extracted feature, the method computes the similarity between the other webinars or features present in different cluster. Based on the similarity of webinars a single class is identified as the group of the webinar. While considering content based clustering approach, there are many features to be included in case of webinar namely, voice, text, speech to text and so on. The process of clustering has the following stages:

Preprocessing

In the preprocessing stage, the clustering algorithm reads a single webinar from the given input set W_i, and separates the audio from the video given. From the extracted sound wave, the method identifies the starting of words and splits the waveform into tiny waves. The extracted and

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splitted waveform set will be given for the speech analysis.

Speech to Text Synthesizing

In this stage, the method maintains a large set of wave form which has waveform for different words and its equivalent text. The method compares with the each of the sound file and computes the wavelet analysis to compare the amplitude and frequency values of the sound file. Based on this the method computes the similarity between each of the sound file. There may be N number of words and sound files present in the single class; the method has to compare with all the sound files to compute the similarity. Based on computed similarity value a single wave file will be selected and concern text is identified as the result. The identified results are used to perform clustering.

Clustering

The term set generated from the speech analysis becomes the input for the clustering process. From the input set of terms, and the term set maintained for each class of topic or subject, the method computes the similarity measure which computes the similarity between the terms of class and the input term set. According to the similarity measure a single class will be selected and the webinar will be assigned to the concern selected class.

B.Types of Clustering

For clustering there are many techniques available which are discussed earlier, we discuss few of them here.

K-Means Clustering

K-means clustering approach performs grouping of web documents according to the similarity between the documents. The similarity of the document is computed based on the Euclidean distance between them. Initially, the k-means approach selects set of data points and assigns each cluster with initial data points. Then, it computes the Euclidean distance between all the data points of clusters to measure the similarity of data points. Based on the measured similarity the exchange of data point from one cluster to another will be done. This process will be iterated till there is no such exchange of data points between any of the cluster.

Hierarchical Clustering

The hierarchical clustering functions basically in joining closest clusters until the desired number of clusters is achieved. This kind of hierarchical clustering is named agglomerative because it joins the clusters iteratively. There is also a divisive hierarchical clustering that does a reverse process, every data item begin in the same cluster and then it is divided in smaller groups. The distance measurement between clusters can be done in several ways, and that's how hierarchical clustering algorithms of single, average and complete differ.

In the single-link clustering, also known as minimum method, the distance between two clusters is considered to be the minimum distance between all pairs of data items. In the complete link clustering, also known as maximum method, the distance between two clusters is considered to be the maximum distance between all pairs of data items. The clusters found by the complete link algorithm are usually more compact than the ones found by the single link. However, the single link algorithm is more versatile. In the average link clustering, the distance between two clusters is

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equal to the average distance between all data. A variation of this method uses median distance, which is less sensitive to greater data variation than the average distance.

Expected Maximization

The expected maximization algorithm does not have a training phase and starts with testing set and group them by iterative comparison. The method finds the parameters of the probability distribution and based on the probability value the class will be assigned to the data points. The algorithm's input are the data set (x), the total number of clusters (M), the accepted error to converge (e) and the maximum number of iterations. For each iteration, first is executed the E-Step (E-expectation), that estimates the probability of each point belongs to each cluster, followed by the M-step (M-maximization), that re-estimate the parameter vector of the probability distribution of each class. The algorithm finishes when the distribution parameter converges or reach the maximum number of iterations.

Dissimilarity Matrix Calculation

Dissimilarity may be defined as the distance between two samples under some criterion, in other words, how different these samples are. Considering the Cartesian plane, one could say that the Euclidean distance between two points is the measure of their dissimilarity. The Dissimilarity index can also be defined as the percentage of a group that would have to move to another group so the samples to achieve an even distribution. The Dissimilarity matrix is a matrix that expresses the similarity pair to pair between two sets. It's square, and symmetric. The diagonal members are defined as zero, meaning that zero is the measure of dissimilarity between an element and itself. Thus, the information the matrix holds can be seen as a triangular matrix. MARCHIORO et al. (2003) [1] used the matrix of dissimilarity to determine the differences between oat specimens and discover good generators for the future generations. The concept of Dissimilarity may be used in a more general way, to determine the pair wise difference between samples. As an example, this was used by da Silveira and Hanashiro (2009) [2] to study the impact of similarity and dissimilarity between superior and subordinate in the quality of their relationship. The similarity notion is a key concept for Clustering, in the way to decide which clusters should be combined or divided when observing sets. An appropriate metric use is strategic in order to achieve the best clustering, because it directly influences the shape of clusters. The Dissimilarity Matrix (or Distance matrix) is used in many algorithms of Density-based and Hierarchical clustering, like LSDBC. The Dissimilarity Matrix Calculation is used, for example, to find Genetic Dissimilarity among oat genotypes [1]. The way of arranging the sequences of protein, RNA and DNA to identify regions of similarity that may be a consequence of relationships between the sequences, in bioinformatics, is defined as sequence alignment. Sequence alignment is part of genome assembly, where sequences are aligned to find overlaps so that long sequences can be formed.

Density based clustering

The density based clustering works based on the density properties of the database is derived from a human natural clustering approach. By looking at the two-dimensional database showed in figure 1, one can almost immediately identify three

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clusters along with several points of noise. The clusters and consequently the classes are easily and readily identifiable because they have an increased density with respect to the points they possess. On the other hand, the single points scattered around the database are outliers, which means they do not belong to any clusters as a result of being in an area with relatively low concentration.

Fuzzy Clustering

Fuzzy C-means (FCM----Frequently C Methods) is a method of clustering which allows one point to belong to one or more clusters. The method was developed by Dunn in 1973 and improved by Bezdek in 1981 and it is frequently used in pattern recognition. The FCM algorithm attempts to partition a finite collection of points into a collection of C fuzzy clusters with respect to some given criteria. Thus, points on the edge of a cluster may be in the cluster to a lesser degree than points in the center of cluster. The FCM algorithm is based on minimization of the following objective function:

$$J(U, c_1 c_{2,\ldots,} c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} d_{ij}^{2}$$

The FCM is also known as fuzzy c-means nebulous because it uses fuzzy logic [Zadeh 1965] so that each instance is not associated with only one cluster, but has a certain degree of membership for each of the existing centroids. For this, the algorithm creates a matrix **U** associatively, where each term μ_{ij} represents the degree of membership of sample i to cluster j. In the FCM algorithm have a variable fuzziness m such that $1.0 < m < \infty$ where m and being a real number. The closer m is to infinity (∞), the greater the fuzziness of the solution and the closer to 1, the solution becomes increasingly similar to the clustering of binary k-means [Bezdek 1981]. A good choice is to set m = 2.0.

You can see both the k-means and FCM together in the same pseudo-code described in (Algorithm 1). In it, we have the k-means or FCM only by changing the formula to calculate the terms μ_{ij}, changing the average fuzzy [Zadeh 1965] for a binary choice, showing that FCM is indeed the K-Means cloudy.

In (Algorithm 1), the manner stating that $|A-B|^2$ is the distance away Euclidean to the a to b taking as input: set of samples x_i ($1 < i < N$), plain number of clusters K factor cloudiness me a factor of Tolerance, we leave on the: a cluster vector c_i ($1 < i < K$) and a matrix U determines the associatively of each sample with each of the clusters. It should be noted that the values of the matrix U depend only on H (array that stores the distances are the examples of clusters) and the value of m. The upgrade of the clusters depends solely on the values of the iteration matrix U in iteration.Similarly there is N number of clustering techniques like graph based techniques and so on. Whatever be the algorithm used, to cluster the webinars the above discussed procedure is mandatory.

II .Literature Review

In this section, we discuss about the different approaches discussed earlier by the researchers to cluster the webinar and to cluster e-learning documents. Exploratory study of multi-criteria recommendation algorithms over technology

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enhanced learning datasets (Nikos Manouselis,2014) [1], investigate such a real life implementation of a multi-criteria recommender system and try to identify the needed adjustments that need to take place in order for it to better match the requirements of its operational environment. More specifically, we examine the case of a multi-attribute collaborative filtering algorithm that has been supporting the recommendation service within a Web portal for organic and sustainable education. Our study particularly explores the experimental performance of the already implemented algorithm, as well as an alternative one, using data from the intended application, a simulated expansion of it, and from similar portals. The results of this study indicate the importance of the frequent experimental investigation of a recommender system's various design options, and the need for the exploration of adaptive implementations in real life recommender systems.

Slow Learners: Role of Teachers and Guardians in Honing their Hidden Skills [2], to create greater awareness and discussion about slow learners. Learners in this category will exist in almost every class, yet at present a systematic way of identifying and supporting them does not exist. There is no doubt that the individual teachers have developed many effective techniques for supporting those learners who need additional help. It would be valuable therefore if opportunities could be created for teachers to share and discuss their work with slow learners. It is also important for further research to build on this initial study to develop guidelines to assist teachers in supporting slow learners.

Using Learning styles data to inform e-learning design : A study comparing undergraduates [4], details mixed-methods research with three cohorts teaching and learning in e-learning environments in higher education: novice undergraduate e-learners, graduate e-learners, and educators teaching in, or designing for, e-learning environments (Willems, 2010). Quantitative findings from the Index of Learning Styles (ILS) (Felder & Silverman, 1988; Felder & Soloman, 1991, 1994) reflect an alignment of the results between both the graduate e-learner and e-educator cohorts across all four domains of theILS, suggesting homogeneity of results between these two cohorts. By contrast, there was a statistically significant difference between the results of the graduate and educator cohorts with those of the undergraduate e-learners on two domains: sensing-intuitive ($p=0.015$) and the global-sequential ($p=0.007$), suggesting divergent learning style preferences. Qualitative data was also gathered to gain insights on participants' responses to their learning style results.

A Model for an Intelligent and Adaptive Tutor based on Web by Jackson's Learning Styles Profiler and Expert Systems [5], integrates an intelligent and web-based E-Learning with expert system technology to be able to model the learning styles of the learners using Jackson's model. It is intelligent because it can interact with the learners and offer them some subjects in Pedagogy view. Learning process of this system is in the following. First it determines learner's individual characteristics and learning styles based on a

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questionnaire in Jackson's learning styles profiler. Learning styles profiler is a modern measure of individual differences in learning style. Then learner's model is obtained and an Expert system simulator plans a "pre-test" and rates him. The concept would be presented if the learner scores enough. Subsequently, the system evaluates him by a "post-test". Finally the learner's model would be updated by the modeler based on try-and-error. The proposed system can be available Every Time and Every Where (ETEW) through the web. It improves the learning performance and has some important advantages such as high speed, simplicity of learning, low cost and be available ETEW.

A Dynamic Web Mining Framework for E-Learning Recommendations using Rough Sets and Association Rule Mining [7], attempts to engage e-learners at an early stage of learning by providing navigation recommendations. E-learning personalization is done by mining the web usage data like recent browsing histories of learners of similar interest. The proposed method uses upper approximation based rough set clustering and dynamic all k^{th}order association rule mining using Apriori for personalizing e-learners by providing learning shortcuts. The essence of combing association rule and clustering is that, using clustered access patterns can reduce the data set size for association rule mining task, and improves the recommendation accuracy.

Student Learning Ability Assessment using Rough Set and Data Mining Approaches [9], all learners are not able to learn anything and everything complete. Though the learning mode and medium are different in e-learning mode and in classroom learning, similar activities are required in both the modes for teachers to observe and assess the learner(s). Student performance varies considerably depending upon whether a task is presented as a multiple-choice question, an open-ended question, or a concrete performance task. Due to the dominance of e-learning, there is a strong need for an assessment which would report the learning ability of a learner based on the learning skills under various stages.

Effectiveness of Data Mining – based E-learning system [10], E-learning is emerging as the new paradigm of modern education. Most of the e-learning systems have limitations such as scarcity of content, lack of intelligent search and context sensitive personalization problems, which are the challenging tasks for researchers. This motivated the author to take up this problem and the method implemented through this work suggests the instructors to use the combination of the data mining based e-learning system (DMBELS) was designed. The main aim of the model developed is to get consistency in content delivery, quality content in learning materials, students self-learning concept, and performance improvement in their examination. A study has been conducted to measure the effectiveness of data mining technique based e-learning system (DMBELS) among the students of SCSVMV University in concepts of First Aid awareness course.

Using Instructive Data Mining Methods to Revise the Impact of Virtual Classroom in E-Learning [11], in the past few years, Saudi universities have boarded to utilize e-learning tools and technologies to expand and look up their educational services. After a few years of carrying

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out e-learning programs, a discussion took place within the directors, supervisors, executives and managers or decision makers of the e-learning associations regarding which activities are the most impact on the learning development for online students. This research is expected to inspect the impact of a number of e-learning actions on the students' learning development. The results show that involvement in virtual classroom sessions has the most considerable impact on the students' final scoring or grade. This paper presents the procedure of applying data mining methods to the web observing records of students' behaviors in a practical learning environment. The main idea is to rank the learning activities supported on their importance in order to develop, students' performance by focusing on the most important ones.

An Educational Data Mining Model for Online Teaching and Learning [12], this study contains two major parts. First, this study proposed a generic model for Educational Data Ming (EDM) studies by reviewing EDM literature and the existing data mining model. Second, the procedures of the EDM model are demonstrated with a case study approach. The case study results showed patterns and relationships discovered from the EDM model that could be applied to improve online teaching and learning and to predict students' academic performances.

An e- Learning Recommendation System using Association Rule Mining Technique [13], the fast growth of e-learning around the world is inspiring many educational and business institutions to adopt the adaptive personalized method of teaching and learning. However the success of E-learning does not depend only on the academic setup but also on proper realization of its vital requisites. This paper presents an idea for building recommendation system for the e-learning system using Association Rule Mining Techniques for the best selection of e-learning resources or learning materials. This paper analyzes students' log of a Learning Management System (LMS) Model, and data gathered from a survey dataset addressing students academic, interaction and personal information. Data mining and statistical tools have been used to find relationships between students' LMS access behavior, study habits and overall performances.

A Dynamic Web Mining Framework for E-Learning Recommendations using Rough Sets and Association Rule Mining [15], attempts to engage e-learners at an early stage of learning by providing navigation recommendations E-learning personalization is done by mining the web usage data like recent browsing histories of learners of similar interest. The proposed method uses upper approximation based rough set clustering and dynamic all kth order association rule mining using Apriori for personalizing e-learners by providing learning shortcuts. The essence of combing association rule and clustering is that, using clustered access patterns can reduce the data set size for association rule mining task, and improves the recommendation accuracy.

Data mining for Individualized Hints in eLearning [16], present a tool where both past and current student data is used live to generate hints for students who are completing programming exercises during a national programming online tutorial and competition. These hints can be links to notes that are relevant to the problem detected

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and can include pre-emptive hints to prevent future mistakes. Data from the year 2008 was mined, using clustering, association rules and numerical analysis, to find common patterns affecting the learners' performance that we could use as a basis for providing hints to the 2009 students. During its live operation in 2009, student data was mined each week to update the system as it was being used. The benefits of the hinting system were evaluated through a large-scale experiment with participants of the 2009 NCSS Challenge. We found that users who were provided with hints achieved higher average marks than those who were not and stayed engaged for longer with the site.

Using data warehouse and data mining resources for ongoing assessment of distance learning [20], discusses the use of Data Warehouse and Data Mining resources to aid in the assessment of distance learning of students enrolled in distance courses. Information considered relevant for the assessment of distance learning is presented, as is the modeling of a data warehouse to store this information and the MultiStar environment, which allows for knowledge discovery to be performed in the data warehouse.

Smart Recommendation for an Evolving e-Learning System: Architecture and Experiment [23], propose two pedagogy features in recommendation: learner interest and background knowledge. A description of paper value, similarity, and ordering are presented using formal definitions. We also study two pedagogy-oriented recommendation techniques: content-based and hybrid recommendations. We argue that while it is feasible to apply both of these techniques in our domain, a hybrid collaborative filtering technique is more efficient to make "just-in-time" recommendations. In order to assess and compare these two techniques, we carried out an experiment using artificial learners. Experiment results are encouraging, showing that hybrid collaborative filtering, which can lower the computational costs, will not compromise the overall performance of the RS. In addition, as more and more learners participate in the learning process, both learner and paper models can better be enhanced and updated, which is especially desirable for web-based learning systems. We have tested the recommendation mechanisms with real learners, and the results are very encouraging.

A Two-Phase Fuzzy Mining and Learning Algorithm for Adaptive. Learning Environment [24], propose a Two-Phase Fuzzy Mining and Learning Algorithm, integrating data mining algorithm, fuzzy set theory, and look ahead mechanism, to find the embedded information, which can be provided to teachers for further analyzing, refining or reorganizing the teaching materials and tests, from historical learning records.

Data mining techniques for teaching result analysis using rough set theory [29]: proposes a concept map for each student and staff and finds the result of the subjects and also recommending for sequence of remedial teaching. This paper uses rough set theory for dealing with uncertainty in the hidden pattern of data. For each competence the lower and upper approximations are calculated based on the brainstorm.

Analysis of New Teaching Model for Undergraduates in University Based on the

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Environment of Information Technology - A Case Study [30], for Specialty of Information Management & Information System: proposes and explains three new teaching models in detail. Thirdly, based on analysis of the ability system for the specialty of information Management & Information System, this paper tries to design the new teaching models and construct a framework for platform of teaching for undergraduate based on networks. Finally, a design concept of the platform is discussed detailed.

Experience from teaching performance analysis of object-oriented systems [31]: reports the experience from teaching "Performance Analysis of Object-Oriented Systems" which was offered for the first time in the spring of 2004. The class was designed for juniors/seniors and graduate students majoring in Computer Science and Computer Engineering. The main focus of this course is on the implementations of class loading, Just-In-Time compiler, threading, and garbage collection in virtual machines supporting Object-Oriented languages such as Java and C#. We adopted Microsoft Shared Source Common Language Infrastructure (SSCLI) as the main experimental platform and the "Shared Source CLI Essentials" as one of the main accompanying textbooks. We find that the combination of SSCLI and the book provides a very effective means to deliver the course contents. In this paper, a complete documentation of the course design, the evaluation of students' work, and the instructor's reflection is presented

Impact of E-learning system using Rank-based Clustering Algorithm [32], implemented through this work suggests the instructors to use the combination of E-learning System Using Rank-Based Clustering Algorithm (ESURBCA) was designed. The main aim of the model developed is to get consistency in content delivery, quality content in learning materials, students self-learning concept, and performance improvement in their examination. A study has been conducted During June 2013 to September 2013, the author collected samples of 1631 from final year and Second year of BCA, B. SC and B. Sc-IT students were trained through e-learning system architecture and the objectives of this study is 1. To measure the effectiveness of E-learning System Using Rank-Based Clustering Algorithm (ESURBCA) among the students of Mercury College of arts and science And Sankara arts and Science College in concepts of Programming in JAVA Course. The newly designed E-learning System using Rank-Based Clustering Algorithm (EUSRBCA) shows an improvement over the existing systems with better results. From the various evaluations carried out, the performance of the system found to be good comparatively to other systems in e-learning domain.

A Clustering Methodology of Web Log Data for Learning Management Systems [33], proposed a methodology for analyzing LMS courses and students' activity. This methodology uses a Markov Clustering (MCL) algorithm for clustering the students' activity and a Simple KMeans algorithm for clustering the courses. Additionally we provide a visualization of the

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results using scatter plots and 3D graphs. We propose specific metrics for the assessment of the courses based on the course usage. These metrics applied to data originated from the LMS log files of the Information Management Department of the TEI of Kavala. The results show that these metrics, if combined properly, can quantify quality characteristics of the courses. Furthermore, the application of the MCL algorithm to students' activities provides useful insights to their usage of the LMS platform.

Cluster Analysis of Behavior of E-learners [34], proposes the analysis of students' behavior using data mining tools and techniques. Classification and clustering techniques are used to analyze the relationship between usage of courses and performance of students. Students' performance depends upon their grades, how much time they spend in learning, usage of courses as well as richness of course quality. The study uses data from previous approach, E-learning data from Greek University. This paper uses same approach with different data mining tools and techniques.

Generic agent based Cloud Computing architecture for E-Learning [39], proposes Agent based e-learning which is helpful in managing the information overload, it can serve as academic expert and manages creation of programming environment for learners. There are many characteristics that an E-learning environment has to support; they are Interaction, Data Security, User Personalization, Adaptability, Intelligence, Interoperability, Accessibility and User Authentication. E-learning must also support a few other features like cost effectiveness, reusability, storage capacity, powerful computing and virtualization which can be provided by Cloud computing.

Cloud e-Learning: A New Challenge for Multi-Agent Systems [40], proposes that Cloud e-Learning, a new approach to e-learning, will open opportunities for learners, by allowing personalization, enhancing self-motivation and collaboration. The learners should be able to choose what to learn, what sources to use, with and by whom, how and in what pace, what services and tools to use, how to be assessed, whether to get credits towards a degree etc. In such a dynamic environment, the need for Multi-Agents Systems is necessary. Actors in Cloud e-Learning would need automated facilitation in all services involved. We outline few indicative scenario for Cloud E-Learning in which smart agents will act on behalf of the learners, teachers and institution in order to maximize the benefit of the proposed concept.

From the review of the literature, the methods are proposed to cluster the web log data or web documents to support E-Learning, which suffers with the problem of clustering webinars and to support E-Learning.

III. Comparative Study

The different approaches have been evaluated in the performance of Predicting user interest and generating recommendations to the E-Learners. Each method has their own merits and demerits but the quality of providing E-learning support only can be measured by the understandability and the rate of vision and how informatics the webinar is and so on. According to the above discussion and the factors, we have compared the performance of the methods

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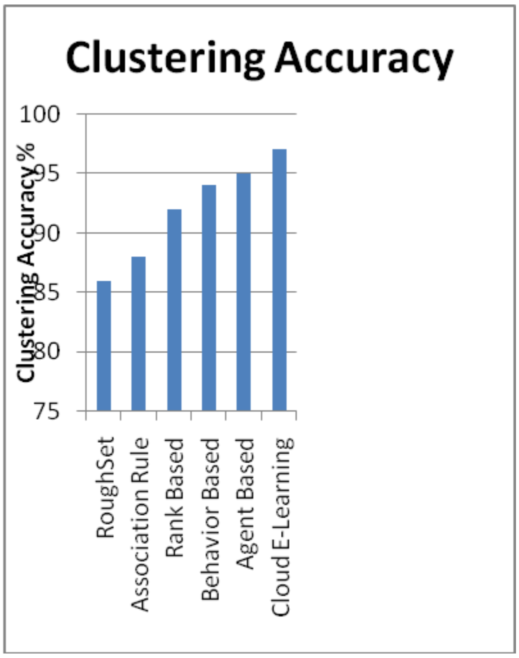
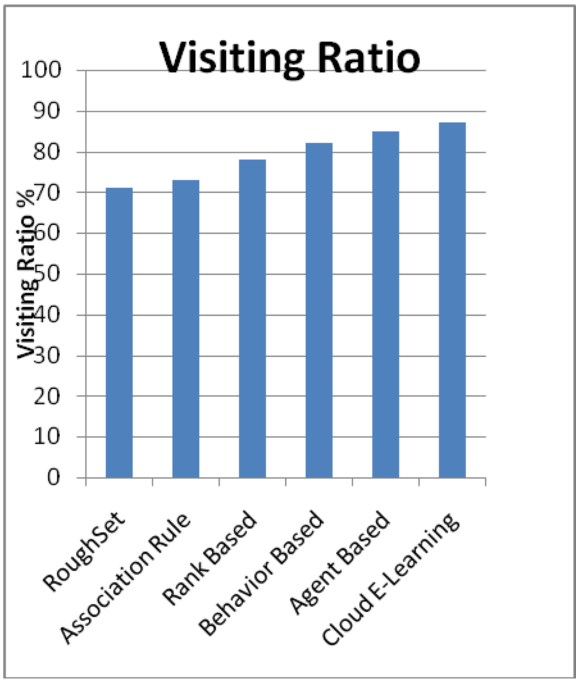
discussed as follows: Even though there are many approaches discussed in the literature, we found comparing the efficiency of the few methods will be an optimal one and compare their efficiency as follows:



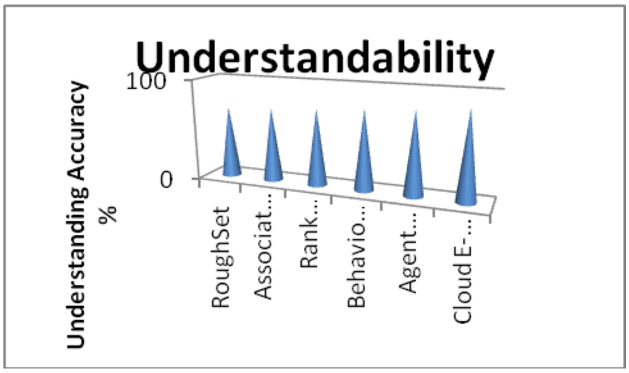
Graph 1: Comparative Result of Clustering Accuracy

Graph1 shows the comparative result of clustering accuracy produced by different methods and it shows that each method has different clustering accuracy and Cloud E-learning has more accuracy than other methods.



Graph 2: Comparison of Visiting Ratio

The graph 2 shows the comparison result of visiting ratio produced by different methods. It shows that the visiting ratio of webinars becomes higher when they are grouped in a cloud than other methods.



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Graph 3: Comparison result of understanding ratio

The graph 3 shows the comparative result on understanding ratio which has been performed by collecting the feedback of different learners. It shows the method has understandability as less one.

IV. Conclusion

In this paper, the E-Learning methods and recommendation systems with different clustering mechanism has been reviewed in detail. Different methods uses different clustering algorithm and they rank the webinars based on number of factors. But they produce only an average efficiency in E-Learning which is not suitable for modern day's education. There are number of webinars presented by different tutors and they are not clustered based on content but most of the methods cluster the webinars based on the Meta data. This reduces the quality of E-Learning recommendation and requires further research in this area of clustering webinars and need research in recommendation systems.

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