LEARNING STYLES BASED COLLABORATIVE FILTERING FOR E-LEARNING RECOMMENDER SYSTEM

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CERTIFICATE

This is to certify that the dissertation entitled "**Learning Styles Based Collaborative Filtering for E-Learning Recommender System**", being submitted by **Pragya Dwivedi** to the School of Computer and Systems Sciences, Jawaharlal Nehru University, New Delhi, in partial fulfillment of the requirement for the award of the Degree of **Master of Technology in Computer Science and Technology**, is a bona fide work carried out by him under the guidance and supervision of **Prof. K. K. Bharadwaj**.

The matter embodied in the dissertation has not been submitted for the award of any other Degree or Diploma.

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ABSTRACT

The recent development in multimedia technology and emergence of the Internet has a great impact on education. E-learning, broadly refers to online learning through courses and training, is becoming more prevalent. A good e-learning system delivers appropriate learning materials to learner at the time and locations to facilitate learners' acquisition of knowledge and skills. Generally the technology of recommender system (RS) has traditionally focused on e-commerce activities and is used various techniques to select items for the users according to their interest. However, applying these techniques in eLearning scenarios is not a straight forward approach, since the context and specific goals are different.

Personal preferences of users have a great impact on recommendation. In the domain of e-learning RS these personal preferences like learner's goal, learning styles, learning path etc., plays an important role in improving and enhancing the educational aspects of learners.

Learning style being one of the most important preferences of learners is considered in our proposed e-learning RS. In order to analyses the effect of learning styles on recommendation we first employed GA K-means algorithm on learning styles, for finding the best clusters and then recommendations are generated using collaborative filtering. Experimental results demonstrate that incorporating the learner's learning styles with collaborative filtering enhances accuracy of prediction.

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Chapter 1

Introduction

1. Introduction

Now the era is internet era, internet accessing is the part of life, because every information is present on web. Due to overloading of information, search becomes difficult. For solving such type of problems recommender system is introduced on web.

Recommender systems have become an important research area .There has been a lots of work done both in the industry and academics on developing new approaches for recommender systems over the previous years. It constitutes a problem-rich research area, because of the copious of practical applications that help users to deal with information superfluity and provide personalized recommendations, contents, and services to them (Adomavicius & Tuzhilin, 2005). In industry field like e-commerce environment there are so many examples like Amazon.com (Linden, 2002) recommender system for book recommendation etc. In academics environment like E-learning recommender system.

E-learning means "The delivery of a learning, training or education program by electronic means, like computer based" (Derek Stockley2003)

In competitive era e-learning is playing a major role, it is very useful for those people that have no time to attend the classes ,it provides the learning any where , any time . There are so many techniques that are applied on user's characteristics for reaching the user's best need.

E-learning can include greater varieties of equipments such as CDs and DVDs and in online training or education as the name implies, "online" involves using the Internet. CDs and DVD can be used to provide learning materials offline. Distance education provided the base for e-learning's development. E-learning can be "on demand". It overcomes the problem of timing, attendance and travel difficulties. One of the most covet characteristics of e-learning systems is that of being personalized (Khribi, 2008) since they have to be used by a wide variety of students with different skills. Different students want to learn in different ways. Some of them process information reflectively while others actively. Some students prefer abstract material while others prefer concrete examples. Thus, to be effective, e-learning systems should consider each student's learning preferences and skills.

E-learning recommender systems that provide recommendations to the users, related to subjects, users learning styles, their behavior. In E-Learning, recommender systems deals with information about learners and learning activities and recommend items such as papers, web pages, and other reading materials which meet the pedagogical characteristics and interests of learners(Lee & Duncan, 2007). Collaborative filtering approach has also been used in many recommender systems in E-Learning for reducing the complexity of the recommendation process.

1.1 Recommender Systems

Recommender Systems are a step towards paradigm shift from "search to discovery". It is internet based software tool that enables the users to be presented items which they may not know of, thus supporting "discovery rather than search".

Due to explosive growth of web, there is huge amount of information available on the web resulting in information overload which is a major problem for the users. RSs deal with this information and product overload and make the suggestions most relevant to the user's preference (Mobasher, et al., 2000). Recommender system have their way into many entertainment and e-commerce sites(Schafer, et al., 2001)and not only help people find items of interest but also form communities of interest(Terveen & Hill, 2001).

Recommender systems (RSs) cover an important field within collaborative services that are developed in the Web 2.0 environment and enabling the users to explore their opinion in a sophisticated and powerful way (Bobadilla, et al., 2009) RS can be considered as social networking tools that provide dynamic collaborative communication, interaction and knowledge.

RSs comprise a wide variety of applications, although, those related to movie recommendations are the most well-known and most widely-used in the research field Nevertheless, the collaborative e-learning field is strongly growing, it consider the various aspects like education, training, materials related to courses.

1.1.1 Recommender systems techniques

- **Collaborative filtering (CF)**

Collaborative recommender systems (or collaborative filtering systems) try to predict the utility of items for a particular user based on the items previously rated by other users. More formally, the utility u(p, I) of item I for user p is estimated based on the utilities u(p_j ,I) assigned to item s by those users $p_j \epsilon P$ who are "similar" to user p.

In brief we can say

The user will be recommended items people with similar tastes and preferences liked in the past. (Adomavicius & Tuzhilin, 2005).

For example, in a movie recommendation application, in order to recommend movies to user p, the collaborative recommender system tries to find the "neighbours" of user p, i.e., other users that have similar tastes in movies (rate the same movies similarly). Then, only the movies that are most liked by the "neighbours" of user p would be recommended. A different approach popularized by Amazon(Linden, et al.,2003)is the item based CF. where association among items are established using historical rating information. Item based CF performs is better than user based CF when number of item is relatively static (Sarwar, et al., 1998).

For CF there are three steps process –

- Similarity measurement- Pearson similarity measure, cosine similarity etc. (Anand, et al., 2007).
- Neighbourhood generation (Jameson, et al., 2003).
- Prediction using Resnick formula (Resnick, et al.,1994)

Advantages

- To identify cross-genre niches
- No overspecialization and adaptiveness

Disadvantages

- Sparsity (Zhang & Pu, 2007; Billsus & Pazzani,1998).
- Scalability and cold-start (Adomavicius & Tuzhilin, 2005).

- **Content-based filtering (CBF)**

'The user will be recommended items similar to the ones he preferred in the past.'

For example, in a movie recommendation application, in order to recommend movies to user c, the content-based recommender system tries to understand the commonalities among the movies user c has rated highly in the past (specific actors, directors, genres, subject matter etc.). Then, only the movies that have a high degree of similarity to whatever the user's preferences are would be recommended.

For finding similarity between items some similarity measures are used as-

Pearson similarity measure, cosine measurement etc. and Resnick formula is used for prediction. Example of such systems is NewsWeeder.

Advantages

- No requirement of domain knowledge
- Adaptiveness and implicit feedback sufficient

Disadvantages

- Limited content analysis
- Overspecialization
- New user ramp-up problem (Adomavicius and Tuzhilin, 2005),
- Scalability (Bell, et al.,2007).

- **Utility-based recommendations**

Utility based recommenders make suggestions based on a computation of the utility of each object for the user. The utility function(Manouselis & Costopoulou, 2007). may be gathered using a dialogue between the system and the users to infer which product features does the user emphasize on.

For example to recommend a home, an e- commerce site asks the user how important the home features. (Burke., 2002).

- **Knowledge-based recommendations**

Knowledge-based recommendations attempts to suggest object based on inferences about a user's needs and preferences(Burke, 2002). Knowledge based recommender system avoid the ramp-up problem, because its recommendations does not depend upon user ratings. It does not have collaborative information about user because it judgment not depend upon individual taste. Popular knowledge based recommender systems are recommender.com and Entrée system (Burke, 2002)

- **Demographic filtering**

Categorize the user based on demographic attributes such as age, gender education etc. and recommendation are based on these demographic features. The main advantage of demographic filtering that it does not rely on user's rating history so avoid the new user problem.

Examples are Lifestyle finder (Krulwich, 1997) one of the most popular recommender system, which assign s user to one of 62 preexisting clusters based on few concerning the user lifestyle.

Another approach of demographic filtering is to collect the information using web pages (Pazzani, 1999).

- **Hybrid recommender system**

There are different methods to combining various techniques to implement new approach different hybridization techniques such as switching , weighted, mixing, cascade etc. (Burke, 2002).Collaborative filtering hybridized with content based and demographics features(Al Shamri & Bharadwaj,2008). Hybrid of Content and Collaborative is used by Fab (Balabanovic & Shoham, 1997).

1.2 E-learning

Electronic learning (or **E-Learning** or **eLearning**)

It is a type of Technology supported education and training where the medium of instructional delivery is computer-based. *(Wikipedia, 2008)*

Today technology in information system changes also the state of art in education .There is tremendous trend towards e-Learning to access huge amount of information world–wide. E-Learning is an umbrella term that describes the learning done at a computer it is usually connected to a network giving us the opportunity to learn everything anytime, anywhere. E-Learning can be as rich and as valuable as classroom experience or even more. (Tan and Guo , 2008).Instruction based design for e-Learning has perfected and refine over many years using established teaching principles with many benefits to students. *E-Learning* is used exchangeable in a wide variety of contexts. In companies, it refers to the strategies that use the company network to deliver training courses to employees (Wikipedia, 2008).for an example , In the United states, it is defined as a planned teaching/learning experience that uses a wide spectrum of technologies, mainly Internet or computer-based, to reach learners. If we take the example of Universities, e-learning is used to define a specific mode to attend a course or programs of study where the students rarely, if ever, attend face-to-face for on-campus access to educational facilities likes e-books, articles, because they study online(Chao & Chen, 2009).

1.2.1 Recommender system for e-learning

Because of rapid increase of learning content on the web, it will be time consuming for learners to find contents they really want to need to study .It's very challenging task to offer the right thing to right person in right way (Yu, et al. , 2007).

Recommender systems for e-Learning need to consider the specific demands and requirements and improve the educational aspect of learner (Tan and Guo , 2008.). E-Learning recommender systems deal with information about learners, learning activity and recommend items such as papers, WebPages, reading materials to meet specific interest of learners. Individual context of the learner and underlying domain are the most influencing factors for e-learning recommender system, which differs from other RSs.

1.2.2 Learning styles

Learning style is an indicator of how a student learns and likes to learn

(Gregorc & Ward,1977; Chu, et al., 2009).

Every student have different characteristics, different preferences. so it's very necessary to considers the learners preferences to reach the users need. With the popularization of Internet, the demand of e-learning has greatly increased. Numerous research works related to e-learning have been done to enhance teaching and learning quality in e-learning environments. Among these studies, researchers have pointed out that adaptive learning is a critical requirement for exalting the learning performance of students. Adaptive learning provides the adaptive learning materials, learning strategies and/or courses according to a student's learning styles. Successfully teaching addresses the needs of the individual student (Learning style is an indicator of how a student learns and likes to learn (Gregorc & Ward,1977; Chu, et al., 2009). Hence, the first step for achieving adaptive learning environments is to identify students' learning styles.

Learning styles are divided into different dimension like visual\verbal, sequential\global etc. ,each play a major role in recommendations. It is an important aspect of personalization in web based learning.

1.3 GA K-means

- **Genetics Algorithm**

Genetic algorithm is stochastic search technique that can search large and complicated spaces. It is based on biological phenomenon as natural genetics and evolutionary principle. In particular, GAs is suitable for parameter optimization problems (Goldberg, 1989). with an objective function subject to various hard and soft constraints (Shin & Han, 1999). The GA generally solves a complex space in an efficient way, follow by the biological evolution of selection, crossover, and mutation. This algorithm uses natural selection, survival of the fittest, to solve optimization problems (Kim, 2004).

The first stage of GA is problem representation. The problem must be represented in a simple and appropriate so easily manipulated by the GA. Thus, the problem is described in terms of genetic code, as chromosome DNA. The GA often works with a form of binary encoding. If the problems are coded as chromosomes, a population is initialized - a set of chromosomes. Each chromosome in a population gradually evolves from biological operations. There is no general rule for determining the population size. Once the population size is chosen, the initial population is randomly generated (Bauer, 1994). After the initialization step, each chromosome is evaluated by a fitness function. Depending on the value of the fitness function, chromosomes associated with those most suitable will be reproduced more often than those related to individuals unfit (Davis, 1994).The GA works with three operators that are iteratively used. The selection operator determines which individuals may survive (Hertz & Kobler, 2000).

(a) Crossover crossover operator allows the search to fan out in various directions looking for effective and attractive solutions. It allows that crossover is performed between two selected individuals, called parent, by exchanging part of strings starting from randomly chosen crosspoint . There are three crossover methods:
single point, two-point, and uniform.

- **Single point crossover** A crossover operator that randomly selects a crossover point within a chromosome then interchanges the two parent chromosomes at this point to produce two new offspring .Consider the following 2 parents which have been selected for crossover.

Parent1:	1	0	1	1	0	1	1	0
Parent2:	0	1	0	1	1	0	0	1

After interchanging the parent chromosomes at the crossover point, the following offspring are produced

Offspring1:	1	0	1	1	1	0	0	1
Offspring2:	0	1	0	1	0	1	1	0

Figure 1.1: One point crossover

- **Two Point crossovers**

  A crossover operator that randomly selects two crossover points within a chromosome then interchanges the two parent chromosomes between these points to produce two new offspring.

  Consider the following 2 parents which have been selected for crossover.

Parent1:	1	1	0	0	1	1	0	0
Parent2:	0	0	1	1	1	1	1	1

After interchanging the parent chromosomes between the crossover points, the following offspring are produced:

Offspring1:	0	0	0	0	1	1	1	1
Offspring2:	1	1	1	1	1	1	0	0

Figure 1.2: Two point crossover

(b) Mutation: Mutation is a genetic operator that is used to maintain the genetic diversity of a generation of a population of chromosomes algorithm to another. The basic example of a mutation operator involves a probability that a bit arbitrary in a gene sequence will be modified from its original state. A common method of implementation of the mutation operator is to generate a random variable for each bit in a sequence. This random variable says whether or not a particular bit will be modified. This transfer procedure, based on the biological mutation is called single point mutation. Other types are the inversion and mutation in floating point. The aim of the gases transformation is the preservation and introduction of diversity. Mutation algorithm to avoid local minima by preventing the population of chromosomes from becoming too similar to each other, slowing or even stopping evolution. This manipulation also extract the fact that most GA systems avoid only taking the fitness of the population in the production of the next selection, but rather a random (or semi-random) with a weighting towards those who are better form.

1	0	1	1	1	0	**0**	1	$\longrightarrow$	1	0	1	1	1	**1**	0	1

Figure 1.3: Mutation

Finally, the GA tends to converge on an optimal or near-optimal solution through these operators (Wong & Tan, 1994) The GA is commonly used to improve the performance of complex techniques of artificial intelligence.

❖ K-means Algorithm

The K-means method is a widely used clustering procedure that searches for a nearly optimal partition with a fixed number of clusters. It uses an iterative partition approach. The process of K-means clustering is as follows:

a) Firstly choosing randomly initial seed that present as the number of clusters, K is selected and an initial partition is built by using the seeds as the centroids of the initial clusters.
b) By some formulation each record is assigned to the centroid that is nearest, thus forming a cluster.
c) Keeping the same number of clusters, the new centroid of each cluster is calculated.
d) Iterate Step (b) and (c) until the clusters stop changing or stop conditions are satisfied.

The K-means algorithm has been popular because of its ease and simplicity of application. However, it also has some drawbacks. First, it does not deal properly with overlapping clusters and clusters can be removed from the center by outliers. In addition, the result may depend on seed initial consolidation, but there is no mechanism to optimize the initial seed.

GA has been used to overcome the limitations of traditional clustering algorithms which is K-means algorithm.(Lletı′,et al., 2004) proposed the use of the integrated genetic algorithm and K-means clustering to select relevant input variables. GA K-means uses GA to select optimal or sub-optimal initial seeds in K-means clustering.

In this dissertation, we propose recommender systems for e-learning, based on learner's learning styles. Here we are using clustering technique GA K-means on learning styles and also compute prediction by the technique of collaborative filtering.

1.4 Structure of thesis

The rest of thesis is organized as follows. Chapter 2 presents relevant information about E-learning, role of recommender system in e-learning and some characteristics like learning style of learner. GA k-means algorithm applies on learning style and collaborative filtering based prediction discussed in Chapter 3. Experimental result is presented in Chapter 4. Finally, Chapter 5 presents conclusions and future work.

Chapter -2

E-learning Recommender systems

2. E-learning recommender systems

In this chapter, we describe e-learning, why it is useful? Where it is required? E-learning merits & demerits (Lee, 2007). Focusing on the recommender systems for e-learning. These recommender systems are based on different preferences of learners. Here we mainly emphasize on learner's learning styles that are classified in many dimensions.

2.1 E-learning

E-Learning pioneer Bernard Luskin argues that the "E" must be understood to have broad meaning if e-Learning is to be effective. Luskin says that the "e" should be interpreted to mean exciting, energetic, enthusiastic, emotional, extended, excellent, and educational in addition to "electronic" that is a traditional national interpretation.

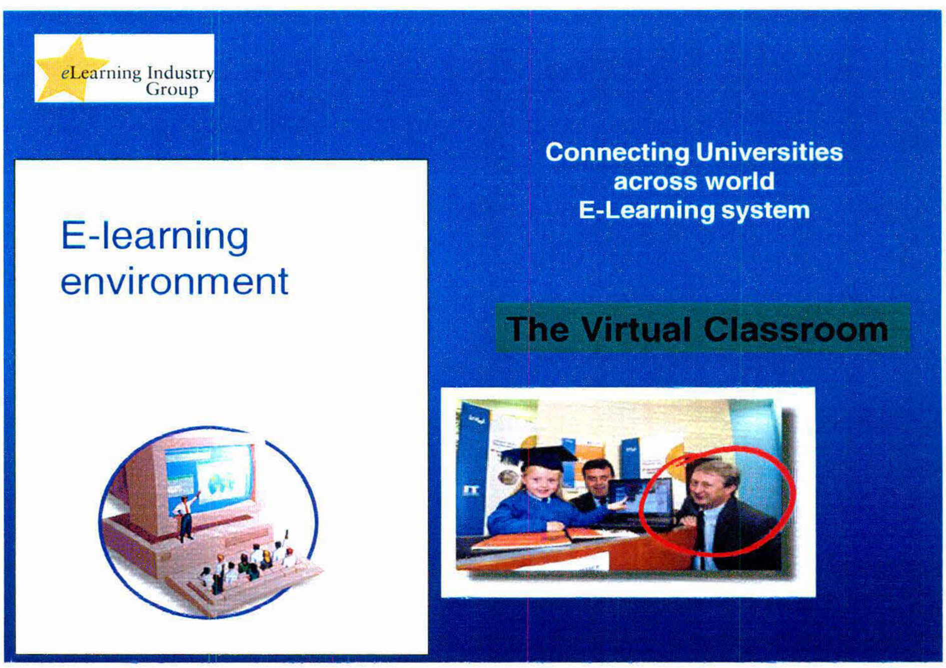

Figure 2.1 E-learning Environment

In higher education especially, the growing trend is to create a virtual learning environment (VLE) (which is sometimes combined with a system of information management (MIS) to create a Managed Learning Environment) in which all aspects of a course are handled by a coherent user interface standard throughout the institution. A growing number of physical universities, colleges and new online only began offering a limited set of degree and certificate programs via the Internet to a wide range of levels and across a wide range of disciplines(Chao & Chen, 2009). While some programs require students to attend some campus classes or orientations, many are delivered completely online. In addition, several universities offer online services to help students, such as advice and online registration, e-counseling, online textbook purchase, student governments and student newspapers.

E-Learning can also refer to educational web sites such as those offering learning scenarios, assignments ,worksheets and interactive exercises for learner .The term is also used extensively in the business sector where it generally refers to cost-effective online training.

The recent trend in the area of e-Learning is screen casting(Wikipedia,2008). There are many tools available screencasting, but the latest bombilate is all about the web based screen casting tools that allow users to create screencasts directly from their browser and make the video available online so that viewers can listen to video directly.

The reference to six questions with common linguistic characteristic the initial "Wh.." and the response to them illustrates the educational impact of the system in our, educational,technological and industrial sectors.(Mouzakitis, 2009)

Those are: "What?" "Which?" "Why?" Where?" "When?" and "Who?"

- What is e-Learning?

  It is a type of Technology supported education and training where the medium of instructional delivery is computer-based.(Wilkipedia, 2008).
- Which is the main objective of e-Learning course delivery?

  Providing opportunities to learners in exploiting the technology to enhance and improve learning and teaching quality.(ICTP-Information Communication TechnologyProject,2007)

- Why is e-Learning an important mode of instructional courses delivery?

  It has a major role in promoting increased student autonomy(Laurillard, D. 1972) It gives students opportunities (among others) to connect in the world outside the classroom, to research topics that would otherwise be inaccessible (Shaffer & Resnick , 1999). In the information age, knowledge is power and building knowledge in organizations empowers them to compete, grow and succeed. E-Learning offers a solution that is highly cost effective, totally customizable and easy to assess. By converting training courses to e-learning time and money are saved and organizations benefit from. (Inspired eLearning,2008).

- Where is it recommended to implement e-Learning course delivery?

  There are different platforms where e-learning courses are delivered likes university, business.

In Universities levels for improving the quality of management and education so that they become able to learn education, training in modern way and in field of lifelong learning

In Business perspective in order to develop employee's skills, improve the capability of the vocational training system to meet the needs of industry (University of New South Wales)

- When is it recommended to have recourse to the e-Learning system?

Learners perspective:

(a) When it is not possible to attend the classes due to residence in remote geographical regions.

(b) When people have no time for attending the classes due to working.

System perspective:

(a) It should be used for new markets.

(b) To make easier the delivery of specific courses that requires special pedagogical support.

(c) When teaching time should be reduced.

- Who should be involved with e-Learning?

In academic sector:

(a) For e-Learning design, a large staff is involved.

(b) Learning resources like books CDs etc.

(c) Staff developers, Teaching practitioners, Students supporting staff, Students, Lecturers, Management and Researchers.

In technical sector:

Technical staff, Web developers and Managers.

Merits of e-Learning

- Class work can be scheduled around personal and professional work

  If you are in home or other places rather than class or doing some work then it is possible to attend the classes in virtual classroom by using e-learning site. There is no need to go to school to attend lecture.

- Learners may have the option to select learning materials that meets level of knowledge and interest E-learning considered the learning preference so it provide the best material for learner according to their needs. it also provide learning path for better understanding.

- Self -paced learning modules allow learner to work at their own pace.

  Depending on learner's speed of learning it provide level and their related exercise, so that learners are comfortable in their subject

- Different learning styles are addressed and facilitation of learning occurs through varied activities.

- Reduce travel cost and time to and from school

De-merits of e-Learning

- Unmotivated learners or those with poor study habits may fall behind
- Slow or un-reliable internet connection can be frustrating
- Managing learning software can involve a learning curve

2.2 Role of recommender systems for E-learning

E-learning allows learners to access electronic course contents through the internet and study them in virtual classrooms. It brings many benefits in comparison with traditional learning paradigm, e.g., learning can be taken at any time, at any place (e.g., campus, home, and train station) but traditional learning it is not possible. However, with the rapid increase of learning content on the Web, it will be time consuming for learners to find contents they actually want to study. The challenging task in an information-rich world is not only to make information available to people at any time, at any place, and in any form, but to provide the right thing to the right person in the right path. Therefore, e-learning recommender systems should not only provide flexible content delivery, but support adaptive and dynamic (Olga, 2008) Content recommendation.

One of the ideas outlined in the operating philosophy of the RS is based on equality among its users, not only their access to services, but also and especially with regard to the contribution of each of the recommendations that they could receive the rest. The RS used to generate recommendations for each user based on the ratios provided by users with the most similar contributions to them. Equal treatment for users is appropriate and practical in the majority of the RS, for example, there is no reason in advance to believe that a user is more qualified than another to make Recommendations on movies, travel, hotel, etc. However, there is a group of RS in which this situation has no meaning so much. The RS of e-learning are the most paradigmatic in this unusual situation, it is easy to distinguish between advanced and novice users, taking an example between the reports created by teachers and by students, those have different level of learning because teacher has more knowledge than student

,some other difference level are those provided by the advanced students (eg years) and those who begin their studies.

A recommender system in an e-learning context is a software agent that tries to "intelligently" recommend actions to a learner based on the actions of previous learners. This recommendation could be an on-line activity such as doing an exercise, reading posted messages on a conferencing system, or running an on-line simulation, or could be simply a web resource. Web-based adaptive learning systems have been focusing on the inter-relations between users and the system .In adaptive environment, material and courses are

fixed. Whereas, in evolving system the learning items related to the course could be added, adapted, or deleted. (Soonthornphisaj, et al., 2006).

2.3 Classification of Learning styles

E-Learning environments are based on a range of delivery and collaborative services. Introducing personalized recommender system in e-Learning environments that can support learning recommendations to the students.

Bates and Leary- stated that ***"it is not only important that students are given access to the most appropriate tools and environments that present information in an engaging manner, but that also provide appropriate support for the diversity of individual student learning styles".***

(Hamad, et al., 2008)

The academic success for any student in any learning environment is influenced by emotional, biological, psychological, and cultural factors. In order to facilitate academic success, it is very necessary to provide learning experiences that are accessible to all students with all learning preferences.

Learning Styles

"Learning styles," are the result of educational experience, and cultural background. "Learning styles" (LS) can help to guide students to the study techniques that are most likely to be effective to them. It can give an indication on how students can response to different types of lecture delivery and consequently if they like to approach new material(Chang, et al.,2009). Students may like to work in small groups, while some may prefer to work individually. On the instructor's side, (LS) can be used to help in enhancing and improving the lecture presentations.(Chang, et al., 2009)

There are many models that are defining the learning styles. some of well-known models are

David Kolb's model

The David A. Kolb styles model is based on the Experiential Learning Theory. The ELT model outlines two related toward grasping experience: Concrete Experience and Abstract Conceptualization, as well as two related approaches toward transforming experience: Reflective Observation and Active Experimentation (Kolb, 1984).

According to Kolb, learning styles are combinations of the individual's preferred approaches. These learning styles are as follows:

- Converger;
- Diverger;
- Assimilator;
- Accommodator

Accommodating, Converging, Diverging and Assimilating – depending on his approach to learning via the experiential learning theory model.

Honey and Mumford's model

Honey and Mumford's model adapted the Kolb's model. (Honey & Mumford, 1992).

The Honey & Mumford stages are:

- Having an experience

- Reviewing the experience
- Concluding from the experience
- Planning the next steps.

They discover the self development tool that's differ from Kolbs learning style model .Honey and Mumford model are widely used in government sector in UK.

Learning style model by Kolb (1984) and Honey and Mumford (1982), FSLSM seems to be most appropriate for the use in educational systems. Most other learning style models classify learners as belonging to a few groups, whereas Felder and Silverman describe the learning style of a learner in more detail, distinguishing between preferences on four dimensions. Another main issue is that FSLSM is based on tendencies, indicating that learners with a high preference for a certain behavior can act sometimes differently. The description of FSLSM focuses on the different dimensions as well as the characteristic behavior and preferences of learners for each dimension.

Felder and Silverman (1988)

Proposing different descriptions and classifications of learning types. Felder and Silverman describe the learning style of a learner in more detail, distinguishing between preferences on four dimensions (Felder & Silverman, 1988). Another main issue is that FSLSM is based on tendencies, saying that learners with a high preference for certain behavior can also act sometimes differently. Felder's model comprises 32 learning styles. Each learning style can be defined by the answers to the following five questions:

i. What type of information does the student preferably perceive: sensory (external) sights, Sounds, physical sensations, or intuitive (internal) possibilities, insights, hunches?

ii. Through which sensory channel is external information most effectively perceived: visual pictures, diagrams, graphs, or verbal words, sounds?((Felder & Silverman, 1988).

iii. With which organization of information is the student most comfortable: inductive or deductive?

iv. How does the student prefer to process information: actively through engagement in physical activity or discussion, or reflectively through introspection?

v. How does the student progress towards understanding: sequentially in continual steps, or globally in large jumps, holistically.

PERCEPTION	Sensing / Intuitive
INPUT	Visual / Verbal
PROCESSING	Active / Reflective
UNDERSTANDING	Sequential / Global

Table 2-1: Classification of Learning Styles

The first dimension distinguishes between an active and a reflective way of processing information. Active learners learn best by working actively with the learning material by applying the material and trying things out. Furthermore, they tend to be more interested in communication with others and prefer to learn by working in groups where they can discuss about the learned material. In contrast, reflective learners prefer to think about and reflect on the material. Regarding communication, they prefer to work alone or maybe in a small group together with one good friend.

The second dimension covers sensing versus intuitive learning. Learners who prefer a sensing learning style like to learn facts and concrete learning material. They like to solve problems with standard approaches and also tend to be more patient with details. Furthermore, sensing learners are considered as more realistic and sensible; they tend to be more practical than intuitive learners and like to relate the learned material to the real world. In contrast, intuitive learners prefer to learn abstract learning material, such as theories and their underlying meanings. They like to discover possibilities and relationships and tend to be more innovative and creative than sensing learners.

The third, visual-verbal dimension differentiates learners who remember best what they have seen, e.g. pictures, diagrams and flow-charts, and learners who get more out of textual representations, regardless of the fact whether they are written or spoken.

In the fourth dimension, the learners are characterized according to their understanding. Sequential learners learn in small incremental steps and therefore have a linear learning progress. They tend to follow logical stepwise paths in finding solutions. In contrast, global learners use a holistic thinking process and learn in large leaps. They tend to absorb learning material almost randomly without seeing connections but after they have learned enough material they suddenly get the whole picture. (Garcia, et al., 2007)

Detection techniques of Learning Styles

There are mainly two approaches for detection of Learning Style:

- Automatic Detection
- Questionnaire bases

Automatic Detection

There are various techniques for extracting the learning styles of student, likes Evaluating Bayesian network's precision (Garcia et al., 2007) , Automatic detection of learning styles for an e-learning system (Ozpolat & Akar, 2009) etc.

In the Bayesian network' precision evaluate Bayesian networks_ (BN) precision for representing and detecting students' learning styles in a Web-based education system. This technique useful because it enables us to model both quantitative and qualitative information about student's behavior. Besides, Bayesian inference mechanisms enable us to make inferences about the students learning styles. In this model, the nodes in the BN represent the different student behaviors that determine a given learning style. The arcs represent the relationships between the learning style and the factors determining it. The information used to build the Bayesian model is obtained by analyzing students_ log files. These log files contain records of the tasks carried out by the students in the system and the participation of students in activities such as chat rooms and forums(Garcia, et al., 2007). In the development of the Web-based course, the proposed BN model will enables to discover student's learning styles with high precision.

Questionnaire based detection (Graf et al.,2007)

On the questionnaire bases ILS (Index of Learning Style) method is used. . The Index of Learning Styles (ILS), developed by Felder and Soloman, is a 44-item questionnaire for identifying the learning styles according to FSLSM. Each learner has a personal preference for each dimension(Felder & Spurlin, 2005). These preferences are expressed with values between +11 to -11 per dimension. This range comes from the 11 questions that are posed for each dimension. When answering a question, for instance, with an active preference, +1 is added to the value of the active/reflective dimension whereas an answer for a reflective preference decreases the value by 1. Therefore, each question is answered either with a value of +1 (answer a) or -1 (answer b). The ILS is an often used and well investigated instrument to identify the learning styles. (Felder & Spurlin, 2005) provide an overview of studies dealing with analyzing the response data of ILS regarding the distribution of preferences for each dimension as well as with verifying the reliability and validity of the instrument.

The eg of ILS is-

- He is tending to
    a) Understand about a subject detail but may be fuzzy about its whole structure.
    b) Understand the whole structure but may be fuzzy about details of subject.

- When you are learning something new, it helps you to
    a) Talk about this new thing.

b) Think about this new thing.

- You think ,If you were a teacher, you would rather teach a course
    a) That deals real life situations and with facts .
    b) That deals with ideas and theoretical aspects.

- You give preferences to get new information in terms of
    a) Pictures, diagrams, graphs, or maps bar charts.
    b) Written files or verbal information.

- Once you understand
    a) All the parts, you understand the whole thing.
    b) The whole thing, you see how the parts fit.

- In a study group working on difficult material, you are more likely to
    a) Jump in and contribute ideas.
    b) Sit back and listen.

In question first if learner tick the answer a then it represent learner Sequential learning style because he wants to study in subject deeply. If its answer is (b) then it represents its Global learning style.

In example four if learner chooses the answer (a) then it shows Visual learning, picture, and diagram are the part of visual learning .if (b) then it represent Verbal learning style.
We are using one of these method for finding the learning style of learner .These learning style explains the learners behavior and preferences, that is very useful recommendation

Chapter 3

Proposed Framework for E-learning Recommender system

3. Proposed Framework for E-learning Recommender system

In our proposed work we are considering two matrix, one matrix is based on learning style using GA K-means and another is based on collaborative filtering. In first matrix using the learning style datasets .For the second matrix using the movie lens datasets. By taking test fraction of these two we calculate the recommendation for learner.

Learne r	Perception Sens.\intu. 1\0	Input Visu.\Ver. 1\0	Processing Acti.\refl. 1\0	Understandin Sequ.\Glob. 1\0			Book1	Boo k 2	Subj ect1	Terc her1	Teac her2
Jon	1	0	1	1			1		3	2	3
Mahi	1	1	1	0			1	4	3		
Seena	0	0	1	1			4		2		1
Shiv	0	1	0	1					2		
Som	1	1	1	0			1	4	3		
Ram	0	0	0	1				2		5	5
Vib	1	0	1	1							
Vibu	1	1	1	1			1		5	5	
Renu	0	0	0	0			5		1		1

Learner, Som, Percption learning style is 1, is represented as sensing

Learning styles Matrix

Rating Matrix

learner Shiv Rating on subject 1

Table3-1: Framework of E-learning Recommender system

3.1 Learning styles matrix using GA K-means

As we have previously seen that learning styles play a major role in e-learning for recommendation. We have already discussed how to calculate learning styles and how many dimension of learning styles?

Learning style dataset

We have randomly generated the learning style dataset. In this dataset learning style divided into four dimensions and each has two scale mapping. We are representing the learning styles values in binary form. Each column represents one dimension and two mode of learning. Here we present the sample of this datasets.

User	Perception Sensing\Intuitive 1 \ 0	Input Visual\Verbal 1 \ 0	Processing Active \Reflective 1 \ 0	Understanding Sequential\Global 1 \ 0
SWATI	1	0	0	1
ABHILASHA	0	1	0	1
DEEPA	0	1	1	1
SHWETA	1	0	1	1
VIBHOR	0	1	1	0

Table 3-2: Learning Styles Dataset

In this dataset as an example of Swati , Swati learning style represented as ,she has Sensing, likes to study in Verbal form, her processing is Reflective and her understanding is Sequential. After generating dataset, constructing the clusters on the basis of GA K-mean.as we have discussed earlier about GA fundamentals and k-mean clustering algorithm. Now we define GA K-means.

GA K-mean Algorithms

GA K-means Algorithm is a hybridization of GA and K-means Algorithm. In K-means one drawback is choosing the initial seed.GA K-means is an optimization technique that solves the problem of best initial seed. So we are choosing the GA K-means for finding best cluster for learning style dataset.

Procedure of GA K-means Algorithm (Kim & Ahn, 2008).

a) In the first step, the system generates the initial population that would be used to find global optimum initial seeds. The values of the chromosomes for the population are initiated into random values before the search process. To enable GA to find the optimal initial seeds, we should design the structure of a chromosome properly as a form of binary strings.

b) The second step is the process of K-means clustering, set the maximum number of iterations for centroid adjustment in K-means. After the process of K-means, the value of the fitness function is updated. For finding optimal initial seeds, we applied a fitness function names as "intraclass inertia to find the initial seeds then intraclass intertia is minimized after K-means clustering finishes.

c) In this step, GA performs genetic operations such as, crossover , mutation and selection on the current population. By this action a new generation is produced. After that, Step (b) and (c) are repeated until the stopping conditions are satisfied.

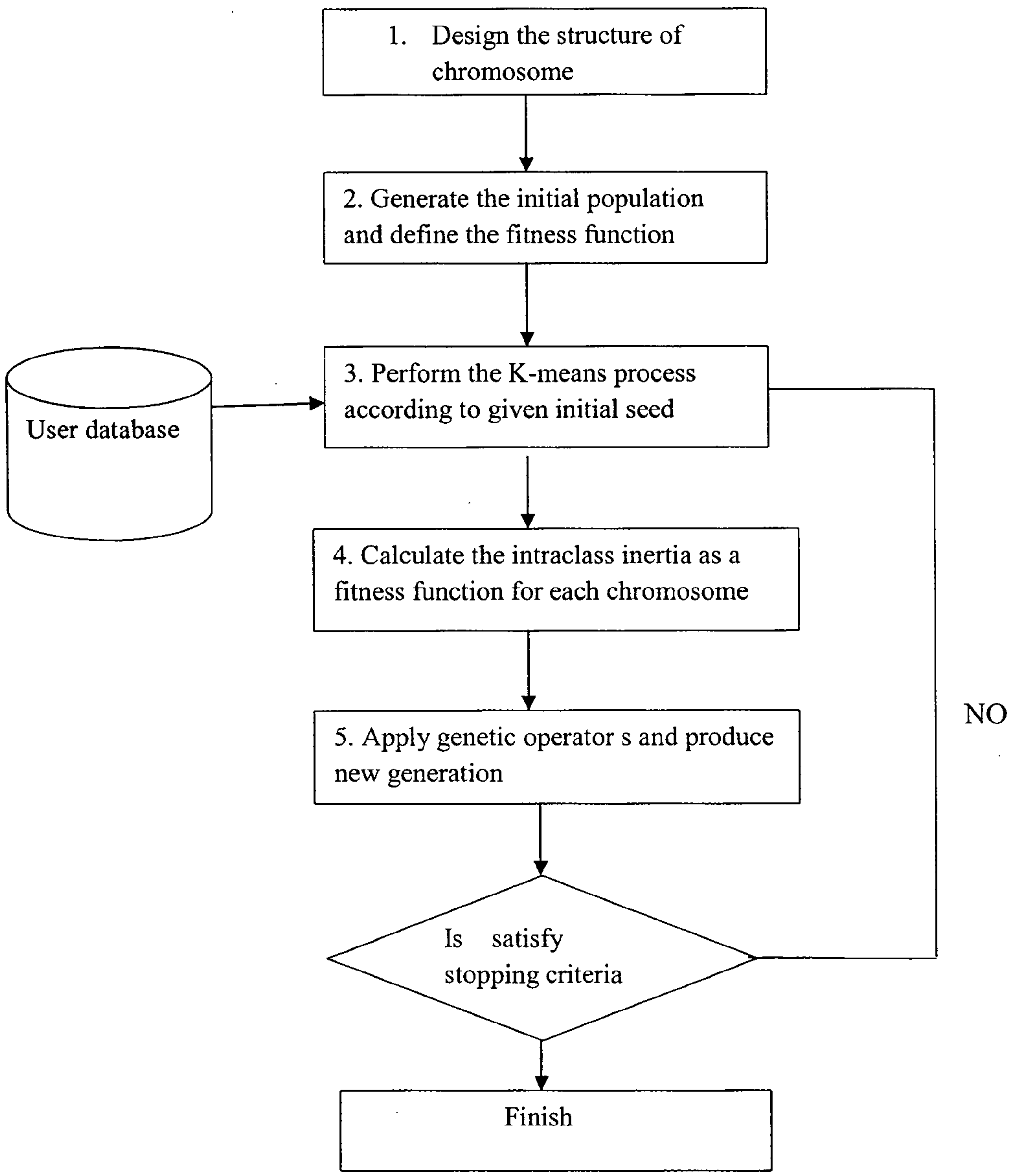

Figure 3.1: Framework of GA K-means algorithm (Kim & Ahn, 2008)

- **Chromosome Representation**

We are forming the chromosome by using the learners learning style. Here we are using four learner combine them to form the chromosome. These learner also represent initial seed as cluster no in cluster analysis. Here four cluster are formed so cluster1 initial seed is Seena same as other represent.

Chromosome 1	Seena				Vibu				Som				Shiv			
	0	0	1	1	1	1	1	1	1	1	1	0	0	1	0	1

Figure 3.2: Representation of Chromosome

If dataset consist only binary data then one represent one dimension value.if data in continuous ranges then it represented in set of vector form. In our dataset we are forming the cluster only using binary 1\0 values.

- **Fitness Function**

There so many fitness functions are available for testing the compactness of cluster. The choice of fitness function is usually very specific to the problem under consideration. By using the fitness function, we are calculating the fitness of chromosome to find the best initial seed for K-mean algorithm. So find the best cluster that contains the set of learning style

$$E = \sum_{i=1}^{k} \sum_{p \epsilon C_i} |p - m_i|^2 \qquad (3.1)$$

E = Sum of square-error for all objects in database.

P = Point in space representing given object.

m_i = Mean of cluster C_i .

k = no of clusters

Steps employed to learn the best initial seed-

a) Initially a set of 20 chromosomes representing weight for four criteria is randomly generated.
b) The fitness of each chromosome in the population is evaluated using fitness function describe above all chromosome are arranged in ascending order of fitness.
c) For each generation
    - A new population is generated by selected chromosome by selecting chromosomes pair wise from top eight chromosomes of the population and crossover is performed and mutation is performed on the last two chromosome at randomly generated points. This gives us ten new populations that would replace the last 10 chromosome having high fitness value.
    - Now fitness of all twenty chromosomes is calculated using formula of fitness and arranged all in ascending order of fitness.
d) process become stable when solution become stable and not changing further iteration .it is over served that after 100 iteration the solution becomes stable for most of the user.

3.2 Collaborative filtering based Matrix

Collaborative filtering is the technique of using peer opinions to predict the interests of others. Active user is matched against the database to discover neighbors, who have historically had similar interests to Active user. Items that neighbors like are then recommended to the target user. The GroupLens project at the University of Minnesota is a popular collaborative system. Collaborative information filtering techniques play a key role in many Web 2.0 applications. While they are currently mainly used for business purposes such as product recommendation, collaborative filtering also has potential for usage in e-Learning applications (Loll & Pinkwart, 2009).

Collaborative systems have been widely used in so many areas, such as Ringo system recommends music albums (Shardanand & Patti, 1995), MovieLens system recommends movies, Jester system recommends jokes . Collaborative filtering system overcomes some limitations of content-based filtering. The system can suggest items (the things to be recommended, such as books, teachers etc.) to users and recommendations are based on the ratings of items, instead of the contents of the items, which can improve the quality of recommendations.

- **Similarity Computation**

There are many ways to compute the similarity such as cosine similarity, jaccard similarity,pearson correlation similarity etc. the most common similarity is described here

- Pearson-correlation based similarity: Pearson correlation measures the degree to which a linear relationship exists between two variables.

$$sim(x,y) = \frac{\sum_{s \in S_{xy}} \left(r_{x,s} - \bar{r_x}\right)\left(r_{y,s} - \bar{r_y}\right)}{\sqrt{\sum_{s \in S_{xy}} (r_{x,s} - \bar{r_x})^2 \, (r_{y,s} - \bar{r_y})^2}} \tag{3.2}$$

Sim(x,y) means similarity between user x, user y.

$\mathbf{r_{x,s}}$ rating of usre x on item s.

$\mathbf{S_{x,y}}$ be the set of all items correlated by both users x and y.

$\mathbf{r_{y,s}}$ rating of usre y on item s.

$\bar{r}_x$ average rating of user x

$\bar{r}_y$ average rating of user y

By this formula calculating the similarity between two users.

- **Prediction** After the similarity computation ,following formula using for prediction

Resnick's prediction

$$p_{a,i} = \bar{r_a} + \frac{\sum_{u=1}^{k}(r_{u,i} - \bar{r_u}) \times sim(a,u)}{\sum_{u=1}^{k}|sim(a,u)|} \tag{3.3}$$

u_1, …, u_k are the *k*-nearest-neighbors to *a*

$r_{u,i}$ = rating of user u on item *i*

Mean Absolute Error (MAE) MAE is used to compute the accuracy of prediction

$$MAE(a) = \frac{1}{|S_k|}\sum_{i=1}^{|S_k|}|p_{a,i} - r_{a,i}| \tag{3.4}$$

a=active user of dataset

i=item of active user

- S_k = set of test ratings of active user a.

- The overall MAE of all active users can be computed as

$$MAE = \frac{1}{N_A}\sum_{a \epsilon N_A} MAE(a) \tag{3.5}$$

This is general overview of collaborative filtering for any recommender systems. Now in our proposed scheme due lack of dataset, we are using movie lens dataset. In this dataset movies work as books, teachers, subjects. Here present a sample of dataset in which is rating based sparse matrix.

USERS	Book1	Book2	Teacher1	Teacher2	Subject1	……
SWATI	1	3		3		
ABHILASHA			5			
DEEPA	2		4		2	
SWETA		4		1		
HANUMAN	1		5		2	

Table 3-3: User Ratings Matrix

Proposed scheme

Our main aim of proposed scheme is to increase the accuracy of prediction , for this we are using human behavior as learning style with the collaborative filtering, as discussed in previous section. Computation of similarity of collaborative filtering with learning styles and without learning style is calculated by Pearson correlation formula as discussed earlier. Compare the accuracy of prediction with learning styles and without learning. This scheme is explained by the algorithm.

Algorithm

INPUT: Datasets

i) Movielens Dataset
j) Learning styles Dataset

OUTPUT: Comparison of prediction accuracy by using collaborative filtering without learning styles (PCF) and with learning styles (LSCF).

/ * the proposed scheme process is divided into two parts i.e PCF and LSCF */

PART1: PCF

- ❖ Finding the test case prediction using collaborative filtering without learning styles

  Dataset : Movie lens

  Technique: collaborative filtering

  (a) Compute the similarity (using pearson similarity measure formula 3.2)

  (b) Generate the neighbourhood of active users

  (c) Predict test cases of active users (using Resnick prediction formula 3.3)

  (d) Compute the error for each test case of active user

  (e) Compute the MAE for the active user(formula 3.4)

  (f) Compute the mean absolute error for all active users (MAE formula 3.5)

PART2: LSCF

- ❖ Finding the test case prediction using collaborative filtering with learning styles

  Step1: To find the optimal clusters

  Dataset: Learning styles

  Technique: GA k-means clustering

  - Generate chromosome
  - Apply GA k-mean algorithm
  - Obtain optimal best clusters

  Step2: Apply collaborative filtering using clusters formed in step-1 by GA k-means.

  Dataset : Movielens

  Technique : Collaborative filtering

2. (a)

   if

   Active user is a member of one of these clusters

   then

   - Compute the similarity of the active user within that cluster (using Pearson similarity formula 3.2)
   - Generate the neighbourhood of active users using that cluster
   - Predict test cases of the active user within that cluster(using Resnick Prediction formula 3.3)

- Compute error for each test case of the active user
- Compute the mean absolute error for the active user(MAE formula 3.4)

2. (b) Repeat 2. (a) For all the active users

End

❖ Compare the MAE of PCF with LSCF.

//* end of proposed scheme algorithm *//

Chapter 4

Experiments and Results

4. Experiments and Results

In this chapter we described the used dataset, results of experiments on different datasets which are subparts of the main dataset. The experiments are conducted to compare the proposed Learning Style based Collaborative Filtering (LSCF) with the simple Pearson Collaborative Filtering (PCF). Due to the lack of any well-known dataset for e-learning, we used movie-Lens dataset in a synthetic way. In this synthetic datasets we used movies as courses, teachers and reading materials.

4.1 Movie-Lens dataset

It is the main dataset which is widely used in the recommendation research. It is the benchmark dataset from Movie-Lens at the University of Minnesota. This dataset was collected by GroupLens research project at the university. This dataset has several files- Data File, User File, Genre File and Item File.

Files	Description
Data Files	In this file there are 100,000 ratings provided by 943 users on 1682 movies. In this dataset, each user has rated at least 20 movies.
Genre Files	In this file, genres list is presented to describe each movie.
User File	Each user is described by demographic features. In this file demographic features are presented.
Item File	A movie is described by nineteen genres. Binary values are used for presence or absence of a particular genre in each movie.

Table 4-1: Description of Movie-Lens files

This dataset consists of 100,000 ratings (1-5) from 943 users on 1682 movies. Each user has rated at least 20 movies. Simple demographic information for the users are used like age, gender, occupation, zip-code). Occupations of users are classified as administrator, artist, doctor, engineer, entertainment, executive, healthcare, homemaker, lawyer, librarian, marketing, none, other, programmer, retired, salesman, student, technician and writer. Nineteen genres of movies are as unknown, action, adventure, animation, children's, comedy, crime, documentary, drama, fantasy, film-noir, horror, musical, mystery, romance, sci-fi, thriller, war and western. We decided to use Movielens for the following reasons: it is publicly available; it has been used in many collaborative-based RS models. In this datasets, we assumed user as learner/user, movies as teachers, subjects and books. Some movies id are considered as teachers, some as subjects and remaining movies id as books.

4.2 Experimental setup

We considered only those users who have rated at least 50 movies. Only 568 users are satisfied this condition out of 943 users for better neighborhood generation. We took five different datasets containing 150, 250, 350, 450, and 550 users called ML150, ML250, ML350, ML450 and ML550 respectively. All these datasets are satisfied by the above condition. This is to demonstrate the effectiveness of the proposed scheme LSCF under varying number of users. Each of these datasets was randomly split into 35 % training data and 65 % test data. The ratings in the training set are used for neighborhood construction and for prediction of ratings while the ratings of the items in the test set are treated as items unseen by the active user.

4.3 Experiments to compare the proposed LSCF approach with PCF for E-learning

Experiments are conducted to compare the predictive accuracy of the proposed LSCF approach with PCF. This scheme is compared against PCF under different configurations enable comparison between CF under MAE.

4.4 Performance Measure

Performance evaluation is main issue for any system. Generally, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) are used for the prediction accuracy of a recommender system. In our experiment, we used MAE for prediction accuracy. We showed that our proposed method is good as that of PCF in our e-learning environment.

4.5 Result Analysis

The results of our experiment as given in Table 4.2 also depicted in Figure 4.1 clearly show that the proposed LSCF for e- learning surpasses the simple PCF method in terms of prediction accuracy. We have also given user-wise comparison of MAE for PCF and LSCF for all the users in Dataset ML250. User-wise MAE is compared as the average MAE over all predictions for an active user. Results given in Figure 4.2 through 4.7 clearly show that Comparison of user-wise MAE of LSCF approach with PCF.

Dataset	PCF Method (MAE)	LSCF Method (MAE)
ML 150	.8995	.8585
ML 250	.8915	.8417
ML 350	.8928	.8359
ML 450	.8973	.8366
ML 550	.9035	.8353

Table 4-2: MAE Comparison between PCF and LSCF

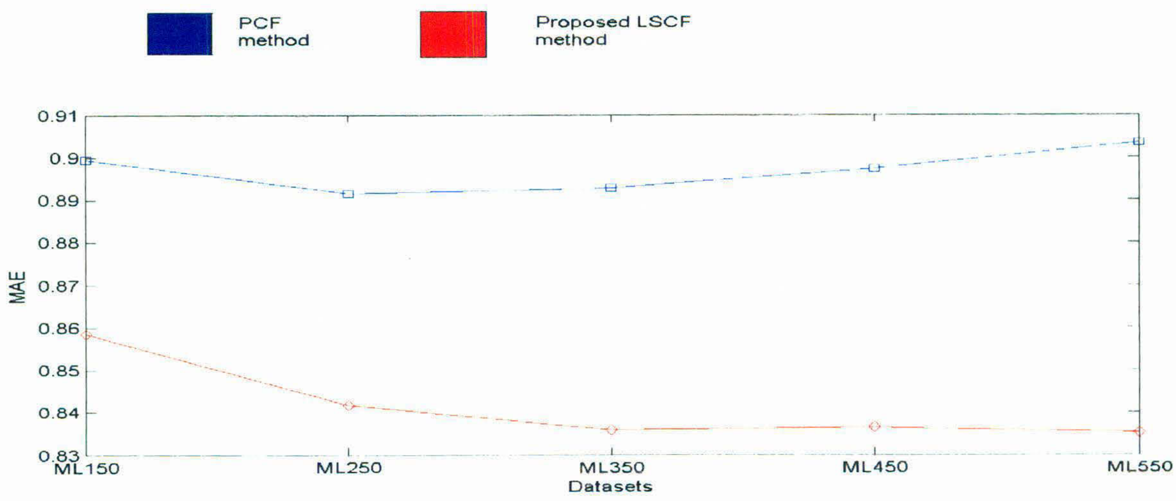

Figure 4.1: Average Mean Absolute Error for different datasets by PCF and proposed LSCF methods

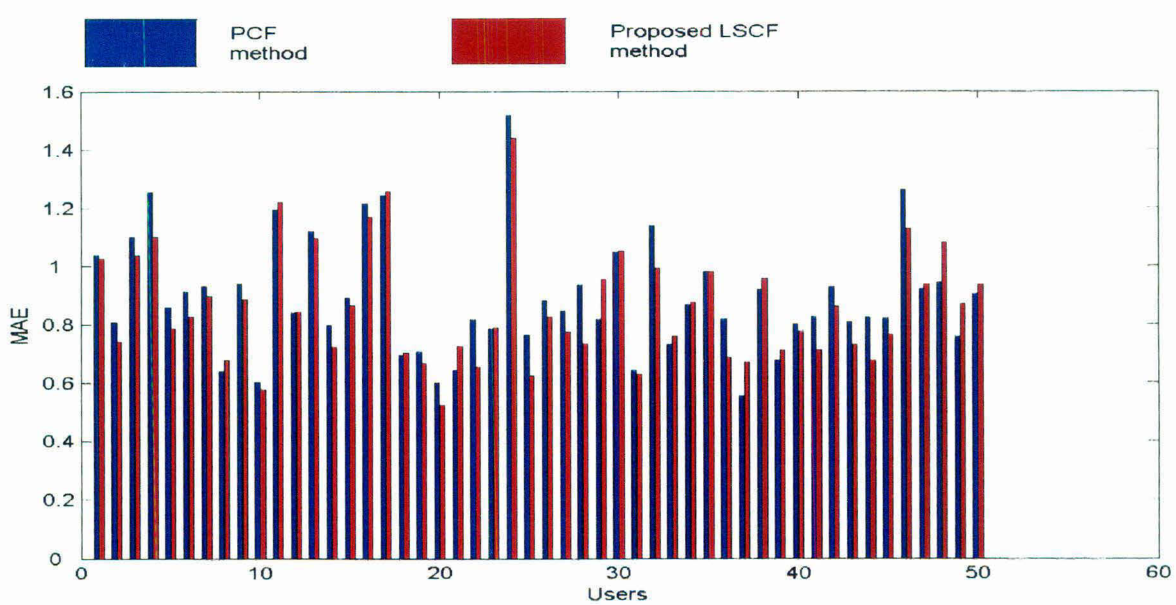

Figure 4.2: Mean Absolute Error for users 1-50

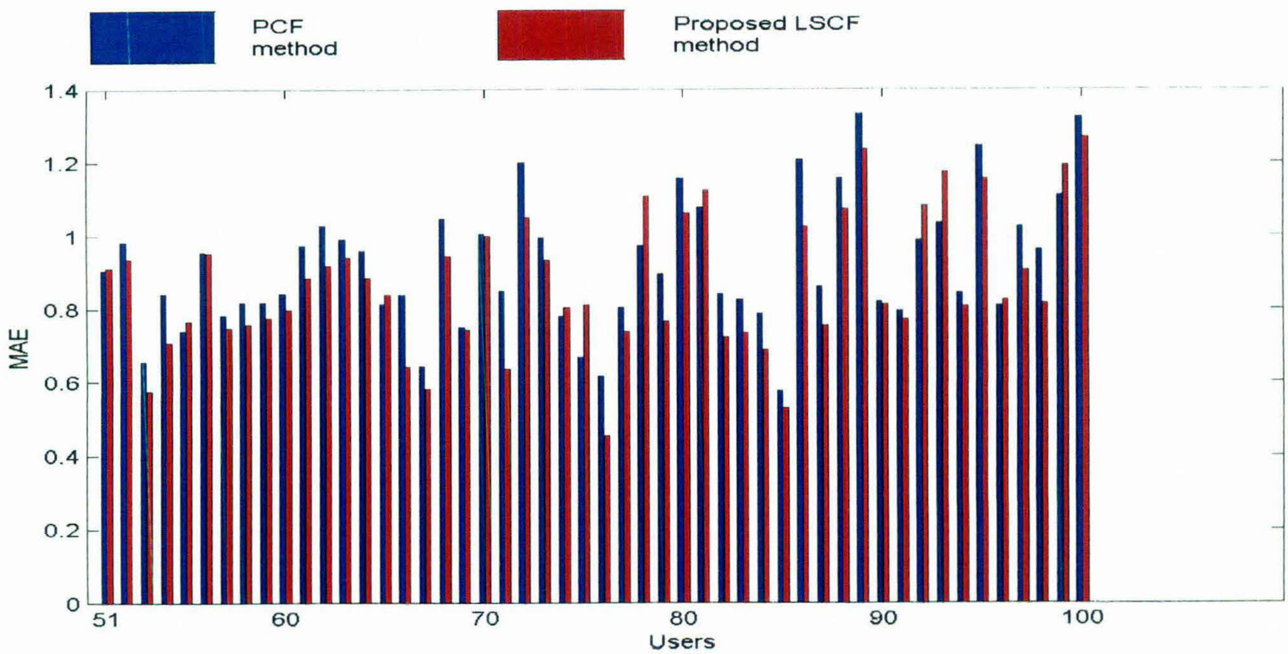

Figure 4.3: Mean Absolute Error for users 51-100

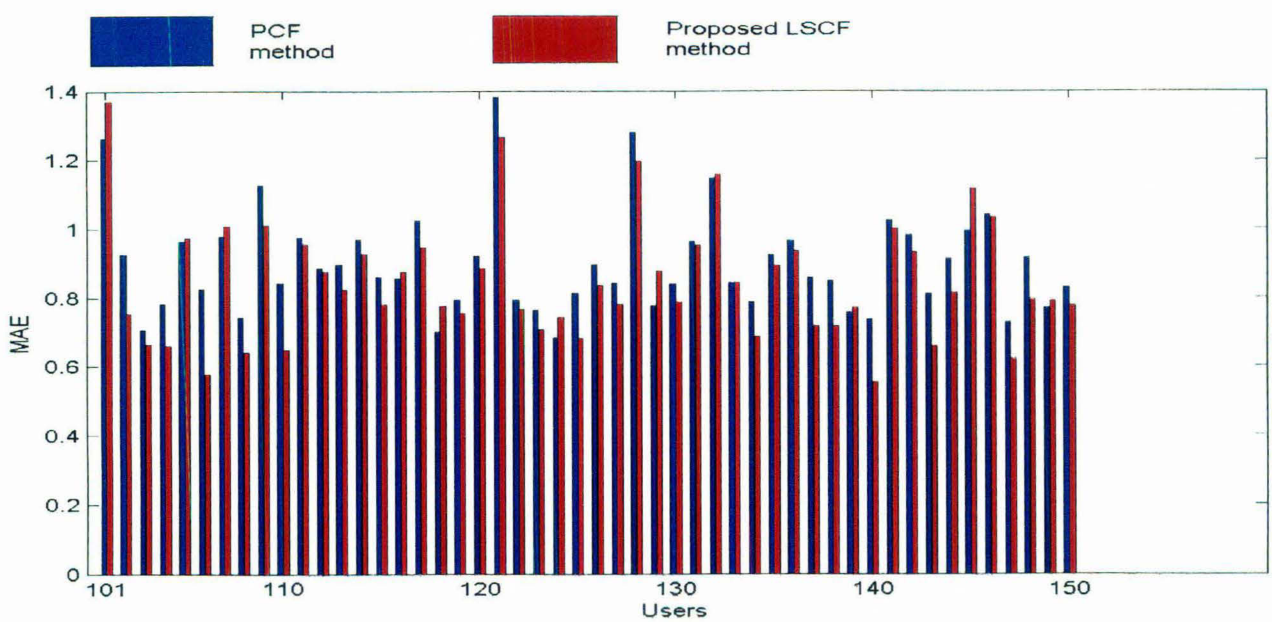

Figure 4.4: Mean Absolute Error for users 101-150

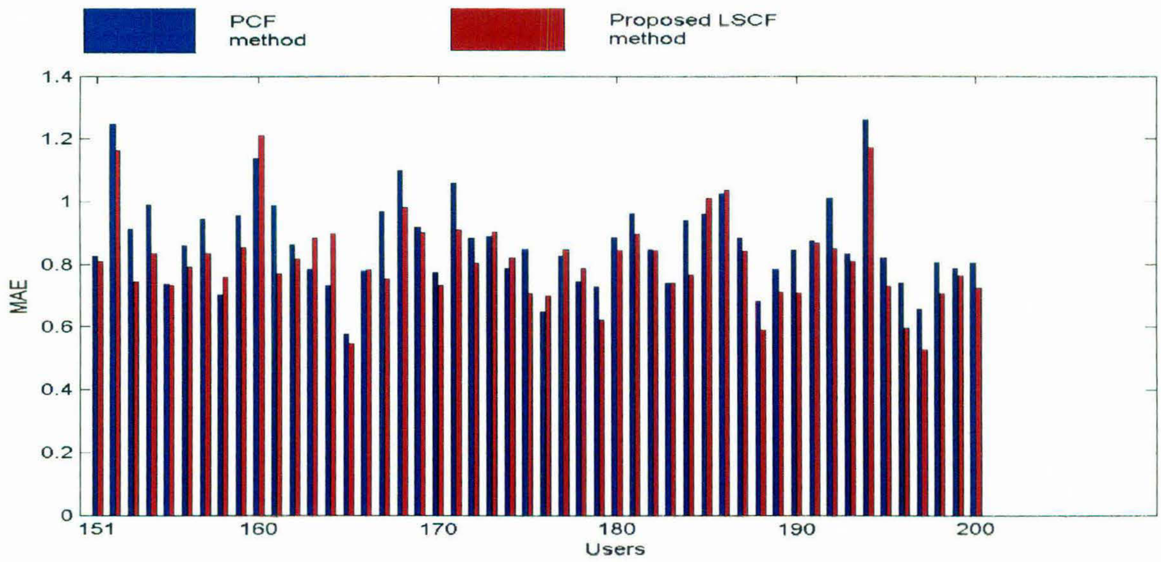

Figure 4.5: Mean Absolute Error for users 151-200

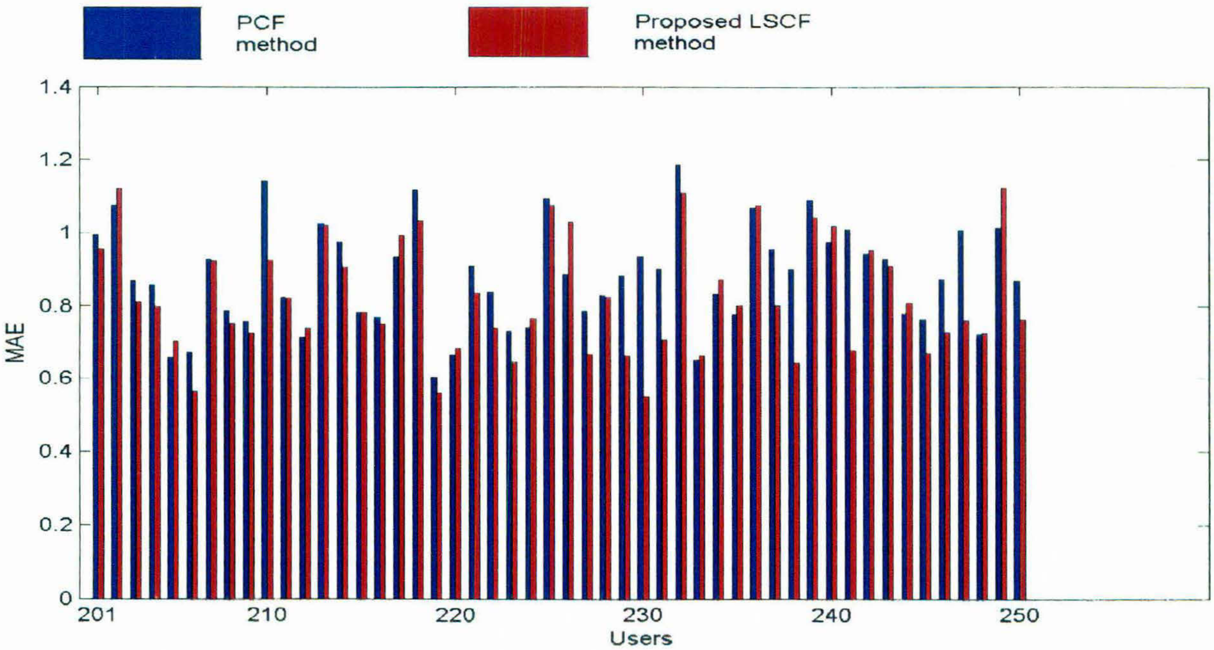

Figure 4.6: Mean Absolute Error for users 201-250

Chapter 5

Conclusion And Future work

Conclusion

E-learning recommender systems consider specific .demand and preferences of learners. Accuracy is the major issue of recommender systems. Normally, PCF technique is used to design a recommender system for e-learning.

In this dissertation, we considered one of the major preference i.e learners' learning styles .We used learning styles as a key factor to enhance the accuracy of simple PCF and proposed a LSCF approach to design E- learning recommender system .We employed GA k-means algorithm to form clusters on the basis of learning styles. Through the experiments it is established that there is a considerable increase in the accuracy of prediction by taking a LSCF approach. Results show that incorporating learning styles with collaborative filtering outperforms simple collaborative filtering approach.

Future work

In the present work we have considered learning style as a preference of learners. Future work will be directed to extend the learner profile by using the various preferences such as emotion (Shen, et al., 2009) and motivation as well as learning path in providing adaptive learning environment.

We have used clustering technique as GA k-mean on learning styles in this work. For further study we can consider classification methods like Decision Tree and Markov Model (Huang, et al., 2009) in order to classify the learners based on learning styles.

Content information may be beneficial in e-learning environment. As an extension we can also include the content information in LSCF method for better coverage and accuracy. One of the important future research direction would be to see how motion of trust and reputation (Bharadwaj and Al-Shamri, 2009)can be incorporated into LSCF framework.

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