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Multimedia Recommendation System for Web-based Learning using Support Vector Machine Technique

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ABSTRACT*—E-learning recommendation frameworks has attracted great attention as a solution towards addressing the issue of data overloading in e-learning environments and providing relevant recommendations to online learners. It attempts to augment Web search engines with personalized multimedia recommendations of search results which match student's learning competencies and behaviors. This study focuses on improving the performance of recommendation systems by utilizing data mining techniques. This paper proposes a multimedia-based recommendation approach from user profiles using the Support Vector Machine technique.*

KEYWORDS—Data retrieval, E-learning, Search engine, Student profiling, Data mining.

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I. INTRODUCTION

E-learning, which refers to learning using electronic tools usually on the Internet such as web search engines. In current situations, it enables learners of all ages, competencies, and inclinations, to search for information or knowledge "anywhere at anytime".

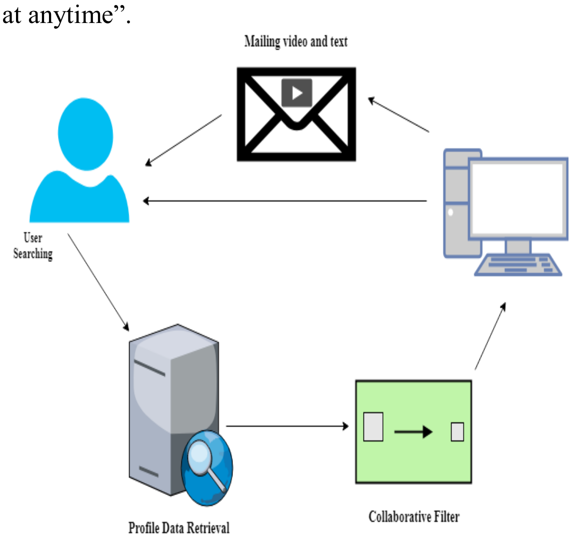

Fig 1 Overview of Multimedia recommendation System

It also enables learner's instant access to particular information. Keywords are required in making a web search and it creates an impression that learners or students are given the same keywords when making their search through any major business web crawlers such as Google, Yahoo or Bing.

Recommendation frameworks became an important research area since the appearance of the first papers during mid-1990s on collaborative filtering. The interest in this area still stays high because it constitutes an issue rich research area and because of the lot of practical applications that help users to deal with overload information and gives more personalized recommendations, content, and services to them. In this context, the user's profile information should be considered together with their queries by Web links.

This is particularly important in the educational environment where students have different educational backgrounds and learning behaviors which indirectly, influence their learning progress and acceptability. Search engines are often assessed with respect to the relevancy of web pages to particular inquiries whereas in reality, the search request may barely represent a portion of the user's overall information requirement. This is because the same query may require different sets of information, depending on user's needs. The classic recommendation algorithm known as user collaborative filtering where the correlation is measured between pairs of the user was widely recognized as providing high-quality predictions and recommendations. Therefore, Online Multimedia Recommendation is proposed using SVM clustering concept.

II. RELATED WORKS

Recommendation system solves the problem of information overloading by giving the recommended or targeted content to the users. Ahmed I Saleh et.al proposes a new user profile learning system to promote the recommendation accuracy of vertical recommendation systems. The proposed profile learning model [1] employs the vertical classifier that has been utilized in multi arrangement module of the Intelligent. In this paper, Adaptive Vertical Recommendation (IAVR) system is used to find the user's interest, and then build the user's profile.

Modern internet search engines became a critical assistant for people's existence. Through interacting with internet search engines, users exhibit customized information in varied aspects. While this information is important to improve user experience, it is mostly used only in the web search domain. In this paper, a technique to leverage web search engine users' behavior data to perform image recommendation is introduced. To this end, it has developed a two-stage method to label users' preferences for images through crowdsourcing techniques. The two-stage annotation consists of inferring a user's general interests and estimating if this user will be interested in an image. A Baseline algorithm to demonstrate the promise of the proposed cross-domain recommendation framework is also implemented.[2]. With the growing institution of Internet infrastructure, a more and more online service promotes the prosperity of the Internet becoming available to end user. Anyway, two issues arise during this information increase. First, users ought to access several individual sites to urge their services, which consumes lots of time and contains some copy work. Second, user traces in numerous websites could have been used to provide a lot of personalized services. This system can integrate several web services to form a personal web, derive request-specific user data, and provide personalized service by content-based filtering and user intention inference. Using a research assistant application as a case study, we show how this framework helps to deliver personalized services.

A learner classification is a vital method in providing online lessons to suit each individual learner. The idea of learner classification is considered on learning behavior and performance. There are two important processes for generating the classification model as follows: 1) Applying K-means clustering to investigate learning behaviors of every learner based on learner's profile from e-learning system, and 2) Applying a decision tree classifier to produce the learner classification model based on the learning behaviors and student's performance. The experimental results display the learner classification model is achieved in 83.8% of precision, 85.4% of recall and 85.5% of F-measure [3].

The growing variety of popularization within the World Wide Web promotes e-learning via web. During e-learning, the users can simply share, reuse, and organize the knowledge. Using the search engine the e-learners search the web pages by the set of keywords. But the pages which are unrelated to our tags come frequently are the major problem nowadays. There is always a semantic gap between searching the web pages and its representation. Ontology-based Text Mining (OBTM) with the help of human concept makes the search meaningfully and gives the relevance site first. Here e-learning with the help of several OBTM techniques such as Concept Weight Based Ontology (CWBO), NLP Based Text Mining (NBTM), Based on Data Quality (BDQ), Personalization (P), Question Answering System (QAS) and Rule-Based Recommendation System (RR) are analyzed. In this paper, ontology-based information retrieval system using web ontology languages and analyzed the importance of handling concepts using tools Wordnet or Hownet is proposed. Here ontology is created after the preprocessing process with e-learning documents such as stop word removal, stemming, and whitespace removal and so on. and proved that the proposed ontology-based NBTM information retrieval technique is efficient and effective in terms of precision and recall parameters [4].

K.D. Rajab et.al compares the effectiveness of e-learning [5] and face-to-face education in the previously neglected context of Saudi Arabia. The analysis done in this paper, considers the potential benefits offered by e-learning in crisis zones such as the southern border region of Najran, Saudi Arabia. The results show that there is no statistical or practical distinction between online and personal learning with respect to student performance. This also demonstrated that e-learning is capable of delivering the educational goals of higher learning institutions to areas wrecked by wars. E-Learning offers students a secure learning environment, engaging platforms, and most importantly a quality education. The findings of this paper contribute to a growing body of scholarship on the effectiveness and implementation of e-learning in the Middle East .

Kavita Jakhar et.al introduces a new content based recommendation system [6]. This system is fully based on the users interest, users profile and the rating they are giving to the search item. In this paper, Collaborative filtering is done with the Support Vector Machine. This technique is good for huge category of items and gives better results compared to other techniques.

The unprecedented growth of the Internet, its accessibility, and usability has increased students dependencies on the Web for quick search and recovery of learning resources. However, current search engines [7] tend to depend on the correct keywords. This eliminates other characteristics, such as the individual's learning capability and readiness for specific learning materials. As a result, the same set of search-keywords delivers the same search results.

This situation hinders the optimization of the Web search engines in supporting the heterogeneity of its users in their learning endeavors. This paper plans to address the issue. It makes an attempt to enhance Web search engines with customized recommendations [8] of search results which match students' learning competencies and behaviors. The outcomes drawn from our experiments suggest that our novel approach can provide a notable improvement in terms of performance and satisfaction for the students [9]. Web search tool recovery effectiveness studies are usually small scale, using only limited query samples. Input queries are selected by the researchers. These problems are addressed by taking a random representative sample of 1,000 informational and 1,000 navigational queries from a noteworthy German search engine and comparing Google's and Bing's results based on this sample. Jurors were found through crowdsourcing, and data were collected using specialized software, the Relevance Assessment Tool RAT. It is found that although Google outperforms Bing in both query types, the difference in the performance for informational queries was rather low. However, for steering queries, Google found the right answer in 95.3% of cases, whereas Bing only found the correct answer 76.6% of the time.

Naji Ahmad Albatayneh et.al proposes a new recommendation model [10] which recommends the interesting post to the users in online discussion forum. It uses semantic content-based filtering and users learning rate. The output of this proposal is evaluated with other existing filtering techniques and the result shows that is gives a better result. This techniques improves the performance of the learner.Text-oriented content is difficult for the user to learn and profile data is not secure. With the help of multimedia recommendation system using Support Vector Machine algorithm and Advanced Encryption Standard (AES), this issue can be eliminated.

II. PROPOSED SYSTEM

A. Problem Definition

Text-oriented content is difficult for the user to learn and profile data is not secure. With the help of multimedia recommendation system using Support Vector Machine algorithm and Advanced Encryption Standard (AES), this issue can be eliminated.

B.System Model

In the proposed system, content-based recommendation recommends the most likely matched item. User content is gathered and clustering is applied to provide required search. It is the collection of user history and user behavior There are three kinds of user behavior: access preference, social activities and reading history User generally watch a video with specific type of keyword. Clusters are formed with certain rules. These keywords are searched and cluster based information is merged. In either case, these metrics were applied to an area of rated knowledge(withheld from the recommendation) to assess accuracy. Error and correlation scores work admirably testing recommendations as an approach to recovering missing data but do much less well at assessing whether they can recommend valuable items previously to the unknown user.

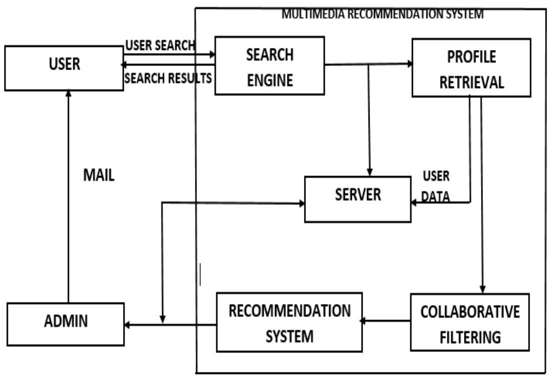

Fig 2 Architecture Diagram for Multimedia Recommendation System

C.Support Vector Machine Algorithm

Support vector machines (SVMs) are an accumulation of related administrative learning strategies used for classification and regression .They belong to a group of generalized linear classifiers. In another terms, Support Vector Machine (SVM) is a classification and regression prediction tool that uses machine learning theory to maximize predictive accuracy while automatically avoiding over-fit to the data.

Support Vector machines can be outlined out as frameworks which use hypothesis space of linear functions in a high dimensional area, trained with a learning algorithm from optimization theory that implements a learning bias derived from measurable learning hypothesis. Support vector machine was initially well known with the NIPS community and now is an active part of the machine learning research around the world.

SVM becomes illustrious, once utilizing pixel maps as input; it gives exactness comparable to sophisticated neural networks with elaborated features in a handwriting recognition task. It is likewise being utilised for many applications, such as hand writing analysis, face analysis and so forth, especially for pattern classification and regression-based applications.

Identify the right hyper-plane (Scenario-1): Here, we have three hyperplanes (A, B and C). Now, determine the right hyperplanes to classify star and circle. Select the hyper-plane which isolates the two classes better. In this state, hyper-plane "B" has excellently performed this job.

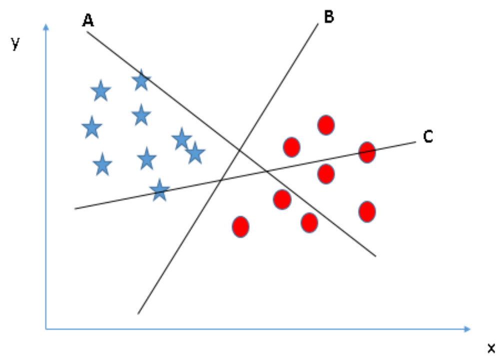

Fig 3 Identify the right hyper-plane (Scenario-1)

Identify the right hyper-plane (Scenario-2): Here, we have three hyperplanes (A, B and C) and all are segregating the classes well. Now, How can we identify the right hyper-plane?

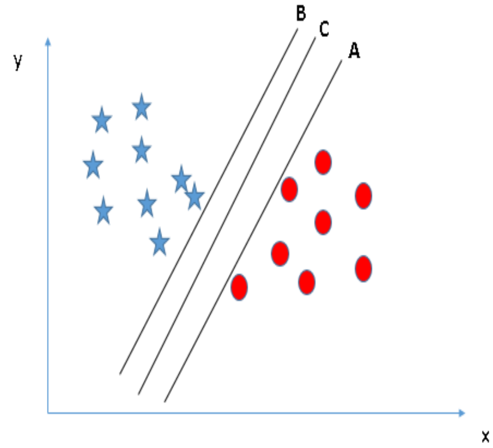

Fig 4 Identify the right hyper-plane (Scenario-2.(A))

Here, expanding the distances between closest data point (either class) and hyper-plane will help us to decide the right hyper-plane. This distance is called a margin. Above, you can see that the edge for hyper-plane C is high as contrasted with both A and B. Hence, we name the right hyper-plane as C. Another lightning explanation for selecting the hyper-plane with higher margin is robustness. If we choose a hyper-plane having low margin then there is high chance of miss-classification.

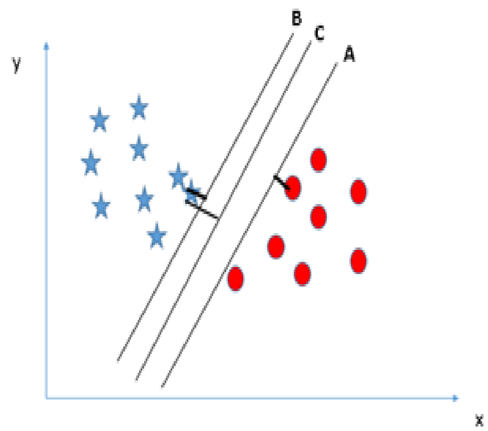

Fig 5 Identify the right hyper-plane (Scenario-2.(B))

Identify the right hyper-plane (Scenario-3): Use the rules as discussed in the previous section to identify the right hyper-plane. Some of you may have selected the hyper-plane B as it has a higher margin compared to A. But, here is the catch, SVM selects the hyper-plane which orders the classes accurately prior to maximizing margin. Here, hyper-plane B has an arrangement mistake and A has classified all accurately. Therefore, the right hyperplane is A.

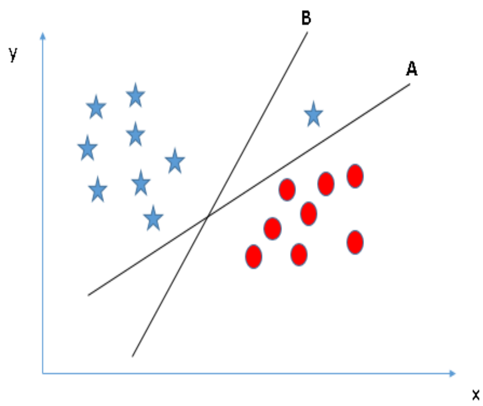

Fig 6 Identify the right hyper-plane (Scenario-3)

D. Advanced Encryption Standard (AES)

AES appears as the recent generation block cipher and considerably will increase within the block size up to 128 bits with the key sizes 128 bits, 192 bits, and 256 bits. The number of rounds set with individual key size is the 10, 12, 14 for the 128 bits, 192 bits, 256 bits. The parameters Key size, Block size, Number of rounds, Round key size, and extended key size are denoted as Ks, Bs, Nr, Rks, Eks, respectively.

Key size (words/bytes/bits)	Block size (words/bytes/bits)	No. of. Rounds	Round key size(words/bytes/bits)	Expanded key size(words/bytes/bits)
4/16/128	4/16/128	10	4/16/128	44/176
6/24/192	4/16/128	12	4/16/128	52/208
8/32/256	4/16/128	14	4/16/128	60/240

Fig 7 Advanced Encryption Standard Parameters

The data blocks are used as the array of bytes and represented in a matrix that is referred to the state array which changed in every step of encryption and decryption process. Each round pursues some steps during the encryption procedure to complete each round. After the final step, the state array is converted into the output matrix. The procedure for each round comprises of four layers i.e. substitute byte, shift rows, mix column and add the round key. In the primary layer, S-box of order 8 is applied to every byte. For linear mixing, the second and third layers are utilized. In these layers, the columns are mixed, and rows of the array are shifted.

The subkey bytes are XORed with every byte of the cluster in the fourth layer. The round operation is completed iteratively that is based on the key size. The decryption process has also the similar operation and same sequences of transformation like the encryption, but it is utilized within the reverse order. The transformation is an inv-substitute byte, inv-shift rows, inv-mix columns and adds the round key that assigns the key schedule form as identical for encryption and decryption process. All operation of AES can be consolidated into XOR operation and a query table, so the implementation can be very efficient and fast.

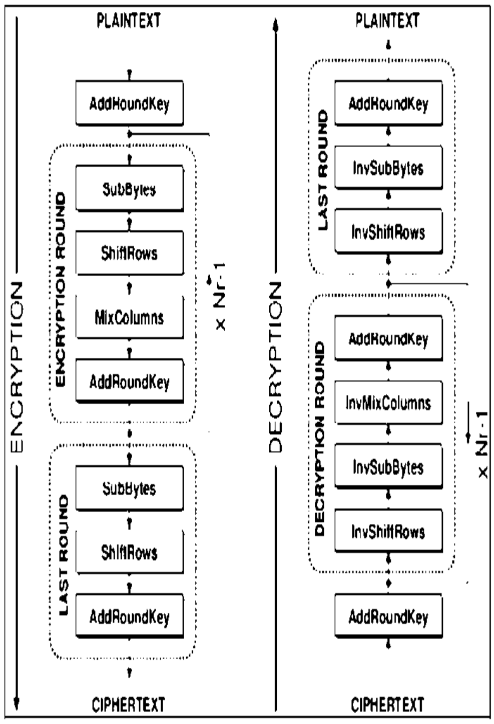

Fig 8 Advanced Encryption Standard Algorithm

E. Modules Description

- Student Profiling module
- Student searching module
- Recommendation module

1. Student Profiling Module

- Creating a profile - Creating the user profile.
- User history - All member logs are collecting and analyzing.
- History maintenance - Member log histories are maintained by admin.

2. Student Searching Module

- Search URL - The user will search for their needed URL in the web page.
- View Result - Displays the final result about the needed website.

3. Recommendation Module

- Student Profile Classification - Analyze and matching the student profile along with searching results.

- Result Clustering - Clustering the searching result as Recommendation structure.

F.Complexity involved in the proposal

In Web-based learning. most personalized systems consider learner preferences, interests in providing personalized services. learner ability usually is disregarded as an important factor in implementing personalization mechanisms. The amount of information available on the internet in digital form is very huge and growing. So, it's made difficult to find precise search result according to user preference

III. EXPERIMENTAL ANALYSIS

A. Simulation Environment

The proposed system was implemented using Netbeans IDE 8 running on a personal computer with a 2.07 GHz Intel (R) Core (TM) I3 CPU, 4 GB RAM and Windows 10 as the operating system.JAVA is used to create UI and My sql is used as a back end.

B. Result Analysis

In this proposed model, the user do registration process to login into the web-based learning page. In this page we can search for any topic. Based on the user profile and user areas of interest the web page will be displayed.

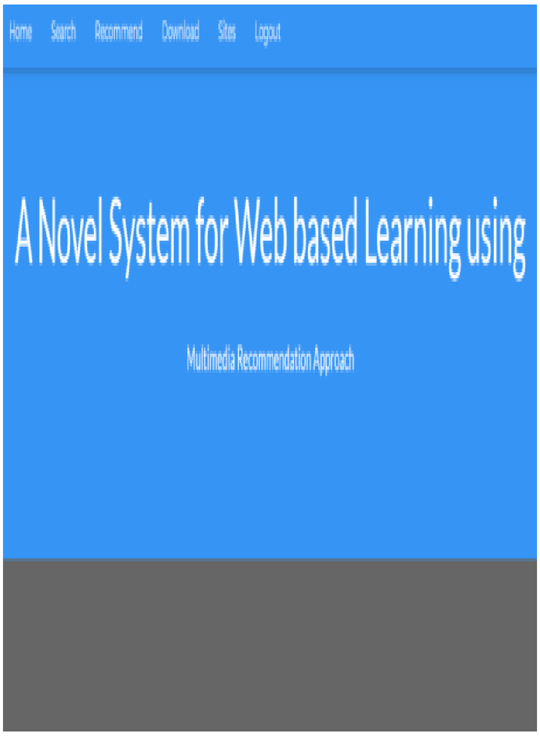

Fig 9 Home Page

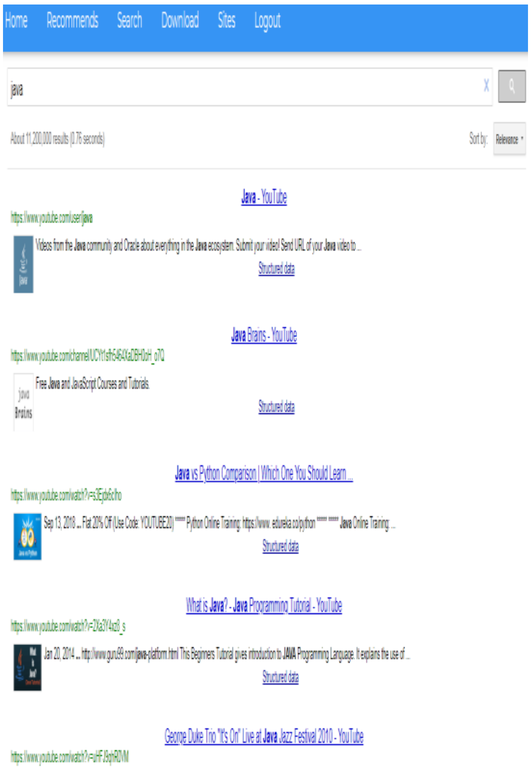

Fig 10 Search Page

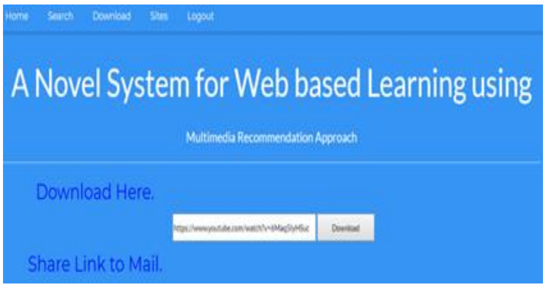

Fig 11 Download page

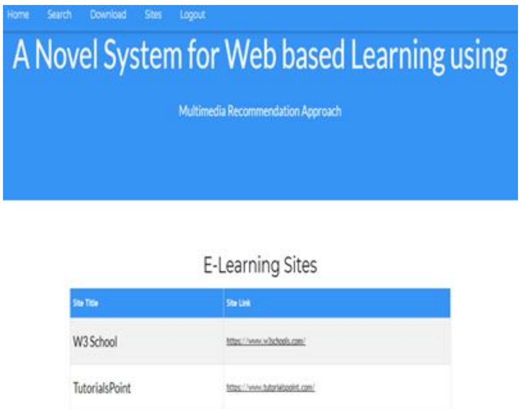

Fig 12 Showing recommended sites page

IV. CONCLUSION

Search engines have been extensively used by the students for educational purposes; they deliver similar contents regardless of students' profiles. This is not beneficial to the students because the same contents may not meet the requirements of every student. Web search results that are personalized to a student's learning profile is therefore necessary. In this study, a personalized multimedia recommendation approach for Web search in e-learning was proposed using the Support Vector Machine algorithm. We designed adaptive system that comprises dynamic profiling and content re-ranking mechanisms that will cater to students in finding Web-based learning materials based on their academic records and learning behavior. Additionally, the possibility of trying to exploring the system augments the Google search engine with the ability to recommend and prioritize the top five most suitable links to students depending on their personal profiles. In future work improved recommendation technique can be used which tends to give more accurate and expected result to user.

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