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Full Length Research

New Personalized Recommendation System for E-Learning

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Customized E-learning dependent on the recommender framework is perceived as one of the most interesting investigations in the field of education. Most of the researchers designed a various recommender e-learning approach which utilizes recommendation techniques for educational data mining specifically for identifying e-learners' learning preferences. However, it does not provide satisfactory results. To increase the recommendation accuracy and minimize the query processing time, the proposed system designed a new personalized recommendation. Initially the learning styles of learners are taken out from server blogs. After the completion of preprocessing, similarity computation and recommendations are done. First, the system applies the content-based filtering approach to calculate the recommendation list. The outcomes are ranked depends on the adjusted cosine similarity of their content. Then apply a collaborative approach to categorize the active learner in one of the learner's groups. The investigational outcomes show that the designed scheme attains higher performance matched with the previous system in terms of query processing time, MAE and accuracy.

Key words: Vector space model, recommendation system, adjusted cosine, document frequency.

INTRODUCTION

E-learning situations are ending up progressively mainstream educational foundations. The fast development of e-learning has changed conventional learning and displayed another circumstance to both teachers and students. Instructors are thinking that it's harder to direct understudies to choose appropriate learning materials because of increasingly learning materials on the web. Students are thinking that it is hard to settle on a choice about which of learning materials best meet his/her situation and need to peruse. In this manner, on the instructor's side, teachers need a programmed approach to inspire input from students to guide their learning procedure. On the student's side, it would be exceptionally valuable an e-learning framework could naturally direct the student's exercises and intelligently create and suggest learning materials that would enhance the learning (Mojisola et al., 2015).

Because of a lot of learning assets on the web, it is hard to discover learning assets related to student preference (Thai-Nghe et al., 2010). E-learning recommender frameworks expect to prescribe a grouping of things to students, that is, to suggest the most productive or viable ways inside an expansive among of learning assets to accomplish a particular fitness. In addition, it is extremely trying for an educator to choose the best learning procedure for every student and to apply it in a genuine classroom and the current eLearning frameworks are not giving a superior office to follow the student's advancement. It drives students to collaborate less with the e-Learning framework or keep out from eLearning. One scheme to deliver this issue is to utilize recommender framework methods, which can help e-learning via consequently prescribing the most reasonable learning assets to the students as indicated by their customized inclinations and profile (Bachari et al., 2011).

Some researchers underline that considering the students' dimensions of information can advance customized learning execution (Jovanović et al., 2009). Along these lines, the capacity of students significantly affects personalization. The customized e-learning framework is developed to utilize item response theory which gives customized learning based on the troubles of parameters of materials and students' reactions (Chen et al., 2005). A customized versatile English vocabulary learning framework is developed that depends on item response theory (IRT) and learning memory cycles, which prescribes

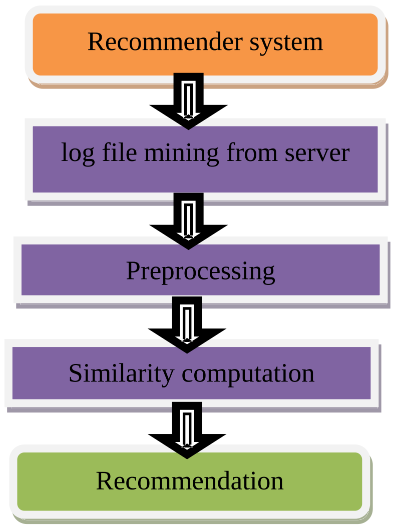

Figure 1. Flow diagram of the proposed system

fitting English vocabulary for getting the hang of as indicated by individual student's vocabulary capacities and memory cycles (Chen and Chung, 2008). A customized multi-specialist e-learning framework is developed using IRT and Artificial Neural Network (ANN) (Baylari and Montazer, 2009).

Literature Survey

A hybrid recommender framework for learning materials is proposed to enhance the exactness and nature of suggestions (Salehi et al., 2013). The explicit attribute-based based recommender module considers loads of understood properties of students' material as chromosomes in hereditary calculation and afterward these loads or conclusions of students are streamlined by historical rating after which proposals are produced utilizing Nearest Neighborhood Algorithm (NNA). The second module utilizes a Preference Matrix(PM) to demonstrate student's interests dependent on unequivocal qualities of learning materials, new similarity measure is presented and afterward, suggestions are created utilizing NNA. An online programmed suggestion framework is proposed for students' navigation histories as well as developing similarities and dissimilarities among the substance of the learning assets (Khribi et al., 2009). A collaborative filtering scheme is designed to calculate the most appropriate documents for the student (Soonthornphisaj et al., 2006). Fresh learning materials can be prescribed to students with a high level of similarity. They were additionally proposing another e-learning system utilizing web benefits.

The machine learning calculations are utilized to find out about the understudy's inclinations after some time (Carmona et al., 2007). First, they utilize all the foundation information accessible about a specific understudy to fabricate an underlying choice model dependent on learning styles. This model would then be able to be adjusted with the information produced by the understudy's communications with the framework to reflect all the more precisely his/her present inclinations. Various ongoing investigations in the space of e-learning advancement concentrated on the utilization of ontology in supporting versatile learning and personalization of course content (Bhaskaran and Santhi, 2019). The thought depends on the way that each student inclines toward particular kinds of preparing material as indicated by his/her learning style, needs, and premiums, and ontology can fill the hole to organizing course content in a way that encourages simple conveyance obviously substance to various styles of individual students.

PROPOSED METHODOLOGY

The proposed Enhanced Vector Space Model (EVSM) depicts a suggestion module of a recommendation framework, which can naturally adjust to the premiums and knowledge of students. This framework perceives distinctive examples of learning style and students' propensities via testing the learning styles of students and mining their server logs. This framework finishes customized recommendations of the learning content as per the appraisals of these regular sequences, given by the recommendation framework.

In the recommender module, if it is a new student, the proposed framework welcomes the student to take the initial ability level test to create the student profile dependent on learning style. When the student finishes the underlying test, the outcome is put away in the student model and afterward, the framework produces the suggestion list for explicit students dependent on the outcome. When the student connects with the framework, information mining systems use to gather data about student's learning styles, for example, navigational examples, inclinations, accessed contents, bookmarks and so to manufacture student profiles and to produce an intelligent recommendation. In this module, there are three stages to pursue, for example, cleaning and preprocessed, similarity calculation, and suggestion model. The flow diagram of the designed system is shown in Figure 1.

The recommender module produces appropriate suggestions to students dependent on their learning style. This module utilizes content-based separating and collaborative filtering to do that. First, apply the content-based filtering scheme, the term vector is submitted to the process suggestion list. Results are ranked by the adjusted cosine similarity of their substance. Then apply the collaborative methodology to classify the dynamic student in one of the student's gatherings.

Recommendation Process

The student's initial preferences tend to be noisy. Henceforth applicable courses/Articles/Videos ought to be separated from them. To do this, it is critical to apply numerical functions to

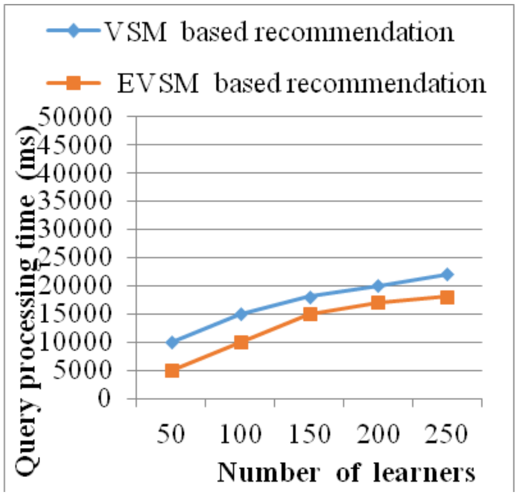

Figure 2. Query processing time comparison

them with the goal that materials can be chosen dependent on a few criteria, for example, similarity or diversity. Subsequently, we use a vector space model to denote student's initial courses /articles/recordings inclinations.

Vector space model is developed to denote reports in a multi-dimensional arithmetical way to concern numerical functions to the documents. It denotes the report as a vector. The vector is fit for containing sub-vectors inside it. Each attribute of the documents is denoted as an individual vector. Concerning the given issue of the research, an item (course/article/video) is considered as a vector, and its attributes, for example, keywords/learning items will be sub-vectors. Every item is denoted as a point in the vector space and it expects that the most pertinent items are the closest ones. To evaluate an/a course/article/video, their significant sub vectors are contrasted and one another and comparability estimated utilizing adjusted Cosine Similarity and TF-IDF loads. In this way, adapt the similar Vector Space Model into our exploration.

Time-Frequency (TF) can be denoted as tft,d is the frequency of a corresponding term t within a given record d. The equation for TF weight is as follows.

$$w_{t,d} = \begin{cases} 1+\log_{10} tf_{t,d} & \text{if } tf_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Document Frequency (DF) gives the number of records that include a particular term t and is denoted as dft. Inverse Document Frequency (IDF) on the other hand decreases the importance of highly used terms and produces an important to less often used items as well.

$$idf_t = \log_{10}(\frac{N}{df_t}) \tag{2}$$

TF-IDF weight is the multiplication of both TF and IDF weights and gives the term-specific weight of the scheme. This value is utilized in attained adjusted cosine similarity.

$$w_{t,d} = (1 + \log tf_{t,d}) \times \log_{10}(\frac{N}{df_t}) \tag{3}$$

Cosine similarity is computed by similarity among two vectors. The system can leverage it to calculate the similarity among two courses based on a corresponding feature p. As the system utilizes TF-IDF weights in computing the adjusted cosine similarity, cosine similarity measure does not consider the circumstance in which a particular user utilizes a diverse rating scale. Adjusted cosine similarity lights up it by subtracting the average rating given by the user u. It considers the qualification in the rating scale used by each user. Adjusted cosine similarity subtracts the average rating of user u for all the things evaluated by user u.

$$\text{Adjusted cosine similarity} = \frac{\sum_{i\in I}(r_{u,i}-\bar{r}_u)(r_{v,i}-\bar{r}_v)}{\sqrt{\sum_{i\in I}(r_{u,i}-\bar{r}_u)^2+\sum_{i\in I}(r_{v,i}-\bar{r}_v)^{2}}} \tag{4}$$

By evaluating the similarity of each course in the users the initial inclination list with the rest of the courses in the same list, the system can discover what are the courses that give the higher similarity value with the TF-IDF weighting method.

RESULTS AND ANALYSIS

The simulation of the proposed model is developed in Java. The performance chart of the proposed recommendation scheme is computed and distinguished with the existing recommendation strategies to query processing time, Mean Absolute Error (MAE) metric, and accuracy (Mojisola et al., 2015; Thai-Nghe et al., 2010; Bachari et al., 2011; Jovanović et al., 2009; Chen et al., 2005; Chen and Chung, 2008; Baylari and Montazer, 2009; Salehi et al., 2013; Khribi et al., 2009; Soonthornphisaj et al., 2006; Carmona et al., 2007; Bhaskaran and Santhi, 2019; Bhaskaran et al., 2020; Bhaskaran et al., 2021). In this proposed research work, Book-Crossing dataset is collected from https://gist.github.com/entaroadun/1653794**.** The dataset comprises three tables as BX-users, BX-books, and BX-book ratings.

Query Processing Time Analysis

Figure 2 shows the comparison of the proposed recommendation and existing VSM based recommendation scheme in terms of query processing time (Bhaskaran and Santhi, 2019; Bhaskaran et al., 2020; Bhaskaran et al., 2021). The number of learners is taken in the x-axis and the query processing time is considered as the y-axis. The proposed system accomplished better output than the current system, which is proved in the experimental result.

MAE Analysis

To figure the measurable exactness, the MAE metric is used, which is a calculation of the suggestions deviations from their

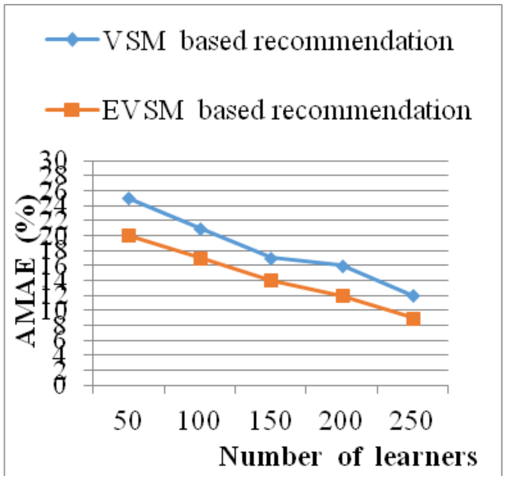

Figure 3. MAE comparison

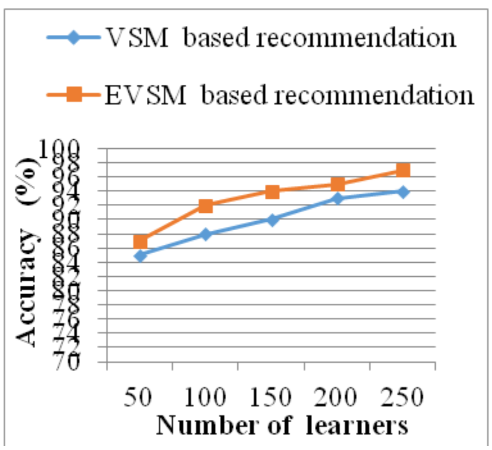

Figure 4. Accuracy comparison

actual learner indicated values. Figure 3 represents the MAE comparison of the proposed and existing VSM based recommendation strategy. The number of learners is considered in the x-axis and MAE is taken as the y-axis. The investigational outcomes show that the designed method attains a minimum MAE value compared with the previous method.

Accuracy Analysis

The system perfectly chooses the suitable presentation methods. Figure 4 represents a comparison of accuracy performance for the proposed recommendation and, existing VSM based recommendation strategy. The designed system accomplished better output than the current system, which is proved in the experimental result.

CONCLUSIONS AND FUTURE WORK

This paper has outlined the development of a vector space recommendation approach for an e-learning system. This approach utilized both content-based filtering and collaborative filtering approaches to improve the performance of a personalized system. In this proposed work, an adjusted cosine similarity measure is presented to evaluate the similarity between learners. The investigation results show that the designed system attains superior results compared with the existing approach in terms of query processing time, MAE, and accuracy. In future, the various optimization algorithms such as firefly algorithm and Particle Swarm Optimization (PSO) algorithms are utilized to improve the recommendation accuracy (Marappan and Sethumadhavan, 2018; Marappan and Sethumadhavan, 2020).

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