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Enhancing Learner Engagement through his Own Experiences which will be Catalysed by AI Teacher as well as Human Teacher

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Abstract: *In this Paper, E-learning has become an essential factor in the modern educational system. In today's diverse student population, learning must recognize the difference in student personalities to make the learning process more personalized and to help overcome leaning model. The learner engagement increases the learner satisfaction and improves the learner performance in learning. Today's recommender system is a relatively new area of research in machine learning. It is a main idea to build relationship between the users (learner characteristics), learning material and makes the decision to select the most appropriate learning material to specific learner. The objective of recommendation system in learning methodology is to present the learner with most required learning material so that he does not wastes his time in traverse from one material to another. This method done with the help of artificial intelligence algorithms like Collaborative Based Filtering, Content Based Filtering, Hybrid Content-Collaborative Based Filtering, k-mean clustering and also used to matrix factorization techniques.*

Index Terms - E-Learning, Recommender system, Data mining, learning style, Human teacher, learning objective, Machine learning, Matrix Factorization.

I. Introduction

Learner engagement is a measure that reflects the quality and quantity of a learner's participation in their learning process and every other aspect of their educational program. E-learning is indeed a revolutionary way to provide education in life long term, comparing with the traditional face-to-face style teaching and learning. Learner Engagement in learning is important to guarantee a good academic result. It leads to achievement by increasing the quality of Learner Engagement. That is, content understanding and skill capabilities are enhanced when learner are committed to building knowledge and employing deeper learning strategies. Recommendation Systems are software tools based on machine learning and information retrieval techniques that provide recommendations for potential useful items to someone's interest. Most of the modern e-Learning systems are still producing the same educational resources in the same way to learners with various profiles it is specifically on personalized motivations in the form of feedback, advices and reminders in learning content.

A recommender system is a chunk of software that helps users to identify the most interesting and relevant learning items from a large number of items. Recommender systems may be based on collaborative filtering (by user ratings), content-based filtering (by keywords), and hybrid filtering (by both collaborative and content-based filtering). The scope of the learner engagement system is the integration of collection and analysis of data from a variety of sources facilitates retrieval and analysis of data to allow individuals to make informed decisions about allocating resources and enabling interventions that promote successful learning strategies. Although much research has been done on the recommendation system; but as far as the author's knowledge, most researchers focus on the accuracy of recommendation systems in predicting recommendations rather than knowledge acquired by students with the help of artificial intelligence algorithms.

II. Related work

Hanaa el fazazi, mohammed qbadou, intissar salhi, khalifa mansouri [1] In this paper focus on personalize an e-learning system according to the learner's requirements and knowledge level in a learning process. This system should adapt the learning experience according to the goals of the individual learner. Its present a recommender e-learning approach which utilizes recommendation techniques for educational data mining specifically for identifying e-learners' learning preferences. The proposed approach is based on three modules, a domain module which contains all the knowledge for a particular area, a learner module which uses to identify learners' learning preferences and activities and a recommendation module which pre-processes data to create a suitable recommendation list and predicting performances. Recommended resources are obtained by using level of knowledge of learners in different steps and the range of recommendation techniques based on content-based filtering and collaborative approaches. Several techniques such as classification, clustering and association rules are used to improve personalization with filtering techniques to provide a recommendation and assist learners to improve their performance. Then, the system presents the recommendation list according to the results of learner's evaluation and profile. In the same context and in order to develop the learning process our future work will be oriented to a new approach about adapting the recommendation process with student learning styles.

Mohamed Soliman Halawa, Essam M. Ramzy Hamed, and Mohamed Elemam Shehab [2] the proposed model used a learner dataset, which allowed us to have a more accurate prediction based on the actual activity of the student. The learning activity is generated and personalized by the framework according to the user's previous knowledge, preferences and needs. The personalized recommendation model which takes the leamer's personality and learning style into account. And include more relationships that would allow much more powerful inference by including more preferences and learner's behavior, and adjust these characteristics into the ontological learner model, and introduce the automatic allocation of the learning contents according to the student's learning style, knowledge and skills. This methodology provides a more accurate evaluation and prediction of student personalities with the help of data mining algorithms. Using the proposed recommendation model and applying the model recommendation to the research sample showed a positive change in the student commitment and engagement to the courses in the e-Learning system.

Dina Fitria Murad,Yaya Heryadi, Bambang Dwi Wijanarko [3] Recommender System (RS) has become a revolutionary concept facing the big data era. Recommendations in the form of advice for users, is very useful to support achieving student using online learning environment. Many of the techniques provided by the recommendation system used of collaborative filtering and content-based filtering. For online learning it is possible to use both techniques and also to use other techniques such as hybrid, knowledge-based and so on. This learning mode were expected to reduce geographical Barrier (e.g. the students can learn from anywhere) and time barrier (e.g. students can learn in their convenient anytime). In contrast to conventional ways of learning, communication between students and lectures in e-learning is not face-to-face but is facilitated by software called Learning Management System (LMS). In general, LMS is a web based platform used to automate and centralize the administration of online learning activities such as registration, learning material delivery, tracking and reporting on learning progress. Learning Management system also provides different functionalities like user management, shipping only, organization, online assessment, question handler, reporting, and communication and collaboration services. Then effective LMS must provide a learning environment to learners, so administrators can use to easily manage other online learning services and manage users.

Huimin Qi, Ming Cui, Mingming Xiao [4] These e-Learning platforms can simultaneously provide favourable and instructive learning environment for a large number of students. With this personalized service, users are able to reduce search time and the cost of using the service, get personalized service, and increase reliability to the personalized system. Personalized resource recommendation system is the most important sub-modules in personalized learning system.. Data mining include many modelling techniques, for instance: Neural Networks, Genetic Algorithms, Classification, Clustering and Visualization methods. Data Mining could be used to extract knowledge from e-learning systems through the analysis of the information available in the form of data generated by their users

Ghauth, K., I., and Abdullah, N [5] Recommender systems have been a useful tool to recommend items in many online systems, including e-learning. However, not much research has been done to measure the learning outcomes of the learners when they use e-learning with recommender system. Instead, most of the researchers were focusing on the accuracy of the recommender system in predicting the recommendation rather than the knowledge gain by the learners. This research aims to compare the learning outcomes of the learners when they use several types of e-learning recommender systems. Based on the comparison made, a new e-learning recommender system framework that uses content-based filtering and good learners' ratings to recommend learning materials, and in turn is able to increase the student's performance. The results show that students who used the proposed e-learning recommender system produced a significantly better result in the post-test. The results also show that the proposed e-learning recommender system has the highest percentage of score gain from pre-test to post-test.

Khribi, M. K., Jemni, M., & Nasraoui, O.[6] Recommended learning resources are computed based on the current learner's recent navigation history, as well as exploiting similarities and dissimilarities among learners' preferences and educational content. The proposed framework for building automatic recommendations in e-learning platforms is composed of two modules: an off-line module which pre-processes data to build learner and content models, and an online module which uses these models on-the-fly to recognize the students' needs and goals, and predict a recommendation list. Recommended learning objects are obtained by using a range of recommendation strategies based mainly on content based filtering and collaborative filtering approaches, each applied separately or in combination.

Osmar R. Za¨ıane [7] In this paper, Recently proposed an approach to build a software agent that uses data mining techniques such as association rules mining in order to build a model that represents on-line user behaviours, and uses this model to suggest activities or shortcuts. These suggestions can help learners better navigate the on-line materials by finding relevant resources faster using the recommended shortcuts and assist the learner choose relevant learning activities that should improve their performance based on on-line behaviour of successful learners. The currently testing this recommender system approach on an on-line course and will evaluate the recommendations using questionnaires as well as a log that is keeping track of selected recommendations by the users.

III. Technologies used

A. Content-based filtering:

Content-based filtering technique is a domain-dependent algorithm and it highlight more on the analysis of the attributes of items in order to generate predictions. CBF uses different types of models to find similarity between documents in order to generate meaningful recommendations. In content-based filtering technique, recommendation is made based on the user profiles using features extracted from the content of the items the user has evaluated in the past When documents such as web page ,publications and news are to be recommended, CBF technique is the most successful.. Items that are usually related to the positively rated items are recommended to the user.

It could use Probabilistic models like Decision Trees, Vector Space Model such as Term Frequency Inverse Document Frequency (TF/IDF) or Naive Bayes Classifier, Neural Networks to model the relationship between different documents within a collection. These techniques make recommendations by learning the underlying model with either statistical analysis or machine learning techniques. Content-based filtering technique does not need the profile of other users since they do not influence recommendation. Also, if the user profile changes, Content -Based Filtering technique still has the potential to adjust its rec-commendations within a very short period of time.

B. Collaborative-based filtering:

Collaborative filtering is a domain-independent prediction technique for content that cannot easily described by metadata such as e-learning and music. Collaborative filtering technique works by building a database (user-item matrix) of preferences for items by users. It then equal users with relevant interest and partiality by calculating similarities between their profiles to make recommendations. Such users build a group called neighbourhood. A user gets recommendations to those items that he has not rated before but that were already positively rated by users in his neighbourhood. Recommendations that are produced by CF can be of either prediction or recommendation. The technique of collaborative filtering can be divided into two categories like memory-based technique and model-based technique.

1) Memory based techniques:

The items that were already rated by the user before play a applicable role in searching for a neighbour that shares appreciation n with him. Once a neighbour of a user is found, different algorithms can be used to combine the preferences of neighbours to generate recommendations. Due to the effectiveness of these techniques, they have achieved widespread success in real life applications. Memory-based Collaborative Filtering can be achieved in two ways through item-based and user-based techniques.

a) User based collaborative filtering technique:

User based collaborative filtering technique calculates similarity between users by comparing their ratings on the same item ,and it then computes the predicted rating for an item by the active user as a weighted average of the ratings of the item by users similar to the active user where weights are the similarities of these users with the target item.

b) Item based collaborative filtering technique:

Item-based filtering techniques compute predictions using the similarity between items and not the similarity between users. It builds a model of item similarities by retrieving all items rated by an active user from the user-item matrix, it determines how similar the retrieved items are to the target item, then it selects the k most similar items and their corresponding similarities are also determined. Prediction is made by taking a weighted average of the active users rating on the similar items k.

2) Model-based techniques:

This technique employs the previous ratings to learn a model in order to improve the performance of Collaborative filtering Technique. The model building process can be done using machine learning or data mining techniques. These techniques can fast recommend a set of items for the fact that they use pre-computed model and they have proved to make recommendation results that are similar to neighbourhood-based recommender techniques.

Examples of these techniques include Dimensionality Reduction technique such as Matrix Completion Technique, Singular Value Decomposition (SVD), Regression, Latent Semantic methods and Clustering. Model-based techniques analyse the user-item matrix to identify relations between items they use these relations to compare the list of top-N recommendations. Model based CF techniques clarify the sparsity problems associated with recommendation systems.

C. Hybrid Filtering:

Hybrid filtering technique is a combination of multiple recommendation techniques like, merging collaborative filtering (CF) with content-based filtering (CB).

Hybrid approaches can be implemented in several ways: by making content-based and collaborative-based predictions separately and then combining them; by adding content-based capabilities to a collaborative-based approach.

D. Matrix Factorization:

Matrix factorization is simply a family of mathematical operations for matrices in linear algebra. To be specific, a matrix factorization is a factorization of a matrix into a product of matrices. In the case of collaborative filtering, matrix factorization algorithms work by decomposing the user-item interaction matrix into the product of two lower dimensionality rectangular matrices.

One matrix can be seen as the user matrix where rows represent users and columns are latent factors. The other matrix is the item matrix where rows are latent factors and columns represent items.

IV. Proposed work:

The aim of our recommender system is to recommend interesting learning resources and useful material to learners based on their preferences in the education-learning context. The system was organized using three basic components such as a content Model, Learner Model, and Recommender Model. The recommender module helps to decide whether a given learning scenario is suitable for specific learner preferences or not. This module utilizes the collaborative filtering model to classify a learning strategy as "suitable" or "not suitable" for the learner.

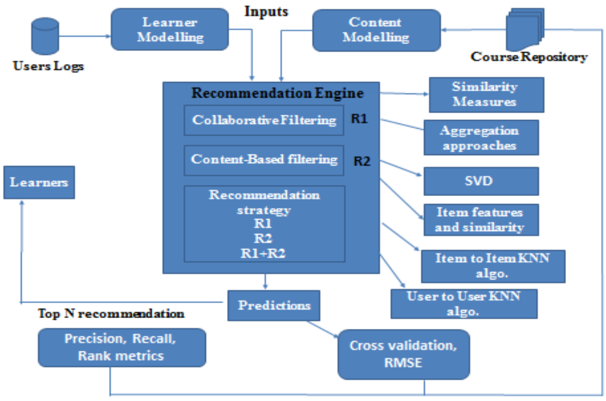


Figure -1: Architecture of Proposed Work

This proposed model will have some major modules, which are:

1. Learner Modelling:

This module will be responsible for storing the learning profile like name, age, region, country etc. With the help of user logs or dataset.

2. Content Modelling:

This module will be responsible for storing study logs like books, video. Notes, authors, authors id etc.

It needs to find the items are similar in pacification or users buying similar items in the large data structure. Then matching these results and suggest a new recommended item list to the user.

Recommendation Engine:

The recommender module helps to decide whether a given learning scenario is suitable for specific learner preferences or not. This module utilizes the collaborative filtering to classify a learning strategy as "suitable" or "not suitable" for the learner. The learning scenario is achieved by the four steps.

I. Cleaning and pre-processing-

The data preparation is an important issue for all methods utilized in data mining, as real-world data tends to be missing or containing errors, or outlier values which deviate from the expected data.

II. Normalization –

In which the data is transformed or combined into forms appropriate for mining. Learning object recommendation sequence is based on learners rating. The recommender module helps to produce Attribute

Values are defined based on the range of total scores obtained by a student in assessments in relation to each factor as indicated in the following table:

Table 1: attribute values based on the range of total scores

Range in [0..10]	**Attribute value**
>=8	Excellent
>=6	Very Good
=5	Good
>=5	Average
>=3	Poor
<3	Very Poor

Learning object recommendation sequence is based on learners rating. LO's sequence take into consideration the evaluation on the content, the number of stars voted for this content, learner reputation and the number of likes and dislikes in order to evaluate the content.

$Rating\ LO = \sum(L) + \sum(O)$ (1)

Where $\sum(L)$ represents, the total number of evaluations of a learner and

$\sum(O)$ represents the total number of evaluations of the contents of this learner.

After weighting learning resources, the reference model for each learner is defined as a Learner-Learning Object Rating matrix with N rows in which N denotes the number of learners L={l1, l2,..... ln} and M columns denote the number of learning objects O={O1, O2,...., Om}.This matrix uses a 0-to-5 rating scale where: 5 means that the learner is strongly satisfied with the selected learning object, 1 means that the learner is not at all satisfied with the learner object, and finally the score 0 indicates that the learning object is not yet explicitly rated or used at all.

III. Similarity computation-

Once learner's model is identified, we apply the method based collaborative filtering in order to create virtual communities of interests.

This step is carried out by improving the most known classifier algorithm K-Nearest-Neighbourhood (K-NN) in several domains. The critical step in collaborative filtering algorithms is the similarity computation between users or items. There are various approaches to calculate the similarity, the most commonly employed measurement of similarities is Cosine Similarity. The similarity between two learners' x and y with Cosine similarity is calculated as follows:

$$w(x,y): \frac{\sum_j^m R_{x,j} \times R_{y,j}}{\sqrt{\sum_j^m R_{x,j}}^{\,2}\sqrt{\sum_j^m R_{y,j}}^{\,2}}$$

In the above equation: Rx, j and Ry, j are learner x's ratings and learner y's ratings for the learning object. If the learner x and y have a similar rating for a learning object, w(x, y) > 0. |w(x, y)| indicates how much learner x tends to match with learner y on the learning object that both learners have previously rated. If they have different ratings for learning object w(x, y) < 0. |w(x, y)| Indicates how much they tend to disagree on the learning object that both again have already rated. Hence, if they don't agree each other, w(x, y) can be between -1 and 1. After calculating the similarity between learners, an NxN similarity matrix is generated, where n is the number of learners.

Then, to predict the unrated learning object j in the rating matrix by the active learner x, the K most similar learners which have highest similarities with the current learner will be selected and use these as the input to compute the prediction for x on j.

IV. Recommendation

In this step we compute prediction for each learning object unselected by the target learner. Finally, the learning objects with high ratings are used to compute learning resources in descending order. To make a prediction for the active learner x on certain learning object j, we can take a weighted average of all the ratings on those learning objects according to the following formula:

$$P_{x,j} = \bar{R}_x + \frac{\sum_{y=1}^{n} w(x,y)(R_{y,j} - \bar{R}_y)}{\sum_{y=1}^{n} |w(x,y)|}$$

In this equation, Ry, j denote the rating for the learning object j by user y.

3. Prediction-

To predict the recommendation for a user u the algorithm uses s to compute the neighbor's N ⊂ U of user u. When N is computed then the algorithm combines the rating of user to generate predictions for items that a user prefers. It calculates the weighted average as expressed in Eq.

C. Methodologies

For implementation of prototype for our proposed architecture, various tools and methods have been used which are as follows:

1. NumPy

NumPy (Numerical Python) is mainly used for performing scientific operations in Python. It is a Python library that gives a multidimensional array object, different determined objects, (for example, masked arrays and matrices), and an arrangement of schedules for fast operations on arrays, including scientific, logical, shape manipulation, discrete Fourier transforms, selecting, sorting ,I/O, basic statistical operations, basic linear algebra, and much more.

2. Matplotlib

Matplotlib is a Python 2D/3D plotting library which can used in web application servers, python scripts, and GUI toolkits. It can generate bar charts, plots, histograms, scatterplots, error charts, area plot etc., with some few lines of code. Here we have used matplotlib to plot loss and accuracy graph.

3. Pandas

It is an opensource python library that will perform data preprocessing and data manipulation. It is used to create, manipulate, and wrangle the data and it can handle missing values, noisy values, unknown values etc. It's also a powerful solution for the time series data. It has a data structure named as DataFrame to store and handle multidimensional data.

4. Scikit-learn

Scikit-learn is probably the most useful library for machine learning in Python. The sklearn library contains a lot of efficient tools for machine learning and statistical modeling including classification, regression, and clustering and dimensionality reduction.

Supervised learning algorithms- supervised machine learning algorithm you might have heard about and there is a very high chance that it is part of scikit-learn. Starting from Generalized linear models (e.g. Linear Regression), Support Vector Machines (SVM), Decision Trees to Bayesian methods – all of them are part of scikit-learn toolbox. The spread of machine learning algorithms is one of the big reasons for the high usage of scikit-learn. I started using scikit to solve supervised learning problems and would recommend that to people new to scikit / machine learning as well.

Cross-validation: There are various methods to check the accuracy of supervised models on unseen data using sklearn..

Unsupervised learning algorithms: Again there is a large spread of machine learning algorithms in the offering – starting from clustering, factor analysis, and principal component analysis to unsupervised neural networks.

Feature extraction: Scikit-learn for extracting features from images and text (e.g. Bag of words).

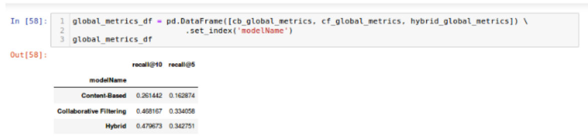
5. Jupyter Notebook

It is an IDE for the python. The Jupyter Notebook is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations and narrative text. Uses include: data cleaning and transformation, numerical simulation, statistical modeling, data visualization, machine learning, and much more. Notebook documents contains the inputs and outputs of an interactive session as well as additional text that accompanies the code but is not meant for execution. In this way, notebook files can serve as a complete computational record of a session, interleaving executable code with explanatory text, mathematics, and rich representations of resulting objects. These documents are internally JSON files and are saved with the. ipynb extension. The notebook extends the console-based approach to interactive computing in a qualitatively new direction, providing a web-based application suitable for capturing the whole computation process: developing, documenting, and executing code, as well as communicating the results.

V. RESULT AND ANALYSIS

We analyzed an all recommendation approach such as content based filtering, Collaborative filtering using matrix factorization model for extracting features from the learning method of the learner and classified into one of the model of recommendation system and found the issues/limitations. So here we have used the data mining based approaches like hybrid recommendation system and finally comparing the three recommendation module with the based on different algorithms.

A. Experimental results


In [58]:
```
global_metrics_df = pd.DataFrame([cb_global_metrics, cf_global_metrics, hybrid_global_metrics]) \
                            .set_index('modelName')
global_metrics_df
```
Out[58]:

modelName	recall@10	recall@5
Content-Based	0.261442	0.162874
Collaborative Filtering	0.468167	0.334058
Hybrid	0.479673	0.342751

Figure- 2 : Comparative experimental results

B. Evaluation Parameter Graph

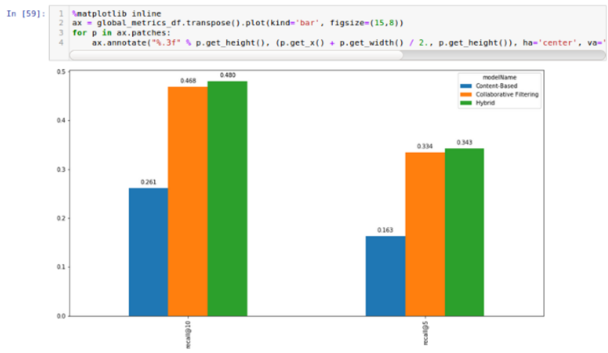


Chart- 1: Evaluation graph

Conclusion

In this paper, the above discussion, we can conclude that various Existing mechanisms for Enhancing Learner Engagement. The main concept of E-learning recommender system is act as a guide for a learner for finding the relevant and useful learning resource which meets the expectation of learners and helps in enhancing his learning with the help of machine learning technologies and data mining techniques such as recommendation system and libraries that includes NumPy, Pandas, Matplotlib and Sklearn. In this work we have presented details of the basic principles on which e-learning recommendation system. In order to build a model that represents on-line user behaviors, and uses this model to suggest activities or shortcut like this content-based, collaborative filtering and hybrid recommendation system .It is helps to improve the students' performance, increase the learning process and personalized motivation.

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