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An Intelligent Recommendation System to Evaluate Teaching Faculty Performance using Self Adaptive HMM and PSO

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Abstract— The addition of recommender systems has completely changed the landscape of digital marketing. The use of recommender systems in digital marketing, e-commerce, entertainment, and healthcare, among other industries, has greatly increased business. The right ideas have improved ease of usage and user experience as well. Nonetheless, there hasn't been much research done on the use of recommender systems in the field of education. This paper suggests a recommender system based on machine learning to provide a framework of suggestions for the teaching faculty based on different performance metrics. In terms of improving students' academic and research performance, it can have a significant impact on the education system as a whole. The accurate recommendation in this work has been achieved by the usage of self-adaptive HMM. Particle swarm optimization (PSO) has been used to optimize the tuning parameters in order to lower the model's temporal complexity. The recommendation in this work has been derived through the use of collaborative filtering. Through the experimental investigation, the suggested systems' performance was confirmed, and it was discovered that their accuracy was greater than 90%.

Keywords-Recommender Systems, Collaborative Filtering, Hidden Markov model, Changing Preference, Dynamic Models,Latent class models, particle swarm optimization.

I. Introduction

The previous several decades have seen a revolutionary shift in the education sector as a result of information and communication technology breakthroughs. Very positive changes have resulted from the teaching and learning process' digital revolution. Students' learning characteristics, particularly their capacity for creativity and design thinking, have enhanced as a result of the integration of new communication technologies with traditional teaching techniques. The students' expectations have also increased to an extremely high level, which has forced teachers to acquire new abilities in addition to their existing expertise, such as technical proficiency, emotional intelligence, soft skills, and communication skills.

Additionally, it has altered academicians' and educational administrators' perceptions of the teaching profession. The underfunded schools place a strong emphasis on making the most of teachers' expertise and abilities. This paradigm change has forced educators to keep up with cutting edge knowledge, current events, and opulent technology. Teachers must possess a strong will, exceptional skill, and adequate preparation to keep up with the rapid changes in the world of education. The difficulties differ according on the educational level, such as elementary, middle, and upper secondary. For professional courses like engineering, medicine, pharmacy, management, etc., the prerequisites will be significantly different. The prerequisites of a subject determine what theoretical and practical topics must be covered during instruction. The process is quite difficult due to the variety of content delivery methods. The degree of education in a multidimensional curricular environment varies, as do the intelligence quotients of the students enrolled in the relevant courses.

Teachers' success has traditionally only been assessed based on the academic performance of their students. However, because of the variation in students' abilities and IQs, the evolving paradigm has rendered it incomplete; as a result, evaluating teachers' effectiveness based solely on student performance is frequently not warranted. Thus, a system for evaluating instructors' performance using direct evaluation parameters is necessary throughout the entire teaching and learning process.

The last ten years have seen a significant increase in interest in recommender systems due to their user-friendly architecture for making recommendations based on the information at hand. Additionally, it provides the customer with a more customized experience. Recommender systems' potential can be used in the sphere of education to provide teachers with suggestions and recommendations.The right teacher for a given scenario can be used to enhance the entire teaching-learning process by determining the areas in which he excels and where he still needs to grow. But this method of evaluating the teaching process using a recommender system depends on a lot of different factors, which makes it a very complicated problem.

This work proposes an intelligent recommender system for the assessment of instructors' performance at the educational institution utilizing a self-adaptive Hidden Markov Model. Additionally, it offers suggestions based on the examination and evaluation. The model for the recommender system has been derived in this study using a variety of criteria, including student assessment, the quality of the intake, innovative practices, experiential learning approaches, etc. to present a recommendation framework. The recommended recommender's performance was assessed and trained on a dataset obtained from an educational institution's ERP. The use of a self-adaptive HMM-based recommender system for instructor recommendations is the main contribution of this research project. PSO has been used to optimize the HMM framework's parameters in order to lower the time complexity.

The structure of the paper is as follows: The overview of current methods for teacher performance evaluation and recommendation systems is covered in section II. Section III provides the mathematical foundation for the collaborative filtering employed in the recommender system. Section IV discusses the suggested self-adaptive HMM-based recommender system optimized with PSO. The paper's conclusion is found in Section VI, after which Section V analyzes the suggested strategy's efficacy using performance metrics.

II. RELATED WORK

Countless research have delved into the complex topic of teacher evaluation in the field of education. In recent years, numerous approaches have been proposed that take into account different factors that could influence performance in one way or another. These include statistical, stochastic, and intelligent frameworks. In order to assess the merits and shortcomings of the several strategies they suggest, this section reviews numerous research findings. After looking at the downsides all together, we found a research gap and a subsequent rationale. Here we will go over some research projects that deal with the problem of teacher evaluation and various state-of-the-art decision-making algorithms:

Using a variety of tasks and a rewards-based approach, Fletcher et al. [1] suggested a system for evaluating competency. These tasks and instructions allowed the teacher to showcase their potential in their work. Some of the actions used by the writers to investigate competency include performance reviews, staff assessments, evaluations of performance and evaluations, ratings of service, evaluations of employees, personnel reviews, and performance evaluations by measurement.

To incorporate study of employee performance using a different set of criteria, Grote et al. [2] broadened the evaluation framework. An analytical process was used to evaluate several aspects of an employee's career advancement, including wage increases, promotions, layoffs, training and development, and more. Based on the successful results, Hamsa et al. [3] decided to incorporate these evaluation methods into educational institutions' staff performance reviews as well. A few situations involving developing nations were utilized to demonstrate the orientation of these nations' educational systems. They have collected a large dataset on the students' academic and extracurricular achievements using information technology methods. With these statistics, we were able to build the statistical decision model that represented the students' and teachers' performance.

Iam-On and Boongoen [4] created a statistical analysis to evaluate performance utilizing the following systems: learning management system (LMS), student information system (SIS), course management system (CMS), and the database of the local institute. With the help of the derived model, a formal method was created to track the development of the learning and teaching process in real time. Using data mining techniques, Migueiset al. [5] were able to uncover valuable insights within the data. Among the many ways in which micromanagement can enhance educational systems is by allowing for the identification of fast and slow learners and the development of individualized strategies for each.

With the merging of data mining and educational systems, the new term Education Data Mining (EDM) was proposed by Altujjar et al. [6] and Zhang et al. [7]. The massive volumes of data generated by student work, evaluations and comments from stakeholders, etc., have prompted educational institutions to embrace EDM. The findings of these models have motivated the developing countries to modify their approaches to education.

In order to enable instructors to alter their methods according on the outcomes of performance evaluations, Pandey and Taruna [8] devised the adaptive technique. To uncover the data's hidden information, the writers delve into data intelligence. In accordance with Thai-Nghe et al.[9], essential elements of EDM as seen by learners. They spoke on how EDM can help students improve their performance and self-assessment by looking at their academic and extracurricular history to see what they might do in the future. Additionally, this technique has the potential to suggest the courses that every student should study.

To validate the model, Helal et al. [10] correlated a series of features with the teacher evaluation form; these features included high school course grades, assignments, and test results. Consideration of students' psychological characteristics and social media activity is also made when examining the different aspects of the features analysis. Thanks to the exhaustive feature collection, we can now evaluate students' academic achievement with more precision. This can have repercussions for the teacher's evaluation as a whole.

III. RECOMMENDER SYSTEMS AND COLLABORATIVE FILTERING

With its recommendations for products, the recommender system is an intelligent model that guides the user experience and aids in decision-making. These suggestions are based on the information that is currently accessible regarding different factors that other users have taken into account when conducting business in the same industry. The problem of recommendation may be formulated as $f: U \times I \rightarrow R$ where f represents the utility function, U and I represent the user space and item space respectively which comprise of the features or attributes of the users and items. R is the set of predicted ratings represented as non-negative numbers. It is generated through the projection of f over the combinations of users and items. The most optimal value of u represented by $u_j^* = \arg Max_{j \in I} f(u,i)$ will be the recommended item for a specific user u.

Collaborative filtering is a well-liked recommendation paradigm that lets recommender systems base predictions and suggestions on user ratings. Following the gathering and examination of all the evaluations and ratings, we then offer the current user a pertinent suggestion. The core of its operation is the notion that user groups with similar preferences are comparable. There are two primary categories of collaborative filtering: item-item and user-user. The principle of classification in user-user CF is predicated on the degree of similarity between the assessments of various users. This is determined by the user's activities and interactions with various objects.

It can be represented through the similarity function defined by $s: U \times U \rightarrow R$. However, when there are a lot of users, the scalability issue with the temporal complexity of user-user CF arises. In contrast, item-item CF predicts the user's orientation toward the items based on the rating patterns of the items and their corresponding similarities. Additionally, it is discovered to be resilient to the scalability problem and unaffected by user volume. The similarity function derived in item-item CF is derived as $s: I \times I \rightarrow R$. Despite specific implementation constraints, both collaborative filtering methods are user-friendly and reasonably accurate across a range of fields. It becomes clear that the user-based method works better when there are more things than people. Results are better with item-based approaches when there are more users than things. This study uses item-item CF to provide suggestions for instructors since there are fewer criteria utilized to assess their performance compared to the number of teachers.

IV. PROPOSED METHODOLOGY

The proposed project is a school-based recommender system for teachers that takes into account a number of factors. There are quantitative and qualitative aspects to these features. These characteristics are arbitrary since the process stakeholders are dependent on one another's actions. Consequently, a probabilistic framework based on the Hidden Markov model is suggested in this research. The goal of the upgrade was to make the HMM model more organically adaptable. Parameters are adjusted based on the error numbers, which are monitored continuously by the framework. The model in this approach is adaptive since it deals with operational dynamic uncertainty.

A stochastic model is presented to resemble the time varying user preferences in terms of joint probability as

$$p(U,I) = \sum_Y p(Y)\,p(U|Y)p(I|Y) = \sum_Y p(U)\,p(Y|U)p(I|U) \quad (1)$$

A user and an item occurring within the observation space are considered independent events if we know the distribution of the latent class (Y) for the observation space. This is shown in (1). The user's whole preference for each product can then be encoded using the latent classes. Mapping user preferences over a dynamic latent class model yields the Hidden Markov Model (HMM). The overall HMM model is constructed using a number of parameters, including the transition probability table (A), the related observation model, and the initial state probability distribution for each user (π). In this work, we examine a model for the distribution of beginning states that is constructed as

$$\sum_u \sum_n p(Y_u^1 = n | X; \Gamma^{n-1}) \log \pi_n \quad (2)$$

where Γ^{n-1} is the parameter estimation of previous iteration, Y_u^1 represents the latent estimate of u[th] user at first iteration and π_n is the probability distribution for nth iteration. $p(Y_u^1 = n | X)$ represents the summary statistics of the posterior distribution. Similarly the transition model derived in this work is given by

$$\sum_u \sum_{t=2}^{T} \sum_i \sum_j p(Y_u^{t-1} = i, Y_u^t = n | X; \Gamma^{n-1}) \log A_{ij} \quad (3)$$

where t resembles to the transition instance. The respective observation model is given by

$$\sum_u \sum_{t=1}^{T} \sum_j p(Y_u^t = n | X; \Gamma^{n-1}) \log p(N_u^t) \quad (4)$$

Now you can get the best likelihood estimate by tweaking each of the three models separately. In order to construct the overall HMM model, the problem is transformed into an estimate of Maximum-a-Posteriori (MAP) estimations by combining (2), (3), and (4). Using the Bayes theorem, we may deduce the maximum posterior distribution even further. Additionally, it resolves the issue of the model being overfitted due to the minor outliers in the training sample. The final prediction can be made using the adjusted observation model given in (4). After that, the parameters of the final HMM model are optimized using particle swarm optimization. Each particle in PSO represents a possible solution for optimizing the parameters of an HMM, and the technique employs a stochastic approach to evolution. The technique is repeated until the optimal solution is not obtained, with each iteration including shifting the parameters within the space. In the HMM framework, the ideal weights represent the final outcome.

The optimal solution in PSO is derived through the following folmulation:

$$v[] = W \times v[] + c_1 \times r \times (p_{best}[] - present[]) + c_2 \times R \times (g_{best}[] - present[]) \quad (5)$$

And $present[] = present[] + v[]$ (6)

Here *v[]* represent the weight vector, W is the inertia weight, c_1 and c_2 are the acceleration constants. P_{best} and g_{best} represent the individual extremes and global extremes of the algorithms respectively. Variables r and R are the random numbers ranging from 0 to 1. The weights calculation is done iteratively on the basis of present solutions.

The overall algorithm used in the proposed HMM based teacher recommender system shown below in algorithm 1.

Algorithm 1 HMM based Recommender system Algorithm

1. Collect the user data and Item data for the complete time T.
2. Initialize the model parameters π, A, Γ.
3. Compute the values of initial state distribution using the model given in (2)
4. Evaluate the transition model using (3)
5. Tune the observation model given in (4) through MAP estimates and modify the weights.
6. Derive the final estimates through the PSO model

V. Experiment Analysis

Analyzed the efficacy of the proposed recommender system by collecting real-time feedback from teachers and other stakeholders within an educational institution. The main elements include job skills (qualification ID, experience ID, level ID), user skills (user qualification, user experience), research papers, and other characteristics of the teachers. In addition, several supplementary elements are considered, such as student grades, evaluations, and feedback. Four teachers are rated based on these ten traits. Data from over one thousand pupils is collected and subsequently converted into a substantial dataset. During the compilation of the dataset, qualitative attributes such as soft skills, communication proficiency, sensitivity, and extracurricular competence are also considered. The proposed Hidden Markov Model (HMM)-based recommender system is trained using the provided dataset. The suggested paradigm leads to the creation of three distinct categories of teaching: primary, secondary, and higher secondary, as well as college teaching. The recommender system utilizes these training qualities to generate an output and accurately classify which teacher should be recommended for each teaching level. A teacher possessing a postgraduate degree should be classified as a secondary or higher secondary teacher, whereas a teacher holding a doctorate, substantial experience, and commendable publications should be recommended for college-level instruction. Nevertheless, the categorizations and the associated decision-making process are not a trivial matter. The phenomenon of natural selection poses a significant challenge due to the dynamic nature of behavioral features that undergo changes over time.The efficacy of the proposed model is evaluated based on many parameters, such as accuracy, precision, and recall. The performance of this system is compared to several conventional recommendation frameworks, including hybrid recommenders, content-based filtering, and cost-sensitive collaborative filtering. Table 1 displays a comprehensive analysis of several tactics and demonstrates that the suggested recommender is surpassing the others in performance.

Table 1. Performance Comparison

Technique/metrics	Accuracy	Precision	Recall
Content based filtering	0.473	0.060	0.679
Cost sensitive Collaborative filtering	0.921	0.143	0.132
Hybrid recommender	0.509	0.089	1
Proposed Recommender	0.965	0.150	0.135

VI. Conclusion

In this study, we provide a recommender system for teachers that takes advantage of the HMM architecture to manage the probability distribution of the attributes. The recommendation is based on a multitude of main and secondary elements that impact the characteristics of the educational entity in direct and indirect ways. Several criteria are used to judge the class of the instructor in this work. These include the following: research papers, ratings, comments, job-related skills, user-related skills, communication skills, soft skills, and student evaluations. The decision-based categorization approach encompasses elementary, secondary, higher secondary, and tertiary education. By adjusting the parameters of the HM model, the PSO algorithm determines the best possible proposal solutions. The HMM framework is adaptive since its weights are changed based on the error. One way to measure how well the proposed method works is by looking at its recall, precision, and accuracy. Additionally, it outperforms the other conventional methods when put side by side.

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