Knowledge-based recommendation system using semantic web rules based on Learning styles for MOOCs

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Abstract: With web-based education and Technology Enhanced Learning (TEL) assuming new importance, there has been a shift towards Massive Open Online Courses (MOOC) platforms owing to their openness and flexible “on-the-go” nature. The previous decade has seen tremendous research in the field of Adaptive E-Learning Systems but work in the field of personalization in MOOCs is still a promising avenue. This paper aims to discuss the scope of said personalization in a MOOC environment along with proposing an approach to build a knowledge-based recommendation system that uses multiple domain ontologies and operates on semantically related usage data. The recommendation system employs cluster-based collaborative filtering in conjunction with rules written in the Semantic Web Rule Language (SWRL) and thus is truly a hybrid recommendation system. It has at its core, clusters of learners which are segregated using predicted learning style in accordance with the Felder Silverman Learning Style Model (FSLSM) through the detection of tracked usage parameters. Recommendations are made to the granularity of internal course elements along with learning path recommendation and provided general learning tips and suggestions. The study is concluded with an observed positive trend in the learning experience of participants, gauged through click-through log and explicit feedback forms. In addition, the impact of recommendation is statistically analyzed and used to improve the recommendations.

Subjects: Information & Communication Technology; ICT; Engineering Education; General Engineering Education

Keywords: Collaborative Filtering; Clustering; Content-Based; Felder Silverman Learning Style Model; Learning Style; Ontology; Recommendation System; Rule-based Filtering; Semantic Web

PUBLIC INTEREST STATEMENT

The main aim of the research emphasizes on building of a recommendation system that operates for MOOC environment using knowledge base and ontology. The implementation focuses on generation of the learner ontology of a learner’s performance and the course ontology of the course with different learning elements. The learning style model employed to classify learners is the Felder Silverman Learning Style Model which uses four criteria: processing, perception, understanding and input to classify a learner. Usage data are recorded through a designed novel browser extension which is then stored and modelled accordingly. Recommendations are given through a hybrid approach that uses underlying contextual knowledge in conjunction with cluster based collaborative filtering and rules written in SWRL. Recommendation of individual course elements within a MOOC vis-à-vis readings, quizzes, forums etc. are made based on a learner’s learning style dynamically to make the learning experience more engaging.
1. Introduction
Owing to a steady growth of learning materials on the web, and a similar trend in the number of learners interacting with said materials, E-Learning Platforms have become an indispensable part of contemporary pedagogy. Massive Open Online Courses (MOOCs), due to their “massive” and “open” nature, draw a much larger learning audience compared to traditional E-Learning Platforms. They offer a much higher number of courses that each then have multiple modules with each module having a mix of different multimedia-based course elements. These elements can be reading materials, video lectures, quizzes, resource links and forums to name a few. It is for this reason that MOOC platforms have been at the forefront of innovation in the web-based aspects of contemporary pedagogy (Daniel, 2012).

However, most MOOC platforms are not without faults of their own. A large number of learners enrolled in a course never complete it and thus course drop-out rates are high. Furthermore, owing to their massive structure and thus larger number of courses across multiple disciplines, learners find it difficult to pick and choose courses of their liking. Courses usually follow a "one-fit-for-all" structure when it comes to sequencing/organization of course elements that needs to be followed for the completion of the course without much room for changes based on individual needs. Most MOOC platforms also do not take into consideration, important aspects of a learner such as, knowledge level, learning style, goals, skills etc. to make a personalized learning experience. Data generated through interaction with different MOOC platforms is also difficult to track and bridge together as linked data in the ontology format (Jordan, 2014; Assami et al., 2018).

A solution to the problem of difficulty in navigating through MOOC platforms has been found in recommender system. Recommender systems, ever since their introduction, have been suggested to provide a more personalized experience to a learner and thus an over-all better course-flow. While recommender system in the field of e-commerce, such as those used by Amazon and eBay, have shown great results, their usage and implementation in the field of MOOC platforms has been lagging. With the general shift toward linked data each day, the rising number of MOOCs and the learners who enroll in them, an intelligent and adaptive recommendation system that keeps the learners engaged is imperative.

Recommendation systems essentially recommend relevant objects to a learner through different algorithmic approaches. Some of the most widely used approaches have been content-based recommendations, collaborative filtering, social-networking approach, knowledge-based approach, group-based approach etc. Recommender systems that utilize multiple algorithms in conjunction with each other have been termed as Hybrid recommendation systems (J. Tarus et al., 2017; Rabahallah et al., 2018).

Knowledge-based recommendation systems utilize underlying information or knowledge of learner behavior and interaction along with product knowledge to make recommendations. Ontologies, as formal models of shared conceptualizations have been able to adequately model this underlying knowledge representing learner behavior, item, learner profile data etc. across multiple platforms, each with different underlying constructs.

Criteria such as previous knowledge, skill set, learning style etc. have been suggested by contemporary literature to model a learner interacting with an E-Learning Platform (B Jenaru & Smeureanu, 2016). Learning style has been identified as an important aspect of any learner both online and in physical classrooms. Learning style of a learner essentially deals with how a learner interacts with course elements as well as how he navigates through the course structure. Multiple learning style models have been suggested to classify a learner such as Kolb Model, Honey-Mumford learning style model and Felder Silverman Learning Style Model (Felder & Silverman, 1988). Each of the learning style model has its own criteria to classify learners along with suggested teaching style for each. Different learning models have seen success to different degrees when implemented in MOOC environment.
In this paper, we discuss building of a knowledge-based recommendation system that operates on one of the most used MOOC platforms. The implementation uses two domain ontologies vis-à-vis the learner ontology and the course ontology. The former is a model of a learner complete with concrete aspects such as grades and deadlines and a more abstract concept in learner's learning style. The course ontology is a model of the course the learner enrolls in with its different elements such as video lectures and quizzes etc. The learning style model employed to classify learners is the Felder Silverman learning style model which uses four criteria: processing, perception, understanding and input to classify a learner (Felder & Silverman, 1988). Usage data are recorded through a novel browser extension which is then stored and modelled accordingly. Recommendations are given through a hybrid approach that uses underlying contextual knowledge in conjunction with cluster-based collaborative filtering and rules written in SWRL. The primary contribution of this paper is a state-of-the-art system that makes dynamic recommendations of individual course elements while a learner is going through said course. Recommendation of individual course elements within a MOOC vis-à-vis readings, quizzes, forums etc. are made based on a learner’s learning style dynamically to make the learning experience more engaging.

The paper is structured as follows: In section 2, we discuss about the related work done previously in the field. In section 3, we discuss our approach and the methodology used along with the extension, the ontologies, the data recorded, and the rules implemented. Section 4 is used for discussion of experimentation and result analysis vis-à-vis the effect of the recommendation system in the learning experience of the test group. In section 5, we discuss the conclusion along with the scope of future works in the field.

2. Related work

This section provides a survey of the ongoing work and work previously done in the field of recommendation systems in MOOC environments focusing on learner’s model. Since the research work focuses on clustering the learners based on learning styles and providing recommendations to learners in MOOCs, various approaches of recommendation systems are studied along with the techniques of structuring the learning styles to generate the learner model. Yu Li et al. (Li et al., 2005) have explored a hybrid collaborative filtering method based on item and learner techniques, by combining collaborative filtering based on item and collaborative filtering based on learner together. Collaborative filtering based on item and learner analyze the learner-item matrix to identify similarity of target item to other items, generate similar items of target item, and determine neighbor learners of active learner for target item according to similarity of other learners to active learner based on similar items of target item. Authors have discussed first the limitations of traditional collaborative filtering and have suggested incorporating learner parameters with collaborative filtering. As the learner has several characteristics based upon the components of the learning management system and its difficult to analyze the learner without understanding the learning styles associated with it. Hence considering learning styles in this approach can improve the efficiency of learning.

Fatiha Bousbahi and Henda Chorfi (Bousbahi & Chor, 2015) have addressed the difficulty for learners to find courses which best fit their personal interests. Authors have proposed a system that recommends appropriate MOOCs in response to a specific request of the learner. Using the Case Based Reasoning (CBR) approach and a special information retrieval technique, the system proposes to the learners the most appropriate MOOCs (from different providers) fitting her/his request based on learner profile, needs and knowledge. The system is not emphasizing on the recommendations which are important during the course in order to complete the course in time. The learner profile can be used to prepare the learner model which will be helpful for recommendation system to provide course recommendations and content recommendations.

Saman Shishehchi et al. (Shishehchi et al., 2012) have developed a knowledge based personalized e-learning recommendation system based on ontologies. Furthermore, this study discusses about appropriate recommendation technique based on learning system characteristics. Authors
have designed ontology for learner and learning material to provide the recommendations based on pedagogical model and learning style. However, the learning styles of the learner is vague during the online course and it is difficult to incorporate into recommendation system. Authors have not considered any standard learning style model to identify the learning styles of the learners which will be useful to understand the learner model systematically for generating ontology and recommendations.

Bouchra Bouhi’s and Mohamed Bahaj’s (Bouhi & Bahaj, 2019) proposed architecture is a redesigned architecture of the classical 3-tiers web application architecture with an additional semantic layer. This layer holds two semantic subsystems: An Ontology-based subsystem and SWRL (Semantic Web Rule Language) rules one. The Ontology subsystem is used as a reusable and sharable domain knowledge to model the learning content and context. The SWRL rules are used as recommendation and filtering technique based on learning object relevance and weightage. The SWRL can be further enhanced based on learner model which can have learning styles as a strong parameter to define the rules. The learning styles are important in learning content and context of recommendation system.

Kahina Rabahallah et al. (Bellogin & Parapar, 2012) have proposed a MOOCs recommender system combining memory-based Collaborative Filtering (CF) techniques and ontology to recommend personalized MOOCs to online learners. Further, they have used ontology to provide a semantic description of learner and MOOC, which is incorporated into the recommendation process to improve the personalization of learner recommendations whereas CF computes predictions and generates recommendation. Authors have used similarity computation for learners and MOOCs based on ratings. The approach only considers the recommendation of MOOCs to other learners based on ratings and not the recommendation of contents or components inside the course. The ontology is only defined by considering the level of learners and not emphasized on learning styles of the learner.

Alejandro Bellogin and Javier Parapar (Obeid et al., 2018) have discussed about cluster-based collaborative filtering method. Furthermore, authors have discussed the performance of method could be improved if standard similarity metrics such as Pearson’s correlation is used when predicting the learner’s preferences. The cluster-based collaborative filtering is suitable for generating the learner model based on learning styles.

Charbel Obeid et al. (Shishehchi et al., 2010) have proposed an approach for developing ontology-based recommender system improved with machine learning techniques to orient learners in higher education. The main objective of the ontology-based recommender system is to identify the learner requirements, interests, preferences, and capabilities to recommend the appropriate major and university for each one. As the learner’s preferences are vague during online courses it is necessary to identify the learning styles of the learners and further provide the recommendations.

Saman Shishehchi et al. (Limonelli et al., 2009) have proposed a semantic recommender system for e-learning by means of which, learners will be able to find and choose the right learning materials suitable to their field of interest. The proposed web-based recommendation system comprises ontology and web ontology language (OWL) rules. Rule filtering is used as recommendation technique. Authors have proposed recommendation system architecture which consists of two subsystems; Semantic Based System and Rule Based System. The similar kind of approach is further modified by detecting the learning styles of the learners as per standard learning style model.

Carla Limonelli et al. have proposed LS-Plan framework for personalization and adaptation in e-learning. Framework includes Adaptation phase along with learner model which focuses on Knowledge and Learning styles which are the components that are managed by the framework. The framework is extensively defined to understand the personalization preferences based on learning styles. This framework is useful to understand and incorporate personalization parameters into the design of learner’s ontology.
Carla Limongelli et al. (Limongelli et al., 2011) have also proposed an approach for personalization in Moodle based e-learning system. This system aims, with the benefits of customized systems to develop an innovative learning content delivery system based on the personalization of the learning experience. The proposed system integrates Moodle with an engine, LS-Plan, which provides automated sequencing of the learning material based on the learner’s knowledge and learning styles. However, this approach can be extended to MOOC environments by integrating the concept of ontology and semantic web.

Baba Mbaye (Mbaye, 2018) has proposed an ontology-based collaborative filtering recommendation system for recommending learners’ online learning resources based on a decision algorithm. In the approach, ontology is used to model and represent domain knowledge about the learner and learning resources. Author has designed this approach to understand learning preferences and planning to provide recommendations based on the same. The experimentation and results related to work is not mentioned in the paper.

Maryam Tayefeh Mahmoudi et al. (Mahmoudi et al., 2013) have proposed a semantic approach to increase performance of retrieving educational materials based on using frames. Here, frames are used to represent the very knowledge necessary for realizing the similarity/relevance between query and supportive materials. The approach is based on semantic relations between the required contents from the learners. The approach is limited to the content recommendations in the online courses.

Kolekar et al. (Kolekar et al., 2019) have proposed rule-based approach for adaptive e-learning system to provide recommendation by changing the learner interface components dynamically during the course. Authors have defined many rules to provide customized recommendations based on learner’s learning styles. The approach can be extended in the MOOC environment by considering learners model as an ontology. The approach is used to identify learning styles and define the rules using semantic web language which are used in the MOOC environment for recommendations.

Mohammed E. Ibrahim et al. (Ibrahim et al., 2018) have developed a framework of an ontology-based hybrid-filtering system called OPCR. This approach aims to integrate information from multiple sources based on hierarchical ontology similarity with a view to enhancing efficiency and learner satisfaction and to provide learners with appropriate recommendations. OPCR ontology identifies the similarity between the items’ profiles and the learners’ profiles and utilizes for recommendation. The framework is not considering the learning preferences or learning patterns of the learner in the form of learning styles.

Panagiotis Symeonidis and Dimitrios Malakoudis (Symeonidis & Malakoudis, 2016) have implemented MoocRec.com web portal that recommends courses to learners so that, they can acquire those skills that are expected from their ideal job posting. MoocRec’s recommendation engine is based on Matrix Factorization (MF) model combined with Collaborative Filtering (CF) algorithm, which exploits information from external resources (i.e. learners’ skills, courses’ characteristics etc.) to predict course trends and to perform rating predictions according to them. This portal is not considering the learners preferences or learning material in the recommendation strategy.

Anderson et al. (Anderson et al., 2003) have discussed overview of the RACOFI (Rule-Applying Collaborative Filtering) multidimensional rating system and it is related technologies. This paper is useful to understand the approach of collaborative filtering including rules. This approach can be extended in MOOC for designing collaborative filtering-based recommendation system.

Sarwar et al. (Sarwar et al., 2002) have proposed clustering based collaborative filtering for personalization in e-commerce application. The k-nearest neighbor clustering is specially implemented to generate special recommendation for the e-commerce products. This kind of approach can be designed and implemented in the online education specially for MOOC environment by considering the clustering of learners’ learning preferences.
Tarus et al. (J.K. Tarus et al., 2018) have presented literature review on ontology-based recommenders for e-learning. The review consists of studies related to ontology-based recommendation for e-learning, different recommendation techniques used by ontology-based e-learning recommenders and categorization of the knowledge representation technique, ontology type and ontology representation language used by ontology-based recommender systems. Lastly, authors have discussed about improving the quality of recommendations in e-learning environment by considering knowledge of learning preferences as learning styles.

Jeremić et al. (Jeremić et al., 2013) have discussed about the integration of Social and Semantic Web technologies, often referred to as the Social Semantic Web (SSW). Authors have identified the main principles on which such SSW-supported personal learning environments are based, and illustrate them through the design, implementation, analysis, and evaluation of the system. This approach further explores the potential and implications that novel data-driven technologies have on the interactive and collaborative aspects of personal learning environments.

Wang and Wang (Wang & Wang, 2020) have done extensive survey on semantic web and ontology for e-learning. Authors have systematically reviewed research on ontology for e-learning from 2008 to 2018. Survey provides information regarding major uses of ontology in e-learning systems, how to prepare educational ontology, and which are the semantic based e-learning systems are available. This information is useful to make recommendation system and our research work is used same for extending it to MOOC environment.

As per the literature discussed so far, learning style of learner is one of the important parameters which needs to be identified in the MOOC environment. The research work focuses on the following phases: Detection of learning styles of learners to generate Learner Ontology, cluster-based collaborative filtering based on learner clusters, preparation of rules in SWRL using Learner and Course Ontology, implementation of rules for recommendations of courses, contents and other important components of MOOC environment.

3. Methodology
The knowledge-based hybrid recommendation system discussed in this section is truly hybrid in the sense that it incorporates multiple approaches used in contemporary literature and improves upon them. The cold start problem is dealt with through the use of underlying knowledge in the form of ontology, the poor performance in finding similarity between learners with collaborative filtering in case of very large number of the same is dealt with learner clustering etc. usage data are recorded through a novel browser extension which is also used to provide recommendation pop-ups. The designed recommendation system can suggest course elements inside a specific MOOC and a way to navigate through them along with learning suggestions. The details of this extension, the ontologies it operates on along with the algorithms and rules used have been detailed in the following subsections. The general structure and flow of the system is shown in Figure 1.

The learner, while going through a course, generates usage data which is captured by our browser extension. This data are used to dynamically predict learning styles and to augment the two domain ontologies used. The data captured along with predicted learning style is fed to the recommendation engine that first draws learner clusters based on said learning style. Finally, cluster based collaborative filtering module together with SWRL module is used to make recommendation list and learning suggestions. The recommendations are generated using the two filtering modules and provided to the learner in the form of pop-ups that are processed internally by the browser extension. Further the impact of recommendation system is analyzed using statistical analysis and analysis is fed back to the recommender system again.
4. Browser extension
The browser extension designed here essentially works by scraping usage parameters of a learner, while he/she is going through the course elements, such as interaction period, quiz grades etc. as shown in Figure 2. Counters are used to keep track of the number of revisits made to a particular course element. Details about the immediately next and previous course elements in the pre-defined section are also maintained.

The extension captures several aspects of a learner profile however personal information such as names, email-ids, phone numbers are not recorded to make the learners comfortable with the extension in a privacy context. Each learner is associated with a SHA-256 hash-key which is used to identify his/her usage.

The extension is made available on Mozilla Add-On store and Chrome Web store. The extension is unobtrusive, light weight and has no effect on the browsing experience in any way. Google Cloud Platform (GCP) services have been used to maintain high security standards through end-to-end encryption.

Recommendations and suggestions are provided through the extension itself through pop-ups that can be opened and collapsed at will. The listings in these pop-ups act as hyperlinks to course elements or other courses which can be accessed directly by clicking on particular listing. Due to the above listed light weight nature, security standards and efficient data collection, the extension is able to work round the clock, reliably scraping data.
5. Ontology
A knowledge-based recommendation system utilizes underlying contextual knowledge to make recommendations. In this approach, we have chosen ontology to represent this underlying contextual knowledge. Ontologies have been used to great success in modelling learner behavior semantics in the field of E-learning while also having the quality of being shared and scaled. Two ontologies have been used vis-à-vis the learner ontology and the course ontology, details of which...
have been discussed in the following sub-sections. Web ontology Language (OWL) has been used with rules written in SWRL.

6. Learner’s ontology
The learner ontology is used to represent both static and dynamic attributes of the learner. Static attributes are mostly identification criteria such as the SHA-256 key, platform used, browser etc. while dynamic attributes are used to represent currently enrolled courses, learning style, grades, revisits, completion fraction etc. The learner class has three subclasses, the sub-class elementUsageMetrics is used to store usage parameters, the personalInfo stores static identification details and the subclass learningStyleCluster is used to store the learning style of the learner under the Felder Silverman Learning Style Model (Sammour et al., 2015). Next, elementUsageMetrics has different course elements such as videos, quizzes etc. as subclasses. Each of these subclasses is associated with properties for usage parameters which then store the data generated as individuals. Similarly, learningStyleCluster has four subclasses corresponding to the four criteria of FSLSM with each then having three subclasses corresponding to the three clusters designated for each criterion. For example, the subclass inputCluster has three subclasses vis-a-vis strong-mod-visual, mild and strong-mod-verbal. These correspond to the FSLSM categories of strongly/moderately visual, mild visual-verbal preference and strongly/moderately verbal. This construct follows for each of the remaining three criteria. The personalInfo class has subclasses for identification criteria which store scrapped data as individuals. The created ontology along with properties is represented in Figure 3. The data properties of learner ontology are shown in Figure 4.

7. Course ontology
The MOOC platform that we have chosen to build our system on is SCORM compliant which has been considered while modelling the course ontology. The fact that there should exist a degree of coherence between the learner model and the course model has been considered too. The course ontology is thus modelled with the learner ontology structure in mind. This model, again, holds static and dynamic attributes. Static attributes include course name, course provider, course duration, course fee along with the set of all course elements vis-a-vis video lectures, reading material etc. Dynamic attributes include current enrollment, current completion etc. In our approach, we focus more on the static attributes, specially the course element. The class course has subclasses courseInfo and courseElements. The subclass courseInfo then has all the details of the course as individuals of subclasses like courseName, courseProvider, language, fee etc. The class courseElement has subclasses corresponding to each type of course element that store element details as individuals. The details of the course ontology along with its properties is shown in Figure 5.

8. Learning style
Many learner characteristics such as learner skill level, previous knowledge, skill set, desired job, learning style etc. have been used, independently or in conjunction with each other, to make recommendation to learners. In the case of learning style, different models have been suggested in contemporary literature to categorize learners such as Kolb Learning Style Model, Honey-Mumford Learning Style Model, Felder Silverman Learning Style Model (FSLSM) etc. In this approach, we have chosen FSLSM to capture learner characteristics. The choice of MOOC may involve concepts such as previous knowledge, innate interest, job requirement etc. however once a MOOC is chosen, navigating through it is different course elements by any learner is largely based upon his/her learning style. Learning style can accurately capture a learner’s preferred medium of learning, his pace, his inclination towards group activities and peer reviews etc. It is for these reasons that learning style has been chosen. A diagram for FSLSM and it is categories has been shown in Table 1.

9. Clustering learners
Each learner is either balanced or is inclined towards a single type under each of the four criteria vis-a-vis processing, perception, input and understanding. Under each criterion, two types of learners have been defined: for processing we have active and reflective learners, for perception
Figure 3. Learner’s ontology.
we have sensory and intuitive learners, for input we have visual and verbal learners and lastly for understanding we have sequential and global learners.

Under each criterion, each learner has either a strong preference for one, a moderate preference for one or a balanced or mild preference for the two. While learners with strong-moderate preference prefer a specific type of course element, such as a strong-moderate verbal learner preferring reading materials and articles, a learner with mild preference is vacillating in his/her approach and may prefer either type (reading material or video lectures in this example) in moderation. This behavior is captured through usage data scrapped and stored by the learner. Parameters are scaled, measure and compared to predict learning style. Learners can have strong or moderate preference for one style or a mild preference for two. Based on this, learners are drawn into three clusters for each criterion. For any criterion, a learner can be a part of either strong-mod-A or strong-mod-B or mild/balanced, where A and B are the two types under any
criterion. This gives us a total of 12 clusters, 3 clusters each for the 4 criteria. Clusters under the same criterion do not overlap however might show a change in size if sufficient number of learners show a change in their learning style. Since each learner behaves a certain way under each criterion, clusters between these surely overlap to different degrees. These clusters are drawn using learning style detection algorithms discussed in detail in our paper (Kolekar et al., 2016). A visual representation of the clusters is shown in Figure 6.

10. Collaborative filtering
Collaborative filtering has been in discussion since the first recommender system. The main idea behind the technique is that learners that have similar usage patterns in the past will behave similarly in the future. When a new learner (referred to as active learner), is on the platform, a list of learners is drawn to search for similar learners. Different gauges of similarity such as cosine-similarity, Pearson’s coefficient, clusters etc. have been considered to find the k nearest neighbors (kNN algorithm). The ratings of these k nearest neighbors are then used to predict ratings for courses/course elements for the active learner. Based on these predicted ratings, an active learner can be recommended top n courses/course elements. This is how collaborative filtering works in the classical sense. However, two main problems have been pointed out with this method of implementation of collaborative filtering. The first one being that of having limited ratings about courses with low enrollment or having inadequate rating history of a new learner, collectively called the cold start problem. Contemporary literature has suggested multiple approaches to deal with cold start problem such as context-based (CB) recommendations which involve reuse of contextual information. In this approach, the underlying knowledge is the form of semantically linked data is used to take care of cold start. In case there are not enough learners enrolled in the course, the system recommends course elements exclusively based on learning style while if the learner has not had much interaction with the system to be classified with a learning style, the over-all highest rated course elements are recommended. The other problem that collaborative filtering-based systems face is that of scalability. As the number of learners increases, the processing it requires to find k nearest neighbors increases. If this is coupled by a growing number of courses, each complete with many distinct course elements, the performance of classical

| Learning category | Learning styles | Features description |
|-------------------|----------------|----------------------|
| Processing        | Active vs. Reflective | Reflective learners like to think about the material; prefer individual or very small group communication. Active learners learn by direct interaction with the material; prefer group communication. |
| Input             | Visual vs. Verbal   | Visual learners are better in understanding with multimedia contents such as images, charts, graphs, videos. Verbal learners are better in understanding with written or audio. |
| Understanding     | Sequential vs. Global | Sequential learners prefer in learning sequentially like topic wise with logical connections. Global learners prefer randomly selection of topics as per their knowledge then understanding concept fully. |
| Perception        | Sensing vs. Intuitive | Sensing learner are detail oriented and considering practical examples to understand. Intuitive learners are creative in nature and understands from theoretical concepts and fundamentals. |
collaborative filtering decreases exponentially. Multiple approaches such as context based collaborative filtering and hybrid-learner based-item based collaborative filtering have been suggested to tackle this which work by effectively reducing the size of the dataset the algorithm has to operate on. In our approach, a similar idea is employed by clustering learners based on their learning style. This effectively reduces the dataset while also saves processing time by eliminating learner-based or item-based similarity calculation for a large number of individuals (Li et al., 2005; Rabahallah et al., 2018).

11. Learner ratings

Recommendation systems that utilize collaborative filtering or some elements of it require a learner to rate individual items. In related literature both latent interaction metrics and direct ratings have been used for this to different degrees and, at times, in conjunction with each other. Constructs such as course ratings, course feedback forms etc. have been used to map learner's ratings with a course, this is a case of direct rating. However, there are cases when the platform has no constructs for direct learner ratings, or it is absence at the level of granularity the system works on. The MOOC platform that our approach works on has a direct learner feedback at the course level but no such construct for member course elements.

Thus, to counter this, we have utilized certain latent interaction metrics for the member course elements ratings. In this approach, we have chosen average time spent on and average revisits made to an element as primary latent metrics since we found that learners prefer to revise the course with elements in line with their learning style. Average time and time spent per revisit essentially eliminate an element skip (skipping through elements to reach a specific element) or a false load (loading into an element for accessing other course elements). Metrics like element interaction sequence, quiz completion status etc. are used with a lower associated weight. The calculated ratings thus represent learner's preference of said item. These ratings are used to find learning styles as well as make recommendations.

To identify the learning styles of the learner's certain interaction parameters are identified and captured through browser extension in the MOOC environment. Examples of some parameters such as totalTime, actualTime spent on learning contents to compute completionTime of the learning contents for the specific module of the course. Also, number of visits, revisits for various
types of materials or assessments used to calculate visit score. The moves to the next elements or skipped elements captured to compute the score related to local or global move. Also, active participation of learners towards additional components such as forums and assessments are used to compute participation score. Based on defined score values of Felder-Silverman Learning Style Model (FSLM) ILS Questionnaire approach the computed score values of all interaction parameters are mapped to identify the learning styles of the learners. The detailed algorithms and identification of exact metrics for learning styles mapping are explained in our another communicated research. The base of the work is referred from (Kolekar et al., 2016).

12. Similarity through clusters
As discussed earlier, one of the drawbacks of classical collaborative filtering is that it cannot be scaled efficiently with growing item size and learner size. In this approach learner clustering is used to solve this issue. Learners are clustered as strong-mod-A, strong-mod-B, and mild/balanced under each criterion of FSLSM. The example cluster ontology of Input category is shown in Figure 7.

Once a learner enrolls in a course, his learning style metrics are fetched. As he starts a module (say week for a week wise organized course), usage parameters of learners who took the course and have similar learning style are fetched. The collaborative filtering algorithm runs on this reduced item set to provide top n course elements as recommendations. All criteria, however, are not directly used for course element recommendation. Criteria such as perception and understanding are used to lay down a recommendation structure. A learner with a strong-mod sequential preference will be provided recommendation from the current topic he is going through while one with a strong-mod global preference will be recommended course elements from topics that come later on in the course or those that have come before and are foundational, one with a mild preference can expect a balanced set of recommendations from all topics of the module. Similarly, in the case of perception, an intuitive learner is recommended quizzes and assignments after completing a smaller fraction of a topic while a sensory learner is recommended the same after completing a larger part. Thus, learning style clusters help in both rating/preference prediction and element delivery method. The clusters under perception- sensory/intuitive are used in the following subsection to make rule-based recommendations for quizzes, assignment etc. The process of rating prediction follows from classical collaborative filtering using the following equation 1 (J.K. Tarus et al., 2018):

![Figure 7. Cluster ontology of learners based on FSLM.](https://doi.org/10.1080/23311916.2021.2022568)
\[ r_{ij} = r_i + \frac{\sum k \text{similarities}(u_i, u_k)(r_{kj} - r_k)}{NR} \]  

where:

NR: Number of Ratings.

U_i: Active learner.

U_k: Similar learner.

r_{kj}: rating of learner k to item j.

r_k: mean rating of learner k.

r_i: mean rating of learner i.

r_{ij}: Predicted rating of learner i to item j.

Pearson’s coefficient has been considered over cosine-similarity. The equation 2 has been used to find most similar learners from the reduced dataset (Raballah et al., 2018; Bellogin & Parapar, 2012).

\[ \text{sim}(U_i, U_u) = \frac{\sum_{i=1}^{n-1}(r_{ai} - r_u)(r_{ai} - r_u)}{\sqrt{\sum_{i=1}^{n-1}(r_{ai} - r_u)^2} \sqrt{\sum_{i=1}^{n-1}(r_{ai} - r_u)^2}} \]  

where:

r_{ai}: rating of learner u for item i.

r_u: mean rating of learner u.

r_{ai}: rating of learner v for item i.

r_v: mean rating of learner v.

If the similarity score is close to +1, this indicates a strong positive correlation.

If the similarity score is close to −1, this indicates a strong negative correlation.

13. Algorithm

This subsection provides the algorithm implemented for the previously discussed phase-wise approaches. The results achieved are displayed as pop-ups that change dynamically as the learner progresses through the course.

14. Algorithm 1: generation of dynamic recommendations

The course element recommendations are shown in Figures 8 and 9. These recommendations are useful for a learner to attempt rest of the module based on previous performances of assessments and content study.
15. SWRL rules
Lastly, the rule-based recommendations are implemented through SWRL. SWRL uses OWL-DL and OWLLite with the unary/binary sublanguage of the Rule Markup Language (RuleML) and follows an antecedent-consequent structure where if antecedent follows, consequent also follows. The rules made are concerned with learning sequence, quiz results, quiz access and general suggestions based on performance. The underlying ontological information is used to supplement these rules. The rules incorporated as part of our approach are as follows.

16. Semantic rules for recommendations
The recommendations made through these rules are shown in Figure 9. First part of the figure shows a suggestion learner will receive if his performance is not up to the mark at the end of a topic. The second part shows the suggestion learner will receive if he has been interacting with the platform for extended duration of time without a break.

17. Experimentation and result analysis
The recommendation system designed through this approach was tested on a total of 447 learners. These learners were enrolled in “Big Data Modelling and Management Systems” offered by UCSD as a part of the curriculum, apart from extracurricular courses that they were enrolled in. Three approaches were used to measure the effectiveness of the recommendation system: a click through log-based approach, a paired t-test based approach and an explicit rating-based approach (Kolekar et al., 2016). The learners were provided the access to our browser extension thirty days prior to the completion deadline of the six-week long course. Their performance over the course of the roughly two-week long period in which they did not have access to the extension was also adequately and accurately captured by our extension by scraping historic
usage-data (previous visits/attempts/scores etc.) recorded by the MOOC platform. At the end of the thirty-day period, certain observations were made following the aforementioned tests which have been discussed in the following subsections.

18. Click-Through log based approach
As discussed in the previous section, the recommendations made are in the form of hyperlinks and thus can be clicked on to be directly navigated to the particular course elements. Recommendation pop-ups are shown after every 20 minutes of usage or after completion of three course elements, whichever comes earlier. The recommendation pop-up can be manually seen too by clicking on the extension icon and can be dismissed through the use of the close (X) button at any time. The effectiveness of recommendations made is found using the following equation 3:

$$CTR = \frac{TC}{TRe}$$

where:

CTR: Click Through Rate.

TC: Total Number of Clicks Made.

TRe: Total Number of Recommendations Popped-up.

The metric CTR helps us gauge how a learner interacts with the pop-ups. This is based on the idea that a learner that finds recommendations useful will access more of them. Because of the hyperlink structure of the recommendation pop-up, it gets dismissed after redirecting learner to the chosen element and thus each time a pop-up appears, it can be used or dismissed giving us a clear indication of a positive or a negative response (Silveira et al., 2019; Sikka et al., 2012).

All learners clicked on at least one of the recommended course elements with the average CTR of 447 learners being around 0.67. The maximum CTR observed was 0.83 and minimum observed CTR was around 0.34. Around 77% of the learners had a CTR of greater than 0.5 which shows an overall good effectivity. The general distribution has been shown in Figure 10 for first 50 learners.

Figure 10. Analysis of recommendations using Click Through Rate.

19. Statistical significance using paired t-test
An important tool in gauging the effectiveness of any recommendation system is to measure changes in user experience, performance, or other context-specific metrics before and after the employment of said recommendation system. In this approach, we have chosen to gauge the effectiveness of our
recommendation system by considering average quiz scores before (two-week period) and after (four-week period) the use of our browser extension as two different groups and have subsequently performed a paired t-test on these two groups to find any statistical difference between them. The paired sample t-test or dependent sample t-test is used to measure the mean difference of two paired sets of values. Average quiz scores corresponding to each learner are measured twice: before and after accessing the recommendation system. We perform this test at two levels of granularity with a 5% significance level and 95% confidence interval.

We start at the upper level where we aim to measure the overall effectiveness of our recommendation system. At this level, we use an upper-tailed paired t-test where the alternate hypothesis is accepted only if the mean difference between average scores after and average scores before accessing the recommendation system increases, that is, students score better after accessing the recommendations. The value of n is set at 447.

For this, we have the following two hypotheses:

Null Hypothesis ($H_0$): The scores do not improve (upper-tailed) after using the recommendation system. There is no statistical difference.

Alternate Hypothesis ($H_a$): The scores improve after using the recommendation system.

We list out the average scores of students before and after access to the recommendation system and perform the paired t-test as shown in equation 4.

$$t = \frac{\sum d}{\sqrt{\frac{n \sum d^2}{n-1} - \sum d}}$$

Where $d$: difference per paired value and $n$: number of samples.

Steps to perform paired t-test: 1. First calculate (after-before) difference. Calculate average of it. 2. Calculate standard deviation. 3. Calculate t values from student table with df = 446 (n-1 = 447-1), $t$ = 1.679 from table. 4. Now calculate $t_c$ which is our calculated t value. If $t_c > t$, our test passes as we get value in the rejection region. 5. Null hypothesis is rejected.

We calculate the $t_c$ value using the computed average sample difference, standard deviation and degrees of freedom and compare it to the $t$ value calculated from the student t table. We find the value of $t_c$ to be 3.121 which is greater than 1.679 which helps us reject the null hypothesis and validate our alternate hypotheses that the average quiz scores of students using the recommendation system improve. With this result, we can conclude that the recommendations did have a positive impact on student’s learning experience during the course of the study.

Besides a holistic overview of the performance of our recommendation system, we also wanted to assess it is working at an even greater granularity: at the level of learner clusters. Each learner is part of one of three clusters for each of the four criteria, thus, all information regarding the learner’s learning style can be obtained from his presence in these clusters. This time, we run both upper-tailed and lower-tailed paired t-test for each of the four criteria of the Felder Silverman Learning Style Model by further dividing the learners into three distinct clusters under each criterion: strong-mod-A, mild, and strong-mod-B. For each criterion, the number of learners in individual clusters vary (thus, n varies for each test) however, all clusters add up to 447 learners. We use both upper-tailed and lower-tailed t-tests as at such a granularity (learner cluster-level), scores can even be negatively affected in some rare cases. With this test, we aim to gauge how learners of different learning styles respond to recommendations made. Again, we start by listing average quiz scores of learners before and after
access to the recommendation system for each cluster and find the mean difference between the two groups to see if they are statistically different.

As before, we draw the following two hypotheses:

**Null Hypothesis (H₀):** The scores do not change significantly after using the recommendation system.

**Alternate Hypothesis – 1 (H₁):** The scores improve after using the recommendation system (upper-tailed).

**Alternate Hypothesis – 2 (H₂):** The scores reduce after using the recommendation system (lower-tailed).

Our findings in the form of p values for these tests are compiled in Table 2.

| FSLSM categories | Strong-mod-A | Mild | Strong-mod-B |
|------------------|--------------|------|--------------|
| Understanding    | 0.034        | 0.039| 0.025        |
| Processing       | 0.185        | 0.044| 0.216        |
| Perception       | 0.042        | 0.033| 0.029        |
| Input            | 0.022        | 0.028| 0.038        |

From the table above, we can see that for mild preference for each criterion, we have found a positive change in average quiz scores (t₁ > t) and thus the first alternate hypothesis follows. Learners who have mild or balanced preference benefit the most from the recommendations and consistently show improvements in their performance. This is consistent with findings in contemporary literature.

Furthermore, we can observe how the t-test validates the first alternate hypothesis for all clusters for the understanding and input criterion (t₁ > t). For “input”, this is in accordance with expectations as there are two distinct types of course elements on MOOC platforms – visual (videos, walkthroughs, charts, tables etc.) and verbal (reports, discussion prompts etc.) and learners with strong preference for either perform better on quizzes when they are recommended course elements in accordance with their preferences. Similarly, results follow expectations for the “understanding” criterion as our system is capable of recommending course elements both internal and external to the module. Learners with strong global or strong sequential preferences thus perform better when recommended suitable course elements.

We can also see that the second alternate hypothesis holds true for strong-mod-A cluster for “processing” criterion (t₂ < t). This can be explained by the idea that learners with strong preference for an active style of learning tend to learn by problem solving and direct involvement with the course material. They attempt quizzes after completing a smaller fraction of the module compared to learners having mild or weak preferences. The reduction in performance is small but exists as they are recommended quizzes more frequently than most other learners. On the other hand, learners with a strong reflective learning style show an overall improvement in their average quiz scores when they are recommended course elements in accordance with their learning style.

Lastly, while learners with strong sensing or intuitive capabilities (under the “perception” criterion) show some improvement in grades (and thus follow the first alternate hypothesis), the improvement is comparatively less noticeable (t₃₂ < t₃₁). It is for this reason that we fail to
reject the null hypothesis for these clusters. This can be attributed to the smaller number of students with strong preference for either of these learning styles (6 and 8) when compared to strong preferences under other criteria. This is mostly because of fewer course elements catering to the “perception” criteria on online learning platforms (practical/real-world experiments) and a general preference for a mix between the two (sensory and intuitive) in learners.

All in all, our recommendation system works adequately as shown by tests conducted at two different levels of granularity and our findings are consistent with previous questionnaire-driven studies in the field.

20. Explicit feedback rating approach
Certain aspects of our approach, such as usability and user satisfaction, cannot be statistically gauged by using tests discussed in contemporary literature. To gauge these and other such aspects, we designed an explicit feedback system. The learner, on completion of the course, is provided with a feedback pop-up, similar to recommendation pop-ups, that helps us gauge the success of our recommendation system. Feedback is measured under five different criteria: effectiveness, personalization, adaptability, usability, and future usage, each represented with a question and marked out of 5. The maximum points on the feedback form thus being 25. Figure 11 shows the feedback form pop-up.

![Figure 11. Explicit Analysis of Recommendations using Feedback Approach.](https://doi.org/10.1080/23311916.2021.2022568)

| Feedback Form |
|---------------|
| 1. Were the recommendations helpful to you during the course duration? | 1 | 2 | 3 | 4 | 5 |
| 2. Did you find the recommendations in line with your style of learning? | 1 | 2 | 3 | 4 | 5 |
| 3. Did the recommendations change and improve as you progressed through the course? | 1 | 2 | 3 | 4 | 5 |
| 4. Was the recommendation pop-up unobtrusive and easy to operate? | 1 | 2 | 3 | 4 | 5 |
| 5. Will you use this system for other courses you enrol in the future? | 1 | 2 | 3 | 4 | 5 |

Effectiveness is essentially used to gauge how relevant were the recommendations in understanding the concepts. Personalization is used to gauge how learner specific were the recommendations made and if learners found them in line with their learning style. Adaptability is essentially used to gauge how recommendations evolved and adapted to any changes in learner’s learning style. Usability is a measure of how accessible the recommendation pop-up in the sense of ease of use was, position on the screen, size, listing style etc. Future usage is concerned with if the learner had a good experience with our extension and if he or she will opt for this recommendation system in other courses (Kolekar et al., 2019).

The average score out of 25 was 18 with the maximum score being 24 and the minimum score being 11. Around 73% of the people had a total score greater than 15 which is in line with what we observed in the previous tests. The results show generally favorable feedback with a substantial fraction of learners rating highly in the “future usage” criteria. The case of personalization, which was a major aspect of this approach, was similar, with learners finding recommendations in line with their learning style and orientation. Of the five criteria, the lowest scores were observed for “usability” from which we can conclude that the recommendation delivery method (pop-ups) can be improved to be made more visually appealing. The graphical representation of computed average score of feedback is shown in Figure 12. Since our goal was to provide for a more personalized learning experience, the scores for the “personalization criteria” are also shown separately in Figure 13.
21. Conclusion

In this paper, we have proposed a truly hybrid knowledge-based recommendation system that incorporates both clusters-based collaborative filtering and rule-based recommendation using SWRL. The incorporation of learning style based on the Felder Silverman Learning Style Model to cluster learners reduces processing time and makes the algorithm more efficient. Cold start problem is dealt with underlying contextual knowledge and lastly SWRL is used to draw up rules for rule-based recommendation.

The novelty of this approach lies in the fact that the granularity for recommendations is to the level of individual course elements which has not been explored much, to the best of our knowledge, in contemporary literature. Even module wise course element recommendations are made dynamically and can change majorly depending on learner behavior. Rule based recommendations provide for a smooth learning experience while making suitable suggestions as the learner goes through the course. From the previous section, it can be inferred that the recommendation system has had mostly favorable feedback and has provided learners involved with a personalized course experience. The scope of improvements pertaining to this approach lies mainly in the field of learner characteristics modelling where we aim to incorporate other contextual and behavioral constructs like previous knowledge, job requirements, skill-set etc. in the future. The recommendation delivery pop-up will also to be tweaked to recommend adequate course elements without overwhelming the learner. The feedback form may also be worked upon and may be entirely replaced by tracked implicit usage metrics such as change in quiz scores, or number of assignments reviewed etc.
List of Abbreviations

- Technology Enhanced Learning (TEL)
- Massive Open Online Courses (MOOC)
- Semantic Web Rule Language (SWRL)
- Felder Silverman Learning Style Model (FSLSM)
- Case Based Reasoning (CBR)
- Collaborative Filtering (CF)
- Rule-Applying Collaborative Filtering (RACOFI)
- Social Semantic Web (SSW)
- Google Cloud Platform (GCP)
- Web ontology Language (OWL)
- k nearest neighbors (kNN)
- Content-based (CB)
- Rule Markup Language (RuleML)
- Click Through Rate (CTR)

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