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FOUNDATIONS

A hybrid recommender system for e-learning based on context awareness and sequential pattern mining

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Abstract The rapid evolution of the Internet has resulted in the availability of huge volumes of online learning resources on the web. However, many learners encounter difficulties in retrieval of suitable online learning resources due to information overload. Besides, different learners have different learning needs arising from their differences in learner's context and sequential access pattern behavior. Traditional recommender systems such as content based and collaborative filtering (CF) use content features and ratings, respectively, to generate recommendations for learners. However, for accurate and personalized recommendation of learning resources, learner's context and sequential access patterns should be incorporated into the recommender system. Traditional recommendation techniques do not incorporate the learner's context and sequential access patterns in computing learner similarities and providing recommendations; hence, they are likely to generate inaccurate recommendations. Furthermore, traditional recommender systems provide unreliable recommendations in cases of high rating sparsity. In this paper, we propose a hybrid recommendation approach combining context awareness, sequential pattern mining (SPM) and CF algorithms for recommending learning resources to the learners. In our recommendation approach, context awareness is used to incorporate contextual information about the learner such as knowledge level and learning goals; SPM algorithm is used to mine the web logs and discover the learner's sequential access patterns; and CF computes predictions and generates recommendations for the target learner based on contextualized data and learner's sequential access patterns. Evaluation of our proposed hybrid recommendation approach indicated that it can outperform other recommendation methods in terms of quality and accuracy of recommendations.

Keywords Recommender systems · Hybrid recommendation · Context awareness · E-learning · Collaborative filtering · Sequential pattern mining

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1 Introduction

As learning resources increase exponentially on the World Wide Web, learners in e-learning environments experience difficulty in choosing relevant learning resources due to information overload. Recommender systems can overcome this problem by filtering and recommending to the learner appropriate learning resources based on the personalized learner preferences. E-learning recommender systems can provide suggestions for relevant and useful online learning resources to learners using e-learning (Ricci et al. 2011). Recommender systems play an important role of automatic recommendation of relevant items to users in domains such as e-commerce and e-learning (Pan et al. 2010; Erdt et al. 2015).

Traditional recommendation techniques such as collaborative filtering (CF) and content-based (CB) recommendation approach rely on user/item rating and content features, respectively, in computing similarities, making predictions and generating recommendations of items to users. However, in e-learning recommender systems, learner preferences change from context to context. Traditional recommendation techniques such as CB and CF deal with only two types of entities, namely *items* and *users*, and do not consider their context when making recommendations (Adomavicius and Tuzhilin 2011; Zheng et al. 2015). However, accurate recommendation of learning resources requires incorporation of learner's context information and sequential access patterns to improve personalization and accuracy of recommendations. Contextual information such as learning goals and knowledge level need to be taken into account in making recommendations to the target learner. Furthermore, since different learners may have different sequential access patterns, then sequential access patterns should also be integrated in computing learner's recommendations. By incorporating context awareness and learner's sequential access patterns into the recommender system, the recommendation results will be more personalized to the learner preferences. A learner whose knowledge level is *beginner* at the current context may have different preferences for learning resources when the knowledge level of the same learner changes to *intermediate* in future context. The recommendation problem arising from differences in learner's contextual characteristics can be addressed by using context-aware (CA) recommendation method with SPM. In the context of e-learning, CA-based recommender systems take into account the learner's context when modeling the learner preferences and generating recommendations. De Campos et al. (2010) point out the importance of incorporating other additional information about the user including user's context information to improve the quality of recommendations.

In this paper, we propose a hybrid recommendation approach for recommending learning resources to learners by incorporating context awareness and SPM algorithm into the recommender system. In our method, we use context awareness to incorporate additional contextual information about the learner, while SPM algorithm is used to mine the web logs and discover the learner's sequential access patterns. The contributions of this work that distinguishes it from previous studies include:

- First, we incorporate context awareness and learner's sequential access patterns into the recommendation process to achieve improved personalization of recommendations. Context awareness is used to incorporate learner's contextual information such as knowledge level and learning goals, while SPM algorithm is used to discover the learner's sequential access patterns and filter the recommendation results according to these sequential access patterns.
- Secondly, in computing the learner/learning item similarities, we take into account the learners contextual information to enhance the accuracy of predictions.
- Lastly, we show through experimental evidence that our recommendation approach combining CF, CA and SPM algorithm provides more accurate recommendations than other related recommendation methods.

The rest of this paper is structured as follows. In Sect. 2, we present the background on recommendation techniques which include collaborative filtering, context awareness and sequential pattern mining. In Sect. 3, we discuss the related work relevant to this study. In Sect. 4, we describe the recommendation model and the hybrid algorithm. In Sect. 5, we present the experiments, results and discussion and finally, in Sect. 6, conclusion and future work.

2 Background

Recommender systems play a significant role in the field of e-learning as a solution toward overcoming information overload problem. They are classified according to the technique used in recommendation. Burke (2007) and Jannach et al. (2011) distinguish between different classes of recommendation techniques which include collaborative filtering, content-based, knowledge-based (KB), demographic-based, utility-based and hybrid recommendation. Other more recent recommendation techniques include context-aware-based (Adomavicius and Tuzhilin 2011; Zheng et al. 2015), trust-aware- based, fuzzy-based (Zhang et al. 2013), social-network-based (He and Chu 2010), ontology-based (Tarus et al. 2017a) and group-based (Dwivedi and Bharadwaj 2015) techniques. In this section, we give a brief overview of the recommendation techniques relevant to this study.

2.1 Collaborative filtering

Collaborative filtering recommends items to the active user that other users with similar tastes liked in the past. The similarity between two users is calculated based on the similarity in the rating history of the users (Schafer et al. 2007; Yao et al. 2015). A rating measures the degree of interest in an item by the user. Computation of similarity between users or items is the principle behind CF. The most widely used algorithm for CF is the k-nearest neighbor (kNN) (Adomavicius and Tuzhilin 2005; Bobadilla et al. 2011). Figure 1 summarizes the entire process of recommendation in CF.

Collaborative filtering deals with user and item entities. The rating function R in traditional CF recommender systems can be defined as:

$R : User \times \ Item \rightarrow Rating$

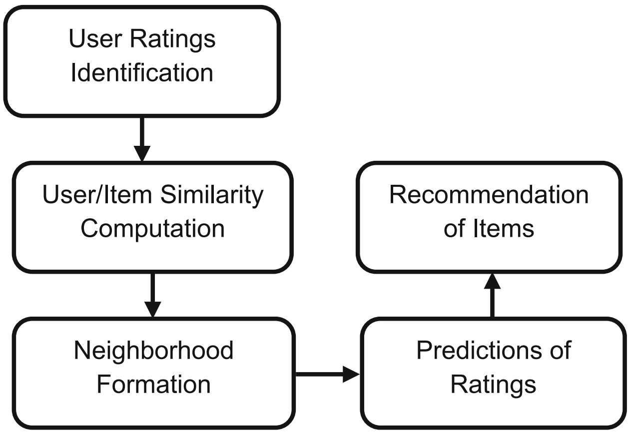

Fig. 1 Recommendation process in collaborative filtering

Table 1 Rating matrix for collaborative filtering

	Item 1	Item 2	Item 3
Learner 1	4	5	?
Learner 2	1	3	5
Learner 3	5	5	3
Learner 4	3	4	5
Learner 5	4	5	4

This is a two-dimensional (2D) rating function since they consider only the *User* and *Item* dimensions in the recommendation technique. The traditional recommendation problem entails the estimation of ratings of items that the user has not yet seen (Adomavicius and Tuzhilin 2011). The rating table (Table 1) illustrates the representation of a 2D CF rating matrix. Learner 1's rating of Item 3 can be predicted based on Learner 1's similarity to other learners in terms of their ratings of Item 1 and Item 2.

Though collaborative filtering is the most popular recommendation technique (Ricci et al. 2011), its major drawback is the new user and new item problems (Rashid et al. 2008; Barjasteh et al. 2016). The new user and new item problems are commonly referred as cold-start problem (Son 2015; Barjasteh et al. 2016) which occurs in scenarios where it is not possible to make reliable recommendations due to an initial lack of ratings for new users or items (Adomavicius and Tuzhilin 2005; Schafer et al. 2007). Other drawbacks associated with collaborative filtering include scalability and data sparsity problems. Data sparsity (Zhao et al. 2015a; Ranjbar et al. 2015) occurs when few users have rated the same item, hence no overlap in the rating preferences.

2.2 Hybrid recommender systems

The hybrid filtering method hybridizes the features of two or more recommendation techniques, e.g., CB and CF recommendation techniques to benefit from the strengths of each technique and improve performance (Ghauth and Abdullah 2010; Liu et al. 2012). Hybrid recommendation technique is very useful because it can overcome most of the limitations experienced by the individual recommendation approaches. Previous studies on recommender systems have shown that combining different recommendation techniques provides improvement in performance (Chen et al. 2014; Zhao et al. 2015b; Nilashi et al. 2014).

Table 2 Example of rating matrix in CA recommender system

Learner	Learning object	Knowledge level	Rating
Learner 1	i_1	Beginner	5
Learner 2	i_1	Advanced	3
Learner 3	i_1	Beginner	5
Learner 1	i_1	Intermediate	**?**
Learner 3	i_1	Intermediate	4

2.3 Context-aware (CA)-based recommendation

According to Dey et al. (2001), context refers to any information that is used in characterization of the situation of an entity. An entity can either be a person, object or place that is considered to be relevant to that interaction between the user and the application, and it includes both the user and applications themselves. In the context of this study, the learner context information includes the *knowledge level* and *learning goals*. These contextual characteristics change according to situations as the learner acquires more knowledge. Context-aware recommender systems use context in their recommendation process for purposes of providing recommendations that are suitable for a specific user context (Gaeta et al. 2016). In context-aware scenario, ratings are modeled as a function of users, items as well as context; hence, the rating function can be defined in three dimensions (3D) as:

$R\colon User \times Item \times Context \to Rating$

where *User* and *Item* belong to the domains of users and items, while *Rating* belongs to the domain of ratings, and *Context* is the contextual information related to the application (Adomavicius and Tuzhilin 2011). The user/item rating dimension was extended in order to add context dimensions which can help in personalization of recommendations according to user context. Table 2 illustrates an example of a rating matrix in CA recommender systems scenario with *knowledge level* as context.

Different learner contexts in CA recommendation can impact on the learner preferences and ratings by the learners and also similarity and prediction of ratings for the target learner. For example, in Table 2, the change of *knowledge-*

level context of Learner 1 from *Beginner* to *Intermediate* can influence the rating of the learning resource. Learner 1's rating for item i_1 when the knowledge-level context changes from *Beginner* to *Intermediate* can be predicted using contextual similarity with other learners. Inclusion of learner context into the recommendation process helps improve personalization of recommendations to the target learner.

Contextual information can be acquired explicitly, implicitly or through inferring the context (Adomavicius and Tuzhilin 2011). Explicit method involves physical and manual input from users, while in implicit method, the contextual information is captured automatically from the environment. Contextual information can also be inferred through the use of data mining or statistical methods (Verbert et al. 2012; Adomavicius and Tuzhilin 2011). Adomavicius and Tuzhilin (2011) identify three paradigms for incorporating contextual information in recommender systems, namely contextual modeling, contextual pre-filtering and contextual post-filtering.

In contextual pre-filtering paradigm, information about the current context denoted as c is used to select and construct the relevant set of data records or ratings (Adomavicius and Tuzhilin 2011). Subsequently, the ratings can be predicted by using any of the traditional two-dimensional (2D) recommendation techniques on the selected data (Verbert et al. 2012).

2.4 Context-aware recommender systems in e-learning

Context-aware recommender systems in e-learning recommend learning resources to the learners based on the current context of the learner (Adomavicius and Tuzhilin 2011; Do et al. 2015). Aggregation of context information about the learner into the recommendation process facilitates more accurate recommendations of learning resources to learners with similar ratings according to learner context. The ability to incorporate additional context information into the recommendation process makes hybridized context-aware recommender systems more personalized to the learner preferences.

2.5 Sequential pattern mining

Sequential pattern mining (SPM) was first introduced by Agrawal and Srikant (1995). Sequential pattern mining refers to the process of discovering all subsequences that appear frequently on a given sequence database (Mabroukeh and Ezeife 2010; Mooney and Roddick 2013). A sequence is an ordered list of itemsets. SPM algorithm mines the sequence database looking for repeating patterns (frequent sequences) that are useful for finding association between the different items in their data for purposes of prediction. The commonly used algorithms for SPM include Generalized Sequential Pattern (GSP), Sequential PAttern Discovery using Equivalence classes (SPADE), FreeSpan and PrefixSpan (Mabroukeh and Ezeife 2010). GSP and PrefixSpan are the widely used sequential pattern algorithms. GSP mines sequential patterns by adopting a candidate subsequence generation-and-test approach, based on the apriori principle (Agrawal and Srikant 1995; Pei et al. 2004). The apriori property states that "All nonempty subsets of a frequent itemset must also be frequent" (Mabroukeh and Ezeife 2010). The major strength of GSP algorithm is pruning by apriori, hence reducing the search space. However, GSP algorithm is not efficient in mining large sequence databases having numerous patterns. SPADE is a sequential pattern mining algorithm that performs the patterns mining by growing the subsequences one item at a time by apriori candidate generation (Zaki 2001). It adopts vertical data format with the search space decomposed into sub-lattices that can be processed independently in main memory. The bottle necks of SPADE are a huge set of candidates generated multiple scans of database; hence it is inefficient for mining long sequential patterns. FreeSpan mines sequential patterns by partitioning the search space and projecting the sequence subdatabases recursively based on the projected itemsets (Han et al. 2000). It starts by creating a list of frequent 1-sequences from the sequence database called the *frequent item list (f-list)* and then constructs a lower triangular matrix of the items in this list. The strength of FreeSpan is that it searches a smaller projected database in each subsequent database projection. However, the major overhead of FreeSpan is that it may have to generate many nontrivial projected databases. If a pattern appears in each sequence of a database, its projected database does not shrink (Pei et al. 2004). PrefixSpan algorithm on the other hand is a projection-based pattern mining algorithm. It initially scans the whole projected database to find frequent sequences and count their supports. PrefixSpan examines only the prefix subsequences and projects only their corresponding postfix subsequences into projected databases (Han et al. 2000). The key advantage of PrefixSpan is that it does not generate any candidates. It only counts the frequency of local items and utilizes a divide-and-conquer framework by creating subsets of sequential patterns (projected databases) that can be further divided when necessary. The major cost of PrefixSpan is the construction of projected databases recursively (Mabroukeh and Ezeife 2010).

A comparison of the SPM algorithms in previous studies in terms of performance has shown that GSP algorithm outperforms both FreeSpan and SPADE in many situations. Although PrefixSpan is more efficient than GSP algorithm in terms of execution time and memory usage for large databases, GSP algorithm on the other hand provides better performance due to apriori pruning for average-sized databases (Mabroukeh and Ezeife 2010; Mooney and Roddick 2013). Furthermore, GSP algorithm has very good scale-up properties with respect to the average data sequence size. In our work, we adopted GSP algorithm due to its good performance for medium-sized sequence databases where execution time is negligible. Moreover, previous studies such as Huang and Shiu (2012) and Xinyi et al. (2014) have shown that GSP algorithm is efficient and able to generate all possible candidate sequences without missing any actual sequences; hence, it is suitable for application in e-learning environments due to its high accuracy.

3 Related work

Hybrid and context-aware recommender systems have received great attention by researchers in the recent years as an alternative recommendation technique in e-learning domain. As a result, a number of studies have been carried out on hybrid and CA recommender systems for e-learning. For instance, Verbert et al. (2012) present comprehensive survey on CA recommender systems that have been deployed in technology enhanced learning (TEL) settings. The results of their survey show that there has been much advancement in the development of CA recommender systems for TEL in recent years. Ruiz-Iniesta et al. (2014) propose a recommendation strategy based on context awareness for recommending educational resources such as lecture notes, exercises and questions to learners in a computer science course. This system uses contextual information of the user such as knowledge about that particular field. On the other hand, Gallego et al. (2012) proposed a model for generating proactive CA recommendations in e-learning systems. Their system takes into account the current social, location and user context as contextual information in the recommendation process. Do et al. (2015) propose a CA recommendation framework to suggest a number of suitable learning materials for learners. Their experimental results reveal that incorporation of contextual information into the recommendation process improved the performance of their recommender.

Furthermore, Hu et al. (2013) present an intelligent personalized CA recommendation system using rules engine in an e-learning environment. In this system, user contextual information is captured from external social networks, whereas rules engine is used to manage a set of rules for each user to offer personalized recommendation. Salazar et al. (2015) propose an approach of incorporating context awareness services within an adaptive ubiquitous multi-agent system (U-MAS) learning environment for recommending educational resources. Their results demonstrated the effectiveness of their approach in virtual learning environments and improving learning processes. In addition, Huang et al. (2011) propose a CA recommender system by extracting, measuring and incorporating significant contextual information in recommendation. In their approach, significant attributes to represent contextual information were extracted and measured to identify recommended items based on rough set theory. Their evaluation experiments show that their proposed CA approach is helpful to improve the recommendation quality. Moreover, Anderson et al. (2015) describe an ontology-based reasoning framework to create CA applications. By utilizing ontology in their system, context information was described semantically. Liu and Wu (2015) propose a generic framework to learn context-aware latent representations for CA collaborative filtering. Their experimental results demonstrate improved performance by their CA model. More recently, Zheng et al. (2015) proposed context similarity as an alternative contextual modeling approach. Their experimental results demonstrate that learning context similarity is a more effective approach to CA recommendation than modeling contextual rating deviations.

Romero et al. (2007) described a personalized recommender system for recommending links to students. Their system uses clustering and SPM algorithms for discovering personalized recommendation links. Similarly, Hariri et al. (2012) proposed a CA music recommender system based on latent topic sequential patterns. Their recommender system uses the patterns discovered by PrefixSpan algorithm to predict the next topic in the playlist. In our previous work, we proposed a hybrid knowledge-based recommendation method for e-learning resources based on ontology and sequential pattern mining (Tarus et al. 2017b). Although Romero et al. (2007), Hariri et al. (2012) and Tarus et al. (2017b) both employed SPM in their proposed recommender systems, our work is different in the sense that we combine CF, CA and SPM in our hybrid recommendation approach. Furthermore, in our study, the recommender uses both ratings and contextual information in computing similarities between learners as well as generating predictions of learning items, hence making recommendations more personalized to the learner. GSP algorithm is used in our method to discover learner's historical sequential access patterns, while CA incorporates learner's additional information such as learning goals and knowledge level into the recommendation process. Recommender systems in e-learning differ from other domains since learners have different characteristics such as differences in learning style, learning goals and knowledge level among others, which can influence learner preferences.

The review of the literature has revealed that a number of studies have been carried out on e-learning recommendation. However, our work focuses specifically on hybridization and incorporation of additional knowledge into the recommendation process by combining CF, CA and SPM to improve personalization and performance of the recommender system. To the best of our knowledge, none of the previous studies combined CF, CA and SPM in their recommendation process in e-learning domain.

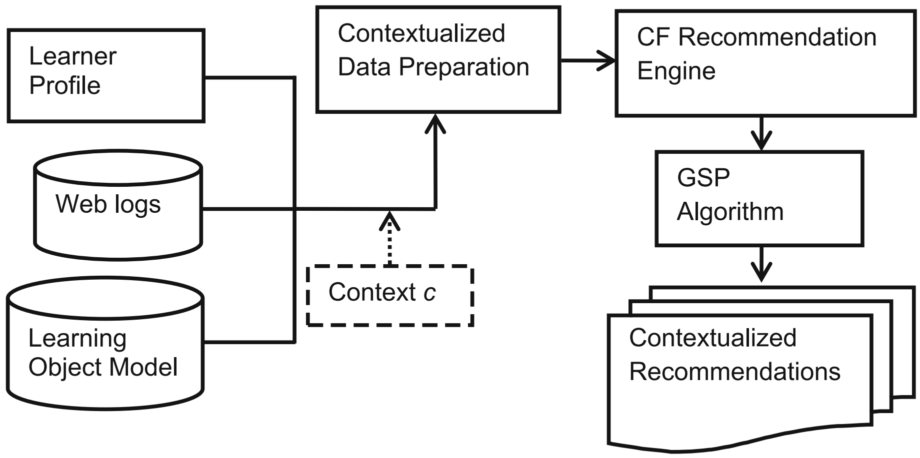

Fig. 2 Recommendation model for the proposed hybrid recommendation approach

4 Recommendation model and the hybrid algorithm

The proposed hybrid recommendation approach in this study combines CF, CA and SPM in recommendation of e-learning resources. This section presents the recommendation model (Fig. 2) and also explains how the proposed recommendation algorithm works.

4.1 The recommendation model for e-learning resources recommendation

The hybrid recommendation model in Fig. 2 summarizes the functionality of the proposed hybrid recommendation approach. The main components of the recommendation model are the learner profile, learning object model, contextualized data preparation, recommendation engine, SPM algorithm and contextual recommendations components. In this subsection, we explain the functions of the main components of the model.

The *learner profile* component stores information and preferences about the learner. Information contained in the learner profile component is acquired using both implicit and explicit methods. Learner's data such as personal demographic data (name, gender, age, etc.) as well as learner's contextual information such as knowledge level and learning goals among others are stored in the learner profile. The learner contextual information is used by the proposed hybrid recommender system to personalize the learner profile and preferences. Similarly, the *learning object model* component contains information about the learning resources. This component stores information about the learning resources that include format of the learning resources which may be text, image, audio or video. Learning resources will be recommended to the target learner based on learner's ratings on learning resources and contextual information.

In the *contextualized data preparation* component, cleaning of the web logs, preparation of learner's contextual information and learning resource's data into a suitable format for the recommender system take place. The *recommendation engine* component then analyzes the contextualized data arising from aggregation of learner preferences, contextual information and ratings. Using this contextualized data, the *CF recommendation engine* computes similarity and predicts the ratings for the target learner taking into consideration the learner's context. The recommendation engine then generates *top N* recommendations of learning resources based on contextualized learner preferences.

The *SPM algorithm* is a sequence pattern mining algorithm. In our model, SPM algorithm is used for mining the web logs to discover the learner's sequential access patterns for the target learner. The sequential access patterns discovered by the algorithm are then applied to the *top N* recommendation results to filter the recommendations according to the learner's sequential access patterns. Finally, the target learner receives the final c*ontextualized recommendations* based on the learner's contextual information and sequential access patterns.

4.2 Implementation of the hybrid algorithm

The proposed recommendation approach entails three main steps: (1) Incorporating context information *c* into the recommendation process using contextual pre-filtering method. (2) Computing learner similarities and prediction of ratings of learning resources based on contextualized data. (3) Generating *top N* contextualized recommendations for the target learner and applying the GSP algorithm to the results to filter the final recommendations according to the learner's sequential access patterns. These steps are summarized in the recommendation framework illustrated in Fig. 2 and explained in detail in this subsection.

4.2.1 Incorporating context information into the recommender system

The paradigm adopted for incorporation of contextual information (Fig. 2) into the recommender system is contextual pre-filtering method proposed by Adomavicius and Tuzhilin (2011). The benefit of adapting context pre-filtering approach is easy integration with any traditional recommender system. In this study, one dimension of learner's contextual information, namely *knowledge level*, is considered. Knowledge level as context dimension in this proposed hybrid recommendation approach change with time and situations as the learner's knowledge improves. For example, a learner with little background knowledge on a subject may have knowledge-level context as *beginner.* However, as the learner acquires more knowledge with time, the learner's knowledge-level context can change to *intermediate.* The initial contextual data *knowledge level* is captured during new learner account registration. During registration into the system, the new learner is tested with some online evaluation questions to determine the knowledge level of the learner based on the test score. This approach of learner's knowledge-level data capture was also employed in a related study on ontology-based recommender system for e-learning by Tarus et al. (2017b). The recommender system then updates the learner profile and subsequently keeps track of the learner's knowledge-level contextual change by administering the online knowledge-level test at periodical intervals.

Contextualized data are used in computing the learner similarities and predictions of ratings of learning resources by the target learner. For example, in Table 2 in the previous section, for a target learner whose contextual *knowledge level* = {*beginner*} to receive recommendations of learning resources, only the ratings for other similar learners with context *knowledge level = {beginner}* will be considered in computation of rating similarity and predictions.

For purposes of computations in the dataset and use by the recommender system, we define *knowledge level* context with 3 values as follows:

Knowledge level = {*beginner, intermediate, advanced*} = {*1, 2, 3*}.

The assigned values of the elements of knowledge level {1, 2, 3} are used in the contextualized rating matrix of learners, learning resources and context values.

4.2.2 Measuring learner similarities and computing predictions of learning resources

Once the context information has been captured by the recommender system, similarities of learners and predictions of contextualized ratings of learning resources are computed by the recommendation engine component (Fig. 2). In computing similarities of ratings, contextual information is taken into account. In this study, *Pearson correlation coefficient* was used to compute the learner similarities (Jannach et al. 2011). Contextual similarity $\mathrm{Sim}(C_l, C_u)$ between the target learner l and learner u is calculated as follows (Eq. 1):

$$\mathrm{Sim}(C_l, C_u) = \frac{\sum_{a=1}^{m}(R_{l,a} - \overline{R_l})(R_{u,a} - \overline{R_u})}{\sqrt{\sum_{a=1}^{m}(R_{l,a} - \overline{R_l})^2}\sqrt{\sum_{a=1}^{m}(R_{u,a} - \overline{R_u})^2}} \tag{1}$$

where $R_{l,a}$ is the rating given to learning resource a by target learner l and $\overline{R_l}$ is the mean rating of all the ratings provided by target learner l based on learner's contextual information. $R_{u,a}$ is the rating given by learner u to learning resource a, and $\overline{R_u}$ is the mean rating of all ratings provided by learner u based on learner's contextual information, while m is the total number of learning resources. Unlike in CF, contextual information is utilized in computing the ratings and the mean rating.

To compute predictions of contextualized ratings of learning resource b for the target learner, the kNN (k nearest neighbors) approach of the most similar learners obtained in eq. 1 who have rated the learning resource b is used (Jannach et al. 2011). The goal is to predict the rating $R_{l,b}$ by target learner l for a new learning resource b using the rating given to b by other similar learners (nearest neighbors). To compute the predicted rating $P_{l,b}$ of learning resource b by the target learner l, we use the prediction formula in Eq. 2 (Jannach et al. 2011):

$$P_{l,b} = \overline{R_l} + \frac{\sum_{u=1}^{n}(R_{u,b} - \overline{R_u}) \times \mathrm{Sim}(C_l, C_u)}{\sum_{u=1}^{n}\mathrm{Sim}(C_l, C_u)} \tag{2}$$

where $P_{l,b}$ is the prediction for the target learner l for a learning resource b, $\overline{R_l}$ is same as in Eq. 1, n denotes the total number of learners in the neighborhood, $R_{u,b}$ is the rating given by learner u to learning resource b, and $\mathrm{Sim}(C_l, C_u)$ is the contextual similarity between target learner l and learner u.

4.2.3 Generating contextualized recommendations and application of SPM algorithm

To generate contextualized recommendations, GSP algorithm is applied to the *top N* to filter the *top N* recommendation results according to the learner's sequential access patterns. In this work, we adapted the GSP algorithm due to its suitability and efficiency in recommendation of e-learning resources. The *top N* recommendations of the learning resources for the target learner l are generated based on contextualized learner similarities and predicted ratings. The recommendation process is illustrated in Algorithm 1 where M is a set of learning resources $\{a, b\}$ and learning resource a has been rated by the target learner and learning resource b

represents unrated learning resources by the target learner of which predictions of ratings are being sought. C is the context representing knowledge level in this study. The elements of knowledge level are {*beginner, intermediate, advanced*} represented by values {1, 2, 3}. $R_{l,a}$ is the rating of learning resource a by target learner l, and $P_{l,b}$ is the predicted rating for unrated learning resource b by the target learner l. Other learners denoted as u have rated learning resource b. Once the *top N* recommendations are being obtained, the GSP algorithm is applied on the recommendation results to filter the *top N* recommendations according to the learner's sequential access patterns. Algorithm 1 shows the procedure of generating the final contextualized recommendations based on GSP algorithm.

Algorithm 1: Generate Recommendations

Input
Learners L = {l, u}
Learning Resources M = {a, b}
Context C = {*Knowledge Level*}
$C \in \{1, 2, 3\}$
Ratings
$R \in \{1, 2, 3, 4, 5\}$

Output
Predicted ratings, *top N*, Final hybrid recommendations

Method
Initialization:
$l \in L,\ u \in L,\ \ a \in M,\ b \in M$
$u = u_1, u_2, u_3, \ldots, u_m$
for $(i = 1;\ i <= m;\ i{+}{+})$ **do**
  Compute target learner's contextual similarity $Sim(C_l, C_u)$ using Eq. (1)
end for
Predict ratings $P_{l,b}$ for target learner l for unrated item b using Eq. (2)
Generate contextualized *top N* recommendations
Apply GSP algorithm to *top N*
Output the final recommendations for target learner l

Discovering sequential access patterns using GSP algorithm involves three main phases: (i) determining the support of each learning resource (*first phase*); (ii) generation of potential frequent sequences (*candidate sequence generation*); and (iii) deleting the candidate sequences whose support count is less than the minimum support (*pruning phase*). In e-learning resources recommendation, the learner's sequential access patterns are important and should be considered in the recommendation process. Therefore, the GSP algorithm is applied on the initial recommendation results *top N* to filter the recommendation results according to the sequential learning access patterns of the learner. The final contextualized recommendations to be recommended to the target learner are based on both the learner's contextual information and sequential access patterns.

5 Experiments and evaluation

5.1 Experimental setup and dataset

Sets of experiments were conducted in order to evaluate the performance of the proposed recommendation approach (*GSP–CA–CF*). The dataset was obtained from a university that is using a learning management system (LMS) to support teaching and learning for students using e-learning. It was collected for a period of 6 months from September 2015 to March 2016. The total number of learners using the LMS to support their learning during the period of experiment was 1200. The LMS allows learners to rate the learning resources on a scale of 1–5 (1–very irrelevant, 2–fairly irrelevant, 3–irrelevant, 4–relevant, 5–very relevant). The recommender system is able to suggest learning resources to the learners by matching their preferences and contextual information. The initial context information (*knowledge level*) was collected during registration of learners to the LMS and is subsequently updated periodically as the learners use the LMS to access online learning resources. The contextual information of the learners, namely knowledge level keep changing with time and situations as the learner's knowledge on a subject improves. Learner's knowledge level can change to *beginner, intermediate* or *advanced* as situations change. During the dataset collection periods, the learner ratings and learner's contextual information were extracted from the recommender system database and sequential access patterns obtained by mining the web logs using the GSP algorithm. The dataset was then split into training subset (80%) and test subset (20%) for purposes of experimental evaluation. The dataset description is shown in Table 3.

For purposes of evaluating the effectiveness of the proposed hybrid recommendation approach, three other algorithms were evaluated over the same dataset described in Table 3 and their results compared. The algorithms that were evaluated are: (i) the proposed hybrid recommendation algorithm combining SPM, CA-based and CF algorithms (*GSP–CA–CF*); (ii) CA based combined with CF (*CF–CA*); (iii) GSP algorithm; and (iv) *CF* algorithm.

5.2 Experimental results

The main goal of this work was to propose a hybrid recommendation approach based on SPM, CA and CF algorithms for recommending learning resources to learners in e-learning environments. In this subsection, we analyze and present the experimental results and evaluation metrics to test the performance and effectiveness of the proposed recommendation approach (*GSP–CA–CF*).

Table 3 Dataset description

No. of learners	No. of LOs	No. of ratings	Context scale	Rating scale
1200	756	57153	1–3	1–5

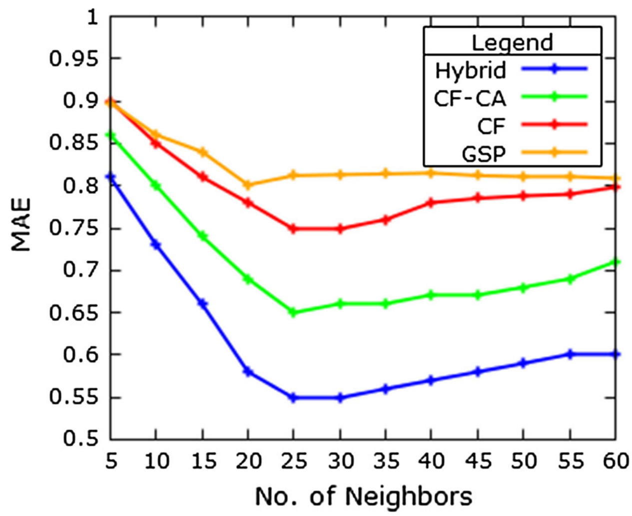

Fig. 3 Accuracy and sensitivity to neighborhood size

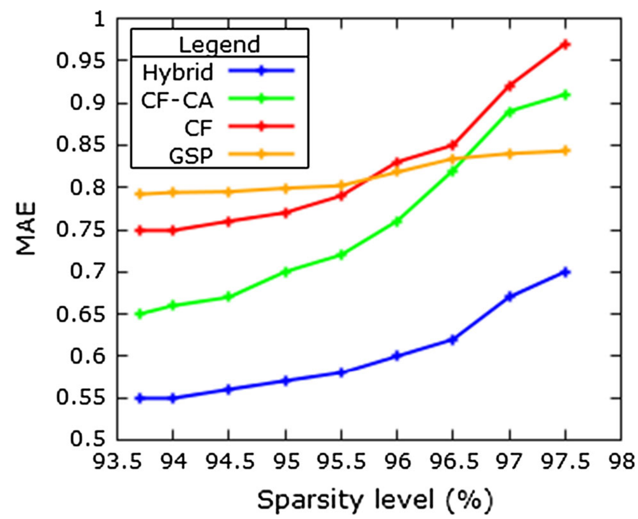

Fig. 4 Quality of prediction against sparsity

5.2.1 Accuracy experiments

A series of experiments were conducted while varying the sizes of neighborhoods so as to establish the optimum size of neighborhood for best results to use in subsequent experiments. The size of nearest neighbors in recommender systems has an impact on both prediction accuracy and quality of recommendations (Sarwar et al. 2000; Chen et al. 2014). Similarly, experiments were carried out to measure the prediction accuracy for the four recommendation algorithms under different sizes of neighborhood. The accuracy of predictions is computed using the MAE (Eq. 3). The lower the value of MAE, the higher is the prediction accuracy.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|p_i - r_i| \quad (3)$$

where n represents the number of cases in the test set, p_i represents the predicted rating of an item and r_i is the true rating (Cobos et al. 2013). Figure 3 shows the sensitivity to neighborhood size and the accuracy of predictions against the number of nearest neighbors for the four recommendation algorithms measured using MAE.

From Fig. 3, it is evident that the accuracy of prediction for the proposed hybrid recommendation approach (*GSP–CA–CF*) as well as the other three recommendation algorithms (*CF–CA, GSP* and *CF*) increases steadily as we increase the number of neighbors from 5 to 25 attaining the optimum prediction accuracy when the number of nearest neighbors is 25. After 25, the curve for the four algorithms *(GSP–CA–CF*, *CF–CA, GSP* and *CF*) begins to rise at smaller intervals; hence, the accuracy of prediction decreases for the four algorithms as the number of neighbors increases beyond 25. Therefore, we selected 25 as the optimal size of neighborhood for the rest of the experiments. Furthermore, it can be observed from Fig. 3 that the proposed recommendation algorithm (*GSP–CA–CF*) provides better accuracy in comparison with the other three recommendation algorithms for any number of nearest neighbors.

5.2.2 Experiments with different levels of sparsity

Experiments to measure the effect of different levels of sparsity on prediction accuracy of the proposed hybrid recommendation algorithm were carried out. The test was carried out using a neighborhood size of 25 which was our optimum neighborhood from the previous experiment. Our original data sparsity level was 93.7%. Figure 4 shows the results on the effect of level of sparsity on the prediction accuracy.

From Fig. 4, it can be observed that our proposed hybrid recommendation algorithm (*GSP–CA–CF*) has the lowest MAE compared to the other three recommendation algorithms at all levels of sparsity. As the sparsity level increases, the MAE also increases for three recommendation algorithms (*GSP–CA–CF, CF–CA, CF*). On the contrary, there was little change on the MAE of *GSP* algorithm as the sparsity level increases. It is evident from Fig. 4 that our proposed recommendation approach (*GSP–CA–CF*) outperforms the other three recommendation approaches with regard to accuracy of predictions at any level of sparsity.

5.2.3 Performance measure

The task of a recommender system in e-learning is to recommend useful learning resources to the learners. To measure the performance of the proposed recommendation method *(GSP–CA–CF)*, we use recall, precision and F1 measure

Table 4 Confusion matrix for recommender systems

	Recommended	Not recommended
Retrieved	True positive *(tp)*	False negative *(fn)*
Not retrieved	False positive *(fp)*	True negative *(tn)*

metrics. We evaluate and compare the performance of the proposed hybrid recommendation approach (*GSP–CA–CF*) against three other recommendation algorithms, namely *CF–CA*, *GSP* and *CF*, in terms of recall, precision and F1 measure. Recall and precision can easily be computed with the aid of confusion matrix shown in Table 4.

In using precision and recall evaluation metrics, learning resources are rated on a scale of 1–5. Learning resources rated 1–3 are considered "*not relevant*," while those rated 4–5 are considered "*relevant*." Precision is the ratio of recommended learning resources to the number of learning resources selected (Ricci et al. 2011; Manning et al. 2009).

$$\text{Precision} = \frac{\text{Recommended learning resources}}{\text{Total learning resources}} = \frac{tp}{tp + fp} \tag{4}$$

Recall on the other hand is the ratio of correctly recommended learning resources to the relevant learning resources (Ricci et al. 2011; Manning et al. 2009).

$$\text{Recall} = \frac{\text{Correctly recommended learning resources}}{\text{Relevant learning resources}} = \frac{tp}{tp + fn} \tag{5}$$

Table 5 shows the performance of the proposed hybrid recommendation approach (*GSP–CA–CF*) in comparison with three other recommendation algorithms, namely *CF–CA, GSP* and *CF*, in terms of precision and recall for different numbers of recommendations.

It is evident from Table 5 that the proposed recommendation algorithm (*GSP–CA–CF*) outperforms all the other three recommendation algorithms in terms of both precision and recall metrics for any number of recommendations. The bold values in the last two columns of Table 5 represent precision and recall respectively of the proposed hybrid recommendation approach. It can also be observed that increase in number of recommendations results in decrease in precision for all the four algorithms. In contrast, as the number of recommendations increases, recall increases as well for all the four algorithms.

F1 measure metric combines both precision and recall into a single value for ease of comparison as well as to get a balanced view of performance (Sarwar et al. 2000). The F1 Metric gives equal weight to precision and recall.

$$F1 = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision+recall}} \tag{6}$$

Figure 5 shows the performance in terms of F1 measure of the proposed hybrid recommendation approach (*GSP–CA–CF*) in comparison with the other three recommendation methods, namely *CF–CA, GSP* and *CF*.

The proposed recommendation approach (*GSP–CA–CF*) shows good performance in comparison with the other three recommendation algorithms in terms of F1 measure (Fig. 5) for all number of recommendations.

5.2.4 Learner satisfaction with recommendations

At the end of the experiments, learners were evaluated on their satisfaction with recommendations from the proposed hybrid algorithm. To carry out this evaluation, a closed-ended questionnaire was administered to the 1200 learners which sought to find out whether the learner was satisfied or not satisfied with the recommendations. Erdt et al. (2015) identified "user satisfaction" as one of the important evaluation measures for e-learning recommender systems. Figure 6 shows the responses of the respondents on whether they were satisfied or not satisfied with the recommendations from the proposed hybrid method. From Fig. 6, majority of the learn-

Table 5 Performance of the recommendation algorithms in terms of precision and recall

No. of Recs	GSP		CF		CF–CA		GSP–CA–CF	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
4	0.390	0.219	0.412	0.220	0.449	0.231	**0.481**	**0.244**
8	0.364	0.221	0.397	0.233	0.443	0.242	**0.476**	**0.256**
12	0.356	0.226	0.384	0.234	0.438	0.248	**0.462**	**0.272**
16	0.348	0.235	0.371	0.242	0.419	0.267	**0.445**	**0.290**
20	0.342	0.248	0.356	0.259	0.388	0.301	**0.420**	**0.336**
24	0.324	0.259	0.332	0.268	0.359	0.321	**0.396**	**0.373**
28	0.302	0.268	0.311	0.290	0.339	0.352	**0.367**	**0.405**
32	0.245	0.277	0.263	0.304	0.314	0.379	**0.348**	**0.451**

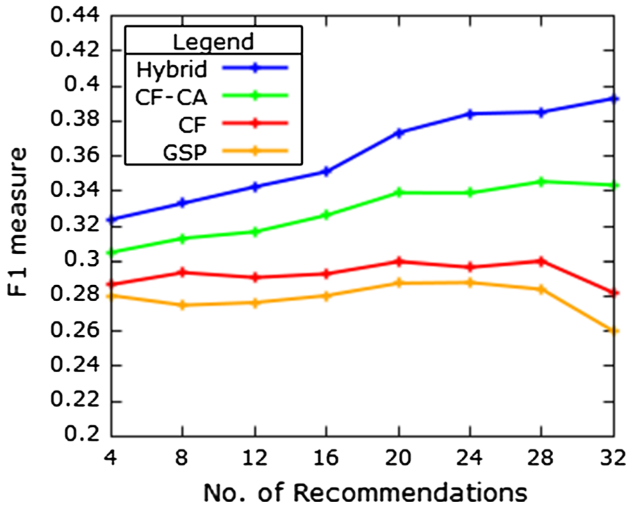

Fig. 5 F1 measure of our proposed hybrid approach against number of recommendations

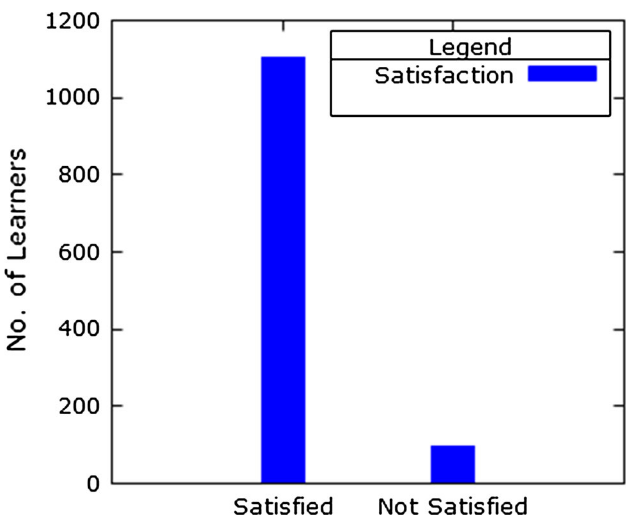

Fig. 6 Learner satisfaction with recommendations of proposed hybrid algorithm

ers (92%) were satisfied, while only 8% were not satisfied with the recommendations.

5.3 Discussion

In order to evaluate the effectiveness of the proposed hybrid recommendation algorithm (*GSP–CA–CF*), similar experimental evaluations were conducted for the other three recommendation algorithms over the same e-learning dataset. The three other recommendation algorithms were CF combined with CA-based (*CF–CA*), the GSP algorithm and the *CF* algorithm. From the experimental results of the proposed hybrid recommendation algorithm (*GSP–CA–CF*), it was evident that the proposed recommendation approach outperforms the other recommendation algorithms in all aspects. For instance, the proposed recommendation algorithm (*GSP–CA–CF*) generates more accurate predictions of ratings and recommendations than the other three recommendation approaches, namely *CF–CA, GSP* and *CF*. The optimum prediction accuracy was obtained when the neighborhood size was 25. The proposed hybrid recommendation algorithm outperformed the other three recommendation approaches in terms of precision, recall and F1 measure. Moreover, the proposed recommendation approach provided better prediction accuracy than the other three recommendation algorithms at all levels of sparsity. However, there was an increase in MAE for *GSP–CA–CF, CF–CA* and *CF* algorithms with increase in level of sparsity. The GSP algorithm showed minimal change in MAE as the level of sparsity increases. This can be attributed to the use of learner's sequential access patterns rather than ratings in making predictions of learning resources. The experimental results demonstrate that combining SPM, CA and CF improves the performance and quality of recommendations. Further, it was evident that majority of the learners were satisfied with the recommendations from the proposed hybrid recommendation algorithm.

The hybrid recommendation algorithm proposed in this work is used for prediction and recommendation of online learning resources in e-learning environments. E-learning resources that can be recommended include lecture notes, examinations, assignments, tutorial videos and audios among others. Even in cases of multi-course learner taking different unrelated subjects such as mathematics and physics, the proposed hybrid recommendation algorithm will predict the learning resources correctly by using SPM algorithm to mine the web logs and discover the learner's historical sequential access patterns that are useful for making predictions. The proposed hybrid recommendation method is flexible, and with slight modifications, it can as well be used in other domain application fields such as movie recommendation and prediction of medical prescriptions.

5.4 Future trends for CA recommender systems in e-learning

An interesting future trend in research on CA recommendation approach in e-learning domain is the increased research interest on use of context awareness in e-learning recommendation systems. There is a clear trend toward hybridization of new recommendation techniques such as context awareness with traditional recommendation techniques and also integration of other technologies including data mining and machine learning into the recommendation process. Techniques like CA-based recommendation approach in e-learning incorporate context dimensions into the recommendation process such as knowledge level and learning goals among others making recommendations more personalized and relevant to the needs of the learner in an e-learning environment. Hybridization of recommendation techniques has the potential of improving the quality of recommendations in e-learning recommender systems.

Secondly, research in e-learning resource recommendation using context awareness is likely to evolve and mature further alongside other evolutions in fields such as the web, artificial intelligence, knowledge management, data mining and machine learning.

6 Conclusion and future work

In this paper, we proposed a hybrid recommendation approach based on context awareness and sequential pattern mining for recommending learning resources to learners in e-learning environments. The proposed hybrid recommendation algorithm uses GSP algorithm for mining the web logs and discovering the learner's sequential access patterns; context awareness for incorporating learner's contextual information such as knowledge level; and collaborative filtering for generating recommendations based on contextualized data. GSP algorithm is applied to the contextualized recommendations to filter the recommendations according to the learner's sequential access patterns and generate the final recommendation results for the learner. By combining recommendation techniques in this proposed hybrid recommendation approach, recommendations are personalized according to the learner's context and sequential access patterns. Experimental results reveal that the proposed recommendation approach provides better performance and recommendation quality. Moreover, the proposed hybrid approach can help alleviate data sparsity problem by making use of contextual information and learner's sequential access patterns to make predictions in the absence of overlapping learner ratings.

Our future research will focus on hybridization of recommender systems with emerging tools in the field of artificial intelligence and data mining with a view to improving and optimizing the recommendation results.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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