LSBCTR: A Learning Style-Based Recommendation Algorithm

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***Abstract*—This Research Full Paper presents a hybrid algorithm for the recommendation of Learning Objects (LO) aimed at students' learning profiles. In this sense, the Learning Styles-based Collaborative Topic Recommender (LSBCTR) algorithm was developed based on the Collaborative Topic Regression (CTR) model, a hybrid recommendation algorithm that combines a method of Collaborative Filtering (CF) and probabilistic topic modeling. The Learning Style is incorporated into the CTR to predict LO classification. The proposed model controls which classifications are more effective in the students' learning process and which LO recommendations fit better to the student's learning profile. Experiments were carried out in a real-world dataset collected from a Virtual Learning Environment (VLE) that was based on the inventory proposed by Felder and Soloman.**

***Index Terms*—Hybrid Recommender System, Learning Style, Collaborative Topic Regression.**

I. Introduction

Recommender Systems (RS) are intelligent systems that offer items with a higher probability of attending to the interest of a user [1]. They are applied in the most varied areas, such as social networks, e-commerce, e-health and others [2],[3]. These systems have been adopted in order to assist users in decision making, that means, which items to buy, which music to listen to, which movie to watch or which news to read [1],[4]. Nowadays, RS systems play an essential role in personalizing results on several sites, such as: Amazon, YouTube, Netflix, Tripadvisor, among others [5].

In the educational context, Educational Recommender System (ERS) aims to recommend educational resources, such as Learning Objects (LO), appropriate to students learning profile, which can be obtained, for example, through the use of Learning Styles (LS), that will determine how learners interact, react and learn with the use of a learning object. The LS are aimed to reflect the individual characteristics referring to the tasks of organizing, perceiving, processing, remembering and thinking to solve a problem and in our context making it possible for the ERS systems to provide relevant content to the learner [6].

Various techniques and approaches are used in the ERS to recommend resources. Among the classic approaches, such as Collaborative Filtering (CF), Content-Based (CB) and Utility-Based (UB), CF is one of the most used [7] and still plays a dominant role in almost all types of recommendation systems. However, Hybrid Recommender Systems (HRS) are gaining attention and proving to be more efficient for recommending educational resources, since the use of isolated techniques can present problems [8]. Hybrid strategies combine isolated techniques to obtain a process that is a combination of techniques in order to combine the advantages and minimize the disadvantages of each of the chosen techniques [9].

The Collaborative Topic Regression (CTR) is a hybrid model proposed by Wang and Blei [10] to recommend existing and recently published articles, that applies concepts from CF and CB to determine the likelihood of preferences between users and the articles.

The main research question of this work is: is it possible to recommend a LO through a recommendation system that uses a hybrid algorithm and considers the individual learning profile?

This paper aims to present the Learning Styles-based Collaborative Topic Recommender (LSBCTR), a recommendation algorithm that incorporates educational aspects to the CTR. The LSBCTR considers students' learning profiles in the recommendation process to suggest educational resources that are more appropriate to each profile. Unlike other related works, LSBCTR adds processing elements that differentiate students' profiles and considers the usefulness of this resource, based on the individual learning profiles. This difference makes it possible to recommend to each student a LO for a personalized teaching-learning experience

In this work, it was used the Felder and Silverman model (FSLSM) [11] due to its accessibility, acceptability and use among researchers for investigations in educational environments [12]. The FSLSM describes LS through four dimensions, providing comprehensive details of those dimensions and has a reliable and validated LS assessment tool, to provide adaptability in learning systems.

The article is structured as follows: Section II the concepts are presented in order to guide the understanding of this article; Section III related works are presented; in Section IV the concepts are introduced and the LSBCTR algorithm is presented; Section V experiments are presented and the results are discussed; and, finally, the conclusions and future work are presented in Section VI.

II. Background

This section presents some conceptual foundations necessary to understand the work: Learning Objects (LO), Learning Style (LS), recommendation techniques and the Collaborative Topic Regression (CTR) model.

A. Learning Objects (LO)

Learning Objects (LO) are defined as any and all entities that can be used in the teaching-learning process, digital or non-digital, offered in multiple formats and languages [13]. They can be cataloged and made available in repositories distributed on the Internet, making it possible to use, reuse or reference them in different learning contexts, in the most diverse areas of knowledge [13]. For the context of this work, LO are understood as digital materials, available in different formats and languages, such as: texts, videos, software, games, images, evaluations, among others, with the premise of mediating and qualifying the educational process.

For their identification and location, LO need metadata, that are structures that describe LO's characteristics and functionalities and assist in the processes of their indexing, recovery and reuse in systems, that is, they offer precious information about how and under what conditions it is possible to use of a particular LO.

The most known metadata standard is Learning Objects Metadata (LOM) [13], which specifies the syntax and semantic of the LO' metadata, that is, a conceptual scheme that defines how metadata should be structured to describe the characteristics of a specific LO. This standard focuses on the minimum set of attributes necessary to allow these LO to be manipulated, found and evaluated, allowing their use in several languages and facilitating their search. Among the ways to describe these resources, in addition to their content, some tags are used freely by users for their classification.

B. Felder-Silverman Learning Style Model

Learning Style (LS) is a description of a possible way in which a student acquires, retains and retrieves information [14]. Studies have considered LS as an indispensable element that directly affects the students' learning process [15]. Thus, it is necessary to have a model for obtaining the students' LS that, if accurately identified, allow its use systematically in online environments [6] to provide personalization and adaptability. Although it is considered that LS are not necessarily exclusive, that means, a student may have affinities with more than one LS, it is considered that only one of them stands out.

The Felder-Silverman model (FSLSM) [11] is considered the most stable LS model and is separated into four dimensions [16]. Notice in Figure 1, that the dimensions are characterized in pairs of LS.

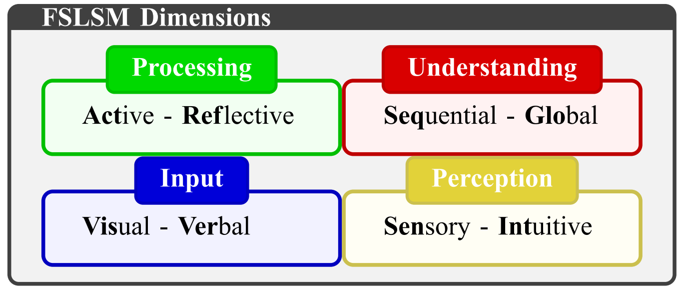

Figure 1. FSLSM dimensions – for each dimension

The Processing dimension (Active - Reflective) expresses how the learner prefers to process the information. An Active student prefers to try things out, work with other people in groups, and a Reflective one prefers to think, work alone, or with a partner. The Understanding dimension (Sequential - Global) determines how a student prefers to organize and progress towards understanding the information, preferring that information is presented in a progressive, linear, orderly manner and s/he learns in small incremental steps. On the other hand, a Global apprentice prefers holistic thinking, thus having a vision of the whole, of the objectives, to then visualize the parts, think about systems and learn in great leaps.

The Input dimension (Visual - Verbal) expresses in what format the student prefers that the information be presented. A visual learner prefers visual presentations, figures, diagrams and flowcharts and a Verbal one prefers written and spoken explanations. The Perception dimension (Sensory - Intuitive) indicates how the learner prefers to perceive or receive information. A Sensory student prefers concrete, practical thinking, concerned with facts and procedures and an Intuitive one prefers conceptual thinking, innovative and concerned with theories and meanings.

From the four dimensions of FSLSM it is possible to obtain sixteen combinations. To assess these dimensions, Felder and Soloman Felder and Soloman [17] developed the Learning Styles Index - ILS[1] , a questionnaire based on 44 items to which each learner responds according to their learning preferences, allowing them to describe trends in stronger preferences and weaker through a numerical scale.

C. Recommendation Techniques

Recommendation systems are classified according to the method used in the recommendation process; four techniques are presented below [9]:

- **Collaborative Filtering (CF):** The principle is in the exchange of experiences between people who have common interests, considering past evaluations of users with similar tastes to recommend items;
- **Content-based filtering (CB):** Lists item content descriptions with users' preferences (ratings, visits, etc.), in order to check whether the item is relevant or not;
- **Utility-Based (UB):** Performs a calculation of the utility of each object for the user. Such calculations can be based on the user's preferences;
- **Hybrid:** Lists more than one filtering technique simultaneously, overcoming the limitations of each modality and allowing a more accurate result.

[1] http://www.engr.ncsu.edu/learningstyles/ilsweb.html

D. Matrix Factorization for Collaborative Filtering

Probabilistic Matrix Factorization (PMF) [18] is a recommendation method for CF technic that employs a linear probabilistic model with observation of Gaussian noise to represent latent characteristics, both for users and for items; therefore, the forecast is whether the user will like the item with internal product among its latent representations [10]. The applied concept is to factor the matrix of incomplete classification R into two matrices with a joint latent low dimension of dimension k: the latent matrix $U \in \mathbb{R}^{n.k}$ of the users and the latent matrix $V \in \mathbb{R}^{m.k}$ of the items, where each user i and each item j is represented as latent vectors $U_i \in \mathbb{R}^m$, $V_j \in \mathbb{R}^n$, respectively [10], [19].

Values 0 (zero) in the classification matrix do not necessarily mean negative evaluations, as well as absent or unknown evaluations [10]. Thus, weights need to make little contribution to prediction compared to known assessments. This case is known as a single class problem, where only positive evaluations are available [19].

As a solution to this problem, weights of confidence are inserted [20], [21]. The values 0 (zero) are assessed as a low value b and the counter values 0 (zero) are considered by a higher value a to such that $a > b > 0$. Given R, the approach must find U and V in order to minimize the loss of squared error regularized with the weight function of confidence [19], according to Equation 1:

$$\underset{U,V}{argmin} \sum_{i \in I, j \in J} C_{ij}(R_{ij} - U_i^T V_j)^2 + \lambda_i \sum_{i \in I} \|U_i\|^2 + \lambda_v \sum_{j \in J} \|V_j\|^2 \quad (1)$$

Where λ_u, λ_v are the regularization parameters and C_{ij} is the confidence weight of the classification R_{uj}, according to the function presented Equation 2:

$$C_{ij} = \begin{cases} a, & if R_{ij} \neq 0 \\ b, & \text{otherwise} \end{cases} \quad (2)$$

With U and V already estimated, it is possible to evaluate the similarity of the user u in relation to the item j through the Equation 3:

$$\hat{R}_{ij} = U_i^T V_j \quad (3)$$

The matrix factoring process consists of calculating the classification forecast R_{ij} given the user preference vector U_i^T and the preference vector of the object V_j.

E. Collaborative Topic Regression

The CTR algorithm comprises a component of collaborative filtering CF, it is a content-based component and thus uses the Latent Dirichlet Allocation (LDA) [22] to learn the proportions of items' topics, and the Probabilistic Matrix Factorization (PMF) [18] to model user ratings.

LDA is a probabilistic model for collections of discrete data such as corpus[2] of documents, being used as a representative of topic models [10]. The basic principle of topic modeling is the discovery of latent patterns that are significant in a relationship between documents and terms, with the aim of discovering thematic structures hidden in large collections of documents. "Topic" is an expression used considering that the subject addressed in a set of documents extracted automatically, that is, topic is defined as a distribution of terms in a set of words that are shared and occur frequently in semantically related documents [10], [23].

The algorithm to calculate these expectations naturally balances the influence of the content of articles and preferences of other users [24]. In summary for the educational context these techniques are described as:

- PMF is a method that seeks out which LO are interesting for a similar set of learners;
- LDA is a method that searches a collection of LO, through their textual descriptions, which are similar by weighting them based on the probability of the words that represent the resource in relation to a topic.

Thus, a topic generated by the CTR presents a set of learning resources that are interesting for a group of similar learners, including a list of weighted LO and the words that annotate those resources, that is, words that represent the LO [24].

III. Related Work

The following will present some works that present recommendation algorithms as well as some work on the educational area. Among the surveys that modified the confidence weights of the PMF algorithm. Alzogbi [19] adapts the weight of confidence to reflect changes in users' interests over time and in this way the author gives less weight to old classifications than to recent ones. In Li *et al.* [25] the confidence weights are designed to recognize the frequency with which the user visited an item and therefore the confidence of frequent items is reinforced to distinguish other infrequent items.

For the educational context, CTR was used in the ERS. Shu *et al.* [26] applied CTR with CNN (Convolutional Neural Network) for LO recommendation. Deng *et al.* [27] applied CTR with the Deep Neural Network (DNN) in the context of social networks to recommend LO. Cai *et al.* [28] Use CTR related to a simple bi-relational graph model for article recommendation. Dai *et al.* [29] applied CTR to recommend articles (quotes) in a group-based context, to use a two-part network. Wang *et al.* [30] used or CTR to recommend articles, in his work he applied a stacked denoising technical autoencoder (SDAE). Zhang *et al.* [31] employs CTR to get recommendations for articles in a context based on social networks. Zheng *et al.* [32] expanded the CTR to consider tags in recommending articles. Peralta *et al.* [24] in its study verified that Dublin Core and IEEE LOM metadata standards can be used CTR for applying LO.

When analyzing the publications: (a) we observed the use of LOM metadata, but it was not possible to identify the use of LS for recommendation of LO using the hybrid CTR technique in any case; (b) all performed experiments based on previously collected datasets.

[2]Collection or set of documents on a given topic.

IV. Learning Styles-based Collaborative Topic Recommender

To consider the students' learning profile in the recommendation processes of LO, it is proposed the Learning Styles-based Collaborative Topic Recommender (LSBCTR), one hybrid recommendation algorithm able to consider the learning profile of a student in the recommendation process of LO using the CTR.

The LSBCTR, using the CTR algorithm, learns and creates latent models of students and models of LO from the textual content and ratings, to incorporate the LS in the recommendation processes. For this, we extend the confidence weight function, seeking to add to the model the characteristics of the students' learning profiles, as to recommend a resource it is necessary to consider how useful is this resource, regarding to his/her LS and so offering a personalized learning experience. In the CTR algorithm, the confidence weights are used to assign higher weights to known ratings. In the LSBCTR algorithm, it is attached one complementary function to the ratings to give different levels of importance to the different previous known classifications.

As mentioned previously, in the proposal of this work, the LS will influence the process of selection of LO, as they will be a basis for comparison with the student-target LS. Thus, the more distant from the target student's LS a classification is, the less its importance in representing the student's LS.

Consider two apprentices A and B, in which A is one visual student and B one verbal student. Suppose that both of them have ratings for one subject like: $R_{A,i}$, $R_{B,i}$ respectively. Although these classifications should be similar, it is known that the LS of students A and B are different; one student is visual so most likely prefers to watch a video content than read a document in *pdf*, while the verbal student prefers the opposite.

The following is detailed the calculation of the score based on students' LS, how to classify the weights of confidence and the learning and prediction of the model.

A. Score based on the Learning Style (LS)

To recommend a didactic content it is considered how useful will this item to one particular learner, considering his/her LS.

One possibility is to identify the similarity between the student's profile and the profile described in the LO's metadata. The correlation between the profiles allows us to identify what resources are relevant to the student and, the lower they resemblance, the lower is the probability of the LO reflect the student's profile. So, scoring the LO based on the LS information acquired from LO metadata will produce a list of LO adhering to profile of the target learner.

B. Problem and Notation Statement

We assume $I = \{i_1, \cdots, i_n\}$ as the set of learners and $J = \{j_1, \cdots, j_m\}$ as the set of LO and assuming that the LS is represented in a vector. Therefore, the student profile (i_{LS}) can be represented by one vector of LS-FSLSM, in which the pair of dimensions ranging from 0 to 1 (or from 0% to 100%), according to Equation 4.

$$i_{LS} = (act, ref, vis, ver, seq, glo, sen, int) \tag{4}$$

It is possible to observe that the Equation 4 has pairs of attributes of the dimensions of the LS (X ,Y) , illustrating how the LS of student can vary from perfect X to perfect Y (the percentage of X and Y must add up to 100%) [16]. In Table I are some examples of LS students vectors . It is highlighted that a combination of LS is a vector formed by 4 dimensions of FSLSM being possible to obtain 16 combinations.

Table I
LSs vectors examples (Adapted from [16])

	Processing		Input		Understanding		Perception	
	act	***ref***	***vis***	***ver***	***seq***	***glo***	***sen***	***int***
Renan	0.65	0.35	0.65	0.35	0.35	0.65	0.35	0.65
Thais	0.55	0.45	0.65	0.35	0.65	0.35	0.73	0.27
Rox	0.35	0.65	0.55	0.45	0.73	0.27	0.45	0.55

To assess the dimensions of a student's LS is used the ILS of FSLSM, where each dimension is represented by 11 questions among the 44 present in the questionnaire. The LS analysis is given by the score obtained from the responses among two alternatives to each questions (a and b) so consequently the computed result of one dimension should be one unique number between $+11$ and -11. The results between 1 and 3 show a preferred slightly balanced between the styles of one dimension. Should the result be between 5 and 7, there is one moderate tendency for the styles, since results between 9 and 11 the method argues that the assessed has a preference too high for one of the styles, indicating one difficulty of learning in environments that do not support this dominant style [17].

The calculation of a student preference can be represented by a vector based on this scale ($+11$, -11) quantified from the student's responses to the ILS questionnaire [16]. For example, consider the responses in the dimension of participation, where the styles are active and reflective, is $7a - 4b = 3a$. This result demonstrates that the student has a slightly balanced preference between the styles of this dimension, however the style that stands out is the active and when translating their responses to a vector represented by proportions ranging from 0 to 1 (or from 0% to 100%), the relationship between A and B must add up to 100%, so for that dimension we obtain 0.65% and 0.35%, for LS active and reflexive respectively.

The algorithm considers that the LO has a keyword and is associated with a representation of a set of words on the vocabulary set related to the domain. LO are provided in various formats and media to meet the LS of each apprentice and must be described through their material.

Therefore, a learning object profile (j_{LS}) can be represented by a FSLSM LS vector, indicating the category of students to which this LO is suitable, as can be seen in Equation 5.

$$j_{LS} = (act, ref, vis, ver, seq, glo, sen, int) \tag{5}$$

In Table II some profiles of LO are presented:

Table II
Examples of LO profiles (Adapted from [16])

	Processing		Input		Understanding		Perception	
	act	***ref***	***vis***	***ver***	***seq***	***glo***	***sen***	***int***
LO_1	0.7	0.3	0.5	0.5	1	0	0.3	0.7
LO_2	0.2	0.8	0.8	0.2	1	0	0.4	0.6
LO_3	0.5	0.5	0.2	0.8	0.1	0.9	0.6	0.4
LO_4	0.5	0.5	0.5	0.5	0.5	0.5	0.3	0.7

The creation of a vector representing the LO and considering their metadata is based on the premise presented by Mendes *et al.* [33] that seeks, based on the Felder and Silverman model and in the IEEE-LOM metadata, to define points of relationship between LO and LS.

In addition, each student has a set of relevant items, recorded in the classification matrix $R \in \mathbb{R}^{n.m}$. An entry $R_{ij} = 1$ represents whether the learner (i) is interested in the Learning Object (j), otherwise, $R_{ij} = 0$ representing absent or unknown assessments. In this sense, the student's i_{LS} learning profile should serve as a confidence parameter (C_{ij}) for the R_{ij} classification. A one-class scenario was adopted in which only relevant LO are known. Therefore, values $R_{ij} = 0$ do not necessarily represent negative ratings, but also unknown ratings.

To determine the similarity between the items and profiles, a numerical measure was used, calculating the degree of similarity between the LS of the target student and each learning object $j \in J$. The system is based on similarity, therefore, for calculating the correlation between data, Pearson's correlation with n dimensions was used:

Pearson's Correlation Coefficient is also called "product-moment correlation coefficient" and was chosen considering the study carried out by Nafea, Siewe, and He [16], that compared the metrics of Euclidean similarity, Manhattan, Pearson and cosine, concluding that for the recommendation scenario, Pearson performed better. Pearson's correlation coefficient is presented in Equation 6.

$$Sim(LS, LO_k) = \frac{\Sigma_{k=1}^{n}(LS_k - L\bar{S})(LO_k - L\bar{O})}{\sqrt{\Sigma_{k=1}^{n}(LS_k - L\bar{S})^2}\sqrt{\Sigma_{k=1}^{n}(LO_k - L\bar{O})^2}} \tag{6}$$

Where,

- n - number of dimensions of the learning profile;
- LS_k - dimensions of the learner's LS;
- LO_k - LS dimensions of the Learning Object;
- $L\bar{S}$ and $L\bar{O}$ - are the average values of LS and LO, respectively.

Usually the computed correlation coefficient is a numerical value between $[-1, 1]$, which expresses the strength of the linear relationship between two variables. When Sim is closer to 1, it indicates a strong positive relationship. A value of 0 indicates that there is no relationship. Values close to -1 signal a strong negative relationship between the two variables.

In this way, the degree of similarity between the target learner's LS and each LO in their list of classifications is calculated. For each LO, the LO with the greatest similarity to the target apprentice's LS are weighted, keeping the least representative in lower classifications.

C. The LSBCTR algorithm

Given I, J and R, the objective is to predict for each student $i \in I$, the set of main LO (J) relevant to his/her Learning Style (LS). Considering the R classification matrix, similarity scores are calculated, as shown in Algorithm 1.

Algorithm 1: LSBCTR Recommender Algorithm

```
Input: Items' LS, Rating matrix R
Output: LS Score of users for the S Items'
Initialize S to an empty list;
for all i ∈ I do
    P := {j|R_ij = 1} ;
    Initialize S_ij to 0;
    for j = 1 to |P| − 1 do
        S_ij := Pearson-Similarity(i_EA, P_jEA);
    end
end
return S
```

For each student (i) is asked his/her grades for a determ LO (j). Then, based on his/her LS, the similarity between the student's LS (i) is calculated for each of the items (j). In the LSBCTR algorithm, Pearson's correlation was used to calculate the similarity between two LS and the result is a set of LS scores for all users (S), which will be used in the calculation of confidence weights.

D. Confidence Weights Classifying

The weight of confidence of a classification quantifies its importance in representing the user's interest, as originally presented by Mnih and Salakhutdinov [18]. With scores based on Learning Style "S" for all users, an exponential decay function (Equation 7) is applied to calculate the Q_{ij} confidence weights for all learner ratings.

The score based on the LS Learning Style S_i controls the decay function and, therefore, plays the role of a similarity factor, that is, the higher the score the greater the similarity between the LS. This is a desired behavior to explain the difference in LS. In this way, the relation of LO users with higher LS scores will result in greater visibility to the detriment of lower weights.

$$Q_{ij} = \frac{1}{1 + e^{-S_{ij}}} \tag{7}$$

E. Learning and Predicting the Model

After calculating the confidence weights of the classifications, the latent topic vectors U and V of R and θ are learned in a similar way to CTR. Confidence scores are not obtained from Equation 2 and in this case the calculated confidence weights are used.

Thus, the C_{ij} confidence matrix is defined as follows:

$$C_{ij} = \begin{cases} max(Q_{ij}, b), & \text{if } R_{ij} = 1 \\ b, & \text{otherwise} \end{cases} \tag{8}$$

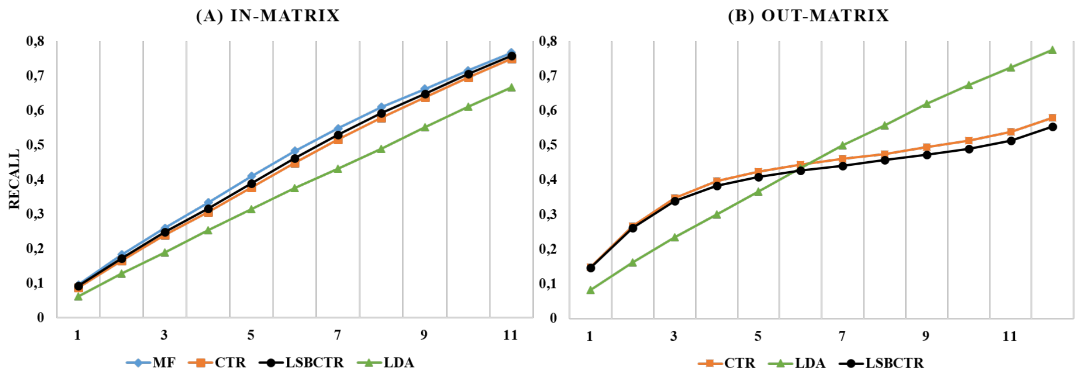

Figure 2. Recall comparison on in-matrix and out-of-matrix prediction tasks by varying the number of LO.

Here, b is the confidence score for the unknown classifications, $\{R_{ij}|R_{ij}=0\}$ e is defined as a small value. After finding U and V, the predicted ratings are approximated using Equation 3.

V. Experiments

In this section, we present the configuration of the experiment conducted in a real-world dataset, results and analysis.

A. Dataset

A dataset originated from an e-learning context was used, as it contains characteristics of learners reflected by their LS and their learning resources. The dataset used consists of a subset of the data provided by Maaliw III and Ballera [15], which collected information from a LMS - Moodle (Learning Management System - Moodle Learning Management System) for detecting and identifying students' LS. This dataset[3] is composed of log files from the Course of Introduction to $C{+}{+}$ (Computer Programming 1) from Southern Luzon State University (SLSU) in the Philippines, and the records that were analyzed are from a period between 2012 and 2016. It has information about students' responses to the questionnaire, description of 84 LO among visual materials, video presentations, textual materials, audios, examples, glossaries and etc; and, a total of 52,815 lines extracted from their navigation patterns (interactions); In total, 507 students participated and answered the ILS-FSLSM questionnaires.

B. Evaluation

In the experiments carried out, the understanding of Wang and Blei [10] was followed, which used only the recall metric, since the $R_{ij}=0$ classifications are uncertain, as they may or may not represent the learner's interest in LO, making it difficult to use of that metric as the precision metric. Given the M recommendations, for each apprentice, the $recall@M$ is calculated according to Equation 9:

$$Recall@M = \frac{\texttt{number of LO the apprentice likes in top M}}{\texttt{total number of LO the apprentice likes}} \quad (9)$$

[3] Available: https://www.researchgate.net/publication/336313470_Reduced_Log_Files_Data_Sets_for_Mining_Student%27s_Learning_Styles

For the experiments carried out, the data were divided into five subsets of training and testing. Test suites contain student ratings that appear in the training suite. This is because the method used does not address the problem of new users. Two different tasks were used to evaluate the model as described by [10]: *1) In-matrix:* It considers the case where each student has a set of LO that they did not classify, but that was classified by at least one other student; *2) Out-of-matrix:* Consider the case of new LO not yet classified.

C. Experiment Settings, Results and Analysis

In the perspective of replicating the experiment carried out by Wang and Blei [10] and in order to demonstrate the consistency of the dataset, the following parameters were used in the experiments: For Matrix Factorization (MF), the settings used were: $K=200$, $\lambda_u=\lambda_v=0.01$, $a=1$ and $b=0.01$; For CTR and LSBCTR, $K=200$, $\lambda_u=0.01$, $\lambda_v=0.1$, $a=1$ and $b=0.01$; For the LDA, the latent vector is fixed by LO $\lambda_v=\theta_j$, as described in [10].

Figure 2 shows the result of the experiment for the In-matrix (A) and Out-of-matrix (B) predictions in a variation of recommended LO of $M=1\cdots 12$. In case (A): LDA shows a lower performance compared to the evaluated techniques, CTR presents a performance slightly inferior to the LSBCTR and MF slightly superior to the LSBCTR, almost equivalent. In case (B) MF cannot recommend any LO, as the task is predict LO not yet classified; LDA has a linear progression, LSBCTR and CTR have slightly similar performance, in this case showing a variation when compared to LDA.

The purpose of the evaluation was to verify the LSBCTR algorithm's accuracy concerning the dataset. In this sense, the recall metric was used, which seeks to identify false negatives. For example, when evaluating the recovered recommendations, it seeks to find all LO considered relevant to the student, even if in the process some are not relevant (false positive situation). When analyzing the results, it appears that the LSBCTR obtained for MF: The LSBCTR obtained a performance slightly inferior to the MF for the in-matrix evaluation; for CTR: LSBCTR performed slightly better in the in-matrix evaluation and slightly lower in the out-matrix evaluation; for LDA:

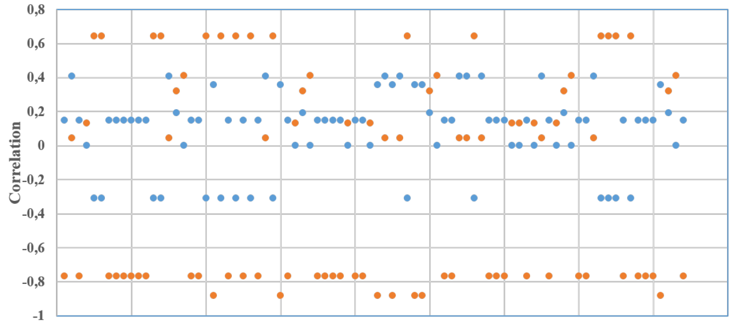

Figure 3. Correlation of the apprentice #32 (blue) and #286 (orange) for the LO in the dataset

LSBCTR achieved a superior performance in the in-matrix evaluation and an irregular one in the out-matrix evaluation.

The LSBCTR shows a satisfactory performance, as it does not suffer great variations concerning the CTR, its reference model. It is believed that the reason for its low performance with the MF and LDA algorithms is probably a consequence of the low amount of LO in the dataset.

D. Exploratory Study of Students' Profile

A characteristic of the CTR is the possibility to demonstrate the student's latent space by the topics learned from the data. In this way, the topics understood serve as a summary of the interests of the students and, concomitantly, a property of the LS is the possibility of correlating the profiles of the learners to that of the LO and thus, the similarity between the two profiles serves as a metric to identify the relevance from an LO to a student's LS.

For a student it is possible to find the main corresponding topics, classifying the inputs of the interface of its latent vector (u_j). In order to explore the data, the topics discovered from them are verified, which LO are related to a certain topic and which LO and topics a student is interested in.

To exemplify the recommendations and compare them between CTR and LSBCTR, 2 (two) students with opposite LS were selected, in order to represent the prediction of LO for 2 (two) different LS profiles, among the 16 (sixteen) possible combinations. Table III shows the LS vectors of the selected students.

Table III
Learning Style vectors from dataset

Learner	Processing		Input		Understanding		Perception	
ID	***act***	***ref***	***vis***	***ver***	***seq***	***glo***	***sen***	***int***
(32)	0.73	0.27	0.45	0.55	0.45	0.55	0.73	0.27
(286)	0.45	0.55	0.73	0.27	0.65	0.35	0.18	0.82

Figure 3 show the results of Pearson's similarity of these students for all LO in the dataset used (represented in blue and orange). Note that the correlations of the LO are represented in a variation of $[-1, 1]$. Values closer to 1 (top) indicate a strong positive relationship, a value 0 (center) indicates that there is no relationship and values close to -1 (lower) indicate a strong negative relationship.

After analyzing the results for student #32, it is possible to notice that the LO (represented in blue) with greater similarity to the student's LS, close to 1 (at the top), are LO with characteristics according to the LOM: *Structure:Linear*, *Type of Interactivity:Mixed*, *Type of Learning Resource:Video* and *Level of Interactivity:High* Note that the LS of the student for the presentation dimension is Verbal and the LO are basically Visual. This is a consequence of the structure of its LS vector (see Table III). It is possible to perceive that the relationship between Verbal and Visual is moderate and the characteristic Level of Interactivity: High related to LS-Active represents greater relevance for the correlation between the profiles.

For student #286, it is clear that the LO (shown in orange) with greater similarity to the student's LS (see Table III), close to 1 (at the top), are LO with characteristics: *Structure:Atomic*, *Type of Interactivity:Mixed*, *Type of Learning Resource:Image* and *Level of Interactivity:Medium*. After analyzing its LS vector, it is noticed that the correlation is adherent with its profile, thus representing all its dimensions; student #286 has his LS vector with explicit tendencies within the dimensions Perception, Presentation and Organization of his LS.

The most non-similar LO (represented in blue, correlations close to -1) of the LS of students #32 and #286 have characteristics: *Structure:Atomic*, *Type of Interactivity:Mixed*, *Type of Learning Resource:Image* e *Level of Interactivity:Medium* and *Structure:Linear*, *Type of Interactivity:Expository*, *Type of Learning Resource:Text* and *Level of Interactivity:Medium*,, respectively. Thus reflecting each of its LS dimensions.

In this way, it is noticed that when performing the vectorization of the LS of students and LO it is possible to reflect their profiles in a balanced way, allowing a greater agreement when the profiles are correlated because, if the definition of these attributes is carried out in an arbitrary way, it may not reflect the LS of the profiles. For example, when arbitrarily defining the LS of the student #32 in Verbal $= 1$, the result of the similarities would be other.

Table IV presents an example for the two students and their three main topics, obtained from the analysis of the topics with the highest proportion of the vector (θ_j), after executing the LDA; corresponding to their position in the latent space through the topics with the greatest weight. The 10 main LO suggested were listed, as provided by the CTR. The last column shows whether the LO already corresponds to a resource in the student's list of classifieds. After analyzing the main topics listed, it was identified that the apprentice #32 and

Table IV
Classification for two apprentices, as predicted by CTR and LSBCTR

		Predicted by CTR		Predicted by LSBCTR		
Learner (ID #32)	top 3 topics	assessment, self, quiz, test, exam, verification, exercises glossary, constants, values, global, c++, vocabulary, literals return, functions, void, function, value, array, example, use	Rated by the learner?			Rated by the learner?
	10 tops LOs	1. Quiz: Exercise 3 (LO_ID: 50)	✓	1. Quiz: Exercise 3 (LO_ID: 50)	-	✓
		2. Defining functions that return a value (LO_ID: 40)	×	2. Procedural Abstraction (LO_ID: 46)	↑	×
		3. Procedural Abstraction (LO_ID: 46)	×	3. Quiz: Exercise 5 (LO_ID: 82)	↑	✓
		4. Quiz: Exercise 5 (LO_ID: 82)	✓	4. Quiz: Exercise 1 (LO_ID: 16)	↑	×
		5. Quiz: Exercise 4 (LO_ID: 68)	×	5. Quiz: Exercise 4 (LO_ID: 68)	-	×
		6. Quiz: Exercise 1 (LO_ID: 16)	×	6. Quiz: Exercise 2 (LO_ID: 33)	↓	✓
		7. Input using cin (LO_ID: 33)	✓	7. Defining functions that return a value (LO_ID: 40)	↓	×
		8. C++ Terminology (LO_ID: 15)	✓	8. Input using cin (LO_ID: 15)	-	✓
		9. Output Using cout (LO_ID: 3)	✓	9. C++ Terminology(LO_ID: 3)	-	✓
		10. Example - A rounding function (LO_ID: 13)	✓	10. Example - A rounding function (LO_ID: 42)	↑	✓
Learner (ID #286)	top 3 topics	glossary, constants, values, global, c++, vocabulary, literals assessment, self, quiz, test, exam, verification, exercises computer, chapter, step, c++, graph, programming, structure	Rated by the learner?			Rated by the learner?
	10 tops LOs	1. Defining functions that return a value (LO_ID: 40)	×	1. Defining functions that return a value (LO_ID: 40)	-	×
		2. The FOR Statement (LO_ID: 29)	×	2. Local Variables (LO_ID: 45)	↑	✓
		3. Procedural Abstraction (LO_ID: 46)	×	3. Multidimensional Array Basics (LO_ID: 65)	↑	✓
		4. Production Graph (LO_ID: 62)	×	4. Glossary: Glossary 1 (LO_ID: 18)	↑	×
		5. Multidimensional Array Basics (LO_ID: 65)	✓	5. The FOR Statement (LO_ID: 29)	↓	×
		6. Local Variables (LO_ID: 45)	✓	6. Glossary: Glossary 2 (LO_ID: 35)	↑	×
		7. Glossary: Glossary 4 (LO_ID: 70)	✓	7. Procedural Abstraction (LO_ID: 46)	↓	×
		8. Glossary: Glossary 5 (LO_ID: 84)	✓	8. Glossary: Glossary 3 (LO_ID: 52)	↑	✓
		9. Glossary: Glossary 2 (LO_ID: 35)	×	9. Glossary: Glossary 4 (LO_ID: 70)	↓	✓
		10. Glossary: Glossary 3 (LO_ID: 52)	✓	10. Declaring and Referencing Arrays (LO_ID: 54)	↑	✓

#286 have interests in subjects such as "*assessment*" and "*constants*"; "*glossary*", "*functions*" and "*structure*", respectively.

Table IV presents the results of the 10 main suggested LO, as provided by the LSBCTR, extracted from the classifications for the 2 (two) target students. The last column shows whether the LO already corresponds to a resource in the list of classified by the student, that is, registered in its classification matrix ($R_{ij} = 1$). For analysis, the rise (↑) or decay (↓) of LO in the student list is illustrated. When analyzing Table IV, it is possible to notice that for students #32 and #286, their classifications suffered variations when compared to the recommendations made by CTR. This fact occurs due to the inclusion of LS in the prediction of the weight of confidence (C_{ij}). It is noticed that the resources at the top of the classifications are known and have a positive correlation in relation to the student's profile and, therefore, are better considered in the recommendation process.

The LSBCTR classification process assumes that the LS is used to calculate the C_{ij} confidence weight for known resources, "classified by the student", that is, registered in the classification matrix as provided by Equation 8 (see Subsection IV-E); scores for unknown classifications are defined by a small b-value, giving them less weight. This does not imply that resources unknown to the students will not be classified or will be sub-positioned, since the prediction considers other data (information of learners' classifications and textual resources). With the application of the LSBCTR, as an example for students #32 and #286, it is possible to realize that when expanding the equation of confidence weights (C_{ij}), to add the concept of LS, the predictions are influenced by his/her LS. Consequently, it is considered that the classifications from the LSBCTR represent the student's profile reflecting their preferences, therefore, it appears that the recommendations exercise a UB behavior in the classifications, as they provide a rise (↑) to resources consonants or decay (↓) to those not consonant with the student's profile.

VI. Conclusion and Future Work

In this article, we present the LSBCTR, an algorithm based on recommendation strategies and educational methodologies, to reflect the characteristics of students' LS in order to enhance the learning process by adapting the LO recommendations to his/her profile. The LSBCTR algorithm extends the CTR algorithm, improving the algorithm's confidence weights to include students' LS characteristics. Based on the profiles translated into vectors, we calculated the correlation seeking the LO's relevance to the target student's LS.

In order to calculate the similarity between these two profiles, it is necessary to know the dimensions of the students' LS and its attributes concerning these dimensions to obtain the calculation of the usefulness of the LO to the student's profile, using Pearson's correlation. We then use the scores to calculate confidence weights for known classifications, which control the contribution of classifications by adjusting the CTR.

The main point of the article is that to catch a realistic recommendation that reflects the interests of a student it is essential to carry out an evaluation to recognize his learning profile, as well as to identify the LS profiles of the LO. So, as each student has his LS and each LO reflects differents LS, based on their characteristics, the correlations must be calculated for each student individually.

The main aspect that we plan to research in the future is: (a) carrying out experiments in real time and concurrently with academic contents offers in order to be able to verify their performance, evaluate and eventually make possible adjustments to the algorithm; (b) incorporate other models of LS, expanding the idea of vectors of learners and LO, since the FSLSM model is a widely used tool but does not address all possibilities of learning styles; and, (c) expand the idea of LS vectors, based on, for example, the LOM, so that it is possible to use the weighted vectors of other preferences of the learner, such as: language, technological restriction, age, among others.

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