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Non-Deterministic Approach for Learning Styles' Detection through Deep Belief Network

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ABSTRACT

The migration from industrial learning to personalized learning is one way to increase learners' abilities and improve their learning skills or preferences. This article designs a model for optimizing the dynamic detection of learner learning styles, which are hardly perceptible since the subjective nature of the learners' interactions on E-learning systems, and the stochasticity of learning styles. A new approach based on semi-supervised learning has been defined using modified Deep Belief Network (DBN), to detect efficiently learning style. It takes account of prior knowledge of expert model and analyse student behaviour to build a learning styles model, for improving their learning. This model will analyse the behaviour of a learner and adapts its training activities. It will also consist in defining an intelligent layer above LMS to ensure the efficient personalization of learning activities. The proposed approach has been validated with an average of 2168 students' semi-structured data, enrolled for the online courses in Moodle LMS. Initially, the students' learning descriptors are extracted from the web log files of LMS and then pre-processed to build the inferencing DBN model. The performance observed, highlights the importance of this method for efficient inference of learning styles, then therefore, ensure an efficient customization of learning activities on Adaptive E-learning System.

1. Introduction

In Learning Management System (LMS), fewer educational strategies consider the individual characteristics of learners. This is one of the observations that prevents learners from overcoming their learning outcomes, as learners do not learn from their natural abilities because they are constrained by learning activities that do not fit with their learning experiences. There is also a lack of effective monitoring in their LMS learning pathways. Several scientific works highlight this remark (Ling & Abdul-Rahman, 2018, Bernard, Chang, Popescu & Graf, 2017, Garcia, Amandi, Schiaffino & Campo 2007, Brusilovsky & Peylo, 2003), we have identified problems and critically analyzed their approaches. We have found that one of the major and recurring trends that emerge is to allow the personalization of learner learning. They

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learn effectively when they have learning materials appropriate to their needs. To make this possible, data-driven approaches have been built to ensure personalization in such systems, as part of the field of adaptive and intelligent education systems (AIES). The problem of customization is only an interface of the central problem. One of the underlying problems that makes customization effective is: automatic detection of learning styles. To solve this problem, our research will consist to model learning style indicators among learners, computed from LMS data sources. To discover the distribution of learning style indicators and effectively calculate a learner's learning styles.

Artificial intelligence models play an important role in many scientific fields: Robotics, Natural Language Processing, Image Processing, Object Recognition, Sentimental Analysis. Etc. (Goodfellow, Bengio & Courville 2018; Russel & Norvig, 2010). they are found in education (Castro, Vellido, Nebot, & Mugica, 2007), allowing new learning systems to cope with a learner interest and need. Learner centric education is one of the trends of the future e-learning system (Barber, Donnelly & Rizvi, 2013). The transition from industrialized to personalized education would on one hand, enable a learner to benefit from rich learning activities and limit the duration of learning, on the other hand to increase his performance (Bernard & al, 2017) through the construction of machine learning model for improving teaching and learning.

Many works have been retrieved in the research of automatic learning styles detection. (Feldman, Monteserin & Amandi, 2015) illustrates a review of last 20 years research activity in the domain and categorizes the approaches in two parts, classical approach (Dung & Florea, 2012; Graf , 2010) which use simple rules to predict learning styles and dynamic approaches (Hasibuan, Nugroho, & Santosa, 2019; Ling & al, 2018; Bernard & al, 2017; Amir, Sumanyo, Sensuse, Suchayo & Santoso, 2016; Hsu, Wang, & Huang, 2010; Garcia & al, 2007) which are data-driven, using student behaviour data in E-learning platforms: Amongst these dynamic approaches, we have (Ling & al, 2018) who used an augmented decision tree to infer learning styles, in other way,(Bernard & al, 2017; Villaverde, Godoy, & Amandi, 2006) used Multi-Layer Perceptron to infer learning preference of student. Novel approaches (Hasibuan & al, 2019; Ling & al, 2018, Bernard & al, 2017) are hybrid relying classical approaches, referring for example to Index of Learning Styles (ILS) and dynamic approaches, this strategy permits some improvements, but we still have some limitation regarding the stochastic nature of learning styles (Syriaf, Sahid, Nugroho & Santosa, 2017; Dorçà, Lima, Fernades & Lopes 2013, Graf & al, 2009), and the cost to initialize learning styles using ILS.

The next of this article is articulated as follows: in section 2), we will describe the theoretical concepts of this research and a non-deterministic adaptive E-learning system architecture for teaching using learning styles, in section 3) we will design a model for non-deterministic and automatic detection of learning styles, in section 4) We will validate our approach as well as the problem-solving process defined then in section 5), we will conclude and give the perspective works

2. Basics Concepts

2.1 Learning Style

A learning style describes the behaviour adopted by a learner during a learning activity (Graf & Kinshuk, 2009; Bernard & al, 2017). This is the way in which he analyses and understands the concepts of a learning activity. It has three dimensions:

- Perceptive, the way in which he perceives the information presented to him,
- Cognitive the set of actions that the learner can mobilize to process the information
- Metacognitive, referring to the ability to reason about perceived information.

It can vary from learner to learner, as well as not all learners react in the same way to the information presented to them. For example, some learners effectively conceptualize when the information they perceive is represented by illustrations, others when confronted with exercises, some learners require step by step learning: iterative and sequential. A learning style itself can thus be, an abstraction of a learner's learning process. There are several theoretical models of learning style: Felder and Silverman (FSLSM, KOLB, VARK). Of all these models, the one that is used the most is FSLSM (Ling & al, 2018, Feldman & al, 2015).

2.2. Non-deterministic learning style adaptive E-learning architecture.

From review we have observed that the general design of adaptive E-learning System using learning styles has many components. In Fig. 1 we show the purposed the new architecture based on data-driven and non-deterministic learning style. The Instructional environment provides to student the viability to learn from remote and in pace way from their computers or devices; it can be Blended Learning Environment or Distance Learning. It contains the Learning Management System Frontend (LMS-frontend) which present web pages to the user, and the LMS system Backend which contains the database and all the business logic of the platform. The instructional model which organize the learning activities and learning objects. It contains, the Instructional design module. The student model which is characterized by the student profile and its interactions between the instructional environment, and the instructional model.

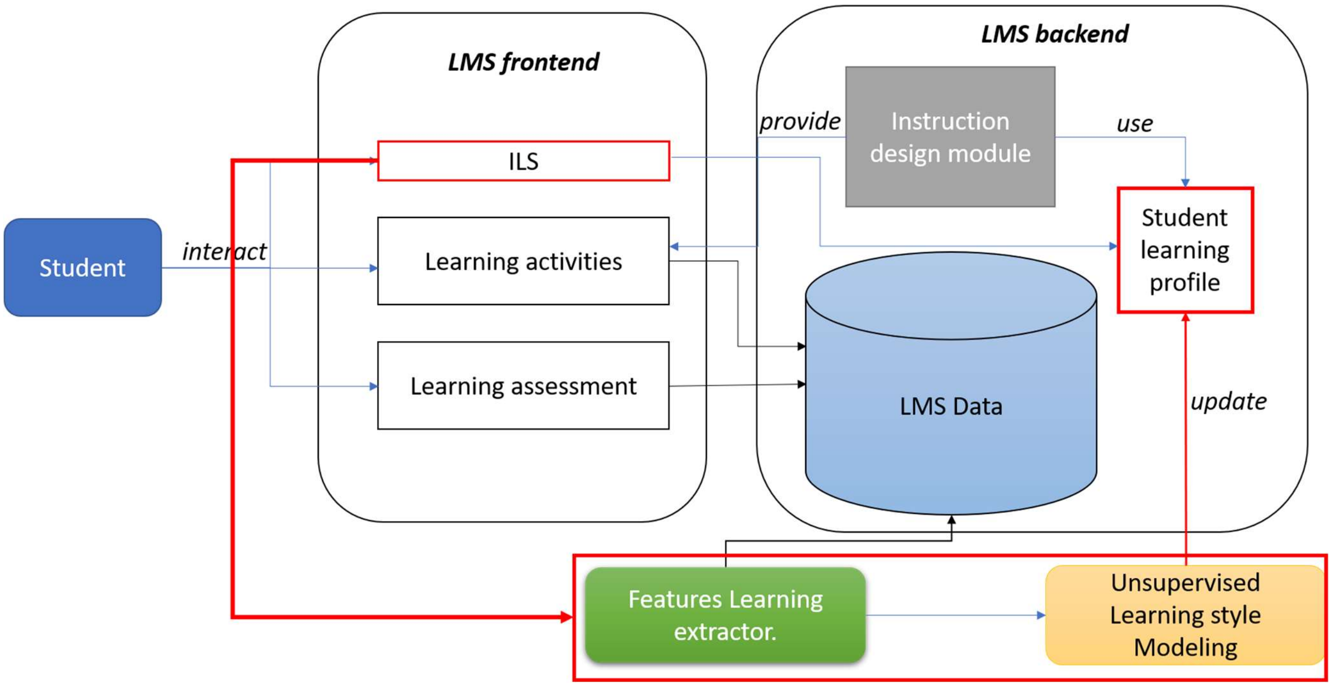

Fig. 1: Architecture of a non-deterministic adaptive E-learning system based on learning style.

The connected learner is subjected to a first phase of the ILS (Felder & Soloman & al, 1997) which allows to have a system initialization for each learner. Once done, the learner can explore and interact with the educational content (Learning object, activities, assessment,) available in several formats and offered by the component Instruction design module, it can be for example a SCORM component. The learner's interactions stored in the database are then extracted. A pre-treatment phase is then performed to prepare the learning indicators to be modelled. The model will analyses the distribution of learning indicators and dynamically infer the learning style, once detected, the model will update the learning profile of this learner, it will have two roles in the platform modeling the traces of learning, as well as learning profiles. The design training module will refer to the learner's learning profile and provide him with learning activities appropriate to his learning style.

For this research amongst all these components we will focus in the ILS, the student model and the unsupervised model approach. Previous studies used ILS as an expert knowledge to classify student learning style but in real word when practicing it is difficult to them to be canonical because they contain some uncertainty we describe why in section 2.5), we will use this prior knowledge combine with the student model : learning descriptors in database and student profile, to build another form of ILS but non deterministic as the learning will be considered as unsupervised and stochastic. By just focusing on learner interactions and on real time.

2.3 Deep Belief Nets

A Deep Belief Net is a neural network that belongs to the larger set of deep neural networks, it is a generative graphical model using probabilities to learn on data. A DBN can limit the problems associated with the exploding weights of the gradient method observed in the highly connected multilayer perceptron learning algorithm (Goodfellow & al, 2018; Lecun 2015; Hinton, Osindero & Teh., 2006), which is used in learning styles detection by (Hasibuan & al, 2019; Bernard & al, 2017). DBN can make possible to reconstruct the input data, from the modeling distribution of the latent variables. It is composed of several structured layers called Restricted Boltzmann Machines (RBM).

2.3.1 Restricted Boltzmann Machine (RBM)

An RBM is a stochastic neural network, capable of being trained in unsupervised mode to generate samples according to a distribution of complex probability specified by examples (Hinton & al., 2006). It has a visible layer (v) and a hidden layer, consisting of hidden or latent variables (Goodfellow & al, 2018) these layers are interconnected by weights.

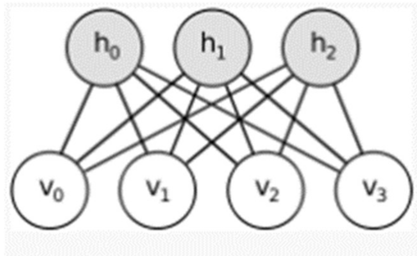

Fig. 2. An RBM graph model

This structure will construct a representation of v, by encoding the variables of v to obtain h which will be an abstract representation of v resulting from the learning of the distribution of learning data. This learning is defined by minimizing an energy function *E (v, h)*,

$$E(v,h) = \sum_i a_i v_i + \sum_k b_k h_k + \sum_i \sum_j w_{i,j} v_j \qquad (1)$$

With $v_i, h_i \in \{0,1\}$

The parameters of the model to be discovered by the algorithm being θ = <a, b, w>. The input variables of the layer v of an RBM are independent of each other, hence the absence of a link between it. The encoding of the layer from v is defined by the joint probability distribution of *v* on a neuron of *h* by:

$$p(v,h) = \frac{e^{-E(v,h)}}{Z} \qquad (2)$$

The Z function is a partition function that normalizes this probability. The marginal distribution on layer h, from the inputs.

$$p_\theta(v) = \sum_h p(v,h) \qquad (3)$$

The objective of the optimization of θ is to maximize the resemblance between the marginal distribution $p_\theta(v)$ generated by the RBM and the experimental distribution observed within the training set E. For this reason, we will maximize the likelihood

$$Vr(x) = \prod_{x \in E} p_{\theta(x)} \qquad (4)$$

Or by using its corollary, the optimization of the log likelihood

$$lVr(x) = -\sum_{x \in E} \log(p_{\theta(x)}) \qquad (5)$$

2.3.2 RBM learning.

Unlike other neural network algorithms based on gradient backpropagation, a DBN has a specific learning algorithm. (Hinton & al, 2006) proposes the contrast divergence (*CD*) method which is a probabilistic algorithm that will generate sequences of samples approximating with efficiency hidden layers unit in h according to the marginal probability *pθ (v)*, observed in the training data. It makes it possible to maximize the likelihood in Eq.4, to do so, it would be necessary to define the gradient of *lVr (x)* to optimize the parameters θ of the model.

2.4 Supervised learning approaches

Many approaches use supervised methods, support vector machines(Amir & al, 2016), multilayer perceptron, decision trees, Bayesian-inspired approaches (Ling & al, 2018, Garcia & al, 2007), etc. could be functional, it is necessary to define the mechanisms of definition of learning styles as ILS (Felder & Silverman) which will be considered as labelled data for each of these approach in order to define their learning algorithm. This is where the problem arises, because these learning styles admit inherent properties that make their inference effectively incomplete, they are uncertain and stochastic.

2.5 Limits

Learning styles have a stochastic nature within them (Dorçà & al, 2013, Graf & al, 2010). The fact that supervised approaches recommend the use of prototype Index of Learning Style (ILS) questionnaire to initialize learning styles to adjust the learning phase of models, inadvertently induces some error as uncertainty. The learner who completes a form in user's interface can answer questions without being objective in its answers or having subjective answers (Syriaf, Sahid & al, 2017, Dorça & al, 2013); This decreases the certainty of estimating or approximating the learner's actual learning style and therefore limits his learning in the online training platform. Also noteworthy is the fact that, they are learners who do not have a dominant learning style and who conform to any form of learning strategy. These properties make complex the automatic and efficient detection of learning styles. Optimizing the detection of learning styles should therefore consider the following three points: the non-determinism of learning styles (stochastic character), the subjectivity of learning styles, and the lack of data features and size required to model them.

In order to personalize learning in E-learning, several approaches have been illustrated, particularly recommendation systems (Manouselis, Draschler, Verbert & Duval, 2012); but these are cost effective because they force the type of interaction that the learner can have on the platform, and they associate others persons to recommend kind of learning objects used by learner. Thus, limiting the pedagogical nature of the learning process, since the student should learn by himself (centric learning). The definition of a non-supervised adaptive E-learning system using learning styles could improve these limits.

3. Model design

In real life, data doesn't traduce often the reality. It may be possible that they are uncertain or variant this intuition supports the aim of (Dorçà & al, 2013, Graf & al, 2010) who state that learning styles are stochastic. Therefore, we can expect that some approaches as supervised learning, which learn from labels, could failed during the inference of learning styles. so, the problem is elsewhere, it is non-deterministic and the approaches which deal well with this kind of problem in artificial intelligence are unsupervised. To dynamically infer learning styles, we will need to extract the traces of learning activities of each learner in the system. Online learning systems can store these different activities in database. Once the extraction of the learning characteristics is done, the analysis of the features describing learning in the system is possible, the approach encountered is in line with the thoughts of (Ling & al, 2018, Bernard & al, 2017), recommending that new detection methods should play a leverage role between conventional detection approaches; based on system with simple rules, associated with elements of statistics (Dung & al, 2012, Graf & al, 2010) and data driven methods, which consists in the modeling of learner's learning profiles from the traces left in the system.

Our method which is generic can be apply in any kind of adaptive E-learning system, and any type of Learning style model containing categorized dimensions (Kolb, VARK, FSLSM,). It uses generative approach from graphical model, not yet use in the field of automatic learning styles detection. Indeed, generative approach in Deep Neural Network models estimate input distribution of data instead of learning objective (labelled data): learning styles, as used in supervised approaches; this property of generative models permits to avoid the stochasticity and the uncertainty of learning styles. The method is articulated in three (03) stages:

Step 1: Extraction of the activity traces on the online learning platform.

. The learning system saves all the learner's interactions, these traces define the behaviour of the learner on the platform. Each trace is categorized according to its belonging to a learning style dimension. This preliminary step consists of defining learning variables or indicators that are significant for learner monitoring on the platform.

We present a generic algorithm, not dependent of a learning platform, but interaction variables of learning styles present in a learning system, in order to extract the matrix of system learning indicators

$\boldsymbol{S}$ The set of learners.

I The set of possible interactions in a learning system

$\boldsymbol{LS}$ The set of learning styles,

$\mathbf{A} \subseteq \mathbf{I}$ The set of interactions related to a learning style

$\boldsymbol{a_j^i} \in \boldsymbol{A}$, Is a learning property, where the j-th learning interaction corresponds to the i-th learning style.

$\boldsymbol{hint(a_j^i)}$ Is an indicator of learning (Bernard & al, 2017, Graf & al, 2009) this indicator indicates the frequency of interaction of a learner on a_j^i.

$\boldsymbol{\Gamma} = \bigcup_{s \in S} \boldsymbol{X_s}$

***Algorithm 1*: Learning style feature behaviour extraction**

$\Gamma = \emptyset$
foreach $s \in S$:
$X_s = \emptyset$
foreach $a_j^i \in A$:
if interact (s, a_j^i)
$X_s = X_s \cup hint(a_j^i)$
$\Gamma = \Gamma \cup X_s$

For each learner in the system we extract the interactions corresponding to the learning style involved. From these interactions, we calculate the associated learning indicators; these are defined by the function ***hint ()***

$$hint: \begin{array}{c} LS \times A \rightarrow C \\ (x, y) \mapsto h(x, y) \end{array} \tag{6}$$

C define a discrete space with value in {0,1,2,3}, describing the level of involvement of a learner in an interaction (learning activity).

Step 2: Prior inference of learning styles

The work of (Graf & al, 2010; Amir & al, 2016) has shown that it is possible to have a prior estimate of a learner's learning styles using literate approach and using them for initialize the dynamic detection process. This calculation is done experimentally by weighting the resultant interactions of each learner.

$$LS_i = \frac{\sum_{j=1}^{P_i} hint_{i,j}}{n} \tag{7}$$

This estimation will be refined with our generative model, by analysing the distribution of learning indicators *hint(i,j)* because they do not contribute to equal weight in learning style computation (Bernard & al, 2017).

Step 3: Learning style modeling.

We have seen in Section 2 the different methods available for the automatic detection of learning styles, and that for an efficient calculation, it is necessary to understand the learning behaviour of a learner on the platform without however definitively assigning a style of learning. theoretical learning; to do so, we must use an unlabelled learning algorithm based on groupings. In order to group individuals in class of the same category and deduce learning styles, the latter emerging from themselves.

The unsupervised learning algorithm used in this article belongs to the family of deep neural networks: Deep Belief Network (Goodfellow & al, 2018, Hinton & al 2006). It is a probabilistic algorithm that will analyse the probability distribution of the learning indicators constructed in step 1; on the one hand to effectively estimate the notion of uncertainty related to a learning style, on the other hand to build a learning behaviour recognition's model of the learner. Our adapted DBN model includes an unsupervised learning layer consisting of RBM, and a supervised learning layer with a single perceptron function to classify learning styles.

We define an isomorphic function *discretize ()* that takes a value as input and transforms it into a d-bit sequence. It is important to discretize here to reduce some numerical computation issues as overflow/underflow when optimizing the parameters of the model, and this prepare the visible units to be used by the DBN model.

$$discretize: \begin{array}{c} A \rightarrow \{0,1\}^d \\ (x) \mapsto discretize(x) \end{array} \tag{8}$$

The new characteristic vector of the visible layer of DBN will be $(discretize \circ hint)(x)$

***Algorithm 2*: learning style model building**

Inputs:
Γ : Set of training, validation set
lh: Number of hidden layers
Outputs
Θ: Model parameters.

1. **Initialise** θ = <a, b, w>., alpha

$\mathbf{Feat_{DBN}} = \emptyset$

2. Foreach X in **Γ**

$disX = discretize\ (X)$

$\mathbf{Feat_{DBN}} = \mathbf{Feat_{DBN}} \cup disX$

3. Foreach layer ***l*** in the graph

3.1 While not converged

3.1.1 Select v in $\mathbf{Feat_{DBN}}$ in training set

. Generate h' Sample of h given v (Positive stage)

$$P(h_i = 1|v) = \sigma(b_j + \sum_{i=1}^{m} w_{i,j}^{l} * v_i)$$

. reconstruct visible unit (Negative Stage)

$$P(v_i = 1|h) = \sigma(a_i + \sum_{j=1}^{n} w_{i,j}^{l} * h'_j)$$

. Update model parameters

$w_{i,j}^{l}(t+1) = w_{i,j}^{l}(t) + alpha * (P(h_i = 1|v) - P(v_i = 1|h))$

3.1.2 Compute cost reconstruction

$E_\theta = E(v,h)$ see Eq.1

4. Learn the weights of the last hidden layer lh with $\mathbf{Feat_{DBN}}$ validation set

4.1 while not converged

4.1.1 Select v_i in $\mathbf{Feat_{DBN}}$ in validation set

. **Generate h' Sample of** $\boldsymbol{v_i}$ from learn parameters $w_{i,j}^{lh-1}, \dots, w_{i,j}^{1}$

. **Compute output of the model**

$y_i = \sum_{j=1}^{n} w_j^{lh} * h'_j$

. **Update model parameter** w_i^{lh}**.**

4.1.2 Compute prior cost

Where σ is an activation function, which can be the sigmoid or the Rectifier Linear Unit (ReLU) function.

$$\sigma(x) = \begin{cases} \frac{1}{1+e^{-x}} & sigmoid \\ max(0,x) & ReLU \end{cases} \quad (9)$$

The algorithm generates a DBN model that learns the distribution of learning indicators on a dataset. This DBN-based model can detect learner learning styles effectively by excluding bias due to uncertainty or stochasticity.

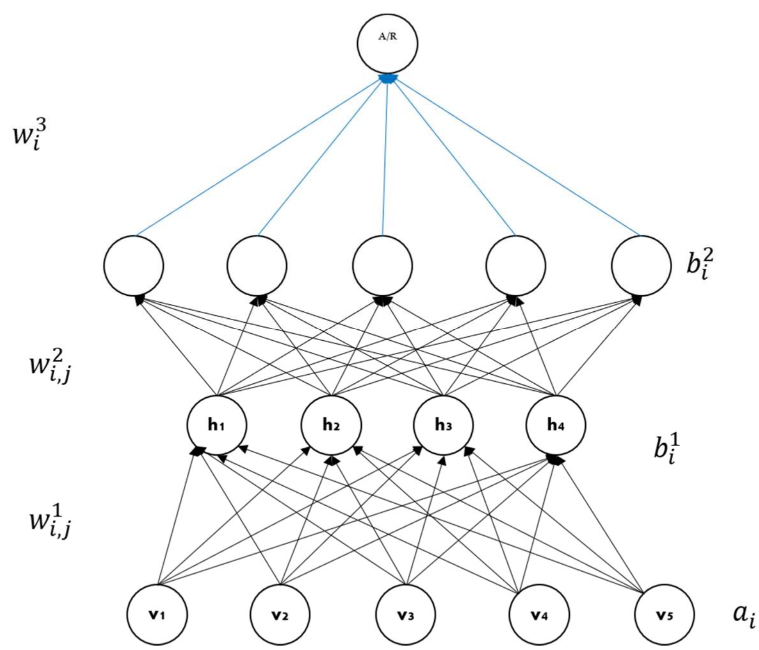

Fig. 3. An upgrade Deep Belief Network to infer Active/Reflective Learning style

The first part of the model uses unsupervised learning, section 3 of the Algorithm 2, to permit the model to learn the distribution on learning style's features descriptor. At this level the contrastive divergence algorithm will be capable to analyse the pattern introduce in the model regarding either the uncertainty of visible units or their stochasticity, as a probabilistic model it will perform to learn latent transitions $\boldsymbol{h_i}$ of the variable $\boldsymbol{v_i}$ during the learning of parameters $\boldsymbol{w^1_{i,j}}$; $\boldsymbol{w^2_{i,j}}$ $\boldsymbol{b^1_i}$, $\boldsymbol{b^2_i}$,$\boldsymbol{a_i}$ using equations in section 2.3.1), to estimate another input same size $\boldsymbol{v'_i}$ defining the generative input of the model, which can have a better stability according to the dataset distribution. And as dataset is bigger as the algorithm breakdown all this different transition to have the best similarity between the visible input and the generative one (Lecun & al, 2016; Goodfellow & al, 2018), thus ensuring the confidence of the layer containing the generative input. The second part of the model is a perceptron model using gradient descent to learn the last parameters $\boldsymbol{w^3_i}$ to infer the final value of the learning style. Fig 3 illustrate how the Active/reflective learning is compute using our method. By this way, we can learn all kind of categorized learning styles regarding their learning descriptor.

4. Evaluation and discussion

4.1 Evaluation

To evaluate this research method, we used Felder & Silverman Learning Style Model (FSLSM) they are as the most used in literature review and best suited for E-learning activities (Ling & al, 2018, Feldman & al, 2015). We noticed in general, a strong insufficiency of public tracking data on e-learning systems. that captures interactions between learners and the system; review data are for the most part of time part proprietary and do not have public access, also, they have reduced size which is not relevant in the sense that they have low dimensionality and not reliable to context where there is huge students interacting in the system, where we can have more than 1000 student for a online class. Having a large dataset is a benefit for deep learning model to improve generalization of data (Goodfellow & al, 2018, Hinton & al; 2006). To overcome this shortcoming, we used the traces of the Moodle learning system data for research, which is open and sufficiently provided to experiment a fully online learning format. There were 6,119 students enrolled in this course and 2 facilitators, 2168 agreed to use their data for research purposes (Elizabeth, 2017).

4.1.2 Learning descriptor

On the analysis of the Moodle logfile, we have been able to identify the dimension of the 4 dimensions of Felder and Silverman learning styles (FSLSM). It is noticed that, this method is generic and applies to any learning style model. These are learning styles: *Active/Reflexive, Sensitive/Intuitive, Visual/Verbal* and *Sequential/Global.* From the learning activities found in the database we have distributed the Moodle modules present according to the learning style dimensions of Felder and Silverman

Table 1.
Moodle modules distribution through Learning Style.

Active/Reflexive	**Sensitive/Intuitive**	**Visual/Verbal**	**Sequential/Global**
Forum	Feedback	Glossary	Page
Quiz	Book	Lesson	Wiki
Chat	Choice	Forum	Lesson
Lesson	Lesson	Bigbluebutton	Choice
Survey			
Workshop			

In this log file, we found 13 (thirteen) activity modules. These modules are distributed in the 3 Felder & Silverman Learning Style Model retrieved in the log file of this system. See tab, this distribution follows the work guidelines of (Liyanage, Gurawardena & Hikarawa, 2016, Graf & al, 2010). For all these modules, we extracted 124 journal event interactions to pre-process the learning descriptors of each learner, see Fig 4. These interactions constitute the learning variables of the detection model.

4.1.3 Pre-processing: Pattern behaviour selection

The Pareto curve in Fig 4 describes the distribution of decreasing cumulative frequency learning indicators. From this curve, we used learning indicators having a frequency higher than 10%, for a total of 63 groups of activities present in the log file of the database. We applied the algorithm 1) to extract the learning indicators variables. Before passing the data to learning models it is necessary to identify the most relevant learning indicators in the data see Table 2. To make it effective, we calculate the maximum learning indicator of each learner, and make the disjoint meeting of them; this ensure that each learner has at list one learning preference in the system, then we select features which are related to the learning style prior estimation by visualizing if there is a relationship between them.. This characteristic vector defines the representative variables for training the model.

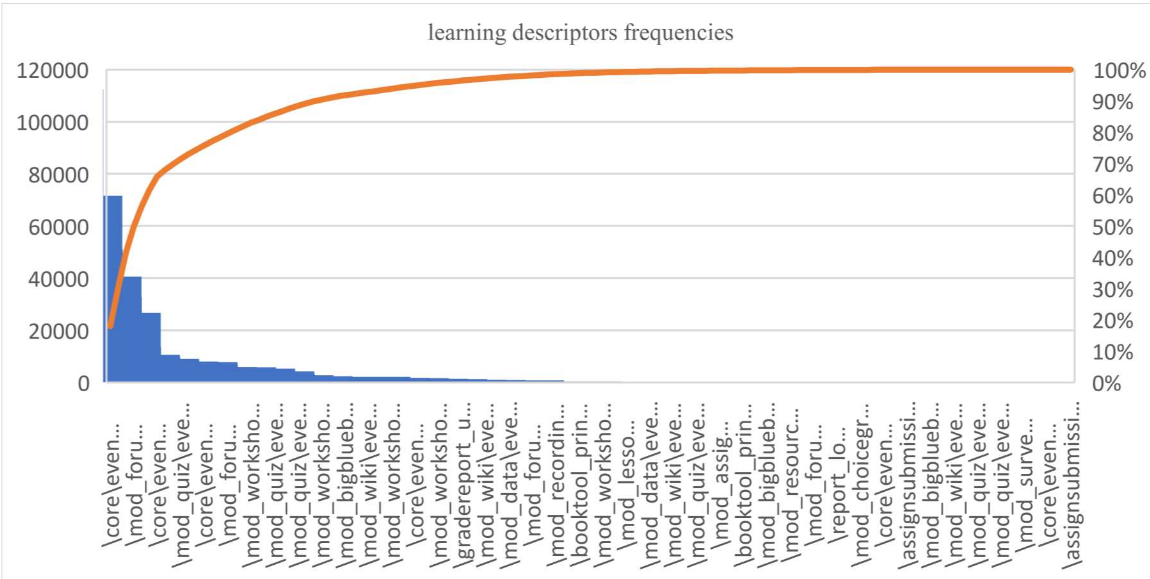

Fig. 4. Frequency of learning activities

For the *Active/Reflective* learning style, after crossing and analysing the high-input descriptors for the detection model, we identified 11 variables as models' learning indicators inputs. For example, we see from Fig. 5.a. That there is a correlation between the number of participation in the forums and the learning style category *Active/Reflexive*, it is the same observation in Fig. 5.b. For the visits' number in the course content according to the learning style. This method was applied to the Felder & Silverman learning style dimensions to identify significant variables for the learning style detection models. From this analysis we also noticed that the learners are not categorized by the *Sensitive/Intuitive* type because the learning descriptors of this dimension did not interest the learning activities of the learners.

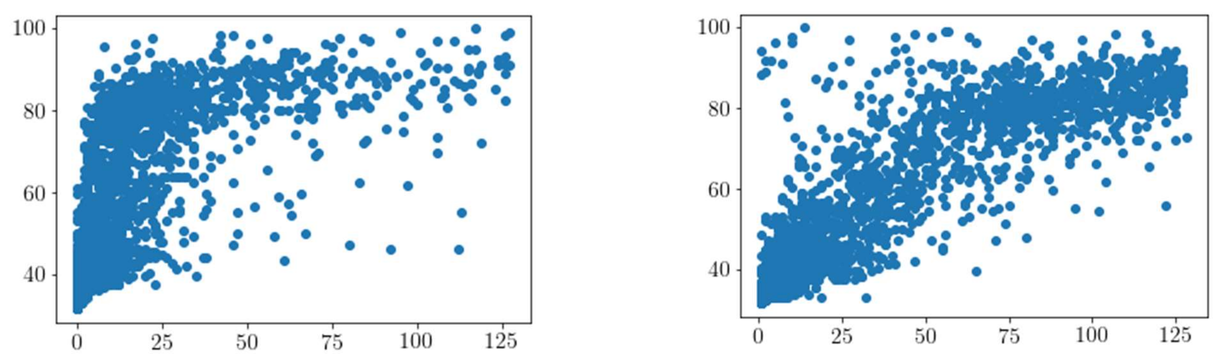

Fig.**5**. a) Forum (*mod_forum_event_discussion_viewed*) learning descriptor impact on Active/Reflexive learning style. b) Chat (*mod_chat_event_discussion_viewed*) descriptor impact on Active/Reflexive learning style.

Table 2
Moodle relevant learning indicators model inputs after selecting relevant feature for each learning FSLSM.

Active/Reflective (A/R)	Visual/Verbal (V/V)	Sequential/Global S/G
-core_event_course_viewed -mod_folder_event_course_module_viewed -mod_forum_event_discussion_viewed -mod_forum_event_course_module_viewed -mod_forum_event_discussion_subscription_created -mod_workshop_event_submission_viewed -mod_forum_event_assessable_uploaded -mod_workshop_event_course_module_viewed -mod_data_event_course_module_viewed -mod -choicegroup_event_course_module_viewed -mod_chat_event_sessions_viewed	-mod_forum_event_course_module_viewed -mod_forum_event_discussion_viewed -mod_glossary_event_course_module_viewed -mod_forum_event_discussion_subscription_created -mod_bigbluebuttonbn_event_bigbluebuttonbn_activity_viewed -mod_forum_event_course_searched -mod_forum_event_assessable_uploaded -mod_recordingsbn_event_recordingsbn_resource_page_viewed -mod_lesson_event_content_page_viewed	-mod_page_event_course_module_viewed -mod_wiki_event_page_viewed -mod_wiki_event_page_history_viewed -mod_choice_event_course_module_viewed -mod_choice_event_answer_submitted -mod_wiki_event_course_module_viewed -mod_lesson_event_content_page_viewed

4.1.4 Model parameterization

We subdivided the data into three (03) parts, one part for the training data of the model is 60% of the total dataset, part for the validation data 20% total dataset and part for the data performance test (20%). Validation data is used to select the best parameters for model training. After using the validation data, we obtained the following best model parameters:

Table 3
Hyper parameterisation of ANN: Multi-Layer Perceptron.

Learning Style	#features input layer	# hidden node in hidden layer	Algorithm halt condition	Learning error threshold	# Iterations	Training algorithm
A/R	11	10	Early stopping	0.01	100	Backpropagation
V/V	5	3	Early stopping	0.001	1000	Backpropagation
S/G	5	3	Early stopping	0.01	1000	Backpropagation

The early stopping method avoids overfitting of the model, the validation data is introduced into the training stage to control its learning.

Table 4
Learning Parameters of the DBN

Learning Style	#Hidden layer	#Hidden node in hidden layer	#visible binary variable (input)	# iterations	Sampling step of contrastive divergence
A/R	2	12	44	100	1
V/V	2	8	15	100	1
S/G	2	7	15	100	1

4.1.5 Performance

The evaluation was done on a multi-layer perceptron neural network with 1 binary output: 1 to say that the calculated output belongs to the required learning style dimension, and 0 otherwise. We used the confusion matrix to calculate the accuracy of the model.

Two algorithms have been used. The multilayer perceptron's method with the backpropagation algorithm (Hasibuan & al, 2019; Bernard & al, 2017), and our model DBN. They gave good results, but from our modified Deep Belief Net, we record a gaining factor of **13.11%**.

Table 5.
Comparative evaluation of the models.

Approach	**Active/Reflective (A/R)**	**Visual/Verbal (V/V)**	**Sequential/Global (S/G)**	**Avg**
LSID-ANN	92.25%	63.28%	86.96%	80.83%
LSID-DBN	**97.12%**	**90.45%**	**94.24%**	**93.94%**

Given the nature of unobserved data and learning descriptors in some learners, the LSID-ANN model did not have enough strong predictive power on the Visual / Verbal and Sequential / Global learning styles. The DBN model considers a better analysis of the distributions of learning descriptors. Indeed, the first phase of the training process being unsupervised, removes from the learning style detection experiment the non-deterministic nature of the descriptors. The second phase of the DBN uses a regression technique to predict the probability of observing a learning style, which is then applied a confidence level of 0.5 to infer the existence or not of the learning style.

4.2 Discussion

The results obtained at the end of this study show us that for an efficient calculation of learning styles outside an automatic learning algorithm, we must find the most important learning indicators in order to generate a learning model, since in real cases, many learning descriptors in the system have a weak distribution that prevents enriching learning models. We also observe that the discretization of learning indicators promotes the distribution of learning descriptors for DBN type neural networks. The use of DBN learning is much more relevant to the Artificial Neural Net, regarding the subjectivity and stochasticity nature of learner behaviour on the e-learning platform. The methodology developed in this work is effective for the detection of learning styles, it could be further refined considering also the time parameter, which was not included in the data modeling because the log file does not provide the duration of each learner's learning activity. The dataset used was to roll out our approach, for more efficient results it would be possible to build a clean dataset on local learners in order to have a better contextualization and adaptation of the learning objects regarding the fitted learning styles.

5. Conclusion

The personalization of learning in E-learning systems requires learner to be at the centre of their learning. In order to move from industrialized to personalized education, it is important that each training manager facilitate learning by providing learning resources aligned with learner learning styles. We have seen that theoretical models have had define categories of learners using learning styles that can be used to provide learners with rich learning activities, these methods admit of limitations by the subjectivity of questionnaires (ILS) dynamic detection techniques of learning styles have been proposed. Our study allowed us to develop a detection approach considering the stationary and non-deterministic aspect of learning styles. This approach allowed us to study the distribution of learning indicators for the inference of learning styles. It has an advantage over existing approaches in that it allows to reuse a model already learned in other online training courses using techniques such as model learning transfer (finetuning). The results we have obtained can be exploited in online training systems with the adaptable architecture proposed in this article to make learning activities dynamic and personalized. Further works will consist of applying this resulting model on E-learning platforms in the universities system and see its impact on personalized learning object recommendation.

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