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Identifying and tracking learning styles in MOOCs: A neural networks approach

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ABSTRACT: Learning styles identification using learners' behavior and the actions they perform on a MOOC environment constitute in our opinion not just an interesting research issue but also an important solution to improve MOOC effectiveness. Indeed, providing learners with learning resources and activities that suit to their preferences and learning styles increases their satisfaction improve learning performances and save time (efficiency). In this paper, we propose an approach that uses neural networks to identify and track learners learning styles, then to provide them the appropriate resources, activities, etc. through adaptive recommendation system. The purpose of this paper is to examine the point of view of literature on MOOCs, learning styles and their use in MOOCs environment and our proposed solution to integrate an adaptive recommendation system with MOOC taking into accounts the plurality of participants' learning styles.

KEYWORDS: MOOC, TEL, Learning style, Machine learning, Neural networks, Adaptation.

1 INTRODUCTION

Massive Open Online Courses (MOOCs) have generated a great deal of excitement for their potential to make traditional university material accessible to a very wide audience. However, despite the growing popularity of MOOCs, considerable skepticism about their success and efficacy [1]. The completion rate is very low approximately 10% [2]. Recent studies showed a 20% rate of completion [3].to try to reduce dropout rates and increase the learner's completion rates, our work is focused on improving MOOC effectiveness through taking into account advantages of learning style theories into MOOC adaptation process in order to make learners aware of their learning styles and providing them with learning resources that match their individual learning styles [4].

In this paper, we study an important issue of learning performances and propose a neural network based solution. The issue comes from individual differences, each learner has his way of learning which is cover the way of receiving and processing information.

To identify learners' learning styles, many systems ask learners to complete questionnaires, which is not appropriate because learners tend to choose answers arbitrarily when questions are too long. Therefore, we introduce an approach, which combines collaborative approach (questionnaire), and automatic (learners' behavior) ones to identify and track learners learning styles.

Recognized learning styles are the backbone of our adaptive recommendation system, which can be used to provide adaptive navigation support, recent work has shown that providing learners with learning resources and activities that suit their preferences and learning styles increases learner's satisfaction [5], improve learning performances (effectiveness) and save time (efficiency).

In the rest of this paper, we will present a theoretical background on learning styles. Then we will describe our approach, telling how machine learning can be used to identify and track the learning styles of learners. Finally, a conclusion will be drawn and our future work will be exposed.

2 STATE OF THE ART

Learners learn through a variety of different learning styles [6]. The concept of learning styles is not a simple task. In the literature, there are multiple definitions of the term “learning style”:

The term “learning style” refers to the way in which an individual concentrate on processes, internalizes, and retains new and difficult information [7]. Smith & Dalton [8] defined learning style as a unique and habitual behavior of acquiring knowledge and skills through every day study or experience. While Felder & Silverman [9] described it as the way, in which persons receive and process information. Moreover, Kolb [10] had his own opinion as to what a learning style is. He defined it as the process of creating knowledge through the transformation of experience. Honey and Mumford defined learning style as “a description of the attitudes and behaviors which is an individual’s preferred way of learning” [11].

In the last decade, many learning style models have been proposed, some of these learning style models have been found more appropriate for distance learning than others [12]: Kolb’s learning style model [13]. The Honey and Mumford's learning style model [13] and Felder and Silverman’s learning style model [14].

In the following lines, we will first, present Kolb and Felder-Silverman learning style models that researchers found more appropriate for distance learning, second we will present studies of several research works that combine Learning Styles and MOOCs.

2.1 LEARNING STYLES MODELS

2.1.1 FELDER-SILVERMAN LEARNING STYLES MODEL

The Felder-Silverman learning style model (FSLSM) was created by Richard Felder and Linda Silverman in 1988. It focuses on aspects of learning styles on engineering students. FSLSM describes learning styles in more detail by characterizing each learner according to four dimensions; each of these dimensions is defined in table 1.

Table 1. Filder-Silverman dimensions

Dimension	Learning styles	Description	Learning objects
Perception The type of information the learner prefers to perceive.	Sensory	Sensory learners like to learn from concrete material such as examples.	Examples Exercises Quiz
	Intuitive	Intuitive learners prefer to learn abstract material such as theories.	Abstract learning object
Input The way in which learners prefer to receive external information.	Visual	Visual learners learn best from what they see.	Recorded videos Images – graphics
	Verbal	Verbal learners prefer to learn from words (spoken or written)	Textual explanation documents Audio Additional reading
Processing The way perceived information is converted into knowledge.	Active	Active learners prefer to learn by trying things and working with others	Forum access Forum post
	Reflective	Learner prefer to learn by thinking things through and working alone	Exercises Examples
Understanding The way learners progress towards understanding.	Sequential	Sequential learners tend to go through the course step by step in a linear way.	Learner access for learning concepts Step by step exercises
	Global	Global learners prefer to learn in large leaps, skipping to more complex material	Outline

For identifying learning styles based on this model, Felder and Soloman created the Index of Learning Styles (ILS). It is a 44-item questionnaire (11 items for each of the 4 dimensions) each item has two exclusive options (a & b). Learners’ personal preferences for each dimension are expressed with values between +11 to -11 per dimension, with steps +/-2.

Each dimension is divided into three categories. If the score is between 3 to -3, learner is categorized into “well balanced”. If learner’s score is between -5 and -7, or between 5 and 7, he/she classified into “moderate preference”. If learner’s score is between -9 and -11 or between 9 and 11, he/she is grouped into “strong preference” [15], as shown in the figure 2.

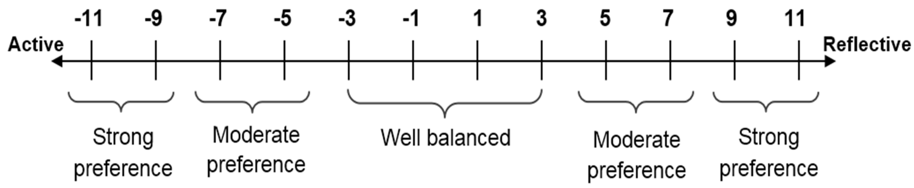

Fig. 1. Scales of learning style dimensions

FSLSM is one of the most often used model in adaptive educational systems in recent times and some researchers even argue that FSLSM is the most appropriate model for use in adaptive systems [15].

2.1.2 KOLB’S LEARNING STYLE MODEL

Kolb’s learning style model, one of the best models of learning styles was developed by David Kolb [10], this model (Fig. 1) is presented as a transformation process beginning from reflection and ending by experimentation. The Kolb learning cycle is based on four-stage:

- Concrete experience (CE) – feeling.
- Reflective observation (RO) – watching.
- Conceptualization (AC) – thinking.
- Active Experimentation (AE) – doing.

A combination of these four stages yields four types of learning styles presented as follows:

- Accommodator (CE/AE): Prefers practical hands-on approach to problems.
- Converger (AC/AE): Attracted to technical tasks and problems.
- Diverger (CE/RO): Prefer to watch rather than do, tending to gather information and use imagination to solve problems.
- Assimilator (AC/RO): Interested in ideas and abstract concepts.

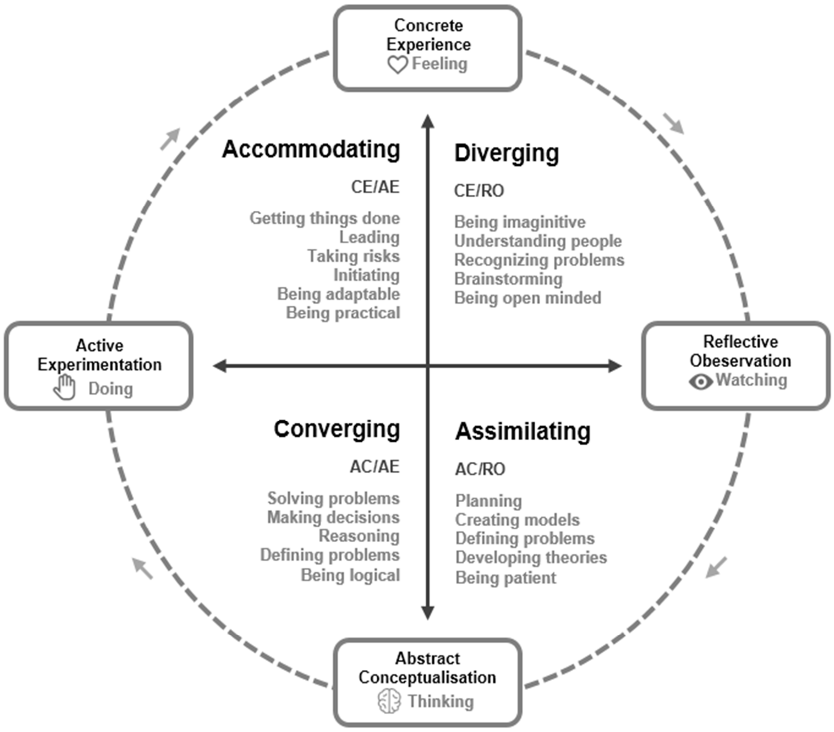

Fig. 2. Kolb's learning style model

For identifying learning styles based on Kolb's learning style model, Kolb developed the learning style inventory (LSI). Which consists of 12 item questionnaire that asks learners to rank four sentence endings that correspond to the four learning styles (4= most you like; 1=least you like).

2.1.3 SUMMARY

In our view, identifying and examining these models is important for several reasons. The first one is to understand the types of learners and evaluate their Learning styles. The second is to research methods and practices that can be applied in order to sustain learners' Learning styles, and consequently improve learners learning performances. The third is to identify which model is more adapted to MOOCs environments. The forth reason is to identify specific needs of learners to adapt the content and learning modalities.

2.2 NEURAL NETWORKS

The aim of this section is to describe the artificial neural networks. We will focus on a multi-layer neural network (ANN) (Fig. 1), which is the most popular algorithm in the area of neural networks

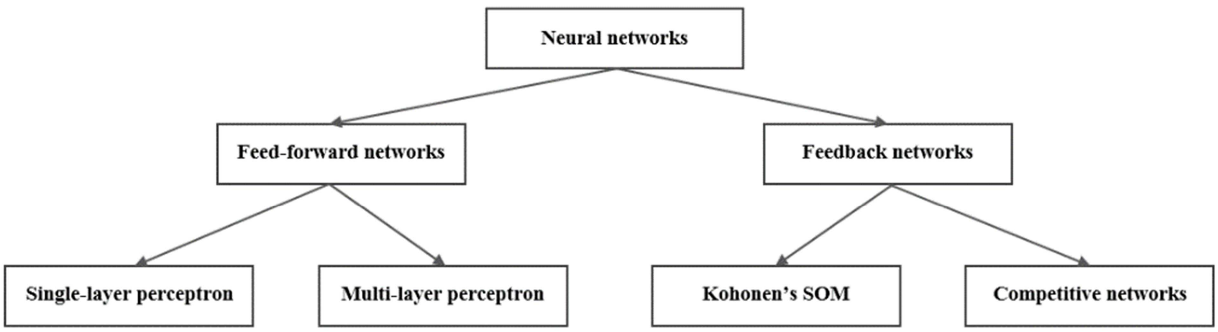

Fig. 3. A taxonomy of neural networks

Haykin defined neural network as “a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use” [16].

Multi-layer neural network is typically composed of several layers of nodes. The first or the lowest layer is an input layer where external information is received. The last or the highest layer is an output layer where the problem solution is obtained. The input layer and output layer are separated by one or more intermediate layers called the hidden layers. The nodes in adjacent layers are usually fully connected by acyclic arcs from a lower layer to a higher layer [17]. Figure 4 gives an example of a fully connected multi-layer neural network with one hidden layer.

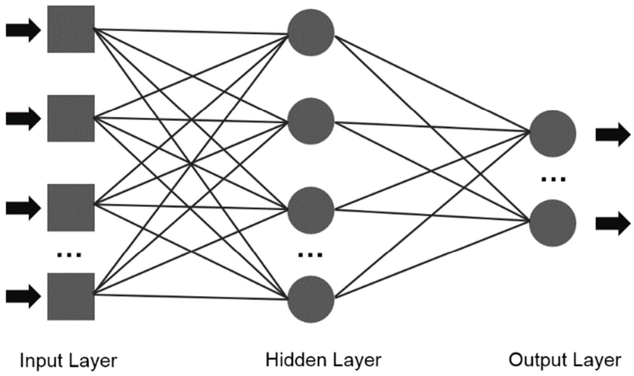

Fig. 4. The neural networks architecture

2.3 LEARNING STYLES & NEURAL NETWORKS

In this section, we enumerate several works concerning identification of learning styles using neural networks.

In Table 2, the first column “authors” indicates the analyzed works, the second column “platform” describes the system used to identify learning styles, the third column “LS model” indicates the learning styles model used, the fourth column “learner model information” presents the information used to build the user model, the last column “LS identification techniques” indicates the learning styles identification technique used.

Table 2. Works analyzed

Authors	Platform	LS model	Learner model information	LS identification techniques
Kolekar 2010 [18]	E-learning	Felder	Learner behavior	Neural networks
Zatarain-Cabada 2010 [19]	Intelligent Tutoring Systems (ITS)	Felder	Learner behavior	Neural networks
Annabel Latham 2013 [20]	Conversational intelligent tutoring system (CITS)	Felder	Learner behavior	Multilayer Perceptron Artificial Neural Network
Heba Fasihuddin 2014 [21]	Open learning environments	Felder	Learner behavior	Neural networks
Jason Bernard 2015 [22]	-	Felder	Learner behavior	Neural networks

Identifying these works are important for several reasons:

- Compile and analyze the state-of-the-art about Learning Styles in Online Learning environments.
- Define methods and practices that are applied in order to identify Learning styles.
- Conduct research on how to identify these Learning styles in MOOC environments by investigating the use of Neural Networks practices

Although many research works addressed to identify learning styles in MOOCs environments, there is not yet any tangible research that focuses on Neural Network process.

3 OUR APPROACH

In this section, we describe our approach on how neural network can be used to identify and track the learning styles of learners. At the beginning, learner's learning styles is obtained from the learner profile or/and questionnaire, then learning styles can be modified and tracked dynamically and automatically by observing learner's behavior and actions they perform in a MOOC environment.

The architecture of our approach and its components can be seen in figure 5. Our approach consists of six stages: Data Collection – Pre-processing - Feature Extraction - Classification - Learner Profile- Adaptation (recommendation).

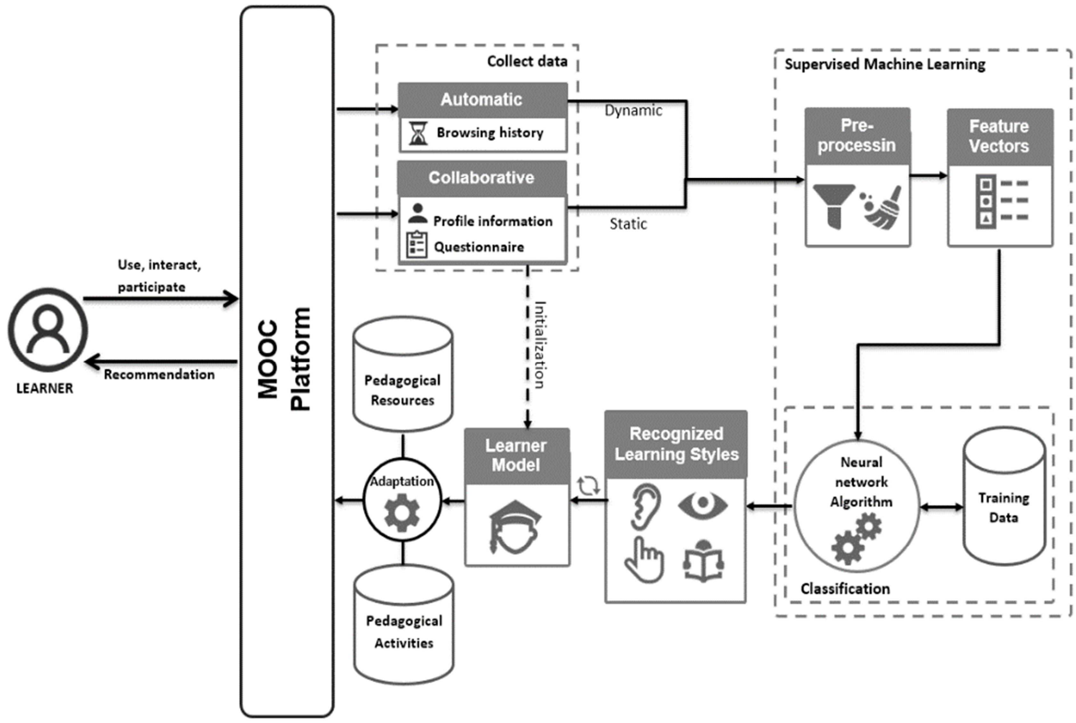

Fig. 5. A process of identification of learning styles using neural networks

3.1 DATA COLLECTION

During the first stage, our goal is to collect data; we will gather data by two different ways: collaborative and automatic. In the collaborative approach, learners are asked to provide their preferences explicitly by filling in a questionnaire, such as the ILS questionnaire [21].In the automatic approach, we use the behavior of the learners and their actions with the systems while they are learning [21].

We choose to combine automatic and collaborative approaches because the collaborative approach first allows us to initialize the learner model in the beginning of MOOC, then we use the automatic approach to update learner model dynamically.

3.2 PRE-PROCESSING

Pre-processing operation is the first step performed on raw collected data. This step aims to:

- Clean data collected of low-quality information.
- Transform the data into a clean format, which can be used by our system, for example, calculate the number of videos watched by a learner.
- Prepare data for analysis through neural network.

3.3 FEATURE EXTRACTION

After Pre-processing, a feature extraction method will be applied to extract the most appropriate characteristics that can be used to identify learning styles of learners.

This stage aims at creating vectors from the characteristics of each learner. These characteristics are gathered from the data collection stage. These vectors serve as an input for our neural network so that we can identify the learner learning style.

The construction of our vectors is done through two crucial steps: a theoretical study and an empirical one. The theoretical study will allow us to identify the data and traces, which will help us in the process of defining each element of the vector. We are now working on this.

The empirical study will allow us to define the pertinent characteristics that will serve to create our vectors such as the number of watched videos, the number of posts in the forum, etc.

3.4 CLASSIFICATION

In this phase, we expect the use of a neural network for the detection and recognition of learning styles. Two classification types can be defined: supervised and unsupervised [23] classifications. In this research, we rely on a supervised classification, which consists of two processes: training and testing process.

Step 1-Training -

In this step we aim to create training dataset from fixed dimension vectors, these are obtained from characteristics of each learner. After this, learning Dataset will be presented to the neural network for learning about the properties for each learner styles.

Step 2 -Testing-

This step consists of creating a model that can measure the performance and accuracy of test dataset.

- The process of this step begins when new learners enroll to the platform.
- The system will then extract vectors from the characteristics of these learners
- These vectors will constitute the input for our trained neural network (input layer).
- Finally, our neural network seeks to predict the learner styles closer that belongs to each learner (output layer) (fig.6).

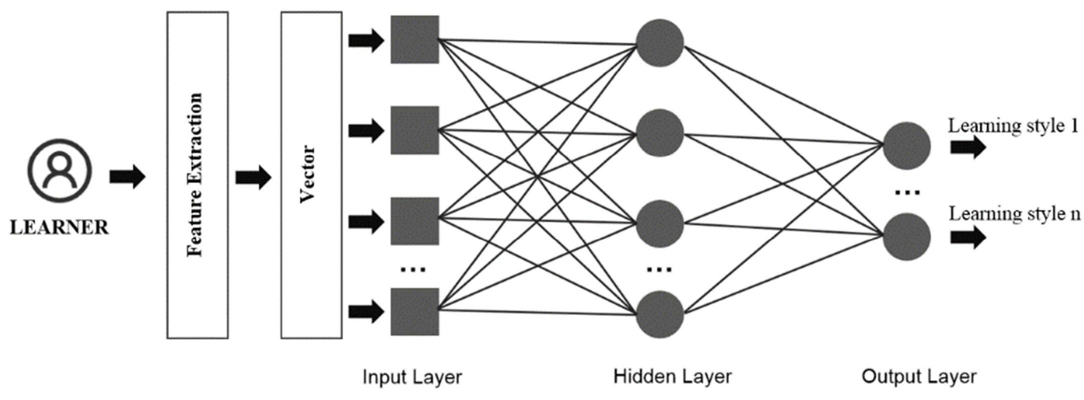

Fig. 6. The neural network architecture

3.5 LEARNING STYLE RECOGNITION & LEARNER MODEL

On the one hand, learner model can be initialized statically in a collaborative way such as asking learners to complete a questionnaire in the beginning of MOOC. On the other hand, the learner model can be updated automatically through neural network techniques that exploit learner's behaviors while they are using the system.

3.6 Adaptation process

After identifying learning style for learners, we aim to provide relevant content to the learner according to his learning style through navigational support.

In a nutshell, the adaptation can be done as follows:

- Identification of learners who have the same learning style.
- Create learners' clusters based on their profiles.
- Recommendation of appropriate resources for each cluster (not individuals) via navigational support [24].

4 Conclusion & perspective

This paper shed light on the relation between learning styles, MOOC environments, and machine learning. We are positive that this approach will make MOOCs benefits from the advantages of using learning styles to improve learning personalization.

Based on the findings, our research proposed to design a suggestion to adapt MOOC environments through traces analysis. The adaptation of these environments aims to provide relevant content to the learner via navigational support. Concrete implementation of these general suggestions and validations of their effectiveness are however left as future works. These experimentations will be done on courses prepared and hosted on Ibn Zohr University servers in Morocco. In this work we first introduce learning styles theories. In addition, we described our methodology on how neural network can be used to identify the learning styles of learners based on the actions they perform in MOOC.

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