# Analyzing the Influence of Learning Styles on Students' Behavior in a Social Learning Environment<sup>§</sup>

Elvira Popescu\*, Florin Leon\*\*

 Department of Computers and Information Technology, University of Craiova, Craiova, Romania (e-mail: <u>popescu\_elvira@software.ucv.ro</u>)
 \*\* Department of Computer Science and Engineering, Technical University "Gheorghe Asachi" of Iaşi, Iaşi, Romania (e-mail: fleon@cs.tuiasi.ro)

**Abstract**: Learning style is one of the students' characteristics which play an important role in learning, referring to the individual manner in which they approach a learning task. Many studies have investigated the relationship between students' learning styles and their behavior in learning management systems or other traditional educational systems. With the increased adoption of Web 2.0 tools in instructional settings, it is interesting to also explore the influence of learning styles on students' usage patterns of these social media tools. Hence, this paper focuses on students' behavior in a social learning environment which integrates four Web 2.0 tools (wiki, blog, microblogging tool, social bookmarking tool); students' learning styles are categorized according to Felder-Silverman model. The analysis is based on typical machine learning algorithms for classification, association rule induction and feature selection. The investigation includes 3 scenarios: i) the analysis of the number of student actions with each social media tool); ii) the dominant tool corresponding to a learning style; and iii) the temporal evolution of the number of actions and their category. Results show that learning styles have a limited influence on the students' level of interaction with each of the four social media tools considered.

*Keywords:* social media, Web 2.0 tools, social learning environment, learning styles, behavioral patterns, machine learning, classification, association rule induction, feature selection

## 1. INTRODUCTION

Even if not yet part of the educational technology mainstream, Web 2.0 tools "have reached a high level of maturity and have been increasingly adopted in educational practices worldwide" (Jeremic et al., 2013). This overarching term refers to various applications built on the Web 2.0 infrastructure, such as blog, wiki, social bookmarking tool, social networking service, microblogging tool, media sharing service etc., all of which are also known as social media tools. These technologies can be used to foster communication and collaboration between learners and help create online learning networks. Some practical ways in which selected Web 2.0 tools can support teaching and learning are synthesized in (Conole and Alevizou, 2010), (Homola and Kubincova, 2009), (Orehovacki et al., 2012). Overall, studies report a general positive impact of social media tools on learning, leading to an increase in the effectiveness of the learning process and especially in the learner motivation and satisfaction (Popescu, 2013).

In this context, it is interesting to investigate the

relationship between students' individual differences and their preference and behavior toward the social media tools; this would help identify the success factors of using Web 2.0 tools in educational settings. In particular, in this paper we focus on learning style as one of the individual differences that play an important role in learning, according to educational psychologists (Popescu, 2009).

Learning style refers to the individual manner in which a person approaches a learning task. For example, some learners prefer graphical representations and remember best what they see, others prefer audio materials and remember best what they hear, while others prefer text and remember best what they read. There are students who like to be first presented with the definitions followed by examples, while others prefer abstract concepts to be first illustrated by a concrete, practical example. Similarly, some students learn easier when confronted with hands-on experiences, while others prefer traditional lectures and need time to think things through. Some students prefer to work in groups, others learn better alone. These are just a few examples of the many different preferences related to perception modality,

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processing and organizing information, reasoning, social aspects etc., all of which can be included in the learning style concept (Popescu, 2009).

During the last decades, many learning style models have been proposed, which differ in the learning theories they are based on, the number and the description of the dimensions they include. For the current study, we focus on one of the most popular models in technologyenhanced learning (Derntl and Graf, 2009), namely the Felder-Silverman learning style model (FSLSM) (Felder and Silverman, 1988). According to FSLSM, learners are characterized by their preferences on four dimensions: active versus reflective; sensing versus intuitive; visual versus verbal; sequential versus global. Active students learn by trying things out and enjoy collaborative working, while *reflective* students like to think about the material first and prefer working alone. Sensing learners have a preference toward facts and details and they tend to be practical and careful, whereas intuitive learners prefer abstract material, they like to innovate, to discover possibilities and relationships. Visual learners remember best what they see (pictures, diagrams, schemas etc.) while verbal learners get more out of words, either spoken or written. Sequential learners tend to gain understanding in linear steps, while global learners learn in large leaps, they are fuzzy about the details of the subject but are able to make rapid connections between subjects. It should be noted that these learning styles are seen as tendencies and not fixed, rigid labels.

Up to now, researchers have investigated the relations between students' learning styles and their behavior in traditional e-learning systems (learning management systems, educational hypermedia systems). Examples include rule-based approaches (Graf et al., 2009; Popescu, 2009), Bayesian networks (Garcia et al., 2007), decision trees (Cha et al., 2006; Ozpolat and Akar, 2009), neural networks (Villaverde, 2006) or reinforcement learning algorithms (Dorca et al., 2013) for dynamic identification of students' learning styles. However, students' behavior in the emerging social learning environments (which is the focus of this paper) has been far less explored.

The rest of the paper is structured as follows: section 2 provides an overview of the few related works which investigate the relationship between students' learning styles and their preference or behavior toward social media tools. Section 3 describes the context of our study and the approach used for data collection. Section 4 offers a brief overview of the machine learning algorithms used for analyzing the data. Section 5 details the analysis process and the results obtained. Some discussions and conclusions are included in section 6.

## 2. RELATED WORK

Saeed and Yang (2008) reported on one of the first studies which explored the correlations between students' learning style and their preferences toward Web 2.0 tools. FSLSM was used and the associated Index of Learning Styles (ILS) questionnaire (Soloman and Felder, 1998) was applied at the beginning of the course in order to identify students' styles. Learners' preferences toward Web 2.0 tools were elicited by means of another dedicated questionnaire; students were asked to rate various tools (including blog, wiki, podcast, vodcast but also email and Blackboard LMS) on a scale from 1 to 5, for various learning activities (e.g., reviewing lectures, submitting group projects, having group discussions, etc.). 89 students enrolled in a Web programming course responded to both questionnaires and were included in the study. Pearson correlation was applied and a few significant relationships were discovered: i) intuitive learners (who, according to FSLSM, prefer discovering possibilities and relationships and are always ready to try out new things) preferred blogs; ii) sensing learners preferred email (a more traditional communication tool, in line with their more careful and detail-oriented nature); iii) visual learners preferred vodcasts (not surprisingly, taking into account their preference toward pictures, diagrams, flow charts etc.); iv) sequential learners preferred podcasts (since they tend to gain understanding in linear steps and follow logical stepwise paths, so they could run the sequence of lectures at their own pace over and over again to get a better understanding of the course content). No correlations were found for the active/reflective dimension.

The authors also performed a second study (Saeed et al., 2009), in which they analyzed the effects of cognitive style (adaptors versus innovators) (Kirton, 1976) on learner acceptance of blogs and podcasts. The context of study was again the Web programming course, in which they included blogs and podcasts as support tools. Kirton's Adaption-Innovation inventory was used to identify students' cognitive style and a dedicated questionnaire was used to elicit students' perceptions regarding ease-of-use and usefulness of the Web 2.0 tools. 187 students filled in the two questionnaires and were included in the study. The results showed that innovator students are more likely to perceive blogs and podcasts as useful and easy-to-use as compared to *adaptor* students. Furthermore, innovators perceive podcasts as more useful, but less easy-to-use than blogs.

Derntl and Graf (2009) investigated the effects of the learning style on the blogging behavior of students in an undergraduate course on software architectures and web technologies. 77 students were enrolled in the course but only 74 of them filled in the ILS questionnaire (for identifying learners' FSLSM dimensions) and were included in the study. Students were asked to use blogs as a kind of personal journal, including insights and remarks on the tasks, problems encountered and solutions found, reflections on the project and teamwork, etc.; however, the blogging activity did not count toward the students' grade. The blogging activities were integrated into the course learning management system and various student actions were recorded in a log file. Rank correlation analysis was used in order to find relationships between the students' learning style and these blogging actions. No significant results were found regarding: i) the number of visits to the blogging environment; ii) the frequency of reading others' blogs; iii) the preference for using links from the 20 recent blog postings. Some significant correlations were found for the active/reflective dimension: i) active students tend to post more frequently to their blogs than reflective students; ii) reflective students' ratio of reading other blog postings vs. posting to their own blogs is significantly higher than that of active students; iii) active students use charts displaying the number of postings and peer rating more often than reflective students. One significant correlation was found for the sequential/global dimension as well: sequential learners tend to write longer posts than global learners. Overall, the results show that the blogging behavior is only slightly influenced by the learning style, at least from a quantitative point of view; the blog content needs to be further analyzed in order to take into account the quality of students' contributions as well.

Lau and Lee (2010) analyzed the influence of learning style and competence level on students' perceptions regarding the utility of various e-learning services, tools and content. The VAK learning style model is used, categorizing students as visual, auditory or kinesthetic (or a combination thereof). The learning style was identified by means of a dedicated inventory, while students' opinions were gauged by means of a Likert-style survey. 31 students participated in the study and filled in both questionnaires. While the opinion survey addressed a variety of issues (e.g., knowledge acquisition services, services, performance assessment communication services, content media type and instructional role), here we summarize only the findings related to Web 2.0 tools. Visual and auditory students rated wikis as highly useful services, regardless of their competence level; auditory students with lower knowledge level also perceived blogs as useful, while kinesthetic students favored media sharing services for their online video tutorials. Social networking systems (such as Facebook) were among the top rated communication services for all students, regardless of their learning style. However, it should be mentioned that the paper only provided descriptive results and the statistical significance of the findings was not addressed.

Grekinis (2011) explored the relationship between learning style and blogging performance, in the context of an undergraduate introductory environmental science course. Kolb's learning style model was used, and a dedicated inventory was applied at the beginning of the course to categorize students as assimilators, accomodators, convergers or divergers (Kolb, 1984). 70 students were enrolled in the course and consequently participated in the study. During the semester, they were asked to complete 8 blog assignments, consisting of both informational posts and personal reflections on the topics presented in class. Students' blogging performance was evaluated according to several criteria (preparation of blog entry, quality of content, personal reflection, proper citations, use of graphics and multimedia, comments on others' entries), which counted for 40% of the students'

final grade. At the end of the semester, a Chi square test was applied to investigate the relationship between the learning style and the grade received for blogging; no significant difference was obtained, so learning styles were not found to influence students' blogging performance.

Several other authors investigated the correlations between learning style and self-reported preference for social media tools used for educational purposes, with various results, e.g.:

- Shahsavar and Tan (2010) reported no significant relationships between students' *field-dependent/field-independent* style (Witkin, 1962) and their attitude toward blogs;
- Chen et al. (2007) reported that *intuitive* students (according to FSLSM) were willing to deliver their knowledge and experience through blogs, as opposed to the students with *visual* preference.

Overall, the reported findings are somewhat contradictory; a few correlations have been found, but they are not consistent throughout the studies. It should be mentioned, however, that various learning style models were involved and different experimental settings were employed. Also, most of the studies were based on student self-reported data, e.g., preference, acceptance or attitude toward social media tools, captured by means of questionnaires. Derntl and Graf's paper (2009) is a notable exception, relying on actual student performance and analysis of behavioral patterns. Our study also explores the relationships between the actual student interaction with the Web 2.0 tools and the FSLSM dimensions. As far as analysis techniques are concerned, statistical correlation tests were the main methods employed in the above studies; in contrast, our approach is based on machine learning algorithms for classification, association rule induction and feature selection. More details regarding the experimental settings are presented in the following section.

## 3. CONTEXT OF STUDY

The context of our study is a course on "Web Applications' Design" (WAD), delivered to 4th year undergraduate students in Computer Science from the University of Craiova, Romania. A project-based learning (PBL) scenario was used, in which students had to design and implement an authentic Web application (such as a virtual bookstore, an online auction website, a professional social network, an online travel agency), performing all the stages of real-life application development. Due to the complexity of the tasks, the project spanned over the whole semester. Students had to collaborate in teams of 4-5 peers; 45 students were enrolled in the course and 11 such teams were formed (Popescu, 2012).

The project activity was done in a blended mode: there were weekly face-to-face meetings between each team and the instructor (for checking the project progress, providing feedback and answering questions) and for the rest of the time students had to use social software tools as support for their communication and collaboration activities. More specifically, four Web 2.0 tools were selected by the instructor:

1. Blogger - for documenting the progress of the project (i.e., a kind of "learning diary" - reporting each accomplished activity, describing problems encountered and asking for help, reflecting on their learning experience); publishing ideas, thoughts, interesting project-related findings; communicating with the peers, providing solutions for the peers' problems, critical and constructive feedback, interacting with other teams;

2. MediaWiki - for collaborative writing tasks among the members of a team; gathering and organizing their knowledge and resources regarding the project theme; clearly documenting each stage of the project as well as the final product;

3. Delicious - for storing links to resources of interest for the project (i.e., a kind of "personal knowledge management tool"); sharing discovered bookmarks with peers; tagging and rating the collected resources; checking the resources shared by peers (and especially by own team members);

4. Twitter - for staying connected with peers and posting short news, announcements, questions, and status updates regarding the project.

More details regarding the PBL scenario can be found in (Popescu, 2012).

All student actions on the four social media tools were monitored and recorded by means of a dedicated platform called eMUSE. The platform gathers learner actions from each of the disparate tools, stores them in a local database for further processing (together with a description and an associated timestamp) and presents them to the instructor in suggestive graphical formats. The whole range of functionalities provided by eMUSE can be found in (Popescu, 2014). Figure 1 provides an overview of the data collection mechanism implemented in eMUSE. The technical solution adopted for learner tracking and data collection is accessing the Web 2.0 tools by means of open APIs or Atom/RSS feeds in order to retrieve the students' actions. This integration of content from several external sources to create a new Web application, with added value for the user, is known as *mashup* technique - which is also reflected in the platform name (eMUSE - empowering MashUps for Social E-learning).

The number of actions performed on each tool was computed for each student after the course, as a quantitative measure of the level of involvement of the student with the Web 2.0 tools. Overall, at the end of the semester about 1700 student actions were stored in the platform database; the distribution of actions over time and over the four tools is illustrated on the right side of Fig. 1 (as it appears to the instructor in eMUSE).

While the students' actions were automatically collected by the eMUSE platform, their learning styles were elicited by means of a dedicated inventory, the Index of Learning Styles questionnaire (ILS) (Soloman and Felder, 1998). ILS consists of 44 questions, each with two possible answers. As a result of the test, the learning style of the student is described on a scale between -11 and +11 (with a step of +/-2) for each FSLSM dimension; e.g., a score of +9 on the *visual/verbal* dimension implies a strong *visual* preference, while a score of -3 implies a mild *verbal* preference. ILS was applied at the beginning of the semester; 42 students filled it in and were therefore included in the analysis, as described next.



Fig. 1. Data collection mechanism provided by eMUSE social learning environment

#### 4. OVERVIEW OF MACHINE LEARNING ALGORITHMS USED

Our goal was to investigate whether there are dependencies and connections between the actions of the students on the four Web 2.0 tools (as recorded by eMUSE), and their learning styles. To this end, we used typical machine learning algorithms for classification,

association rule induction and feature selection. In what follows, we give a brief presentation of the methods used.

*Classification* is a procedure in which individual instances are placed into groups, or classes, based on quantitative information on one or more of their characteristics, referred to as attributes. Classification is a supervised technique, i.e. the model is built based on a training set of instances whose classes are known. The information contained in the training set, with instances whose corresponding class labels are known, can be used to classify new, previously unseen instances, based on an explicit or an implicit model (Leon et al., 2010).

For the present analysis, the main goal was to determine a symbolic, explicit model that can be easily interpreted. Also, it was important to use algorithms that belong to different classification paradigms, which can provide different perspectives about the problem at hand. Therefore, we chose a decision tree inducer, *C4.5*, and a generalized instance-based method, *NNGE*.

C4.5 (Quinlan, 1993) generates a decision tree by recursive partitioning of data. The algorithm considers all the possible attribute tests that can split the data within a node and chooses the test that gives the best information gain, i.e. the partitioning that would result in the most homogenous child nodes. It can handle both symbolic and numerical attributes. The algorithm supports tree pruning at the end of the training process, which cuts off some parts of the tree in order to avoid overfitting.

Non-Nested Generalized Exemplar, NNGE (Martin, 1995) is an extension of the classic instance-based learning, where the training instances are simply stored and new ones are classified on the basis of their closeness to their "neighbors" in the training set. The *n* attributes define an *n*-dimensional Euclidean space in which the concepts are represented. NNGE works with generalized exemplars, which can be either hyper-rectangles in the *n*-dimensional space or single training instances, i.e. points, known as "trivial hyper-rectangles". The exemplars are not allowed to nest or overlap, thus reducing overfitting. This is achieved by testing each potential new generalization to ensure that it does not cover any negative examples, and by modifying any generalizations that are later found to do so. The algorithm tries to generalize new examples to their nearest neighbor of the same class, but if this is impossible due to intervening negative examples, no generalization is performed. If a generalization later conflicts with a negative example, it is modified to maintain consistency.

When the dataset has many attributes, some of them may be more important, while others can even be irrelevant to the classification. The relative importance of attributes can be discerned by using *feature selection* algorithms.

One such algorithm is *ReliefF* (Kononenko et al., 1997), whose basic idea is to assess the importance of an attribute according to its ability to distinguish between instances that are close to one another. For an instance, the algorithm searches for its neighbors from the same class and from a different class. Assuming that only one neighbor is used, if the instance and the same-class neighbor have different values for an attribute, this is not desirable because the attribute separates two instances of the same class. Therefore, the quality estimation of that attribute is decreased. If the instance and its other-class neighbor have different values for an attribute, this is desirable since the attribute separates two instances of different classes, and thus contributes to the classification goal. Therefore, the quality estimation of the attribute is increased. The process is repeated for all the instances of the problem. In general, ReliefF searches for k nearest

neighbors in each class and can handle multi-class problems.

Association rule induction aims at finding regularities in the trends of the data: one tries to find sets of instance values that frequently appear together. Such information is usually expressed in the form of rules. An association rule expresses an association between (sets of) items. However, not every association rule is useful, but only those that are expressive and reliable. Therefore, the standard measures to assess the quality of an association rule are the support and the confidence, both of which are computed from the support of certain item sets (Aflori and Leon, 2004).

In order to extract the rules, the Apriori algorithm (Agrawal and Srikant, 1994) was employed. The algorithm is based on the observation that if any given set of attributes S is not adequately supported, any superset of S will also not be adequately supported. For example, if we know that  $\{A, B\}$  is not supported, it follows that  $\{A, A\}$ B, C},  $\{A, B, D\}$ , etc. will also not be supported. The algorithm first determines the support for all single attributes (sets of cardinality 1) in the data set, and deletes all the single attributes that are not adequately supported. Then, for all supported single attributes, it constructs pairs of attributes (sets of cardinality 2). If there are no pairs, it finishes; otherwise it determines the support for the constructed pairs. For all supported pairs of attributes, "candidate" sets of cardinality 3 (triples) are built. Again, if there are no triples, it ends; otherwise it determines the support for the constructed triples. It continues likewise until no more candidate sets can be produced.

Many times, some attributes are symbolic and others are numeric. For example, to apply the classic Apriori algorithm one needs to transform the numerical attributes into symbolic ones as a preprocessing phase. *Discretization* transforms continuous attribute values into a finite number of intervals and associates a discrete value to each of them. One of the simplest methods is the equalwidth discretization, which divides the range of values into k intervals with equal width. Although practical, discretization can lead to important information loss.

From the implementation point of view, in the present analysis we used *Weka* (Hall et al., 2009), a popular collection of machine learning algorithms.

## 5. ANALYSIS AND RESULTS

The case studies focused on 3 scenarios: i) the analysis of the number of actions in a category (i.e., with each social media tool); ii) the dominant tool corresponding to a learning style; and iii) the temporal evolution of the number of actions and their category.

#### 5.1 Scenario 1. The Number of Actions

In this scenario, we considered only the total number of actions which a certain student performs on each of the 4 tools. We investigated whether it is possible to predict a student's learning style based on the Web 2.0 tools he/she uses for communication, collaboration and learning support.

We constructed a dataset with each of the 4 descriptors (sequential/global - SG, active/reflective - AR, sensing

*/intuitive - SI, visual/verbal - VV*) as the class and the number of actions for each tool as the inputs.

The learning styles were discretized into 6 categories, based on the scores obtained on the ILS questionnaire: *BigNegative* (-11 and -9), *Negative* (-7 and -5), *SmallNegative* (-3 and -1), *SmallPositive* (+1 and +3), *Positive* (+5 and +7), *BigPositive* (+9 and +11). For example, for the *SG* dimension, a positive value indicates a tendency toward the *sequential* style, while a negative value indicates a *global* style. The number of actions was discretized into 5 categories (*VeryLow, Low, Medium, High, VeryHigh*).

A part of the decision tree induced by *C4.5* for the *SG* style is presented next. In parentheses, the number of correctly classified and incorrectly classified instances are noted, respectively. Thus, a resulting rule, although inexact (14 correctly classified instances and 9 exceptions) is, e.g.: "If the number of *Wiki* actions is *VeryLow* and the number of *Delicious* actions is *VeryLow*, then *SG* is *SmallPositive*."

As *C4.5* uses the information gain criterion to split data, and *Wiki* (i.e., the number of actions performed on the wiki) corresponds to the first split, it implies that *Wiki* is the most important factor to describe the *SG* model.

The rules (generalized exemplars) provided by *NNGE* are of the following form (in parentheses, at the end, the number of instances covered by that rule is indicated):

Blogger in {VeryLow} and Delicious in {VeryLow} and Twitter in {VeryLow} and Wiki in {VeryLow,Low} ⇒ SG = SmallPositive (3)

The algorithms were also applied for the other learning style dimensions. The resulting decision trees are quite large, which shows that there are no compact rules to describe the learning style depending on the discretized number of actions.

Also, there are many rules provided by *NNGE*, with many single instances which cannot be included into a generalized exemplar.

Table 1 presents the error rates and some descriptors of each model. The unpruned version of the C4.5 algorithm was used, because it consistently provided better results for our learning problems. For the decision trees, the number of leaves was used as an indicator of the tree complexity. In terms of the number of rules given by NNGE, the number of generalized exemplars or hyperrectangles (H) and the number of individual instances or

singles (S) are mentioned.

Table 1.	Classification perform	nance for the learning
styles as a	function of the discret	tized number of actions

	SG	AR	SI	VV
C4.5 error	47.61 %	47.62 %	35.71 %	33.33 %
C4.5 no. leaves	17	17	17	21
NNGE error	23.81 %	26.19 %	28.57 %	33.33 %
NNGE no. rules	9H / 9S	8H / 11S	6H / 9S	3H / 18S
Most relevant attribute	Wiki	Delicious	Twitter	Wiki

The *ReliefF* feature selection algorithm was applied to identify the most relevant attributes for each classification problem. The results refer only to the algorithm performance on the training sets. Since these errors are very large, there is no point in further applying cross-validation to test the generalization capability. It is clear that the models do not capture the data well.

Beside classification, the *Apriori* algorithm was applied to find association rules. First, we analyzed only the relationships between the number of actions. In the parentheses, the confidence of the rule is indicated. The rule  $A \Rightarrow B$  has confidence *c* if c% of the transactions in the dataset that contain *A* also contain *B*. The first 3 high-confidence rules found are the following:

Twitter=Low ⇒ Wiki=VeryLow (1) Blogger=VeryLow, Twitter=Low ⇒ Wiki=VeryLow (1) Twitter=VeryLow, Wiki=VeryLow ⇒ Blogger=VeryLow (0.94)

For example, one can interpret the first rule as: "When the number of *Twitter* actions is *Low*, the number of *Wiki* actions is always *Low*."

Then, the dataset with the number of actions and the learning styles was analyzed. The first 5 high-confidence rules are in this case:

Delicious=VeryLow, SI=BigPositive ⇒ Twitter=VeryLow (1) Twitter=VeryLow, Wiki=VeryLow ⇒ Blogger=VeryLow (0.94) Delicious=VeryLow, Twitter=VeryLow ⇒ Blogger=VeryLow (0.94) Delicious=VeryLow, Twitter=VeryLow, Wiki=VeryLow ⇒ Blogger=VeryLow (0.93) Blogger=VeryLow, VV=BigPositive ⇒ Wiki=VeryLow (0.92)

However, it seems that these rules do not provide any clear, useful causal relationships. We could only infer that the students with a low level of activity on one tool tend to have a weak performance on other tools as well.

Beside the investigations presented above, the following ones were also attempted: i) the percentages of actions out of the total number of actions, for a student, instead of the actual number of actions; ii) discretization with 3 classes instead of 5; and iii) the comparison of learning styles within student teams. The results were not better than before.

The high errors on the training set in case of classification

can be explained, in part, by the discretization process, where the equal-width interval method may not have captured the trends in the data in a flexible enough manner. However, it is possible to apply C4.5 and NNGE on the unprocessed numerical inputs as well. We performed the same analysis on numerical data, where the inputs were the number of actions for each tool, as percentages out of the total number of actions of a student. Since no information is lost in the inputs, the training set errors are much lower, as shown in Table 2.

 Table 2. Classification performance for the learning

 styles as a function of the relative number of actions

	SG	AR	SI	VV
C4.5 error (TS)	17.64 %	29.41 %	14.71 %	17.65 %
C4.5 no. leaves (TS)	9	8	9	8
C4.5 error (CV)	64.71 %	91.18 %	61.76 %	70.59 %
NNGE error (TS)	0 %	0 %	0 %	0 %
NNGE no. rules (TS)	9H / 6S	9H / 11S	9H / 5S	9H / 5S
NNGE error (CV)	76.47 %	85.29 %	61.76 %	58.82 %
Most relevant attribute	Blogger	Delicious	Twitter	Twitter

By performing 10-fold cross-validation, the error rates become very high. Even if the algorithms, especially the instance-based *NNGE*, can exactly capture the data, the models do not generalize well.

One can notice that the most relevant attribute has changed compared to the corresponding value for SG and VV in Table 1 (i.e. *Wiki*). The resulting decision tree for SG is listed below. The most relevant attribute given by C4.5's information gain criterion (*Twitter*) is now different from the value given by *ReliefF* (*Blogger*). These changes also suggest that there are no stable trends to be identified in the dataset.

```
Twitter <= 3.45
  Twitter \leq 0 \Rightarrow SG = Negative (3)
L
  Twitter > 0 \Rightarrow SG = BigNegative (2/1)
Twitter > 3.45
| Delicious <= 10.19
| Delicious \leq 0 \Rightarrow SG = SmallNegative (7/1)
  | Delicious > 0
| | Delicious <= 9.09 \Rightarrow SG = SmallPositive (2)
| | Delicious > 9.09 \Rightarrow SG = SmallNegative (2/1)
| Delicious > 10.19
| Delicious <= 25.81</p>
| | Twitter <= 27.78 \Rightarrow SG = SmallPositive (5)
| | Twitter > 27.78 \Rightarrow SG = Negative (3)
| | Delicious > 25.81
| | Twitter <= 15.85 \Rightarrow SG = SmallNegative (2)
| | Twitter > 15.85 \Rightarrow SG = SmallPositive (8/3)
```

We present next the hyper-rectangles with the largest number of instances for each learning style, as provided by *NNGE*:

4.55<=Blogger<=25 and 0<=Delicious<=10.19 and 12.1<=Twitter<=50
and 25<=Wiki<=77.27 $\Rightarrow$ SG = SmallNegative (6)
0<=Blogger<=7.32 and 0<=Delicious<=23.33 and
6.67<=Twitter<=18.18 and 70<=Wiki<=77.27 ⇒ AR = SmallNegative
(4)
15.09<=Blogger<=55.56 and 8.89<=Delicious<=42.11 and
3.45<=Twitter<=38.64 and 0<=Wiki<=46.55⇒ SI = Positive (6)
4.26<=Blogger<=22.22 and 13.79<=Delicious<=40.91 and
17.58<=Twitter<=44.83 and 0<=Wiki<=60.44⇒ VV = BigPositive (8)

Unfortunately, it seems to be difficult to gain specific insights from these rules that are in line with the theoretical assumptions. Even worse results are obtained when considering the direct relation between an individual tool and a learning style. No single preference toward a learning tool is directly correlated to a learning style.

## 5.2 Scenario 2. The Dominant Tool

In the second scenario, we tried the opposite approach: to see which communication tool is dominant, and then which one is second-dominant, depending on the learning style. Again, the error on the training set is low, but the cross-validation error is much higher, as shown in Table 3.

 Table 3. Classification performance for the dominant use of a tool as a function of the learning styles

	First Dominant	Second Dominant
C4.5 error (TS)	18.75 %	9.38 %
C4.5 no. leaves (TS)	16	24
C4.5 error (CV)	56.25 %	46.88 %
NNGE error (TS)	6.25 %	0 %
NNGE no. rules (TS)	7H / 7S	9H / 5S
NNGE error (CV)	50 %	46.88 %
Most relevant attribute	SI	Dominant, then AR

The *NNGE* rules with most instances, for each tool, are the following:

SG in {BigNegative, Negative, BigPositive} and AR in {SmallNegative,
SmallNegative, Positive, BigPositive} and VV in {Negative,
SmallNegative, Positive, BigPositive} ⇒ Dominant = Wiki (6)
SG in {Negative, SmallPositive} and AR in {Negative, SmallNegative,
BigPositive} and SI in {SmallPositive} and VV in {Positive, BigPositive}
$\Rightarrow$ Dominant = Twitter (3)
SG in {SmallPositive} and AR in {Positive} and SI in {SmallPositive} and
VV in {SmallPositive} $\Rightarrow$ Dominant = Delicious (1)
SG in {SmallPositive} and AR in {SmallNegative} and SI in {Positive}
and VV in {BigPositive} $\Rightarrow$ Dominant = Blogger (1)

Some sections of the decision trees for the dominant tool are given next:

```
\begin{array}{l} \mathsf{SI} = \mathsf{SmallPositive} \\ | & \mathsf{AR} = \mathsf{SmallPositive} \Rightarrow \mathsf{Dominant} = \mathsf{Delicious} (2/1) \\ | & \mathsf{AR} = \mathsf{Positive} \Rightarrow \mathsf{Dominant} = \mathsf{Wiki} (4/1) \\ ... \\ \mathsf{SI} = \mathsf{Positive} \\ | & \mathsf{SG} = \mathsf{SmallNegative} \Rightarrow \mathsf{Dominant} = \mathsf{Wiki} (4/2) \\ | & \mathsf{SG} = \mathsf{SmallPositive} \Rightarrow \mathsf{Dominant} = \mathsf{Wiki} (6/2) \\ ... \end{array}
```

SI = BigPositive  $\Rightarrow$  Dominant = Wiki (7)

```
35
```

as well as for the decision tree of the second-dominant tool:

```
Dominant = Blogger \Rightarrow SecondDominant = Wiki (1)

Dominant = Delicious

| SI = SmallPositive \Rightarrow SecondDominant = Wiki (2)

| SI = Positive \Rightarrow SecondDominant = Twitter (2)

...

Dominant = Twitter \Rightarrow SecondDominant = Delicious (5/2)

Dominant = Wiki

| AR = SmallNegative \Rightarrow SecondDominant = Twitter (7/1)

| AR = SmallPositive

| SG = SmallNegative \Rightarrow SecondDominant = Twitter (2)

| SG = SmallPositive \Rightarrow SecondDominant = Twitter (2)

| AR = Positive

| VV = Positive \Rightarrow SecondDominant = Twitter (2)

| AR = BigPositive \Rightarrow SecondDominant = Delicious (3)

| AR = BigPositive \Rightarrow SecondDominant = Blogger (2)

...
```

The first high-confidence association rules provided by *Apriori* are the following:



An interesting finding is the first association rule, which states that the dominant tool for a highly *sensing* student is the wiki. Indeed, wiki contributions are generally based on facts and practical aspects, and are more elaborate, requiring attention to details and careful writing, requirements which are in line with the *sensing* students' nature.

Overall, the classification rules are rather complex and their interpretation is not obvious. The fact that the dominant tool greatly influences the choice of the seconddominant one is also a valid result, but it does not bring additional information about the actual problem, i.e., the relationship between the tools and the learning styles.

#### 5.3 Scenario 3. The Evolution in Time

In this scenario, we analyzed the action data taking time explicitly into account. As a pre-processing step, we discretized the period of data collection into 5 equal intervals, and we eliminated the students with only two or three actions. Then, we computed: i) the total number of actions in each time interval; and ii) for each tool, the percentage of its total number of actions in that time interval.

Figure 2 presents the cumulative number of actions for two students, one with a strong *sequential* preference (SG = 9) and one with a strong *global* preference (SG = -9). If the time intervals are denoted as *I1*, *I2*, ... *I5*, the corresponding rules for the two graphs are:

```
I1=17 and I2=34 and I3=32 and I4=0 and I5=16 \Rightarrow SG = BigPositive (1) I1=1 and I2=18 and I3=13 and I4=5 and I5=21 \Rightarrow SG = BigNegative (1)
```

when using the actual number of actions and:

I1=17.17 and I2=34.34 and I3=32.32 and I4=0 and I5=16.16  $\Rightarrow$  SG = BigPositive (1) I1=1.72 and I2=31.03 and I3=22.41 and I4=8.62 and I5=36.21  $\Rightarrow$  SG = BigNegative (1)

when using percents.



Fig. 2. The difference in behavior between a typically *Sequential* student and a typically *Global* one

These partial results can be considered to be in line with the theoretical description of the *SG* learning style: *sequential* students tend to gain understanding in linear steps, at a more constant pace, while *global* students learn in large leaps and they contribute more toward the end of the semester, once they get the big picture.

However, these partial results are not confirmed by the general model. Table 4 shows both the training set and the cross-validation errors, and it is clear that, again, there is no general model to be captured in this way. Similar results were obtained when considering the relations between individual tools and learning styles.

Finally, association rules were generated for all the available data: the total number of actions in the 5 time intervals (*Total1, Total2,..., Total5*), the number of actions corresponding to the 4 tools in the 5 time intervals (*Blogger1, Blogger2,..., Wiki5*) and the 4 learning style dimensions.

The high-confidence rules with the highest support are displayed below, including class association rules, where the learning styles are always in the right hand side of the rule:

Total3=VeryLow, Blogger1=VeryLow, Blogger3=VeryLow, Blogger5=VeryLow, Twitter1=VeryLow, Twitter2=VeryLow ⇒ SG=SmallPositive (1)
Twitter2=VeryLow, Twitter5=VeryLow, Wiki3=VeryLow ⇒ AR=Positive (1)
Biogger3=VeryLow, Biogger2=Low $\Rightarrow$ SI=Positive (1) Total3=VeryLow, Biogger2=VeryLow, Wiki2=VeryLow $\Rightarrow$ VV=BigPositive (1)

and general association rules:

Delicious2=VeryLow $\Rightarrow$ Total4=VeryLow (1)				
Total3=VeryLow $\Rightarrow$ Total4=VeryLow (1)				
Wiki4=VeryLow $\Rightarrow$ Total4=VeryLow (1)				
Wiki4=VeryLow $\Rightarrow$ Delicious2=VeryLow (1)				
Delicious2=VeryLow, Wiki4=VeryLow $\Rightarrow$ Total4=VeryLow (1)				

#### Table 4. Classification performance for the learning style as a function of the number of actions in the 5 time intervals

	SG	AR	SI	VV
C4.5 error (TS)	23.52 %	26.47 %	11.76 %	17.65 %
C4.5 no. leaves (TS)	8	7	9	7
C4.5 error (CV)	73.53 %	73.53 %	55.88 %	64.71 %
NNGE error (TS)	0 %	0 %	0 %	0 %
NNGE no. rules (TS)	10H / 7S	9H / 6S	8H / 6S	8H / 10S
NNGE error (CV)	76.47 %	73.53 %	55.88 %	55.88 %
Most relevant attribute	I3	15	I3	13

As an overall assessment of the obtained results, the rules are quite complex and hard to interpret, especially when they involve a combination of tools. Also, similar conditions appear for different classes (e.g. *Negative* vs. *Positive*) and different conditions appear for the same class or similar classes (e.g. *SmallPositive* and *Positive*). Some potential causes for these inconclusive results are provided in the next section.

#### 5. DISCUSSION AND CONCLUSION

In this paper we investigated whether there are dependencies and relationships between the students' learning style (according to FSLSM) and their preference toward certain Web 2.0 tools used as learning support instruments (according to the number of actions performed on that tool). The results showed that the learning styles have a limited influence on the students' level of activity involving each of the four tools (Blogger, MediaWiki, Delicious, Twitter). In what follows, we provide some possible explanations for these results.

We only took into consideration the students' actions which involve an active interaction or a contribution to the social media tools (e.g., posting or commenting on a blog, but not reading a blog; adding a bookmark on Delicious, but not browsing the peers' bookmarks etc.). Thus we did not completely capture the preference for a certain tool; for example, a *reflective* student may have spent a lot of time reading his/her colleagues' blog posts or analyzing their contributions on the wiki, but this type of interaction was not measured. This limitation comes from the type of student actions that can be collected from the social media tools, as they are provided by means of feeds or APIs.

Also, we did not take into account the content of the students' contributions and the learning tasks they refer to. For example, a sensing and an intuitive student may have had the same number of actions on the blog, but the former may have posted mainly facts, source code and practical examples, while the latter may have contributed with theoretical aspects and innovative ideas. Furthermore, the recorded actions refer to various types of learning activities: creating content (blog post-entry, wiki revise-page, wiki upload-file), social interactions (delicious add-friend-to-network), organizing content (delicious post-bookmark), communication and feedback (blog post-comment, twitter post-tweet) (Popescu, 2014), but in our current analysis we did not discriminate among them; this is a limitation that we plan to address in our future work.

Finally, it may be that the learning styles do not influence the students' preference and behavior toward the four Web 2.0 tools. This could be explained by students' flexibility to accommodate a wide variety of emerging social media applications into their learning environment, without being limited to a particular tool (Saeed and Yang, 2008). This also suggests that our instructional scenario and the tools it relies on are not biased toward any particular learning style. Indeed, these findings are in line with another analysis that we conducted taking into consideration the students' course grades, which showed that FSLSM dimensions have weak or no correlations with the student performance (Giovannella et al., 2013).

Nevertheless, further studies are needed to fully understand the relationships between learning style and preference toward social media tools in educational contexts. These will involve additional action types (as described above), more analysis algorithms (including also a qualitative dimension), as well as a larger number of students.

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#### REFERENCES

- Aflori, C. and Leon, F. (2004). Efficient distributed data mining using intelligent agents. In *Proc. 8th International Symposium on Automatic Control and Computer Science*, Iasi.
- Agrawal, R. and Srikant, R. (1994). Fast algorithms for mining association rules in large databases. In *Proc. VLDB* 1994, pp. 487-499.
- Cha, H.J., Kim, Y.S., Park, S.H., Yoon, T.B., Jung, Y.M.,

and Lee J.H. (2006). Learning styles diagnosis based on user interface behaviors for the customization of learning interfaces in an intelligent tutoring system. In *Proc. ITS 06*, pp. 513-524, LNCS 4053, Springer.

- Chen, L.C., Chu, P.Y, Lin, C.C., and Cheng, Y.M. (2007). The effects of knowledge sources and learning styles of the elders on their motivations to use weblog tools for lifelong learning. In *Proc. ICALT 2007*, pp. 737-738.
- Conole, G. and Alevizou, P. (2010). *A literature review of the use of Web 2.0 tools in Higher Education*. The Open University, UK.
- Derntl, M. and Graf, S. (2009). Impact of learning styles on student blogging behavior. In *Proc. ICALT 2009*, pp. 369-373, IEEE CS Press.
- Dorca, F.A., Lima, L.V., Fernandes, M.A., and Lopes, C.R. (2013). Comparing strategies for modeling students learning styles through reinforcement learning in adaptive and intelligent educational systems: An experimental analysis. *Expert Systems with Applications*, 40(6), pp. 2092-2101.
- Felder, R.M. and Silverman, L.K. (1988). Learning and teaching styles in engineering education. *Engineering Education*, 78(7), preceded by a preface in 2002: <u>www4.ncsu.edu/unity/lockers/users/f/felder/public/Papers/LS-1988.pdf</u>.
- Garcia, P., Amandi, A., Schiaffino, S., and Campo, M. (2007). Evaluating Bayesian networks' precision for detecting students' learning styles. *Computers & Education*, 49(3), pp. 794-808.
- Giovannella, C., Popescu, E., and Scaccia, F. (2013). A PCA study of student performance indicators in a Web 2.0-based learning environment. In *Proc. ICALT 2013*, pp. 33-35.
- Graf, S., Kinshuk, and Liu, T.C. (2009). Supporting teachers in identifying students' learning styles in learning management systems: An automatic student modelling approach. *Educational Technology & Society*, 12(4), pp. 3-14.
- Grekinis, D. (2011). Self-reported perceptions and learning styles of undergraduate students using blogs in an environmental science course. In *Proc. ICERI* 2011, pp. 1445-1451.
- Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., and Witten, I.H. (2009). The WEKA data mining software: an update. *SIGKDD Explorations*, 11(1), pp. 10-18.
- Homola, M. and Kubincova, Z. (2009). Taking advantage of Web 2.0 in organized education (a survey). In: *Proc. ICL 2009*, pp. 741-752.
- Jeremic, Z., Jovanovic, J., and Gasevic, D. (2013). Personal learning environments on the social semantic Web. *Semantic Web*, 4(1), pp. 23-51.
- Kirton, M.J. (1976). Adaptors and innovators: a description and a measure. *Applied Psychology*, 61, pp. 622-629.
- Kolb, D. (1984). *Experiential learning*. Englewood Cliffs, Prentice Hall.
- Kononenko, I., Simec, E., and Robnik-Sikonja, M. (1997). Overcoming the myopia of inductive learning

algorithms with ReliefF. *Applied Intelligence*, 7, pp. 39-55.

- Lau S.B.Y. and Lee, C.S. (2010). Contextualising elearning services and content for computing course in higher education based on learning style and competency level. *Int. J. Learning Technology*, 5(3), pp. 211–242.
- Leon, F., Lisa, C., and Curteanu, S. (2010). Prediction of the liquid crystalline property using different classification methods. *Molecular Crystals and Liquid Crystals*, 518, pp. 129-148.
- Martin, B. (1995). *Instance-based learning: nearest neighbor with generalization*. Master of Science Thesis, University of Waikato, New Zealand.
- Orehovacki, T., Bubas, G., and Kovacic, A. (2012). Taxonomy of Web 2.0 Applications with Educational Potential. In: *Transformation in Teaching: Social Media Strategies in Higher Education*, pp. 43-72, Informing Science Press.
- Ozpolat, E. and Akar, G.B. (2009). Automatic detection of learning styles for an e-learning system. *Computers* & *Education*, 53(2), pp. 355-367.
- Popescu, E. (2009). Diagnosing students' learning style in an educational hypermedia system. In Cognitive and Emotional Processes in Web-based Education: Integrating Human Factors and Personalization, pp. 187–208, Advances in Web-Based Learning Book Series, IGI Global.
- Popescu, E. (2012). Project-based learning with eMUSE: an experience report. In *Proc. ICWL 2012*, pp. 41-50, LNCS 7558, Springer.
- Popescu, E. (2013). *Social learning environments*. Sitech, Craiova.
- Popescu, E. (2014). Providing collaborative learning support with social media in an integrated environment. *World Wide Web Journal*, 17(2), Springer, pp. 199-212.
- Quinlan, R. (1993). C4.5: Programs for machine learning. Morgan Kaufmann Publishers, San Mateo, CA.
- Saeed, N. and Yang, Y. (2008). Using learning styles and preferences to incorporate emerging e-learning tools in teaching. In *Proc. ICALT 2008*, pp. 967-971, IEEE CS Press.
- Saeed, N., Yang, Y., and Sinnappan, S. (2009). Effects of cognitive style on user acceptance of blogs and podcasts. In *Proc. ICALT 2009*, pp. 293-297.
- Shahsavar, Z. and Tan, B.H. (2010). The influence of students' cognitive styles on their attitudes toward using blogs. In *Proc. E-Learn 2010*, pp. 2158-2164.
- Soloman, B. and Felder, R.M. (1998). *Index of learning styles questionnaire*. Available at: www.engr.ncsu.edu/learningstyles/ilsweb.html.

Villaverde, J.E., Godoy, D., and Amandi, A. (2006). Learning styles' recognition in e-learning environments with feed-forward neural networks. *Journal of Computer Assisted Learning*, 22(3), pp.

Witkin, H.A. (1962). *Psychological differentiation: Studies of development*. Wiley.

197-206.