Tweets reveal more than you know: A learning style analysis on Twitter

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Abstract. Adaptation and personalization of e-learning and technology-enhanced learning (TEL) systems in general, have become a tremendous key factor for the learning success with such systems. In order to provide adaptation, the system needs to have access to relevant data about the learner. This paper describes a preliminary study with the goal to infer a learner's learning style from her Twitter stream. We selected the Felder-Silverman Learning Style Model (FSLSM) due to its validity and widespread use and collected ground truth data from 51 study participants based on self-reports on the Index of Learning Style questionnaire and tweets posted on Twitter. We extracted 29 features from each subject's Twitter stream and used them to classify each subject as belonging to one of the two poles for each of the four dimensions of the FSLSM. We found a more than by chance agreement only for a single dimension: active/reflective. Further implications and an outlook are presented.

1 Introduction

Over the last decade, personalization and adaptation in E-learning has become a mainstream component in E-learning systems. Such adaptations provide learners with a personalized learning experience that is either unique to each individual or unique to a particular group of learners. The goals are clear: to keep the learners motivated and engaged, to decrease the learners' frustration, to provide an optimal learning environment and, of course, to increase the learners' expertise in a particular subject.

In order to provide adaptation, the system needs to have access to relevant data about the learner. What is deemed relevant in this context depends on the facilities that are provided by the system. Adaptation can be provided on a number of levels with varying granularity. It can be based on gender [1], on the learners' level of expertise [2, 3], on the learners' culture [4] or on the learners' learning styles [5].

The latter, adaptation according to the learners' learning styles, is also the focus of this paper. We note that there is controversy surrounding the learning style hypothesis [6], which states that enabling a learner to learn with material that is tailored to her own learning style will outperform a learner who learns the material tailored to a learning style that is not her own. As of today no studies have conclusively shown that this hypothesis actually holds for a wide range of people. Although learning styles may not yield improved results with respect to objective measures (such as testing the increase in learner expertise), learning styles are of importance for E-learning systems to improve the learners' satisfaction in the material and to keep them engaged by offering them learning that is appropriate for their self-perceived learning style.

At the same time a question raises: Do Twitter users actually provide information about their learning style or how they learn? In paper by [7] the authors investigates why people continue using twitter. Among others it could be shown that users continue using Twitter, because of positive content gratification. Content gratification was comprises by disconfirmation of information sharing and self-documentation (the way users learn, keep track what they are doing, document their life). Therefore it can be argued that tweets are produced to report about users' learning behaviour intentionally. In addition, in this paper data mining is also based on phrases which are derived from exiting questionnaire and should cover some non-intentional phrases in regard to learning behaviour.

Over the years, a number of learning style models have been proposed, among them Kolb's Experiental Learning Theory [8], Fleming's VARK learning styles inventory [9] and Felder-Silverman-Learning-Style-Model (FSLSM) [10, 11]. Independent of the particular model chosen, the procedure to determine a learner's learning style is always the same: the learner fills in a standardized questionnaire (specific to the model) and based on the answers given the different dimensions of the model are determined. One of the problems with this approach is that the learner may be unwilling to spend a lot of effort on this procedure[3]. More importantly though, learners cannot be expected to repeatedly fill in such a questionnaire, which, if a system is used for a long time may become necessary, as there is evidence that learning styles change over time [12]. Thus, an automatic approach to infer the learning style of a learner is likely to be more precise in the long run.

Ideally, we are able to determine the learner's learning style without asking the learner for explicit feedback. One potential solution to this problem lies in the social Web whose rise has made people not merely consumers of the Web, but active contributors of content. Widely adopted social Web services, such as Twitter[4], Facebook[5] and YouTube[6], are frequented by millions of active users who add, comment or vote on content. If a learner is active on the social Web, a considerable amount of information about her is available on the Web and, depending on the particular service used, most of it is publicly accessible. We envision E-learning systems in the future to simply ask the learner about her username(s) on various (publicly accessible) social Web services where the

[3] The ILS questionnaire for instance consists of 44 questions.
[4] `http://www.twitter.com/`
[5] `http://www.facebook.com/`
[6] `http://www.youtube.com/`

learner is active on. Then, based on the learner's "online persona", aggregated from the social Web, the system can automatically infer the learner's learning style. We have already shown in previous work [13] that it is possible to derive a basic profile of the learner's knowledge in a particular domain from the learner's activities on the microblogging platform Twitter. In this work now, we are interested to what extent it is possible to derive information about a learner's learning style from the same social Web stream.

In the EU project ImREAL (Immersive Reflective Experience-based Adaptive Learning) intelligent services are developed to augment and improve simulated learning environments among others, to bring real world users data, e.g. content retrieved from tweets, into the simulation to link real world experiences to the simulation. In this paper the following hypothesis is investigated: the information the learner can provide in the learning style questionnaire is already implicitly available in the learner's utterances in the social Web. If this is indeed the case, the research question then becomes of how to extract this implicit information and transform it into the different dimensions of the learning styles models.

We consider the collaborative work of machine learning and psycho-pedagogical approaches presented here as a preliminary study - if we were able to show success in predicting a learner's learning style based on the learner's tweets with a number of simple features, we have evidence that this is a path that is worth investigating further.

The remainder of the paper is organized as follows: in Section 2 related work is presented. Section 3 describes our pilot study and the setup of the experiments. The results are then presented in Section 4 and the paper is concluded with a discussion and an outlook to future work in Section 5.

2 Related Work

We first describe previous work that sheds light on why people use Twitter. Then, we turn to previous works that have attempted what we set out to do too: to infer a learner's learning style from implicit information available about the learner, that is without letting the learner fill in a questionnaire.

2.1 The Use of Twitter in Scientific Research

Two questions that have been investigated by a number of researchers in the past are what is the people's motivation to use Twitter and what do the people actually post about. Java et al. [14] determined four broad categories of tweets: daily chatter (the most common usage of Twitter), conversations, shared information/URLs and reported news. Naaman et al. [15] derived a more detailed categorization with nine different elements: information sharing, self promotion, opinions, statements and random thoughts, questions to followers, presence maintenance, anecdotes about me and me now. Moreover, they also found that the approximately eighty percent of the users on Twitter focus on themselves (they are so-called "Meformers"), while only a minority of users are driven largely by sharing information (the "Informers"). Westman et al. [16] performed a genre analysis on tweets and identified five common genres: personal updates, direct dialogue (addressed to certain users), real-time sharing (news), business broadcasting and information seeking (questions for mainly personal information). Finally, Zhao et al. [17] conducted interviews and asked people directly about their motivations for using Twitter; several major reasons surfaced: keeping in touch with friends and colleagues, pointing others to interesting items, collecting useful information for one's work and spare time and asking for help and opinions. These studies show that a lot of tweets are concerned with the user herself; we hypothesize that among these user centred tweets, there are also useful ones for the derivation of the learner's knowledge profile.

A number of Twitter studies also attempt to predict user characteristics from tweets. While we are aiming to extract a learner's learning style, Michelson et al. [18] derive topic profiles from Twitter users which are hypothesized to be indicative of the users' interests and expertise. In a number of other works, e.g. [19–21], elementary user characteristics are inferred from Twitter, including gender, age, political orientation, regional origin and ethnicity.

2.2 Learning Style Investigations

A number of previous works exist that infer learners' learning styles based on their behaviour *within* the learning environment. In [22] the outline of such a system is sketched, though no experiments are reported. Garcia et al. [23] investigated to what extent it is possible to infer a learner's learning style (specifically the ILS variant) from the learner's interaction with a Web-based E-learning system and a class of Artificial Intelligence students. They relied on a number of features that model the students' behaviour on the learning system. Some examples of the chosen features are the type of reading material (concrete or abstract), the amount of revision before an exam, the amount of time spent on an exam, the active participation on message boards and chats within the learning environment, the number of work examples accessed and the exam result. The approach was evaluated on 27 students with promising results; the most accurate prediction was possible for the perception dimension (intuitive vs. sensing) with a precision of 77%, followed by the understanding dimension (sequential vs. global) with 63% precision and the processing dimension (active vs. reflective) with 58% precision. The input dimension (visual vs. verbal) was not investigated in this study. In contrast to this work, the features in our experiments are at a lower level - we aim to utilize features that are independent of a particular learning environment and also do not require a specific amount of interaction with the environment first before the learning style can be predicted.

Sanders and Bergasa-Suso [24] also developed a Web-based learning system that monitors user activity to infer the learning styles. Features include the amount of data copied and dragged, the length of the page text, the ratio of text to images, the presence or absence of tables, mouse movements, etc. While initially their predictions did not perform much better than a naive predictor that assigns the majority class to all instances [25], after a number of data post-processing steps, they achieved accuracies well above such a naive predictor for the active/reflective and the visual/verbal dimension[7].

Finally we note that instead of inferring the learning style from the learner's actions within the learning environment, a number of works have also investigated to infer the learning style from other user characteristics such as the Big-Five personality model, e.g. [26].

Our work differs from these previous works in two ways. First of all, our approach is independent of a particular learning environment. We rely on traces the learner left in the past on the social Web. This has the distinct advantage that when a learner starts using a novel E-learning system the learning style can be computed immediately, while in [23, 24, 22] a certain amount of interaction is required on part of the learner before the learning style can be inferred. This can also mean that by the time the system has identified the learning style of the learner and is ready to provide material according to the learner's preferences, the learner has already turned away to a better fitting learning system. Secondly, the features we use in our pilot study are very low-level compared to the features in the previous works; we rely on features that can be extracted from any Twitter stream and as such, the results we report here will be the lower boundary of what is possible.

3 Methodology

In line with previous works, in particular [24, 23], we use the following methodology and procedure to investigate our hypothesis: In the period of November 2011 and March 2012, the web-link to a new ILS online version was distributed via different social web network channels such as Twitter, Facebook, LinkedIn and large e-mail lists of different EU-projects and Universities (e.g. University of Graz and Graz University of Technology). In a late stage of this process (end of February), people who tweeted at least once they would be a certain type of learner, e.g. I am an active learner, were directly contacted via Twitter and asked to participate in the survey. Each participant was requested to read the introduction, fill in some personal information such as gender, age, level of education and the degree of which they were familiar with the term learning style. In addition, they were asked to provide their Twitter username and to fill in the ILS items. The instruction included information about the purpose of the study, that the data would be treated anonymously and that each participant had the chance to draw one of three 20 Amazon.com-vouchers. Duration time of filling in all required data was about 15 minutes.

[7] Please note the the results between different papers are not directly comparable due to differences in the precision formula employed and the number of classes present for each dimension - [23] include a NEUTRAL class for each dimension which is absent in [25] and [24]

We then evaluate these questionnaires and the found learning styles of each user are our ground truth, that we try to predict in the next stage. We crawl the tweets of the respective Twitter accounts and derive features from them. Then, we employ a machine learning algorithm to classify each user into the different dimensions based on these features.

Next, we first introduce the learning style model we selected in more detail and then we outline how we derived the features and the machine learning approach.

3.1 The Felder-Silverman Learning Style Model

One of the most popular learning style models is the Felder-Silverman Learning Style Model (FSLSM) [10, 11] which describes the most prominent learning style differences between engineering students on four dimensions:

- **Sensing/intuitive**: Sensing learners are characterized by preferring to learn facts and concentrate on details. They also tend to stick to concrete learning materials, as well as known learning approaches. They like to solve problems by concrete thinking and by applying routine procedures. Intuitive learners on the other hand prefer to learn abstract concepts and theories. Their strengths lie in discovering the underlying meanings and relationships. They are also more creative and innovative compared to sensing learners.
- **Visual/verbal**: This dimension distinguishes learners preferences in memorizing learning material. The visual learner prefers the learning material to be presented as a visual representation, e.g. pictures, diagrams or flow charts. In contrast, verbal learners prefer written and spoken explanations.
- **Active/Reflective**: This dimension covers the way of information processing. Active learners prefer the 'learning by doing' way. They enjoy learning in groups and are more open to discuss ideas and learning material. On the contrary, reflective learners favour to think about ideas rather than work practically. They also prefer to learn alone.
- **Sequential/Global**: On this dimension learners are described according to their way of understanding. Sequential learners learn in small steps and have a linear learning process, focusing on detailed information. Global learners, however, follow a holistic thinking process where learning happens in large leaps. At first, it seems that they learn material almost randomly without finding connections and relations between different areas, but in a later stage, they perceive the whole picture and are able to solve complex problems.

3.2 The Index of Learning Style

The ILS [11] is a self-assessment instrument based on the Learning Style Model [10, 11]. Participants are asked to provide answers to 44 forced-choice questions with two answer options. Each of the four learning style dimensions is covered by 11 items, with an 'a' or b answer option corresponding to one of the poles of the continuum of the corresponding learning style dimension, e.g. active (a) vs. reflective (b). It is suggested to count the frequency of a responses to get a score between 0-11 for one dimension. This method allows a fine gradation of the continuum starting from e.g. 0-1 representing strong preferences for reflective learning till 10-11 strong preference for active learning. Therefore, a preference of a pole of the given dimension may be mild, moderate or strong. Reliability as well as validity analyses revealed acceptable psychometric values. For internal consistency reliability ranging from 0.55 to 0.77 across the four learning style scales of the ILS were found by [27]. Furthermore, factor analysis and direct feedback from students whether the ILS score is representing their learning preferences provided sufficient evidence of construct validity for the ILS.

For the presented study, a new online version of the ILS was created to incorporate a new design, instructions and to add text and check-boxes for required information, such as the Twitter username and some demographic data. We distributed the call for participation on various channels, including university mailing lists and Twitter. In total, 136 people responded and filled in the questionnaire. In a post-processing step we removed subjects: (i) whose Twitter account is protected[8], (ii) whose Twitter account listed less than 20 public tweets, (iii) who provided an invalid or no Twitter ID, and (iv) who did not complete the ILS questionnaire. After this data cleaning process, a total of 51 subjects remained whose learning styles are predicted across all experiments reported in this paper.

3.3 Twitter-based Features

We derived a set of 29 features from the Twitter stream of each subject. They are listed in Table 1 and can be ordered into four broad classes: features derived from the account information (e.g. number of followers and total number of tweets), features derived from individual tweets whose scores are aggregated (e.g. the percentage of tweets with URLs, the percentage of tweets directed at another user, the average number of nouns or adjectives used by a user), features based on tweet semantics (e.g. the percentage of tweets containing terms indicating anger or joy) and features derived from the external pages that were linked to by the users in their tweets (e.g. the fraction of content words vs. non content words in those pages).

We relied on a number of existing toolkits and resources to derive those features. The tweet processing pipeline is shown in Figure 1. The following steps are executed:

- A Language Detection library[9] is relied upon to determine the language a tweet is written in.
- If the tweet is not in English, the Bing Translation web service[10] is used to translate the text into English.

[8] Tweets of users with a protected user account are not publicly accessible
[9] http://code.google.com/p/language-detection/
[10] http://api.microsofttranslator.com

Table 1. Overview of the 29 features used as input for the classifiers.

	Features
Twitter-account based	#tweets, #favourites, #listings, #friends, #followers, $\frac{\#friends}{\#followers}$
Tweet style & behavior	%tweets with URLs, #languages used, %directed tweets, %retweets, %tweets with hashtags, average (av.) and standard deviation (std.) of #terms per tweet, av. and std. of #tagged terms per tweet, av. #nouns per tweet, av. #proper nouns per tweet, av. #adjectives per tweet
Tweet semantics	av. #anger terms, av. #surprise terms, av. #joy terms, av. #disgust terms, av. #fear terms, av. #sadness terms, %emotional tweets
External URLs	av. #images in external URLs, av. $\frac{\#content\ words}{\#non\text{-}content\ words}$ in external URLs

- The Stanford Part-of-Speech Tagger[11], a library that tags English text with the respective parts of speech (noun, adjective, etc), is relied upon to determine the tweeting style.
- Boilerpipe[12] is a library that parses web pages that the subjects referred to in their tweets. The output of running Boilerpipe distinguishes between content parts of a web page and non-content parts (copyright notices, menus, etc.). We rely on it to determine the number of actual amount of text (versus images) on a web page.
- Finally, we determine the sentiment of the user by relying on WordNet Affect [28]: it is a set of affective English terms that indicate a particular emotion; there are 127 anger terms (e.g. *mad*, *irritated*), 19 disgust terms (e.g. detestably), 82 fear terms (e.g. dread, fright), 227 joy terms (e.g. triumphantly, appreciated), 123 sadness terms (e.g. oppression, remorseful) and 28 surprise terms (e.g. fantastic, amazed). Each tweet is matched against this dictionary and the number of emotional tweet for each dimension are recorded.

3.4 Classification approaches

Since our goal is an initial study on the feasibility of determining one's learning style from a number of tweets, we use two common machine learning approaches: Naive Bayes and AdaBoost[13]. Due to the small number of users, we rely on k-1 cross-validation for training and testing. Furthermore, as the two classes in each

[11] http://nlp.stanford.edu/software/tagger.shtml
[12] http://code.google.com/p/boilerpipe/
[13] We use the Weka Toolkit for our experiments.

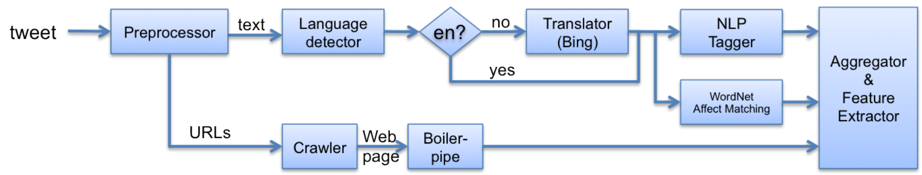

Fig. 1. Tweet processing pipeline.

dimension are not distributed equally, we set up a cost-sensitive evaluation where an error for the less likely class per dimension was punished with a factor of 5 (the error is punished with a score of 1 for the majority class). The results are reported in terms of the classification precision, recall, F_1 and Cohen's Kappa [29] (κ). We focus on the last evaluation measure in particular as it measures the inter-annotator agreement, taking into account the element of a chance agreement. Here, the ground truth and the predicted learning style act as the two annotators of the data. A $\kappa \approx 0$ indicates that the annotators agree as often as they would by chance, a value below zero indicates an agreement that is lower than by chance and values above 0 determine different levels of agreement that are better than random agreement. A $\kappa \in (0, 0.2]$ indicates a slight agreement, while $(0.2, 0.4]$ indicate moderate agreement and so on. In general, the larger the value of κ the larger the agreement; when $\kappa = 1$ the agreement is perfect.

4 Results

4.1 Generating the Ground Truth

Due to the odd number of questions in the ILS questionnaire for each dimension, a subject can always be assigned to one of the two opposite ends of the spectrum. In this pilot study, we ignore the strength of the association and we simply assign each subject to the pole with the greater score. The distribution of the subjects across the four dimensions proposed in the ILS approach are presented in Table 2. It is evident that the split between subjects in the two opposite poles of each dimension is not uniform. To place this distribution in context, we also report the distributions that were found in [25] and [30]. While the visual/verbal and active/reflective dimensions are robust to the subject population, we observe considerable differences among the three studies in the global/sequential and intuitive/sensing dimensions.

Based on the absolute scores, which show the clearest distinction in the visual-verbal dimension as well as the intuitive-sensing dimension, we hypothesize that the classifier will be performing better on those dimensions than the others.

Table 2. Distribution of our 51 subjects across the four dimensions of the ILS questionnaire. We report the number of subjects that fall into each category, as well as the mean (μ) and standard deviation (σ) with respect to the score. For comparison, we also report the distribution that were reported in other user studies.

		ILS-Twitter study				[25]	[30]
		#subjects	%	μ	σ	%	μ
Input	**visual**	42	82%	7.31	2.44	76%	8.14
	verbal	9	18%	3.67	2.45	24%	2.86
Processing	**active**	31	61%	6.07	2.35	57%	5.99
	reflective	20	39%	4.91	2.34	43%	5.01
Understanding	**global**	36	71%	6.64	2.41	66%	5.00
	sequential	15	29%	4.34	2.40	34%	6.00
Perception	**intuitive**	35	69%	6.69	2.67	48%	4.32
	sensing	16	31%	4.29	2.68	52%	6.68

4.2 Results on the classification process

In Table 3 we now report the performance our classifiers achieved when classifying the subjects according to the four ILS dimensions. We note, not surprisingly, that classification into the majority class results in high precision and recall values, though if we consider κ we also note that only for a single dimension, namely active/reflective, can we say with relative certainty that the classification approaches perform better than agreement by chance. This holds for both classifiers. The other dimensions show only slightly significant results for one or the other classifier, though not both. Thus, we have to conclude that the simple features we introduced are sufficient for the active/reflective dimension, though they are not indicative for any of the other dimensions in the ILS framework.

Table 3. Results of predicting the different learning style dimensions for our data set.

		active	**reflective**	**visual**	**verbal**	**global**	**sequential**	**intuitive**	**sensing**
Naive Bayes	Prec.	0.644	0.667	0.833	0.333	0.668	0.000	0.688	0.333
	Recall	0.935	0.200	0.952	0.111	0.917	0.000	0.943	0.063
	F_1	0.763	0.308	0.889	0.167	0.786	0.000	0.795	0.105
	κ	0.1547		0.086		-0.109		0.007	
Ada-Boost	Prec.	0.697	0.556	0.814	0.125	0.733	0.364	0.649	0.214
	Recall	0.742	0.500	0.833	0.111	0.725	0.267	0.686	0.188
	F_1	0.719	0.526	0.842	0.118	0.806	0.308	0.667	0.200
	κ	0.2463		-0.058		0.0783		-0.131	

5 Conclusions

Twitter learning style analysis could be used to complete user profiles with respect to learning preferences and as a result they could result in more efficient adaptation and personalization of simulators, e-learning systems or other technology-enhanced learning software. Providing feedback to learners about their learning preferences could be helpful, but it should be relied upon with caution. There have to be explicit explanations that the learning style is a tendency of certain preferences and the assessment does not overrule ones own judgments [11], but rather can be seen as advice or suggestion. Bearing this in mind the Twitter analysis of learning styles could lead to smoother, non-invasive assessment of personal learning preferences.

In this paper, we have performed a first study with the goal to infer a learner's learning style from her Twitter stream. We selected the ILS model due to its validity and widespread use and collected ground truth data from 51 study participants. We extracted 29 features from each subject's Twitter stream and used them to classify each subject as belonging to one of the two poles for each of the four dimensions of the ILS model.

We found a more than by chance agreement only for a single dimension: active/reflective. Here, the agreement was slight to moderate, while for the other three dimensions no agreement between the prediction and the ground truth above agreement by chance was found.

Moreover, there are some limitations inherent in ILS which need to be taken into account. Felder and Spurlin [11] point out the limitation of learning style assessment and the purposes for which it should be used.

We conclude that, while there is some evidence that a Twitter signal contains useful information (as evident in the classification results of the active/reflective dimension), such a classification in general is hard and more complex features need to be derived. Thus, future work will focus on deriving more complex features that are more in agreement with the different learning dimensions, instead of relying on low-level features that can only be somewhat indicative when viewed in isolation.

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