Behavior Analysis in a learning Environment to Identify the Suitable Learning Style

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Abstract. *Personalized adaptive systems rely heavily on the learning style and the learner's behavior. Due to traditional teaching methods and high learner/teacher ratios, a teacher faces great obstacles in the classroom. In these methods, teachers deliver the content and learners just receive it. Moreover, teachers can't cope with the individual differences among learners. This weakness may be attributed to various reasons such as the high number of learners accommodated in each classroom and the low teaching skills of the teacher himself/herself, Therefore, identifying learning styles is a critical step in understanding how to improve the learning process.*

This paper presented an automatic tool for identifying learning styles based on the Felder-Silverman learning style model in a learning environment using a social book marking website such as www.tagme1.com .

The proposed tool used the learners' behaviour while they are browsing / exploring their favorite web pages in order to gather hints about their learning styles. Then the learning styles were calculated based on the gathered indications from the learners' database.

The results showed that the proposed tool recognition accuracy was 72% when we applied it on 25 learners with low number of links per learner. Recognition accuracy increased to 86.66% when we applied it on 15 learners with high number of links per learner.

Keywords: e-Learning, learning style, learning object, Social software, PLE, Adaptive Web Education

Introduction

E-learning, as well as traditional learning is concerned with the evaluation and analysis of the learner's behavior which is an inescapable stage in the evaluation process of the learning quality. E-learning is a concept which concentrates strongly on the learner and how to improve the quality of the learning process.

The term e-Learning 2.0 is used to refer to new ways of thinking about e-learning inspired by the emergence of Web 2.0. From an e-Learning 2.0 perspective, conventional e-learning systems were based on instructional packets that were delivered to learners using Internet technologies. The role of the learner is to learn from the readings and preparing assignments. In contrast, the new e-learning places increased emphasis on social learning and use of social software such as blogs, wikis, podcasts and virtual worlds such as Second Life. This phenomenon has also been referred to as Long Tail Learning

Learning styles are various approaches or ways of learning. They involve educating methods, particular to an individual, which are presumed to allow that individual to learn best. Most people prefer an identifiable method of interacting with, taking in, and processing information. Based on this concept, the idea of individualized "learning styles" originated in the 1970s, and acquired "enormous popularity". There are many learning style models in literature such as the learning style model by Kolb, Honey and Mumford, and Felder and Silverman.

Everyone has a learning style, and as an learner it may be of great benefit for you to know what your particular style may be. Knowing how to absorb and retain information may help you recognize your strong points as well as your not-so-strong areas. The benefit? It can help you when it comes to deciding how best to study for an exam, for example, read a book or write a paper.

There are many tests available to help you and your students discover your best learning style and we presented a tool that is able to provide teachers and learners with better information.

Social software encompasses a range of software systems that allow users to interact and share data. Social software applications include communication tools and interactive tools. Communication tools typically handle the capturing, storing and presentation of communication, usually written but increasingly including audio and video as well. Interactive tools handle mediated interactions between a pair or group of users.

There are tools for online communication such as Social network services that allow people to come together online around shared interests, hobbies or causes, and Social bookmarking that some websites allow users to post their list of bookmarks or favorites websites for others to search and view them. These sites can also be used to meet others sharing common interests. Examples include Digg, Delicious, StumbleUpon, Reddit, and Furl.

Our proposed tool aims to increase the percentage of learner's absorption through identifying his/her suitable learning style by following and analyzing the learner's behavior through his/her interactions with the web pages contents using social bookmarking software such as tagme site (www.tagme1.com). Up to our knowledge, we think that this is the first time that social bookmarking software and learning styles are intergraded at one place to improve the speed and the quality of the learning process. This happens through an automatic identification of a learning style and presentation of personalized learning materials based on the learner's learning style.

The paper is organized as follows. The learning style model, especially Felder-Silverman learning style model, we discuss some related work and different used methods in section 2. Tool architecture with presenting its stages (Pre-processing, Data collection , Choosing Patterns / features, Choosing model , Learning style model , Calculating learner learning style in section 3.The experiment and results in section 4 . Finally, in section 5, conclusion and future work are discussed.

2. Background and Related Work

2.1. Learning Style and Learning Style Models

The field of learning styles is complex and is affected by several aspects and leads to different concepts and views. Many learning style models exist in literature such as the learning style model of Kolb, Honey and Mumford, and Felder and Silverman.

The David A. Kolb style model is based on the Experiential Learning Theory. Kolb explains that different people naturally prefer a certain single different learning style. Various factors influence a person's preferred style: Notably in his experiential learning theory model (ELT), Kolb defines three stages of a person's development (Acquisition, Specialization and Integration), and suggests our propensity to reconcile and successfully integrate the four different learning styles as shown on Kolb's learning styles - matrix view below.

	doing (Active Experimentation - AE)	watching (Reflective Observation - RO)
feeling (Concrete Experience - CE)	**accommodating (CE/AE)**	**diverging (CE/RO)**
thinking (Abstract Conceptualization - AC)	**converging (AC/AE)**	**assimilating (AC/RO)**

Table. 1. Kolb's learning styles - matrix view

In the mid 1970's Peter Honey and Alan Mumford adapted David Kolb's model for use with a population of middle/senior managers in business. They published their version of the model in The Manual of Learning Styles (1982) and Using Your Learning Styles (1983).

Two adaptations were made to Kolb's experiential model. Firstly, the stages in the cycle were renamed to accord with managerial experiences of decision making/problem solving. The Honey & Mumford stages are:

1. Having an experience 2. Reviewing the experience 3. Concluding from the experience
4. Planning the next steps.

Secondly, the styles were directly aligned to the stages in the cycle and named Activist, Reflector, Theorist and Pragmatist. These are assumed to be acquired preferences that are adaptable, either at will or through changed circumstances, rather than being fixed personality characteristics

While there are still many open issues with respect to learning styles, all learning style models agree that learners have different preferences in learning. Furthermore, many educational theorists and researchers consider learning styles as an important factor in the learning process and agree that incorporating them in education can facilitate learning for learners. Learning styles can be considered in different ways. A first step is to make learners aware of their learning styles and show them their individual strengths and weaknesses. Consequently learners understand why learning is sometimes difficult for them and is the basis for developing their weaknesses.

2.2. Felder-Silverman learning style model

Felder-Silverman learning style model (1988) seems to be the most appropriate for use in computer-based educational systems (Carver et al., 1999, Kuljis and Liu, 2005). Most other learning style models classify learners in few groups, whereas FSLSM describes the learning style of a learner in more detail, distinguishing between preferences on four dimensions as follows:

No	Dimension	Definition 1	Definition2 (Tagme website features)
1	**Verbal**	Require written or spoken	Send feedback, add hobbies, add link description, add tags
	Visual	Remember what they have seen	Add graphic link , add media link
2	**Sequential**	Learn in linear steps	Download manual, add reading part link , install toolbar, add tags
	Global	Holistic or learn in large leaps	Add summery link , only link store , register on website
3	**Active**	Learn by trying things	Add practice link, send to, create network, add hobbies , not download manual
	Reflective	Learn by thinking things out	Add Private link, add read content link, not create networks, not sent to link
4	**Sensing**	Learn concrete material and tend to be practical	Add practice link >1 , add content fact link
	Intuitive learners	Learn concepts	Add practice link=1 , add concepts link

Table. 2. Felder-Silverman learning style model and Tagme assumed features

2.3. Related Work

Much work has been done on identification of learning styles in adaptive systems such as DELES (Graf 2007) that detects learning styles from the learners' different patterns of behavior, such as the number of visits in a forum, the number of times they participate in a chat, the number of postings in a forum and the number of visits, and the time a learner takes to deal with an exercise.

Despite the tremendous efforts done in this field, but access to the perfect stage was not reached because of many reasons (Shute 2007):

1. First, learners can provide inaccurate data due to lack of knowledge about their own characteristics,
2. Second, during the online learning process, completing the questionnaire can be time-consuming, which might frustrate learners and lead them to provide invalid data in order to arrive at the content more quickly. These systems use collaborative student modeling or a self-reported informational approach for detection of learning styles.

3. The Proposed Tool Architecture

In this section, we present our proposed tool that is easy for learners to use, for automatic detection of learning styles. Our approach integrates information about learning styles, social software and learning objects repositories, to help educational systems to provide personalized and more efficient adaptation based on learning styles. The general form of detecting learning style tool architecture is illustrated in Figure 1 which is composed of the following several basic stages:

a. Pre-Processing (Data collection):
   This stage includes collecting raw data of learners and preparing his/her behavior's database,
b. Choosing Patterns / features
   Data are extracted from the learners' database and detected patterns that indicate a preference for a specific dimension,
c. Model Choice (Learning style model)
   At this stage we choose Felder-Silverman learning style model,
d. Calculating learner learning style,
   - Patterns provide indications about learning styles,
   - All indication values are summed up where information was available,
   - The results were normalized on a range from 0 to 1
     0 … the learner has a strong negative preference for this learning style
     1 … the learner has a strong positive preference for this learning style
e. Evaluation
   - Learners filled out the ILS questionnaire,
   - Results of ILS were compared with the results of our approach based on a 2-item scale (distinguishing e.g. between an active and reflective learning style),
   - Measuring the efficiency of the results of the proposed tool, the correct identification of the learner's learning style as well as how close the predicted learning style to the learning style that is based on the ILS values, the following measure was proposed by García et al. (2007):

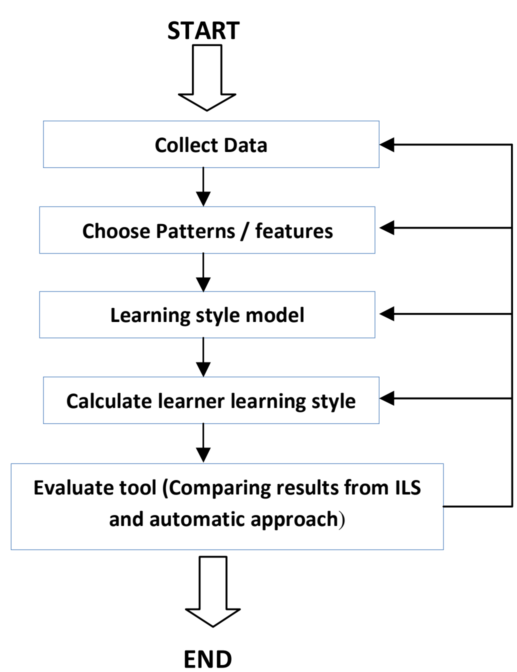

Figure. 1: Detecting learning style tool design cycle

3.1. Data collection

The learner's interactions with tagme were tracked in order to get information about their learning behavior. To keep the data extraction process as simple as possible, the representation of data in each table was based on the event-based way data are stored in tagme database. For example, a table includes data about each link of a learner and the description of it. We extracted raw data (patterns of behavior) from each table at Bookmarks database related to each learner's behavior and each pattern.

From the learner's database we can track his/her behavior and detect values for each pattern of the behavior such as if the learner adds a graphic link at his/her database we can increase his/her preference for a visual learning style.

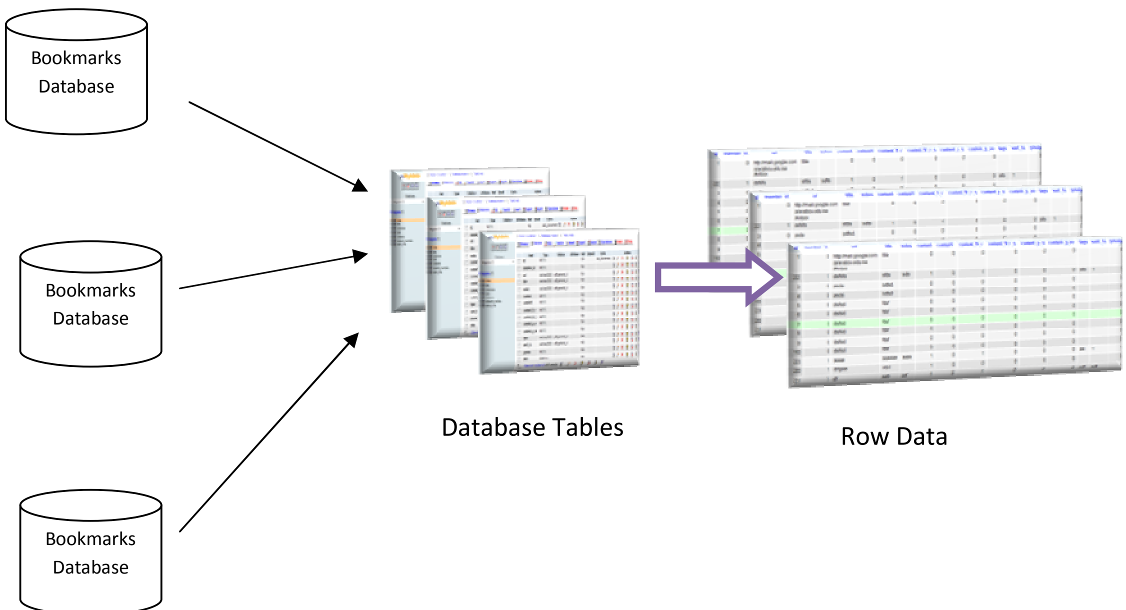

Figure 2: Data collection process

3.2. Patterns (Features) of Behavior

Detecting learning styles occurs by detecting patterns that indicate a preference for a specific dimension. We focused on commonly used features, such as user profile and links and some html tags. The patterns of behavior considered for detecting learning styles are:

- **User profile**
  Hobbies, hours on the Internet
- **Adding Link**
  Title, description, content, tags, sent to, private, practice, number of practices ,
- **Adding network**
  Create network, adding members
- **Other**
  Search
  Download user manual
  Feedback

Register on website
Toolbar

3.3. Learning Style Model Choice

We chose Felder and Silverman, 1988 that describes the learning styles by using scales from +11 to -11 for each dimension for the following reasons:

- The most appropriate for educational systems,
- Describes learning style in more detail,
- Represents also balanced preferences,
- Describes tendencies.

3.4. Learning Styles from Patterns of Behavior

3.4.1. Active/Reflective Learners

As for FSLSM, active learners tend to process information actively by doing something with the learned material, such as discussing it, explaining it, or testing it. Thus we can assume that the following behavior gives us indications about the learner's preference for an active learning style:

- Adding practice link, sending links to his friends, creating a network, adding his/her hobbies at his/her profile and not downloading user manual.

As for FSLSM, reflective learners tend to think about and reflect on the learning material. Moreover they prefer to work alone. Thus we can assume that the following behavior gives us indications about the learner's preference for an active learning style:

- By make a lot of his links as Private, read content , not send links to his friends , no networks

3.4.2. Sensing/Intuitive Learners

As for FSLSM, sensing learners tend to learn facts and concentrate on learning materials. Sensing learners also dislike challenges/complications and like to solve problems through well-established methods. Sensing learners usually work carefully and slowly. Thus we can assume that a sensing behavior of learners can be predicted through doing practice more than once and adding links that contain facts.

As for FSLSM, intuitive learners welcome challenges and are bored by details. Intuitive learners tend to work faster. Furthermore, they like innovation and dislike repetition. Thus we can assume that an intuitive learner is the one who does not repeat practice, adds concepts content and adds his/her links without description.

3.4.3. Visual/Verbal Learners

As for FSLSM, visual learners remember best what they see: Demonstrations, films, diagrams, and pictures; and create appropriate mental images of them. Thus we can assume that spending less time on reading contents that contain graphics/diagrams and adding graphics / media links gives an indication about the learner's preference for a visual learning style

As for FSLSM, verbal learners prefer words either oral or written, as their method of learning. Thus we can assume that any reading of content, adding feedback, adding hobbies at his/her profile and links description, and adding tags filed gives an indication about the learner's preference for a verbal learning style

3.4.4. Sequential/Global Learners

As for FSLSM, sequential learners not only explore material sequentially, in detail but also follow linear reasoning processes when solving problems. Thus we can assume that reading user manual, reading content partially and using toolbar adding tags gives an indication about the learner's preference for a sequential learning style.

As for FSLSM, global learners are not interested in obtaining details of the contents being presented but instead, they like to get an overview of the contents. Using this way of learning, they get the big picture and build their own cognitive map of the contents. Thus we can assume that adding summery links, adding links without any descriptions and registering on a website are indications about the learner's preference for a global learning style.

3.5 Calculation of Learning Styles

Learning styles are calculated from the raw data taken from data extraction component at Section3.1. Learning styles are calculated in this way for each dimension based on the ordered data. Ordered data for each pattern can take the values 1, 0 indicating, for instance, a low or strong state. Ordered data for each pattern can also take the values 1, 0 indicating a low or strong state.

4. Experiment and Results

In order to measure the efficiency of the results of the proposed tool, the correct identification of the learner's learning style as well as how close the predicted learning style to the learning style that is based on the ILS values, the following measure was proposed by García et al. (2007):

$$\text{Precision} = \frac{\sum_{i=1}^{n} Sim(LS_{predicted}, LS_{ILS})}{n} \cdot 100$$

Where "LS predicted" refers to the learning styles predicted by the proposed tool, LS_{ILS} represents the learning styles from the ILS questionnaire, and "n" is the number of learners. The function Sim compares its two parameters "LS predicted" and "LS_{ILS}" and returns "1" if both are equal and "0" if they are opposite.

In order to evaluate the proposed tool, we conducted a primary study with 25 learners. The learners participated in a bookmarking site such as tagme (www.tagme1.com) and the learners interactions with the site were tracked in order to get information about their learning behavior.

Furthermore, we asked the learners to fill out the ILS questionnaire to get information about their learning styles via tagme site

Table3 illustrates the comparison between ILS and proposed tool LS primary results of 25 learners.

This table contains data about learners' behavior and values of each pattern of 25 learners as a primary study. This study includes the result of ILS of each learner and the proposed tool result values and total number of links for each learner. We assume that our tool is able to detect learner's learning style if the value of the learner's preference is equal or more than value 7 at ILS approach.

Table 3: The comparison between ILS and proposed tool LS primary results of 25 learners

No	DB_ID	Name	Links	Proposed tool result								ILS result							
				Active	Reflective	Visual	Verbal	Sensing	Intuitive	Sequential	Global	Active	Reflective	Visual	Verbal	Sensing	Intuitive	Sequential	Global
1	3	abdelaziz hamada	18	5	1	0	1	2	1	1	0	10	1	10	1	10	1	4	7
2	4	Akram Saadooni	22	2	3	14	0	11	0	1	0	7	4	9	2	4	7	6	5
3	6	Amir zaki	9	1	6	0	2	7	0	3	0	8	3	8	3	10	1	7	4
4	9	Mohammad Samy	13	3	1	3	0	11	2	0	5	3	8	7	4	7	4	6	5
5	11	Eman mohamed	28	6	1	6	4	6	0	5	4	9	2	9	2	8	3	5	6
6	14	Muhammad Sleem	14	2	5	7	2	6	1	2	0	7	3	8	2	5	6	5	5
7	15	Ahmed Boghdady	11	4	1	0	0	3	2	0	3	9	2	11	0	6	5	7	4
8	17	Mohamed Barakat	9	3	2	3	0	3	1	0	0	7	4	9	2	7	4	6	5
9	28	Abdulrazak Aman	10	2	1	1	0	1	0	0	0	3	8	9	2	5	6	7	4
10	30	Maryam Ahmed	20	6	1	5	1	4	0	1	3	7	4	10	1	6	5	4	7
11	33	Rabee Elbes	8	1	0	0	6	2	3	6	0	6	5	11	0	7	4	5	6
12	79	Nonna AroOod	6	2	7	1	0	0	0	0	3	7	4	8	3	4	7	4	7
13	116	Hussain Al-Qahtani	6	1	7	0	0	0	0	0	0	3	8	7	4	7	4	6	5
14	140	Bakri AlBakri	6	6	3	0	2	2	4	2	0	5	6	6	5	8	3	6	5
15	199	Saud massad	9	1	6	0	0	0	0	0	0	6	5	8	3	7	4	6	5
16	254	Adel D	11	2	1	0	2	5	0	2	1	5	6	7	4	9	2	9	2
17	293	Quest User	5	2	5	0	1	0	0	1	0	7	4	7	4	7	4	4	7
18	323	Abdulrhman jabari	12	3	12	3	6	3	9	6	0	3	8	5	6	6	5	5	6
19	383	Mohamed Ibrahim	12	2	1	0	1	0	1	1	0	7	4	9	2	7	4	5	6
20	401	Duaa.saleem	6	1	1	1	1	3	1	1	1	6	5	7	4	3	8	4	7
21	461	Emad naser	4	4	0	1	0	3	1	0	1	7	4	7	4	5	6	9	2
22	474	Sura raad	3	1	4	0	1	0	0	1	1	1	10	10	1	6	5	6	5
23	489	Areej alnasr	6	7	7	0	1	5	1	1	0	3	7	6	5	6	5	4	7
24	505	Safaa Al Harbi	12	2	1	0	0	1	0	0	1	7	4	8	3	6	5	5	6
25	513	Malak alnassar	5	2	1	0	1	2	0	1	0	3	8	5	6	7	4	7	4

	Detected
	Not Detected

We make a comparison between ILS and proposed tool LS with the value that ILS detects where the learner has a high value of moderate preferences (equal or more than 7 at ILS approach) as shown on Figure 3 below which presents the value of each preference on ILS :

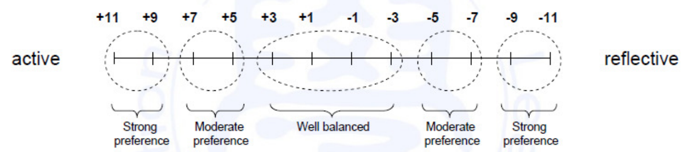

Figure. 3. Scales of the dimensions examples

Table 4 illustrates the tool recognition accuracy. This table contains the result values of 25 learners with 265 links, the numbers of detected learning style using proposed tool (18/25) and the efficiency of the tool.

Table 4: The tool recognition accuracy

No of learners	No of links	Average links	No of detected LS	Efficiency
25	265	11 per user		
ILS			25	
Proposed tool			18	72%

Table 5 illustrates a comparison between ILS and proposed tool LS primary results based on high link number for 15 learners This table contains data about learner's behavior and values of each pattern of 15 learners with a high average number of links for each learner as a primary study. This study includes the result of ILS of each learner, the proposed tool result values and the total number of links for each learner. We assume that our tool is able to detect the learner learning style if the value of the learner's preference is equal or more than value 7 at ILS approach.

Table 5: The comparison between ILS and proposed tool LS primary results based on a high link number for 15 learners

No	ID	Name	Links	Proposed tool								ILS							
				Active	Reflective	Visual	Verbal	Sensing	Intuitive	Sequential	Global	Active	Reflective	Visual	Verbal	Sensing	Intuitive	Sequential	Global
1	3	abdelaziz hamada	18	5	1	0	1	2	1	1	0	10	1	10	1	10	1	4	7
2	4	Akram Saadooni	22	2	3	14	0	11	0	1	0	7	4	9	2	4	7	6	5
3	9	Mohammad Samy	13	3	1	3	0	11	2	0	5	3	8	7	4	7	4	6	5
4	11	eman mohamed	28	6	1	6	4	6	0	5	4	9	2	9	2	8	3	5	6
5	14	Muhammad Sleem	14	2	5	7	2	6	1	2	0	7	3	8	2	5	6	5	5
6	15	Ahmed Boghdady	11	4	1	0	0	3	2	0	3	9	2	11	0	6	5	7	4
7	27	Elsayed Abd Elkader	14	1	1	0	1	0	0	1	0	5	6	10	1	8	3	6	5
8	28	Abdulrazak Aman	10	2	1	1	0	1	0	0	0	3	8	9	2	5	6	7	4
9	30	Maryam Ahmed	20	6	1	5	1	4	0	1	3	7	4	10	1	6	5	4	7
10	52	Taara Sllom	61	0	1	0	1	0	0	1	0	3	8	9	2	6	5	7	4
11	130	Eman Al-Hamed	12	7	9	0	2	9	7	3	3	3	8	6	5	8	3	6	5
12	254	Adel D	11	2	1	0	2	5	0	2	1	5	6	7	4	9	2	9	2
13	323	abdulrhman jabari	13	4	13	3	6	4	10	6	0	3	8	5	6	6	5	5	6
14	383	mohamed Ibrahim	12	2	1	0	1	0	1	1	0	7	4	9	2	7	4	5	6
15	505	Safaa Al Harbi	12	2	1	0	0	1	0	0	1	7	4	8	3	6	5	5	6

(dark grey)	Detected
(light grey)	Not Detected

Table 6 illustrates the tool recognition accuracy. This table contains the result values of 15 learners with 271 links, the numbers of detected learning style using proposed tool (13/15) and the efficiency of the tool.

Table 6: The tool recognition accuracy

No Of learner	No of links	Average links	No of detected LS	Efficiency
15	271	18 per user		
ILS			15	
Proposed tool			13	(13/15)*100=86.66%

As can be seen from Table 4, the tool recognition accuracy is 72% when we apply our proposed tool on 25 learners with a low number of links.

The recognition accuracy of our proposed tool increased to 86.66% when we applied it on 15 learners with a high number of links as shown in Table 6.

5. Conclusion and Future Work

This paper presented an automatic tool for identifying learning styles based on the Felder-Silverman learning style model in a learning environment using a social book marking website.

Applying the proposed tool enabled us to detect learning styles from the learners ' behavior . There was no need for learners to fill out a questionnaire to get their learning style. Also, the detection/calculation could be done automatically by the learning styles detection/calculation tool. the study compared the results of the proposed automatic tool with the results of the ILS questionnaire. The results showed that the tool is suitable for identifying learning styles with respect to the FSLSM.

With this tool, teachers and learners were expected to improve their classroom performance as it provides information on the teaching learning styles.

Future work will deal with the potential of improving the selected patterns of automatic detection of learning styles, improving and evaluating the reliability of our proposed tool in order to provide teachers and learners with better information.

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