

Learner's Annotative Activity as a Data Source of Personalized Web Services Recommendation

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Abstract: Since information retrieval for relevant learning resources to support teachers or learners is a pivotal activity in Technology enhanced learning (TEL), the deployment of recommender systems has attracted increased interest. In this paper, we propose an approach of recommendation of web services from the annotative activity of the learner to assist him in his learning activity. This process of recommendation is based on two preparatory phases: the phase of modelling learner's personality profile through analysis of annotation digital traces in learning environment realized through a profile constructor module and the phase of discovery of web services which can meet the goals of annotations made by the learner via the web service discovery module. The evaluation of these two main modules (web service discovery module & profile constructor module) through empirical studies realized on groups of learners based on the Student's t-test showed significant results.

Keywords: Annotation, learner, recommender system, personality traits, ontology, web service

1. Introduction

Technology enhanced learning (TEL) aims to design, develop and test sociotechnical innovations that will support and enhance learning practices of both individuals and organizations (Manouselis et al., 2011). It is therefore an application domain that generally covers technologies that support all forms of teaching and learning activity (Montebello, 2017). Since information retrieval (in terms of searching for relevant learning resources to support teachers or learners) is a pivotal activity in TEL, the deployment of recommender systems has attracted increased interest (Manouselis et al., 2011).

During the learning process, the learner's activities are numerous and especially varied. This diversification is important to both educational plans and psychological plans (Omheni et al., 2017a). Thus, the learner can choose to read, write, listen, discuss, experiment, or annotate various resources to achieve his learning goals (Azouaou et al., 2013). Among these activities, we focus in our research on the annotative activity of the learner because annotation practice is very common and omnipresent (Kalboussi et al., 2015b). While reading, the learner usually uses comments, highlights, circles sections and posts it to annotate the consulted resources (Cabanac et al., 2010; Marshall, 2009).

On other hand, it's evident for anyone who has taught a course that learners are not a homogeneous group. They come into courses with major individual differences among their level of knowledge about subject matter content, their intellectual and metacognitive skills, their beliefs and attitudes toward the topic and toward learning (Ambrose et al., 2014) as well as their human personality characteristics. For such reasons, it's necessary to adapt the teaching process to different student characteristics through designing personalized educational experiences that fit the individual characteristics of the users. Recently, the recommender systems are presented as a new technology in educational context to deliver a learning support to learners. In this context, many educational

recommender systems are designed with different functionalities and recommendation services (Kalboussi et al., 2016a; Beham et al., 2010; Vesin et al., 2013).

Generally speaking, the recommender system needs to capture the traces that users leave in an environment which is used thereafter as a basis of knowledge for the system to provide accurate recommendations (Buder et al., 2012). Recently, the tendency of using the Recommender Systems (RSs) that support learners in online learning environments through individualizing their learning experiences to fit the needs of each student is increased.

In current work, we present the architecture of an educational recommender system that bases their recommendation services on the learner's annotation traces yielded during the learning process. The educational recommender system is composed essentially of four basic modules: annotation module; web service discovery module; profile constructor module and recommendation module. The evaluation of the two principal modules (web service discovery module & profile constructor module) through empirical studies realized on groups of learners based on the Student's t-test showed significant results.

The rest of this paper is structured as follow. In *Section 2*, we give a brief overview on the literature of recommender systems in the educational context. Thereafter, *Section 3* presents the architecture of our system and details its principal components. *Section 4* evaluates the two main modules constituting the architecture of the proposed educational recommender system. Finally, we draw some conclusions and we cite certain possible directions for future works.

2. Related Work

The recommender systems are widely applied in various interesting application domains such as e-commerce, entertainment, and others. Nevertheless, it was only around early 2000 when the first application of recommender system appeared in the domain of education (Manouselis et al., 2012). Certain works transfer the technology of recommender systems from commercial to educational contexts on a one-to-one basis regarding the datasets and methods used to deliver recommendations without taking account to the particularities of learning environment (Buder et al., 2012).

For instance, certain learning portals integrate recommender engines to assist their users during their learning experiences (Manouselis et al., 2009). In order to allow the recommender engines to produce an efficient recommendation, the system collects datasets which include such usage related data (ratings, votes, tags, reads or downloads, bookmarks, etc.) and apply data analysis techniques (collaborative filtering, content-based filtering and hybrid filtering technologies) to help users find items that are likely of relevance (Verbert et al., 2011).

Buder et al. (2012) suggest that recommendation in the learning context is more challengeable than in other contexts. In fact, the educational recommender systems deal with information about learners and Learning Activities (Drachsler et al., 2007) which means that it should be personalized with consideration to learner's characteristics (level of knowledge, learning activities, learning achievement, learning goals, learning style, personality traits, etc.). Thus, the posed issue concerns the data to be gathered from the user side, how to be acquired (explicitly or implicitly) and how to be analyzed to extract the needed knowledge for recommendation purposes.

In our work, we suggest taking advantage of the annotation activity used typically in the learning context for different purposes and which may reflect certain learners' characteristics useful as input data for the recommendation process (Mazhoud et al., 2015).

3. Annotation-based Recommender System

The architecture of the annotation-based recommender system under present discussion is shown in Figure 1 which illustrates the interaction between the various modules of the system along with the flow of information/data. We follow, in our framework, a novel approach of recommendation based on learners' characteristics extracted from their annotation traces yielded during learning experience.

We choose to follow learners through their annotation activities for many reasons. For instance, annotation is a practice which bridges between reading and writing (Marshall, 1998) and constitutes the most prominent habits of active reading activity.

The architecture of our proposed recommender system consists of four principal modules: The Annotation Module, the Web Service Discovery Module, the Profile Constructor Module and the Recommendation Module. In what follow, we describe briefly the works carried out for each module of our system, and we give an overview about their basic functionalities.

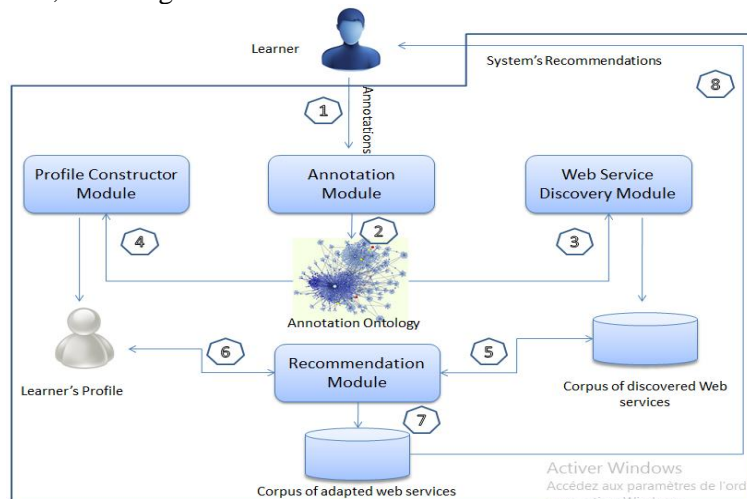


Figure 1. The Architecture of the Annotation-based Recommendation System.

3.1 The Annotation Module

Through the annotation module, the learner makes a set of annotative acts during his reading activity that will be stored in the annotation ontology (see Figure 2) which is composed of three aspects of the annotation (contextual, physical and semantic).

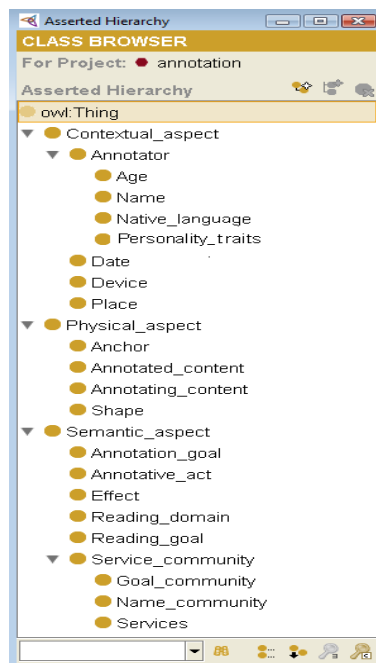
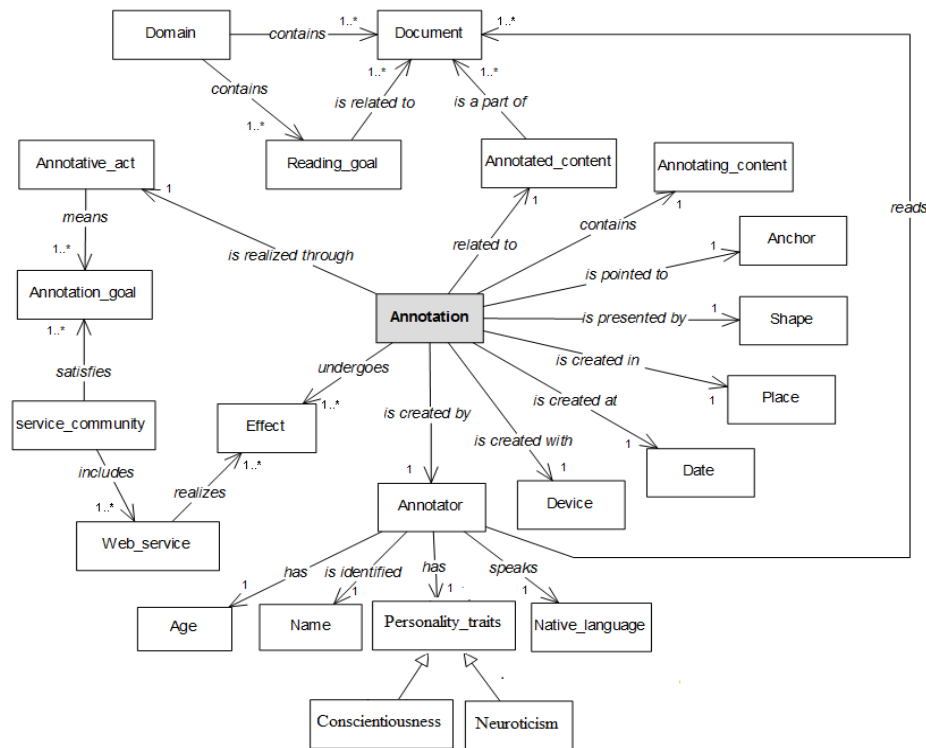


Figure 2. The annotation Ontology.

The relationships between the ontology's concepts are described as follows (see Figure 3): An annotation is created by the annotator with a device and has a space-temporal context (place and date). It is presented by a particular shape, is pointed to an anchor and related to an annotated content which is a part of the read document. The annotation contains an annotating content. The annotator is identified by name, has an age, speaks a native language and has some personality traits (conscientiousness and neuroticism) which can be accurately predicted from his annotations. The

annotator reads a document in a specific domain that contains a set of documents and a set of reading goals. The annotation is realized through an annotative act which may mean one or more annotation goals. A service community satisfies one or several annotation goals. This service community includes one or more web services that realize one or several effects. The annotation undergoes one or more effects.

Figure 3. Relationships between concepts of annotation ontology



3.2 Web

Service Discovery Module

In the course of “pen-and-paper” annotative activity, the learner presents implicitly through some made annotations a need for assistance that helps him to meet the goal of such annotations. For example, if he annotates an incomprehension of a word or a read passage, the annotator really tries to understand what is annotated through several means: to use a dictionary, to look for other documents in relation to the annotated document or to ask for the help from an expert in the domain of reading (Marshall, 2009). All these means presented previously in “pen-and-paper”, helping the learner to meet the annotation goal, take shape in the world of web in the form of services. Thus, we wonder and ask: why not bind these web services to the developed annotation systems?

This correlation should be based essentially on the semantics of the annotation so that the service will be invoked directly in an intelligent way from the annotation of the annotator. Surely, such features offered by a web service can help the user of such an annotation system to satisfy the goal of his annotation in a process of active reading. Even if there are some recommender systems that present dictionaries or translators to their annotators, this assistance is independent of the semantics of the performed annotation. In other words, the annotation tools do not propose these dictionaries or translators due to an annotation made by the reader, but it is the annotator who calls and uses himself these means manually.

To take advantage of the success of web services on the one hand and to better exploit the semantics of the annotative activity in other, we propose in this article the idea of a recommender system of web services through the learner’s annotative activity. Based on a new approach presenting the learner’s annotative activity as a means to invoke web services implicitly (Kalboussi et al., 2013a), the proposed recommender system tries to assist the reader via web services during his learning activities. Therefore, we consider the annotation not only as a means of memorization of the learner’s reactions in the reading process but also as a potential source of web services invocation

that can assist the annotator and help him to satisfy his annotation goal. So, from a user's annotation, our system is able to interpret a semantics implicitly expressed which presents a need for a web service to meet annotation goals (Kalboussi et al., 2016a). Based on this extracted semantics, the annotation system discovers and invokes the requested web service. These new features are based on an ontology of annotation which presents the different properties of the learner's annotative activity available to computer processing (Kalboussi et al., 2013b; 2016b). The relations among the elements composing the semantic aspect of the annotation ontology can be described as the follows: The reader chooses to read a document in a specific domain. Each domain of reading contains a set of reading goals which are strongly related to the type of the read document. For example, in the e-learning domain, the likely goals of reading a poem are learning and understanding it, while the likely goal of reading a comic story is enjoyment. Motivated by this reading goal, the reader begins to read and annotate the consulted document. The annotative activity is the result of an active reading, so this activity certainly helps the annotator to satisfy his reading goal. For that purpose, we present for each reading goal the list of annotative acts realized by the annotator in the reading process. For each annotative act, the corresponding one or several annotation goals are presented. This objective represents semantics implicitly expressed by the annotator through the annotative act for a need for means which answer the goal of this annotation. Services community represents these needed means. Thus, for each annotation goal, there is corresponding a service community whose goal coincides with the goal of the annotation.

3.3 The Profile Constructor Module

The annotation activity is “*a basic and often unselfconscious way in which readers interacts with texts*” (Marshall, 2009). Furthermore, the annotation is described as a natural human activity that is used in daily life as an integral part of reading practices (O'hara et al., 1907). Every annotator has unique individual patterns in making annotations (Naghsh, 2007). According to Jackson (2001), “*if you ask annotators today what systems they use for marking their books and where they learned them, they generally tell you that their methods are private and idiosyncratic.*” Hence, the individuality of annotation patterns shows us very plainly that there can be some sort of connection between annotation practices and learners' personality characteristics.

In our prior work (Omheni et al., 2017a); we seek the connection between learners' annotation practices and their personality traits in the “pen-and-paper” context. We conducted an empirical study to validate our hypothesis of correlation of annotation behaviors to the human traits. Our findings show significant correlation of annotation practices to certain personality traits (Consciousness and Neuroticism).

In (Omheni et al., 2017a) we explore the validity of our hypothesis in the context of digital annotation. Our results are significant and coherent to our prior findings in the “pen-and-paper” context. These works constitute the basis of the functionality of the profile's constructor module. In fact, the annotations yielded by learners during their learning activities is stored in the annotation ontology and used to model the personality profile of learners which is composed of three basic phases:

- The analysis of annotation activity to extract certain features cited in (Omheni et al., 2017b).
- Prediction of learner's personality traits based on the extracted annotation's features.
- The storage of the constructed learner's personality profile to be used later in the personalization process of user's recommendations.

The constructed personality profile will be used as input data to the recommendation module to filter and adapt the list of web services compiled with regard to the objectives of learners' annotations.

3.4 The Recommendation Module

The recommendation module receives a data flow from both the profile constructor module and the web service Discovery module. The received data is composed of a compiled list of the found web services with regard to learner's objectives deduced via his annotation practices and his personality profile which is built by reference, also, to his annotation traces.

We hope refining and filtering the list of service regarding the learner’s personality characteristics. For instance, the learner with high level of Neuroticism prefers a web service which reacts instantaneously to display the required result. Thus, the system recommends the services with low response time to satisfy the learner’s personality characteristics.

The filtered web services list will be sent to learner to select the desired recommendation for execution. The selected web service will be invoked and the system stores the user choice to be used later in refining process of system’s recommendation. So, to automate the process of deduction of the appropriate web service according to the learner’s personality traits, we propose to use a pattern of annotation. The proposed pattern allows the deduction of the annotation goal from its shape, and then based on this objective; the system interprets the web services community which assists the user to achieve the goal of the annotation. Finally, according to the learner’s personality traits (conscientiousness and neuroticism), the recommendation module selects the appropriate web service to be invoked by the annotator. The patterns are represented by an ontology that refers to the elements of the annotation ontology. Indeed, an annotation pattern represents a conceptual solution to a problem related to the annotative activity. The annotation pattern proposes a solution (the semantic of the annotation) to a problem (find this semantic for a given annotation shape in a given context according to learner’s personality traits). Our annotation pattern is composed of five elements presented in Table 1.

Table 1: Annotation pattern

Pattern name				
Pattern destination				
Problem to be solved	Physical aspect	Anchor		
		Shape		
		Annotated content		
Pattern context	Contextual aspect	Annotator	Name	
			Personality traits	Conscientiousness Neuroticism
			Age	
			Native language	
		Date		
		Place		
		Device		
Proposed solution	Semantic aspect	Annotative act		
		Annotation goal		
		Service community	Name	
			Goal	
		Effect		

4. Evaluation

We propose in this article an approach of recommendation of web services from the annotative activity of the learner. This process of recommendation is based on two preparatory phases: the discovery of web services which can meet the goals of annotations made by the learner (web service discovery module), and modelling learner’s personality profile through analysis of annotation digital traces in learning environment (profile constructor module).

We focus in this stage of work on the evaluation of the two modules mentioned above through empirical studies realized on groups of learners based on the Student’s t-test to evaluate the utility of our proposed approach.

4.1 Evaluation of the Web Service Discovery Module

To evaluate the effectiveness of the web service discovery module, we integrate this module in an annotation system called “New-WebAnnot” (see Figure 4) developed in the work of Kalboussi et al.

(2014, 2015a). The choice of this tool is justified by the fact that it represents an annotation system offered to the learner to annotate his learning activates.



Figure 4. The annotation system “New-WebAnnot”.

We tested the use of this system by a contribution to another classic annotation tool that does not provide assistance with web services for two different students’ samples. The experiment lasted four reading sessions of a set of English courses. In two different samples (A, B), 60 students (A with $N_1 = 30$ and B with $N_2 = 30$) had spent two sessions per week that lasted an hour of reading in university room equipped with computers.

- Computers in sample A are equipped with the annotation plug-in “New-WebAnnot” in their Mozilla Firefox web browser.
- Computers in sample B are equipped with a classic annotation plug-in ‘Annozila’ in their Mozilla web browser.

We presented to the students of sample A six categories of web services which can be invoked during the annotation session to meet the goals of some annotations made by the learner. These services are:

- *Dictionary service*: helps explain terms;
- *Translator service*: helps translate text;
- *Memory service*: helps memorize information;
- *Agenda service*: helps plan tasks in the future;
- *Summarizer service*: helps summarize texts;
- *Social network service*: helps share information with others via social networking.

We asked to the students to annotate English courses consulted in a specialized website which offers a free training in English. The objective of this experiment is to test the motivation of each student sample towards the presented annotation system. We try to prove that the assistance offered by our annotation system through web services motivates students to annotate more the consulted documents. To measure this motivation, we define two metrics:

- X : the number of annotations in a session for each student.
- Y : the duration of the annotation session for each student. The maximum duration of an annotation session is 60 min, which represents the time reserved for each reading session.

The choice of these two factors is justified by the fact that a student motivated to annotate realizes logically a high number of annotations, and his session of annotation lasts more than that of an unmotivated student.

The objective of this evaluation is to answer the following question: Is there a difference in the number of annotations (X) and the duration of the annotation session (Y) between the two student samples?

This means that we should test the following hypotheses:

- Null hypothesis (H_0): there is no significant difference in the means of X and Y between both samples; $H_0: \mu X_A = \mu X_B$ and $\mu Y_A = \mu Y_B$.
- Alternative hypothesis (H_1): there is a significant difference in the means of X and Y between both samples; $H_1: \mu X_A \neq \mu X_B$ and $\mu Y_A \neq \mu Y_B$.

We use the Student’s t-test statistical approach to calculate the value t_{exp} with degrees of freedom ($ddl = N_1 + N_2 - 2$).

- If $t_{exp}(\text{experimental}) < t_{th}(\text{theoretical})$, there is no significant difference (H_0).
- If $t_{exp}(\text{experimental}) \geq t_{th}(\text{theoretical})$, there is a significant difference (H_1).

The results of the Student’s t-test are obtained through the tool STATISTICA in Table 2.

- For the variable X :
 - $t_{exp} = 19.586$,
 - $t_{th} = 3.496$ for ($ddl = 58 \in [50, 60]$) and ($\alpha = 0.001$),

$t_{exp} > t_{th} \Rightarrow$ rejection of the null hypothesis (H_0) and acceptance of the alternative hypothesis (H_1).

So, we can conclude for the variable X (number of annotations of the students) that a difference between means in samples A and B at the 99.99% level is very highly significant. $P = 0.00021$ indicates that there is one in 5000 chance of being wrong for this result.

• For the variable Y :

- $t_{exp} = 13.553$,

- $t_{th} = 3.496$ for ($ddl = 58 \in [50, 60]$) and ($\alpha = 0.001$),

$t_{exp} > t_{th} \Rightarrow$ rejection of the null hypothesis (H_0) and acceptance of the alternative hypothesis (H_1).

So, we can conclude for the variable Y (duration of annotation session) that a difference between the means in samples A and B at the 99.99% level is very highly significant. $P = 0.00012$ indicates that there is one in 10,000 chance of being wrong for this result.

These results proved that there is a highly significant difference between samples A and B for the mean of X ($P = 0.00021$) and the mean of Y ($P = 0.00012$). $\mu_{XA} > \mu_{XB}$ and $\mu_{YA} > \mu_{YB}$. Thus, it is clear that our annotation system motivates more the students in sample A to annotate than the ‘Annozila’ tool proposed in sample B.

Table 2: Result of Student’s t-test realized with STATISTICA

<i>Tests t: Classmt sample (Spreadsheet)</i>									
<i>Groupe1: A / Groupe2: B</i>									
	<i>Average A</i>	<i>Average B</i>	<i>value of t</i>	<i>dl</i>	<i>P</i>	<i>N Actives A</i>	<i>N Actives B</i>	<i>Ratio F Variances</i>	<i>P Variances</i>
<i>Number of annotations during a session</i>	13.608	6.283	19.586	58	0.00021	30	30	1.347090	0.427247
<i>Duration of annotation session</i>	53.850	39.275	13.553	58	0.00012	30	30	1.616937	0.211690

4.2 Evaluation of the Profile Constructor Module

To assess whether the profile constructor module measures accurately the user’s traits, we integrate this module in the annotation system “New-WebAnnot” used in the previous evaluation, and we invited learners to annotate consulted resources on the web via this annotation tool to achieve their reading and annotation activities. Next, learners were instructed to answer a standard Five Factor Model questionnaire (the NEO-IPIP Inventory) to obtain a feedback regarding their personality based on their responses.

To show the system’s efficiency to measure accurately the scores of reader’s conscientiousness and neuroticism traits compared to the values determined using the NEO-IPIP Inventory, we applied the paired t-test to compare the scores of certain user’s personality traits obtained through the two different methods of measurement. We look to determine whether there is a significant difference between the paired values of scores. Both measurements are made on each subject in the selected sample, and the test is based on the paired differences between these two values. The test statistic is calculated as $t = \frac{\bar{x}}{\sqrt{s^2/n}}$, with \bar{x} is the mean difference, s^2 is the sample variance, n is the sample size and t is a Student t quantile with $n-1$ degrees of freedom. In our case $n = 100$.

Tables 3 and 4 show descriptive statistics of t-test measure of the difference significance between the paired values of user’s conscientiousness and neuroticism traits scores measured with two different methods: the “New-WebAnnot” system and the Neo-IPIP inventory.

Table 3: A t-test measure of the difference significance between the paired values of Conscientiousness scores measured with two different methods

Scores measured with	Mean	Std.Dv.	t-value	p-value
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“New-WebAnnot” system	25,78	4,90	-	-
Neo-IPIP inventory	26,50	20,25	-0,36	0,72

Table 4: A t-test measure of the difference significance between the paired values of Neuroticism scores measured with two different methods.

Scores measured with	Mean	Std.Dv.	t-value	p-value
“New-WebAnnot” system	64,66	6,74	-	-
Neo-IPIP inventory	63,37	21,16	0,63	0,53

Analytical results indicate that the scores of user’s Conscientiousness and Neuroticism characteristics obtained through the annotation system “New-WebAnnot” did not differ significantly ($Sig1 = 0,72 > 0.05$; $Sig2 = 0,53 > 0.05$) versus the scores measured using the Neo-IPIP inventory (Table 1 and Table 2). Thus, the experimental results show the possibility to measure some personality traits (Conscientiousness and Neuroticism) with reasonable accuracy by reference to reader’s digital annotation practices.

5. Conclusion and Futures Works

In this paper we presented a new approach of an educational recommender system which refers to learners’ annotations activities to implement personalized recommendations. We explained the architecture of our recommendation system consisted essentially of four basic modules: annotation module; web service discovery module; profile constructor module and recommendation module.

The evaluation of the two main modules (web service discovery module & profile constructor module) through empirical studies realized on groups of learners based on the Student’s t-test showed significant results. Our prior works show plainly the opportunity to consider annotations to extract certain learners’ characteristics (personality traits and learning goals) with regard to learning context (reading materials).

As future works, we hope to experiment our recommender module to test its viability. So that, we will report our experimental data and we’ll give more details about our system. Furthermore, we expect taking advantage of the combination of learner’s personality and his annotation goals which may guide our recommender system to derive other learning parameters like: learning achievement, knowing that several studies show the influence of human personality and annotation on learning performance which is useful to tailor the recommendation technology to the educational context and help to assist efficiently the learners during their learning activities.

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