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Enhancing Learner's Activities through Recommendations based on Annotations

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Abstract: 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 this paper, we propose an approach of recommendation of web services from the annotative activity of the learner to assist him throughout learning activities. This process of recommendation is based on two preparatory phases: the phase of modeling learner's personality profile through analysis of annotation digital traces in learning environment realized via 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: Recommender system, annotation, learner, personality traits, web service

1. Introduction

During the learning process, the learner's activities are numerous and especially varied. Thus, the learner can choose to read, write, listen, discuss, experiment, or annotate various resources to achieve learning goals. 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 to annotate the consulted resources (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 (Abel et al., 2010; Beham et al., 2010; Vesin et al., 2013).

In current work, we present the architecture of an educational recommender system which 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 principals 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,...) 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 usually in the learning context for different purposes and which may reflect certain learners' characteristics useful as input data for the recommendation process.

3. Annotation-based Recommender System

We follow, in our framework, a novel approach of recommendation based on learners' characteristics extracted from annotation traces yielded during learning experience. 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 (see Figure 1).

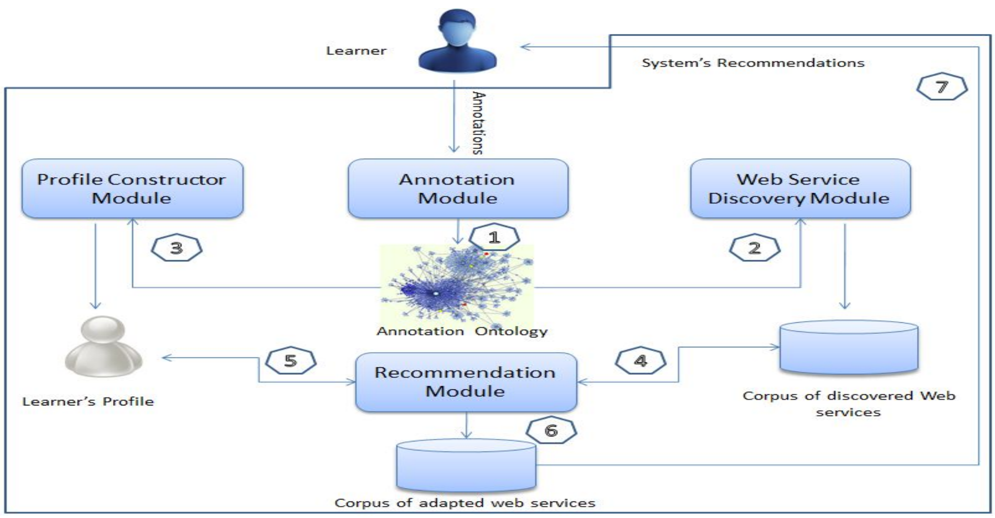

Figure 1. The Architecture of the Annotation-based Recommendation System.

The operating strategy of our recommender system is briefly described in the following steps: the annotation module saves the learner's annotations in an annotation ontology (*step 1*). Based on this ontology, on one hand, the web service discovery module offers a list of web services that can satisfy the goal of such annotation (*step 2*), and on the other hand, the profile constructor module interprets learner's personality profile through analysis of annotation digital traces (*step 3*). Afterwards, the recommendation module selects (*step 4*) and personalizes (*step 5*) a web service from those presented in the corpus of discovered web services by using the learner profile. The output of the recommendation module is presented as a corpus of adapted web services (*step 6*). Finally, the personalized web service is recommended to the learner (*step 7*).

In what follow, we describe the works carried out for the three important modules of our system, and we give an overview about their basic functionalities.

3.1 Web Service Discovery Module

Based on a new approach presenting the learner's annotative activity as a means to invoke web services implicitly (Kalboussi et al., 2013b; 2013c), the proposed recommender system tries to assist the reader via web services during 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 learner and help him to satisfy annotation goal. So, from a user's annotation, our system is able to interpret a semantics which presents a need for a web service to meet annotation goals (Kalboussi et al., 2014). From 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 (Kalboussi et al., 2013a; 2015a). The relations among the elements composing the semantic aspect of the ontology can be described as the follows: Motivated by 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 learner to satisfy his reading goal. For that purpose, we present for each reading goal the list of annotative acts realized by the learner in the reading process. For each annotative act, the corresponding one or several annotation goals are presented. This objective represents semantics expressed by the learner through the annotative act for a need for means which answer the goal of this annotation.

3.2 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., 1997). Every learner has unique individual patterns in making annotations (Naghsh, 2007). 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., 2014a; 2014b), 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., (2015a; 2015b) 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 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., 2014a; 2015a).
- 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.

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.

3.3 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 annotation practices and personality profile which is built by reference, also, to 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.

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" developed in the work of Kalboussi et al. (2014). 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.

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. Computers in sample *A* are equipped with our new annotation plug-in in their Mozilla Firefox web browser and computers in sample *B* are equipped with a classic annotation plug-in in their Mozilla web browser.

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 parameters: *X* which represents the number of annotations in a session for each student and *Y* which defines the duration of the annotation session for each student.

This means that we should test the following hypotheses:

- Null hypothesis: there is no significant difference in the means of *X* and *Y* between both samples.
- Alternative hypothesis: there is a significant difference in the means of *X* and *Y* between both samples.

We use the Student's t-test statistical approach to calculate the values of the experiment. The results of the Student's t-test are obtained through the tool STATISTICA in Table I. The 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). Thus, it is clear that our annotation system motivates more the students in sample *A* to annotate than the tool proposed in sample *B*.

Table 1: Result of Student's t-test realized with STATISTICA

Tests t : Classmt sample (Spreadsheet) Groupe1: A / Groupe2: B									
	Average A	*Average B*	*Value of t*	*dl*	*P*	*N Actives A*	*N Actives B*	*Ratio F Variance*	*P Variance*
Number of annotations during a session (X)	*13.608*	*6.283*	*19.586*	*58*	*0.00021*	*30*	*30*	*1.347090*	*0.427247*
Duration of annotation session (Y)	*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.

Tables 2 shows 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 2: A t-test measure of the difference significance between the paired values of Conscientiousness (CON) and Neuroticism (NEU) scores measured with two different methods

Scores measured with	Mean		Std.Dv.		t-value		p-value	
	CON	NEU	CON	NEU	CON	NEU	CON	NEU
"New-WebAnnot" system	25,78	64,66	4,90	6,74	-	-	-	-
Neo-IPIP inventory	26,50	63,37	20,25	21,16	-0,36	0,63	0,72	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 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 Future 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 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 learning process.

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