Dipartimento di Informatica e Automazione
Via della Vasca Navale, 79
00146 Roma, Italy

A Teacher Model to Speed Up the Process of Building Courses

Carla Limongelli, Matteo Lombardi, Alessandro Marani, Filippo Sciarrone

RT-DIA-202-2013 **January 2013**

Università Roma Tre,
Via della Vasca Navale, 79
00146 Roma, Italy

This work has been submitted to UMAP 2013

ABSTRACT

Building a new course is a complex task for teachers: the entire process requires different steps, starting with the concept map building and ending with the delivery of the learning objects to students through a learning management system. Teachers have to spend a lot of time to build or to retrieve the right learning material from local databases or from specialized repositories on the web. Consequently, having a system supporting this phase is a very important challenge, considering that each teacher expresses her own pedagogy as well. Here we propose a system to help teachers to prepare new courses. The system core is represented by a novel teacher model based both on a didactic and dynamic semantic network containing concepts and learning material and on Teaching Styles as proposed in the literature by Grasha. This framework gives teachers the possibility to share their teaching experience as well. A first experimentation of the system gives positive results.

1 Motivations and Goals

2 Motivations and Goals

Quality of teaching is undoubtedly one of the most important ingredients for student learning and consequently for a course of success independently from the delivery platform. The process of preparing a new course is a very complex process where the teacher is involved in several tasks such as: i)building the concept map; ii)retrieving learning material from some didactic repositories or building a new one; iii) building a didactic storyboard; iv)delivering the course on a suitable didactic environment. Our research addresses the course building process, in order to give teachers an instrument to speed up the overall process, decreasing their working load and increasing the quality of their didactic material. We propose a personalized approach to the course building process, where a model of the teacher, is based both on the Teaching Experience (TE) and on Teaching Styles (TS). The TS is based on the Grasha TS model [6], composed of five different dimensions while the TE is a dynamic framework which changes with the teacher's didactic choices, i.e., with her teaching experience and teaching styles. Such a semantic network is a directed graph composed by those concepts and by those learning materials used by teachers of a community to build courses. To each node of the network are linked all those learning materials used by the teacher to build a didactic concerning that particular concept. Furthermore, each link of the network has an associated weight which changes with time according to a dynamic temporal low based on the ant theory [5]. Starting from this framework, in this paper we address the following research question: can our teacher model help teachers to retrieve didactic material in order to build new courses faster and better? To test this research questions we built a framework, i.e., a 3-tier web application and by means of a sample of teachers we experimented their TM. In the literature there is few research on teacher's modeling, as the works of Grasha [6] and Felder and Silvermann [4] while the student modeling aspect has been more widely addressed (see for example [1, 7, 8]. We believe that a teacher centered research should be addressed as well, in order to give teachers a personalized support taking into account their own pedagogy, styles of teaching, and teaching experience. Our model takes into account all these components in a dynamic way. The paper is structured as follows. In Section 3 the proposed model is shown.In Section 4 we propose the learning material mechanism. In Section 5 is shown the prototype system embedding the dynamic framework while in Section 6 the first experimentation of the model is performed. Finally in Section **??** conclusions are drawn.

3 The Teacher Model

To represent a teacher it is necessary to know at least both her way of teaching and her teaching experience. The teacher's teaching style and the information about concepts and materials chosen for the different courses taught, contribute to describe the Teacher Model. It has an *educational* component given by Teaching Styles, and an *ontological* one, given by all her own courses during her teaching activity: Teaching Experience (TE). In particular, the educational component builds a teacher profile regardless of the specific course taught. This component will be helpful to identify teachers who have similar

teaching styles. The ontological component is the teaching experience, where courses are represented by ontologies. Summarizing, we have: $TM =$<Teaching Style, Teaching Experience>.

3.1 The Teaching Styles

As we said in the previous Section, Teaching Styles are devoted to detect pedagogical attitudes of the teacher. In our work we used the model of teaching styles proposed by Grasha [6], where they are represented by the following five categories: *Expert, Formal Authority, Personal Model, Facilitator and Delegator*. Each style is represented by a real number in the range $TS = [1.0, 7.0]$ and teachers can detect their own teaching styles at the Grasha-Riechmann Teaching Style Survey web site[1].

3.2 Teaching Experience

Teaching Experience representation is more complex to manage being composed by information coming from all courses built by the teacher. A course is represented by an ontology, i.e., a direct graph, based on prerequisite relationships between nodes, i.e., the concepts used by a teacher in all her courses. Every concept is linked to all the didactic material retrieved and used to explain that concept. The union graph of all the ontologies related to a teacher represents her teaching experience and we call it Didactic Semantic Network (DSN).The DSN contains all the courses taught by the teacher over her teaching life.

We define a course by the following triple: $C_j =< L_j, T_j, O_j >$ where L_j represents the general level of the course (elementary, middle school, university level...), T_j indicates how many times the teacher thought that course and O_j is the ontology related to that course.

A concept c_k is defined as:

$$c_k =< name, L_k, \{RC_q\}, \{< LM_i, n_{k_i}, e_k >\} >$$

where *name* is the name associated to that concept, L_k is the level associated to that concept, RC_q is a prerequisite concept and LM are possible learning materials associated to that concept with some information about the use of that material from the rest of the community (n) and the teacher herself (e).

The set of all concepts contained in teacher's courses constitutes the DSN of the Teacher Model. Given a teacher we define her DSN as follows:

$$DSN = \bigcup_{j=1}^{n} O_j$$

where n is the number of courses thought by that teacher and O_j their ontologies.

At the beginning a teacher has associated only her Teaching Styles, while her teaching experience is empty.

[1] http://longleaf.net/teachingstyle.html

3.3 The Connection Concept - Learning Material

Each concept c in the DSN is associated to a list of Learning Materials and each association is labeled with a weight $\rho_{k,i}$ that depends on $n_{k,i}$, representing the *social* aspect, and e_k and the *personal* aspect of the teacher. The parameter $n_{k,i}$ represents how many times the i-th material has been chosen for the concept k-th by all the teachers belonging to the community, so tracing the popularity of this link. This component excludes, if used alone, the personal choices of the teacher: the parameter e_k represents the experience of the teacher in teaching the concept k-th. Therefore, is fair to give a higher weight to the link as the teacher acquires experience in teaching the concept k-th.

We define the weight ρ as:

$$\rho_{k,i} = n_{k,i}\lambda + e_k(1-\lambda) \quad \text{with } \lambda \in [0,1] \tag{1}$$

The contribution of the individual components is balanced by the value assigned to the constant λ. A high value for λ shifts the weight on social aspect, on the contrary teacher experience is magnified. n and e are updated as follows:

$$n_{k,i}^{new} = \begin{cases} n_{k,i} + 1 & \text{if someone else has chosen that } LM_i \\ n_{k,i} & \text{else} \end{cases} \tag{2}$$

$$e_{k,i}^{new} = \begin{cases} e_{k,i} + 1 & \text{if the teacher has chosen that } LM_i \\ e_{k,i} & \text{else} \end{cases} \tag{3}$$

Another key feature is the dynamic computation of weights. What we want to look for is a strengthening of connections when the teacher selects a given LM, and a consequential weakening of all other connections between the concept and the LMs that are not chosen.

3.3.1 Weight updating

In order to model the behavior of the connections with time, we observe that in the literature there are mainly two approaches to such problems of learning: the Logistic function that is usually employed for weights updating in Artificial Neural Networks [9], and the ANT System approach by pheromone updating [5].

Logistic function is defined in $[0,1]$; in our case, since ρ is always a positive number, the interesting co-domain is restricted to $[0.5,1]$. We might overcome this problem by letting ρ to assume also negative values, but it would raise a semantic problem, in fact ρ would lead to give too high advantage to the new materials associated. Indeed, the first choice of a material for a certain concept, $\rho_{k,i}$ would be equal to 1 since both $n_{k,i}$ and e_k are equal to 1, in fact the convex combination of two numbers equal to 1, (regardless of the value of λ) will always be equal to 1. Therefore it would happen that the logistic function would assign as first choice $\rho = 0.5$. To address this problem we can shift the x-axis by a positive constant, however, since such a function domain interval is $(-\infty, +\infty)$ is not easy to understand how to translate the logistic function without making it too expensive to climb to 1 and maintaining the fair semantic meaning.

A better tailored approach for our purpose is the ANT System approach by pheromones updating [5] based both on evaporation rate and on the choice made by ants (teacher) to follow (choose) or not a given path (link between concept and LM). This function

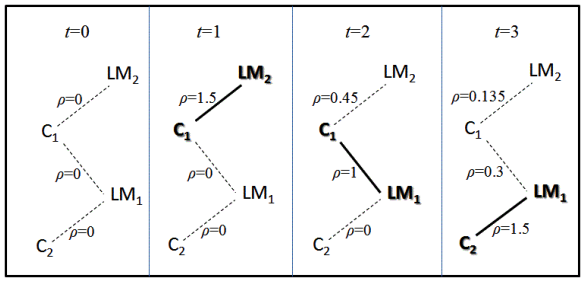

Figure 1: The evolution of weights.

Table 1: Weights updating.

	(C_1, M_2)			(C_1, M_1)			(C_2, M_1)		
t	n	e	$\rho_{1,2}$	n	e	$\rho_{1,1}$	n	e	$\rho_{2,1}$
0	3	0	0	2	0	0	2	0	0
1	3	1	1.5	2	0	0	2	0	0
2	3	1	0.45	2	1	1	2	1	0
3	3	1	0.135	2	2	0.3	2	2	1.5

is inversely proportional to the length of the path followed by ants, and directly proportional to the number of ants that have chosen that path, since they leave a fixed amount of pheromones. In our case the system proposes to the teacher the choice of the LM with highest ρ and if the teacher chooses that material the weight becomes stronger, on the other way the weight decreases, basing on the following function:

$$\rho_{k,i}(t+1) = (1-\tau)\rho_{k,i}(t) + \Delta\rho_{k,i}(t) \tag{4}$$

where τ is the evaporation rate, and $\Delta\rho_{ij}(t)$ is defined as

$$\Delta\rho_{k,i}(t) = \begin{cases} n_{k,i}\lambda + e_k(1-\lambda) & \text{if } LM_i \text{ is chosen to explain } C_k \\ 0 & \text{else} \end{cases} \tag{5}$$

where $n_{k,i}\lambda + e_k(1-\lambda)$ is the weight $\rho_{k,i}$ (see Eq.1).

3.3.2 An Example

Let us show with an example the weight updating in the case of two concepts C_1 anc C_2 and two learning materials LM_1 and LM_2. At the beginning there are no associations among them (see Fig. 1). Let us also suppose that LM_2 has been already chosen 3 times from other teachers ($n = 3$) and LM_1 twice. In any case for $t = 0$ all the weights are 0. At $t = 1$ the teacher chooses LM_2 for the concept C_1, so by applying 4 we have $\rho_{1,2}(t = 1) = 0.3 \cdot 0 + 3 \cdot 0.5 + 0 \cdot 0.5 = 1.5$, being $\rho_{1,2}(0) = 0$ and $\Delta\rho_{k,i}(0) = 3 \cdot 0.5 + 0 \cdot 0.5$. The experience e related to LM_1 increases by 1 (see 3). The entire computation is shown in Tab. 1. Moreover function 4 is normalized in $[0, 1)$ by means of *arctangent* function, that provides a smooth growth of the weights.

4 Learning Material Retrieval

With respect to Learning Material suggestion, we implemented two algorithms for LM retrieving. A *dummy search*, with the only purpose of verifying the actual added value of search that uses the teaching model presented.This research is concerned with simply search for all the materials associated with any concept that has the same name as the concept teacher is looking for LM, without distinction from the teaching context, ontology, the cluster membership of teachers who have used that material, etc. ... Therefore, with this simple search will be possible to compare other Learning Material Retrieval techniques.

An *ontological search* algorithm, that selects the ontologies basing on a *distance relation* among ontologies. The LM associated to the closest ontology is suggested to the teacher.

The algorithm for distance evaluation is briefly described form a qualitative point of view. It is based on the idea presented in [3] that defined an algorithm for stating concepts similarity w.r.t. the ontology that contains them. For our purpose we consider three kind of distances:

- The Hamming distance between the nodes common to both ontologies d_h
- The incidence of common nodes on the nodes common to both ontologies d_N
- The ratio of excess nodes (Nodes Exceeding Ratio, NER), defined as the ratio between the cardinality of ontology largest and the cardinality of the of common nodes (CN).

$$d = d_h + d_N + NER$$

For this similarity measure, symmetry and reflexive properties hold, but it is not a metric since triangle inequality does not hold. This is due to the fact that for graphs sometimes triangle inequality is too restrictive or incompatible with the considered problem domain [2].

5 The Prototype System

In this Section we briefly describe the framework implemented to experiment the LM selection by teachers whose model has been just proposed. The system is still a working progress, but the main functionality are already provided. In fact the system can:

- create a community of teachers;
- classify teachers into groups according to their Teaching Styles;
- record all actions taken by the teachers in the development of the courses;
- save the associations of Learning Material with the concepts taught in the courses;
- suggest teachers learning materials deemed most relevant for each concept;
- record selected LM, updating the SDN of the teacher who made the selection.

Finally, the system wa implemented as a 3-tier web application, available at http://193.204.161.55:8080/

6 TM Evaluation

In this Section we propose a first evaluation of the TM as explained in Section 3. We evaluated the model and its added value to the retrieval of learning material from the local database. To this aim we used our prototype available on the web to allow remote teachers to partecipate to the experiment.

6.1 The Research Question

As stated in Section 2, the research question to test is if the proposed TM can help teachers in the course building process. In the first evaluation the teacher, after having used the system was asked to assess the ranking of didactic material as proposed by the system while in the second evaluation the teacher was asked to assess her model. According to the proposed TM, we evaluated the TE component of the model. In this first evaluation we set the parameter λ to 0.5 in order to balance in the same way the two TM components. The retrieval method was based on an ontology distance metric:first the nearest ontology was found in the didactic semantic network, and second the didactic material has been proposed.

6.2 The Evaluation Process

The experimental evaluation was divided into the following steps:

1. *The sample.* It was composed by 20 teachers, 10 from University and 10 from technical high school, randomly selected.

2. *Teaching Styles detection.* Here the teachers were required to take a self-evaluating method questionnaire from the internet at the Grasha-Riechmann Teaching Style Survey web site[2]. The Grasha-Reichmann Teaching Style Inventory is a web-based assessment, that asks for a Likert-type response to 40 of questions designed to objectively categorize teaching styles, according to the Grasha TS model. A teacher is asked to respond to statements such as *I set high standards for students in this class.* The teacher responds within a five-point range from *strongly disagree* to *strongly agree.* Teaching styles are then calculated via a numeric score and the results are presented in a table that presents whether the respondent is low, moderate or high, based on the numeric outcome, in a particular style. As output one has five real numbers representing her teaching styles. These numbers were used by the system to insert each teacher into the Grasha clusters to set the TS component. In Fig. 2 the TS distribution of the sample is shown.

3. *Local Repository Analysis.* Teachers were invited to analyze the learning material already stored in the local repositoy[3], with the possibility of adding new didactic objects.

4. *Concept map building.* In this phase teachers were required to build a new concept map to start a new course on java programming. In Fig. 2 we show a screen shot

[2]http://longleaf.net/teachingstyle.html
[3]http://193.204.161.55/fondinf

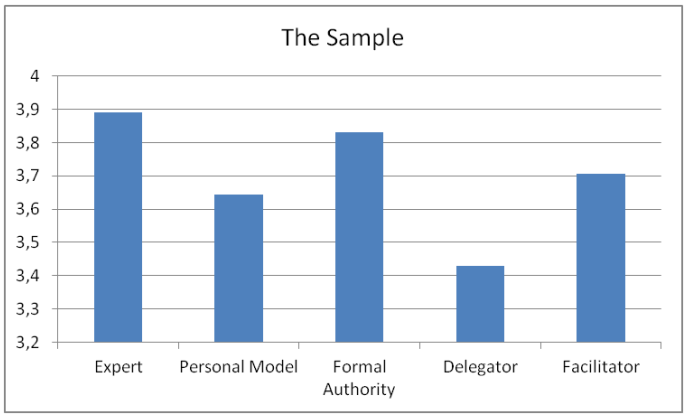

Figure 2: The distribution of the Grasha Teaching Styles of the sample.

of the concept map setting: teachers could build the ontology starting from the concepts already stored in the local data base. The system allowed for concept prerequisite setting. In this way a didactic semantic network for each teacher was built.

5. *Learning material retrieval.* In this step teachers were asked to retrieve didactic material from the local repository. The system, in order to better evaluate the different components of the TM, proposed two modalities of retrieval: i)dummy retrieval,i.e., the learning material was retrieved and proposed without taking into account the TM;ii)TE retrieval: the learning materials are proposed to the teacher starting from the concepts shared among different ontologies, as explained in Section 3, i.e., by means of an ontology distance metric. In Tab. 2 an example of retrieval is shown. The user searched for some learning material from the local repository, to link to the boolean concept. The system retrieved three materials:booleani1, booleani2 and booleani3 and the user was required to assess the ranking of the retrieved learning material through a 7-points Likert scale(not at all, strongly disagree, disagree, neutral, agree, strongly agree, very strongly agree). Next the teacher was asked to select the learning material to link to the boolean concept. This procedure to be performed for each concept of the course to build.

Material ID	**Weight**
boolean1	0.65
boolean2	0.48
boolean3	0.17

Table 2: An example of learning material retrieval and ranking: the boolean concept.

6. *Model assessment.* Finally, once having completed the connections learning material-concept, teachers were required to assess their own model through a 7-points likert scale. In particular teachers assessed the ranking of the proposed material for each concept of their course to build.

6.3 Experimental results

The results are shown in Fig. 3 e Fig. 4. In Fig. 3 the evaluations on the retrieved material, ranked by the system according to the teacher model is shown. As we can see, the dummy retrieval system, histograms with full color, have their distribution shifted towards low levels of the likert scale with respect to the ontological retrieval, represented by dashed histograms. Most users have appreciated the contribution of the user model. In Fig. 4 we show the last assessment, i.e., the teacher model assessment. Here also the 70% of users have appreciated their model, expressed as the way by means the system proposes a ranking of didactic material.

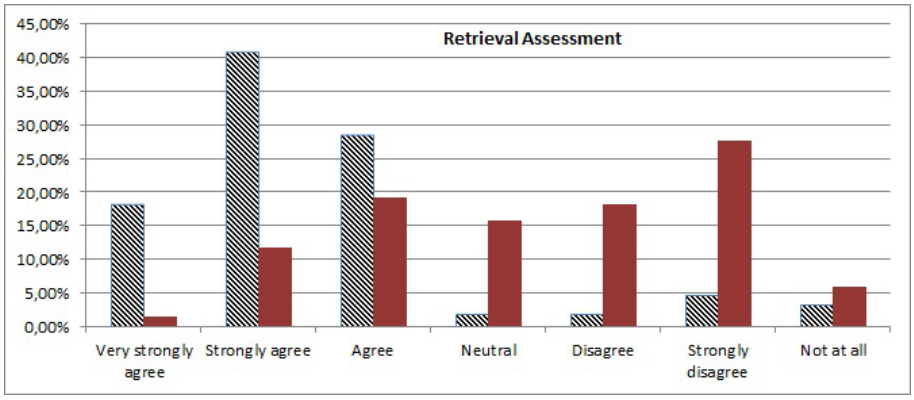

Figure 3: Experimental results for the retrieval assessment.

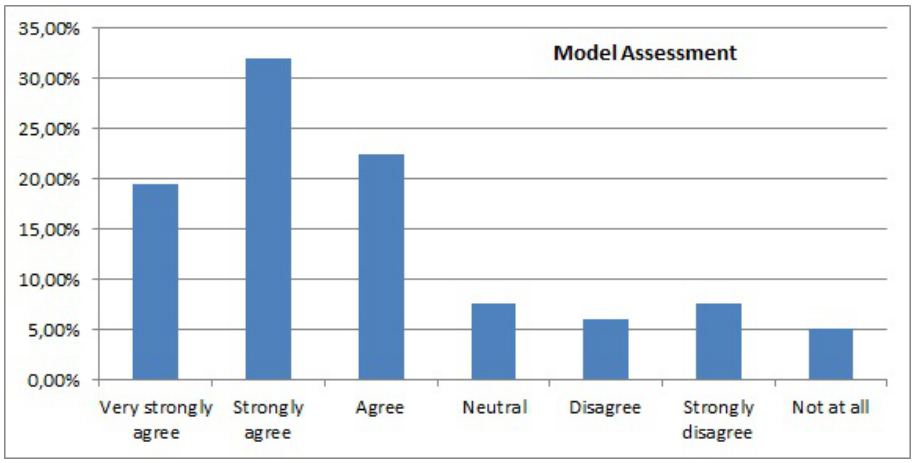

Figure 4: Experimental results for the TM assessment.

6.4 Research Conclusions

With respect to our research question, we can say that the first experimental results are encouraging. Certainly we did not perform a hypothesis test to inference from our sample to the entire universe of teachers, but this task is planned for the next future. Moreover here we tested one component only of the TM, i.e., the TE component.

References

[1] P. Brusilovsky and E. Millan. User models for adaptive hypermedia and adaptive educational systems. In P. Brusilovsky, A. Kobsa, and W. Nejdl, editors, *The Adaptive Web: Methods and Strategies of Web Personalization*, volume 4321 of *Lecture Notes in Computer Science*, pages 3–53. Springer-Verlag, Berlin Heidelberg New York, 2007.

[2] Horst Bunke and Kim Shearer. A graph distance metric based on the maximal common subgraph. *Pattern Recogn. Lett.*, 19(3-4):255–259, March 1998.

[3] Rosario Culmone, Gloria Rossi, and Emanuela Merelli. An ontology similarity algorithm for bioagent. In *Proceedings of the Workshop Agents in Bioinformatics (NETTAB 02), Bologna 12-14 July*, 2002.

[4] R. M. Felder and L. K. Silverman. Learning and teaching styles in engineering education. *Engineering Education*, 78(7):674, 1988.

[5] M. Dorigo G.Di Caro L.M. Gambardella. Ant algorithms for discrete optimization. *MIT Press Journals*, 5(2):137–172, 1999.

[6] A. Grasha. *Teaching with Style: A Practical Guide to Enhancing Learning by Understanding Teaching and Learning Styles.* Alliance, 1996.

[7] Carla Limongelli, Alfonso Miola, Filippo Sciarrone, and Marco Temperini. Supporting teachers to retrieve and select learning objects for personalized courses in the moodlels environment. In *ICALT*, pages 518–520, 2012.

[8] Carla Limongelli, Filippo Sciarrone, Marco Temperini, and Giulia Vaste. Adaptive learning with the ls-plan system: A field evaluation. *IEEE Transactions on Learning Technologies*, 2(3):203–215, 2009.

[9] Tom Mitchell. *Machine Learning.* McGraw-Hill, New York, 1997.