Handling Uncertainty and Multiple Perspectives for Learner Modeling by Cognitive Mapping

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Abstract. This research deals with two issues for learner modeling: uncertainty and multiple perspectives. Hence, it proposes a process called cognitive mapping to acquire and describe objects of a domain of study, and set fuzzy-causal relationships among them. Objects are characterized as linguistic variables that are instantiated by linguistic terms; whereas relations are outlined by means of fuzzy-rule bases. So objects and relations are statements of qualitative knowledge that are measured in terms of nature and degrees of bias to reveal uncertainty. The representation of multiple perspectives of the learner is sketched through the topology of a cognitive map and the qualitative measures attached to objects and relationships. This approach was tested in an E-learning trial, its outcomes show the effectiveness of the learner model to enhance the apprenticeship of volunteers due to the successfully handle of uncertainty and multiple perspectives.

Keywords. uncertainty, multiple perspectives, learner model, cognitive maps

Introduction

Learning modeling is the process by which a Web-based Education System (WBES) acquires information about its user, transforms such knowledge, and outlines the result into an internal representation [1]. This complex process pursues to describe conceptual objects and phenomena, such as the personality and the apprenticeship of a learner.

A learner model is usually a dynamic representation of the emerging skills and knowledge of the user. Such model embraces a knowledge repository and an engine to set beliefs about a learner, and achieve some kind of inference about her/his behavior.

Therefore, learning modeling faces some issues, such as: uncertainty and multiple perspectives. Uncertainty means: imprecision, incompleteness, temporality, non-monotonicity, and unsoundness. Multiple perspectives give away that: a learner is a target of representation from several viewpoints according to specific goals of study, domains that are taken into account, and the attributes, methods and tools that are used.

Uncertainty has been tackled from several research lines, for instance: some works use Bayesian networks to depict probabilistic learner models that estimate student’s knowledge [2]. Also, fuzzy set theory is used in the assessment of students to personalize her/his navigation [3], and the prediction of the final mark achieved by a learner by means of fuzzy inductive reasoning [4].

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As regards multiple perspectives, there are some interesting works such as: the Theoretical Perspectives Model, which states that student success is determined by the student’s internal, the family, the school, and the broader social, economic, and policy contexts [5]. The system for student modeling LeCo-EAD provides three companions: collaborator, learner, and trouble maker. Such companions work together and support learners [6]. Also, the research on an implicit communication channel to provide knowledge about: problem domains, communication, and learners’ stereotypes [7].

According to the related works, my learner modeling approach merges fuzzy logic theory with causality by means of cognitive mapping. This paradigm manages uncertainty and multiple perspectives in the way stated in the subsequent sections: 1) sets the underlying model; 2) depicts the representation of uncertainty; 3) states how multiple perspectives are generated, outlined, and handled; 4) resumes a case study to test the approach. In the last section the results are set, and the future work is stated.

1. Underlying Model

The learner modeling based on cognitive mapping takes into account the student model’s formal foundation stated by Self [8], and the review of cognitive mapping [9]. Both items are used in this approach in the way explained in the following two sections.

1.1. Learner Model Representation

The learner model’s repository essentially holds knowledge and beliefs about a student. Knowledge is stated by a set of facts that reveals some attributes of the learner with certainty and precision, e.g. the affirmation that: “a student is absolutely blind”. Beliefs are truthful judges that assert, with some degree of uncertainty or imprecision, that a learner owns some attributes, e.g. the statement that: “a user meets a high depression”.

Facts and judges are affirmations with different level of certainty and precision. They are stated by propositions of the propositional calculus. Hence, such affirmations can be assessed as true or false. So it is said that: the learner model is aware of the user according to the assertions that it holds about her/him. Hereby, Eq. (1) depicts the set of prepositions ($p$) that the learner model ($m$) asserts ($A_p$) about a given learner ($U$).

Thus, for any domain oriented to characterize a student, as the teaching domain ($T$), the learner model owns a set of propositions ($A_m p$) that it asserts that is true about the learner, such as: $T_m (U)$ in the way shown in Eq. (2). In consequence, any domain embraced by a learner model is stated through Eq. (2). So, letter $T$ is replaced by the symbol that identifies another domain, such as: $P$, $L$, $C$, and $K$ which correspond respectively to personality, learning preferences, cognitive, and apprenticeship domains.

Wherefore, the repository of the learner model ($LM$) about a given user holds the union of sets of propositions believed by the learner model in the way shown in Eq. (3).

$$A_m (U) = \{ p \mid A_m p \ (U) \}$$

$$T_m (U) = \{ p \mid A_m p \ (U) \cap p \in T \}$$

$$LM \ (U) = T_m (U) \cup P_m (U) \cup L_m (U) \cup C_m (U) \cup K_m (U)$$
1.2. Cognitive Maps Conceptual Model

Cognitive Maps (CM) is a term used to name a mental model that a human being develops to represent a causal phenomenon. The interest in causality lies in: cause-effect viewpoint is a reference for a post-hoc explanation of real world events. The baseline of causality rest on a philosophical principle which claims that: any fact has a cause, and given the same conditions, the same causes produce the same consequences.

A CM is externalized as a digraph, whose nodes represent objects of the study domain, and its arcs show cause-effects relationships between objects. The arrowhead of an arc reveals the individual’s belief about: how an object is the responsible for the perturbation on the state of another object. Based on the common sense of people, causal inferences are achieved to estimate behavior along the time.

The description of a CM is done by qualitative knowledge. Thus, objects are stated as concepts, and relationships are set as influences. Concepts are outlined by a term, a definition, and a state. Term labels the concept, definition sets the meaning, and state reveals a concept’s attribute that is qualitative measured. Such quantity shows a kind of level or a variation. A level brings out the difference between a state’s value and its normal value in a given time, e.g. if the normal intelligence quotient (IQ) is 100 points, and a user holds 120, the state’s level of her/his IQ is: high. Variation shows a tendency during a while. So a cording to the evolution of a state, a variation is outcome, e.g. if a learner is not interested in math at the beginning of a course, but after her/his first lecture she/he is excited, it could be said that: the state’s variation is: increases much.

As regards influences, they are represented by a couple of terms and a label. Terms identify concepts involved in a causal relationship. The label reveals a sort of bias. When two concepts (ca $\rightarrow$ cz) hold a causal relation, it is a direct relation. But, if at least one concept, cb, appears in the path that joins a couple of concepts (ca $\rightarrow$ cb $\rightarrow$ cz), this is an indirect relationship. Indirect relations are based upon the syllogism hypothetic. Feedback occurs when in a path one concept appears two or more times, as (ca $\rightarrow$ cb $\rightarrow$ … $\rightarrow$ cz $\rightarrow$ ca); whereas a concept’s self-feedback is depicted as: ca $\rightarrow$ ca.

2. Dealing with Uncertainty

Learner modeling faces uncertainty due to the domains used to represent a user embrace intangible attributes of a learner. Also, criteria devoted to evaluate those attributes outcome approximate measures. Hence, in this approach uncertainty is met from three questions: 1) Which are the paradigms to evaluate the domains? 2) How to measure level and variation values for the concepts’ state of the domains? 3) How to represent the causal bias that a concept exerts on another concept? The responses for such questions are resumed as follows [10]:

2.1. Paradigms Used to Evaluate the Learner Model Domains

According to the formal model, five paradigms are used to evaluate the learner model’s domains. The decision took into account the soundness of the model, the empirical evidence, and their orientation to the teaching field. Such paradigms are described next:

The teaching domain depicts the attributes of the lectures delivered by a WBES. Its evaluation reveals the learning theory (objectivist, constructivist,…), the media (video, text,…), the interactivity (passive, dynamic,…), and the content’s complexity.
The personality domain is evaluated by the Minnesota Multiphasic Personality Inventory (MMPI). This test estimates the presence of mental issues, behavior patterns, and customs. The diagnostic reveals a scale of intensities for 45 personality attributes.

Gardner’s Multiple Intelligence model (GMIM) is used to measure eight styles of the learning preferences domain, such as: intrapersonal, interpersonal, linguistic, and logical. A level of liking for each style grows from a quiz that the learner answers as true or false. Later on, a qualitative measure is stemmed form a numerical conversion.

The cognitive domain is characterized by means of the Wechsler Adult Intelligent Scale (WAIS). The test measures eleven verbal and performance skills. Afterwards, the IQ is estimated according to the quantity achieved by the two types of skills. Next, the quantitative values are shifted to qualitative measures by means of a conversion scale.

Apprenticeship domain is tackled from the Taxonomy of Educational Objectives (TEO) proposed by Bloom. The scale owns six tiers to revel the level of mastering that a learner holds about a concept. Layers are identified according to an ascending order of mastering as follows: knowledge, comprehension, application, analysis, synthesis, evaluation. A tier is assigned when learner successfully masters specific cognitive tasks.

2.2. Assignment of Values to the Concept’s States

The measurement of concepts’ state produces uncertainty, because of evaluation paradigms outcome values that are an approximation of abstract attributes. This issue is met by the application of the Fuzzy Set theory [11]. Hereby, the state of the concepts is considered as a linguistic variable. The assumption facilitates to attach variation or level values. Such qualitative values are called linguistic terms. A term is graphically shaped by a membership function like a trapezoid, a triangle, or a Gaussian bell. The suitable set of terms for a given concept’s state is called a universe of discourse (UOD).

A UOD devoted to depict levels embraces terms that are arranged in ascending degree of intensity, such as: {null, quit low, low, medium, high, quit high}. Variations are stated by a UOD that gives away negative and positive series of intensities. These series are arranged in descending and ascending order, and includes a neutral term as follows: {decreases much, medium, low, maintains, increases low, medium, much}.

2.3. Representation of Causal Bias between Concepts

The relation between two concepts expresses a merge of causal and fuzzy knowledge. Causality reveals that: the state’s value of a cause concept exerts a causal bias on the state of an effect concept that is able to update its level or variation current value. The causal bias is fuzzy measured by direction and intensity. Direction reveals an excitatory effect, or an inhibitory bias. Intensity gives away the degree of influence produced on the state of the effect concept. Both viewpoints are stated by linguistic terms of a UOD.

A concept’s state is set as a linguistic variable that is instantiated by terms of a UOD, so it is necessary to define a fuzzy rules base (FRB) [11]. A rule contains an antecedent and a consequent. The antecedent reveals the condition to be met in order to produce a bias. The consequent shows the bias that is exerted on the effect concept’s state. Thus, a fuzzy rule claims that: according to the linguistic term that a cause concept’s state holds in any point of time, the state’s value of the effect concept shifts to the measure set by the consequent linguistic term. A FRB holds just one fuzzy rule for each linguistic term of the UOD attached to the cause concept. The fuzzy-causal inference is fully stated in [10, 11], whereas an example of a CM is shown in Figure 2.
3. Representation of Multiple Perspectives

According to the target of study, an individual is represented by a learner model. Such model embraces one or more domains. A domain owns characteristics that focus on specific learner’s attributes. The description of such attributes is set by an evaluation paradigm. The sort of paradigms devoted to depict a domain could be plentiful. These factors explain: how learner modeling deals with multiple perspectives. Thereby, in this section the factors that represent such viewpoints are identified. Moreover, a process to outcome perspectives is stated. Also, the management of such perspectives is resumed.

3.1. Sources to Outcome Multiple Perspectives

The contribution of my learner modeling approach is the introduction of CM, as a tool to depict a learner. Hence, the representation of multiple perspectives of a given individual is quite easy according to the following arguments:

1) The number and variety of domains included in the learner model. This work shows five domains, but the approach can be extended to include many more. 2) The paradigms used to evaluate each domain can be replaced by others. 3) The quantity of attributes that characterize a domain can be altered according to the research. 4) The value of the concepts’ state can be different. More than one UOD can be set to reveal several gray levels of uncertainty. 5) The quantity and the nature of the relationships in a CM. Relations are introduced or ignored in a version of a CM to reveal a perspective. A relation can be measured from different fuzzy-causal viewpoints, so one FRB is outcome to represent each of them. 6) A CM can be tailored in several ways (topology, state’s values, FRB) to outcome different perspectives that focus on specific targets.

A huge number of perspectives for a learner model grow from the combinations of the following factors: the number of domains, the sort of evaluation paradigms, the quantity of attributes, the kinds of values for estimating the concepts’ state, the number of options for measuring relations, and the ways to tailor the topology of a CM.
3.2. Development of Multiple Perspectives

Essentially, a perspective of the learner model is characterized by means of a given version of CM. Any CM contains a repository and an engine. The repository holds information about concepts, values for the concepts’ state, relationships, and one FRB attached to each relation. The engine represents the mechanism to achieve fuzzy-causal inferences [10, 11]. The items and the topology of a version of CM represent a particular viewpoint. However, due to a learner model is analyzed from multiple perspectives, a general framework is used to depict, outcome, and manipulate each CM.

The representation schema owns three layers. The first layer holds the ontology that semantically defines the components of a CM. Also, it owns a meta-data file to set the structure of the domain’s repositories. In the second tier, the knowledge about the domains that describe the learner and the content is administrated. Thus, apprenticeship, personality, cognitive skills, and learning preferences attributes are stated by a set of files. Also, the teaching domain is outlined in a repository. The third layer is a work area, where the values produced during the exploration of a CM are stored [10].

A version of a CM is tailored according to one specific combination of instances of domains, evaluation paradigms, attributes, relations, and topologies. The approach automatically scans the ontology and the domain’s repositories to outcome a particular perspective. Any version of CM is stored in the third layer of the representation schema.

Once a version of CM is set, a simulation is fulfilled to predict causal behavior and outcomes. The simulation deals with a CM as a dynamic system. So fuzzy-causal inferences are carried out to estimate the bias that concepts exert each other. The mathematical bases used to achieve such qualitative reasoning are stated in [9, 10, 11]. Also, the empirical testing of the application of this inductive engine is set in [10].

The simulation is resumed as follows: 1) the state of each concept is initialized by the measured values for attributes of the five domains; 2) a dynamic simulation starts with discrete increments of time; 3) for every time, the bias that exerts on each concept is estimated, and as result, the state of the concept is updated; 4) if the value of the states does not change any more: the simulation ends, otherwise a new cycle begins.

3.3. Management of Multiple Perspectives

The existence of multiple perspectives for describing a given learner is useful. Hence, in this approach is claimed that: one reason to use a learner model in a WBES is to enhance the apprenticeship of the student. Thus, a requirement is set for the lectures that a WBES delivers to the learner: lectures are tailored according to different learning theories, media, ways of interactivity, and complexity. As a result, for any lecture there must be several options. This constraint means that: a learner can be stimulated through different options of lecture. However, a learner is restricted to take just one option of lecture. Wherefore, the question is: what is the best option of lecture to deliver?

The response to such question grows from the advice that a qualitative decision model gives to a WBES [10]. This model defines a cycle of tasks that is resumed next: 1) for any lecture: identify its authored options; 2) for each option: tailor the version of CM that depicts such perspective; 3) run the simulation process over the version of CM; 4) track the behavior and outcomes stemmed from the simulation; 5) compare the level of apprenticeship predicted by the simulation of each version of CM; 6) select the option that predicts the highest learning achievement; 7) deliver the best option of lecture to the student; 8) evaluate the apprenticeship acquired by the learner.
4. Case Study

Learning modeling is a field that requires experimental testing. The criterion of success is set through a reference factor. Thereby, in order to test this approach, the experiment seeks to measure the learning achievement of a sample of volunteers in a WBES scenario. The criterion of success is set as: the apprenticeship acquired by participants, whose lectures were chosen by the selection of the best perspective of their learner model, must be higher than the learning achieved by subjects, whose lectures were randomly chosen. Given such guidelines, the account of the trial is explained next.

4.1. Knowledge Acquisition

200 volunteers from Bachelor and postgraduate levels were recruited from 26 states of Mexico. Afterwards learning preferences, personality, and cognitive skills tests were online applied. During this stage, 150 participants deserted, so that at the end just 50 composed the universe. Next, the WBES delivered lectures of the teaching domain, “scientific research”, to train the universe. As a result, a sample of eighteen individuals was randomly chosen. With this sample, two sets of nine people were randomly assigned to two teams: control and experimental. Finally, a pre-measure about ten key topics, e.g. hypothesis, law, theory, was achieved. The score was the total of levels that the learner got for the ten key topics according to the six tiers of TEO, i.e. if a learner mastered the comprehension level for the concept law; this means that she/he rightly answered the question related to the knowledge level too, but she/he failed to answer the question regarding to the application level; hence, she/he receives a score of two levels. Once the learner answered the test, a total was outcome with a range of [0, 60].

4.2. Stimulus Provision

During the trial, just one lecture for each key topic was delivered to subjects. So members of the control team received lectures in a random way. On the other hand, volunteers of the experimental team were taught according to the advice provided by the learner model. Such advice grew from the qualitative decision model, early stated in section 3.3 and fully detailed in [10]. Afterwards, a post-measure was done. Thus, the same test about the ten key topics was provided to members of both teams.

5. Discussion and Future Work

As a result of the statistical analysis, a sample of measures applied to both teams is set in Table 1. In the rows 1 to 3 appear one attribute of the learning preferences, personality, and cognitive domains respectively. The first two reveal a “balance” between the teams; but, row 3 reveals that the IQ of the experimental team is lower than the IQ of the control team. Row 4 shows the pre-measure about the ten key topics, so the experimental team held a lower level than the one revealed by the control team. However, in rows 5 and 6, experimental team got a higher level of learning than the one acquired by control team. In order to propagate the sample’ results to the universe, an analysis of variance was done. As a result control team outcomes a low probability ($P$) of 0.1216 and the experimental team arrives to a $P$ of 0.0059, as appears in Figure 2.
Table 1. A sample of measures achieved by control and experimental teams during the trial.

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Control team</th>
<th>Experimental team</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logical learning style</td>
<td>44.4% quite high, 55% high</td>
<td>44% quite high, 44% high, 11 medium</td>
</tr>
<tr>
<td>Maturity personality</td>
<td>22% high, 22% medium, 55% low</td>
<td>11% high, 22% medium, 66% low</td>
</tr>
<tr>
<td>Intelligence quotient</td>
<td>44% high, 22% medium, 33% low</td>
<td>55.5% medium, 44.4% low</td>
</tr>
<tr>
<td>Pre-measure 10 topics</td>
<td>Total: 42 levels; Mean 4.7 levels</td>
<td>Total: 38 levels; Mean 4.2 levels</td>
</tr>
<tr>
<td>Post-measure 10 topics</td>
<td>Total: 174 levels; Mean 19.3 levels</td>
<td>Total: 19 levels 8; Mean 22 levels</td>
</tr>
<tr>
<td>Learning achievement</td>
<td>Total: 132 levels; Mean 14.7 levels</td>
<td>Total: 160 levels; Mean 17.8 levels</td>
</tr>
</tbody>
</table>

![Regression graph](image)

**Figure 2.** Regression graph of a regression diagram for the experimental and control teams.

In conclusion, this approach shows that the apprenticeship of people is enhanced by means of the suitable support of a learner model, which is able to deal with uncertainty and multiple perspectives. As a future work, the design of psychological tools oriented to the Web is required. Also, research about new predictive models is needed. Moreover, dynamic generation and updating of the learner model is considered.

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**References**