Case-Based Reasoning Diagnosis of Students' Cognitive Profiles on Historical Text Comprehension

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Abstract

In this contribution we present a Diagnosis model of students' cognitive profiles on Historical Text Comprehension using Case-Based Reasoning (CBR-DHTC). The proposed innovation provides a human-like diagnosis of students' cognitive profiles complementing expert's empirical knowledge with case-based knowledge acquisition. We describe the underlying model for diagnosis that was used to guide this approach. Details concerning the modeling of case structure, the definition of taxonomies, similarity measures and case adaptation rules are de-scribed. The case base initialization methodology as well as preliminary evaluation is presented. Finally, the paper ends with our conclusions and future plans.

1. Introduction

A human expert solves a diagnostic problem using rules derived from his previous experience, whereas a novice history teacher requires complete and concrete rules to vaguely estimate how his students comprehend the historical text. Our previous work presented a diagnostic model that estimates students' cognitive profiles of Historical Text Comprehension (HTC) [2]. Artificial Intelligence (AI) offers tools for the design of computer-based diagnostic models, which imitate humans in the diagnosis process [3]. One AI methodology that can be applied successfully to this problem domain is Case-Based Reasoning (CBR). CBR integrates the right balance between hard to acquire expert knowledge and more easily acquired knowledge in the form of cases. So, in the building of an Intelligent Tutoring System (ITS), CBR helps more easily than other methods to overcome problems of knowledge acquisition from the expert. Various cognitive and computational models have addressed the use of CBR, which involves the ideas of retrieving and adapting previous experience in the form of cases, to support diagnosis [4, 5]. CBR has been used in educational systems such as for modeling the memory and reasoning capabilities of a novice, for case based coach, or tutoring and help systems [6].

This paper describes the design methodology of a model for diagnosis of students' cognitive profiles on HTC using CBR. This methodology allows the diagnostic model to imitate efficiently human expert's reasoning process complementing it with empirical knowledge organized in a case base.

In Section 2 we outline the underlying model for diagnosis of student's cognitive profiles on HTC. In Section 3 we present the development of the CBR design methodology: the modeling of case structure and knowledge contained in local and global taxonomies, flexible similarity measure mechanisms, adaptation rules and the case base initialization method. In Section 4 preliminary evaluation of the system in use is presented. In Section 5 we conclude and give some short-term perspectives.

2. The DHTC Model for Diagnosis of Student's Cognitive Profiles

2.1. Student's cognitive models of comprehension

Historical text comprehension, according to the MO-COHN model, is a special kind of text comprehension that has to do with argumentative discourse and is associated with causal connections between events [1]. When comprehending a historical text the student recognizes or not instances of the three cognitive categories: *state*, *event* and *action.* Given an historical text and appropriate questions, the significance that the student attributes to a cognitive category throughout his answers, defines his *position* [2, 7]. The corresponding *justification* of student's position can be scientific or not. The *argument,* that is both the position and the corresponding justification, can be scientific or non-scientific. The argument that indicates if the student recognizes or not the cognitive category, is considered complete in case both position and corresponding justification are right. In case of right position and wrong justification, the corresponding argument re-.3 garded as a non-scientific. The same stands in case of wrong position and right justification. The recognition of instances of the cognitive categories indicates that the student uses elements of scientific thought when he tries to answer appropriate questions related to a historical text. DHTC model formulates the cognitive models of comprehension based on experimental results. Table 1 depicts in detail the general categories of cognitive models considered [6]: *Historical Thought* (HT), *Towards Acquiring Historical Thought* (TAHTnx) and *Non-Historical Thought* (NHT). TAHTnx cognitive models are categorized in more detail according to the number n of recognized by the student categories and to the number x of in-stances recognized categories. TAHT1 means that the student recognizes 1 instance of a cognitive category. TAHT1x means that the student recognizes x instances of a cognitive category, where x>1. The same stands for TAHT2, TAHT2x, TAHT3 and TAHT3x. The number n of recognized categories and the number x of recognized instances of every cognitive category formulate the cognitive profiles.

Table 1. Cognitive models and cognitive profiles of DHTC model.

Cognitive models		Number and types of rec-ognised cognitive catego-ries	Cognitive plofiles
NHT		-	very low
TAHT	TAHT1	1 event or 1 state or 1 action	low
	TAHT1x	more than one events or more than one states or more than one actions	nearly low
	TAHT2	(1 event and 1 state) or (1 event and 1 action) or (1 state and 1 action)	below in-termediate
	TAHT2x	(more than one events and states) or (more than one states and actions) or (morez than one events and actions)	
	TAHT3	1 event, 1 state and 1 action	nearly high
	TAHT3x	more than one events, states and actions	high
HT		all events, states and actions	very high

Table 1 also shows the correspondence between cognitive models and possible combinations of scientific arguments for a historical text and the corresponding cognitive profiles. The cognitive profiles determine the degree of students' learning difficulties. For example, students with *very low* profile seem to have non-historical thought and are considered to have serious difficulties in thinking historically.

2.2. Handling the qualitative information

The use of alternative answers during the experimental research, introduces a first level of approximation in de-scribing student's observable behavior, moreover in rep-resenting student's cognitive state and process. On the other hand, the hypothesis of a *complete argument* may deprive the diagnosis of valuable information and intro-duce an additional level of approximation.

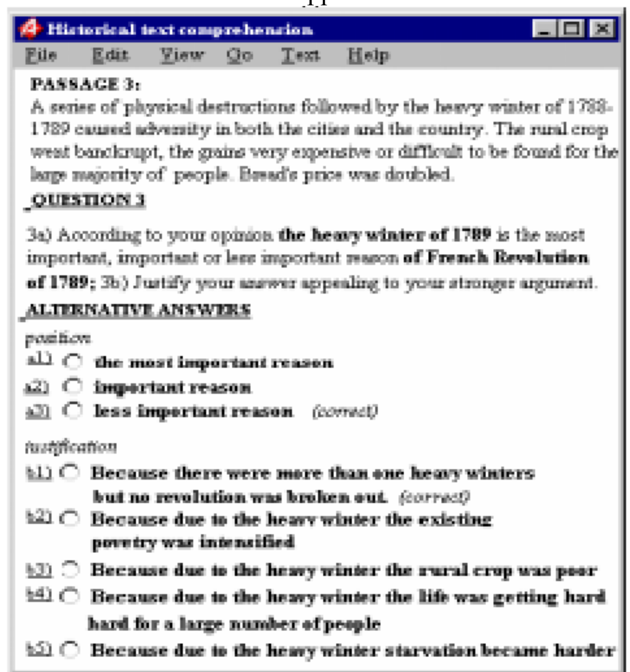

Figure 1. Part of historical text concerning the outbreak of French Revolution, questions and alternative answers.

Figure 1 depicts a part of a historical text that refers to a factor which is an instance of the category *event,* the questions 3a and 3b and the corresponding alternative answers [2]. The alternative answers a1 to a3 concern *position* supported by the student whereas the alternative answers b1 to b5 concern the corresponding *justification* supported by the student. Answers a3 and b1 constitute the scientific argument whereas all other combinations consist non-scientific arguments.

Cognitive profiles must reflect not only the quantity of *complete argument*s, but also their quality and the degree of their completeness. The quality of an argument is connected with the kind of recognized cognitive categories. The completeness of an argument is connected with the strength of position and justification. In order to exploit valuable information of this kind, detailed quantitative and qualitative descriptions pertaining to the *quality* and the *completeness* of the arguments are attached to every cognitive profile. The descriptions, that constitute the *profile descriptor*s, denote different perspectives of this profile and are defined according to the strength of the arguments. A *nearly low* profile of a student can be accompanied by the profile descriptor: “The student gives *one scientific argument of the cognitive category event, two pseudo scientific arguments of the cognitive category action and all other arguments non-scientific*".

3. The CBR-DHTC model

The CBR-DHTC model assesses student’s HTC giving two assessment results: the cognitive profile and the profile descriptor. The cognitive profile expresses a general assessment of student’s comprehension status focusing on his reasoning abilities, what he comprehends and what he does not. Moreover, the profile descriptor focuses on the student’s specific learning difficulties reflecting the cognitive categories.

3.1. The case based reasoning approach

The underlying principle of CBR is the idea to remember solutions to already known problems for their reuse during novel problem solving [6]. Typically a case, as a piece of knowledge representing an experience, comprises the *problem*, the *solution* and the *outcome*. A case-based reasoned solves new problems by adapting solutions that were used to solve old problems [8]. The similarity between two cases is mostly assessed by a numeric computation of selected surface features of the problem descriptions. The design of a diagnostic model of student’s cognitive profiles on HTC allows reasoning to be performed in the manner of an expert and based on his previous experience that is enhanced in the structure of a case base. To support this reasoning we propose a methodology that follows the steps [5, 9]: 1) analyze and author the case structure, 2) define the importance of features, the relationships and the similarity measures, 3) adapt cases and 4) initialize the case base.

3.2. Modeling the case structure

Given a historical text with questions and alternative answers, student is asked to select one answer for every question. The information is expressed in the form of an *information vector* or a *situation* Sit. A diagnostic case is represented as a list of value-pairs including student’s name and answers and completed by the empirically justified solution F, which includes his *cognitive profile* and his *profile descriptor.* In general, we may have a historical text with N factors: M *actions, K events and L states.* For simplicity, we consider a historical text with five factors: one *state*, one *event* and three *actions.* The case has the following syntactic form: C=(*casename*, *Sit*, *s-profile, profile descriptor*), where *casename* is the name of the student, *Sit*=<*p-action*1, *j-action*1, *p-action*2, *j-action2, p-action*3, *j-action3, p-event1, j-event1, p-state1, j-state*1>, where *p-action1* and *j-action1* concern the student’s position and justification for action1 respectively, *p-event1* and *j-event1* concern the student’s position and justification for event1 and *p-state*1and *j-state1* concern the student’s position and justification for state1, *s-profile* is the cognitive profile, and *profile descriptor*=<*action1, action2, action3, event1, state1*>

The case model is represented in an object-oriented fashion. The case is represented with objects (the fields). Objects consist of object classes or subclasses and are described by attributes. There are three object classes: *Position*, *Justification* and *Profile*.

Object class Position has two subclasses: *Scientific* and *Non-Scientific.* In subclass *Scientific* belong five objects that are represented by the following attributes: *p-event1, p-state1, p-action1, p-action2, p-action*3, (which stand for position). Possible values of each attribute are taken from the set: *{most important, important and less important}*. In subclass *Non-scientific* belong five objects, the same as *Scientific,* that take values from the same set.

Object class *Justification* has two subclasses: *Scientific* and *Non-Scientific.* In subclass *Scientific* belong five objects that are represented by the following attributes: *j-event*1, *j-state*1, *j-action1, j-action2, j-action3* (which stand for justification). Possible values of *Scientific* type: are taken from the set: *{event, state*, *action}*. In subclass *Non-scientific* belong five objects (the same as *Scientific*). Possible values of *Non-Scientific* attributes: are taken from the set: *{experience, attitudes, quantitative, continuity, cyclic}*.

Object class *Profile* has two objects: *HT* and *NHT* that are represented by the attribute: *s-profile* and one subclass *TAHT.* For objects *HT* and *NHT s-profile* takes the values *very high, very low* respectively*.* In subclass *TAHT* belong three objects: *TAHT-high*, *TAHT-moderate* and *TAHT-low* that are represented by the attribute *s-profile* and possible values are taken from the sets: *{high, nearly high}, {above intermediate, below intermediate} and {nearly low, low}* respectively*.*

3.3. Modeling the taxonomy

For defining the attribute types we use taxonomies [10]. The underlying data structure of a taxonomy is an nary tree in which the nodes represent symbolic values. The tree is able to behave like an indexing tree to support case-based reasoning. Within the tree, symbolic and numeric attributes can be represented and efficiently handled. The symbols at any node of the tree can be used as attribute-values in a case or a query. A taxonomy represents an additional relationship between the symbols through their position within the taxonomy tree. This relationship expresses knowledge about the similarity of the symbols in the taxonomy. The taxonomy contains knowledge of two types: 1) about classes of objects that are rep-.5 resented by inner nodes of the taxonomy tree and 2) about the similarity between leaf nodes of the taxonomy tree.

3.4. Modeling the similarity measures

The similarity measure is the basis of the retrieval process in a case-based reasoning system and allows the system to be flexible and incremental. Local similarity measure determines the similarity between two attribute-values and for each object and constitutes a measure of how many features the compared objects have in common. Two types of similarity are defined: Similarity of taxonomies and Similarity measures for Case Representations.

3.4.1. Similarity of taxonomies. Definition of the local similarity measure for the leaf nodes of a taxonomy complies with the following general constraint [11]:

(1)

$$Sim(K, K_1) \le Sim(K, K_2) \qquad if <K, K_1> < <K, K_2>$$

It states that the similarity $Sim(K, K_1)$ between the leaf nodes K and K_1 is smaller than the similarity $Sim(K, K_2)$ between the leaf nodes K and K_2 if the nearest common predecessor (inner node) $<K, K_1>$ of K and K_1 is located in the tree below the nearest common predecessor $<K, K_2>$ of K and K_2 .

Our model of similarity computation requires numeric values in [0..1], in order to express the local similarity between leaf nodes and this value is further used in the computation of a global similarity. Every inner node Ki of the taxonomy is annotated with a similarity value Si.[0..1]. The deeper the nodes are located in the hierarchy the larger the similarity value can become. The similarity value that is assigned to a node should be justified by the features that all of the objects that belong to this inner node have in common.

We define the local similarity between two objects K1 and K2 as follows [11]:

$$Sim(K_1, K_2) = \begin{cases} 1 & if \quad K_1 = K_2 \\ S_{<K_1,K_2>} & otherwise \end{cases} \qquad (2)$$

$S_{<k1,k2>}$ is the similarity value assigned to the node $<K_1, K_2>$, that is the nearest common predecessor of K_1 and K_2. Based on his experience, expert defines local similarity values. Features with high degree of similarity have values closer to 1.

3.4.2. Similarity measures for case representations. A weighted sum of the local similarity measures is used as a global similarity assessment mechanism The global similarity computation between two objects can be divided into two steps: the computation of an *intra-class similarity* SIMintra and the computation of an *inter-class similarity* SIMinter [12]. Local similarities are computed for all at- tributes and the resulting values are aggregated (weighted sum) to the intra-class similarity, formally written:

$$SIM_{intra}(q,c,) = \Phi(sim_{Ai}(q.Ai, c.Ai), \dots, sim_{Ax}()q.Ax, c.Ax)) \quad (3)$$

Φ is the aggregation function, $q.A_i$ and $c.A_i$ denote the value of the attribute A_i in the query and case object, respectively, and sim_{Ai} is the local or object similarity of the attribute A_i. The final global similarity Sim(q, c) between a query object q and a case object c is computed as the product of the inter- and the intra-class local similarities, i.e.:

$$Sim(q,c) = SIM_{intra}(q,c)*SIM_{inter}(class(q), class(c)) \quad (4)$$

where class(q) and class(c) denote the object class of the object q and c, respectively SIM_{inter} (class(q), class(c)) is defined according to equation (2). Global similarity computation is built on an object-oriented case base. The case retrieval mechanism finds the m most similar cases for a given query case applying recursive tree search and a priority queue is continuously updated. As input we need the query case, the number of most similar cases, the taxonomy trees represented by their root nodes and the similarity measures.

3.5. Adaptation Process

Adaptation rules are formalized in order to describe how an old case r that is retrieved can be adapted to fit the current query case q and stored into the case base for future use [6, 10]. The rule computes a target case t out of the retrieved and the query and stores it into the case base for future use. Example of an adaptation rule: "IF *(p-eventK$_q$=important) AND (p-eventK$_r$=less important)* THEN *(eventK$_t$ =almost scientific)".* It means that IF the significance of the event K in the query case is grater than the significance of the event K in the retrieved case THEN the profile descriptor specified in the target case is computed as less scientific (for example *almost scientifi*c) than that of the retrieved case. The human expert evaluates the validity of adaptation. Corrections to some adaptation rules are made, if necessary.

3.6. Case base initialization

For case base initialization we addressed the following methodology [13]: we assumed the construction of a homogeneous case base where all cases share the same record structure. We conducted a research with 40 high school students and appropriate historical text and questions in order to have a sample of the distribution of cases to cognitive profiles. The cognitive profiles were judged by hand. Taking into account the experimental results we identified that the frequency of occurrence of cases with.6 *Very Lo*w, *Low* or *Nearly Low* cognitive profiles is greater than other profiles. Consequently, as most of the students are expected to have *Very Lo*w, *Low* or *Nearly Low* cognitive profile, the majority, almost 70%, of initial cases in the case base must belong to the corresponding subgroups. The knowledge contained in similarity measures was enriched with appropriate knowledge of the 40 episodic cases and was complemented with 20 simulated cases that the expert judged necessary for the problem domain.

4. Experiment

We implemented CBR-DHTC model using the application development tool CBR-Works [10]. We experiment CBR-DHTC using a historical text and 10 questions. The system learned from 60 cases (40 episodic cases coming from students plus 20 simulated cases coming from the expert). During the preliminary trials we evaluated the model in terms of diagnosis accuracy and accept-ability to one human expert. The cases were grouped into four sets of 5 cases each, to assess the improvement in CBR-DHTC model performance as it gained experience during the learning process. The system attempted to as-sign the correct cognitive profile to each case. If the sys-tem was unable to assign a cognitive profile or assigned an incorrect cognitive profile to a case, we added that case into the case base. CBR-DHTC demonstrated satisfactory performance in the four test series as the human expert judged. It correctly classified 72% of the query requests on the first attempt. Its performance improved as it gained experience: in the last two test series, it correctly classified 84% of the cases. Even though the sample is rather small to reach a safe conclusion and given the small amount of cases in the case base, the results indicate that CBR-DHTC can indeed perform diagnosis in a way that gives results similar to the way human experts evaluated students.

5. Conclusions

This CBR methodology for designing a diagnosis model of students' cognitive profiles of HTC is an approach, which imitates human expert's reasoning in infer-ring the student's cognitive profiles. Empirical knowledge expressed in the form of adaptation rules is complemented by the exploitation of experience-cases. First trials showed good performance of the model. This model, which im-proves an existing diagnostic model, is expected to interest mainly AI researchers. It can reduce human experts' work in the complex real world problem of diagnosis of students' cognitive profiles on HTC by offering a tool for quick assessment. History teachers, who wish to assess their students' cognitive profiles and their learning difficulties in order to design and experiment a different personalized teaching strategy, may find the model interesting. The significance of this model is that holds potential for use in individualized history learning in the construction of an ITS.

To better overcome problems with managing the uncertainty in the acquisition of knowledge we plan to use fuzzy logic. We also plan to handle case adaptation by facilitating the retrieval process.

6. References

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