Epistemological Remediation in Intelligent Tutoring Systems

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Abstract. This paper presents an approach to student's errors diagnosis in intelligent tutoring systems and to the remedial instruction to overcome those errors. Our contribution aris es from two key components. Firstly, a diagnosis model, which based on the nature of the learner's input, as well as its exercise knowledge model., uses Bayesian induction (*a posteriori maximization*) to find the most probable causes of a failure Secondly aremedial instruction model which will be the focus of this paper. This model will use the epistemological nature of the faulty skill that was diagnosed.

1. Introduction and overview

Cognitive diagnosis and remedial instruction are fundamental elements of instruction. The importance of cognitive diagnosis is due to the fact that it guides the instructional plan: all the teaching actions depend on its result. According to Ohlsson (1987), cognitive diagnosis is the process which allows a tutor to assess the cognitive state of its pupil after any kind of performance has been observed. Direct remediation is an active subject in traditional education as in intelligent tutoring systems (ITS) (Woolf and Hall 1995). Remediation by means of instructional planning has also been widely studied (Wasson 1998). In this article, our goal is to propose a remediation framework at the finest level. Indeed, most models of instructional planning and remediation describe how a failure/error is detected, as well as the various approaches by which they could be overcome: presentation of similar examples or problems, analogies, simulation, explanations (Conati et al. 1997). These techniques proved their value in real educational contexts (Algebra-Tutor), but our idea is based on a different philosophy. Our goal is to provide formal knowledge models for remediation pedagogy. This mainly aims at providing ITS authors with computational models of remediation at the lowest level of this process: the level where interaction with the lear ner occurs. Using the domain of Logic Programming (LP) basics, we will show how this could be achieved if we assume that the whole process is centered on the epistemological features of the skills to remedy.

In some well-structured domains, the objective is to acquire first factual knowledge and propositions. Thereafter, the acquisition of procedural skills follows, and they may further be used in complex problem solving skills acquisition (Brien 1997). Our investigation relates to the diagnosis and remediation of students in ITS, which promote learning in that type of domain. We use the fact that the generic cognitive processes associated with each intellectual skill of the field can be modeled (Paquette 2002; Nkambou et al. 2003). In this way, our main assumption is that the internal unfolding of the remediation can be described in a more formal way. We will call *epistemological remediation* a remediation approach which uses the epistemological nature of a faulty skill.

The paper is structured as follows. Firstly, we will briefly present the architecture of a system we developed to support our propositions, as the presentation of those ideas will be illustrated with some examples from that system behaviour. Secondly, we describe how Gagne's epistemology (Gagne and Briggs 1993) can be instantiated in the LP context, stressing out the relevance of our perspective. Thirdly, the remediation framework is presented. Details on the diagnosis model may be found in Tchétagni and Nkambou 2004, it will not be presented here due to space limitations. Briefly, a part from the classical approaches to diagnosis models (buggy rules, constraint violation, etc.), we introduced another approach based on the Bayesian induction mechanism called *Most Probable Explanation*. This particular approach may be useful when the exhaustive problem space or task graph associated with a problem is not available or is not appropriate to represent the solving behaviour in that problem. Regarding remediation, we will emphasize on a clear distinction between two sub-models: the knowledge model which refers to a particular remedial capability (it can be seen as a pedagogic model) and the knowledge model which refers to the processing needed to apply a remedial approach for a particular skill. Finally, we will discuss about the current research on the use of artificial intelligence tools to perform diagnosis and remediation in ITS, and conclude.

2. The current system architecture

The current system (figure 1) prototype consists of : 1) the learner model; 2) an profiler agent, which supports diagnosis and remediation functionalities; 3) learning exercises and problems. Each training exercise has an associated knowledge model. The exercise itself can be of various types depending on the reasoning process it demands. For this reason, 4 levels of exercise are differentiated: level 0 exercises related to the acquisition of concepts and propositions; level 1 exercises related to the acquisition of a rule via the capacity to apply or use it in the given context; level 2 exercises which deals with the application of a procedure through the use of suitable rules in the given context; level 3 exercises which relate to problem solving activities.

We used the CKTN (Nkambou et al. 2003) model to generate the LP course. These objectives are structured in a pre-requisite hierarchy. Each objective has learning activities. Each learning activity is either an instructional activity or a training activity. An instructional activity is supported by one presentation resource or more (text), we do not use this kind of resource as input to the student model. A training activity is supported by what we call intelligent resources, i.e. self-contained resources with their knowledge model or problem space and we shall see the rationale of this choice below.

The knowledge model associated with an exercise contains references to all the skills of the learner model that are used in that exercise. For levels 1 exercises and above, the knowledge model will have two components: 1) the default component, which contains references; 2) a dynamic component, which will either define the causality of each associated skills in the success of that exercise (what is the probability of success, given that one skill is acquired), or define a behavior model for that exercise whenever available (like a problem space, a procedural model, etc.). For procedures for example, the dynamic model will describe an execution sequence for the production rules to be used. For problem solving, the model will be a space problem. This approach is justified from the facts that: 1) the tutor should know what the student is doing at any time in order to adapt its strategies; 2) the learner model should be continuously updated while he is solving exercises and problems. The learner model overlays the objective hierarchy and is interpreted as a Bayesian network (Tchetagni and Nkambou 2002).

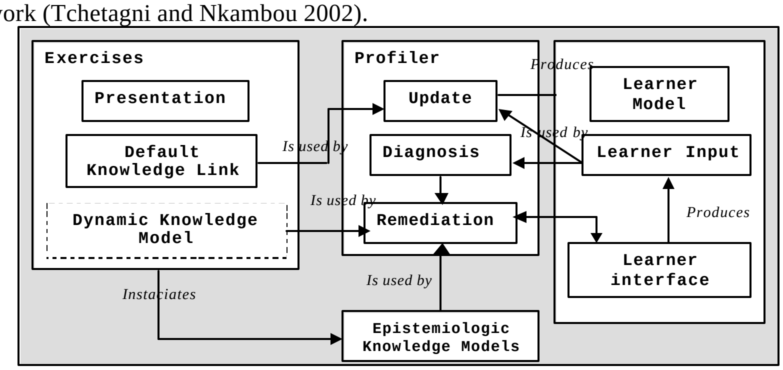

Fig. 1. System components and interactions

3. Knowledge and skills in logic programming

A LP basic course can be conceived in 2 main modules: the language or grammar of terms acquisition and the application of the fundamental procedures of unification and resolution. The grammar of terms can be seen as a *concept* acquisition objective since all the terms in LP have attributes, which should be known in order to correctly identify terms. Unification of two compound terms may be seen as a two stages *procedure*, based on *rules* related to the unification of simple terms: first try to unify the 2 *functors* of each term, then try to unify *vis-à-vis* arguments in both terms. In the following, we use Gagné epistemology to describe formal epistemological models of skills, which will support remedial instruction. Thus, we consider skills such as: concepts, propositions, rules and procedures.

Concepts are objects sharing the same properties. Identification, classification, distinction are the abilities or cognitive processes most often associated with them in an LP course. Concept instance *identification* implies the recognition of its class attributes or basic characteristics. Figure 2 illustrates the corresponding model. Indeed, we tried to capture different philosophies of what is supposed to be a concept, in order to be able to manage a good range of situations. Thus as we can see, a concept is seen as a prototype with attributes as well as an entity defined by the relations between its properties or elements.

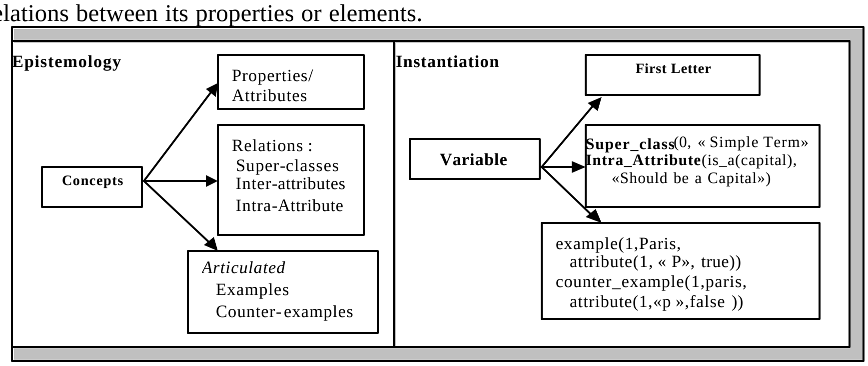

Fig. 2. Epistemological models of concepts

In LP, rules are omnipresent. For example, the notion of dependent variable is built on a rule related to the state of a variable. The unification algorithm is based on applying rules, which themselves are built on the grammar of terms. It is thus of primary importance for diagnosis that the rules are correctly modelled in the system: their conditions and their consequences, an explicit expression to formulate the link between them (Figure 3). The conditions are propositions relating concepts while the consequences are other propositions or actions possibly performable by the learner. Then, procedures such as unification can easily be defined by specifying their phases, each one involving a set of rules. For the learner acquiring the ability to execute or apply a procedure, the most important thing is to know the ordering of the procedure stages. Then for each stage, the rule(s) that apply to the execution context should be applied or executed. Once again, remedial instruction will use these models.

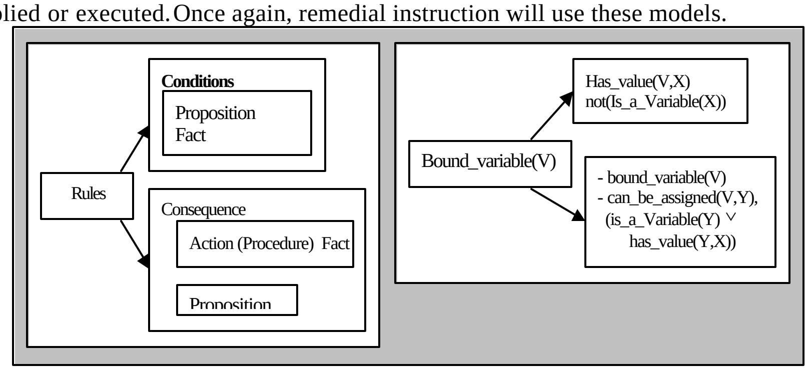

Fig. 3. Epistemological models for rules and procedures

Relevance of epistemological remedial instruction

According to Lindsay and Norman 1997, acquiring a concept implies the possession of: that concept class, the associated sub-concepts (which are the attributes of the studied concept), the relationships between these sub-concepts, and if possible some examples of the concept. According to Brien 1997, concept acquisition is achieved by building schemas and these schemas correspond to its attributes with their inter-relationships. Therefore, learning is demonstrated by the ability to instantiate a schema for a particular concept instance. Our model of concept follows naturally this cognitive hypothesis. For production rules and principles, the condition and the action are built from propositions that use themselves some concepts. Acquiring the ability to apply or execute a procedure follows the same logic: it is necessary to include/understand the main process in terms of the sub-processes that make it up. Each sub-process generally corresponds to a set of rules. The sets of rules make it possible to determine the appropriate action to trigger in a given situation. Our procedural model is in agreement with these facts.

4. Remedial instruction

Remediation is straightforward once the output of the diagnosis is given. Remediation should help the learner to understand the exercise and to solve it correctly after failure. We defined 2 remedial approaches: recall and articulation. In the next sections, we will outline how these approaches provide a more abstract model of remediation.

Recall

The learner's model often reveals relevant information for the remediation process. For example, how to interpret the fact that a learner is unable to solve an exercise that is connected to a well mastered skill according to its model? Lack of attention or guessing is sometimes responsible for that (Siemers and Angelides 1998). Thus, rather than engaging an in-depth remediation, the system may proceed to a simple recall. While recall may be thought as a trivial remedial approach, its remedial aspect relies on its repetitive character, forcing the learner to *remind or recall an already experienced learned process or schema*. When the diagnosed problem is a concept, the system will state its attributes and most importantly *their values in the current problem context*, ensuring the transfer from theory to practice. This is where our "epistemological knowledge models" become important. They allow the tutor to dynamically generate this information. For a rule, the system will state its conditions and consequences again in the current context. Figure 4 shows an example of recall where the system detects that a pattern is missing in the solution, in this case, an animal (salmon, fish). Each item in the exercise is linked with an epistemological knowledge model instance (here the concept of compound term), which incorporates examples for concepts. Thus, the profiler analyzes this model, produces and enunciates its attributes and finally gives an example. A natural language converter is associated with the profiler. This process is very basic: it takes the propositions that comprise the epistemological knowledge model and produce a natural language version of them. For example, in the description: concept (variable,var), has a (co, first_letter), we state that the concept of "variable" has as a distinctive attribute called first letter. The converter can translate this kind of description into a human friendly phrase. Recall is similar to re-teaching. From an instructional and a learning point of views, recall is relevant either when the learner model informs that the diagnosed skill is supposed to be acquired, or when the learner's solution is un-interpretable but incorrect. Recall also has a cognitive validity since according to Brien 1997, the acquisition of declarative knowledge may happen by: 1) subordination; 2) superposition; 3) composition. Recall relatively expresses the composition since it implies the combination of several known *schemas or frames* into a new frame that corresponds to the recalled element.

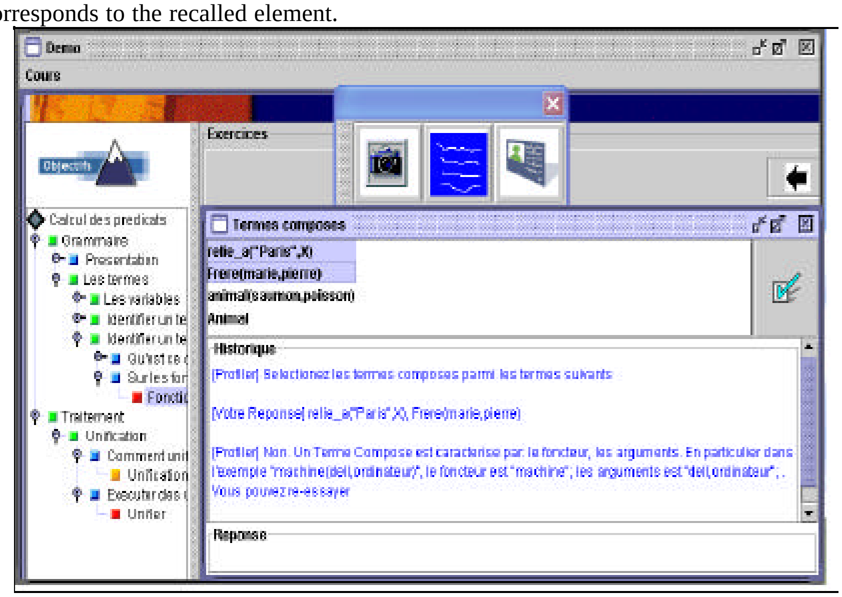

Fig. 4. Knowledge model of recall processing and demonstration

Methodology of the recall remedial instruction

The conduction of a remedial dialog depends on the corresponding remedial strategies. In the following, we explain how this is achieved when the recall is used. In this case, the tutor proceeds in 2 steps. First, he recalls the features of the diagnosed skill. Second, he prompts the student to answer again the same question (Figure 5). This pedagogical model is a template that shall be integrated in the overall pedagogical knowledge base of an intelligent tutor.

Articulation

Articulation-based remediation allows to come along with the learner in hulling the exercise in order to let him reach the solution *himself*, favouring in this way *knowledge construction*. In that sense, articulation is a significant way to remedy the student errors. Indeed, using a dialog, questions exploiting the nature of diagnosed skills are asked to the learner, in the context of the corresponding exercise. For example, if the *identification or recognition* of a concept is lacking, the system will ask the student to *enumerate the attributes* of this concept. If some attributes are absent or are attributed invalid values, the system will also question the student about those attributes

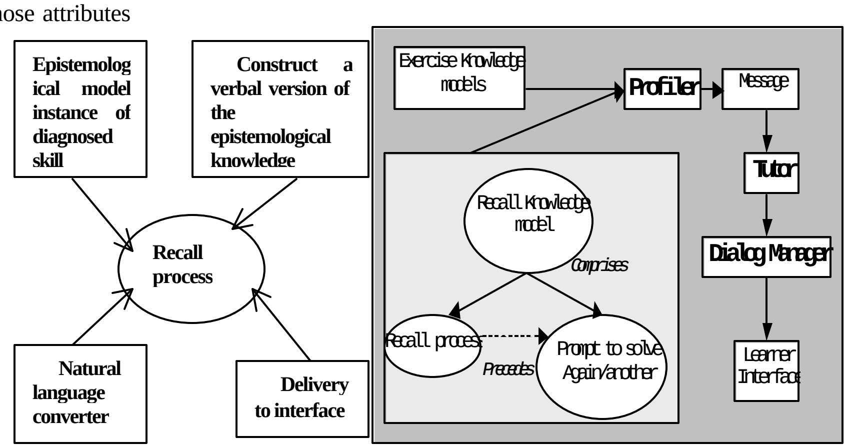

Fig. 5. Pedagogical knowledge model for the recall approach

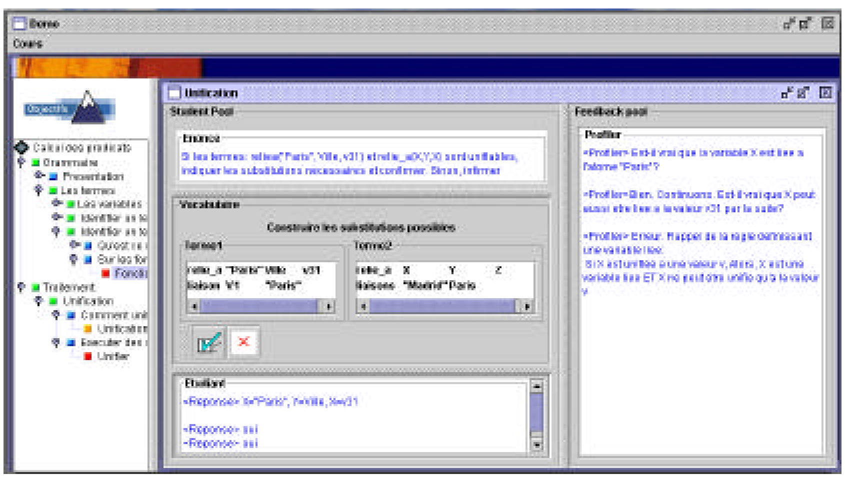

Fig. 6. Making the learner articulate elements in concept and rule usage

Figure 6 illustrates a student's error in solving a unification problem. He is unable to unify 2 terms while it is possible. The systems clearly diagnosed that the faulty rule is the one defining the notion of bound variable and its implications. Firstly, the profiler questions the learner on the conditions of this rule in the current problem context. Then the same is done on the consequences. If the learner's difficulties persist, the systems enunciate the complete rule with an example. Note that even if one ends by stating the information on a skill as in a recall approach, this occurs at the end of a dialog with the learner, where he should probably have to realize the important aspects of the skill. The articulation of a procedure is based on the articulation of the production rules or principles, which correspond to each stage of that procedure. This is possible since the dynamic knowledge models of exercises that involve procedural and problem solving skills are based on production rules and principles.

Figure 7 and 8 illustrate the domain-dependant processing knowledge model associated with the articulation approach and the corresponding pedagogical knowledge model respectively. Briefly, the profiler uses the instantiated epistemological knowledge model associated with the diagnosed skill and uses its content to conduct articulation.

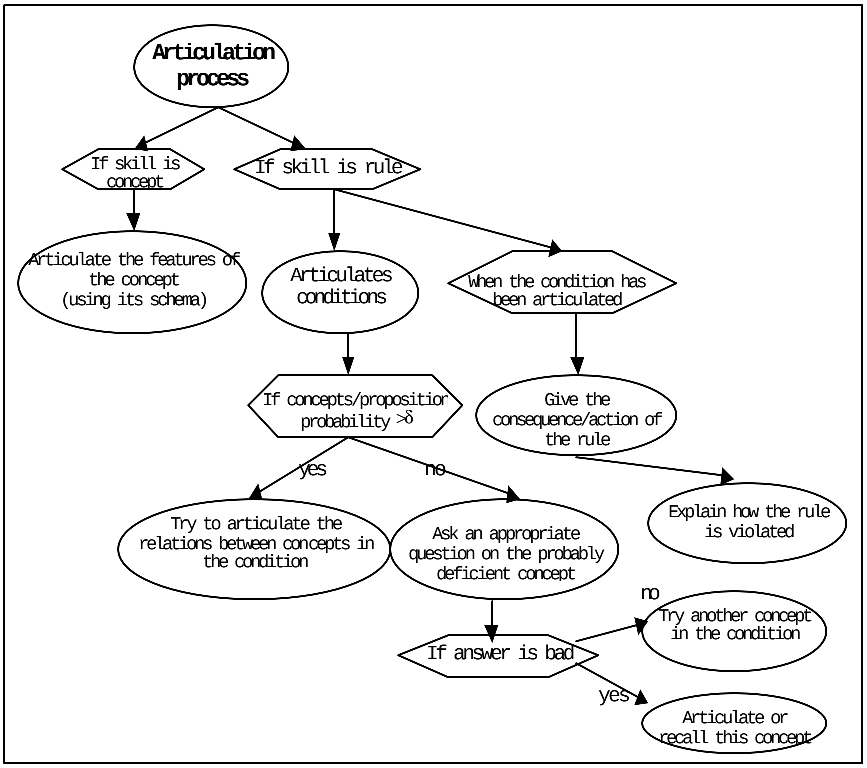

Fig. 7. Knowledge model of articulation processing

Articulation relates to knowledge construction or self-explanation. In this paper, we demonstrate a formal way to use this approach where the nature of the diagnosed skill is exploited as well as the cognitive processes underlying it. Our assumptions are also valid since Gagne et Briggs 1993 prescribe that concepts are better understood by pinpointing their distinctive characteristics. As well, pinpointing their components and the relationships between those components allows a better learning of rules and procedures.

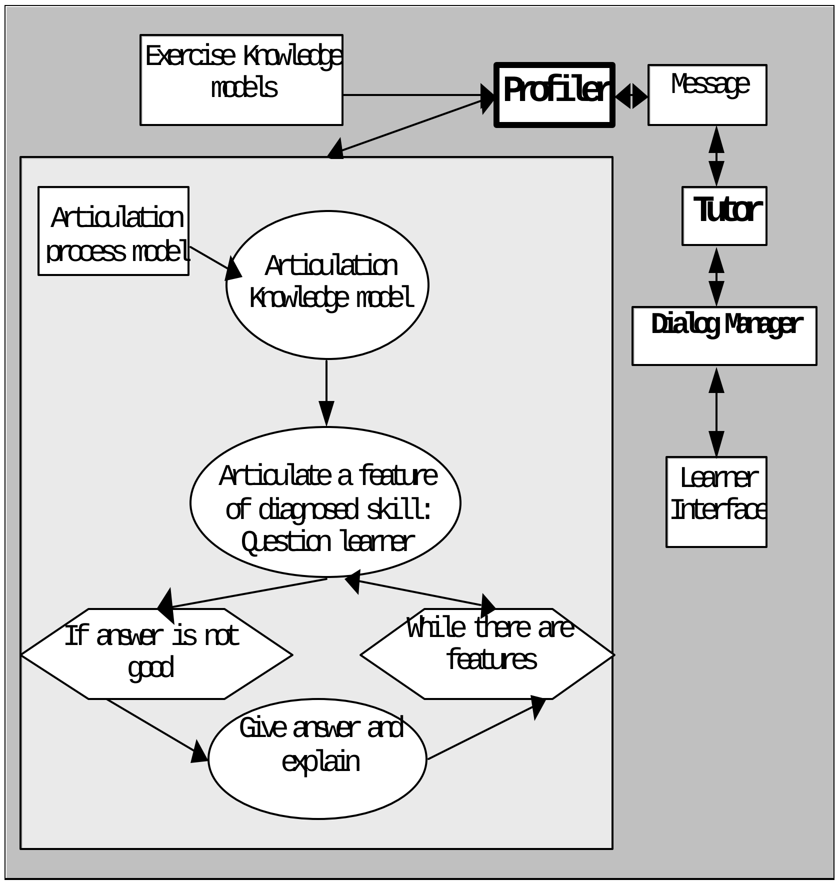

Fig. 8. Pedagogical knowledge model for remedial articulation

Related Work

Diagnosis and remediation is a hot issue in ITS research and almost all well known systems implement it. SOPHIE (Brown et al. 1982) performs model-based diagnosis but despite its natural language processing abilities, which allow immediate feedback, it is not able to constructively help the student understand its problem or reach the solution. Algebra Tutor (Koedinger et al. 1997) uses a model tracing technique to diagnose errors, to produce flags and suggestions when a mal-rule is encountered. Knowledge construction dialogs have been used by VanLehn et al. 2000 to help a learner encountering difficulties: the learner is presented with a new situation intended to provide him a deeper understanding of the current problem. Self-explanation (Conati and VanLehn 2000) is a tutorial approach where the learner is encouraged to self-explain their understanding of an example and its solution.

First of all, we think that the remedial instruction we propose here can be used by many of the preceding approaches. In fact, feedback, coaching and hinting consists in: 1) recalling a rule to the learner; 2) giving the appropriate rule when the tutor guesses what the learner is trying to do. The studies on natural language based dialog for knowledge construction is the approach most similar to articulation. Rather than providing the learner with the rule to apply in a given situation, the Atlas component of Van Lehn et al. decides when to trigger a dialog with the learner in order to make him understand the rule. Our articulation approach is similar. However, it extends to other knowledge elements such as concepts, and it uses the learner model. In fact, it could break down the articulation dialog when a rule is diagnosed and it happens that it is in fact a component of that rule (a concept) that is not well mastered.

7. Conclusion

Our main contribution in this paper is from a conceptual perspective. We proposed a formal framework integrating diagnosis and remediation approaches in *well-structured domains* such as LP. The proposed techniques have been successfully applied to exercises solving scenarios-simulation in a prototype basic course. We do not just recall or articulate the diagnosed faulty skills. Remediation also occurs in the context of the problem currently solved by a student. This was possible because each remedial approach was associated with 2 models: 1) a processing model which governs how our profiler-agent uses the contents of the epistemological knowledge model instances associated with a diagnosed skill to generate human friendly utterances; 2) a pedagogical model of remediation which dictates how the tutor should conduct the dialog with the learner in that particular remedial approach. Thus, our future work will contribute to the formalisation of pedagogical and content processing knowledge needed for epistemological remediation. Future work concerns the evaluation of this approach from the learner view: no matter if we present an example, a feedback, a hint, does the fact of exploiting the nature of knowledge in a remedial tutoring context enhance the learner performance?

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