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## **TECHNICAL REPORT**

**CTR/36-04**

**Knowledge Representation in Risk.**

**Antoaneta Serguieva and Tariq Khan**

# Knowledge Representation in Risk Analysis Facilitating Cognitive Diagnosis

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**Abstract.** The development of intelligent educational systems faces the challenging problem of cognitive diagnosis. This necessitates the development of methods for analyzing learner performance and inferring cognitive states. We will focus on the transformation of model-based technical diagnosis into perception-based cognitive analysis. The purpose of cognitive analysis, in contrast to device diagnosis, leads to development of novel approaches to interpreting learner performance. We support the view that Zadeh's computational theory of perception compliments qualitative methodologies by providing an additional level of information granulation and a computational inference engine. The computational theory of perception is considered complimentary to qualitative methods when processing and reasoning with perception-based information, and this perspective will allow us to reformulate performance analysis.

The adopted view throughout this article is that concepts in any domain, as well as their interrelations, are better communicated through a variety of models, each providing partial definition or exemplification from a different perspective. Generalised constraints are further generalisation of the notion of model and introduce a unified approach to knowledge representation at various levels of information granulation and perception. The problem-solving knowledge involving a domain concept is described with a set of generalised constraints arranged in a multi-model space along various dimensions. The modelling dimensions will be explored through an exemplary domain in risk management.

**Keywords.** knowledge representation, risk modelling, cognitive analysis.

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## 1 Motivation

The development of intelligent educational systems faces the challenging problem of cognitive diagnosis. The ability to analyse user understanding marks a higher system IQ. It promotes a superior support to learners in their attempt to understand and solve problems in any domain. Thus the implementation of cognitive diagnosis raises as a legitimate requirement in engineering intelligent systems, and this necessitates the development of approaches to analysing user performance and inferring cognitive states. The aim is to evaluate the current state of a student's understanding of domain concepts and interrelations, focusing on the identification of representation models currently understood at unsatisfactory level according to the ongoing criteria. As the problem-solving knowledge components are the student's perceptions of the models, these components are not completely defective or absolutely perfect, not replaceable but rather improvable. Therefore, the ultimate goal of student diagnosis is to allow her to learn domain knowledge up to her best, and demonstrate it through improved problem-solving abilities. The superior direct aim and ultimate goal of cognitive analysis, in comparison with device diagnosis, necessitate the development of novel approaches to interpreting student performance. The challenge is attracting a line of research recognising the role of qualitative representation [4], simulation [2] and reasoning [5].

There exist a wealth of methods for diagnosing the performance of technical systems and identifying faults. They have served as a basis in broadening the limits of technical diagnosis towards approaching the borders of cognitive analysis. We will focus on the transformation of model-based technical diagnosis into model-based or rather perception-based cognitive analysis. The adopted view throughout this article is that concepts in any domain, as well as their interrelations, are better communicated through a variety of models, each providing partial definition or exemplification from a different perspective.

The rationale behind exploiting technical diagnosis as a basis for cognitive analysis states the benefits of identifying similarities and differences towards calibrating research transfer and guiding future exploration. In this context, the similarity-difference reasoning undertaken in [10] acts as a point of departure when considering model-based approaches. The recognised resemblance concerns the involvement of problem-solving knowledge, while disparity relates to the complexity of knowledge representation, the depth and direction of diagnosis, the interactivity of the process, and the ultimate goal. Therefore, the problem-solving knowledge involving each domain concept will be described with a set of models arranged in a multi-model space along various dimensions [9, 7, 14], where a model is characterised with its depth in each dimension representing a perspective or level of concept definition. Furthermore, the student's perception of a model is a component in her problem-solving 'device' or her knowledge, and we may not simply interpret such component as either faultless or defective and due replacement. The component is rather at a progressive stage of accomplishment or understanding by the learner [15].

As reminded in [18], even knowledge representation in technical domains should consider along deterministic and probabilistic models using, beyond some status of technical complexity or environmental uncertainty, qualitative and possibilistic models as well. The description evolves further when the knowledge concerns not only a technical system but its interaction with an operator, as is the case in most industrial and some medical domains, reflecting accompanying uncertainty and imprecision. Finally, problem-solving knowledge representation in systems with predominant human involvement and judgement, as in some medical, most financial and all social domains, require using veristic, fuzzy probability, fuzzy graph models, etc., while applying the 'don't know', 'don't need', 'can't solve', and 'can't define' rationales [18, 20]. The 'don't know' rationale applies when the values of variables or parameters

are not known sufficiently precise to justify using conventional modelling techniques. The 'don't need' motivation presents situations where exploiting the inherent tolerance for imprecision achieves tractability, robustness, low solution cost or better rapport with reality. The 'can't solve' reason reveals domain problems that cannot be solved through quantitative modelling and computing. The 'can't define' principle relates to domain concepts that are too complex to allow definition through a set of numerical criteria. Therefore, a generalisation of the notion of model is required to represent domain knowledge at various levels of imprecision. It is found in the generalised constraint introduced by Zadeh [16–20]. Both quantitative and qualitative models form important, though special classes of generalised constraints. Thus the multi-model domain representation will be reformulated as multi-constraint domain description, and imprecision will be recommended as one of the dimensions in the multi-perspective domain space [15].

Subsequently, a learner's perception of domain information will reflect her bounded ability to resolve detail and unbounded capability for information compression. When she solves a domain problem, the same four rationales will arguably play role, though with a subtle difference. In domain description, they demonstrate the limitations on the attempt of experts to abstract knowledge from the real domain. In domain perception, they reflect the limitations on the attempt of students to understand the abstracted domain. The contribution of the computational theory of perception [20] to the capability of qualitative diagnostic methods to process and reason with perception-based information will allow us to reformulate performance analysis. Observing either accurate or faulty performance of a non-interactive device is sufficient for the corresponding diagnostic task. An identical approach to cognitive analysis is unsatisfactory, and we will incorporate the expressed student's perception of a problem as inherent part of her problem-solving performance. Performance evaluation is also carried out according to the tutor's perception of required problem-solving competency.

## 2 Knowledge Representation

Cognitive diagnosis may be considered as the process of inferring a cognitive state from observations of performance. In the context of an intelligent educational system (IES), a cognitive state is the state of a student's understanding of the target knowledge represented in the expert unit, and the focus is on the student's performance in solving tasks generated by the pedagogical unit and the diagnostic module. The IES imposes further requirements on the solution of the diagnostic problem:

- i/ facilitating the analysis of a particular student regarding a given domain;
- ii/ allowing IES reconfigurability within different domains;
- iii/ assuring the analysis of any student interacting with the system;
- iv/ providing for the communicability of diagnostic results between different IES units;
- v/ equipping the adaptability of IES↔learner interaction.

The development of a conceptual framework for the cognitive-diagnosis module works through the above multiple objectives to identify the following problem decomposition:

- I/ building a multi-perspective framework for domain description based on multiple generalised constraints;
- II/ formulating a perception-based framework to represent the task-solving knowledge of students within some/any domain;
- III/ specifying the diagnostic rule and processing perception-based information to infer corresponding cognitive states.

In the rest of this section, we approach the first two sub-problems within the overall diagnostic effort.

## 2.1 Domain Framework

A representation framework for domain knowledge will allow reconfigurability within various domains. When serving as a basis for the expert and the pedagogical units as well as the diagnostic module, the framework will guarantee the communicability of diagnostic results within the educational system. Domain concepts and interrelations are introduced into the framework through problem-solving knowledge. The variety of problem-solving information is appreciated through classifying the following types of knowledge, as described in Figure 1.

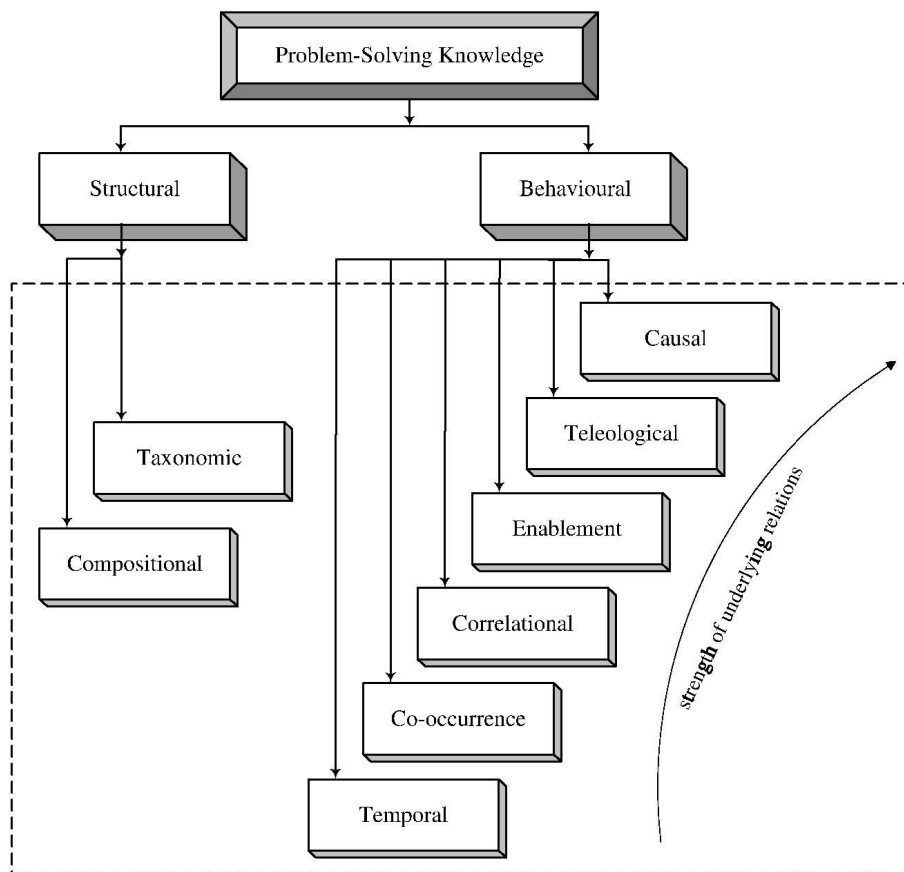


Fig. 1. Classification of problem-solving knowledge

Structural knowledge captures taxonomic and compositional dependencies. Taxonomic knowledge communicates type-subtype subordination and inheritance of properties between objects. Any subtype object will inherit the general type characteristics and attached problems, however they can be further specified. Compositional relations provide information about the elements of an object. Next, behavioural knowledge is accounted for by a number of relational types, where the strength of dependencies increases from temporal and co-occurrence, through correlational and enablement, to teleological and causal relations. Causal knowledge aims at cause-effect dependencies among factors. Teleological dependencies focus on a goal and pull the conditions that will bring that goal. Enablement knowledge reveals that one event capacitates another event, and there exists a prerequisite relation between them. Still the relation is not as strong as the preceding two types, and does not imply that any of the events is the driving or the dragging force for the other. Correlation suggests observed dependencies between events but not responsibility of the one for causing the other. Correlational models are mostly used in data mining or short-term predictions. Co-occurrence relations focus on observed coexistence of events at a particular moment or over a time period, without necessarily involving any sounder connection between them. Temporal information describes time sequencing of events involved in a procedure or algorithm. The time sequencing may be derived from a theory or heuristics, or the reason of the sequencing may not be of interest.

Thus we have adopted domain description through problem-solving knowledge, and problem-solving knowledge representation through various types of relation. Suitable techniques are applied to model each type of relation, and diverse modelling techniques have been considered in [14]. From logic and rules, along causal networks and Petri nets, to equations - it is shown that the association modelling technique  $\leftrightarrow$  relational type is many-to-many rather than one-to-one or all-to-all. Every

model stands for a piece of problem-solving knowledge, and a model description is only complete if also indicating the relational type. It is further demonstrated in [14] that each modelling technique accepts modifications while exploring the rationales of 'don't know', 'don't need', 'can't solve' and 'can't define' in representing the same relation. Effectively, this will introduce a new modelling dimension of relations. Along that dimension, we assume the types defined in [19, 20]: equal, possibilistic, veristic, probabilistic, probability value, usuality, random set, fuzzy random set, fuzzy graph. To express the wealth of information along that line of relations, Zadeh introduces the concept of generalised constraint (1) as a generalisation of the notion of model.

$$X \text{ isr } R \quad (1)$$

$$r \in \{e, d, v, p, \lambda, u, rs, rfs, fg\}$$

*e* : equal

*d* : possibilistic

*v* : veristic

*p* : probabilistic

*λ* : probability value

*u* : usuality

*rs* : random set

*rfs* : random fuzzy set

*fg* : fuzzy graph

*X* is a constrained variable, *R* is a modelled constraining relation, *isr* is a variable copula defining the way in which *R* constrains *X*, and thus *r* is an indexing variable standing for the relational type. The advantage of generalised constraints is the ability to represent information at both the crisp and fuzzy levels of information granulation. Crisp granulation has a key role in the qualitative process theory. Therefore, qualitative modelling will be incorporated along the new modelling dimension.

Singular information may be considered as a special case of granulation, and the relevant models will be reformulated as generalised constraints. Thus, the introduction of the dimension of imprecision transforms the multi-model space into a multi-constraint representation. The types of problem-solving knowledge in Figure 1 also contribute to the domain structure and bring the perspectives of generality, scope, and resolution. To keep up with the idea above that a model description is only complete if also indicating the relational type, and to suggest an analogy with the notation in (1), the multiple constraints along the three perspectives are specified as in definitions (2,3,4).

$$X \text{ isr}_{generality} R \quad (2)$$

$$r_{generality} \in \{t, co, c, en, te, ca\}$$

*t* : *temporal*

*co* : *cooccurrence*

*c* : *correlational*

*en* : *enablement*

*te* : *teleological*

*ca* : *causal*

$$X \text{ isr}_{scope} R, \quad r_{scope} \in \{ \textit{taxonomy classes} \} \quad (3)$$

$$X \text{ isr}_{resolution} R, \quad r_{resolution} \in \{ \textit{composition levels} \} \quad (4)$$

The dimension of generality evolves along the behavioural types of knowledge, where weaker relations - i.e. temporal and co-occurrence - involve specific knowledge as used in procedures, while stronger relations - e.g. teleological and causal - rely on more abstract domain principles. Scope corresponds to taxonomic knowledge, suggesting that a higher taxonomy class is consistent with a broader problem scope. Resolution aligns compositional relations, where a detailed compositional level communicates increased resolution. Then we can introduce with (5) the description of a generalised constraint in the structured domain [15].

$$X \text{ is } r_{resolution} r_{scope} r_{generality} r_{imprecision} \text{ } R \quad (5)$$

$$r_{resolution} \in \{ \textit{compositional levels} \}$$

$$r_{scope} \in \{ \textit{taxonomy classes} \}$$

$$r_{generality} \in \{ \textit{t, co, c, en, te, ca} \}$$

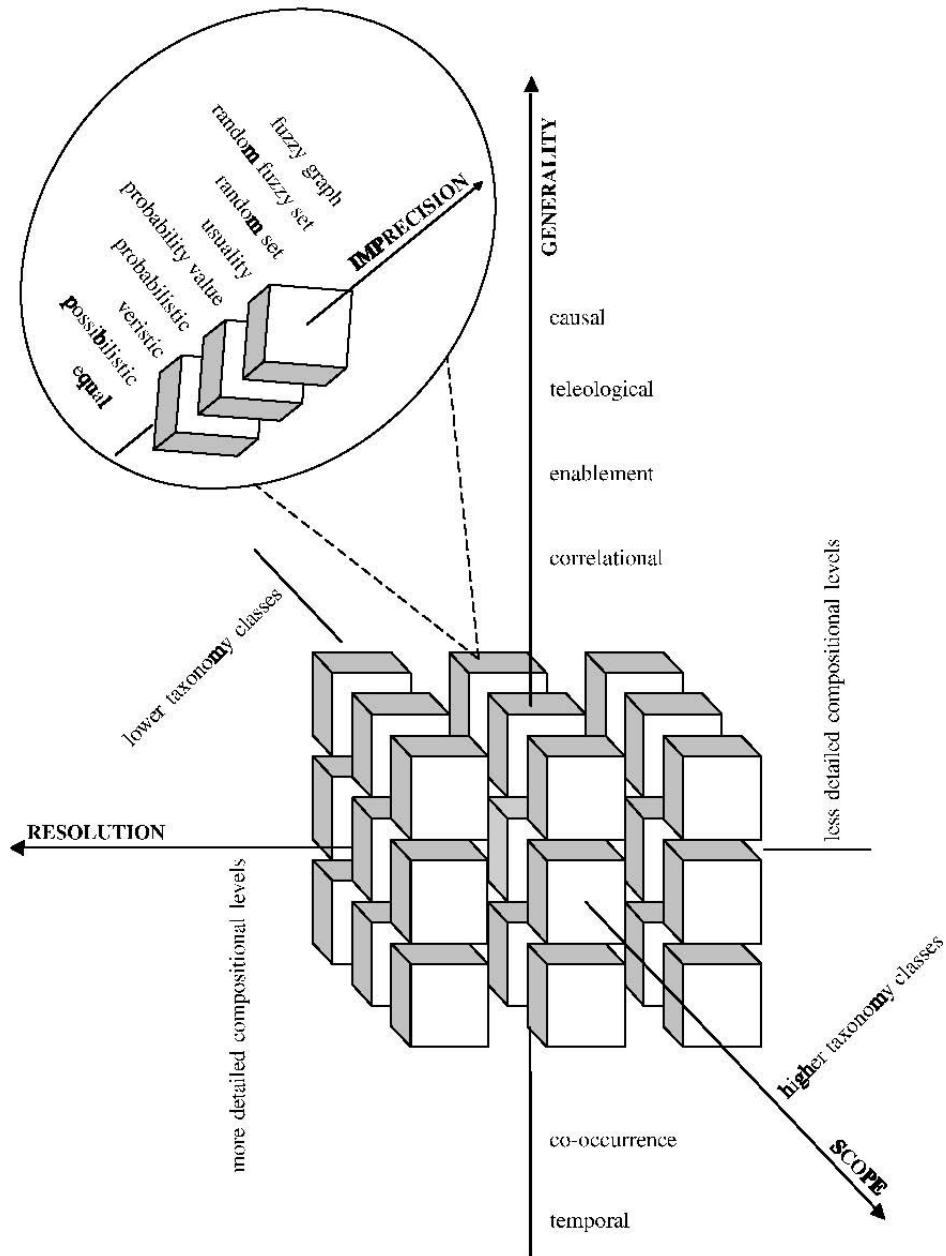
$$r_{resolution} \in \{ \textit{e, d, v, p, \lambda, u, rs, rfs, fg} \}$$

The first three perspectives in (5) are involved in describing various domains, while the dept of the fourth dimension - and therefore the relational types included - will increase from technical, through industrial and medical, to financial and social domains, exploring relevant imprecision. Overall, considering the four dimensions, represented domain information may be singular, crisp granulated or fuzzy granulated.

We have produced a representation framework that may be instantiated in various target domains. This solves the first sub-task identified within the overall diagnostic effort, and meets the reconfigurability objective for the intelligent educational system. When the framework serves as a basis for the expert, pedagogical and diagnostic modules, it further contributes to the objective of communicating diagnostic results within the IES.

## 2.2 Student Framework

Student representation is introduced as a lighter framework over the well-structured domain framework. There are three guiding principles in exploiting the wealth of domain constraints – learner description is *model-choice dependent*, *experience related* and *perception based*. Thus, hovering over or jetting through the domain structure and exploring the multifaceted representation of problem-solving knowledge, it is possible to develop a flexible student description.



**Fig. 2.** Multiple-constraint multi-perspective domain and student representation

The adopted view that learning through problem-solving is advantageous to students suggests that domain constraints represent problem-solving knowledge involving domain concepts and interrelations. However, the solution of a problem may require explicitly or imply implicitly a set of constraints instead of a single one. Furthermore, the association problem ↔ set of constraints is one-to-many rather than one-to-one, and there are a number of sets providing solution to the same domain task. Thus the student's choice of a constraint set will reflect her understanding of the task and the related domain concepts. The choice may include an incorrect set or one of the correct sets. With training and experience in a target domain, the student will follow the route from a novice to an expert, and her choice will rather focus on the most appropriate of the correct sets of constraints, considering the secondary characteristics of the task. For example, providing a satisfactory solution that concerns the lowest necessary level of relational strength along the third perspective, or recommending the sufficient level of precision for an efficient solution along the fourth dimension, etc.

A generalised constraint (5) not only describes a relation but also its position within the domain structure. In Figure 2, a cuboid presents the position of constraints with identical identifiers along the first three perspectives, and then each cuboid expands in the fourth dimension. The student's perception of a target domain will reflect the bounded human ability to resolve detail and unbounded capability for information compression [17]. Thus human cognition is by definition fuzzy (f-) granular. F-granulation in human knowledge formation is a further consequence of the fuzziness of concepts of indistinguishability, similarity, proximity and functionality. Therefore, if the learner has to express her understanding of the domain task, in addition to choosing a relevant set of constraints, this will reveal any compressed information that may play role in her decision. This will contribute an important aspect to the student

framework, and may also give an insight into the remarkable human ability to make rational choices under partial knowledge. It is demonstrated in [19, 20] how propositions made in natural language translates into imprecise relations formulated as generalised constraints. Conveniently, the domain framework here is already described through generalised constraints. Therefore, the student framework will be compatible, and we can introduce a unified approach to domain and learner representation [15].

Though compatible, the student framework is choice dependent, experience related and perception based. As a rule, a corresponding piece of knowledge in the domain framework will not match its position in the learner framework, e.g. the perception based principle introduces further imprecision and slides the representation along the forth dimension in Figure 2. An exemplary student's description may be viewed as a distorted and incomplete domain framework. Still, the unified representation permits detecting the deviation of a subset of constraints related to a domain problem, and observing the convergence to the true subset through learning and diagnostic sessions.

Formulating a representation framework capable of describing a variety of students, as well as the same student at different stages of her learning progress, solves the second sub-task in the diagnostic problem. This meets the objective of facilitating the analysis of a particular student regarding a given domain, as well as the objective of assuring the analysis of any student interacting with the system. The compatibility with the domain framework further contributes to the objectives of communicability of diagnostic results within the system and the IES reconfigurability within different domains.

### 3 Perception Based Diagnosis

We are currently applying the developed knowledge representation approach to the third sub-problem in cognitive analysis - specifying the diagnostic rule and processing perception-based information to infer corresponding cognitive states. Its solution will equip the adaptability of IES↔learner interaction when the ongoing diagnostic results are employed into subsequent consecutive learning and diagnostic sessions. A preview of this work is included here.

A generalised constraint, as the building unit in domain representation, is able to describe versatile knowledge - from straightforward dependencies between two variables to complex systems. A domain task relates to a number of constraints positioned throughout the multi-perspective space. A learner selects a subset of domain constraints to solve the task. She further expresses her perception of the task through propositions in natural language. Both types of response are considered important to student analysis and characterise the nature of human performance. In order to process the relevant information and infer a cognitive state, it is necessary to represent the meaning of the perception in a form that permits computation. We will employ for this purpose the computational theory of perceptions (CTP) [19, 20].

Words are generally considered as labels for fuzzy granules, and f-granularity of perceptions places them beyond the means of analytical methods based on predicate logic or probability theory. In CTP, a proposition  $p$  is viewed as an answer to a question  $q$ , and the meaning of  $p$  is represented as a generalised constraint on a variable. As a rule,  $q$  is implicit rather than explicit in  $p$ , and the same proposition has different meanings - represented with different generalised constraints - when  $p$  is considered the answer to different questions. Therefore, the variable and the constraint are also implicit in  $p$ . For example, the question we implicitly ask is how the student's understanding of a domain deviates

from the correct knowledge, while she may be giving an answer to the question how much she knows about the particular task the diagnostic module has presented her with. Importantly, a proposition is viewed as a carrier of information, and its canonical form  $CF(p)$  places in evidence the constrained variable and the constraining relation, thus defining the information that  $p$  carries. Constraint-centered semantics of natural languages, as part of the computational theory of perceptions, suggests that a system of generalised constraints must be available in order to derive the canonical form of  $p$ . Then the translation

$$\begin{array}{ccc}
 & \textit{translation} & \\
 p & \Rightarrow & X \textit{ is } r \textit{ } R \\
 & \textit{explicitation} & 
 \end{array} \quad (6)$$

is viewed as explicitation of the constraint variable  $X$ , the defining indexing variable  $r$  and the constraining relation  $R$ . Conveniently, the domain framework in section 2.1 has been developed as a system of generalised constraints and will meet the above requirement. Thus the explicitation (6) will take the form in definition (7).

$$\begin{array}{ccc}
 & \textit{translation} & \\
 p & \Rightarrow & X \textit{ is } r_{\textit{resolution}} r_{\textit{scope}} r_{\textit{generality}} r_{\textit{imprecision}} R \\
 & \textit{explicitation} & 
 \end{array} \quad (7)$$

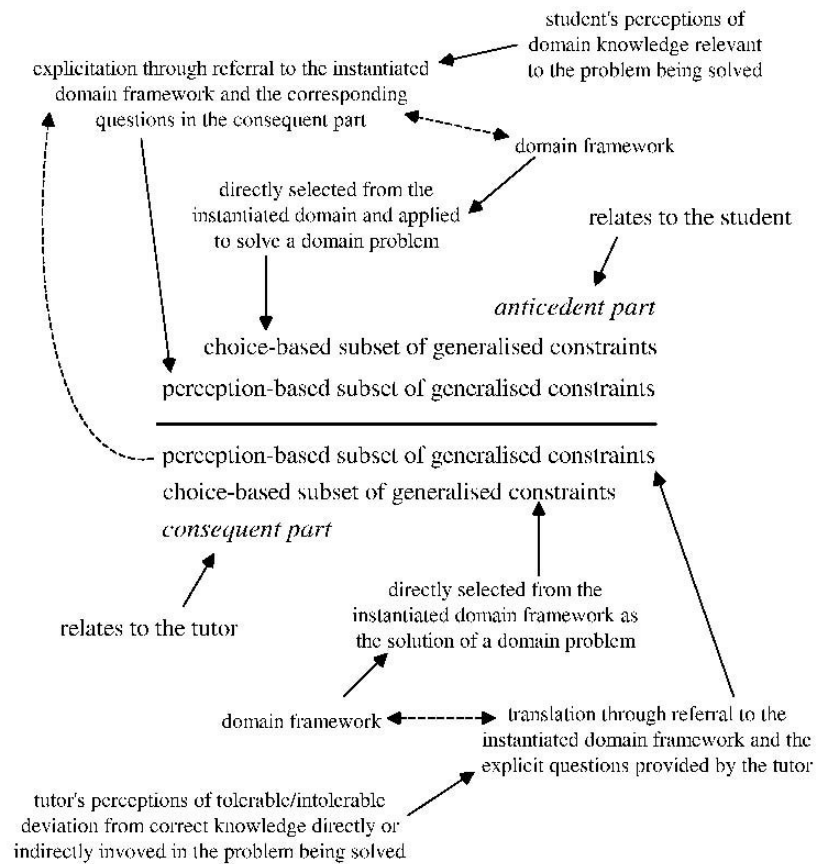
To summarise, the student's choice of models and her perception of the domain task both represent her problem-solving knowledge. Both types of information are translated as generalised constraints, due to the adopted domain framework. Logically, both subsets of constraints will form together the antecedent part of the cognitive diagnosis rule. A point to remember is that the subset derived from the student's choice simply includes the domain constraints directly employed by the learner in

solving the domain task. On the other hand, the subset derived from the student's perception first refers to the domain as a system of constraints necessary to identify the available relational types  $r_{i_1} r_{i_2} r_{i_3} r_{i_4}$ , and then uses the domain as an explanatory database to explicitate the constraint variable, the constraining relation and the relational type. Still a learner's perception may have various interpretations and thus several competing constraints. The explicitation is only possible when considering the question that the student's proposition answers and this is specified in the consequent part of the diagnostic rule. Note that the perception based subset in the antecedent part does not necessarily include existing domain constraints, however the elements of the subset will comfortably take their place along the four dimensions, as they involve the same type of relations as any other domain constraint and concern existing variables or relations.

By analogy with the antecedent part, the consequent part of the diagnostic rule consists of a choice based subset and a perception based subset of constraints, however, here they relate to the tutor. The former gives the correct choice or the most appropriate correct choice of constraints solving the domain task, while the latter explicitates the tutor's perception of allowed/disallowed deviations from this choice or tolerable/intolerable discrepancies in the student's perception of this and any further knowledge concerned indirectly in the task. The tutor's perceptions are translated into generalised constraints using the domain as an explanatory database, however, the questions here are explicit, and they are the same ones that will apply when explicitating the perception based subset in the antecedent part. Figure 3 presents the formulation of the diagnostic rule in cognitive analysis.

Thus we reformulate cognitive analysis as perception based analysis, and the computational theory of perceptions transforms reasoning with

perceptions into propagation of generalised constraints, or effectively granular computing. This involves successive combination and modification of constraints, following the rules of generalised constraint propagation. The principle rule of inference in the computational theory of perception is the generalised extension principle.



**Fig. 3.** Formulation of the cognitive diagnosis rule

For example, if the student-related antecedent constraint,

$$S(X) \text{ } isr_{resolution_A} r_{scope_A} r_{generality_A} r_{imprecision_A} \text{ } A$$

and the tutor-related consequent constraint,

$$T(X) \text{ } isr_{resolution_C} r_{scope_C} r_{generality_C} r_{imprecision_C} \text{ } C$$

are possibilistic, indicated with  $r_{imprecision_A} = r_{imprecision_C} = d$ , then the extension principles will take the form (8) and the membership function will be evaluated with  $\mu_C$  (9).

$$\begin{aligned} \frac{S(X) \text{ } isr_{resolution_A} r_{scope_A} r_{generality_A} d \text{ } A}{T(X) \text{ } isr_{resolution_C} r_{scope_C} r_{generality_C} d \text{ } C} &\equiv \\ \equiv \frac{S(X) \text{ } isr_{resolution_A} r_{scope_A} r_{generality_A} d \text{ } A}{T(X) \text{ } isr_{resolution_C} r_{scope_C} r_{generality_C} d \text{ } T(S^{-1}(A))} &\quad (8) \end{aligned}$$

$$\mu_C(v) = \mu_{T(S^{-1}(A))}(v) = \sup_{u|v=S(u)} \mu_A(S(u)) \quad (9)$$

Generalised constraint propagation provides for the valued explanatory element in cognitive analysis. Within a range of domains and formulations of the diagnostic rule, this approach will comfortably achieve the diagnostic objectives.

#### 4 Further Research and Conclusions

A demonstration application is under development, which will illustrate how the methods described here can be applied in a real setting. The application involves instantiating the domain framework within the area of risk analysis, particularly assets and derivatives valuation and risk analysis. It is described in [13] how a problem formulation within the domain may benefit from exploring the forth dimension. In [12], a handful of models are further selected, still exploiting mostly the rationales behind the imprecision perspective. In [14], a few problems are identified within the domain, and then about thirty models are developed representing the problems through various modelling techniques and with characteristics

that will allow positioning across the multi-perspective space. Next in [11], a multi-level evolutionary strategy has been developed. It proved effective in overcoming the stalling effect while dealing with imprecise data, and employed a dynamic objective function. It is a good start to address an evolutionary diagnostic strategy. Finally, some progress has been made towards building object-oriented software patterns for model-based reasoning, which has potential for enabling re-use of modelling components. [8].

The immediate objective is to finalise the exemplary domain representation, and implement cognitive diagnosis as processing of perception-based information through generalised constraint propagation. The next goal is to build the diagnostic evolutionary strategy. An additional task is to develop a prototype diagnostic module for evaluation purposes.

It has been well recognised in the literature that qualitative reasoning is the relevant approach to cognitive diagnosis. Qualitative representation and reasoning capture the way people deal with and manage within the world [4]. Qualitative techniques are assisted by quantitative means to achieve desired effects. In [5], for example, a combination of qualitative constraints and numerical reasoning is used to detect physically impossible designs students may produce in thermodynamics. The reason described in [2] is that the calculi underlying qualitative reasoning are relatively weak.

The computational theory of perception complements qualitative representation in providing a further mode of information granulation. While numerical data are singular and qualitative data are c-granular, information is also perceived by people as f-granular. Qualitative reasoning is further complemented, as CTP is a reasoning engine able to process information in all modes of granulation, including the qualitative

mode. Cognitive analysis has been mainly attempted within technical domains. The representation of domain knowledge and its perception through generalised constraints provides a unified approach that will lessen the burden of domain complexity on the diagnostic task.

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