Interactive Learning Environments, 2 (2), 111-137.

A FRAMEWORK FOR LEARNER MODELLING

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ABSTRACT

This paper presents a comprehensive conceptual framework and notatior
modelling in intelligent tutoring systems. The framework is based upon the c
distinction between behaviour, behavioural knowledge, and conceptual kno
'vertical' dimension) and between the system, the learner, and the system's
of the learner (in a 'horizontal' dimension). All existing techniques for learr
are placed within this framework. Methods for establishing the search spac
models and for carrying out the search process are reviewed. The frameworl
where particular learner modelling techniques are focussed and shows that
complementary since they address different parts of the framework.

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Pierre Dillenbourg and John Self

1. THE FRAMEWORK

Learner models are important within computer-based systems intended learning because they provide the means to support individually-adapted in task of 'learner modelling' or 'cognitive diagnosis' (that is, the task of build model) is defined later, but, in short, it is the process of inferring the learne by analysing his or her behaviour.

Although a number of learner modelling techniques have been develo modelling remains a serious problem for the implementation of computer-bas systems. Simply enumerating these techniques does not really help us: framework describing precisely the role of these techniques in order to c adequacy. As we will see, it turns out that many of the techniques are not al address different aspects of the learner modelling problem.

The aim of this report is to provide a comprehensive conceptual fran learner modelling. The framework we propose includes a formalism, a termi graphical representation of the learner modelling process.

The purposes of this framework are :

1. to define a consistent terminology for use in research on learner modelling
2. to describe several approaches to learner modelling and to make precise tl focus,
3. to describe especially the contributions of machine learning techniques,
4. to emphasize the importance of conceptual aspects in learner modelling,
5. to identify (implicit) underlying assumptions.

1.1 The vertical dimension

Vertically (see Figure 1), the framework discriminates three related er relationship between these entities is that they all concern the same *problem do* adapt the definition proposed by Van de Velde (1988), a problem domain is (P, B, Solution) where:

P is the set of problems in Ω

B is the set of possible behaviours in Ω

Solution is a relation between P and B, i.e. Solution is a subset of P x B.

A *behaviour* (B) is defined as a sequence of actions performed by an agen potential solution for some problem (P) belonging to P. A behaviour will be d the following syntax: `behaviour(agent,problem) =` B_AP. The agent may be the lea or the computer system. B, the set of possible behaviours, is generally very l includes any correct, incorrect, or even inconsistent behaviour.

The *behavioural knowledge* (bk) of the domain corresponds to Van de Vel concept of *problem solver*. A problem solver contains an inference structure anc theory. The inference structure is a set of *inferential primitives* and *inference relatio* be used to infer some behaviour B (from B) for a given problem P (from P).

The *conceptual knowledge* (ck) contains the definition of the concepts unde the behavioural knowledge. The discrimination between the behavioural an knowledge corresponds to the "shallow" vs "deep" knowledge issue raise system design (as will be discussed below). The deep knowledge consists theories and problem solving knowledge; the shallow knowledge is a p description of the problem solutions.

As shown in Figure 1, the conceptual knowledge may exceed the problem i.e. it may enclose concepts which are usable for problems not present i following example, ck's concepts such as "disease" or "symptoms" are not rest bk's context of heart disease diagnosis. For example :

Ω	the problem of heart disease diagnosis
B_DP	the diagnosis produced by a doctor for a particular patient
bk	set of Mycin-like rules for diagnosis and the inference engine
ck	representation of the heart, concepts for diseases, etc.

< about here: Figure 1. The vertical dimension of the framework >

Globally, the vertical relation is one of **consistency**. The relation betwe behavioural knowledge and the behaviour has a level of consistency depe logical theory inscribed in the behavioural knowledge. This relationship ma top-down as a "*running* " process: the behaviour is the result of running the l knowledge on a particular problem of P. The relationship between the con behavioural knowledge may be viewed top-down as some *knowledge comp* process.

The consistency between two entities will be denoted in our framework fo the symbol ¢ ($0<¢<1$), where $¢=1$ denotes complete consistency (thus ¢ d measure of the agreement between two entities, not strict logical consistency, of course be just true or false):

$¢(bk, B_AP)$ indicates the consistency between the behavioural know and A's behaviour for problem P.

$¢(ck, bk)$ indicates the consistency between the conceptual behavioural knowledge sets.

$¢(B_AP, ck)$ indicates the consistency between A's behaviour for prol and his conceptual knowledge.

As we will see, most work on learner modelling postulates high value various ¢. In general, the quality of the diagnosis built will be a function of t the ¢. By definition, a behaviour results directly from bk and indirectly frc hence we can state that normally $¢(ck, B_AP) < ¢(bk, B_AP)$.

When we want to refer indifferently to bk or ck, we will use *k.

1.2 The horizontal dimension

By contrast to the vertical dimension, the horizontal one (see Figure 2) **discrepancies** between the same entities possessed by different agents. The modelling context involves two agents, namely the learner and the system. learner modelling is to build the best representation of the learner (we will i what might be meant by 'best' in this context). Our model emphasizes the fa only a computerised representation of the learner's knowledge, an approxim the system has no direct access to his or her knowledge.

This horizontal dimension clearly indicates that our framework adopts a perspective. The term "*differential modelling*" is often used when the learner's be and knowledge is represented with respect to the system's behaviour and kı the formalism used in this framework, we use the expression R_Ax to de representation that an agent A has of some object x.

So the model horizontally discriminates three entities :

S the system,

L the learner,

R_SL the system's representation of the learner.

< about here: Figure 2. The horizontal dimension of the model >

A discrepancy will be represented by Δ. Three kinds of discrepancy m between these entities :

Δ(L,S) the difference between the learner and the system. (This considered to describe learner errors, since the system is supposed to be "correct")

$\Delta(S, R_S L)$ the difference between the system and the system's repres of the learner. (This may be regarded as the representa $\Delta(L, S)$, built by the system, or in other words $\Delta(S, R_S L)$ $R_S\Delta(L, S)$.)

$\Delta(L, R_S L)$ the difference between the learner and the system's repres of the learner. (This represents the error in learner mode the difference between the actual learner and the diagno by the system.)

There is a clear difference between 'discrepancies' and 'consistencies': dis indicate differences between two similar entities (e.g. two behaviours), while emphasize the logical link between very different things (e.g. an agent's know behaviour).

1.3 The model

The two described dimensions are crossed for forming the model : each vertical dimension exists for each entity of the horizontal dimension (see Fi model contains the following components:

- $R_S ck$ the system's (representation of) conceptual knowledge.
- $R_S bk$ the system's (representation of) behavioural knowledge.
- $B_S P$ the system's behaviour on problem P.
- $R_L ck$ the learner's (representation of) conceptual knowledge.
- $R_L bk$ the learner's (representation of) behavioural knowledge.
- $B_L P$ the learner's behaviour on problem P.
- $R_S R_L ck$ the system's representation of the learner's (representa conceptual knowledge.
- $R_S R_L bk$ the system's representation of the learner's (representa behavioural knowledge.
- $R_S B_L P$ the system's representation of the learner's behaviour on pr

< about here: Figure 3. The model >

This set might be extended with representations such as :

- $R_L R_L ck$ the learner's representation of his own representation conceptual knowledge (metacognition).
- $R_L R_S ck$ the learner's representation of the system's conceptual knov crucial issue in interface design).

...

The word "system" might be replaced by "ITS", or more precisely by one components. The standard ITS components are the expert (or domain model) pedagogical model), the diagnoser + learner model and the interface. W speaking about the knowledge required for solving a class of problems (i.e. R_S the system's behaviour (i.e. B_SP), the "S" refers to the expert component. Si "S" in R_SR_Lbk is the diagnoser component. Such a discrimination among th components is however not pertinent in our formalisms because the diagnost highly depends on the expert knowledge for building the diagnosis.

The main *input* to the learner modelling process is R_SB_LP. The system's be B_SP and its representations of knowledge R_Sbk and R_Sck constitute other inpu learner model is not built *ex nihilo* but is incrementally adapted from a previ then R_SR_Lbk and R_SR_Lck are also to be considered as items of input.

A major advance of ITS over traditional Computer Assisted Instruction is account what the learner has and has not understood. This means that the the learner modelling process is a description of R_Lbk and/or R_Lck. Globally, CAI may be located at the first level of the model (behaviour), most ITSs reac level (behavioural knowledge) and some of them reach the third level (knowledge). The flavour of this model is to put the emphasis on the conceptu

To indicate that the representations of learner knowledge are diagnose some behaviour, we write

$$R_SR_L{*}k = f(B_LP)$$

where f is some diagnostic function.

The *learner model* is, according to this model, R_SR_Lbk and/or R_SR_Lck, i.e. the c described above. The word "model" may have various significations, fror enumeration of characteristics or numeric parameters (as in traditional CAI) to set of knowledge, close to the idea of mental model proposed by cognitive scie

The *learner modelling process* (or diagnosis process) is the process of inferr learner model (or diagnosis) from a learner's behaviour. A possible goal of modelling process is to obtain the best image of R_Lck and R_Lbk, i.e. to m $\Delta(R_Lck, R_SR_Lck)$ and $\Delta(R_Lbk, R_SR_Lbk)$.

The system needs to be informed about the quality of its output, i.e. to r appraisal of the value of $\Delta(R_L{*}k, R_SR_L{*}k)$. We call this information *diagnosis feedb* It is clearly different from the didactic feedback used in tutorial interactio feedback confirms to the system that its representation of the learner fits wit representation, while didactic feedback, on the other hand, tells the lear representation fits with the system's representation. We will later on describe for obtaining this feedback :

- *behavioural prediction* : the learner's behaviours are used to confirm the diag to choose among current hypotheses,

- *explicit interaction* : the learner is asked to confirm the system's diagnosis,

- *behavioural simulation* : $R_S R_L bk$ is run to produce a predicted $B_L P'$ which is comp to $B_L P$ - if they match the diagnosis is confirmed (under the postulate that process is isomorphic to human reasoning).

- *didactic prediction* : if the learner model is valid, it can be used to select a action, i.e. to predict the efficiency of this action or to anticipate the learner after the action. If the predicted changes happen, the diagnosis is confirmed (problems which are described in section 4.4.2).

At this stage, we are of course glossing over a great many details and most of these issues will, we hope, be addressed.

1.4 The model's context

Here we list some implicit assumptions which are generally present modelling work :

Assumption 1 : Learner modelling is related to some idea of what tutoring is: I diagnostics for taking decisions, which means that it is the system which ta some of the didactic decisions, and not the learner. (A possible alternative ju learner modelling is that it enables the ITS to show the learner his own misconceptions, etc.)

Assumption 2 : The learner model is seldom exhaustively described (wh theoretically impossible given the infinite amount of common sense knowled More often, it is by default assumed to be closely related to the system's (c behavioural) model. This means that only the discrepancies between these knowledge need to be represented (hence the "diagnosis" term, defined in s This is the basic assumption of any differential approach, but it is also a m criticism of work in learner modelling since many systems represent 'expert which is known to be very different to that of learners.

Assumption 3 : Learners are often viewed as correctly applying an incorrect a (i.e. in our formalism, $R_L bk$ is wrong but $¢(B_L P, R_L bk)$ is high), while instead mo in education considers the learners as incorrectly applying a correct algorithm

Assumption 4 : Differential modelling proceeds as if there were representa knowledge in the learner's head which can be compared, piece by piece, with representations and that reasoning occurs by manipulating such representati be a computational convenience or it may reflect a profound philosophical nature of knowledge. In the latter case, it has been challenged by recent wo cognition (e.g. Clancey, 1990). But this is a debate about the content (if ar even the advocates of situated cognition emphasise that an agent (such as the have representations of another agent's knowledge (R_SR_L*k) in order to comm that agent.

Our model integrates the discrimination of Wenger (1987) between 'b diagnosis' (related to R_SR_Lbk in our model) and 'epistemic diagnosis' (related our model). However, the framework does not address what Wenger calls diagnosis'. The emphasis is on the dynamic modelling of learner knowledge modelling longer-term, knowledge-independent, individual attributes. The ju this is not that such attributes are necessarily unimportant (although the de have not yet found great need for them) but that ITS research has yet to co any detail. In particular, there are no significant techniques for inferring s from learner's behaviour. If such attributes were to be added to the framew would not be expressed in a differential fashion but as an extra dimension t column.

Our distinction between bk and ck is related to that of Clancey (1986) 'situation-specific model' and a 'general model'. The general model "descr known about the world - for example, knowledge about stereotypic patients, treatment plans"; the situation-specific model "includes the specific problem transformed or reorganized in some way, depending on the nature of the ta 1986, p395). Thus, the situation-specific model adopts (using some inferenc part of the general model to generate specific behaviour to solve a proble considers in detail how the qualitative structure of these models and inferen differ in different domains. In comparison, our model is rather domain-indep we are not concerned directly with the contents of the various compon framework for different domains but more with the general relationships components and how the various learner modelling techniques relate to these

Our model has to be simpler than the reality, as manifested in existing these are rather undisciplined agglomerations of miscellaneous techniques. only useful if it erases non-pertinent details in order to give a clear view of t process. This means we will have to abandon irrelevant details or to "cut th our descriptions of some systems in order to integrate them neatly within th Nonetheless, we feel that the framework captures the essential distinguishin the various techniques (as described in sections 3 and 4).

2. TERMINOLOGY

The terminology we outlined in the previous section has now to be elabo of the terminology of learner modelling has been introduced for a specific a approach. This specificity reduces the ability to generalize across approach d one approach X is described by characteristics A and B, it does not mean that dependent on each other, or specific to X, but that X results from a combinat B. We believe our discipline will progress if some general descriptors are Obviously, since these generalised descriptors lose the specificity that th introduced, there is a risk in proposing less specific descriptions. This will later, where approaches and systems are described individually. In the me common terminology will favour comparisons between approaches and identification of the focus of various approaches. We aim for instance to sho approaches are not incompatible but complementary, because the points o differ constitute different parts of the diagnosis process.

2.1 The meanings of "behaviour" and “solution”

Until now, we have used "behaviour" to describe the *solution* proposed to P by the learner or by the system. For an equation 3x+5=20, the solution is medical diagnosis problem, the solution is the diagnosed disease, etc. characteristic of the learner's behaviour is that it is observable by the sy *learner's behaviour* B_LP is defined as a sequence of actions the learner performs system interface then $B_LP = R_SB_LP$.

This definition is less clear when we consider the "product versus proc Some ambiguity arises because some intermediate steps of the inference p produce behaviour : for instance, the sequence of transformations written wh equation or the sequence of questions asked by the doctor. In AI literatu ‘solution’ is used for describing not only the final solution but also the solu Hence we prefer to call the sequence of actions which relate P to B (or in ot some trace of the inference process) the *solution path*. The *solution* is usually the of the solution path. This definition does not eliminate the ambiguity con instance in theorem proving, where the solution process (the sequence transformations) is indeed the expected solution.

When some steps of the solution path are made observable to the system, considered to be a part of the behaviour. Hence, the *learner's behaviour* may be c the observable subset of the solution path, generally including the last step.

Our definition of a learner's behaviour emphasizes the mental/o characteristics of inference steps. This distinction does not hold for systems s system's inference steps from P to B may be hidden or made observable by t

Subsequently, we will focus on the subset of the *system's behaviour* B_SP w
corresponds (in a sense to be discussed) to the learner's behaviour.

We will also see that, in many cases, learner modelling will not be perfor
single behaviour but from a set of behaviours $\{B_LP\}$ produced for a set of pr
We will see later on the rationale for enlarging the behaviour to a larger s
inference process or to several behaviours.

2.2 Classes of discrepancies

The ITS literature has given different names to the various Δ relat
(discrepancies between the model's columns), as shown in Figure 4:

2.2.1 System - (represented) learner discrepancies

The first kinds of discrepancy are between the system's knowledge
(represented) learner knowledge. These discrepancies have been (inconsist
misconceptions, bugs, mal-rules, etc. We try here to propose some stricter
These discrepancies are the key objects in the learner modelling process whic
been approached in a *differential* way, i.e. by characterizing the learner's knowl
differences with respect to the system's knowledge.

< about here: Figure 4. Misconceptions, bugs and errors >

A *misconception* refers to a discrepancy at the conceptual level. The
misconception is the discrepancy between the system's and the learner's rep
ck. Since the system has no direct access to the learner's representati
misconceptions are approximated by the discrepancy between the system'
system's representation of the learner's ck :

$$\Delta(R_Sck, R_Lck) \approx \Delta(R_Sck, R_SR_Lck)$$

A *bug* refers to a discrepancy at the behavioural level. By contras
psychological connotation of the word "misconception", the term "bug" con
language of computing: in the early work of Brown and Burton (1978), discre
represented by buggy procedures. Since the system has no direct access to
representation of bk, bugs approximate the relation between the learner's an
representations of bk:

$$\Delta(R_Sbk, R_Lbk) \approx \Delta(R_Sbk, R_SR_Lbk)$$