

A Learner Model Reason Maintenance System

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Abstract.

Learner Modeling is a dynamic process. Creating and maintaining models of learners by an interactive system is not a precise task, and it requires guesses and abductive generation of explanation of the learners' actions. In addition, learners change their behavior while interacting with the system. Therefore, these systems need some mechanisms to maintain the rationality of the learner models created. For this maintenance to be rational, we enunciate two basic principles: system consistency and learner accuracy.

We present a system AMMS (Agent Model Maintenance System) to maintain learner models in accordance with these two principles, which were followed by introducing reasons (endorsements) for the hypotheses created about the learner. These reasons (which are based on the acquisition rules) are kept in the AMMS, so it is possible to choose the most trustable learner model by using a "trust" function.

1 Introduction

This document describes the mechanisms whereby a learner modeling system is able to keep the consistency of learner models. The process of modeling learners is a very dynamic one for two main reasons: (1) the acquisition of the model is based on guesses about the learner which may need to be constantly checked and revised; (2) the learner himself changes his behavior which therefore implies a change in the model.

A learner modeling system has three main parts: an acquisition module; a reasoning system and a reason maintenance system. The acquisition module generates hypotheses about the learner to be included in the model. The reasoning system performs inferences in the model itself, according to reasoning mechanisms ascribed to the learner. The reason maintenance system keeps the justifications of all inferences made, both by the acquisition and by the reasoner, deciding the state of the learner model.

Acquiring learners' models (from their actions) is a hard task, because it signifies not only making inferences about their knowledge from the expected behavior, but also creating hypotheses about their misconceptions because of "incorrect" behavior. Most of the acquisition process is consequently not certain, and many facts generated into the model may have to be revised.

In order for a learner modeling system to be able to perform the maintenance of these models, some reason maintenance techniques have to be used. Because learners models are beliefs of a system about the beliefs of a learner, the rationality of the belief maintenance

is based on two principles: system consistency and learner accuracy. These two principles impose some extra features and behavior on the Reason Maintenance Systems to deal with learner models.

In this report we describe the mechanisms of one such reason maintenance systems (AMMS), its main features and the communication with the learner modeling system. The system (AMMS) provides a set of functions to keep justifications for the facts kept in the model, and answers questions from the modeling system about the state of the learner model.

The main contribution of this work lies fundamentally on the way the changes in the learner models are performed. The approach presented is a consequence of adopting the view that the acquisition methods used to create hypotheses about the learner are the ones that bring the uncertainty to the modelling process, therefore, need to be used in that revision.

2 The Learner Model Maintenance Problem

A Learner Model \mathcal{LM} is a set of explicitly represented facts about the learner. They can, for example, represent preferences, beliefs, skills or actions. The \mathcal{LM} is constructed by the **Learner Modeling System** during the interaction with the learner and based on the learner's behavior. Learner modeling has several processes: generating hypotheses to explain the learner's behavior (called the *acquisition process*); changing the model to keep its consistency and adequacy to the learner's behavior (called the *maintenance process*); using the model to predict the learner's behavior (called *learner's simulation or reasoning process*). The learner modeling system keeps the model in order for an **application** to use it and adapt the interaction to the particular learner. The application can be for example an Interactive Learning Environment or a Tutoring System or even an Advisory system. We will assume that the learner modeling system is separated from the application that interacts with the learner (with some restrictions).

To keep the model, the system will follow two main principles:

System Consistency The \mathcal{LM} should be consistent from the point of view of the system's beliefs.

Learner Accuracy The model should reflect all the actions performed by the learner and the hypotheses generated must justify and be consistent with those actions.

These two principles give some guidelines for the creation and maintenance of the model.

Let's look at a situation of learner modeling. The sentences to be included in the \mathcal{LM} can be actions, beliefs or simply characteristics of the learner. The sentence which states that the learner believes p is represented by $B_l(p)$.

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To make the example simpler we will denote *the Moon turns around the Earth* by a and *the Moon is a satellite* by b .

Situation 1

(a) Previous $\mathcal{LM} = \{B_l(a)\}$.

(b) From the acquisition rule

[normally] If $B_l(a)$ THEN $B_l(b)$

the system infers that $B_l(b)$.

So, $\mathcal{LM} = \{B_l(a), B_l(b)\}$.

(c) The learner says that he does not believe b .

(d) The system uses an acquisition rule that says if the learner "says" something then he believes it and $\neg B_l(b)$ will be included in the \mathcal{LM} .

At this point

$\mathcal{LM} = \{B_l(a), B_l(b), \neg B_l(b)\}$.

If the application needs to make an intervention to the learner based on the belief the learner has about b , that will be difficult because the model has both $B_l(b)$ and $\neg B_l(b)$. This model seems not to respect the two principles for learner model maintenance: system consistency and learner adequacy. Although it seems perfectly possible for a learner to believe b and not b at the same time intuitively in this situation it appears not to be the case. So, for the system to react and argue with the learner about b , it needs to "trust"³ either $B_l(b)$ or $\neg B_l(b)$.

3 AMMS Basic Principles

The AMMS is an auxiliary tool to be used together with the learner modeling inference mechanism in order to keep the justifications for each fact to be included in the learner model.

The AMMS uses a network of justifications to keep the dependencies of the facts in the model. The network used by the AMMS is a 2-tuple $\langle \mathcal{N}, \mathcal{J} \rangle$, where \mathcal{N} is the set of nodes in the net and \mathcal{J} the set of justifications. There are four types of nodes in the net: assumptions \mathcal{A} ; justified assumptions \mathcal{JA} ; "endorsements" \mathcal{E} ⁴ and premisses \mathcal{P} . Every fact in the learner model has an associated node in the net. The learner modeling system can create assumptions while making a choice deriving new facts in the learner model. The assumptions $a \in \mathcal{A}$ can be used by the cognitive diagnosis subsystem in order to get an hypotheses that justifies the learner's incorrect behavior. Assumptions are nodes marked by the modeling system and they justify the nodes that depend on the choices made during the modeling process.

There are two types of assumptions: **normal assumptions** used for problem solving when making a decision and **justified assumptions** used to create hypotheses to explain the learner's behavior. The justified assumptions are supported by the acquisition mechanisms (by endorsement nodes).

When the modeling system creates an hypothesis to explain the learners behavior based on an acquisition rule A , that rule (A) endorses that hypotheses. In the AMMS this is dealt with by creating a justified assumption which has the A "endorsement" in its justification.

³ This notion of "trust" will be defined later in this document.

⁴ The idea of *endorsements* [4] has been used in Murray's work [11]. In this document, we will use the idea of an endorsement to be an explicit recorded argument for an hypotheses, but we give our own formal definition within the framework presented.

The premisses are certain acquired facts (which can be, for example, some actions performed by the learner).

When the modeling system derives a new fact about the learner it will create a new justification which will be included in the set \mathcal{J} in the net.

A justification is:

$a_1, a_2, \dots, a_n \rightarrow b$

where the a_1, a_2, \dots, a_n are the antecedent nodes and b is the consequent.

The AMMS records the dependencies of the nodes by keeping those justifications, such that assumptions can appear in the antecedents of a justification.

Apart from the types of nodes mentioned, there is one special type *false*. This node is used to represent an inconsistency in the net.

The main idea of Reason Maintenance systems is to keep labels of the nodes representing the state of the system's belief in the fact corresponding to the node.

This will allow it to answer questions such as:

making assumptions (A) does the learner believe p (according to the learner model)?

This is done by computing the extensions of A that support p .

In the AMMS case, a label is a set of environments where an environment is a set of assumptions (either normal or justified assumptions). The set of nodes derived from a consistent environment is called a **context**. *False* cannot be derived from a consistent environment. The assumptions in the environments can be either In or Out-assumptions. Intuitively we can understand an Out-assumption as the assumption to be used when the modeling system makes an inference based on the absence of information.

In order to define the Out assumptions we will use two meta-predicates: IN and OUT, and define them in the same way Dressler did in [5]. For each node x and every context c , the node can either be IN or OUT with respect to that context: $IN(x, c) \leftrightarrow x \in c$ and $OUT(x, c) \leftrightarrow x \notin c$. The Out-assumptions are defined by: $Out(x)$ holds in context c iff $OUT(x, c)$.

In order for the AMMS to prevent an assumption (x) holding together with $Out(x)$, a justification must be included in the net:

$x, Out(x) \rightarrow false$

using the inference rule *consistent belief rule* [5], which is $(x, Out(x) : false)$. Another inference rule was introduced, the *nogood rule* [5], which is:

$(\{a_1, a_2, \dots, a_n, Out(x)\} inconsistent : \{a_1, a_2, \dots, a_n\} \vdash x)$.

An extension of an environment E with respect to a set of assumptions O is the set of nodes derived from the minimal set of assumptions M such that $E \subseteq M$ and $\forall_{Out(b_i) \in O} : Out(b_i) \in M \vee M \vdash b_i$.

3.1 The Situation 1 revisited

The case in situation 1, using the AMMS will be the following:

- (a) $label(B_i(a)) = \{\{\}\}$.
- (b) the acquisition rule is interpreted as a normal default rule (where M is read as "it is consistent to assume"[13]):
 $B_i(a) \wedge MB_i(b) \text{ Then } B_i(b)$
and the justification given to the AMMS will be:
 $B_i(a), Out(\neg B_i(b)) \rightarrow B_i(b)$
and the $label(B_i(b)) = \{\{Out(\neg B_i(b))\}\}$
- (c) Interaction step.
- (d) the acquisition rule is:
 $say_i(X) \wedge MX \text{ Then } X$
so: $say_i(\neg B_i(b)), Out(B_i(b)) \rightarrow \neg B_i(b)$
the labels are: $label(B_i(a)) = \{\{\}\}$
 $label(B_i(b)) = \{\{Out(\neg B_i(b))\}\}$
 $label(\neg B_i(b)) = \{\{Out(B_i(b))\}\}$

However, the environment $\{Out(\neg B_i(b)), Out(B_i(b))\}$ is no-good (because of the justification introduced associated with the negation).

There are two possible extensions :

$$E_1 = \{B_i(a), B_i(b), say_i(\neg B_i(b)), Out(\neg B_i(b))\}$$

and $E_2 = \{B_i(a), \neg B_i(b), say_i(\neg B_i(b)), Out(B_i(b))\}$

one where $B_i(b)$ holds and another where $\neg B_i(b)$ holds.

4 Trusting Hypotheses

Unfortunately the result obtained in the previous example is not what a teacher would use to plan a tutorial intervention. Intuitively, we would say that the learner does not believe b (he just said so!), forgetting the inference made by the system from the belief a . We would say that we **trust** more the acquisition rule in step (d) than the rule in step (b).

Such trust depends on the process by which the facts in the model are acquired, hence, on the acquisition rules (or mechanisms). Thus, these "rules" (or mechanisms) have to be kept by the AMMS, as well, as kinds of "reasons" for the hypotheses generated.

The system will keep these reasons as a special kind of node called "endorsement". We will say that the acquisition mechanisms will endorse the hypotheses they generate.

Based on these endorsements, we can define a new type of environment, an *E-environment* which is also kept in the label of the nodes:

Definition 1 An *E-environment* EE is a set of assumptions and/or endorsements, such that for all justified assumptions $ja \in EE$ if "e endorses ja" then $e \in EE$.

The E-environments not only contain assumptions but also the endorsements used to support some of the hypotheses. If an endorsement e belongs to the E-environment of a node we say that the node holds endorsed by e .

The previous example will be:

- (a) $label(B_i(a)) = \{\{\}\}$.
- (b) the rule is interpreted as a normal default rule:
 $B_i(a) \wedge MB_i(b) \text{ THEN } B_i(b)$
and the justification given to the AMMS will be:
 $e(\text{generalization}) : B_i(a), Out(\neg B_i(b)) \rightarrow B_i(b)$
and the
 $e - label(B_i(b)) = \{\{Out(\neg B_i(b)), e(\text{generalization})\}\}$
- (c) Interaction step.
- (d) the acquisition rule is:
 $e(\text{self Assessment}) : say_i(X) \wedge MX \text{ THEN } X$
so: $say_i(\neg B_i(b), Out(B_i(b)) \rightarrow \neg B_i(b)$
the labels are:
 $label(B_i(a)) = \{\{\}\}$
 $e - label(B_i(b)) = \{\{Out(\neg B_i(b)), e(\text{generalization})\}\}$
 $e - label(\neg B_i(b)) = \{\{Out(B_i(b)), e(\text{self Assessment})\}\}$

Before continuing one must say a bit more about the role of the acquisition rules, what they stand for in learner model acquisition, and how this notion of "endorsement" is related with it. Learners interact with a system (here called the application) performing actions. From these actions the acquisition process generates hypotheses to explain the learner's behavior. These hypotheses are obviously dependent on the actual state of the learner model. So, these acquisition rules are a kind of directive to make guesses as to the choice of hypotheses. Hence, some of these rules (and mechanisms) are stronger than others. They can, for instance, depend on the evidence of the action performed by the learner or on the domain of the interaction. This diversity of acquisition rules (and methods) needs to be taken into account in the justifications of the hypotheses generated.

Because the endorsements are part of the environments it is simple to choose one, if we can establish a relation between sets of endorsements. Such a relation represents the trust on the acquisition mechanisms. Based on this relation \ll and \ll_e , we can filter the stronger environments using the following function:

Definition 2 The **trust function** is a function from a set of *E-environments* into an *E-environment* y such that:

$$y = trust(X) \text{ such that for all } x \in X \ y \ll_e x \text{ or } y = x.$$

In the previous example we know that a self assessment acquisition is stronger than a generalization so:

$$\text{selfAsses} \ll \text{gen}$$

consequently we will achieve the intuitive situation where the system trusts the $\neg B_i(b)$ more than the $B_i(b)$.

One pitfall of this system comes from the definition of the relation \ll , which may depend on the domain, on the acquisition techniques and on the granularity required from the learner model.

For instance in the case of stereotype-based acquisition, a taxonomy of stereotypes is usually provided. This taxonomy combined with the way the triggering is defined may be sufficient to create a virtual taxonomy in order to establish the relation \ll (this has been done in [12]). Using this relation one can establish a relation between sets of endorsements (called \ll_e).

5 Related Work

There are several studies in the area of learner modeling that deal with the problem of uncertain learner models⁵ and their maintenance.

Huang, McCalla and Greer [6] [7] base the process of modeling the learner on two types of knowledge: stereotypical and deductive knowledge. This distinction brings two types of belief revision (evolutionary and revolutionary). In the same way, the use of belief revision for keeping the consistency of the models of the users is used by C. Tasso in a shell called UMT (see [2] and [3]). In UMT the revision mechanism is based on the fact that the non-monotonic inferences are performed based on stereotypes, and the revision is therefore dependent on their hierarchy. We argue however that stereotypical knowledge is just one case of default acquisition, which should be handled in the same way as any other acquisition, provided that a degree of trust is established before hand.

Another study, by Kono, Mizoguchi and Ikeda [10] [8] also takes the approach that the acquisition should justify the beliefs held in the model. Their work uses the concept of an **oracle** (a learner answer to a question) which is used in those justifications. However they do not make the model dependent on the process of acquisition, although some heuristics are used to guide the revision process. On the other hand, because the justifications are based on the oracles (actions of the learners) they can handle learner changes.

In Murray's work, the endorsements are arguments for and against the beliefs in the learner model. The endorsements presented in [11] are grouped in classes with different reliabilities. This correspond to an ordering among them, as in the AMMS case.

The approach of Van Arragon [1] to learner model acquisition is based on defaults as well, and uses the Nested Theorist to formalize that acquisition. In his work it is shown that default reasoning is a good technique to acquire learner models.

Finally, the idea of explicitly represented acquisition rules is deeply explored by Kass in [9] where a set of acquisition rules is defined for user model acquisition. These rules are also used to generate hypotheses in the GUMAC system.

6 Conclusions

We formulated the problem of maintaining models of learners and the principles that underly such maintenance. We presented a system (AMMS) which allows these principles to be followed. This system can be seen as an auxiliary tool to be used in a learner modeling system. AMMS has two extra types of nodes (endorsements and justified assumptions) to be able to cope with justifications based on the acquisition mechanisms.

Hence, we presented a way of guiding the maintenance of a learner model by the mechanisms of acquisition of such model.

To test the ideas described, the AMMS has been used to support stereotype based acquisition and to support the representation in the model of learners' conceptual change.

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⁵ We will restrict ourselves to non-numerical approaches to learner modeling.