# Towards a Trace-Based Adaptation Model in e-Learning Systems

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# Towards a Trace-Based Adaptation Model in e-Learning Systems

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**Abstract:** Adaptive learning systems aim to personalize and adapt resources and learning strategies according to learners' knowledge acquisition and behavior. In this paper, knowledge acquisition is estimated by using traces learners left during their learning activities. Learner's traces considered are activity duration and number of attempts to solve a given problem, upon which we developed a trace-based evaluation model. The latter is integrated into a trace-based adaptation model made of ontological rules and reasoning mechanism to deliver adapted resources and personalized learning strategy, represented as learning paths, which are sequences of situations containing resources. The reasoning mechanism is implemented as a state-transition process governed by an adaptation algorithm we proposed.

**Keywords:** Evaluation, adaptation, ontology, situation, resource, trace.

## 1. Introduction

Personalized adaptation of learning materials and navigation paths through learning resources has been considered as an important aspect for the development of efficient e-learning systems (Van Seters, Ossevoort, Tramper, & Goedhart, 2012; Brusilovsky, 2001). The adaptation process takes into consideration different parameters such as learners' characteristics or preferences, and/or attributes of learning contents (Wang & Wu, 2011), often considered as resources. The inconvenient of such approaches lies in the fact that learners' characteristics or preferences are inputs that the adaptive system must acquire before any adaptation process. These items of information are often static and need to be continuously updated in order to obtain valid and good content and learning strategy adaptations. Therefore, we introduce in this paper a trace-based adaptive e-learning system in which traces are meta-data about learner's behavior during a training session (Djouad, Settouti, Prié, Reffay, & Mille, 2010). Indeed, given the possibility to attach the duration and number of attempts to an interactive training activity, we can make use of these information as traces to evaluate both learner level and progress (Lebis, Lefevre, Guin, & Luengo, 2015). To estimate learner's knowledge acquisition, we have considered our trace-based evaluation model, previously introduced in (Chachoua, Tamani, Malki, & Estraillier, 2016). Based on both traces and students assessment model, our e-learning adaptive system builds a state-transition model in which states represent situations (made of learning resources such as lecture, quiz, exercise, etc.) and transitions express adaptation steps from one state to another, according to traces collected about learner activities.
The adaptation process generates a dynamic learning path from a situation to another forming a teaching strategy adapted to learner knowledge status. In addition, the transitions in our trace-based adaptive model are governed by logical rules and reasoning mechanism to maintain the consistency of the system. The logical rules and reasoning mechanism are implemented within a domain ontology we designed for trace-based situation to describe the main concepts in our system, namely, *scenario*, *situation*, *learner*, *resource* and *trace*.

The remainder of the paper is organized as follows. Section 2 summarizes some definitions about traces, and recalls our modeled trace-based assessment process. Section 3 details our trace-based adaptation model. Section 4 discusses some related works in the domain of adaptive e-learning systems. Section 5 concludes the paper and gives some perspectives.

## 2. Background

In this section we recall the evaluation model based on traces (Chachoua, Tamani, Malki, & Estraillier, 2016). In Subsection 2.1 we define concepts of trace, modeled trace, quantitative scoring function, trace-based quantitative scoring function, and scenario and situation concepts. In Subsection 2.2 a reminder of our trace-based assessment and evaluation model is provided.

### *2.1 Definitions*

**Definition 1.** (Trace). The notion of trace refers to log files describing events happened in a given system. In our context, a digital trace is any piece of information captured by observation processes within an e-Learning activity. It consists in chronologically observed objects, captured and saved on a support. Such traces are handled by Trace-Based Systems (TBS) (Settouti, Prié, Marty, & Mille, 2009) made of **Observer**, **Trace model** and **M-Trace** components (Mille, Champin, Cordier, Georgeon, & Lefevre, 2013).

**Definition 2.** (Trace-Based Quantitative Evaluation Function (Chachoua, Tamani, Malki, & Estraillier, 2016)). Let $f$ be a quantitative scoring function defined from $2^A$ to [0, M], and $T$ a trace defined over a domain $\mathbb{D}$. A trace-based quantitative scoring function is a binary function $g$ defined from $2^A \times \mathbb{D}$ to [0, M] as follows:

$$g: 2^A \times \mathbb{D} \rightarrow [0, \mathrm{M}]$$
$$(a, d) \mapsto \mathrm{g(f(a), d)},$$ such that $g$ is **bounded**, **fair** and **minimal**.

**Definition 3.** (E-learning Scenario and Situation). We define an e-Learning scenario $S$ as a sequence of situations $S = \{S_0,..., S_{i-1}, S_i, S_{i+1},..., S_n\}$. Each situation $S_i$ is a set of resources ordered by their level of difficulty denoted by $S_i = \{R_1 \prec R_2 \prec \cdots \prec R_m\}$, where $R_j$ with $j \in \{1, \ldots, m\}$ is a resource

### *2.2 Trace-Based Evaluation Model*

We recall that an activity $A_i$ has a full mark $M_{A_i}$, set by an expert or a trainer, and an optimal duration $D_{A_i}$, and an authorized number of tries $T_{A_i}$. Let us denote the duration taken by a learner and his/her number of attempts by $d$ and $t$ respectively. Therefore, the evaluation of the learner, denoted by $M_{A_i}(\mathcal{M}_{A_i}, d, t)$ (see Formula (1) below), according to these parameters is as follows.

$$M_{A_i}(\mathcal{M}_{A_i}, d, t) = \begin{cases} \mathcal{M}_{A_i} & if\ (d \leq D_{A_i}) \wedge (\mathrm{t} \leq T_{A_i}) \\ M_{A_i}(\mathcal{M}_{A_i}, d,) & if\ (d > D_{A_i}) \wedge (\mathrm{t} \leq T_{A_i}) \\ M_{A_i}(\mathcal{M}_{A_i}, t) & if\ (d \leq D_{A_i}) \wedge (\mathrm{t} > T_{A_i}) \\ \mathcal{M}_{A_i} e^{-\gamma\left(\frac{t-T_{A_i}}{T_{A_i}} + \frac{d-D_{A_i}}{D_{A_i}}\right)} & otherwise. \end{cases} \quad (1)$$

such that:

- if $(d \leq D_{A_i}) \wedge (\mathrm{t} \leq T_{A_i})$ then $M_{A_i}(\mathcal{M}_{A_i}, d, t) = \mathcal{M}_{A_i}$ corresponding to the ideal situation,
- if $(d > D_{A_i}) \wedge (\mathrm{t} \leq T_{A_i})$ then $M_{A_i}(\mathcal{M}_{A_i}, d, t) = M_{A_i}(\mathcal{M}_{A_i}, d)$ such that:

$$M_{A_i}(\mathcal{M}_{A_i}, d) = \begin{cases} \mathcal{M}_{A_i} & if\ (d \leq D_{A_i}) \\ \mathcal{M}_{A_i} e^{-\alpha\left(\frac{d-D_{A_i}}{D_{A_i}}\right)} & otherwise. \end{cases} \quad (2)$$

- if $(d \leq D_{A_i}) \wedge (\mathrm{t} > T_{A_i})$ then $M_{A_i}(\mathcal{M}_{A_i}, d, t) = M_{A_i}(\mathcal{M}_{A_i}, t)$ such that:

$$M_{A_i}(\mathcal{M}_{A_i}, t) = \begin{cases} \mathcal{M}_{A_i} & if\ (\mathrm{t} \leq T_{A_i}) \\ \mathcal{M}_{A_i} e^{-\beta\left(\frac{t-T_{A_i}}{T_{A_i}}\right)} & otherwise. \end{cases} \quad (3)$$

- if $(d > D_{A_i})$ and $(\mathrm{t} > T_{A_i})$, then we sum the extra-time and the extra number of attempts and we define the evaluation function $M_{A_i}(\mathcal{M}_{A_i}, d, t)$.
- α, β, $\gamma \in [0, 1]$ are attenuation constants. They allow computing scores in $[0, \mathcal{M}_{A_i}]$. If α, β and $\gamma$ are close to 0, then $M_{A_i}(\mathcal{M}_{A_i}, d, t)$ approaches $\mathcal{M}_{A_i}$. If α, β and $\gamma$ approach 1 then $M_{A_i}(\mathcal{M}_{A_i}, d, t)$ approaches 0. The closer to 1 α, β and $\gamma$ are, the harsher the attenuation will be.

## 3. Trace-Based Adaptation Model

In this section we detail our trace-based adaptation model. Subsection 3.1 describes the architecture of our adaptation process. Subsection 3.2 details the concepts of our domain ontology model. Finally, Subsection 3.3 describes the reasoning strategy for adaptation in the form of an algorithm.

### *3.1 Trace-Based Adaptation Process*

As illustrated in Figure 2, the architecture of our trace-based adaptation process is made of:

- **M-trace database**: it is a modeled trace management system, which maintains a database that stores learners' modeled traces,
- **Situation and resource knowledge database**: it is a knowledge base of situations and resources describing learning activities and teaching materials as an ontology modeling concepts of our domain in terms of classes and properties,
- **Evaluation model**: it implements our trace-based assessment model,
- **Strategy processor**: it implements the reasoning process to generate adapted situations and resources (Algorithm 1). The process receives as inputs traces from the m-trace database, the mark computed by the *Evaluation model*, and the current resource in the current situation. The result produced is the next resources and situation.

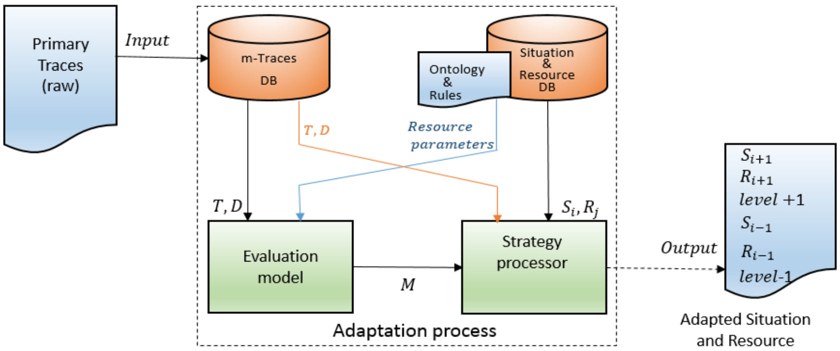


Figure 2. Trace-based adaptation architecture.

### *3.2 Ontology trace-based description*

We define our ontological trace-based model which takes into consideration the notion of situation (Pham, Rabah, & Estraillier, 2013). Figure 3 describes our ontological domain as:

- **Situation**: defines the interaction sequences in a training scenario to achieve an objective. A situation can be (but not limited to) a lecture, a quiz, a test, a practical work or directed work,
- **Scenario**: is a succession of situations execution until reaching a global goal. A scenario is designed by an expert or a teacher,
- **Resource**: is a learning material learners can use in a given situation,
- **Learner**: is an actor which interacts with resources in a given situation of training,
- **Mark**: is the evaluation process of learner activity based on time and number of attempts traces as detailed in our previous work (Chachoua, Tamani, Malki, & Estraillier, 2016),
- **Time trace**: is the duration took by a learner to complete the objective of the situation,
- **NB Attempts**: is the number of times taken by a learner to achieve a situation's objective.

### *3.3 Trace-Based adaptation strategy*

In this subsection we make use of Definition 3 to build a state-transition diagram as presented in Figure 4. The diagram illustrates the sequence of situations $S_i$ in a *scenario* $S$. A *state* represents a learning *situation* $S_i$, which uses a set of resources $R = \{R_1, \dots, R_m\}$ to achieve a goal $G_i$. A *transition* between states requires a set of conditions to meet. *Conditions* are trace-based values such as a mark $M_{R_j}^{S_i}$, which is computed based on duration trace $D_{R_j}^{S_i}$ and number of attempts $T_{R_j}^{S_i}$.

The user starts from a situation $S_i,\ i\ \in \{0, \dots, n\}$ and a resource $R_j$ of $S_i$ where $j \in \{1, \dots, m_i\}$ and $m_i$ is the number of resources in situation $S_i$. The starting point can be defined by the system according to learner's skill level. Algorithm 1 computes a trace-based mark to assess a learning knowledge acquisition and determines the next resource and situation.

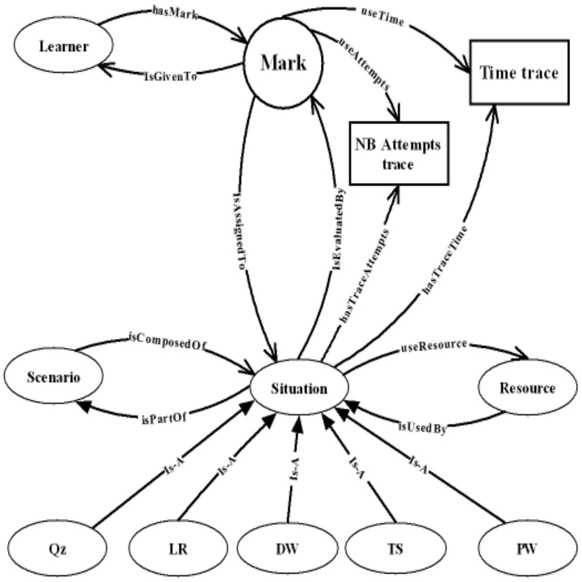


Figure 3. Fragment of trace-based situation ontology.

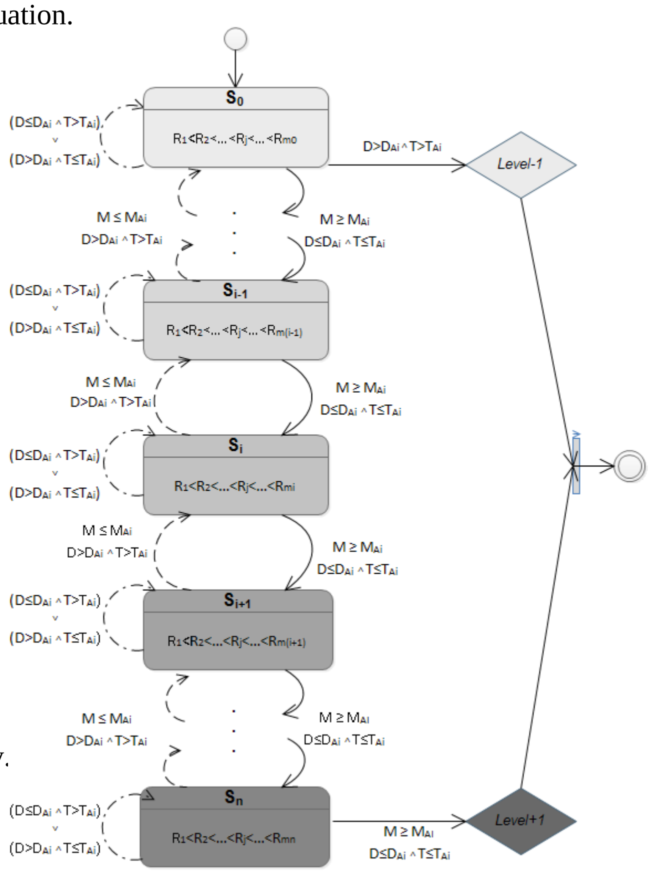


Figure 4. State-Transition diagram for situation and resource adaptation.

## 4. Related Work

Several adaptation processes have been proposed in different contexts to implement learning adaptive systems such as in (Hwang, Kuo, Yin, & Chuang, 2010; Mustafa & Sharif, 2011; Sosnovsky & Brusilovsky, 2015), in addition to adaptive e-learning hypermedia systems, which exploit navigational and presentation adaptations to implement learning styles and their dimensions (Felder & Spurlin, 2005). But, few of them make use of traces as a basis of the adaptation process. We can cite (Zouhair, Amami, Boukachour, Person, & others, 2013) in Computer Environment for Human Learning domain, in which a learner monitoring system has been designed to detect learner difficulties and drop out causes, and acts accordingly relying on a dynamic trace-based reasoning. However, the trace model, the analyzing process and the domain ontology have not been detailed.

In a web-based e-learning environment, an adaptive platform, called *Lecomps*, has been developed (Sterbini & Temperini, 2009) that builds adaptive personalized learning paths, by using learning goals, learner's knowledge and individual learning styles. It relies on a constraint logic-based engine to build learning objects LOs (Felder & Spurlin, 2005) and compliant with Bloom's and ACM's Taxonomies (Gorgone, Davis, Valacich, Topi, & others, 2002). A similar approach has been used to build personalized learning paths based on student's learning status (Hwang, Kuo, Yin, & Chuang, 2010). However, this approach does not provide adaptive adjustment in case of failure.

In the field of educational game (EG), (Göbel, Mehm, Radke, & Steinmetz, 2009), developed (i) a *macro-adaptation*, which is about scene sequences, and (ii) a *micro-adaptation*, which is about elements of scenes. Both adaptations are used in (Gros & Maina, 2015) to develop an extended adaptation that allows altering a predefined sequence and varying the level of difficulty by activate/deactivate game rules. Our approach does not need to predefine any sequence of situations. They are defined dynamically according to the level of the learner and his/her knowledge acquisition.

It is noteworthy that SCORM norm (Costagliola, Ferrucci, & Fuccella, 2006) considers both duration and attempts in test activities as parameters to set for tests but no traces have been used.

SCORM has then been extended in (Rey-López, Díaz-Redondo, Fernández-Vilas, Pazos-Arias, & others, 2009) to propose ADL-SCORM allowing an adaptive course creation based on user profile.

**Algorithm 1:** Trace-based adaptation process.
**Input:** Current situation $S_i$ and resource $R_j$ and their traces $D_{R_j}, T_{R_j}$.
**Output:** Next adapted situation $S_k$ or resource $R_m$.

$M = M_{A_j}(M_{R_j}, D_{R_j}, T_{R_j})$ { $M_{R_j}$ is the mark of $R_j$ }
**if** $(M = M_{R_j})$ **and** $(i < n)$ **and** $(j < m_i)$ **then**
    $S_i \leftarrow S_{i+1}$
    $R_j \leftarrow R_{j+1}^{i+1}$ { $R_{j+1}^{i+1}$: $(j+1)th$ resource of situation $S_{i+1}$ }
**else if** $(M = M_{R_j})$ **and** $(i = n)$ **then** $level \leftarrow level + 1$
    **end if**
**else if** $(D \leq D_{R_j}$ **and** $T > T_{R_j})$ **or** $(D > D_{R_j}$ **and** $T \leq T_{R_j})$ **then** $S_i \leftarrow S_i$
    **if** $j > 0$ **then** $R_j \leftarrow R_{j-1}$
    **else if** $i > 0$ **then**
        $S_i \leftarrow S_{i-1}$
        $R_j \leftarrow R_j^{i-1}$
        **end if**
    **end if**
    **end if**
**if** $(D > D_{R_j}$ **and** $T > T_{R_j})$ **then if** $(i > 0)$ then
        $S_i \leftarrow S_{i-1}$
        $R_j \leftarrow R_0^{i-1}$
    **else** $level \leftarrow level - 1$
    **end if**
**end if**
**end if**

The adaptation has been considered at both Sharable Content Objects and activities. Both adaptations depend on parameters deducted from the user's profile. Although SCORM includes a model of sequencing and navigation centered on the scores, it does not dictate how scores are computed, neither it uses traces. Besides, the Advanced Distributed Learning (ADL)'s training and learning architecture considering a set of standardized Web service specifications and Open Source Software has been designed to enrich SCORM by creating a rich environment for connected training and learning and its API called Experience API (xAPI) (ADL, 2014) that enables tracking across platforms. However, in our work we focused on learners' trace modeling for training strategy adaptation, which is considered as future research for xAPI (Poeppelman, Hruska, Long, & Amburn, 2015).

In IMS-LD, (Burgos, Tattersall, & Koper, 2007) considered 8 adaptation contexts, namely: *Interface*, *Learning flow*, *Content*, *Interactive problem solving support*, *information filtering*, *user grouping*, *evaluation*, and *changes on the fly*. Our approach could be seen as a trace-based instantiation of *Learning flow*-based adaptation, where learning processes are dynamically adapted as dynamic and personalized learning paths, so that the student can take varying itinerary depending on his/her performance, evaluated by our trace-based scoring function.

Finally, In (Amorim, Lama, Sánchez, Riera & Vila, 2006), an ontology to represent the semantics of the IMS Learning Design (IMS-LD) specification has been proposed, based on semantic technologies (Protégé, OWL) to enhance the expressiveness of XML implementation of IMS-LD conceptual model. However, it does not consider any trace modeling and student evaluation concepts, which are implemented in our ontological model.

## 5. Conclusion

We have developed a trace-based adaptation model for both resource and training path strategy. The adaptation model is based on our evaluation model proposed previously which performs learner assessment according to traces they produced during learning activities. Our adaptation model automatically generates adapted paths using a state-transition model. The ontological adaptation model focuses on five principal models namely, scenario, situation, learner, resource and trace.

The next step in our work is the implementation and validation of our trace-based adaptation model. To do so, it is important to have on hand an e-learning application and a collection of modeled traces. The former is an online laboratory for SQL training which has been already developed (Chachoua, Malki, & Estraillier, 2016), and its extension to our adaptation model is in progress.

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