Explanation and e-Learning: A First Pass

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Abstract

In the development of e-Learning systems, there is a recognizable trend towards more and more adaptive systems aiming to become assistants for the individual learner. This has led to systems making a lot of decisions and suggestions without asking the learner, e.g., presenting "best-fitting" content, by using methods and techniques from the field of Artificial Intelligence (AI). The increasing complexity of e-Learning systems raises the question whether such systems should explain their decisions. In this paper, we try to examine to what extent explanations are possible and useful in a first pass.

1 Motivation

In everyday human-human interactions, and, thus, especially in learning situations explanations are an important vehicle to convey information in order to understand each other. According to Roger Schank, a distinguished cognitive psychologist and computer scientist, explanations are considered the most common method used by humans to support their decision making [Sch86b].

As soon as we, as humans, cannot follow a conversation,

- we ask our conversation partner about concepts that we did not understand,
- we request justifications for some fact or we ask for the cause of an event,
- we want to know about functions of concepts,
- we want to know about purposes of concepts, and
- we ask questions about his or her behavior and how he or she reached a conclusion.

All those questions and answers are used to understand what has been said and meant during a simple conversation or during some lecture given by a human tutor or by a machine. An important side effect of explanations is that the process of explaining certainly has some effect on one's trust in the competence of a person or machine: We keep our trust, we increase or decrease it. At least, providing explanations makes decisions more transparent, thus, helping us keeping up our learning spirit.

The need for explanations provided by knowledge-based systems is well-known and was addressed by such fields as expert systems. The abilities on the part of machines are still very limited in human-machine interaction, but existing research results are worth looking at.

In this paper, we try to examine to what extent explanations are possible and useful in e-Learning. In the following section, we will have a look at explanations in general and revisit some of Roger Schank's work on explanation in AI. We will recapitulate categories of explanations and major quality criteria for explanations. In Section 3, we present our view on e-Learning and the major components of e-Learning systems, before we examine where explanations are useful and what kind of explanations should be given. The paper closes with an outlook on future steps.

2 Explanation and knowledge-based systems

In the following, we examine explanations in general, explanations studied in expert system research, and aspects of good explanations.

2.1 Explanation basics

Explanations are studied in depth in Philosophy of Science. There, scientific explanations, which are answers to why-questions, are mainly discussed [Sch93]: "Can some fact E (the *explanandum*) be derived from other facts A with help of general laws L (with $L \cup A$ called *explanans*)?"

In real world situations, explanations are often literally false due to moral, pedagogical, and other context-dependent reasons [Coh00]. Such explanations are designed to satisfy the questioner (at least temporarily). Nevertheless, they do not necessarily fulfill the purpose the questioner expects them to. For example, imagine the situation where a little girl asks her parents about where babies come from. The explanation most probably will not answer her question, it will just make her stop asking. The adequacy of explanations as well as of justifications depends on pragmatically given background knowledge. What counts as a good explanation in a certain situation is determined by context-dependent criteria [Coh00]. Major aspects of good explanations will be presented in Subsection 2.3.

The main purpose of explanations is to explain a solution and the path that led to the solution, and to explain how the respective system works as well as how to handle the system. Explanations, therefore, must be *inclusive* as well as *instructive* [Sch86a], i.e., they must cover more system behavior than is to be explained at a given moment, and they must instruct us in how to handle the system in the future.

An important consequence of the explanation capabilities of a system is that as soon as such a system explains its own actions not only to those who inquire about how the system works, but also to itself, the system becomes an *understanding system*, according to Schank's spectrum of understanding. The spectrum ranges from *making sense* over *cognitive understanding* to *complete empathy* [Sch86b]. In this spectrum, work on computer understanding can only reasonably claim one half of the spectrum, i.e., from making sense to cognitive understanding, as its proper domain.

Schank distinguishes three classes of questions that humans ask themselves about the world around them [Sch86a]: the physical world (e.g., "What general principles of physics can explain why things are happening the way they are?"), the social world (e.g., "What is the expected behavior of a social institution we deal with?" or "When is it in violation of that behavior?"), and individual patterns of behavior (e.g., "What behavior can be predicted by the knowledge that an individual belongs to a given group?" or "Why does a given group behave the way it does?").

The three classes together with the above mentioned spectrum of understanding can help deciding what can be reasonably explained by a computer. Most explanations certainly can be given with respect to the physical world, providing scientific explanations. In a world of software agents, recognizing, identifying, and explaining individual patterns of agent behavior becomes increasingly important.

The purpose of explaining is not only a technical one. The (human) user is also interested in how much trust he or she can have in a system. An obvious approach to increasing the confidence in a system's result is to output explanations as part of the result [MS88]. Belief in a system can be increased not only by the quality of its output but, more important, by evidence of how it was derived [Swa83]. The user wants to have a sense of control over the system [SM93].

2.2 Useful kinds of explanations

Expert Systems are an important kind of knowledge-based systems. They are designed to solve problems similar to a human expert in a particular, well-defined domain. The ability to explain the solution and the reasoning process that led to the solution is a major characteristic of so-called First-Generation Expert Systems. It is seen as an important activity for any knowledge-based system as it satisfies the user's need to decide whether to accept or reject a recommendation.

The explanations of First-Generation Expert Systems were often found unsatisfactory and the dialogues unnatural [Ric03], i.e., explanations often were nothing more than (badly) paraphrased rules, important aspects were missing, or too much information was given. In order to improve on dialogs, Second-Generation Expert Systems focused on context, goals and actions, methods and justifications to support explanations, together with an even richer knowledge representation.

According to Spieker [Spi91], there are five useful kinds of explanations in the context of Expert Systems:

Conceptual explanations Conceptual explanations are of the form "What is ...?" or "What is the meaning of ...?". The goal of this kind of explanation is to map unknown concepts to known ones. Conceptual explanations can be given in different forms, i.e., in form of definitions ("What is a bicycle?" "A bicycle is a land vehicle with two wheels in line."), as theoretical propositions ("What is force?" "Force is Mass times Acceleration."), by showing its prototypical usage ("What is a bicycle?" "The thing, the man there crashed with."), or by showing its function ("What is a bicycle?" "A bicycle serves as a means of transport.").

Why-explanations Why-explanations describe the cause or the justification for a fact or the occurence of an event. One has to clearly distinguish between causes and justifications. Whereas the first concept is causal in nature and not symmetrical, the latter only provides evidence for what has been asked for. Consider the answers to the following question: "Why does the universe expand?". A justification would be: "Because we observe a red shift of the light emitted by other galaxies". A causal explanation is: "Because the whole matter was concentrated at one point of the universe and because the whole matter moves away from each other." The Doppler effect is only an indication of the universe's expansion, it is not the cause of it.

How-explanations How-questions ask for an explanation of the function of a device or the causal chain of events leading to an asked for event, e.g., "How does an internal combustion engine work?" "In internal combustion engines, the burning of fuel takes place inside the engine; that is, burning takes place within the same cylinder that produces energy to turn the crankshaft …").

Purpose-explanations The goal of *Purpose-explanations* is to describe the purpose of a fact or object. Typical questions are of the form "What is … for?" or "What is the purpose of …?". For example, "What is the purpose of a valve in a combustion engine?" "The valve is used to seal the intake and exhaust ports."

Cognitive explanations Cognitive explanations explain the activities of the respective system. They are also a special case of why-explanations. Cognitive explanations explain or predict the behavior of 'intelligent systems' on the basis of known goals, beliefs, constraints, and rationality assumptions. They are further divided into action explanations ("Why was this seat post selected?" "For the given price, only one other seat post was available. But that was too short.") and negative explanations ("Why was no carrier chosen?" "A carrier is only available for touring bikes. The user did not choose a touring bike.").

The first four categories of explanations describe variations of scientific explanations, which answer questions based on laws of nature, thus explaining the physical world. Expert Systems answer such questions by using the knowledge contained in their knowledge base. Cognitive explanations, on the other hand, reflect a system-related view. They deal with the processing of the system. In a way, cognitive explanations explain the social world and individual patterns of behavior.

2.3 Aspects of good explanations

Expert Systems research early on operationalized explanations and derived guidelines on what makes an explanation good. Five aspects of good explanation in a knowledge-based system are deemed important and fall into three classes [Swartout and Moore, 1993]. The first requirement is concerned with how the explanations are generated. The second and third are requirements on the explanations themselves. The fourth and fifth both concern the effect of an explanation facility on the construction and execution of a knowledge-based system.

Fidelity An explanation must be an accurate representation of what the knowledge-based system does. Therefore, the explanations must be based on the same knowledge that the system uses for reasoning.

Understandability The generated explanations must be understandable, conceptually as well as regarding its content. This involves factors such as *terminology*, *user sensitivity*, *abstraction*, and *summarization*. Swartout and Moore further identified the factors *perspectives*, *feedback*, and *linguistic competence*. The system should be able to explain its knowledge from different perspectives and should allow for follow-up questions, if the user indicates that he or she does not understand (part of) an explanation. The explanations should sound 'natural' and adhere to linguistic principles and constraints.

Sufficiency The system has to 'know' what it is talking about. Enough knowledge must be represented in the system to answer the questions users could have. Explanation knowledge cannot be derived from problem solving knowledge solely. Knowledge acquisition, therefore, must be extended to also address explanation needs. Asking questions on what the system should explain later on when it is deployed, of course, helps to acquire problem solving knowledge more completely.

Low construction overhead Explanation must either impose a light load on the construction of a knowledge-based system, or any load that is imposed should be rewarded, for example, by easing some other phase of the knowledge-based system's life cycle. The question of what should be explained by a knowledge-based system is surely domain and application specific. If the users can be provided with explanations beforehand by training or easy to grasp documentation one should probably not add complex explanation capabilities.

Efficiency The explanation facility should not degrade the run time efficiency of the knowledge-based system.

Studies indicate that novice users prefer higher-level explanations mixed with background information and low level explanations, whereas experts tend to prefer low-level explanations [DTC03]. Novice users also tend to prefer explanations that justify results (why-explanations), while experts are more interested in anomalies and tend to prefer explanations that explain the reasoning trace (how-explanations, cognitive explanations). Unfortunately, there is no simple relation between the level of user expertise and the level of detail described, and appropriate user models are hard to develop [Caw93]. Swartout and Moore [SM93] suggest to use stereotypical user models where the level of detail is customized to each stereotype.

Another important observation to be aware of and a fact that makes it a lot harder to develop even user stereotypes is that experts usually do not have a detailed model of the user in mind. That may be part of the reason why users frequently do not fully understand an expert's response to their questions and why they frequently ask follow-up questions. We also have to deal with that the users often do not know what they do not understand.

From those observations, Moore and Swartout [MS88] developed a list of requirements for an explanation facility. It must be capable of

- monitoring the effects of its utterances on the hearer,
- recovering if feedback indicates that the listener is not satisfied with the response,
- answering follow-up questions, taking into account previous explanation—not as independent questions
- offering further explanations even if the user does not ask a well-formulated follow-up question, and
- making use of information available in the user-model—if one exists—but not require it.

With the kinds of explanations, the respective quality aspects, and the requirements on explanations facilities in mind, we will now have a look at e-Learning and e-Learning systems, before we examine where there explanations might be of use in Section 4.

3 e-Learning and e-Learning systems

In this section, we will first give a brief introduction on e-Learning and e-Learning system from our point of view, followed by a description of the main system components relevant for explanation.

3.1 Fundamental ideas

Taking a look at publications concerning "e-Learning", one finds out that there doesn't seem to be a common understanding of this term (the missing of exact definitions in the whole area of intelligent tutoring systems was already claimed in [Sel92]). In many cases, e-Learning is just understood as a stand-alone system where the learner is only interacting with a computer and some collaboration tools. We think that this is too restrictive and define e-Learning as *eletronically supported learning*, i.e., we deal with a *blended learning* scenario where a variety of media and methods (e.g., a lecture, a seminar, or any group work) can be used.

Of course, if we try to examine to what extent explanations are possible and useful in e-Learning, we are in particular interested in the e-Learning system, not in the abilities of human teachers or tutors.

The use of "new media" to enable new, attractive and complex presentations and the use of collaboration tools like chat, forum or a blackboard is typical for an e-Learning system. But that does not involve explanation issues. The most important difference is, that content (e.g., learning objects) are arranged by an author or by the system with the objective to teach a certain topic.

Before we think about where there is a need for explanation in an e-Learning scenario, we first have to take a look at the system components relevant for that topic.

3.2 System components

There are a lot of e-Learning systems using very differents architectures, but there are some "meta-components" which are part of (at least almost) every system independent from the concrete implementation and system architecture, e.g., learning objects, user related data, engines for presentation and reasoning, etc. We will now focus on the components relevant for explanation issues: *learning objects*, *user related knowledge*, and *reasoning core*.

Learning objects According to [JMRR04], there are always a lot of relations, links and cross references in any kind of learning material. Some content is prerequisited to understand other material, examples or images are useful for different purposes, some keywords are explained in different places and so on. In a book, the learning material is or should be, at least, arranged in a reasonable way – sequentially, of course – to enable the reader to understand it. But if one is interested in something not presented on the current page, the book's index, a bookmark – or even other sources – have to be used to find the respective information.

In contrast to a book, e-Learning gives the great opportunity to use a huge multimedia repository and to adapt to the user's individual needs and preferences. The learning material no longer has to be presented in a static way. If there's more than one way to do it, there's no more need for restriction to one way. The system can try to propose next steps, and presentation style or difficulty can be chosen by the user or be automatically selected by the system. To generalize: All relations and links existing within the learning material can be used to help the user and to create or offer individual scenarios.

To realize this opportunity, the content must be structured into relatively small fragments called learning objects. According to LOM[1] we define a *learning object* as an *arbitrary entity (digital or non-digital) that can be used, reused or referenced in an electronically supported learning process*. There are *atomic learning objects* (like an asset in the LOM Standard) and *complex learning objects* (e.g., a whole storyboard) aggregated from other ones. All learning objects have to be annotated with adequate metadata to provide information about relations to other objects, technical prerequisites, presentation style and so on. There are many different metadata standards for learning objects; among the most popular ones are the standards developed by LOM and SCORM[2].

The learning objects used by an e-Learning system not neccessarily satisfy the same standards and metadata formats, and they need not be stored in just one database. The content may be distributed and very heterogenous. Projects like ELENA[3] deal with this problem using ontologies to enable interoperability.

User related knowledge Information about the user is the key factor to enable adaptive, personalized behaviour of an e-Learning system. But in contrast to a teacher in a face-to-face situation, an e-Learning system is, at least today, very limited in the ways it can track a learner's behaviour. For example, emotions play a very important role in the learning process [Pic97], but it is very hard or even impossible to find out how a learner feels. Nevertheless, the system must gather some information about the user. This can be done by acquiring data directly from the user (e.g., by using a questionnaire), by capturing data about his behaviour (tracking) or by infering properties. The information will be stored in a so called *user model* [ZA01]. A user model is an explicit representation of some relevant characteristics (which have to be chosen in advance) of a user. The construction of user models is a very complex task requiring expertise in many fields like cognitive science, psychology, artificial intelligence, cognitive science, linguistics, psychology, human-computer interaction, etc.

[1] LOM is the Learning Object Metadata working group of the IEEE Learning Technoloy Standards Committee; see http://grouper.ieee.org/groups/ltsc/wg12

[2] Sharable Courseware Object Reference Model, see http://www.adlnet.org

[3] http://www.elena-project.org

Reasoning core e-Learning systems often try to draw conclusions using various kinds of input. These conclusions depend on *system knowledge* (i.e., all knowledge that does not change when moving from one domain to another and that does not depend on specific users), *application knowledge* (i.e., information about the current learning object(s)) and the current user. For example, a system will always use the same adaptation mechanisms relying on the same knowledge in every situation with any learner and any content.

We distinguish three main kinds of decisions in e-Learning systems:

- Infering from user log data to create an entry in the user model (e.g., assigning the user to a predefined user type or estimating a user's knowledge about a certain topic).
- Valuing the result of a test or an exercise. This can be rather simple if we have simple tests like a multiple choice question, but there are also more complex types of exercises allowing the input of a whole algorithm (e.g., a lisp program), free text answers or even the upload of complex objects like a PMML[4] in the DaMiT[5] system [GLM03, SD02].
- Adapting to a user's needs and preferences. This can be done by choosing different kinds of learning objects (concerning presentation styles or difficulty), showing/hiding links and functions and so on. Adaptive systems (not only in the context of e-Learning) usually have three main components: *sensors*, *actors* and *rules*.

There can be various inference engines in an e-Learning system using different KI techniques such as bayesian networks, k-nn, neural networks etc., but they always depend on system knowledge, information about the user and the current content.

4 Explanation and e-Learning

When does a learner need explanations in an e-Learning scenario? Of course, when there's something he or she doesn't understand regarding learning material. But we are not interested in this kind of explanation here, because it only depends on application knowledge. Instead, we want to focus on the characteristics of e-Learning., i.e., explanations depending on everything that is system related and based on system knowledge. What does that mean? In contrast to many traditional forms of learning, the learner, and not the teacher is in control when using an e-Learning system. But it depends on the system and the current scenario which choices there are and which choices will be presented in a concrete situation. Whenever a decision is made and the user has the feeling of not having full control about what is going on, there may be the need for explanation. Explaining a system's decision, e.g., how lectures are composed and knowing on what motivations new lectures are grounded, can drastically help to motivate the learner to move on and it can help to ease the learning process.

As shown in Section 3.2 there are three main scenarios where decisions are made:

1. adapting to a user's needs and preferences
2. analysis and valuation of tests or exercises
3. construction of the user model

We will now try to relate each of these scenarios to the explanation categories introduced in Section 2.

4.1 Adapting to a user's needs and preferences

According to the classification of Specht [Spe98] one can distinguish four dimensions of adaptivity in e-Learning:

- *adaptation means*, i.e., what means are used to adapt?
- *adaptation information*, i.e., what information is used to adapt?
- *adaptation purpose*, i.e., why is adapted?
- *adaptation process*, i.e., how is adapted?

Whenever the e-Learning system tries to adapt to a user's needs and preferences, these dimensions can be used for explanation matters.

Figure 1 shows an example screenshot with some links to related topics as result of some adaptation process. Here, the e-Learning systems offers three related topics to the user; "topic a" is marked with a (green) arrow, "topic b" is marked with a stop sign while "topic c" is not marked at all. Intuitively, we assume that "topic a" would be the best choice for us, while "topic b" should not be chosen. Anyway, a learner might ask for some explanation here. What kind of explanation can or should be offered?

[4] Predictive Model Markup Language, see http://www.dmg.org/
[5] http://damit.dfki.de

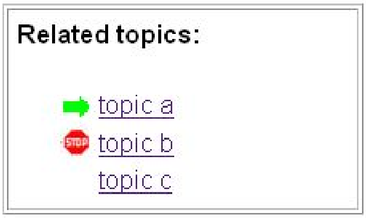

Figure 1: An adaptation example

- Conceptual explanations: An explanation of the meaning of the arrow and the stop sign.
- Why-explanations: Why is “topic a” marked with a (green) arrow, and why is “topic b” marked with a stop sign? The system could explain “topic a is marked with a green arrow because it seems to be the most appropriate topic; topic b is marked with a stop sign because some requirements are not met”.
- How-explanations: How where the three topics marked? An explanation could be: “The prerequisites of the respective learning objects were compared to the user’s knowledge. The topics were marked accordingly”.
- Purpose-explanations: The information required for this explanation is the adaptation purpose. In this case, the aim is to recommend a „best“ next step and to prevent the user from following a futile path.
- Cognitive explanations: Which algorithm and which input was used to mark the topics? For example, the system could explain: “The prerequisites of topic a are x, y and z. In the user model x, y and z are marked as known concepts. So the marking algorithm A selected a green arrow to mark the topic.”

4.2 Analysis and valuation of tests or exercises

Analysing simple tests or exercises like true/false questions or multiple choice questions is very simple and obvious for a user, but there are often very complex questions in e-Learning systems where explanations can be useful.

The valuation often implies the need for explanation, because a learner is always interested in how the result of a test was accomplished, especially if he thinks that the valuation is wrong or unfair.

- Conceptual explanations: An exercise may just be valued with “true” or “false”, but there may also be other “fuzzy” categories like “almost right” or a per cent rating which may imply the need for explanation.
- Why-explanations: The system should be able to describe what led to the rating of a test or an exercise.
- How-explanations: The process of analysing and rating should be described.
- Purpose-explanations: This category seems not to be relevant here.
- Cognitive explanations: For example, if a system can explain how a fill in blank question is analyzed in detail, a learner may understand that a bad result was just due to a misspelling that the system did not recognize.

4.3 Construction of the user model

Whenever a learner is in any way categorized, he may be interested in how that happened. An externalisation of the ideas used to infer information is needed. This is of special interest when the system tries to estimate the knowledge or progress of a learner, because this has a deep impact on many adaptation processes.

- Conceptual explanations: What is the meaning of used concepts, i.e., slots and associated entries in the user model? For example, in the context of stereotype user modeling, the explanation of different user types can be very important: A user might not understand what the term “learner type” and the correspondent entry means.
- Why-explanations: The system should be able to describe what led to an entry.
- How-explanations: A description of how entries in the user model are derived.
- Purpose-explanations: How is the information in the user model used by the system? What are the impacts of slots and entries?
- Cognitive explanations: A detailed explanation of which algorithm with which input was used to infer a certain information.

5 Conclusion

In this paper, we examined explanations in e-Learning systems in a first pass. Although Expert Systems research addressed explanations in depth, the research results did not spread that much. We described five major kinds of explanations and respective quality aspects. After presenting our view on e-Learning and the main components of e-Learning systems with respect to explanations we identified three main kinds of decisions that need to be explained, i.e., regarding the adaptation process, regarding tests and exercises, and regarding the user model. We then tried to relate those decisions to the above mentioned kinds of explanation. A more systematic account of explanations accompanied by an implementation is already under way.

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