

Context-Based Explanations for E-Collaboration

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INTRODUCTION

E-collaboration is generally defined in reference to ICT used by people in a common task (Kock, 2005; Kock, Davison, Ocker, & Wazlawick, 2001). However, when speaking of e-collaboration, people seems to put more the emphasis on “e-” than on “collaboration”; that is, on the ICT dimension of the concept that on the human dimension. Along the human dimension, e-collaboration requires to revisit previous concept of cooperation, conflict, negotiation, justification, explanation, etc. to account for the sharing of knowledge and information in the ICT dimension. We discuss in this chapter of explanation generation in this framework.

Any collaboration supposes that each participant understands how others make a decision and follows the series of steps of their reasoning to reach the decision. In a face-to-face collaboration, participants use a large part of contextual information to translate, interpret and understand others’ utterances use contextual cues like mimics, voice modulation, movement of a hand, etc. In e-collaboration, it is necessary to retrieve this contextual information in other ways. Explanation generation relies heavily on contextual cues (Karsenty & Brézillon, 1995) and thus would play a role in e-collaboration more important than in face-to-face collaboration.

Fifteen years ago, Artificial Intelligence was considered as the science of explanation (Kodratoff, 1987). However, there are few concrete results to reuse now from that time. There are several reasons for that. The first point concerns expert systems themselves and their past failures (Brézillon & Pomerol, 1997):

- There was an exclusion of the human expert providing the knowledge for feeding the expert systems. When an expert generally provided something like “Well, in the context A, I will use this solution,” the knowledge engineer retained the pair {problem, solution} and forgot the initial triple {problem, context, solution} provides by

the expert. The reason was to generalize in order to cover a large class of similar problems when the expert was giving a local solution. Now we know that a system needs to acquire knowledge within its context of use.

- On the opposite side, the user was excluded from the noble part of the problem solving because all the expert knowledge was supposed to be in the machine: the machine was considered as the oracle and the user as a novice (Karsenty & Brézillon, 1995). Thus, explanations aimed to convince the user of the rationale used by the machine without respect to what the user knew or wanted to know. Now, we know that we need to develop a user-centered approach (Brézillon, 2003).
- Capturing the knowledge from the expert, it was supposed to put all the needed knowledge in the machine, prior the use of the system. However, one knows that the exception is rather the norm in expert diagnosis. Thus, the system was able to solve 80% of the most common problems, on which users did not need explanations. Now, we know that systems must be able to acquire incrementally knowledge with its context of use.
- Systems were unable to generate relevant explanations because they did not pay attention to what the user’s question was really, in which context the question was asked. The request for an explanation was analyzed on the basis of the available information to the system.

Thus, the three key lessons learned are (1) KM stands for management of the knowledge in its context; (2) any collaboration (including e-collaboration) needs a user-centered approach; and (3) an intelligent system must incrementally acquires new knowledge and learns corresponding new practices.

Focusing on explanation generation, it appears that a context-based formalism for representing knowledge and reasoning allows to introduce the end-user in the

loop of the system development and to generate new types of explanations.

With new findings about context available now, a new insight is possible on past problems abandoned previously by lack of a relevant solution at that time, like incremental knowledge acquisition, practice learning and explanation generation. Previously, they were considered as distinct problems. Now their integration in the task at hand of the user offers new options, especially for e-collaboration.

Hereafter, the chapter is organized in the following way. First, we comment briefly previous works on explanations in order to point out what is reusable. Second, we discuss explanation generation potentialities in a context-based formalism called contextual graphs. Finally, we show what explanations can bring in e-collaboration, maybe more than in face-to-face collaboration.

BACKGROUND

Explanations in Knowledge-Based Systems

The first research on explanations started with rule-based expert systems. Imitating a human reasoning, the presentation of the trace of the expert system reasoning (i.e., the sequence of fired rules) was supposed to be an explanation of the way in which the expert system reaches a conclusion. Rapidly, it was clear that it was not possible to explain heuristics provided by human experts without additional knowledge. It was then proposed to introduce a domain model. It was the second generation of expert systems, called the knowledge-based systems. This approach reached also its limits because it was difficult to know in advance all the needed knowledge and also because it was not always possible to have models of the domain. However, the main weakness was the lack of consideration for the user and what the user wanted as explanation. The user's role was limited to be a data gatherer for the system. A second observation was that the goal of explanations is not to make identical user's reasoning and the system reasoning, but only to make them compatible: the user must understand the system reasoning in terms of his own mental representation. For example, a driver and a garage mechanic can reason differently and reach the same diagnosis on the state of the car. The situ-

ation is similar in e-collaboration where specialists of different domains and different geographical areas must interact in order to design a complex object. A third observation is that the relevance of explanation generation depends essentially on the context use of the topic to explain (Abu-Hakima & Brezillon, 1994; Karsenty & Brezillon, 1995). We discuss this point later in the chapter.

Beyond the need to make context explicit, first in the reasoning to explain, and, second, in the explanation generation, the most challenging finding is that lines of reasoning and explanation must be distinguished, but considered jointly, the line of explanation being able to modify the line of reasoning (Abu-Hakima & Brézillon, 1994). Thus the key problem for providing relevant explanations is to find a uniform representation of elements of reasoning and of context.

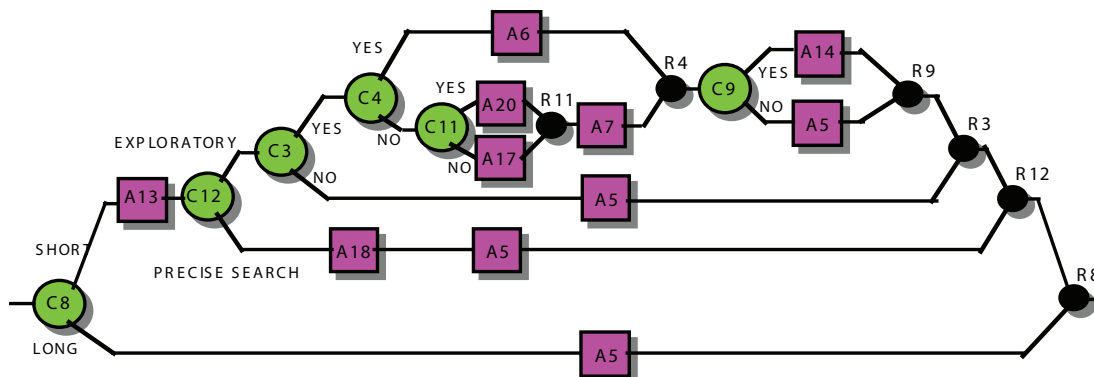
Explanations and Contexts

A frequent confusion between representation and modeling of the knowledge and reasoning implies that explanations are provided in a given representation formalism, and their relevance depends on explanation expressiveness through this formalism. For example, ordinary linear differential equation formalism will never allow to express—and thus explaining—the self-oscillating behavior of a nonlinear system. Thus, the choice of representation formalism is a key factor for generating relevant explanations for the user and is of paramount importance in e-collaboration with different users and several tasks.

A second condition is to account for, make explicit, and model the context in which knowledge can be used and reasoning held. For example, a temperature of 24°C in winter in Paris (when temperature is normally around 0°C) is considered to be hot in Paris and cold in Rio de Janeiro (when temperature is rather around 35°C). Thus, the knowledge must be considered within its context of use for providing relevant explanations, like to explain to a person living in Paris why a temperature of 24°C could be considered as cold in some other countries. (We will not discuss in this chapter the problem of affordance such as the use of an umbrella to walk or to protect from the sun and not the rain.)

There is now a consensus around the following definition “context is what constrains reasoning without intervening in it explicitly” (Brezillon & Pomerol, 1999), which applies also in e-collaboration (although

Figure 1. Activity “exploitation of an information” (Brézillon, 2005)



with more complex constraints) where reasoning is developed collectively. In e-collaboration, explanation generation is a means to develop a shared context among the actors in order to have a better understanding of the others (and their own reasoning), to reduce needs for communication and to speed up interaction.

From our previous works on context (e.g., see Brézillon, 2005), several conclusions have been reached. First, a context is always relative to something that we call the (current) focus of attention of the actors. Second, with respect to this focus, context is composed of external knowledge and contextual knowledge. The former has nothing to see with the current focus (but could be mobilized later, once the focus moves), when the former can be more or less related directly to the focus (at least by some actors). Third, actors address the current focus by extracting a subset of contextual elements, assembling and structuring them all together in a proceduralized context, which is a kind of « chunk of knowledge » (Schank, 1982). Fourth, the focus evolving, the status of the knowledge (external, contextual, into the proceduralized context) evolves too. Thus, there is a dynamics of context that plays an important role in the quality of explanations.

As the context exists with the knowledge, a context-based generation of explanations do not requires an additional effort if such an explanatory knowledge is integrated in the knowledge representation at the time of their acquisition and the representation of the reasoning (see Brézillon, 2005, on this aspect). However, this supposes to have a context-based formalism allowing a uniform way to represent elements of reasoning and of contexts.

CONTEXTUAL GRAPHS AND EXPLANATION GENERATION

A contextual graph represents the different ways to solve a problem. It is a directed graph, acyclic with one input and one output and a general structure of spindle (Brézillon, 2005). Figure 1 gives an example of contextual graph. A path in a contextual graph corresponds to a specific way (i.e., a practice) for the problem solving represented by the contextual graph. It is composed of elements of reasoning and of contexts, the latter being instantiated on the path followed (i.e., the values of the contextual elements are required for selecting an element of reasoning among several ones). Elements in a contextual graph are actions (square boxes in Figure 1), activities (complex actions like subgraphs), contextual elements (couples C-R in Figure 1) and parallel action groupings (a kind of complex contextual elements). A contextual element is a pair composed of a contextual node (e.g., C4 in Figure 1) and a recombination node (e.g., R4).

Some mechanisms of aggregation and expansion (like in conceptual graphs of Sowa, 2000) provide different local views on a contextual graph at different levels of detail by aggregating a subgraph in an item (a temporary activity) or expanding it. This representation is used for the recording of the practices developed by users, which thus are responsible for some paths in the contextual graph, or at least some parts of them.

In this context-based formalism of representation, we have established a typology of explanations, based on previous works and exploiting the capabilities of contextual graphs. By adding a new practice, several contextual information pieces are recorded automatically (date of creation, creator, the practice-parent) and

others are provided by the user himself like a definition and comments on the item that is introduced. Such contextual information is exploited during the explanation generation. Thus, the richness of contextual-graph formalism leads in the expressiveness, first, of the knowledge and reasoning represented, and second of the explanations addressing different users' requirements. The main categories of explanations developed in contextual graphs are:

- **Visual explanations:** They correspond to a graphical presentation of a set of complex information generally associated to the evolution of an item, e.g. the contextual graph itself, the decomposition of a given practice, the series of changes introduced by a given user, regularities in contextual graphs, and so forth.
- **Dynamic explanations:** They correspond to the progress of the problem solving during a simulation addressing questions as the "what if" question. With the mechanisms of aggregation and expansion, a user can ask an explanation in two different contexts and thus received two explanations with different presentations (e.g., with the details of what an activity is doing in one of the two explanations). The dynamic nature of the explanation is also related to the fact that items are not introduced chronologically in a contextual graph. For example, the contextual element C12 in Figure 1 has been introduced after C3 when it is situated before it in the practice development (i.e., C3 is in the "future" of C12 but one of the reason of the introduction of C12). Finally, the proceduralized context along a practice is an ordered series of instantiated contextual elements, and changing the instantiation of one of them is changing of practice and thus changing of explanation.
- **User-based explanations:** The user being responsible of some practice changes in the contextual graph, the system uses this information to tailor its explanation by detailing parts unknown of the user and sum up parts developed by the user.
- **Micro- and macroexplanations:** Again, with the mechanisms of aggregation and expansion, it is possible to generate an explanation at different levels of detail. For complex item like an activity or a subgraph, it is possible to provide on them a microexplanation from an internal viewpoint

on the basis of activity components. A macro-explanation from an external viewpoint is built with respect to the location of the activity in the contextual graph like any item.

- **Real-time explanations.** There are three types. First, the explanation is asked during a problem solving when the system fails to match the user's practice with its recorded practices. Then, the system needs to acquire incrementally new knowledge and learning the corresponding practice developed by the user (generally due to specific values of contextual elements not taken into account before). This is an explanation from the user to the machine. Second, the user wished to follow the reasoning of a colleague having solved the problem with a new practice (and then we are back to simulation). Three, the system tries to anticipate the user's reasoning from its contextual graph and provides the user with suggestions and explanations when the user is operating.

Moreover, these different types of explanation (and others that we are discovering progressively) can be combined in different ways like visual and dynamic explanations.

FUTURE TRENDS

When the machine fails to address correctly a problem, the machine may benefit of its interaction with the human actors to acquire incrementally the missing knowledge and learn new practices. As a consequence, the machine will be able to explain later its choices and decisions. Contextual graphs are able to manage incremental acquisition and learning, and begin to provide some elementary explanations. After a while, a contextual graph is a kind of corporate memory for this specific problem solving.

As a general learned lesson, expressiveness of the knowledge and reasoning models depends essentially of the representation formalism chosen for expressing such models. This appears a key element of e-collaboration with multiple sources of knowledge and different lines of reasoning intertwined in a group work. This is a partial answer to our initial observation that e-collaboration would be better understood if we consider jointly its two dimensions, the human dimension and the technology dimension. Then, explanation genera-

tion would be revised in order to develop “collective explanations” for all the (human) participants in the e-collaboration, that is in each mental representation. Going one step further, it would be possible to compare with another view where ICT is controlled by an “intelligent agent” interaction in the e-collaboration with human agents.

CONCLUSION

Relevant explanations are a crucial factor in any collaboration between human actors, especially when they interact by computer-mediated means like in e-collaboration. First because an e-collaboration loses some advantages of a face-to-face collaboration in which a number of contextual elements are exchanged in parallel with the direct communication. Second because an e-collaboration can benefit of new ways to replace this “hidden exchanges” of contextual cues between actors by the use of the computer-means themselves. For example, it is possible to consider new types of explanation in an e-collaboration.

Explanation generation is very promising for e-collaboration because explanations use and help to maintain a shared context among actors of an e-collaboration. We are now in a situation in which computer-mediated interaction concerns human and software actors. Software must be able to react in the best way for human actors. For example, for presenting a complex set of data, a software piece could choose a visual explanation taking into account the type of information that human actors are looking for. We show that making context explicit allows the generation of relevant explanations. Conversely, explanations are a way to make contextual knowledge explicit and points out the relationships between context and the task at hand, and thus develop a real shared context.

A key factor for the success of relevant explanations is to use a context-based formalism that represent all the richness of the knowledge and reasoning that is in the focus. A good option is to consider context of use simultaneously with the knowledge. This supposes to have a context-based formalism like the contextual graphs introduced in this chapter. In such formalism, elements of reasoning and of contexts are represented in a uniform way. As a consequence, this allows developing new types of explanation like visual explanations, dynamic explanations, and real-time explanations.

Indeed, we have developed a new typology of explanations that include past works on explanations but goes largely beyond. Moreover, these different types of explanations are not independent and can be combined together to provide richer explanations.

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KEY TERMS

Context: Elements that constrain a problem solving without intervening in it explicitly. Two parts are distinguished in the context with respect to a focus, namely the contextual and external knowledge.

Contextual Graphs: A context-based formalism for representing elements of reasoning and of contexts in a uniform way.

Context-Based Reasoning: A reasoning often cannot be separated from the context in which it takes place. In a rule, the conclusion is intertwined with conditions. Such reasoning is decision making, interpretation, diagnosis, pattern recognition.

Explanation: A presentation by an explainer to an explainee in order to allow the explainee to link a striking information in his/her mental representation of the world based on contextual cues. The line of explanation is not the line of reasoning to explain.

Practice: The result of the transformation made by an actor of a procedure for taking into account the specificity of a given context. This is a contextualization of a procedure.

Proceduralized Context: The subset of contextual knowledge pieces that are selected, collected, assembled, organized structured in a chunk of knowledge to be used in the current focus (e.g., the current step of problem solving).

Shared Context: Part of the contextual knowledge that is elaborated progressively by actors and thus shared, even if not identical.