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Context and Explanation in e-Collaborative Work

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ABSTRACT

In a face-to-face collaboration, participants use a large part of contextual information to translate, interpret and understand others' utterances by using contextual cues like mimics, voice modulation, movement of a hand, etc. Such a shared context constitutes the collaboration space of the virtual community. Explanation generation, on the one hand, allows to reinforce the shared context, and, on the other hand, relies on the existing shared context. The situation is more critical in e-collaboration than in face-to-face collaboration because new contextual cues are to be used. This chapter presents the interests of making explicit context and explanation generation in e-collaboration and which types of new paradigms exist then.

INTRODUCTION

An important challenge for virtual communities is the development of new means for interaction, especially in collaborative work. Any collaboration supposes that each participant understands how others make a decision and the 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 by using contextual

cues like mimics, voice modulation, movement of a hand, etc. All these contextual elements are essential in the determination of a shared context among virtual-community members, a shared context that constitutes the collaboration space of the virtual community. Explanation generation, which relies heavily on contextual cues (Karsenty and Brézillon, 1995), would play a role in e-collaboration more important than in face-to-face collaboration.

Twenty years ago, Artificial Intelligence was considered as the science of explanation (Kodratoff, 1987). However, few concrete results can be

reused from that time (e.g. see PRC-GDR, 1990). There are several reasons for that. The first point concerns expert systems (and knowledge-based systems after) themselves and their past failures (Brézillon and Pomerol, 1997).

There was an exclusion of the human expert providing the knowledge for feeding the expert systems. The “interface” was the knowledge engineer asking the expert “If you face this problem, which solution do you propose?” The expert generally answered something like “Well, in the context A, I will consider this solution,” but the knowledge engineer only retained the pair {problem, solution} and forgot the initial triple {problem, context, solution} provided 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 in a specific context. Now, we know that a system needs to acquire knowledge and 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 and 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 of 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 to 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 and nothing about the 20% that users did not understand. Now, we know that systems must be able to acquire incrementally knowledge with its context of use in order to address more specific problems of users.

Systems were unable to generate relevant explanations because they did not consider what the

user’s question was really, and in which context the question was asked. The request for an explanation was analyzed on the basis of the available information to the system. Now, we know that the system must understand the user’s question and after build jointly with the user the answer.

Thus, the three key lessons learned are: (1) KM (i.e. knowledge management normally) stands for management of the knowledge in its context; (2) any collaboration needs a user-centered approach; and (3) an intelligent system must incrementally acquire new knowledge and learns corresponding new practices. We present in (Brézillon, 2007) and (Brézillon and Brézillon, 2007) a context-based formalism for explaining concretely the differences often cited but never clearly identified between prescribed and effective tasks (Leplat and Hoc, 1983), procedures and practices (Brézillon, 2005), logic of functioning and logic of use (Richard, 1983).

Focusing on explanation generation, it appears that a context-based formalism for representing knowledge and reasoning allows the introduction of the end-user in the loop of the system development and the possibility for generating new types of explanations. Moreover, such formalism allows a uniform representation of elements of knowledge, of reasoning and of contexts.

Hereafter, the chapter is organized in the following way. First, we install the background of our proposal. This background comprises two parts: the consideration of explanations in knowledge-based systems. In a second part, we show the relationships between explanation and context, what context is (the general framework, the shared context, granularity of context). The following section presents different types of explanations in the contextual-graphs formalism that we introduce first. The following section discusses a case study of collaborative answer building.

BACKGROUND

This section introduces briefly the evolution of the way in which explanations have been considered in experts systems and after in knowledge-based systems. In a second part, we show that it was clear that there is a relationship between explanation generation and context, the lack of concrete works on context at that time (end of the eighties) has seriously limited the interest of explanations in knowledge systems.

Explanations in Expert Systems and Knowledge-Based Systems

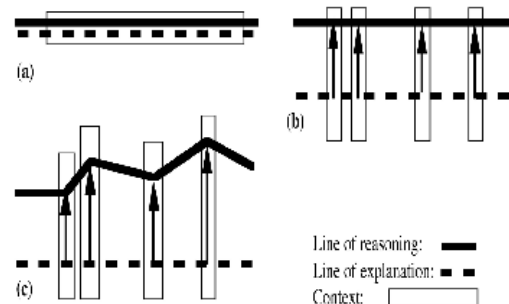
The first research on explanations started with rule-based expert systems. Imitating a human reasoning, the presentation of the trace of the expert-system reasoning (i.e. the sequence of fired rules) was supposed to be an explanation of the way in which the expert system reaches a conclusion. Indeed, it was right, but explanations were generated at the implementation level. The following step was the use of canned texts where “Firing of Rule_23 allows to checking rule_7” was replaced by something like “The available facts allow to identify the failure on equipment piece B3, and this leads to check if it is a mechanical problem”. Explanations thus moved from the implementation level to a representation level. However, the logic behind the chaining of the rules (why rule_7 is chosen first for example) was hidden. An important reason discovered lately is that a part of the control knowledge was put in the inference engine implicitly by the knowledge engineer (by imposing the ordering of rule checking for example). Thus, it was not possible to go another step above (i.e. a modeling level after the implementation and representation levels).

Rapidly, it was clear that it was intractable 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 also reached 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. 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 situation is similar in 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 (Karsenty and Brézillon, 1995; Abu-Hakima and Brézillon, 1995).

Even if expert systems are now abandoned, there are important results that we can yet reuse, such as the base for new explanations proposed by Spieker (1991) and the qualities for relevant explanations established by Swartout and Moore (1993). Thus, 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. Figure 1 illus-

Figure 1. Line of reasoning versus line of explanation (Abu-Hakima and Brézillon, 1995)



trates the evolution of the research on explanation generation (Abu-Hakima and Brézillon, 1995). Figure 1(a) gives the initial view on explanation generation by a strict superposition of the lines of reasoning and explanation (the firing of rule 23 allows to check Rule7). Figure 1(b) represents the first evolution corresponding to the introduction of domain knowledge, the knowledge that is not necessary for reasoning but for explanation. This was the first separation of the line of reasoning and the line of explanation. Figure 1(c) shows that lines of reasoning and of explanation interact, and providing an explanation may modify the line of reasoning. The line of explanation was considered during the development of the line of reasoning and not produced after the reasoning of the system. This corresponds to a collective building of a shared context jointly with problem solving.

Thus the key problem for providing relevant explanations is to find a uniform representation of elements of knowledge, 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 depend 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 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. This concerns the needed distinction between data, information and knowledge. For example, a temperature of 24°C (the datum) in winter in Paris (when tem-

perature is normally around 0°C) is considered to be hot (the “French information”) and cold (the “Brazilian information”) in Rio de Janeiro (when temperature is rather around 35°C during winter). 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. Temperature = 24°C is a datum. A process of interpretation leads to an information (hot or cold). Information is data with meaning built on the basis of the knowledge that the person possesses. The knowledge is specific to a person and constitutes the context in which a person evaluates (and eventually integrates) information pieces in his mental representation. Indeed, this is more particularly the part of the knowledge that the person finds more or less related to the information. It corresponds to a mental representation that the person built from its experience for giving meaning to the information and eventually integrates the information in the body of contextual knowledge already available. When information cannot be related totally to the mental representation, an explanation is required for making explicit the links between the information and the contextual knowledge of the person. We will come back on this point on the following.

There is now a consensus around the following definition “context is what constrains reasoning without intervening in it explicitly” (Brézillon and Pomerol, 1999), which applies also in e-collaboration (although with more complex constraints) where reasoning is developed collectively. 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, 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 contextual knowledge » (in the spirit of the “chunk of knowledge” of 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 does not require an additional effort because the 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 knowledge, of reasoning and of contexts.

WHAT IS CONTEXT?

A Conceptual Framework for Modeling Context

One of our aims is to take in account the context. There are a lot of definitions of context, but we refer to the definition of Brézillon and Pomerol (1999) who consider context as the sum of two types of knowledge. First, there is the part of the context that is relevant at the current step of the answer building, and the part that is not relevant. The former part is called contextual knowledge, and obviously depends on the decision maker and on the decision at hand. The latter part is called external knowledge and appears in different sources,

such as the knowledge known by the participant but let implicit with respect to the current focus, the knowledge unknown to the participant (out of his competence), contextual knowledge of other actors in a team, etc. Here, the focus acts as a discriminating factor between the external and contextual knowledge. However, the frontier between external and contextual knowledge is porous and moves with the progress of the focus. In our viewpoint, context is what surrounds a focus (e.g. the decision making process or the task at hand) and gives meaning to items related to the focus. On the one hand, context guides the focus of attention, i.e. the subset of common ground that is pertinent to the current task. Indeed, context acts more on the relationships between the items in the focus than on items themselves, modifying their extension and surface. On the other hand, the focus allows identifying the relevant elements to consider in the context. It specifies what must be contextual knowledge and external knowledge in the context at a given step.

For example, a focus on the driving task mobilizes contextual knowledge such as the fact of knowing the meaning of the traffic signs, the fact to have learned how to drive, etc., i.e. knowledge that could eventually be used when the focus evolves. Some knowledge from driver's personal context could also be considered such as a previous experience in the driving task. For example, this corresponds to the choice of a specific method at a given step of a task. For driving-situation solving, a driver has several solutions, e.g. several behaviors for crossing an intersection. Indeed, some contextual elements are considered explicitly, say for the selection of the behavior and thus can be considered as a part of the way in which the problem is solved at the considered step.

A sub-set of the contextual knowledge is proceduralized for addressing specifically the current focus. We call it the proceduralized context. The proceduralized context is a sub-set of contextual knowledge that is invoked, assembled, organized, structured and situated according to the given focus

and is common to the various people involved in decision making. A proceduralized context is quite similar, in the spirit, to the chunk of knowledge discussed in SOAR (Schank, 1982), and, in its building, to Clancey's view (1992) on diagnosis as the building of a situation-specific model. A proceduralized context is like a local model that accounts for a precise goal in a specific situation (at a given step). In a distinction reminiscent to cognitive ergonomics (Leplat and Hoc, 1983), we could say that the contextual knowledge is useful to identify the task at hand whereas the proceduralized context is relevant to characterize the task realization, i.e. the activity.

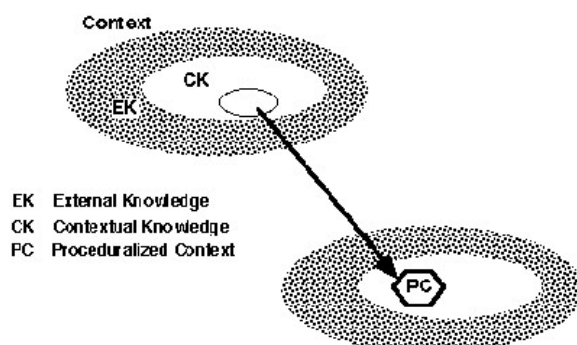
An important issue is the passage of elements from contextual knowledge to a proceduralized context. This proceduralization process, which depends on the focus on a task, is task-oriented just as the know-how and is often triggered by an event or primed by the recognition of a pattern. This proceduralization process provides a consistent explanatory framework to anticipate the results of a decision or an action. This consistency is obtained by reasoning about causes and consequences and particularly their relationships in a given situation. Thus, we can separate the reasoning between diagnosing the real context and, anticipating the follow up (Pomerol, 2001). The second step needs a conscious reasoning about causes and consequences.

Brézillon and Brézillon (2007) discuss a second type of proceduralization, namely the instantiation of contextual elements. This means that the contextual knowledge or background knowledge needs some further specifications to perfectly fit the decision making at hand. The precision and specification brought to the contextual knowledge is also a part of the proceduralization process that leads from the contextual knowledge to the proceduralized context. For each instantiation of a contextual element, a particular action will be executed. There are as many actions as different instantiations. However, once the corresponding action is executed, the instantiation does not mat-

ter anymore and the contextual element leaves the proceduralized context and goes back in the contextual knowledge. For example, arriving to a crossroad, a driver looks at the traffic light. If it is the green signal, then the driver will decide to cross. The instantiation of the contextual element "traffic light" (green signal) has guided the decision making process and then the decision is made. The color of the traffic light does not matter once the decision is made. Figure 2 illustrates our view on context for one person.

Contextual knowledge is more or less similar to what people generally have in mind about the term 'context'. Contextual knowledge is personal to an agent and it has no clear limit (the infinite dimension of context for McCarthy, 1993). Contextual knowledge is evoked by situations and events, and loosely tied to a task or a goal. When the task becomes more precise, a large part of this contextual knowledge can be proceduralized according to the current focus of the answer building. Although the contextual knowledge exists in theory, it is actually implicit and latent, and is not usable unless a goal (or an intention) emerges. When an event occurs, the attention of the actor is focused and a part of the contextual knowledge is proceduralized. Contextual knowledge appears back-stage, whereas the proceduralized context is front-stage in the spotlights.

Figure 2. The three types of context

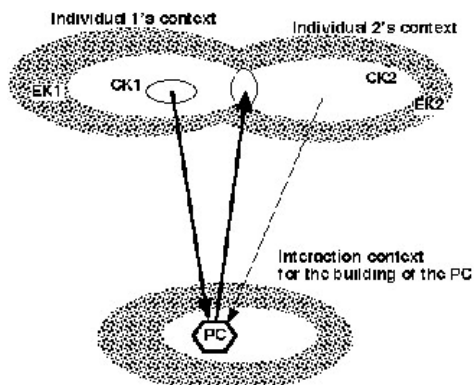


Moreover, the context must rather be considered as a status of knowledge (external, contextual or proceduralized context) linked to the focus of attention. The context has a dynamic dimension that corresponds to a movement between contextual knowledge and a proceduralized context during the evolution of the focus of attention (i.e. when the decision making process progresses). From one step to the next one, either a piece of contextual knowledge or external knowledge enters the proceduralized context or the proceduralized context moves into the contextual knowledge of the actor once used in the current focus which then evolved. Participants face the problem of organizing and structuring contextual knowledge to transform it in a relevant proceduralized context for their answer-building process. This movement between the contextual knowledge and the proceduralized context is realized inside the individual context of each participant. Here eventual explanations are for the explainer himself.

Shared Context and Proceduralized Context

The construction of the *proceduralized context* from *contextual knowledge* is often a process of communication in a work group. Figure 3 represents how the *proceduralized context* is built

Figure 3. A representation of the interaction to build the proceduralized context



from *contextual knowledge* during the interaction between two participants. The shared context contains proceduralized pieces of knowledge in the focus of attention of the two participants. These pieces of knowledge are extracted from the *contextual knowledge* of each participant, are jointly structured by the two participants, and result in a shared knowledge. For example, the first utterance of a participant gives a rule such as “Stop at the next station if the alarm signal is triggered”. Then, on the request of the second participant, the first one may add some pieces of knowledge related to his first utterance. If this knowledge chunk belongs to the common part of the *contextual knowledge* of the participants, the pieces are integrated into a mutually acceptable knowledge structure, and then are moved to the *proceduralized context*. Here, the co-building of the proceduralized context implies that, first, their interpretations are made compatible, and, second, the proceduralized context will go to enrich their shared contextual knowledge after, thanks to explanations. Thus, during the interaction process, ties between participants of a decision group are reinforced and this will impact the constitution of new decision groups in the future.

The *proceduralized context* contains all the pieces of knowledge that have been discussed and accepted (at least made compatible) by all the participants. The *proceduralized context* will become again a part of the shared *contextual knowledge* of each participant while it will get off the focus of the *interaction context*. Later, this chunk of knowledge previously *proceduralized* may be recalled, as any piece of *contextual knowledge*, to be integrated in a new *proceduralized context*. Thus, the more a participant is experimented, the more he possesses available structured knowledge. This is very similar to the externalization process in sense given by Nonaka and Takeuchi (1995). Let us also note that the proceduralized context can be shaped in procedures whether implicit or explicit. In other words, parts of *contextual knowledge* are compiled into short cuts or

implicit procedures as a result of learning. The proceduralized context building appears such as a kind of contextualization for the current focus. Thus, the focus and its context must be considered jointly for optimizing interaction among participants.

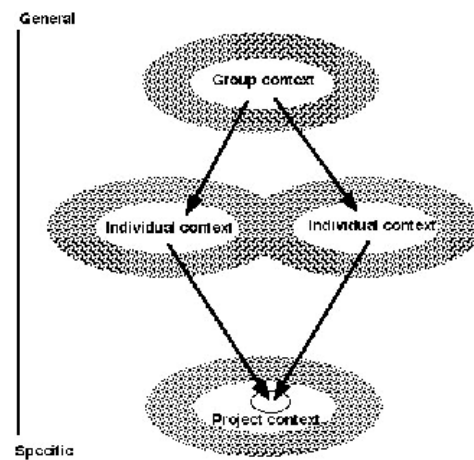
The previous example of joint proceduralization explains that whereas the *proceduralization process* is primarily subjective, it can also be shared and results into some common context in communities sharing the same background and expertise. The shared contextual knowledge is build by interaction among participants. It constitutes a reference for the actors like the “Référentiel Opératif commun” discussed in Leplat and de Terssac (1990). The more the shared context will be developed, the more efficient will be the decision group.

Granularity of Context

In the previous section, individual contexts and the shared context does not present the same granularity. As said previously, it would be more convenient to consider context as a status of the knowledge (external or contextual knowledge, and temporarily in a proceduralized context), and information is what is transferred between contexts. For the case study that is described below, we distinguish at a general level the group context, at an intermediate level, the individual contexts of the participants, and at the finer level, the context of the project on which are interacting collaboratively the participants in the group. Figure 4 gives an illustration of the situation.

According to our view on context, the contextual knowledge at a granularity level is transformed in a proceduralized context at the finer granularity. For example, a contextual information piece of the group context could be “find a compromise between a relevant information for the readers of the newspaper and the notoriety of the sponsors of the newspaper.” This contextual knowledge in the group context will be interpreted at the indi-

Figure 4. Granularity and dynamic of context



vidual context of the persons writing the article in a proceduralized context such as provide the information without direct links with the sponsors.

In Figure 4, individual contexts concern individuals and the group context, say a firm. Now the firm evolves in an arena (e.g. a market) in which the firm must fight and survive among other firms. Thus at this level, individual contexts concern the firms and the interaction context would correspond to a market. This means that the two views on a firm—the internal view with individuals, and the external view with the other firms—are strongly related, and the more the internal view will be coherent, the more the firm will be powerful externally.

AN EXPLANATION TYPOLOGY IN CONTEXTUAL GRAPHS

The Formalism of Representation

The development of our conceptual framework leads to the implementation of Contextual Graphs, which allows a uniform representation of elements of knowledge, of reasoning and of contexts. Then, in such representation formalism, we come back on the types of explanation that are possible to

generated in contextual graphs because “explanatory knowledge” is a natural part of the knowledge in knowledge systems. A key point here is that contextual graphs are representation formalism as workflows, Petri nets, Bayesian nets, etc. However, the main difference is that Contextual Graphs is a user-centered formalism (Brézillon, 2003): any user (e.g. a psychologist) needs less than one minute to learn and use the software (freely available at <http://www.cxg.fr>).

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 6 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 a branch, i.e. an element of reasoning among several ones). Figure 5 provides the definition of the elements in a contextual graph. A more complete presentation of this formalism and its implementation can be found in (Brézillon, 2005).

Elements of a contextual graph are: actions, contextual elements, sub-graphs, activities and temporal branching. An action is the building block of contextual graphs. We call it an action but it would be better to consider it as an elementary task. An action can appear on several paths.

This leads us to speak of instances of a given action, because an action, which appears on several paths in a contextual graph, is considered each time in a specific context.

A contextual element is a couple of nodes, a contextual node and a recombination node; A contextual node has one input and N branches [1, N] corresponding to the N instantiations of the contextual element already encountered. The recombination node is [N, 1] and shows that even if we know the current instantiation of the contextual element, once the part of the practice on the branch between the contextual and recombination nodes corresponding to a given instantiation of the contextual element has been executed, it does not matter to know this instantiation because we do not need to differentiate a state of affairs any more with respect to this value. Then, the contextual element leaves the proceduralized context and (globally) is considered to go back to the contextual knowledge.

A sub-graph is itself a contextual graph. This is a method to decompose a part of the task in different way according to the context and the different methods existing. In contextual graphs, sub-graphs are mainly used for obtaining different displays of the contextual graph on the graphical interface by some mechanisms of aggregation and expansion like in conceptual graphs (Sowa, 2000). An activity is a particular sub-graph (and thus also a contextual graph by itself) that is identified by participants because appearing on different paths

Figure 5. Elements of a contextual graph

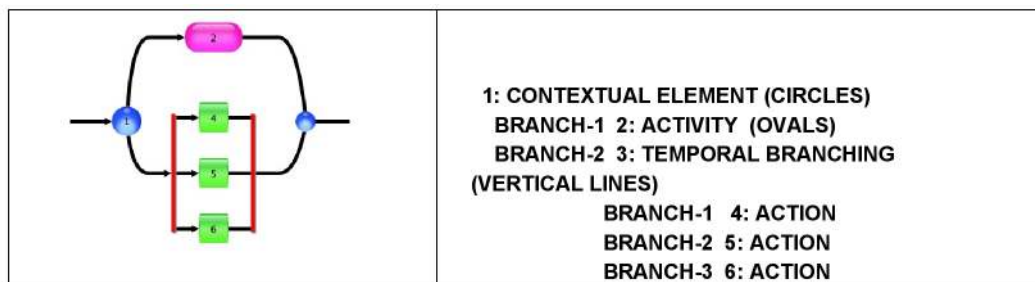
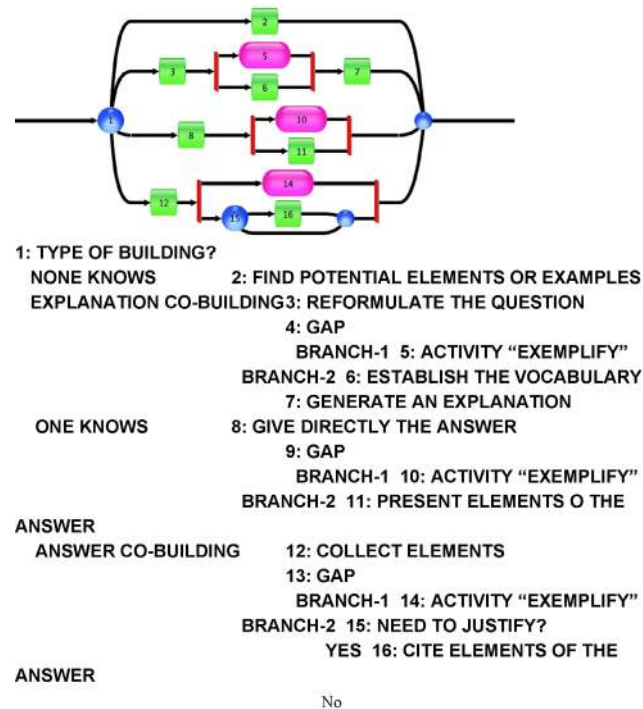


Figure 6. Contextual Graph of the different collaborative building processes



and/or in several contextual graphs. This recurring sub-structure is generally considered as a complex action. An activity is a kind of a contextualized task. An activity is similar to a scheme as considered in cognitive ergonomics (Leplat and Hoc, 1983). Each scheme organizes the activity around an object and can call other schemes to complete specific sub-goals.

A temporal branching expresses the fact (and reduces the complexity of the representation) that several groups of actions must be accomplished but that the order in which action groups must be considered is not important, or even could be done in parallel, but all actions must be accomplished before continuing. The temporal branching is for context what activities are for actions (i.e. complex actions). This item expresses a problem of representation at a lower granularity. For example, the activity "Make train empty of travelers" in the SART application (Pomerol et al., 2002) accounts for the damaged train and the helping train. There

is no importance to empty of travelers first either the damaged train or the helping train or both in parallel. This operation is at a too low level with respect to the general task "Return back rapidly to a normal service" and would have otherwise to be detailed in the three paths in parallel leading to the same sequence of actions after. Some mechanisms of aggregation and expansion provide different local views on a contextual graph at different levels of detail by aggregating a sub-graph 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.

A CASE STUDY

How collaboration can improve document comprehension? Starting from the C/I comprehension

model developed by Kintsch (1998), Brézillon et al. (2006) set up a series of several experiments aiming to test whether the ideas evoked during a prior collaborative situation can affect the comprehension processes and at which representation levels this may occur. The hypothesis was that collaboration affected directly the construction of the situation model. In order to test this hypothesis, Brézillon et al. (2006) built an experimental design in two phases: 1) a collaboration phase, and 2) a comprehension phase (reading and questionnaire). In the comprehension phase, the authors run several experiments (with an eye-tracking technique) where participants of the experiments had to read a set of texts varying both semantically and from the layout. The general purpose was to correlate the verbal interactions occurring during the collaboration and the behavioral data (eye-movements and correct answers to questions) recorded during reading.

Here, we only discuss the modeling in the Contextual Graphs formalism of the collaborative verbal exchanges between two participants. The goal was to build an efficient task model that would be closer to the effective task(s) than the prescribed task. Such a “contextualized prescribed task” is possible, thanks to a formalism allowing a uniform representation of elements of decision and of contexts. This study has two side effects. There are, first, the need to make explicit the shared context for building the answer, and, second, the relative position of cooperation and collaboration between them. The shared context is the common background from which the two participants of the experiments will build collaboratively the answer to questions such as “How does the oyster make pearls?” (The expected answer is “A pearl arises from the introduction of a little artificial stone inserted into the oyster sexual gland. The oyster neutralizes the intrusive, the stone, surrounding it of the pearlier bag. Once closed, this pearlier bag secretes the pearlier material: the mother-of-pearl”.) The quality of the answer depends essentially of the richness of the shared context.

The building of this shared context is a step of the process that we study. Even if one of the participants knows the answer, s/he tries to build this shared context, and the answer building thus is enriched with the generation of an explanation for the other participant.

Our goal was to provide a representation of the different ways to build an answer according to the context of the question. Along this view, the context of the question is the shared context in which each participant introduces contextual elements from his/her individual context. In a collaborative decision making process, such a shared context must be built. The shared context contains contextual elements on which participants agree, eventually after a discussion and having provided an illustration. A subset of this shared context is then organized, assembled and structured to build the answer. The result of this answer building is a proceduralized context (Brézillon, 2005). In this chapter, we put these results in the larger framework of collaborative decision making that discriminates a procedure and the different practices, the prescribed task and the effective task, the logic of functioning and the logic of use, etc. A practice is assimilated to a contextualization of a procedure. Thus, our goal was to analyze how an answer is built, its basic contextual elements and the different ways to assemble these elements. The modeling of the answer building is made, thanks to contextual graph. The main results that we obtained were the following ones. Two models have been built, the *dialog model* and the *answer collaborative building model*. The *Dialog model* contained 4 phases:

- E1. Reformulate the question
- E2. Find an example
- E3. Gather domain knowledge (collection)
- E4. Build the answer from either characteristics or explanatory elements (integration)

For each pair of participants and for each question, we looked for the ordering of the 4 phases

Table 1. Different mean values for phases E1 to E4: frequencies into the collaboration (Col.1), Range of occurrences (Col.2), and Frequencies of occurrences (Col.3)

	Collaboration	Range	Frequencies
E1	1	1,27	70
E2	10	2,05	58
E3	120	1,98	133
E4	71	1,77	129

and which phase is a collaboration phase. Results are presented into Table 1.

For example, column 1 indicates that collaboration used mostly phase E3 (i.e. gathering domain knowledge to constitute the shared context) and unlike phase E1 (Reformulation of the question). Column 2 shows that phase 1 appeared mostly at the beginning of exchange and phase E2 (Find an example) at the end. Column 3 reveals that phases E3 and E4 (construction) are the most frequent phases carry out into the exchange. Furthermore, collaboration appeared the most often at the beginning of exchanges. See (Brézillon et al., 2006) for more details.

We obtain in this way a typology of explanations in a collaborative building of answers. The typology aims to classify whether the answer has been given and the granularity of this answer. We thus distinguish:

Answer required at the right granularity
 Answer required but at a superficial level
 Answer required but too detailed
 Partial answer

Answer partially false
 False answer
 No answer.

The granularity of the answer depends on the degree of development of the shared context.

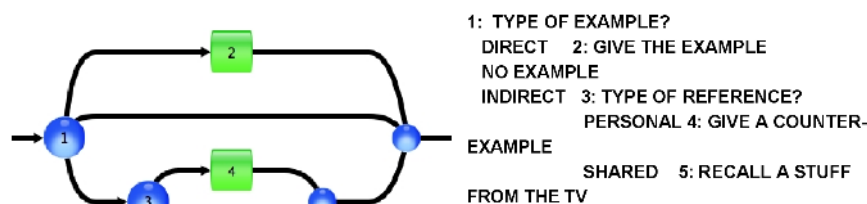
The Collaborative Building Model of the Case Study

The *contextual graph* of the collaboration model is represented in Figure 6 and the activity (the pink oval) is detailed in Figure 7. The collaboration model is composed of 4 paths:

Path 1: Both partners do not know the answer
 Path 2: Both partners do not know the answer but each has elements of explanation,
 Path 3: Co-building of the answer,
 Path 4: One of the partners knows exactly the answer and provides it.

Interestingly, results show that when participants collaborated by co-building the answer (Path

Figure 7. Details of the activity “Exemplify” represented by ovals in Figure 6



3), they gave mostly the correct answer either at superficial level (b) or partial answer (d). When either Path 2 (elements of answers) or Path 4 (One-Way) has been used, no difference in the type of answers emerges.

Path 1: No Knowledge about the Answer

Both participants do not know the answer. They have no elements of the answer at all. However, they try to utter some rough ideas (example, a parallel with a known topic) in order to trigger a constructive reaction of the other.

Path 2: Elements of the Answer

Both participants do not know the answer but think to have elements for generating an explanation. Generally, a participant leads the interaction by proposing elements or asking questions to the other. Explanation generation is a kind of justification or validation to themselves of their general understanding of the question, without trying to build an answer.

Path 3: Two-Ways Knowledge

Both participants have a partial view of the answer, know some of the elements of the answer and try to assemble them with the elements provide by the other. They have the same position in the answer building, and there is no need for explanations between them or for external observer. This is a situation of maximal cooperation. However, without external validation, the quality of the answer is rather variable.

Path 4: One-Way Knowledge

One of the participants knows exactly the answer, provides it immediately and spontaneously, and spends his/her time after to explain the other

participant. Here the cooperation is unidirectional like the information flow.

Indeed, we can expect a relatively continuous spectrum between the path where one participant knows exactly (Path 4) and the situation where none of the participants knows (Path 1).

An Explanation Typology Based on Contextual Graphs

We 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 participant 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 participants' requirements. The main categories of explanations identified in contextual graphs are:

Visual explanations correspond to a graphical presentation of a set of complex information generally associated with 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 participant, regularities in contextual graphs, etc. Note that we are dealing with contextual graphs with an "experience-based" knowledge base.

Dynamic explanations. They correspond to the progress of the answer building during a simulation addressing questions as the "What if" question. With the mechanisms of aggregation and expansion, a participant can ask an explanation in two different contexts and thus receives 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, in Figure 6, the contextual element 15 (“Need to justify?”) has been added after (1) the action 16 (“Cite elements of the answer”), (2) finding a situation where both explainer and explainee know all elements. Thus, there is no need to justify. 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 participant 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 participant and sum up parts developed by the participant. Such an explanation allows the author of a practice to identify the contextual elements that he had not taken into account initially and that has been introduced by other participants).

Context-based explanations. The definition of the proceduralized context (an ordered sequence of instantiated contextual elements) shows that a given item (say the activity “exemplify” represented by an oval in Figure 6) on different branches of the contextual graph appears in different contexts. This means that the explanation of the activity on any branch will be different from explanations on the two other branches. We exploit this finding in our driver-modeling application for representing “good” and “bad” behaviors of car drivers on a unique contextual graph (Brézillon and Brézillon, 2008). Thus a relevant explanation relies heavily on the building of the proceduralized context (different for each item such as different instances of the same activity), and because the contextual graph can be incrementally enriched, explanations can be richer also.

Micro- and macro-explanations. Again, with the mechanisms of aggregation and expansion, it is possible to generate an explanation at different levels of detail. For such a complex item like an activity (or any other sub-graph), it is possible to provide on them a micro-explanation by using an

internal viewpoint based on 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, similarly to a context-based explanation as discussed above. This allows to providing (at least) two different types of explanation on the activity “Exemplify” at the macro level for the explainer and at the micro level for the explainee. Note that the explainer also may ask a micro-explanation in case of doubt on explainee’s understanding. This twofold explanation is linked to the notion of activity, but can be used by any participant with aggregation and expansion of local sub-graphs of parts of the whole contextual graph.

Real-time explanations. There are three types of such explanations. First, the explanation is asked during an answer building when the system fails to match the participant’s practice with its recorded practices (e.g. a new explainer may decide to provide a personal experience as an example not considered in Figure 7). Then, the system needs to acquire incrementally new knowledge and to learn the corresponding practice developed by the participant (generally due to specific values of contextual elements not taken into account before). This is an explanation from the participant to the machine. Second, the participant 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 participant’s reasoning from its contextual graph and provides the user with suggestions and explanations when the user is operating. These suggestion and explanation rely on the contextual elements that are explicitly considered in the contextual graph. Note that it is because the system fails to represent a user’s practice that the user explains to the system the new practice by introducing new knowledge, knowledge that the system can reuse after. Moreover, these different types of explanation (and others that we are discovering progressively) can be combined in different ways such as visual and dynamic explanations.

Lessons Learned on the Case Study

Cooperation and collaboration are two ambiguous notions that have different meanings across domains, and sometimes from one author and another one. The difference between cooperation and collaboration seems related to the sharing of the participants' goal in the interaction. In cooperation (co-operation), each participant aims at the same goal and the task is divided in sub-tasks, each sub-tasks being under the responsibility of a participant. Thus, each participant intervenes in the shared goal through a part of the task. In collaboration, participants have different goals but interact in order to satisfy at least the goal of one of them, or one of his sub-goal. An example is the Head of a service and his secretary, often called a collaborator. The secretary takes in charge a part of the Head's task, but only as a support for the complex tasks of the Head (i.e. by collecting all the needed information for the Head that will make the decision).

However, we think that the difficulty to agree between cooperation and collaboration relationships is the lack of consideration for the dynamic dimension of the relationships. Two participants may cooperate at one moment and collaborate at another moment. The shift comes from their background (their individual contexts) with respect to the current focus and their previous interaction (the shared context). If one participant can fix the current focus, then the other only agrees, and there is a minimal cooperation, i.e. collaboration for validating the answer. If none of the participants knows how to address the current focus, they try together, first, to bring (contextual) elements of an answer, and, second, to build the answer as a chunk of knowledge (Schank, 1982) or a proceduralized context, i.e. a kind of chunk of contextual knowledge (Brézillon, 2007). This is a full cooperation. Several lessons could be learned from this study:

- Repetition of the question occurs when the participants of the experiments wish to be sure to understand correctly the question, i.e. to be able to find some relationships between elements of the questions and contextual elements of their mental representation of the domain (or maybe to have time to build their mental representation of this question).
- An answer can be given at different levels of granularity. Thus, we observe correct answer at the right level as well as at a too low level of granularity (too many details) or too high level (rough description of the answer). For example, "gas" instead of "CO₂" for sparkling water. Participants of the experiments have a problem for finding the right granularity of their answer. One can know the answer but not the elements or even the rationale (e.g. everybody knows that a refrigerator keeps cold the food, but few knows that this relies on the 2nd principle of the Thermodynamics). As a consequence, participants may express an external and superficial position.

Collaboration as a minimal expression of cooperation: one leads the interaction and the other only feeds in information (or only agrees), reinforces the statement of the other. When participants of the experiments gather contextual information, the goal is not to build immediately the answer because they want first to determine the granularity that their answer must have. Once, the level of granularity is identified, the selection of pieces of contextual knowledge to use in the proceduralized context is direct. When they cannot identify the right level of granularity, they enter the process of an explanation generation.

An explanation is given to: (1) justify a known answer, (2) progress in the co-construction of the answer by sharing elements and their interconnection; (3) when participants are not sure of the granularity of the answer (e.g. participants speak

of ‘gas’ instead of ‘CO₂’ for sparkling water). The explanation (given for an answer) is frequently less precise than an answer (generally at a macro-level), and is often for use between the participants. Several groups were confused and explain instead of giving the answer (thus with additional details not necessary). The answer appears to be a kind of minimal explanation.

CONCLUSION

In a virtual community, people have feature in common (e.g. French speaking people in New York), but it is not sufficient for collaboration. A collaboration supposes the sharing of several contextual cue (a language, social cues, an environment, etc.) that will impact the collaboration. Relevant explanations are a crucial factor in any collaboration between human actors, especially when they interact by computer-mediated means. First, 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, collaboration can benefit of new ways to replace this “hidden exchanges” of contextual cues between actors by the use of the computer-means themselves.

Explanation generation is very promising for collaboration because explanations use and help to maintain a shared context among actors. 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.

In this chapter we argue that a key factor for the success of relevant explanations is to use a context-based formalism, like Contextual Graphs, that represent in a uniform way all the richness of the knowledge and reasoning in the focus. A good option is to consider context of use simultaneously with the knowledge. As a consequence, this allows developing new types of explanation like visual explanations, dynamic explanations, real-time explanations, etc. 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 can be combined together to provide richer explanations.

However, this is only the first step. A promising path is to explore intelligent assistant systems. Indeed, computer-mediated means can keep and reuse a trace of interaction between human actors. In real-time situations, the human actor cannot lose time to answer questions of a machine because the actor is generally under time pressure (e.g. an incident solving in a control room), but the machine can act in parallel with actors in a kind of personal simulation replaying similar past situations, and making suggestions when appropriate. In that sense, the machine may become an excellent secretary, fixing alone all the simple problems of human actors, and preparing a complete folder on complex situations letting actors make their decision. Here, the machine generates explanations for humans.

Conversely, 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. Now, there is a software piece called Contextual Graphs that is able to manage incremental acquisition and learning, and begins to provide some elementary explanations.

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 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 collaboration would be better understood if we consider jointly its two dimensions, the human dimension and the technology dimension. Then, explanation generation would be revised in order to develop “collective explanations” for all the (human) participants in the collaboration that is in each mental representation.

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