

# Using Contextual Graphs for Supporting Qualitative Simulation Explanation

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## Abstract

We proposed in a previous research an explanatory dialogical agentbased tool for explaining a qualitative simulation algorithm. The main limitation of an agent in our explanatory system was its incapacity to adapt itself to a changing context. The main reason concerns the agent's inability to share and understand, through its cognitive component, new contextual information not directly accessible for reasoning on it. In this paper, we present the basis on a new functionality of agents that allows contextual information to be freely distributed among agents and we model agent activity by using contextual graphs, a context-based formalism of representation allowing a uniform representation of elements of knowledge, reasoning and contexts.

**Keywords.** Qualitative Simulation, Explanation, Context.,Contextual graphs

## Introduction

Laraba (2006) proposed a framework for explaining a qualitative simulation algorithm. Explanation was viewed as a problem solving process with its own reasoning and knowledge. An explanatory tool was then proposed and described at a high level of abstraction resulting on a dialogical agent-based This explanatory system cooperated with the end-user to provide him with the best explanation enhancing his comprehension of the QSIM algorithm. Explanations depend essentially on the context in which the user and the explanatory system interact. Such contextualized explanations are the result of a process and constitute a medium of communication between the user and the system

The main limitation of an agent in our explanatory system is its incapacity to adapt itself to changes of the context. The reason comes from the agent's inability to share and understand, through its cognitive component, a new contextual information that is not directly accessible for reasoning on it. In our explanatory system, an agent needs to handling a context representation for developing a shared context with other agents cooperating to generate the best explanation.

In this paper, we present a new functionality of agents that allows contextual information to be freely exchanged among agents, facilitating the generation and understanding of relevant explanations. Hereafter,

Section 2 introduces contextual graphs and their relation with explanations. Section 3 recalls our previous work. Section 4 presents the revision we made of the system for including a model of context and Section 5 proposes modeling revised agent activity using contextual graphs.

## Contextualized Explanations

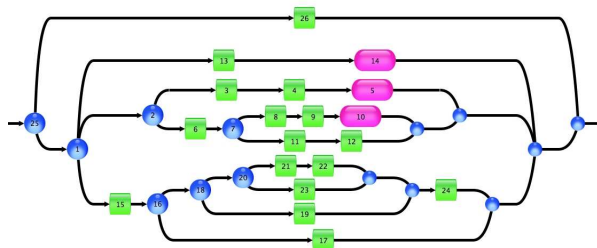
### Introducing Context

Context has always played an important, if little understood, role in human intelligence. This is especially true in human communication and decision making. Context awareness allows an agent to develop his/her mental representation of the world and of others with which s/he interacts. Contextual elements come from different sources: each agent, the task accomplishment, the situation in which the task is realized, the environment, etc. A shared context allows many important aspects of human interaction to remain implicit when agents interact.

At least, there is now a consensus around the following definition "context is what constrains reasoning without intervening in it explicitly" (Brezillon and Pomerol, 1999)

### Introducing Contextual graphs

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 (Brezillon, 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).



- 25: Is the site already known?  
 Yes 26: Look for new stuffs  
 No 1: What is the link target?  
 Html page 13: Open the target in a new window  
 14: Activity-1  
 PDF, DOC or PS page  
 2: Is there a html version?  
 Yes 3: Open target in new window  
 4: Look for the keywords  
 5: Activity-1  
 No 6: Download the document  
 7: Have I time now?  
 Yes 8: Open the document  
 9: Look for the keywords  
 10: Activity-1  
 No 11: Record document  
 12: Close the window  
 PPT page  
 15: Open the target in a new window  
 16: Duration of the download?  
 Short 18: Is it for a course?  
 Yes 20: Can page content be found?  
 Yes 21: Copy the slide  
 22: Paste it in a ppt doc  
 No 23: Note idea for later  
 No 19: Explore the presentation  
 24: Go to the next slide  
 Long 17: Close the window

**Fig. 1.** Activity exploitation of a Web page (from Brézillon, 2005)

### Contextual graphs and Explanations

The acquisition of a new practice in a contextual graph corresponds to the addition of actions and contextual elements justifying the addition if the action(s). Moreover, several other contextual information pieces either are recorded automatically (date of creation, author, the practice-parent) or provide by the user (a definition and comments on the item that is introduced, etc.). An explanation is generated from the whole set of these contextual elements, thanks the formalism of representation allowing this. Thus, the expressiveness of an explanation depends essentially on the richness of contextual-graph formalism.

### Our previous work

We considered an end-user observing QSIM progress on a particular physical phenomenon, say, the trajectory of a ball thrown in the air (Kuipers, 2001). The end-user wishes to have more ample information, and asks the explanatory system a query in natural language. For example, a query may be "why does such qualitative state appear after this number of transitions?" This may concerns the behaviour tree that is produced by the

qualitative simulator, and represented by a qualitative table of state transitions (supposing that the user is well introduced in qualitative simulation). Another user that is novice in qualitative simulation could ask a query like "why does the ball change trajectory at that time?"

Laraba (2006, 2007) discusses some interesting points about explanatory reasoning and knowledge models. The first point is that some explanatory tasks need particular knowledge from different sources and feed by different subtasks executing simultaneously different sub-queries. For example, the task "Why-not-know" can be replaced by the sub-tasks "Why-not-know-C" for collecting constructive knowledge, "Why-not-know-D" for gathering domain knowledge and "Why-not-know-CC" for seeking cooperative and contextual knowledge. The interest is that other tasks of high level such as "Why-how-know" can be decomposed on the same basis of sub-tasks "Why-how-know-C", "Why-how-know-D" and "Why-how-know-CC". It is easy to establish a kind of library of such sub-tasks and to allocate them to agents (Laraba, 2007).

The second point is that interaction between the explanatory tool and the user also can be managed by a set of specific tasks. It is the case of the tasks "Analque", "Consexp" and "Genexp" (Sansonet et al., 2002). Again, such tasks can be allocated to specific agents.

Thus, it looks natural to design and develop the architecture of the explanatory tool in an agent-based formalism of representation to express the required distribution characteristics that we discuss in the following. For space constraints, our discussion will be limited to two tasks, namely "Why-how-key" and "Why-not-key".

### Agent Activity

The agent "Anque" introduces the explanatory process when it receives a user's query. After checking the syntactic and semantic validity of the query, it will detect its object by identifying the type of adverb that is used. Finally, the needed knowledge is determined and, eventually, other agents are solicited either to confirm the detected interrogation by choosing one of the agents "Why-how-key" and "Why-not-key", or to extract the knowledge necessary for the production of the explanatory text by opting for one of the following agents: "Whow-know-C", "Whow-know-D", "Whow-know-CC", "Whot-know-C", "Whot-know-D", "Whot-know-CC".

Then, the agent "Conex" takes over the construction of the explanatory text that the agent "Genexp" will generate in naturel language and transmit to the end user. The end-user may be satisfied with it and the explanatory process is then interrupted, or not satisfied and the system is required to provide another explanation. The explanatory process is then either boosted such as described previously for a new request or relaunched after the explanatory knowledge updated otherwise. Both tasks are taken over by agent "Anque".

## Agent Model

To consider the cognitive processes operated during the various explanatory activities of an agent, we propose a

dialogical agent modular architecture including four components represented in Figure 2.

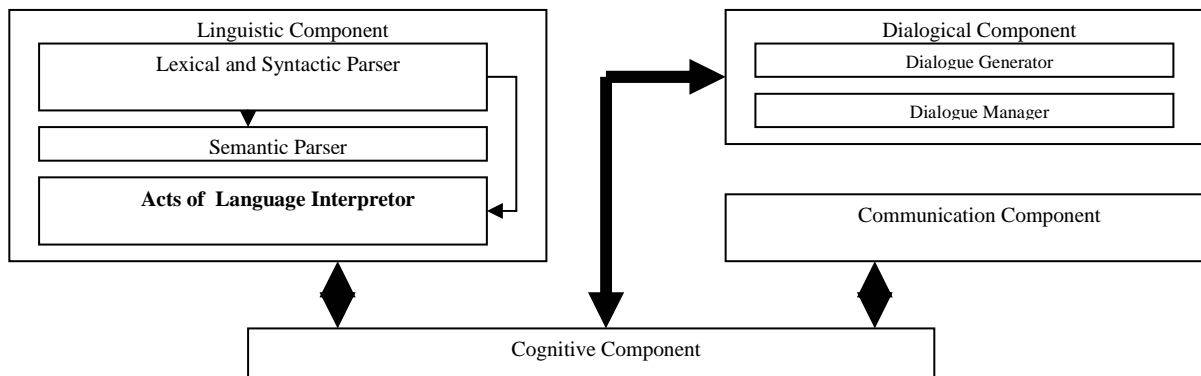


Fig. 2. Agent model

## Discussion

A better understanding of each end-user's needs and of the appropriate agents for our explanatory system needs context-specific information. Contextual knowledge intervenes in an implicit way in the explanation production process such as the knowledge elaborated during explanatory reasoning. Contextual knowledge appears at different levels from the knowledge retrieved from sources to the knowledge needed in the building of the explanation and its generation to the end-user.

This supposes that an agent in our explanatory system needs context not only to being explicitly represented but also shared and understood among agents cooperating to provide end-user with the best explanation. This is the goal of the new functionality that we plan for allowing contextual information to be freely distributed among

agents. It will provide agent with the ability to capture context and to reason on it.

The introduction of the new functionality supposes an extension of our explanatory tool by adding a Context-Aware component to it, including:

- A context-capture sub-component: which acts when a new end-user request is received, to gather end-user personal information, his skills, his intervention location and time and some surroundings information that it transmits to the context-reasoning sub-component.
- A context-reasoning sub-component: which gathers the end-user profile according to the information transmitted by the context-capture sub-component, and transmits this information to the cognitive agent.

Then, the following revised agent model is obtained.

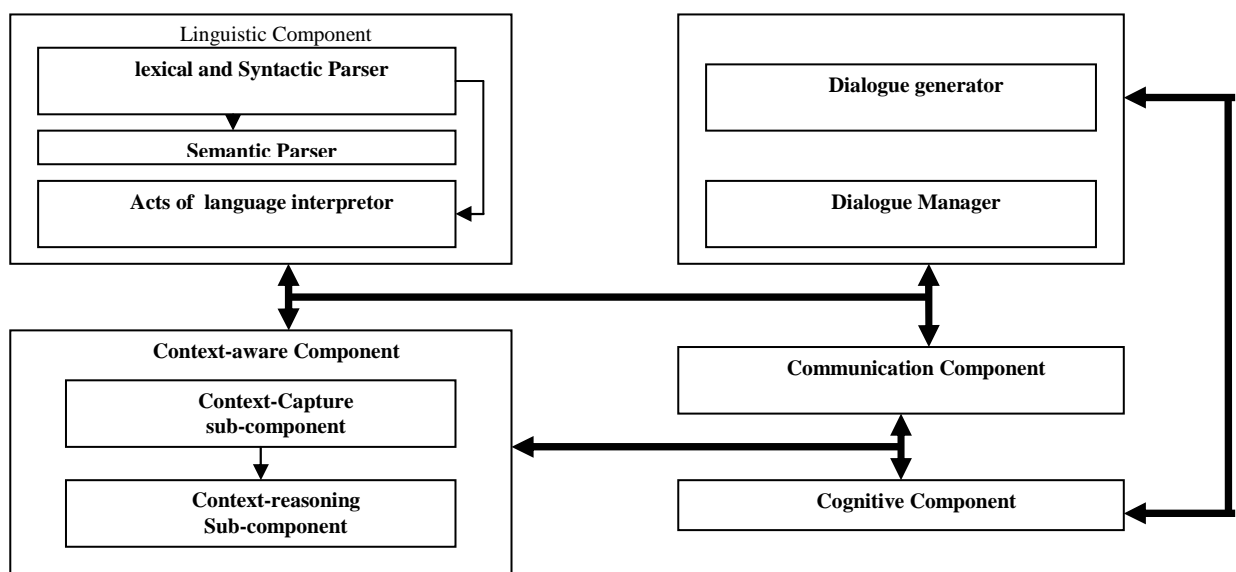
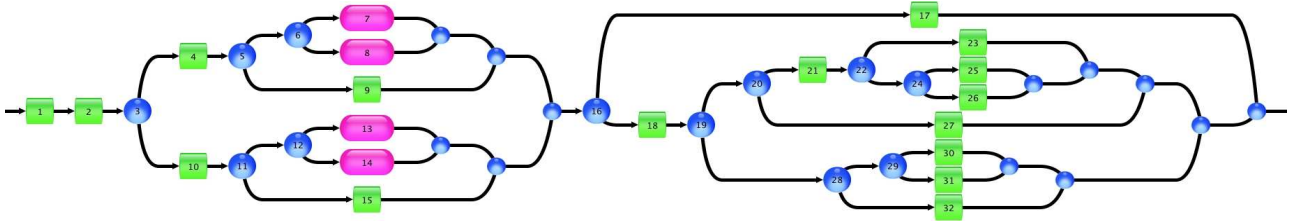


Fig. 3. : Revised Agent-model

## Activity modeling in the revised agent

New agent activity is modeled using contextual graphs. Figure 4 shows the contextual graph for the “throwing ball” example. It shows how the explanatory system determines the type of simulation (4: Initiate a classical

simulation or 10: Initiating a qualitative simulation) that is needed according to user’s preferences (2: get user information) and how deciding in the example to present to user according to his profile (5: type of user).



1: Thrown ball movement Simulation

2: Get user information

3: User preference?

Classical simulation

4: Initiate a classical simulation

5: Type of user?

First user case 6: An Expert-user?

Yes 7: First Example

No 8: Second Example

Other user case 9: Deal with other user case

Qualitative simulation 10: Initiating a qualitative simulation

11: Type of user?

First user case 6: An Expert-user?

Yes 7: First Example

No 8: Second Example

Other user case 9: Deal with other user case

16: Are explanations needed?

No

17: Trigger an explanation by explanatory agent

Algorithm EXPLIQSIM18: Analyze user intervention

19: Request?

Analyze user request

20: valid request?

Yes 21: Analyze user question

22: Why-How?

Yes 23: Explain type\_1

No 24: Why-not?

Yes 25: Explain type\_2

No 26: Conclude on a failure

No 27: Conclude on a failure

Other intervention

28: Knowledge?

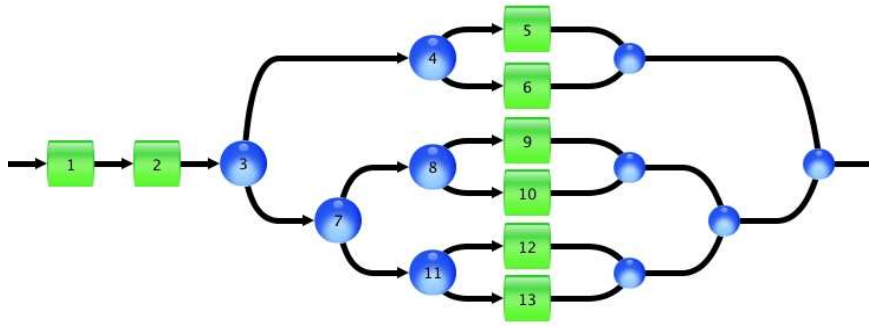
Yes 29: Compatible?

No 30: Conclude on a failure

Yes 31: Update

No 32: Conclude on a failure

**Fig. 4 :** Contextual graph for “throwing ball” example with its legend



- 1: Throwing-ball
- 2: Reasoning
- 3: Reasoning type?
  - First type
    - 4: Manually ?
      - Ball thrown horizontally    5: Apply reasoning\_1
      - Ball thrown vertically      6: Apply reasoning\_2
  - Second type
    - 7: With a software?
      - Case\_1
        - 8: Integral calculus?
          - Ball thrown horizontally    9: Apply reasoning\_3
          - Ball thrown vertically      10: Apply reasoning\_4
        - Case\_2
          - 11: Differential equations calculus?
            - Ball thrown horizontally    12: Apply reasoning\_5
            - Ball thrown vertically      13: Apply reasoning\_6

**Fig. 5** : Contextual graph for “Activity example” with the definition of the elements

The contextual graph shows different ways to simulate the throwing ball phenomenon. The first two paths in the contextual graph correspond to two specific ways (i.e. two practices) for simulating that phenomenon, namely classical simulation and qualitative simulation. When a path is selected (Action 3 or Action 5 in the contextual graph) according to the information collected about the user (preferences and knowledge), first, the corresponding elements of context are instantiated and, second, an element of reasoning is selected. This information and other information pieces that deal with some practice changes (the user is responsible of) in the contextual graph are used by the explanatory agent for generating an explanation, and to tailor its explanation by

### Conclusion

This study relies on the realization of an explanatory tool that we developed earlier. The important step in the evolution of the explanatory tool concerns, first, the use of contextual knowledge as a part of the body of explanatory knowledge, in the realm of Karsenty and Brezillon’s claim (1995) and, second, the use of Contextual Graphs for modeling agent activity. This allows the generation of two types of explanation (user-

detailing parts unknown of the user and sum up parts developed by the user. Such an explanation might be asked by the user after observing the simulation process (Action 8 in the contextual graph) or triggered by an explanatory agent (Action 7 in the contextual graph) that anticipates user’s reasoning from the contextual graph and then providing him with suggestions or explanations. In both cases explanatory agent may fail 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 system.

based explanation and real-time explanation) among those that Brezillon (2008) discussed.

The next step would be to integrate more intimately context modeling within this architecture. We think that making context explicit in an explanatory system will have positive consequences: first a better management of the knowledge upstream, and second a better management of interaction with end-users.

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