Explanation as Contextual Categorization

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Abstract. Our concern is the explanation generation in a representation based on contextual categorization. We point out that the explicit consideration of the context is necessary for the generation of relevant explanations. We present how the model captures the context necessary for explanation and we report some results compatible with the hypothesis that explanation is based on categorical networks according to a model based on the Galois lattice.

1 Introduction

In the past 30 years, Artificial Intelligence research aimed at developing automated reasoning systems and programs for solving problems. In 80's, the question was to develop systems that were able to explain their line of reasoning. Although at that time Artificial Intelligence was the science that explored the most deeply the explanation process, an implicit assumption was to consider explanations as a vehicle for transferring information and knowledge from the machine to the user, supposing that the machine was the oracle and the user the novice [1]. Feedback were used by the system to tailor its explanation to user's needs. However, such feedback were limited to acceptance signs, and users rarely may intervene in the generation of explanations. An opposite position was taken in the SEPT application by letting the user build alone his explanation [2]. This was not a better solution because users had to tackle complex commands as an additional task with their work and temporal constraints. An actual perspective is that the user and the system must cooperate to solve jointly the problem and to co-construct the explanation of the solution [1].

Because a good explanation is a contextualized explanation, the lack of contextual information about the task at hand has been recognized as a weakness of rule-based systems[4]: there is a lack of consideration for context, a recurrent problem in knowledge engineering. Our position is that explanation is based on context, and that context can be processed through a contextual categorization mechanism.

Consider, for instance the sentence "*I heard a lion in my office this morning*" [4]. This is an ambiguous sentence since either the lion (interpretation a) or the person (interpretation b) can be in the office and the other in the near outside. Additional context such as "*This is what the man says when he enters the Police station*" will favor the former while "*This is what the man says after he explains he was watching on a TV program on animals in his office*" will favor the latter. Our proposal is to

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demonstrate that and how an explanation rest on categories of actual objects using actual relational properties that the human cognitive system builds up. Starting with sentence 1, object-person and object-lion are put in the same category because they have the property of “*being close from each other*” and to be both located in the office place (the building that comprises the office). Subcategories are “the person” and “the lion” (Figure 1).

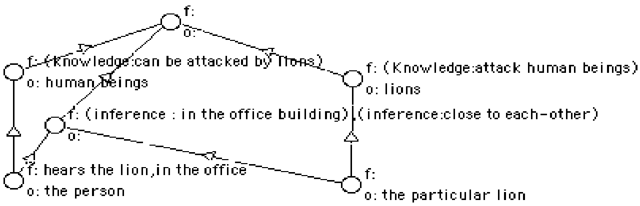

Fig. 1. According to the contextual categorization theory, when listening “I heard a lion in my office this morning”, 1. actual objects “the person who is talking” and “the particular lion” are depicted as objects (o), 2. they are instantiated as subordinate categories with their specific features (f), 3. the categories /person/ and /particular lion/ are linked to their known categories and properties /human beings – can be attacked by lions/ and /lions-attacks human beings/ and are linked to their contextual superordinate category of being close to each-other (by inference because the person hears the lion) and located in the same building (by inference because they are close to each-other in a place that comprises the office). Notice that alternative interpretation locating the actual lion in the office instead of the person would exhibit the same network of contextual categories

From the network of contextual categories of Figure 1, one can tell the story, as “This is a story about human beings and lions. In an office’s building there were a person and a lion and the person hears the lion”. First, note that this description matches both interpretation a and b. This is one of the features of contextual categorization, which is the capability of extracting commonalties while it compute contextual diversity. Other important feature is that description/explanation can be generated by top-down parsing the network of categories.

Another context of the "hearing a lion" situation might be provided as follows: "I work in an university near a zoo that I can see from the window of my office. There are lions in that zoo. I often hear lions roar. It just was the case this morning." Then, the network of categories relating to the situation is rectified: the places of the lion (the zoo) and of the person (the office at the university) are differentiated, and the university will be near the zoo, and the superodinate known category for the actual lion will be “lions in zoo” (that do not attack human-beings”).

The question addressed in this paper concerns the way in which relevant explanation can be built from such a network of categories. One general purpose is to define the content and the format of an explanation according to the context.

The paper is organized as follows. Section 2 introduces explanation. We propose an inventory of current work about explanation, mainly about how explanation is generated and we detail the parameters and factors that influence explanation. Section 3 presents how context plays a key role in explanation generation by identifying different contexts. Then we describe the contextual categorization framework for building explanation (Section 4) and we report data that support our proposal. Finally, we conclude (section 5) by discussing how our framework might be completed in order to be a general model of the construction of contextually based explanation.

2 What Is Explanation?

Derived from the Latin word *explicatio(nem*), and from *explicare* which means literally “to unfold”, from *plicare*, “to fold” (used until the XVIIe century). This word appeared in the French language in 1322, and was borrowed from the French into the English language in 1528.

According to different dictionaries as sources (Larousse, Hachette) but also to dictionaries of psychology, explanation is both the action of explaining as well as a development intended to make something comprehensible. It can also mean an account of something or a clarification concerning a series of actions taken. In French, it can also mean the supervision of someone, a discussion, quarrels concerning the supervision of someone. In cognitive psychology, an “explanation” occurs when a subject adopts a system of meaning, coherence, a presumption of a structure in a text or of a phenomenon. In a general sense, explanation has the aim of solving a problem of comprehension. Let us retain, in the extended meaning, that explanation corresponds to any operation implied in the constitution of the understanding of a phenomenon.

According to the goal of explaining, we can distinguish different kinds of explanation: account, alibi, annotation, apology, clarification, comment, commentary, definition, demonstration, description, elucidation, excuse, gloss, exemplification, explication, exposition, illumination, illustration, interpretation, justification, plea, reason, solution, indication. There are other kinds of explanation in French such as analogy, answer, argument, causes, controversy, debate, development, discussion, dispute, exegesis, explanation, exposure, hermeneutics, information, key, motive, note, notices, paraphrase, precision, reason, study, talk, translation.

All the different kinds of explanation do have a content. They are also constructed according to a format and they are communicated through a medium. Explanation also depends on other factors such as the purpose of the explanation, the explainer and the explainee, feedback and task constraints. In our approach, we consider explanation between two actors, two people or a person and a machine. Our research is restricted to the content of explanation and its format.

Content. The content of any explanation comprises the phenomenon to be explained either explicitly or implicitly, and additional information. Additional information (1) has to be related to what is to be explained either as knowledge or as inference, and (2) has to be drawn from the same domain or, if drawn from a different domain, should show similar relations between elements (analogy). Finally, the content has to integrate contextual information in order to highlight the phenomenon to be explained.

Format. The content has a certain structure, a format that sequentially structures the content. For example, "*A whale is said to be mammal because whales breast-feed, their children*" is one kind a format. "*Whales breast-feed their children. A whale is said to be a mammal*" is another kind of format.

3 The Context, a Key Factor for Explanation Generation

3.1 Preliminary

Mackie [5] has already stressed the context-dependency of explanation as a process of making a distinction between some current situation and another class of situations. Thus, context – involving both explainer beliefs and goals – is crucial in deciding how good an explanation is, and a theory of contextual influences can be used to determine which explanations are appropriate.

Leake [6] considers the relationships between explanations and context in the framework of case-based reasoning. An explanation is required when there is a conflict between an event and a model that we have of the place where the event occurs. Leake argues that such a conflict is a property of the interaction between events and context: Any particular fact can be anomalous or non-anomalous, depending on the situation and on the processing we are doing. For example, 25°C may be considered hot weather for Paris, France, but cold for Rio de Janeiro, Brazil. To be relevant to an anomaly, explanations must resolve a belief conflict underlying the anomaly. To resolve an anomaly, an explanation must account for why prior reasoning led to false expectations or beliefs. Any anomaly would allow the retrieval of explanation for identical anomalies, provided that the same anomaly was always described the same way and that distinct anomalies always received distinct characterization. Finally, Leake lists ten major explanation purposes triggered by anomalies that rely on several elements of context (expected/believed conditions, previously unexpected conditions, possible repair points, actor's motivations, etc.).

Thus, explanation and context are strongly intertwined. Explanations make context explicit in order to clarify a step in the reasoning process. They are a means to point out the links between the problem at hand and shared knowledge in its current state.

The way in which an explanation must be chosen and generated depends essentially on the context in which the two actors find themselves. An explanation always takes place relative to a space of alternatives that require different explanations according to the current context. Comparing two explanations leads seeing how their contextual spaces differ. Thus, taking into account context is necessary to study explanation [7].

3.2 The Different Contexts

From an engineering point of view, the context is a collection of relevant conditions and surrounding influences that make a situation unique and comprehensible [8]. However, there are other points of view on context. In the accomplishment of a task, a person identifies which knowledge is relevant to the job based on previous experience. What Brézillon and Pomerol [3] call “contextual knowledge” are pieces of knowledge judged relevant and which can be mobilized at a specific step in the decision making process. A subset of the contextual knowledge at that step is invoked, structured and situated according to the focus corresponding to the step in the decision making process. This subset is called the proceduralized context.

An important issue is the transition from contextual knowledge to the proceduralized context. Proceduralization depends on the focus on a task, even for a political conversation which can be based on how a political program should work. Thus, proceduralization, like “know how”, is task-oriented and is often triggered by an event or primed by the recognition of a pattern. Another aspect of proceduralization is that people transform contextual knowledge into functional knowledge or causal and consequential reasoning in order to anticipate the result of their own actions. Proceduralization requires a consistent explicative framework in order to anticipate the results of a decision or an action. This consistency is obtained by reasoning about causes and consequences in a given situation. We can thus separate the reasoning between diagnosing the real context and anticipating the follow up. The second step requires conscious reasoning about causes and consequences.

A second aspect of proceduralization concerns a kind of instantiation. This means that the contextual knowledge or background context needs further specification to fit the task at hand. Precision and specification brought to bear on the contextual knowledge are also a part of the proceduralization process. For instance, it has been shown [9] that there are different levels of context, from the more general to the more specific and heterogeneous. A context at one level (e.g. the group context) contains rules that are instantiated at the level below (e.g. individual contexts). For example, when the rule is a speed limit of 50 km/h in a city (group context), a driver will control the speed of his vehicle using the accelerator and brake pedals (individual context).

4 Contextual Categorization

Contextual categorization is a component of diverse theories or models about human cognition that comprises perceptual categorization [10], categorization for text understanding [11], or task oriented categorization [12]. We describe how contextual categorization Theory works and how it can help modeling the generation of explanation and how it can be used for modeling the transition from contextual knowledge to proceduralized knowledge. Contextual categorization is founded on a basic and simple mechanism that is applied to process environmental inputs of any kind. It is of interest because it has two main results: (i) it shows the organization of both present objects and of present properties, or, more precisely, how properties are distributed to form categories of objects and (ii) it reflects the organization of the world. The contextual categorization model operates on Galois Lattices to create a single hierarchy of categories with transitivity, asymmetry and irreflexivity, when given the O_n X P_m boolean table which indicates for each of the n objects, O, whether it does or doesn’t have each of the m properties, P. The maximum number of categories is either 2^n-1, or m if m < 2^n-1, in a lattice whose complexity depends on the way properties are distributed across objects (table 1). For instance, having three objects (a, b c), the maximum number of categories is seven: the categories that factorizes respectively abc, ab, ac and cd shared properties and the categories that comprehend respectively a, b, and c unshared properties.

The Galois lattice corresponding to the binary description in table 1 is shown in Figure 1 as a hierarchy of Categories of objects defined by properties. The link between categories is a "KIND-OF" link: Y is a kind of X. Due to the inheritance principle; category Y includes properties of category X. This can be seen in the Boolean table in table 1. The Galois Lattice can be used to build a hierarchy of categories that merges when factorizing the properties [13]. The categories are contextual because they are a function of what objects are in the current situations and rather than simply a function of pre-existing categories in long-term memory. This is an alternative to case-based theories that need to encode each of the contexts in which an object could be met. The hierarchy of categories provides a circumstantial and contextual structure of the objects present. What is fundamental to contextual categorization, is that contextual categorization computes each unique object in the context of all the other objects that form its unique context.

Table 1. A binary description of "I heard a lion in my office this morning" that corresponds to the Galois Lattice in Figure 1

a	human beings	the person	lions	the particular lion
hears the lion		1		
(Knowledge :attack human beings)			1	1
(inference : in the office building)		1		1
(inference :close to each-other)		1		1
(knowledge :can be attacked by lions)	1	1		
in the office		1		

Explanation is based on description. We propose, first, that contextual categorization is the mechanism that is used to describe the phenomenon to be explained and, secondly, that the description is obtained by constructing the Galois lattice of the situation including the context. Third, that explanation is constructed syntactically by parsing the Galois lattice.

4.1 Building a Description for Explanation

Consider the material shown in Figure 2. It is an example of a set of characters we use in our experiments. We use such material for simplicity's sake. However, the objects in other situations might be, for instance, the cars involved in an accident, or different results obtained from experiments, etc. Each display contains a number of objects. One object differs from all the others (i.e., an intrusive object) and participants are asked to detect the intrusive object [14] and to explain the way in which it is different. The intrusive object is the only specimen in its category. For example, in the sample presented Figure 2, the intrusive object is *i* because the set of objects are letters; both vowels and consonants; however, *i* is the only vowel and thus it is the intrusive object.

The goal of this particular experiment was to demonstrate that both detection and description are based on contextual categorization.

From a cognitive point of view, seeking an intrusive object is seeking an object that has fewer characteristics in common with the other objects in the set. To complete the task, the participant has to use a categorization process considering the relevant properties of the situation (contextual properties). Once the contextual network of categories has been built, subjects easily evaluate the number of properties shared by each object in the set. Thus, they are able to indicate the object that has the fewest properties in common with the others. We call this object the intrusive object.

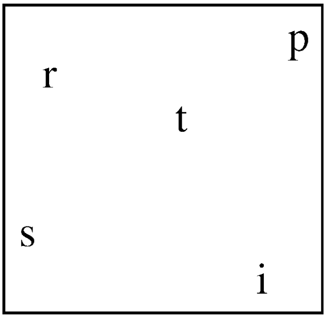

Fig. 2. An example of a set of objects to be described

Participants can be asked to explain their choices and to justify why they chose an object as being the intruder. Thus, we can observe whether they exploit the network of contextual categories that can be built from the display. In other words, we are interested in the process of construction of explanation with the hypothesis that the structure of explanation is related to the structure of the information considered, which is to say the relation between contextual knowledge and proceduralization.

Consider the following set of 9 objects: “3,2”, “a small rectangle”, “E”, “a beetle”, “π”, “51”, “a dog”, “H”, “a large square”. They can be put in categories that both group and differentiate them. For instance, “3,2” and “51” might be considered as “numbers” while “rectangle” and “square” can be grouped as “geometric shapes” and “H” and “E” grouped as “roman letters.” But in addition, “3,2”, “51”, “H”, “E” and “π” can be seen as “characters”.

Figure 3 provides the network of categories in which the objects can be simultaneously grouped and differentiated. Our assumption is that the participant having to name the category to which the intrusive object belongs has to differentiate it from its context and will use the most specific level that differentiates the intrusive object from its context. For instance, “E” surrounded by squares and rectangles can be called a letter and the justification for choosing “E” as intrusive can be “because it is the only letter.” In contrast, “E” surrounded by “H” and “π” will be considered as “the only vowel”.

First, this task of recognition makes it possible to control the context of the intruding object. Indeed, placing “E” among consonants or large rectangles does not lead to the same effects of context. Second, we can vary the context surrounding the intruder with objects belonging to categories more or less distant from it. In the example referred to above, if “E” is surrounded by consonants, then it is placed in a context that is semantically close: there are only two arrows joining the vowel category to the consonant category. In contrast, if we place “E” in a set of “large rectangles”, seven arcs are necessary to connect these two categories. The context of the intrusive object ”E” is more distant.

We tested the material in a pre-experiment. 84,05 % of the responses we obtain from 41 participants were fitting the predictions. These results are compatible with Treisman & Gelade’s pop-out theory [15], although we explain the effect in terms of categorization and context rather than in terms of filter theory. In addition we found that more the context goes away from the intrusive object, more the explanation was enriched. In this case, the participants don't systematically observe that quoting the distinctive category of the intrusive object provides a sufficient explanation. Moreover, we observe another kind of effect of context. It seems more obvious to detect a consonant among vowels than a vowel among consonants. In consequence, there are contexts that simplify the task. We suppose that this effect comes from the number of objects included in the contextual category. Indeed, in the vowel category, we count six instances: *a, e, i, o, u* and *y* in opposite to the consonant category that comprises 20 of them.

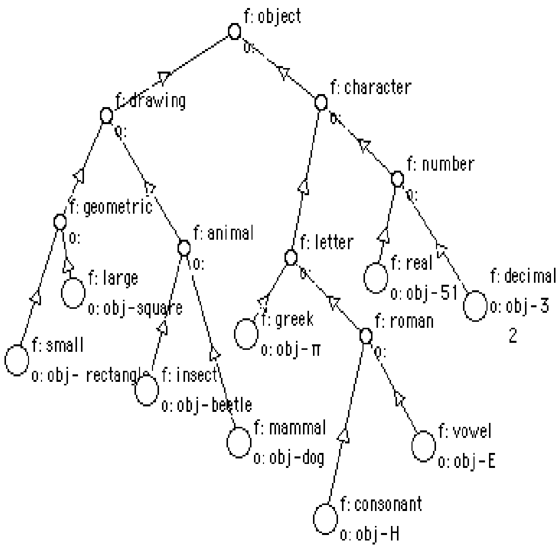

Fig. 3. The hierarchy of the set of categories that structures the set of 9 objects: "3,2", "a small rectangle", "E", "a beetle", "π", "51", "a dog", "H", "a large square".

4.2 Building a Structure for Explanation

Explanation is the process of providing information to someone who already does have some prerequisite knowledge (which should be first evaluated). For instance, in order to explain what is a duck, "a duck" can be defined as being an "animal", like a "chicken", but going in the water. This example is based on a specific explanation: the *description* where causal bonds between events and objets, so the time, are not considered. The description just rest on our categorized knowledge to provided names of objects (categories) and properties.

Such explanation-based verbalization was studied by Ganet [16], from data collected by Faure [17] with participants having to judge similarity between two sounds (sound 1 and sound 2) and to explain their judgment. To do so, twelve sounds were presented in couples providing 12 X 11 verbalizations by each of 20 listeners. We reasoned as if explanation-based verbalization were computed as predicted by contextual categorization, then participants should provide properties in their description in a strict order, revealing how they proceduralize their contextual knowledge.

We labeled "A" the properties common to both sounds (as in the sentence "the two sounds are soft"), "B" the properties describing sound 1 (as in the sentence "the first sound is rich and hot"), "C" the properties describing sound 2 (as in the sentence "the second sound is dry"), "D" the relational properties used to compare sound 2 to sound 1 (as in the sentence "but the second sound is more brilliant than the first") and "E" the relational properties used to compare sound 1 to sound 2 (as in the sentence "the first sound was longer than the second"). An explanation such as "I found the two sounds dissimilar because if they are both quite hot, the second is brilliant and longer than the first" was then coded an "ACD" explanation while an explanation such as "the second sound was dry but shorter than the first which was soft and the two are low" was then coded as a "CDBA" explanation. contextual categorization and listening order from first to second sound predict that participants should build their explanation in a "A then B then C then D then E" order, which means than the following structured explanation based verbalization "ABCDE". Among 325 possible formats, 31 (for example as "ADE", "AC", "A", "DE", "D") are compatible with predictions while the remaining 294 formats ("BA", "CDBA", "ACBDE", "ED") are not predicted by contextual categorization.

Table 2 show the percentage of each type of feature (A, B, C, D and E) given as a first, second, third, four and fifth feature given by the participants. The first feature the participants enounced the most was of type A (67 %). The second was of type B, and so on. Although only 31 of 325 types (9 %) of possible verbalizations were compatible with contextual categorization, 53 % of the verbalizations corresponded to our strict predictions. More over, the more frequent verbalization was of the ABC form (10%), followed by ABCD (6%), by A (5.2 %), AD (5%) and BC (4.2. %). Each of the predicted form was six times more frequent than the non-predicted form. In addition the 13 most frequent forms of explanation were 54% of the total amount of verbalization. Among them, ten were predicted (unpredicted were AED, BCA and ABDA) and corresponded to 78 % of them. In summary, contextual categorization appears to be a good approximation of modeling such human descriptive explanation. More important, these results permit us to continue our research and exploring more deeply the explanative process with its other type of explanation.

Table 2. Percentage of feature of type A, B, C, D and E as a function of the order in the verbal explanation. Type A features were given 63 % as the first feature. Type B features were given 37 % as the second feature and so on

	t1	**t2**	**t3**	**t4**	**t5**
A	63,12	4,38	10,98	9,86	9,35
B	20,50	37,37	11,53	9,13	5,61
C	4,12	23,71	40,07	21,88	21,50
D	3,95	17,61	27,88	36,78	34,58
E	8,31	16,92	9,55	22,36	28,97

5 Conclusion

Earlier expert systems, like MYCIN, align their explanation facility directly with the reasoning paths that define movement across contexts of the diagnostic system. Thus, all traces of reasoning that represent the traversed contexts are kept and their contents provided to the user for explanation. Here, the definition of context is restricted to knowledge and to steps of inferences but MYCIN is not selective in its construction of explanations.

In other systems, such as that described by Wick [18], an explanation facility is aligned only periodically with the reasoning of the system. In Wick's system, only some parts of the contexts that the system reasons with, are explained to the user. In this approach, additional explanatory knowledge (the domain knowledge and the expertise that are not directly necessary for the task at hand) may be used to generate enhanced explanations. This implies that the explanation path separates from the path of reasoning to produce effective explanations. Context is here an extended version of the previous one because it also contains domain and task knowledge not directly considered in the reasoning of the problem solving, and eventually some information on users through a model. One problem with such an approach is that it may be unsuitable for critical applications whose results may affect the safety of processes and people.

Another approach for explanation is to accept that the reasoning of the system is often different from that of the user. Thus, the user and the system may have different interpretations on the current state of the problem solving. The differing interpretations will be compatible if the user and the system make proposals, explain their viewpoints and spontaneously produce information [2]. In order to align the system's reasoning with that of the user and vice versa, the user and the system must co-construct the explanation in the current context of the problem solving. People who are trying to understand something often may offer an explanation that embodies their current understanding, expecting to have it corrected [19]. Thus, explanations become an intrinsic part of the problem solving and, as a consequence, the line of reasoning of the system may be modified by explanation. This leads to cooperative problem solving. Again, context here is an extended version of the context in the previous approach because it also integrates direct information from users, mainly on the basis of their actions on the system and on the real-world process.

If it seems acceptable that explanations intervene in the evolving context of interaction, it is difficult to say more about this for two reasons. Firstly, the co-building of explanations is an accepted idea but rather very few studies consider it. Secondly, context being not a mature domain of research, its dependency upon explanations is not really considered. For example, Lester and Porter [7] propose a model of explanation generation that includes simple methods for representing and updating context. However, their model makes assumptions about the representation of the context, not about how it is processed.

An alternative can be found in the line of Bever & Rosembaum work [20], we can see the semantic analysis as the form of a semantic hierarchy of features characterized by a principle of cognitive economy of which the first effect is to bring back the infinite diversity of the environment to a finished number of category. A formalism which seems adapted for that is the lattice of Galois [21] [13]. In the line of the theory on the categorization known as "based on the properties", we use the Galois lattice for description and the formation of the categories, a category being defined by a set of surface properties (visible properties), structural properties (parts and fitting of the parts of the object), functional properties (for what the object is used) and procedural properties (how we use it). These categories are used to group the objects which are gathered because they share common properties. The properties are used to form categories but the categories are also used to allot properties [22] [36]. Our general assumption is that the lattice of Galois is also a suitable formalism to explain the cognitive construction of the verbal production of the comparisons which are made to build up explanation.

Our approach might be useful for Automatic Generation Of Explanation if we could diagnose the user description of the data. As shown with our current experiments, the labels the participants use to describe the objects might reflect the level of differentiation, which is to say the way they conceptualize the data. The context appears very useful and deserve to be considered.

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