

KNOWLEDGE CLASSIFICATION FOR DESIGN PROJECT MEMORY

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1. Introduction

Design is a collaborative activity, in which several actors with different skills work together to reach a given goal. Design project team is a short-lived organization; at the end of the project actors are engaged in other projects with other organizations. Moreover, projects can be done by several companies; actors can belong to different countries (i.e. in big companies). Given these types of organizations, the challenge for knowledge management is how to learn from past design projects to help to solve new design problems. Knowledge is commonly defined by data and information used by an actor in a specific context [Matta et al. 2001]. So knowledge is produced in project activities for a given goal. Knowledge management aims at enhancing organizational learning in a company based on knowledge produced. It is defined as a cycle of transformation from tacit to explicit knowledge in a company [Nonaka 1991]. This type of organizational learning will be based on “knowing how” and “knowing when” [Easterby-Smith and Lyles 2003].

In this paper, we try to face the problem of learning from design projects. As mentioned above, we need to make explicit the “knowing how” as well as “knowing when”. These elements are in general produced in decision-making process related to a given context. Therefore, the questions we are going to answer are:

- How to represent decision-making process in design projects?
- How to extract knowledge in decision-making process?
- Is the knowledge valuable for reuse purpose?

We discuss in this paper these questions and present an approach that help to keep track of decision-making process and to classify design rational concepts in order to enhance learning from it.

2. Background

In design projects several actors work together for a given goal. Facing a specific problem, actors propose solutions related to different aspects of the problem. Then they discuss integration of these solutions to solve the problem [Matta et al. 1998]. In this collaborative decision-making process, knowledge is produced. This knowledge is not generally explicit in a project. Meeting report is not sufficient to extract this knowledge. So, it is necessary to develop techniques to represent collaborative decision-making in design.

Knowledge produced in collaborative activity is different from one related to a given field [Ducellier et al. 2013]:

- The nature of knowledge is different: The profession knowledge is related to a field and contains routines and strategies developed individually from experiences that involve a number of experiments. The cooperative knowledge is related to several fields, i.e. several

teams (of several companies) and several disciplines collaborate to carry out a project. So there is a collective and organizational dimension to consider in cooperative knowledge. Representing domain knowledge consists in representing the problem solving (concepts and strategies) [Schreiber et al. 1994]. On the contrary, emphasizing knowledge in cooperative activity aims at showing organization, negotiation and cooperative decision-making [Matta et al. 2001]. Otherwise, knowledge observed in a corporative constitutes one experiment to be structured.

- Capturing of knowledge is different: The realization of a project in a company involves several actors, if not also other groups and companies. For example, in concurrent engineering, several teams of several companies and in several disciplines collaborate to carry out a design project. The project teams are regarded as co-partners who share decision-making during the realization of the project. This type of organization is in general dissolved at the end of the project [Matta et al. 2001]. In this type of organization, knowledge produced during the project has a collective dimension, which is in general volatile. The documents produced in a project are not sufficient to keep track of this knowledge. In most of the cases, even the project manager cannot explain it accurately. This dynamic character of knowledge is due to the cooperative problem solving where various ideas are confronted to reach a solution. So extracting knowledge by interviewing experts or from documents is not sufficient to show different aspects of the projects, especially negotiation in decision-making process. Traceability, direct knowledge capturing and classification are needed to extract and structure knowledge from this type of organization.

We propose a project memory structure in order to represent collaborative decision-making in design projects. A project memory describes "the history of a project and the experience gained during realization of a project" [Matta et al. 2001]. It must consider mainly:

- The project organization: different participants, their competences, their organization in sub-teams, the tasks that are assigned to each participant, etc.
- The reference frames (rules, methods, laws...) used in the various stages of the project.
- The realization of the project: the potential problem solving, the evaluation of the solutions as well as the management of the incidents.
- The decision-making process: the negotiation strategy that guides the making of decisions as well as the consequences of the decisions.

Several methods were defined to represent design rationale in a project. We note mainly QOC [Buckingham Shum 1997], IBIS [Conklin 1988], DRCS [Klein 1993], etc. These approaches offer a structure to represent negotiation in a collaborative decision-making as Question, Option, Criteria and Argument. DRCS language proposes several views to link decision-making to project context (result, task, etc.). We use this type of representation in order to keep track of collaborative decision-making from design meetings. Traces build links between main characteristics of decisions, actor's role and skills, tasks and project phases, and product parts versions (Figure 1).

This trace is a representation of an example of collaborative design problem solving. We need to identify recurrent decision-making situation in order to identify routines and collaborative problem solving strategies related to project types and problems. We know that strategies can be developed when human, repeating an action several times, can identify a routine which can be applied to similar situations [Richard 1990]. We propose in this work to classify collaborative decision-making traces in order to identify routines and problem solving characteristics that help for learning.

3. Knowledge classification

In the section above, the attempt to represent knowledge in design projects by traceability of project memory is introduced, however, information, which is structured in project memory, is not sufficient to represent knowledge for learning purpose. In order to classify knowledge in project memory, information has to be structured, and more importantly mapping low-level data into other forms that might be more compact, more abstract, or more useful [Fayyad 1996]. Therefore, a knowledge classification method to extract knowledge from design project memory is proposed.

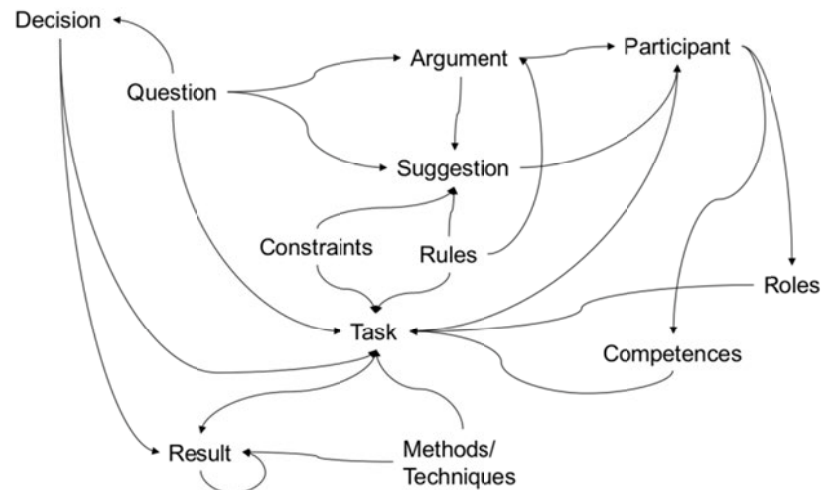


Figure 1. Project memory representation structure

3.1 What is knowledge

The nature of knowledge plays a quite important role in knowledge classification. On one hand, according to cognitive science, memory is where information is stored and knowledge is generated. There are two types of memory: short-term memory and long-term memory. Information is registered in short-term memory with a limited duration, it can be gathered in order to maximize the capacity of memorization [Miller 1956]. For each time a concept is rehearsed while it is in short-time memory, it is reinforced in long-term memory, as a result, contextual information can be encoded into more abstract and more organized concept networks in long-term memory [Claire and Kolmayer 2006], and knowledge reside in the concepts as well as associations inbetween. Therefore, knowledge can be considered as useful conceptual networks that reside in long-term memory in human mind. On the other hand, knowledge engineering, as an application of logic and ontology, attempts to represent knowledge of human mind by building computable models of some domain for some purpose. The famous semiotic triangle has shown three dimensions of knowledge: “sense”, “reference” and “sign”. Sign stands for the object that human refers to, and sense is the concept or idea associated with sign and object [Peirce 1974]. For the same object, people with different background can give different signs; concept alters according to different context. To represent the meaning triangle, approaches based on semantic network, ontology, logic etc. has been developed.

3.2 Knowledge classification

A knowledge engineer can interpret expert experiences to conceptualize them then formalize them into explicit representation, where knowledge can be recognized and learned. Logic, ontology and semantic network are frequently referred to for knowledge representation. A semantic network graph enable knowledge engineers to communicate with domain experts in language and notations that avoid the jargon of AI and computer science [Sowa 2000]. Ontology is a description of shared concepts. It consists of term, definitions, axioms, and taxonomy [Gruber 1995]. In our representation of project memory, a semantic network graph is proposed. Ontological hierarchy of concepts is employed for classification. Classification can be defined as the process in which ideas and objects are recognized, differentiated, and understood [Cohen and Lefebvre 2005], while knowledge classification is the process in which knowledge is recognized and reasoned. Classification algorithms are used in biology, documentation, etc. [Cohen and Lefebvre 2005]. They help to recognize an object with characteristics, related to a predefined hierarchy. We focus on knowledge classification in design project memory in order to not only represent the knowledge structure, but also classify knowledge to reuse it.

3.3 Knowledge classification for design project memory

The goal of project memory is to enhance learning from expertise and past experience [Matta et al. 2013]. Current representation approaches emphasize on organizing and structuring the experience and

let human to interpret concepts. The problem is that human can only learn from others by matching to one's own experience, and the knowledge level between expert and learner are always not the same. Instead of a single, best classification system that suits everyone, everywhere [Micas 1998], we have to come up with classification models suited within specific contexts [Mai 2004]. Therefore, to enhance learning in an organization, the knowledge modeling has to emphasize the "know what" and "know how" [Monika et al. 1995], [Easterby-Smith et al. 2011], and the context in which the knowledge is produced has to be represented as knowledge "know why".

The traditional knowledge engineering method that we mentioned above ignore completely or partially the mutual influence between context and solution [Matta et al. 2000]. More effort has been done recently to model project memory, we note especially DyPKM [Bekhti and Matta 2003]. DyPKM is an approach developed specifically for representation of project memory during project realization. Through information capture and content structuring, information produced during the project can be traced and structured. A general structure and a criteria tree are proposed for content structuring. Although DyPKM take context modeling into consideration, it is not sufficient for the knowledge classification of project memory. Traceability of project memory makes effort on modeling the ontological existence of concept classes, but little on knowledge extraction. A knowledge representation has to contain ontological existence, logical rules and computational application [Sowa 2000]. So an appropriate knowledge classification has to not only represent ontology of project memory, but also propose useful knowledge-oriented classification views for learning purpose.

Firstly, in order to classify knowledge from different context, the general semantic network of project memory (Figure 2) is decomposed into 4 sub-networks:

- Decision-making process: this part represents the core activity of design project, which helps designers to learn from negotiation and decision-making experience.
- Project organization makes decision: this part represents interaction between organization and decision, which provides an organizational view of decision-making.
- Project organization realizes project: this part represents arrangement of task and project team organization, which focuses learning on project management.
- Decision-making and project realization: this part represents the mutual influence between decision and project realization, which reveals part of work environment and background.

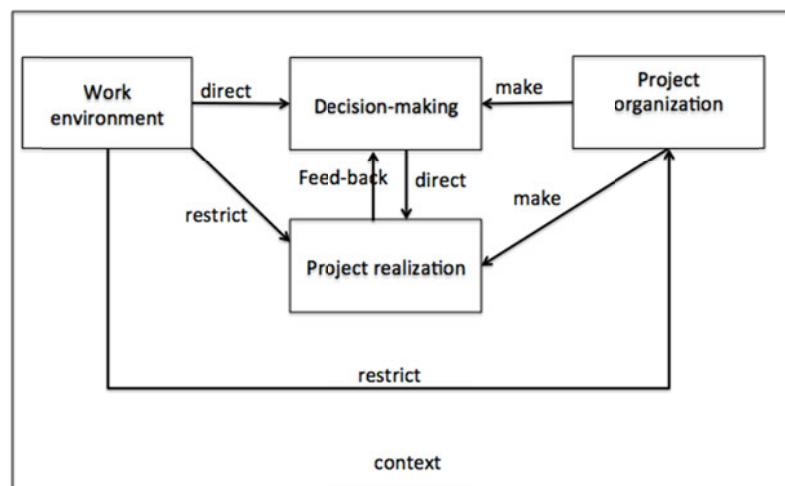


Figure 2. General semantic network of project memory

Secondly, in each sub-network, important concepts that are involved in potential knowledge extraction are highlighted, and ontological class hierarchy or criteria tree is constructed for classification. Thirdly, machine-learning technique is employed to generate rules between concepts or even networks (Figure 3). In this paper we focus on decision-making process in order to illustrate our approach and to discuss the contribution of project memory in design.

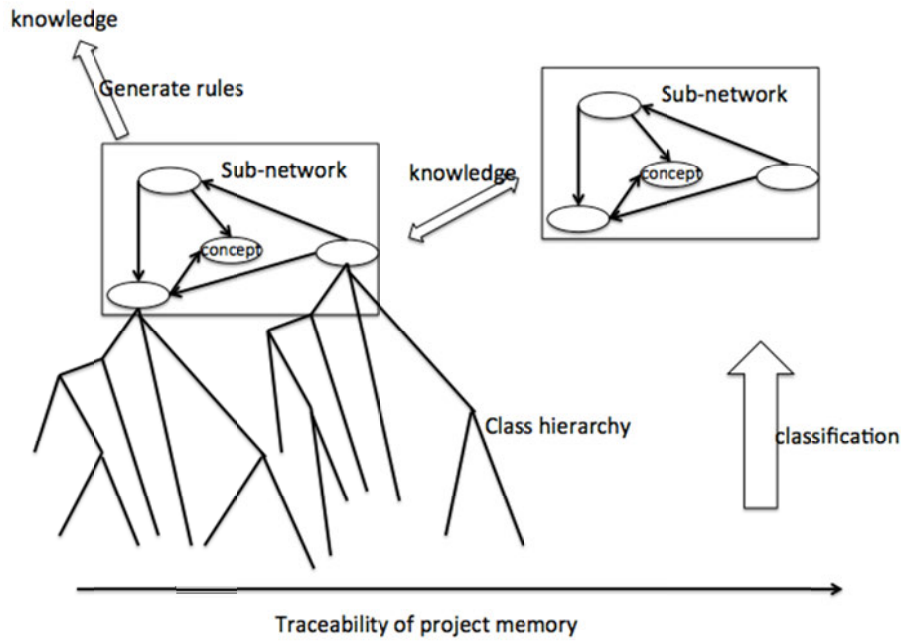


Figure 3. Knowledge classification framework

4. Knowledge classification in decision-making sub-network

According to the representation structure of project memory (Figure 1), the concepts that are identified in a decision-making process are: issue, proposition, argument and decision. Issue is the major question or problem that we need to address, proposition is solution proposed to the issue, and argument evaluate the proposition by supporting or objecting them, which can push proposal evolve into another version [Moran et al. 1996], [Buckingham Shum 1997], [Conklin 1998]; argument can also aim at issue which can possibly modify the specification of the issue. Decision is made by selecting the best proposition for the issue and setting up a goal for next step of project realization. One of the most important and useful knowledge that we want to represent is the context behind design rationale [Moran et al. 1996]. Three concepts are highlighted to represent the knowledge “why” in decision-making process: argument, decision, and issue. We believe the triangle network can represent the major process of decision-making as well as the reason and context of the decision.

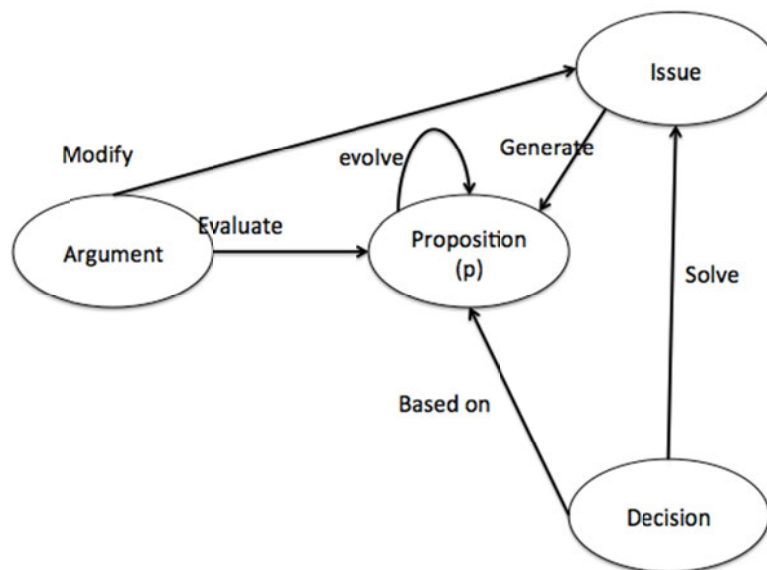


Figure 4. Decision-making sub-network

The argument criteria tree is based on evaluation criteria of design rational in the field of engineering design, and class hierarchy of issue and decision is based on research result of design project management [Ducellier 2002], [Pahl et al. 2007]. In the criteria tree, we attempt to take project context into consideration by adding work environment and project constraint. However, no classification can be argued to be a representation of the true structure of knowledge [Mai 2004], the model that we propose in this paper is, what we believe, the most approximate and useful representation of design project for learning purpose. In order to optimize the classifier, class hierarchy or even representation network need to be adapted to a specific applied domain.

For the argument and propositions, we introduce a predicate argument (criteria, times,role). Times represents how many times that this argument appears during a meeting. The role represents from which role that this argument is emitted.

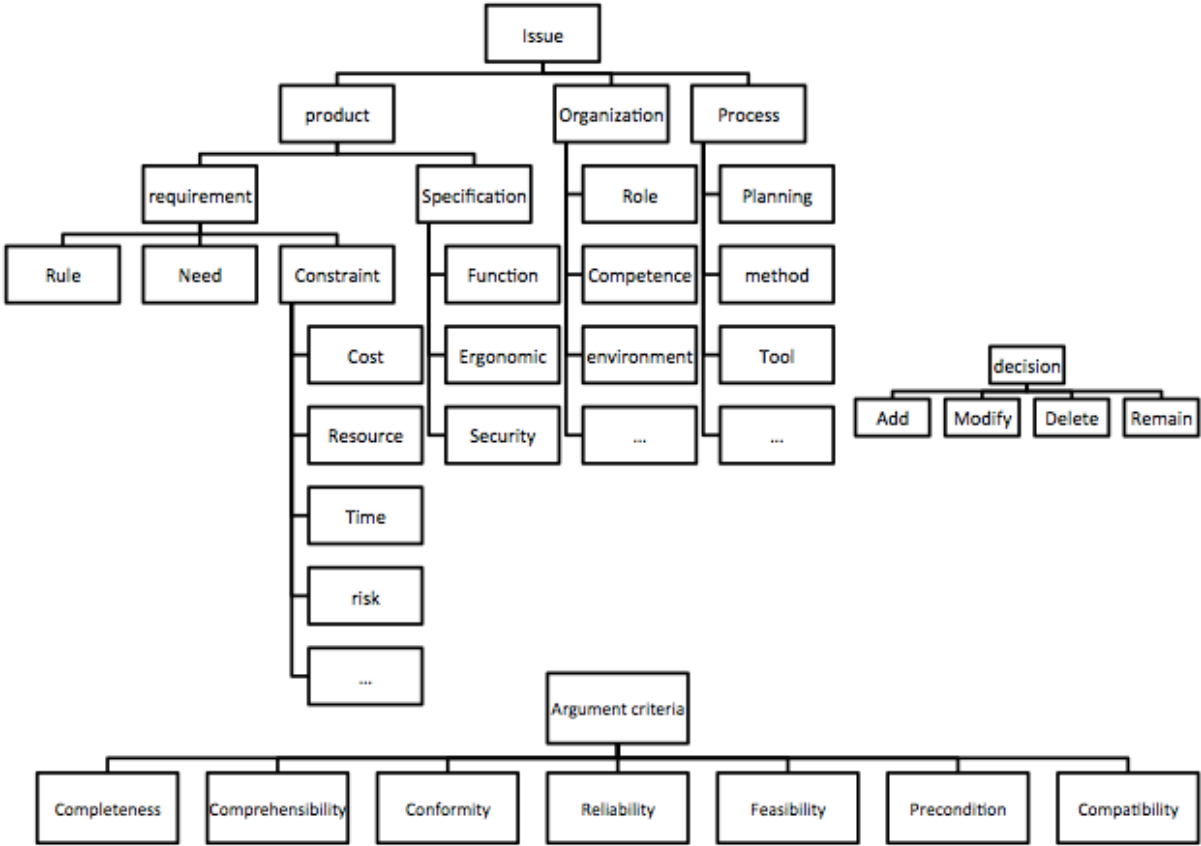


Figure 5. Ontological hierarchy

The ability to extract general information from example sets is a fundamental characteristic of knowledge acquisition. In order to generate rules that represent interrelations between concepts or sub-networks, machine-learning techniques are introduced. Machine learning algorithms can figure out how to perform important tasks by generalizing from examples. One of the most mature and widely used algorithms is classification [Domingos 2012]. As there are literally thousands of algorithms for machine learning, an evaluation of major machine learning techniques is carried out in search for the appropriate algorithm (Table 1) [Michie et al. 1994], [King et al. 1995], [Dietterich 1997]. Our intention is to classify project memory into rule-based knowledge, and project memory data is not extremely large, which leads us to choose an algorithm of rule-based methods. As noted above, a concept in project memory depends on the context. So, we aim at representing links between concepts in classification in order to reveal the knowledge behind structured graphs. ITRULE, an algorithm that can induce an optimal set of concepts or rules from a set of examples, is proposed so far for project memory classification [Goodman and Smyth 1992]. The advantage of this algorithm is in the

flexibility of representation, allowing it to learn many different concepts. The general rule extracted from examples is taken to be in the form of production rules, i.e. if condition A then condition B with probability p. A brief example on mechanical design project decision-making process is illustrated simply to show the knowledge classification method.

Table 1. Evaluation of machine learning techniques

| Machine learning techniques | Classification method | Learning type | Knowledge representation |
|-----------------------------|--|----------------------------------|--------------------------|
| Statistical methods | Calculate the density function; classify the sets by the resemblance of PDF. | Supervised learning | Weak |
| Decision tree methods | Classify the data by “mental fit”, knowledge-oriented separations. | Supervised/unsupervised learning | Strong |
| Rule based methods | Classify the data by relational rules (proposition) | Supervised/unsupervised learning | Strong |
| Artificial neural network | Simulate the classification process by nodes and weights. | Supervised/unsupervised learning | Weak |

4.1 Example

Two cases with the same issue are demonstrated in this section. The problem is that the wishbone suspension breaks during test. A decision-making process was initiated in search for a solution for this problem. For each case, propositions for solutions are proposed by team members, and arguments are listed for each propositions. Decision for both cases is re-dimension the wishbone. Decision-making process is traced during meeting using Memory meetings tools [Matta et al. 2013]. The detailed decision-making process is illustrated in Figure 6.





| Issue: wishbone suspension breaks during the test of vehicle | Proposition | Argument (Criteria) |
|---|--|---|
|  <p>Case 1</p> | Change the material of wishbone from steel to titanium  | <ul style="list-style-type: none"> + interchangeability of this part can be maintained, so it can still be replaceable (compatibility) - Titanium material is more expensive for manufacturing (precondition) |
| | Re-dimension the wishbone to make it stronger | <ul style="list-style-type: none"> + interchangeability of this part can be maintained (compatibility) - No existing solution exists (feasibility) |
| | Change the design specification of wishbone and redesign it | <ul style="list-style-type: none"> + More profound study will be carried out (completeness) + Quality can be increased (precondition) - Interchangeability of this part is not guaranteed (compatibility) - Project time can be longer, and cost may be more expensive (precondition) |
|  <p>Case 2</p> | Re-dimension the wishbone to adapt to test requirement | <ul style="list-style-type: none"> + interchangeability of this part can be maintained, so it can still be replaceable (compatibility) - No existing solution exists (feasibility) |
| | Redesign completely the wishbone  | <ul style="list-style-type: none"> + Existing design solution (feasibility) - New design is not compatible with other parts (compatibility) - Project date will be delayed (precondition) |

Figure 6. Structured decision-making process

Based on the structured information, a classification according to the predefined class hierarchy is carried out (Figure 7).

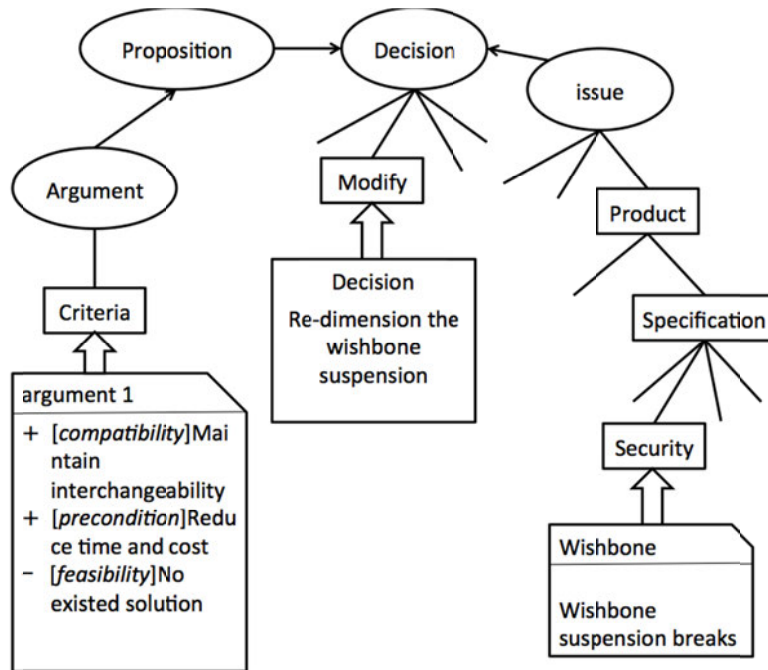


Figure 7. Concepts with classification hierarchy

The single classification graph shows that for the issue “wishbone suspension breaks” which is categorized as a security issue of product specification, the solution “redesign the wishbone suspension” is decided in regard to two important criteria “compatibility” and “precondition”. The graph shows that interchangeability of wishbone suspension and project cost as well as time can be crucial for the decision. However, supposing in another situation where the two elements are not strong enough for a specific issue, the result could be different. Hypothetically, more similar situations occur in a project memory, and then knowledge can be generated by the classification of similar graphs. A possible form of knowledge which can be put in ITRULE as: if issue {security, wishbone suspension breaks}, then decision {modify, redesign the wishbone suspension} and argument {compatibility; precondition} with a possibility of p. This type of graph shows the reason of a solution related to a specific problem in product context. But we know that solutions can be different corresponding to the organizational context of a project, for instance: actor's skills, enterprise policy, etc. So the graph must be connected to organization and work environment graphs. For instance in this example, the decision “redesign” has been made because there is constraint on project cost and time, additionally, wishbone suspension as a common part of vehicle fabrication is supposed to be easily interchangeable; at the same time, competences or techniques mastered by the project team, which is a context of organization, can also have a strong influence on feasibility of redesign of wishbone suspension.

5. Conclusion and discussion

In this paper, the question “can we learn from design-making process in design projects” is answered. At the beginning, we demonstrate the concept “project memory” in order to introduce a representation structure that is adapted to the new trend of collaborative concurrent engineering. Then, a knowledge-oriented classification method is proposed. At last, decision-making process is elaborated by this method. We show a technique in order to extract deep knowledge in project realization by using classification and generating rules between project concepts. So, learning from past is guided by recommendations showing at the same time, knowing-why and knowing-how and also link to detailed examples illustrating these recommendations.

There are still some points that need to be discussed. We believe, for design community, the most useful learning knowledge resides in the triangle of “decision, argument and issue”, but is it the single learning angle? We consider at the same time negotiation, which is possibly represented by “proposition, argument and decision”, could be worth classifying for learning. Because decision-making process contains not only the ideal solution, but also the negotiation process, in which all the propositions (accepted one and refused ones) are evaluated by arguments. Decision triangle gives us “why” decision is the ideal solution for certain issue while negotiation triangle gives us “why” some propositions are selected and the others are refused. Moreover, in order to represent more accurately the dynamic process of decision-making without changing designer’s work manner, we envision to simply note how many times the same argument occurs.

As it is shown in the generic semantic network of project memory, decision-making process is a sub-network that is interconnected with other parts of project memory. Since design rationale is the most useful learning angle for designers, we highlight the sub-network of decision-making process for design community. However, other views of project memory can prove to be useful for other roles in a project. For example, the interaction between project organization and project realization can be useful for managers to learn from past project experience on how to organize a project group for certain tasks.

As we can see the example that we introduced in this paper is an instance demonstration, future test on a larger database will be carried out for the classification of graphs or even knowledge rules.

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