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MEMBERSHIP AND TYPICALITY IN CONCEPT REPRESENTATION: FROM COGNITIVE PSYCHOLOGY TO INFORMATION TECHNOLOGY

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alle persone che mi sono state vicine
e hanno condiviso con me questo percorso

Contents

Abstract

The thesis concerns knowledge representation in humans and machines. In particular it focuses on the role of concepts in knowledge representation, a topic at the intersection of Cognitive Psychology (CP) and Information Technology (IT).

When humans and machines need to interact, problem dependent on different mechanisms for representing the same knowledge emerge. This issue is broadly debated in the recent literature. An optimal interaction between humans and machines could be eventually achieved by taking into account the human cognitive side of knowledge representation and by making these computational representations cognitively plausible for individuals.

The thesis focus on *Membership* and *Typicality* in human categorization and takes into account the role that such factors could assume in concept representation in IT, by analyzing their impact on categorization in Web ontologies.

The thesis is structured into a first part that describes the specific theoretical contributions of CP and IT, emphasizing the commonalities between the two perspectives, and a second empirical part that reports six original studies, five laboratory experiments and an online survey. Laboratory experiments were based on sentence verification tasks performed by participants, where *Membership* and *Typicality* were directly contrasted, with the goal of measuring the effect of such factors on categorization. The online survey explore users' attitudes and opinions towards schema.org, a general ontology for the Semantic Web.

Findings are consistent with the idea that — in addition to *Membership* — *Typicality* should be considered in concept representation and supports the conclusion that, to be more usable, Information Technology should prefer cognitively plausible ontologies.

PREFACE

The thesis concerns knowledge representation in humans and machines. In particular it is focused on the role of concepts in knowledge representation, a topic at the intersection of two disciplines: Cognitive Psychology (CP) and Information Technology (IT).

Concepts are still an open problem for all disciplines interested in knowledge representation (e.g., cognitive psychology, philosophy). With the emergence of Information Technology and the growing need for data and knowledge management by computers, the need of representing concepts in the most efficient way arose in disciplines such as ontology engineering (Ramesh, Parsons, & Browne, 1999; Yeung & Leung, 2006b, 2006a, 2010; Stark & Esswein, 2012; Frixione & Lieto, 2013b; Lieto, 2013). Taking into account the importance that such information representation plays in modern technologies, it is necessary to consider this issue from a broad perspective, taking also into account human cognition, which adds significant value to the concept representation in IT (Ramesh et al., 1999; Yeung & Leung, 2006b, 2006a, 2010; Stark & Esswein, 2012; Lieto, 2013; Wilmont, Hengeveld, Barendsen, & Hoppenbrouwers, 2013).

In computer science, ontologies are conceptual models augmented by formal axioms (Gruber, 1993) that enable information sharing on the Web (Yeung & Leung, 2006b, 2010). Historically, the design of such ontologies has been led by membership-based rules, mainly because of the computational languages (e.g., Description Logics) used to describe them. In other words, ontologies were designed so that the resulting data would be most accessible for computer-based data processing. However, concepts in these models are considered as crisp sets, without taking into consideration that crisp sets are, indeed, inadequate in modeling concepts (Straccia, 1998; Yeung & Leung, 2006b; Warren, Mulholland, Collins, & Motta, 2014). Therefore, these models can not take into account how humans represent concepts in their mind and the importance of Typicality in categorization (Rosch, Simpson, & Miller, 1976; Straccia, 1998; Yeung & Leung, 2006b; Hampton, 2007; Pitt, 2013; Warren et al., 2014).

Together with the growing understanding that the overall usefulness of ontologies is also influenced by the reliability and effort of agents that specify conceptual elements in ontology development (Hepp, 2008), the role of human cognitive functioning for concept representation in ontologies is becoming more and more significant (Ramesh et al., 1999; Yeung & Leung, 2006b, 2006a, 2010; Stark & Esswein, 2012; Lieto, 2013; Wilmont et al., 2013). Taking into account how humans represent concepts in their minds is crucial to enhance the usability of ontologies, which must support task performance.

An analysis of the literature on the human's concepts — from the early contributions by Aristotle, through philosophical theories to the results of experimental psychology — shows two factors as the main players in human concept representation: Membership and Typicality (Britz, Heidema, & Meyer, 2009; Yeung & Leung, 2006b; Cai, Leung, & Fu, 2008; Yeung & Leung, 2010; Aimè, Fürst, Kuntz, & Trichet, 2010; Lieto, Minieri, Piana, Radicioni, & Frixione, 2014; Frixione & Lieto, 2013b; Frixione, 2013; Frixione & Lieto, 2014). To establish whether an instance belongs to a given category, Membership utilizes — following the Aristotelian logic — necessary and jointly sufficient rules (definitory features), whereas Typicality utilizes the similarity between the instance and the prototype (defined by the best set of features that characterize such a category). According to Typicality, the similarity between an instance and the prototype is a function of the number of shared features.

Currently, artificial classifier systems are almost always Aristotelian, with the representation of categories based on well-defined rules, not allowing any ambiguity in categorization, as would be obtained by systems based on Typicality or similarity.

The experiments reported in this thesis test the idea that concept representation in the IT field — as anticipated in the literature (Britz et al., 2009; Yeung & Leung, 2006b, 2010; Aimè et al., 2010; Lieto et al., 2014; Frixione & Lieto, 2013b, 2014) — should also consider Typicality, beyond Membership.

The thesis is structured into a theoretical part (chapters 1-5) and an empirical part (chapters 6-9), followed by a general conclusion (chapter 10).

The first part describes the specific theoretical contributions of CP and IT, and emphasizes the commonalities between the two perspectives. After an introduction (chap. 1) about the interdisciplinary nature of the topic of the thesis, chapter 2 is devoted to the analysis of human concepts, their representation and use, the cognitive processes involved, and the psychological theories of concepts (chap. 2). These first chapters show that concept representation is a topic that involves both CP and IT, and that the relevant literature strongly supports the main idea that concepts can be considered as composed by Membership and Typicality factors. Chap. 3 focuses on concepts as represented and used by machines in IT and discusses the different formalisms of concept representation in IT, Sematic Web, and Ontologies. Chap. 4 leads to a joint analysis of concept representation at the intersection of CP and IT, focusing on aspects where both disciplines come into contact (e.g., fuzziness). Finally, chap. 5 describes the cognitive efforts in Ontology lifecycle, presenting an original literature survey, carried out during the six months of internship spent in Munich, where I followed a research project "*Cognitive barriers in Web Ontologies*" at the Universitat der Bundeswehr (in the *E-business and Web Research Group*, directed by Prof. Martin Hepp).

The second part of the thesis reports six original studies, introduced in chap. 6: five lab experiments based on sentence verification tasks (chap. 7 - 8), and an online survey conducted to evaluate some aspects of schema.org, an ontology used in the Semantic

Web (chap. 9). Lab experiments are based on sentence verification tasks performed by participants, where Membership and Typicality are directly contrasted and with the goal of measuring the impact of such factors in categorization tasks.

The experimental hypotheses can be briefly summarized as follows: the Typicality factor emerges in categorization tasks and it is modulated by further factors (the modality of presentation of sentences, the conceptual frameworks in which the sentence is evaluated, the format of the instances to categorize, and sentence polarity). The last work is an ecological experiment aimed at exploring the role of the same factors (Membership and Typicality) in a categorization task based on an ontological classification. Final considerations and conclusions are reported in chap. 10.

FIRST PART: THEORIES OF CONCEPT REPRESENTATION

1 Introduction

The thesis concerns **knowledge representation** in humans and machines: in particular it is focused on the role of **concepts** in knowledge representation.

Concepts are considered as labels of a set of ideas or objects (Brandimonte, Bruno, & Collina, 2006), or a "representation of a class or individual" (Smith, 1989) that is a "generalization of an external reality", used as "a medium for communication" or "as mean of reasoning" (Healy, Proctor, & Weiner, 2003). Concept representation is considered important in psychology because of its role in cognitive processes of humans and other animals. Concepts are used in almost all human cognitive processes, and they are paramount for ordinary life as organizers and managers of the external and internal environments (Eysenck & Keane, 2015), reducing a wasteful cognitive cost associated with analyses and inferences whenever an instance is encountered (Margolis & Laurence, 2007).

Concepts are equally important for Information Technology (IT), the discipline that deals with the representation and use of knowledge in a computational form. An important goal of IT is to represent information and knowledge in the most efficient way, managing the huge amount of avaiable data (Gruber, 1995; Daconta, Obrst, & Smith, 2003; van Harmelen, Lifschitz, & Porter, 2008).

Cognitive Psychology and Information Technology have developed indipendently, focusing on different goals regarding concept representation. In fact, humans and machines have to perform different tasks and thus their internal mechanisms regarding concept representation are selected by the final objective of their specific tasks (Cohen & Lefebvre, 2005).

If humans have developed cognitive processes of categorization to cope with the external environment on the bases of communalities and differences between things, machines have to perform tasks in the most efficient way, using formal and strict rules to represent knowledge through computational languages.

For instance, you can consider that the initial goal for prehistoric individuals was survival and, probably, the most efficient way to achieve it was to be able to categorize the external world by finding similar and different attributes for things, to label them and to communicate them to others. When an individual had to find something to eat, the only way to avoid being poisoned was to recognize and categorize edible from inedible food based on their attributes. Concepts and categories were thus important in a varying environment to survive, and nowadays they are fundamental, given that they represent the bases of most cognitive processes (Cohen & Lefebvre, 2005; Friedenberg & Silverman, 2005).

On the other hand, in IT the knowledge representation problem has always been an important issue since the birth of Artificial Intelligence (Friedenberg & Silverman, 2005; Gagliardi, 2009). There the necessity arose to create mechanisms and tools that were efficient in order to compensate for humans cognitive limits (e.g., the amount of analyzable data and their speed of processing). To provide an example, in machine learning — the field of study regarding programs that learn improving their perfomance (Gagliardi, 2009) — the only possible internal knowledge representations for automatic classifiers were based on a set of classification rules defined as conditions that an instance had to satify to be part of a class.

When humans and machines need to interact, it emerges the problem of the different mechanisms of representing the same knowledge, an issue broadly debated in the recent literature (Ramesh et al., 1999; Chiew & Wang, 2003; Lieto, 2013; Engelbrecht & Dror, 2009; Stark & Esswein, 2012; Wilmont et al., 2013). An optimal interaction between humans and machines could be eventually achieved by taking into account the human cognitive side of knowledge representation, and by making these computational representations cognitively plausible for individuals (Lesot, Mouillet, & Bouchon-Meunier, 2006; Frixione & Lieto, 2013b, 2013a). For instance, in machine learning other algorithms should be taken into consideration, e.g., classification rules based on istances (istance-based representation) or rules with exceptions, based on psichological evidences about categorization (Gagliardi, 2007, 2009).

1.1 Main goal

The literature regarding concept representation in humans compares two factors — **Membership** and **Typicality** — and reveals the critical role played by both in categorization as sustained in several conceptual theories.

The thesis focus on *Membership* and *Typicality* in human categorization, taking also into account the role that such factors could assume in concept representation in Information Technology, and analying their impact on categorization in Web ontologies.

The main goal of the thesis is to highlight, and contribute to new experimental results to the controversial empirical studies in psychology regarding concepts and categorization, identifying possible relations with some theories of concepts (e.g. the Heterogeneity Hypothesis by Machery and Seppala (2011), and the Fuzzy Set Theory of Concepts by Zadeh (1965, 1975)). The starting idea for this thesis concerns the fact that *Membership* has been primarly considered in concept representation and categorization because of the strong impact of classical conceptual theories (Smith & Medin, 1981; Murphy, 2002) regarding the necessary and jointly sufficient attributes in psychology. As an example, the category *square* involves a set of properties (e.g., it has four sides of equal length, it has four right angles, it is a regular poligon) and an instance must satify these characteristics to be a member of such class. Properties are therefore necessary and jointly sufficient, i.e., it is necessary that an instance have all of them to be considered as a member of the class and, moreover, if an instance owns jointly these proprieties, it is sufficient to state its belongingness. Futhermore these properties are considered as definitory, because they determine the class membership (Larochelle, Cousineau, & Archambault, 2005). On the other hand, in the last 50 years, many experimental results have highlighted the importance of *Typicality* for this issue (Rosch et al., 1976; Kamp & Partee, 1995; Osherson & Smith, 1997; Hampton, 1993, 2007; Lesot et al., 2006; J. Smith, 2014). Several authors emphasised the role that such factor could play in categorization, and the experiments described in this thesis would like to support and contribute to the ongoing researches about concepts and categorization, considering it in a broad approach involving also the knowledge representation in Information Technology.

Experiments are based on sentence verification tasks performed by participants, where *Membership* and *Typicality* are directly contrasted. There are five lab experiments that have the goal of measuring the impact of such factors in categorization tasks. The hypothesis can be briefly summarize as follows: i.e., the factor *Typicality* emerges in categorization tasks and it is modulated by further factors (the modality of presentation of sentences, the conceptual frameworks in which the sentence is collocated, the format of the instances to categorize, and sentence *Polarity*).

In addition, considerations and analyses regarding the *Membership* and *Typicality*'s impact on categorization in Web ontologies are taken into account, focusing on the role that such factors, following a cognitive approach, could assume in IT, in particular in ontologies. The idea supported by several authors (Lesot et al., 2006; Yeung & Leung, 2006b, 2010; Frixione & Lieto, 2013b, 2014; Lieto et al., 2014) is that *Typicality*, in addition to *Membership*, could have a critical role also in concept representation in ontologies. This issue are investigated, analyzing a typical ontology used on the Web, *schema.org* (Guha, Brickley, & MacBeth, 2015; Mika, 2015). This study represents an ecological experiment that would like to initially explore the role of *Typicality* in ontologies through a categorization task.

1.2 An interdisciplinary thesis

The thesis embraces an interdisciplinary approach that involves two different (and apparently distant) disciplines:

- **Cognitive Psychology** (CP)
- **Information Technology** (IT)

Psychology is concerned with empirical studies, through experimental methods, whereas Information Technology involves computational approaches, using modeling and computer simulations. The differences are also recognized in the way the two disciplines consider concepts: CP uses an elaborate model, taking into account different conceptions and variables to consider the belongingness of instances to a given class; on the contrary, IT mostly utilizes an Aristotelian approach based of necessary and sufficient rules which is considered indispensable to use information in automated procedures, even if in the last 50 years there were several studies on *Typicality* in knowledge and concept representation reasearch that emphasized its role in categorization (Rosch & Mervis, 1975), expecially for "non classical" concepts, and underlined the importance of making these two disciplines interact (Gagliardi, 2007; Frixione & Lieto, 2013b).

The thesis is concerned with how knowledge and concept representation is treated by CP and by IT, trying to bridge the gap between two different fields, which look so distant, even though they deal with similar problem (Friedenberg & Silverman, 2005).

It is important to explain why Cognitive Psychology seems to be an enhancement to the field of Information Technology regarding concept representation. There are several contributions and studies that reveal the role and the relevance of CP for this issue (Chiew & Wang, 2003; Sowa, 2005; Engelbrecht & Dror, 2009; Stark & Esswein, 2012). A lot of tasks and tools in IT involve humans having to model, develop and use tools in a proper way. Considering that there are several evidences from CP about the complex role played by cognitive processes in concept representation and categorization (Cohen &

Lefebvre, 2005), it is important to understand which processes are implicated in similar tasks in IT (e.g. conceptual modelling that concerns reasoning with concepts and their relationships) to provide better cognitive support for agents (Ernst, Storey, & Allen, 2005; Sowa, 2005; Falconer & Storey, 2007; Wilmont et al., 2013; Nossner, Martin, Yeh, & Patel-Schneider, 2015). In fact, individuals involved in conceptual representation in IT should be able to create a model that could consider their own mental ideas with inputs from the environment, using a computation language that allows a proper specification. Therefore, there are several cognitive mechanisms implicated in such tasks (e.g., relational reasoning, abstraction, esecutive control, attention) (Hepp, 2007) and it represents just an example of the importance of cognitive contributions to the discipline of IT. Ramesh et al. (1999) have already explained why cognition should have a role in IT, expecially in conceptual modelling.

Lieto (2013) proposed some suggestions from CP to the development of systems oriented to knowledge representation: e.g., to keep distincted the two different reasoning systems, following the *Dual Processes Approach* (Evans & Frankish, 2008) (see section 4.1 for a digression), to keep distincted prototipicality from compositionality of concepts, and to develop hybrid models of concepts based on different representation formats. Moreover, based on the dicotomy in CP between *Prototype* and *Exemplar* Theory, some approaches have been already adopted as classifiers in IT: e.g., the *Nearest Prototype Classifier (NPC)* based on prototypes, and the *Nearest Neighbour Classifier (NNC)* based on exemplars (Gagliardi, 2007, 2009; Lieto, 2013).

Furthermore, during the past decades Description Logics, DL (the computational language mostly used in IT to represent knowledge) have been extensively studied regarding its decidability and computational tractability, but lacking the study of its usability. Warren et al. (2014) posed this problem investigating the role that Psychology could have in explaining the accuracy of human reasoning with DL statements. Furthermore, following a cognitive perspective, Britz et al. (2009) tried to model *Typicality* into DL.

Yeung and Leung (2006b, 2006a, 2010) have also underlined the importance to incorporate cognitive principles to make ontologies (see chap. 3) more usable and understable for humans. In many fields (e.g., diagnostic medicine, risks evaluation, ...) ontologies and conceptual maps are used to support human decisions. Therefore, these tools assume a strong role for the ultimate decision because they guide the reasoning, providing some options: it becomes fundamental to make them able to interact in a proper way with humans (Gagliardi, 2007; Ceusters & Smith, 2010; Lucchiari, Folgieri, & Pravettoni, 2014) . Also Yeung and Leung (2006b, 2006a, 2010); Aimè et al. (2010); ? (?); Frixione and Lieto (2012, 2014) have strongly sustained the implementation of *Typicality* factor in concept representation in IT.

Also in the field of learning and education is very important the usage of Information Technology to enhance and support learning mechanisms, but knowledge and concepts have to be cognitively avaiable to acheive this goal.

After considering the main theoretical contributions from both CP and IT in concept representation and providing an original and accurate literature survey about cognitive efforts and limits of users in Ontology lifecycle, the thesis presents a series of empirical contributions concerning mental representation of concepts, comparing different theories of concepts. An online study about the evaluation of schema.org, a real ontology used in the Semantic Web, is also supplied.

1.2.1 Cognitive Psychology

The term "*cognition*" refers both to the processes related to knowledge, especially the act of knowing, including reasoning, remembering, and perception and also the content of these processes (i.e., concepts and memories) (Brandimonte et al., 2006). This concept identifies the actions of "perceiving and knowing" (perception and knowledge) (Stillings & al., 1995, p.1) and specifically, the term *"cognitive processes"* identify the "higher mental processes, such as perception, memory, language, problem solving and abstract thinking" (Brandimonte et al., 2006). These processes are considered procedures that allow the acquisition of input from the external environment and a subsequent internal processing, with the aim of producing a behavioral output (Stillings & al., 1995).

It is very interesting that the term "cognition" originates from Latin, was translated from the Greek "gnosis" in "cognition" and then used by Western philosophical tradition referring to the word "knowledge" (Brandimonte et al., 2006).

"Psychology" (Friedenberg & Silverman, 2005, p. 16) has the aim of studying the mind and the human behavior. It is the first discipline that set itself the goal of studying the mental phenomena and behavior using purely scientific methods (Friedenberg & Silverman, 2005) (Healy et al., 2003). Focusing specifically on the scope of knowledge, *"Cognitive Psychology "* can be considered as a specialization of this science. It is defined as the study of mental or cognitive processes, such as perception, reasoning, language, learning, memory, etc., through the use of a scientific approach. The ultimate goal is the understanding of human cognition, by analysis of the behavior. Since these mental procedures are impossible to measure directly, researchers employ inferential activity: using different tasks, they analyze the results to infer the components behind the visible output. According to Eysenck and Keane (2015), *"cognitive processes"* are defined as procedures that enable the information acquisition from the external environment and, through an internal processing, lead to the production of a behavioral output. They

are, therefore, linked to the representation of internal knowledge, whether in the form of personal experiences, on general knowledge about the world (Eysenck & Keane, 2015).

For the purposes of this thesis, it becomes interesting to provide some ideas and explanations about a specific cognitive process, particularly important in the management and representation of knowledge and concepts: the *"categorization"*. Categorization is a procedure involved in concept representation, and it regards mental ideas and objects: their recognition, the differentiation, the understanding, and it emphasizes the relationship that can exist or not between an instance and the category or the concept (Cohen & Lefebvre, 2005).

An important role in CP is played by the *"models"*, they are defined as reality portions that consist of a series of conceptualizations in a particular domain and that it can be expressed through a specific modeling language (Guizzardi, 2005). In the specific context of cognition, the *"cognitive models"* are simplifications of mental functions, derived from observation of the objective behavior, and from inferences of internal processes of the brain (Chiew & Wang, 2003).

1.2.2 Information Technology (IT)

"Information Technology" — together with *"Computer Science"*, and *"Computational Science"* — are just some of the disciplines that share the same subject: information and its representation and use. *"Information"* is considered any aspect or attribute of the natural world that can be abstract, digitized, represented and mentally processed (Chiew & Wang, 2003).

Computer science is the "information science" (Chiew & Wang, 2003), the discipline that treats the information through the use of automated procedures. On the other hand, the term "computational science" is applied to any branch of mathematical, physical and natural sciences that use the power of computers for the resolution of highly complex problems. Information Technology (IT), finally, includes all of the methods, tools, and technologies that transmit, receive and elaborate information, and deals with the representation of the information in computer science. In this thesis, I will deal only with IT.

Models play a role in these disciplines, too: the so-called *"data models"* are simply patterns that represent data, and *"data modeling"* is the process to create and use them.

1.3 A bridge between Cognitive Psychology (CP) and Information Technology (IT)

Modern technological contents (as delivered, for example, by mobile phones, computers...) have become increasingly embedded within everyday environments. This technological shift involves complex interactions between humans and devices, and it requires multidisciplinary investigations (involving psychology, cognitive science, and engineering, computer science, etc.) (Weiser, 1993). Multidisciplinary human-centered design investigations help to provide deeper insight into how to make these interactive devices able to interface with users, focusing on a different point of view of the same issue (Still, 2009).

Cognitive Psychology (CP) and Information Technology (IT) share a common ground: the knowledge and concept representation; although it is used in a different way and for different purposes. On one hand, there are the concepts as used by humans, i.e., considered from a cognitive point of view and employed in the categorization by natural cognitive systems; on the other, there are the concepts used in categorization by computers artificial systems. A possible bridge to connect these two disciplines could be of great help to broaden the views of both, but mainly to improve their mutual enrichment. A shared language would be surely necessary for a thorough and comprehensive understanding.

Taking a broad perspective, Cognitive Science, with his multidisciplinary approach, methods, and tools, can assist IT in facing the problem of concept representation (Cohen & Lefebvre, 2005).

"Cognitive science" is to be considered, accordingly, as the field of interdisciplinary studies of systems and processes that manipulate information (Brandimonte et al., 2006). It is viewed as the interdisciplinary scientific study of the mind (Friedenberg & Silverman, 2005, p.2). It is born from the fields of Psychology and Artificial Intelligence (AI) (Chiew & Wang, 2003) and it spans various disciplines: psychology, linguistics, computer science, philosophy and neuroscience, who share the study of the mind and its functions and, for most of them, even the scientific methods (Friedenberg & Silverman, 2005, p.2). That is why Cognitive Science is generally considered as "the science of mind" (Stillings & al., 1995, p. 1) and aims at identifying the functional architecture of cognition, that is properly defined as the set of rules and representations that mediate the thought (Chiew & Wang, 2003). The understanding of mental processes, using a multidisciplinary perspective, leads to the formulation of laws and generalizations characterizing all intelligent behavior (Chiew & Wang, 2003, p. 115).

Moreover, several disciplines already exist that use an interdisciplinary approach to studying the human interface between the user and the computer: an example is the *"Human-*

Computer Interaction (HCI)" (Jacko, 2012). Specifically, this discipline encompasses different branches, such as cognitive science, artificial intelligence, computer science, etc., which work jointly with the aim of developing efficient and interactive systems for humans, and to create an interaction that can be usable and useful as much as possible (Sears & Jacko, 2007). The human-machine interaction is at the heart of the study in this discipline (Dzbor & Motta, 2007), and it becomes obvious that cognitive factors are of primary importance to be considered in this interdisciplinary approach.

Another discipline that is gaining ground is the *"Cognitive Informatics"* (Chiew & Wang, 2003), a good example of how scientific progress is moving towards the interaction between these two distinct sciences. Cognitive Informatics is the extension of contemporary computing (Chiew & Wang, 2003), and it is considered an interdisciplinary science between the Cognitive Sciences and the IT, which aims to investigate the mental and neural mechanisms of the brain and mind along with the study of the information procedural mechanisms. It has to be mentioned the First IEEE International Conference on Computers Cognitive (ICCI'02) in 2002 as a key moment for the official recognition of the Cognitive Informatics research (Chiew & Wang, 2003). This discipline brings valuable contributions in different fields: computer science, computational science, mathematics, cognitive science, psychology and so on (Chiew & Wang, 2003).

In this multidisciplinary approach the *"Conceptual Data Model"* could be mentioned that describes the concepts and some of their attributes, as well as the relationships that exist between them, through the use of *integrity rules* that guarantee a significant internal consistency. A more consistent digression on this topic will be provided in chap. 3, but it is at least important to mention the importance of such models in the representation of concepts and knowledge: in fact the purpose of modeling is the expression of the meaning of the terms (or concepts) and their relationships in order to ensure a consistent and meaningful knowledge representation of a particular group of users in a specific experiential domain (Ramesh et al., 1999).

1.3.1 Concept representation

Cognition and representation are related: the issue of mental representation is strongly linked with cognitive theories. Most of these theories assume that the human mind forms a sort of internal representation (Brandimonte et al., 2006). For that reason, it is important to investigate and understand how the mind could represent knowledge (and concepts) from the external (and internal) environment.

Therefore, the issue of concept representation involves both generic knowledge representation and concepts themselves.

Knowledge representation

It is hard to give an exhaustive definition of such a general term as "*knowledge representation*". Knowledge — i.e., its representation, use, ways and means to deal with it — has always been at the center of interest and study, and philosophy has always tried to provide answers, although in a uncertain way. Already in ancient times, philosophers had shown a keen interest in the representation of reality and knowledge, discussing, for example, as a mental image could reflect the external world or, even, if it was possible to be able to get a full understanding of the world, etc.

Only at the beginning of the last century the issue of representation and the acquisition of knowledge was addressed and studied in depth for the first time, but considered only from a purely psychological point of view (i.e., in terms of knowledge as arising from "personal experience"' stored in memory) (Chiew & Wang, 2003). Tolman (1948) in the 40s, firstly coined the term *"cognitive map"* to describe a type of mental representation of concepts and their relationships that aimed to understand the external environment and the inner mind. This idea is strongly bound to the idea of knowledge representation.

Some generic definitions of knowledge, recognized by now, can be viewed as the sum of what you know, as an understanding both practical and theoretical of a topic or as an understanding derived from personal experience (Brinklow, 2004).

With the strong progress in the field of *Information Technology (IT)*, and specifically in the *"Semantic Web"* the question of data accumulation and information storage has become a trending topic. With the new possibility of storing huge amounts of materials (Gandon et al., 2015) in many different formats, the representation of knowledge and its use become essential (Cregan, 2007; Peroni, Motta, & D'Aquin, 2008). The management of information assumes, therefore, primary importance, in a way that should be considered human-readable, as well as effective from the technological point of view. Many data, poorly understood and not easily available, can not provide much value.

Knowledge is properly an organized and context-dependent information that is, nowadays, considered by most companies as the resource with the highest intrinsic value. Thus, many fields of investigation related to knowledge management were developed (Ju, 2006) including: the acquisition processes (with the use of tacit knowledge as an information resource); information retrieval (storing and retrieving information through the use of computational tools); knowledge transfer (transfer and sharing of information and knowledge in a format that is understandable and usable for humans; knowledge application (hence the application of such knowledge in the field, through the use of support tools) and information architecture (i.e., the creation of virtual environments for data sharing). These are just some of the fields in which current data management has impacted strongly.

Concepts

The *"concept"* is a proper mental representation of a class or an individual (Smith, 1989). A simple object is different from a concept, as a real and concrete entity opposed to something that is, above all mental, abstract and intangible, and that includes the generalization of many encountered instances, and by combining several different aspects (Olive', 2007).

In the concepts we can distinguish between their *"extension"* and their *"intension"*. By extension of a concept we refer to all instances that might be part of the concept, while the term intension identifies the shared properties for that mental representation.

Furthermore, a concept of "x" is an idea of the mind, defined as a group of entities that are categorized as "x" in the world. For this reason, the cognitive process of categorization is so important in the management of conceptualization in mind. Anderson (1978) emphasized that the existence of concepts, seen as mental representations, is underlying the use of processes that operate on them (categorization *in primis*).

In summary, concept representation is the representation (cognitive or computational, as mentioned) of mental concepts, considered as an abstract and intangible generalization of an idea or object.

1.3.2 Concept representation between CP e IT: an open issue

Several authors (Chiew & Wang, 2003; Yeung & Leung, 2006b; Lesot, Rifqi, & Bouchon-Meunier, 2008; Stark & Esswein, 2012; Frixione & Lieto, 2012, 2013b; Lieto, 2013; Lieto et al., 2014; Lieto, Radicioni, & Rho, 2015) have been arguing about the dialog and the interaction between CP and IT in the last decade.

It is important to mention here the most important tools that are used in concept representation — ontologies — that try to take into account both CP and IT perspectives. Briefly, an ontology is a "specification of a conceptualization" (Gruber, 1993, p. 200), "a description [...] of the concepts and relationships that can exist for an agent or a community of agents " (Gruber, 1993, 1995); or a standardized form of the concepts representation and their relationships in a particular domain (Dermeval et al., 2014).

Frixione and Lieto (2013b) argued that concept representation is, indeed, an open issue in the field of knowledge representation, and in particular in ontology engineering. They suggested that concepts are considered by Cognitive Psychology not as a unitary phenomenon and they can not be represented only by necessary and sufficient rules, as artificial systems usually do. In the past there was an initial tentative to present concepts in prototypical terms, suggested by Cognitive Psychology, through "Frames" (Minsky, 1975) or Semantic Networks" (Quillian, 1968) that, however, did not obtaining satisfactory results because of their approssimation and their lasck of formal definition (Lieto, 2013).Therefore, the implementation of *Descriptive Logics, DL* was taken into account because they were computationally more efficient (see chap. 3 for a more detailed account). Actually, DL are widely adopted in ontology representation, even if they lack to present *Typicality* of concepts (Frixione & Lieto, 2013b).

Fuzzy and non-monotonic logic extension of DL were then proposed, but they posed some problems, still unsolved (Frixione & Lieto, 2013b).

Some authors, as Frixione and Lieto (2013b), also proposed some recent contributions and suggestions from Cognitive Science and Psychology, such as the *Dual Process Approach* (concept representation not as an unitary phenomenon but deriving from the use of two different cognitive systems: see chap. 3). They stressed the importance of considering concept representation using prototype and exemplar-based approaches, that can be utilized in various situations, underlining pro, and cons in the usage of both (singularly or together in a hybrid system) kind of representations (Frixione & Lieto, 2012), on the basis of several empirical discordant results.

Another proposal from the cognitive perspective is given by *Conceptual Spaces*: a sort of geometric representation of concepts, where knowledge consists in some qualitative dimensions, and instances are points in that structure (similarity is then calculated according to the distance from a measured central value) (Gärdenfors, 2000; Frixione & Lieto, 2013b). This solution offers a framework to represent concepts in term of both exemplars and prototypes (Frixione & Lieto, 2013b), going beyond the limits of the Aristotelian approach and also integrating it in DL representation.

In summary, the idea on which these new approches are grounded is that it can be possible to consider concepts in term of a hybrid prototype/exemplar-based representation and to adopt as a common computational framework (Frixione & Lieto, 2013b). A possible technical, efficient and easily applicable solution remains an open issue, and it is still under investigation.

2 Concepts in Cognitive Psychology

The term *"concept"* has been described as: "a mental representation of a class or individual and deals with what is being represented and how that information is typically using during categorization" Smith (1989, p.116). The author emphasizes the fact that the concept is an internal representation, and that this information is typically used by a cognitive process: the *categorization*.

In psychology, there are many ways in which concepts are considered. Healy et al. (2003) provide some examples: they describe them as "components of thoughts", as "generalizations of an external reality", as "a medium for communication", or as "means or methods of inductive reasoning". Margolis and Laurence (2007), according to the knowledge principle, consider them as ways to handle external information in a general manner, reducing a wasteful cognitive cost associated with analysis and inferences whenever one encounters an instance of that category. Concepts are *"entities"* (Machery, 2009) that are described by their attributes or, even, through the relationships between different concepts, or through the categorization processes that conspicuously involves them. Categorizing, mental ideas are treated, and the items are recognized, differentiated and understood, creating broader relationships between individual instances and concepts or categories, through inclusion and exclusion, subordination and superordination relations (Cohen & Lefebvre, 2005).

Murphy (2002) identifies concepts as "mental glue" to keep the mental world stable and coherent, representing general knowledge and what we know about it, giving a sense to the encountered things.

2.1 Theory of Concepts in Psychology

Psychological research has embraced the study of concepts since its very beginning (Machery, 2006; Murphy, 2002; Zarl & Fum, 2016). Theories of concepts pursue the goal of describing and identifying properties that are shared with all concepts (Belohlavek & Klir, 2011, p. 15).

The main psychological contribution regarding human concept representation and use are (Murphy, 2002; Gagliardi, 2007) :

- the **Classical Theory of Concepts** (or **Classical view**);
- the **Prototypes** paradigm;
- the **Exemplars** paradigm;
- the **Theory-Theory** and;
- other theories or contributions (e.g., **Hybrid Theories**; **Heterogeneity Hypothesis**; **Fuzzy Set Theory of Concepts**).

The *Classical Theory of Concepts* (or *Classical View*) (Smith & Medin, 1981; Murphy, 2002; Belohlavek & Klir, 2011; Zarl & Fum, 2016) regards concepts as rules or definitions, i.e., properties that are necessary and jointly sufficient to determine if a specific entity is an instance of the concept in question. Concepts are defined using sets whose instances that are defined by several rules. A concept of a specific category x presents some necessary and sufficient attributes or properties to be x (Belohlavek & Klir, 2011). Therefore, if an element meets all the properties, it is a member of the class.

Classic studies in psychology highlight that natural categories are affected by a *family-resemblance principle* (Rosch & Mervis, 1975; Smith & Medin, 1981). These outcomes suggest that each category presents some peculiar features shared only by the members of such class and not by the others.

Since several empirical contributions, the *Classic Theory of Concepts* had to be re-evaluated, taking into considerations further paradigms, assimilated under the term "similarity-based" view, "probabilistic view" or the so-called "knowledge approach" (Machery, 2009). They are not real detailed theories, but rather families of theories or contributions (i.e., *Prototypes* paradigm, *Exemplars* paradigm, and *Theory-Theory*).

Since it is impossible to define which paradigms could explain better the theory of concepts, further different hypotheses were put forward (e.g., *Hybrid Theories*; the *Fuzzy Set Theory of Concept* — an alternative framework for concepts that relied on the idea of fuzzy sets —, Zadeh (1965), the *Heterogeneity Hypothesis* by Machery (2006)).

2.2 The *Classical Theory of Concepts*: the necessary and sufficient rules

The *Classical Theory of Concepts* (or *Classical View*) (Smith & Medin, 1981; Murphy, 2002; Belohlavek & Klir, 2011) regards concepts as rules or definitions (necessary and sufficient properties to determine the membership of an instance). Following Smith and Medin (1981), it is possible to delineate this view, using three main assumptions: a) the concept is delineated as a sort of summary description of a whole category and b) the features that represent concepts are necessary and jointly sufficient. An instance to be part of the class has to have these set of features. c) The third assumption concerns the net of features in subset relations: e.g., more specific concepts in the hierarchical structure have some features not shared with the superset class.

The *Classical Thory of Concepts* seems to be reasonable and intuitive, but it can not explain several empirical phenomena found by psychologists in some of their experiments (Zarl & Fum, 2016). Several authors — e.g., Barsalou (1989) — empirically demonstrated that people have difficulty in generating lists of necessary and sufficient properties if it is required to define a concept. Moreover, people disagree with each other, and sometimes they disagree also with themselves, when they try to identify the features characterizing many everyday concepts or when the same person have to generate different lists on diverse occasions, respectively (Bellezza, 1984). It results because most of our concepts are vague, and do not have clearly defined boundaries. This vagueness sometimes could lead to the disadvantage that none of our categories will ever fit completely with the world and that there will sometimes be difficulties in discriminating if an instance belongs or not to a concept.

Hampton (1993) claimed, for example, that for people some elements are just barely members of a class and other elements are just merely non-members. However, members and non-members form a continuum without clear boundaries between them: while it is easy to categorize unambiguous instances (clear members or clear non-members), it is critical determining whether an in-between element belongs or not to a particular category (Zarl & Fum, 2016).

McCloskey and Glucksberg (1978) already found that people were pretty consistent between two sessions of membership decisions for exemplar-category pairs and that there was low inter-variability between them when elements were clearly member or not of the category (e.g., apple-fruit and cucumber-furniture, respectively). They disagreed and were frequently inconsistent in the case of borderline elements (e.g., curtains-furniture).

Rosch (1973) provided a further embarrassing result for the *Classical Theory*: the fact that people consider certain elements as better exemplars of a concept than others, e.g., sparrows and robins are considered as better birds than ostriches or penguins. This phenomenon is known as the *Typicality effect*, and it represents one of the most robust, and valid one in the study of concepts.

Summarizing, following the discussion in Smith and Medin (1981), four general criticisms of the *Classical Theory* are pointed out. i) There is no consideration of functional features (only structural ones are taken into account), but for artificial classes, most of the time, the defining features are indeed functional. ii) The theory does not consider disjunctive concepts. iii) Furthermore, there are several unclear cases, and people disagree very often in membership judgment. iv) Finally, there is evidence that many concepts do not have defined features (even though the *Classical Theory* strongly assume it).

There does not exist only general criticism about the *Classical Theory*, but experimental evidence highlights several contradictions in considering correct this approach: the Typicality effect is the best-known result that turns out from psychological studies, and then the Family Resemblance Measures as determinants of *Typicality* (Rosch & Mervis, 1975). Family Resemblance principle means that categories form coherent clusters in psychological similarity space, or rather that a pair of members shares features following variable and probabilistic similarity relationships. Family Resemblance categories present a graded structure, with central and peripheral members, with different level of typicality (Rosch & Mervis, 1975; J. Smith, 2014).

Typicality effect is an effect that is clearly explained by all the other three main concepts approaches, even though in a different way (e.g., only *Prototype View* assumes that prototypes are specific mental constructs (Frixione, 2013)).

Graded *Membership* and *Typicality* cannot be modeled according to the theoretical account on which such approach is based, because of their incompatibility with the *Classical Theory of concepts* (Zarl & Fum, 2016).

2.3 Other theories: *Prototypes* and *Exemplars*

The so-called *prototypical* approach is better associated with models of several cognitive processes: for instance, some phenomena in categorization or induction are explained in a better way by prototypes theories (Belohlavek & Klir, 2011), contrary to the *Classical Theory of Concepts*.

It has been demonstrated that several natural categories have a fuzzy internal structure and boundaries and that they were not constituent by equal and undifferentiated instances (Rosch, 1973), as indeed argued by past psychological and linguistic researchers. “Internal structure" means that categories are composed of a "core meaning" which consists of the "clearest cases" (best examples) of the category, "surrounded" by other category members of decreasing similarity to that core meaning (Rosch, 1973, p. 112). "Graded structure" means the different degree of Typicality that each exemplar has in a category. Several authors have argued the consistency regarding general agreement of the participants about the judgments of typicality, including as regards the categories with fuzzy and uncertain boundaries (Rosch, 1988; Rosch, 1975b; Rosch and Mervis, 1975).

These results depend on the fact that most of our concepts are vague, and they do not have clearly defined boundaries (Belohlavek & Klir, 2011). If vagueness sometimes constitutes a definite asset, it has the disadvantage that none of our categories will ever fit completely with the world, and there will always be cases in which it will be difficult to discriminate whether an instance belongs to a concept or not.

It has been demonstrated that *Typicality* affects people's performance in several cognitive tasks in a variety of ways. Typical exemplars of a category are classified faster and more accurately than atypical ones (Rips, Shoben, & Smith, 1973); they are mentioned more frequently when asked for the members of the category (Mervis, Catlin, & Rosch, 1976); they are more likely to be considered as elements of the category (Hampton, 1979); they support better analogical inferences (Rips, 1975), and they are the first to be learned in artificial category learning tasks (Rosch et al., 1976).

There are some interesting contributions that try to explain the role played by *Typicality* considering as a consequence of some "ecological constraints" (Frixione, 2013). Typicality effect is seen as an outcome of how the world interacts with human's mind and not as a result of the structure of human's mind. Because of categorization (that is a conceptual ability) is extremely important for many cognitive tasks, it implies that components of cognitive architecture should develop some strategies and solutions (prototypical behaviour to classify the environment) to cope with constraints by external world (e.g., limited information, fuzzy, vague, artificial, and unknown categories). It is "an example of a convergent evolution within the mind" (Frixione, 2013, p. 5)

In the 1970s the *Prototypes* approach quickly replaced the *Classical Theory of Concepts* (i.e., empirical contributions from Eleanor Rosch, Michael Posner, Edward Smith, James Hampton) (Machery, 2009): for instance, Rosch et al. (1976) demonstrated that prototypicality is a function of the total cue validity of the attributes of the members of a category. In other words, it was found that the more prototypical members are those who own more than one attribute in common with members of the same category, and fewer attributes in common with members of other categories.

Concepts are prototypes, which are representations of the "best exemplar" of a category

(Murphy, 2002; Frixione, 2013), but are not necessarily portrayals of realistic examples. They might be sort of abstract instances with most of the combined typical features of that category (Machery, 2009). Typical features are shared by most central members of a class, whereas peripheral members show very few of them. *Prototypical Theories* claims that humans derive from observed category members a prototype, which represents a central tendency, using it then to compare newly encountered members every time (Briscoe & Feldman, 2011).

Contrary to the *Prototypical* approach, concepts are considered as sets of exemplars by the *Exemplars* paradigm, proposed by Brooks (1978) and Medin and Schaffer (1978). Therefore, exemplars are representations of instances explicitly stored within the memory and for this approach, there are not abstract extracted features that represent a class (there is no a central tendency), but only entities encountered and stored (Belohlavek & Klir, 2011). However, this approach presents some limitations: i.e., most of the experiments involve stimuli, like dot patterns, geometrical figures, that are artificial; and it fails to explain many higher cognitive competencies (Belohlavek & Klir, 2011).

Moreover, Gagliardi (2007) claims that "the representation based on instances is consistent with the theory of *Prototypes* and with the theory of *Exemplars*, and then is the type of representation to be used in accordance with the *Typicality View*. Other representations, making use of the classification rules, can be considered a model of classical categorization theory, so they lack a true cognitive plausibility".

Many researchers tried to combine these two approaches in order to obtain some hybrid models that could take the best implications from each one (e.g., prototype formation and exemplar memorization) (Briscoe & Feldman, 2011).

2.4 The *Theory-Theory*

Another paradigm was developed later in the 1980s: the *Theory-Theory* that assumes that concepts can be viewed as mental (or scientific) theories (Murphy, 2002; Belohlavek & Klir, 2011; Frixione, 2013). It is an approach of difficult interpretation: some versions of it consider concepts as sort of theoretical terms of a scientific theory. Some psychologists consider them as elements of theories, whereas others as theories themselves (Machery, 2009).

It adopts a form of holistic point of view about concepts. This paradigm rejects the similarity-driven approach; concepts are viewed as pieces of different knowledge (i.e., functional, generic, causal and nomological) used in cognitive processes that explain why things happen (phenomena or states of affairs) (Machery, 2009). In fact, it is also known as “the knowledge approach” (Murphy, 2002).

Furthermore, this paradigm argues that concepts could be used in processes similar to the reasoning strategies used in scientific thoeries (e.g., inferences). Theory theorists support the idea of “the causal effect” in categorization: the fact that participants in experimental tasks are supposed to use some causal knowledge to bear on these tasks (Machery, 2009).

Moreover, this approach was often used to describe and explain children cognitive development: children as a sort of scientists that make observation, conduct experiments, and generilize theories, modeling their “conceptual scheme” (Glymour, 2001).

2.4.1 New contributions: *Hybrid Theories*, the *Heterogeneity Hypothesis*, and the *Fuzzy Set Theory of Concepts*

Several recent contributions and approaches have tried to find new solutions, based on experimental evidence: e.g., Nosofsky, Sanders, Gerdom, Douglas, and McDaniel (2016) argue the need to call into questions the Family-Resemblance Principle. Their outcomes suggest that some categories (e.g., rocks class, used in their experiments) violate this principle, showing a disorganized interior structure.

Various *Hybrid Theories* have been proposed since 1970s (Machery & Seppala, 2011), trying to combine two or more distinct approaches. These theories consider a class as represented by a concept that is composed of separate parts, that store different kind of information and that are used in distinct cognitive processes (Osherson & Smith, 1981).

For instance, *Rulex* (Nosofsky, Palmeri, & McKinley, 1994) represents an effort to match rules and exemplars. Moreover, Osherson and Smith (1981) proposed that concepts are composed of a core (a sort of definition, with a set of properties) and an identification procedure (a prototype). Each part is involved in different cognitive processes: e.g. in categorization, authors proposed a prototype-based process and a definition-based one.

In the same way, Machery (2009) and Machery and Seppala (2011) proposed a further approach — the *Heterogeneity Hypotesis* (HH) — that contrasts with some ideas sustained by *Hybrid Theories*. The HH assumes that there are different types of concepts (i.e., prototype, sets of exemplars, and theories), instead of different parts that compose a concept, as *Hybrid Theories* sustains. These distinct concepts are used in different type of cognitive processes: a prototype-based categorization process, an exemplar-based categorization process, and a theory-based categorization process (Belohlavek & Klir, 2011, p. 37).

The *Fuzzy Set Theory of Concepts* derived from the fuzzy approach. Zadeh (1965) was a sustainer of a discipline, called *fuzzy logic*, and of the possibility to implement these ideas into the representation of cognitive concepts. Fuzzy logic is a mathematical logic used when knowledge have intermediary truth-values (a continuum from 0 to 1), and when classical logic is, therefore, inadequate to formalize reasoning with some arguments. The term "fuzzy logic" can also refer to fuzzy sets, fuzzy relations, and all the systems and methods that allow intermediated-values. In this perspective, concepts are viewed as fuzzy sets — instead of classical sets — with unclear boundaries and with members that can have different levels of *Typicality* (Belohlavek & Klir, 2011, p. 5). Each member can have a various degree of membership of a specific class that depends on the degree of its being part of such fuzzy set (the membership function of the fuzzy set) (Belohlavek & Klir, 2011, p. 50).

In conclusion, as Murphy (2002) have already argued, it is pointless that one theory of concepts could exert more influence that the others. It is critical to find a solution and a compromise between different theories, being able to describe and explain all the concepts. However, it 's hard to find a critical test that is able to discriminate between them. Some authors have even criticized the use of the concept "concept" in psychology (Slaney & Racine, 2011).

3 Concepts in Information Technology

The nature of knowledge has always been a trending topic for philosophers (and later for psychologists), but only recently it became a question that has involved other disciplines, such as computer science, artificial intelligence, and information technology. (Wielinga, 2013). Before the advent of the computer age, mathematical logicians also tried to formalize declarative knowledge (van Harmelen et al., 2008).

Knowledge Representation (KR) — defined as the study of how world knowledge (and common sense concepts) can be represented and used by reasoning processes (Frixione & Lieto, 2013a) — became a critical issue with the birth of Artificial Intelligence (AI) in the 1950's, and then with the advent of computer systems. Knowledge and information acquisition and representation were some of the biggest problems for these new disciplines. Knowledge acquisition research leads to a series of guiding principles for knowledge modeling, e.g., the fact that knowledge is essential, that there are different types of knowledge and that their acquisition requires interpretation.

In Information Technology (IT), and specifically on the Web, there exists a huge amount of data which are mostly raw, unstructured, and heterogeneous. The growing amount of weakly structured and heterogeneous data and the poor support for user interaction are factors that makes it compelling to find a way to deal with them and to find sadisfactory solutions. The fact that more and more data are published online leads to many problems related to the capacity to extract, compare and use such information (Berners-Lee, Hendler, & Lassila, 2001). The Hypertext Markup Language (HTML) — the markup language used on the Web — does not permit to preserve the data structure and to extract information from such contents. Therefore data on the Web are largely disconnected, and the link between different Web sites is weak due to the poor specification of meaning about the kind of relations between different sources (Meusel, Petrovski, & Bizer, 2014). Because of the distributed nature of the Web, data are heterogeneus and this leads to a lack of consensus between different data publishers (e.g., homonyms and synonyms are examples of heterogeneity in natural language, and they require contextual information to be understood).

More recently, knowledge researchers began to build an application that faces the vast knowledge bases. The *Linked Open Data initiative* (Bizer, Heath, & Berners-Lee, 2009) — called *Linked Data approach* — (Frixione & Lieto, 2013b) allows the access to such a vast amount of knowledge and integrated different data representations and data sources through a unique framework (building a semantic bridge between data). The languages that made it possible are Semantic Web languages: as for instance, OWL.
Therefore, ontologies could link and coherently integrate all the distinct pieces of knowledge through the ontology mapping: for instance, Wordnet (Fellbaum, 1998).

Further problems are mainly related to concept representation in ontologies. The fact that knowledge is primarily represented by natural language leads to consider concepts as the main study object. Most important aspects to consider are, for instance, the ambiguity in concept labels, the different between the hierarchical structures of ontologies in similar domains, the fuzziness of concepts rather than the Aristotelian approach that consider concepts with clear boundaries (Wielinga, 2013).

Knowledge and information are, therefore, strictly related to concepts, which are sorts of organized information and knowledge and, in the same way, have to be represented in IT, especially in ontologies for the Semantic Web (Frixione & Lieto, 2013b).

The problem of representing concepts in artificial systems, and in ontologies, has been well recognized and it is still an open and unresolved issue in IT field (B. Smith, 2003; Guarino, 1998; Guarino, Oberle, & Staab, 2009; Gagliardi, 2007; B. Smith, 2002; Margolis & Laurence, 2007; Guarino & Musen, 2015; Hepp, 2008; Stark & Esswein, 2012; Frixione & Lieto, 2013a). In fact, modern classification in the Web are well characterized by an enormous amount of data to categorize, and ontologies are powerful tools to deal with them.

Ontologies are tool to represent knowledge and can be defined as sorts of conceptual models. A "*model*" could be defined as a portion of reality. It is composed of a set of conceptualization in a given domain, and it can be expressed by using a specific modeling language (Guizzardi, 2005). Refering specifically to a data model, it is simply a model that represents data and the *data modeling* is the processes used to create it. More particularly, a conceptual data model describes some "*concepts*" (that are *entities*) and some *attributes*, and expresses *relationships* between them, using integrity rules to guarantee consistency of values. The main aim of such a model is the expression of the meaning of terms (or concepts) and their correct relations used in a specific domain, constituting in such way a framework to express users' knowledge (Ramesh et al., 1999). Therefore, conceptual modeling is the effort to specify and compress different information into an effective, communicative and understandable tool used by experts, designers and end-users (Embley & Thalheim, 2011; Ramesh et al., 1999).

The *Entity Relationship Model (ER)* is a kind of conceptual model that is very often used because of its completeness and accuracy (Embley & Thalheim, 2011), It was developed around 40 years ago (Chen, 1976; Ramesh et al., 1999) and it includes *entities* (noun and even role naming), *attributes* (with a primary key), *relationships* between them (expressed by tuples of entities) and a *values set* regarding them. Likely, the remarkable success of this model within the "*Conceptual Modeling and Design*" is due to the fact that the ER model can captures the way how people arrange real world data, in addition to the fact that it is popular for conceptual design, ensuring good databases designs (Ramakrishnan & Gehrke, 2002).

In conclusion, in the computer science field, knowledge representation consists in: a formal structure and rules of inference (logic), a formal specification of a shared conceptualization regarding a specific domain (ontology or conceptual model) and a formal computable model (computation) (Ju, 2006).

3.1 Different formalisms of concept representation

Classical logic is the most used language to represent knowledge (van Harmelen et al., 2008, p. 3) which embraces the language of *first-order predicate* formulas. Formulas consist in a propositional signature with symbols (called "atoms" or "variable") and logic connectives, and they can assume values of TRUE or FALSE.

Description Logic (DL) is a class of logical formalisms and a subset of the first order predicate calculus (Sheremet, Tishkovsky, Wolter, & Zakharyaschev, 2007). It allows representing concepts in ontologies and is computationally efficient, even if it fails to represent concepts in term of prototypes, as the cognitive study of concepts suggests. For instance, *OWL (Web Ontology Language)* is a classic formalism used in the Semantic Web (see the section 3.2 for an in-depth analysis of such extension of the Web) (Frixione & Lieto, 2013a).

Sometimes, logic-based and similarity-based methods are integrated together in a single knowledge representation formalism (e.g., *Similarity Description Logic* (Sheremet et al., 2007)).

Other approaches have been designed trying to deal with some aspects of concepts and to represent them in prototypical terms: e.g., *fuzzy logic* and *non-monotonic extensions of DL*, even if those also present several unresolved problems (Frixione & Lieto, 2013a). Fuzzy logic is incorporated into ontologies, allowing to formalize vague data better and leading to the so-called *fuzzy ontology* (Zadeh, 1965; Calegari & Ciucci, 2007), where any concept and any relation is fuzzy. Fuzzy logic is incorporated in ontologies using a *Fuzzy-OWL language* or a *Fuzzy Description Logic* (Calegari & Ciucci, 2007).

3.2 The Semantic Web

The *World Wide Web* is a means of distribution of information, designed to be used by humans, using the machine tool (Di Noia, De Virgilio, Di Sciascio, & Donini, 2013, p. xii). In 1989, Tim Berners-Lee developed it: at the time it was just presented as a system for the management of all the information obtained in the experiments in the research center where he worked (CERN, the European Organization for Research nuclear, Geneva). The aim was to use hyperlinks to link the information stored in the documents. Thus, as a result of this first idea, he developed what we now know as World Wide Web (Di Noia et al., 2013, p.1). The notion of the Web is inseparable from that of an open community: because everyone can contribute in some way to its development and use (Allemang & Hendler, 2008, p. 2). It is worth quoting the AAA slogan: "*Anyone can say about Anything Any topic*" that fully characterizes the peculiarity of just described (Allemang & Hendler, 2008, p. 6): everyone can contribute in any way to the infrastructure of the Web.

In 2001 Tim Berners-Lee (Berners-Lee et al., 2001), proposed an extension of the Web (the *Semantic Web*) compared to how it was conceived until that moment: the information must be clear and unambiguous, computer-interpretable, creating a strict collaboration between men and computers (Di Noia et al., 2013, p.2).

The *Semantic Web* wants to consider humans as the ultimate target of the Web, and as the end user of all available information. It should, therefore, be an open terrain of knowledge and information exchange, with a multifaceted cooperation. To allow it, however, computers must have access to information, which have to be structured in a certain way, usable for the machine through inference rules for automated reasoning (Di Noia et al., 2013, p. xii). In fact, it is considered a sort of extension of the Web, which allows assigning meaning to information, creating a strict cooperation between users and computers, also in terms of giving support to humans in tasks involving information on the Web (Berners-Lee et al., 2001). The Semantic Web has aquired a role of support for a deployed Web in the form of an elaborate and exhaustive data model, as a kind of conceptual space by the meaning expressed by information (Antoniou & van Harmelen, 2008).

Among the computational formalisms used in the Web, an important role is played by the"*Resource Description Framework (RDF)*", that is the modeling of the data used by the Semantic Web to represent and distribute the data online (Allemang & Hendler, 2008, p. 6). Under this point of view, the user can contribute to the growth of the Web, but in a way in which the information inserted may be combined with other data. Design provided by RDF allows it.

To support the grouth of sharing, cooperation and collaboration, modeling comes in handy. Defined as "the process of organizing information to use in the community" (Allemang & Hendler, 2008, p. 24), it is the activity of reorganizing the common knowledge and managing the chaos of information and data, and, in the case of the Semantic Web, to support data sharing. It is an ongoing process. Thus, at any time, information can be usable, updated and comprehensible thanks to these models (Allemang & Hendler, 2008).

As already mentioned, there are some basic languages for representing information in the Semantic Web: e.g., RDF, RDFS, OWL, and later, RDFa (Resource Description Framework in Attributes) and Microdata (Meusel et al., 2014). These computational languages allow the explicit description of the relationships between different data: the relations are expressed in the form of subject/predicate/object or established between the two figures, even if they are absent. It also becomes clearly necessary that such data are to be univocal, so as not to cause confusion: the URI (Uniform Resource Indicator), a generalization of the most known URL (Uniform Resource Locator), solves this problem by providing the unique tags for each information (Allemang & Hendler, 2008).

3.2.1 The semantic issue

Referring to the issue of the structured information required by computers for data managing, it becomes clear that the question of the role played by semantics is of prime importance to achieve this goal. Making information semantically understandable for machines and men should become the primary purpose.

There are numerous applicative tools used for concept and information representation in the Web. However, it is necessay to consider how these formalisms can fully convey the real semantic meaning of the represented entities. If these formal entities can capture the real semantics of information, or if they limit or extend interpretation. A representation may be the best from the computational point of view; another may take into account some peculiarities of information, but be less efficient. The point is to find the right balance between efficiency and effectiveness. For instance, the *Description Logic* language was extensively studied in term of decidability and computational tractability (Warren et al., 2014), but very few studies investigate the usability of it (e.g., comprehension, the accuracy of human reasoning with DL). Warren et al. (2014) underline the cognitive difficulties of using DL, despite its great computational efficiency.

3.3 Ontologies

3.3.1 Definition and use

The term *"ontology"* originates in philosophy: the element of the word *onto*- comes from *"onto-"* ("been", "that is"), the past participle of the verb *"eimi"* ("be') and *"-logia"* (logical discourse) (Garshol, 2004). It is considered the branch of philosophy concerning the organization and the nature of reality (Guarino et al., 2009), viewed as a specific categories system to suit a certain vision of the world (Guarino, 1998).

In 1993, Gruber (1993) introduced the technical term *"Ontology"* in computer science and in particular in the context of information sharing, with the meaning of "specification of a conceptualization" (Gruber, 1993). A "conceptualization" is defined as "an abstract, simplified view of the world that we wish to represent for some purpose. Every knowledge base, knowledge-base systems, or knowledge-level agent is committed to some conceptualization, explicitly or implicitly" (Gruber, 1995, p. 908). "Specification" means that these tools are developed to render explicit the conceptualization that, most of the time, is tacit (B. Smith, 2003). Quoting again to Gruber, ontology is defined as "a description [...] of the concepts and relationships that can exist for an agent or a community of agents " (Gruber, 1993, 1995). Guarino and Giaretta (1995) suggested an integration for such a definition: the ontology could be considered as a logical theory that would give an explicit and partial representation of a conceptualization.

In summary, ontologies can be therefore defined as a standardized form of the representation of concepts and their relationships in a particular domain (Dermeval et al., 2014), or as genuine agreements or specifications within a community in respect of such representations (Hepp, 2008).

Domain ontologies represent knowledge of experts (Engelbrecht & Dror, 2009) that elicit and extract domain knowledge using several elicitation techniques. Human knowledge representation is considered as a model to develop and model ontologies.

Ontologies are composed by *entities*, *attributes*, *relationships* and *axioms* that describe the real world (Calegari & Ciucci, 2007). The basic relationship is the *ISA* (is a) link that describes a taxonomic and hierarchical structure of concepts (Engelbrecht & Dror, 2009). Through this tool, systems and humans can easily communicate and exchange information and knowledge (Calegari & Ciucci, 2007).

Ontologies have started playing a crucial role in IT since 2005, becoming essential in many tasks in the IT field concerning information-retrieval or text-processing, and represents an instrument to exploit open data for interoperability or everything related to making information and knowledge explicit (Guarino & Musen, 2015). In the future, these models will likely contribute more and more to enhancing the power of intelligent systems in the Artificial Intelligence discipline. Since their birth, domain-specific ontologies emerged in different and multiple fields. The most known are: e.g., the *Gene Ontology* in biology (Ashburner, Ball, Blake, & et al., 2000), the redefinition and standardization of definitions and relationship regarding the *International Classification of Diseases* (Tudorache, Falconer, Nyulas, & et al., 2010), the *Financial Industry Business Ontology (FIBO)* (Bennet, 2013), *schema.org* in the Web field (Guarino & Musen, 2015).

According to Hepp (2008), it is evident the role that cognitive processes might take within what can be defined as the ' *"ontology lifecycle"*, starting since its inception, through the implementation, up to its use. In fact, as Stark and Esswein (2012) suggest in their exhaustive literature review, many authors had already started to take into account cognitive theories in the work of ontology modeling.

3.3.2 Ontologies in the Web

Ontologies in computer science, and also in the Web — the first application field of that tools nowadays — are defined as conceptual models argued by formal axioms (Gruber, 1993). They specify a shared definition of classes, data, properties and relationships. In fact, paraphrasing the definition of ontology, in the field of study of the Semantic Web, it is described as: "a formal description of concepts [...] in a given domain knowledge, having each one some properties, and especially the relationships between them [...] Pescarmona (2003, p.2).
Therefore, the system must be able, through the use of the ontology, to determine the concepts, the topics and the relationships between them, and, in the same way, the user must be able to find the desired information within multiple indexed concepts through it (Pescarmona, 2003).

The problem that ontologies cope with in IT is information management: e.g., different database systems have different frameworks for information representation, with distinct terms or the same but refers to various entities. Ontologies addressed this issue, supplying a unique common reference, a sort of shared taxonomy of entities (B. Smith, 2003), in just one common ontology, instead of distinct databases. This represents a significant advantage.

In the Sematic Web, ontologies can conceptualize a specific domain, integrating and sharing different information systems and applications: (e.g., e-commerce, web portals, and knowledge management are based on ontologies) (Calegari & Ciucci, 2007).

There are also some difficulties in developing such neutral and shared accepted model for different data communities. A solution was the idea of a top-level ontology with general and canonical definitions, used as a common neutral denominator and then specified for different domains (e.g., medicine, biology, law) (B. Smith, 2003).

Schema.org

An example of ontology is provided in this section to clarify the fuctioning and the usage of such a tool. Furthermore, this ontology was also utilzed as a model in a experiment, reported in the further empirical part.

Because of the large amount of information available on the Web (Dhingra & Bhatia, 2015), there is a strong need to provide a kind of support to represented information in a properly way. Ontologies try to solve this problem, being a technique for knowledge representation, knowledge management and information retrieval (Dhingra & Bhatia, 2015).

In the Web, services and infrastructure need to access and exchange structured data to describe the real world (entities and relationships). The increasing growing of interest in big data leads to the need of integrating data from different sources, supplying a shared schema (or vocabulary) (Guha et al., 2015).

Schema.org is a set of vocabulary that enables to present a broad range of topic (e.g., person, events, places, products, etc.). The goal is to provide a shared and single vocabulary (a single integrated scheme) (Guha et al., 2015). The main purpose of schema.org is to help webmasters to publish their data.
Schema.org was born in 2011 by three sponsor (i.e., Google, Yahoo, and Microsoft) and then Yandex (Mika, 2015) and now it counts 638 classes and 965 relations. It has a hierarchical structure, with classes and superclasses and relationships are polymorphic (they present more domains and more ranges).

Figure 3.1 shows an example of the type *Person* in Schema.org (http://schema.org/ Person) with part of its documentation. There is a feature that describes the position in the hierarchy of the class (i.e., Think <Person), below there is a brief description, followed by a table with several properties of such class, with the expected values.

Thing > Person

A person (alive, dead, undead, or fictional).

Property	Expected Type	Description
Properties from Person		
additionalName	Text	An additional name for a Person, can be used for a middle name.
address	PostalAddress	Physical address of the item.
affiliation	Organization	An organization that this person is affiliated with. For example, a school/university, a club, or a team.
alumniOf	EducationalOrganization	An educational organizations that the person is an alumni of. Inverse property: alumni.
award	Text	An award won by this person or for this creative work. Supersedes awards.
birthDate	Date	Date of birth.
birthPlace	Place	The place where the person was born.
brand	Organization or Brand	The brand(s) associated with a product or service, or the brand(s) maintained by an organization or business person.
children	Person	A child of the person.
colleague	Person	A colleague of the person. Supersedes colleagues.
contactPoint	ContactPoint	A contact point for a person or organization. Supersedes contactPoints.
deathDate	Date	Date of death.
deathPlace	Place	The place where the person died.
duns	Text	The Dun & Bradstreet DUNS number for identifying an organization or business person.
email	Text	Email address.
familyName	Text	Family name. In the U.S., the last name of an Person. This can be used along with givenName instead of the name property.

Figure 3.1. Example of the *Person* type in schema.org. There are several properties from the class, with the meanings and expected values (Mika, 2015).

Schema.org is used in various applications (e.g., for e-mails in order to extract structured information into, for instance, maps or calendar; *Microsoft's Cortana* for e-mails; *Pinterest* to provide notes, *Apple's IOS 9* for searching applications) (Guha et al., 2015).

It markups a lot of Web pages (al least 12 million sites) and several extensions are already under construction.

Hereunder, a list of the major Web sites that have adopted schema.org, divided by categories.

CATEGORY	SITES
News	nytimes.com, guardian.com, bbc.co.uk
Movies	imdb.com, rottentomatoes.com, movies.com
Jobs / Careers	careerjet.com, monster.com, indeed.com
People	linkedin.com, pinterest.com, familysearch.org, archives.com
Products	ebay.com, alibaba.com, sears.com, cafepress.com, sulit.com, fotolia.com
Video	youtube.com, dailymotion.com, frequency.com, vinebox.com
Medical	cvs.com, drugs.com
Local	yelp.com, allmenus.com, urbanspoon.com
Events	wherevent.com, meetup.com, zillow.com, eventful.com
Music	last.fm, myspace.com, soundcloud.com

Figure 3.2. List of the major Web sites that have published schema.org (Guha et al., 2015).

3.3.3 Ontologies as applicative tools for e-business

In the last decades, purchasing goods online has been an ongoing trend (Hepp, 2008; Guha et al., 2015; Mika, 2015). This fact leads to an immediate consequence: the importance of the product searches and product recommendation (the problem of the consumer choice). Products have to be represented in a proper way in order to satisfy users' needs.

The growing amount of weakly structured and heterogeneous product data, the complex keyword-based searches, and the poor support for user interaction are all factors that hinder an efficient finding of the desidered product on the Web. The growing of data (and the consequent increasing specificity) leads to a very large variety of available products, and if they are not stored in a well-structured form, it implies significant problems for comparability and searching,

The *Business-to-consumer (B2C)* electronic commerce is currently the commercial activity of users who surf the Web. Whenever you search for a product, select, compare and buy, you interface with a collection enormous of information, which, to be efficient and usable for the machine, but mainly by man, must be structured in a specific way. The Semantic Web comes to the rescue by providing software agents that allow the interpretation of the products and services data, giving the option of managing between unmanageable datasets. To be precisely used by software, they must, as mentioned, be presented in a certain way (Antoniou & van Harmelen, 2008).

On the Web, there exist different systems that categorize and organize Webshop products, but often they are not comparable, providing different terminology or classes.

It is important to note that ontological engineers do not try to find the truth, but to adequate ontologies to the pragmatic enterprise. The goal is to conceptualize and describe objects in a shared and common way, make them pertinent for the client and reusable in application domain knowledge (B. Smith, 2003).

Ontologies or any conceptual models, which seeks to better represent concepts and things, increasingly important in the specific e-business initiatives, are taking on a role (Hepp, 2007, 2008; Guha et al., 2015; Mika, 2015). Historically, attention in the construction of such tools has always been to improve the processing of the online data, making more accessible and usable information using computational processes types. Recently, the importance that ontologies may take in the application for e-business has grown, especially for online search, classification, storage of consumables, purchase, to be as much cognitive plausible as possible. Users need a way to interface with computers in order to simplify their interaction, making the data that are available computationally into objects with which it is possible to interface (Canali, 2005; Kotis & Vouros, 2005; Yamauchi, 2007). It is, therefore, important to pay attention to the cognitive factors that may take place in the creation and use of such methodologies: the study of the involved cognitive processes becomes evident (Ernst et al., 2005; Maes & Poels, 2006; Falconer & Storey, 2007; Yamauchi, 2007; Engelbrecht & Dror, 2009; Everman & Fang, 2010; Stark & Esswein, 2012; Lieto, 2013).

As an example of an ontology that takes into account the semantics of representing products and services in the Web, *GoodRelation* represents in a proper way product description in the Semantic Web, covering needs of e-commerce scenario in this community (Hepp, 2007). In fact, GoodRelation (in RDFa and Microdata syntax), together with schema.org (mainly in Microdata) (Meusel et al., 2014), describes a large amount of online product data (Hepp, 2012). It annotates goods and services on the Web, improving the usability and efficiency.

It is a standard vocabulary and can be viewed as an extension of e-commerce schema.org. The idea is to use four different entities for representing a typical e-commerce scenario (i.e., the Agent-Promise-Object Principle). There is an agent (e.g., an organization or a person), a promise (e.g., an offer of a transfer of some rights or a provided services by the agent), an object (a product o a service) and a location (Hepp, 2007).

4 Concepts between Cognitive Psychology and Information Technology

There is a strong interest in the construction of a bridge between these two disciplines, making them interact and help each other.

In this chapter a digression about the possible interaction between these sciences is provided, underling the needs and the benefits derived from such a interplay.

Quoting Brinklow (2004) about knowledge and explicit concepts, the following section aims to take into account the growing role played by knowledge in the process of concept representation in IT, taking into account the state of the art of this issue.

"The transition from tacit knowledge to an explicit concept is precarious and requires successful negotiation through a multiplicity of cognitive barriers. How is this cognitive transition to be achieved?" (Brinklow, 2004, p.11).

Although the author focuses primarily on cognitive factors in the creation, modeling and use of ontologies (therefore a very specific topic), this new way of conceiving the two disciplines as joint partners can be extended., also in the general consideration of the role of cognition and Cognitive Psychology in the context of the generic representation of the concepts and knowledge in IT.

In 1997 the *"First Workshop on Cognition and Conceptual Modeling"* took place in Los Angeles, where cognition and conceptual modeling in computer science were considered jointly for the first time. In 1999, Ramesh et al. (1999) stressed the importance that this event for the two scientific communities. Cognition, also called the *"Science of knowledge"*, emerged as a fundamental tool for a re-evaluation of the techniques and methods used so far in the conceptual modeling.

Therefore, there are various aspects and steps to be taken into account: the need to increase the degree of expressiveness of the ontologies or any form of knowledge representation in a computational context. It is made with the aim of improving the representation of these tools and considering therefore in depth the internal structure of concepts, taking into account the classes as artifacts and also focusing on the notion of causality.

The basis of how cognition involved in the mental representation of concepts can be helpful to represent knowledge in computer science.

Knowledge and concept representation are common ground for both the disciplines, although each has a different use: Cognitive Psychology deals with the formulation of theories and rules regarding the human mental functioning, while IT cares to optimize IT tools, such as *ontologies*. As already reported in section 3.4, ontologies are standardized forms for the representation of certain concepts and their relationships in a particular domain (Dermeval et al., 2014). The study of human knowledge representation can contribute to the development of such tools (Engelbrecht & Dror, 2009) taking into account the cognitive barriers — as already suggested by Brinklow (2004) — using an understandable and informative natural language, and taking in consideration the structure of ontologies (that is characterized by human knowledge representation).

Considering that experts use their internal representation of concepts to elicit information to develop ontologies, it is necessary to take into account this subjective information. Therefore it is critical not to forget that internal representations of concepts are cognitive-dependent and are not stable. In Information Technology, is growing more and more the awareness regarding the role played by cognitive factors and, therefore, the role that research in Cognitive Psychology might impact in this area is apparently considered (Ramesh et al., 1999; Chiew & Wang, 2003; Brinklow, 2004; Ernst et al., 2005; Siau & Tan, 2005; Engelbrecht & Dror, 2009; Falconer & Storey, 2007; Yamauchi, 2007; Everman & Fang, 2010; Stark & Esswein, 2012; Wilmont et al., 2013; Warren et al., 2014; Nossner et al., 2015).

The possibility of using a multidisciplinary perspective is determining, with the aim of reaching a defined representation of human knowledge-based, that is understandable, usable and cognitively plausible for people. New disciplines, such as *"Cognitive Informatics"* (Chiew & Wang, 2003), are good examples of how things are moving in this direction.

4.1 Cognition and Ontologies, a state of the art

It is important to keep the cognitive processes involved in the IT area, with the aim of being able to implement a representation of the concepts that is as much cognitively plausible as possible. The perception, the way you build and make sense of the surrounding world, the causal inferences, and many others, are matters that need to enter in this research domain (Siau & Tan, 2005). The recent development of the Sematic Web (and the ontologies) requires the description and the sharing of information that have to be understood and usable by machine and human (Cai et al., 2008).

The main problem faced in this thesis is that traditional ontologies are Aristotelic (i.e., represent categories as crisp sets of instances), whereas concepts are not.

Frixione and Lieto (2013b) argued that concept representation is, indeed, an open issue in the field of knowledge representation, and in particular in ontology engineering. They suggested that concepts are considered by Cognitive Psychology as not a unitary phenomenon and can not be represented only by necessary and sufficient rules, as artificial systems do. Suggestions from Cognitive Psychology lead to an initial tentative to present concepts in prototypical terms, through "frames" (Minsky, 1975) or early "semantic networks" (Quillian, 1968) but without obtaining satisfactory results, it reached to implement a class of formalism (Descriptive Logic, DL: see cap. 3 for a more detailed account) that were computationally more efficient. DL are widely adopted in ontology representation, even though they lack *Typicality* of concepts (Frixione & Lieto, 2013b).

To solve this problem, some tentative of modelling *Typicality* in DL were proposed by some authors (Britz et al., 2009) and *Fuzzy* and *non-monotonic logic* extension of DL were develop, but posing further difficulties, still unsolved (Calegari & Ciucci, 2007; Frixione & Lieto, 2013b).

As suggested by Frixione and Lieto (2013a), there are some recent contributions and suggestions from Cognitive Psychology, such as:

- Dual Process Approach
- Pseudo-Fodorian Proposal
- Prototypes and Exemplar

The authors argued that reasoning is not a unitary cognitive process and that prototypical effects could depend on different representation mechanisms (Frixione & Lieto, 2013a). Thus, to overcome this issue, some artificial representation systems could be developed and, hereby, described.

The *Dual Process Approach* involves several theories that assume the existence of two different cognitive systems: *Type 1* (phylogenetically older, automatic, parallel, faster) and *Type 2* (the more recent, conscious, sequential, slower, and based on explicit rule following) (Frixione & Lieto, 2013a; Frixione, 2013). Empirical evidence shows a strong tendency to refer to prototypical information in categorization (Frixione, 2013), as well as to necessary and sufficient conditions. Authors assume that DL systems typically represent a sort of Type 2 module, with difficult, sequential and slow tasks. However, exceptions should be represented in another way, concerning a kind of Type 1 system (in a faster and automatic way). Thus, as human reasoning works, conceptual representation systems in IT should take into account the two kinds of systems.

The *Pseudo-Fodorian Proposal* follows main Fodor's assumptions regarding concepts (Fodor, 1987). According to his ideas, concepts are compositional, and most of them are considered as "atoms" (symbols without any internal structure). Concepts can not be composed by prototypical representations, even though there are some typical representations associated with the concept itself, that are disjointed and assigned to a different component of the representational system (Fodor, 1987; Frixione & Lieto, 2013a). This part should be responsible for prototypical effects and exception representations, whereas the compositional part can be represented in term of classical DL knowledge base.

Furthermore, Frixione and Lieto (2013a) take into account the three main positions and theories in CP: *prototypes views*, *exemplar views*, and *theory-theories*. All of them assume the prototypical effect role in conceptualization. The problem is that these positions tend to be mutually exclusive. Thus the authors (Frixione & Lieto, 2013a) tried to integrate them into a hybrid representation architecture to consider concept representations and prototypical effects in conceptualization. There are some empirical attempts to implement these prototype and exemplar-base approaches in conceptual representation. The choice to integrate these two approaches depends on many factors: i.e., there are some concepts that benefit more from an exemplar-based representation, and others in term of prototypes; there is an advantage in terms of technological point of view for representing some non-classical concepts in a proper way; sometimes a task is involved which benefit more from exemplars, sometimes from a prototypical representation. The idea is to add to a component based on *Description Logic* (DL), a further one that implements prototypical part. The first one can express necessary and sufficient conditions, whereas the latter is an external structure to DL knowledge base and can be a sort of lists of attributes (weighted) that specify and are linked to the concept itself. Contrarily, exemplars are represented in the DL component because of each exemplar adheres, in fact, to the necessary and sufficient conditions to be effectively an exemplar.

The intention is to utilize a sort of geometric representation of knowledge (a conceptual space), offering a computational and representational framework in term of both prototypes and exemplars (in nonclassic terms). The adoption of conceptual spaces, in addition to DL representations, should avoid misuses of DL formalism. The idea is to use them as *Linked Data*, making it possible to perform reasoning based on geometric representations on conceptual spaces, independently of OWL based (logic based) (Frixione & Lieto, 2013a, 2013b; Frixione, 2013).

It is just an example of a possible implementation of the cognitive approach to IT: the adoption of a hybrid prototypes-exemplar architecture for concept representation that might improve ontological knowledge bases.

Another example of implementing the cognitive approach into computer tools is proposed by Lesot et al. (2008). The idea is to use cognitive prototype view for a machine learning principle, with the goal to use a sort of fuzzy prototypes to characterize data sets (e.g., it represent the common features in subset members and the differences between the other data). It is necessary to consider the degree of typicality of members (derived from the internal resemblance and the external dissimilarity), creating an aggregation of members that are typical in order to obtain a fuzzy prototype (to a deeper explanation with a practical example, see: Lesot et al. (2008)).

Furthermore, Cai et al. (2008) presented a model of ontology with a multi-prototype concept, able to represent also object with *Typicality*. They also argued the importance of approximate as better as possible human's cognition.

4.2 The fuzziness

Fuzzy Set Theory, born from a generalization of the classical logic, has become a powerful logic and mathematical theory, applied in several areas and disciplines (e.g., decision support, engineering, management, medicine) (Zimmermann, 2010).

Fuzziness can be viewed as a solution to fill the gap between different kinds of concept representation. The *Fuzzy set Theory of Concepts* was an alternative hypothesis to find a solution in the controversy between different theories of concepts and it is defined as the ability to process vagueness in human reasoning (Huang, 2015). Fuzziness and uncertainty are also notions that have been considered in recent times as a matter to pay attention, being a concept strictly related to everyday social and cultural life and considering the role of *Fuzzy Set Theory* as a bridge between the hard sciences (IT) and humanities (CP) — as, for instance, Zimmermann (2010) and (Tabacchi & Termini, 2012, 2014) argued —.

4.2.1 Fuzzy logic

Classic logic represents the most known logic, with the assumption that there are two truth-values (*false* or *true*) and that any truth-value of its components define its logical formula. These two assumptions are called respectively “bivalence” and “truth-functionality” (Belohlavek & Klir, 2011, p. 2). Classical logic is strictly related to the *Classic Set* theory: for each instance, its value is true if it is a member of the associated set.

Zadeh (1965) introduced the idea of *fuzzy set* in what has become a classical paper, but only ten years later, he started using the term “fuzzy logic”, defining it as “a fuzzy extension of a multi-valued logic which constitutes base logic for fuzzy logic” (Zadeh, 1975, p.409).

If classical logic is adequate to reason with formulas that involve bivalent propositions (each one can be only true or false), fuzzy logic can manipulate knowledge that has intermediary truth-values and most of the propositions that are used to communicate between people are not bivalent. Every time you talk about percentages or use a term as ”moderate,” you refer to an intermediated true-values (Belohlavek & Klir, 2011). Furthermore, most objects refer to a fuzzy set with unclear boundaries: the membership of them is a matter of degree. Instead of the set [0,1] of truth-values, fuzzy logic allows degrees of values from 0 and 1. For these reasons (human communication based on not bivalent propositions and fuzzy sets), fuzzy logic can overcome the inadequacies of classical logic and classical sets. In brief: it is a generalization of the classical logic that supports better propositions (especially considering the natural language with vague terms) used by humans (Belohlavek & Klir, 2011).

Formally, a *fuzzy set* is defined by a function that defines the degree of membership of each member with a specific value, interpreted as a measure of how much the element belongs to the class defined by the function. For instance, if the degree of membership of Andy to the class *rich* is 0.8 and Bob’s degree is 0.9, both can be considered quite rich, with Bob being a little richer than Andy (Zarl & Fum, 2015).

Summarizing, *Fuzzy sets* can be considered as an extension of classical sets and fuzzy logic is a generalization of the classical logic. While the characteristic function of the classical set maps its domain into the set [0,1], comprising only two values, the fuzzy set’s function can express an infinite number of elements: all the real numbers in the interval [0,1], including its limits. In this sense, a classical set is a subset of a fuzzy one. While classical sets consider 0 and 1 as Boolean entities (*true* or *false*), the degrees of membership of fuzzy sets have a intermediated true numerical value. It represents the degree of how much the object is considered a member of the fuzzy set. *Membership function* is defined as the function that assigns a degree of *Membership* to instances of a particular set. One of the most important consequences of this fact is: *fuzzy sets* can be mathematically manipulated in ways that are not allowed by classical set (Zarl & Fum, 2015) (several basic operations: e.g., complements of fuzzy sets, intersections or unions of fuzzy sets, averages between fuzzy sets and so on) (Belohlavek & Klir, 2011).

4.2.2 Fuzzy concepts

Fuzzy logic met the psychology of concepts for some reason: e.g., the fact the concepts are better described if they are considered as fuzzy sets and their membership as a degree of it (due mainly to the advent of the prototypical approach and the graded structure of concepts that are pretty close to the fuzzy set perspective), and the fact that fuzzy logic is viewed as a generalization of classic one (Belohlavek & Klir, 2011).

Belohlavek and Klir (2011) describe the different attitudes toward fuzzy logic in the psychology of concepts. While, in the 1970s, fuzzy logic was accepted as an approach to describe concepts in psychology, in 1981, Osherson and Smith (1981) — in a very influential paper — sustained several arguments again the use of fuzzy logic in this area, defined it as useless in the psychology of concepts. Belohlavek, Klir, Lewis, and Way (2009) underlined many misconceptions and logical inconsistency about Osherson and Smith's argument: e.g., the fact that authors had considered the *Fuzzy Set Theory* as a theory of concepts, some arguments regarding concepts' properties (claiming that fuzzy logic is not able to satisfy such requirements), some errors regarding the expressive power of fuzzy logic and so on (Belohlavek & Klir, 2011).

Several authors, later, contributed to the work of revisiting fuzzy logic in the psychology of concepts. In the book "*Concepts and Fuzzy logic*" (Belohlavek & Klir, 2011), where fuzzy logic was taken again into account in the psychology of concepts, authors as Eleanor H. Rosch (UC Berkeley), James A. Hampton (CU London), Edouard Machery (U Pittsburgh), and Jay Verkuilen, Rogier Kievit, and Annemarie Zand Scholten (CUNY New York) showed interest in research cooperation to reestablish the valence of such approach.

Concepts are crucial in daily human life (and in all their cognitive processes). Several psychological types of research were carried out focusing on the graded structure and the graded *Membership* in categories, demonstrating that many psychological processes are indeed affected by graded *Membership* of concepts: e.g., categories association (Rosch, 1973; Rosch & Mervis, 1975), speed of processing (reaction times) (Rips et al., 1973; Rosch, 1973; Rosch & Mervis, 1975; Murphy, 2002), categories learning (Rosch, 1973; Rosch & Mervis, 1975; Rosch et al., 1976; Murphy, 2002), probability judgment (Kahneman, Slovic, & Tversky, 1982), natural language as good indicator of graded structure (Lakoff, 1973), inference (Murphy, 2002). Furthermore, prototypes are the representations that people use to have an image of a concept, and it varies in term of abstraction, representing well the idea of the graded structure of concepts (Belohlavek & Klir, 2011).

It seems clear that concepts can be treated as fuzzy sets and several authors have studied the fuzziness and the *Fuzzy Set Theory of Concepts* — just to cite a few: Lesot et al. (2006, 2008); Zimmermann (2010); Huang (2015) —. Recently, also Hampton (2007, 2011) focused on the graded *Membership* and vagueness of concepts in his studies. Vagueness (that can be considered as graded *Membership*) has become recognized in concept representation, in particular, in association with the *Prototype* Theory. The role played by prototypes in determining vagueness was already treated by Kamp and Partee (1995) and Osherson and Smith (1981) but claiming that *Typicality* and vagueness were distinct phenomena: vagueness was considered as a factor that determines if an instance is or not (and with what degree) member of, whereas *Typicality* reflected the representativeness of a member respect to a category (a degree of similarity of an instance with its prototype) (Hampton, 2007). Therefore for them, *Typicality* involved a psychological dimension, whereas vagueness (or degree of *Membership*) concerned logical dimension.

4.2.3 Fuzzy ontologies

Ontologies have played a critical role in recent years, in knowledge and concept representation, as applications in the Semantic Web (Calegari & Ciucci, 2007).

As also Calegari and Ciucci (2007) argued, ontologies are not able to represent concepts in a proper way. It is due to the fact that many concepts can not be considered as a crisp set. Therefore the idea was to incorporate fuzzy logic (Zadeh, 1965) into ontologies, developing a *fuzzy ontology*. Some extension of fuzzy logics were thus proposed: e.g., *Fuzzy Description Logic*, *Fuzzy-OWL*.

Fuzzy ontology is a hierarchical relationship between concepts in a domain, that is developed using fuzzy logic. It represents knowledge with even a partial belongingness (i.e., the fuzzy *Membership* degree). Some fuzzy ontologies models were proposed, trying to develop a model able to represent concepts in an efficient and usable way (Calegari & Ciucci, 2007; Cai, Au Yeung, & Leung, 2012; Yeung & Leung, 2006b, 2010).

Yeung and Leung (2006b, 2010) proposed a model of a Fuzzy ontology where *Membership* (referring to the term "likeliness") and *Typicality* are distinguished using different values/parameters. The goal was to develop a model that reflects human thinking, where likeliness is the parameters to evaluate if an object is or not an instance of a concept and *Typicality* is the degree of representativeness of it.

In the fuzzy ontology, the concept is defined by rules, as a vector of properties with different weights. Each property presents a value from 0-1, and each concept differs from the others because of properties weights. An exemplar is defined by how much the value of properties is shared with the concept itself.

4.3 Different kind of concept representations: *Membership* vs *Typicality*

I would like to focus on the idea that concepts can be represented by two kinds of factors: *Membership* and *Typicality*. There are two different factors that can describe instances in a category and that represent distinct ways to consider a conceptual belongingness of an instance:

- **Membership** as necessary and sufficient rules to establish if an instance is or not part of a category.
- **Typicality** as a similarity measure to evaluate the distance between an element and the class prototype and the other instances.

Membership is often considered also as vagueness (degree of *Membership*) in concepts, in the sense that concepts can have unclear boundaries and members present different degrees of belongingness (Straccia, 1998). It is called "*Fuzzy Membership*" (Yeung & Leung, 2006b).

In the Cognitive Psychology, *Typicality* (Galotti, 2004) refers to the goodness degree of instances as exemplars in concepts. In fact, when people have to give examples of category members, they are more likely to give typical exemplars than atypical ones (Murphy, 2002).

Therefore, there are concepts that can be considered fuzzy and vague (in the sense of the *Fuzzy Theory of Concepts*), but the problem is that the fuzziness does not consider separately *Typicality* and *Membership*: there are some problems regarding modelization if one factor is stronger that the other. Arigoni (1993) claims that cognitivists face some problems regarding the application of *Typicality* in concept representation, basing on the *Fuzzy Set Theory of Concepts*. In fact, this theroy fails to comply with some requirements of concept representation, for instance the fact the elements of a class do not have the same degree of salience in representing concepts. Specifically, the *FST* is pretty inadequate when concepts involve interactions among themself: the application of operation to concepts, based on *FST*, leads to contradictory or false results.

There are several studies that support (or contrast) the role of these two factors in categorization. On the one hand, Kamp and Partee (1995); Osherson and Smith (1997) considers *Typicality* and *Membership* as two distinct functions. Osherson and Smith (1997) argued that two instances could be clear members of a category, but at the same time differ in their *Typicality*. Quoting the authors, the function of *Membership* (M) differs from the *Typicality* (T) one. For instance, $M_{(bird)}(robin) = M_{(bird)}(penguin) = 1$ is different from $T_{(bird)}(robin) < T_{(bird)}(penguin)$. Therefore, the authors sustain that the two factors reflect different underlying cognitive processes. On the contrary, Hampton (2007) views *Typicality* and *Membership* as derived from the same similarity function and underlines the role of context in categorization in relation with them.

4.4 *Membership*, *Tipicality*, and concept representation in ontologies

Ontologies in computer science are conceptual models that are augmented by formal axioms (Gruber, 1993). Ontologies are widely used as knowledge representation models in various areas of application, especially in the emerging Semantic Web (Yeung & Leung, 2006b, 2010). They also aim at specifying a shared specification of conceptual elements, like classes, properties, attributes, for data interoperability and other purposes.

Ontologies have been predominantly governed by membership-based rules and, by using ontology languages (e.g., mainly the *Description Logics*) to describe classes, they are able to represent concepts in a particular domain. In other words, ontologies were designed so that the resulting data would be most accessible for computer-based data processing. However, concepts in these models are considered as crisp sets, without taking into consideration that crisp sets are, indeed, inadequate in modeling concepts (Straccia, 1998; Yeung & Leung, 2006b; Warren et al., 2014). Therefore, these models can not take into account how humans represent concepts in their mind (i.e., the importance of the *Typicality* in categorization) (Rosch et al., 1976; Hampton, 2007; Pitt, 2013; Warren et al., 2014). Together also with the growing understanding that the overall usefulness of ontologies is also influenced by the reliability and effort of agents that specify conceptual elements in the ontologies development (Hepp, 2008), the consideration of the human cognitive functioning is becoming more and more significant in ontologies concept representation (Ramesh et al., 1999; Yeung & Leung, 2006b, 2006a, 2010; Stark & Esswein, 2012; Lieto, 2013; Wilmont et al., 2013).

The main cognitive theories of concepts are thus taken into account, and the recent findings in this psychological and cognitive field become to be considered, highlighting how humans represent ideas and concepts in their mind to enhance the efficacy of ontologies — that has to be a help and support for humans task.

As emerged from the literature analysis, *Typicality* (Britz et al., 2009; Yeung & Leung, 2006b; Cai et al., 2008; Yeung & Leung, 2010; Aimè et al., 2010; Lieto et al., 2014; Frixione & Lieto, 2013b; Frixione, 2013; Frixione & Lieto, 2014) is been considered in ontology concept representation, in addition to *Membership*, taking into account the fact the humans usually base their categorization on prototypicality and typical features.

As Yeung and Leung (2006b, 2010) have argued, ontologies should be considered in a different way: taking into account the *Typicality*, even beyond the classical membership rules. They even claim that *Membership* should be even considered as fuzzy because there do not exist defined borders in the concepts: each one has graduated levels of a categorical organization with different degrees of *Membership*. Therefore, each instance could be a central (very close to the prototype of the concept; defining it more representative or typical) or a borderline member (an instance that shares very few features with the prototypical ones) of that category. These authors propose a cognitive model of concepts to use in ontologies, that consider both (fuzzy) *Membership* and *Typicality* (Yeung & Leung, 2006a), suggesting different parameters to weight different levels of both factors.

Based on the psychological *Dual Process Theory* of reasoning and rationality (Evans & Frankish, 2008) and on the cognitive research about concepts (Murphy, 2002; Machery, 2009), several authors (Lieto et al., 2014; Lieto & Damiano, 2014; Frixione & Lieto, 2014) support the idea that ontologies should be developed adding a conceptual scheme (that represents a sort of prototype) to the membership rules, implemented by DL. Concerning what the *Dual Process Theory* (Evans & Frankish, 2008; Augello et al., 2015; Sun, 2015) assumes — there are two different kinds of cognitive systems and processes regarding concept representation — Frixione and Lieto (2013b) stressed that it is fundamental to keep *Typicality* separate from the classic way to represent them (in term of the set of necessary and/or sufficient conditions).

Frixione and Lieto (2013b) argue that prototypes could be implemented as something separated from the DL knowledge base because these logics can not express more than necessary and sufficient conditions. Prototypes should be represented by a list of attributes/values linked to the concept, adding information to the DL base component. Therefore, they suggest the possibility to create a hybrid conceptual representation in ontologies, taking into account this perspective. For an exhaustive explanation regarding the conceptual space used in their studies to represent such concepts, see: Frixione and Lieto (2013b); Lieto and Damiano (2014).

5 Cognitive efforts in ontology lifecycle: a literature survey

During my 6 months internship spent in Munich, I followed a reasearch project "*Cognitive barriers in Web Ontologies*" at the Universitat der Bundeswehr (in the E-business and Web Research Group, Prof. Martin Hepp).

In this chapter, an exhaustive overview of the cognitive implications in Web ontology lifecycle is also provided, regarding an issue that only partly matches the main topic of the thesis (i.e., the representation of concepts). Regardless, it is an example of how Cognitive Psychology and Information Technology can interact each other, and it is a useful contribution that helps to give a clear idea of the cognitive aspects implicated in the ontology lifecycle. However, ontology is strictly related to the use of concepts, and it is important the role that cognition assumes in representing them. Thus, also the efforts and the cognitive limits related to the development and the modeling of an ontology by humans, can be considered.

5.1 Cognitive efforts and barriers in ontologies lifecycle

Human Computer Interaction (HCI) is an interdisciplinary research field that studies the problems of the interface between human users and computer-based systems (Jacko, 2012). As Dzbor and Motta (2007) underlined in their paper, the term "interaction" represents the investigation core of this field and involves three roles: the user, the technology, and their work together. Moreover, they considerate human-ontology interaction as a subset of all possible HCI interactions, and thus we can also contemplate this interaction in such a way. However, we should consider that, in this interplay, there are important problems to take into account that can affect the whole ontology lifecycle: challenges and barriers by agents behind the design and the usage of such a model.

It appears critical to consider the prominent cognitive processes role within the ontology lifecycle, taking into account also the cognitive efforts or barriers. These aspects could hinder the whole understanding and sharing of the ontology contents (Stark & Esswein, 2012). In diverse ontology lifecycle steps, various users involve different cognitive processes and efforts. Certainly, another factor to keep in mind, even if it deviates slightly from general central theme, is the evaluation and analysis of all the user's cognitive aspects who interface with these methodologies: the *"Modeler"*, who is the creator of the ontology, or the *"Data publisher"*, or even the end *"Data Consumer"* that lastly interfaces with it. All of them must grapple with their cognitive functioning, that offers undoubtedly advantages but can lead, at the same time, also to some limitations in the use and development of these tools, if they do not take into account these human cognitive factors.

Siau and Tan (2005) focus on three different steps: starting from the analysis of the cognitive challenges that modelers can meet in the representation of a shared knowledge, through the data publishers' decision-making (marketing and technical choices), up to the consideration of the understanding and the use of the final output by the end users.

In this section, a digression regarding cognition in the design and usage of Web Ontology will be reported. It regards an akin and parallel research field relating to the importance of considering the cognitive factors in ontology lifecycle: taking into account all the persons that contribute and participate to ontology life (i.e., modeler, data publisher and data consumer). The topic concerns the link between Cognitive Psychology and ontologies.

A vast literature regarding the cognitive barriers and efforts in ontology lifecycle was analyzed: starting from the strains in developing of an ontology, the using of graphic visualization taking into account cognition perception limits and facilities to the complete understanding of the contents by final users.

For this literature review, several papers were selected and taken into account.

In appendix A, there is a list of procedures and materials used for this pourpose.

5.2 Goal

The goal is to take into account cognitive processes and limitations by different users in the ontology lifecycle, considering these three separate activities clusters:

- **Cluster 1**: Cognitive challenges for a Modeler
- **Cluster 2**: Cognitive challenges for a Publisher of Data
- **Cluster 3**: Cognitive challenges for a Consumer of Data

Briefly, a Modeler is an agent that create, manipulate and maintain a concept model; a Publisher of Data has to decide which models is the best for the publishing, "aligning" and "merging" with previous different ones. In conclusion, a Consumer of Data is the final user of the ontology.

See Appendix B for an overview about the clusterization of papers, by year of publication and by main topic. Furthermore, in Appendix C two tables regarding the topic of papers and the types of contributions are provided.

5.3 Overview

Ehrlich (2008) highlights that already in the early 1980s within the field of HCI, there was a keen interest in interface designers role in making computers easier to use. This idea could also be transferred to the creation and development of ontologies, taking into account the cognitive impact on such activities. Summarizing the papers' main general contents, we can argue that cognitive contributions play a fundamental role in order to enhance the ontology usage quality. Just to report some excerpts: understanding of what kind of mental models are constructed and utilized by users (Ehrlich, 2008; Johnson-Laird, 2010) makes modelers more aware, drawing ontologies more suitable and usable consequently. Alternatively, again: the consideration of individual differences among agents involved in ontology development (between modelers or also between them and end users), the attention to cognitive variables involved in modeling, or even the comprehension of their interactions and influences on final outcomes (Ramesh et al., 1999). Already Valusek and Fryback (1985) highlighted some possible individual communication problems between agents due in particular to their cognitive limitations (viewed as barriers in information processing and problem-solving). Furthermore, there are also some social cognitive aspects to consider during the development of conceptual models; there can be a strong variability between end users and modelers, related specifically to their frames of references or to their backgrounds (Valusek & Fryback, 1985) This can thus compromise the perfect final knowledge sharing.

As highlighted above, some papers were pretty generic about the impact of cognitive aspect to ontology development and can not be systematically included into one of the three clusters. They regard: 1) cognitive-based ontology methodologies or approaches (Kotis & Vouros, 2005); 2) cognitive support tools for agents, taking into account human cognitive limitations (Siau & Tan, 2005); and 3) ontology quality evaluation with a cognitive perspective. 4) In addition, some papers concern generic cognitive processes that cover all the three ontology stages (e.g., human inference, (Yamauchi & Yu, 2008)).

Regarding the cognitive based ontology development approach, a recent engineering methodology (HCOME, *Human-Centered Ontology Engineering Methodology*, by Kotis and Vouros (2005)) is presented, with a strong consideration of the end users role. In fact, its aim is to use a human-centered approach during the whole ontology lifecycle taking into account the way people develop their knowledge and conceptualizations in the context of their day to day activities. Studying cognitive abilities, daily tasks, capacities and goals of people (through other disciplines as psychology, cognitive science, etc.), a new way to maximize the value of such tools in society stands out. With the same human-centred approach, in 2015 Gavrilova and Leshcheva (2015) carried out a pilot study to validate a method (KOMET, *Knowledge and cOntent structuring via METhods of collaborative ontology design*) for ontology design based on users' cognitive aspects with a strong emphasis on visualization.

In the cognitive supporting topic, Siau and Tan (2005) suggested the use of various kinds of cognitive mapping as technical tools to enhance quality in conceptual modeling (mainly for modelers in requirements determination). It aims to determine better what concepts are present, taking into account them in various situations and also focusing on their mutual relationships. (Ernst et al., 2005) also underlined the need for cognitive support tools, extending them to other several tasks during the ontologies development (e.g., navigation, modeling, verification and all their subtasks).

Finally, in conceptual models quality evaluation, human cognition plays also an important role. We can discriminate between participants' knowledge and individual interpretations about the measure of the perceived quality (Siau & Tan, 2005). A cognitive structure of the problem determines the agent's knowledge, whereas a cognitive ability to interpret such model influences own interpretation (Siau & Tan, 2005). Given the growing awareness about the importance of high-quality conceptual models, it is thus fundamental to take into account the perceived quality of ontologies bringing into play several cognitive aspects, examining the substantial literature review about past models quality evaluations by Lindland, Sindre, and Solvberg (1994); Maes and Poels (2006) and underlining the needings to enhance such perceived quality considering mainly the end users' perspective. The authors carried out two experiments to evaluate and test the appropriate dimensions for quality evaluation from users' perspective into a theoretical model. Further investigations regarding this issue have been carried out by Siau and Tan (2005) that focused strongly on the role of individual human cognition for evaluation. They started to emphasize the human constraints as information processors and problem solvers: e.g., faulty reasoning, automaticity, or even the use of heuristic-driven biases (that can lead to an imperfect approximation of the domain, getting to a lower semantic quality). At the same time, the role of cognition at the socio-level, underlying reference frames functions in systems development and use, can have an effect on correct model interpretation (but more suitable visualization techniques can also improve pragmatic quality). In addition, further cognitive aspects that can affect quality are: e.g., imperfect approximations, limitations in human cognition capacity, different model languages preferences (natural language vs formal modeling one) and wrong semantic interpretations (Yamauchi & Yu, 2008).

In conclusion, a contribution that it could be considered a good example of a cognitive process that covers all the three ontology stages is the human inference (Yamauchi & Yu, 2008). Every agent, as well as everyone in his everyday life, has to cope with the problem of giving judgment or making some inferences. In particular, users are predisposed to use inductive judgments when they face with some concepts and their properties. Through psychological experiments, authors understood how modelers could usually utilize some concepts' features or labels in order then to contribute to a better ontology representation: they found out the predominance of basing on noun labels instead of attribute labels to make an inference. It leads necessarily to a deeper consideration of the vocabularies used for linguistic classes by ontology developers or analysts.

5.3.1 Modeling Perspective

The term "*modeling*" in information systems (or more specifically "*conceptual modeling*" refers to the elicitation and description of general knowledge (or conceptualization) required by an information system (Olive', 2007)). In fact, in order to perform its function, this system needs some defined knowledge. Modeling constitutes the first and the most important phase in the ontology development, and it is a necessary procedure to obtain a conceptual scheme (or ontology), that represents the description of such knowledge on which an information system refers to.

Modelers are agents that create, develop, manipulate, and maintain a concept model (ontology); they are agents with the final goal of building and maintaining an ontology. During the ontology lifecycle phases, they interface with a lot of cognitive challenges in different moments. In fact, they should start with a clear and definite idea of what they want to represent; then they have to abstract the most important concerned concepts, considering the best way possible to represent entities, attributes, and relationships. It is important to underline that all these tasks require a lot of cognitive processes: e.g. attention, memory, abstraction, reasoning, naming, problem-solving (Wilmont et al., 2013). It is thus important to take into consideration these implicated processes, reviewing from cognitive and psychological literature some relevant definitions and contributions:

- *Abstraction* of some concrete objects or events, involving mental imageries (see also: (Theodorakis, Analyti, Constantopoulos, & Spyratos, 1999), where he considers a contextualization as an abstraction mechanism for conceptual modeling).
- *Attention*: "a state of focused awareness on a subset of the available perceptual information" (Gerrig & Zimbardo, 2002)
- *Memory*: "the mental capacity to encode, store, and retrieve information" (Gerrig & Zimbardo, 2002), that is limited in the human brain, (especially the working memory; see: (Miller, 1956) with the "magic number plus minus 7"). It is important also to stress out the hierarchical structure proposed for the long term memory and the prototype theory of concepts (Rosch et al., 1976), as a model of representing concepts in taxonomies or even in ontologies, in order to reproduce human mind as best as possible.
- *Inductive and deductive reasoning*: the first one is "a form of reasoning in which a conclusion is made about the probability of some state of affairs, based on the available evidence and past experience" (Gerrig & Zimbardo, 2002) whereas the other one is described as "a form of thinking in which one draws a conclusion that is intended to follow logically from two or more statements or premises" (Gerrig & Zimbardo, 2002).
- *Naming*: it is a general issue regarding human communication and Furnas (1981) firstly also refers this as a problem to consider in the HCI field (see also: Cregan (2007) for further contributions).
- *Problem solving*: "a form of thinking that is directed toward solving specific problems and that moves from an initial state to a goal state by means of a set of mental operations" (Gerrig & Zimbardo, 2002).

5.3.2 Data Publisher Perspective

Data publisher are agents that publish online the ontology, and they have to decide which model is the best for the publishing, "aligning" and "merging" with previous different ones.

Publishers of data are the users that have the onerous task to choose the best ontology to utilize and find suitable concepts, understanding them in term of their semantic meanings and their boundaries. Sometimes they have to assess the compatibility of a given concept in the ontology with a concept in a local database model, or again to verify the compatibility of two related concepts in multiple ontologies. It is possible to refer to these kinds of technical procedures with the term "*alignment*" that it could be compared to a sort of analogy formation (Nossner et al., 2015). In such tasks in the publishing phase, there are again several cognitive components to evaluate and, specifically, a lot of cognitive processes that take place. Some of them are:

- *Naming understanding*: the capacity to understand the semantic meaning that modeler would like to express with a specific term (Cregan, 2007).
- *Mental representation*: as an object, an event or a general idea with semantic properties (content, reference, truth conditions, truth value, etc.) (Pitt, 2013).
- *Analogical and similarity- based processes*: mental procedures with which different concepts or ideas are considered in order to find shared features and, consequently, to establish a relation between them (Markman, 1997).
- *Inductive and deductive reasoning*, as in the modeling phase.
- *Decision making*: the process of choosing between alternativesÕæ selecting or rejecting available options (Gerrig & Zimbardo, 2002).

5.3.3 Data Consumer perspective

Consumers of data (or Users) are the last agent that can cope with the ontology. They are the final users of the ontology and the last agents that can cope with the ontology. Therefore they can also be defined as end-users. These agents are concerned with reading and understanding the model firstly and then even interacting with it. Gathering the information within the model, they should construct an internal representation of the described domain integrating it with their previous experience, in order to better understand the main topic and interact with the schema (Gemino & Wand, 2003).

It is evident how many cognitive efforts are involved in these kinds of activities:

- *Mental representation* (Pitt, 2013), as described above.
- *Naming understanding*: the capacity to understand the semantic meaning that modeler would like to express with a specific term (Cregan, 2007).

- *Memory*: (short and long term memory), as defined for modeling.

- *Inferential processes*: "missing information filled in on the basis of a sample of evidence or on the basis of prior beliefs and theories" (Gerrig & Zimbardo, 2002), Yamauchi (2007) for the role of inference in information systems.

- *Quality evaluation*: it could be seen as a judgement ("the process by which people form opinions, reach conclusions, and make critical evaluations of events and people based on available material; or also, the product of that mental activity" Gerrig and Zimbardo (2002)), with a strong emphasis on perceived quality (in this case the usability and the easiness of a conceptual model) (Maes & Poels, 2006).

- *Inductive and deductive reasoning*, as in the modeling phase.

- *Decision making*: "the process of choosing between alternatives; selecting or rejecting available options" (Gerrig & Zimbardo, 2002).

5.4 Analysis of cognitive challenges in the ontology lifecycle

In this section, a consistent and exhaustive model of the cognitive challenges in the entire lifecycle of ontologies in computer science is provided. As a starting point, activities in existing ontology engineering methodologies are mentioned, trying to extend the specification of the often rather basic notions of subactivities by expanding them into the actual cognitive challenges (1) at the interface between reality and the minds of the human beings involved and (2) the cognitive challenges within those humans.

The goal is to provide a complete understanding of the role of cognition in the creating and usage of ontologies.

5.4.1 Clusters of activities

In this section, it is presented the set of cognitive tasks that human stakeholders in the entire lifecycle of an ontology are potentially facing, grouping these tasks into three clusters. The clustering is based on the role of the human stakeholder in the interaction with the ontology, namely:

- being involved in the creation and maintenance of the ontology (*modeler*),

- being involved in the mapping of existing or future data sources to the conceptual elements in the ontology in order to create a knowledge representation based on the respective ontology (*publisher of data*), and
- being involved in the consumption of the resulting knowledge representation, e.g. in the role of an application developer who wants to formulate queries against the knowledge representation (*consumer of data*).

The three roles in the interaction with the ontology are not disjoint. The same human individual can interact with the ontology or populated knowledge representation in more than one role. Wilmont et al. (2013) pointed out the role of cognitive processes, in particular, relational reasoning and abstraction, in conceptual modeling. These are based fundamentally on integration and maintenance of information, that represent somehow the essence of the ontology. They also discussed executive control, attention and working memory as possible facilitators of the mentioned ones above. In the description of the activities, the goal and the expected output of the cognitive tasks (what is the result of the task) are defined.

Cognitive challenges for a modeler

There are a lot of theoretical and practical manuals wich aim to explain in a very exhaustive way all the steps needed to be finalized by modelers, all the methodologies and the approaches used so far (for an overview, see Gomez-Perez, Fernandez-Lopez, and Corcho (2004); Hepp (2008); Olive' (2007)). From these manuals, it appears clear what it should obtain as a final output and by means of which steps, but it also emerges a great lack: the consideration of the cognitive challenges that modelers can encounter in these phases and how to cope with such difficulties.

Modelers should start with an evident and definite idea about what they want to represent; then they have to abstract the most important concerned concepts, naming them in the best way possible to make those comprehensible for everyone, and finally to realize similar concepts. However, all these tasks involve a lot of cognitive processes: e.g. attention, thinking, memory, abstraction, reasoning, naming, problem-solving (Wilmont et al., 2013).

It is demonstrated (Engelbrecht & Dror, 2009) how the cognitive research can contribute to the ontologies development and how such specific cognitive processes involved in conceptual modeling can be investigated, leading to a higher comprehension and coping with difficulties encountered in different steps. In according with some ontology modeling phases (Gomez-Perez et al., 2004), prominent problems are:

- the understanding of requirements from the other stakeholders and the knowledge elicitation (with the consideration also on human cognitive limits regarding the information mental managing) (e.g., Rosch et al. (1976); Anderson (1978); Theodorakis et al. (1999); JohnsonLaird (2010); Brinklow (2004))
- the naming of labels (e.g., Furnas (1981); Yamauchi (2007); Yamauchi and Yu (2008). There is the problem to define names that can reflect the intention of the type and that are, at the same time, intuitive. Naming is a generic problem in human communication and human-computer interfaces (Furnas, 1981), but in the ontology lifecycle, it is more relevant in the modeling stage. While users of the ontology need to grasp the intended meaning of a term, only the creators of the ontology face the naming problem in the narrow sense
- the disambiguation between different types of concepts, taking into account the semantic meaning that a type (and its chosen name) can convey, in relation also to previous existing conceptual models
- the wording of textual definitions of concepts (with the consideration of the day-to-day language used in the content of ontologies, expressed by domain experts, or even the biases in human reasoning when they perform some abstract analysis tasks) (e.g., JohnsonLaird (2010); Peroni et al. (2008))
- the defining of right and selected properties and attributes for each concept, considering deeply what are the main and more intuitive features to convey (Yamauchi, 2007; Yamauchi & Yu, 2008)
- the adding of additional axioms to better express the meaning of such specific model (and the consideration of the understanding of causal, inductive and deductive relations expressed by those), and
- finally, the structuring of ontologies with the issue of arranging types in hierarchies, choosing the relationships between concepts (taking always into account how the human knowledge representation can affect it) (e,g., Rosch et al. (1976); Theodorakis et al. (1999); Yeung and Leung (2006b); Ehrlich (2008); Gavrilova and Leshcheva (2015)).

It is critical to consider one of the early stages of the software development lifecycle for modelers (Siau & Tan, 2005): the understanding of requirements from the other stakeholders (i.e., the identification of the purpose and the scope of an ontology, Gomez-Perez et al. (2004)). Requirements management is the process of documenting, analyzing, prioritizing and agreeing on requirements and then controlling changes and communicating to relevant stakeholders. It is a continuous process throughout a project (Dermeval et al., 2014), and it is also recognized (Siau & Tan, 2005) as a social cycle that involves several agents (i.e. managers, end-users, analysts). It is, therefore, important to stress the big role in successful information system development that this process has. Being a big and significant challenge to achieving, it is fundamental to take into account all the cognitive activities that take part. For example, individual cognitive features in this phase have a strong influence on the outcome (content and shape) of domain ontology (Gavrilova & Leshcheva, 2015) because each modeler has personal cognitive peculiarities that affect his work (education, experience, personality, different cognitive style and so on).

Regarding the naming issue, especially in a technical sense, there is an interesting aspect to take into consideration: the usability of *Description Logics*, that are a family of formal languages to express knowledge. To be specific, the *Web Ontology Language* (OWL) is used to describe concepts in ontologies and is based on such *Description Logics*. Modelers could encounter cognitive difficulties facing with this kind of logic languages. Warren et al. (2014) pointed out this issue, trying to study and systemize some cognitive barriers, also proposing remedies for some of them. Their investigation revealed again the importance of evaluating the cognitive task in the entire ontology process, demonstrating how psychological theories or cognitive contributions could be useful to explain and improve some of these cognitive activities. The main findings were: participants usually make these misconceptions (i.e., confusion regarding the choice of names, the use of "not" and "and", the inheritance of property features and, the use of existential quantifier Warren et al. (2014)). It is worth to note that further investigations have already been suggested: the use of different languages, the role of diagrams in complementing reasoning, and the relationship with possible developed mental models during thinking processes.

Cognitive challenges for a Publisher of Data

Regarding publishers of data, there are again a lot of technical manuals that describe methods, tools or steps that everyone involved in these tasks has to consider (for an overview see Gomez-Perez et al. (2004); Hepp (2008); Olive' (2007); Euzenat and Shvaiko (2007)) Thus, the publisher of data can encounter several theoretical and practical problems during ontology lifecycle that, as underlined above, also involve cognitive challenges. These are:

- the finding of the best ontology and the suitable concepts (with a special consideration of support tools for these tasks: e.g., LOV (Baker, Vandenbussche, & Vatant, 2013) and Watson (D'Aquin & Motta, 2011)

- the correct understanding of intention (borders) of a concept (figuring out what fits and what does not fit a concept). Also, the consequent deductive reasoning to infer properties to the instances from the concept should be considered as cognitive challenges in this step (E. Smith, 1995)
- the assessing of compatibility of a concept in the ontology with a concept in a local database model (also involving analogical cognitive processes and linguistic comprehension (Kashyap & Sheth, 1996; Markman, 1997; Kotis, Vouros, & Stergiou, 2004; Euzenat & Shvaiko, 2007)
- the summarization of model contents (Theodorakis et al., 1999; Peroni et al., 2008)
- the evaluation of compatibility of two related concepts in multiple ontologies (e.g., in ontology alignment Kashyap and Sheth (1996); Euzenat and Shvaiko (2007))
- or even the creation of a new ontology having two others, regarding the same domain, as starting input (e.g., in ontology merging Vipul and Gale (1997); Kotis et al. (2004)).

Concerning the finding of the best ontology and the suitable concepts, these two steps are addressed in the current literature mainly from the perspective of support tools in the form of ontology search engines, like Falcon (Azevedo, Vaz de Carvalho, & Carrapatoso, 2012), Watson (D'Aquin & Motta, 2011), and ontology metadata, like LOV (Baker et al., 2013):

- Falco
- Watson
- LOV

However, we argue that the cognitive challenges of these steps (i.e., finding the best ontology and the most suitable concepts by publishers) should be considered independently of possible tool support, because (1) the performance of human users in mastering these tasks affects the overall performance of an ontology (Ramesh et al., 1999; Stark & Esswein, 2012; Wilmont et al., 2013), (2) the performance of these tasks is also likely be influenced by modeling decisions, naming, and the HCI / presentation of the ontology (Ehrlich, 2008; Engelbrecht & Dror, 2009) and thus a multidimensional problem that needs to be understood before effective tooling support can be provided. For example, the modeling decisions, like the level of disambiguation (e.g., distinguishing between the legal operator of a restaurant, a place housing a particular restaurant, and the name and brand of a particular restaurant) and the naming decisions (e.g., very precise terminology from an expert's perspective vs. terms intuitive for lay people) can influence the performance of an ontology in these two tasks and also in the further ones (in the understanding the intention of a concept, in the summarizing of contents, in the assessing the compatibility of a concept with a concept in a local database model or between multiple ontologies or also in creating a new ontology). Since ontologies are socio-technical artifacts, we must take into account all those social and contextual parameters when assessing the quality and technical contribution of an ontology or the underlying individual modeling decisions. A conceptually superior ontology is only a better ontology if its conceptual distinctions can be communicated and applied by the all of this stakeholders.

A publisher of data, as well as a consumer of data (see the following section), could be involved in ontology summarization (Peroni et al., 2008), that means the understanding of what the ontology is about. Also, he could face with this task in order to obtain a clearer vision of an ontology. In contrast with previous studies regarding the ontology understanding through the key concepts identification, Peroni et al. (2008), integrated some statistical and topological measure with some criteria from cognition to find a stronger correlation between their method and possible results obtained by human experts, underlying the role of cognitive processes in this field again. Furthermore, findings from cognitive science can enhance the quality of such a tools: e.g., exploring the way how people can identify concepts that are rich in information in a psycholinguistic sense, or discovering which are the criteria they mostly consider for this task.

Finally, one particular mention is due to the *alignment*, that is the process and the result of determining correspondences between concepts. This task involves, as it can be hypothesized, several cognitive challenges (e.g., analogical reasoning, deductive and inductive reasoning). Also for this complicated task, several supporting tools are been proposed, but also a general consideration about cognitive processes involved has been considered. Ontology alignment tools find classes of data that are "semantically equivalent" (Euzenat & Shvaiko, 2007). For cognitive scientists interested in ontology alignment: concepts are viewed as nodes in a semantic network (a sort of conceptual system). The question that arises is: if everyone has unique experiences and thus different semantic networks, how can we ever understand each other? It is the cognitive point of view when you deal with a conceptual model, and it is very important to consider it in the specific context of alignment by publishers. Most of current ontologies alignment systems use initially fully automated or semiautomatic algorithms to map and integrate different ontologies. Then, it is necessary to commit to a human engineer the final analysis to verify the outcomes (Kotis et al., 2004). It is clear how the cognitive contributions could be considered influential in this task: Nossner et al. (2015) examined a new alignment system (COGMAP) based on cognitive, inspired and interactive approach. Taking into account all needs by publishers for such a procedure, it has the purpose of improving the final outcome, also minimizing the necessary human supervision.

Cognitive challenges for a Consumer of Data

Consumers of data are the last agents that can cope with the ontology. Therefore they can also be defined as the end-users. As already defined, it is clear how important is the role of consumers of data, being the main beneficiaries of this process. Thus, it is also fundamental to highlight their cognitive efforts and, especially, their cognitive limitations encountered in understanding and using these tools as conceptual models. As this study (Ciancarini, Di Iorio, Nuzzolese, Peroni, & Vitali, 2014) argued, every end-user have to deal with ontologies or any conceptual models (in this case a *Citation Typing ontology*), understanding it and adopting it. They usually should create own mental models that most of the times differ from the modelers' ones in order to utilize those for their purpose. Authors clearly described several cognitive challenges that users have to cope with final ontologies and several possible changes that modelers could consider to make those more cognitively usable.

The main cognitive problems by consumers of data are:

- the selection of a concept for a query
- the complete understanding of the ontological commitment of a concept, involving also inductive and deductive reasoning between concept instances and conceptual categories, (Yamauchi & Yu, 2008)
- the causal reasoning between different types in an ontology or between distinct ontologies
- the summarization of model contents (Theodorakis et al., 1999; Peroni et al., 2008), and
- the ontology quality evaluation, with a consideration of easy of use, efficacy, and usefulness by users (Maes & Poels, 2006; Siau & Tan, 2005).

Consumers of data should select the correct concept for a query when they cope with an ontology. Thus they ought to understand which is the best one to choose, realizing at the same time what modelers aim to commit through this term, its intension and its relations with other concepts. Several cognitive processes are involved, and thus several supporting tools are proposed to help them.

Furthermore, various authors have suggested taking into account a user-centred approach (and the resulting cognitive challenges involved) in the ontology development, improving the final usability of data consumers: e.g., *HCOME, Human-Centered Ontology Engineering Methodology* (Kotis & Vouros, 2005), or *KOMET, Knowledge and cOntent structuring via METhods of collaborative ontology design* (Gavrilova & Leshcheva, 2015) for an ontology design based on users' cognitive aspects with a strong emphasis on visualization).

5.5 Inputs and results of the cognitive challenges

The richness of the presentation of the ontology has a strong impact on the ability of stakeholders to grasp and apply the intended meaning of conceptual elements in such ontologies.

Several features can be evaluated in the ontology presentation to verify the real influence over cognitive challenges for each cluster of activities. Some examples are the use of video, images or audio material, the name used for an entity (human readable-name), the descriptions, the use of different participants' mother languages, the position in a hierarchy or even the use of different axioms to express relationships and properties. In the following tables, all cognitive subchallenges for each agent are reported. There are also input and output descriptions for each activity.

Cognitive Sub-challenges	**Input**	**Output**
Concepts Abstraction	Example instance data, elements from existing data models, distinctions given by top-level ontologies	Conceptual element for the ontology typed according to the relevant top-level ontology (e.g. "grape of vine as a RDF:Class")
Concepts Naming	Different possible names for a concept, names from existing data models	Accuracy of understanding of selected names Differences between names in different languages
Disambiguating Different Types of Concepts	Different types of concept	Accuracy of disambiguation Semantic distance between different types
Finding a Textual Definition	Concept type, different textual definitions to choose also from existing conceptual models	Readability efficiency of the text Deep understanding of the meaning
Defining Concepts Properties and Attributes	Different properties and attributes, also from existing conceptual models	Accuracy of selected properties and attributes that can define in an exhaustive and correct way a specific concept
Adding Additional Axioms	Original axioms	Accuracy of selected new axioms to specify the new model Expressiveness efficiency of such axioms
Arranging Types in a Hierarchy	Different types with several relations between them, several existing hierarchies from other ontologies	Model understanding Model efficiency Understanding of causal relations, inductive and deductive relationships between types Perceived readability

Table 5.1. Cluster 1. Cognitive sub-challenges for modelers.

Cognitive Sub-challenges	**Input**	**Output**
Finding the best ontology and the suitable concept	Several ontologies and single type / or instance from an ontology	Selection accuracy of the best ontology for the purpose Accuracy of the most suitable element in the ontology confidence (risk of error)
Understanding the intension of a concept	A concept from the ontology	Accuracy of its instances memberships Accuracy of deductive reasoning between concepts and its instances
Assessing the compatibility of a concept in the ontology with a concept in a local database model	Concept from the ontology	Percentage of overlapping with another concept from local database model
Summarization of contents of an ontology	A whole ontology	Understanding of contents of the ontology, with a regard to the relations between types, their properties and attributes Accuracy of summarization of contents
Assessing the compatibility of two related concepts in multiple ontologies (*Alignment*)	Two concepts from different ontologies	Percentage of overlapping between these two concepts (*alignment*)
Creation of a new ontology (*Merging*)	Two different ontologies with the same domain context	A new ontology that takes into account both, summarising and merging their contents

Table 5.2. Cluster 2. Cognitive sub-challenges for pubblisher of data.

Cognitive Sub-challenges	Input	Output
Selecting a concept for a query	Query and different concepts	Accuracy of selected retrieving information
Understanding the ontological commitment of a concept	A selected concept from the ontology	Accuracy of its instances memberships Accuracy of deductive reasoning between concepts and its instances
Inductive reasoning	Concept instances	Accuracy of inductive reasoning between concepts and its instances
Causal reasoning	Two concepts or types from the ontology	Accuracy of causal reasoning
Summarization of contents of an ontology	A whole ontology	Understanding of contents of the ontology, with a regard to the relations between types, their properties and attributes Accuracy of summarization of contents
Quality evaluation	Types, properties, attributes and the whole ontology	Perceived ease of use, usefulness and efficacy Deep understanding readability

Table 5.3. Cluster 3. Cognitive sub-challenges for consumers of data.

SECOND PART:
Experiments

6 Introduction to the Experiments

The second part of this thesis focuses on the empirical contributions.

In the following chapters (i.e., Chap. 7-8-9), six experiments, carried both in the laboratory setting and on the Web, are reported, which aimed to investigate the role played by *Membership* and *Typicality* in human categorization.

6.1 Brief introduction to the experiments: objectives and goals

The experiments concern three different themes, i.e.:

- The role of *Typicality* and *Membership* in the acceptance of contradictory categorizations
- The relation between *Fuzzy Set Theory of concepts* and the graded *Membership* and *Typicality* effects.
- The role of *Membership* and *Typicality* in Web ontologies.

6.1.1 The role of *Typicality* and *Membership* in the acceptance of contradictory categorizations

The acquisition, representation, and use of concepts have been debated and have been a consistent hallmark of psychological research for almost a century, especially during the

'70s giving rise to opposing theories. Concepts were considered as variously represented by rules, prototypes or exemplars (Smith & Medin, 1981; Murphy, 2002). The Heterogeneity Hypothesis (Machery, 2009) challenges the dominant conceptions: it states that there are three different kinds of concepts for each category that are based on knowledge of various kind and that can simultaneously coexist in the mind of the user.

The main goal of the experiments is to investigate the most significant prediction of the *Heterogeneity Hypothesis*, the *contradiction acceptance*, related to the concept representation problem. Following Machery's assumptions, the rationale on which the experiments are based is that, if participants consider two mutually contradictory sentences about the same entity and category as true, they should be able to utilize two different concepts for the same category, based on typicality or membership rules.

Therefore, two experiments are presented which investigate the contradiction acceptance in the *Heterogeneity Hypothesis*.

6.1.2 The relationship between *Fuzzy Set Theory of concepts*, and the graded *Membership* and the *Typicality* effects

The *Fuzzy Set Theory of concepts* (FST) claims that: "often it happens that the concepts encountered in the real world do not have precisely defined criteria of membership, i.e., they are vague ..." (Straccia, 1998). In addition, the FST takes into account the typicality of instances in order to consider the vagueness of concepts (or graded *Membership*) (Rosch et al., 1976). While FST considers vagueness and *Typicality* as different manifestations of the same phenomenon, several authors — i.e., Kamp and Partee (1995) — have argued that *Typicality* and fuzzy *Membership* should be determined by distinct processes.

Three experiments are presented, carried out with the same method but with different situational contexts. These conditions examine whether graded *Membership* and *Typicality* could be considered as independent factors, influencing the performance of human participants involved in sentence verification tasks, or if they are interrelated.

The main aim of the experiments is to investigate the role played by *Membership* and *Typicality* in categorization using sentences verification tasks.

This section concludes with a general discussion of the experimental findings and the problems they pose for models of concepts based on the FST.

6.1.3 The role of *Membership* and *Tipicality* in Web ontologies

Ontologies in computer science are conceptual models that represent different entities in a given domain (Hepp, 2008). Historically, ontologies were developed following concept representation based on membership rules, because this was the most efficient way to represent class and concepts using computational language (e.g., Descriptive Logic). On the other hand, *Typicality* also affects human categorization; thus it is fundamental consider how this factor could have an impact on the ontology use by users, because of the cognitive aspect of categorization.

The aim is to measure and analyze the consensus given by participants regarding ontology classes in schema.org (Guha et al., 2015; Mika, 2015) and to explore the possible role played by *Typicality* and *Membership* in applicative tools, specifically in web business and marketing, analyzing the ability to use defined ontological classes.

The experiment aims to investigate how some aspects of the ontology schema.org (kind of instances, instances format, and provided documentation) can affect the users' categorization comprehension and coherence.

7 The role of *Typicality* and *Membership* in the acceptance of contradictory categorizations

[Zarl, F. & Fum, D. (2014). Theories of Concepts and Contradiction Acceptance. In P. Bernardis, C. Fantoni, & W. Gerbino (Eds.), TSPC2014, *Proceeding of the Trieste Symposium on Perception and Cognition* (pp. 157 - 161). EUT Edizioni Universita' di Trieste]

The work presented in this chapter concerns the role that different approaches to concept representation play in supporting the empirical psychological findings. In particular, it investigates which paradigm (the *Heterogeneity Hypothesis* or the *Hybrid Theory of Concepts*) could better explain the phenomenon of accepting contradictory sentences about the same instance and category (Zarl & Fum, 2014).

In this study, the terms "Prototype" and "Theory" often refer to the conceptual ideas of "Typicality" and "Membership" respectively. Furthermore, the terms "similarity, prototype, and typicality" can be treated as interchangeable, as the same as "theory, necessary and sufficient rules, and membership".

7.1 Contradiction acceptance: *Hybrid Theory of Concepts* vs *Heterogeneity Hypothesis*

Different theories of concepts consider them as as variously represented by rules, prototypes or exemplars (Smith & Medin, 1981). Even data from neuropsychological research and neuroimaging were taken into account (Gerlach, 2007; Mahon & Caramazza, 2009; Wang, Conderm, Blitzer, & Shinjkareva, 2010), but it was not possible to define which theory could best explain the empirical findings Murphy (2002) argued that it seems now clear that all these theories are, to a greater or lesser extent, wrong and that new ways of thinking about this issue are required.

The so-called *Hybrid Theories of Concepts* (Anderson & Betz, 2001; Keil, Smith, Simons, & Levin, 1998; Miller & Johnson-Laird, 1976; Nosofsky et al., 1994; Osherson & Smith, 1981; Rips et al., 1973) or more radical positions such as the *Heterogeneity Hypothesis* (henceforth: HH) put forward by (Machery, 2009), cast doubts on the different interpretations suggested by the other theories of concepts and on the usefulness of the very notion of concepts in psychology.

In fact, concepts are considered in psychology as representing "those bodies of knowledge that are used by default in the processes underlying the higher cognitive competencies (Machery, 2009, p.7), and they are commonly recognized as represented with a shared and common set of properties (see: Medin, Lynch, and Solomon (2000), Murphy (2002)). These properties are used to explain how we categorize, reason inductively, draw analogies, etc.

Because of the existence of different uses of cognitive functions as categorizing, reasoning inductively and making analogies, the *Heterogeneity Hypothesis* postulates that our cognitive processes rely on distinct bodies of information (i.e. on several distinct kinds of concepts) that have little in common, apart from coreferentiality (i.e. the fact that they refer to the same entity) (Zarl & Fum, 2014).

Therefore, the HH suggests that there exist at least three types of concepts, able to store and utilize knowledge of a different kind: i.e., *prototypes*, sets of *exemplars* and the so-called *theory-theories*. These heterogeneous representations can simultaneously coexist, and they can be used (in a many-to-many relation) by different cognitive processes, giving thus raise to the variety with which these processes may occur.

However, Hybrid Theories provide a different explanation for this diversity: each category is represented by a single concept, which can be composed of different parts, and the distinct parts of a concept can be employed in various forms of the same cognitive process. According to (Osherson & Smith, 1981), a concept can be composed of: (i) a set of necessary and sufficient properties to define the concept, and (ii) a prototype. These two components come into play in two distinct form of categorization: one prototype similarity-based and the other on membership rule-based.

Hybrid Theories and the HH assume some differences about the output of the cognitive processes. Hybrid Theories claim that the separate representations work together contributing to a consistent and coordinated result. On the contrary, for the HH, each concept is involved in an entirely separate process and could lead to conclusions that may be uncoordinated or even contradictory (Zarl & Fum, 2014).

Machery and Seppala (2011) carried out some experiments to investigate the theories' predictions of the HH that required the evaluation of pairs of contradictory sentences. Participants were asked to establish (on a seven-point Likert scale) their agreement on affirmative or negative classification statements.

Following Machery, if participants agree with two mutually contradictory sentences, they should be able to utilize two different concepts for the same class. It was further hypothesized that contradiction acceptance would be higher for sentences allowing the use of conflicting membership criteria (the *target sentences*) in comparison with (the *control* ones), where the criteria coincided. To exemplify, because tomatoes are technically (i.e., following a membership-based approach) fruit but share many properties with vegetables (i.e., according a typicality-based approach), it would be possible to accept both: *"In a sense tomatoes are vegetables"* and *"In a sense tomatoes are not vegetables"*. On the other hand, control sentences like *"In a sense lions are animals"* and *"In a sense lions are not animals"* should not be considered simultaneously true because lions are animals and that they are also typical animals. Thus, the *Heterogeneity Hypothesis* allows contradiction acceptance, at least for certain kinds of sentences. On the other hand, Hybrid Theories would have a tough time in explaining the phenomenon, denying the existence of multiple representations for the same category.

Machery and Seppala (2011) obtained findings that support the HH: these results are compatible with the idea that people could hold multiple concepts for the same category. In their first experiment, for example, the average percentage of agreement with both pairs of contradictory sentences was 27.9% for the *target* propositions and 2.78% for the *control* ones. In their second study — an on-line replication of the first experiment — the effect was even stronger: contradiction acceptance was 41% for the *target* and 4.6% for the control sentences (in the case of non-native speakers of English), and 64% and 16.2% for native speakers, respectively. The evidence is however not conclusive because the experiments present an insufficiency of data analysis and some limitations in the procedure utilized. In particular, the authors did not provide any statistical tests that could determine the significance of their experimental findings, just reporting the percentages of the different types of responses. Regarding the procedure, the number of sentences used was quite low: only nine pairs in total which included six target and three control sentences.

To further explore this issue, two experiments were carried out to investigate the role played by *Membership* and *Typicality* in the acceptance of contradictory sentences about the same category. Experiment 1 replicates the procedure utilized in Machery and Seppala (2011) with the same goal of establishing whether people could hold multiple concepts for the same category. Experiment 2 tests wheter this effect could be modulated by the conceptual framework adopted in evaluating a sentence — an idea already put forth by Hampton, Dubois, and Yeh (2006) who were, however, unable to corroborate it.

To adhere to the terminology adopted by previous studies (Machery & Seppala, 2011), *Membership* (i.e., the fact that necessary and sufficient rules are used to categorize) was represented by terms such as *theory, technical approach*, whereas *Typicality* (i.e., the fact that bolongniness judgments are based on resemblance) are implicated in all the terms such as *protypical, commonsense...*).

7.2 Experiment 1

The experiment aimed to extend the results found in the first study in Machery and Seppala (2011). In comparison to Machery and Seppala (2011)'s experiment, greater attention was payed to the theoretical constructs, to the control over the experimental material, and to the evaluation of the results through stricter statistical tests. The experiment asked participants to determine the degree of agreement with the statements contained in pairs of contradictory sentences. The major differences with Machery and

Seppala (2011) consisted in the introduction of a new type of control sentence. Furthermore, participants were divided into two groups: in the *Pair* group the contradictory sentences were presented in pairs and participants were asked to evaluate them at the same time. In the *Single* group each sentence was introduced separately in random order to avoid that its assessment could be somehow affected by the evaluation given to the other sentence of the pair.

7.2.1 Method

Participants

40 participants (31 females), all living in the Trieste area and native Italian speakers, whose age varied from 20 to 42 years (mean = 26.1, sd = 4.8) took part in the experiment. Subjects were randomly assigned to the two experimental conditions: *Pair* group vs *Single* group.

Materials

In the experiment, participants evaluated 32 pairs of sentences (64 sentences in total). The sentences were written in Italian to the participants in the experiment, but here they are translated into English. A pair of sentences was composed by an affirmative statement and its negation. Subjects and predicates of the sentences were properly balanced within each kind of sentence to obtain all their possible combinations. Four different kinds of sentences were thus used:

- **T1**: The subject of the sentence was similar to the prototype concept of the phrase predicate, but it did not belong to its extension (e.g.,"*In a sense bats are birds*")
- **T2**: The subject was dissimilar to the predicate prototype but, in fact, it was an atypical member of its extension (e.g., '*In a sense penguins are birds*").
- **T3**: The sentence subject was both similar to the predicate prototype, and it was a member of its extension (e.g., '*In a sense canaries are birds*"). Sentences T1 and T2 correspond to the target sentences utilized by Machery and Seppala (2011), and T3 correspond to their control sentences. In the experiment, to balance the *Membership* and *Typicality* factors, we utilized another kind of statements, i.e.,
- **T4**: The subject was both dissimilar to the predicate prototype and did not belong to its extension (e.g., '*In a sense toads are birds*").

It is evident that the subjects of sentences T1 and T2 — the *Target* sentences — which allow the use of different evaluation criteria (*Typicality* vs *Membership*), are *borderline* members of their natural classes, while in sentences T3 and T4 — the *Control* ones — subjects are *typical* members of their categories. As a consequence of the materials construction, negative T1 and T4 sentences should normally be considered as true (high agreement) when judged according to normative membership criteria while positive sentences should be considered as false. On the other hand, the affirmative sentences should be judged as true in the T2 and T3 conditions, while the negatives as false. The Italian expression *"In un certo senso"* (in English *"In a sense"*) should be allowed the shifting between the two different ways to represent concepts to evaluate sentences — based on *Typicality* (prototype) or *Membership* rules (Machery & Seppala, 2011).

Table 7.1 provides a sample of the materials utilized in the experiment.

Type 1	*In a sense bats are birds* *In a sense bats are not birds* *In a sense dolphins are fish* *In a sense dolphins are not fish*
Type 2	*In a sense penguins are birds* *In a sense penguins are not birds* *In a sense seahorses are fish* *In a sense seahorses are not fish*
Type 3	*In a sense canaries are birds* *In a sense canaries are not birds* *In a sense cod are fish* *In a sense cod are not fish*
Type 4	*In a sense toads are birds* *In a sense toads are not birds* *In a sense beavers are fish* *In a sense beavers are not fish*

Table 7.1 A sample of sentences used in the experiment (Zarl & Fum, 2014).

Design

A 2x2 mixed design was adopted, having the modality of sentence presentation (*Pair* vs *Single*) as a between subjects factor and the kind of sentence (*Target* vs *Control*) as a within factor. Furthermore, for each condition (*Pair* and *Single*), four variants (A-B-C-D) were provided, in order to avoid order effects regarding the sentences presentation.

Procedure

All the sentences (64 in total and in Italian) were gathered in a leaflet whose pages contained eight sentences each. Next to each sentence was provided a 7 cm line whose extreme points were marked with the labels "*Completamente in DISACCORDO*" ("*Completely disagree*") and "*Completamente d'ACCORDO*" ("*Completely agree*"), respectively. This is a sort of *Visual Analog Scales (VAS)* used to gather subjective continuous ratings, with the same function of the Likert scale. It allows to subjects to specify their level of agreement to a sentence by indicating a position along a continuous line between two end-points (Hasson & Arnetz, 2005).

Participants had to indicate the degree of their agreement with the sentence by putting a vertical mark on the line. To participants in the *Pair* condition, each page included four randomly pairs of sentences. In each pair, the order of presentation of the positive and negative sentence was randomized. For the participants in the *Single* group, each page contained eight different sentences (affirmative or negative) chosen randomly from the total of 64 possible ones.
To facilitate the comparison with the data reported in Machery and Seppala (2011) participants' responses were translated into a seven-points Likert scale with marks comprised between 0 and 1 cm scored as 1, marks comprised between 1 and 2 cm scored as 2, etc.

An example of an original page (sentences in Italian) with eight sentences is reported — in a *Pair* condition first, and then in the *Single* one. It is clearly notable the difference between these two groups: in the first one, there are coupled sentences, while, in the single one, all the sentences are randomized.

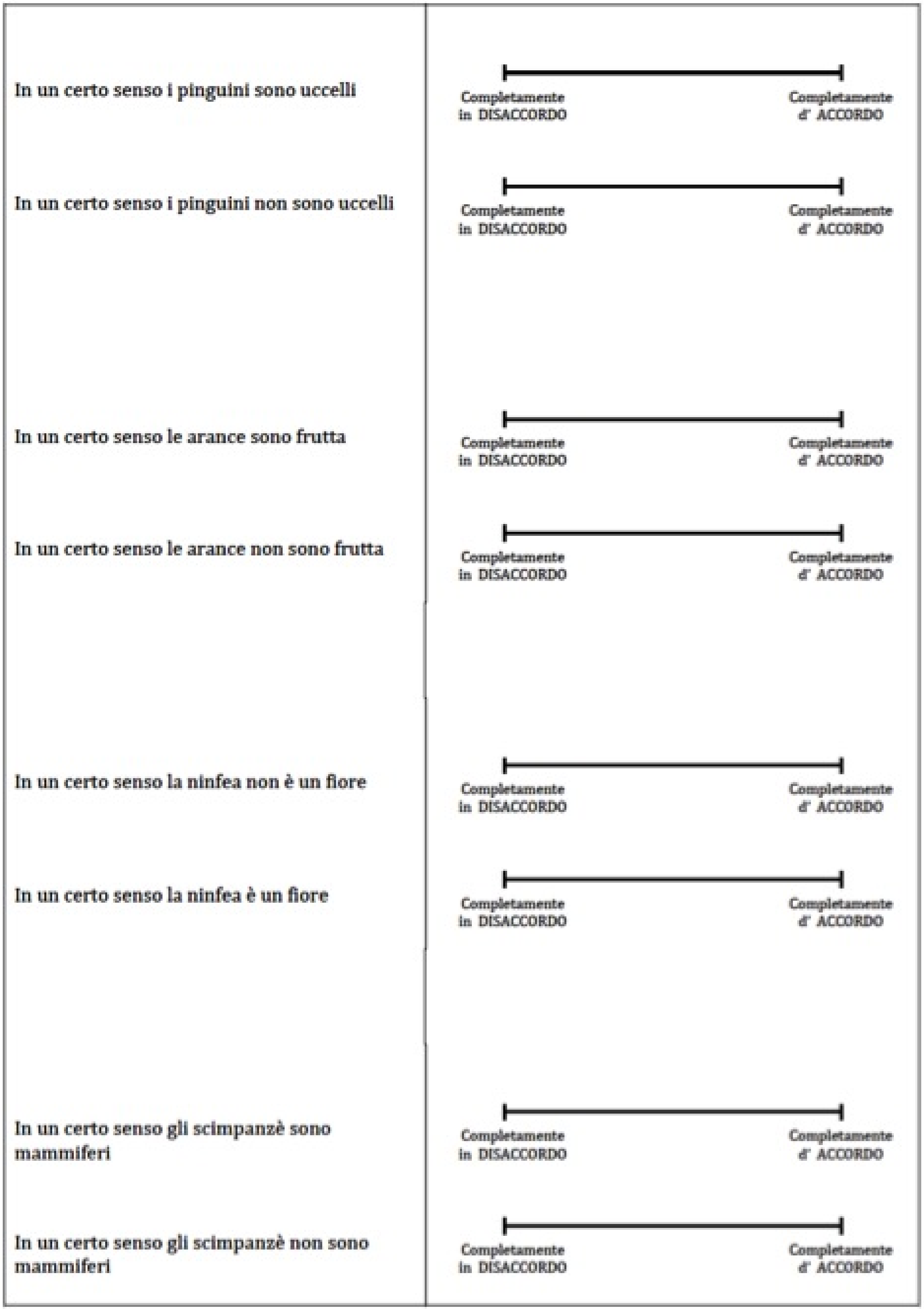
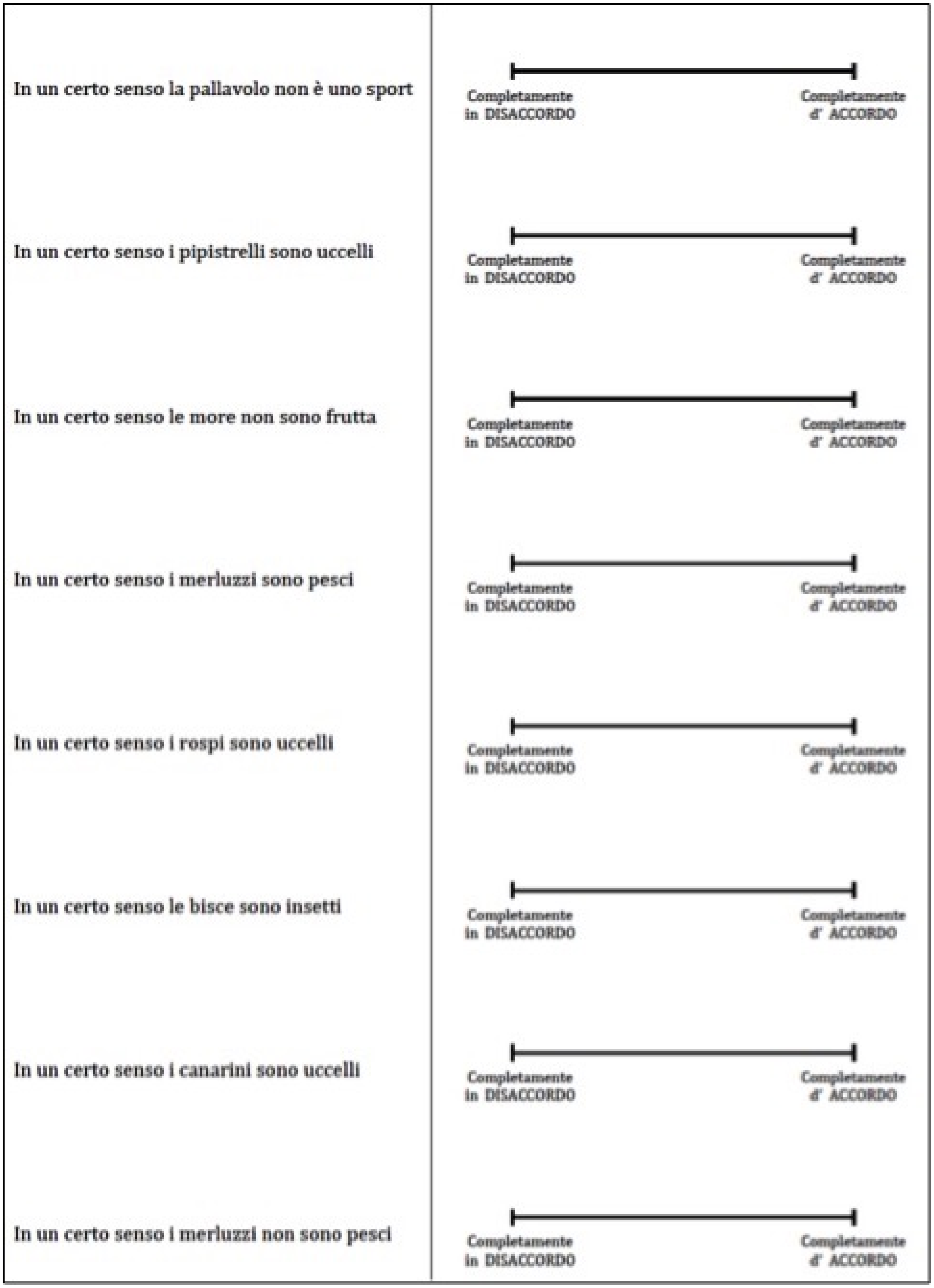


Figure 7.1 Pair condition: affirmative and negative sentences are shown in pair.



In un certo senso la pallavolo non è uno sport	Completamente in DISACCORDO	Completamente d' ACCORDO
In un certo senso i pipistrelli sono uccelli	Completamente in DISACCORDO	Completamente d' ACCORDO
In un certo senso le more non sono frutta	Completamente in DISACCORDO	Completamente d' ACCORDO
In un certo senso i merluzzi sono pesci	Completamente in DISACCORDO	Completamente d' ACCORDO
In un certo senso i rospi sono uccelli	Completamente in DISACCORDO	Completamente d' ACCORDO
In un certo senso le bisce sono insetti	Completamente in DISACCORDO	Completamente d' ACCORDO
In un certo senso i canarini sono uccelli	Completamente in DISACCORDO	Completamente d' ACCORDO
In un certo senso i merluzzi non sono pesci	Completamente in DISACCORDO	Completamente d' ACCORDO

Figure 7.2 Single condition: affirmative and negative sentences are randomized.

In order to clarify the relations between instances and classes, it is important to make clear what participants should consider during the evaluation. Basing on some theories of concepts, it is known that different classes and elements could share some features, both characteristic and definitory. In categorization tasks, you should compare such features to establish correspondences or a discrepancies between the two classes and their elements. For instance, considering *bats* and *birds*, each class has different features (characteristic ones that regard *Typicality* and definitory ones that concern *Membership*, that can coincide). When you have to categorize an element comparing two possible classes, you should try to find some correspondences between their features. In figure 7.3 an example is displayed. *Bats* shares with *birds* some features that are considered as characteristic because most of their elements own these attributes, but the classes do not share the other two that are considered strictly definitory for categorial belongingness.

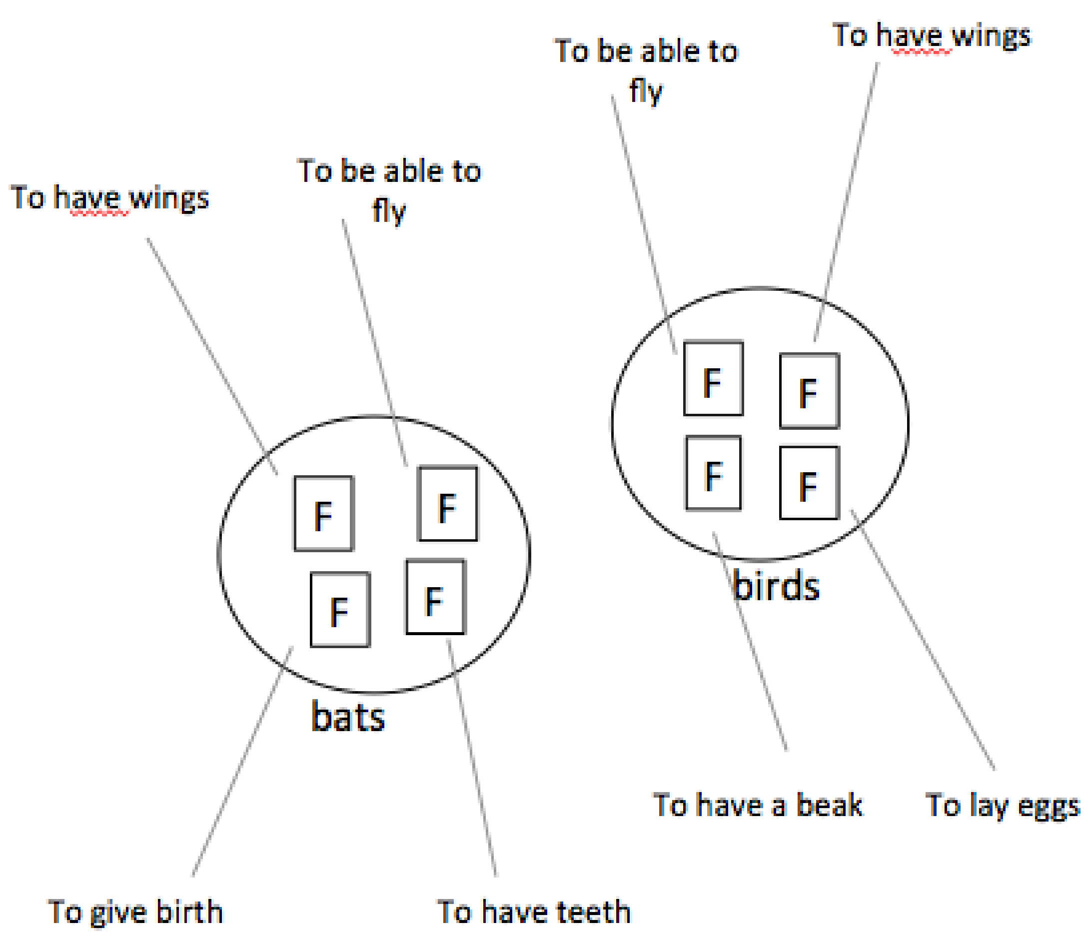


Figure 7.3. An example of two classes with their features.

Scoring criteria

As discussed in section 7.1, the main difference between the predictions made by the HH and the Hybrid Theories concerns how much participants are willing to accept mutually contradictory sentences. In fact, it is not easy to establish when this happens. In their experiments, Machery and Seppala (2011) used two dependent variables: (a) the percentage of participants that had given an answer greater than or equal to 4 to both sentences of a pair, and (b) the absolute value of the difference between the answer given to the positive and the negative sentence of each pair. The reason behind these measures is clear: to accept a contradiction it is necessary that both the sentences (positive and the negative) be considered true. Moreover, at the same time, the difference between the scores should be small — e.g., if a proposition of a sentences pair receives a score of 7 (corresponding to a *"Completely agree"*) and the other one a score of 4 (corresponding, more or less, to "not sure"), it is not licensed to assume that the participant holds both sentences as true.

The criteria used in (Machery & Seppala, 2011) are not entirely satisfactory to establish when a real contradiction is present. In addition to the difference between the scores of the sentences of a pair (which it is called *Delta*, see Figure 7.3), the absolute value of the scores should be considered, too. Thus, there is a difference between a *Delta* = 1 deriving from the scores of 5 and 4 and a *Delta* of the same quantity resulting from a 7 and a 6. The first one denotes a situation of uncertainty while the latter indicates a real contradiction. In addition to the dependent measures used in (Machery & Seppala, 2011) (the scores difference), a new variable was taken into account: the *Sum* of scores of the two sentences. Contradictory sentences should, therefore, be characterized by a low *Delta* and a high *Sum*, indicating that the participant was pretty confident about their agreement. To compute the number of contradictions, therefore, those pairs whose the "expected true" sentence obtained a score less than 4 were discarded from the analysis. This to avoid to take into account some people' mistakes due to the ignorance of the natural superordinate class of a given concept (for instance, the belief that *"In a sense carrots are fruit"*). Therefore, for the remaining sentences, the criteria utilized to acceptance the contradictory pairs were:

- **Delta**: lower than or equal to 2 (*Delta* <=2) and
- **Sum**: higher than 10 (*Sum* >10).

Here, an example of a pair of sentences, where 1 represents the first sentence agreement by a participant in the visual scale, while 2 the second one. *Delta* is the absolute difference value between 1 and 2; and the *Sum*, indeed, the sum of their values.

It should be remembered that the participants' judgments were translated into a Likert scale ranging from 0 (complete disagreement with the statement) to 7 (complete agreement), corresponded to the centimeters on the page.

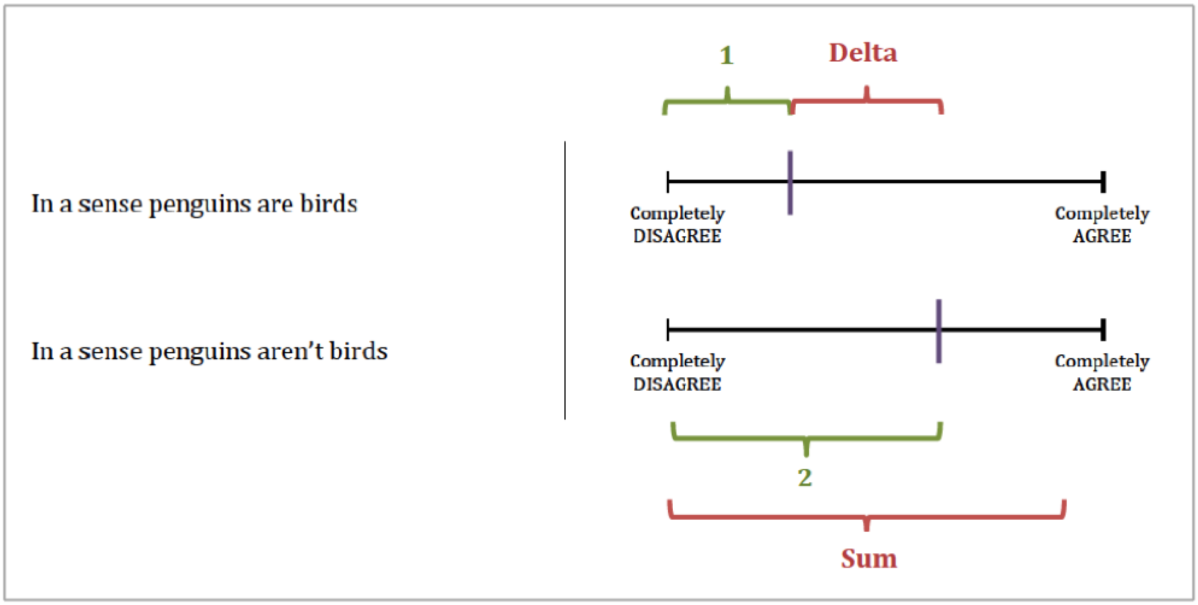


Figure 7.4 Delta and Sum criteria.

7.2.2 Results

Table 7.2 reports the average number of accepted contradictory pairs in the two experimental conditions (*Single* and *Pair*). The results seem to be compatible with the HH: participants did accept contradictory statements. The analysis of variance (ANOVA), taking into account the condition (*Pair* and *Single*) as between factor and the sentence kind (*Target* and *Control*) as within factor, reveals that the acceptance was higher ($F(1, 38) = 5.733; p = 0.02$) for the *Target* sentences than for the *Control* ones.

	CONTROL	TARGET
SINGLE	1.85	2.70
PAIR	0.30	0.90

Table 7.2. Mean number of contradictions accepted in Exp.1 for condition (Zarl & Fum, 2014).

However, there are some significant reservations to be made regarding this result. First of all, the percentage of "real" contradictions in our experiment was much lower than that reported by Machery and Seppala (2011). Furthermore, the ANOVA showed a significant difference ($F(1.38) = 12.04; p = 0.001$) between the *Pair* and *Single* conditions. In the *Pair* condition, contradiction acceptance was 5.65% for the *Target* and 1.56% for the *Control* sentences, while in the *Single* condition, the percentages were 14.37% and 8.75%, respectively.

By adopting a stricter criterion for contradiction (and maybe more realistic), in comparison to the previous experiment by Machery and Seppala (2011), it was found that participants were unwilling to agree with pairs of contradictory sentences presented together (the *Pair* condition), even if the sentences present as subjects borderline instances of their "natural" categories. This finding undermines some empirical evidence in favor of the HH. On the other hand, when the same pairs of sentences were presented separately (the *Single* condition), participants could accept them as both true: this, according to Machery and Seppala (2011), should be at odds with the predictions of the Hybrid Theories.

Therefore, a crucial role played by the contextual framework within which a sentence is evaluated was hypothesized, in order to understand the reasons for this difference The hypothesis of the role played by the context is based on several empirical observations (Braisby, 1993; Braisby & Franks, 1997; Braisby, Franks, & Harris, 1997; Hampton et al., 2006): i.e., major instability and vagueness in categorization judgments could derive from the absence of an explicit context for categorization.

7.2.3 Discussion

As Hampton et al. (2006, p. 1432) stated: "In everyday language, words are used in specific contexts with specific communicative goals, and this contextual support is missing in standard categorization experiments. If individuals respond to the lack of context by arbitrarily constructing one of their own, differences in the resulting conceptual representations would create instability."

Following Machery and Seppala (2011), all the sentences were introduced by "*In a sense...*". The phrase probably did not allow to establish a clear framework to categorize. Therefore, when the contradictory paired sentences were presented simultaneously, participants evaluated them within the same contextual framework (this could explain the lower number of contradictions in the *Pair* condition). On the other hand, when sentences were presented separately in the *Single* condition, participants could choose every time the different perspective (or framework) through which the sentences are evaluated (increasing thus the number of contradictions).

Experiment 2 was carried out to investigate and assess the plausibility of this hypothesis.

7.3 Experiment 2

Experiment 2 investigated the role played by the contextual framework examining whether contradiction acceptance could be reduced by providing a clear context to participants for sentence evaluation. The hypothesis is based on the fact that a homogeneous criterion for categorization (i.e., belongingness evaluation) would be encouraged by the providing of such a context, thus reducing (and almost zeroing) the number of contradiction acceptances.

In addition to a *Neutral* context (which introduced the sentences with the expression "in a sence" and did not therefore provide any indication about the context according to which the sentence should be evaluated), two other conditions, namely *Theory* and *Prototype*, were provided. The *Theory* context emphasized the normative, theoretical aspects of classification, whereas the *Prototype* context stressed the similarity between the instances as the factor to based the categorization of a typical member of the putative class.

7.3.1 Method

Participant

60 University of Trieste students (48 females) — all Italian native speaker, whose age varied from 18 to 53 years (mean = 23.1, sd = 8.0) — participated in the experiment. Participants were randomly assigned to three experimental conditions respectively called: *Neutral, Prototype*, and *Theory*.

Materials

Different instructions regarding the contextual framework according to which the sentences should be evaluated were provided to participants. In the *Theory* group the instructions highlighted the role played by strict membership rules for concepts categorization, in according to a taxonomy based on them. In the *Prototype* condition, to participants were told that concepts are related according to their similarity. Finally, in the *Neutral* group the instructions did not provide any specific indication about the context to be adopted.

In the experimental task, the same sentences of Experiment 1 were used. In the *Theory* group, they were introduced by the Italian expression "*In senso tecnico...* " ("*In a technical sense...*"), while each sentence in the *Prototype* condition started with the words "*Secondo il senso comune...*" ("*According to common sense...*"). Finally, propositions in the *Neutral* condition — the same of the *Single* condition of the previous Experiment 1 —, were introduced by "*In un certo senso...*" ("*In a sense...*").

Design

A 3x2 mixed design was adopted: participants were assigned to three experimental groups (*Neutral*, *Prototype*, and *Theory*) which constituted the between subjects factor, while the sentence kind (*Target* vs *Control*) was the within subjects factor. As in Experiment 1, there were four versions of task for each condition (*Neutral*, *Prototype*, and *Theory*).

Procedure

The procedure was the same used in the *Single* condition of Experiment 1 (see section 7.2.1).

7.3.2 Results

Table 7.3 reports the average number of accepted contradictions for the different kinds of sentences in the three experimental conditions.

	CONTROL	TARGET
NEUTRAL	0.95	1.65
PROTOTYPE	0.90	0.60
THEORY	0.55	0.50

Table 7.3. Mean number of contradictions accepted in Exp.2 for each condition.

An ANOVA was run, taking into account the condition (*Neutral*, *Prototype* and *Theory*) as between factor and the sentence kind (*Target* and *Control*) as within factor. The statistical analysis revealed a significant main effect of the context ($F(2,57) = 3.97, p = 0.02$), while no difference was found in the average number of contradictions arising from the *Target* and *Control* conditions. Furthermore, a post-hoc comparison carried out with the *Tuckey HSD test* showed a significant ($p = 0.011$) difference between the *Neutral* and the *Theory* conditions, while any significant difference between *Neutral* vs *Prototype* and *Prototype* vs *Theory* was revealed.

The amount of contradiction acceptance in the *Prototype* and *Theory* conditions — that differ for the provided defined context from the *Neutral* one — was however extremely low.

Table 7.4 and Table 7.5 describe the data regarding the *Target* and the *Control* sentences. Table 7.4 reports the mean scores assigned to the affirmative and negative statements of the *Target* sentences: T1 and T2. It is important to remember that the participants' judgments were translated into a Likert scale ranging from 1 (corresponding to a complete disagreement with the statement) to 7 (complete agreement).

Condition	**T1**		**T2**	
	Aff	**Neg**	**Aff**	**Neg**
Neutral	3.55	5.72	6.05	2.58
Prototype	2.39	5.96	5.81	2.63
Theory	2.78	5.78	6.03	2.54

Table 7.4. Mean scores assigned to the *Target* sentences: T1 and T2.

Table 7.4 shows that participants are quite willing to agree more with the T1 negative sentences (e.g. *"In a sense bats are not birds"*) and the T2 affirmative sentences (e.g. *"In a sense penguins are birds"*). It is an effect independent from the contextual framework to which participants were exposed: in fact, there was no difference among the scores in the different experimental conditions.

Table 7.5 reports the same data regarding the sentences agreement for the *Control* sentences: T3 and T4. For these statements participants almost completely agreed with the T3 affirmative sentences (e.g., *"In a sense canaries are birds"*) (i.e., scores of 6.69; 6.58, and 6.67) and the T4 negative ones (*"In a sense beavers are not fish"*). Also for this condition, there was no effect of the contextual framework according to which they were asked to evaluate them.

Condition	**T3**		**T4**	
	Aff	**Neg**	**Aff**	**Neg**
Neutral	6.69	1.54	1.89	6.56
Prototype	6.58	1.63	1.52	6.52
Theory	6.67	1.48	1.52	6.53

Table 7.5. Mean scores assigned to the *Control* sentences: T3 and T4.

In summary, in the *Theory* and *Prototype* conditions there was a drastic reduction of the number of contradictions when a definite contextual framework was provided. *Target* sentences virtually became identical to the *Control* ones, not changing the perspective according to which the sentences were evaluated. In particular, in both experimental conditions participants seemed to adopt a theoretical, normative stance (a membership-base categorization) instead of a similarity-based one between the instance to be evaluated and a typical exemplar of the putative class.

7.3.3 Discussion

In Experiment 2, a vague and neutral context (*Neutral* condition) was contrasted with both a theoretical (membership-based) and a prototypical one (similarity-based). The *Theory* and the *Prototype* conditions (i.e., with a more specific provided context) lead to a very low number of contradictions: participants performed in a way that somewhat undermines the HH. Furthermore, there was no difference between these two conditions regarding the criterion used to categorize. In fact, participants seemed to follow a membership-rules criterion instead of *Typicality*.

7.4 General discussion

Two experiments are reported that have tested some predictions sustained by the *Heterogeneity Hypothesis* vs the *Hybrid Theories of Concepts*. One of differences in their predictions concerns the people's willingness to accept contradictory statements.

By applying a stricter criterion for defining a "contradiction", in Experiment 1 participants were unwilling to agree with pairs of contradictory sentences when both propositions were presented simultaneously for evaluation (in the *Pair* condition). This result differs from what was obtained by Machery and Seppala (2011). On the other hand, they were more inclined to accept them when sentences were presented separately (in the *Single* condition).

However, this (partial) contradiction acceptance in Experiment 1, may have another explanation. It might derive from something different from the simultaneous access to separate concepts for the same category, as (Machery, 2009; Machery & Seppala, 2011) claims. The ambiguous phrase like *"In a sense..."* might have induced the participants to evaluate sentences taking into account different contextual frameworks each time propositions were presented separately. For instance, in a sense, i.e. in according to a strict and scientific criterion and membership-based rules, it is true that bats are not birds, but in another sense (i.e., taking into account that they share several features with this class and their prototype, the flight property), it is also true that bats can be considered as birds.

In classification tasks the context has been manipulated in several studies — for a review see Murphy (2002, pp. 413-422). Hampton et al. (2006) provided different instructions to participants, contrasting a purely pragmatic classification context with a more technical one. These conditions were compared with a no-context control condition. However, categorization was not influenced by the context.

In order to better investigate this issue, in the second Experiment, a neutral context was contrasted with both a theoretical and a prototypical one. As the results highlighted, providing a specific context had no effect on the contradiction acceptance: *Neutral* condition showed a higher number of contradictions that the other two conditions. This result undermines the prediction by the HH. Furthermore, no difference was found between the *Theory* and the *Prototype* condition: participants seemed always to follow a criterion based on *Membership* rules (ignoring the *Typicality*).

In any case, it seems clear that the adoption of a definite context might reduce the vagueness and inconsistency in the use of concepts, limiting the necessity to resort to multiple representations for the same conceptual category (according to the HH) or to separate parts of the same concept (according to the Hybrid Theories). These results seem to reduce the impact of the HH on the theory of concepts, highlighting some problems. At the same time, also the Hybrid Theory present several limitations in concept representation. The results are thus not conclusive because it is hard to find a critical test to discriminate between different perspectives, as Murphy (2002) has already argued.

Furthermore, it is important to recognize that further limits are observed that could restrict the generalization of results. They regard the internal validity of experiments: e.g., few participants in each experimental condition, the materials presented only in Italian, the length and the possible boredom of the task.

8 *Fuzzy Concepts* and graded *Membership* and *Typicality* effects

[Zarl, F. & Fum, D. (2015). Membership vs Typicality in Sentence Verification Task: Implication for the Fuzzy Set Theory of Concepts. In P. Bernardis, C. Fantoni, & W. Gerbino (Eds.), TSPC2015, *Proceeding of the Trieste Symposium on Perception and Cognition* (p. 43). EUT Edizioni Universita' di Trieste]

[Zarl, F. & Fum, D. (2016). Concept Membership vs Typicality in Sentence Verification Task. In A. Papafraugou, D. Grodner, D. Mirman, & J. Trueswell (Eds.), TSPC2015, *Proceeding of the 38th Annual Conference of the Cognitive Science Society* (pp. 1134 - 1139). Austin, TXC: Cognitive Science Society]

The *Membership* and *Typicality* factors have been considered within the framework of the *Fuzzy Set Theory of concepts* (FST). Herein the relationship that exists between them, and already found in the study of concepts, is discussed.

8.1 Introduction to the FST and its relationship with graded *Membership* and *Typicality*

Psychology has focused on the study of concepts since its very beginning, leading to many different theories of concepts and various perspectives about their representations and uses.

The *Classical view* (or the Classical Theory of Concepts) (Smith & Medin, 1981) views concepts as sets of rules or definitions: i.e., as necessary and jointly sufficient properties to determine the belongingness of a given entity to the concept in question. From a formal point of view, concepts can be populated with those istances that are defined by the rules. Therefore, an element can be a member of a concept, if it meets all the necessary properties, or it is not, if it lacks at least one necessary property. There is no difference among these members as far as their belongingness is concerned because all the elements of a set satisfy the same membership conditions. On one hand, the *Classical view* is pretty reasonable and intuitive, but, on the other hand, it is inadequate to explain several empirical phenomena, found in many psychological experiments, regarding the *Tipicality* role in categorization and the vagueness of the classes: e.g.,Rosch (1973); Rips et al. (1973); Rips (1975); Mervis et al. (1976); Rosch et al. (1976); Hampton (1979); Barsalou (1989); Bellezza (1984); Hampton (1993).

Graded *Membership* and *Typicality* are incompatible with the *Classical View of Concepts* and cannot be modeled according to the set-theoretic account of such theory. Soon after the discovery of these phenomena, many perspectives were put forward to explain them.

Among them, the *Fuzzy Sets Theory* , introduced by Zadeh (1965), allowed overcoming the limitations of the traditional rules-based approach (e.g., dealing with classes of objects that are not clearly defined). The idea of *Fuzzy sets* have been considered since their beginning as a promising formalism to represent concepts because these kind of categories are critical and pervasive in the human language processes.
However, the idea of *fuzzy sets* rapidly declined among cognitive scientists as a consequence of the publication of a critical paper by Osherson and Smith (1981). For many years the *fuzzy sets* approach practically disappeared from the literature. Only recently, Belohlavek and Klir (2011) shown that many arguments raised against *fuzzy set* were fallacious, contributing to reevaluate this approach and restate their relevance for the study

of concepts.

Using a function with a interval of real numbers [0,1] as range, *fuzzy sets* can be used to model graded *Membership* and *Typicality*. The question that arises is whether graded *Membership* and *Typicality* should be considered as separate phenomena — however, depended on a common underlying factor — or whether they should be viewed as different dimensions, captured by various functions.

Various authors proposed different points of views about this issue: Cai et al. (2012) claimed that graded *Membership* and *Typicality* have different nature and that they are not related. For instance, elements of a concept can obtain a high degree of *Membership* and a low degree of *Typicality* (like *ostrichs* as members of the class of *birds*) while, on the other hand, some entities might have a *Membership* degree close to zero and a higher degree of *Typicality*. This is the case that occurs when people consider some entities as exemplars of a given class even if they do effectively not belong to it (e.g., *whales* as *fish* or *tomatoes* as *vegetable*).

Cai et al. (2012) stated that graded *Membership*, and *Typicality* play different roles in categorization, and thus they have to be computed in different ways. For the *Membership*, the *Classical View*, with its necessary requirements to define a concept, is taken into account, while for *Typicality* an additional mechanism is provided, ranking the instances that meet all the membership conditions (and whose values approximate therefore 1). In this case, the non-defining features, widely shared among the set members, are tallied. It can lead to the assignment of *Typicality* values to entities that present characteristic properties of the concept, but without being members of it.

Kamp and Partee (1995), too, deny a single measure to quantify both the degree of *Membership* and *Typicality* of an instance, considering the latter as the value of proximity to the best example (or prototype) of the concept. Authors considered if the two functions could be considered as connected and if they could eventually coincide for some concepts. For instance, the concept of *male nurse* is an example of lack of correlation Kamp and Partee (1995): the fact of knowing the degree of *Membership* — which depends on the intersection of the classes of *males* and *nurses* — does not help to calculate *Typicality*. However, knowing the *Typicality* value of an instance of concepts like *red* or *chair* helps to establish its membership degree.

A further interesting point of view on this issue is raised by Hampton (2011): he considered *Typicality* and graded *Membership* as separate functions, but based on the same underlying similarity measure. More particularly, "[t]ypicality is a monotonically rising function of similarity, whereas *Membership* is a nondecreasing function of similarity that starts at 0, starts to rise at a certain point k_1, and then reaches a ceiling of 1 at a further point k_2, where k_1 and k_2 are above the minimum and below the maximum values that similarity can take.” (Hampton, 2011, p.219)

To better define the relationship between graded *Membership* and *Typicality*, and their possible connections with the *Fuzzy Set Theory of Concepts*, the following experiments were carried out.

8.2 *Membership* vs *Typicality* in categorization task

The main aim of the experiments was to investigate the role played by *Membership* and *Typicality* in categorization using sentences verification tasks.

Three experiments are presented, carried out using the same method but with different situational contexts. These conditions examined whether graded *Membership* and *Typicality* could be considered as independent factors, influencing the performance of human participants involved in sentence verification tasks, or if they should be considered as interrelated. In the end, a general discussion of the experimental findings is reported, discussing the model of concepts based on the FST.

The experiments investigated the role that graded *Membership*, and *Typicality* play in sentence verification tasks. Participants were asked how much they agreed with a series of sentences of the type: *“...Xs are/are not Ys”*. The sentences differed in the relationship that connected an instance with its putative category: X could be a typical member of Y, an atypical member, a non-member sharing common features with the members of Y, and a clear non-member of Y. Therefore, *Membership* and *Typicality* were orthogonally manipulated, as it was varied the polarity (affirmative vs negative) of each sentence in each experiment.

The context in which membership judgments were made differs between the experiments. It seems intuitive that the degree of agreement with a statement could vary according to the particular viewpoint taken by participants (or the specifically provided context) and not only on the intrinsic relationship between an entity and class. (For a review of studies on the effects of context on concept classification task see: Murphy (2002, pp. 413-422)).

By adopting different kinds of contexts, therefore, *Membership* and *Typicality* were investigated to determine their generality, robustness, and influence on the concept categorization processes underlying the sentence verification task.

8.3 Experiment 3

Experiment 3 investigated whether the effect of *Membership* and *Typicality* could be modulated by providing participants with a purposive context for sentence evaluation. Hampton et al. (2006) adopted a very similar approach: instructions contrasted a purely pragmatic classification context with a more technical one, comparing them with a no-context condition. In their study, however, classification was not influenced by the different frameworks.

To emphasize the possibile role of context, Experiment 3 forced the use of different sentence verification criteria by introducing appropriate cues also in the sentence text.

8.3.1 Method

Participant

60 University of Trieste students (48 females) — whose age varied from 18 to 53 years (mean = 23.1; sd = 8.0) — participated to the experiment. Participants were randomly assigned to three experimental conditions: *Technical*, *CommonSense*, and *Neutral*, respectively.

Materials and Procedure

64 Italian sentences (divided into 32 pairs), the same used in Experiment 1, were adopted in Experiment 3 too.

Sentences involved a relation between an instance and a category and were constructed by balancing the gender and the number of instances and categories which were both of natural (e.g., tomato-fruit) and artificial (e.g., *volleyball-sport*) kind. A sentence in each pair was affirmative, while the other negated it. By varying the three factors of *Membership*, *Typicality*, and *Polarity*, eight different types of sentences were constructed.

The table below provides an example of each kind of sentence:

- positive sentences are labeled with P, and negative sentences are labeled with N.
- M means that the instance is a member of the category, while $\overline{\mathrm{M}}$ negates it.
- T means that the instance shares some common features with members of the category (it is typical), while $\overline{\mathrm{T}}$ negates any similarity between the instance and category.

The interpretation of the positive sentences is simple:

- PMT means that the instance is a typical member of the category,
- $\mathrm{PM\overline{T}}$ that it is an atypical member.

The labeling of negative sentences, obtained by negating the labels of the positive ones, is based on the criteria participants would follow in agreeing with the sentence content. So, for example, accepting the $\mathrm{P\overline{M}T}$ sentence *"...penguins are not birds"*, which negates the $\mathrm{PM\overline{T}}$ *"...penguins are birds"*, means denying *Membership* while acknowledging *Typicality* as evaluation criterion because penguins, even if they are in fact birds, lack some features that are typical of this category.

Sentence kind	**Text**
PMT	*. . . canaries are birds*
$\mathrm{PM\overline{T}}$	*. . . penguins are birds*
$\mathrm{P\overline{M}T}$	*. . . bats are birds*
$\mathrm{P\overline{MT}}$	*. . . toads are birds*
NMT	*. . . toads are not birds*
$\mathrm{NM\overline{T}}$	*. . . bats are not birds*
$\mathrm{N\overline{M}T}$	*. . . penguins are not birds*
$\mathrm{N\overline{MT}}$	*. . . canaries are not birds*

Table 8.1 A sample of sentences used in the experiment (Zarl & Fum, 2016).

The sentences of each experimental condition were introduced by a different phrase which provided a context for their reading. In the case of the *Technical* group, the sentences began with the expression *"In a technical sense..."*, while those of the *CommonSense* group were introduced by the words *"According to common sense..."* (Zarl & Fum, 2014). For the *Neutral* condition the phrase *"In a sense"* was borrowed by Machery and Seppala (2011) who used it to force the different interpretations for the concepts in their experiments. The instructions varied regarding the context according to which participants were asked to evaluate the sentences, too. For the *Technical* group, the instructions highlighted the fact that concepts are structured according to a taxonomy based on strict membership rules. Participants assigned to the *CommonSense* condition were said that a looser interpretation of concepts would take into account the similarity that exists between them. Finally, the instructions for the *Neutral* group were quite general and did not provide any specific indication about the setting to be adopted. All the sentences were gathered in a leaflet whose pages contained eight sentences drawn randomly from the total pool. Next to each sentence was printed a 7 cm line whose extreme points were marked with the labels *Completely disagree* and *Completely agree*, respectively. Participants had to indicate their degree of agreement with the sentence by putting a vertical mark on the line (Hasson & Arnetz, 2005). The position of the mark was measured at the next millimeter and converted into a score in the [0,70] interval of integers.

Design

A 3x2x2x2 mixed design was adopted having Context (*Technical*, *CommonSense*, and *Neutral*) as a between subjects factor and Membership (*Yes* vs *No*), Typicality (*Yes* vs *No*), and Polarity (*Positive* vs *Negative*) as factors within. For each context, four different versions were provided to avoid order effects of sentences presentation.

8.3.2 Results

A four-way mixed ANOVA was run on the experimental data, with one variable between-subjects (*Context*) and three variables within-subjects (*Membership*, *Typicality*, and *Polarity*).
All the main effects of the within-subjects factors were significant:

- *Membership*: sentences with instances as members of the category obtained higher ratings than sentences in which instances were a non-member ($F(1,57) = 338.67$; $p<0.001$).
- *Typicality*: sentences in which the instance was similar to the category typical members scores were higher than those of sentences in which there was no similarity between the instance and the category ($F(1,57) = 443.91$; $p<0.001$).
- *Polarity*: positive sentences obtained higher judgments than negative ones ($F(1,57) = 64.10$; $p<0.001$).

On the other hand, there was no effect of the different contexts on the participant's performance, and any significant interaction with the other factors.
The table below reports the average scores for the different sentence kinds. The contextual conditions have been collapsed in the table, in order to facilitate the comprehension of the data.

An interesting three way interaction *Membership* x *Typicality* x *Polarity* ($F(1,57) = 4.58$; $p<0.05$) was found among the within-subjects variables. Even if the interaction effect has

Positive			Negative	
	$\overline{\text{M}}$	M	$\overline{\text{M}}$	M
$\overline{\text{T}}$	13.21	44.27	9.21	33.46
T	36.00	62.80	27.79	54.50

Table 8.2 Average scores — all sentences, contextual conditions collapsed.

quite a small magnitude, it constitutes an original and unexpected result that requires an adequate explanation (see section 8.6).

Moreover, a further analysis of the data was run, taking into account only the sentences is which the two criteria (*Membership* and *Typicality*) were directly contrasted to determine which criterion was more influential in determining the participants judgments. A two way mixed ANOVA was carried out, having *Context* as a variable between, and Criterion (i.e., *Membership*, for the PM$\overline{\text{T}}$ and NM$\overline{\text{T}}$ sentences, vs *Typicality*, for the P$\overline{\text{M}}$T and P$\overline{\text{M}}$T ones) as variable within. A significant main effect ($F(1,57) = 19.13$; $p<0.001$) of *Criterion*, with *Membership* sentences obtaining significantly higher ratings than *Typicality* ones (average scores of 38.86 and 31.90, respectively), was revealed.

8.4 Experiment 4

Experiment 4 is considered a control experiment, with the aim of ascertaining the generality of the obtained effects of the previous ones. It investigated the influence of the presented material on *Membership* and *Typicality*, (and their possible interaction with Polarity). In the Experiment 1, in fact, it was found that participants were more likely to agree with contradictory sentences assigning high ratings to both, when the sentences were displayed separately in random order (e.g., ' *'In a sense penguins are birds"* vs *"In a sense penguins are not birds"*. Contradiction acceptance was lower in the *Pair* condition (i.e., when sentences were presented together).

8.4.1 Method

Participant

40 italian participants (31 females) — whose age varied from 20 to 42 years (mean = 26.1, sd = 4.8) — were engaged in the experiment. They were randomly assigned to two experimental conditions: *Pair* vs *Single*.

Materials and Procedure

The same sentences and instructions of Experiment 3 were used: *"In a sense..."* introduced the propositions, adding no further hint for the interpretation. In the *Single* condition, the procedure was identical to the previous experiment (sentences in random order); whereas in the *Pair* condition, sentences were presented together (one below the other on the same page). For this condition, the pairs presentation order and the order of presentation of negative and positive sentences were properly randomly balanced.

Design

A 2x2x2x2 mixed design was adopted with Context (*Pair* vs *Single*) as a variable between, and *Membership*, *Typicality*, and *Polarity* as variables within subjects.

8.4.2 Results

The experiment showed the same pattern of results of Experiment 3.
A four-way ANOVA revealed the only main effects of:

- *Membership* ($F(1,38) = 181.04$; $p<0.001$),
- *Typicality* ($F(1,38) = 124.872$; $p<0.001$), and
- *Polarity* ($F(1,38) = 52.889$; $p<0.001$).

Table 8.3 displays the mean scores for the different sentences. Because the *Context* did not prove significant, the data are presented without taking it into account.

	Positive		Negative	
	$\overline{\text{M}}$	M	$\overline{\text{M}}$	M
$\overline{\text{T}}$	14.49	50.15	7.31	37.38
T	36.12	59.82	25.72	55.26

Table 8.3 Average scores—all sentences, contextual conditions collapsed.

The ANOVA confirmed also the three-way interaction *Membership x Typicality x Polarity* ($F(1,38) = 14.21$; $p<0.001$) already found in Experiment 3, become here more perspicuous. The gain due to *Typicality* is clearly greater for the non-members $\overline{\text{M}}$ in the case of Positive sentences, and for members M, in the Negative ones. Moreover, the ANOVA revealed another interesting interaction *Context x Membership* (F(1,38) = 6.25; p<0.05), absent in Experiment 3. I.e., the participant's judgments become more polarized (i.e. with higher scores for M sentences and lower scores for the $\overline{\mathrm{M}}$ ones) in the *Pair* condition, in comparison to the *Single* one. This polarization effect obtained in the *Pair* condition confirms what had already been pointed out previously by Zarl and Fum (2014).

	Member M	Non-Member $\overline{\mathrm{M}}$
Pair	58.88	21.20
Single	51.64	30.25

Table 8.4 The *Context* x *Membership* interaction (Zarl & Fum, 2016).

Finally, a second ANOVA was performed, taking into account the *Polarity* for the M$\overline{\mathrm{T}}$ and $\overline{\mathrm{M}}$T to determine which criterion, between *Membership* and *Typicality*, was more influential in determining the participants judgments. This mixed two-way ANOVA had *Context* as between-subjects factor and *Criterion* as factor within. It revealed only the significant main effect (F(1,38) = 31.32; p<0.001) of *Criterion*, with *Membership* sentences (mean = 43.76) obtaining significantly higher ratings than *Typicality* ones (mean = 30.92).

8.5 Experiment 5

Experiment 5 was carried out to check the effect of the introductory phrase of the sentences and to acertain whether the previous findings could somehow depend on it. The idea for this experiment derived from some occasional remarks made by participants in Experiment 4 and by those assigned to the *Neutral* condition of Experiment 3. They after reading some sentences introduced by *"In a sense..."*, asked *"In which sense?"*.
Experiment 5 aimed to contrast the simple assertion or negation of *Membership* with the sentences introduced by *"In a sense..."*, adopted in the previous experiments to induce a neutral context for sentence interpretation.

8.5.1 Method

Participant

The participants were 64 residents in the Friuli-Venezia Giulia region in Italy (49 females) whose age varied from 19 to 63 years (mean = 25.74; sd = 8.2).

Materials and Procedure

There were two different conditions between subjects: the *Neutral* condition and the *No-Context* condition. For participants in the *Neutral* one, the materials and the procedure were identical to those used of the *Single* condition of Experiment 4 (and of the *Neutral* condition of Experiment 3). In the *NoContext* condition the same sentences were presented without the introductory phrase *"In a sense..."* (e.g. *"Penguins are birds"*, *"Canaries are not birds"*, etc.).

Design

The same 2x2x2x2 mixed design of Experiment 4 was adopted, but the levels of the between-subjects *Context* variable were *Neutral* and *NoContext*, respectively.

8.5.2 Results

The same pattern of results found in the previous experiments was replicated in Experiment 5, too. More particularly, the *Context* factor did not have any statistically significant effect on the participant's performance indicating that the previous findings were not influenced by the presence of the introductory phrase *"In a sense..."*. The table below reports the average scores for the different conditions.

	Positive		Negative	
	$\overline{\mathrm{M}}$	M	$\overline{\mathrm{M}}$	M
$\overline{\mathrm{T}}$	11.68	47.62	5.94	32.99
T	37.05	64.05	22.38	54.64

Table 8.5 Average scores—all sentences, contextual conditions collapsed (Zarl & Fum, 2016).

Again, a four-way ANOVA revealed the significant main effects of:

- *Membership* ($F(1,62) = 433.67$; $p<0.001$),
- *Typicality* ($F(1,62) = 585.33$; $p<0.001$),
- *Polarity* ($F(1,6262) = 188.44$; $p<0.001$), and
- their three-way interaction ($F(1,62) = 19.72$; $p<0.001$) indicating the greater advantage due to *Typicality* that occurs in the Positive $\overline{\mathrm{M}}$ sentences.

Furthermore, contrasting directly *Membership* and *Typicality*, a mixed two-way ANOVA, using *Context* and *Criterion* as factors, was carried out on sentences. It shown a significant ($F(1,62) = 40.48$; $p<0.001$)) main effect of *Criterion*, obtaing the *Membership* (mean = 40.31) higher scores than the latter (mean = 29.72).

8.6 General discussion

The three experiments in the previous section lead to concordant results.

First of all, the graded *Membership* and the *Typicality* effects characterizing concepts were confirmed, underlying their role in determining the degree of agreement with statements that assert or deny the belongingness of an instance to class. Between the two factors, *Membership* played the dominant role. The analyses run in all the experiments revealed that when the factors were directly contrasted, participants assigned higher scores to sentences with atypical members of the class in comparison with those which the instances simply shared some similarity (typical) with the class members but are non-members. This is a general result that was not affected by providing participants with different evaluation contexts. The *Membership* criterion played the dominant role in judgments even when explicitly participants were instructed to take into account the similarity between the instance and the typical exemplars of the class (Experiment 3). This trend of results, that are against the hypothesis of the thesis about the importance of the *Typicality*, could be explained taking into account the experimental setting. Using four different conditions (i.e., T1-T2-T3-T4) for the same class, probably lead to activate various elements and attributes of the same category. The four element differ for *Membership* and *Typicality* respectively, but, for istance, if a participant had to evaluate a belongingness of a "penguin" to the class "bird", would be influenced by the element "bat" already seen in the task. In fact, the "bat" could had already activated some attributes to compare with the"bird" 's ones, that could regarded membership based-rules, leading to a kind of "forced" answer, because of the saliency of some attributes.

In Experiment 4, the simultaneous comparison between contradictory statements (in the *Pair* condition) led to a polarization of judgments (showing higher scores for sentences asserting *Membership* and lower scores for those denying it, even if the instance was a member of the class) but did not change the general pattern of results.

The same pattern of results was also found in Experiment 5, when assertions and negations were expressed directly in the sentences (*no-context* condition) or were somehow dampened by the introductory phrase *"In a sense"*.

It seems evident that *Membership* and *Typicality* are not independent factors, but they interact with each other in a subtle way. In the affirmative sentences, the gain in the score due to *Typicality* is higher for non-members than for the members of a category while it is virtually identical for the negative sentences. It represents the most interesting and original finding deriving from all the experiments and, at least to our knowledge, no existing model of concepts can predict and explain it.

Furthermore, the experimental results highlight some interesting issues for models of concepts based on the *Fuzzy Sets Theory of Concepts*: the role of *Typicality* in negative sentences, and the matter of the score given to a sentence and its negation.

Focusing on the interpretation of negative sentences: following a strictly logical point of view, if you deny that an instance is a member of a set, it can be considered the same to stating that it is a member of the complement set. For example, if you negate that *bats* are *birds* is like you argue that they are *non-birds*. These kinds of concepts, defined in a negative way, are often cited (Connolly, Fodor, Gleitmain, & Gleitman, 2007) as examples of concepts without a prototype. In this sort of situation, the similarity between the instance and the class *non-birds* should not play any role, although it is not difficult to establish whether a certain instance is a *non-bird*.

The problem is that in these experiments *Typicality* manifest its effect also in negative sentences: the N$\overline{\text{M}}$T *"Penguins are not birds"* receives higher scores than the N$\overline{\text{MT}}$, *"Canaries are not birds"*, and the same effect occurs for the sentences whose instance is a member of the category. In a personal communication, it has been suggested: "the fact that *Typicality* is present in negative sentences does not mean that it is the effect of any prototype for the negation of the concept. It just means that participants are still capable of evaluating the distance of a non-member to the prototype of the positive category in terms of similarity". The problem is that what is considered as a strong pragmatic effect of negation, cannot be easily adapted and modeled into the mathematical theory of *Fuzzy Sets*.

9 Role of *Membership* and *Typicality* in Web ontologies

This study was run in collaboration with prof. M. Hepp, *E-Business and Web Science Research Group, University of Munich, Germany.*

The aim was to analyze the impact of the richness of presentation, i.e., the influence of cues on the quality of consensus, to be precise, on the ability of human users to use ontology classes in a consensual and reliable way,of an ontology on its correct usage by humans. Furthermore, the study also aims to investigate how some aspects of the ontology schema.org (kind of instances, instances format, and provided documentation) can affect the users' categorization comprehension and coherence.

9.1 *Membership* and *Typicality* in schema.org

Ontologies in Computer Science are conceptual models that are augmented by formal axioms and are shared by a community, aiming at specification of conceptual elements that exist in a given domain (Gruber, 1993; Guarino & Giaretta, 1995; Hepp, 2007). Historically, the design of such ontologies has been governed by the final usefulness of the conceptual distinctions for the consumption and processing of the respective data and knowledge bases. In other words, ontologies were designed so that the resulting data would be most accessible for computer-based data processing. Membership-based rules are almost always adopted, principally because of the computational languages (e.g., the *Description Logics*) used to describe classes in Web ontologies. This languages represent the most efficient way to represent data for computers, and it is surely a good compromise in knowledge representation. However, the consideration of human cognitive functioning is recently becoming more and more significant in ontologies concept representation (Stark & Esswein, 2012; Frixione & Lieto, 2013b), so that becomes necessary to take into account the cognitive theories of concepts, and all the findings in the psychological field. In fact, giving importance to how humans represent ideas and concepts in their mind results critical to enhancing the efficacy of ontologies, that should help and support humans in different tasks (Ramesh et al., 1999; Lesot et al., 2008; Peroni et al., 2008; Aimè et al., 2010; Stark & Esswein, 2012; Frixione & Lieto, 2013b; Lieto, 2013). As emerged from the psychological literature analysis, *Typicality* (Britz et al., 2009; Yeung & Leung, 2006b, 2010; Aimè et al., 2010; Frixione & Lieto, 2013b, 2014) should be considered in ontology concept representation.

The issue of *Typicality* could be considered related to the way concepts are presented and there are some studies that underline the role played by it, especially in the concepts recognition and understanding tasks performed on the Web (Lupyan & Thompson-Schill, 2012; Kannan, Talukdar, Rasiwasia, & Ke, 2011).

9.2 Experiment 6

The aim was to measure and analyze the consensus given by participants regarding ontology classes in schema.org, trying to decompose and take into analysis two different factors implicated in categorization: *Membership* and *Typicality*. Ontologies do not usually consider *Typicality* in their categories, even if this is fundamental in cognitive categorization functioning. So, based on some *Membership* rules (attributes) given by schema.org, different levels of *Typicality* of exemplars in the ontology were taken into account for the evaluation of the task (i.e., the validation of the ontology). It is, therefore, important to evaluate if participants reliably agree between different levels of *Typicality*, in order to understand the role of such factor.

The research questions that were dealt with in the experiment are as follows:

- **RQ 1:** How does the number of features in the presentation of an ontology influence the ability of human users to apply the ontology correctly?
- **RQ 2:** Which types of features are the most effective?
- **RQ 3:** Are the effects of the number and kind of features uniform across different Types in the ontology or do the effects differ very much by the Type?
- **RQ 4:** Are there any effects of *Typicality* and *Format* as independent variables on belongingness judgments?
- **RQ 5:** Are there any interaction effects between *Typicality* and *Format* on belongingness judgments?

A computer-based experiment was set up, in which participants had to classify randomly generated sets of objects into given disjoint and overlapping categories derived from schema.org Types. Instances were part or not of a category, varying in the modality of *Format* (image or text) and in *Typicality* (different levels of similarity to the prototype concept). Furthermore, each task randomly displayed a varying number of features for the concept, that could enhance or diminish its understanding.

The aim of this study was to analyze the participants' performance using instances from schema.org, considering the *Typicality*, the *Format* modality, and the *provided documentation* (the displayed features) as independent factors.

9.2.1 Method

Participants

73 participants (32 female), whose age varied from 23 to 65 years (mean=32.12; sd=6.76), took part in the experiment. They filled a brief questionnaire at the beginning of the experimental session, providing some personal information (age, gender, field and level of education, field profession, the level of English skill, mother tongue, and nationality), to be used in aggregated way for further cluster analyses. Participants varied in term of nationality and mother tongue (mainly were Italians n=29; Germans n=20; English n=12; and the others came from different European and extra-European countries).

Materials

Twelve categories were randomly selected from schema.org, based on their popularity. One of the classess (['SearchAction']) was removed because of its inadequacy for the structure of the experiment. Thus, the choosen categories were: ['WebSite'], ['WebPage'], ['Product'], ['ImageObject'], ['Offer'], ['Person'], ['BlogPosting'], ['PostalAddress'], ['Article'], ['Organization'], ['Blog'].

For each category, a balanced set of questions was generated according to a Typicality(4)xFormat(2) within-subject design. Manually craft examples of instances for the classes might have different *Typicality* distance (the four levels of *Typicality*):

- **Central Member** = T1
  An exemplar that is very typical of a category and that shares almost all the attributes of the class.

- **Borderline Member** = T2
  An exemplar that is considered a borderline member of a category. It is part of it but it is not so typical (i.e., it does not share all the most typical attributes with the class).

- **Controversial nonMember** = T3
  It is a non-member of a category, but it shares some specific attributes with it.

- **Obvious nonMember** = T4
  A very clear non-member of a class. It has no attributes shared with the class. It might be considered as a central exemplar (typical) of another category.

Examples might be either an *image* or *text* (the two levels of *Format*).

To be considered as a valid inclusion relation, the concept instances and the category had to share the same attributes as defined by schema.org. A set of n=88 instances were created, resulting from a mix of T1, T2, T3, and T4; either represented by text or by an image. For each case the belongingness was established, based on the agreement judgments provided by two indipendent experts. 88 ISA questions of the form *"IS exemplar x An instance of category c?"* were generated: 8 questions for each of the 12 classes. For each class, 8 questions were generated resulting from the product of the 2 formats (image vs text)and 4 typicality levels (T1-T4). Each participant received 44 queries derived from 4 randomized queries for each of the 11 classes.

In the categorization task, another variable (i.e., the so called *provided documentation*) was considered. For each ISA question, the class to evaluate was described with 6 possible different features derived from schema.org, that aim to add further information for each category. A class could be defined only by its human-readable name, and it was considered the baseline feature condition (it means n=0 of provided features).

The six features (with examples for *Organization*) were:

- Description: *An organization such as a school, NGO, corporation, club, etc.*
- Position in the hierarchy: *Thing >Organization*
- More specific types: *Airline; Corporation; EducationalOrganization; GovernmentOrganization; LocalBusiness; NGO; PerformingGroup; SportOrganization*
- Examples: *Apple Inc.*
- Counter-examples: *Oxford Street*
- Pitfalls (exceptions): *"Robert Bosch" is an Organization even if it seems to be a name of a Person.*

The starting idea was to define the first three features as strictly descriptive, depicted necessary and jointly sufficient attributes, and there were directly derived from schema.org, representing, somehow, membership-base rules. The other ones were manually created from the attributes of schema.org classes and elements, and were merely intensional, considering them as an intent of representing typicality and representativeness.

The set of shown features remained the same for the same user and the same type in order to avoid memorization effects (if a user had seen a feature for the same type before, the effects of the features would be blurred).

The aim was to measure the influence of all these variables (*Tipicality, Format* and *provided documentation*) on categorization.

Design

A *Typicality*(4)x*Format*(2) within-subject design was adopted, having four levels of *Typicality* (*central Member (T1)*, *borderline Member (T2)*, *controversial nonMember (T3)*, and *obvious nonMember (T4)*) and two levels of Format (exemplars represented by *text* or an *image*).

The documentation (the provided class features for each query) presented 2 different levels: *no-documentation* (when no features were presented to participants) vs *full documentation* (when all the 6 features were provided). Intermediate values (1, 2, 3, 4, and 5 features) were excluded as conditions in the analysis because of the too many variable cases to evaluated due to the randomization. The amount of documentation(2) was analysed in the 11 different Types, obtaing an *documentation*(2)x*Types*(11) within-subject design.

Procedure

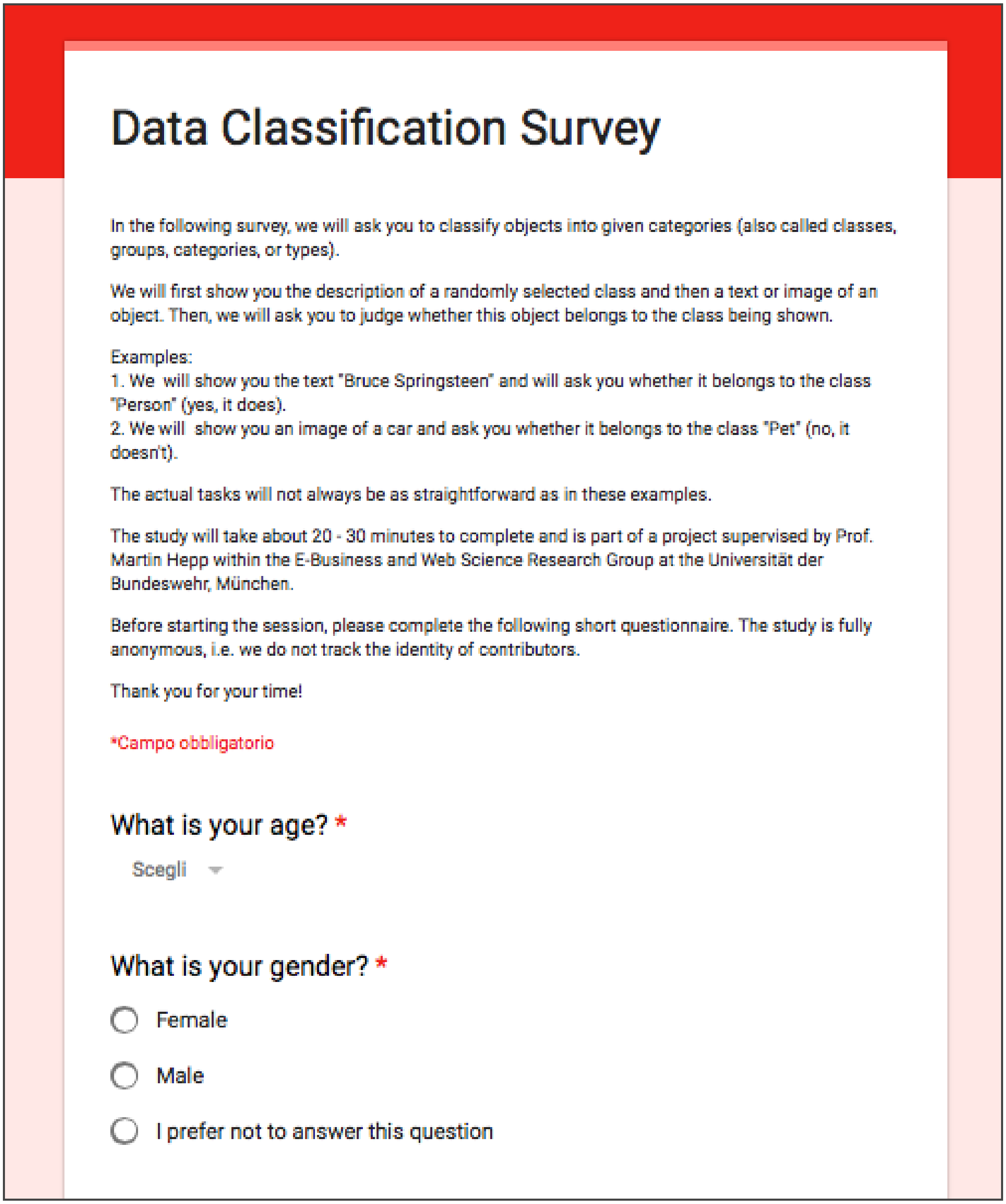
An online experiment was set, in which participants were shown a schema.org type with a randomly set of documentation features.

Participants had to categorize random instances (represented using either textual or imagery format), by answering Yes or No to an ISA question of the form *"IS exemplar x An instance of category c?"*. After the Y/N answer the participant evaluated his/her confidence on a 4-point Likert scale (with *1= easy (I am very confident)* and *4= very hard (I had to guess)*).

Googler Forms, enhanced by a specific home developed algorithm, was used to generate the online survey providing each participant with a different set of randomized questions. After participant's approval, he/she received a link in his/her e-mail address, together with some precise instructions to fill it, and that redirected to a web page with the survey. Then, he/she could begin to fill it, and all the information were directly collected in a database, stored online, in *Google Drive*. The presentation of the online survey had the goal to remind the schema.org web page aspect: e.g., using a red bar on each page where the human-readable name of the category was presented.

Figure 9.1 shows an example of the first web page displayed to participants, followed by an example of one of the 88 possible ISA questions of the survey. It intentionally appears similar enough to the schema.org web page, where types are presented, following the same display pattern (name of type on the top with a red bar, and features below).

Figure 9.2 displays an example of the survey web page with the ISA question: at the top of the page, the task is described, below the name of the Type is followed by the 6 possible features. An ISA question is then provided, and the difficulty rating of that specific answer is added. A blank space for a final comment is supplied at the end.



Data Classification Survey

In the following survey, we will ask you to classify objects into given categories (also called classes, groups, categories, or types).

We will first show you the description of a randomly selected class and then a text or image of an object. Then, we will ask you to judge whether this object belongs to the class being shown.

Examples:
1. We will show you the text "Bruce Springsteen" and will ask you whether it belongs to the class "Person" (yes, it does).
2. We will show you an image of a car and ask you whether it belongs to the class "Pet" (no, it doesn't).

The actual tasks will not always be as straightforward as in these examples.

The study will take about 20 - 30 minutes to complete and is part of a project supervised by Prof. Martin Hepp within the E-Business and Web Science Research Group at the Universität der Bundeswehr, München.

Before starting the session, please complete the following short questionnaire. The study is fully anonymous, i.e. we do not track the identity of contributors.

Thank you for your time!

*Campo obbligatorio

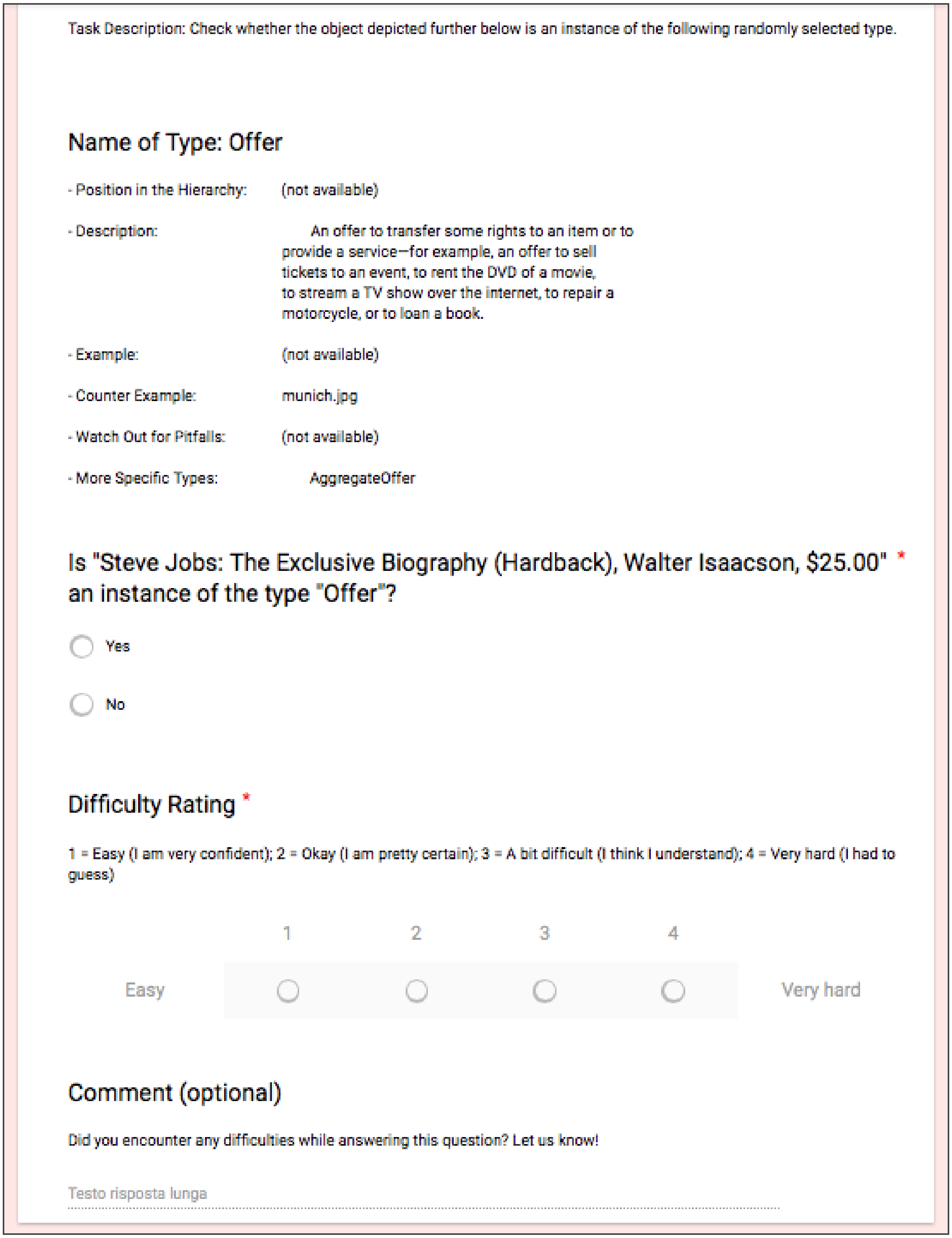
What is your age? *

Scegli

What is your gender? *

- Female
- Male
- I prefer not to answer this question

Figure 9.1. First page of the survey displayed to participants, with the survey instructions and the queries regarding personal information.



Task Description: Check whether the object depicted further below is an instance of the following randomly selected type.

Name of Type: Offer

- Position in the Hierarchy: (not available)
- Description: An offer to transfer some rights to an item or to provide a service—for example, an offer to sell tickets to an event, to rent the DVD of a movie, to stream a TV show over the internet, to repair a motorcycle, or to loan a book.
- Example: (not available)
- Counter Example: munich.jpg
- Watch Out for Pitfalls: (not available)
- More Specific Types: AggregateOffer

Is "Steve Jobs: The Exclusive Biography (Hardback), Walter Isaacson, $25.00" an instance of the type "Offer"? *

Yes

No

Difficulty Rating *

1 = Easy (I am very confident); 2 = Okay (I am pretty certain); 3 = A bit difficult (I think I understand); 4 = Very hard (I had to guess)

	1	2	3	4	
Easy					Very hard

Comment (optional)

Did you encounter any difficulties while answering this question? Let us know!

Testo risposta lunga

Figure 9.2. Example of an ISA question in the survey.

On the average a participant received:

- one query about the image of a member (T1 and T2) of each of the 11 classes;
- one query about text (e.g., the instance name) referring to a member (T1 and T2) of each of the 11 classes;
- one query about the image of a member (T3 and T4) of a class different from the 11 selected for the trials or included in the residual 10;
- one query about text (e.g., the name) referring to a member (T3 and T4) belonging to a class different from the 11 used in the trials or to a class included in the residual 10;
- some trials with *no-documentation* and some with *full-documentation*.

9.2.2 Results

An analysis of individual responses provided by users in the framework of the *Unequal Variance Model* of *Detection Theory* was run.

Single Detection Theory (SDT) is a model used to measure the sensitivity in making decisions under a condition of uncertainty.

The model assumes that a stimulus/target/sentence might be present/true and that a user can detect/reply in an affirmative or negative way. These different 4 patterns of responses are then obtained:

	reply "YES"	reply "NO"
stimulus YES	**HIT**	**MISS**
stimulus NO	**FALSE ALLARM (FA)**	**CORRECT REJECTION (CR)**

Table 9.1. Table that summarizes the 4 possible pattern of responses/performance.

In SDT, d' and c are calculated as follows:

- **d'= z(Hit) - z(FA)**, conventional measure in *Detection Theory* to measure user's **sensitivity** in the Y/N categorization task [d' ranges from zero (no sensitivity, corresponding to p(Hit)= p(FA)), to infinity, corresponding to a perfect performance];
- **c= -0.5 [z(Hit) - z(FA)]**, conventional measure in *Detection Theory* to measure user's **criterion** in the Y/N categorization task. Positive values corresponds to a prevalence of "No" responses, typical of a "conservative" user; negative values corresponds to a prevalence of "Yes" responses, typical of a "liberal" user.

The indices of performance for the *Unequal Variance Model* are:

- **da** for sensitivity (like *d'*, *da* is from 0 for chance level to + infinity for perfect performance), and
- **ce** for criterion (like *c*, positive values mean a bias for "No", negative values a bias for "Yes").

Oneway analyses with ***Typicality*** and ***Format*** as independent variables

The four levels of query exemplars used in the experiment were defined as follows: T1= *central members*; T2= *borderline members*; T3= *controversial non-members*; and T4= *obvious non-members.*

A separate oneway analyses of responses to ISA questions using *Typicality* and *Format* as independent variables was also run:

- *Typicality*: grouping *Borderline Member and Controversial non-Members* (T2 and T3) vs *Central Member and Obvious non-Member* (T1 and T4), and comparing these two different levels of *Typicality* called respectively:
  - *central exemplars* (T1 and T4)
  - *borderline exemplars* (T2 and T3)
- *Format* (image vs text)

The following results were obtained:

- a strong significant effect of *Typicality* (2-tailed $t_{(72)}$=15.73, p<0.0001), confirming that ISA judgments were more accurate for *central exemplars* than *borderline exemplars*, as aspected;
- no effect of *Format* (2-tailed $t_{(72)}$=0.756, p=0.452);
- a significant response bias (criterion effect) for *Typicality*: participants showed higher yes rate for *borderline* than *central exemplars* (p=0.00011);
- no criterion effect in the *Format* analysis.

A significant effect of *Typicality* emerged, confirming that ISA judgments were more accurate for central (T1 and T4) than borderline exemplars (T2 and T3); whereas there was no effect of *Format.* The response bias was statistically significant only in *Typicality* analyses: participants showed a liberal bias in the *Typicality* analysis (higher yes rate in questions involving borderline than central exemplars) but any bias effect in the *Format* analysis.

The difference between *central* and *borderline* exemplars, significant for both indices of performance, is showed in Table 9.2.

	da	ce	probability	T	df
central	2.18	0.08	< 0.00001	15.73	72
borderline	1.06	-0.08	0.00011	4.09	72

Table 9.2. Indices of performance (ce and da) of *central* and *borderline* exemplars.

Apart from the obvious advantage for *central* exemplars, the more conservative user attitude in answering central positive queries, compared to the liberal (more yes than no responses, independent of accuracy) attitude in answering the borderline positive queries was found. This is in contrast with those frequently found in the literature on Y/N tasks: when the query is objectively more challenging, respondents become less accurate and more conservative in using the positive answer.

Exemplar *Format* (image vs text) affects belongingness judgments

The "belongingness" is considered the concise dimension that synthesizes the type membership Yes/No judgment and users' confidence in delivering it. To evaluate the effect of *Format* (image vs text) on belongingness judgments, responses were scaled to the 4 "image" queries ($T1_{image}$ - $T2_{image}$ - $T3_{image}$ - $T4_{image}$) and the 4 "text" queries ($T1_{text}$ - $T2_{text}$ - $T3_{text}$ - $T4_{text}$) separately, in the following way.
A raw belongingness score was synthetized by taking the product of the dichotomous Y/N response (with Y= 1 and N= -1) and the 4-points rating (with 0.25= min and 1= max confidence). The confidence was derived from the 4-points Likert scale used in the survey, where 1 corrisponded to *"I am very confident"* (now 1) and 4 to *"I guess"* (now 0.25). To better represent a suitable scale, the 4-points Likert scale was transformed to a 0-1 scale, using intermedied values (0.25= min confidence; 0.5= 3 in the original Likert scale; 0.75= 2 in the original Likert scale and 1= max confidence). The 0 values were deliberately substituted with 0.25 to avoid any problems related to the arithmetical product of 0 value in the analysis. Regardless, this transformation was possible because only 57/3212 queries received a 4 (that would have corresponded to 0 here) in the experiment and it had not such a heavy weight in the accumulative analysis.

Raw query scores (ranging from -1 to 1) were standardized within the appropriate format subset (image vs. text). Average and standard error of the mean (SEM) values are shown in Figure 9.3.

The four levels of query exemplars were defined as follows: T1= *central members*; T2= *borderline members*; T3= *controversial non-members*; T4= *obvious non-members.*

Summarizing:

- the product of rating (0.25-1) x (+1) for *Yes* and the product of rating (0.25-1) x (-1) for *No* were taken as raw response scores, for every participant, for each query;
- the difference of the two averaged products was taken as the individual belongingness score for each of the 8 query types.

Figure 9.3 shows the relative positioning of the 8 query subsets on the belongingness dimension. The positions of $T4_{image}$ vs. $T4_{text}$ queries in the negative half of the belongingness dimension did not differ, indicating a strong *Format*-independent consensus among participants on the rejection of obvious non-members. However, the two scaling patterns differed in other respects. In particular the positions of $T1_{image}$ vs. $T1_{text}$ were significantly different, with $T1_{image}$ obtaining a higher belongingness score than $T1_{text}$ (2-tailed $t_{72} = 3.94$, p = 0.0002). To summarize the *Format* effect, users say "yes" to central positive exemplars more frequently and more confidently when they are represented through an image than by text.

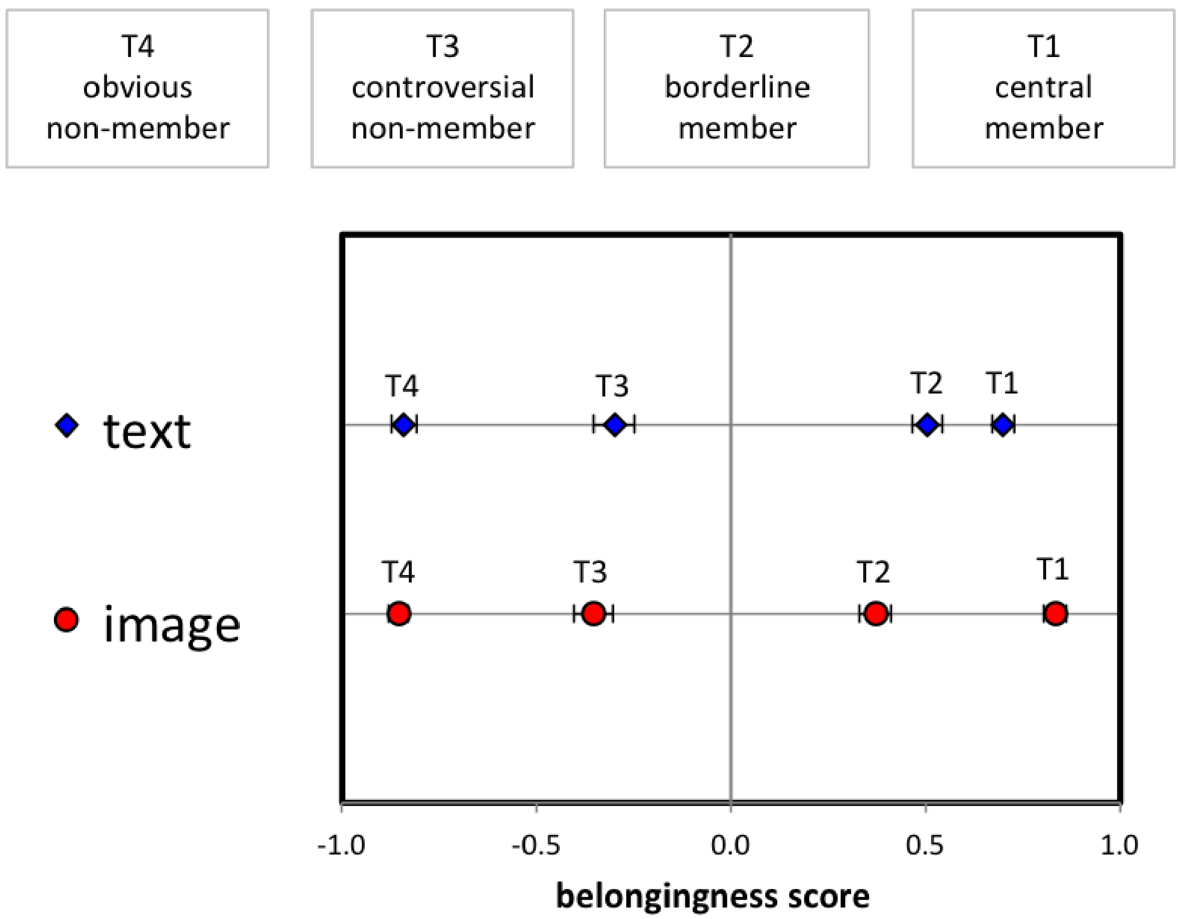


Figure 9.3. Positioning of different queries according to *Format* (image vs. text) and exemplar *Typicality* level (from T1 to T4). Means and sem values are derived from the combination of Y/N responses and 0.25-1 confidence ratings.

level of Typicality	T1	T2	T3	T4
text	0.699	0.504	-0.300	-0.841
image	0.833	0.371	-0.355	-0.854

Table 9.3. Table with the means of 4 levels of *Typicality* reported in Figure 9.3, both for image and text.

The table synthesizes the mean values for the 4 levels of *Typicality* for the two *Format* conditions. each Y/N responses were multiple with the 0.25-1 confidence rating, obtaining a weighted belongingness score. Saying *"Yes"* with high confidence is different from replying the same, but conveying extremely uncertainty.

T4 positions for Image and Text did not differ, suggesting that the *obvious non-member* was such (=obvious) to the same degree, independent of *Format*. Even the relative position of T3 (*controversial non-member*) within the T1-T4 interval did not differ as a function of *Format*.

However, the two scaling patterns were significantly different in various other respects:

- T1 positions were different, with $T1_{(image)}$ obtaing a higher belogingness score than $T1_{(text)}$ (2-tailed $t_{(72)}$= 3.94, p= 0.0002);
- the total T1-T4 interval was larger for image than text (2-tailed $t_{(72)}$= 2.857, p= 0.005);
- the relative position of T2 (*borderline member*) within the T1-T4 interval differed as a function of *Format* (2-tailed $t_{(72)}$= 2.435, p=0.017), with the T2 (*borderline member*) closer to the T1 (*central member*) for text.

It is worth notice to make explicit one aspect of the belongingness pattern shown in Figure 9.3.

The pattern obtained with image queries is a useful comparison, in the sense that it demonstrates that such material led to a symmetric distribution of belongingness scores (about zero, the max uncertainty point) within the sample of 73 participants.

Interestingly, such a pattern was not replicated with text queries. We do not know if the asymmetry depends — at least partially — on the specific nature of the exemplars/queries. However, its direction is important: rejecting an obvious non-member was easier than accepting a central member.

Table 9.4 with the values of symmetry is provided, both for text and for image condition. Either T1-T4 and T2-T3 were respectively coupled to calculate the means and standard deviations for each condition (T1-T2-T3-T4 for image and text) derived from the raw scores. Even the t value and the probability are provided.

	symmetry							
	text		image		text		image	
	T1	T4	T1	T4	T2	T3	T2	T3
mean	**0.699**	**0.840**	**0.833**	**0.854**	**0.692**	**0.447**	**0.513**	**0.487**
sem	0.029	0.032	0.030	0.025	0.058	0.074	0.055	0.070
p	symmetry	0.002	symmetry	0.566	symmetry	0.019	symmetry	0.791
df		72		72		72		72
t		3.179		0.576		2.390		0.266

Table 9.4. Table with the values of symmetry, calculated between T1 and T4, and T2 and T3, both for text and image. The table shows a symmetric distribution of belongingness scores only for image queries.

The result can be compared to classic data from matching experiments using a same/different task. Such experiments show a speed-accuracy tradeoff (the present online survey did not provide data on response times) and — importantly — higher accuracy for ”DIFFERENT” than ”SAME” judgments when participants were invited to be “cautious on same responses”. There is evidence in the literature that complexity of the match also matters. In simple global matching ”SAME” responses can be easier, but when the match requires analytical processing of several features (like in responding to membership queries), then the ”DIFFERENT” response can be easier.

Clearly, there was no manipulation of instructions in the Web survey. Hence, it is only possible to speculate about the fact that participants were slightly “cautious to say Yes” in the “text condition”.

The following consistent finding was obtained: when data are split according to image vs. text and analyzed according to the *Detection Theory*, the value of the criterion index “ce” is 0.0179 (slightly conservative bias) for text and 0.0001 (no bias) for images. However, the difference is not statistically significant.

Amount of documentation affects belongingness judgments (Doc Effect)

The **Doc effect** is the expected increase of categorization sensitivity as an effect of the amount of information available to the user. Two subsets of queries out of the whole set of 3212 queries (resulting from 73 users 44 queries) were selected:

- 524 queries: in which users were presented only with the name of the Type (with the label *“not available”* for each of the 6 features)
- 476 queries in which the Type name was followed by information for each of the 6 features.

The following performance measures in 22 conditions (2 subsets x 11 Types) was computed across users, who heterogeneously populated the 22 conditions, as a consequence of randomization:

- **d’= z(Hit) - z(FA)**, conventional measure in *Detection Theory* to measure user’s sensitivity in the Y/N categorization task [d’ ranges between zero, no sensitivity, corresponding to p(Hit)= p(FA), to infinity, corresponding to perfect performance];
- **c= -0.5** [**z(Hit) - z(FA)**], conventional measure in *Detection Theory* to measure user’s criterion in the Y/N categorization task. Positive values corresponds to a

prevalence of "No" responses, typical of a "conservative" user; negative values corresponds to a prevalence of "Yes" responses, typical of a "liberal" user.

- **doc gain = d'(docmax) - d'(docmin)**, describing the expected sensitivity gain due to more information available in the documentation;
- **criterion shift = c(docmax) - c(docmin)**, describing a possible criterion change due to more information available in the documentation.

In this analysis user's sensitivity performance was not weighted with confidence rating to avoid to many variables taking under control.

Figure 9.4 shows the positioning of each of the 11 types in the space defined by **doc gain** on the abscissa and **criterion shift** on the ordinate. The correlation between the two measures is significant ($r = 0.70$; $p = 0.016$). The increase of available information has different effects on different types, leading to large variability of both doc gain and criterion shift measures. However, the two measures are strongly related: the increase of sensitivity explains about half of the variance of the criterion change ($r^2 = 0.493$). Types that benefit from supplementary information (like *Website* and *Organization*) are also those in which users tend to become more conservative (less "Yes" responses).

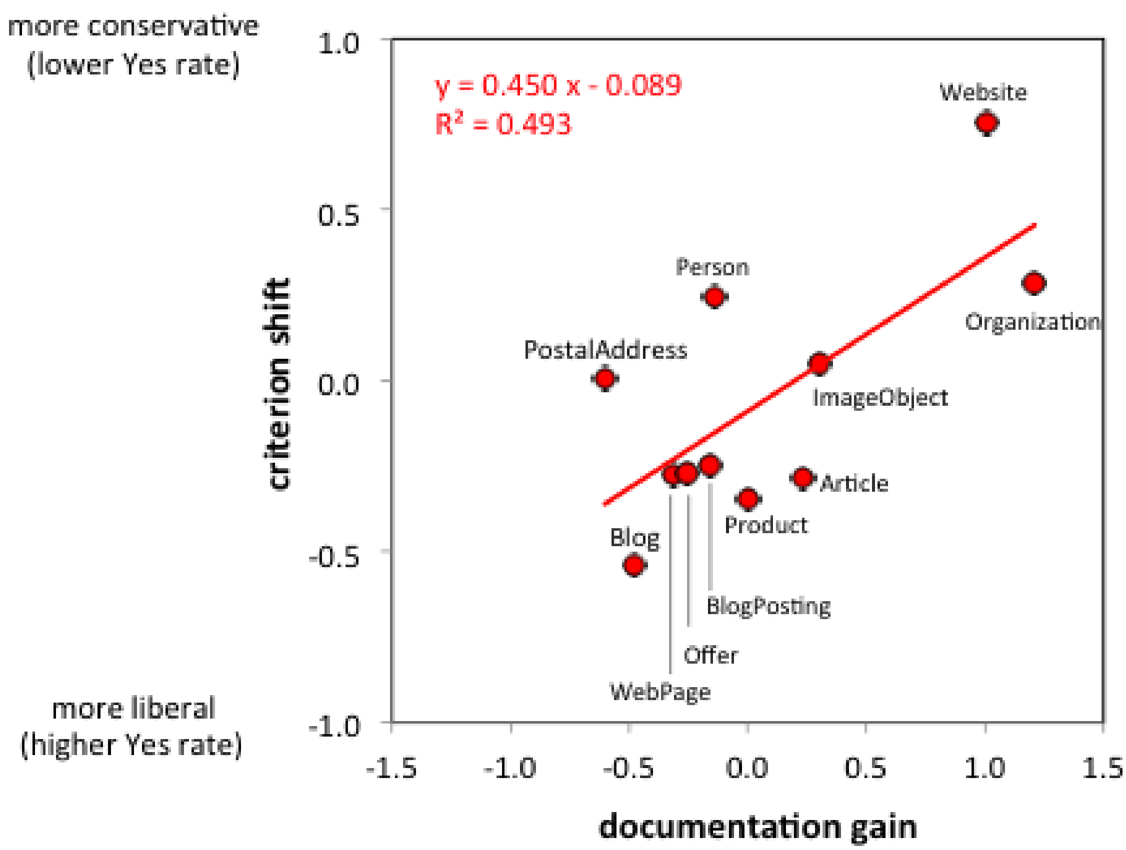


Figure 9.4. Correlation between criterion shift (c(docmax) - c(docmin) and documentation gain (d'(docmax) - d'(docmin) for the 11 types.

Figure 9.5 shows the scatterplot of the 11 Types in the space with **d'(docmin)** on the abscissa and **doc gain** on the ordinate. Values of d'(docmin) range from 1.34 of *BlogPosting* to 2.68 of *PostalAddress*, with evenly spaced values for the other 9 Types. Such a large variability in the condition in which only Type names are available could depend on several factors, including differences in categorization difficulty intrinsic to Types as well as to queries. Also, the gain due to the availability of the 6 features is quite variable, ranging from an unexpected sensitivity decrement of -0.602 (*PostalAddress*) to a strong increment of 1.209 (*Organization*). Interestingly, for both measures the min-max range is 1:2; but they are uncorrelated (r = -0.052), though the removal of two outliers (*PostalAddress* and *Organization*) would reveal a hidden positive correlation (r = 0.54; p= 0.129, two tailed) between the amount of doc gain and d'(docmin).

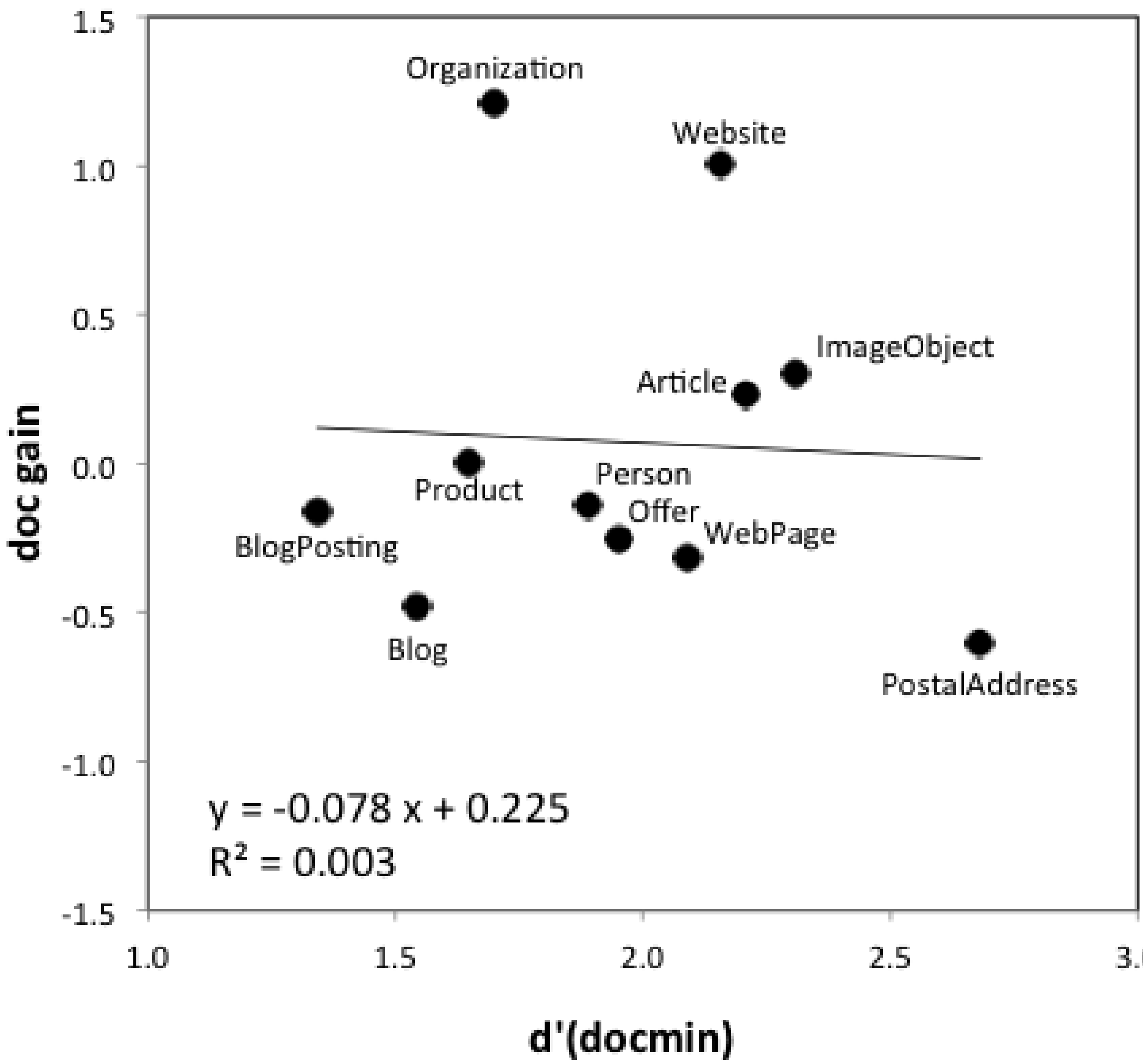


Figure 9.5. The 11 Types are represented in a 2D space defined by the following coordinates: along the x-axis, sensitivity in the absence of supplementary information provided by features [d'(docmin)]; along the y-axis, the sensitivity change due to additional information [doc gain].

9.2.3 Discussion and Conclusion

In this Experiment, an approach for measuring the effect of ontology presentation has been presented, considering *Format*, *Typicality* and the *amount of documentation* on users' categorization task performance, according to 11 selected Types of schema.org.

Going back to the research questions, it is possible to argue as follows:

RQ4-5: *Typicality* plays a role in categorization tasks, both as a main and independent factor and even in interaction with *Format*. Therefore, it should be taken into account in concept representation, especially in a field like the Semantic Web, where be intuitive and efficient is fundamental, mirroring the human cognitive functioning.
In fact, different levels of *Typicality* vary in relation to the *Format* (text or image): showing different belongingness patterns. Only the pattern obtained with image queries presents a symmetric distribution of belongingness scores (about zero, the max uncertainty point), not replicated with text queries. Furthermore, central members represented by images obtain higher belongingness score that textual ones whereas borderline members show an opposite effect (higher score for text that image).

RQ1-2-3: There is no effect of documentation on different levels of *Typicality* or *Format*. It is worth noting the impact of the provided documentation on the various types. Characteristic features in schema.org (or generally in Web ontology) seems to have different effects on different Types. In fact, the number of features is not correlated with the performance itself but has a different effect on Types. Furthermore, Types can not be new for all the participants because they are the most used ones in the Semantic Web and Web ontologies and users had some personal experience in surfing the Web (as collected from the initial demographic questionnaire). For that reason, it is possible to argue that features probably have more impact on different Types than on performance in general. Anyway, it should be better to investigate it in future studies, taking into account existing conceptualizations in users' mind, and the terminology that can activate different conceptual schemas. Also from these results, it appears the need to customize the selection of features by Type and user group.

Regarding the role of documentation, there is a correlation between the gain due to the provided documentation and the criterio shift. For instance, some Types befit more from more features (like *Organization*), but at the same time make them more conservative (lower Yes rating) to accept Type belongingness.

The fact that Types show a greater variation in performance than the features, it indicates the role of categories in ontologies. Therefore, it means that an important requirement for ontology engineering is to draw upon Types and their name that can activate share conceptual schemas in users' mind. This underline the role that ontology engineer has in choosing and shaping the intension of conceptual instances, in place of focusing on the best computational process to represent them.

Furthermore, sometimes, providing more documentation leads to better or worse performance; but this is also influenced by different Types. It should be investigated the role of such documentation because it is not always true that more is better, and the overload is very often a big problem in IT field.

For instance, the same feature can have different effects for different Types: in fact, for instance, *"Position in the hierarchy"* increase the sensitivity performance for five of 11 Types, whereas decreasing it for the other six.

The fact the study is based on some of the most popular Types in schema.org, lead to the consequence that there would be a few limits to validity. For instance, users might have been exposed to the documentation at schema.org before, memorizing it and then using this information in the replies into the survey; or the content of the features selected from schema.org might present some mistakes. To go beyond similar limitations, in possible future works, this experiment could be replicated, substituting these schema.org Types with fictional ones of an unknown domain for the participants.

Even though the study provides significant findings, the results can not be generalized because it was just a first exploration using only some concepts — although the most popular ones — in a single ontology (schema.org). Therefore, the intention is to further investigate with experiments, by employing different concepts as items or, even, create some fictional ones, aiming at avoiding potential bias that could affect the performance (e.g, prior knowledge, being experts in a specific domain, not univocal concepts, wrong translation of some concepts, inedequate features to describe some ontological concepts). Moreover, another plan is to analyze the impact that the characteristics of individuals have in their ability to apply the conceptual elements from the ontology.

CONCLUSIONS

10 General conclusions and future perspectives

This thesis has embraced two different disciplines — Cognitive Psychology (CP) and Information Technology (IT) — focusing on a topic at the intersection of both: knowledge representation.

An important goal of the thesis was to bridge the gap between these two separated fields, which look distant at first sight, even though they deal with almost the same problem. The thesis, in fact, concerns knowledge representation in human and machines, focusing in particular on the role of concepts in knowledge representation and with special attention to formal ontologies.

Concepts are an open problem for all disciplines interested in knowledge representation. With the emergence of Information Technology and the increasing demand to store and manage data and knowledge by computers, the need of representing concepts in the most efficient way has exponentially grown, trying to take also into account a cognitive perspective to add significant value to concept representation in IT.

The first part of the thesis has widely treated the state of the art of this issue, underlying the specific contributions of CP and IT, and emphasizing commonalities between these two perspectives. Furthermore, the empirical part has described the thesis' original contributions regarding cognitive representation of concepts that compare two factors: *Membership* and *Typicality*, both confirming a critical role played in categorization, as sustained by several conceptual theories emerged from literature.

The starting idea was to take into account how these two factors could impact human categorization, highlighting and contributing to new experimental results to the controversial experimental studies in psychology regarding concept representation. The aim was to focus on these two factors, trying to decompose the cognitive processes of categorization (and the concepts themselves) into different mechanisms and representations, comparing this perspective with other critical approaches, and suggesting possible relations with other theories of concepts (e.g. the *Heterogeneity Hypothesis* by Machery and Seppala (2011) and the *Fuzzy Set Theory of Concepts* by Zadeh (1965, 1975).)

In addition to these psychological considerations, the attention was focused on the contribution that cognitive research could assume in IT, in particular in ontologies field, considering the importance that these tools have in representing concepts and knowledge. Therefore, analyses regarding *Membership* and *Typicality*'s impact on categorization in Web ontologies were carried out. The online survey revealed the effect that *Typicality* of instances could have on human's categorization, giving further support to the idea that this factor should be properly considered in representing concepts in IT.

Summarizing, the empirical contributions in this thesis, although not completely conclusive, have supported the idea that – in addition to *Membership* — *Typicality* should be considered in concept representation. *Typicality* has an impact in categorizing and representing concepts together with the *Membership*, even though the results obtained seemed to demonstrate the supremacy of the *Membership* factor, when these factors are directly contrasted. This trend could be explained by the fact that the experimental setting had played an important role in choosing the categorization criterion. Nevertheless, *Typicality* had played a relevant role in categorization tasks, interacting with other variables, as already demonstrated in the literature (see the effect of context in categorization in Hampton et al. (2006)). The effect of *Typicality* was modulated by other factors in the process of categorization: the contextual framework, the polarity of the sentence (i.e., whether the sentences are positive or negative), the way assertions are presented, and the format of the instances to categorize (texts or images) could influence the use of such criterion in categorization. Providing a contextual framework, *Tipicality*-based categorization was reduced in favor of *Membership*-base one. Furthermore, *Typicality* assumes a different role in sentences with diverse *Polarity*: i.e., in the affirmative assertions, the gain in the score due to *Typicality* is higher for non-members than for the members of a category while it is virtually identical for the negative sentences. Further analyses should be carried out to verify and confirm the role that such interactions play in *Tipicality*-based categorization.

Moreover, the impact of these factors was also demonstrated in the online categorization task. *Typicality* of instances played a role in the task and significantly interacted with the *Format* of presentation (text or image) on human categorization accuracy. The effect of *Typicality* thus varies in relation to the *Format*of presentation: central members (more typical) obtained higher belongingness scores than textual ones, whereas bordeline members have showed an opposite effect (higher score for text than image).

It is thus evident that in Information Technology concepts should be represented in ontologies in a way that would make them cognitively plausible and usable.

The thesis presents some limitations due principally to the fact that, as also claimed by Murphy (2002), it is impossible to find a critical test to obtain decisive proofs in favor of a specific theory of concepts and against competing one. There are also other limitations regarding lab experiments and the online survey, as discussed in previous chapters.

Even with these limitations, the thesis provide significant results that show how many cognitive aspects are implicated in all the activities involving IT, and thus highlights how it is important to develop tools that better approach those employed by humans.

It is now evident, as also demonstrated in the literature that cognition is strongly implicated in several aspects of the IT field and that the contributions derived from Cognitive Psychology (as the role of *Membership* and *Typicality* in the representation of concepts and categorization) can be useful for developing tools, based on conceptual representation, to be used in human-machine interfaces.

Based on these findings, further studies should be carried out in order to clarify the role played by these factors in concept representation and their interaction with other variables.

It would be also interesting to see how *Membership* and *Typicality* could be applied in a machine learning context, where algorithms are consumers and producers of ontologies, and to investigate how they are impacted by ontology engineering methods.

Another crucial implication is the importance of the relationship between concepts and their translations into the different human languages: very often it is not taken into consideration the fact that a same idea or concept can be expressed in many different ways and translated into various languages (Peroni et al., 2008; JohnsonLaird, 2010). As a simple example, while in english the prototipical *bird* is the *robin*, in Italian is the *canarin*, or maybe, the *sparrow*.

11 Appendix

11.1 Appendix A

For the literature survey (chap. 5), there was the necessity to define some core terms in order to have a clearer idea about the topic: e.g. “cognitive science”, “cognitive processes”, “cognitive barriers” and “concepts” as well as “computer science”, “conceptual modelling”, “ontology” and “knowledge representation” (also finding out for each of them some synonyms or even a few of subconcepts). The goal was to establish a starting classification like ACM (for further information see: http://dl.acm.org/ccs/ccs.cfm) about the cognition and the conceptual models to better approach the papers' survey. From this model, main keywords have been extracted to be used for the papers' search. Precisely, they were: i.e. “cognition”, “ontology”, “conceptual modeling”, “cognitive tasks”, and “users”.

This is the complete list of each journal and conferences finally considered in our literature analysis. Journals embrace several topics: from computer science and Semantic Web to psychology because of our interdisciplinary approach to the issue. Conferences taking into account are indeed mainly addressed to the computer science, information systems field and conceptual modeling.

Journals:

- Applied Ontology (IOS Press)
- American Psychologist (American Psychological Association)
- Communication of the ACM (CACM) (Association for Computing Machinery)

- Computer (IEEE Computer Society)
- Data and Knowledge Engineering (DKE) (Elsevier)
- IEEE Software (IEEE Computer Society)
- IEEE Transactions on Professional Communication (IEEE Professional Communication Society)
- Information Systems (IS) (Elsevier)
- International Journal of HumanComputer Studies (Elsevier)
- Journal of Experimental Psychology: Human Perception and Performance (American Psychological Association)
- Journal of Information Science (JIS) (SAGE)
- Journal of Web Semantics (Elsevier)
- Knowledge Acquisition (Elsevier) (now incorporated in International Journal of HumanComputer Studies)
- Knowledge and Information Systems: An International Journal (KAIS) (Springer)
- Lecture Notes in Computer Science (LNCS) (Springer)
- Library Hi Tech (Esmerald)
- Memory and Cognition (Springer)
- MIS Quarterly (MISQ) (Management Information Systems Research Center, Carlson School of Management, University of Minnesota)
- Nous (Wiley Online Library)
- Psychological Review (American Psychological Association)
- Proceedings of the National Academy of Sciences (PNAS) (HighWire Press)
- Semantic Web Interoperability, Usability, Applicability (SWJ) (IOS Press)
- The VLDB Journal (Springer)
- Frontiers in Artificial Intelligence and Applications (FAIA)

Conference and Workshop Series:

- Asian Semantic Web Conference (ASWC)
- Brazilian Symposium on Software Engineering (SBES)
- Computer Personnel Research Conference (SIGCPR)
- European Semantic Web Conference, now Extended Semantic Web Conference (ESWC)
- Formal Ontology in Information Systems (FOIS)
- Hawaii International Conference on System Sciences (HICSS)
- IEEE Conference on Human Factors and Power Plants
- IEEE International Conference on Cognitive Informatics (ICCI), now IEEE International Conference on Cognitive Informatics and Cognitive Computing (ICCI CC)
- International Conference on Augmented Cognition (ICAC)
- International Conference on Biomedical Ontology,àô (ICBO)
- International Conference on Conceptual Modeling (ER)
- International Semantic Web Conference (ISWC)
- International Workshop on Ontology Matching (OM)
- International Workshop on the WorldWide Web and Conceptual Modeling (WCM)
- Workshop on Cognition and Conceptual Modeling

From a starting list papers (more or less 100-120) and after a brief abstracts lecture, 28 articles were selected to be analyzed deeply. Overall, they concern the link between cognitive science and ontologies, and specifically the issue of cognitive processes and barriers in ontology agents. However, several ones concern also more general topics in this field, such as the perceived ontology quality (Siau & Tan, 2005), and how to improve it and measure it (Maes & Poels, 2006; Everman & Fang, 2010), the necessity to take into account a different human-centered methodology (Kotis & Vouros, 2005), and how to develop and manage this approach. Finally, some of them provide descriptions and possible implementations of cognitive supports (Falconer & Storey, 2007) requested by agents in order to be helped in their (cognitive) work with ontologies. We decided to consider also a few of them to supply a wider framework of the main topic.

11.2 Appendix B

Overall, the terms "Cognition" and "Ontology" were presented in papers or books online with different frequencies: as soon as the 2000s, the ontological issue began to be effectively relevant in publications in comparison with the cognitive contributions. Unfortunately, it was not possible to do a jointed search using the both terms together. It could be very interesting also to understand when they started to appear concurrently.

For the analysis, we focused more on the recent papers for two main reasons: firstly, because there is just a recent awareness regarding the possible link between this two separate research fields; Next, because it is important to know the current state of the art relating to a certain topic, in order to carry out further experiments related to. In the following graph (Fig. 11.1), the papers frequencies distribution over the years is showed.

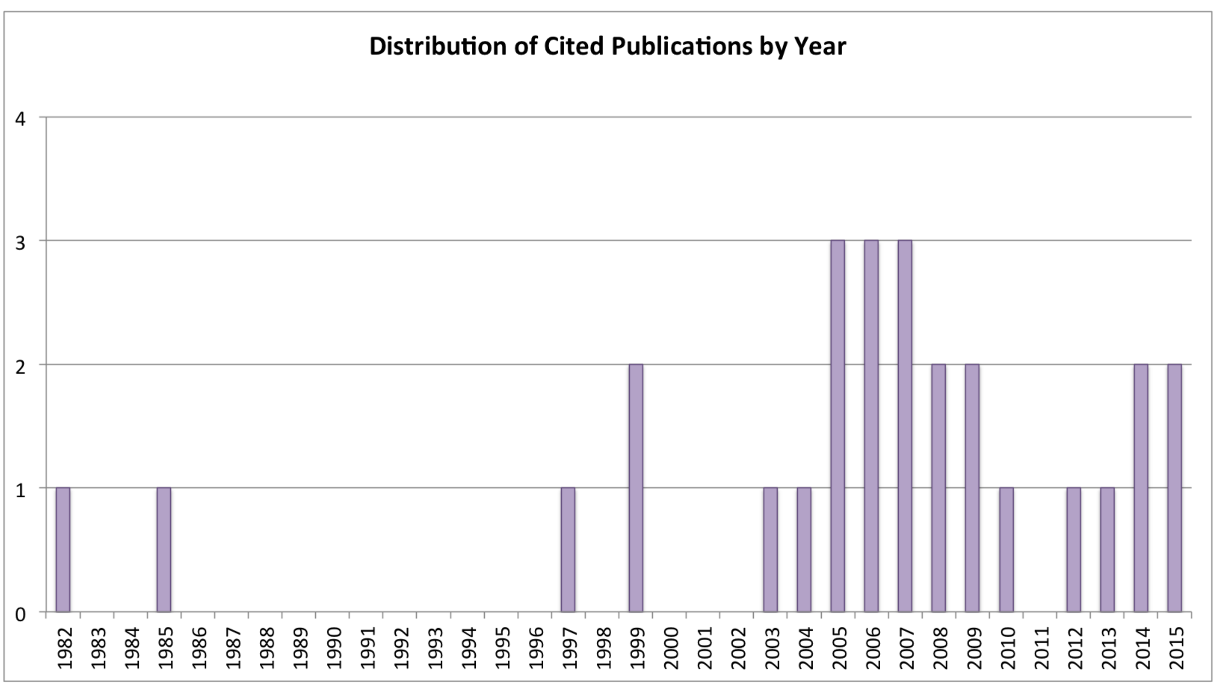


Figure 11.1 Papers by year of publication.

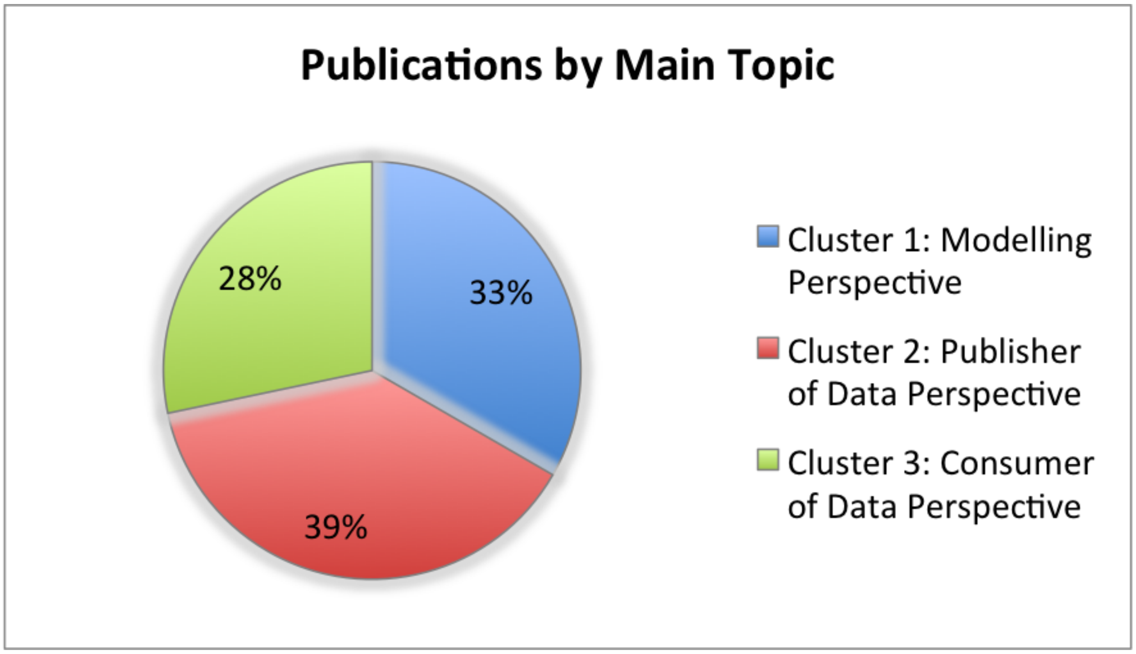


Figure 11.2 Papers by main topic.

In Fig. 11.2, a percentage of cluster contributions of all papers is reported. In the apple pie, all the 28 articles (also those that are considered more generic), were taking into account, trying to figure out an overall distribution. The various percentages do not differ a lot, indicating that each ontology agents are involved almost equally in our papers' analysis of such topic.

11.3 Appendix C

In addition, in the following table (Tab. 11.1), there is a summary of all the papers topics, described by the three different clusters:

- **Cluster 1**: Cognitive challenges for a Modeler
- **Cluster 2**: Cognitive challenges for a Publisher of Data
- **Cluster 3**: Cognitive challenges for a Consumer of Data

The symbols (-, - -, +, ++) are used in order to illustrate argumentations of each essay for each different activities cluster. Another column "Comments" is added to provide a papers' portrait that don't fit perfectly our clusters and that sometimes refers to general delineations or specifications of some modeling methodologies or approaches.

In Table 11.2, a summary of the types of contributions for each article is presented. There are papers that describe experiments, use cases (i.e., when authors analyze problems in a specific context), literature reviews, theory contributions, tools validations or different methodologies and approaches.

Ref. key	Authors	Title	Year	Cluster 1	Cluster 2	Cluster 3	Comments
Warren et al., 2014	P. Warren, P. Mulholland, T. Collins, E. Motta	The Usability of Description Logics Understanding the Cognitive Difficulties Presented by Description Logics	2014	++	+	-	
Burton-Jones et al., 2005	A.Burton-Jones, V. C. Storey, V. Sugumaran, P. Ahluwal	A Semiotic Metrics Suite for Assessing the Quality of Ontologies	2005	-	-	+	Metric to asses ontology quality
Cregan, 2007	A. Cregan	Symbol Grounding for the Semantic Web	2007	+	+	-	Correspondence problem between symbol and referent
Engelbrecht and Dror, 2009	P.C.Engelbrecht I. E. Dror	How Psychology and Cognition Can Inform the Creation of Ontologies in Semantic Technologies	2009	++	+	+	General cognition contribution in ontology development
Ernst et al., 2005	N. a. Ernst, M. A. Storey P. Allen	Cognitive Support for Ontology Modeling	2005	++	-	--	Cognitive support
Ciancarini et al., 2014	P. Ciancarini, A. Di Iorio, A. G. Nuzzolese, S. Peroni, F. Vitali	Evaluating Citation Functions in CiTO: Cognitive Issues	2014	--	+	++	Ontology quality evaluation
Noßner et al., 2015	J. Noßner, D. Martin, P. Z. Yeh, P.F.Patel-Schneider	CogMap: A Cognitive Support Approach to Property and Instance Alignment	2015	--	++	--	Cognitive support
Kotis and Vouros, 2005	K. Kotis and G. Vouros,	Human-Centered Ontology Engineering: The {HCOME} Methodology	2005	+	+	+	Human-centred ontology methodology
Maes and Poels, 2006	A. Maes G. Poels	Evaluating Quality of Conceptual Models Based on User Perception	2006	-	-	++	Ontology quality evaluation
Peroni et al., 2008	S. Peroni E. Motta M. D'Aquin	Identifying Key Concepts in an Ontology, through the Integration of Cognitive Principles with Statistical and Topological Measures	2008	-	++	+	
Siau and Tan 2005	K. Siau X. Tan	Improving the Quality of Conceptual Modeling Using Cognitive Mapping Techniques	2005	+	+	+	Ontology quality
Yamauchi, 2007	T. Yamauchi	The Semantic Web and Human Inference: A Lesson from Cognitive Science	2007	+	+	+	Human inference reasoning in inductive judgment
Wilmot et al., 2013	I. Wilmont S. Hengeveld E. Barendsen, S.J.B.a. Hoppenbrouwers	Cognitive Mechanisms of Conceptual Modelling: How Do People Do It?	2013	++	+	-	General cognition contribution in ontology development
Stark and Esswein, 2012	J. Stark W. Esswein	Rules from Cognition for Conceptual Modelling	2012	++	+	+	General cognition contribution in ontology development

Chiew and Wang, 2003	V. Chiew Y. Wang	From Cognitive Psychology to Cognitive Informatics	2003	-	-	-	General cognition contribution in computer science
Ramesh et al., 1999	V. Ramesh J. Parsons G. J. Browne	What Is the Role of Cognition in Conceptual Modeling? A Report on the First Workshop on Cognition and Conceptual Modeling	1999	+	+	+	General cognition contribution in ontology modelling and development
Evermann and Fang, 2010	J. Evermann J. Fang	Evaluating Ontologies: Towards a Cognitive Measure of Quality	2010	-	-	-	Ontology quality evaluation
Gavrilova and Leshcheva, 2015	T. a. Gavrilova I. a. Leshcheva	Ontology Design and Individual Cognitive Peculiarities: A Pilot Study	2015	++	+	+	
Vipul and Gale, 1997	K. Vipul M. Gale	Knowledge Mining Applications in InfoSluth: An Approach Based on Incorporating Cognitive Constructs in E-R Models	1997	+	++	-	
Falconer and Storey, 2007	S. M. Falconer M. Storey	A Cognitive Support Framework for Ontology Mapping	2007	+	++	-	Cognitive support
Falconer and Storey, 2009	S. M. Falconer M. Storey	CogZ: Cognitive Support and Visualization for Semi-Automatic Ontology Mapping	2009	+	++	-	Cognitive support
Khatri et al., 2006	V. Khatri I. Vessey S. Ram V. Ramesh	Cognitive Fit Between Conceptual Schemas and Internal Problem Representations: The Case of Geospatio–Temporal Conceptual Schema Comprehension	2006	+	+	+	General cognition contribution in ontology development
Kotis et al., 2004	K. Kotis G. A. Vouros K. Stergiou	Capturing Semantics Towards Automatic Coordination of Domain Ontologies	2004	--	++	-	Human-centred ontology approach
Falconer et al., 2006	S. M. Falconer N. F. Noy M. A. Storey	Towards Understanding the Needs of Cognitive Support for Ontology Mapping	2006	+	++	+	Cognitive support
Theodorakis et al., 1999	M. Theodorakis A. Analyti P. Constantopoulos N. Spyratos	Contextualization as an Abstraction Mechanism for Conceptual Modeling	1999	+	+	+	Context abstraction in ontology modelling
Yamauchi and Yu, 2008	T. Yamauchi N. Y. Yu	Category Labels Versus Feature Labels: Category Labels Polarize Inferential Predictions	2008	-	-	-	Inferential reasoning
Robey and Taggart, 1982	D. Robey W. Taggart	Human Information Processing in Information and Decision Support Systems	1982	-	-	-	Human information processing
Valusek and Fryback, 1985	J.R. Valusek D. G. Fryback	Information Requirements Determination: Obstacles Within, Among and Between Participants	1985	+	+	+	Limitations in information requirements

Table 11.1. Papers topics organized by clusters

Ref. Key	Authors	Title	Year	Type of Contribution
Warren et al., 2014	P. Warren, P. Mulholland, T. Collins, E. Motta	The Usability of Description Logics Understanding the Cognitive Difficulties Presented by Description Logics	2014	Experiment
Burton-Jones et al., 2005	A.Burton-Jones, V. C. Storey, V. Sugumaran, P. Ahluwal	A Semiotic Metrics Suite for Assessing the Quality of Ontologies	2005	Initial validation
Cregan, 2007	A. Cregan	Symbol Grounding for the Semantic Web	2007	Theory contributions
Engelbreit and Dror, 2009	P.C.Engelbreit I. E. Dror	How Psychology and Cognition Can Inform the Creation of Ontologies in Semantic Technologies	2009	Theories contributions Literature review
Ernst et al., 2005	N. Ernst, M. A. Storey P. Allen	Cognitive Support for Ontology Modeling	2005	Explorative study Tool validation
Ciancarini et al., 2014	P. Ciancarini, A. Di Iorio, A. G. Nuzzolese, S. Peroni, F. Vitali	Evaluating Citation Functions in CiTO: Cognitive Issues	2014	Experiment Use-case
Noßner et al., 2015	J. Noßner, D. Martin, P. Z. Yeh, P.F.Patel-Schneider	CogMap: A Cognitive Support Approach to Property and Instance Alignment	2015	Experiment
Kotis and Vouros, 2005	K. Kotis G. Vouros,	Human-Centered Ontology Engineering: The {HCOME} Methodology	2005	Theory Literature review Tool validation
Maes and Poels, 2006	A. Maes G. Poels	Evaluating Quality of Conceptual Models Based on User Perception	2006	Experiment
Peroni et al., 2008	S. Peroni E. Motta M. D'Aquin	Identifying Key Concepts in an Ontology, through the Integration of Cognitive Principles with Statistical and Topological Measures	2008	Experiment Tool validation
Siau and Tan 2005	K. Siau X. Tan	Improving the Quality of Conceptual Modeling Using Cognitive Mapping Techniques	2005	Case study Literature review
Yamauchi, 2007	T. Yamauchi	The Semantic Web and Human Inference: A Lesson from Cognitive Science	2007	Experiments
Wilmont et al., 2013	I. Wilmont S. Hengeveld E. Barendsen, S.J.B.a. Hoppenbrouwers	Cognitive Mechanisms of Conceptual Modelling: How Do People Do It?	2013	Theory Literature review
Stark and Esswein, 2012	J. Stark W. Esswein	Rules from Cognition for Conceptual Modelling	2012	Literature review
Chiew and Wang, 2003	V. Chiew Y. Wang	From Cognitive Psychology to Cognitive Informatics	2003	Literature review
Ramesh et al., 1999	V. Ramesh J. Parsons G. J. Browne	What Is the Role of Cognition in Conceptual Modeling? A Report on the First Workshop on Cognition and Conceptual Modeling	1999	Theory contributions
Evermann and	J. Evermann	Evaluating Ontologies: Towards a Cognitive Measure of	2010	Case study

Fang, 2010	J. Fang	Quality		Tool validation
Gavrilova and Leshcheva, 2015	T. a. Gavrilova I. a. Leshcheva	Ontology Design and Individual Cognitive Peculiarities: A Pilot Study	2015	Case study
Vipul and Gale, 1997	K. Vipul M. Gale	Knowledge Mining Applications in InfoSluth: An Approach Based on Incorporating Cognitive Constructs in E-R Models	1997	Case study
Falconer and Storey, 2007	S. M. Falconer M. Storey	A Cognitive Support Framework for Ontology Mapping	2007	Case study Literature review
Falconer and Storey, 2009	S. M. Falconer M. Storey	CogZ: Cognitive Support and Visualization for Semi-Automatic Ontology Mapping	2009	Software demonstration
Khatri et al.,, 2006	V. Khatri I. Vessey S. Ram V. Ramesh	Cognitive Fit Between Conceptual Schemas and Internal Problem Representations: The Case of Geospatio–Temporal Conceptual Schema Comprehension	2006	Experiment
Kotis et al., 2004	K. Kotis G. A. Vouros K. Stergiou	Capturing Semantics Towards Automatic Coordination of Domain Ontologies	2004	Experiment
Falconer et al., 2006	S. M. Falconer N. F. Noy M. A. Storey	Towards Understanding the Needs of Cognitive Support for Ontology Mapping	2006	Literature Review
Theodorakis et al., 1999	M. Theodorakis A. Analyti P. Constantopoulos N. Spyratos	Contextualization as an Abstraction Mechanism for Conceptual Modeling	1999	Theory contributions
Yamauchi and Yu, 2008	T. Yamauchi N. Y. Yu	Category Labels Versus Feature Labels: Category Labels Polarize Inferential Predictions	2008	Experiment
Robey and Taggart, 1982	D. Robey W. Taggart	Human Information Processing in Information and Decision Support Systems	1982	Literature Review
Valusek and Fryback, 1985	J.R. Valusek D. G. Fryback	Information Requirements Determination: Obstacles Within, Among and Between Participants	1985	Theory contributions

Table 11.2. Papers topics organized by type of contribution.

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