Contextual Concept Meaning Alignment Based on Prototype Theory

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Abstract
The introduction of autonomous intelligent agents promises to increase productivity in all parts of economy. Such agents are capable of intentional functioning in natural environments, gathering information, assessing it, making decisions, and initiating actions. Intelligent agents work with the conceptualization of the world, which they constantly develop, test and update in the process of learning. This conceptualization is represented as local ontology, but agents can share and align meanings of concepts with other agents. However, when compared to human conceptualization of concepts, the traditional ontological approach lacks the representation of richness, fuzziness, context-dependent meanings of concepts. In this article we follow the insights from cognitive linguistic and prototype theory to model the multiple, context-dependent meanings of concept as a separate concept ontology. We also argue that intelligent agents can be represented as situation-aware systems, which are constantly aware of their environment and operation context. Therefore, the establishment of correspondence between the current context and the relevant concept meaning comes naturally in the process of learning. Lastly, we propose to use the prototype theory approach for the organization of contexts knowledge as a separate ontology, with the relationship between the local ontology and contexts ontology not unlike the relationship between semantic and episodic memories of humans.

Keywords
Intelligent agent, local ontology, prototype theory, cognitive linguistics, situation aware system

1. Introduction

The introduction of artificial intelligence technologies in all areas of human activity promises to boost the productivity and revolutionize all fields of economy. In important trend in the development such technology is the growing research on the intelligent autonomous agents, capable of intentional functioning in natural environments, gathering information from various sources, assessing it, making decisions, and acting on them [1]. Such agents should be able to use knowledge, reason, learn and communicate with other agents.

Internal knowledge base of an agent is based on the conceptualization of the world, which is constantly used, tested, and updated based on the results of intentional agent activity and interactions with other agents. This conceptualization is formalized as an local ontology.

However, current research in ontological modeling mostly favors fixed, non-flexible and shared approaches for ontology structure and interpretation, which does not suit the specifics of intelligent agent activities, because:

- Agent's knowledge is used and developed locally, reflecting agent's experiences; is constantly updated and tested for consistency in the process of learning. Therefore, there are substantial distinctions between ontologies of different agents.
- Concepts and relationships are fuzzy, have multiple interpretations, depending on their usage.

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- Identifying and modeling context is a primary activity for intelligent agent. Only when context is identified, agent can select the relevant interpretations of ontology concepts and knowledge models associated with this context.

Important insights of how to organize the intelligent agent's knowledge, in our opinion, can be obtained from models and theories of cognitive linguistics, studying the usage and pragmatics of natural language. The use of natural language by humans reflects the flexibility, context-dependence, creativity in making new meanings for old concepts, that is, all the features which should be implemented in intelligent agents.

This article aims to explore how the prototype theory from cognitive linguistics can be used to implement multiple context-related meanings of concepts in intelligent agents local ontologies. We also consider the intelligent agents as situation aware systems and propose to use prototype theory for the identification of contexts, presented as conceptual models and working as analog of human episodic memory.

The article has the following structure. After introduction we present the discussion about current state of concept meaning modeling in cognitive linguistic and concept theories, contrasting it with traditional concept representation in ontologies. In next section we formulate the main research assumptions. In section four we remind the main principles of prototype theory relevant to the context meaning representation modeling. Next section is dedicated to the formal model of concept meaning organization in the form of concept ontology and its relation to context prototypes. In section six we represent intelligent agent as situation aware systems and show how the contextual knowledge is organized and maintained in the process of agent operation as prototypical contexts. In the last section we summarize and discuss the advantages of proposed approach compared to traditional ontological modelling.

2. Background research

2.1. Cognitive linguistic about concepts representation and usage by humans

The study of human conceptualization processes, in our opinion, could provide valuable insights for the organization of conceptualization of the world by intelligent agents. There are many similarities between humans and artificial intelligent agents, both being the autonomous intentional units generating and sharing knowledge.

The important area, providing research in the area of human conceptualization is cognitive linguistic, focused on semantics and pragmatics of natural language as opposed to generative linguistics which strongly commits to syntax and rules. Cognitive linguistic has two foundational principles [2]: non-modularism and non-objectivist view of linguistic meaning.

The principle of non-modularism states that language capacity is not located in specific module of brain, not connected with other cognitive abilities of human. Instead, the language is a product of all cognitive abilities of a person, including visual, kinesthetic skills, conceptualization and categorization skills [2] The non-modularism principle fits well with artificial intelligent agents' operation, especially if we consider them as situation aware systems which obtain and interpret data coming from multiple environment sensors as well as feedback data coming from memory and reasoning.

Non-objectivist principle says that meaning assigned to concepts is dependent on this concept's user or creator. The user of concept views its meaning through the lens of personal experience, narratives, stories, and biases [2]. Each artificial intelligent agent also has its own set of experiences, knowledge gained in the process of resolving problems and executing tasks which results in the modification of concept's meaning in the agent's ontology.

However, in our opinion, the process of diversification of knowledge following the non-objectivist principle is balanced by the opposing process of unification and alignment of concept's meanings happening in the process of communication and interaction of agents. In this way agents are collectively developing and adopting the common shared conceptualizations, where shared, agreed-on meanings coexist with idiosyncratic, unique shades of meanings specific to agents.

The author of [3], highlights such properties of human conceptualization of concepts:

- Vagueness. The categorization of any object is fuzzy. That is, the object can belong to different categories to a different degree.
- Typicality. Within a category, objects differ on how well they are suited to be an example of this category.
- Genericity. People tend to describe a category in general terms, common to most of its objects and not including exceptions and deviations.
- Opacity. There are no clear rules allowing to define whether a specific object belongs to specific category. The basis of categorization is not transparent to its author.

The inherent fluency of concept's meanings presents a modeling challenge which is met by different concept theories.

2.2. Modeling the fluency of meaning with concept theories

According to [4] current theories of concepts have difficulties to model the creative flexibility of natural language, the ability to create new meanings by combining existing ones or implement the context-dependent nature of concept meaning.

According to classical approach, going back to Aristotle [5], the meaning of concept is defined by its properties. Therefore, objects, having the same set of properties belong to the same concept. The same approach in informatics is followed by the formal concept analysis, which is seen as a systematic way of deriving a concept hierarchy from a collection of objects with properties [6]. However, this approach cannot model the inherent fuzziness, context-dependence and fluency of concept meaning. Moreover, the definition of properties is not always straightforward. [4].

The problem of modeling concept meanings better is addressed in a large number of works. The work [7] explores how to model the combination of concepts in sentence using constraints theory. Three constraints or diagnosticity, plausibility and informativeness are considered.

A connectionist approach to representing the contextualized concepts is proposed in [8]. The authors have developed a neural model CONCAT, which learns patterns as features co-occurrences and classifies them into objects and contexts simultaneously. The usage of neural networks to classify and form context models is a promising approach to form contextualized models in real-world applications. However, their mapping into explicit conceptualization models based on ontologies is yet to be done.

The work [4] develops the idea of using the formalism of quantum theory to represent the fluency of concept's meaning. Contrarily to other approaches, a concept is not considered as a container of multiple meanings but an entity in a specific state which changes under the influence of context. Context is mathematically modelled as a process of measurement of a quantum particle.

The concept theories, while providing the valuable insight about modeling the concept fluency and context-dependency don't address the problem of systematic representation and using the conceptual knowledge by intelligent agents.

2.3. Representing the meaning of concepts using ontologies

Ontology is defined as specification of shared conceptualization [9,10]. This definition puts emphasis on the task of creating the common conceptualization, which is aimed to provide for the storage, reuse, understanding of knowledge and communication between intelligent agents.

In that approach a concept is represented as an immutable node in the taxonomy of concepts with a single meaning, defined by its set of attributes. Concept definition, according to Formal Concept analysis [6], is derived from the initial set of individual objects by grouping them by having common attribute sets. This gives us the way to construct ontology from a given set of objects, having properties. Such approach, while creating many advantages has also shortcomings for intelligent agents in real-world situations.

Intelligent agents create and modify their own conceptualizations, reflecting their experiences and expertise. This is an essential part of intelligent agent constant learning process. Ontologies, created by agents are subjective and should be aligned with common ontologies if the need to communicate knowledge arises.

The similar problem appeared and was hard to resolve, when trying to reduce the diverse enterprise information systems databases to the common schema. The failed attempts to integrate conceptualizations even within a single enterprise were the driving force and justification to introduction of loosely - coupled service enterprise information systems architectures [11].

Similarly, in real live (and natural language) the meaning of concept is dependent on the context when it is used. It is fluent and a person operating this concept dynamically and implicitly selects the meaning relevant to current situation.

The concept itself over time becomes fuzzy with multiple meanings, containing a lot of different meaningful nuances. This contributes to the richness of natural language having metaphors, associations, idioms.

Moreover, the meaning of concept evolves over time. A person (or intelligent agent) builds its understanding of concept's observing the objects in the real world and attaching conceptual labels to them. The objects, representing concepts become the prototypes, reference points in the representation of concept's meaning. Later, similar objects are grouped based on their similarity and the meaning of concept is enriched, reflecting even more slightly different nuances and use-cases. The inherent nature of concept fluency is stressed in multiple research articles [12]. The process of concept meaning evolution never stops, because concept constantly gets new meanings, sometimes through association with other concepts.

The ontologies, used by intelligent agents are local, developed and used by specific agent. Since they reflect the interpretations particular to every agent, those local conceptualizations are often named as contextual ontologies [13]. However, those conceptualizations account for contextual differences in ontologies between agents, and not for context-dependent interpretation of concepts within local ontology.

Contextual ontologies [13] discern between local and shared conceptualizations. Local conceptualizations are stored in the memory of specific intelligent agent and mapped to shared conceptualization when the need of communicating with other agents arises. Contexts in [13] are defined as local conceptualizations.

Benslimane [14] accordingly introduces the terms of mono-context ontology and multi-context ontology, where multi-context ontology contains concepts having multiple interpretations.

To handle multiple contexts and reason about them using Description Logic, an extension of OWL – OWL-C - ontology representation language was developed [15]. This language is based on OWL syntax and provides bridge rules allowing to relate concepts, individuals, and roles on the syntactic and semantic levels.

However, the research on local ontologies does not show how specific concept meanings are acquired, nor how they are mapped into their usage contexts.

3. Research assumptions

Let's summarize the research assumptions.

1. An intelligent agent creates and uses a conceptualization of the world, depending to its goals and intents
2. Each intelligent agent uses and constantly updates its knowledge base. This base uses local ontology for the conceptual modeling of knowledge
3. Because the agent's environment and its intents are constantly changing, its knowledge base is changing too in the process of learning. Therefore, the agent's local ontology is dynamic and unique to this agent
4. Agent's ontology could be partly aligned with the ontologies of other agents in process of communication and reusing the knowledge provided by other agents
5. Agent's knowledge is tested for consistency and is updated in the process of resolving the practical tasks

4. Using Prototype theory to represent flexible concept meaning

The central theory of cognitive linguistics, explaining how human conceptualization is formed, is the theory of prototypes. In this theory the concept is defined by the similarity to the most common object representing this concept [2]. When a human thinks about concept it recalls in memory this central object. This works like a mental shortcut allowing him not to burden his mind with all possible nuances and exceptions which belong to the same category as the central object. Thus, the classification of an object to specific category happens by evaluating the similarity to prototype, and not by the recalling and using object's properties [16].

Prototype is defined in Longman dictionary as "something that is one of the first and most typical examples of a group or situation" [17].

Prototype theory is widely used as a basis for modeling knowledge. In [3] authors analyze in detail such properties of concept definitions as Vagueness, Typicality, Genericity and Opacity and why prototype theory is alternative way of understanding the world compared to logic.

The work [18] introduces the novel approach to categorization based on prototype theory. Semantic prototypes are computed using convolutional neural network to highlight an object with distinctive features within the category. This object becomes the semantic prototype of the category. The experiments show, that the prototype obtained successfully describes the category semantics.

An article [19] introduces the Hyperbolic Prototype Learning method, which is a kind of supervised learning method where class labels are represented as points in hyperbolic space. The loss function is based on Busemann function of hyperbolic geometry.

In [20] the authors research the notion of prototypicality. They distinguish between two aspects of prototypicality: flexibility and salience. Flexibility reflects the inherent fuzziness of concepts, having no clear boundaries. Salience reflects the differences in importance, usage and structural weight. Both aspects can be found on the levels of concept definitions and concept instances.

An article [21] explores the relationship between label semantics and prototype theory. It introduces the epistemic model of uncertainty associated with vague concepts. The interpretation of label semantics based on prototype theory and using uncertainty thresholds on the distance between elements and prototypes for description labels is proposed.

The prototype theory approach to model the concepts is promising to resolve problems of context-dependency and fuzzy concept meaning, by using different prototypes in different contexts.

The fuzziness of concept meaning could be modeled by having multiple prototypes within a single concept, used in different contexts. The selection of the right prototype depending on the context is implemented by selecting the prototype which corresponds to the current context.

The learning and evolving the meaning of context by intelligent agent is modeled as creation of new concept version better fitting to the current situation and including it into the definition of concept as another prototype.

This approach provides a straightforward procedure of learning the new meaning of concept. In case of there are no satisfactory meanings within the current definition of concept, the new meaning is created, based on the current use-case (context) of concept; this meaning is next mapped to existing meanings.

Such approach provided additional advantage of providing the crisp definition of concept, once the similarity of current context and prototypical, stored context definition is established. Thus, the application of prototype theory provides a simple solution to formalization of multiple, context-depending meanings within a single concept.

5. The model for flexible concept meanings representation for intelligent agents

The traditional definition of ontology [9] is a cortege

$$On = (SCn, SRl, SA), \quad (1)$$

where SCn is a set of concepts,SRl- set of relationships and SA – set of axioms.

For intelligent agent On is a local ontology, which provides a vocabulary for the formalization of agent's knowledge and reasoning with this knowledge. In this work we focus on the internal structure of concepts with multiple, context-dependent meanings.

In our model the meanings of concepts are organized in a tree-like structure with nodes representing the prototypes of meanings. The nodes are linked with multiple types of relationships, reflecting the inheritance, specialization, usage, and mappings between concept interpretations. Thus, each concept internally is represented as an ontology of concepts prototypes: On_{cn}:

$$On_{cn} = (SP_{cn}, SRl_{cn}, SA_{cn}), \tag{2}$$

where SPr_{cn} is a set of prototypical concept meanings, SRl_cn – is set of relationships between them, SA_cn – is the set of axioms and rules about the interpretation of different concept meanings.

For each concept ontology, there's a root node (Fig.1), containing at minimum the label of concept and its essential attributes. This node unites all other meanings and provides the identity for concept.

One of the nodes in concept tree is selected as default node P_{df}This is the most used prototype of concept; agents typically use it in general situations when no usage of concept is provided. Another designated concept role is reference concept prototype P_{ref}, which correspond to the concept interpretation in some reference or domain ontology. This concept meaning is used in communications with other agents as a common ground for understanding.

Concepts meaning prototypes form clusters around central nodes when child meanings are related to parent with specialization relationship – and the generalization relationship in the opposite direction. Another type of relationships between nodes is mapping relationships allowing to reuse the information from one concept interpretation into another. The mappings are especially important between reference concept and other concepts, allowing for sharing and reusing knowledge between agents.

Contextual dependency between prototypical contexts and specific contexts meanings is represented as relationship established between prototypical context and specific concept prototype. This relationship is formed when intelligent agent uses specific concept interpretation in a specific context/situation. It is reinforced every time when this interpretation is successfully reused in this context, providing feedback. In case, if several concept meanings could be used in specific context, there's a measure, estimating the degree of usefulness of concept meaning in a specific situation. This measure is updated in the process of concept usage. It also can be interpreted as a probability of this meaning usage in specific context, compared to other concepts meanings.

Thus, there are three types of relationships between concepts, which form three subsets in SRl_{cn} :

$$SRl_{cn} = SRl_{isa} \cup SRl_{map} \cup SRl_{use}, \tag{3}$$

where the subset of subsume relations $SRl_{isa} = \{Rl_{isa}\}$ contains individual relationships Rl_{isa} interpreted as specialization of child meaning relative to parent meaning. This relationship is defined by the pair of related prototypes:

$$Rl_{isa} = (P_{cn}^{par}, P_{cn}^{chld}), \tag{4}$$

The subset of mapping relationships $SRl_{map} = \{Rl_{map}\}$ where each mapping is specified as a cortege:

$$Rl_{map} = \left(P_{cni}, P_{cnj}, F_{map}\right), \tag{5}$$

where F_{map} is a mapping function, between prototypes P_{cni}, P_{cnj}:

$$F_{map}: P_{cni} \to P_{cnj}, \tag{6}$$

The subset of contextual usage relationships $SRl_{use} = \{Rl_{use}\}$ contains relationships established between the prototype of context P_{cti} and the concept prototype P_{cnj}:

$$Rl_{use} = (P_{cti}, P_{cnj}, U_{ij}), \tag{7}$$

where $0 < U_{ij} \leq 1$ is the degree usefulness of prototypical meaning P_{cnj} in context P_{cti} interpreted as a frequency of this meaning usage over all contexts.

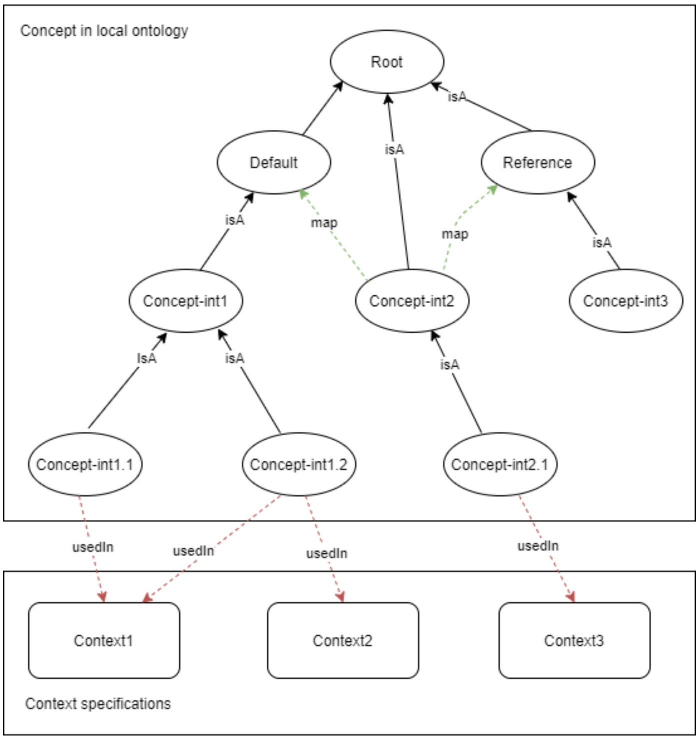

Figure 1: The organization of concept meanings in local ontology.

The authors of [4] provide the method of calculating the distances between concept Cn_i and prototypes available in concept definition, using prototypes and concept properties.

According to it, each prototype P_{cnk} has a set of properties $\{a_{k1}, a_{k2}, \dots, a_{km}\}$ with associated weights $\{w_{k1}, w_{k2}, \dots, w_{km}\}$.

A new concept Cn_ihas also a set of weights $\{w_{i2}, w_{i2}, \dots, w_{im}\}$, where w_{il} refers to the applicability of l-th feature to the concept.

Conceptual distance between the concept Cn_i and the prototype P_{cnk} is calculated as Euclidean distance:

$$d_i = \sqrt{\sum_{j=1}^{m} \left(w_{kj} - w_{ij}\right)^2}. \tag{8}$$

A prototype with the minimal distance from concept Cn_i is chosen to represent this concept meaning.

An alternative approach for finding the prototype is to identify the prototypical context P_{cti}first, and then use relationships pointing to the relevant meaning of concept in the given context.

6. Using prototype theory approach for organization of episodic, contextual memory in situation-aware intelligent agents

Autonomous intelligent agents are operating in different environments, pursuing specific goals, making decisions, performing actions, projecting impact, and learning from the results of those actions. Thus, they could be considered and modeled as situation aware systems. To reach the situational awareness a complex system of interrelated processes should be implemented, including getting raw data from the environment, interpreting it according to available knowledge, building a conceptual model of context and reasoning about it, detecting situations, planning, and implementing actions, assessing the results of such actions, and updating the knowledge.

Many models were developed to study situational aware systems, but the most often used is JDL/DFIG model [22, 23].

This model considers five levels of situational awareness process:

1. Level 0. Signal/Feature assessment. On this level signals from sensors are collected and interpreted as input data

2. Level 1. Entity assessment. The data obtained are interpreted as properties of items recognized in the environment. The knowledge about items and their expected attributes is taken from the local knowledge base
3. Level 2. Situation assessment. The entities involved in current context and their relationships are analyzed to recognize the situations, requiring some kind of action
4. Level 3. Impact assessment. Actions are planned and decisions made according to the situations identified. The impact of decisions and actions on current context and possible consequences are evaluated
5. Level 4. Performance assessment. Gauging the correspondence between current state and agent's goals, performance analysis, updating knowledge using the results of analysis.

The research area of situation aware systems benefits from the research results in numerous areas of artificial intelligence, including neuron networks modeling, ontological engineering, pattern recognition, machine learning

The accepted way to model the domain knowledge in situation aware system is to use formal conceptualizations – ontologies [23]. The modeling of situation aware process heavily relies on conceptual modeling on every level of JDL/DFIG model.

Several developments about the use of ontologies to model situation aware systems were proposed [22]. In [23, 24] we considered how the small ontology-based knowledge models, such as contextual, task, situational, and contextual graphs models could be used in the modeling of situational awareness process.

In our research we use the term "Context" for designation of environment in which agent operates and "Situation" – for detectable set of related conditions, requiring some sort of decision making and reaction from the agent.

On the first stage of JDL model intelligent agent obtains data from sensors and interprets them as attributes and parameters of concepts from agents' ontology On. Objects from environment are recognized using pattern recognition algorithms. The objects and their relationships, as observed by agent form the conceptual model of environment Cm_{env} , described using the elements from local ontology. Concepts and relationships, specifying objects, perceived in the environment form a smaller ontology $On_{env} \subseteq On$ which can be extracted from the On.

However, when analyzing the current context, intelligent agent should also take in consideration other, not directly observable objects, such as agent intentions, important objects derived from reasoning process or prior knowledge. Those objects as well as objects found in the environment are included in the ontology of current context On_{con}. $On_{env} \subseteq On_{con} \subseteq On$

Based on contextual ontology On_{con} the conceptual model of context Cm_{con} is built. This model is used for detecting situations, reasoning, and making decisions about current context. Such model can also be used to find and update the meanings of concepts.

The knowledge about contexts and situations play an important role in human cognition, being an essential part of episodic memory [25]. Knowledge is always interpreted relative to the specific (or typical) situation where it is relevant.

Likewise, for intelligent agent it makes sense to interpret knowledge through the lens of stored contextual models of contexts and situations, being analog to episodic memory – while ontology is an analog of semantic memory of humans. This is a natural way for situation aware system operation because such system is always aware of the context where it operates, constantly building and updating the conceptual model of context.

An agent rarely meets the current situation for the first time. Typically, it has been in a similar condition before. Taking in consideration the large number of possible contexts, their inherent fuzziness (not unlike the concepts in ontology) the knowledge about contexts could be organized according to the principles of prototype theory, where typical situations are stored as prototypes in contextual prototypes repository $SP_{ct} = \{P_{cti} | i = \overline{1, m}\}$.

When the conceptual model of current context Cm_{con} was built, agent calculates the similarity to available contextual prototypes in repository, using similarity function:

$$F_{sim}: (Cm_{con}, P_{ct}) = d_{con}, \tag{9}$$

where d_{con} is the numeric measure of distance. The agent selects a prototype context with the minimal value of distance.

Once the prototypical context is found, an agent:

1. Updates the interpretations of concepts within the contextual model to concept definitions which are relevant to identified context.
2. Obtains access to the relevant knowledge, associated with prototypical context about methods, rules, constraints which can be used.

In case if the calculated distances between current context and contextual prototypes are exceeding the specified threshold d_{con}^{mx} agent recognizes that the situation is unique and new contextual prototype should be created. Prototype contexts are formed as groups of similar contexts, having the similar conceptual models.

7. Conclusion and discussion

Using the approach of prototype theory presents a way to model the multiple meanings of concept, their dependencies. It also naturally relates to the process of learning and new concept's meaning creation by intelligent agent, while preserving the relationship to other meanings. The learning occurs in the process of agent's operation, when presented with an instance of concept, used in specific situation, an agent looks for the relevant prototype among the concept definitions. If the difference between this instance and prototypes available in concept definition is too large, an agent may choose to create the new version of concept meaning and include it into the ontology of concept.

Overall, the prototypes approach creates a richer, more flexible fuzzy concept model, compared to traditional ontological modelling, allowing to quickly select the crisp meaning, depending on usage context.

The typical contexts themselves are treated here as concepts in a separate ontology, like episodical memory of humans. Therefore, the prototype theory is also applicable to the problem of context related knowledge organization and processing. Since the situation-aware intelligent agents are always aware of environment and context in which they operate, the relationship between context and specific concept meaning could be established and stored, allowing to quickly select the meaning relevant to current situation.

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