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A Semantic Framework for Uncertainties in Ontologies

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Abstract

We present a semantically-driven approach to uncertainties within and across ontologies. Ontologies are widely used not only by the Semantic Web but also by artificial systems in general. They represent and structure a domain with respect to its semantics. Uncertainties, however, have been rarely taken into account in ontological representation, even though they are inevitable when applying ontologies in 'real world' applications. In this paper, we analyze why uncertainties are necessary for ontologies, how and where uncertainties have to be represented in ontologies, and what their semantics are. In particular, we investigate which ontology constructions need to address uncertainty issues and which ontology constructions should not be affected by uncertainties on the basis of their semantics. As a result, the use of uncertainties is restricted to appropriate cases, which reduces complexity and guides ontology development. We give examples and motivation from the field of spatially-aware systems in indoor environments.

Motivation

Ontologies are used as a method for making explicit what is known implicitly. They aim at interoperability and reusability among different sources of information. Their terminology provides an interface for communication, either between agents or between agents and humans. Ontologies have a clearly predefined structure with an inherent meaning in itself. This structure consists of a taxonomy of classes, relations between these classes, and axiomatizations. Formally they are defined as "an engineering artifact, constituted by a specific vocabulary used to describe a certain reality, plus a set of explicit assumptions regarding the intended meaning of the vocabulary words" (Guarino 1998). This *certain reality* then requires a precise analysis of a specific domain with respect to its actual semantics.

Ontologies are not primarily supposed to represent uncertainties, as their specifications of a domain are strict and well-defined. As soon as an ontology is used as an instantiation in a system, however, different types of uncertainties arise. In the case of spatial systems we have found that these uncertainties are caused, for instance, by lack of knowledge about the environment, unreliable sources of information, shortcomings in sensorimotor data, unknown or unexpected results of actions, or unknown intentions of other communication partners (specific examples are illustrated in the use case). Even though the ontology itself may not be affected by uncertainties, a system's instantiation of it is. Facts of a domain as specified by an ontology can either be true or false, and a system may be uncertain as to which is the case. The ontology should then provide definitions of uncertainties by specifying syntax and semantics for modeling them.

Often foundational ontologies, such as DOLCE (Masolo *et al.* 2003), do not have any classes or relations reflecting uncertain information. SUMO (Niles & Pease 2001) provides a relation *ProbabilityRelation* that assigns a percentage to the probability of an event, which is still not sufficient as other kinds of probabilities that are not related to events may be required as well. Similarly, the recent version of ResearchCyc[1] defines notions of uncertainty only as *a feeling of being unsure about something* and *probability* for assigning values of likelihood.

Technical aspects of representing uncertainties in ontologies have been investigated in more detail. Although these approaches provide uncertain definitions in ontologies, they focus mainly on questions of complexity and expressivity of certain logics. Such approaches define either uncertainties within an ontology or across different ontologies. Representations for uncertainties in ontologies have recently been developed by enhancing the web ontology language, OWL DL[2]. The language has been extended with Bayesian networks (Ding, Peng, & Pan 2006), fuzzy logic (Stoilos *et al.* 2005), and probabilities (Costa & Laskey 2006). Such approaches allow one specific type of uncertainty to be represented in an ontology. Given the formal definition of an ontology by (Guarino 1998), however, a clear specification of the intended meaning of these uncertainties is missing. So far it has not been studied in detail which kinds of uncertainties are appropriate to describe a *certain reality*. Inter-ontology mappings (Euzenat & Shvaiko 2007) relate conceptualizations across different ontologies mostly for identifying identical definitions, which can be affected by uncertainties. Several solutions for this problem have been pro-

[1] http://research.cyc.com
[2] http://www.w3.org/2004/OWL

posed, including Bayesian networks (Mitra, Noy, & Jaiswal 2005) and probabilities (Calì *et al.* 2007). In general, such approaches determine uncertain mappings either based on classes or instances.

Finally, there are many efforts in the field of vague categorizations in ontologies. This vagueness is, however, attributed to linguistic underspecifications and vague expressions in natural language (Bennett 2005), which is different from defining uncertainties in a domain. Such methods analyze specific linguistic aspects of vagueness, not related to a complete analysis of possible uncertainties in domain ontologies in general. Although vagueness therefore is outside the scope of uncertainties in ontologies, we briefly outline methods for such aspects below.

As ontologies aim to represent the semantics of a certain reality, it is necessary to analyze the possibility of uncertainties in ontologies. We propose a semantically-driven approach for representing uncertainties in ontologies. Uncertainties are not supposed to be modelled by some classes nor to be indicated by logical formalisms. They are mostly caused by agent-based instantiations of the ontology. We therefore analyze the possibility of uncertain aspects in ontological definitions and discuss reasons for this. Different types of uncertainties and their appropriateness are examined. The framework endeavors to combine these aspects by differentiating meanings of uncertainties accordingly. As a result, the framework not only reduces and simplifies complexity, as it narrows down the use of uncertainties to appropriate cases, it can also guide ontology engineers in their development of ontologies, as it indicates meanings of a domain's categorization. Moreover, it reveals uncertain aspects of the domain, on the one side, while implying necessary reasoning strategies, on the other. We therefore characterize possible uncertainties in domains and their reasons, distinguish the different kinds of uncertainties arising, and discuss possible formalizations and reasoning mechanisms.

We give a short overview of uncertainty methods in the next section. We subsequently introduce our semantically-driven approach for providing ontologies with uncertainties by analyzing ontological constructions with respect to their potential of being uncertain. Finally, a use case is shown.

Types of Uncertainties

There are several methods for representing and reasoning with uncertainty in AI. They differ in the type of uncertainty they describe as well as in their reasoning techniques.

Probability theories are one group of methods for dealing with uncertainties. Here, uncertainty is caused by ignorance, i.e., lack of knowledge. Information is either not available or too cost-intensive. Predefined or calculated truth values or probabilities between 0 and 1 are assigned to sentences. Prior and posterior probabilities are based on application-specific assumptions. Ways of processing such values depend on the interpretation of truth values, either as probability, belief, possibility, frequency, similarity, or likelihood. Examples are Bayes' theory, especially Bayesian networks, Dempster-Shafer's Belief theory, or utility theory.

Although non-monotonic logical theories are not intended to specify uncertain information, their assumption that facts are true as long as nothing else is proven also implies a notion of uncertainty. Examples are default logic and circumscription. The former method defines default rules to generate conclusions, i.e., given a prerequisite and certain justifications a predefined conclusion can be drawn. The latter defines abnormal objects in a logical formula. Here, reasoning is based on model preferences, i.e., models with fewer abnormal objects are preferred to other models.

Statistical models are another method to reason with uncertain information. They provide random variables to analyze the chance of an event. These methods are mostly applied to dynamic systems with changing conditions over time, such as hidden Markov models. Here, states are described as *single discrete random variables* (Cappé, Moulines, & Rydén 2005). Ontologies, however, have to follow a different approach to formalize dynamic aspects (Grenon & Smith 2004). Hence, statistical models are less relevant for uncertainties in ontologies.

In the following, we analyze the possibility of uncertainties in ontological constructions with respect to different uncertainty theories and their respective semantics. We aim at elucidating which ontological constructions are affected by which type of uncertainty. If they are affected, we want to provide the particular uncertainty theory that reflects the type of uncertainty best.

A Semantic Approach to Uncertainties

The representation of uncertainties in ontologies is demonstrated by refining syntax and semantics for DL ontologies. The uncertainties are analyzed according to different types, reasons, and occurrences of uncertainties in ontologies.

Table 1 lists all constructions that are relevant to define an ontology.[3] The syntax refers to the ontology definitions given by the web ontology language OWL DL. Thus we focus here on ontologies as theories formulated in description logic (Baader *et al.* 2003), in particular $\mathcal{SHOIN}$. Even though ontologies may be formulated in more or less expressive logics, description logic (DL) is not only widely used and a common standard for ontology specifications but it also provides constructions that are general enough for specifying complex ontologies (Horrocks, Kutz, & Sattler 2006). Moreover, they provide a balance between expressive power and computational complexity in terms of reasoning practicability. While OWL DL ontologies offer all constructions that are generally necessary for defining ontologies, the development of extensions shows that additional features are required for specific purposes, e.g., rules[4], discrete domains (Haarslev & Möller 2003), and also uncertainties.

DL ontologies distinguish between *TBox* and *ABox*. The first specifies the terminology of the domain. The latter specifies all instances within the ontology. These instances are specified in terms of the definitions provided by the TBox. Formally, instances are not part of the ontology itself, but they are structured and defined by the ontological terminology determined by the TBox.

[3]We omit constructions not directly related to ontology specifications, such as annotation properties, for simplicity.

[4]http://www.w3.org/Submission/SWRL

Table 1: DL syntax and semantics with examples

DL Syntax	OWL Semantics	Examples
$C_1 \sqsubseteq C_2$	subClassOf	Office $\sqsubseteq$ Room
$C_1 \sqcap \ldots \sqcap C_n$	intersectionOf	BearingWall $\sqcap$ CurtainWall
$C_1 \sqcup \ldots \sqcup C_n$	unionOf	Elevator $\sqcup$ Staircase
$\neg C$	complementOf	$\neg$ Staircase
$C_1 \equiv C_2$	equivalentClass	OpenOffice$\equiv\neg$ClosedOffice
$P_1 \sqsubseteq P_2$	subPropertyOf	size $\sqsubseteq$ attribute
$P_1 \equiv P_2$	equivalentProperty	connect $\equiv$ isAttached
P^+	transitiveProperty	spatialParthood$^+$
P^-	inverseProperty	compose$^-\equiv$isComposedOf
$\forall P.C$	allValuesFrom	$\forall$ size.Volume
$\exists P.C$	someValuesFrom	$\exists$ compose.Room
$\leq nP$	maxCardinality	$\leq$ 2 sensor
$\geq nP$	minCardinality	$\geq$ 1 neighbor
$= nP$	cardinality	$=$ 2 access
$a : C$	type	k : Kitchen
$\langle a, b \rangle : R$	property	$\langle$ k,building $\rangle$: compose

Uncertainties within Ontologies

In the following, we analyze construction elements of DL ontologies in Table 1 with respect to potential uncertainty.

Class Constructions Classes in an ontology are supposed to define the entities of a certain domain. They specify properties and constraints of all the entities that are instances of a class. Examples are Wall, Window, or Color. Classes categorize the domain into distinct groups with the same semantics, i.e., they structure the domain according to different kinds of members. All classes are meant to be well-defined. Either an instance is a member of a class or not. Hence, there is no indication to use uncertainties with respect to class definitions as such. The construction $C_1 \sqsubseteq C_2$ should therefore be strict. For example, either the class TemperatureSensor is subclass of Sensor or not. The domain can, however, imply that only parts of C_1 are entailed. This case is specified by the union of C_1's parts: C_{11} and C_{12}. Only one of them may then be defined as a subclass of C_2. Their union again defines the class C_1. For example, the union of Thermometer and TemperatureSensor is defined as the class TemperatureMeasureEntity, but only TemperatureSensor is also a subclass of Sensor. Similarly, a concrete instance of Room, for example, may also be seen as an instance of Office to a certain degree. This, however, does not reflect uncertainties of class definitions but uncertainties that arise from the instantiation of classes, as described below.

Note that one may argue for the definition of fuzzy classes in an ontology. This fuzziness, however, is caused by underspecified linguistic terminology, as discussed above. A library, for instance, is not defined by an exact number of books, i.e., by a strict definition. It describes instead a linguistic concept, which is determined by contextual and real world aspects (e.g., the possibility to read and borrow books). Such underspecified linguistic assignments can be interpreted by separate ontological layers, as discussed in (Bateman, Tenbrink, & Farrar 2007). The connection between these layers may then be indicated by uncertainties, i.e., uncertainties *across* ontologies (see below).

Unions and intersections of classes are applicable for constraints or relations among several classes. The domain or range of a property, for instance, may be assigned to a union of classes. For example, the union Wall $\sqcup$ Window $\sqcup$ Door fills the range of the relation border of Room in a someValuesFrom construction. Union and intersection constructions allow flexible relationships in class restrictions and are therefore not influenced by uncertainties. They work merely as operators for other constructions. Similarly, negations of classes are strict. They negate all class definitions and they are also used in particular for defining restrictions of class or relation definitions. A class Table and its negation $\neg$Table have their clear semantics. Specific attributes determine the meaning and behaviour of Table and its negation accordingly. This differs, however, from an instantiation, i.e., an actual entity in the world. This entity may or may not be of the type Table, specified by the construction type (see below).

Equivalent classes are typically used to relate different ontologies. We will discuss this construction in more detail in the next section, as it aims at defining relations across different ontologies. Other use of equivalent classes as a logical operator is clearly not affected by uncertainties.

Property Constructions Object properties define a specific relation among classes. They define the domain and range of classes that are related with each other. Examples of relations are containedIn, size, or sensorRange. Such relations can be classified according to their types, e.g., (Masolo *et al.* 2003). They may therefore specify necessary constraints for classes. While a relation may hold or not, its definition itself is strictly specified, i.e., the general definition of possible relations between instances is not affected by uncertainties. The property definition itself simply defines a relationship and its domain and range. The relation (property) hierarchy of an ontology is therefore well-defined. For example, the property containedIn defines the containment relationship between Room and Building. A specific Room Office1 can then be containedIn a Building OfficeBuilding. Whether this particular instantiation of the property containedIn, namely containedIn(Office1,OfficeBuilding1), is actually true is irrespective of the definition of the relation itself, namely that Room and Building are related by this relation.

The transitiveProperty and inverseProperty constructions define a property to be transitive, e.g., containedIn, or inverse, e.g., neighbor, respectively. These aspects may either hold for a specific relation or not and are therefore not affected by uncertainties. For example, a relation nearTo may define a close distance between two classes and within certain limits may even be considered as transitive to some extent. But given a sequence of instances which are pairwise nearTo each other, it is difficult to say whether the relation nearTo between the first and the last instance still holds. This, however, does not indicate that transitiveProperty has to provide a notion of likelihood. Rather, it indicates that nearTo is not a transitive relation.

Class Restrictions The ontology specifies not only class and relation definitions but also restrictions of classes.

These are given by the constructions allValuesFrom, someValuesFrom, as well as cardinality constraints. allValuesFrom and someValuesFrom constrain the range of a relation to be of a specific type of class. The choice between these two constraints allows a flexible definition within an ontology. Uncertainties in terms of likelihood, for instance, are covered by someValuesFrom. Additional uncertainties are therefore not indicated. It remains questionable, whether a notion of default information is applicable here.

Cardinality restrictions specify the number of relations of a class. In OWL DL, positive integer values can be assigned to the constraints maxCardinality, minCardinality, and cardinality in order to define a necessary amount of relations. This amount can thus define how many relations are required at least, at most, in an interval from minimum to maximum, or with a specific number. This allows a flexible mechanism for constraining relations. Just as for value-related constraints, uncertainties seem not to be necessary here. A Street, for instance, may have a certain number of junction relations, ranging from 0 to n. In order to model domain ontologies, however, it is sometimes essential to define value and cardinality constraints by default, which are not as strict as the ontological constraints described. In the domain of indoor environments, for example, it may be required that an instance x, that contains one instance of type Refrigerator and one instance of type Oven, be of type Kitchen by default. If some of these instances are not related by the relation contains, x is still able to be of type Kitchen. In contrast, DL cardinality restrictions can only assign a specific value (1), a minimum (0), or a maximum (n), which is more restrictive than a default rule. By adding default rules to cardinality restrictions, the TBox can define common facts about the domain. As long as the justifications for x being an instance of Kitchen are not false, the instantiation of this class can be derived.

Instance Constructions Finally, instantiations of classes and relations are specified by an ontology. Instances of classes are defined by type, instances of relations are defined by property. Both definitions are most likely affected by uncertainties, as we have already seen in the example above. A system instantiates an ontology in order to represent its environment. Whether environmental entities are instantiated as a specific type or relation depends on various kinds of uncertainties: Input data of a system is vulnerable to inaccuracy, incompleteness, ambiguity, and incorrectness, because of noise, unreliable sources, or limitations of a system's sensorimotor capabilities. Assumptions or conclusions that are drawn may turn out to be wrong and lead to additional errors. For example, a spatially-aware system has to classify perceived entities on the basis of its sensory input, which is not only affected by noise but also relies on results from a recognition system, as described in (Schill, Zetsche, & Hois 2009). The classification process is consequently affected by uncertainty. In general, complete knowledge of the domain is not fully available in natural environments (open world assumption) and an object's type can hardly be defined without difficulties. Uncertainties influence the instantiation of an object or a relation between objects. Hence, type and property imply notions of probability or belief, depending on uncertainty values from a priori probabilities or expert-defined beliefs.

Table 2: Ontology constructions affected by uncertainties

DL Syntax	Uncertainty	Example
$C_1 \equiv^* C_2$ *or* $P_1 \equiv^* P_2$	similarity	The two parts from different ontologies are similar with a similarity value 3
$\leq nP$ $\geq nP$ $= nP$	default	Given $\langle x, z \rangle$: livesIn and $\langle x, y \rangle$: neighbor, then $\langle y, z \rangle$: livesIn by default
$a : C$	probability	x is of type SlidingDoor with a probability of .8
	belief	The belief for x being a CopyRoom of .9
$\langle a, b \rangle : R$	probability	The probability of a being sensor of b is .2
	belief	The belief of a being a spatialParthood of b is .8

In summary, instantiations of classes and relations may be affected by probabilities or beliefs, while cardinality restrictions may benefit from default rules (cf. Table 2).

Uncertainties across Ontologies

In contrast to the specification of one ontology, the specification of relations between different ontologies appears more likely to be affected by uncertainties. In order to provide semantic integration and information exchange as well as alignments and mappings between ontologies, classes and relations from different ontologies are compared and related with each other. This can be done for ontological definitions (TBox) or for instances (ABox).

Ontological constructions that allow mappings across domains have to define the meaning of possible uncertainties as well. Constructions in OWL DL allow imports of ontologies. Classes and relations of imported ontologies can be related by equivalentClass and equivalentProperty constructions. This is often not sufficient for complex relations between heterogeneous sources, as methods for aligning ontologies show. Such relations can, for instance, be defined by distributed description logics (Borgida & Serafini 2003) or $\mathcal{E}$-connections (Kutz *et al.* 2004). These methods range from single mappings of two instances from different ontologies to complex formulae that describe relations between several classes from different ontologies. Regardless of the complexity of such relationships, parts of one ontology are related to parts of another. For simplicity, we use $\equiv^*$ as a placeholder for mapping operations of various kinds.

The equivalence construction indicates that parts from different ontologies are likely to be *equal* or *identical*. These parts can, for instance, be seen as similar definitions, i.e., the parts resemble each other closely in their representation. The $\equiv^*$ operation (as a placeholder for ontology mapping functions) is therefore affected by an uncertainty that can be defined by similarity values, cf. (Hois & Kutz 2008).[5]

[5]Although probability or likelihood measures could also be

Table 3: Extended constructions in the semantic framework

Extended Syntax	Interpretation
$sim(C_1 \equiv^* C_2) \rightarrow n, n \geq 0$ $sim(P_1 \equiv^* P_2) \rightarrow n, n \geq 0$	similarity across ontologies of related classes or of related properties
$\frac{[\leq n\langle a,b\rangle:R]:[a:C_1,b:C_2]}{[a:C_1]}$ (accordingly for $\geq$ and $=$)	default rules for cardinality restrictions
$m(a:C) \rightarrow [0,1]$ $m(\langle a,b\rangle:R) \rightarrow [0,1]$	belief or probability of class or of property instantiations

Uncertainty Constructions for Ontologies

A semantically-driven framework for appropriate uncertainties in ontologies thus has to integrate different types of uncertainties as analyzed above. Hence, ontology constructions given in Table 1 are extended by the constructions given in Table 2. The result is defined in Table 3.

In detail, inter-ontology mappings are assigned positive values that reflect the similarity of related classes or relations. While 0 indicates closest similarity, no similarity is indicated by infinity. Pre-defined concrete values for this similarity are then indicated together with the definition of the mapping relation. This kind of uncertainty is not influenced by an agent's instantiation of ontologies but by the mapping relation between different ontologies. Concrete values are therefore defined by developers that provide mapping relations themselves or by automatically detected mapping relations. For example, a spatial system may have to use a spatial domain ontology together with an ontology for qualitative spatial relations. The similarity of classes across both ontologies then has to be defined. Given particular instances in the domain ontology (such as a Column inside a Room), a spatial system can then relate these instances to information from the qualitative ontology (such as a specific Region that is a proper part of another region) by assigning specific similarity values to each relation if necessary. In terms of the inference process the closest similarity can be chosen if multiple similarities across ontologies are defined.

Cardinality restrictions are given by default rules (Reiter 1980). As long as the instances a and b are classified as C_1 and C_2 respectively, a is of type C_1 given a specific relation between a and b. Given this definition, default aspects of classes can be defined in an ontology specification. Here, common conclusions with respect to cardinality restrictions are available. For example, a spatial system that navigates in indoor environments can get default information about its surroundings from the ontology. Typical default definitions that are relevant for the system are, for instance, a Refrigerator is containedIn a Kitchen. A system that detects an instance of Refrigerator in its environment may therefore infer that it is located in a Kitchen, e.g., as long as it does not gain further information that the location is a Laboratory.

Agent-based instantiations of classes and relations that are affected by uncertainties are defined by belief values. This belief may then, for instance, be defined by the Dempster-Shafer theory of evidence (Shafer 1976), but also by other probability theories. For simplicity, we use only belief values for uncertainties in instantiations. The semantics of a belief of an agent in a specific instantiation or relation is given by $m(A)$ in Dempster Shafer's theory. Dempster's rule of combination allows the calculations of beliefs accordingly (Shafer 1976). In particular, the combination of all beliefs about the evidence of the type of an instance, e.g., $m(x : Refrigerator)$ and $m(x : Freezer)$, does not have to sum up to 1. Concrete values are supposed to be provided by "experts". If the instantiation of a class is, for instance, uncertain because of ambiguous data from an object recognition process, the concrete uncertainty value from the result of this recognition process can be used. If such uncertainty values are unavailable, they can be approximated by averaged probabilities over class restrictions, e.g., a class defines n relations and a are verified then a belief of $\frac{a}{n}$ is assumed.

used, we omit this possibility for simplicity for the time being.

Use Case: A Spatially-Aware System

Our use case is related to applications of ontologies in spatial systems that perceive and interact with their environment, be it virtual or real. In the long term, we are aiming at a general system capable of dealing with applications in the field of way-finding, navigation, spatial guidance, assistance systems, ambient intelligence, smart offices, and human-computer interaction. For representing the spatial domain of the system, we specified spatial indoor ontologies.

In (Schill, Zetsche, & Hois 2009), we describe sensorimotor aspects of the spatial system, that is supported by ontologies in object recognition and localization tasks. The system relies on the object recognition process that provides object classification results. The results are, however, affected by uncertainties of several kinds, e.g., due to limits of sensorimotor input and processing. Ontological instantiations are indicated by belief values of the Dempster-Shafer theory. High-level reasoning on the basis of these values is provided here. Abstract information of relations between rooms and objects is defined by the ontology, which is independent of low-level data analyses. Here, belief values are, for instance, assigned to rooms providing a specific type of room, e.g., office, kitchen, laboratory.

Different ontologies that describe the spatial domain from different perspectives have to be related with each other in a spatial system. Mapping relations have to be defined across these ontologies accordingly. In (Hois & Kutz 2008), we describe a similarity-based mapping formalism. It connects qualitative spatial information with spatial language. By applying inter-connections between spatial and linguistic information, the system is able to provide an interface for interaction by natural language. Moreover, this mechanism provides a solution for dealing with vagueness in natural language expressions. The similarities can be implemented, e.g., with SIM-DL (Janowicz *et al.* 2007).

Within the domain ontology, we need to define default rules for representing common sense world knowledge, such as typical objects in rooms or typical interactions with objects. This allows the modeling of precise definitions of the environment. The integration of default rules for particular relations between specific types of rooms and their contained objects as well as for specific types of buildings and their contained rooms is currently under development. Such definitions are being applied to improvements of object recognition and localization tasks.

Conclusions and Future Work

In this paper, we have introduced a framework that provides ontologies with uncertainties in appropriate cases. The framework allows us to define different types of uncertain information and limits possible occurrences of these types. A *certain reality* can then be analyzed with respect to these possibilities and can then be specified with such uncertainties where adequate. We use this framework for a spatial application, which combines different ontologies and different types of uncertainties. We are implementing our framework for OWL DL in particular, though the development is still in progress. In summary, we have shown that the ontology constructions are only partially affected by uncertainties. Instantiations are the main constructions that suffer from uncertain information. The way these uncertainties have to be formulated and structured, however, has to be specified by ontological constructions, as introduced above.

Transformations between different uncertainty theories are still an open issue. They provide an approximation for translating one uncertainty theory into another. The relevance of such a translation is left for future work. Also, related reasoning techniques as indicated by the proposed uncertainty theories have to be provided. In order to access this information, for instance, the query language has to support uncertainty-related requests. So far, calculations of uncertainties are only provided outside ontological structures.

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