On the Evolution of Ontologies using Probabilistic Description Logics

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Abstract. Exceptions play an important role in conceptualizing data, especially when new knowledge is introduced or existing knowledge changes. Furthermore, real-world data often is contradictory and uncertain. Current formalisms for conceptualizing data like Description Logics rely upon first-order logic. As a consequence, they are poor in addressing exceptional, inconsistent and uncertain data, in particular when evolving the knowledge base over time.
This paper investigates the use of Probabilistic Description Logics as a formalism for the evolution of ontologies that conceptualize real-world data. Different scenarios are presented for the automatic handling of inconsistencies during ontology evolution.

The year is 50 B.C. Gaul is entirely occupied by the Romans. Well, not entirely... One small village of indomitable Gauls still holds out against the invadors. And life is not easy for the Roman legionaries who garrison the fortified camps of Totorum, Aquarium, Laudanum and Compendium...

[Goscinny and Uderzo, Asterix the Gaul]

1 Introduction

In recent years, ontologies have become standard for knowledge representation in the Semantic Web. While ontologies are usually expressed in Web Ontology Language (OWL) recommended by the W3C [1], the underlying formalism for reasoning about data in the ontology is Description Logics (DL), being a decidable subset of first-order logic [2].
Classical knowledge bases relate to decidable subsets of first-order logic: either something is asserted in the knowledge base or not. It is hence difficult to express exceptions or degrees of belief in first-order-logic-based formalisms. Furthermore, when evolving a classical knowledge base, inconsistencies are likely to occur but hard to resolve.

The need for representing and processing exceptional and uncertain data has been recognized, and several methods were proposed for relaxing first-order logic based formalisms by uncertainty models being capable to handle ontological data. Yet, these approaches do not provide out-of-the-box solutions for the evolution of a knowledge base.
The process of (consistent) evolution of ontological knowledge bases is still only being rarely addressed. The creation of ontologies, especially from large text corpora, is a well-understood problem [3, 4], and, as a result, a rebuild of the ontology is preferred to evolution. This is not desirable in cases where conceptualizations cannot be learned from data or existing knowledge bases have to be used as a baseline [5]. Such problems have to be tackled using evolutionary methods rather than learning.
This paper discusses the use of probabilistic defaults for the evolution of OWL-DL knowledge bases. Evolution is based on the addition of information; information cannot be removed but only falsified or relaxed. Inconsistencies that are likely to occur during the evolution of a knowledge base are resolved automatically. In contrast to existing approaches that either remove data from the knowledge base or try to perform reasoning despite the existence of inconsistent information, the presented approach relaxes the inconsistent information by means of (probabilistic) defaults.
Defaults, introduced by Reiter [6] and re-interpreted by Lehmann [7], facilitate the co-existence of default rules for typical cases together with exceptions from these rules. When querying the knowledge base, more specific knowledge, i.e. the exceptions, is preferred to more general knowledge, i.e. the defaults, exactly providing the desired properties.
While the exception modelling can be solved using defaults alone, probabilistic defaults provide an opportunity to model degrees of belief for such exceptions as they occur during user-assisted ontology evolution. This paper uses the approach of Lukasiewicz [8], currently the only approach providing both default and probabilistic reasoning for OWL-DL ontologies.
This work is structured as follows: After presenting state-of-the art formalisms for representing uncertainty in ontological knowledge bases in Section 2, Probabilistic Description Logics (PDL) are investigated in particular in Section 3. In Section 4 possible inconsistencies occurring during ontology evolution are presented as well as a scheme for automatically resolving them. The paper closes with a discussion in Section 5 about the presented approach and gives an outlook on possible alternatives and future work.

2 Related Work

This section gives an overview over methods for dealing with exceptional, uncertain and vague knowledge, handling of inconsistent information and evolution of OWL-DL knowledge bases.

2.1 Uncertainty and Vagueness

The need for relaxing FOL by means of probabilistic logic programming has been subject to investigation for a long time. They can be distinguished into two groups: approaches directly extending the knowledge base by a probabilistic model and approaches where the knowledge base has to be transformed into another structure like in PR-OWL [9–11] or *Bayes*-OWL [12, 13] where the ontology is transformed into a *Bayesian* Network. However, the transformation causes an evolution scheme to be rather complex making direct approaches more favourable.
Regarding the direct extension, there have been developed some promising approaches recently like Fuzzy OWL, Markov Logic (ML), and Probabilistic Description Logics (PDL) all of which are presented in the following subsections.

Fuzzy OWL enables the expression of vague concepts like "The glass is half full" or "A sports car is fast" [14, 15]. Fuzzy modifiers like "very"or "high" enable statements like "A sports car can ride at high speed". For fuzziness, there has to be specified fuzzy membership degrees which cannot be estimated in a straightforward way for resolving inconsistent information. In addition, the problems to be tackled address more uncertainty than vagueness. This makes Fuzzy OWL - though being a very interesting approach - not applicable. Please refer to [16] for a detailed comparison of addressing uncertainty and vagueness.

Markov Logic is a direct relaxation of first-oder logic: formulas are assigned a weight, and these pairs form a so-called Markov logic network (MLN) [17]. Though being restricted to finite domains, extension to infinite domains are possible [18]. The grounding of an MLN for a set of atoms defines a graph, the so-called Markov network (MN). The log-linear probability of a world is defined as the sum over all formulae of the weighed number of true groundings. The Markov blanket is defined by the true groundings for a world. Note that Markov Logic is not restricted to modelling individuals independently to each other, and is extremely scalable since only the needed information, defined by the Markov blanket, has to be investigated for performing reasoning.
However, Markov Logic, being extremely flexible, default knowledge like "Generally, all Gaul villages are occupied by the Romans with the exceptions of . . . " cannot be expressed in a straightforward way such that the default can co-exist with the exception. Instead the more specific piece of information has to be asserted a higher weight overriding the default. In case of the presence of different contradicting information, the choice of the weights is rather complex when trying to keep the desired semantics.

Probabilistic Description Logics extend classical DL by probabilistic terminological as well as probabilistic assertional knowledge [8]. Like in conditional default reasoning [7], uncertain knowledge is modelled as constraints but enriched with an interval allowing to provide minimal and maximal probability for a constraint. The semantics of a constraint is "Given evidence ϕ, generally the conclusion ψ holds with probability of at least l and at most u" allowing to model exceptions and uncertain information straightforward. Furthermore, PDL allow for relaxing specific knowledge while keeping the strictness of DL for the remaining knowledge base. Hence, PDL is a good choice for evolving ontological knowledge bases.

2.2 Inconsistencies

The handling of inconsistencies in DL knowledge bases, often also referred to as bugs or defects, has been well investigated. Methods exist for finding defects [19] and also for automatically resolving them [20]. Preserving the formalism used comes at the cost of having to remove information. Approximate reasoning [21] gives up correctness, and approaches like multi-valued logics [22] change the underlying formalism significantly.
The presented approach tries to relax the underlying formalism as much as necessary while preserving its semantics as much as possible.

2.3 Evolution

The evolution of ontologies is addressed to preserve the logics [23] or only make small changes, for example, on instance level [24]. In this paper, the evolution of OWL-DL knowledge bases is investigated, relaxing the formalism while allowing any insertion of new information according to OWL-DL.

3 Probabilistic Description Logics

While DL provide formal logical representation and inference, uncertainty about statements like "The chance for an avalanche in the western Alps is between 50% and 75%." cannot be modelled very well. Exceptional knowledge like "Generally, all Gaul villages are occupied by the Romans, but there is still a chance of less than 1% that a Gaul village is not occupied by the Romans." also cannot be dealt with in an straightforward way.
Probabilistic Description Logics (PDL) [8] model both, exceptions and uncertain knowledge using probabilistic (default) conditional constraints. While the exceptions can be modelled as an extension of Lehmann's lexicographical entailment [7], uncertainty is modelled by assigning belief intervals to these conditional constraints. Probabilities are defined for satisfiable and hence possible worlds.
A conditional constraint $(\psi|\phi)\,[l, u]$ means that given evidence ϕ, the probability that conclusion ψ can be drawn lies between l and u. If $l = u = 1$, then the constraint is called a *default*, meaning "Generally, given ϕ, ψ holds", where ψ and ϕ are concepts. As such, a constraint represents a subclass relation $\phi \sqsubseteq \psi$ with a degree of at least l and at most u.

A world I is the (positive) set of all concepts $\phi \in \mathcal{C}$ from a TBox T for which $\{\phi(i)|\phi \in I\} \cup \{\neg\phi(i)|\phi \in \mathcal{C} \setminus I\} \cup T$ is satisfiable for a new individual i.

$$I \models \phi \iff \phi \in I$$

A probabilistic interpretation Pr is a mapping from the set of worlds $\mathcal{I}_\mathcal{C}$ to the unit interval $Pr : \mathcal{I}_\mathcal{C} \to [0, 1]$, such that $\sum_{I \in \mathcal{I}_\mathcal{C}} Pr(I) = 1$.
The probability of a concept ϕ is the sum of probabilities of all worlds in which it (positively) appears:

$$Pr(\phi) = \sum_{I \models \phi} Pr(I)$$

The probability of a constraint $(\psi|\phi)$ is defined in case the evidence has strictly positive probability:

$$Pr(\phi) > 0 \Rightarrow Pr(\psi|\phi) = Pr(\psi \sqcap \phi)/Pr(\phi)$$

Analogous to logical subsumption, a probabilistic interpretation Pr satisfies a conditional constraint $(\psi|\phi)[l, u]$ iff either the evidence has zero probability or the probability of the conclusion lies within the specified interval:

$$Pr \models (\psi|\phi)[l, u] \Leftrightarrow Pr(\phi) = 0 \text{ or } l \leq Pr(\psi|\phi) \leq u$$

A probabilistic interpretation Pr satisfies a set of conditional constraints $\mathcal{F}$ iff it satisfies each constraint in the set:

$$Pr \models \mathcal{F} \Leftrightarrow Pr \models F \quad \forall F \in \mathcal{F}$$

It was furthermore shown that, due to the relation of a probabilistic interpretation to a TBox T and a set of conditional constraints $\mathcal{F}$, the TBox T has a satisfying interpretation iff T has a satisfying probabilistic interpretation [8]. Hence, a satisfying probabilistic interpretation Pr for T and $\mathcal{F}$ is said to model $Pr \models T \cup \mathcal{F}$.
The idea of overriding more general information with (possibly incoherent) more specific information is addressed with the so-called *z-partitions*. A z-partition is an ordered partition $(P_0, \ldots, P_n)$ of a set of conditional constraints P with ascending level of specifity defined by the notion of verification and tolerance, which are defined below.
A probabilistic interpretation Pr verifies a conditional constraint iff the evidence has probability one and the probability of the conclusion lies within the specified interval:

$$Pr \text{ verifies } (\psi|\phi)[l, u] \iff Pr(\phi) = 1 \wedge l \leq Pr(\psi) \leq u$$

As such, verification can be seen as satisfiability with certain evidence and ensures the inheritance of probabilistic properties along subclass relations in entailment.
A set of conditional constraints $\mathcal{F}$ tolerates a conditional constraint under a

TBox T iff $T \cup \mathcal{F}$ has a model that verifies F. Let $P_i^- = P \setminus (P_0 \cup \ldots \cup P_i)$ be the remainder set of P. Then P_i is the set of all conditional constraints $F \in P_i^-$ that are tolerated by the remaining constraints P_i^- under T. The tuple $(P_0, \ldots, P_n)$ forms the unique z-partition for the PTBox (T, P).
As with classical DL, PDL distinguishes between terminological probabilistic knowledge and assertional probabilistic knowledge. As a result, probabilistic class assertions are of the form $(\phi(o)|\top)[l, u]$. They express that individual o belongs to class ϕ with a probability of at least l and at most u. Probabilistic class assertions are accumulated into one PABox P_o for each probabilistic individual $o \in I_P$ for a PTBox (T, P). A probabilistic knowledge base is hence the triple $\mathcal{K} = \big(T, P, (P_o)_{o \in I_p}\big)$. Note that in contrast to Markov Logic, all probabilistic individuals are assumed to be independent of each other.
A probabilistic knowledge base $\mathcal{K}$ is consistent iff its PTBox is satisfiable and $T \cup P_o$ is satisfiable for every $o \in I_P$. Probabilistic individuals may be assigned a degree of class assertion but must not assert contradicting classes.

4 Evolution

It is assumed that during the evolution of a DL knowledge base, only new information is added. The new knowledge, in turn, may violate the consistency of the knowledge base and thus make it unsatisfiable. Classical inference cannot be applied anymore, because from inconsistent information every conclusion, even being frankly incorrect, would be valid.

4.1 Inconsistencies

Inconsistencies are often referred to as defects or bugs and resolving them has been continuously subject to research. In principle, three different approaches are pursued:

1. Removal of axioms causing defects.
2. Addition of information, e.g. for handling exceptions.
3. Reasoning with inconsistent information.

Yet, there are situations where neither of these approaches is applicable, especially when handling contradicting data where all information has to be kept. Accordingly, the formalism for knowledge representation has to be adopted, i.e. relaxing the first-order logic based model while the essence of the information available is being kept. Hence, the approach followed in this paper can be seen as a combination of all three: The troublesome information is erased from the original knowledge base. The knowledge base is enhanced by a formalism relaxing the constraints as much as necessary do perform reasoning while preserving as much of the original meaning as possible. The removed information is converted w.r.t. the relaxed formalism and added to the enhanced knowledge base.
According to [19], inconsistencies can be classified into

1. Inconsistency of Assertions about Individuals
2. Individuals Related to Unsatisfiable Classes
3. Defects in Class Axioms Involving Nominals

This paper provides scheme for resolving all of the above issues. Examples for defects and how to resolve them are presented in Section 4.6.
In the following, it is assumed that a classical consistent knowledge base $KB = (T, A)$ is given. This knowledge base is enriched by an empty PTBox and an empty set of PABoxes $\mathcal{K} = (T, P, (P_o)_{o \in I_P})$.
Inconsistencies of type 1 and 2 occur in the presence of disjoint classes, $B \sqsubseteq \neg A$. An inconsistency may be caused by the insertion of a not directly related subclass or class assertion axiom representing more specific information than the disjointness expresses. The reason for that lies within the disjointness on the more general level and effects the satisfiability of the more specific information. Hence, the removal of the more general cause rather addresses the idea of preferring more specific information to more general information in PDL.

4.2 Resolving Inconsistencies Using Defaults

When using defaults for resolving inconsistent information, two problems have to be tackled: the resulting probabilistic knowledge base has to be consistent again and the proper choice of the disjoints to resolve. While the first can be assured, the latter depends on how resolving of inconsistencies is interpreted.

Consistency can be assured when starting with a consistent knowledge base. This is indeed the case when resolving inconsistencies using defaults, because the original knowledge base is made consistent when resolving inconsistent information.
Let $(\psi|\phi)[1, 1]$ be a default and $\mathrm{PT} = (P, T)$ be a consistent PTBox with $T \cup \{\phi(i), \psi(i)\}$ is satisfiable for a new individual i. Adding $(\psi|\phi)[1, 1]$ to PT, the resulting PTBox $\mathrm{PT}' = (P \cup (\psi|\phi)[1, 1], T)$ is consistent again.
Due to $T \models \psi(i) \sqcap \phi(i)$ there exists a satisfiable world $I = \{\psi, \phi\} \cup \mathcal{C}'$ with $\mathcal{C}' \sqsubseteq \mathcal{C}$. Let furthermore P_i be a partition from the z-partitions of PT and Pr_i the corresponding model, and $\mathcal{I}_{\mathcal{C}i}$ the worlds with $Pr_i(I) > 0$ such that $I \cup \{\psi, \phi\}$ is satisfiable, then satisfiability and verification of that partition does not change when adding $(\psi|\phi)[1, 1]$.
If no such partition exists, then let $P_{n+1} = \{(\psi|\phi)[1, 1]\}$ be a new partition. Since $T \models \psi(i) \sqcap \phi(i)$, there exists a probabilistic interpretation Pr_{n+1} with $Pr_{n+1}(I = \{\psi, \phi\}) = 1$ and 0 else that is a model of PT' and that is verified by $P' \setminus P_0 \cup \ldots \cup P_n$.
As a result, the new PTBox PT' has a z-partition, the TBox is consistent by definition and hence consistency is proved.

The Resolving Disjoints can be determined using the specifity relation for conditional constraints that comes along with PDL and choosing the most general disjoints to be turned into defaults. First, the set of disjoint axioms involved in the inconsistency has to be determined $\mathcal{D} = \{B \sqsubseteq \neg A\}$. Then, these disjoints are turned into a set of defaults $\mathcal{F}' = \{(\neg A|B)[1,1] | B \sqsubseteq \neg A \in \mathcal{D}\}$. These new defaults are added to the PTBox $P' = P \cup \mathcal{F}'$. By application of the z-partition algorithm of [8] to P', the most general partition P_i' that contains one of the new defaults $F \in \mathcal{F}'$ can be determined. Finally, all of the new defaults in P_i' are added to the original PTBox, resolving the inconsistency and forming the new knowledge base:

$$KB = (T, P \cup (\mathcal{F}' \cap P_i'), (P_o)_{o \in I_P})$$

It should be noted that the choice of the resolving disjoints is arbitrary. However, resolving the inconsistencies means turning disjoints into defaults. Since these defaults are asserted a level of specifity in PDL, it is a reasonable assumption that the choice of the disjoints to be resolved should rely upon their level of specifity.

4.3 Terminological Incoherence

Unsatisfiable classes occur when disjoint axioms $B \sqsubseteq \neg A$ are present in the TBox, and there exists one class C for which is a subclass of both A and B. Let A, B, and C be concepts from a TBox T such that

$$\begin{aligned} B \sqsubseteq A, C \sqsubseteq \neg A, C_n \sqsubseteq B_m, \\ B_m \sqsubseteq B_{m-1} \sqsubseteq \ldots \sqsubseteq B_1 \sqsubseteq B, \\ C_n \sqsubseteq C_{n-1} \sqsubseteq \ldots \sqsubseteq C_1 \sqsubseteq C \end{aligned}$$

In order to repair this defect by PDL, the two most general pieces of contradicting knowledge are removed from the TBox and expressed as two defaults $(B|A)[1,1]$ and $(C|\neg A)[1,1]$ and added to the PBox. The resulting PTBox is consistent. It should be noted that strict assertions about $B_i \sqsubseteq A$ and $C_j \sqsubseteq \neg A$ are not possible anymore.

4.4 Assertional Inconsistencies

Unsatisfiable class membership axioms are caused when one individual a is assigned to belong to two disjoint classes C_n and B_m:

$$\begin{aligned} B \sqsubseteq A, C \sqsubseteq \neg A, C_n(a), B_m(a), \\ B_m \sqsubseteq B_{m-1} \sqsubseteq \ldots \sqsubseteq B_1 \sqsubseteq B, \\ C_n \sqsubseteq C_{n-1} \sqsubseteq \ldots \sqsubseteq C_1 \sqsubseteq C \end{aligned}$$

Again, $B \sqsubseteq A$ and $C \sqsubseteq \neg A$ are removed from T, and $(B|A)[1,1]$ as well as $(C|\neg A)[1,1]$ are added to the PTBox. Note that there is no difference whether a is a probabilistic individual or not.

4.5 Defects Involving Nominals

Defects involving nominals are caused by disjoint subclass inclusion axioms when the disjoint classes refer to the same nominals. Since PDL does not allow probabilistic individuals to occur in *oneOf* constructs, the defect has to be resolved analog to Section 4.3.
Assume A, B to be concepts and $B \sqsubseteq \neg A$. Furthermore let $A = N_1, N_2, \dots$ and $B = N_1$ leaving the corresponding knowledge base unsatisfiable. Removing the disjoint axiom from the knowledge base and inserting the default $(\neg A|B)[1, 1]$ to the PTBox will resolve the inconsistency and the knowledge base becomes satisfiable again.

4.6 Example

Related to the example in [8], assume the following TBox $T = \{\text{PP} \sqsubseteq \text{HP}, \text{HP} \sqsubseteq \text{HBP}\}$, meaning that all pacemaker patients (PP) are also heart patients (HP), and heart patients suffer from high blood pressure (HBP). New information is introduced that pacemaker patients shall not have high blood pressure, expressed by $\text{PP} \sqsubseteq \neg\text{HBP}$. Inserting this new axiom, the TBox becomes unsatisfiable. The incoherence is resolved by removing the most general pieces of knowledge from the TBox, turning them into defaults $(\text{HBP}|\text{HP})[1, 1]$ and $(\neg\text{HBP}|\text{PP})[1, 1]$ that are added to the (new) PTBox.
Starting with the same knowledge base as above, is is known that Tim (t) is a heart patient $(\text{HP}(t))$. At some point, it occurs that Tim indeed does not suffer from high blood pressure $(\neg\text{HBP}(t))$ making the knowledge base unsatisfiable, i.e. inconsistent that can be resolved exactly the same way as above by turning the disjoint class axioms into defaults.
According to the example from [19] assume the following knowledge base consisting of $\text{MyFavoriteColor} = \{\text{Blue}\}$, $\text{PrimaryColors} = \{\text{Red}, \text{Blue}, \text{Yellow}\}$ and $\text{MyFavoriteColor} \sqsubseteq \neg\text{PrimaryColors}$. Removing the disjoint axiom and adding the default $(\neg\text{PrimaryColors}|\text{MyFavoriteColor})[1, 1]$ will do the job of making the knowledge base satisfiable again.

5 Discussion and Outlook

This paper presented an approach for the evolution of ontological knowledge bases using (probabilistic) defaults. Inconsistencies that occur during the evolution of the ontology are resolved by defaults in Probabilistic Description Logics. While resolving the inconsistencies, the most general piece of information is removed. The level of generality can be retrieved using the z-partitions of PDL. Although any transformation of the pain-causing subclass inclusion axioms would lead to the desired resolving, it would not follow the idea of preferring more specific knowledge to more general knowledge in default logic as proposed by Lehmann.
While the approach enables automatic inconsistency handling, the assumption

that the most general piece of knowledge is being relaxed might be wrong in certain situations where that very piece of knowledge must be strict in any case. However, it may be reasonable to mark axioms as mandatory strict but then it cannot be guaranteed that the knowledge base can be made satisfiable using defaults. This can only be achieved giving up strictness in any case. An interesting alternative would be a semi-automatic combination of OWL-debugging and the presented approach.
On the one hand, only very basic aspects of incoherence are investigated in this paper. The expressivity of OWL-DL TBoxes, however, allows more complex forms of incoherence. Future work will have to take into account the automatic resolution of more complex causes for incoherence.
Only the use of defaults for resolving inconsistencies was investigated. While this is sufficient for resolving classical inconsistencies, a probabilistic formalism has to be used for resolving inconsistencies of probabilistic knowledge which will be subject to further investigations. In addition, PDL is currently the only approach that allows the use of defaults for OWL ontologies.
Since this paper only addresses the case of uncertain data, it would be interesting to develop an similar method for vague data using Fuzzy OWL. Nevertheless, additional information like fuzzy membership functions has to be provided when making the removed axioms and class assertions vague.
Markov Logic, nonetheless being very performant and flexible, might be an alternative model for evolution. Since the formalism provides less structure, the application of logical patterns might make it more comparable to the inheritance structures of PDL leading to Markov Description Logics.
An implementation of the presented approach will be performed within the "Datacenter Nature and Landscape" (DNL) project [25] modelling a conceptualization for the environmental data of Switzerland. In the same project the use of end-user feedback for the evolution of ontologies for heterogeneous data will be investigated [26].
For the application to ontology mapping [27], a further processing scheme has to be developed taking into account the parallel addition of new information from one ontology to another, opposed to the batch processing scheme that was used in this paper.

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