On the Problem of Weighted Max-DL-SAT and its Application to Image Labeling

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Abstract. For a number of problems, such as ontology learning or image labeling, we need to handle uncertainty and inconsistencies in an appropriate way. Fuzzy and Probabilistic Description Logics are the two major approaches for performing reasoning with uncertainty in Description Logics, but modeling problems such as image labeling still remains difficult and handling inconsistencies is only supported to a limited extent. In this paper, we propose Max-DL-SAT and Weighted Max-DL-SAT as new reasoning services for Description Logics knowledge bases, which applies the idea behind Weighted Max-SAT to Description Logics and leads to a more intuitive representation of certain problems. It supports handling of uncertainty and inconsistencies. The contribution of this paper is threefold: We define a novel reasoning service on Description Logics knowledge bases, introduce an algorithm for solving such problems, and show the application of it to the problem of image labeling.

1 Introduction

Solutions to a number of real world problems are often subject to a set of potentially contradicting constraints, for which a completely satisfying solution does not exist, e.g., in Computer Aided Design or information extraction from text. In Max-SAT, these problem are modeled as a boolean a formula for which one seeks an assignment of truth values that satisfies a maximal number of clauses. In Weighted Max-SAT clauses are associated with weights that model the importance or reliability of certain clauses and the goal is to maximize the accumulated weight of the satisfied clauses in a solution. However, Max-SAT and Weighted Max-SAT are both limited to propositional logic and finding an appropriate problem representation is often hardly intuitive. Ontologies, on the other hand, allow for modeling domains in a more intuitive manner. Description Logics have widely been adopted to model ontologies and to provide reasoning services in a variety of domains. In problems like image labeling [13, 2], we encounter assertions that are associated with a degree and we have to cope with many, potentially contradicting assertions produced by automatic and not fully reliable methods. In order to apply ontological reasoning to such problems, we require new reasoning services. State of the art extensions to Description Logics, such as Fuzzy [15] or Probabilistic Description Logics [8] cover most of these aspects, but other problems still need to be solved. Reasoning on Probabilistic Description Logics still has difficulties regarding the efficiency of the reasoning process. Fuzzy Description Logics can be reasoned about efficiently under min/max co-norm.

In this paper, we introduce a novel reasoning service for handling uncertainty and inconsistencies in Description Logic knowledge bases, called Weighted Max-DL-SAT. We consider Description Logic knowledge bases containing a set of weighted and potentially contradicting axioms. Based on this, we compute a set of consistent axioms with a maximal, accumulated weight. Weighted Max-DL-SAT allows for the almost direct reuse of existing ontologies and provides a very intuitive way of modeling problems that have a Max-SAT like structure, e.g., the aforementioned image labeling problem. In summary, the paper provides a threefold contribution:

1. We define a novel type of reasoning problem, called Weighted Max-DL-SAT.
2. We introduce an algorithm for solving Weighted Max-DL-SAT problems based on the Hitting Set Tree algorithm [12, 6].
3. We apply Weighted Max-DL-SAT to the problem of image labeling.

The rest of the paper is structured as follows: In the next section we give a formal introduction to the Description Logic $\mathcal{ALC}$ and extend its definition to *weighted ontologies*. Then, we introduce the problem of Weighted Max-DL-SAT. Based on this formalizations, we introduce our approach to solve Weighted Max-DL-SAT problems. Afterwards, we introduce an example where we applied Weighted Max-DL-SAT to the domain of spatial reasoning in the context of image labeling, and finally discuss the related work and conclude the paper.

2 Knowledge Representation Using Description Logics

Description Logics constitutes a class of knowledge representation languages that allow for expressing complex concepts in terms of a set of basic constructors. In this section, we specifically introduce the Description Logic $\mathcal{ALC}$, the Attributive Concept Language with Complements. Let N_C and N_R be two disjoint sets of symbols, called the set of *concept* and *role names*, respectively. We will write A, B for concept names, and R for role names. $\top$ and $\bot$ are special concepts, called *Top* and *Bottom*, respectively. A *concept description* C in $\mathcal{ALC}$ is syntactically defined by the following abstract syntax rule:

$$C \rightarrow \top|\bot|A|\forall R.C|\exists R.C|C \sqcap D|C \sqcup D|\neg C\}. \tag{1}$$

The semantics of a concept description is given by an interpretation $\mathcal{I} = (\Delta^{\mathcal{I}}, \cdot^{\mathcal{I}})$, where $\Delta^{\mathcal{I}} = \{a_i, \ldots, a_n\}$ is called the domain of $\mathcal{I}$ and $\cdot^{\mathcal{I}}$ is called the interpretation function. The interpretation function maps each concept name A to a set $A^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}}$, and each role name to a binary relation $R^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$.

The semantics of the constructors are defined as follows.

- $\top^{\mathcal{I}} = \Delta^{\mathcal{I}}$
- $\bot^{\mathcal{I}} = \emptyset$
- $(C \sqcap D)^{\mathcal{I}} = C^{\mathcal{I}} \cap D^{\mathcal{I}}$
- $(C \sqcup D)^{\mathcal{I}} = C^{\mathcal{I}} \cup D^{\mathcal{I}}$
- $(\neg C)^{\mathcal{I}} = \Delta^{\mathcal{I}} \setminus C^{\mathcal{I}}$
- $(\forall R.C)^{\mathcal{I}} = \{x \in \Delta^{\mathcal{I}} | \forall y \in \Delta^{\mathcal{I}} : (x, y) \in R^{\mathcal{I}} \rightarrow y \in C^{\mathcal{I}}\}$

– $(\exists R.C)^{\mathcal{I}} = \{x \in \Delta^{\mathcal{I}} | \exists y \in \Delta^{\mathcal{I}} : (x,y) \in R^{\mathcal{I}} \wedge y \in C^{\mathcal{I}}\}$

Furthermore, we define a T-Box $\mathcal{T}$ as a set of terminological axioms of the form $C \sqsubseteq D$, whereby C and D are concepts. We say that D subsumes C, and an interpretation $\mathcal{I}$ satisfies an axiom $C \sqsubseteq D$ iff $C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$. We define a disjointness between two axioms C and D as $C||D = C \sqsubseteq \neg D$. The A-Box $\mathcal{A}$ is defined as a set of concept assertions $a : C$, where a is an individual name and C a concept description, and role assertions $(a, b) : R$ with a, b individual names and R a role name. Both concept and role assertions area also called *assertional axioms*. A Description Logics ontology $\mathcal{O} = \mathcal{T} \cup \mathcal{A}$ consists of a $\mathcal{T}$-Box $\mathcal{T}$ and an $\mathcal{A}$-Box $\mathcal{A}$.

We extend this definition of an ontology to a *weighted ontology*:

Definition 1 (Weighted ontology). *A weighted ontology is an ontology $\mathcal{O} := \{\alpha_1, \ldots, \alpha_n\}$ such that for every $\mathcal{T}$-Box or $\mathcal{A}$-Box axiom $\alpha \in \mathcal{O}$ an associated weight $w_\alpha \in \mathbb{R}^+$ exists. In case of concrete axioms, we specify the weight in square brackets, i.e., $C \sqsubseteq D[w]$ for $\mathcal{T}$-Box axioms, $a : C[w]$ for concept assertions, and $(a, b) : R[w]$ for role assertions.*

We can now define the reasoning problem Weighted Max-DL-SAT. Our basis is a weighted Description Logic ontology $\mathcal{O} = \mathcal{T} \cup \mathcal{A}$. Each axiom in $\mathcal{O}$ is associated with a weight, which represents the importance or reliability of this axiom to be satisfied.

The problem is to find a consistent subset of the ontology with a maximal summed weight. Formally, we define the Weighted Max-DL-SAT problem as an optimization problem as follows:

$$\text{argmax}_{S \subseteq \mathcal{O} \text{ s.t. } S \text{ consistent}} \Big(\sum_{\alpha \in S} w_\alpha\Big) \tag{2}$$

The result is $\mathcal{O}_r = \mathcal{T}_r \cup \mathcal{A}_r$, a maximal consistent sub-ontology, such that $\mathcal{O}_r \subseteq \mathcal{O}$, $\mathcal{O}_r$ is consistent, and the accumulated weight of all axioms $\alpha_i \in \mathcal{O}_r$ is maximal. In $\mathcal{O}_r$ we call $\mathcal{A}_r$ the consistent Sub-$\mathcal{A}$-Box and $\mathcal{T}_r$ the consistent Sub-$\mathcal{T}$-Box.

3 Solving Weighted Max-DL-SAT Problems

In order to obtain a consistent sub-ontology, we need to resolve all inconsistencies in $\mathcal{O}$. To do so, we have to calculate the weight-minimal set of axioms $\mathcal{O}^-$, such that $\mathcal{O}_r = \mathcal{O} \setminus \mathcal{O}^-$ is consistent. This problem has strong relations to axiom-pinpointing [14], which identifies and eliminates inconsistencies in ontologies. Axiom-pinpointing algorithms compute a minimal set of axioms causing a single inconsistency in an ontology $\mathcal{O}$. Such a set, we call a minimal inconsistent sub-ontology [3] M and it is defined as follows:

Definition 2 (Minimal Inconsistent Sub-Ontology). *A Minimal Inconsistent Sub-Ontology (M) of an ontology $\mathcal{O}$, is defined as a subset $M \subseteq \mathcal{O}$, such that M is inconsistent and $\forall \alpha \in M : M \setminus \{\alpha\}$ is consistent.*

Every M causes a single inconsistency in a particular $\mathcal{O}$. If we remove one axiom of such a M from $\mathcal{O}$, we eliminate this cause of inconsistency in $\mathcal{O}$.

We can formulate this problem as a Weighted Hitting Set Problem. We first give the definition of this set of problems and then explain how Weighted Max-DL-SAT maps to a Weighted Hitting Set Problem:

Definition 3 (Weighted Hitting Set Problem [12]). *Given a set $\mathcal{G}$ and a set of subsets $\mathcal{M}_1, \mathcal{M}_2, ..., \mathcal{M}_n \subseteq \mathcal{G}$ Each element in $\mathcal{G}$ has a positive weight $w_a, a \in \mathcal{G}$ We are looking for a hitting set $\mathcal{H} \subseteq \mathcal{G}$ such that*

- $\mathcal{H} \cap \mathcal{M}_i \neq \emptyset, i = 1, ..., n$
- $\sum_{a \in \mathcal{H}} w_a$ *is minimal*

Now let $\mathcal{O}$ be our ground set, $\mathcal{M}_1, \mathcal{M}_2, ..., \mathcal{M}_n$ the set of all minimal inconsistent sub-ontologies, and the hitting set $\mathcal{H}$ the set $\mathcal{O}^-$ of axioms to be removed from $\mathcal{O}$. Obviously $\mathcal{O}_r$ is weight maximal, when $\mathcal{O}^-$ is weight minimal.

To calculate $\mathcal{O}^-$ for inconsistent ontologies, we propose an adaptation of the Hitting Set Tree (HST) algorithm. The HST algorithm produces a tree T starting with our $\mathcal{O}$ as root node N_1. It calculates a minimal inconsistent Sub-Ontology (MISO) M_j for every node $N_j \in T$. For every axiom α_i in M_j of N_j the algorithm introduces a new sub-node $N_{ji} \in T$. The edge to N_{ji} is labeled with α_i and w_{α_i} and the current ontology for a node N_{ji} is $O_j \setminus \{\alpha_i\}$. To solve our Weighted Max-DL-SAT problem, we have to calculate the cheapest path w.r.t the accumulated weights from the root to a leaf in T. The accumulated axioms of this path represent $\mathcal{O}^-$.

Algorithm 1 Weighted Hitting Set Tree algorithm for computing a solution to Weighted Max-DL-SAT problems.

$\mathcal{O}^- \leftarrow \emptyset$ ▷ initialize result with empty set
$w_{\mathcal{O}^-} \leftarrow \infty$ ▷ set upper bound to infinity
function WHST(O, P)
  $w_P \leftarrow \sum_{\alpha \in P} w_P$ ▷ accumulate path weight
  if $w_P < w_{\mathcal{O}^-}$ **then** ▷ check upper bound
    $M \leftarrow$ calcSingleMISO(O) ▷ calculate M for current ontology
    if $M \neq \emptyset$ **then**
      $M' \leftarrow M$
      ▷ $\forall \alpha \in M$ in decreasing order call WHST
      ▷ for $O \setminus \{\alpha\}, P \cup \{\alpha\}$
      while $M' \neq \emptyset$ **do**
        Select $\alpha \in M'$ s.t. $\forall \alpha' \in M' \rightarrow w_{\alpha'} > w_\alpha$
        $M' \leftarrow M' \setminus \{\alpha\}$
        WHST($O \setminus \{\alpha\}, P \cup \{\alpha\}$)
      end while
    else ▷ if current path weight $<$ upper bound
      $\mathcal{O}^- \leftarrow P$ ▷ set result to path
      $w_{\mathcal{O}^-} \leftarrow w_P$ ▷ set upper bound to path weight
    end if
  end if
end function

In [6] Kalyanpur et. al have shown the completeness of the Hitting Set Tree algorithm regarding the calculation of all justifications for an ontology. Algorithm 1 depicts the concrete $WHST$ algorithm used in our implementation. To increase efficiency, we use a branch & bound like strategy to prune subtrees where no further improvements of the results could be achieved. We use the accumulated weight of an already calculated root-to-leaf path as upper bound, line 19. Initially this bound is set to infinity, line 2. With this lower bound, we can prune any branch of the subtree that could not contain a smaller total path weight. Only if the weight of the current path is lower than this upper bound, a branch has to be considered, line 5.

Algorithm 2 depicts the minimal inconsistent sub-ontology (MISO) calculation [3]. It iteratively adds the axioms α with the smallest weight w_α to the intermediate ontology O until it becomes inconsistent, lines $3 - 6$. Then, we shrink O by iteratively removing the axioms α with the biggest weight w_α if this does not turn O consistent again, lines $8 - 14$. Thus, we are guaranteed to end up with an M, a small, still inconsistent set of axioms in O.

Algorithm 2 Black-box algorithm for computing a minimal inconsistent sub-ontology for $\mathcal{O}$.

1: **function** CALCSINGLEMISO($\mathcal{O}$)
2:     $O \leftarrow \emptyset$ ▷ initialize intermediate ontology
3:     **while** O is consistent **do** ▷ grow intermediate ontology until inconsistency
4:         Select axiom $\alpha \in \mathcal{O} \setminus O$ s.t. $\forall \alpha' \in \mathcal{O} \setminus O \rightarrow w_{\alpha'} \geq w_\alpha$
5:         $O \leftarrow O \cup \{\alpha\}$
6:     **end while**
7:     $O' \leftarrow O$
8:     **while** $O' \neq \emptyset$ **do** ▷ shrink intermediate ontology to minimal inconsistent set
9:         Select axiom $\alpha \in O'$ s.t. $\forall \alpha' \in O' \rightarrow w_{\alpha'} \leq w_\alpha$
10:         $O' \leftarrow O' \setminus \{\alpha\}$
11:         **if** $O \setminus \{\alpha\}$ is inconsistent **then**
12:             $O \leftarrow O \setminus \{\alpha\}$
13:         **end if**
14:     **end while**
15:     **return** O
16: **end function**

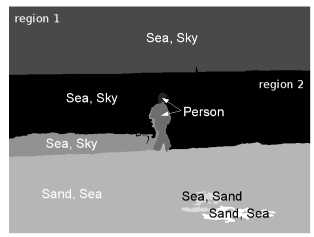
4 Applying Weighted Max-DL-SAT to Automatic Image Labeling

As an example, we present the application of Weighted Max-DL-SAT to the interesting problem of automatically assigning labels to image regions. Typically, these labels refer to "semantic" concepts and provide the means to index regions within an image based on terms understandable for humans. Determining the right labels for a given region is a hard problem, since there is no direct mapping of computable low-level features to the meaning of a region. Automatic methods model regions within images using a set of features and then usually apply machine learning methods in order to learn and subsequently detect a set of possible semantic concepts.

These methods exploit only low-level features extracted from regions of the image, but do not take any context, e.g., spatial context, into account. However, context and background knowledge play a crucial role in automatic image labeling [13, 2]. In our experiments, we utilize spatial relations between image regions as background knowledge to validate the semantic concepts given for specific region.

Figure 1 shows an example of an image (a) and the associated regions with simplified, but still ambiguous hypotheses (b) produced by a classifier. The output of the machine-learning-based classification is used as input to our reasoning process. As background knowledge, we consider knowledge about feasible spatial relations between the semantic concepts, such as *above, below, left, right*. For example, a valid relation might be that *sea* is never depicted above *sky*.

(a) input image



(b) output from ML-based classification

Fig. 1. Input to the reasoning process

4.1 Data Set

The data set consists of 922 images depicting outdoor scenes and was split into 400 training and 522 test images. These images have been segmented using an automatic segmentation algorithm and manually assigned a label from the set of concepts: Sky, Sea, Sand, Road, Building, Foliage, Person, Boat, Mountain, Snow. This dataset has been published[1] and used in previous experiments [13, 10] for the task of spatial reasoning. In addition, the data set also contains different low-level features for each region, different hypotheses generated based on the training data using different classification methods, and a set of extracted fuzzy spatial relations. For our experiment, we used the labels produced by the maximum-likelihood classifier as input to our reasoner.

4.2 Representing Image Labeling with Weighted Max-DL-SAT

The background knowledge is depicted as a $\mathcal{T}$-Box. For each label, we create an atomic concept L. Furthermore, we make all label concepts disjoint and add an axiom $L_1 || \dots || L_n[w_n]$.

The background knowledge about spatial relations has been modeled as a set of binary constraints defining for each label L to which other labels $L'_1, \dots, L'_n$ it might be related by the spatial relation S. To present such knowledge about spatial relations

[1] `http://mklab.iti.gr/project/scef`

in a Description Logic $\mathcal{T}$-Box, we use universal quantification, like $L \sqsubseteq \forall S.(L'_1 \sqcup \ldots \sqcup L'_n)[w_n]$. Thus, for the two labels *Sky* and *Sea* used in figure 1, we would add two axioms $sky \sqsubseteq \forall above.(sea \sqcup sky \sqcup sand \sqcup \ldots)[w_m]$ and $sea \sqsubseteq \forall above.(sea \sqcup sand \sqcup \ldots)[w_m]$. These axioms assure, that sea might only be depicted above other sea regions, while sky might be depicted above sky or sea regions. They are all associated with an very high weight, since we consider the background knowledge as crisp, and therefore do not accept any solutions where any of these axioms is removed. Obviously, this requires that the $\mathcal{T}$-Box is consistent, which is the case in our experiments. Furthermore, the axioms are learned following the approach presented in [13].

Each image i is modeled in a separate $\mathcal{A}$-Box. To generate the $\mathcal{A}$-Box, we use the hypothesis generated by the machine-learning classification process. For each region, we create a single individual r_i. Now, let $w_{i,l}$ be the degree of confidence in the dataset for region r_i labeled with label l. Then we add the concept assertion $r_i : L[w_{i,l}]$ to the knowledge base for each label produced by the classifier for the region. For the two regions *region1* and *region2* depicted in figure 1 this will result in: $region1 : sky[w_{region1,sky}]$, $region1 : sea[w_{region1,sea}]$, $region2 : sky[w_{region2,sky}]$ and $region2 : sea[w_{region2,sea}]$. Additionally to the hypothesis about associated semantic concepts the classification process also generates knowledge about spatial relations between the single regions. To present the spatial knowledge in our ontology, we add for all known relations role assertions like $(r_i, r_j) : S[w_m]$ to the knowledge base. We set the weight of such assertions to very high value, because we do not the accept a solution where one of the spatial relations was removed in order to find a solution. For the regions *region1* and *region2* from figure 1, this will lead to the two role assertion $(region1, region2) : above[w_m]$ and $(region2, region1) : below[w_m]$. Together with the $\mathcal{T}$-Box depicting the background knowledge, this $\mathcal{A}$-Box results in an individual ontology $\mathcal{O}_i$ for each image i. As we can see this ontology contains contradicting statements with: $sea \sqsubseteq \forall above.(sea)[w_m]$, $(region1, region2) : above[w_m]$, $region1 : sea[w_{region1,sea}]$ and $region2 : sky[w_{region2,sky}]$. Such an inconsistent ontology $\mathcal{O}_i$ is the input to our reasoning process.

4.3 Results

In Table 4.3, we have summarized the accuracy of the classifier, Weighted Max-DL-SAT, and the binary integer programming approach presented in [13]. Using Weighted Max-DL-SAT, we can significantly improve the classification rate as provided by the classifier based solely on low-level features. However, we also see that a more specialized method performs clearly better. The latter observation was expected. The BIP approach can employ a more specialized objective function that incorporate the degree of confidence provided with the fuzzy spatial relations, and it employ all fuzzy spatial relations available, not only the one with the highest degree. This information is not used in our modeling of the problem.

Nevertheless, the experiments show that a generic approach based on Description Logics can be applied to a problem like spatial reasoning and leads to a clear improvement. Furthermore, the difference between the specialized method and Weighted Max-DL-SAT is not very large. Specifically, the parameters used for the knowledge extraction have not been optimized in our experiments for Weighted Max-DL-SAT, while

	Classifier	Max-DL-SAT	BIPs
building	0.92	0.90	0.96
foliage	0.70	0.85	0.90
mountain	0.74	0.92	0.91
person	0.58	0.77	0.84
road	0.75	0.56	0.92
sailing-boat	0.49	0.47	0.93
sand	0.67	0.69	0.63
sea	0.71	0.78	0.75
sky	0.17	0.52	0.51
snow	0.71	0.81	0.85
overall	0.62	0.75	0.79

Table 1. Per concept and overall accuracy of the classifier, Weighted Max-DL-SAT, and the Binary Integer Programming approach [13].

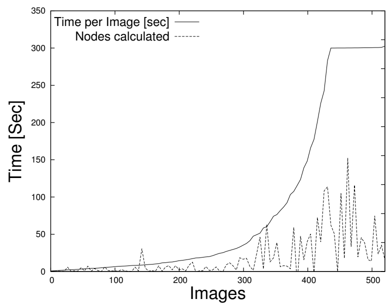
in [13] experiments with optimized parameters were reported. The gained generality of the approach comes at the cost of a loss in accuracy.

The figures in 2 show the system performance results from our experiment. In each figure, we compare two different values (left and right y-axies) per image (x-axis). We sorted the images in increasing order by the first value (left). In figure 2 (a), we show the relation between the over all calculation time per image and the number of nodes per image. In our Experiments, we limited the calculation time per image to $300sec$. We can observe only a weak relationship between calculation time and the number of visited nodes, a tendency towards the more nodes are visited the longer the calculation takes. We can observe multiple outliers especially images with a relative small number of visited sodes compared to the calculation time. Due to the heuristic character of Branch & Bound and because of the calculation of an NP-complete problem like the Weighted Hitting Set Tree, we have to expect such outliers. Figure 2 (b) shows the number of $\mathcal{A}$-Box axioms per image in increasing oder and over all calculation time. Again we can observe multiple outlier but the relation seems to be stronger. Images with more axioms in the $\mathcal{A}$-Box more often tend to exceed the calculation time cap. In figure 2 (c), we show the relation between the over all system performance per image and the time consumption for MISO calculation per image. The MISO calculation time seems to represent a relatively large proportion of the over all system performance. This could be a interesting point for further optimizations. The system could benefit from more detailed studies to increase the efficiency of the MISO calculation. The last figure, 2 d shows the relation between the time consumption for MISO calculation per image and the number of MISOs per image. Here we can also observe an clear relationship. This observation also indicates that where is a potential for further optimizations of the MISO calculation.

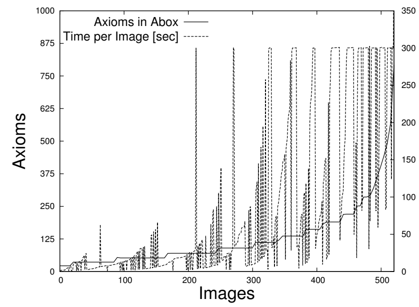
All these behavior result give clear hints about further optimizations of the systems performance. A promising starting point for further optimizations seems to be the MISO calculation. The MISO calculation takes an important part of the over all calculation time and the calculation time for all MISO increases similar to the number of MISOs.

5 Related Work

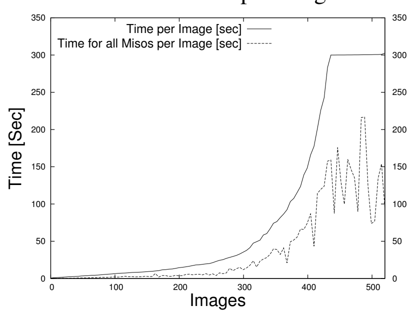
The issues of integrating uncertainty into Description Logics and reasoning with such uncertainty in Description Logics have already been addressed in different ways by



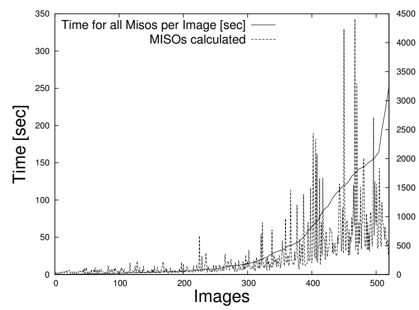
(a) Calculation time in increasing oder and visited Nodes per Image



(b) Axioms per ABox in increasing oder and calculation time



(c) Calculation time in increasing oder and MISO Time



(d) Calculation time for all MISOs in increasing oder and MISOs per Image

Fig. 2. System performance

several researchers. [5, 8, 7] present probabilistic extensions to OWL or investigations on reasoning services for such extension. Some of these approaches allow only for terminological knowledge like [5] others for terminological as well as assertional knowledge [8]. The approaches also differ in the underlying probabilistic reasoning formalism. Two reasoning formalisms could be found in these publications, a formalism based on reasoning in probabilistic logics [5, 8] and a formalism based on inferencing in Bayesian networks [7]. But unfortunately all of these approaches suffer from serve problems regarding the efficiency of reasoning on such knowledge bases. Another approach to uncertainty extension to Description Logics is the use of fuzzy set theory to express the uncertainty. In [16, 15] Straccia presents a general approach to a fuzzy version of $\mathcal{SHOIN}(D)$, the underlying Description Logic of $OWL-DL$. He shows the representation and reasoning capabilities of fuzzy $\mathcal{SHOIN}(D)$. As mentioned in the introduction, reasoning on fuzzy Description Logics can be performed quite efficiently. However, the fuzzy semantics are often mislead by single axioms with a high or low weight, repsectively. In general, both approaches are able to handle degrees associated with axioms, but they are not suitable for handling inconsistencies in every respect.

Reasoning under inconsistency plays a role in the field of ontology learning [4] and ontology debugging [3]. One important method, about finding explanations for a given consequence, e.g., a minimal subset of an ontology that has a particular inconsistency in that ontology as consequence, is axiom pinpointing. Generally, we can distinguish axiom pinpointing methods into two different categories glass-box approaches and black-box approaches. In [1] Baader et al. introduce a glassbox approach for axiom pinpointing. In this paper, we focus on a black-box approach inspired by the work of Kalyanpur et. al. [6].

Interpreting images and extraction of deep-level semantics, can not be done sufficiently only on low-level features. Images often show scenes illustrating abstract concepts like events. To perceive such an event concept, additional background knowledge about the whole scene is required. In [11] Möller et .al introduced abduction as a new inferencing service on Description Logic $\mathcal{A}$-Boxes that enables able to reason from effects (observations/features) to causes (explanations/semantics). In contrast to the approach of Möller where new knowledge is extracted through abduction, our approach focuses on verification of knowledge against a specific model. The approach presented in [2] aims to enhance the semantic image description with the use of fuzzy Description Logics. Based on fuzzy Description Logic knowledge bases specialized reasoning services are used to, e.g. solve inconsistencies resulting from the classification process or extract implicit semantics but all these approaches suffer from the particularities coming with the use of fuzzy Description Logics.

6 Conclusions

We have introduced Weighted Max-DL-SAT as a service for modeling and solving problems with inconsistencies and uncertainty using Description Logics. A core feature of our approach is the ability to handle uncertainty similar to fuzzy or probabilistic Description Logics whereas inconsistency is handled like in a crisp Description Logics manner. This combination of features is useful to many different problems, like ontology learning, semantic information extraction or image labeling. The evaluation on image labeling indicates that we achieve a slightly improvement of the results compared to a classifier based solely on low-level features. Compared to a highly specialized method Weighted Max-DL-SAT looses a bit of accuracy but this was the expected price for the gain of generality of the method. With optimized parameters used for the knowledge extraction and a adjusted modeling, we expect further improvements.

In our future work, we will concentrate on the improvement of the performance of maximal consistent sub-ontology calculation. Our experience has shown that it could be promising to improve the MISO calcualtions in this context. The multiple outlier observed in our results showed us that it might be useful to consider approaches other than out WHST based black box method. On this account, we work on an glass box approach to be able to compare it to our black box method. Some of our results also indicate that the consistency checking in approach is a large cost factor, so the integration of Description Logic approximation techniques, like in [9] could be promising. In the next implementations, we will focus on these three promising optimization strategies for Weighted Max-DL-SAT. In addition, we will apply Weighted Max-DL-SAT to different other interesting problems.

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