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B. Glimm, N. Nikitina, S. Rudolph Institute of Artificial Intelligence | 14.11.2011 Interactive Reasoning-Based Ontology Revision SFB/TRR 62 Kolloquium





Companion systems need some background knowledge

- → Ontologies
 - Ontology revision helps to ensure the quality of an ontology
 - Revision support for building up the knowledge base through reuse or automated learning methods

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Companion systems need some user specific knowledge

- More dynamic and uncertain knowledge
- \rightsquigarrow Reasoning over dynamically changing and uncertain knowledge

Outline

- Motivation
- Ontology and Reasoning Basics
- Semi-automatic Ontology Revision by Example
- Ontology Revision Terminology
- Axiom Ranking
- Decision Spaces
- Empirical Evaluation & Dynamic Ranking Strategies
- Summary & Outlook

Motivation

- Noisy domain statements produced by knowledge acquisition and integration methods
- Manual revision of the acquired information is required to ensure high quality



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Individual:	Birte	Type:	Juniorprofessor
Individual:	Birte	Facts:	holds CS6380.00
Class:	Professor	SubClassOf:	holds some Lecture

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JuniorProfessor	SubClassOf:	Professor
holds	Range:	Lecture
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- Reasoners implement algorithms to check entailment
- Depending on the expressivity of the ontology language such algorithms can be anything between tractable and super-exponential in worst-case complexity

 A single evaluation decision can predetermine the decision for several yet unevaluated axioms

> DistinctEntity MentalEntity SubClassOf **MentalObject**

```
SubClassOf
                           DistinctEntity
Decision
                           MentalEntity
                                  SubClassOf
                           MentalObject
```











Order is important to achieve a good grade of automation


Revision Example

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Ontology Revision

Assumption: Deductive closure of the intended consequences must not contain unintended consequences

- A single evaluation decision can predetermine the decision for several yet unevaluated axioms
- Order influences method effectiveness

Revision States

- A revision state is defined as a tuple (O, O[⊨], O[⊭]) of ontologies with O[⊨] ⊆ O, Ø ≠ O[⊭] ⊆ O, and O[⊨] ∩ O[⊭] = Ø.
 O[⊨]: the set of desired consequences
 - $\mathcal{O}^{\not\models}$: the set of undesired consequences



Revision State Completeness

A revision state is complete, if O = O ⊨ ∪ O ⊭, and incomplete otherwise.



Revision State Refinements

▶ Given two revision states $(\mathcal{O}, \mathcal{O}_1^{\vDash}, \mathcal{O}_1^{\nvDash})$ and $(\mathcal{O}, \mathcal{O}_2^{\vDash}, \mathcal{O}_2^{\nvDash})$, we call $(\mathcal{O}, \mathcal{O}_2^{\vDash}, \mathcal{O}_2^{\nvDash})$ a refinement of $(\mathcal{O}, \mathcal{O}_1^{\vDash}, \mathcal{O}_1^{\nvDash})$, if $\mathcal{O}_1^{\vDash} \subseteq \mathcal{O}_2^{\nvDash}$ and $\mathcal{O}_1^{\nvDash} \subseteq \mathcal{O}_2^{\nvDash}$.



An incomplete revision state (O, O[⊨], O[⊭]) can be refined by evaluating a further axiom α ∈ O \ (O[⊨] ∪ O[⊭]), obtaining (O, O[⊨] ∪ {α}, O[⊭]) or (O, O[⊨], O[⊭] ∪ {α}).



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- We call the resulting revision state an elementary refinement of (O, O[⊨], O[⊭]).



Revision Closure

► The revision closure $clos(\mathcal{O}, \mathcal{O}^{\vDash}, \mathcal{O}^{\nvDash})$ of $(\mathcal{O}, \mathcal{O}^{\vDash}, \mathcal{O}^{\nvDash})$ is $(\mathcal{O}, \mathcal{O}_c^{\vDash}, \mathcal{O}_c^{\nvDash})$ with

•
$$\mathcal{O}_c^{\vDash} := \{ \alpha \in \mathcal{O} \mid \mathcal{O}^{\vDash} \models \alpha \}$$
 and

 $\blacktriangleright \ \mathcal{O}_c^{\nvDash} := \{ \alpha \in \mathcal{O} \mid \mathcal{O}^{\vDash} \cup \{ \alpha \} \models \beta \text{ for some } \beta \in \mathcal{O}^{\nvDash} \}.$



Revision State Consistency

A revision state (O, O[⊨], O[⊭]) is consistent if there is no
α ∈ O[⊭] such that O[⊨] ⊨ α.



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Goals:

- Obtain complete and consistent revision state
- Reduce number of manual decisions
- Reduce the time for automatic decisions

For $(\mathcal{O}, \mathcal{O}^{\vDash}, \mathcal{O}^{\nvDash})$ a consistent revision state:

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- Revision closures reduce the manual effort of revision and ensure the consistency of revision states

Axiom Impact

 The evaluation order has an impact on the degree of atomatization

 $\begin{array}{ll} (\mathcal{O},\mathcal{O}^{\vDash},\mathcal{O}^{\nvDash}) & \text{a consistent revision state with } \alpha \in \mathcal{O} \\ ?(\mathcal{O},\mathcal{O}^{\vDash},\mathcal{O}^{\nvDash}) & |\mathcal{O} \setminus (\mathcal{O}^{\vDash} \cup \mathcal{O}^{\nvDash})| \end{array}$

Approval impact: Number of automatically evaluated axioms in case α is approved: impact⁺(α) = ?(O, O[⊨], O[⊭]) − ?(clos(O, O[⊨] ∪ {α}, O[⊭])),

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- Decline impact: number of automatically evaluated axioms in case α is declined:

 $\mathsf{impact}^-(\alpha) = ?(\mathcal{O}, \mathcal{O}^{\vDash}, \mathcal{O}^{\nvDash}) - ?(\mathsf{clos}(\mathcal{O}, \mathcal{O}^{\vDash}, \mathcal{O}^{\nvDash} \cup \{\alpha\})),$

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► Guaranteed impact: guaranteed(α) = min(impact⁺(α), impact⁻(α)).

Impact Computation

Decision SubClassOf DistinctEntity

impact ⁺	$impact^-$	guaranteed
0	2	0
1	1	1
2	0	0

Decision Spaces: Saving Computational Effort

- Computing the closure and impact measures requires entailment checking:
 - $\alpha E\beta$ iff $\mathcal{O}^{\models} \cup \{\alpha\} \models \beta$
 - $\blacktriangleright \ \alpha C\beta \text{ iff } \mathcal{O}^{\vDash} \cup \{\alpha, \beta\} \models \gamma \text{ for some } \gamma \in \mathcal{O}^{\nvDash}$

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- Decision Space for a particular revision state:
 - Graph with nodes O^2 the unevaluated axioms after closure
 - Relations E and C induce edges

Decision spaces exploit the following properties of E and C:

P1 $(\mathcal{O}^{?}, E)$ is a quasi-order (i.e., reflexive and transitive),

P2 C is symmetric,

P3 $\alpha E\beta$ and $\beta C\gamma$ imply $\alpha C\gamma$ for all $\alpha, \beta, \gamma \in \mathcal{O}^{?}$, and

P4 if $\alpha E\beta$ then $\alpha C\beta$ does not hold.

Pruning the Space of Unknown Elements of E and C

- \overline{E} : complement of E
- \overline{C} : complement of C

Computing E and C

- Rules have an acyclic structure
- $\rightsquigarrow~E$, C , \overline{C} , and \overline{E} can be saturated one after another

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Condensed rule set:

$$\begin{array}{rcl} E & \leftarrow & E^* \\ C & \leftarrow & E \circ (C \cup C^-) \circ E^- \\ \overline{C} & \leftarrow & E^- \circ (\overline{C} \cup Id \cup \overline{C}^-) \circ E \\ \overline{E} & \leftarrow & E^- \circ (\overline{C} \circ C \cup \overline{E}) \circ E^- \end{array}$$

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- Algorithm now initializes the relations and applies the rules
- Executes an entailment check to clarify a missing case
- Closes the relations under the rule set

Complexity of Computing ${\boldsymbol E}$ and ${\boldsymbol C}$

Assuming that entailment checking is a constant time operation:

Lemma

Let $(\mathcal{O}, \mathcal{O}^{\vDash}, \mathcal{O}^{\nvDash})$ with $n = |\mathcal{O}|$ be a revision state. Computing E and C can be done in time $O(n^5)$ and space $O(n^2)$.

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- Entailment checking usually outweighs the other operations
- For the Web Ontology Language OWL entailment checking is N2ExpTime-complete
- Lower complexities for fragments of OWL

Advantages of Decision Spaces

- ▶ Revision closures can be read off the *E* and *C* relations
- Axiom impact can be read off the E and C relations
- Updating a decision space after an axiom approval or decline can be done incrementally

Ontology Revision Use Case

- Empirical evaluation based on data from the NanOn project
- NanOn goals: semi-automatic ontology generation for nano technology
- Ontology captures substances, structures, and procedures used in the domain of nano technology
- Scientific documents are automatically analyzed for the occurrence of NanOn classes and properties by the means of lexical patterns
- Documents are annotated with these terms to facilitate topic-specific information retrieval
- Revision is needed to ensure the quality

Evaluation Results: Reduction of Manual Effort


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 - For larger datasets (e.g., 5,000 axioms and more) the learned validity ratio deviates only 0.3% from the known one

Evaluation Results with Learned Parametrized Ranking



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- ► Impact function (~→ determines oder) can be parametrized with the validity ratio
- Validity ratio can effectively be learned over the course of the revision
- Decision spaces are efficient for determining the revision closure and axiom impact and saved 75% of reasoning calls in our experiments

Ontologies as background knowledge for companion systems

Revision support for building up the ontology (reuse)

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- Ontology extension at runtime needs fully automatic revision
- Can be combined with modularization techniques to extract relevant knowledge

Companion systems also need user specific knowledge

- Longer-term than current sensor data
- More dynamic knowledge
- For example DS-3:
 - We know that a user is unfamiliar with the exercises
 - Detection that user looks puzzled ~ explain exercises
 - We know that a user is familiar with the exercises
 - \blacktriangleright Detection that user looks puzzled \rightsquigarrow clarification why puzzled

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 - We know that a user is familiar with the exercises
 - Detection that user looks puzzled ~> clarification why puzzled
- Also includes forgetting of knowledge
- → Stream reasoning: reasoning with continuously changing knowledge
 - Uncertainty has to be taken into account