

Incremental Approach to Error Explanations in Ontologies

Inference Support for Semantic Annotations

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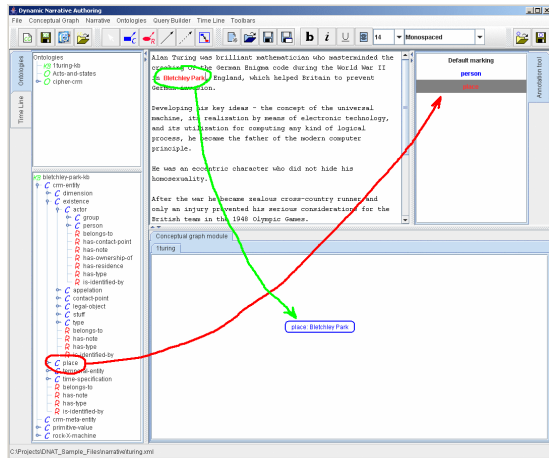
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 - **Modeling error explanations** – the problem discussed in this work.

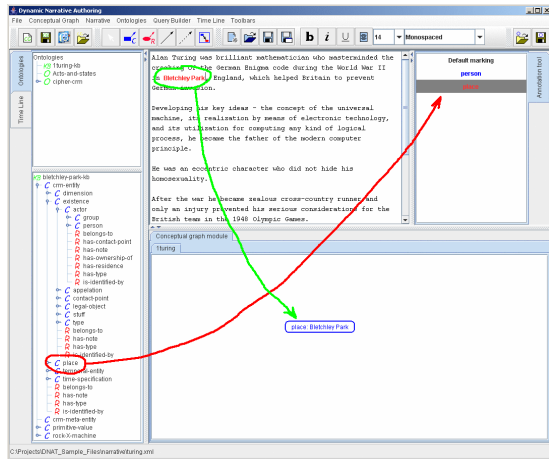
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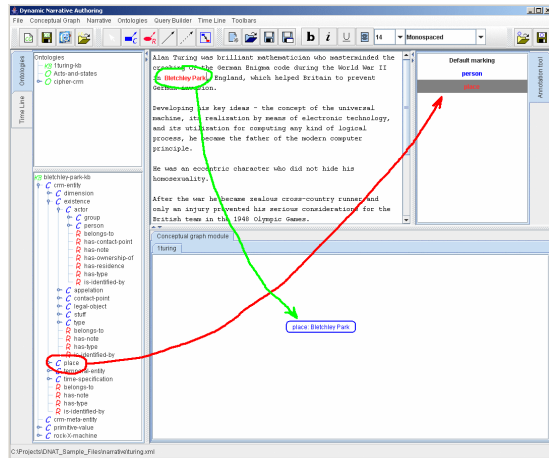
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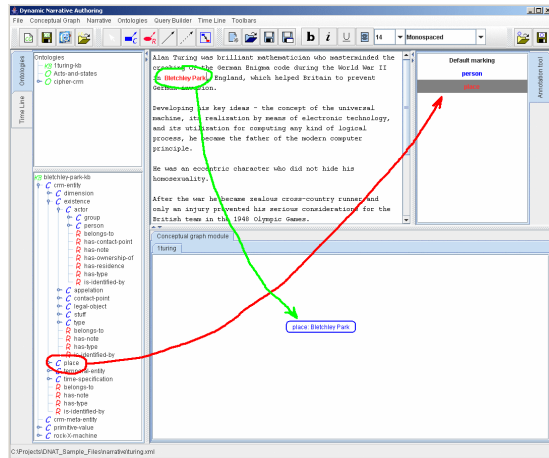
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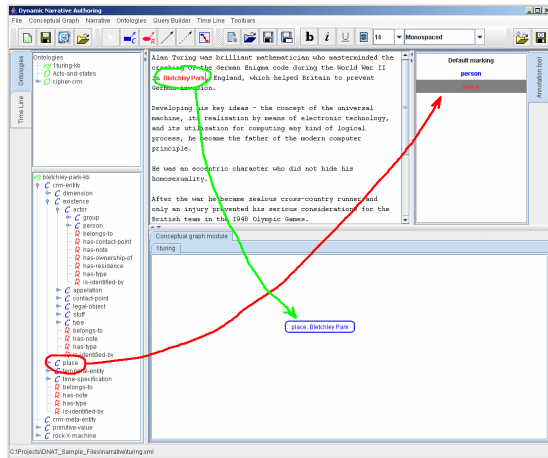
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! This lead us to use a description logic based approach.



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 - **concept and role assertions** – $\textit{school}(\textit{CVUT})$, $\textit{partOf}(\textit{FEL}, \textit{CVUT})$

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<i>madCow</i>	\equiv	$cow \sqcap \exists \text{eats} . (brain \sqcap \exists \text{partOf} . \text{sheep})$
<i>cow</i>	\sqsubseteq	<i>vegetarian</i>
<i>vegetarian</i>	\equiv	$animal \sqcap \forall \text{eats} . \neg animal \sqcap \forall \text{eats} . \neg (\exists \text{partOf} . animal)$
<i>animal</i>	\sqsubseteq	$\exists \text{eats} . \top$
<i>sheep</i>	\sqsubseteq	<i>animal</i>
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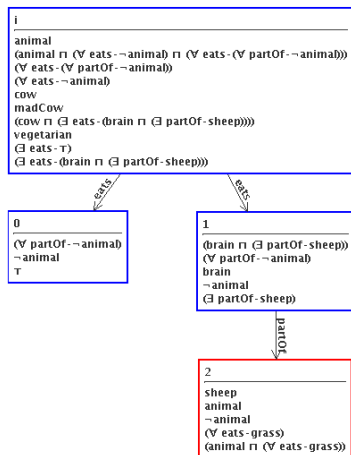
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- Tableau algorithms* prove consistency of given knowledge base by constructing a model for it using a set of inference rules.
- These algorithms terminate upon obtaining a clash-free model candidate – a completion graph – on which no more rules are applicable (consistent), or whenever each completion graph contains a clash (inconsistent).

Completion Graph Example

Testing satisfiability of the concept *madCow* a *SHIN* tableau reasoner may generate the following completion graph. The generated individual 2 contains a clash – individual 2 belongs to both *animal* and $\neg animal$.



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glass-box methods are fully integrated into the reasoner (Schlobach 2006, Kalyanpur 2006).

- + more efficient
- poor reusability, **no fully glass box approach exists for even simpler languages than *SHIN***

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- computing directly all MUPSeS (*allMUPSeSInc2*).

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Having 6 axioms numbered 1...6, a concept is unsatisfiable due to the MUPSes $\{\{1, 2, 4\}, \{2, 4, 5\}, \{3, 5\}, 6\}$. The algorithm works as follows :

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←	[1, 2, 3, 4 , 5 , 6]	$D = [4]$	$e = [4, 3, 2]$

Algorithm for Single MUPS (*singleMUPSInc*)

- Initial axiom list P and an empty reasoner state e .
- “Feed” the reasoner with axioms one by one until an unsatisfiability is detected.
- When an unsatisfiability is detected, the search direction is changed, current reasoner state e is initialized with D , “overlapping” axioms are pruned (emphasized with strikeout) and the last axiom that caused the unsatisfiability (in bold) is put into the MUPS core D .

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- This algorithm can be used with Reiter's algorithm (Reiter 1987) to compute all MUPSes for given concept.

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T is the list of already explored axioms ... satisfiable set

Algorithm for All MUPSeS (2) – Example

Example

Having 3 axioms numbered 1, 2, 3, a concept is unsatisfiable due to the MUPSeS $\{\{1, 2\}, \{1, 3\}\}$. The algorithm works as follows :

–1, [], [1, 2, 3], []

- Each node has the form *cached, D, P, T*.
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- Struck axiom sets represent the tests that are avoided in comparison to *allMUPSeSInc1*.

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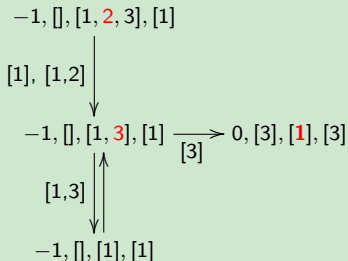
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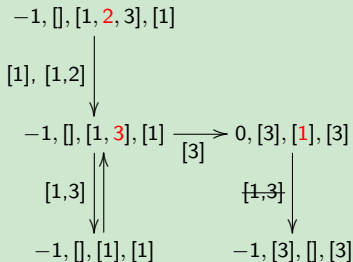


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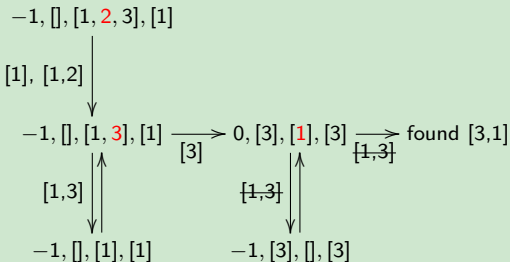


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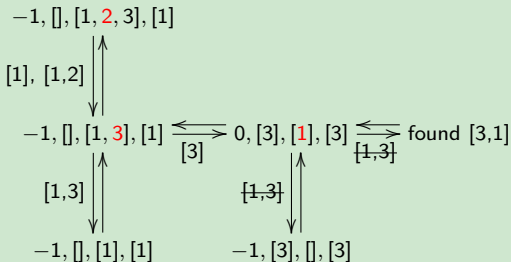


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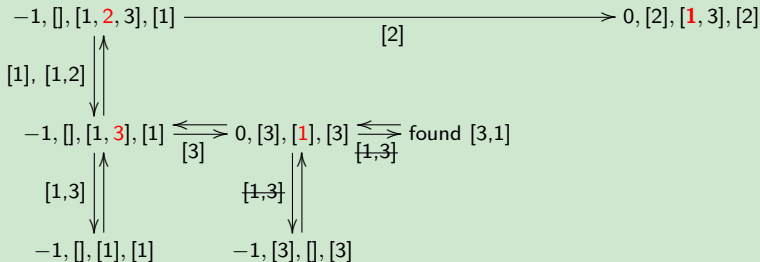


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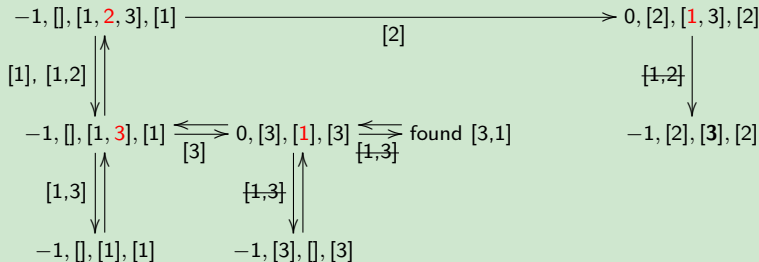


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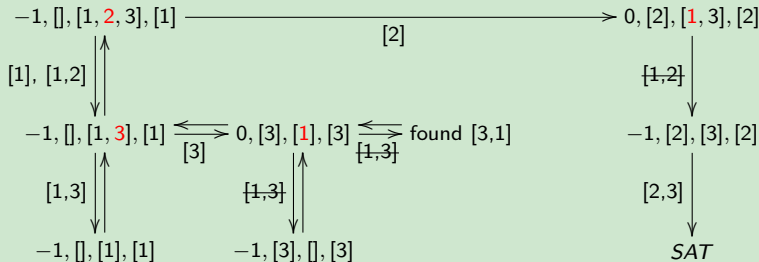


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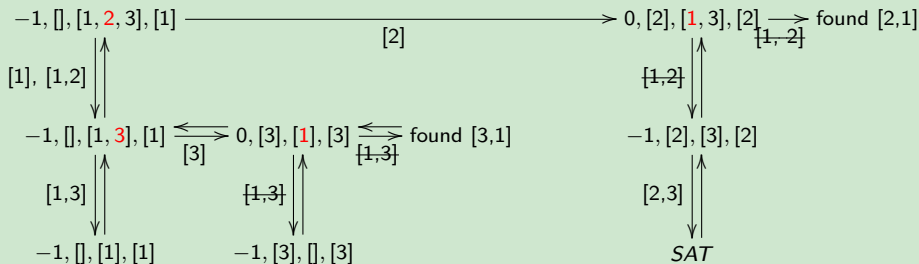


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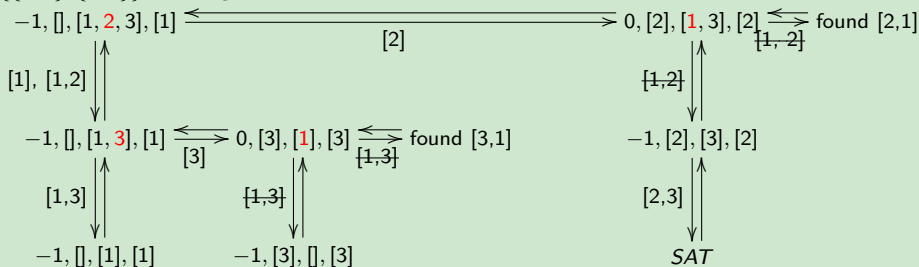


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Comparison of Incremental and Black Box Techniques

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- **allMUPSesInc2** is our modification of *allMUPSesInc1*
- Finding all MUPSes for all concepts in the miniTambis ontology (30/182 unsat. concepts) and the miniEconomy ontology¹(51/338 unsat. concepts):

algorithm	miniTambis (time [ms])	miniEconomy (time [ms])
Reiter + singleMUPSbb	67481	> 15min.
Reiter + singleMUPSinc	19875	19796
allMUPSesInc1	8655	14110
allMUPSesInc2	8516	13970

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Comparison of Incremental Methods w.r.t. Axiom Ordering

- As we need to generate all permutations of the axiom set, we use two small ontologies.

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tambisP	# of IT ⁴	avg # of IT	var of IT
Reiter + singleMUPSinc	268362	124.29	206.81
allMUPSesInc1	75696	35.04	36.44
allMUPSesInc2	61590	28.51	16.76
madCowP	# of IT	avg # of IT	var of IT
Reiter + singleMUPSinc	277200	55.00	8.00
allMUPSesInc1	131040	26.00	0.00
allMUPSesInc2	119520	23.04	0.50

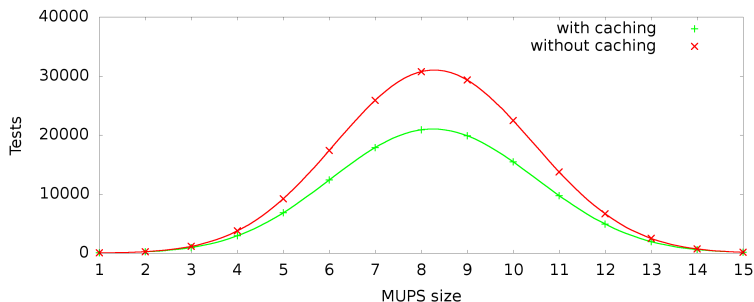
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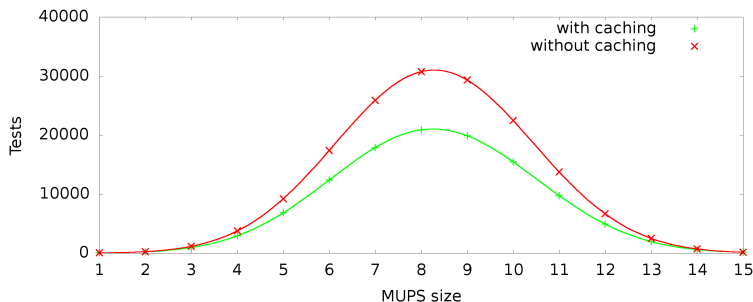
Evaluation of Caching

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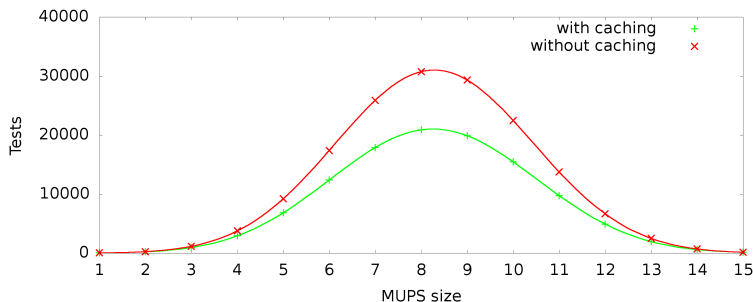
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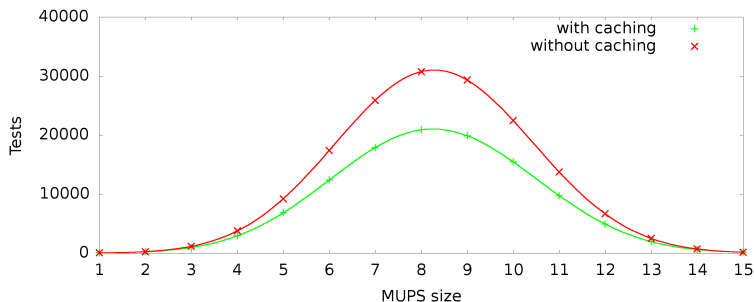
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- For each $1 \leq k \leq n$ (the x-axis) the MUPS set contains all axiom combinations of size k (horizontal axis).
- **The caching is most efficient (about 30% gain) when the MUPSeS are approximately medium-sized w.r.t. the number of axioms.**



Annotation Tool Prototype

Dynamic Narrative Authoring 2

File Help

Knowledge Base Repository

Knowledge Base Repository
<http://krizik.felk.cvut.cz/generat>

Concept Hierarchy / **Role Hierarchy**

- animal
 - vegetarian
 - cow
 - mad+cow
 - sheep
 - giraffe
 - cat
 - person
 - kid
 - man
 - pet+owner
 - grownup
 - dog+liker
 - animal+lover
 - cat+liker
 - woman
 - driver
 - dog+owner
 - leaf
 - dog
 - haulage+company
 - bone
 - vehicle
 - brain

Narrative

Cattle
(From Wikipedia, the free encyclopedia)

Cattle, commonly referred to as cows, are domesticated ungulates, a member of the subfamily Bovinae of the family Bovidae. They are raised as livestock for meat (called beef and veal), dairy products (milk), leather and as draught animals (pulling carts, plows and the like). In some countries, such as India, they are subject to religious ceremonies and respect. It is estimated that there are 1.4 billion head of cattle in the world today.[1]

Cattle were originally identified by **Carolus Linnaeus** as three separate species. These were *Bos taurus*, the European cattle, including similar types from Africa and Asia; *Bos indicus*, the zebu; and the extinct *Bos primigenius*, the aurochs. The aurochs is ancestral to both zebu and European cattle. More recently these three have increasingly been grouped as one species, sometimes using the names *Bos primigenius taurus*, *Bos primigenius indicus* and *Bos primigenius primigenius*. Complicating the matter is the ability of cattle to interbreed with other closely related species. Hybrid individuals and even breeds exist, not only between European cattle and zebu but also with yaks, banteng, **gaur**, and **bison**, a cross-genera hybrid. For

Marking

cow
person

Axioms causing the error:

- (vegetarian = ((\forall eats - (\forall part+of - \rightarrow animal)) \cap (\forall eats - \rightarrow animal)) \cap animal))
 (mad+cow = ((\exists eats - ((\exists part+of - sheep) \cap brain)) \cap cow))
 (cow \sqsubseteq vegetarian)
 (sheep \sqsubseteq animal)

Diagram:

```

graph LR
    Cattle["Cattle  
T  
cow"] -- likes --> Linnaeus["Carolus Linnaeus  
animal+lover  
T  
person"]
    Gaur["gaur  
animal  
T"]
    Bison["bison  
animal  
T"]
  
```

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- The “single MUPS” versions are less efficient than the “all MUPS” versions, but **“single MUPS” versions provide error explanations for free** (using Reiter’s algorithm), while “all MUPS” versions provide only conflict sets.
- An inference services based on the proposed algorithms was **implemented in the new annotation tool prototype**, providing the user with explanations for given concept unsatisfiability.

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Example

`reign(Person, Time, Location)` generates a concept *Reign*, and three new properties `reignPerson`, `reignTime` and `reignLocation`. New axioms are generated that state these properties to be *functional*, to have corresponding domain and range and to allow only syntactically valid n-ary relations.

Future Work (2)

- How to solve the above mentioned problems ?

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