

Towards controlled flexibility for reasoning in DLs

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Description Logics:

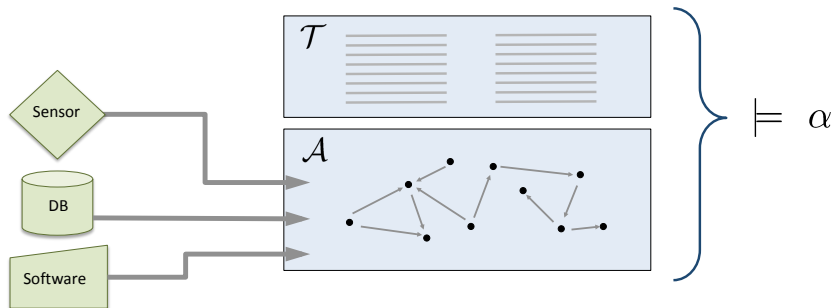
- symbolic representations by declarative formalisms
- fragments of first-order logic
- reasoning is usually decidable

An ontology

- defines notions from an application domain
- uses words from natural language \leadsto conveys meaning to humans
- relates notions to complex expressions (formulated in logic)
 \leadsto gives “meaning” to notions

DL reasoning:

- well-defined
- complexity well understood
- algorithms with guarantees



TBox \mathcal{T}

\vdots

Patient \sqsubseteq Person $\sqcap \exists$ suffers-from.Disease

\vdots

ABox \mathcal{A}

Person(bob)

Disease(cooties)

(bob, cooties)suffers-from

Query types:

- **subsumption** Patient \sqsubseteq Disease
- **instance query** Patient(x)
- **conjunctive query**

$\varphi(x_1, \dots, x_n) : \exists y_1, \dots, y_m. \text{Disease}(x_1) \wedge \text{affects}(x_1, y_2) \dots$

Data:

- knowledge graphs with millions of triples
- gathered automatically from different sources
- ∴ need not be complete, accurate, consistent

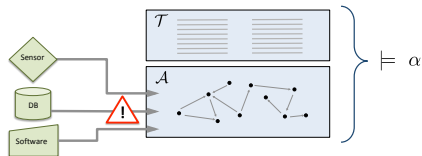
How to deal with data that is

- incomplete
- inconsistent
- inaccurate

Use defeasible DLs

Use inconsistency-tolerant semantics

?



Data and query need not fit

- Query design: precise relational structure / concept memberships not known
- exact queries may be hard to formulate
- data can evolve over time \leadsto E.g. concept drift
- data sources can change over time

Relaxed queries:

- If no query answers, retrieving **more than** classical answers useful.
- safety-critical applications: detect instances **“similar” to critical instances**

How to add flexibility to reasoning to level out inaccuracies in data ?

Goal:

develop reasoning services that admit leeway for querying

Objectives:

- user is in control of relaxation
- relaxation happens local to the query (not the ontology)
- sound, complete & terminating reasoning procedures
- efficient reasoning

Relaxed Reasoning (aka: reasoning under approximate semantics):

- retrieve more than the classical answers
- retrieve also answers that are similar to classical ones
- requires: formalization of similarity

Dual notion:

Query strengthening

- retrieve some classical answers
- retrieve preferred answers
- express preferences in vocabulary of the domain

1. Rough DLs

- qualitative approach
- similarity: **indiscernibility relation**

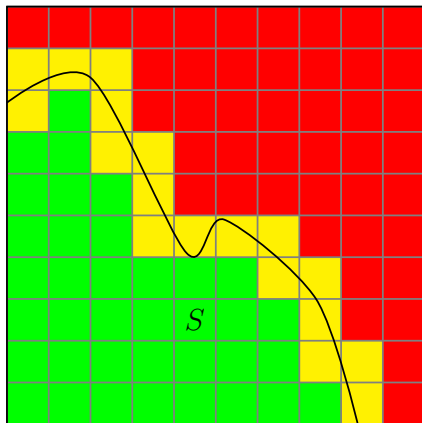
2. Queries relaxed by (dis)similarity measures

- quantitative approach
- similarity: **weighted transducer** or **concept similarity measure**

Approach 1: Rough Description Logics

Rough DLs:

- can express qualitative form of vagueness
- semantics is based on **rough sets**

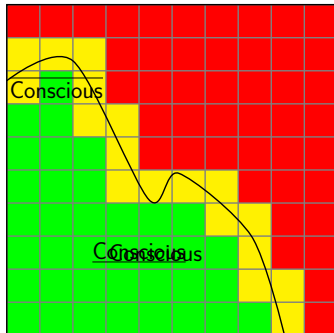


Rough description logics

- Idea: domain partitioned by **indiscernibility relation** ρ into granules (or: by **equivalence relation** \sim into **equivalence classes**)
- populate ABox with ρ obtained from clustering algorithm
- use concept constructors:
 - **lower approximation** \underline{C} — “strong” instances of C
 - **upper approximation** \overline{C} — instances “similar” to those of C

Rough description logics

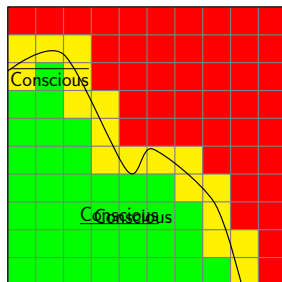
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$$C ::= A \mid \top \mid \perp \mid C \sqcap C \mid \exists r.C \mid \underline{C} \mid \overline{C}$$

Interpretations: $\mathcal{I} := (\Delta^{\mathcal{I}}, \cdot^{\mathcal{I}}, \sim)$

- $\Delta^{\mathcal{I}}$ a set; \sim equivalence relation over $\Delta^{\mathcal{I}}$;
- $\underline{C}^{\mathcal{I}} := \{d \mid [d]_{\sim} \subseteq C^{\mathcal{I}}\}$;
- $\overline{C}^{\mathcal{I}} := \{d \mid [d]_{\sim} \cap C^{\mathcal{I}} \neq \emptyset\} = \bigcup_{\delta \in C^{\mathcal{I}}} [\delta]_{\sim}$

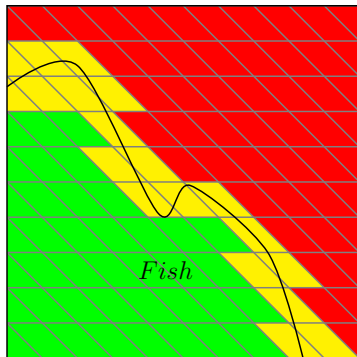
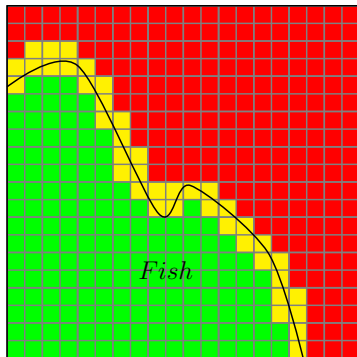


Multiple indiscernibility relations

Rough DLs are well established! \leadsto Consider **multiple partitions**

We learn concepts through **refinement** ...

... or encounter different **perspectives**



Rough \mathcal{EL}_\perp with Multiple Indiscernibility Relations

$$C ::= A \mid \top \mid \perp \mid C \sqcap C \mid \exists r.C \mid \underline{C}_i \mid \overline{C}^i$$

$$1 \leq i \leq n$$

Interpretations: $\mathcal{I} := (\Delta^{\mathcal{I}}, \cdot^{\mathcal{I}}, \sim_1, \dots, \sim_n)$

- $\underline{C}_i^{\mathcal{I}} := \{\delta \mid [\delta]_{\sim_i} \subseteq C^{\mathcal{I}}\};$
- $\overline{C}^{i\mathcal{I}} := \{\delta \mid [\delta]_{\sim_i} \cap C^{\mathcal{I}} \neq \emptyset\} = \bigcup_{\delta \in C^{\mathcal{I}}} [\delta]_{\sim_i}$

\leadsto We can refer to the different equivalence relations

Case 1: linearly ordered equivalence relations

Refining equivalence relations

- Equivalence classes just get **partitioned** further — not restructured!

$$\begin{array}{ccccccc} \sim_1 & \subseteq & \sim_2 & \subseteq & \cdots & \subseteq & \sim_n \\ \text{finest} & & & & & & \text{coarsest} \end{array}$$

- E.g. generated by **one clustering algorithm** and **several thresholds**

Reasoning in multi-rough \mathcal{EL}_\perp with linearly ordered partitions

[PeñalozaT-RuleML+RR24]

- Reasoning remains **in PTime!**
- We constructed a **completion** (consequence-based) algorithm which makes consequences **explicit**
- Creates a **canonical model**
number of **representatives** per concept depends on n

Reasoning in multi-rough \mathcal{EL}_\perp is ...

[PeñalozaT-RuleML+RR24]

1. ...in **ExpTime**

(shown by reduction **to** $\mathcal{SHI}(\text{self})$)

$\mathcal{SHI}(\text{self})$ can express roles with:

- transitivity
- symmetry
- reflexivity

(equivalence relation)

2. ...**ExpTime-hard**

A reduction **from** \mathcal{ELI}

(\mathcal{EL} with inverse roles)

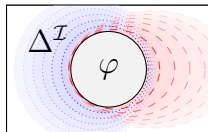
Approach 2: Relaxing queries querying under approximate semantics

Relaxed query **answer** consists of:

- **answer tuple** and
- **numerical value** indicating how much tuple differs from classical answer

Advantages of relaxed queries :

- KB remains classical
- “direction” and the “degree” of relaxation is local to query
- similarity often context dependent
 \rightsquigarrow intent of query?



Relaxed queries: closely related to **top-*k*** queries

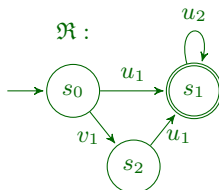
Formulation of relaxed queries:
requires (dis)similarity specification!

Investigated query types and approaches to model (dis)similarity:

1. Concept queries relaxed by concept similarity measures
[EckePeñalozaT- J.Appl.Logic-15]
2. Regular path queries relaxed by weighted transducers

Regular path query (RPQ):

- path language specified by nondeterministic automaton (NFA) \mathfrak{R} or regular expression over relations
- retrieves pairs from graph structure connected by path from $\mathcal{L}(\mathfrak{R})$
- are part of SPARQL and often used for knowledge graphs



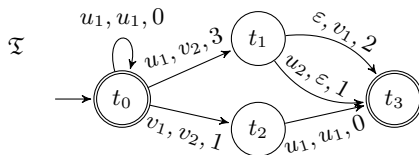
Prior work:

- answering RPQs over DL KBs by [Bienvenu-Ortiz-Simkus-JAIR-15]
- answering RPQs under approximate semantics over graph databases [Grahne-Thomo-'06]

Cost of approximating paths by weighted transducers

Weighted transducer

\approx NFA with **input symbol**, **output symbol** and **weight** in state transitions



For approximate RPQs weighted transducer \mathcal{T} specifies:

- **paths allowed as distortions** of “ideal” paths required by RPQ
- corresponding **distortion costs**

by semi-ring $(\mathbb{N} \cup \{\infty\}, \max, +, \infty, 0)$

Weighted transducers allow to model:

- Neutral transitions allow to preserve classical answers: $(c, d, 0)$.
- ε -transitions allow to use the edit distance as approximation:

$(\varepsilon, s, 2) = \text{delete operation}$ $(r, \varepsilon, 1) = \text{insert operation}$

Accepting run in \mathfrak{T} on w_1 yields: output word w_2 and distortion cost

Cost of **distorting** w_1 into w_2 by \mathfrak{T} :

minimal cost from **all accepting runs** of \mathfrak{T} that transform word u into word v .

Regard **all models** of $\mathcal{K} = (\mathcal{T}, \mathcal{A})$:

Cost of distortion in all models \leadsto use supremum of costs over all models

Certain approximate answers:

$$\begin{aligned} \widetilde{\text{cert}}_{\mathcal{I}}(\mathfrak{R}(x, y), \mathcal{K}) = & \left\{ (a, b, \eta) \mid a, b \in \text{Ind}(\mathcal{A}) \wedge \right. \\ & \left. \eta = \sup_{\mathcal{I} \models \mathcal{K}} \left\{ \min \{ c_{\mathcal{I}}(u, v) \mid u \in \mathcal{L}(\mathfrak{R}) \wedge a \xrightarrow{\mathcal{I}, v} b \} \right\} \right\} \end{aligned}$$

In **DLs with canonical model property**:

use the **universal model** $\mathcal{U}_{\mathcal{K}} \leadsto$ possible for \mathcal{ELH} , DL-Lite $_{\mathcal{R}}$

τ -entailment

Instance: KB \mathcal{K} , transducer \mathcal{T} , RPQ $\mathfrak{R}(x, y)$,
tuple $\bar{a} \in \text{Ind}(\mathcal{A})$ and threshold value $\mu \in \mathbb{N}$.

Question: Is \bar{a} a certain approximate answer of ϕ w.r.t. \mathcal{K} and \mathcal{T} with
approximation cost $\eta_{\bar{a}} \leq \mu$?

cost computation

Instance: KB \mathcal{K} , a transducer \mathcal{T} , RPQ $\mathfrak{R}(x, y)$,
and a tuple $\bar{a} \in \text{Ind}(\mathcal{A})$.

Output: approximation cost $\eta_{\bar{a}}$.

For \mathcal{ELH} and $\text{DL-Lite}_{\mathcal{R}}$:

	τ -entailment	cost computation
2RPQs	in P	poly-time
C2RPQs	in P	poly-time

For \mathcal{EL} :

- bounds are tight
- **hardness** inherited from classical semantics [BienvenuOrtizSimkus-JAIR-15]
- approximation semantics at “no extra cost”

Relaxed reasoning:

- useful to adopt controlled flexibility
- qualitative and quantitative approaches investigated
- complexity is often as in classical case

Future work:

- multi-rough reasoning over data
- Which indiscernibility structure gives rise to PSpace reasoning?
- weighted transducers: other semirings?
- What happens “beyond” the Horn fragment?

Thank you!

Joint work with:

Rafael Peñaloza, Oliver Fernandez Gil