Selected Advances in Data Semantics

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Ontology Modeling

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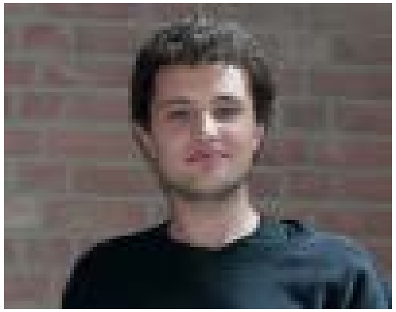
User Interfaces

The Protégé ROWLTab

(work with Md Kamruzzaman Sarker, David Carral, Adila Krisnadhi)


Modeling OWL with Rules

Problem: directly modeling in OWL (in any syntax, including DL syntax) is error-prone and cumbersome.

It appears that rules are much simpler to use for expressing schema information.

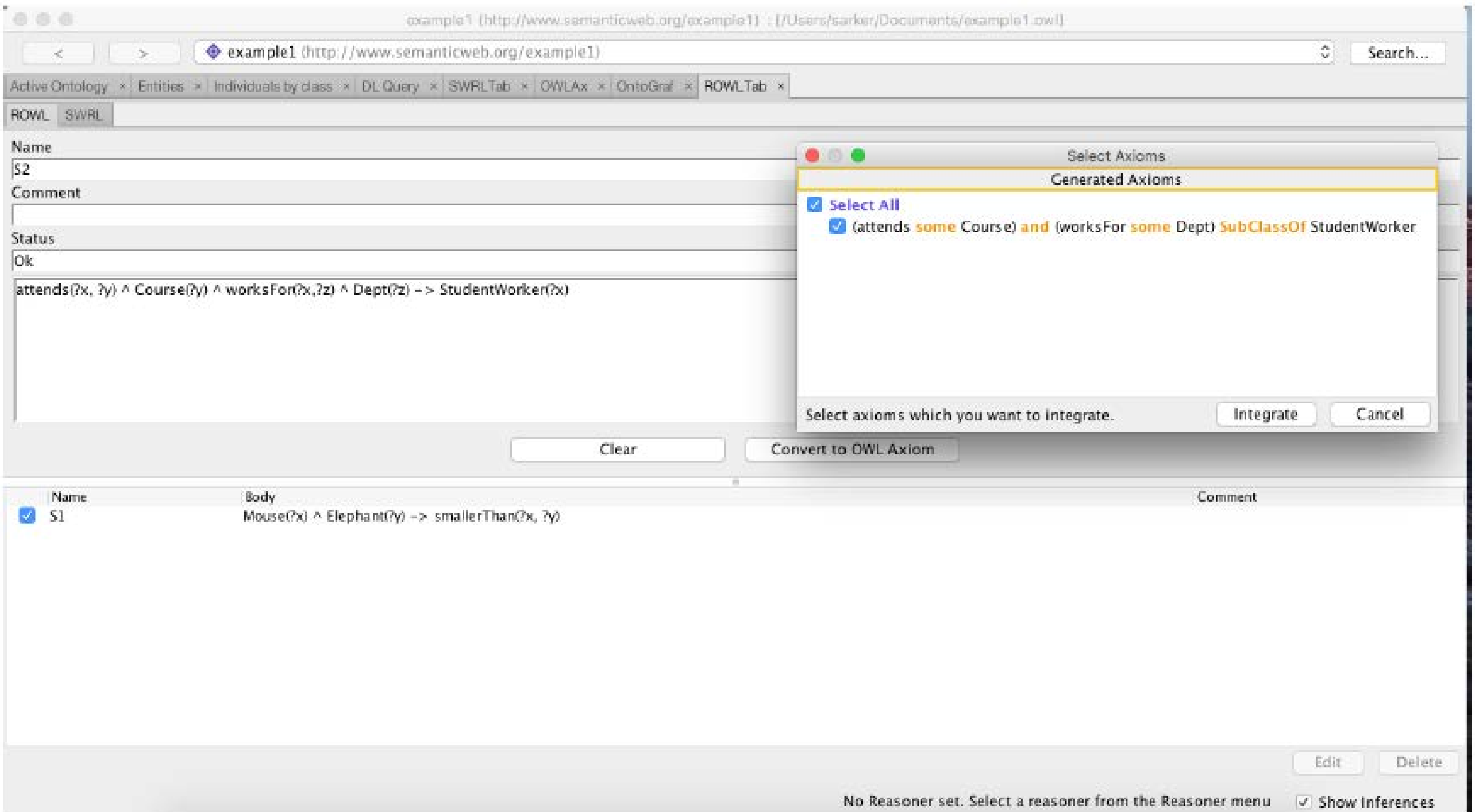
$$\text{Ru3: Person}(x) \wedge \text{hasMother}(x, y) \rightarrow \text{Parent}(y)$$

$$\text{Ax3: } \exists \text{hasMother}^{-}.\text{Person} \sqsubseteq \text{Parent}$$

Hence, we developed a Protégé plug-in which affords the modeling of OWL using rules (to the extent to which rules can be converted into OWL).

Non-convertible rules are stored as SWRL-Rules (with a warning to the user).

ROWL Protégé plug-in



http://dase.cs.wright.edu/content/rowl

User Evaluation

- **Subjects: 12 graduate students from Wright State University with some basic knowledge of OWL and at least minimal exposure to Protégé.**
- **Participants were given 12 natural language sentences to model in Protégé, half with the standard interface, half with ROWL.**
  - **Easy sentences: atomic subclass inclusions**
  - **Medium sentences: Required some role restrictions.**
  - **Hard sentences: Required rolifications.**

$$\text{Ru5: Person}(x) \wedge \text{hasBrother}(x,y) \wedge \text{hasSon}(y,z) \rightarrow \text{hasNephew}(x,z)$$

$$\text{Ax5: Person} \sqsubseteq \exists R_1.\mathsf{Self}, \quad \text{R}_1 \circ \text{hasBrother} \circ \text{hasSon} \sqsubseteq \text{hasNephew}$$

User Evaluation

Group A	Group B	Difficulty
1. Every father is a parent. 2. Every university is an educational institution.	7. Every parent is a human. 8. Every educational institution is an organization.	easy
3. If a person has a mother then that mother is a parent. 4. Any educational institution that awards a medical degree is a medical school.	9. If a person has a parent who is female, then this parent is a mother. 10. Any university that is funded by a state government is a public university.	medium
5. If a person's brother has a son, then that son is the first person's nephew. 6. All forests are more biodiverse than any desert.	11. If a person has a female child, then that person would have that female child as her daughter. 12. All teenagers are younger than all twens.	hard

Time used

Hypothesis:

On medium and hard sentences, participants would be able to model quicker with the ROWLTab than without it.

Sentence Category	Time (in secs)		# clicks		Correctness	
	Protégé avg/std	ROWL avg/std	Protégé avg/std	ROWL avg/std	Protégé avg/std	ROWL avg/std
easy	79/ 41	47/ 9	44/ 38	59/ 19	2.9/0.3	2.9/0.3
medium	312/181	116/61	216/131	141/ 91	2.2/0.5	2.5/0.8
hard	346/218	160/66	351/318	228/168	0.9/0.7	2.5/0.7

Paired t-test:

easy: **$p = 0.002 < 0.01$**

medium: **$p = 0.020 < 0.05$**

hard: **$p = 0.020 < 0.05$**

Correctness

Hypothesis:

On medium and hard sentences, participants would provide more correct answers with the ROWLTab than without it.

Sentence Category	Time (in secs)		# clicks		Correctness	
	Protégé avg/std	ROWL avg/std	Protégé avg/std	ROWL avg/std	Protégé avg/std	ROWL avg/std
easy	79/ 41	47/ 9	44/ 38	59/ 19	2.9/0.3	2.9/0.3
medium	312/181	116/61	216/131	141/ 91	2.2/0.5	2.5/0.8
hard	346/218	160/66	351/318	228/168	0.9/0.7	2.5/0.7

Paired t-test:

easy: $p = 1.0000 > 0.05$

medium: $p = 0.180 > 0.05$

hard: $p = 0.0001 < 0.01$

Clicks

Hypothesis:

None (this was for information only)

Sentence Category	Time (in secs)		# clicks		Correctness	
	Protégé avg/std	ROWL avg/std	Protégé avg/std	ROWL avg/std	Protégé avg/std	ROWL avg/std
easy	79/ 41	47/ 9	44/ 38	59/ 19	2.9/0.3	2.9/0.3
medium	312/181	116/61	216/131	141/ 91	2.2/0.5	2.5/0.8
hard	346/218	160/66	351/318	228/168	0.9/0.7	2.5/0.7

Paired t-test:

- **easy:** **$p = 0.092 > 0.05$**
- **medium:** **$p = 0.030 < 0.05$** **(significant time difference)**
- **hard:** **$p = 0.173 > 0.05$** **(significant time and correctness difference)**

Assessment

- **The hypotheses for time and for correctness (hard questions) were confirmed. For correctness (medium questions) the hypothesis was rejected.**

category	time	clicks	correctness
easy	significant ($p < 0.05$)	not significant	not significant
medium	significant ($p < 0.01$)	significant ($p < 0.05$)	not significant
hard	significant ($p < 0.05$)	not significant	significant ($p < 0.01$)

It appears that medium modeling problems (with some role restrictions) can be done correctly with the standard Protégé interface by this type of user, although more time is needed than when using ROWLTab.

It appears that hard problems (requiring rolification) cannot really be solved using the standard Protégé interface, and the unsuccessful solution attempts in addition require more time.

The Protégé OWLAx plug-in

(work with Md Kamruzzaman Sarker and Adila Krisnadhi)

Our modeling workflow

Our standard modeling workflow:

1. **Define scope**
2. **Make and refine schema diagram using analog media**
3. **Use Protégé to create OWL file**

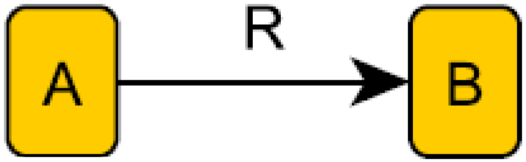
See: Adila Krisnadhi, Pascal Hitzler, Modeling With Ontology Design Patterns: Chess Games As a Worked Example. In: Pascal Hitzler, Aldo Gangemi, Krzysztof Janowicz, Adila Krisnadhi, Valentina Presutti (eds.), Ontology Engineering with Ontology Design Patterns: Foundations and Applications. Studies on the Semantic Web Vol. 25, IOS Press/AKA Verlagpp. 3-22.

It turns out that an elaborate ("complete") axiomatization means adding the same types of axioms over and over again.

We wanted to have an interface that supports our workflow and simplifies repetitive tasks.

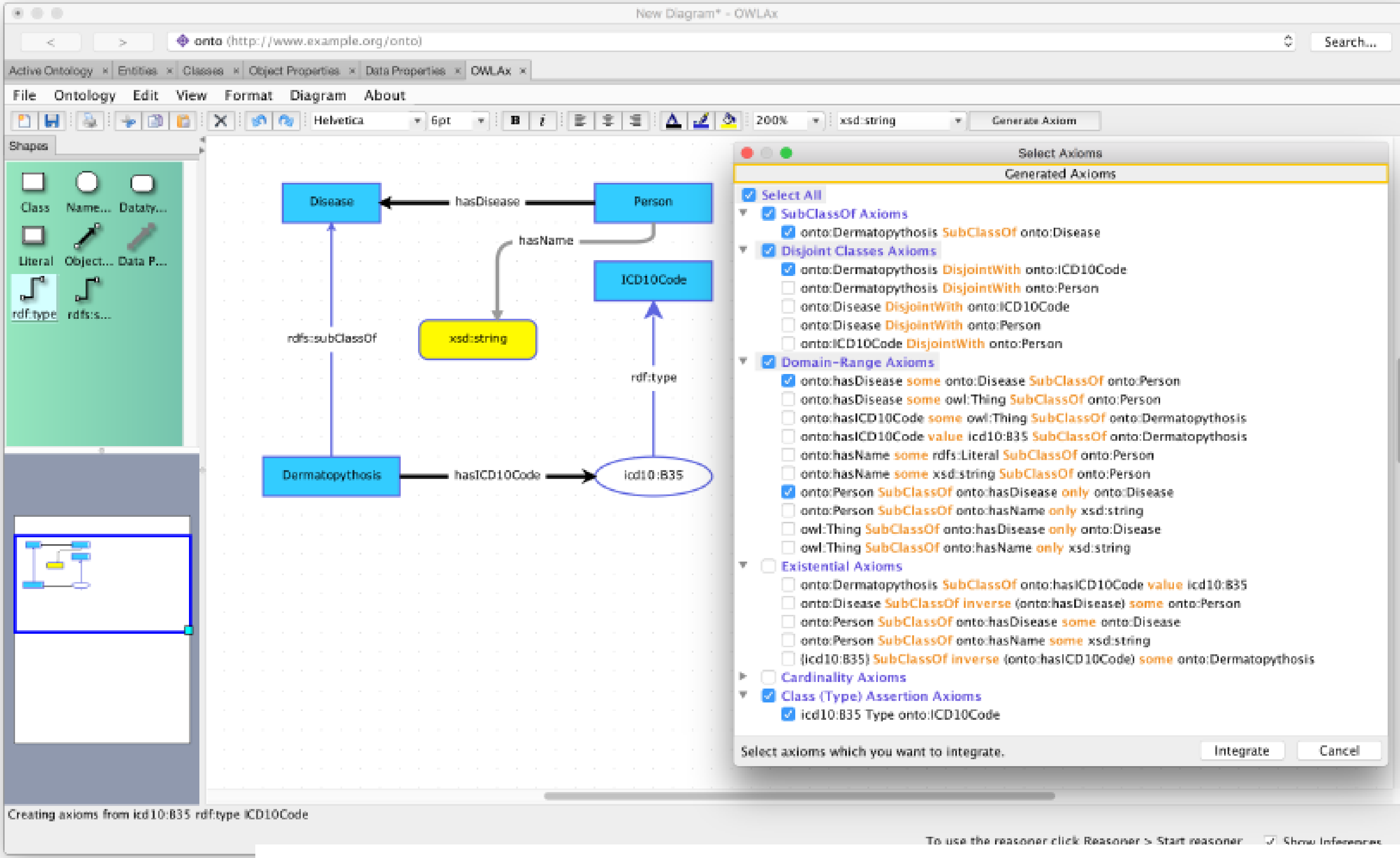
Axioms – Systematically

1. $A \sqcap B \sqsubseteq \bot$
2. $\exists R.\top \sqsubseteq A$
3. $\exists R.B \sqsubseteq A$
4. $\top \sqsubseteq \forall R.B$
5. $A \sqsubseteq \forall R.B$
6. $A \sqsubseteq R.B$
7. $B \sqsubseteq R^{-}.A$
8. $\top \sqsubseteq \leq 1 R.\top$
9. $\top \sqsubseteq \leq 1 R.B$
10. $A \sqsubseteq \leq 1 R.\top$
11. $A \sqsubseteq \leq 1 R.B$
12. $\top \sqsubseteq \leq 1 R^{-}.\top$
13. $\top \sqsubseteq \leq 1 R^{-}.A$
14. $B \sqsubseteq \leq 1 R^{-}.\top$
15. $B \sqsubseteq \leq 1 R^{-}.A$



1. A DisjointWith B (disjointness)
2. R some `owl:Thing` SubClassOf A (domain)
3. R some B SubClassOf A (scoped domain)
4. `owl:Thing` SubClassOf R only B (range)
5. A SubClassOf R only B (scoped range)
6. A SubClassOf R some B (existential)
7. B SubClassOf inverse R some A (inverse existential)
8. `owl:Thing` SubClassOf R max 1 `owl:Thing` (functionality)
9. `owl:Thing` SubClassOf R max 1 B (qualified functionality)
10. A SubClassOf R max 1 `owl:Thing` (scoped functionality)
11. A SubClassOf R max 1 B (qualified scoped functionality)
12. `owl:Thing` SubClassOf inverse R max 1 `owl:Thing` (inverse functionality)
13. `owl:Thing` SubClassOf inverse R max 1 A (inverse qualified functionality)
14. B SubClassOf inverse R max 1 `owl:Thing` (inverse scoped functionality)
15. B SubClassOf inverse R max 1 A (inverse qualified scoped functionality)

OWLAx Protégé plug-in



- In: Proc. ISWC 2016 poster & demos
  http://dase.cs.wright.edu/content/ontology-axiomatization-support

Good axioms

Specificity matters: Problems with domain/range.

Recommendations often heard (but are problematic):

- **Indicate domain and range for your properties.**
- **Reuse as many existing vocabularies as you can.**

But there are problems with this:

Ontology 1:

$\text{Human} \xrightarrow{\text{foaf:name}} \text{xsd:string}$

domain(foaf:name) = Human

Ontology 2:

$\text{Organization} \xrightarrow{\text{foaf:name}} \text{xsd:string}$

domain(foaf:name) = Organization

Logical consequence after merge: **Human $\equiv$ Organization**

Recommendations

- **Make rich axiomatizations**
- **Avoid re-use of external vocabularies (rather provide an additional file with mappings for those who want to use it)**
- **Avoid naïve domain and range axioms.**

Alternative to naïve domain/range: scoped domain and range.

$$\boxed{\quad A \quad} \xrightarrow{\quad p \quad} \boxed{\quad B \quad}$$

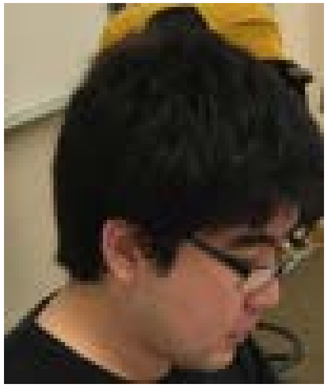
$A(x) \wedge p(x, y) \rightarrow B(y)$ **scoped range**

$B(y) \wedge p(y, x) \rightarrow A(x)$ **scoped domain**

both rules can be expressed in OWL.

LaTeX conversion to Description Logic Syntax

(work with Cogan Shimizu and Matthew Horridge)



LaTeX conversion

- The OWL API has had a LaTeX renderer for DL syntax for quite some time, however it had significant problems:
  - Most OWL files did result in uncompilable LaTeX code.
  - Some bugs or incorrectly rendered axioms.
  - Poor vertical alignment.
  - Many lines too long, even beyond the page margin.

- We wanted to improve this to obtain a practically useful tool.

LaTeX conversion

- We impoved the OWL API LaTeX renderer.
- The code changes are part of the 5.0.6 release.
- We used a heuristics for linebreaks.
- We make use of namespaces now to obtain more readable axioms.
- We sometimes deviate from strict DL syntax to make axioms more readable, and use expressions borrowed from the functional style syntax instead, e.g. for mutual disjointness of classes.
- We tested with all 117 syntactically correct and downloadable ontology design patterns from www.ontologydesignpatterns.org and all of them now typeset without any problems. None of them did typeset without error previously.
- We also provide a GUI and a CLI interface.

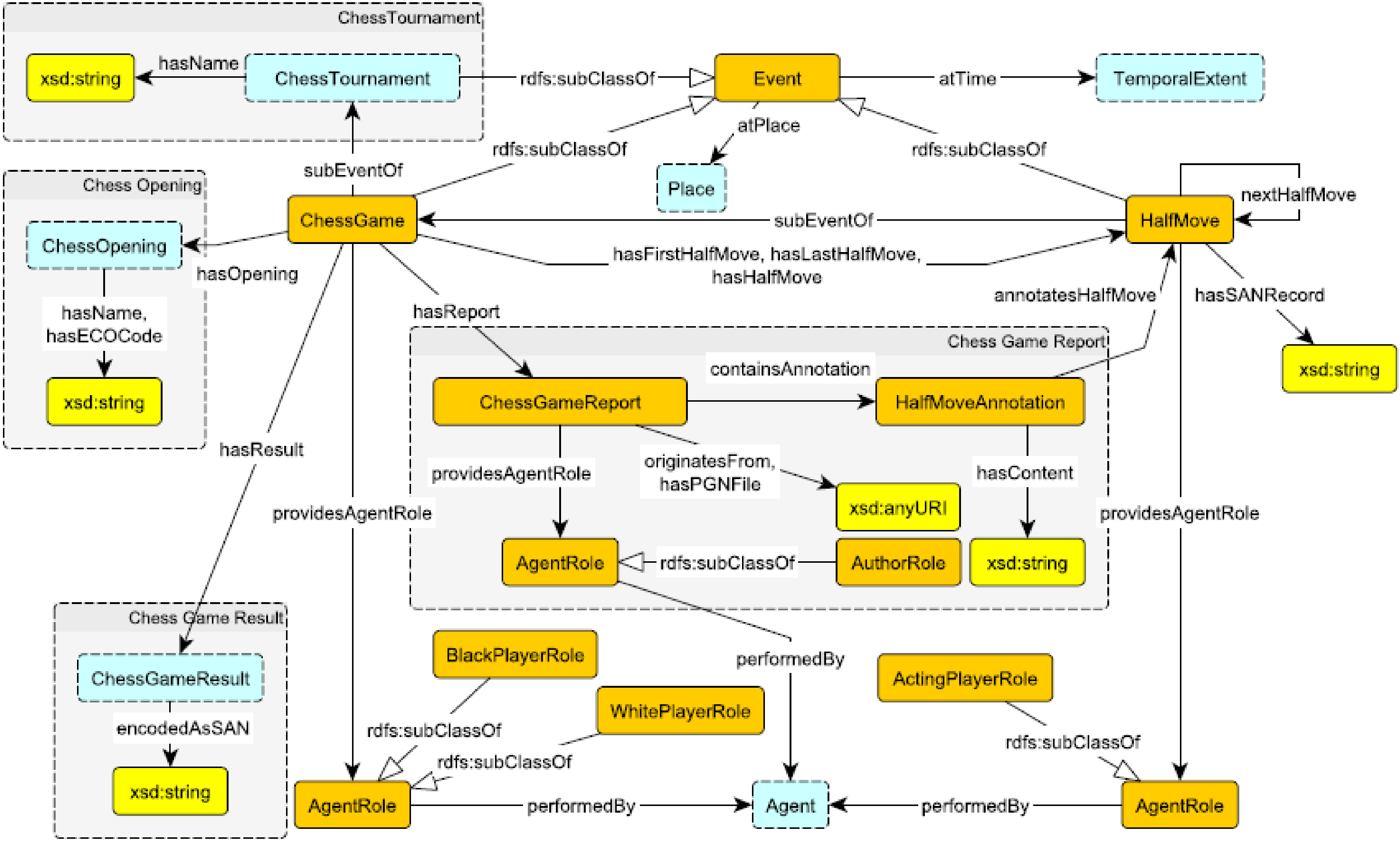
LaTeX conversion

Breaking news:

We ran an initial experiment about understandability of axioms. Our early scanning of the data indicates that both DL-syntax and a semi-rule-type of first-order logic syntax are more easily understandable than the Manchester syntax.

Detailed analysis forthcoming.

Chess Example



Classes

ActingPlayerRole

$$ActingPlayerRole \sqsubseteq AgentRole$$
$$ActingPlayerRole \sqsubseteq = 1 providesAgentRole^{-}.HalfMove$$

Agent

AgentRole

$$AgentRole \sqsubseteq = 1 performedBy.Agent$$
$$AgentRole \sqsubseteq \forall performedBy.Agent$$

AuthorRole

$$AuthorRole \sqsubseteq AgentRole$$
$$AuthorRole \sqsubseteq = 1 providesAgentRole^{-}.ChessGameManifestation$$

BlackPlayerRole

$$BlackPlayerRole \sqsubseteq = 1 providesAgentRole^{-}.ChessGame$$
$$BlackPlayerRole \sqsubseteq AgentRole$$

ChessCompetitionInstance

$$ChessCompetitionInstance \sqsubseteq \forall partOf.ChessCompetitionSeries$$
$$ChessCompetitionInstance \sqsubseteq Event$$

ChessCompetitionRound

$$ChessCompetitionRound \sqsubseteq Event$$
$$ChessCompetitionRound \sqsubseteq \forall subEventOf.ChessCompetitionInstan$$

ChessCompetitionSeries

$$ChessCompetitionSeries \sqsubseteq Event$$

ChessGame

$$ChessGame \sqsubseteq \forall subEventOf.ChessCompetitionRound$$
$$ChessGame \sqsubseteq = 1 hasFirstHalfMove.HalfMove$$
$$ChessGame \sqsubseteq \forall hasResult.ChessGameResult$$
$$ChessGame \sqsubseteq Event$$
$$ChessGame \sqsubseteq \forall hasHalfMove.HalfMove$$
$$ChessGame \sqsubseteq = 1 hasLastHalfMove.HalfMove$$
$$ChessGame \sqsubseteq \exists providesAgentRole.WhitePlayerRole$$
$$ChessGame \sqsubseteq \forall hasOpening.ChessOpening$$
$$ChessGame \sqsubseteq \exists providesAgentRole.BlackPlayerRole$$
$$ChessGame \sqsubseteq \forall hasManifestation.ChessGameManifestation$$

ChessGameManifestation

$$ChessGameManifestation \sqsubseteq \forall containsAnnotation.HalfMoveAnnotation$$
$$ChessGameManifestation \sqsubseteq \forall originatesFrom.xsd{:}anyURI$$
$$ChessGameManifestation \sqsubseteq \forall hasPGNFile.xsd{:}anyURI$$

ChessGameResult

$$ChessGameResult \sqsubseteq \forall encodedAsSAN.xsd{:}string$$

ChessOpening

$$ChessOpening \sqsubseteq \forall hasECOCode.xsd{:}string$$
$$ChessOpening \sqsubseteq \forall hasOpeningName.xsd{:}string$$

Event

$$Event \sqsubseteq \forall atTime.TemporalExtent$$
$$Event \sqsubseteq \exists atPlace.Place$$
$$Event \sqsubseteq \exists atTime.TemporalExtent$$
$$Event \sqsubseteq \forall subEventOf.Event$$
$$Event \sqsubseteq \forall atPlace.Place$$

HalfMove

$\text{HalfMove} \sqsubseteq \leq 1 \text{nextHalfMove.HalfMove}$
$\text{HalfMove} \sqsubseteq = 1 \text{hasHalfMove}^{-}.\text{ChessGame}$
$\text{HalfMove} \sqsubseteq \text{Event}$
$\text{HalfMove} \sqsubseteq \exists \text{providesAgentRole.ActingPlayerRole}$
$\text{HalfMove} \sqsubseteq \forall \text{hasSANRecord.xsd:string}$
$\text{HalfMove} \sqsubseteq \neg(\exists \text{nextHalfMove.Self})$
$\text{HalfMove} \sqsubseteq \forall \text{nextHalfMove.HalfMove}$
$\text{HalfMove} \sqsubseteq \forall \text{subEventOf.ChessGame}$

HalfMoveAnnotation

$\text{HalfMoveAnnotation} \sqsubseteq \forall \text{hasContent.xsd:string}$
$\text{HalfMoveAnnotation} \sqsubseteq \forall \text{annotatesHalfMove.HalfMove}$
$\text{HalfMoveAnnotation} \sqsubseteq \exists \text{hasContent.xsd:string}$
$\text{HalfMoveAnnotation} \sqsubseteq \exists \text{annotatesHalfMove.HalfMove}$

Place

TemporalExtent

WhitePlayerRole

$\text{WhitePlayerRole} \sqsubseteq \text{AgentRole}$
$\text{WhitePlayerRole} \sqsubseteq = 1 \text{providesAgentRole}^{-}.\text{ChessGame}$

Object properties

annotatesHalfMove

atPlace

atTime

containsAnnotation

hasFirstHalfMove

$\text{hasFirstHalfMove} \sqsubseteq \text{hasHalfMove}$

hasHalfMove

$\text{hasHalfMove} \sqsubseteq \text{subEventOf}^{-}$

hasLastHalfMove

$\text{hasLastHalfMove} \sqsubseteq \text{hasHalfMove}$

hasManifestation

hasOpening

hasResult

nextHalfMove

partOf

performedBy

providesAgentRole

subEventOf

Data properties

encodedAsSAN

hasContent

hasECOCode

hasOpeningName

hasPGNFile

hasSANRecord

originatesFrom

Individuals

Datatypes

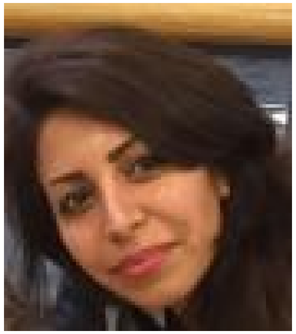
anyURI

string

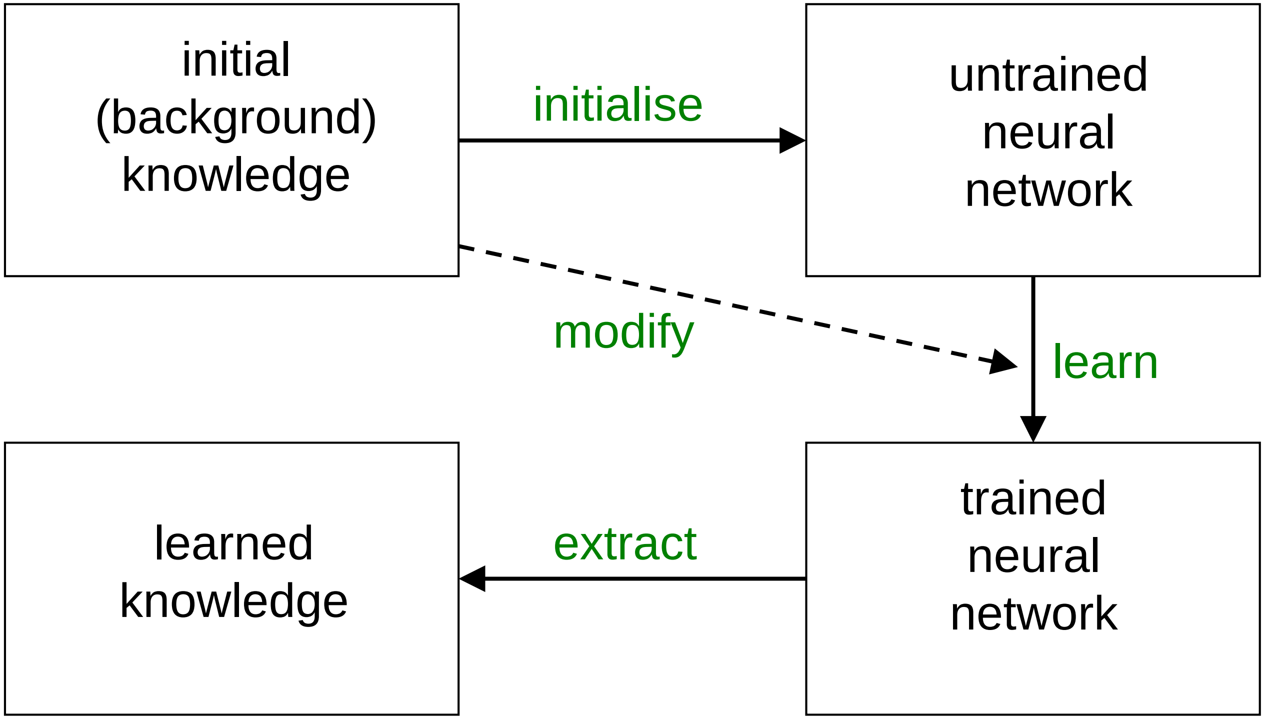
Neural-Symbolic Integration: Explaining neural networks using background knowledge

Propositional rule extraction from trained neural networks under background knowledge

(work with Maryam Labaf)



Neural-symbolic learning cycle



The four main problems of Neural-symbolic Integration.

Extraction

In this case: extracting propositional rules.

General idea:

- **Input value 1 interpreted as "true", value 0 as "false"**
- **Outputs interpreted as true or false according to a threshold**
- **I.e. network function maps binary vectors.**

Garcez et al, 2001: By weight analysis (layer by layer) under differentiable activation functions. Possible in principle but intricate and, arguably, the resulting rule sets are usually rather difficult to understand.

Lehmann, Bader, Hitzler, 2010: Black-box approach (looking at inputs and outputs only).

Lehmann, Bader, Hitzler, 2010

For every monotonic function

$$f : \{0,1\}^n \to \{0,1\}^k$$

there is a unique reduced set of positive propositional rules which capture exactly the function f.

Reduced means: no redundancies, and as small as possible.

Problem: Rule sets can get large and messy, i.e. still very difficult to understand.

Adding Background Knowledge

Can we lift the result just given to include background knowledge?

Given:

- A (reduced) propositional logic program P (extracted from an ANN as above).
- Set I of prop. variables representing ANN inputs.
- Set O of prop. variables representing ANN outputs.
- A background knowledge base K (a propositional logic program).

We then seek a logic program P' (simpler than P) s.t. for all subsets i in I and each o in O we have

$$P \land i \models o \qquad \text{iff} \qquad P' \land K \land i \models o.$$

Adding Background Knowledge

It turns out that

- P' is no longer unique in general
  (even under reduction).
- P' may not even exist
  (unless I is restricted to the left-hand side of rules in K).

- But with suitable K you can get P' which are simpler than P.
  Typical case:

P:		K:		P':	
	$p_1 \wedge q \rightarrow o$		$p_1 \rightarrow r$		$r \wedge q \rightarrow o$
	$p_2 \wedge q \rightarrow o$		$p_2 \rightarrow r$		

Adding Background Knowledge

P: $p_1 \wedge q \rightarrow o$

$p_2 \wedge q \rightarrow o$

K: $p_1 \rightarrow r$

$p_2 \rightarrow r$

P': $r \wedge q \rightarrow o$

Note that K essentially groups input variables. Once could think of r being a "more general concept" than either p1 and p2.

Of course, we have only discussed the propositional case so far, but in order to obtain strong explanations for the input-output behavior of ANNs we need to go beyond propositional.

Description Logic extraction from trained neural networks under background knowledge

(work with Md Kamruzzaman Sarker, Derek Doran, Ning Xie, Mike Raymer)




DL Extraction from ANNs

- **Explain input-output behavior of trained (deep) NNs.**
- **Idea:**
  - **Use background knowledge in the form of linked data and ontologies to help explain.**
  - **Link inputs and outputs to background knowledge.**
  - **Use a symbolic learning system (e.g., DL-Learner) to generate an explanatory theory.**

We got funding for this work through an Ohio Federal Research Network, for 1-2 years initially (to find out whether it works).

DL Extraction from ANNs

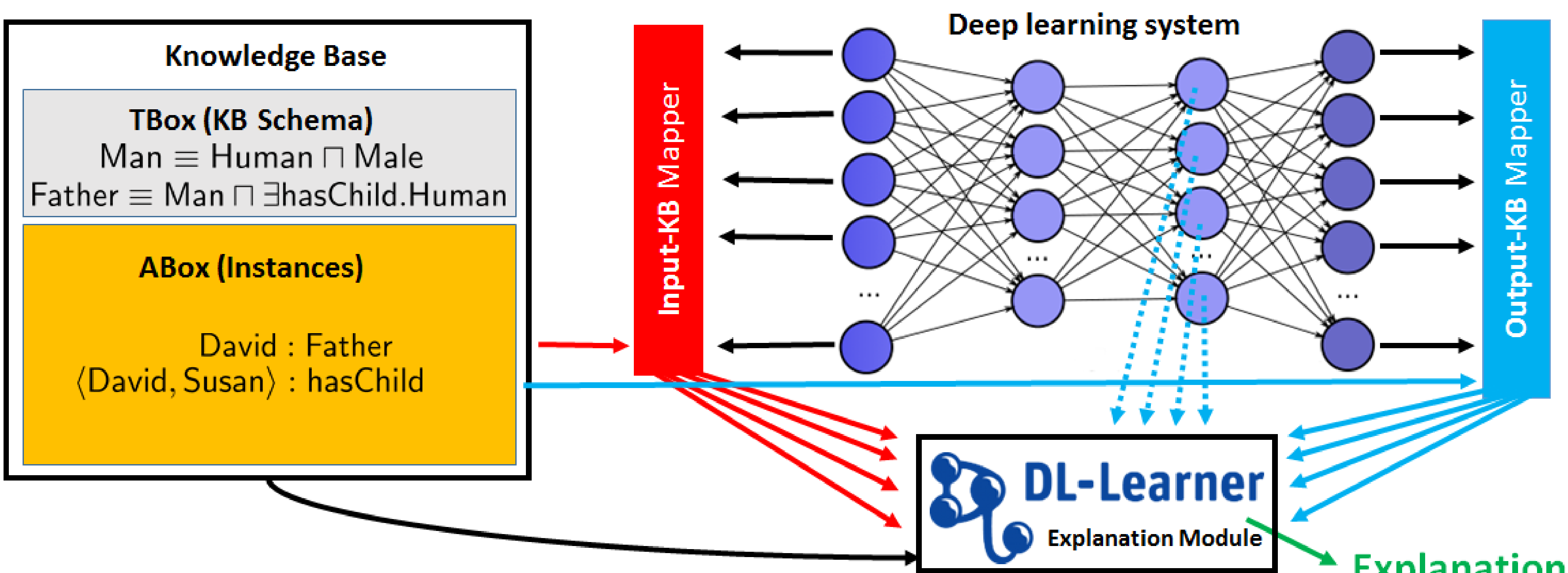
Possible data sources:

- **Linked data / semantic web data**
  - **I.e. structured data on the web, organized in so-called RDF graphs.**
- **Cross-domain ontologies (e.g., SUMO, Proton)**
- **Wikidata**
- **schema.org**

Essentially, all content already readily and publicly available in structured form.

If further domain knowledge is needed: use state-of-the-art approaches for knowledge graph generation in order to obtain structured data from suitable text corpora.

DL Extraction from ANNs



Proof of concept

- Two class problem
  - Food (positive) and Non Food (negative)
- Concepts in background ontology:
  - Food, Market and Swimming Pool
- Object property
  - imageContains
- Positive instances: 3 food individuals and 1 market individual

- Explanation for food concept:
  - Food or (Market and (imageContains some (not (Water))))
  - Food or (Market and (imageContains some (not (Swimming_Pool))))
  - Food or (Market and (imageContains some (not (Person))))
  - Food or (Market and (imageContains some (not (Market))))

Experiment on MIT ADE20K Dataset

- Two class problem
  - OutdoorMuseum – Positive concept
  - Non OutdoorMuseum – Negative concept

- Concepts in background ontology :
  - SUMO hierarchical ontology + concept names starting with letter M in ADE20K training data

- Positive instances: all individuals from OutdooorMuseum concept and 1 individual from language concept (as noise)

- Negative instances: all other individuals in the knowledge base.

MIT ADE20K Results

- **Explanation for OutdoorMuseum:**
  - **(not (TheaterProfession)) and (not (Object))**
  - **(not (MilitaryGeneral)) and (not (Object))**
  - **(not (Mile)) and (not (Object))**
  - **(not (Meter)) and (not (Object))**

- **N.B: Current explanation is not up to the mark.**
- **Possible reasons?:**
  - **Mappings from network inputs to background knowledge are probably overly simplistic?**
  - **Background knowledge not expressive enough?**

- **Main Difficulties: Need to map input features of neural network to semantically meaningful background knowledge entities.**

Explaining hidden neurons

Collaborators Derek Doran and Ning Xie (Web and Complex Systems Lab)

They explore how to determine groups of hidden neurons which often fire together and thus may indicate the “detection” of certain features.

We plan to apply the above mentioned DL-Learner approach also to these groups of hidden neurons, in order to determine which features they detect.

Thanks!

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