The Challenges of the Semantic Web to Machine Learning and Data Mining

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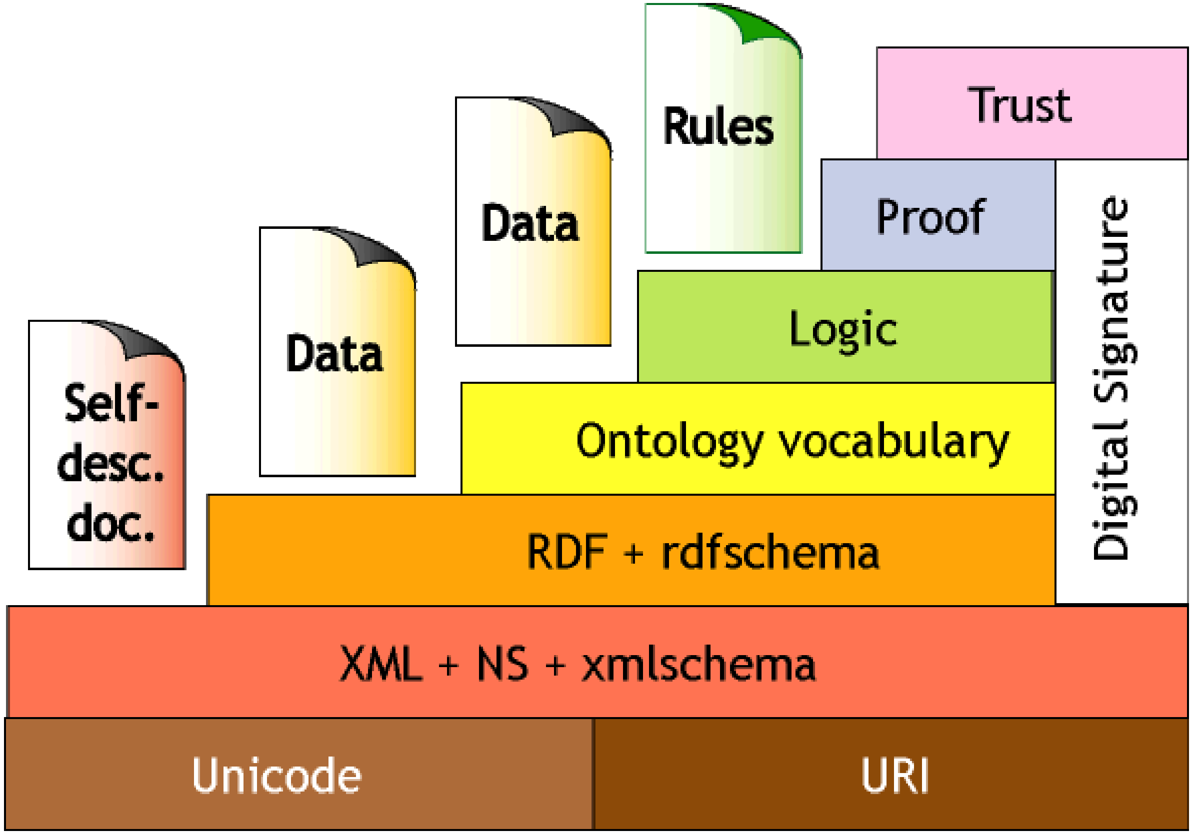
The Semantic Web

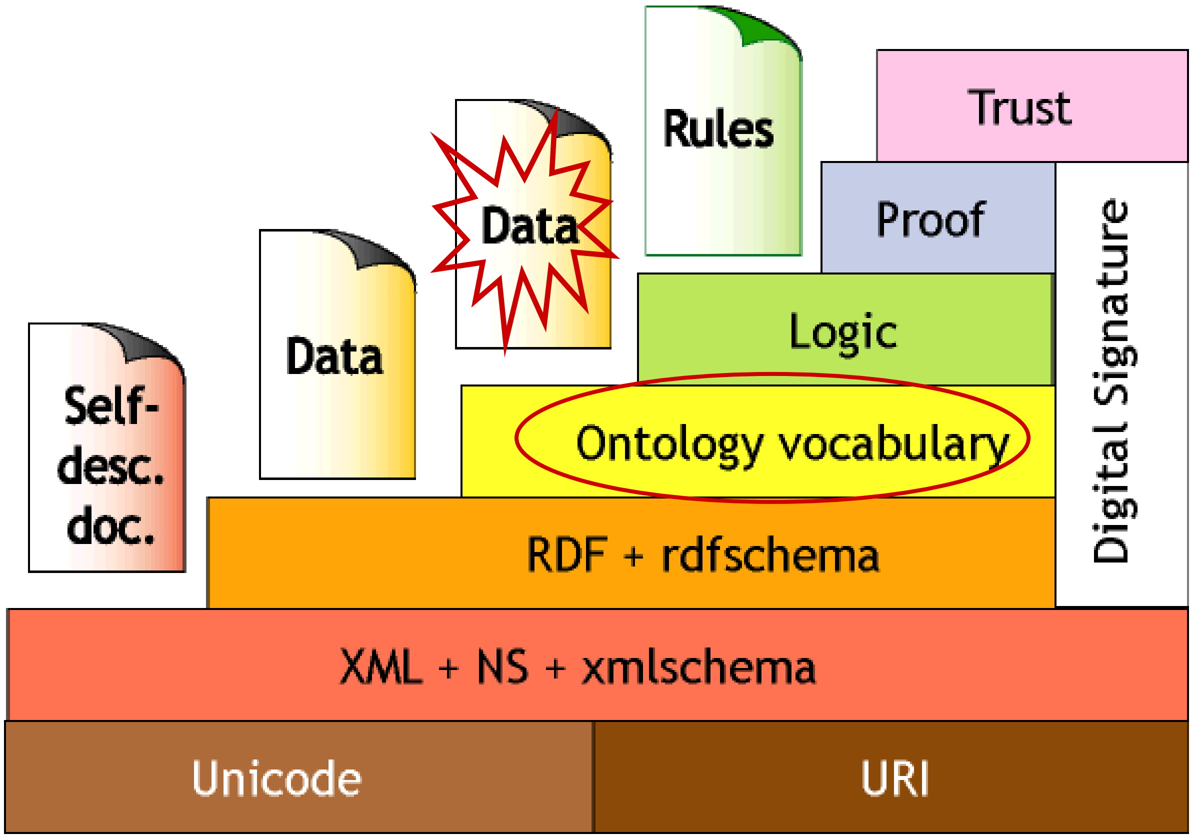
T. Berners-Lee, J. Hendler, and O. Lassila (2001). *The Semantic Web*. Scientific American, May 2001, pp. 34–43.

- ⌘ Evolving extension of the World Wide Web (WWW) in which WWW content can be expressed not only in natural language, but also in a format that can be read and used by software agents, thus permitting them to find, share and integrate information more easily.
- ⌘ Vision of the WWW as a universal medium for data, information, and knowledge exchange.

The Semantic Web: layered architecture



The Semantic Web: layer of ontologies



What is an ontology?

T. R. Gruber (1993). *A translation approach to portable ontologies*. Knowledge Acquisition, 5(2): 199-220.

An Ontology is a

formal specification $\Rightarrow$ Executable

of a shared $\Rightarrow$ Group of persons

conceptualization $\Rightarrow$ About concepts

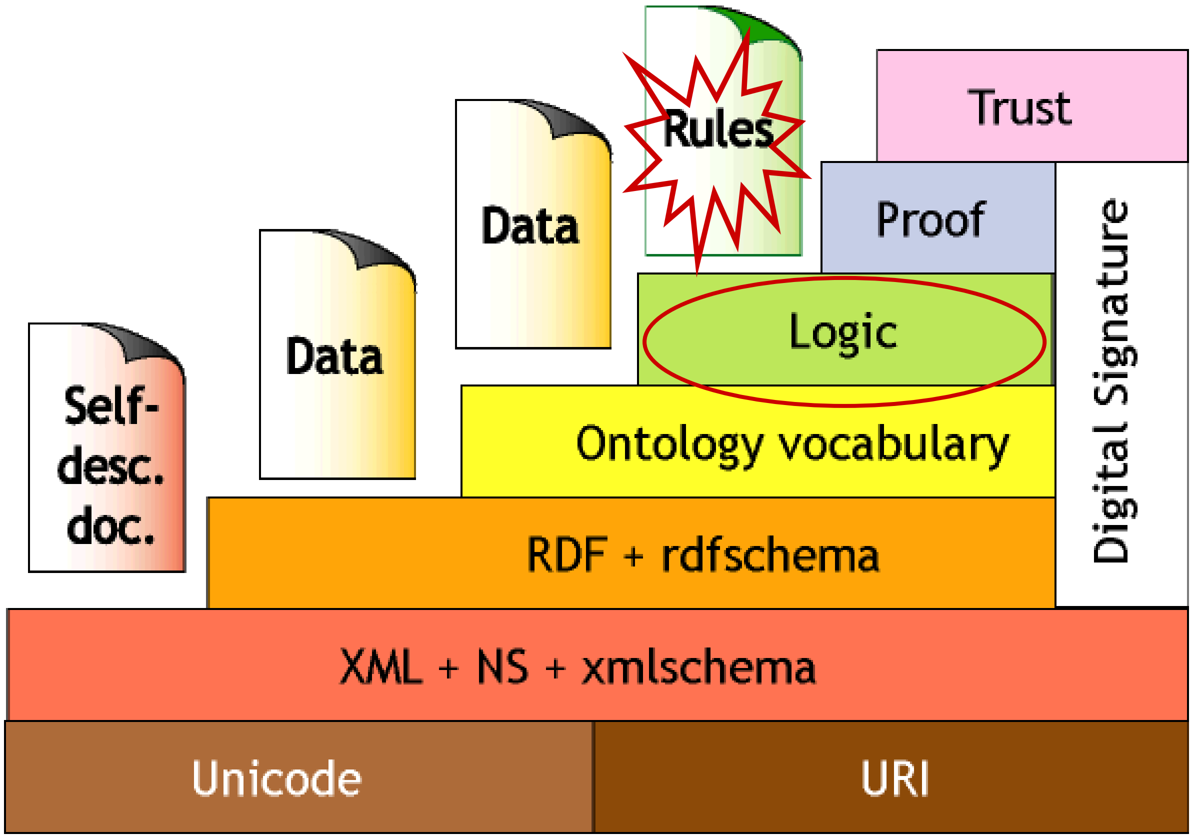
of a domain of interest $\Rightarrow$ Between application and „unique truth“

OWL (Ontology Web Language)

- W3C **recommendation** (i.e., a standard) for Web ontologies
  - http://www.w3.org/2004/OWL/

- Developed by the W3C WebOnt Working Group
- Mark-up language
  - compatible with RDF/XML exchange format
  - based on earlier languages OIL and DAML+OIL

The Semantic Web:
Rules on top of ontologies



SWRL (Semantic Web Rule Language)

- Submitted to W3C for standardization
  - http://www.w3.org/Submission/SWRL/
- Mark-up language
  - compatible with RDF/XML exchange format
  - integration of OWL and RuleML
- W3C RIF (Rule Interchange Format) Working Group

What the Semantic Web can do for ML/DM

1. Lots and lots of tools to describe and exchange data for later use by ML/DM methods in a canonical way!
2. Using ontological structures to improve the ML/DM tasks
3. Provide background knowledge to guide ML/DM systems
   - See PriCKLws@ECML/PKDD-07

What ML/DM can do for the Semantic Web

1. Learning Ontologies (even if not fully automatic)
2. Learning to map between ontologies
3. Deep Annotation: Reconciling databases and ontologies
4. Annotation by Information Extraction
5. Duplicate recognition

Tutorial focus

- The acquisition of ontologies and rules for the Semantic Web is a very demanding task
- The logical nature of ontology and rule languages for the Semantic Web should not be neglected when choosing ML/DM methods to be applied
- Inductive Logic Programming can be a source of solutions to the Knowledge Acquisition bottleneck of the Semantic Web

Tutorial overview

- Part I: "Logical Foundations of Ontology and Rule Languages for the Semantic Web" (1h 30m)
- Part II: "Logic-based ML/DM methods for the Semantic Web" (1h 30m)

The Challenges of the Semantic Web to Machine Learning and Data Mining

Part I: "Logical Foundations of Ontology and Rule Languages for the Semantic Web" (1h 30m)

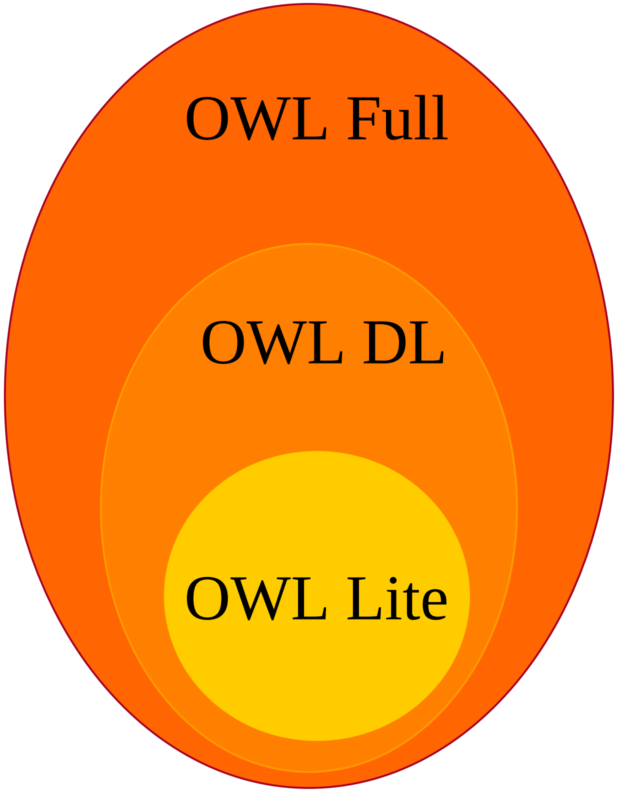
Part I: Overview

- KR systems based on Description Logics
- KR systems combining Description Logics and Horn Clausal Logic (fragments)

Part I: Overview

- *KR systems based on Description Logics*
- KR systems combining Description Logics and Horn Clausal Logic (fragments)

OWL



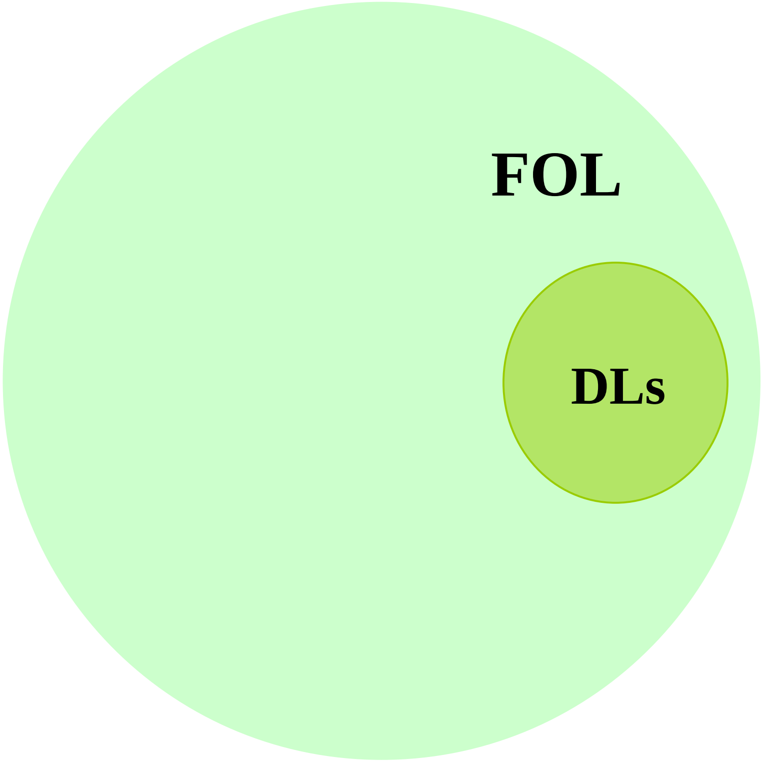
- OWL provide three levels of expressive power
- All three correspond to fragments of First Order Logic but
- OWL DL is based on a family of fragments with desirable computational properties: Description Logics!

OWL DL

- Why Description Logics?
- It exploits results of 15+ years of KR&R research
  - Well defined (model theoretic) semantics
  - Formal properties well understood (complexity, decidability)
  - Known reasoning algorithms
  - Implemented systems (highly optimised)

What are Description Logics?

F. Baader et al. (2003). *The Description Logic Handbook: Theory, Implementation, Applications*. Cambridge University Press, Cambridge, UK.



- DLs are decidable variable-free fragments of First Order Logic (FOL)
  - Describe domain in terms of concepts (classes), roles (properties, relationships) and individuals
- DLs provide a family of logic based formalisms for Knowledge Representation and Reasoning (KR&R)
  - Descendants of semantic networks and KL-ONE

DL Basics

- Concepts (unary predicates/formulae with one free variable)
  - E.g., Person, Doctor, HappyParent, (Doctor $\sqcup$ Lawyer)
- Roles (binary predicates/formulae with two free variables)
  - E.g., hasChild, loves, (hasBrother $\circ$ hasDaughter)
- Individuals (constants)
  - E.g., John, Mary, Italy
- Operators (for forming complex concepts and roles from atomic ones) restricted so that:
  - Satisfiability/subsumption is decidable and, *if possible*, of low complexity
  - No need for explicit use of variables
    - Restricted form of $\exists$ and $\forall$
    - Features such as counting can be succinctly expressed

The DL Family

- Smallest propositionally closed DL is $\mathcal{ALC}$ (Schmidt-Schauss and Smolka, 1991)
- $\mathcal{S}$ often used for $\mathcal{ALC}$ extended with transitive roles (R_+)
- Additional letters indicate other extensions, e.g.:
  - $\mathcal{H}$ for role hierarchy (e.g., hasDaughter $\sqsubseteq$ hasChild)
  - $\mathcal{O}$ for nominals/singleton classes (e.g., {Italy})
  - $\mathcal{I}$ for inverse roles (e.g., isChildOf $\equiv$ hasChild$^-$)
  - $\mathcal{N}$ for number restrictions (e.g., $\geqslant$2hasChild, $\leqslant$3hasChild)
  - $\mathcal{Q}$ for qualified number restrictions (e.g., $\geqslant$2hasChild.Doctor)
  - $\mathcal{F}$ for functional number restrictions (e.g., $\leqslant$1hasMother)
- $\mathcal{S}$ + role hierarchy ($\mathcal{H}$) + inverse ($\mathcal{I}$) + QNR ($\mathcal{Q}$) = $\mathcal{SHIQ}$
- $\mathcal{SHIQ}$is the basis for OWL
  - OWL DL $\approx$ $\mathcal{SHIQ}$extended with nominals (i.e., $\mathcal{SHOIQ}$)
  - OWL Lite $\approx$ $\mathcal{SHIQ}$with only functional restrictions (i.e., $\mathcal{SHIF}$)

$\mathcal{ALC}$ syntax

atomic concept	A	Human
atomic role	R	likes
conjunction	C⊓D	Human⊓Male
disjunction	C⊔D	Nice⊔Rich
negation	¬C	¬Meat
existential restriction	∃R.C	∃hasChild.Human
value restriction	∀R.C	∀hasChild.Nice

- E.g., person all of whose children are either Doctors or have a child who is a Doctor:

Person ⊓ ∀hasChild.(Doctor ⊔∃hasChild.Doctor)

DL Semantics

Semantics given by standard FOL model theory:

Interpretation function $\mathcal{I}$

Interpretation domain $\Delta^{\mathcal{I}}$

Individuals $i^{\mathcal{I}} \in \Delta^{\mathcal{I}}$

John

Mary

Concepts $C^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}}$

Lawyer

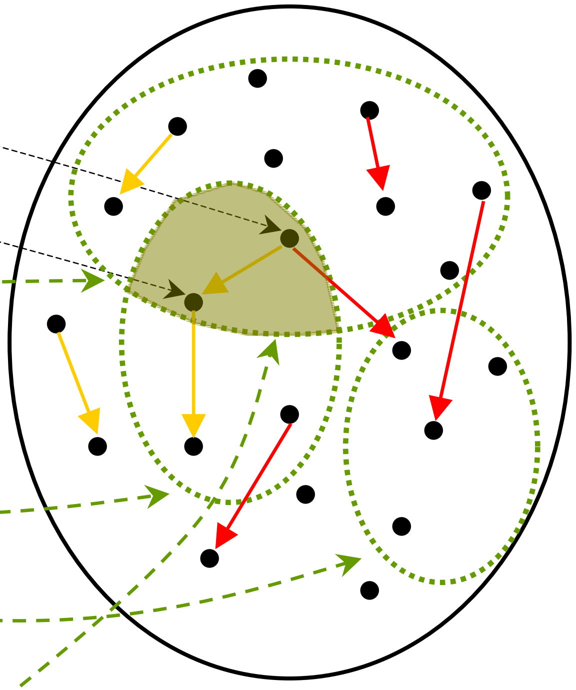
Doctor

Vehicle

Roles $r^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$

hasChild

owns



(Lawyer ⊓ Doctor)

DL Semantics:
Unique Names Assumption (UNA)

R. Reiter (1980). A logic for default reasoning. *Artificial Intelligence*, 13:81-132.

- $a^{\mathcal{I}} \neq b^{\mathcal{I}}$ if $a \neq b$

$\mathcal{ALC}$ semantics

atomic concept	A	$A^I \subseteq \Delta^I$
atomic role	R	$R^I \subseteq \Delta^I \times \Delta^I$
conjunction	$C \sqcap D$	$C^I \cap D^I$
disjunction	$C \sqcup D$	$C^I \cup D^I$
negation	$\neg C$	$\Delta^I \setminus C^I$
existential restriction	$\exists R.C$	$\{x \mid \exists y.\langle x,y \rangle \in R^I \wedge y \in C^I\}$
value restriction	$\forall R.C$	$\{x \mid \forall y.\langle x,y \rangle \in R^I \Rightarrow y \in C^I\}$

DL Deduction Rules

Tableau calculus

- Applies rules that correspond to DL constructors
  - E.g., $\text{John:(Person} \sqcap \text{Doctor)} \rightarrow_{\sqcap} \text{John:Person}$ and John:Doctor
- Stops when no more rules applicable or clash occurs
  - Clash is an obvious contradiction, e.g., $A(x)$, $\neg A(x)$
- Some rules are nondeterministic (e.g., $\sqcup$, $\exists$)
  - In practice, this means search
- Cycle check (blocking) often needed to ensure termination

$\mathcal{ALC}$ Deduction Rules

An algorithm based on **tableau calculus** for $\mathcal{ALC}$

- Tries to build a (tree) model $\mathcal{I}$ for input concept C
- Breaks down C syntactically, inferring constraints on elements in $\mathcal{I}$
- Applies inference rules corresponding to $\mathcal{ALC}$ constructors (e.g. $\rightarrow_{\exists}$)
- Works non-deterministically in PSpace
- Stops when a clash, i.e. a contradiction, occurs (C is inconsistent) or no other rule can be applied (C is consistent)

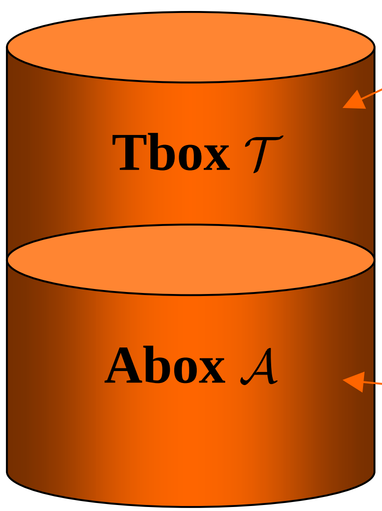
Mapping DLs to FOL

- Most DLs are decidable fragments of FOL
  - $\mathcal{ALC}$ is a fragment of FOL with two variables (L2)
- For mapping $\mathcal{ALC}$ to FOL introduce:
  - a unary predicate A for a concept name A
  - a binary relation R for a role name R
- Translate complex concepts C, D as follows:

$t_x(A)=A(x)$	$t_y(A)=A(x)$
$t_x(C \sqcap D)= t_x(C) \wedge t_x(D)$	$t_y(C \sqcap D)= t_y(C) \wedge t_y(D)$
$t_x(C \sqcup D)= t_x(C) \vee t_x(D)$	$t_y(C \sqcup D)= t_y(C) \vee t_y(D)$
$t_x(\exists R.C)= \exists y.R(x,y) \wedge t_y(C)$	$t_y(\exists R.C)= \exists y.R(x,y) \wedge t_x(C)$
$t_x(\forall R.C)= \forall y.R(x,y) \Rightarrow t_y(C)$	$t_y(\forall R.C)= \forall y.R(x,y) \Rightarrow t_x(C)$

DL Knowledge Bases

Knowledge Base Σ



Terminological part

- *Intensional* knowledge
- In the form of axioms

Assertional part

- *Extensional* knowledge
- In the form of assertions

$\mathcal{ALC}$ Knowledge Bases: syntax

Tbox

- *equality axioms*
  - A≡C
  - Father ≡ Man⊓∃hasChild.Human
- *inclusion axioms*
  - C⊑D
  - ∃favourite.Brewery ⊑ ∃drinks.Beer

ABox

- *concept assertions*
  - a:C
  - john:Father
- *role assertions*
  - <a,b>:R
  - < john,bill>: has-child

Open World Assumption (OWA)

- The information in an Abox is generally considered to be incomplete (*open world*)
- An Abox represents possibly infinitely many interpretations, namely its models
- Query answering requires nontrivial reasoning
- Classical negation!

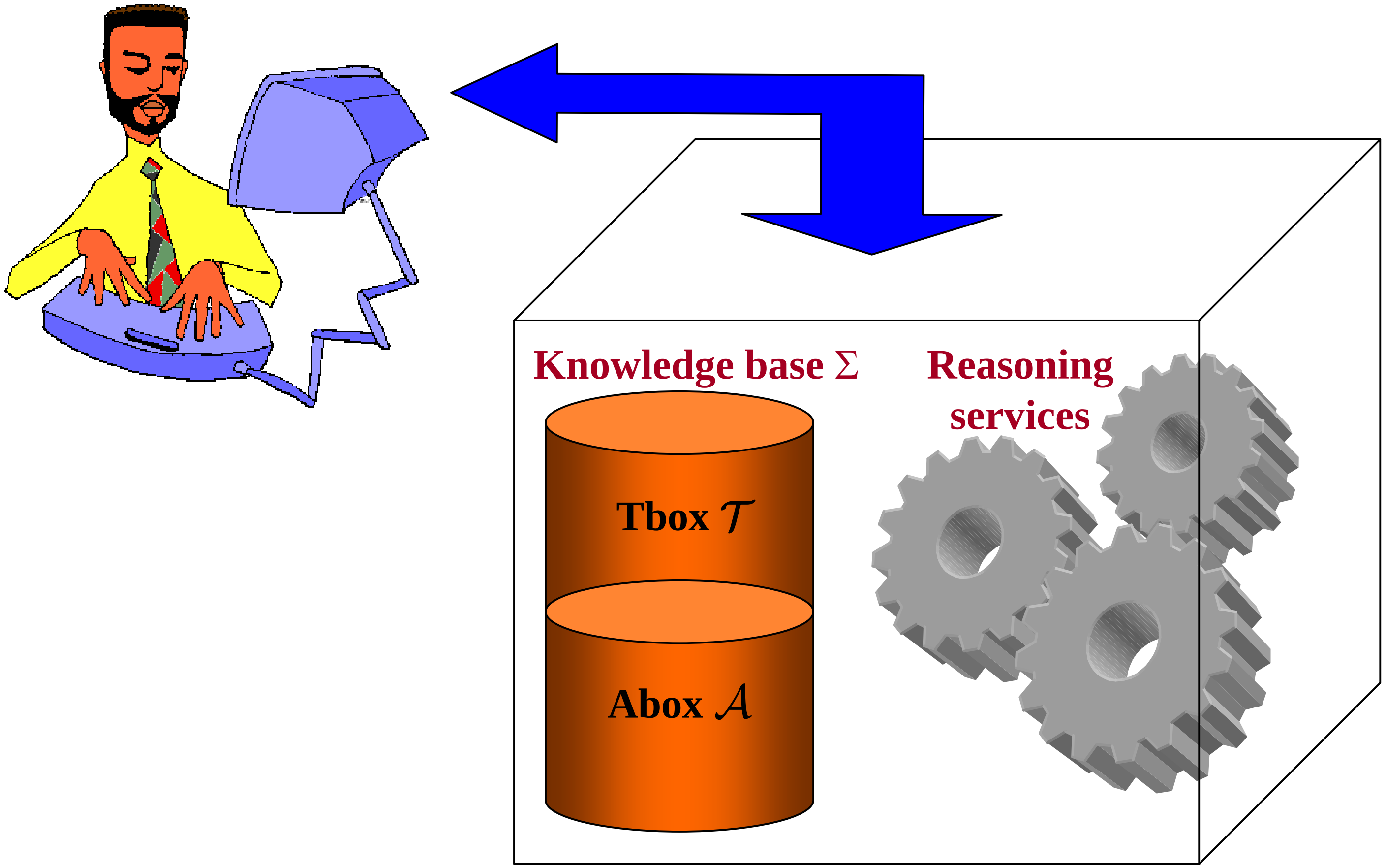
$\mathcal{ALC}$ Knowledge Bases: semantics

An interpretation $\mathcal{I}_{\mathcal{O}} = (\Delta^{\mathcal{I}}, .^{\mathcal{I}})$ satisfies

- an equality axiom $A \equiv C$ iff $A^{\mathcal{I}} \equiv C^{\mathcal{I}}$
- an inclusion axiom $C \sqsubseteq D$ iff $C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$
- a Tbox $\mathcal{T}$ iff $\mathcal{I}$ satisfies all axioms in $\mathcal{T}$

- a concept assertion $a:C$ iff $a^{\mathcal{I}} \in C^{\mathcal{I}}$
- a role assertion $<a,b>:R$ iff $<a^{\mathcal{I}},b^{\mathcal{I}}> \in R^{\mathcal{I}}$
- a ABox $\mathcal{A}$ iff $\mathcal{I}$ satisfies all assertions in $\mathcal{A}$

DL-based KR&R systems



DL-based KR&R systems: standard reasoning tasks

Subsumption

- .. of concepts C and D ($C \sqsubseteq D$)
  - Is $C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$ in all interpretations $\mathcal{I}$?
- .. of concepts C and D w.r.t. a TBox $\mathcal{T}$ ($C \sqsubseteq_{\mathcal{T}} D$)
  - Is $C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$ in all models $\mathcal{I}$ of $\mathcal{T}$?

Consistency

- .. of a concept C w.r.t. a TBox $\mathcal{T}$
  - Is there a model $\mathcal{I}$ of $\mathcal{T}$ with $C^{\mathcal{I}} \neq \emptyset$?
- .. of a ABox $\mathcal{A}$
  - Is there a model $\mathcal{I}$ of $\mathcal{A}$?
- .. of a KB ($\mathcal{T}$, $\mathcal{A}$)
  - Is there a model $\mathcal{I}$ of both $\mathcal{T}$ and $\mathcal{A}$?

DL-based KR&R systems: standard reasoning tasks (2)

- Subsumption and consistency are closely related
  - $C \sqsubseteq_{\mathcal{T}} D$ iff $C \sqcap \neg D$ is inconsistent w.r.t. $\mathcal{T}$
  - C is consistent w.r.t. $\mathcal{T}$ iff not $C \sqsubseteq_{\mathcal{T}} A \sqcap \neg A$
- Algorithms for checking consistency w.r.t TBoxes suffice
  - Based on tableau calculus
  - Decidability is important
  - Complexity between P and ExpTime

Instance check

- .. of an individual a and a concept C w.r.t. a KB Σ
  - Is a:C derivable from Σ? Or equivalently,
  - Is $\Sigma \cup \{a{:}\neg C\}$ consistent?

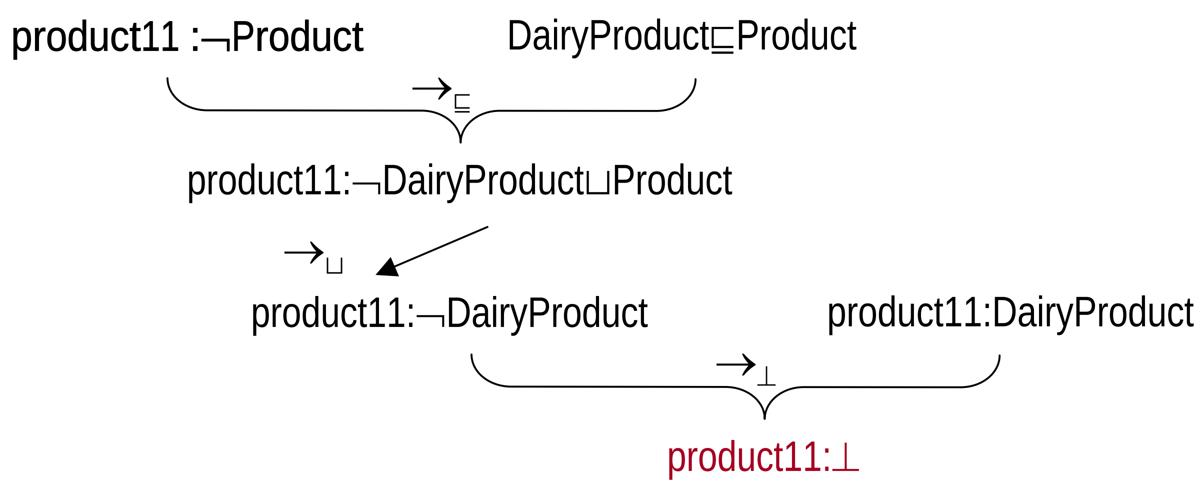
$\mathcal{ALC}$-based KR&R systems: example of instance check

- Σ=DairyProduct⊑Product, product11:DairyProduct, etc.

- Is product11:Product derivable from Σ?

  Or equivalently

- Is Σ ∪{ product11:¬ Product} consistent?



DL-based KR&R systems: non-standard reasoning tasks

Most Specific Concept (MSC)

Nebel, B. (1990). *Reasoning and Revision in Hybrid Representation Systems*. New York: Springer.

- Intuitively, the MSC of individuals in an ABox is a concept description that represents all the properties of the individuals including the concept assertions they occur in and their relationship to other individuals
- The existence of MSC is not guaranteed for all DLs
  - Approximation of MSC is possible!
- However, if the MSC exists, it is uniquely determined up to equivalence

DL-based KR&R systems: non-standard reasoning tasks (2)

Least Common Subsumer (LCS)

W.W. Cohen, A. Borgida, & H. Hirsh (1992). *Computing Least Common Subsumers in Description Logics*. Proc. of the Tenth National Conf. on Artificial Intelligence (AAAI92), pages 754-760. AAAI Press/MIT Press.

- The LCS of a given sequence of concept descriptions is
  - *Intuitively*, a concept description that represents the properties that all the elements of the sequence have in common
  - *More formally*, the MSC description that subsumes the given concept descriptions
- The existence of the LCS for a given sequence of concept descriptions is not guaranteed but ..
- .. if an LCS exists, then it is uniquely determined up to equivalence

Back to OWL DL: DL syntax

Constructor	DL Syntax	Example	FOL Syntax
intersectionOf	$C_1 \sqcap \ldots \sqcap C_n$	Human $\sqcap$ Male	$C_1(x) \wedge \ldots \wedge C_n(x)$
unionOf	$C_1 \sqcup \ldots \sqcup C_n$	Doctor $\sqcup$ Lawyer	$C_1(x) \vee \ldots \vee C_n(x)$
complementOf	$\neg C$	$\neg$Male	$\neg C(x)$
oneOf	$\{x_1\} \sqcup \ldots \sqcup \{x_n\}$	{john} $\sqcup$ {mary}	$x = x_1 \vee \ldots \vee x = x_n$
allValuesFrom	$\forall P.C$	$\forall$hasChild.Doctor	$\forall y.P(x,y) \rightarrow C(y)$
someValuesFrom	$\exists P.C$	$\exists$hasChild.Lawyer	$\exists y.P(x,y) \wedge C(y)$
maxCardinality	$\leqslant nP$	$\leqslant$1hasChild	$\exists^{\leqslant n} y.P(x,y)$
minCardinality	$\geqslant nP$	$\geqslant$2hasChild	$\exists^{\geqslant n} y.P(x,y)$

- C is a concept (class); P is a role (property); x is an individual name
- XMLS datatypes as well as classes in $\forall$P.C and $\exists$P.C
  - Restricted form of DL concrete domains

Back to OWL DL: DL syntax (2)

OWL Syntax	DL Syntax	Example
subClassOf	$C_1 \sqsubseteq C_2$	Human $\sqsubseteq$ Animal $\sqcap$ Biped
equivalentClass	$C_1 \equiv C_2$	Man $\equiv$ Human $\sqcap$ Male
subPropertyOf	$P_1 \sqsubseteq P_2$	hasDaughter $\sqsubseteq$ hasChild
equivalentProperty	$P_1 \equiv P_2$	cost $\equiv$ price
transitiveProperty	$P^+ \sqsubseteq P$	ancestor$^+$ $\sqsubseteq$ ancestor

OWL Syntax	DL Syntax	Example
type	$a : C$	John : Happy-Father
property	$\langle a, b \rangle : R$	$\langle$John, Mary$\rangle$: has-child

- OWL ontology equivalent to DL KB (Tbox + Abox)

Back to OWL DL: an example

- Dairy products are products

```
<owl:Class rdf:ID="DairyProduct">
  <rdfs:subClassOf rdf:about="#Product"/>
   </rdfs:subClassOf>
</owl:Class>
```

- European customers are customers living in European countries

```
<owl:Class rdf:ID="EuropeanCustomer">
 <owl:equivalentClass/>
   <owl:intersectionOf rdf:parseType=" collection">
    <owl:Class rdf:about="#Customer"/>
    <owl:restriction/>
     <owl:onProperty rdfResource="#livesIn"/>
     <owl:allValuesFrom rdf:resource="#EuropeanCountry"/>
     </owl:allValuesFrom>
    </owl:restriction>
   </owl:intersectionOf>
 </owl:equivalentClass>
</owl:Class>
```

Description Logics: Bibliography (only the essential)

- F. Baader, D. Calvanese, D. L. McGuinness, D. Nardi, P. F. Patel-Schneider (2003). *The Description Logic Handbook: Theory, Implementation, Applications*. Cambridge University Press, Cambridge, UK.
- R. Kusters (2001). *Non-Standard Inferences in Description Logics*. Volume 2100 of Lecture Notes in Artificial Intelligence. Springer-Verlag.
- M. Schmidt-Schauß & G. Smolka (1991). *Attributive concept descriptions with complements*. Artificial Intelligence, 48 (1): 1-26.

- On-line material: http://dl.kr.org/courses.html

- C. Peltason (1991). The BACK system—an overview. *SIGART Bull.* 2, 3 (Jun. 1991), 114-119.

- CLASSIC: http://www.bell-labs.com/project/classic/

Part I: Overview

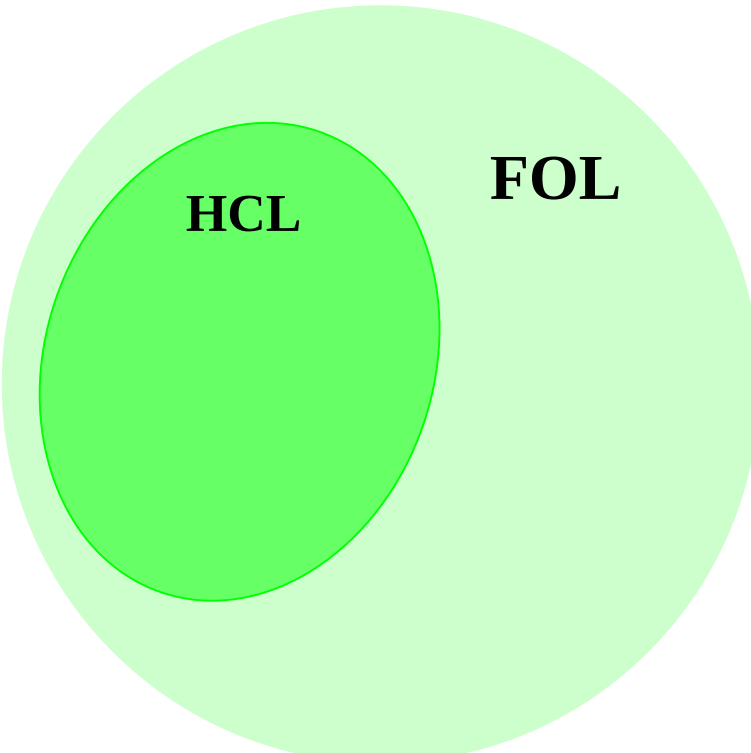
- ⌘KR systems based on Description Logics
- ⌘*KR systems combining Description Logics and Horn Clausal Logic (fragments)*

RuleML (Rule Markup Language)

- Developed to express both forward (bottom-up) and backward (top-down) rules in XML for deduction, rewriting, and further inferential-transformational tasks.
- Based on Datalog (function-free fragment of Horn Clausal Logic)
- Defined by the Rule Markup Initiative (an open network of individuals and groups from both industry and academia)
  - http://www.ruleml.org/

RuleML
Realize your Knowledge

What is Horn Clausal Logic?



- Horn clausal logic (HCL) is the FOL fragment that contains universally quantified disjunctions of literals with at most one positive literal
- It is at the basis of Logic Programming and Deductive Databases

HCL syntax

- Clausal language $\mathcal{L}$ = the set of constant, variable, functor and predicate symbols

- Term: Constant / Variable / Function applied to a term
- Atom: Predicate applied to n terms
- Literal: (negated) atom

- Horn Clause allows the two following equivalent notations
  - $\forall X\ \forall Y(p(X, Y) \vee \neg\ q(X, a) \vee \neg\ r(Y,f(a)))$
  - $p(X, Y) \leftarrow q(X, a), r(Y,f(a))$

- Definite clause (rule): only one literal in the head
- Unit clause (fact): rule without head

HCL Semantics

Herbrand model theory

- Herbrand universe U_H = the set of all ground terms that can be formed out from the constants and function symbols in $\mathcal{L}$
- Herbrand base B_H = the set of all ground atoms that can be formed out from terms in U_H and predicates in $\mathcal{L}$
- Herbrand interpretation I_H = subset of B_H containing all atoms that are true in I_H

HCL Deduction Rules

SLD-resolution

2 opposite literals (up to a substitution) : $l_i\theta_1 = \neg k_j\theta_2$

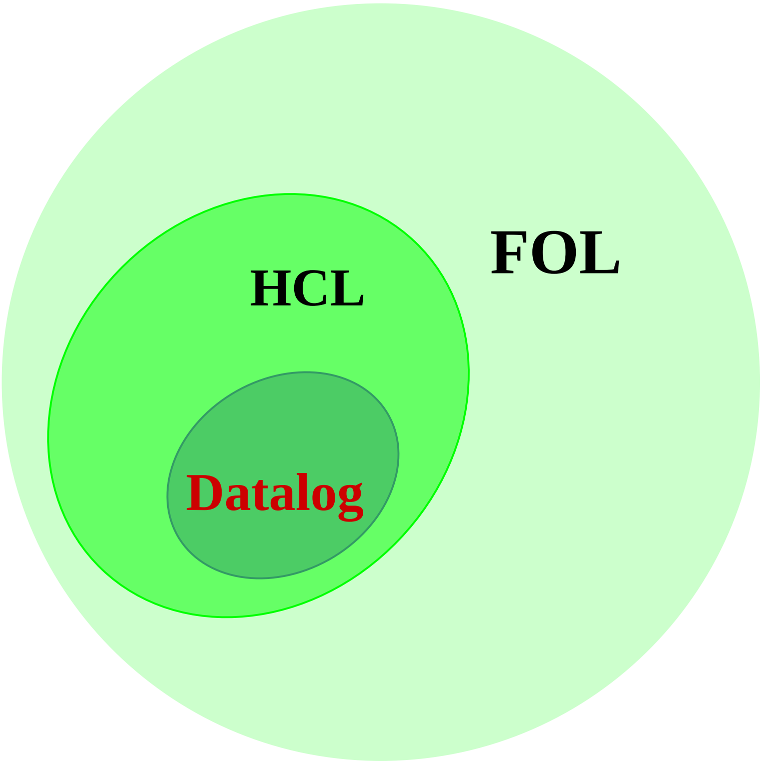
$$\frac{l_1 \vee \ldots \vee l_i \vee \ldots \vee l_n \qquad k_1 \vee \ldots \vee k_j \vee \ldots \vee k_m}{(l_1 \vee l_2 \vee \ldots \vee l_{i-1} \vee l_{i+1} \vee \ldots \vee l_n \vee k_1 \vee k_{j-1} \vee k_{j+1} \ldots \vee k_m)\ \theta_1\theta_2}$$

e.g., p(X) :- q(X) and q(X) :- r(X,Y) yield p(X) :- r(X,Y)
p(X) :- q(X) and q(a) yield p(a).

- complete by refutation!

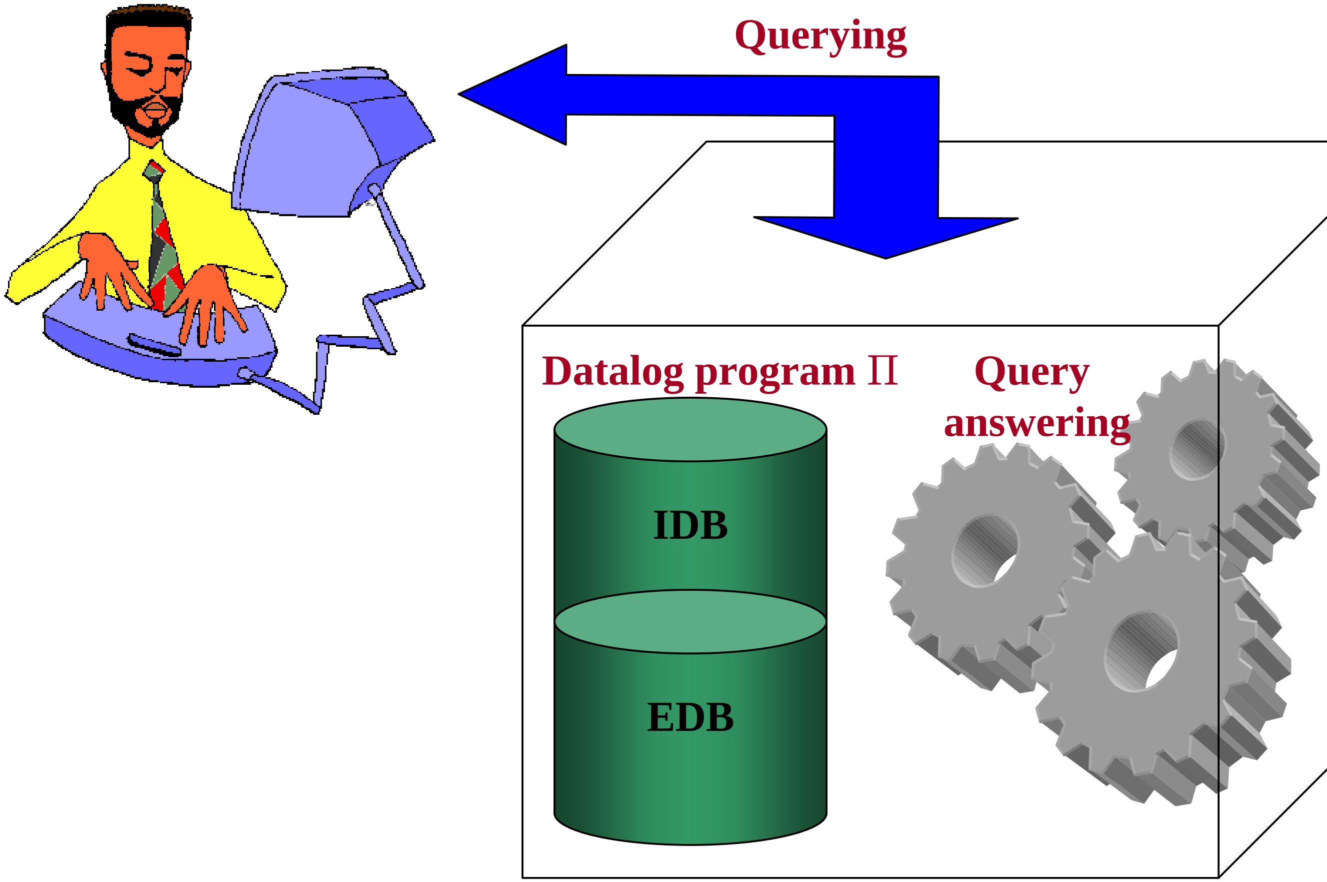
Datalog

S. Ceri, G. Gottlob, & L. Tanca (1990). *Logic Programming and Databases*. Springer.



- It is a function-free fragment of HCL (more precisely of definite clauses)
- It is used as logical language for relational databases
- Query answering by SLD-refutation

Deductive databases



Closed World Assumption (CWA)

- The information in a database is generally considered to be complete (*closed world*)
- A database instance represents exactly one interpretation, namely the one where classes and relations in the schema are interpreted by the objects and the tuples in the instance
- Negation As Failure: what is unknown is false

Datalog: example of query answering

- Π= item(OrderID, ProductID) $\leftarrow$ orderDetail(OrderID, ProductID,_,_,_)
  orderDetail(order10248, product11, '£14',12,0.00)
  Etc.
- Is item(order10248, product11) derivable from Π?
- Is $\Pi \cup \{\neg$ item(order10248, product11)$\}$ consistent?

$\leftarrow$ **item(order10248, product11)**   item(OrderID, ProductID) $\leftarrow$ orderDetail(OrderID, ProductID,_,_,_)

{OrderID/order10248, ProductID/ product11 }

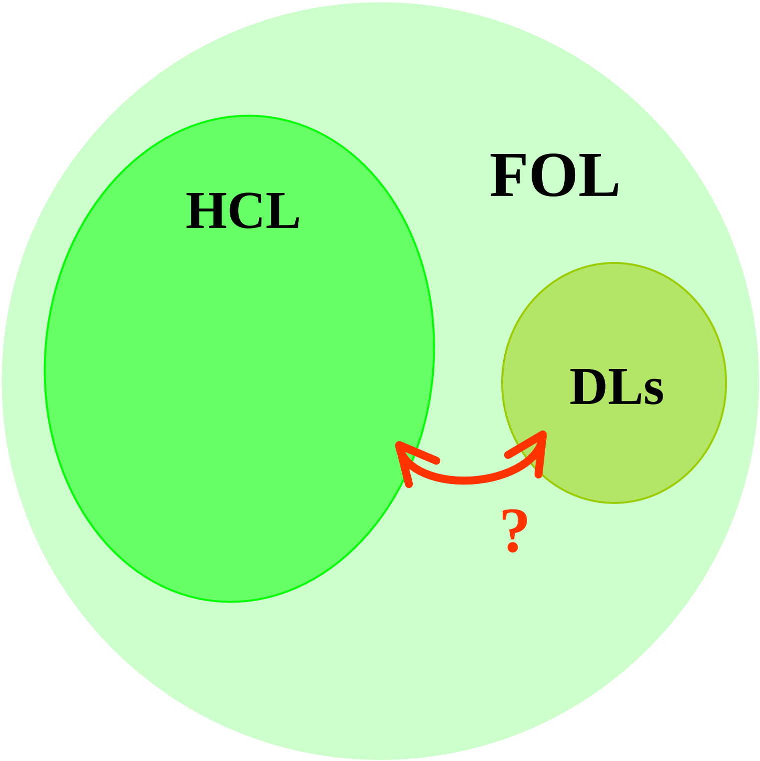
$\leftarrow$ orderDetail(order10248, product11,_,_,_)   orderDetail(order10248, product11, '£14',12,0.00)

{}

$\leftarrow$

DLs and HCL

A. Borgida (1996). On the relative expressiveness of Description Logics and Predicate Logics. *Artificial Intelligence*, 82: 353-367.



- HCL and DLs can not be compared wrt expressive power
  - No relations of arbitrary arity or arbitrary joins between relations in DLs
  - No exist. quant. in HCL
- Can they be combined?

Hybrid DL-HCL KR&R Systems

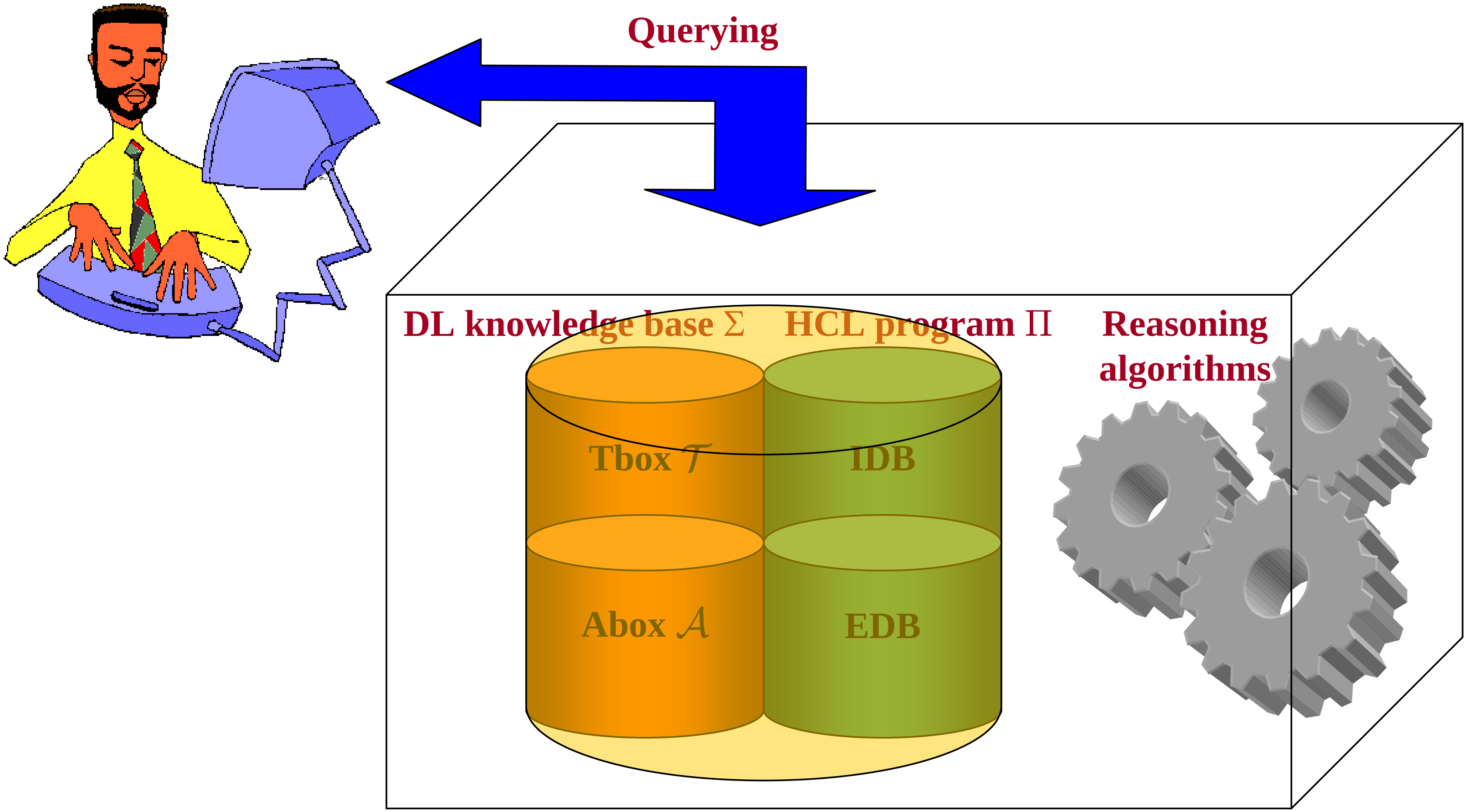
Levy & M.-C. Rousset (1998). Combining Horn rules and Description Logics in CARIN. *Artificial Intelligence*, 104: 165-209.

F. Donini et al. (1998). $\mathcal{AL}$-log: Integrating Datalog and Description Logics. J. of Intelligent Systems, 10(3):227-252.

- It allows more expressive and deductive power
  - CARIN is a family of powerful hybrid languages
  - $\mathcal{AL}$-log is less powerful than CARIN

- It can easily lead to undecidability if unrestricted
  - Some CARIN languages are decidable
  - $\mathcal{AL}$-log is decidable

Hybrid DL-HCL KR&R systems



$\mathcal{AL}$-log syntax

$$\mathcal{B} = < \Sigma , \Pi >$$

$\mathcal{ALC}$ knowledge base

constrained Datalog program

constrained Datalog clauses

$$\alpha_0 \leftarrow \alpha_1, \ldots, \alpha_m \;\&\; \gamma_1, \ldots, \gamma_n$$

where α_i are Datalog literals and γ_j are constraints ($\mathcal{ALC}$ concepts from Σ used as “typing constraints” for variables)

- item(OrderID, ProductID) ← orderDetail(OrderID, ProductID,_,_,_)
  & OrderID:Order, ProductID:Product
- Safeness conditions:
  - Only positive Datalog literals in the body
  - Only one Datalog literal in the head
  - Constraints <u>must</u> refer to variables occurring in the Datalog part
  - Variables in the Datalog part <u>can</u> be constrained

$\mathcal{AL}$-log semantics

$\mathcal{J} = (\mathcal{I}_O, \mathcal{I}_H)$

interpretation for Σ

Herbrand interpretation for Π_D

- $\mathcal{J}$ satisfies $\mathcal{B}$ iff
  - it satisfies Σ, and
  - for each clause $\alpha_0 \leftarrow \alpha_1, \ldots, \alpha_m \;\&\; \gamma_1, \ldots, \gamma_n$, for each of its ground instances $\alpha'_0 \leftarrow \alpha'_1, \ldots, \alpha'_m \;\&\; \gamma'_1, \ldots, \gamma'_n$, either there exists one γ'_i, $1 \leq i \leq n$, that is not satisfied by $\mathcal{J}$ or $\alpha'_0 \leftarrow \alpha'_1, \ldots, \alpha'_m$ is satisfied by $\mathcal{J}$
- OWA of $\mathcal{ALC}$ and CWA of Datalog do not interfere (safeness)
- UNA holds for $\mathcal{ALC}$ and *ground* Datalog

$\mathcal{AL}$-log reasoning

Query answering

- Atomic queries (only Datalog)
- Constrained SLD-resolution= SLD-resolution (Datalog part) + tableau calculus ($\mathcal{ALC}$ part)
  - decidable
  - Sound and complete by refutation

- Queries are answered by constrained SLD-refutation
  - For each ground instance Q' of the query Q,
  - collect the set of all constrained SLD-derivations $d_1, d_2, .., d_m$ of bounded length (with $d_i=Q^i_0..Q^i_{n_i}$) for Q' in Σ
  - Then check whether $\Sigma \models disj(Q^1_{n_1},.., Q^m_{n_m})$

$\mathcal{AL}$-log reasoning: example of query answering

← item(order10248, product11)

item(OrderID, ProductID) ← orderDetail(OrderID, ProductID,_,_,_) & OrderID:Order, ProductID:Product

{OrderID/order10248, ProductID/product11}

← orderDetail(order10248, Y,_,_,_) & order10248:Order, Y:Product

orderDetail(order10248, product11, '£14',12,0.00)

{Y/product11 }

← & order10248:Order, product11:Product

Assuming that this is the only SLD-derivation for the query, the existential entailment problem boils down to prove that

$\Sigma \cup$ { order10248:¬Order, product11:¬Product }

is unsatisfiable!

CARIN syntax and semantics

- Σ is based on any DL (but good results for $\mathcal{ALCNR}$)
- Π contain Horn rules, i.e. definite clauses, where DL literals:
  - can be built from either concept or role predicates
  - are allowed in rule heads
- The semantics naturally follows as in $\mathcal{AL}$-log

CARIN reasoning

Query answering

- Atomic queries (built from either concept, role or ordinary predicates)

- Constrained SLD-resolution= SLD-resolution (HCL part) + tableau calculus (DL part)
  - complete by refutation for non-recursive CARIN-$\mathcal{ALCNR}$
  - Decidable for the non-recursive case
  - Undecidable for the recursive case, unless weaken the DL part or impose rules to be role-safe

Back to SWRL

- SWRL is undecidable!
- Several decidable alternatives to SWRL recently proposed:
  - DL-safe rules (Motik et al., 2005)
  - r-hybrid KBs (Rosati, 2005)
  - $\mathcal{DL}$+log (Rosati, 2006)
  - hybrid MKNF KBs (Motik & Rosati, 2007)

Back to SWRL: an example

item(OrderID, ProductID) ← orderDetail(OrderID, ProductID,_,_,_)
& OrderID:Order, ProductID:Product

```
<ruleml:imp>
  <ruleml:_body>
  <swrlx:classAtom>
      <owlx:Class owlx:name="&Order" /> <ruleml:var> OrderID </ruleml:var>
  </swrlx:classAtom>
  <swrlx:classAtom>
      <owlx:Class owlx:name ="&Product" /> <ruleml:var> ProductID </ruleml:var>
  </swrlx:classAtom>
  <swrlx:individualPropertyAtom  swrlx:property="&orderDetail">
      <ruleml:var> OrderID </ruleml:var> <ruleml:var> ProductID </ruleml:var>.. <ruleml:var> .. </ruleml:var>
  </swrlx:individualPropertyAtom>
  </ruleml:_body>
  <ruleml:_head>
  <swrlx:individualPropertyAtom  swrlx:property="&item">
       <ruleml:var> OrderID </ruleml:var> <ruleml:var> ProductID </ruleml:var>
    </swrlx:individualPropertyAtom>
  </ruleml:_head>
</ruleml:imp>
```

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Hybrid DL-HCL KR&R Systems: Bibliography (3)

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The Challenges of the Semantic Web to Machine Learning and Data Mining

Part II: "Acquisition of Ontologies and Rules for the Semantic Web with Inductive Logic Programming" (1h 30m)

Part II: Overview

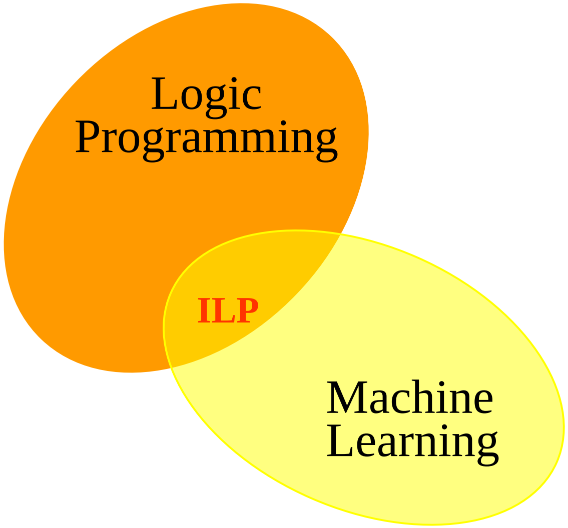
- Introduction to Inductive Logic Programming (ILP)
- ILP and DL representations
- ILP and hybrid DL-HCL representations
- ILP and the Semantic Web: Research directions

Part II: Overview

- *Introduction to ILP*
- ILP and DL representations
- ILP and hybrid DL-HCL representations
- ILP and the Semantic Web: Research directions

Inductive Logic Programming

S.-H. Nienhuys-Cheng & R. de Wolf (1997). *Foundations of Inductive Logic Programming*. LNAI Tutorial Series, Springer.



- *Originally* Induction of rules from examples and background knowledge within the HCL framework
  - Scope of induction: discrimination
  - Class of tasks: prediction

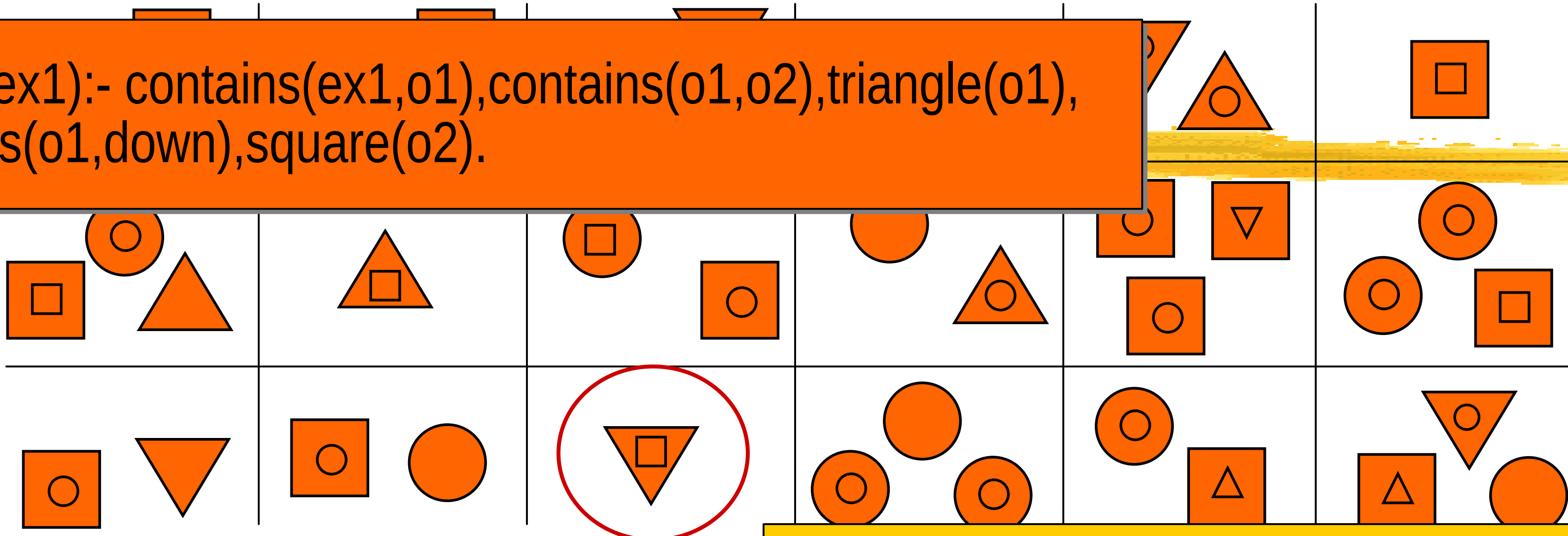
- *Currently* Induction of rules from observations and background knowledge within the framework of FOL (fragments)
  - scope of induction: discrimination/characterization
  - task: prediction/description

ILP Example:
“Bongard problems”

- Simplified version of Bongard problems used as benchmarks in ILP
  - Bongard: a Russian scientist studying pattern recognition
  - Bongard problem: Given some pictures, find patterns in them

- E.g. we want to find a set of hypotheses (clausal theory) that is complete and consistent with the following set of (positive and negative) examples
  - Complete=covers all positive examples
  - Consistent=covers no negative example

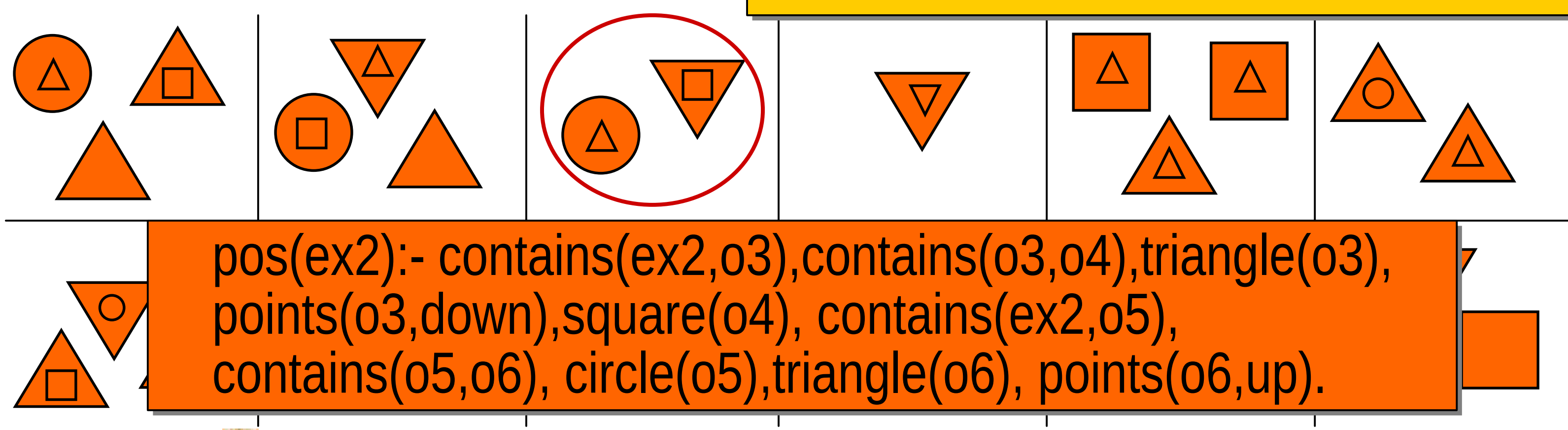
Negative examples



neg(ex1):- contains(ex1,o1),contains(o1,o2),triangle(o1), points(o1,down),square(o2).

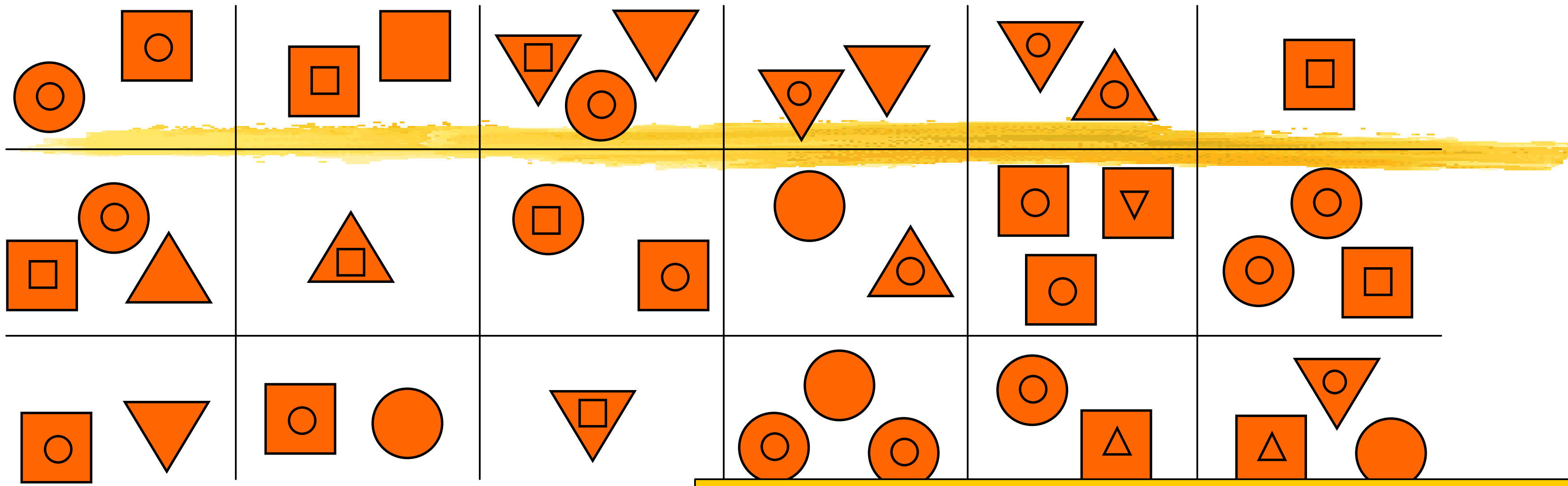
pos(X):- contains(X,O1),contains(O1,O2), triangle(O1), points(O1,down),square(O2)?

Positive examples



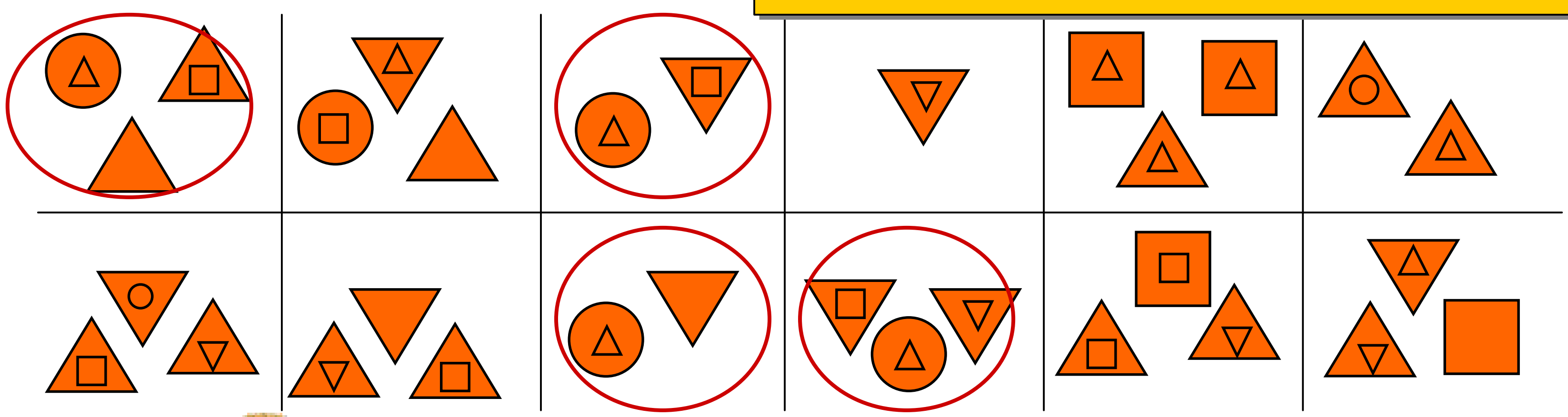
pos(ex2):- contains(ex2,o3),contains(o3,o4),triangle(o3), points(o3,down),square(o4), contains(ex2,o5), contains(o5,o6), circle(o5),triangle(o6), points(o6,up).

Negative examples



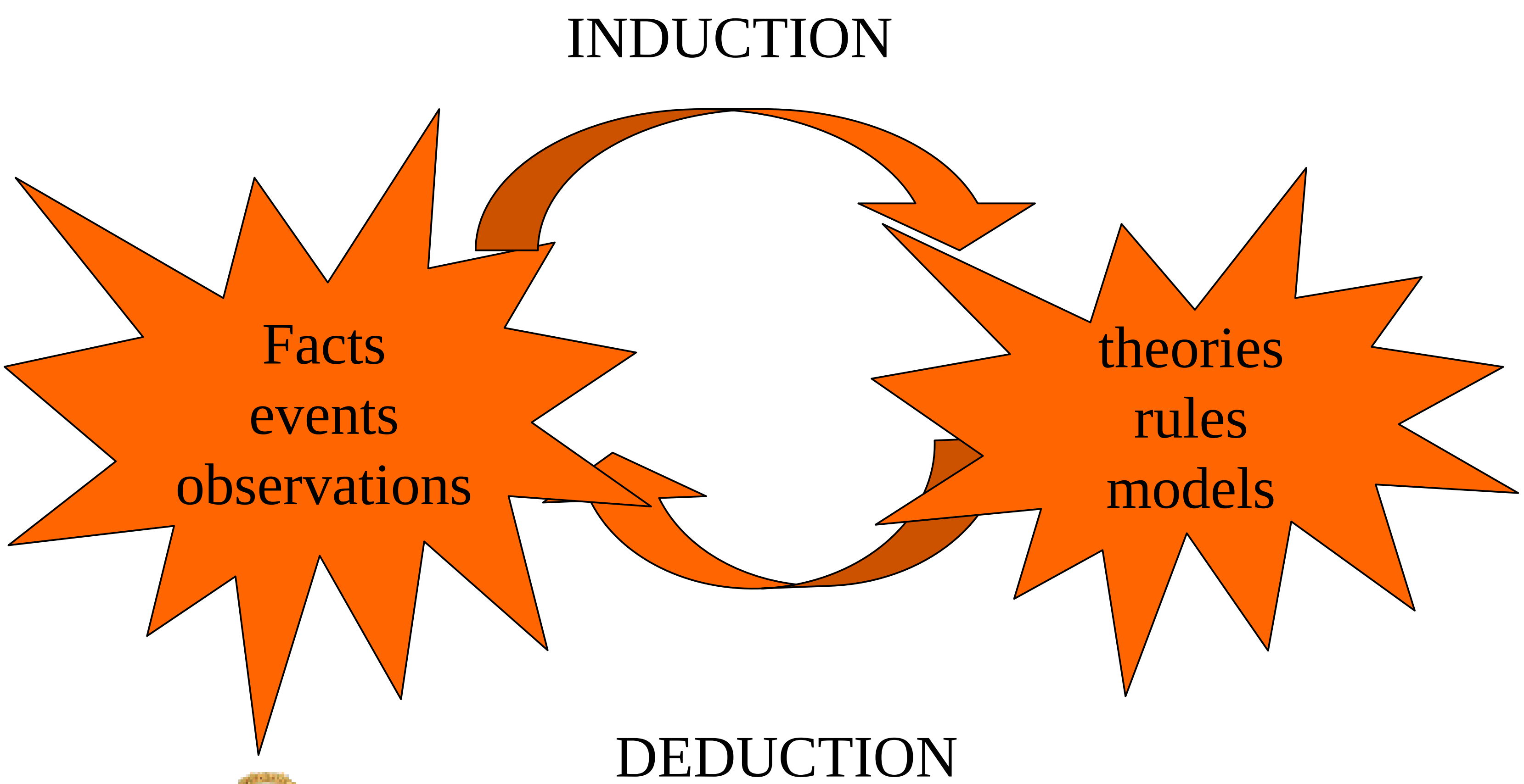
pos(X):- contains(X,O1),contains(O1,O2), circle(O1),square(O2), points(O1,up)?

Positive examples



Induction in ILP

Induction as inverted deduction



Inverse resolution

S. Muggleton & W. Buntine (1988). *Machine invention of first-order predicates by inverting resolution*. Proc. of the 5th Int. Conf. On Machine Learning, pp. 339-352.

- Resolution implements |- for sets of clauses
- Inverting it allows to generalize a clausal theory
- Inverse resolution is much more difficult than resolution itself
  - different operators defined
  - no unique results

Inverse resolution (2)

- Properties of inverse resolution:
  - + in principle very powerful
  - - gives rise to huge search space
  - - result of inverse resolution not unique
    - e.g., father(j,p):-male(j) and parent(j,p) yields father(j,p):-male(j),parent(j,p) or father(X,Y):-male(X),parent(X,Y) or ...
- Need for a ordered hypothesis space

Induction in ILP (2)

Induction as generalization

- Exploits results obtained in Concept Learning (Mitchell, 1982)
  - Generalization = search through a partially ordered space of hypotheses with the goal of finding the hypothesis that best fits the training examples
- Provides a bunch of techniques for structuring, searching, and boundingthe space of hypotheses when the hypothesis language is defined over HCL

Generality orders: θ-subsumption

G. Plotkin (1970). A note on inductive generalization. *Machine Intelligence*, 5:153-163.
G. Plotkin (1971). A further note on inductive generalization. *Machine Intelligence*, 6:101-124.

- θ-subsumption implements |- for single clauses
- C_1 θ-subsumes C_2 (denoted $C_1 \leq_\theta C_2$) if and only if there exists a variable substitution θ such that $C_1\theta \subseteq C_2$
  - to check this, first write clauses as disjunctions
    - $a,b,c \leftarrow d,e,f \quad \Leftrightarrow \quad a \vee b \vee c \vee \neg d \vee \neg e \vee \neg f$
  - then try to replace variables with constants or other variables
- Most often used in ILP
- Syntactic generality!!

Generality orders: θ-subsumption (2)

Logical properties

- Sound: if c_1 θ-subsumes c_2 then $c_1 \models c_2$
- Incomplete: possibly $c_1 \models c_2$ without c_1 θ-subsuming c_2 (but only for recursive clauses)
  - c_1 : p(f(X)) :- p(X)
  - c_2 : p(f(f(X))) :- p(X)
- Checking θ-subsumption is decidable but NP-complete

Generality orders: θ-subsumption (3)

Algebraic properties

- It is a semi-order relation
  - I.e. transitive and reflexive, not anti-symmetric
- It generates equivalence classes
  - equivalence class: $c_1 \sim c_2$ iff $c_1 \leq_\theta c_2$ and $c_2 \leq_\theta c_1$
  - c_1 and c_2 are then called *syntactic variants*
  - c_1 is *reduced clause* of c_2 iff c_1 contains minimal subset of literals of c_2 that is still equivalent with c_2
  - each equivalence class represented by its reduced clause

Generality orders: θ-subsumption (4)

Algebraic properties (cont.)

- It generates a partial order on those equivalence classes
  - If c_1 and c_2 in different equivalence classes, either $c_1 \leq_\theta c_2$ or $c_2 \leq_\theta c_1$ or neither => anti-symmetry => partial order
- Thus, reduced clauses form a lattice
  - Least/greatest upper/lower bound of two clauses always exists and is unique
  - Infinite chains $c_1 \leq_\theta c_2 \leq_\theta c_3 \leq_\theta \ldots \leq_\theta c$ exist
- Looking for good hypothesis = traversing this lattice

Generality orders: generalized subsumption

W. Buntine (1988). Generalized subsumption and its applications to induction and redundancy. *Artificial Intelligence*, 36(2): 149-176.

- $\mathcal{B}$ background knowledge
- C_1, C_2 two definite clauses
- σ a Skolem substitution for C_2 w.r.t. $\{C_1\} \cup \mathcal{B}$

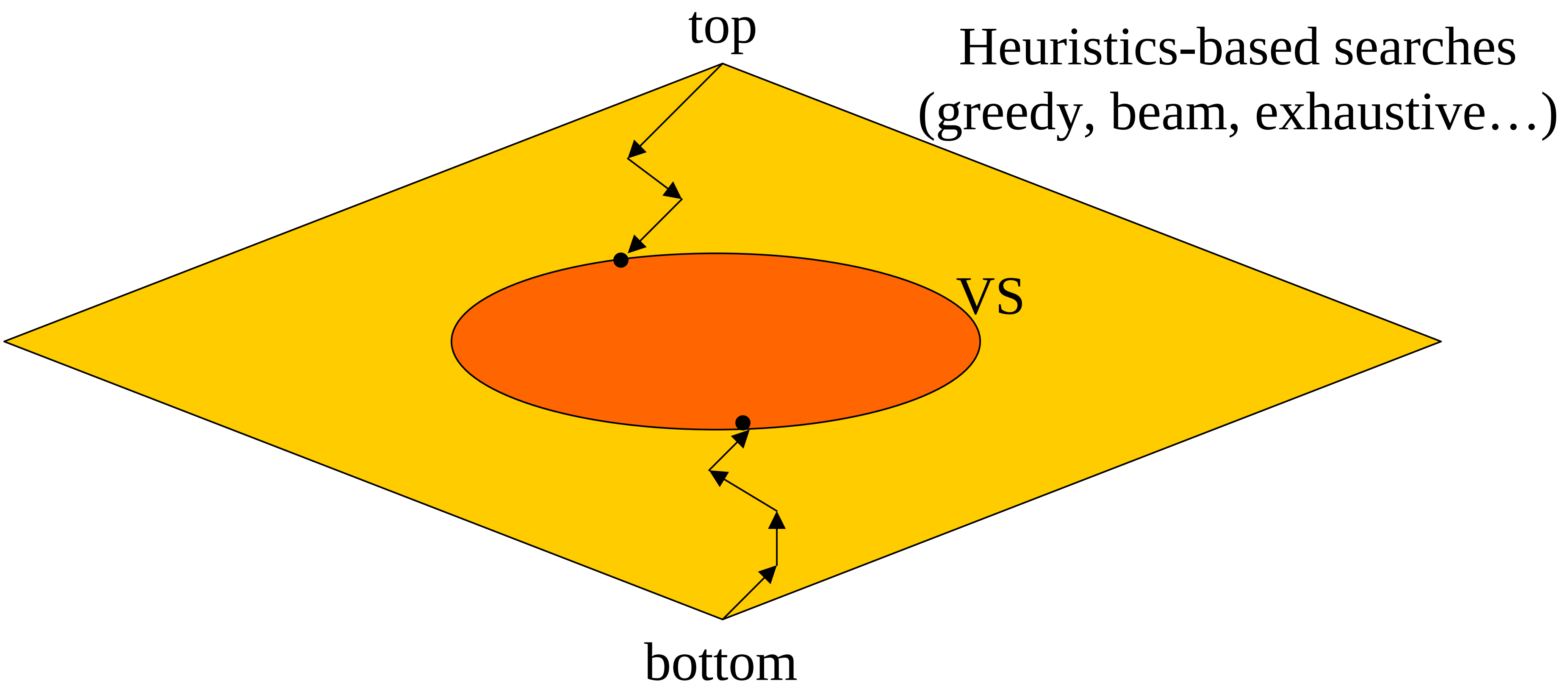
$C_1 \geq_{\mathcal{B}} C_2$ iff there exists a substitution θ for C_1 such that

- $head(C_1)\theta = head(C_2)$
- $\mathcal{B} \cup body(C_2)\sigma \vdash body(C_1)\theta\sigma$
- $body(C_1)\theta\sigma$ is ground.

Generality orders: generalized subsumption (2)

- Background knowledge $\mathcal{B}$
  - pet(X):-cat(X)
  - pet(X):-dog(X)
  - small(X):-cat(X)
- Clauses:
  - C_1 = cuddlypet(X) :- small(X), pet(X)
  - C_2 = cuddlypet(X) :- cat(X)
- Semantic generality!!
  - $C_1 \geq_{\mathcal{B}} C_2$
  - θ- subsumption fails

Refinement operators



Refinement operators: properties

- How to traverse hypothesis space so that
  - no hypotheses are generated more than once?
  - no hypotheses are skipped?
- Properties of refinement operators
  - globally complete: each point in lattice is reachable from top
  - locally complete: each point directly below c is in $\rho(c)$ (useful for greedy systems)
  - optimal: no point in lattice is reached twice (useful for exhaustive systems)
  - minimal, proper, ...

Refinement operators: lgg

G. Plotkin (1970). A note on inductive generalization. *Machine Intelligence*, 5:153-163.

- Bottom-up search in clausal spaces
  - Starts from 2 clauses and compute least general generalisation (lgg)
  - i.e., given 2 clauses, return most specific single clause that is more general than both of them
- We shall consider only the case of clausal spaces ordered according to θ-subsumption
  - lgg under θ-subsumption

Refinement operators: lgg (2)

- Definition of **lgg of terms**:
  - (let s_i, t_j denote any term, V a variable)
  - $lgg(f(s_1,\ldots,s_n), f(t_1,\ldots,t_n)) = f(lgg(s_1,t_1),\ldots,lgg(s_n,t_n))$
  - $lgg(f(s_1,\ldots,s_n),g(t_1,\ldots,t_n)) = V$
- Definition of **lgg of literals**:
  - lgg(p(s1,…,sn),p(t1,…,tn)) = p(lgg(s1,t1),…,lgg(sn,tn))
  - lgg(¬p(…), ¬ p(…)) = ¬ lgg(p(…),p(…))
  - lgg(p(s1,…,sn),q(t1,…,tn)) is undefined
  - lgg(p(…), ¬p(…)) and lgg(¬p(…),p(…)) are undefined
- Definition of **lgg of clauses:**
  - $lgg(c_1,c_2) = \{lgg(l_1, l_2) \mid l_1 \in c_1, l_2 \in c_2$ and $lgg(l_1,l_2)$ defined$\}$

Refinement operators: relative lgg

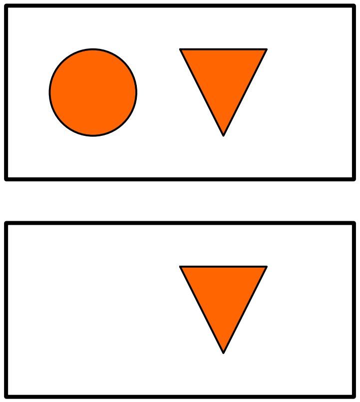
G. Plotkin (1971). A further note on inductive generalization. *Machine Intelligence*, 6:101-124.

- relative to "background theory" B
  - assume B is a set of facts
- $rlgg(e_1,e_2) = lgg(e_1$:- B, e_2 :- B)
- method to compute:
  - change facts into clauses with body B
  - compute lgg of clauses
  - remove B, reduce
- Used in in the ILP system Golem (Muggleton & Feng)

Refinement operators: example

- Given the following 2 simple Bongard configurations, find least general clause that would predict both to be positive

1
2



pos(1).	pos(2).
contains(1,o1).	contains(2,o3).
contains(1,o2).	
triangle(o1).	triangle(o3).
points(o1,down).	points(o3,down).
circle(o2).	

Refinement operators: example

- Method 1: represent example by clause; compute lgg of examples

```
pos(1) :- contains(1,o1), contains(1,o2), triangle(o1),
          points(o1,down), circle(o2).
pos(2) :- contains(2,o3), triangle(o3), points(o3,down).
```

```
lgg(
(pos(1) :- contains(1,o1), contains(1,o2), triangle(o1), points(o1,down), circle(o2)) ,
(pos(2) :- contains(2,o3), triangle(o3), points(o3, down) )
= pos(X) :- contains(X,Y), triangle(Y), points(Y,down)
```

Refinement operators: example

⌘Method 2: represent class of example by fact, other properties in background; compute rlgg

Examples:

pos(1).
pos(2).

Background:

contains(1,o1).	contains(2,o3).
contains(1,o2).	
triangle(o1).	triangle(o3).
points(o1,down).	points(o3,down).
circle(o2).	

rlgg(pos(1), pos(2)) = ? (exercise)

Refinement operators: Shapiro's specialization operator

E. Shapiro (1971). *An algorithm that infers theories from facts*. Proc. of the 7th Int. Conf.on Artificial Intelligence, pp. 446-451.

- Top down search in clausal spaces ordered according to theta-subsumption:
  - $\rho(c)$ yields set of refinements of c
  - theory: $\rho(c) = \{c' \mid c'$ is a maximally general specialisation of $c\}$
  - practice: $\rho(c) \subseteq \{c \cup \{l\} \mid l$ is a literal$\} \cup \{c\theta \mid \theta$ is a substitution$\}$
- Used in many ILP systems

Declarative bias

C. Nedellec et al. (1996). *Declarative bias in ILP*. In L. De Raedt (ed.), Advances in Inductive Logic Programming, IOS Press.

- Language bias
  - Specifies and restricts the set of clauses or theories that are permitted (language of hypotheses)
- Search bias
  - Concerns the way the system searches through the hypothesis space
- Validation bias
  - Determines when the learned theory is acceptable, so when the learning process may stop.

ILP logical settings

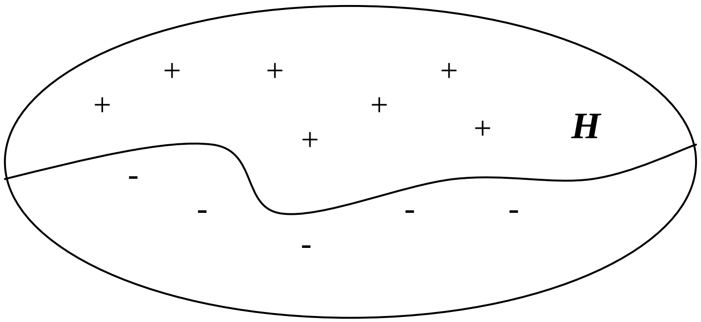
L. De Raedt, L. Dehaspe (1997). *Clausal Discovery*. Machine Learning 26(2-3): 99-146.

- Orthogonality of the following two dimensions
  - Scope of induction
    - discriminant vs. characteristic induction
  - Representation of the observations
    - learning from implications vs. learning from interpretations

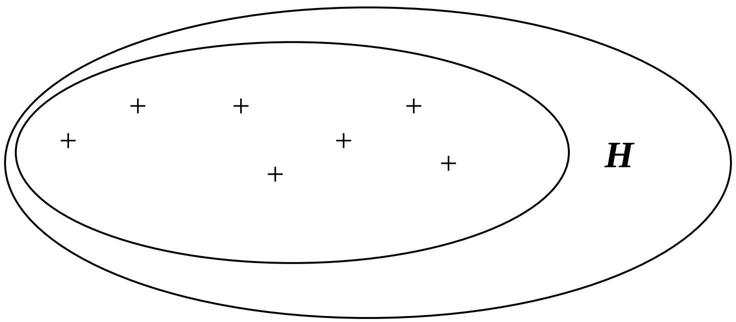
leads to 4 different logical settings for ILP

ILP logical settings:
Predictive vs Descriptive ILP

Prediction



Description



ILP logical settings:
Learning from entailment

Examples:

pos(1).
pos(2).
:- pos(3).

Background knowledge:

contains(1,o1).
contains(1,o2).
contains(2,o3).
triangle(o1).
triangle(o3).
points(o1,down).
points(o3,down).
circle(o2).
contains(3,o4).
circle(o4).

Hypothesis:

pos(X) :- contains(X,Y),
triangle(Y), points(Y,down).

Example = a fact *e*
(or clause *e:-B*)

ILP logical settings: Learning from interpretations

all information that intuitively belongs to the example, is represented in the example, not in the background knowledge!

Examples:

pos(1) :- contains(1,o1), contains(1,o2), triangle(o1), points(o1,down), circle(o2).
pos(2) :- contains(2,o3), triangle(o3), points(o3,down).
:- pos(3), contains(3,o4), circle(o4).

Background knowledge:

polygon(X) :- triangle(X).
polygon(X) :- square(X).

knowledge concerning the domain, not concerning specific examples!

Hypothesis:

pos(X) :- contains(X,Y), triangle(Y), points(Y,down).

ILP logical settings:
Learning from interpretations (3)

- Example as a set of facts (intepretation)
- CWA made *inside* interpretations

Examples:

pos: {contains(o1), contains(o2), triangle(o1), points(o1,down), circle(o2)}
pos: {contains(o3), triangle(o3), points(o3,down)}
neg: {contains(o4), circle(o4)}

Background knowledge:

polygon(X) :- triangle(X).
polygon(X) :- square(X).

constraint on pos

∃Y:contains(Y),triangle(Y),points(Y,down).

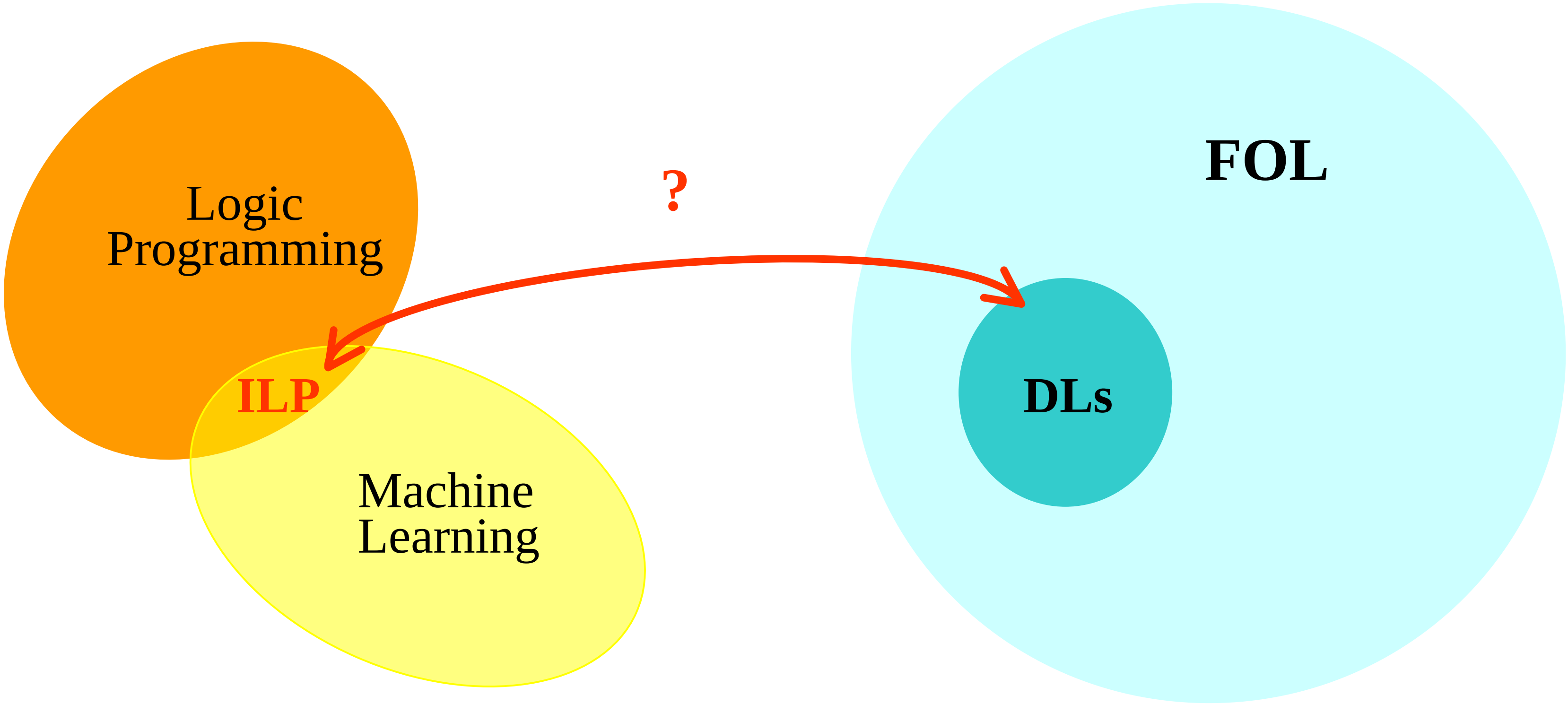
ILP logical settings: some remarks

- When learning from interpretations
  1. You can dispose of an “example identifier”
     - but can also use standard format
  2. You assume CWA for each example description
     - i.e., example description is assumed to be complete
  3. You have class of example related to information inside example + background information, NOT to information in other examples
- Because of 3rd property, more limited than learning from entailment
  - You cannot learn relations between examples, nor recursive clauses
- ... but also more efficient because of 2nd and 3rd property
  - positive PAC-learnability results (De Raedt and Džeroski, 1994), vs. negative results for learning from entailment

Part II: Overview

- Introduction to ILP
- *ILP and DL representations*
- ILP and hybrid DL-HCL representations
- ILP and the Semantic Web: Research directions

Learning in DLs



Learnability of DLs

W.W. Cohen & H. Hirsh (1992). *Learnability of Description Logics*. Proc. of the Fifth Annual Workshop on Computational Learning Theory (COLT92), pp. 116-127. ACM Press.

M. Frazier & L. Pitt (1994). *CLASSIC learning*. In Proc. of the Seventh Annual Conference on Computational Learning theory (COLT '94). ACM Press, New York, NY, 23-34.

- Learnability of sublanguages of CLASSIC w.r.t. the PAC learning model
- LCS used as a means for inductive learning from examples assumed to be concept descriptions

Learning in CLASSIC

W.W. Cohen & H. Hirsh (1994). *Learning the CLASSIC Description Logic: Theoretical and Experimental Results*. Proc. of the 4th Int. Conf. on Principles of Knowledge Representation and Reasoning (KR94), pages 121-133.

- Supervised learning
  - Classified examples: ABox individuals
  - Goal: induce new concepts to be added to the TBox
- Search direction: bottom-up
- Algorithm: LCSLearn/LCSLearnDISJ
  1. Apply the MSC operator to compute the minimal Tbox generalizations of the examples
  2. Apply the LCS operator to generalize the MSC descriptions of examples
- Limits: overly specific concept definitions

Learning in BACK

J.-U. Kietz & K. Morik (1994). *A Polynomial Approach to the Constructive Induction of Structural Knowledge*. Machine Learning 14(1): 193-217.

- Unsupervised learning
  - Unclassified examples: ABox individuals
  - Goal: induce new concepts to be added to the TBox
- Search direction: bottom-up
- Algorithm: KLUSTER
  1. Cluster the ABox individuals into *n* mutually disjoint concepts so that *n* supervised learning problems are obtained
  2. Find a correct definition of each of these concepts as follows:
     1. Compute and evaluate the *most specific generalization* (MSG) of a concept by applying the MSC operator;
     2. Obtain the *most general discrimination* (MGD) of the concept by further generalizing the MSG.

Refinement operators for DLs

L. Badea & S.-H. Nienhuys-Cheng (2000). *A Refinement Operator for Description Logics*. In J. Cussens & A. Frisch (eds): Inductive Logic Programming, LNAI 1866, pp. 40-59

- Complete and proper refinement operator for $\mathcal{ALER}$
- No minimal refinement operators exist for $\mathcal{ALER}$
  - Minimality of all refinement steps can be achieved except for those introducing
- Complete refinement operators for $\mathcal{ALER}$ can not be locally finite
- An upward refinement operator can be obtained by inverting the arrows in the refinement rules of the downward one

Refinement operators for DLs (2)

J. Lehmann & P. Hitzler (2007b). *Foundations of Refinement Operators for Description Logics*. In: Proceedings of the 17th Int. Conf. on Inductive Logic Programming.

- Let $\mathcal{L}$ be a DL which allows to express $\top$, $\bot$, $\sqcap$, $\sqcup$, $\exists$ and $\forall$
  - E.g. $\mathcal{ALC}$
- Maximal sets of properties of $\mathcal{L}$ refinement operators

1. {Weakly complete, complete, finite}
2. { Weakly complete, complete, proper}
3. { Weakly complete, non-redundant, finite}
4. { Weakly complete, non-redundant, proper}
5. { Non-redundant, finite, proper}

- Application: learning in $\mathcal{ALC}$ (Lehmann & Hitzler, 2007a)

Learning in $\mathcal{ALC}$

F. Esposito, N. Fanizzi, L. Iannone, I. Palmisano, & G. Semeraro (2004). *Knowledge-intensive induction of terminologies from metadata*. Proc. of the 3rd International Semantic Web Conference (ISWC04), volume 3298 of Springer LNCS, pp. 411-426.

- Supervised learning
  - Classified examples: ABox individuals
  - Goal: find a correct Tbox concept definition
- Search direction: bottom-up/top-down
- Algorithm: YinYang
  1. Apply the MSC operator to compute the minimal Tbox generalizations of the examples
  2. Apply *downward and upward refinement operators* for $\mathcal{ALC}$ to converge towards a correct concept definition
- http://www.di.uniba.it/~iannone/yinyang/

Learning in $\mathcal{ALC}$(2)

N. Fanizzi, L. Iannone, I. Palmisano, & G. Semeraro (2004). *Concept Formation in Expressive Description Logics*. In J.F. Boulicault et al. (eds.): Proc. of the 15th European Conference on Machine Learning, *ECML04*, pp. 99-110, Springer.

- Unsupervised learning
  - Unclassified examples: ABox individuals
  - Goal: induce new concepts to be added to the TBox
- Algorithm: CSKA
  1. Cluster the ABox individuals into *mutually disjoint concepts* (see KLUSTER)
  2. For each of these concepts find a correct concept definition by applying *downward and upward refinement operators* for $\mathcal{ALC}$ (see Yin/Yang)
- Application: ontology refinement

Learning in $\mathcal{ALC}$ (3)

C. d'Amato, N. Fanizzi, & F. Esposito (2006). *Reasoning by Analogy in Description Logics through Instance-based Learning*. Proc. of the 3rd Italian Semantic Web Workshop.

- Algorithm: kNN-DL
  - instance-based learning system
  - based on structural/semantic *(dis)similarity measures*

N. Fanizzi, C. d'Amato, F. Esposito. *Instance Based Retrieval by Analogy*. SAC 2007 SDRC Track, 11-15 March 2007, Seoul, Korea

- Algorithm: DiVS-kNN
  - instance-based learning system
  - Based on *disjunctive version space*

Learning in $\mathcal{ALC}$(4)

N. Fanizzi & C. d'Amato (2006). *A Declarative Kernel for $\mathcal{ALC}$ Concept Descriptions*. ISMIS 2006: Lecture Notes in Computer Science 4203, pp. 322-331

- Task: classification
- From distances to kernels
  - Kernel is a similarity measure (can be obtained from distances)
  - Kernel machine = algorithm parameterized by kernels

Learning in DLs: bibliography

- J. Alvarez (1998). A Description Logic System for Learning in Complex Domains. Proc. of the 1998 Int. Workshop on Description Logics (DL'98).
- J. Alvarez (2000a). A Formal Framework for Theory Learning using Description Logics. Proc. of Int. Workshop on Inductive Logic Programming (ILP'00), work in progress track.
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Learning in DLs: bibliography (2)

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- W.W. Cohen & H. Hirsh (1994b). *The Learnability of Description Logics with Equality Constraints*. Machine Learning, 17(2):169-199.

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- C. d'Amato, N. Fanizzi, & F. Esposito (2006). *A dissimilarity measure for $\mathcal{ALC}$ concept descriptions*. SAC 2006: 1695-1699
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- F. Esposito, N. Fanizzi, L. Iannone, I. Palmisano, G. Semeraro (2005). *A Counterfactual-Based Learning Algorithm for Description Logic*. AI*IA 2005: 406-417
- F. Esposito, N. Fanizzi, L. Iannone, I. Palmisano, G. Semeraro: *Induction and Revision of Terminologies*. ECAI 2004: 1007-1008

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- N. Fanizzi & C. d'Amato (2006). *A Declarative Kernel for $\mathcal{ALC}$ Concept Descriptions*. ISMIS: 322-331.
- N. Fanizzi, S. Ferilli, L. Iannone, I. Palmisano, & G. Semeraro (2004). *Downward Refinement in the $\mathcal{ALN}$ Description Logic*. HIS 2004: 68-73.
- N. Fanizzi, L. Iannone, I. Palmisano, G. Semeraro (2004). *Concept Formation in Expressive Description Logics*. ECML 2004: 99-110.
- M. Frazier & L. Pitt (1994). *CLASSIC learning*. In Proceedings of the Seventh Annual Conference on Computational Learning theory (COLT '94). ACM Press, New York, NY, 23-34.
- M. Frazier & L. Pitt (1996). *CLASSIC Learning*. Machine Learning, 25 (2-3): 151-193.

Learning in DLs: bibliography (5)

- L. Iannone, I. Palmisano and N. Fanizzi (2007). *An algorithm based on counterfactuals for concept learning in the Semantic Web*. Applied Intelligence, 26(2): 139-159.
- J. Lehmann & P. Hitzler (2007a). *A Refinement Operator Based Learning Algorithm for the $\mathcal{ALC}$ Description Logic*. In: Proceedings of the 17th International Conference on Inductive Logic Programming (ILP) 2007
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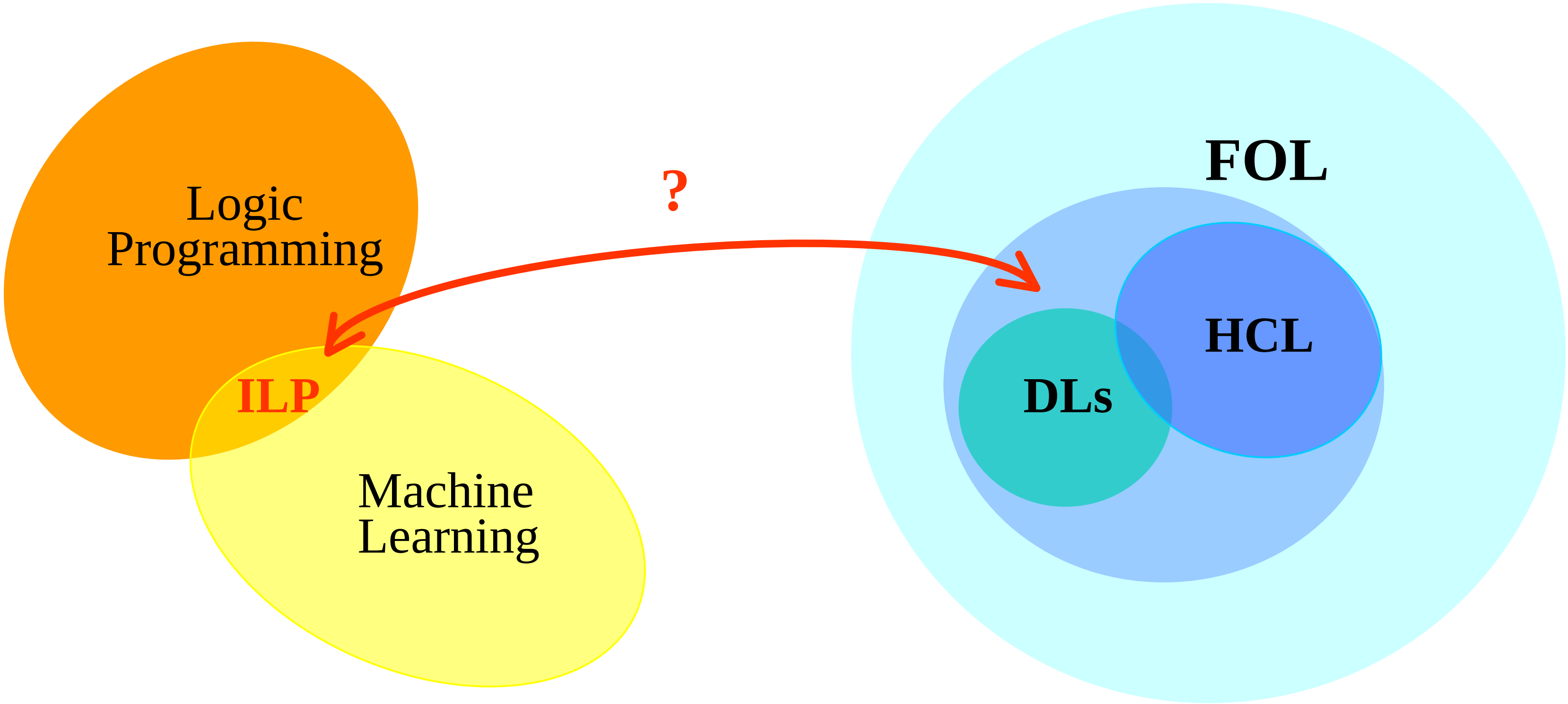
- V. Ventos, P. Brézellec, H. Soldano, D. Bouthinon (1998). *Learning Concepts in C-CLASSIC(delta/epsilon)*. Description Logics 1998

Part II: Overview

- Introduction to ILP
- ILP and DL representations
- *ILP and hybrid DL-HCL representations*
- ILP and the Semantic Web: Research directions

Learning in DL-HCL



Learning in CARIN-$\mathcal{ALN}$

C. Rouveirol & V. Ventos (2000). *Towards learning in* CARIN-$\mathcal{ALN}$. In J. Cussens & A. Frisch (eds): Inductive Logic Programming, Springer LNAI 1866, 191-208.

- Scope of induction: prediction
- Logical setting: learning from interpretations
- Language of hypotheses: definite clauses in CARIN-$\mathcal{ALN}$
- Generality order: adaptation of Buntine's generalized subsumption to CARIN-$\mathcal{ALN}$
- Coverage relations: query answering in CARIN-$\mathcal{ALN}$

Learning in CARIN-$\mathcal{ALN}$ (2)

J.-U. Kietz (2003). *Learnability of description logic programs*. In S. Matwin and C. Sammut (Eds.), Inductive Logic Programming, Springer LNAI 2583, 117-132.

- Method for transforming CARIN-$\mathcal{ALN}$ into Datalog extended with numerical constraints
- Transfer of learnability results known for ILP to learning in CARIN-$\mathcal{ALN}$

Learning in $\mathcal{AL}$-log

F.A. Lisi (2005). *Principles of Inductive Reasoning on the Semantic Web: A Framework for Learning in AL-log*. In F. Fages and S. Soliman (Eds.), Principles and Practice of Semantic Web Reasoning, Springer LNCS 3703, 118-132.

- Scope of induction: prediction/description
- Logical setting: learning from interpretations/learning from implications
- Language of hypotheses: constrained Datalog clauses
- Generality order: adaptation of Buntine’s generalized subsumption to $\mathcal{AL}$-log
- Coverage relations: query answering in $\mathcal{AL}$-log

Learning in DL-HCL: Bibliography

- A.M. Frisch (1991). *The Substitutional Framework for Sorted Deduction: Fundamental Results on Hybrid Reasoning*. Artif. Intell. 49(1-3): 161-198.
- A.M. Frisch (1999). *Sorted downward refinement: Building background knowledge into a refinement operator for inductive logic programming*. In S. Dzeroski and P.A. Flach (Eds.), Inductive Logic Programming, Springer LNAI 1634, 104-115 .
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Part II: Overview

- Introduction to ILP
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- *ILP and the Semantic Web: Research directions*

ILP and the Semantic Web: research directions in theory

- ILP frameworks for learning/mining in more expressive DLs and DL-HCL hybridizations
  - closer to OWL and SWRL
- ILP frameworks for learning/mining under uncertainty and vagueness
  - closer to real-world ontologies
- ILP frameworks for learning/mining from multiple contexts
  - Closer to the real scenario of the Semantic Web

ILP and the Semantic Web: research directions in practice

- Efficient implementations
- Interfacing of ILP systems with specialized reasoners for the Semantic Web
  - (Fuzzy) OWL/SWRL reasoners
- Experimental work on big OWL/SWRL ontologies

ILP and the Semantic Web: applications for learning in DLs

- Ontology Refinement
- Ontology Matching
- Ontology Merging
- FOAF
- Semantic retrieval
- Etc.

ILP and the Semantic Web: applications for learning in DL-HCL

- Ontology Refinement
  - Some concepts are better defined with rules
- Ontology Mapping
- Semantic Web Services
- Business rules
- Policy rules
- Etc.

Potentially all RIF use cases!

Further resources

- Tutorials on the Semantic Web
  - http://www.w3.org/2001/sw/BestPractices/Tutorials
  - http://km.aifb.uni-karlsruhe.de/ws/prowl2006/
  - http://rease.semanticweb.org/
- Tutorials on Machine Learning for the Semantic Web
  - http://www.aifb.uni-karlsruhe.de/WBS/pci/OL_Tutorial_ECML_PKDD_05/
  - http://www.uni-koblenz.de/~staab/Research/Events/ICML05tutorial/icml05tutorial.pdf
  - http://www.smi.ucd.ie/Dagstuhl-MLSW/proceedings/
  - http://ingenieur.kahosl.be/projecten/swa2002/slides/hendrik%20blockeel/Blockeel.ppt