

A brief guided tour along the borders of Logic Programming with Description Logics

Francesca A. Lisi



Department of Computer Science
Lab of Knowledge Acquisition and Machine Learning (LACAM)

francesca.lisi@uniba.it

ICLP 2015 - Sept. 1, 2015

- 1 Motivation
- 2 Description Logics
- 3 Logic Programming and DLs
 - Differences
 - Intersection
 - Integration
- 4 Inductive Logic Programming and DLs
 - ILP in a nutshell
 - Learning hybrid rules with ILP
- 5 Conclusions
- 6 References

Rules complement and extend ontologies

- Rules are a powerful way of modeling knowledge
- Rules have been successfully applied in Logic Programming (LP) and Databases [Ceri et al., 1990]
- Rules play also a role in the *Semantic Web* [Horrocks et al., 2003a]
 - See the Rules Interchange Format (RIF) activity at W3C

Rule acquisition needs automation

- Demanding knowledge engineering activity for very large KBs
 - Rule authoring task more error-prone than rule reviewing
 - Partial automation by applying rule learning algorithms
- Need to take ontologies into account

Description Logics

- Family of logic-based KR formalisms [Baader et al., 2007]
 - Structured incomplete knowledge
 - Focus on entities rather than on relationships
 - Descendants of semantic networks and KL-ONE
- Mapping to decidable FOL fragments [Borgida, 1996]
 - Variable-free syntax
- Killer application: ontologies and Semantic Web

Basics

Atomic concepts Unary predicates/formulae with one free variable (A)

- e.g., *Person*, *Doctor*, *HappyParent*

Atomic roles Binary predicates/formulae with two free variables (R)

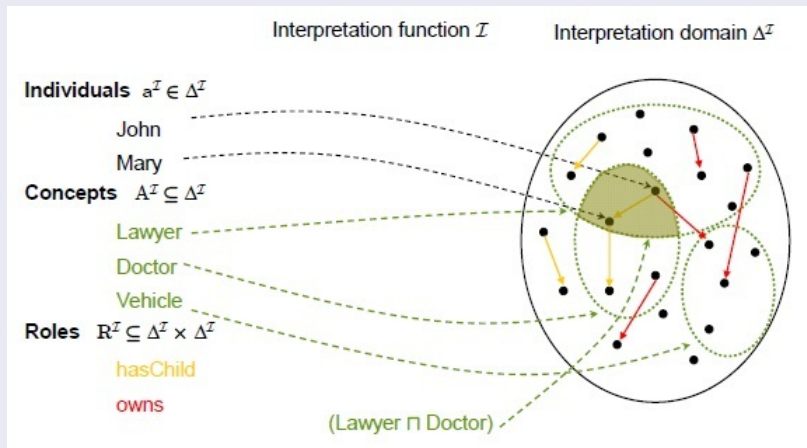
- e.g., *hasChild*, *loves*

Individuals Constants (a)

- e.g., *John*, *Mary*, *Italy*

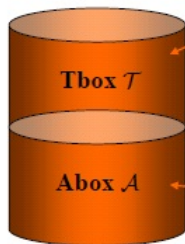
Constructors Operators (e.g., \sqcap) for forming complex concepts and roles from atomic ones restricted so that satisfiability/subsumption is decidable and, if possible, of low complexity

Direct semantics



Knowledge bases

Knowledge Base Σ



Terminological part

- Intensional* knowledge
- In the form of axioms

Assertional part

- Extensional* knowledge
- In the form of assertions

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!

Main reasoning tasks

Consistency check Is the KB satisfiable? *i.e.*, is there a model that satisfies both \mathcal{T} and \mathcal{A} ?

Subsumption check Does $C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$ hold in all models of \mathcal{T} ?

Instance check Is $C(a)$ derivable from Σ ?

Reasoning algorithms based on tableau calculi

Tableau calculus

- 1 Applies rules that correspond to DL constructors
 - E.g., $John : (Person \sqcap Doctor) \rightarrow_{\sqcap} John : Person$ and $John : Doctor$
 - 2 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

Naming conventions for DLs

\mathcal{F}	Functional restrictions
\mathcal{E}	Full existential qualification
\mathcal{U}	Concept union
\mathcal{C}	Complex concept negation
\mathcal{H}	Role hierarchy
\mathcal{R}	Limited complex role inclusion axioms; reflexivity; role disjointness
\mathcal{O}	Nominals
\mathcal{I}	Inverse properties
\mathcal{N}	Number restrictions
\mathcal{Q}	Qualified number restrictions

Notable examples of the DL family

- Smallest expressive DL is \mathcal{ALC} [Schmidt-Schauss and Smolka, 1991]
- \mathcal{SHIQ} [Horrocks et al., 2000] is a very expressive DL
 - \mathcal{S} is an abbreviation for \mathcal{ALC} with transitive roles
 - DL underlying the W3C Ontology Web Language OWL [Horrocks et al., 2003b]
- Efficient query answering in DL-Lite [Calvanese et al., 2007]

Syntax and semantics of \mathcal{ALC} KBs

bottom concept	\perp	\emptyset
top concept	\top	$\Delta^{\mathcal{I}}$
atomic concept	A	$A^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}}$
role	R	$R^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$
individual	a	$a^{\mathcal{I}} \in \Delta^{\mathcal{I}}$
concept negation	$\neg C$	$\Delta^{\mathcal{I}} \setminus C^{\mathcal{I}}$
concept conjunction	$C \sqcap D$	$C^{\mathcal{I}} \cap D^{\mathcal{I}}$
concept disjunction	$C \sqcup D$	$C^{\mathcal{I}} \cup D^{\mathcal{I}}$
value restriction	$\forall R.C$	$\{x \in \Delta^{\mathcal{I}} \mid \forall y (x, y) \in R^{\mathcal{I}} \rightarrow y \in C^{\mathcal{I}}\}$
existential restriction	$\exists R.C$	$\{x \in \Delta^{\mathcal{I}} \mid \exists y (x, y) \in R^{\mathcal{I}} \wedge y \in C^{\mathcal{I}}\}$
equivalence axiom	$C \equiv D$	$C^{\mathcal{I}} = D^{\mathcal{I}}$
subsumption axiom	$C \sqsubseteq D$	$C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$
concept assertion	$C(a)$	$a^{\mathcal{I}} \in C^{\mathcal{I}}$
role assertion	$R(a, b)$	$(a^{\mathcal{I}}, b^{\mathcal{I}}) \in R^{\mathcal{I}}$

Example of an \mathcal{ALC} KB \mathcal{K}

A1 $DairyProduct \sqsubseteq Product$

F1 $DairyProduct(mozzarella)$

Example of instance check in \mathcal{ALC}

Is $Product(mozzarella)$ derivable from the KB \mathcal{K} ? or equivalently, is $\mathcal{K} \cup \{\neg Product(mozzarella)\}$ consistent?

Extensions

- Fuzzy DLs
 - See [Straccia, 2015] for a tutorial lecture
- Probabilistic DLs, e.g., [Lukasiewicz, 2008]
 - See Lamma's invited talk at ICLP 2015 on Thursday morning
- LP and DLs
 - *Focus of this talk!*

Logic Programming and DLs

- What are the differences between LP and DLs?
- Is there an overlap between the two?
- Can we combine them?

A summary

- 1 CWA vs OWA
- 2 Single vs. multiple models
- 3 Negation as failure vs. classical negation
- 4 Strong negation vs. classical negation
- 5 Treatment of equality
 - Unique Names Assumption (UNA) [Reiter, 1980] might not hold in DLs
- 6 Existential quantification
 - Recent work on DATALOG^{\pm} [Cali et al., 2009]
 - See Lukasiewicz's invited tutorial at ICLP 2015 on Thursday afternoon
- 7 Decidability

Exploring the overlap

A partial overlap exists between LP and DLs which allows the extension and/or adaptation of known results in LP to DLs and viceversa

- Horn fragment of DLs
[Krötzsch et al., 2008, Krötzsch et al., 2013, Krötzsch et al., 2015]
- Efficient DL reasoning with LP
[Hustadt et al., 2007, Lukácsy and Szeredi, 2009]

Exploiting the power of combination

- Combination is more than the sum of the parts
- Very expressive FOL languages as an outcome
- Solutions to the semantic mismatch between LP and DLs

Approaches

Non-hybrid Combination within a *homogeneous* semantic framework

- description logic programs [Grosz et al., 2003]
- DL-safe rules [Motik et al., 2005]
- Semantic Web Rule Language (SWRL)
[Horrocks and Patel-Schneider, 2004]

Hybrid Combination within a *heterogeneous* semantic framework

- *Focus of this talk!*

DL-safety [Motik et al., 2005]

- Syntactic restriction to the form of rules
- Helps avoiding unwanted interactions between the LP and the DL parts

Schemes for hybrid integration

Loose coupling The LP part and the DL part are treated as separate and independent components

- e.g., dl-programs [Eiter et al., 2008b] rely on safe interface between an ASP engine and a DL reasoner

Tight integration Separation between the two vocabularies but notion of an integrated model which satisfies both parts

- *Focus of this talk!*

Full integration No separation between the two vocabularies

- e.g., MKNF-knowledge bases [Motik and Rosati, 2007]

Tight integration of LP and DLs I

Overview

	CARIN [Levy and Rousset, 1998]	\mathcal{AL} -LOG [Donini et al., 1998]	$\mathcal{DL}+\text{LOG}^\vee$ [Rosati, 2006]
DL language CL language	any DL Horn clauses	\mathcal{ALC} DATALOG clauses	any DL DATALOG $^\vee$ clauses
DL-safety rule head literals rule body literals	no DL/Horn DL/Horn	yes DATALOG \mathcal{ALC} /DATALOG (no roles)	weakly DL-safe DL/DATALOG DL/DATALOG
semantics reasoning	Herbrand models + DL models SLD-resolution + tableau calculus	idem idem	stable models + DL models stable model computation + Boolean CQ/UCQ containment
decidability	only for some instantiations	yes	for all instantiations with DLs for which the Boolean CQ/UCQ containment is decidable
implementation	yes, e.g.[Goasdoué et al., 2000]	yes, e.g.[Ruckhaus et al., 2006]	unknown

Example: a $\mathcal{DL}+\text{LOG}^{-\forall}$ KB $\mathcal{K} = (\Sigma, \Pi)$

- The DL component Σ

```
[A1] PERSON  $\sqsubseteq$   $\exists$  FATHER-.MALE
[A2] MALE  $\sqsubseteq$  PERSON
[A3] FEMALE  $\sqsubseteq$  PERSON
[A4] FEMALE  $\sqsubseteq$   $\neg$ MALE
    MALE(Bob)
    PERSON(Mary)
    PERSON(Paul)
    FATHER(John,Paul)
```

- The DATALOG component Π

```
[R1] boy(X)  $\leftarrow$  enrolled(X,c1,ft), PERSON(X), not girl(X)
[R2] girl(X)  $\leftarrow$  enrolled(X,c2,ft), PERSON(X)
[R3] boy(X)  $\vee$  girl(X)  $\leftarrow$  enrolled(X,c3,ft), PERSON(X)
[R4] FEMALE(X)  $\leftarrow$  girl(X)
[R5] MALE(X)  $\leftarrow$  boy(X)
[R6] man(X)  $\leftarrow$  enrolled(X,c3,pt), FATHER(X,Y)
    enrolled(Paul,c1,ft)
    enrolled(Mary,c1,ft)
    enrolled(Mary,c2,ft)
    enrolled(Bob,c3,ft)
    enrolled(John,c3,pt)
```

- Notice that $\mathcal{K} \models_{NM} \text{FEMALE}(\text{Mary})$, while $\Sigma \not\models_{FOL} \text{FEMALE}(\text{Mary})$.

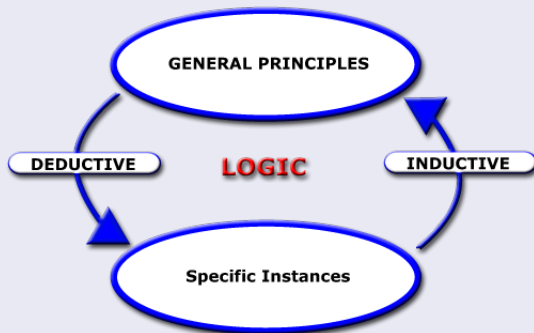
Inductive Logic Programming and DLs

- ILP in a nutshell
- Learning hybrid rules with ILP

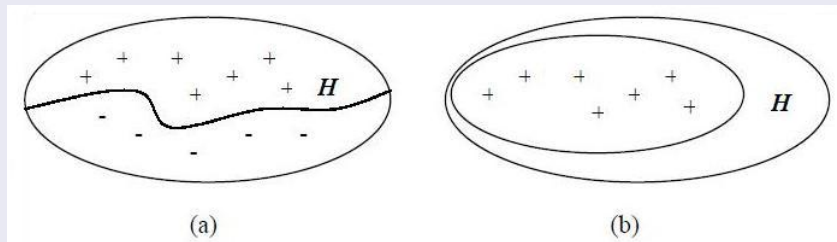
Basics [Muggleton, 1990]

- ILP = LP + Concept Learning
 - Concept definitions as logic programs
- Use of background knowledge (BK)
- Bunch of techniques for structuring, searching and bounding the hypothesis space [Nienhuys-Cheng and de Wolf, 1997]

Inductive inference



Scope of induction

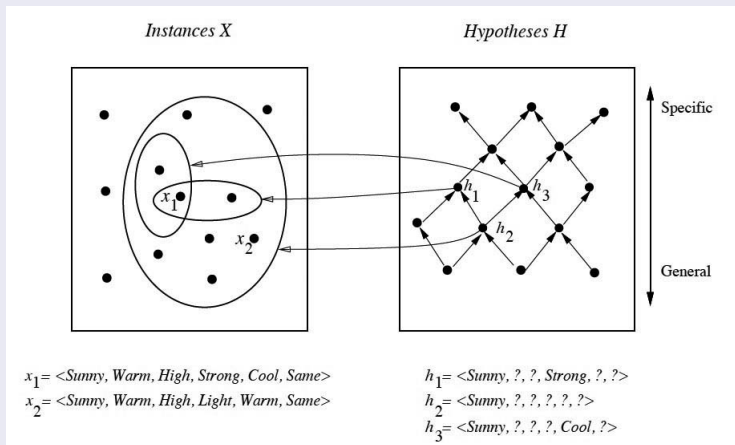


- (a) Discriminate for making predictions on unseen data (e.g., classification)
- (b) Characterize for understanding the available data (e.g., clustering)

Generalization

- It proceeds from a premise about a sample to a conclusion about the population.
 - The proportion Q of the sample has attribute A .
 - Therefore:
 - The proportion Q of the population has attribute A .
- While the conclusion of a deductive argument is *certain*, the truth of the conclusion of an inductive argument is *probable*, based upon the evidence given.
- Instead of being valid or invalid, inductive arguments are either *strong* or *weak*, which describes how probable it is that the conclusion is true.
 - In a *strong* inductive generalization, the sample must represent the population.

Generalization as search [Mitchell, 1982]



Generality orders

- Syntactic** Clause comparison wrt their structure (e.g., θ -subsumption [Plotkin, 1970])
- Semantic** Clause comparison wrt their implications (e.g., generalized subsumption [Buntine, 1988])

Extensions

- Probabilistic ILP
 - See [Riguzzi et al., 2014] for a survey
- Concept Learning in DLs
 - See [Lisi, 2013] for a unified view over literature
- Learning hybrid rules
 - *Focus of this talk!*

Learning hybrid rules with ILP I

Overview

	Learning <i>CARIN-\mathcal{ALN}</i> rules [Rouveirol and Ventos, 2000, Kietz, 2003]	Learning <i>\mathcal{AL}-LOG</i> rules [Lisi, 2008]	Learning <i>$SHIQ$+LOG</i> rules [Lisi, 2010]
prior knowledge	<i>CARIN-\mathcal{ALN}</i> KB	<i>\mathcal{AL}-LOG</i> KB	<i>$SHIQ$+LOG</i> KB
ontology language	<i>\mathcal{ALN}</i>	<i>\mathcal{ALC}</i>	<i>$SHIQ$</i>
rule language	HCL	DATALOG	DATALOG
hypothesis language	<i>CARIN-\mathcal{ALN}</i> non-recursive rules	<i>\mathcal{AL}-LOG</i> non-recursive rules	<i>$SHIQ$+LOG</i> non- recursive rules
target predicate	Horn predicate	DATALOG predicate	<i>$SHIQ$/DATALOG</i> predi- cate
logical setting	interpretations	interpretations/entailment	entailment
scope of induction	prediction	prediction/description	prediction/description
generality order	generalized subsumption	generalized subsumption	generalized subsumption
coverage test	<i>CARIN</i> query answering	<i>\mathcal{AL}-LOG</i> query answering	<i>DL+LOG^V</i> query answer- ing
ref. operators	n.a.	downward	downward/upward
implementation	unknown	yes, see [Lisi, 2011]	no
application	no	yes, see [Lisi and Malerba, 2004]	no

Applications

- Spatial data mining in \mathcal{AL} -LOG [Lisi and Malerba, 2004]
- Semantic Web Mining in \mathcal{AL} -LOG [Lisi, 2011]
- Learning $\mathcal{DL}+\text{LOG}^V$ rules for database design [Lisi, 2010]
- Learning $\mathcal{DL}+\text{LOG}$ rules for ontology maintenance [Lisi, 2014]

Example: a $\mathcal{DL}+\text{LOG}^-$ KB \mathcal{K}

[A1] $\text{RICH} \sqcap \text{UNMARRIED} \sqsubseteq \exists \text{WANTS-TO-MARRY}^- . \top$

[A2] $\text{WANTS-TO-MARRY} \sqsubseteq \text{LOVES}$

[R1] $\text{RICH}(X) \leftarrow \text{famous}(X), \text{not scientist}(X)$

[R2] $\text{happy}(X) \leftarrow \text{famous}(X), \text{WANTS-TO-MARRY}(Y, X)$

UNMARRIED(Mary)

UNMARRIED(Joe)

famous(Mary)

famous(Paul)

famous(Joe)

scientist(Joe)

meets(Mary, Paul, Italy)

meets(Mary, Joe, Germany)

meets(Joe, Mary, Italy)

Example (contd.): What if new knowledge for \mathcal{K} becomes available?

- Let us consider the conceptual changes of \mathcal{K} due to extensional knowledge (*i.e.*, facts of the instance level of the ontology) previously unknown but classified which may become available.
- For example, the new facts `LONER(Joe)`, `LONER(Mary)`, and `LONER(Paul)` concerning known individuals may raise the need for having a definition of the concept `LONER` in the ontology.
- One such definition can be learned from these facts together with prior knowledge about Joe, Mary and Paul.

Example (contd.): learning a rule-based definition of LONER

- Target predicate: LONER
- Examples: $\mathcal{E}^+ = \{\text{LONER}(\text{Mary}), \text{LONER}(\text{Joe})\}$,
 $\mathcal{E}^- = \{\text{LONER}(\text{Paul})\}$
- Language bias: $\{\text{famous}/1\} \cup \{\text{happy}/1\} \cup \{\text{RICH}/1, \text{UNMARRIED}/1\}$
- Candidate hypotheses:
 - $h_1^{\text{LONER}} \quad \text{LONER}(X) \leftarrow \text{famous}(X)$
 - $h_2^{\text{LONER}} \quad \text{LONER}(X) \leftarrow \text{famous}(X), \text{UNMARRIED}(X)$
 - $h_3^{\text{LONER}} \quad \text{LONER}(X) \leftarrow \text{famous}(X), \text{not happy}(X)$
- Valid hypothesis: h_3^{LONER}
- Justification: consistency with examples

- LP and the family of DLs are both based on FOL fragments
- Different semantic assumptions
[Eiter et al., 2008a, Motik and Rosati, 2010, Krötzsch et al., 2015]
 - Partial overlap between the two exists
 - Combination is possible under certain conditions
- Interesting rule learning problems [Lisi, 2014]

Questions?

Thanks for your attention!

References I



Baader, F., Calvanese, D., McGuinness, D., Nardi, D., and Patel-Schneider, P., editors (2007).
The Description Logic Handbook: Theory, Implementation and Applications (2nd ed.).
Cambridge University Press.



Borgida, A. (1996).
On the relative expressiveness of description logics and predicate logics.
Artificial Intelligence, 82(1–2):353–367.



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



Cafı, A., Gottlob, G., and Lukasiewicz, T. (2009).
Datalog[±]: a unified approach to ontologies and integrity constraints.
In Fagin, R., editor, *Database Theory - ICDT 2009, 12th International Conference, St. Petersburg, Russia, March 23-25, 2009, Proceedings*, volume 361 of *ACM International Conference Proceeding Series*, pages 14–30. ACM.



Calvanese, D., De Giacomo, G., Lembo, D., Lenzerini, M., and Rosati, R. (2007).
Tractable Reasoning and Efficient Query Answering in Description Logics: The *dl-lite* Family.
Journal of Automated Reasoning, 39(3):385–429.



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



Donini, F. M., Lenzerini, M., Nardi, D., and Schaerf, A. (1998).
AL-log: Integrating Datalog and Description Logics.
Journal of Intelligent Information Systems, 10(3):227–252.

References II



Eiter, T., Ianni, G., Krennwallner, T., and Polleres, A. (2008a).

Rules and ontologies for the semantic web.

In Baroglio, C., Bonatti, P. A., Maluszynski, J., Marchiori, M., Polleres, A., and Schaffert, S., editors, *Reasoning Web*, volume 5224 of *Lecture Notes in Computer Science*, pages 1–53. Springer.



Eiter, T., Ianni, G., Lukasiewicz, T., Schindlauer, R., and Tompits, H. (2008b).

Combining answer set programming with description logics for the semantic web.

Artificial Intelligence, 172(12-13):1495–1539.



Goasdoué, F., Lattès, V., and Rousset, M.-C. (2000).

The Use of CARIN Language and Algorithms for Information Integration: The PICSEL System.

International Journal of Cooperative Information Systems, 9(4):383–401.



Grosf, B. N., Horrocks, I., Volz, R., and Decker, S. (2003).

Description logic programs: combining logic programs with description logic.

In *Proceedings of the 12th International World Wide Web Conference*, pages 48–57. ACM.



Horrocks, I., Angele, J., Decker, S., Kifer, M., Grosf, B. N., and Wagner, G. (2003a).

Where are the rules?

IEEE Intelligent Systems, 18:76–83.



Horrocks, I. and Patel-Schneider, P. F. (2004).

A Proposal for an OWL Rules Language.

In *Proc. of the 13th International World Wide Web Conference*, pages 723–731. ACM.



Horrocks, I., Patel-Schneider, P. F., and van Harmelen, F. (2003b).

From *SHIQ* and RDF to OWL: The Making of a Web Ontology Language.

Journal of Web Semantics, 1(1):7–26.

References III



Horrocks, I., Sattler, U., and Tobies, S. (2000).
Practical reasoning for very expressive description logics.
Logic Journal of the IGPL, 8(3):239–263.



Hustadt, U., Motik, B., and Sattler, U. (2007).
Reasoning in description logics by a reduction to disjunctive datalog.
Journal of Automated Reasoning, 39(3):351–384.



Kietz, J.-U. (2003).
Learnability of description logic programs.
In Matwin, S. and Sammut, C., editors, *Inductive Logic Programming, 12th International Conference, ILP 2002, Sydney, Australia, July 9-11, 2002. Revised Papers*, volume 2583 of *Lecture Notes in Computer Science*, pages 117–132. Springer.



Krötzsch, M., Rudolph, S., and Hitzler, P. (2008).
Description logic rules.
In Ghallab, M., Spyropoulos, C. D., Fakotakis, N., and Avouris, N. M., editors, *ECAI 2008*, volume 178 of *Frontiers in Artificial Intelligence and Applications*, pages 80–84. IOS Press.



Krötzsch, M., Rudolph, S., and Hitzler, P. (2013).
Complexities of horn description logics.
ACM Trans. Comput. Log., 14(1):2.



Krötzsch, M., Rudolph, S., and Schmitt, P. H. (2015).
A closer look at the semantic relationship between datalog and description logics.
Semantic Web, 6(1):63–79.



Levy, A. Y. and Rousset, M.-C. (1998).
Combining Horn rules and description logics in CARIN.
Artificial Intelligence, 104:165–209.

References IV



Lisi, F. A. (2008).

Building Rules on Top of Ontologies for the Semantic Web with Inductive Logic Programming.
Theory and Practice of Logic Programming, 8(03):271–300.



Lisi, F. A. (2010).

Inductive Logic Programming in Databases: From Datalog to $\mathcal{DL}+\log$.
Theory and Practice of Logic Programming, 10(3):331–359.



Lisi, F. A. (2011).

\mathcal{AL} -QUIN: An Onto-Relational Learning System for Semantic Web Mining.
International Journal on Semantic Web and Information Systems, 7(3):1–22.



Lisi, F. A. (2013).

A declarative modeling language for concept learning in description logics.
In Riguzzi, F. and Zelezny, F., editors, *Inductive Logic Programming, 22nd International Conference, ILP 2012, Dubrovnik, Croatia, September 17-19, 2012, Revised Selected Papers*, volume 7842 of *Lecture Notes in Computer Science*. Springer Berlin Heidelberg.



Lisi, F. A. (2014).

Learning onto-relational rules with inductive logic programming.
In Lehmann, J. and Völker, J., editors, *Perspectives on Ontology Learning*, volume 18 of *Studies on the Semantic Web*, pages 93–111. IOS Press/AKA.



Lisi, F. A. and Malerba, D. (2004).

Inducing Multi-Level Association Rules from Multiple Relations.
Machine Learning, 55:175–210.

References V



Lukácsy, G. and Szeredi, P. (2009).
Efficient description logic reasoning in prolog: The dlog system.
Theory and Practice of Logic Programming, 9(3):343–414.



Lukasiewicz, T. (2008).
Expressive probabilistic description logics.
Artificial Intelligence, 172(6-7):852–883.



Mitchell, T. M. (1982).
Generalization as search.
Artificial Intelligence, 18:203–226.



Motik, B. and Rosati, R. (2007).
A faithful integration of description logics with logic programming.
In Veloso, M., editor, *IJCAI 2007, Proc. of the 20th Int. Joint Conf. on Artificial Intelligence*, pages 477–482.



Motik, B. and Rosati, R. (2010).
Reconciling description logics and rules.
J. ACM, 57(5).



Motik, B., Sattler, U., and Studer, R. (2005).
Query Answering for OWL-DL with Rules.
Journal on Web Semantics, 3(1):41–60.



Muggleton, S. H. (1990).
Inductive logic programming.
In Arikawa, S., Goto, S., Ohsuga, S., and Yokomori, T., editors, *Proceedings of the 1st Conference on Algorithmic Learning Theory*. Springer/Ohmsma.

References VI



Nienhuys-Cheng, S.-H. and de Wolf, R. (1997).
Foundations of Inductive Logic Programming, volume 1228 of *Lecture Notes in Artificial Intelligence*. Springer.



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



Reiter, R. (1980).
Equality and domain closure in first order databases.
Journal of ACM, 27:235–249.



Riguzzi, F., Bellodi, E., and Zese, R. (2014).
A history of probabilistic inductive logic programming.
Frontiers in Robotics and AI, 2014.



Rosati, R. (2006).
DL+log: Tight Integration of Description Logics and Disjunctive Datalog.
In Doherty, P., Mylopoulos, J., and Welty, C. A., editors, *Proc. of Tenth International Conference on Principles of Knowledge Representation and Reasoning*, pages 68–78. AAAI Press.



Rouveirol, C. and Ventos, V. (2000).
Towards Learning in CARIN- \mathcal{ALN} .
In Cussens, J. and Frisch, A. M., editors, *Inductive Logic Programming, 10th International Conference, ILP 2000, London, UK, July 24-27, 2000, Proceedings*, volume 1866 of *Lecture Notes in Artificial Intelligence*, pages 191–208. Springer.



Ruckhaus, E., Kolovski, V., Parsia, B., and Cuenca Grau, B. (2006).
Integrating Datalog with OWL: Exploring the \mathcal{AL} -log Approach.
In Etalle, S. and Truszczynski, M., editors, *Logic Programming, 22nd International Conference, ICLP 2006, Seattle, WA, USA, August 17-20, 2006, Proceedings*, volume 4079 of *Lecture Notes in Computer Science*, pages 455–456. Springer.



Schmidt-Schauss, M. and Smolka, G. (1991).
Attributive concept descriptions with complements.
Artificial Intelligence, 48(1):1–26.



Straccia, U. (2015).
All about fuzzy description logics and applications.
In Faber, W. and Paschke, A., editors, *Reasoning Web. Web Logic Rules - 11th International Summer School 2015, Berlin, Germany, July 31 - August 4, 2015, Tutorial Lectures*, volume 9203 of *Lecture Notes in Computer Science*, pages 1–31. Springer.