Logics in Machine Learning and Data Mining: Achievements and Open Issues

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Overview

1. Introduction
2. Three cases for Logics in ML/DM
   - Combining rules and ontologies
   - Dealing with imprecision and granularity
   - Modeling and metamodeling
3. Final remarks
4. References

Introduction I

Model-free AI vs. Model-based AI

- Current hype about AI due to many successful ML applications
- Deep learning follows the model-free approach
  - ML tasks are function-fitting problems!
- Need to construct and use models ("good old-fashioned AI")
  - Logics and probability as main tools
- Is there any ML algorithm following the model-based approach?

Introduction II

Inductive Logic Programming in a nutshell

- Major logic-based approach to rule learning [Muggleton, 1990]
  - Concept Learning within the LP framework
  - Use of background knowledge (BK)
- Bunch of techniques for structuring, searching and bounding the hypothesis space [Nienhuys-Cheng and de Wolf, 1997]
- Two representative ILP algorithms:
  1. FOIL [Quinlan, 1990]
  2. WARMR [Dehaspe and Toivonen, 1999]
- Several extensions, *e.g.*, towards statistical learning and other probabilistic approaches (see [Riguzzi et al., 2014] for a survey).

Three cases for Logics in ML/DM

1. Combining rules and ontologies
2. Dealing with imprecision and granularity
3. Modeling and metamodeling

Combining rules and ontologies I

Logic Programming vs. Descripion Logics

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 $\text{D}\scriptstyle{\text{ATALOG}}^{\pm}$ [Calì et al., 2009]
7. Decidability

Combining rules and ontologies II

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

- *e.g.*, description logic programs [Grosof et al., 2003]

Hybrid Combination within a *heterogeneous* semantic framework

- *e.g.*, $\mathcal{AL}$-LOG [Donini et al., 1998]

Combining rules and ontologies III

Learning hybrid rules with ILP

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

Combining rules and ontologies IV

$\mathcal{AL}$-QuIn: general features [Lisi, 2011]

- Task: multi-level association rule mining
- Method: levelwise search
- BK: hybrid (relational DB + ontology)
- Knowledge representation formalism: $\mathcal{AL}$-log.
- Upgrade from: Warmr.

Combining rules and ontologies V

$\mathcal{AL}$-QuIn: problem statement

Given

- a relational data set Π
- a taxonomic ontology Σ
- a multi-grained language $\mathcal{L} = \{\mathcal{L}^l\}_{1 \leq l \leq maxG}$
- a set $\{minsup^l\}_{1 \leq l \leq maxG}$ of support thresholds

the problem of *frequent pattern discovery in* Π *at* l *levels of description granularity w.r.t.* Σ, $1 \leq l \leq maxG$, is to find the set $\mathcal{F}$ of all the patterns $P \in \mathcal{L}^l$ frequent in $\mathcal{B} = (\Pi, \Sigma)$, namely P's with support s such that (i) $s \geq minsup^l$ and (ii) all ancestors of P w.r.t. Σ are frequent.

Combining rules and ontologies VI

$\mathcal{AL}$-QuIn: An example

Q_1= q(X) $\leftarrow$ believes(X,Y) & MiddleEastCountry(X)
Q_3= q(X) $\leftarrow$ believes(X,Y) & MiddleEastCountry(X), Religion(Y)
Q_4= q(X) $\leftarrow$ believes(X,Y) & MiddleEastCountry(X), MonotheisticReligion(Y)
Q_5= q(X) $\leftarrow$ believes(X,Y), speaks(X,Z) &
MiddleEastCountry(X), MonotheisticReligion(Y), IndoEuropeanLanguage(Z)

Dealing with imprecision and granularity I

Fuzzy Description Logics

- Several ways of extending DLs with fuzzy logic [Straccia, 2013]
- Some ad-hoc reasoners already available (*e.g.*, *FuzzyDL* [Bobillo and Straccia, 2008])
- Fuzzy quantifiers in Fuzzy DLs [Sanchez and Tettamanzi, 2006]
- Proposal of Fuzzy OWL 2 [Bobillo and Straccia, 2010]

Dealing with imprecision and granularity II

Fuzzy $\mathcal{EL}(\mathbf{D})$ [Straccia, 2005]

- Complex concepts built according to the following syntactic rules:

$$C \rightarrow \top \mid \bot \mid A \mid C_1 \sqcap C_2 \mid \exists R.C \mid \exists T.\mathbf{d}$$

  where

  - $\mathbf{d}$ can be one of the membership functions of fuzzy sets
  - $\sqcap$ and $\exists$ are interpreted as truth combination functions

- Concepts are interpreted as fuzzy sets
- Axioms are graded, *i.e.* have a truth degree α (if omitted, $\alpha = 1$)
  - e.g., $\mathcal{I}$ satisfies an axiom $\langle a{:}C, \alpha\rangle$ if $C^{\mathcal{I}}(a^{\mathcal{I}}) \geq \alpha$
- The *best entailment degree* of an axiom τ w.r.t. $\mathcal{K}$ is defined as

$$bed(\mathcal{K}, \tau) = \sup\{\alpha \mid \mathcal{K} \models \langle \tau, \alpha\rangle\}\ . \tag{1}$$

  For a crisp axiom τ, we also write $\mathcal{K} \models_+ \tau$ iff $bed(\mathcal{K}, \tau) > 0$.

Dealing with imprecision and granularity III

Fuzzy DL Learning

- [Konstantopoulos and Charalambidis, 2010] propose an ad-hoc translation of fuzzy Łukasiewicz $\mathcal{ALC}$ DL constructs into LP in order to apply a conventional ILP method for rule learning.
  - Unsound method
- [Iglesias and Lehmann, 2011] propose to interface CELOE with the *fuzzyDL* reasoner
  - Uncomparable method
- [Lisi and Straccia, 2013] present a method for learning fuzzy $\mathcal{EL}$ GCI axioms from fuzzy DL-Lite KBs.
  - Unimplemented method

Dealing with imprecision and granularity IV

FOIL-$\mathcal{DL}$: general features [Lisi and Straccia, 2014]

- Task: classification rule mining
- Method: sequential covering
- BK: $\mathcal{DL}$ KB
- Hypothesis description language: fuzzy $\mathcal{EL}(\mathbf{D})$.
- Upgrade from: FOIL.

Dealing with imprecision and granularity V

FOIL-$\mathcal{DL}$: problem statement

Given:

- a consistent $\mathcal{DL}$ KB $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$ (the *background theory*);
- an atomic concept A_t (the *target concept*);
- a set $\mathcal{E} = \mathcal{E}^+ \cup \mathcal{E}^-$ of crisp $\mathcal{DL}$ concept assertions labelled as either positive or negative examples for H (the *training set*);
- a set $\mathcal{L_H}$ of fuzzy $\mathcal{EL}(\mathbf{D})$ GCIs of the form $C \sqsubseteq A_t$ (the *language of hypotheses*) where C is a complex concept

Find: a set $\mathcal{H} \subset \mathcal{L_H}$ (a *hypothesis*) such that:

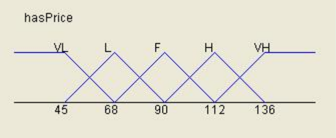
Completeness. $\forall e \in \mathcal{E}^+, \mathcal{K} \cup \mathcal{H} \models_+ e$, and

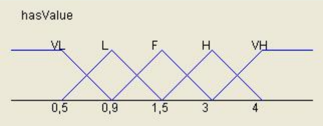
Consistency. $\forall e \in \mathcal{E}^-, \mathcal{K} \cup \mathcal{H} \not\models_+ e$.

Dealing with imprecision and granularity VI

FOIL-$\mathcal{DL}$: An example

Confidence	Axiom
1,000	Hostel subclass of Good_Hotel
1,000	hasPrice_veryhigh subclass of Good_Hotel
0,739	hasDistance some (isDistanceFor some (Bus_Station) and hasValue_low) and hasDistance some (isDistanceFor some (Town_Hall) and hasValue_fair) and hasRank some (Rank) and hasPrice_verylow subclass of Good_Hotel
0,569	hasPrice_high subclass of Good_Hotel
0,289	Hotel_3_Stars and hasDistance some (isDistanceFor some (Train_Station) and hasValue_verylow) and hasPrice_fair subclass of Good_Hotel
0,198	Hotel_4_Stars and hasDistance some (isDistanceFor some (Square) and hasValue_high) and hasRank some (Rank) and hasPrice_fair subclass of Good_Hotel





Dealing with imprecision and granularity VII

Information granulation and DLs [Lisi and Mencar, 2017, Lisi and Mencar, 2018]

Support to **both**

coarser-granularity fuzzy quantified sentences such as

"Many hotels have a low distance from attractions"

and *finer-granularity* fuzzy quantified sentences such as

"Hotel Verdi has a low distance from many attractions"

Modeling and metamodeling I

Model+solver approach in ML/DM

- ML/DM problems as either Constraint Satisfaction Problems or Optimization Problems
- Languages for declarative modeling [De Raedt, 2015]
- Use of efficient solvers, *e.g.*, CP solver in itemset mining [Guns et al., 2011]

Meta-Interpretive Learning

- Novel and promising ILP framework [Muggleton and Lin, 2013]
- Meta-rules (expressed in a higher-order dyadic DATALOG fragment) with procedural constraints
- Meta-interpreter implemented by relying, *e.g.*, on ASP solvers

Modeling and metamodeling II

Higher-order DLs

- [Pan and Horrocks, 2006] propose a stratified Higher-order DL (OWL FA) to cope with meta-assertions about concepts and roles.
- [Motik, 2007] proves that satisfiability in Higher-order $\mathcal{ALCO}$, which is a fragment of OWL Full, is undecidable.
- [De Giacomo et al., 2011] augment a DL with variables that may be interpreted - in a Henkin semantics - as individuals, concepts, and roles at the same time, obtaining a new logic $Hi(\mathcal{DL})$
- [Colucci et al., 2010] introduce second-order features in DLs under Henkin semantics for modeling several non-standard reasoning tasks.

Modeling and metamodeling III

Higher-order DLs in ML/DM

- [Lisi, 2013] extends [Colucci et al., 2010] to some variants of concept learning, thus being the first to propose higher-order DLs as a means for metamodeling in ML.
- [Lisi, 2018] proposes a metaquerying language for mining the Web of Data

Final remarks

Need for integration

1. Learning & Reasoning
2. Symbolic & Sub-symbolic

Angry Birds AI competition

- Simplified and controlled environment for developing future AI systems able to interact with the physical world
- Challenge for AI: Predict the outcome of physical actions without complete knowledge of the world

Open issues in logic-based ML/DM

- scalability
- efficiency

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