PLOW: Probabilistic Logic Over the Well-Founded Semantics

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Poster and Demo presentation (20 minutes) at the AAAI 2019 Spring Symposium on Combining Machine Learning and Knowledge Engineering (AAAI-MAKE)

March 26, 2019

Stanford, California, USA

Acknowledgements and Thanks: This presentation includes, in part, work done by the authors while at Coherent Knowledge and at Kyndi, Inc. It includes, in part, material originally co-authored by: Michael Kifer, Janine Bloomfield, and Paul Fodor.

Version of
March 25, 2019

Overview of Talk

- Goal: Provide an approach for uncertainty in KRR, to be used in combining logical KRR with ML, that has a better balance of expressiveness and computational scalability.
- Contribution: theory and implementation, as extended form of logic programming
  - Fuzzy (t-norms), in addition to Bayesian
- Simple examples, and brief demo
- How influenced by others' work at the Symposium:
  - Applications / use cases
  - Design patterns for adding KRR to ML

Motivation and Background

- Probabilistic logic KRR is a fundamental bridge between ML and KE
- Declarative logic programs (LP) is the central KR of IT
  - DBs: Relational DBs (SQL). Knowledge graphs, a.k.a. graph DBs (SPARQL).
  - Ontologies: OWL-RL, RDF-S.
  - Rules: Prolog; RIF; Production rules, Event-Condition-Action rules.
- LP's non-classical logic – invented by/for computer science not math
  - Humble spirit: avoid reasoning-by-cases/disjunction; avoid proof-by-contradiction; stay grounded
  - Well-founded semantics: 3 truth values, benefits for scalability & robustness
- Rulelog – extended LP with high expressiveness + scalability
  - Defeasibility, higher-order syntax, object-oriented (frame) syntax, quantified classical-like formulas, restraint bounded rationality, provenance; poly-time!
  - But lacks kind of quantitative uncertainty needed to reason productively and efficiently using results from a wide variety of ML approaches
- Distribution semantics – extended LP with Bayesian-flavor probability
  - But lacks good scalability, due to reintroducing head disjunction

Why Need Scalability of the Uncertain KRR for Combining ML and KE

- Inner loop of ML
- KB dev edit-test cycle
- Large KGs/KBs

Presenters' Background

- Kyndi: AI startup combining ML+KRR+NLP; venture-backed
  - Specialized search & question-answering, via advanced knowledge graphs
  - Customers in national intelligence, pharma, other domains

- Benjamin Grosof – Chief Scientist at Kyndi. Previously:
  - Founding CTO/CEO of Coherent Knowledge, AI startup on Rulelog KRR engine
  - Led advanced research portion of Allen Institute for AI's predecessor (Vulcan)
  - MIT Sloan IT professor, DARPA PI, IBM Research projects lead, Accenture exec
  - Co-invented many advances in LP/Rulelog

- Theresa Swift – scientist at Kyndi
  - Also researcher/engineer at US Customs & Border Patrol
  - Lead implementer of XSB
  - Co-founder of Coherent Knowledge
  - Co-invented many advances in LP/Rulelog

Probabilistic LP – Expressive Extension of LP

- Numerical truth values for atoms (and rules) range on real interval [0..1]
- *head* formula can be: \or of disjoint atoms/literals whose weights add to 1
  - friendly(?x)~0.8 \or unfriendly(?x)~0.2 :- student(?x).
- Two major <u>flavors</u> of numerical uncertainty
  1. Bayesian flavor cf. "distribution semantics" [Sato]
     - Superset of Bayesian Networks, expressively
     - General case is computationally intractable, even for function-free
  2. <u>Generalized</u> "<u>triangular norms</u>" (t-norms), a.k.a. fuzzy flavor.
     - Parametrized by choice of the t-norm function F.
     - pr(A \and B) = F(pr(A),pr(B)). I.e., "truth-functional" – key to scalability.
     - E.g., F = *min*. Co-norm for \or: e.g., *max* . Same F is applied to every A,B.
     - Polynomial time for function-free
     - Generalization: F=MinMax, a function on <u>intervals</u>, where the interval is <u>cautious</u> in regard to the potential <u>correlation</u> of A and B.

Bayesian PLP Reasoning: Example

heads(Coin)~0.5 \or tails(Coin)~0.5   :- toss(Coin) \and fair(Coin).

heads(Coin)~0.6 \or tails(Coin)~0.4   :- toss(Coin) \and biased(Coin).

fair(Coin)~0.9 \or biased(Coin)~0.1.

toss(coin).

- Conclude: heads(Coin)~0.51 .

T-Norms

- Full Bayesian reasoning is powerful but (computationally) expensive.

- Epistemically, Bayesian probabilities may not be a good way to represent similarity and relevancy distances. We say, more generally: "measures".

- Hence, T-Norms (Triangular Norms, a generalization of Fuzzy Logic)
  - Godel (i.e., "Min" for conjunction): the measure of A *op* B expresses perfect correlation (+1) of A and B
  - Lukasiewicz: the measure of A *op* B expresses negative correlation (-1) of A and B
  - Product: the measure of A *op* B expresses independence (correlation 0) of A and B
  - "MinMax" (new!): generalizes the measure to an interval [Lukasiewicz, Godel] expressing an interval of truth, cautious in regard to how much correlation of A and B.

PLOW System for Probabilistic LP

- The first to implement the generalized t-norm flavor
- Bayesian flavor (a.k.a. distribution semantics), too
- Lattice flavor qualitative uncertainty, too
- Supports \neg (strong negation)
- Utilizes *undefined* truth value, as do normal LP and Rulelog
- A way to combine deductive reasoning with ML facts and rules
  - E.g., in knowledge graphs
- Implementation extends XSB, and is open source.
  - The PLPs are transformed into normal LP
  - BDDs (Binary Decision Diagrams) are used to collate information from different deduction paths
- In-progress: Aim to integrate tightly with as many Rulelog features as possible. Starting with defeasibility and restraint. Already reusing some of Rulelog's algorithms, theory, implementation!
  - Also in progress: support for running as extension of SWI Prolog, too.

All 3 flavors under 1 roof; mix-and-match.

PLOW Uses

- Similarity relations – e.g., two documents may be more or less related

- Vague properties – e.g., a certain person may be more or less ”tall”

- Relevancy relations – e.g., a document may be more or less relevant to a query

- Confidence measures – e.g., a document may come from a more or less trusted source

- Lower complexity probability measures – such as “evidential” probabilities

Strong Negation in PLOW

- Notation:
  naf(q) denotes default negation of q. (“not believe” q)
  neg(q) denotes strong (a.k.a. explicit) negation of q. (“believe opposite” of q)
- Simple example:

p~0.4.

p~0.5.

p :- undefined.

neg(p)~0.2.

In this case, p~M is

t if M <= 0.5

u if 0.5 < M < 0.8

f if 0.8 < M <= 1

One can view there as being 3 zones (or bands) of measures having the 3 truth values: a zone for (or where) t, a zone for u, a zone for f.

PLOW Paraconsistent/Defeasibility Semantics

- Semantics is an extension of Well-Founded Semantics with Explicit Negation to include quantitative values
  - Uses the coherence principle: strong (i.e., explicit) negation implies default negation.
- Paraconsistent values are mapped to u. This is a kind of defeasible conflict handling.
- Thus, given the assertions:
  - p~0.6
  - neg(p)~0.6
- Then conclude that:

p~M is:

- t for M < 0.4
- u for 0.4 <= M <= 0.6
- f for 0.6 < M <= 1

neg(p)~M is:

t for M < 0.4

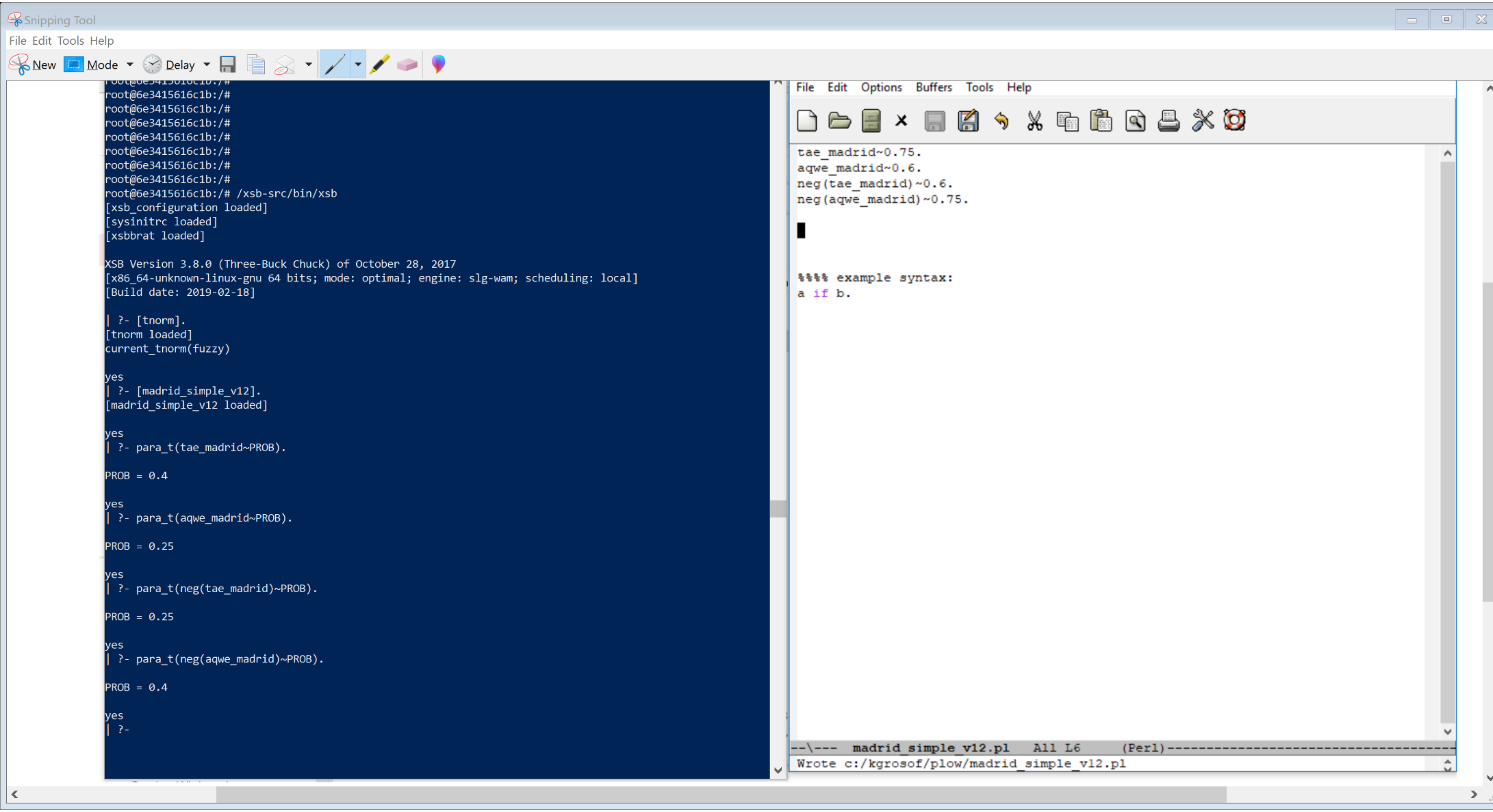
u for 0.4 <= M <= 0.5

f for 0.6 < M <= 1

BRIEF DEMO GOES HERE

The next few slides are screenshots

Overall Demo – XSB/PLOW command line; and KB editor (in Emacs)



Example KB (zoomed)

```
tae_madrid~0.75.
aqwe_madrid~0.6.
neg(tae_madrid)~0.6.
neg(aqwe_madrid)~0.75.
```

Start XSB, PLOW; load example KB

```
root@6e3415616c1b:/# /xsb-src/bin/xsb
[xsb_configuration loaded]
[sysinitrc loaded]
[xsbbrat loaded]

XSB Version 3.8.0 (Three-Buck Chuck) of October 28, 2017
[x86_64-unknown-linux-gnu 64 bits; mode: optimal; engine: slg-wam; scheduling: local]
[Build date: 2019-02-18]

| ?- [tnorm].
[tnorm loaded]
current_tnorm(fuzzy)

yes
| ?- [madrid_simple_v12].
[madrid_simple_v12 loaded]

yes
```

Query the example KB, in PLOW

```
| ?- para_t(aqwe_madrid~PROB).

PROB = 0.25

yes
| ?- para_t(neg(tae_madrid)~PROB).

PROB = 0.25

yes
| ?- para_t(neg(aqwe_madrid)~PROB).

PROB = 0.4

yes
| ?-
```

Conclusions: Contributions

- Multiple flavors of uncertainty for logic programs, all under one roof
  - Bayesian, i.e., distribution semantics. Both general and restricted.
  - Fuzzy, i.e., t-norms. Highly scalable.
  - Lattice, i.e., qualitative
  - Implementation as extension (package) of XSB, inheriting many good features
- Interval t-norm: MinMax
  - With interpretation of bounds on correlation
- Leverages undefined truth value, and supports unstratified NAF
- Supports strong negation (\neg), with basic defeasibility
- Supports well: logical functions, in combination with uncertainty
  - Well-defined: Finite number of finite models, unlike other probabilistic LP approaches. Ensured by restraint + call subsumption (features of XSB).
  - Positioned well to combine with the higher-order syntax (HiLog) feature of Rulelog, useful to represent advanced defeasibility, causality, natural language

Current and Future Directions

- KRR end:
  - Relate MinMax t-norm to approximation of distribution semantics
  - More on defeasibility including prioritization, argumentation meta-rules
  - Explore and roadmap integration with more/rest of Rulelog features
  - Address idempotence issues for product and Lukasiewicz t-norms. Ideas:
    - Path independence cf. IND. Compilation cf. BDDs/circuits. Human-authored control.
  - Converge syntax with LPAD cf. PITA

- ML end:
  - Pursue relationships to important specific ML techniques. Including for:
    - Distribution semantics. E.g., cplint, Problog, PRISM.
    - Neural network deep learning. E.g., via t-norms.
  - Apply to constructing knowledge graphs from NL + structured info
    - As at Kyndi. E.g., in entity tagging.

For More Info

- Rulelog detailed tutorial (3 hours) at KR-2018 conference (Oct. 2018):
  - At: http://benjamingrosof.com/misc-publications/#KR2018RulelogTutorial
  - It links to:
  - http://benjamingrosof.com/wp-content/uploads/2018/11/talk-kr2018-rulelog-tutorial-slides-2.pdf
- Invited talk on: why and how to add KRR to ML (July 2018)
  - At: http://benjamingrosof.com/misc-publications

Thank You