

Probabilistic Logics

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Outline

- Logic
- Logic programming
- Description Logics
- Probabilistic logic programming
- Reasoning with PLP
- Probabilistic Description Logics
- Reasoning with PDL



- Useful to model domains with complex relationships among entities
- Various forms:
 - First Order Logic
 - Logic Programming
 - Description Logics



First Order Logic

- Very expressive
- Open World Assumption
- Undecidable

$$\forall x \textit{ Intelligent}(x) \rightarrow \textit{ GoodMarks}(x)$$

$$\forall x, y \textit{ Friends}(x, y) \rightarrow (\textit{ Intelligent}(x) \leftrightarrow \textit{ Intelligent}(y))$$



- Closed World Assumption
- Turing complete
- Prolog

```
flu(bob).  
hay_fever(bob).  
sneezing(X) ← flu(X).  
sneezing(X) ← hay_fever(X).
```



Description Logics

- Subsets of First Order Logic
- Open World Assumption
- Decidable, efficient inference
- Special syntax using concepts (unary predicates) and roles (binary predicates)

fluffy : *Cat*

tom : *Cat*

Cat \sqsubseteq *Pet*

\exists *hasAnimal*.*Pet* \sqsubseteq *NatureLover*

(*kevin*, *fluffy*) : *hasAnimal*

(*kevin*, *tom*) : *hasAnimal*



- A subset of FOL + inductive definitions [Denecker, Vennekens KR14]
- A subset of FOL + Closed World Assumption (CWA)
- Transitive closure:

path(X, X).

path(X, Y) \leftarrow *edge*(X, Z), *path*(Z, Y).

edge(a, b).

edge(b, c).

edge(a, c).



Semantics of Logic Programming

- Positive programs: Least Herbrand Model
- Normal programs (including negation)

$$\begin{aligned} \text{ends}(X, Y) &\leftarrow \text{path}(X, Y), \sim \text{source}(Y). \\ \text{source}(X) &\leftarrow \text{edge}(X, Y). \end{aligned}$$

$\text{ends}(X, Y)$ is true if there is a path from X to Y and Y is a terminal node, i.e., it has no outgoing edges.

- Clark's completion (Prolog)
- Stable models (Answer Set Programming)
- Well founded (Prolog+Tabling)



Description Logics

- Special syntax using concepts (unary predicates) and roles (binary predicates)
- Translation into FOL

$$\begin{aligned}\pi_x(A) &= A(x) \\ \pi_x(\neg C) &= \neg\pi_x(C) \\ \pi_x(\{a\}) &= (x = a) \\ \pi_x(C \sqcap D) &= \pi_x(C) \wedge \pi_x(D) \\ \pi_x(C \sqcup D) &= \pi_x(C) \vee \pi_x(D) \\ \pi_x(\exists R.C) &= \exists y R(x, y) \wedge \pi_y(C) \\ \pi_x(\forall R.C) &= \forall y R(x, y) \rightarrow \pi_y(C)\end{aligned}$$

and π_y is obtained from π_x by replacing x with y and vice-versa.

Axiom	Translation
$C \sqsubseteq D$	$\forall x \pi_x(C) \rightarrow \pi_x(D)$
$a : C$	$C(a)$
$(a, b) : R$	$R(a, b)$

fluffy : *Cat*
tom : *Cat*
Cat \sqsubseteq *Pet*
 \exists *hasAnimal.Pet* \sqsubseteq *NatureLover*
(kevin, fluffy) : *hasAnimal*
(kevin, tom) : *hasAnimal*

cat(fluffy).
cat(tom).
 $\forall X \text{ pet}(X) \leftarrow \text{cat}(X)$.
 $\forall X, Y \text{ natureLover}(X) \leftarrow \text{hasAnimal}(X, Y), \text{pet}(Y)$.
hasAnimal(kevin, fluffy).
hasAnimal(kevin, tom).



Description Logics

- $KB = \langle ABox, TBox, RBox \rangle$

princeJohn : Tyrant

nottinghamSheriff : Tyrant

Tyrant \sqsubseteq *RichPerson*

\exists *hasStolenFrom*.*RichPerson* \sqsubseteq *GoodThief*

GoodThief \sqsubseteq \exists *hasGivenTo*.*Needy* $\forall X$ *GoodThief*(X) \rightarrow $\exists Y$ *hasGivenTo*(X, Y), *Needy*(Y)

(*robinHood*, *princeJohn*) : *hasStolenFrom*

(*robinHood*, *nottinghamSheriff*) : *hasStolenFrom*

hasGifted \sqsubseteq *hasGivenTo*

existential
quantification
in consequent



Combining Logic and Probability

- Logic does not handle well uncertainty
- Probability Theory/Graphical models do not handle well relationships among entities
- Solution: combine the two
- Many approaches proposed in the areas of Logic Programming, Uncertainty in AI, Machine Learning, Databases, Knowledge Representation



Probabilistic Logic Programming

- **Distribution Semantics [Sato ICLP95]**
- A probabilistic logic program defines a probability distribution over normal logic programs (called **instances** or **possible worlds** or simply **worlds**)
- The distribution is extended to a joint distribution over worlds and interpretations (or queries)
- The probability of a query is obtained from this distribution



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Probabilistic Logic Programming (PLP) Languages under the Distribution Semantics

- Probabilistic Logic Programs [Dantsin RCLP91]
- Probabilistic Horn Abduction [Poole NGC93], Independent Choice Logic (ICL) [Poole AI97]
- PRISM [Sato ICLP95]
- Logic Programs with Annotated Disjunctions (LPADs) [Vennekens et al. ICLP04]
- ProbLog [De Raedt et al. IJCAI07]
- They differ in the way they define the distribution over logic programs



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- <http://cplint.eu>
 - Inference (knowledge compilation, Monte Carlo)
 - Parameter learning (EMBLEM)
 - Structure learning (SLIPCOVER, LEMUR)
- <https://dtai.cs.kuleuven.be/problog/>
 - Inference (knowledge compilation, Monte Carlo)
 - Parameter learning (LFI-ProbLog)



Logic Programs with Annotated Disjunctions

```
sneezing(X) : 0.7 ; null : 0.3 ← flu(X).  
sneezing(X) : 0.8 ; null : 0.2 ← hay_fever(X).  
flu(bob).  
hay_fever(bob).
```

- Distributions over the head of rules
- Worlds obtained by selecting one atom from the head of every grounding of each clause



```
sneezing(X) ← flu(X), flu_sneezing(X).  
sneezing(X) ← hay_fever(X), hay_fever_sneezing(X).  
flu(bob).  
hay_fever(bob).  
0.7 :: flu_sneezing(X).  
0.8 :: hay_fever_sneezing(X).
```

- Distributions over facts
- Worlds obtained by selecting or not every grounding of each probabilistic fact



Distribution Semantics

- Case of no function symbols: finite Herbrand universe, finite set of groundings of each clause
- **Atomic choice**: selection of the i -th atom for grounding $C\theta$ of clause C
 - represented with the triple (C, θ, i)
 - a ProbLog fact $p :: F$ is interpreted as $F : p \vee \text{null} : 1 - p$.
- Example $C_1 = \text{sneezing}(X) : 0.7 \vee \text{null} : 0.3 \leftarrow \text{flu}(X).$, $(C_1, \{X/\text{bob}\}, 1)$
- **Composite choice** κ : consistent set of atomic choices
- The probability of composite choice κ is

$$P(\kappa) = \prod_{(C_i, \theta, k) \in \kappa} \Pi_{i,k}$$



- **Selection** σ : a total composite choice (one atomic choice for every grounding of each clause)
- A selection σ identifies a logic program w_σ called **world**
- The probability of w_σ is $P(w_\sigma) = P(\sigma) = \prod_{(C_i, \theta, k) \in \sigma} \Pi_{i,k}$
- Finite set of worlds: $W_T = \{w_1, \dots, w_m\}$
- $P(w)$ distribution over worlds: $\sum_{w \in W_T} P(w) = 1$



- Ground query Q
- $P(Q|w) = 1$ if Q is true in w and 0 otherwise
- $P(Q) = \sum_w P(Q, w) = \sum_w P(Q|w)P(w) = \sum_{w \models Q} P(w)$



Example Program (LPAD) Worlds

http://cplint.eu/e/sneezing_simple.pl

sneezing(bob) ← *flu(bob)*.
sneezing(bob) ← *hay_fever(bob)*.
flu(bob).
hay_fever(bob).
 $P(w_1) = 0.7 \times 0.8$

sneezing(bob) ← *flu(bob)*.
null ← *hay_fever(bob)*.
flu(bob).
hay_fever(bob).
 $P(w_3) = 0.7 \times 0.2$

null ← *flu(bob)*.
sneezing(bob) ← *hay_fever(bob)*.
flu(bob).
hay_fever(bob).
 $P(w_2) = 0.3 \times 0.8$

null ← *flu(bob)*.
null ← *hay_fever(bob)*.
flu(bob).
hay_fever(bob).
 $P(w_4) = 0.3 \times 0.2$

$$P(Q) = \sum_{w \in W_{\mathcal{T}}} P(Q, w) = \sum_{w \in W_{\mathcal{T}}} P(Q|w)P(w) = \sum_{w \in W_{\mathcal{T}}: w \models Q} P(w)$$

- *sneezing(bob)* is true in 3 worlds
- $P(\textit{sneezing}(\textit{bob})) = 0.7 \times 0.8 + 0.3 \times 0.8 + 0.7 \times 0.2 = 0.94$



Example Program (ProbLog) Worlds

http://cplint.eu/e/sneezing_simple_pb.pl

- 4 worlds

```
sneezing(X) ← flu(X), flu_sneezing(X).  
sneezing(X) ← hay_fever(X), hay_fever_sneezing(X).  
flu(bob).  
hay_fever(bob).  
  
flu_sneezing(bob).  
hay_fever_sneezing(bob).  
P(w1) = 0.7 × 0.8  
flu_sneezing(bob).  
P(w3) = 0.7 × 0.2  
  
hay_fever_sneezing(bob).  
P(w2) = 0.3 × 0.8  
  
P(w4) = 0.3 × 0.2
```

- $sneezing(bob)$ is true in 3 worlds
- $P(sneezing(bob)) = 0.7 \times 0.8 + 0.3 \times 0.8 + 0.7 \times 0.2 = 0.94$



Logic Programs with Annotated Disjunctions

<http://cplint.eu/e/sneezing.pl>

```
strong_sneezing(X) : 0.3  $\vee$  moderate_sneezing(X) : 0.5  $\leftarrow$  flu(X).  
strong_sneezing(X) : 0.2  $\vee$  moderate_sneezing(X) : 0.6  $\leftarrow$  hay_fever(X).  
flu(bob).  
hay_fever(bob).
```

- 9 worlds
- $P(\textit{strong_sneezing}(\textit{bob})) = 0.3 \times 0.2 + 0.3 \times 0.6 + 0.3 \times 0.2 + 0.5 \times 0.2 + 0.2 \times 0.2 = 0.44$



- All languages under the distribution semantics have the same expressive power
- LPADs have the most general syntax
- There are transformations that can convert each one into the others



- Inference: we want to compute the probability of a query given the model and, possibly, some evidence
- Weight learning: we know the structural part of the model (the logic formulas) but not the numeric part (the weights) and we want to infer the weights from data
- Structure learning we want to infer both the structure and the weights of the model from data



Inference for PLP under DS

- Computing the probability of a query (no evidence)
- Knowledge compilation:
 - compile the program to an intermediate representation
 - Binary Decision Diagrams (BDD) (ProbLog [De Raedt et al. IJCAI07], cplint [Riguzzi AIIA07,Riguzzi LJIGPL09], PITA [Riguzzi & Swift ICLP10])
 - deterministic, Decomposable Negation Normal Form circuit (d-DNNF) (ProbLog2 [Fierens et al. TPLP15])
 - Sentential Decision Diagrams (ProbLog2 [Fierens et al. TPLP15])
 - compute the probability by weighted model counting



Knowledge Compilation

- Assign Boolean random variables to the probabilistic rules
- Given a query Q , compute its **explanations**, assignments to the random variables that are sufficient for entailing the query
- Let K be the set of all possible explanations
- Build a Boolean formula $F(Q)$
- Transform it into an intermediate representation: BDD, d-DNNF, SDD
- Perform **Weighted Model Counting (WMC)**



Examples

Throwing coins <http://cplint.eu/e/coin.swinb>

```
heads(Coin):1/2 ; tails(Coin):1/2 :-  
  toss(Coin),\+biased(Coin).
```

```
heads(Coin):0.6 ; tails(Coin):0.4 :-  
  toss(Coin),biased(Coin).
```

```
fair(Coin):0.9 ; biased(Coin):0.1.  
toss(coin).
```



Examples

Mendel's inheritance rules for pea plants <http://cplint.eu/e/mendel.pl>

```
color(X,purple):-cg(X,_A,p).
color(X,white):-cg(X,1,w),cg(X,2,w).
cg(X,1,A):0.5 ; cg(X,1,B):0.5 :-
    mother(Y,X),cg(Y,1,A),cg(Y,2,B).
cg(X,2,A):0.5 ; cg(X,2,B):0.5 :-
    father(Y,X),cg(Y,1,A),cg(Y,2,B).
```

Probability of paths <http://cplint.eu/e/path.swinb>

```
path(X,X).
path(X,Y):-path(X,Z),edge(Z,Y).
edge(a,b):0.3.
edge(b,c):0.2.
edge(a,c):0.6.
```



Applications

- Link prediction: given a (social) network, compute the probability of the existence of a link between two entities (UWCSE)

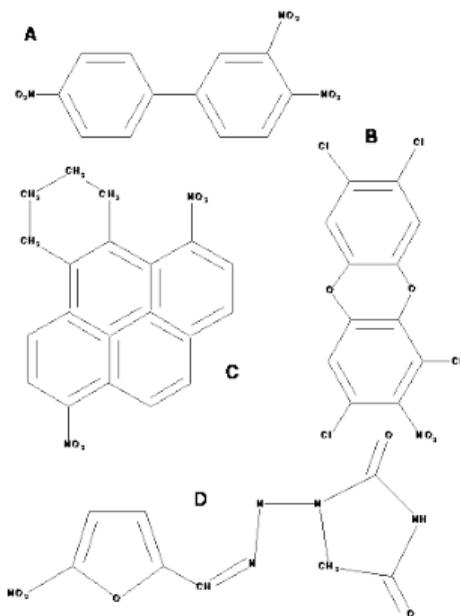


```
advisedby(X, Y) :0.7 :-  
  publication(P, X),  
  publication(P, Y),  
  student(X).
```



Applications

- Chemistry: given the chemical composition of a substance, predict its mutagenicity or its carcinogenicity



```
active(A):0.4 :-  
  atm(A,B,c,29,C),  
  gteq(C,-0.003),  
  ring_size_5(A,D).
```

```
active(A):0.6 :-  
  lumo(A,B), lteq(B,-2.072).
```

```
active(A):0.3 :-  
  bond(A,B,C,2),  
  bond(A,C,D,1),  
  ring_size_5(A,E).
```

```
active(A):0.7 :-  
  carbon_6_ring(A,B).
```

```
active(A):0.8 :-  
  anthracene(A,B).
```

DISPONTE: DIstribution Semantics for Probabilistic ONTologiEs

- Idea: **annotate axioms of an ontology with a probability**, under the assumption that the axioms are independent of each other

$$0.6 :: \text{Cat} \sqsubseteq \text{Pet}$$

- The probability value specifies a degree of belief in the truth of the corresponding axiom.
- DISPONTE applies the distribution semantics of probabilistic logic programming to description logics
- A probabilistic ontology defines thus a distribution over theories (worlds) obtained by including an axiom in a world with the probability given by the annotation



- World w : regular DL KB obtained by selecting or not the probabilistic axioms
- Probability of Q $P(Q) = \sum_w P(Q, w) = \sum_w P(Q|w)P(w) = \sum_{w:w \models Q} P(w)$
 - Probability of a query Q given a world w : $P(Q|w) = 1$ if $w \models Q$, 0 otherwise



Example

- $fluffy$ and Tom are $Cats$ and $Cats$ are $Pets$. Everyone who has a pet animal ($\exists hasAnimal.Pet$) is a $NatureLover$; $donVito$ has two animals, $fluffy$ and tom with probability 0.4 and 0.9 respectively. $NatureLovers$ are $GoodPersons$ with probability 0.2. http://trill-sw.eu/p/don_vito.pl

$fluffy : Cat$

$tom : Cat$

$Cat \sqsubseteq Pet$

$\exists hasAnimal.Pet \sqsubseteq NatureLover$

0.4 :: $(donVito, fluffy) : hasAnimal$ (1)

0.9 :: $(donVito, tom) : hasAnimal$ (2)

0.2 :: $NatureLover \sqsubseteq GoodPerson$ (3)

- $Q = donVito : GoodPerson$, 8 worlds (Q true in 3 of them):

$\{ (1), (3) \}, \{ (2), (3) \}, \{ (1), (2), (3) \}$

$$\text{and } P(Q) = 0.4 \times (1 - 0.9) \times 0.2 + (1 - 0.4) \times 0.9 \times 0.2 \\ + 0.4 \times 0.9 \times 0.2 = 0.188$$



- The probability of a query Q can be computed first finding the explanation or Q in the knowledge base
 - An **explanation** of query Q is a subset of logical axioms of a KB sufficient to entail Q .
- **Problem: In general, justifications are not mutually exclusive!**
 - Encode the justifications into a DNF Boolean formula and use a Binary Decision Diagram (BDD) to make the disjuncts mutually exclusive.



Example of DISPONTE Explanations

The Godfather KB

$C_1 = \text{fluffy} : \text{Cat}$

$C_2 = \text{tom} : \text{Cat}$

$C_3 = \text{Cat} \sqsubseteq \text{Pet}$

$C_4 = \exists \text{hasAnimal.Pet} \sqsubseteq \text{NatureLover}$

$E_1 = 0.4 :: (\text{donVito}, \text{fluffy}) : \text{hasAnimal}$

$E_2 = 0.9 :: (\text{donVito}, \text{tom}) : \text{hasAnimal}$

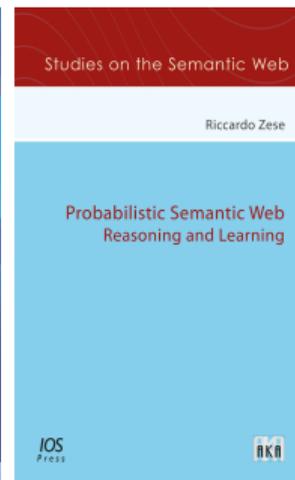
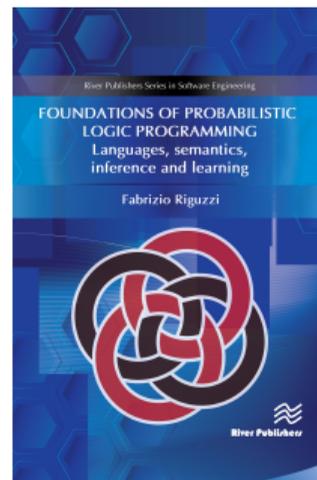
$E_3 = 0.2 :: \text{NatureLover} \sqsubseteq \text{GoodPerson}$

If we forget about the probabilities, the query $Q = \text{donVito} : \text{GoodPerson}$ has 2 justifications

$$\mathcal{J} = \{ \{E_1, C_1, C_3, C_4, E_3\}, \{E_2, C_2, C_3, C_4, E_3\} \}$$

Conclusions

- Logics
- Probabilistic Logics
- Inference
- Open problems
 - Programs with continuous variables
 - Combining Deep Learning with PILP





**THANKS FOR
LISTENING
AND
ANY
QUESTIONS ?**

