Intelligent Systems (AI-2)

Computer Science cpsc422, Lecture 29

Nov, 20, 2017

Slide source: from Pedro Domingos UW

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422 big picture: Where are we?

StarAI (statistical relational AI)

Hybrid: Det +Sto Prob CFG Prob Relational Models Markov Logics

	Deterministic	Stochastic	Markov Lo	DgICS
Query	Logics First Order Logics Ontologies	Belief NetsApprox. : GibbsMarkov Chains and HIForward, Viterbi···.Approx. : Particle Filt	MMs ering	
-	Full ResolutionSAT	Undirected Graphical M Markov Networks Conditional Random F	lodels Fields	
Plannin	g	Markov Decision Proce Partially Observable Ma • Value Iteration	esses and DP	
		Approx. Inferent <i>Reinforcement Learn</i>	nce hing	Representation
	Applications of AI			Reasoning Technique

Lecture Overview

- Statistical Relational Models (for us aka Hybrid)
- Recap Markov Networks and log-linear models
- Markov Logic



Statistical Relational Models

Goals:

- Combine (subsets of) logic and probability into a single language (R&R system)
- Develop efficient inference algorithms
- Develop efficient learning algorithms
- Apply to real-world problems

L. Getoor & B. Taskar (eds.), *Introduction to Statistical Relational Learning,* MIT Press, 2007.

Plethora of Approaches



- Knowledge-based model construction [Wellman et al., 1992]
- Stochastic logic programs [Muggleton, 1996]
- Probabilistic relational models
 [Friedman et al., 1999]
- Relational Markov networks [Taskar et al., 2002]
- Bayesian logic [Milch et al., 2005]
- Markov logic [Richardson & Domingos, 2006]
- And many others!

Prob. Rel. Models vs. Markov Logic

PRM - Relational Skeleton - Dependency Graph - Parameters (CPT)

-weighted logical formulas MARKOV - set of constants NETWORK

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 - Markov Logic Network (MLN)

Parameterization of Markov Networks



Factors define the local interactions (like CPTs in Bnets) What about the global model? What do you do with Bnets?

How do we combine local models?

As in BNets by multiplying them!

 $\tilde{P}(A, B, C, D) = \phi_1(A, B) \times \phi_2(B, C) \times \phi_3(C, D) \times \phi_4(A, D)$ $P(A, B, C, D) = \frac{1}{Z} \tilde{P}(A, B, C, D)$

Assignment		nt	Unnormalized	Normalized			
a^0	60	c^0	d^0	300000	.04	10 11	
a^0	b^0	c^0	d^1	300000	• 04	$\phi_4[D,A]$	$\phi_1[A, B]$
a^0	b^0	c^1	d^0	300000	.04 ,	$d^0 a^0 100$	$a^0 b^0 30$
a^0	b^0	c^1	d^1	30	41×10-6	d^0 a^1 1 (A) $a^0 b^1 5$
a^0	b^1	c^0	d^0	500	•	$d^1 a^0 1$	$\begin{pmatrix} a^1 & b^0 & 1 \\ 1 & 1 & 10 \end{pmatrix}$
a^0	b^1	c^0	d^1	500	•	a* a* 100	a- b- 10
a^0	b^1	c^1	d^0	5000000	. 69		
a^0	b^1	c^1	d^1	500	4	(\mathbf{D})	(B)
a^1	b^0	c^0	d^0	100			
a^1	b^0	c^0	d^1	1000000	•		ALIB CI
a^1	b^0	c^1	d^0	100	I		$\checkmark \qquad \qquad$
a^1	60	cl	d^1	100	•	$c^{0}_{1} d^{0}_{1} 1 (C)$	$b^0 c^0 100$
a^1	b^1	c^0	d^0	10	•	$c^{0} d^{1} 100$	$b^{0} c^{1} 1$
a^1	b^1	c^0	d^1	100000	,	c^{1} d^{1} 1	$b^{1} c^{1} 100$
a^1	b^1	c^1	d^0	100000	,		
a^1	b^1	c^1	d^1	100000	}		

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• Factors/Potential-functions defined over cliques

$$P(x) = \frac{1}{Z} \prod_{c} \Phi_{c}(x_{c})$$

$$Z = \sum_{x} \prod_{c} \Phi_{c}(x_{c})$$

Smoking	Cancer	Φ(S,C)
F	F	4.5
F	Т	4.5
Т	F	2.7
Т	Т	4.5



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Markov Logic: Intuition(1)

 A logical KB is a set of hard constraints on the set of possible worlds INDIVIDUALS-[a, b]

 $\forall x \ Smokes(x) \Rightarrow Cancer(x)$

• Let's make them **soft constraints**:
When a world violates a formula,
the world becomes less probable, not impossible
$$f f$$
 is True $P(w)$ decreases
 $F(w) = F(w) = F(w)$ becomes 15

Smokes(a)=T Cancer(a)=F Smokes(b)=F Cancer(b)=F

Markov Logic: Intuition (2)

- The more formulas in the KB a possible world satisfies the more it should be likely
- Give each formula a weight
- Adopting a log-linear model, by design, if a possible world satisfies a formula its probability should go up proportionally to exp(the formula weight).

P(world)
$$\propto \exp(\sum \text{weights of formulas it satisfies})$$

That is, if a possible world satisfies a formula its **log probability** should go up proportionally to the formula weight.

$$\log(P(world)) \propto \left(\sum weights of formulas it satisfies\right)$$



Markov Logic: Definition

- A Markov Logic Network (MLN) is
 - a set of pairs (F, w) where
 - F is a formula in first-order logic
 - w is a real number
 - Together with a set C of constants,
- It defines a Markov network with
 - One *binary node* for each **grounding** of each **predicate** in the MLN
 - One *feature/factor* for each **grounding** of each formula F in the MLN, with the corresponding weight w



Grounding: substituting vars with constants

(not required)consider Existential and functions



Table 2.2: Construction of all groundings of a first-order formula under Assumptions 2.2–2.4.

function Ground(F)input: F, a formula in first-order logic output: G_F , a set of ground formulas for each existentially quantified subformula $\exists x \ S(x)$ in F $F \leftarrow F$ with $\exists x \ S(x)$ replaced by $S(c_1) \lor S(c_2) \lor \ldots \lor S(c_{|C|})$, where $S(c_i)$ is S(x) with x replaced by c_i $G_F \leftarrow \{F\}$ for each universally quantified variable x for each formula $F_i(x)$ in G_F $G_F \leftarrow (G_F \setminus F_i(x)) \cup \{F_i(c_1), F_i(c_2), \dots, F_i(c_{|C|})\},\$ where $F_i(c_i)$ is $F_i(x)$ with x replaced by c_i for each formula $F_i \in G_F$ repeat for each function $f(a_1, a_2, ...)$ all of whose arguments are constants $F_j \leftarrow F_j$ with $f(a_1, a_2, \ldots)$ replaced by c, where $c = f(a_1, a_2, \ldots)$ until F_i contains no functions

return G_F

Smoking causes cancer.

Friends have similar smoking habits.



 $\forall x \ Smokes(x) \Rightarrow Cancer(x)$

 $\forall x, y \ Friends(x, y) \Rightarrow (Smokes(x) \Leftrightarrow Smokes(y))$



1.5
$$\forall x \ Smokes(x) \Rightarrow Cancer(x)$$

1.1
$$\forall x, y \ Friends(x, y) \Rightarrow (Smokes(x) \Leftrightarrow Smokes(y))$$



1.5 $\forall x \ Smokes(x) \Rightarrow Cancer(x)$

1.1
$$\forall x, y \ Friends(x, y) \Rightarrow (Smokes(x) \Leftrightarrow Smokes(y))$$

Two constants: Anna (A) and Bob (B)



MLN nodes

1.5 $\forall x \ Smokes(x) \Rightarrow Cancer(x)$

1.1 $\forall x, y \ Friends(x, y) \Rightarrow (Smokes(x) \Leftrightarrow Smokes(y))$

Two constants: **Anna** (A) and **Bob** (B)

 One *binary node* for each grounding of each predicate in the MLN

Grounding: substituting vars with constants



• Any nodes missing?

MLN nodes (complete)

1.5 $\forall x \ Smokes(x) \Rightarrow Cancer(x)$

1.1 $\forall x, y \ Friends(x, y) \Rightarrow (Smokes(x) \Leftrightarrow Smokes(y))$



Two constants: **Anna** (A) and **Bob** (B)

One *binary node* for each grounding of each predicate in the MLN



Friends(A,B)

MLN features



1.1 $\forall x, y \ Friends(x, y) \Rightarrow (Smokes(x) \Leftrightarrow Smokes(y))$



Two constants: **Anna** (A) and **Bob** (B)

Edge between two nodes iff the corresponding ground predicates appear together in at least one grounding of one formula



MLN features



1.1 $\forall x, y \ Friends(x, y) \Rightarrow (Smokes(x) \Leftrightarrow Smokes(y))$



Two constants: **Anna** (A) and **Bob** (B)

Edge between two nodes iff the corresponding ground predicates appear together in at least one grounding of one formula





One *feature/factor* for each **grounding** of each **formula F** in the MLN

MLN: parameters

1.5
$$\forall x \, Smokes(x) \Rightarrow Cancer(x)$$

 $f(Smokes(x), \, Cancer(x)) = \begin{cases} 1 & \text{if } Smokes(x) \Rightarrow Cancer(x) \\ 0 & \text{otherwise} \end{cases}$
 $\mathcal{P}^{V2} = \mathcal{P}^{V2} = \mathcal{$

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MLN: prob. Of possible world

• Probability of a world *pw*:



P(world) $\propto \exp(\sum \text{ weights of grounded formulas it satisfies})$

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Learning Goals for today's class

You can:

- Describe the intuitions behind the design of a Markov Logic
- Define and Build a Markov Logic Network
- Justify and apply the formula for computing the probability of a possible world

Next class on Wed Markov Logic

- -relation to FOL
- Inference (MAP and Cond. Prob)

Assignment-4 posted, due on Dec 2