# Intelligent Systems (AI-2)

#### Computer Science cpsc422, Lecture 29

Nov, 18, 2019

Slide source: from Pedro Domingos UW

### 422 big picture

StarAl (statistical relational Al)
Hybrid: Det +Sto
Prob CFG
Prob Relational Models
Markov Logics

**Deterministic** Stochastic

Logics
First Order Logics
Ontologies

- Full Resolution
- SAT

Query

**Planning** 

**Belief Nets** 

Approx. : Gibbs

Markov Chains and HMMs

Forward, Viterbi....

**Approx. : Particle Filtering** 

Undirected Graphical Models
Markov Networks
Conditional Random Fields

Markov Decision Processes and

Partially Observable MDP

- Value Iteration
- Approx. Inference

Reinforcement Learning

Applications of Al

Representation

Reasoning Technique

### Lecture Overview

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

#### **Statistical Relational Models**



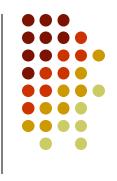
#### **Goals:**

- 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.

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## 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....!

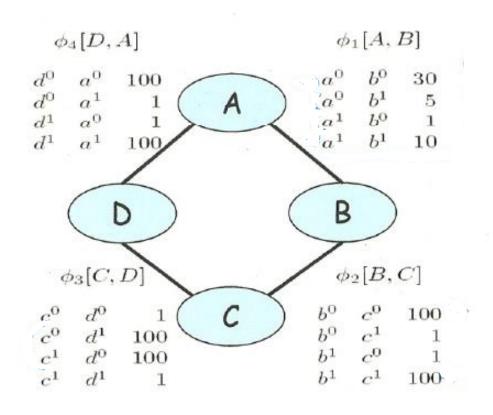
### Prob. Rel. Models vs. Markov Logic



### Lecture Overview

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

#### **Parameterization of Markov Networks**



X set of random  
Vovs: Afactor is  
$$\Phi(Val(X)) \rightarrow |P|$$

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?

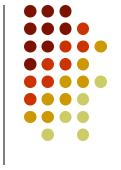
#### As in BNets by multiplying them!

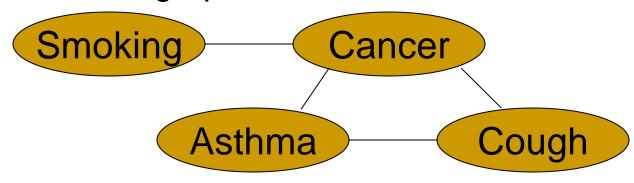
$$\tilde{P}(A, B, C, D) = \phi_1(A, B) \times \phi_2(B, C) \times \phi_3(C, D) \times \phi_4(A, D)$$
$$P(A, B, C, D) = \frac{1}{Z}\tilde{P}(A, B, C, D)$$

| Assignment |       |                | nt    | Unnormalized | Normalized |                                  |                                   |
|------------|-------|----------------|-------|--------------|------------|----------------------------------|-----------------------------------|
| $a^0$      | 60    | $c^0$          | $d^0$ | 300000       | .04        |                                  | / / DI                            |
| $a^0$      | $b^0$ | $c^0$          | $d^1$ | 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           | 4.1×10-6   | $d^0$ $a^1$ 1 ( $A$              | $a^0 b^1 = 5$                     |
| $a^0$      | $b^1$ | $c^0$          | $d^0$ | 500          | <b>'</b> • | $d^1$ $a^0$ $1$                  | $a^1 b^0 1$                       |
| $a^0$      | $b^1$ | $c^0$          | $d^1$ | 500          |            | $d^1 = a^1 = 100$                | $a^1 b^1 10$                      |
| $a^0$      | $b^1$ | $c^1$          | $d^0$ | 5000000      | . 69       |                                  |                                   |
| $a^0$      | $b^1$ | $c^1$          | $d^1$ | 500          | , ·        | ( D )                            | ( B )                             |
| $a^1$      | $b^0$ | c <sup>0</sup> | $d^0$ | 100          | <b>'</b> . |                                  |                                   |
| $a^1$      | $b^0$ | c <sup>0</sup> | $d^1$ | 1000000      | •          | 10 01                            | $\phi_2[B,C]$                     |
| $a^1$      | $b^0$ | $c^1$          | $d^0$ | 100          | •          | $\phi_3[C,D]$                    | ~                                 |
| $a^1$      | $b^0$ | c1             | $d^1$ | 100          |            | $c^{0} d^{0} = 1$ ( 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       |            | $c^1$ $d^0$ 100<br>$c^1$ $d^1$ 1 | $b^{1} c^{0}$ 1 $b^{1} c^{1}$ 100 |
| $a^1$      | $b^1$ | $c^1$          | $d^0$ | 100000       | •          |                                  |                                   |
| 125        | b1    | $c^1$          | $d^1$ | 100000       |            |                                  |                                   |
| $a^1$      | $b^1$ | $c^1$          | $d^1$ | 100000       |            |                                  |                                   |

#### **Markov Networks**

Undirected graphical models





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 | Ф(S,C) |
|---------|--------|--------|
| F       | F      | 4.5    |
| F       | Т      | 4.5    |
| Т       | F      | 2.7    |
| Т       | Т      | 4.5    |

### Markov Networks : log-linear model

Smoking

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

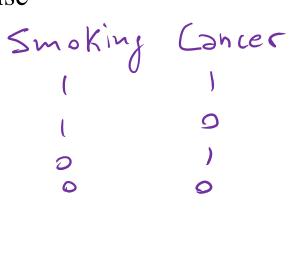
Log-linear model:

each 
$$\Phi(x_c) = e^{w_c + c(x_c)}$$

$$w_1 = 0.51$$

$$f_1(\text{Smoking, Cancer}) = \begin{cases} 1 & \text{if } \neg \text{Smoking} \lor \text{Cancer} \\ 0 & \text{otherwise} \end{cases}$$

$$P(x) = \frac{1}{Z} \exp\left(\sum_{i} w_{i} f_{i}(x_{i})\right)$$
Weight of Feature *i* Feature *i*



**Asthma** 

Cancer

Cough

### Lecture Overview

- Statistical Relational Models (for us aka Hybrid)
- Recap Markov Networks
- Markov Logic

## **Markov Logic: Intuition(1)**

 A logical KB is a set of hard constraints on the set of possible worlds \_ CONSTANT

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







## **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.

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

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## **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





Smoking causes cancer.

Friends have similar smoking habits.



```
\forall x \ Smokes(x) \Rightarrow Cancer(x)
\forall x, y \ Friends(x, y) \Rightarrow \left(Smokes(x) \Leftrightarrow Smokes(y)\right)
```



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

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



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

1.1 \forall x, y \ Friends(x, y) \Rightarrow \left(Smokes(x) \Leftrightarrow Smokes(y)\right)
```

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

#### **MLN** nodes

- 1.5  $\forall x \ Smokes(x) \Rightarrow Cancer(x)$
- 1.1  $\forall x, y \ Friends(x, y) \Rightarrow \left(Smokes(x) \Leftrightarrow Smokes(y)\right)$



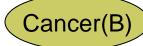
Two constants: **Anna** (A) and **Bob** (B)

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



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

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

Friends(A,B)

Friends(A,A)

Smokes(A)

Smokes(B)

Friends(B,B)

Cancer(A)

Friends(B,A)

Cancer(B)

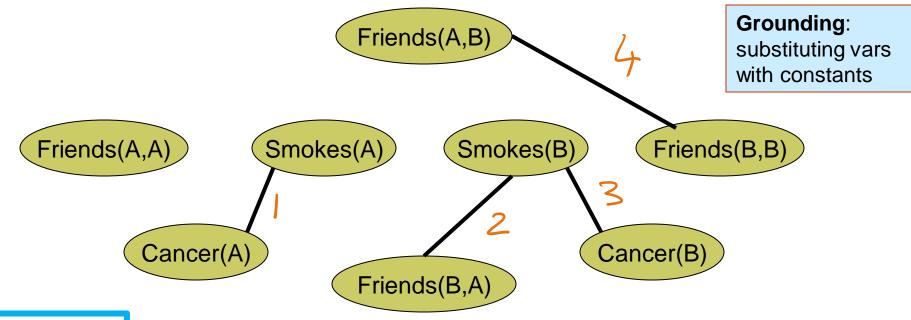
#### **MLN** features

- 1.5  $\forall x \ Smokes(x) \Rightarrow Cancer(x)$
- 1.1  $\forall x, y \ Friends(x, y) \Rightarrow \left(Smokes(x) \Leftrightarrow Smokes(y)\right)$



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



i≿licker.

Which edge should not be there?

A.1

13,2

C.3

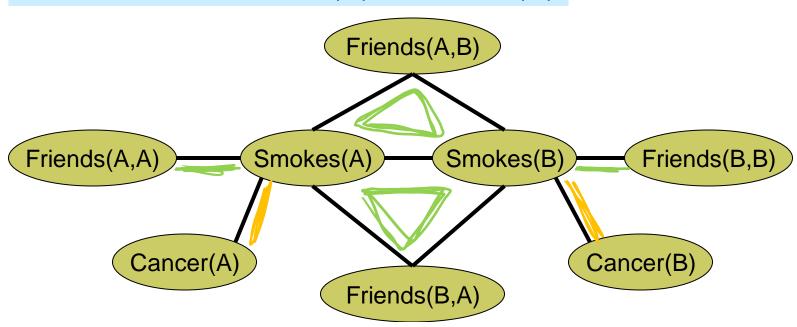
D.4

24

#### **MLN** features

- 6
- 1.5
- $\forall x \ Smokes(x) \Rightarrow Cancer(x)$
- 4
- 1.1
- $\forall x, y \ Friends(x, y) \Rightarrow \left(Smokes(x) \Leftrightarrow Smokes(y)\right)$

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



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



### **MLN**: parameters

For each formula i we have a factor

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

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

### MLN: prob. of possible world

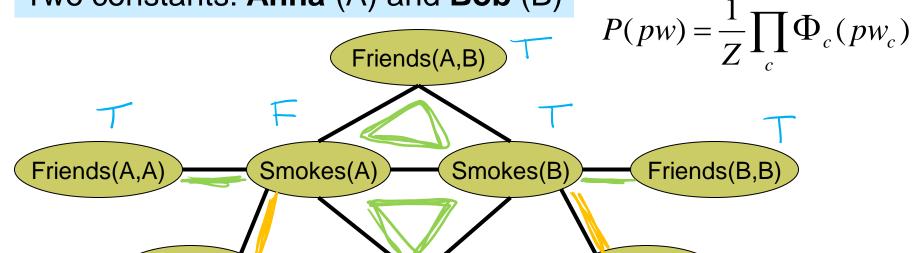
1.5  $\forall x \ Smokes(x) \Rightarrow Cancer(x)$ 

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



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

Cancer(A)



Friends(B,A)

Cancer(B)

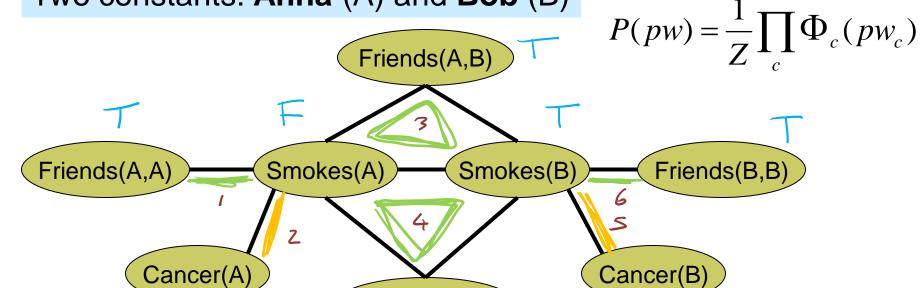
### MLN: prob. of possible world

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

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



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



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Friends(B,A)

### MLN: prob. of possible world

- **6**
- 1.5

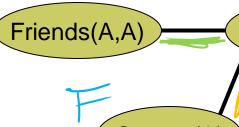
 $\forall x \ Smokes(x) \Rightarrow Cancer(x)$ 

- **(1)**
- 1.1
- $\forall x, y \ Friends(x, y) \Rightarrow (Smokes(x) \Leftrightarrow Smokes(y))$



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

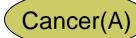




Smokes(A)

Smokes(B)

Friends(B,B)



Friends(B,A)

Cancer(B)



## MLN: prob. Of possible world

Probability of a world pw:

$$P(pw) = \frac{1}{Z} \exp \left( \sum_{i} w_{i} | n_{i}(pw) \right)$$
Weight of formula *i*
No. of true groundings of formula *i* in *pw*

Friends(A,B)

Friends(A,B)

Cancer(A)

Smokes(B)

Friends(B,B)

Cancer(B)

Friends(B,A)

$$M_2(pw) = 2$$
 $M_1(pw) = 1$ 

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

## 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 will be posted this evening, due on Nov 29