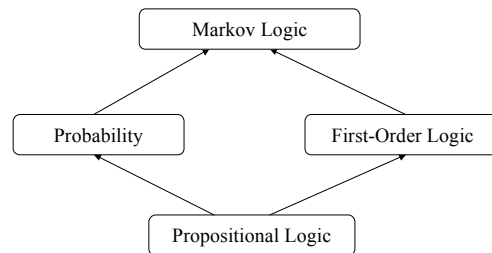


Markov Logic

Putting the Pieces Together



Markov Logic

- A logical KB is a set of **hard constraints** on the set of possible worlds
- Let's make them **soft constraints**:
When a world violates a formula,
It becomes less probable, not impossible
- Give each formula a **weight**
(Higher weight \Rightarrow Stronger constraint)

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

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 of constants, it defines a Markov network with
 - One node for each grounding of each predicate in the MLN
 - One feature for each grounding of each formula F in the MLN, with the corresponding weight w

Example: Friends & Smokers



Smoking causes cancer.
Friends have similar smoking habits.

Example: Friends & Smokers



$\forall x \text{ Smokes}(x) \Rightarrow \text{Cancer}(x)$
 $\forall x, y \text{ Friends}(x, y) \Rightarrow (\text{Smokes}(x) \Leftrightarrow \text{Smokes}(y))$

Example: Friends & Smokers



1.5 $\forall x \text{ Smokes}(x) \Rightarrow \text{Cancer}(x)$
1.1 $\forall x, y \text{ Friends}(x, y) \Rightarrow (\text{Smokes}(x) \Leftrightarrow \text{Smokes}(y))$

Example: Friends & Smokers



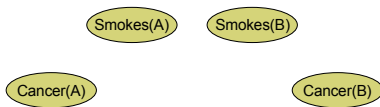
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Two constants: **Anna** (A) and **Bob** (B)

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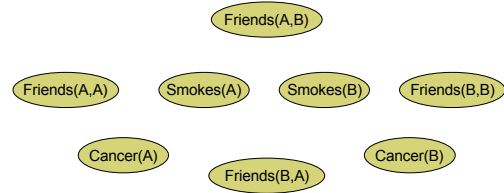
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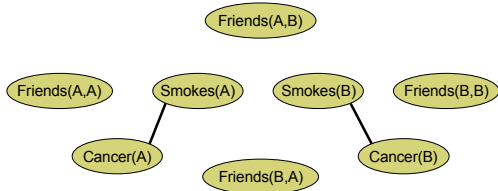
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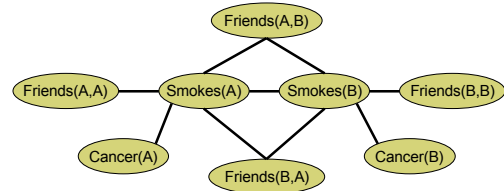
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Markov Logic Networks

- MLN is **template** for ground Markov nets
- Probability of a world x :

$$P(x) = \frac{1}{Z} \exp\left(\sum_i w_i n_i(x)\right)$$

Weight of formula i No. of true groundings of formula i in x

- **Typed** variables and constants greatly reduce size of ground Markov net
- Functions, existential quantifiers, etc.
- Open question: Infinite domains



Relation to Statistical Models

- Special cases:
 - Markov networks
 - Markov random fields
 - Bayesian networks
 - Log-linear models
 - Exponential models
 - Max. entropy models
 - Gibbs distributions
 - Boltzmann machines
 - Logistic regression
 - Hidden Markov models
 - Conditional random fields
- Obtained by making all predicates zero-arity
- Markov logic allows objects to be interdependent (non-i.i.d.)
- Discrete distributions



Relation to First-Order Logic

- Infinite weights \Rightarrow First-order logic
- Satisfiable KB, positive weights \Rightarrow Satisfying assignments = Modes of distribution
- Markov logic allows contradictions between formulas



MAP/MPE Inference

- **Problem:** Find most likely state of world given evidence

$$\max_y P(y | x)$$

Query Evidence



MAP/MPE Inference



- **Problem:** Find most likely state of world given evidence

$$\max_y \frac{1}{Z_x} \exp\left(\sum_i w_i n_i(x, y)\right)$$

MAP/MPE Inference



- **Problem:** Find most likely state of world given evidence

$$\max_y \sum_i w_i n_i(x, y)$$

MAP/MPE Inference



- **Problem:** Find most likely state of world given evidence

$$\max_y \sum_i w_i n_i(x, y)$$

- This is just the weighted MaxSAT problem
- Use weighted SAT solver (e.g., MaxWalkSAT [Kautz et al., 1997])
- Potentially faster than logical inference (!)

The MaxWalkSAT Algorithm



```
for  $i \leftarrow 1$  to  $max\_tries$  do
   $solution$  = random truth assignment
  for  $j \leftarrow 1$  to  $max\_flips$  do
    if  $\sum weights(sat. clauses) > threshold$  then
      return  $solution$ 
     $c \leftarrow$  random unsatisfied clause
    with probability  $p$ 
      flip a random variable in  $c$ 
    else
      flip variable in  $c$  that maximizes
         $\sum weights(sat. clauses)$ 
  return failure, best  $solution$  found
```

But ... Memory Explosion



- **Problem:**
If there are n constants
and the highest clause arity is c ,
the ground network requires $O(n^c)$ memory
- **Solution:**
Exploit sparseness; ground clauses lazily
→ LazySAT algorithm [Singla & Domingos, 2006]

Computing Probabilities



- $P(\text{Formula}|\text{MLN},C) = ?$
- MCMC: Sample worlds, check formula holds
- $P(\text{Formula1}|\text{Formula2},\text{MLN},C) = ?$
- If $\text{Formula2} = \text{Conjunction of ground atoms}$
 - First construct min subset of network necessary to answer query (generalization of KBMC)
 - Then apply MCMC (or other)
- Can also do lifted inference [Braz et al, 2005]

Ground Network Construction



```
network ← ∅  
queue ← query nodes  
repeat  
  node ← front(queue)  
  remove node from queue  
  add node to network  
  if node not in evidence then  
    add neighbors(node) to queue  
until queue = ∅
```

But ... Insufficient for Logic



- **Problem:**
Deterministic dependencies break MCMC
Near-deterministic ones make it **very** slow
- **Solution:**
Combine MCMC and WalkSAT
→ MC-SAT algorithm [Poon & Domingos, 2006]