Intelligent Systems (AI-2)

Computer Science cpsc422, Lecture 31

March, 31, 2021

Slide source: from Pedro Domingos UW & Markov Logic: An Interface Layer for Artificial Intelligence Pedro Domingos and Daniel Lowd University of Washington, Seattle

Lecture Overview

- **MLN Recap**
- **Markov Logic: applications**
  - **Entity resolution**
  - **Statistical Parsing!**

Markov Logic: Definition

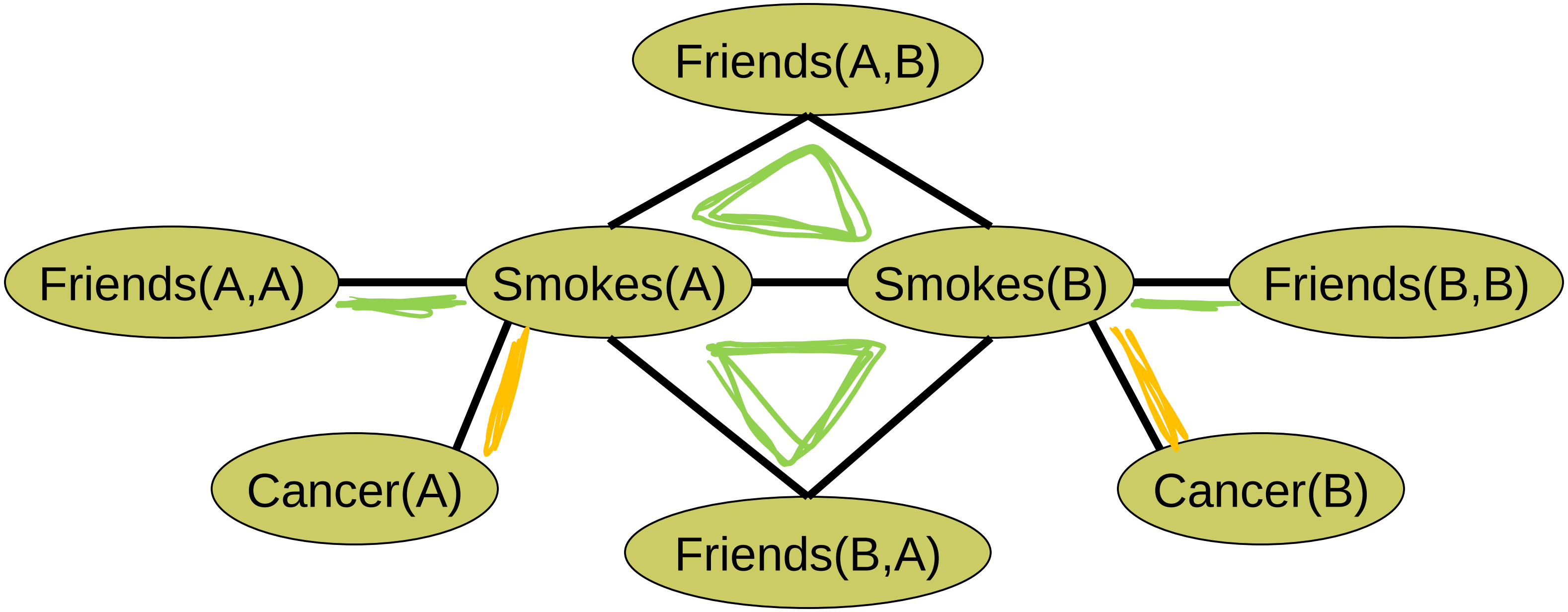
- A Markov Logic Network (MLN) is
  - a set of pairs (F, w) where
    - F is a **formula** in first-order logic
    - w is a **real number**
  - Together with a set C of **constants**,
- It defines a **Markov network** with
  - One *binary node* for each **grounding** of each **predicate** in the MLN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

Grounding: substituting vars with constants

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)



MLN: parameters

- For each grounded formula *i* we have a factor

$\Phi_i(pw) = e^{w_i f_i(pw)}$ ← possible world

w_i weight of formula

$$f_i(pw) = \begin{cases} 1 & \text{when formula is true in } pw \\ 0 & \text{otherwise} \end{cases}$$

- Same for all the groundings of the same formula

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

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

pw_1 . . . .

Smokes(A) T
Cancer(A) F $e^0 = 1$

pw_2 . . . .

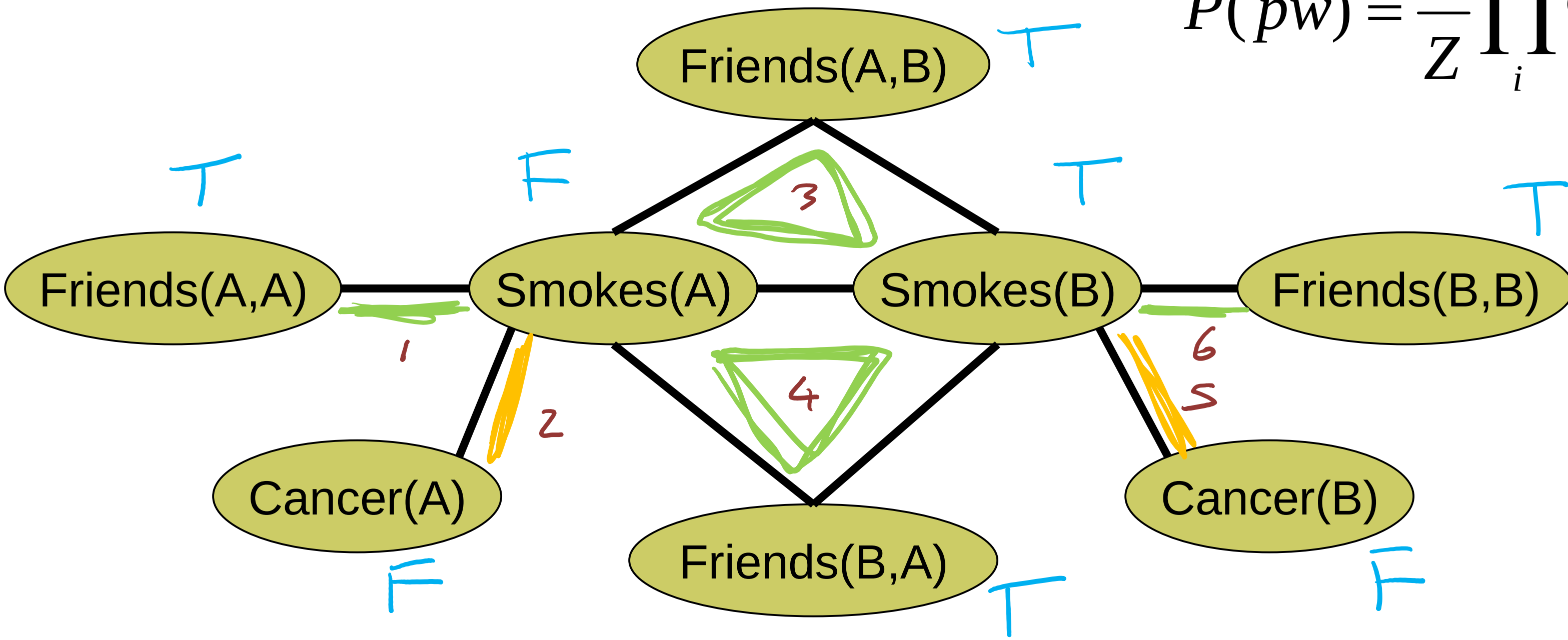
Smokes(A) T
Cancer(A) T $e^{1.5}$

MLN: prob. of possible world

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)

$$P(pw) = \frac{1}{Z}\prod_i \Phi_i(pw)$$



$$P(pw) = \left(\underset{1}{e^{1.1}} * \underset{6}{e^{1.1}} * \underset{3}{e^{0}} * \underset{4}{e^{0}} * \underset{2}{e^{1.5}} * \underset{5}{e^{0}}\right) / Z$$

MLN: prob. Of possible world

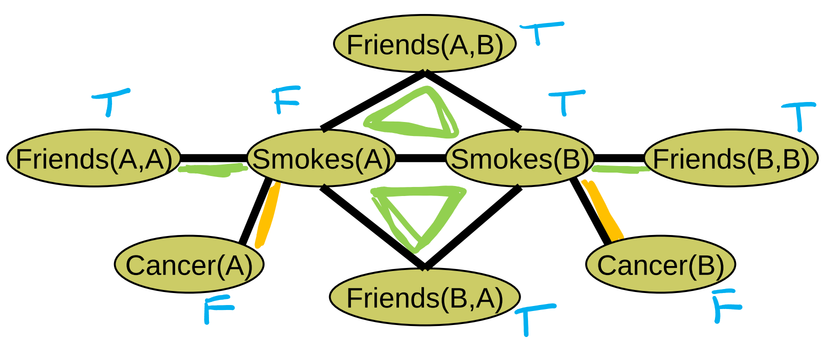
1	1.5	$\forall x\ Smokes(x) \Rightarrow Cancer(x)$
2	1.1	$\forall x, y\ Friends(x,y) \Rightarrow \left(Smokes(x) \Leftrightarrow Smokes(y)\right)$

- Probability of a world pw:

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

Weight of formula *i*

No. of true groundings of formula *i* in *pw*



$$P(pw) = \left(\underbrace{e^{1.1} * e^{1.1}}_{n_2(pw) = 2} * e^{0} * e^{0} * \underbrace{e^{1.5}}_{n_1(pw) = 1} * e^{0} \right) / Z$$

Inference in MLN

- Most likely interpretation maximizes the sum of weights of satisfied formulas (MaxWalkSAT)

$$\arg\max_{pw} \sum_i w_i n_i(pw)$$

- P(Formula) = ? (Sampling interpretations)

- P(ground literal | conjuction of ground literals)… Gibbs sampling on relevant sub-network

Lecture Overview

- Recap MLN
- Markov Logic: applications
  - Entity resolution
  - Statistical Parsing!

Entity Resolution

- Determining which observations correspond to the same real-world objects

- (e.g., database records, noun phrases, video regions, etc)

- Crucial importance in many areas

(e.g., data cleaning, NLP, Vision)

Entity Resolution: Example

SAME?

AUTHOR: *H. POON & P. DOMINGOS*
TITLE: *UNSUPERVISED SEMANTIC PARSING*
VENUE: *EMNLP-09*

SAME?

AUTHOR: *Hoifung Poon and Pedro Domings*
TITLE: *Unsupervised semantic parsing*
VENUE: *Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing*

SAME?

SAME?

AUTHOR: *Poon, Hoifung and Domings, Pedro*
TITLE: *Unsupervised ontology induction from text*
VENUE: *Proceedings of the Forty-Eighth Annual Meeting of the Association for Computational Linguistics*

SAME?

SAME?

AUTHOR: *H. Poon, P. Domings*
TITLE: *Unsupervised ontology induction*
VENUE: *ACL-10*

Entity Resolution (relations)

Problem: Given citation database, find duplicate records
Each citation has `author`, `title`, and `venue` fields
We have 10 relations

provided as evidence

```
Author(bib,author)
Title(bib,title)
Venue(bib,venue)
```

relate citations to their fields

```
HasWord(author, word)
HasWord(title, word)
HasWord(venue, word)
```

indicate which words are present in each field;

to be inferred

```
SameAuthor (author, author)
```

represent field equality;

```
SameTitle(title, title)
SameVenue(venue, venue)
```

```
SameBib(bib, bib)
```

represents citation equality;

Entity Resolution (formulas)

Predict citation equality based on words in the fields

```
Title(b1, t1) ∧ Title(b2, t2) ∧
HasWord(t1,+word) ∧ HasWord(t2,+word) ⇒
SameBib(b1, b2)
```

1000s of rules one for each word

```
(NOTE: +word is a shortcut notation, you
actually have a rule for each word e.g.,
Title(b1, t1) ∧ Title(b2, t2) ∧
HasWord(t1,"bayesian") ∧
HasWord(t2,"bayesian" ) ⇒ SameBib(b1, b2) )
```

Same 1000s of rules for author

Same 1000s of rules for venue

Entity Resolution (formulas)

Transitive closure

`SameBib(b1,b2) ∧ SameBib(b2,b3) ⇒ ???`

A. `SameBib(b1,b2)`

B. `SameBib(b1,b3)`

C. `SameAuthor(a1,a2)`

Entity Resolution (formulas)

Transitive closure

SameBib(b1,b2) ∧ SameBib(b2,b3) ⇒ SameBib(b1,b3)

SameAuthor(a1,a2) ∧ SameAuthor(a2,a3) ⇒ SameAuthor(a1,a3)

***Same rule for* title**

***Same rule for* venue**

Link fields equivalence to citation equivalence – *e.g., if two citations are the same, their authors should be the same*

Author(b1, a1) ∧ Author(b2, a2) ∧ SameBib(b1, b2) ⇒ SameAuthor(a1, a2)

…and that citations with the same author are more likely to be the same

Author(b1, a1) ∧ Author(b2, a2) ∧ SameAuthor(a1, a2) ⇒ SameBib(b1, b2)

***Same rules for* title**

***Same rules for* venue**

Benefits of MLN model

Standard non-MLN approach: build a classifier that given two citations tells you if they are the same or not, and then apply transitive closure

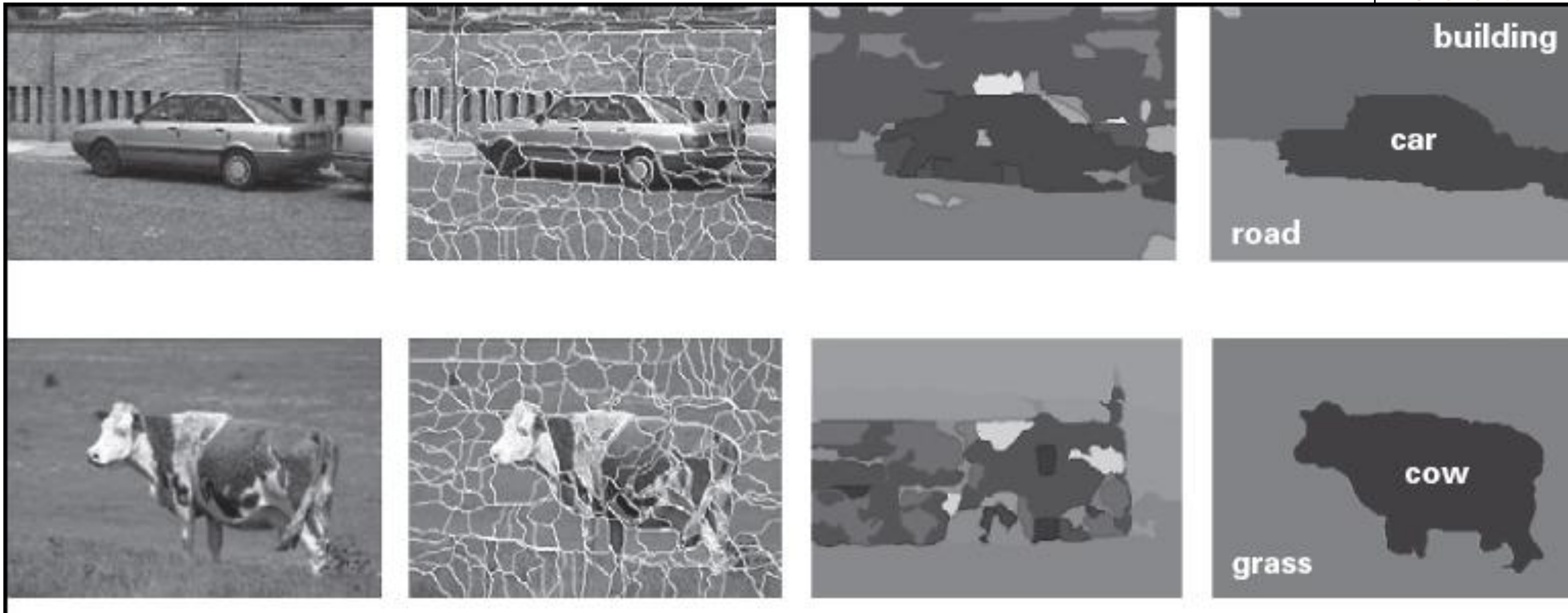
New MLN approach:

- performs *collective* entity resolution, where resolving one pair of entities helps to resolve pairs of related entities

e.g., inferring that a pair of citations are equivalent can provide evidence that the names *AAAI-06* and *21st Natl. Conf. on AI* refer to the same venue, even though they are superficially very different. This equivalence can then aid in resolving other entities.

Similar to……

Image segmentation



(a) (b) (c) (d)

classifying each superpixel independently

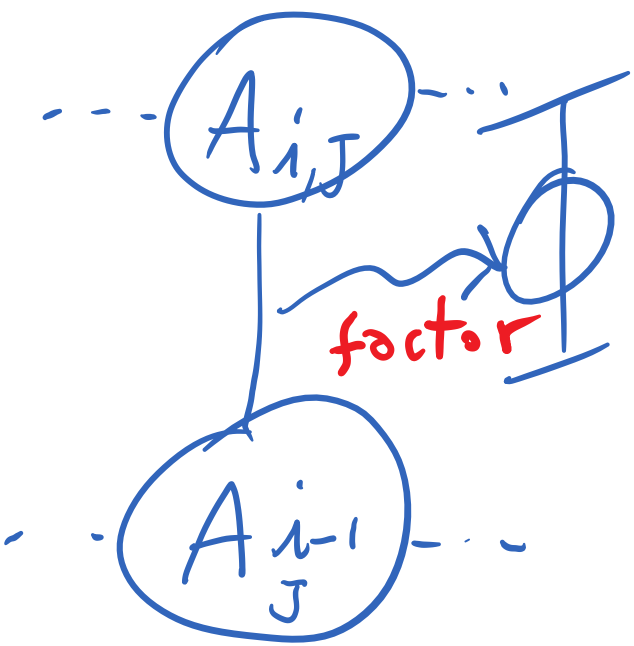
with a Markov Random Field !

Markov Networks Applications (1): Computer Vision

- Each *vars* correspond to a *pixel* (or *superpixel*)
- Edges (factors) correspond to interactions between adjacent pixels in the image
  - E.g., in segmentation: from generically penalize discontinuities, to road under car

favor continuities

SIMPLE EXAMPLE



$A_{i-1,j}$ \ A_{ij}	road	car
road	100	50
car	1	100

Other MLN applications

- **Information Extraction**
- **Co-reference Resolution Robot Mapping** (infer the map of an indoor environment from laser range data)
- **Link-based Clustering** (uses relationships among the objects in determining similarity)
- **Ontologies extraction from Text**
- **…..**

Lecture Overview

- Recap of MLN
- Markov Logic: applications
  - Entity resolution
  - Statistical Parsing!

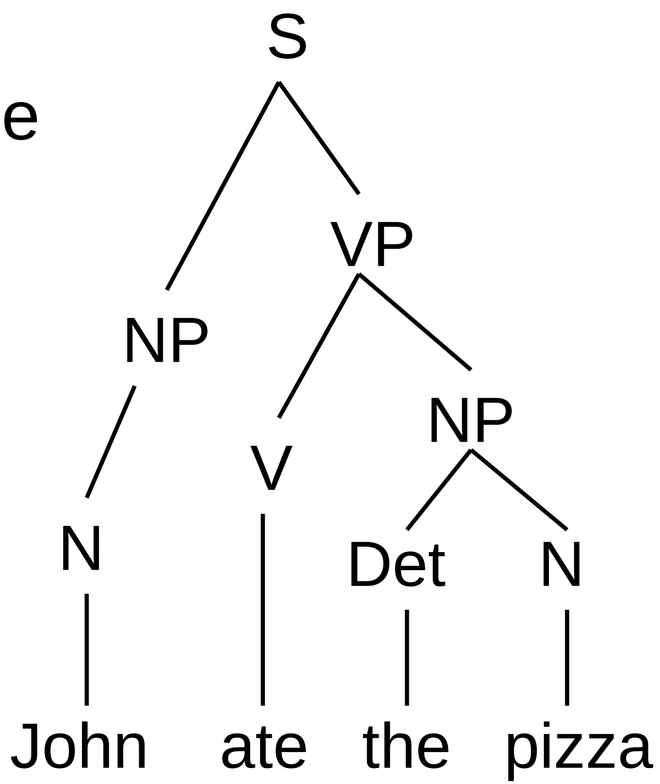
Statistical Parsing

- **Input:** Sentence
- **Output:** Most probable parse
- **PCFG:** Production rules with probabilities

  E.g.: 0.7 NP → N

  0.3 NP → Det N
- **WCFG:** Production rules with weights (equivalent)
- Chomsky normal form:

  A → B C or A → a



Logical Representation of CFG

→ rewrites as ⇒ logical implication

$$S \rightarrow NP\ VP$$

A NP ^ VP => S

B NP(i,j) ^ VP(j,k) => S(i,k)

C S(i,k) => NP(i,j) ^ VP(j,k)

i>clicker

Which one would be a reasonable representation in logics?

0 the 1 dog 2 chases 3 the 4 cat 5

Logical Representation of CFG

$$S \rightarrow NP\ VP$$
$$NP \rightarrow Adj\ N$$
$$NP \rightarrow Det\ N$$
$$VP \rightarrow V\ NP$$

NP(i,j) ^ VP(j,k) => S(i,k)
Adj(i,j) ^ N(j,k) => NP(i,k)
Det(i,j) ^ N(j,k) => NP(i,k)
V(i,j) ^ NP(j,k) => VP(i,k)

Lexicon….

// Determiners

Token("a",i) => Det(i,i+1)

i+1

Token("the",i) => Det(i,i+1)

// Adjectives

Token("big",i) => Adj(i,i+1)

Token("small",i) => Adj(i,i+1)

// Nouns

Token("dogs",i) => N(i,i+1)

Token("dog",i) => N(i,i+1)

Token("cats",i) => N(i,i+1)

Token("cat",i) => N(i,i+1)

Token("fly",i) => N(i,i+1)

Token("flies",i) => N(i,i+1)

// Verbs

Token("chase",i) => V(i,i+1)

Token("chases",i) => V(i,i+1)

Token("eat",i) => V(i,i+1)

Token("eats",i) => V(i,i+1)

Token("fly",i) => V(i,i+1)

Token("flies",i) => V(i,i+1)

Det(0,1) N(1,2)

the cat ate the mouse

0 1 2 3 4 5

0 1 2 3 4

Avoid two problems (1)

- If there are two or more rules with the same left side (such as **NP -> Adj N** and **NP -> Det N** need to enforce the constraint that only one of them fires :

NP(i,k) ^ Det(i,j) => ¬Adj(i,j)

``If a noun phrase results in a determiner and a noun, it cannot result in and adjective and a noun''.

Avoid two problems (2)

- **Ambiguities in the lexicon.**

homonyms belonging to different parts of speech, e.g., *fly* (noun or verb), only one of these parts of speech should be assigned.

We can enforce this constraint in a general manner by making mutual exclusion rules for each part of speech pair, i.e.:

$\neg$ Det(i,j) v $\neg$ Adj(i,j)

$\neg$ Det(i,j) v $\neg$ N(i,j)

$\neg$ Det(i,j) v $\neg$ V(i,j)

$\neg$ Adj(i,j) v $\neg$ N(i,j)

$\neg$ Adj(i,j) v $\neg$ V(i,j)

$\neg$ N(i,j) v $\neg$ V(i,j)

$\neg(A \wedge B)$

Statistical Parsing Representation: Summary

- For each rule of the form A → B C:
  Formula of the form **`B(i,j) ^ C(j,k) => A(i,k)`**

  E.g.: **`NP(i,j) ^ VP(j,k) => S(i,k)`**
- For each rule of the form A → a:
  Formula of the form **`Token(a,i) => A(i,i+1)`**

  E.g.: **`Token("pizza", i) => N(i,i+1)`**
- For each nonterminal: state that exactly one production holds (solve problem 1)
- Mutual exclusion rules for each part of speech pair (solve problem 2)

Statistical Parsing : Inference

- **Evidence predicate:** **`Token(token,position)`**
  E.g.: **`Token("pizza", 3) etc.`**
- **Query predicates:**
  `Constituent`**`(position,position)`**
  E.g.: **`S(0,7} "is this sequence of seven words a sentence?"  but also NP(2,4)`**

- What inference yields the most probable parse?

MAP! Find the most likely interpretation

422 big picture

StarAI (statistical relational AI)

Hybrid: Det +Sto

Prob CFG

Prob Relational Models

Markov Logics

MAP MaxWalkSAT

Deterministic	Stochastic

Query

Logics

First Order Logics

Ontologies

- Full Resolution
- SAT

Belief Nets

Approx. : Gibbs

Markov Chains and HMMs

Forward, Viterbi….

Approx. : Particle Filtering

Undirected Graphical Models

Markov Networks

Conditional Random Fields

Templates

Diff def for Markov Bl

rewrite as ops on factors

Planning

Markov Decision Processes and Partially Observable MDP

- Value Iteration
- Approx. Inference

Reinforcement Learning

Representation

Reasoning Technique

Applications of AI

Learning Goals for today's class

You can:

- Describe the entity resolution application of ML and explain the corresponding representation
- Probabilistic parsing as MLN nt required

Next Class on Mon

- **Start Probabilistic Relational Models**

Keep working on **Assignment-4**

Due **Apr 14**

In the past, a similar hw took students between 8 - 15 hours to complete. Please start working on it as soon as possible!