Intelligent Systems (AI-2)

Computer Science cpsc422, Lecture 31

Nov, 22, 2019

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

TA evaluations

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Also if you have not done it yet, fill out the teaching evaluations

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Lecture Overview

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

Markov Logic: Definition

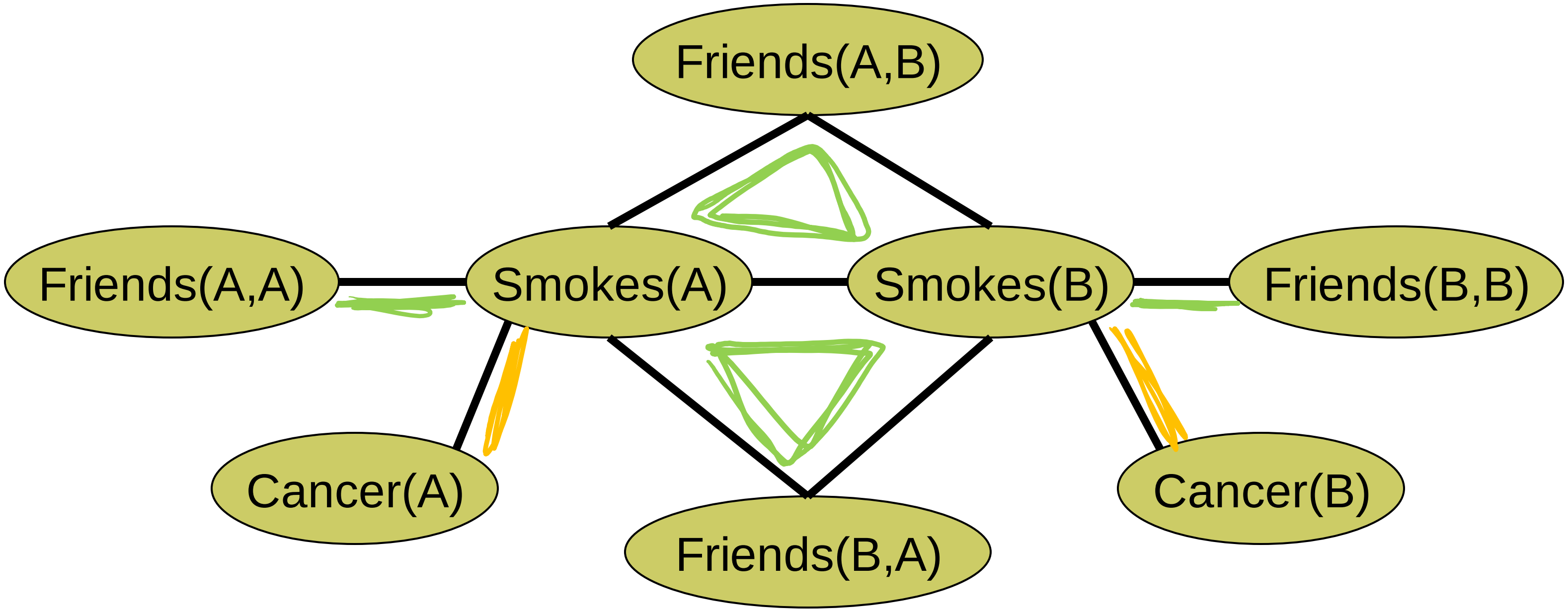
- A Markov Logic Network (MLN) is
  - a set of pairs (F, w) where
    - F is a **formula** in first-order logic
    - w is a **real number**
  - Together with a set C of **constants**,
- It defines a **Markov network** with
  - One *binary node* for each **grounding** of each **predicate** in the MLN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

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

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

pw_1 ....
Smokes(A) T
Cancer(A) F $e^0 = 1$

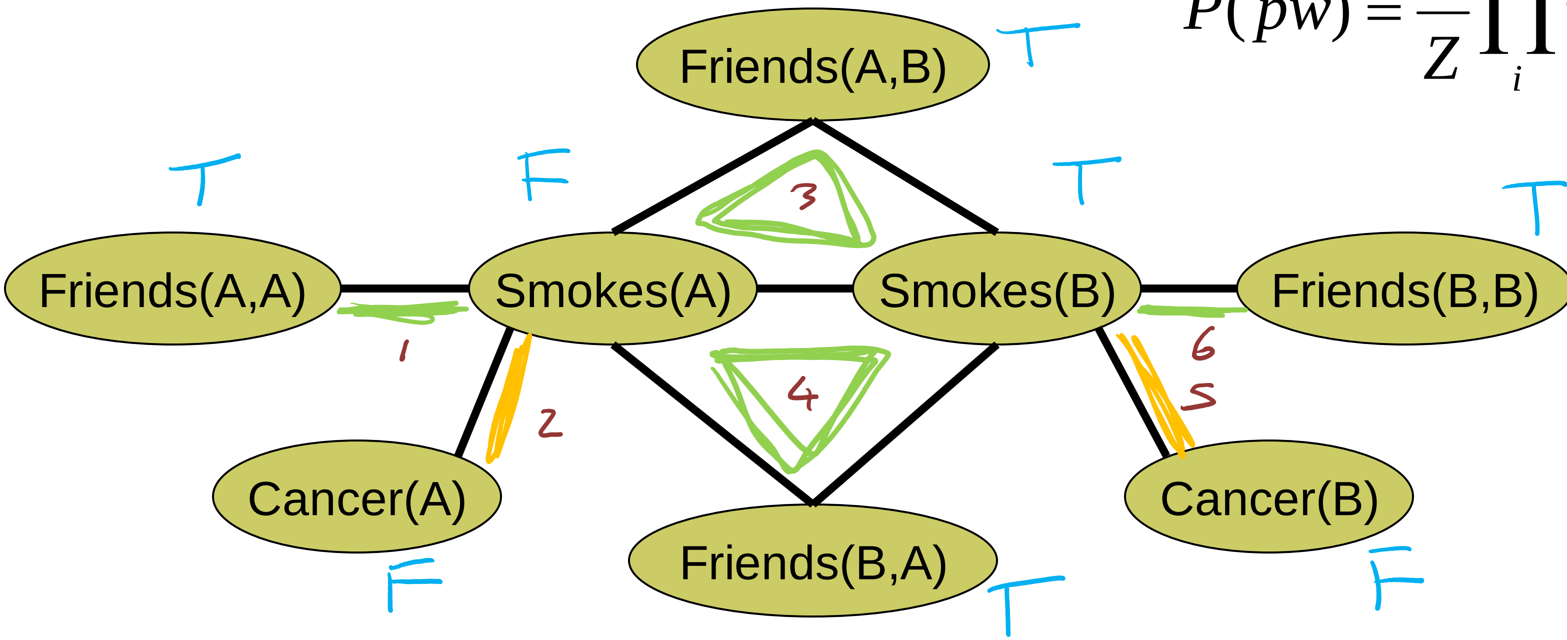
pw_2 ....
Smokes(A) T
Cancer(A) T $e^{1.5}$

MLN: prob. of possible world

1.5	$\forall x\ Smokes(x) \Rightarrow Cancer(x)$
1.1	$\forall x, y\ Friends(x,y) \Rightarrow \big(Smokes(x) \Leftrightarrow Smokes(y)\big)$

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

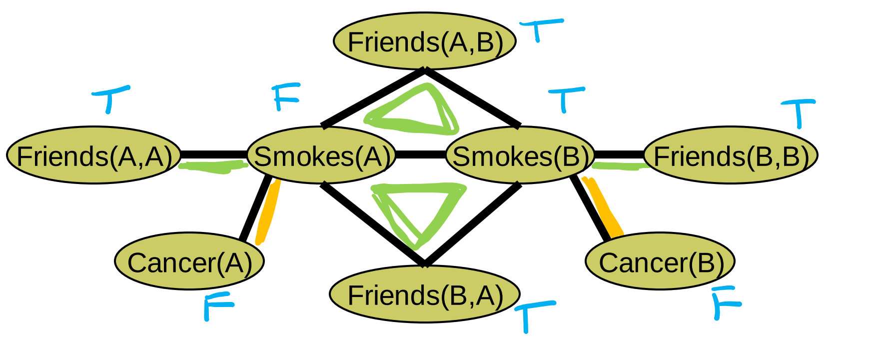
1	1.5	$\forall x\ Smokes(x) \Rightarrow Cancer(x)$
2	1.1	$\forall x, y\ Friends(x, y) \Rightarrow \left(Smokes(x) \Leftrightarrow Smokes(y)\right)$

- 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

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?

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?

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

SAME?

SAME?

SAME?

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;

SameAuthor (author, author) represent field equality;
SameTitle(title, title)
SameVenue(venue, venue)

to be inferred

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) ⇒ 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

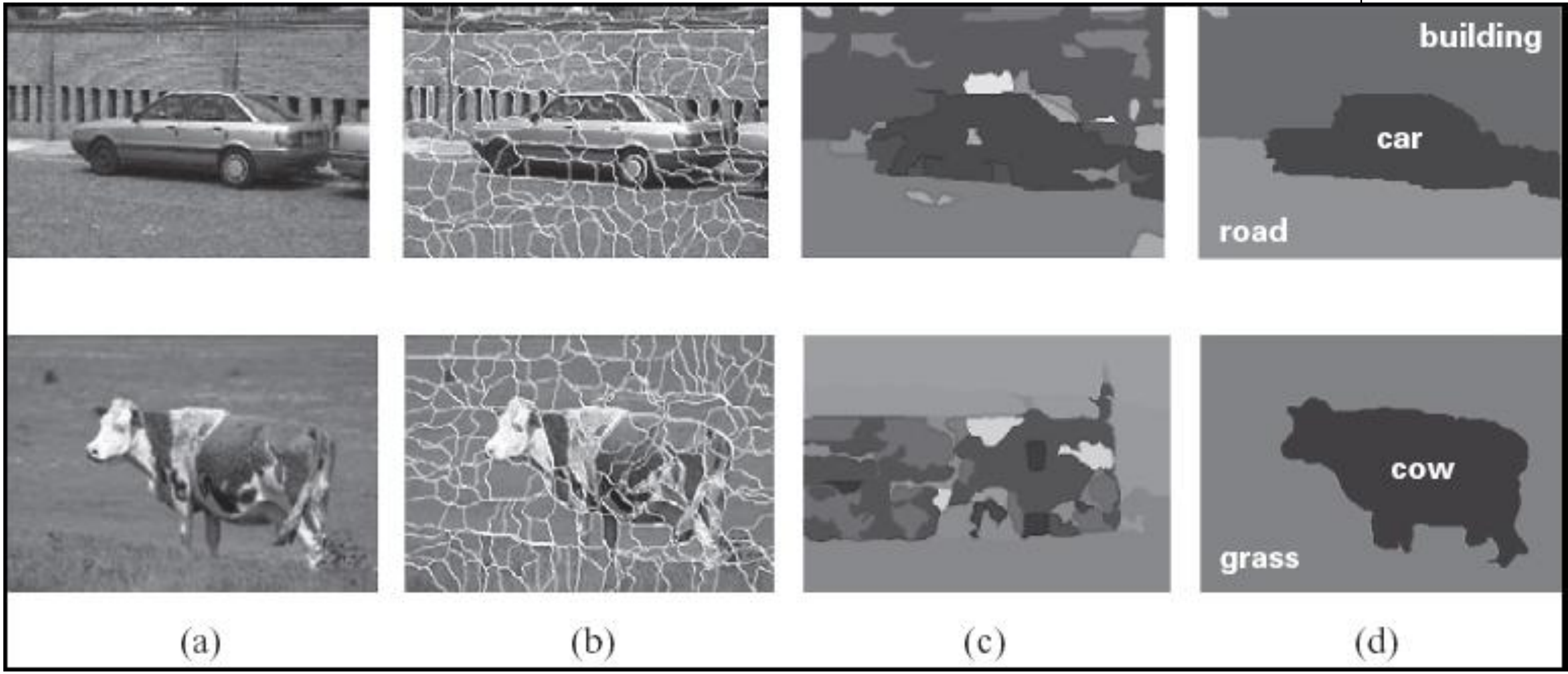
New MLN approach:

- 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



classifying each superpixel independently

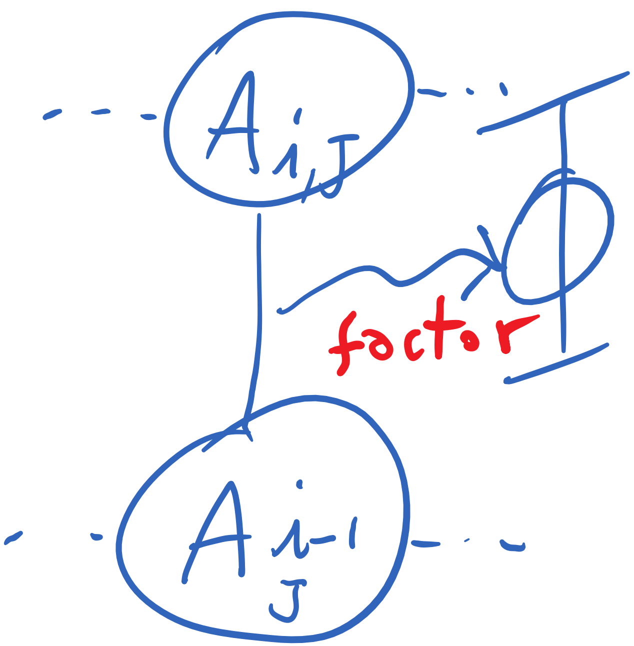
with a Markov Random Field !

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!**

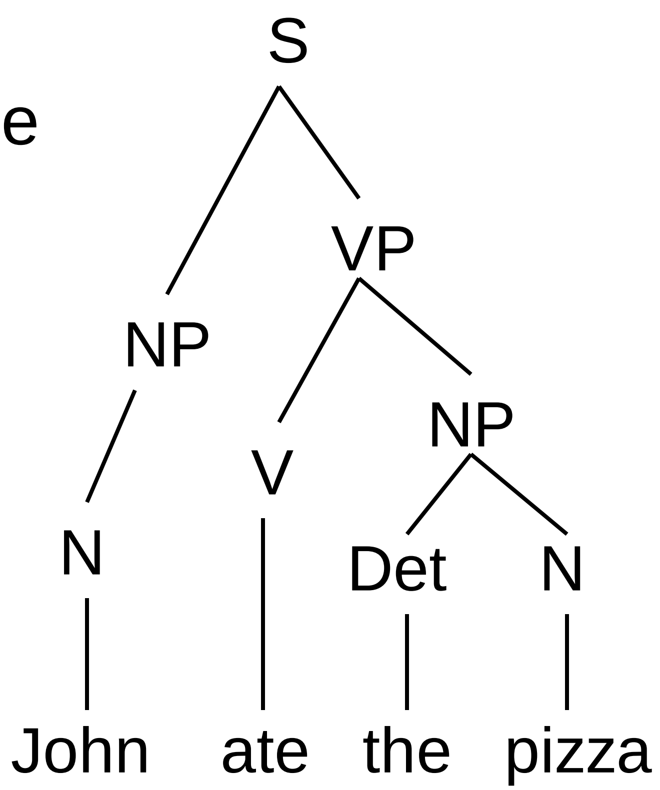
Statistical Parsing

- **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

$\rightarrow$ rewrites as $\Rightarrow$ logical implication

$S \rightarrow NP\ VP$

A $NP \wedge VP \Rightarrow S$

B $NP(i,j) \wedge VP(j,k) \Rightarrow S(i,k)$

C $S(i,k) \Rightarrow NP(i,j) \wedge VP(j,k)$

iclicker.

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

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.:

¬ Det(i,j) v ¬ Adj(i,j) $\neg(A \wedge B)$
¬ Det(i,j) v ¬ N(i,j)
¬ Det(i,j) v ¬ V(i,j)
¬ Adj(i,j) v ¬ N(i,j)
¬ Adj(i,j) v ¬ V(i,j)
¬ N(i,j) v ¬ V(i,j)

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!

Semantic Processing

Example: John ate pizza.

Grammar: S → NP VP   VP → V NP   V → ate
NP → John   NP → pizza

```
Token("John",0) => Participant(John,E,0,1)
Token("ate",1) => Event(Eating,E,1,2)
Token("pizza",2) => Participant(pizza,E,2,3)

Event(Eating,e,i,j) ^ Participant(p,e,j,k)
  ^ VP(i,k) ^ V(i,j) ^ NP(j,k) => Eaten(p,e)

Event(Eating,e,j,k) ^ Participant(p,e,i,j)
  ^ S(i,k) ^ NP(i,j) ^ VP(j,k) => Eater(p,e)

Event(t,e,i,k) => Isa(e,t)
```

Result: `Isa(E,Eating), Eater(John,E), Eaten(pizza,E)`

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*
Planning		*Markov Decision Processes and Partially Observable MDP* • Value Iteration • Approx. Inference *Reinforcement Learning*

Templates

Diff dot for Markov Bl

rewrite as ops on factors

Representation

Reasoning Technique

Applications of AI

Learning Goals for today's class

You can:

- Compute Probability of a formula, Conditional Probability
- Describe the entity resolution application of ML and explain the corresponding representation

Next Class on Mon

- **Start Probabilistic Relational Models**

Keep working on **Assignment-4**

Due **Nov 29**

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