Intelligent Systems (AI-2)

Computer Science cpsc422, Lecture 17

Oct, 18, 2017

Slide Sources
D. Koller, Stanford CS - Probabilistic Graphical Models
D. Page, Whitehead Institute, MIT

Several Figures from
"Probabilistic Graphical Models: Principles and Techniques" *D. Koller, N. Friedman* 2009

422 big picture: Where are we?

StarAI (statistical relational AI)

Hybrid: Det +Sto

Prob CFG

Prob Relational Models

Markov Logics

	Deterministic	Stochastic
Query	*Logics* *First Order Logics* *Ontologies* *Temporal rep.* • 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*

Applications of AI

Representation

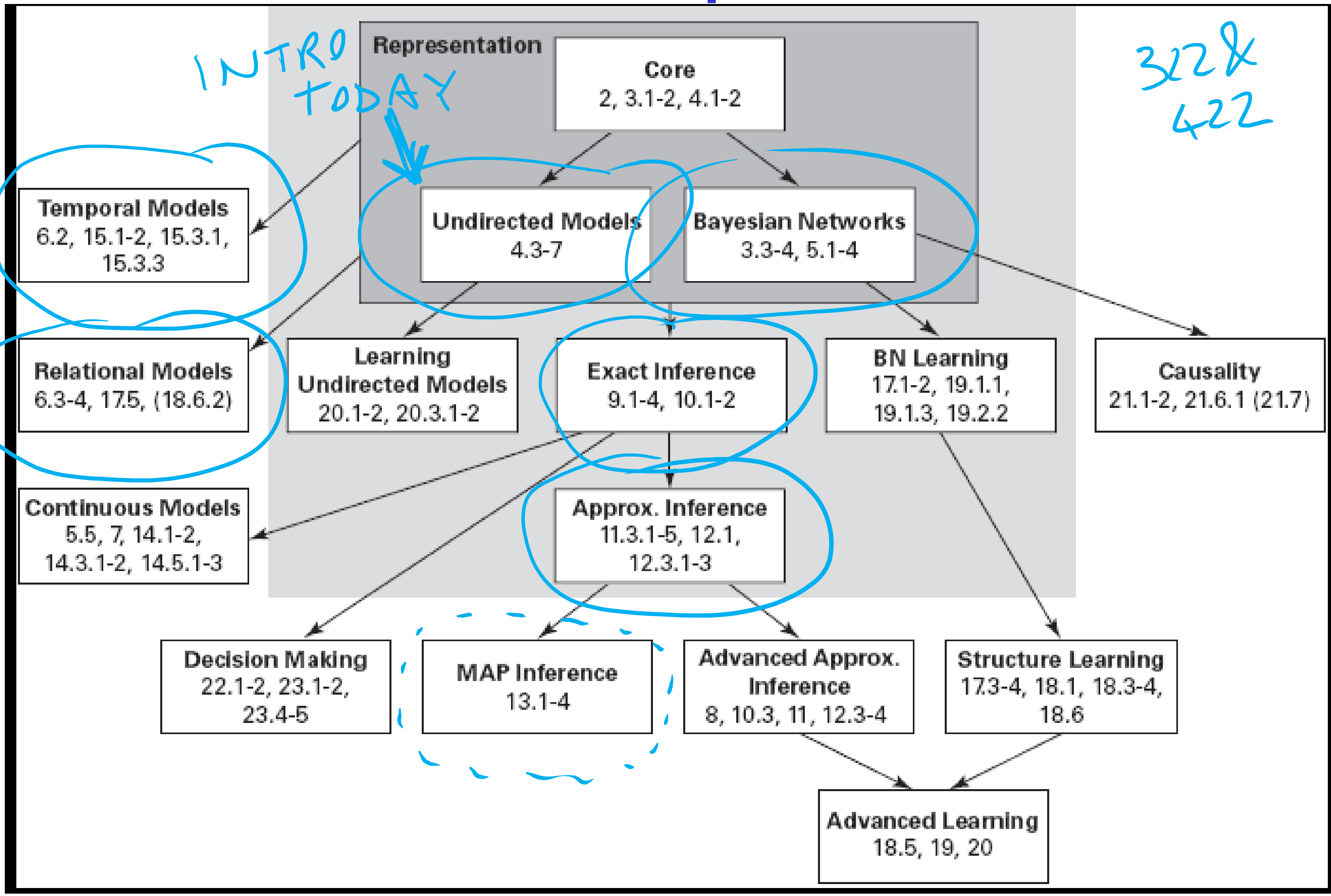
Reasoning Technique

Lecture Overview

<u>Probabilistic Graphical models</u>

- Intro
- Example
- Markov Networks Representation (vs. Belief Networks)
- Inference in Markov Networks (Exact and Approx.)
- Applications of Markov Networks

Probabilistic Graphical Models

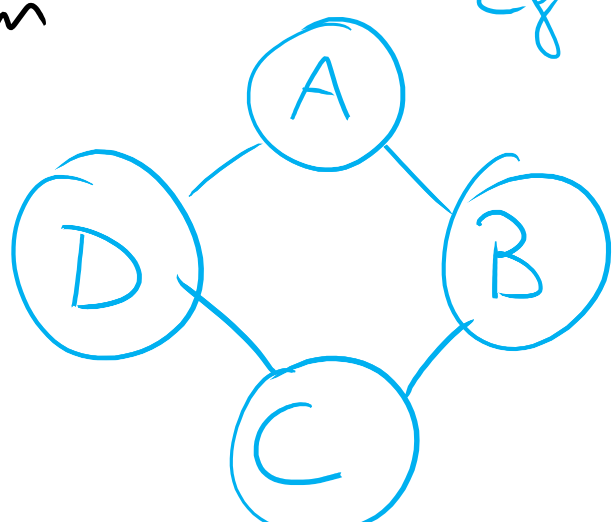


From "Probabilistic Graphical Models: Principles and Techniques" *D. Koller, N. Friedman* 2009

Misconception Example

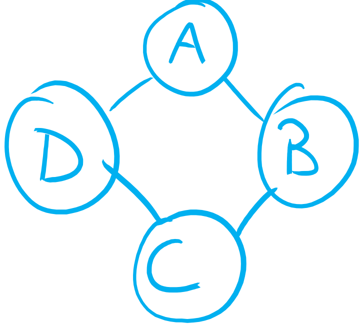
- Four students (Alice, Bill, Debbie, Charles) get together in pairs, to work on a homework
- But only in the following pairs: AB AD DC BC
- Professor misspoke and might have generated misconception
- A student might have figured it out later and told study partner

Four random vars



eg A random var
two values
a^1 Alice has the misc.
a^0 Alice doesn't have the misc.

Example: In/Depencencies



Are A and C independent because they never spoke?

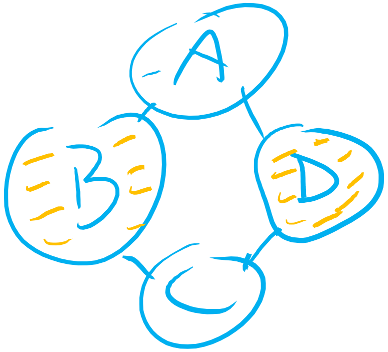
a. Yes

b. No

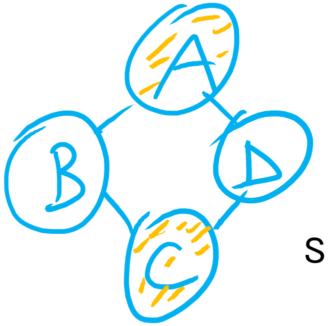
c. Cannot Tell

No, because A might have figured it out and told B who then told C

But if we know the values of B and D….



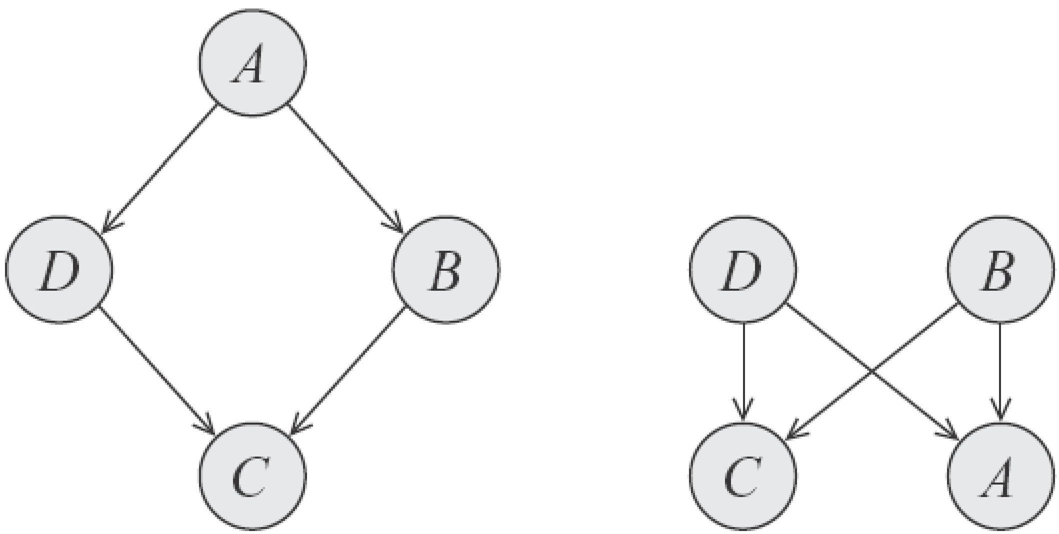
And if we know the values of A and C



Which of these two Bnets captures the two independencies of our example?

$(A \perp C \mid B D)$

$(B \perp D \mid A C)$



a.

b.

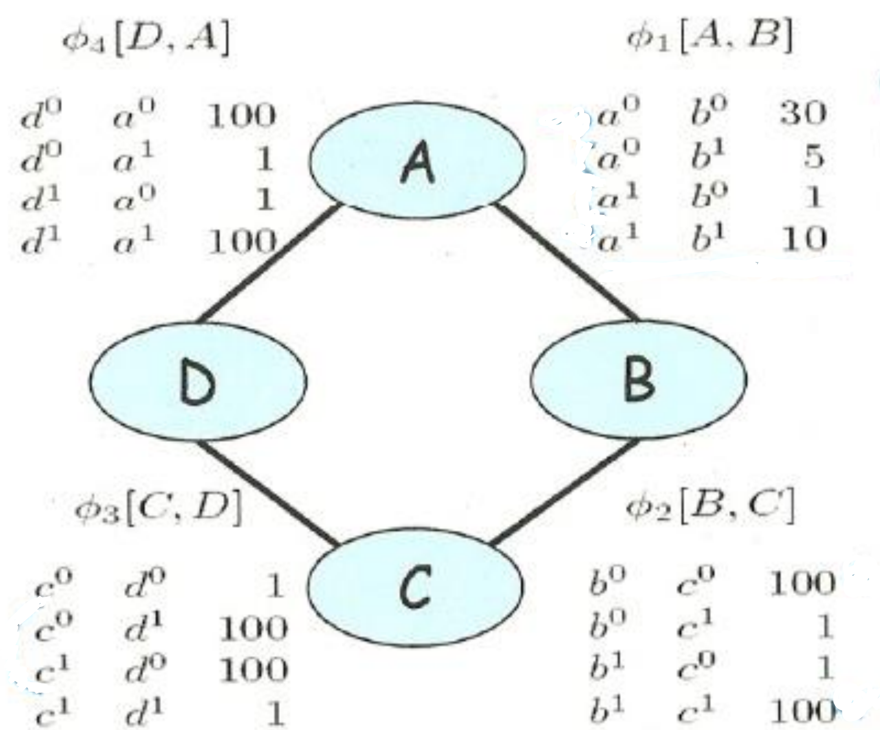
in a. $B \not\perp D \mid C$

in b. same

c. Both

d. None

Parameterization of Markov Networks



X set of random vars: A factor is $\Phi(Val(X)) \to \mathbb{R}$

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?

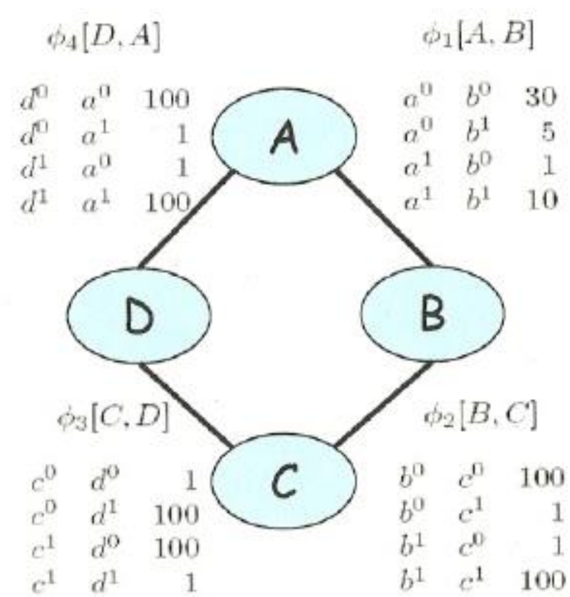
As in BNets by multiplying them!

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

$$P(A,B,C,D) = \frac{1}{Z}\tilde{P}(A,B,C,D)$$

P(A, B) ?

Assignment				*Unnormalized*	Normalized
a^0	b^0	c^0	d^0	300000	.04
a^0	b^0	c^0	d^1	300000	.04
a^0	b^0	c^1	d^0	300000	.04
a^0	b^0	c^1	d^1	30	4.1×10^{-6}
a^0	b^1	c^0	d^0	500	.
a^0	b^1	c^0	d^1	500	.
a^0	b^1	c^1	d^0	5000000	.69
a^0	b^1	c^1	d^1	500	.
a^1	b^0	c^0	d^0	100	.
a^1	b^0	c^0	d^1	1000000	.
a^1	b^0	c^1	d^0	100	.
a^1	b^0	c^1	d^1	100	.
a^1	b^1	c^0	d^0	10	.
a^1	b^1	c^0	d^1	100000	.
a^1	b^1	c^1	d^0	100000	.
a^1	b^1	c^1	d^1	100000	.



Multiplying Factors (same seen in 322 for VarElim)

(unrelated to our running example)

A B

a^1	b^1	0.5
a^1	b^2	0.8
a^2	b^1	0.1
a^2	b^2	0
a^3	b^1	0.3
a^3	b^2	0.9

B C

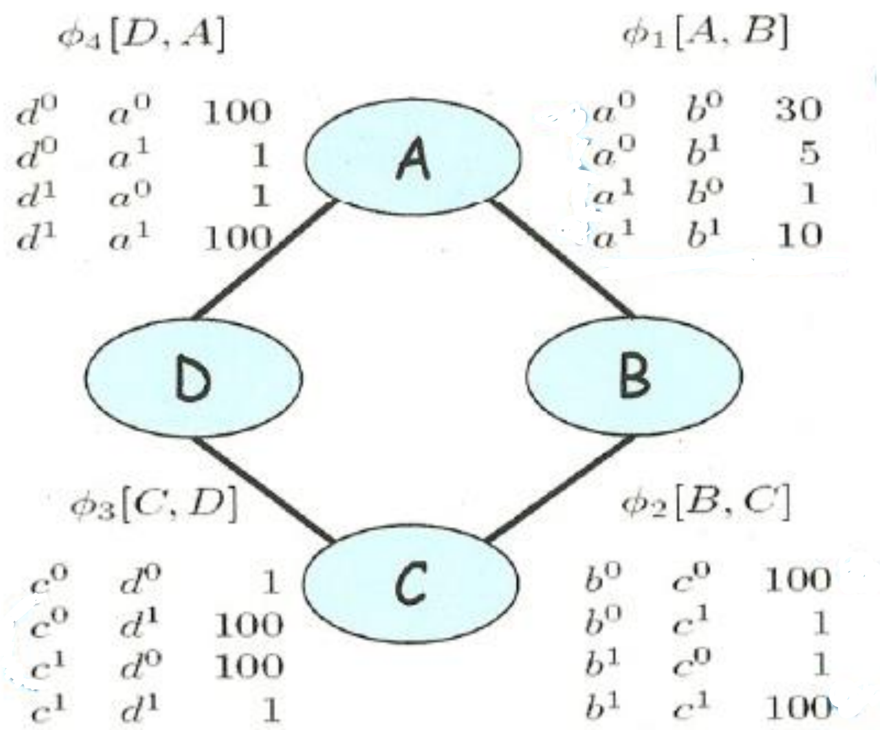
b^1	c^1	0.5
b^1	c^2	0.7
b^2	c^1	0.1
b^2	c^2	0.2

$\Rightarrow$

a^1	b^1	c^1	$0.5 \cdot 0.5 = 0.25$
a^1	b^1	c^2	$0.5 \cdot 0.7 = 0.35$
a^1	b^2	c^1	$0.8 \cdot 0.1 = 0.08$
a^1	b^2	c^2	$0.8 \cdot 0.2 = 0.16$
a^2	b^1	c^1	$0.1 \cdot 0.5 = 0.05$
a^2	b^1	c^2	$0.1 \cdot 0.7 = 0.07$
a^2	b^2	c^1	$0 \cdot 0.1 = 0$
a^2	b^2	c^2	$0 \cdot 0.2 = 0$
a^3	b^1	c^1	$0.3 \cdot 0.5 = 0.15$
a^3	b^1	c^2	$0.3 \cdot 0.7 = 0.21$
a^3	b^2	c^1	$0.9 \cdot 0.1 = 0.09$
a^3	b^2	c^2	$0.9 \cdot 0.2 = 0.18$

in this example
A has three values
a^1 a^2 a^3

Factors do not represent marginal probs. !



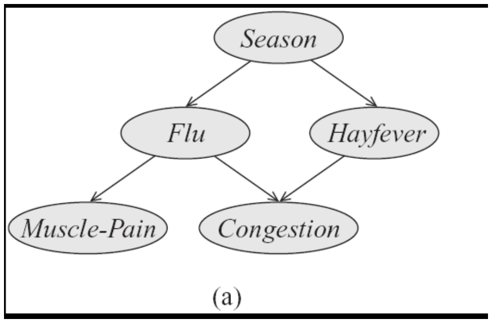
a^0 b^0	0.13
a^0 b^1	0.69
a^1 b^0	0.14
a^1 b^1	0.04

Marginal P(A,B)

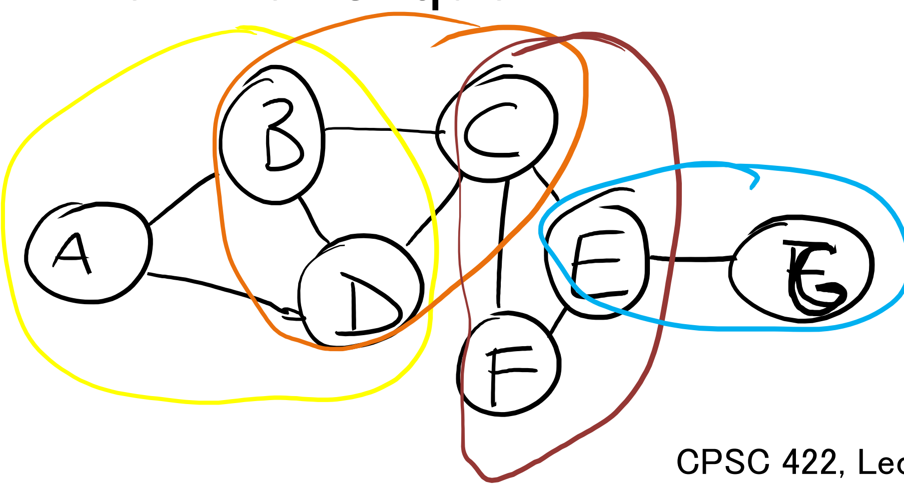
Computed from the joint

Step Back…. From structure to factors/potentials

In a Bnet the joint is factorized….



In a Markov Network you have one factor for each maximal clique

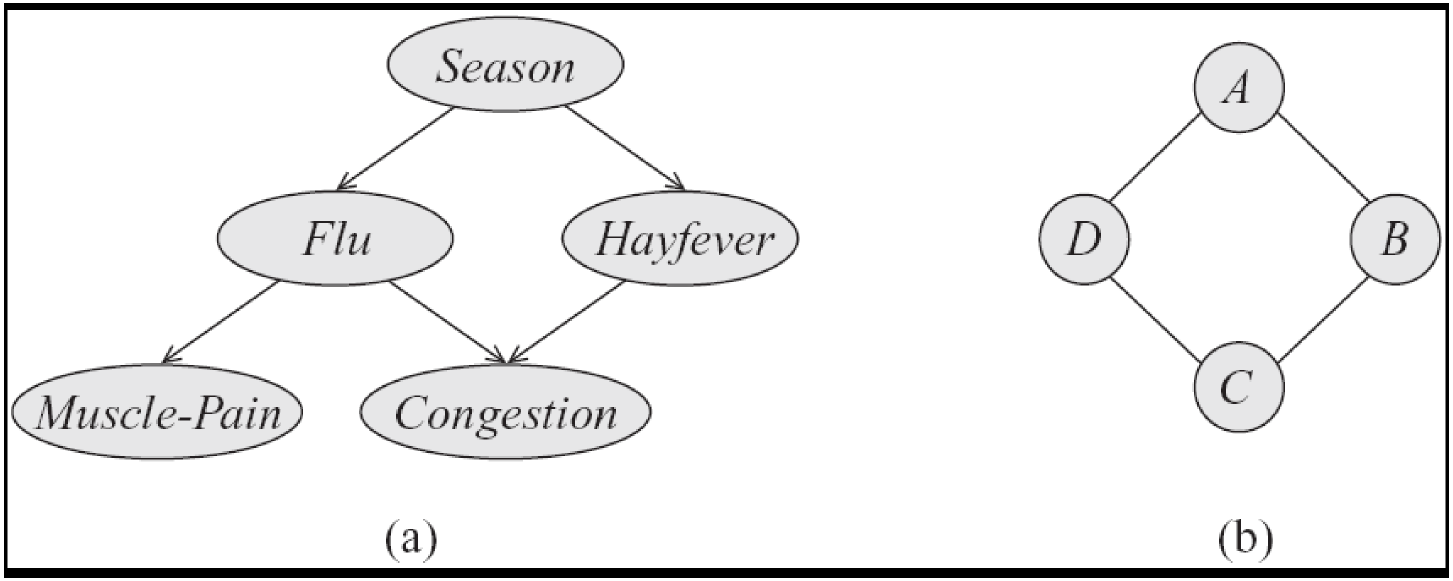


$\Phi_1(A\,B\,D)$

$\Phi_2(B\,D\,C)$ $\Phi_4(E\,G)$

$\Phi_3(C\,E\,F)$

Directed vs. Undirected



Independencies

$(F \perp H \mid S)$

$(C \perp S \mid F, H)$

$(M \perp C, H, S \mid F)$

$(A \perp C \mid B D)$

$(B \perp D \mid A C)$

Factorization

$P(S, F, H, M, C) =$

$P(S) * P(F \mid S) * P(H \mid S) * P(M \mid F) *$

$P(C \mid F H)$

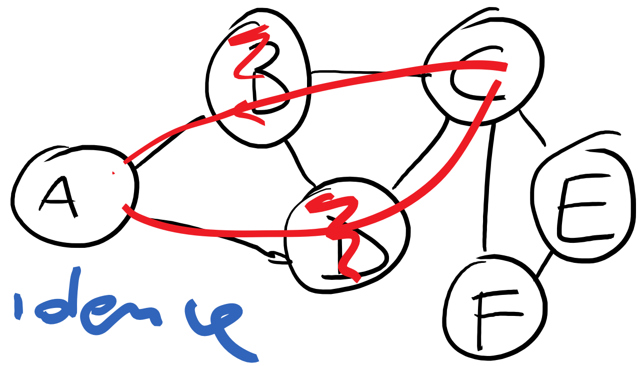
$P(A B C D) = \frac{1}{Z} \Phi_1(A B) *$

$* \Phi_2(B C) * \Phi_3(C D) * \Phi_4(A D)$

General definitions

Two nodes in a Markov network are **independent** if and only if …

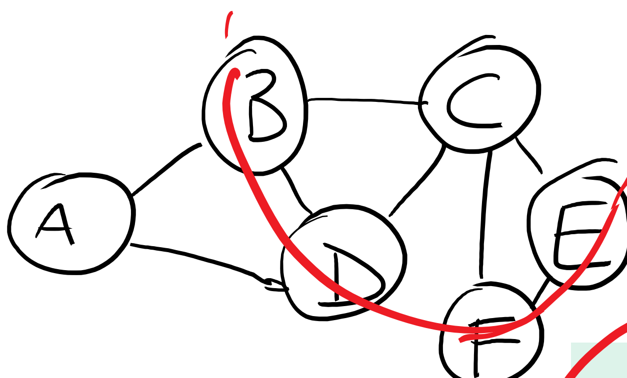
all paths between them are blocked by evidence



eg for A C

So the **markov blanket** of a node is… ?

eg for C



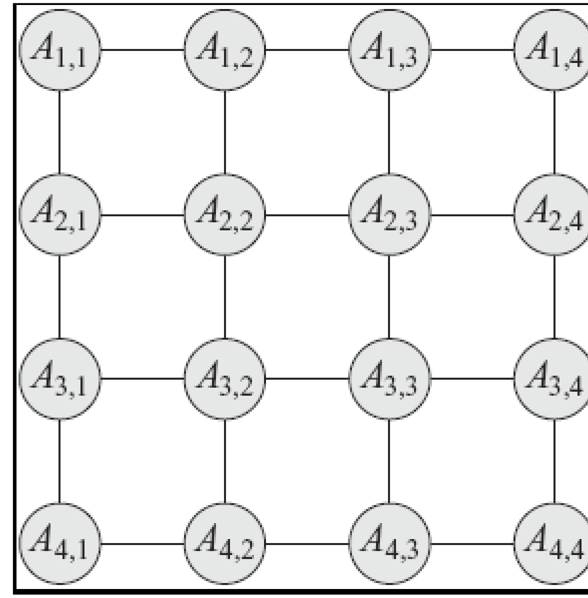
iclicker.

a. All the parents of its children

b. The whole network

c. All its neighbors

Markov Networks Applications (1): Computer Vision



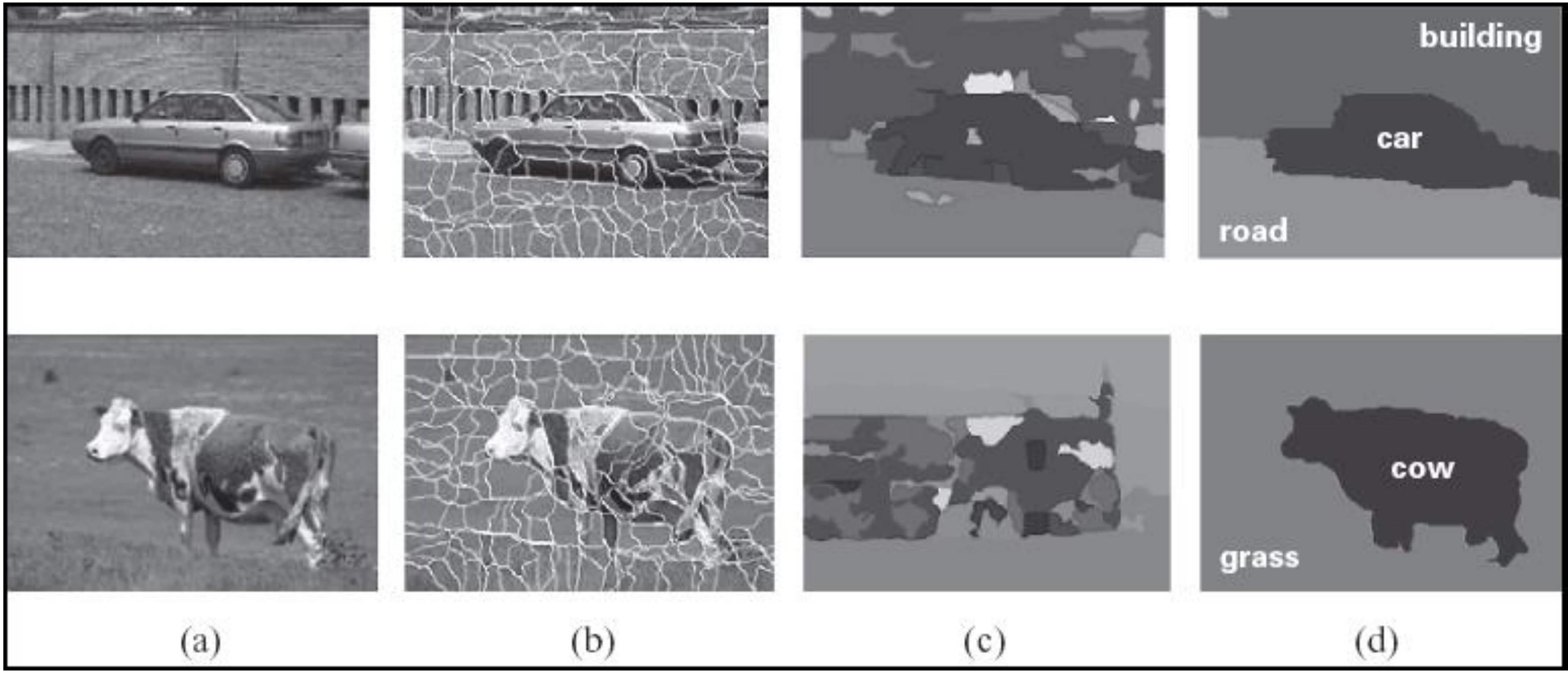
Called **Markov Random Fields**

- Stereo Reconstruction
- Image Segmentation
- Object recognition

Typically **pairwise MRF**

- 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

Image segmentation



classifying each superpixel independently

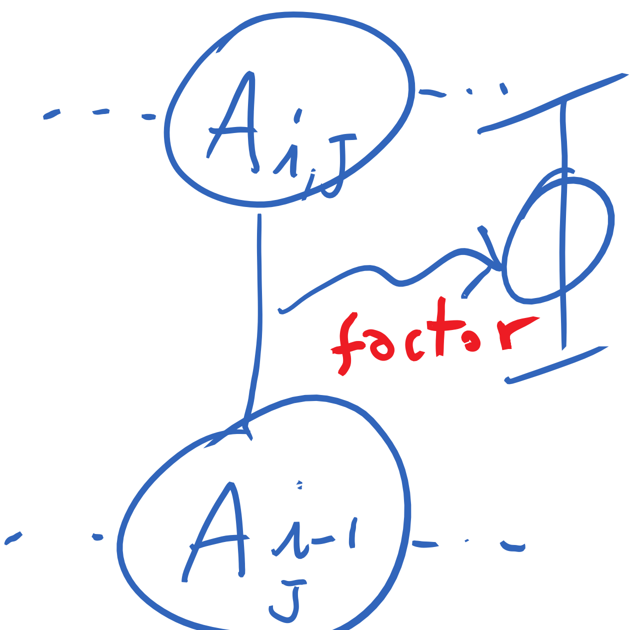
with a Markov Random Field!

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

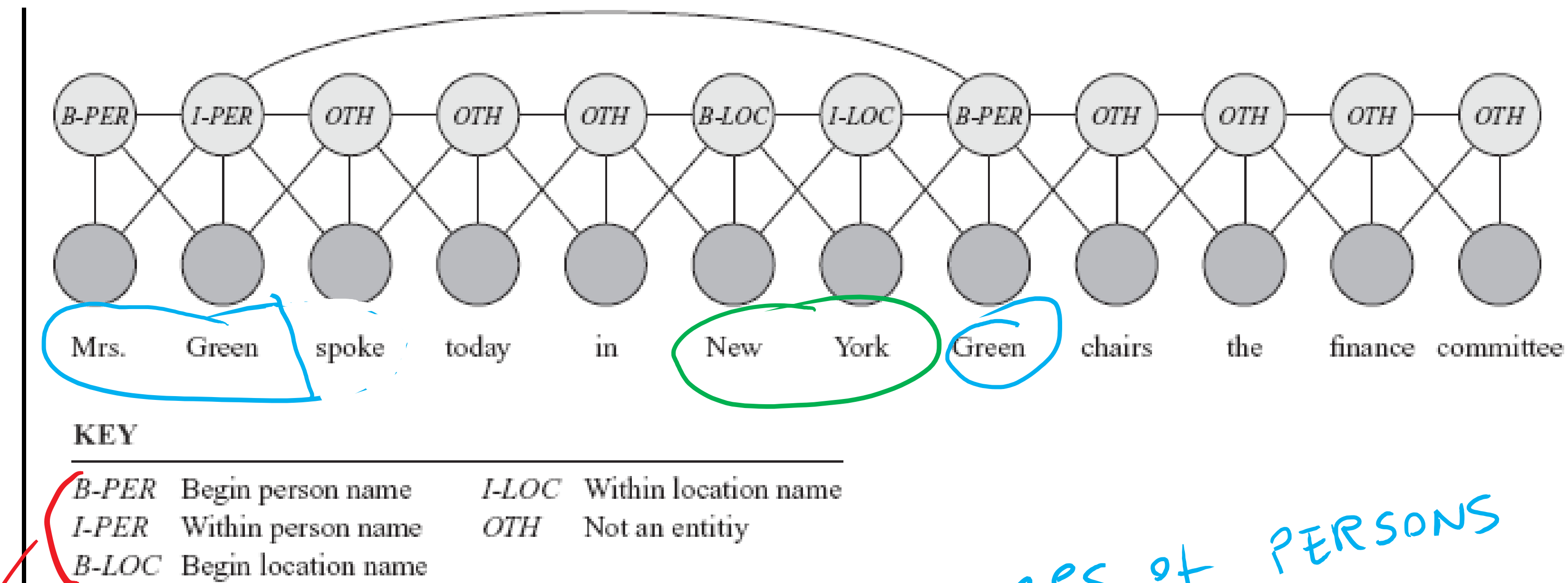
SIMPLE EXAMPLE



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

Markov Networks Applications (2): Sequence Labeling in NLP and BioInformatics

Conditional random fields (next class Fri)



5 possible states (similar to HMM)

recognize names of PERSONS LOCATIONS etc

NAMED ENTITIES

Learning Goals for today's class

- **You can:**

- Justify the need for undirected graphical model (Markov Networks)
- Interpret local models (factors/potentials) and combine them to express the joint
- Define independencies and Markov blanket for Markov Networks
- Perform Exact and Approx. Inference in Markov Networks
- Describe a few applications of Markov Networks

One week to Midterm, Wed, Oct 25, we will start at noon sharp

How to prepare….

- Keep Working on **assignment-2** !
- Go to **Office Hours**
- **Learning Goals** (look at the end of the slides for each lecture – complete list has been posted)
- Revise all the **clicker questions** and **practice exercises**
- **More practice material** has been posted
- Check questions and answers on Piazza

How to acquire factors?