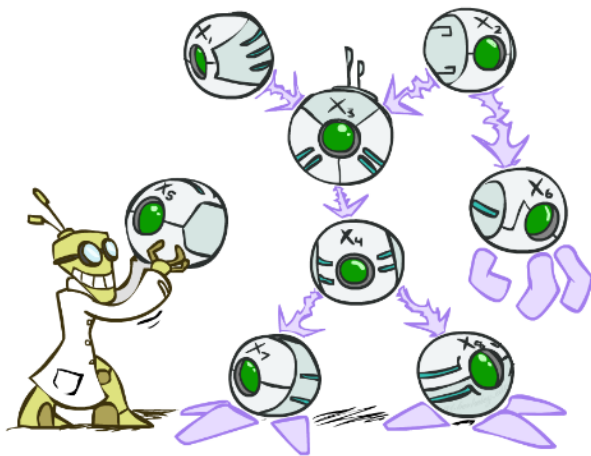


Announcement

- Midterm postponed
 - Due to restriction on offline meetings
 - Time & Location: TBA
- Programming 2
 - Due on Thursday
- Programming 3 and Homework 3
 - Released on Thursday

Bayesian Networks



AIMA Chapter 14.1, 14.2, PRML Chapter 8

Example Application: Topic Modeling



Introduction

- A large body of text available online
 - It is difficult to find and discover what we need.
- Topic models
 - Approaches to discovering the main themes of a large unstructured collection of documents
 - Can be used to automatically organize, understand, search, and summarize large electronic archives
 - Latent Dirichlet Allocation (LDA) is the most popular

Plate Notation

- Representation of repeated subgraphs in a Bayesian network



Plate Notation

- Representation of repeated subgraphs in a Bayesian network

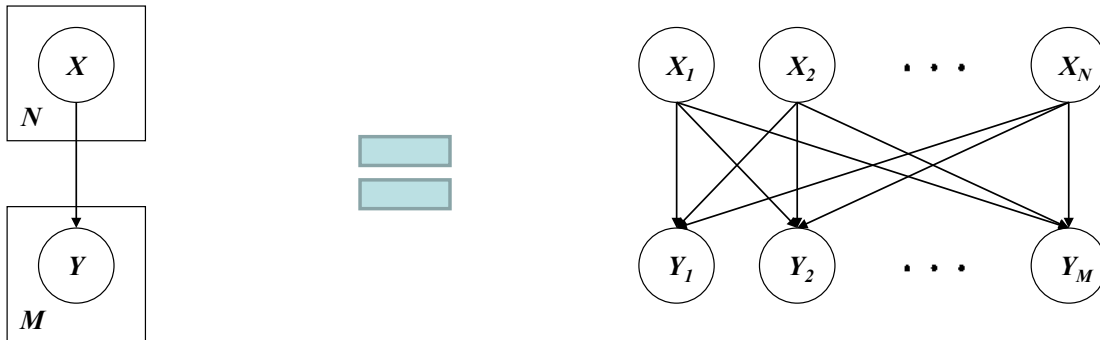
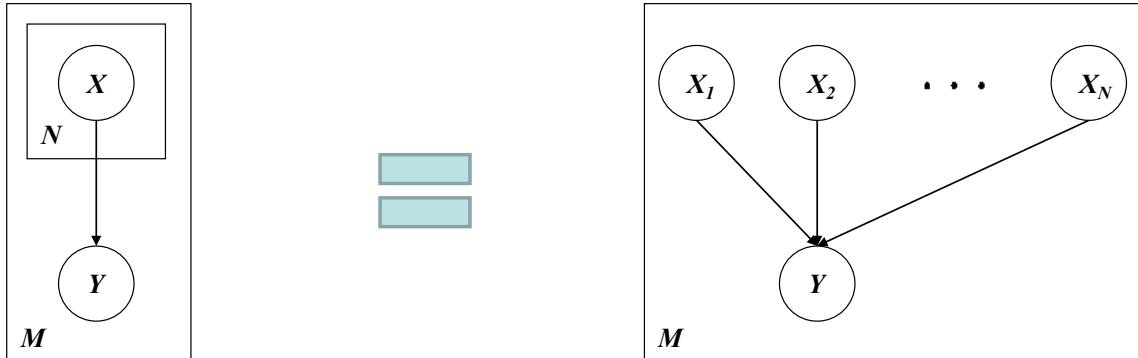
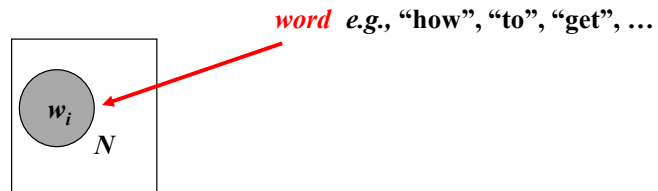


Plate Notation

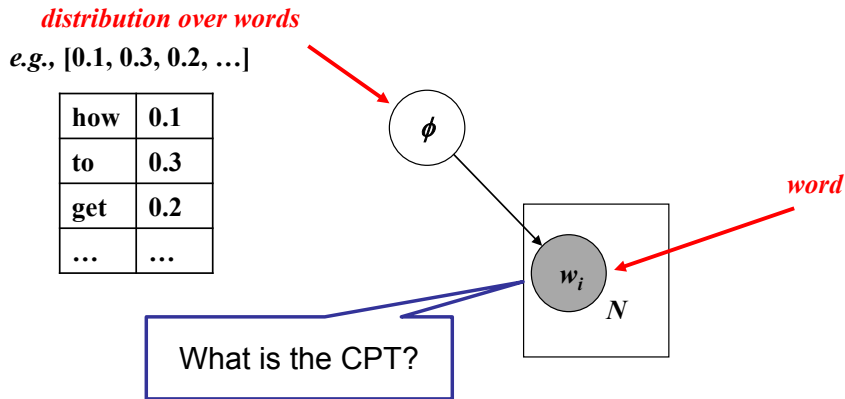
- Representation of repeated subgraphs in a Bayesian network



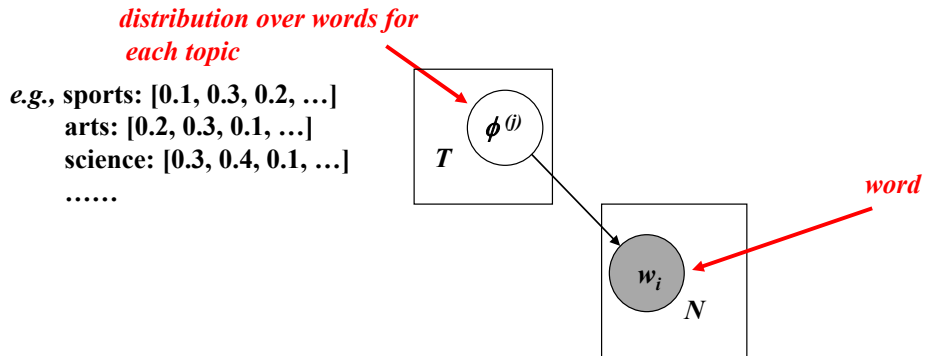
How to generate a document



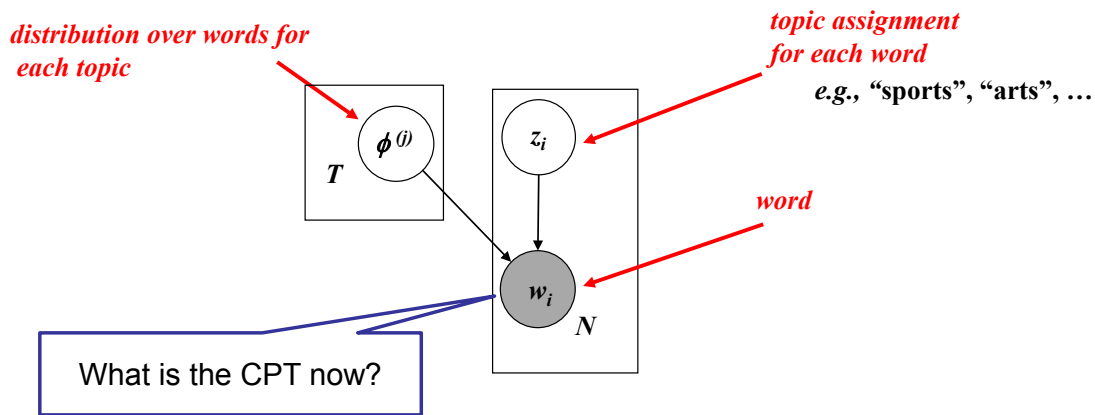
How to generate a document



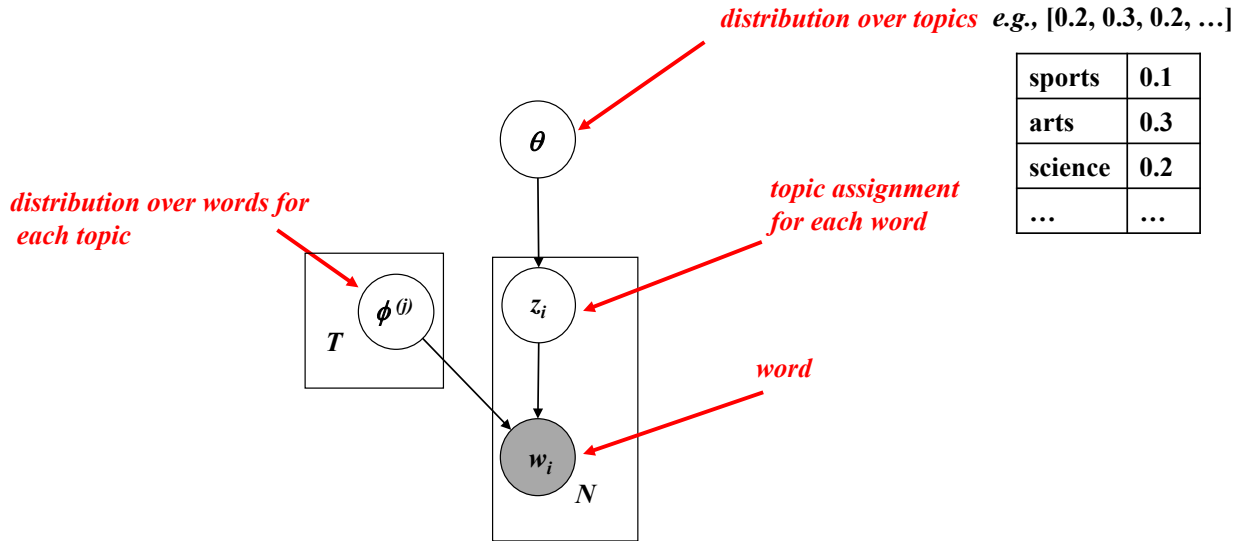
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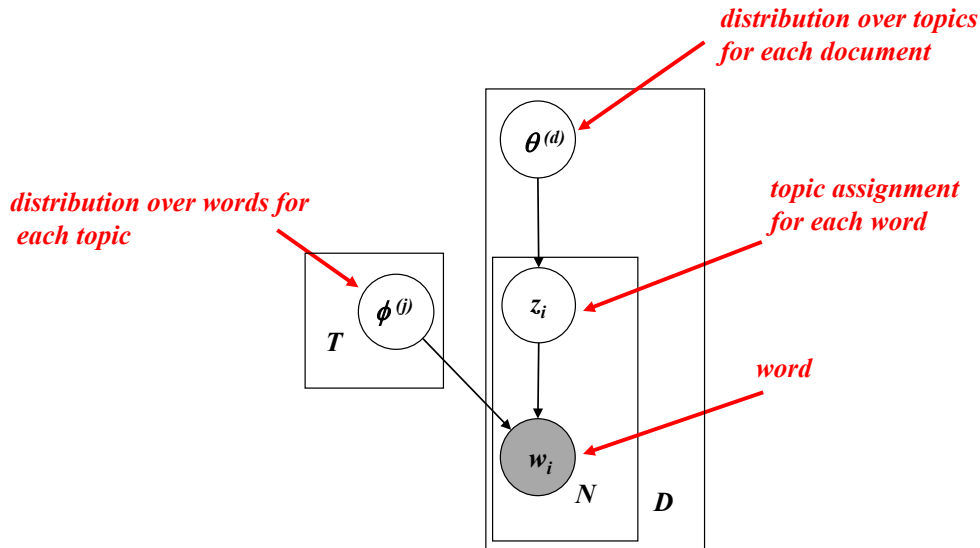
How to generate a document



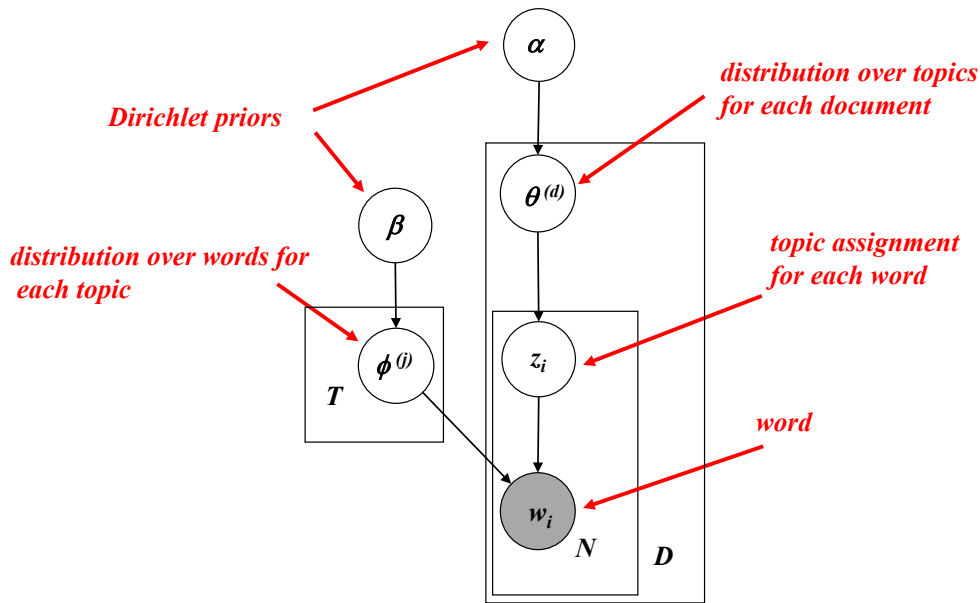
How to generate a document



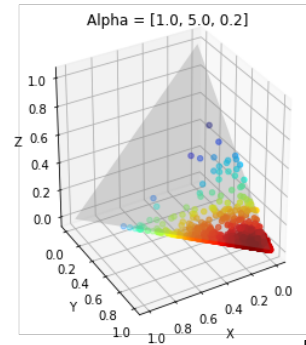
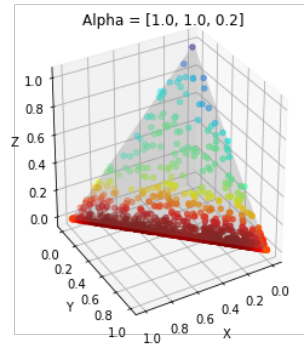
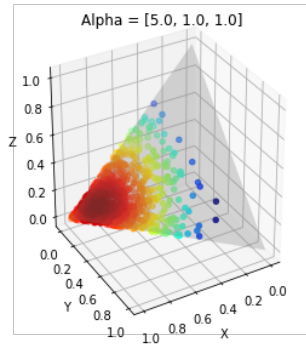
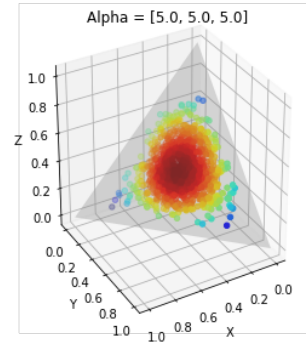
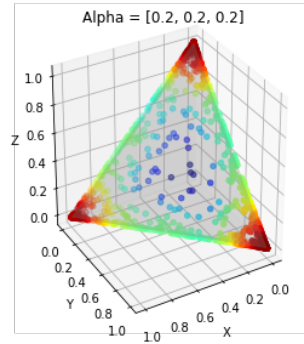
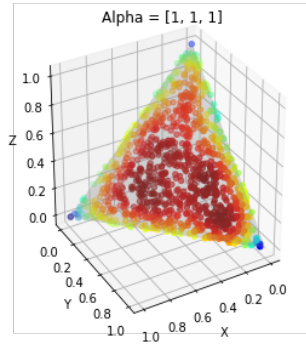
How to generate documents



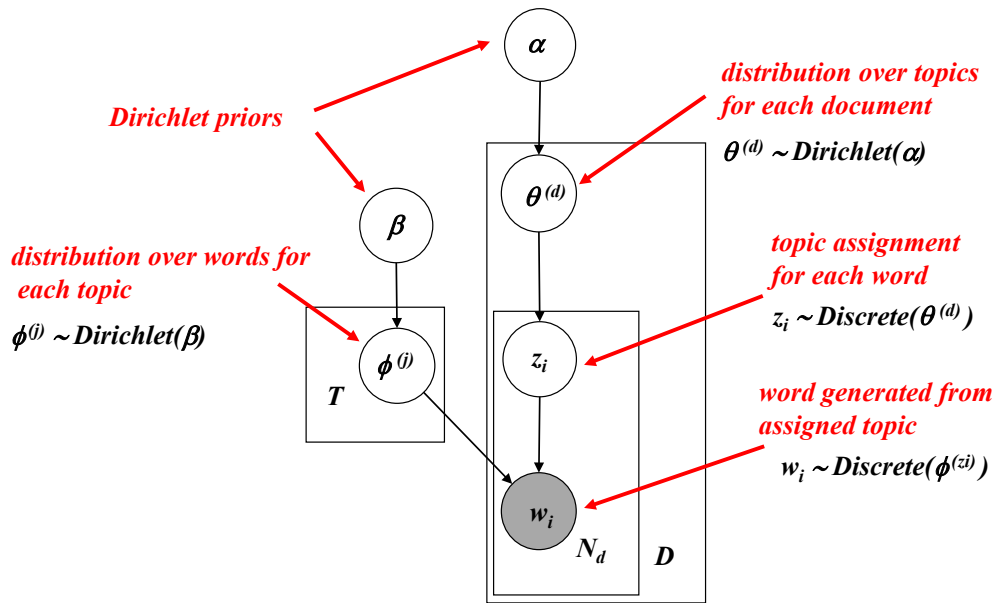
How to generate documents



Dirichlet Distribution



Latent Dirichlet Allocation (LDA)



Illustration

Topics

gene	0.04
dna	0.02
genetic	0.01
...	

life	0.02
evolve	0.01
organism	0.01
...	

brain	0.04
neuron	0.02
nerve	0.01
...	

data	0.02
number	0.02
computer	0.01
...	

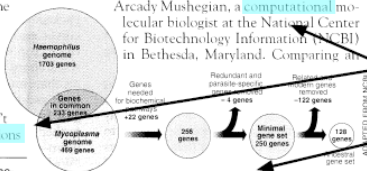
Documents

Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK—How many **genes** does an **organism** need to **survive**? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for **life**. One research team, using **computer** analyses to compare known **genomes**, concluded that today's **organisms** can be sustained with just 250 **genes**, and that the earliest life forms required a mere 128 **genes**. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those **predictions**

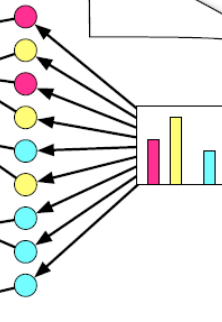
"are not all that far apart," especially in comparison to the 75,000 **genes** in the human genome, notes Siv Andersson, a research University in Sweden, and arrived at the 800 number. But coming up with a consensus answer may be more than just a **genetic numbers** game, particularly as more and more **genomes** are completely mapped and sequenced. "It may be a way of organizing any newly **sequenced genome**," explains Arcady Mushegian, a **computational** molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an



* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

Stripping down. **Computer analysis** yields an estimate of the minimum modern and ancient genomes.

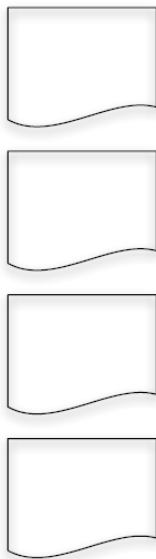
Topic proportions and assignments



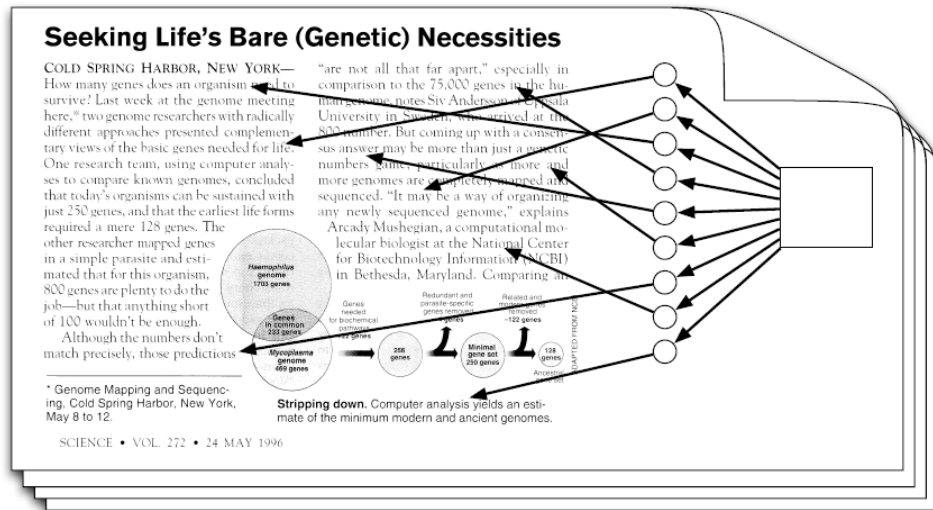
- Each **topic** is a distribution of words; each **document** is a mixture of corpus-wide topics; and each **word** is drawn from one of those topics.

Illustration

Topics



Documents



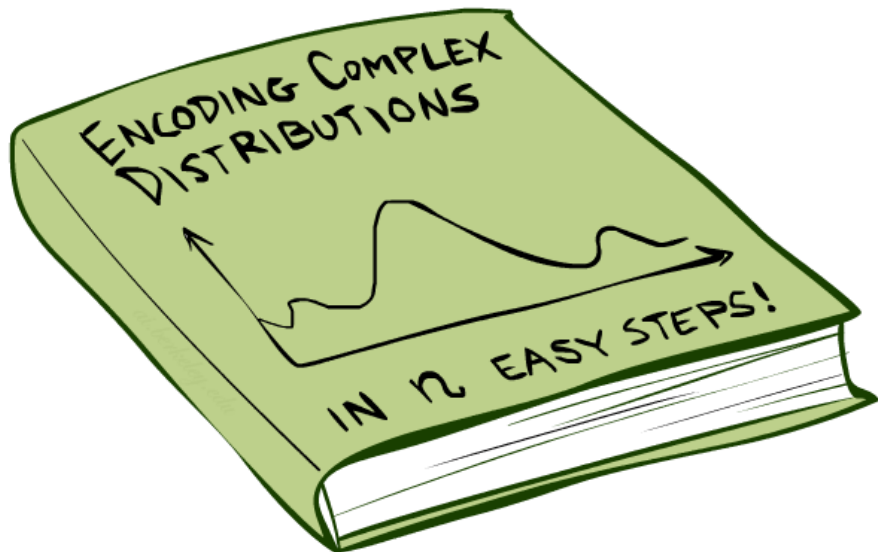
Topic proportions and assignments

- In reality, we only observe documents. The other structures are hidden variables that must be inferred. (We will discuss inference later.)

Topics inferred by LDA

“Arts”	“Budgets”	“Children”	“Education”
NEW	MILLION	CHILDREN	SCHOOL
FILM	TAX	WOMEN	STUDENTS
SHOW	PROGRAM	PEOPLE	SCHOOLS
MUSIC	BUDGET	CHILD	EDUCATION
MOVIE	BILLION	YEARS	TEACHERS
PLAY	FEDERAL	FAMILIES	HIGH
MUSICAL	YEAR	WORK	PUBLIC
BEST	SPENDING	PARENTS	TEACHER
ACTOR	NEW	SAYS	BENNETT
FIRST	STATE	FAMILY	MANIGAT
YORK	PLAN	WELFARE	NAMPHY
OPERA	MONEY	MEN	STATE
THEATER	PROGRAMS	PERCENT	PRESIDENT
ACTRESS	GOVERNMENT	CARE	ELEMENTARY
LOVE	CONGRESS	LIFE	HAITI

Markov Networks



Markov Networks

- A Bayesian network encodes a joint distribution with a directed acyclic graph
 - A CPT captures uncertainty between a node and its parents
- A Markov network (or Markov random field) encodes a joint distribution with an undirected graph
 - A potential function captures uncertainty between a clique of nodes

inde: if observed (blockings)

Markov Networks

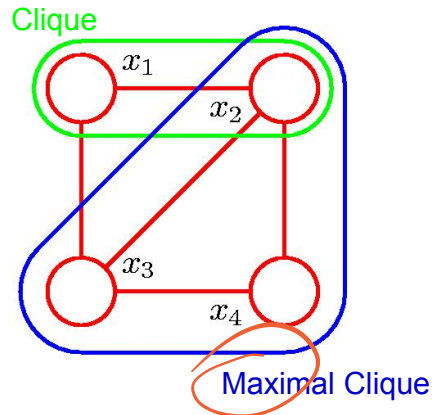
- Markov network = undirected graph + potential functions
 - For each clique (or max clique), a potential function is defined
 - A potential function is not locally normalized, i.e., it doesn't encode probabilities
 - A joint probability is proportional to the product of potentials

$$p(\mathbf{x}) = \frac{1}{Z} \prod_C \psi_C(\mathbf{x}_C)$$

where $\psi_C(\mathbf{x}_C)$ is the potential over clique C and

$$Z = \sum_{\mathbf{x}} \prod_C \psi_C(\mathbf{x}_C)$$

is the normalization coefficient (aka. partition function).



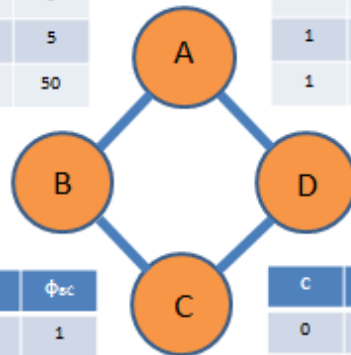
Markov Networks

A	B	C	D	$\phi_{AB}\phi_{BC}\phi_{CD}\phi_{AD}$
0	0	0	0	250
0	0	0	1	37500
0	0	1	0	50000
0	0	1	1	625000
0	1	0	0	1125
0	1	0	1	168750
0	1	1	0	50000
0	1	1	1	625000
1	0	0	0	250
1	0	0	1	375
1	0	1	0	50000
1	0	1	1	6250
1	1	0	0	112500
1	1	0	1	168750
1	1	1	0	5000000
1	1	1	1	625000

$$Z = 7520750$$

A	B	ϕ_{AB}
0	0	50
0	1	5
1	0	5
1	1	50

A	D	ϕ_{AD}
0	0	5
0	1	50
1	0	50
1	1	5

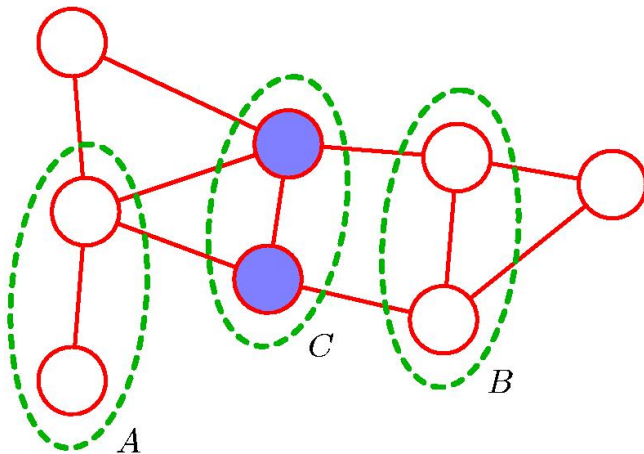


B	C	ϕ_{BC}
0	0	1
0	1	5
1	0	45
1	1	50

C	D	ϕ_{CD}
0	0	1
0	1	15
1	0	40
1	1	50

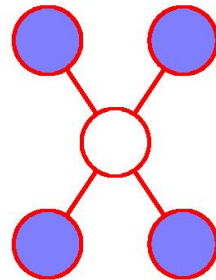
Markov Networks

- Conditional independence and Markov blanket in MN



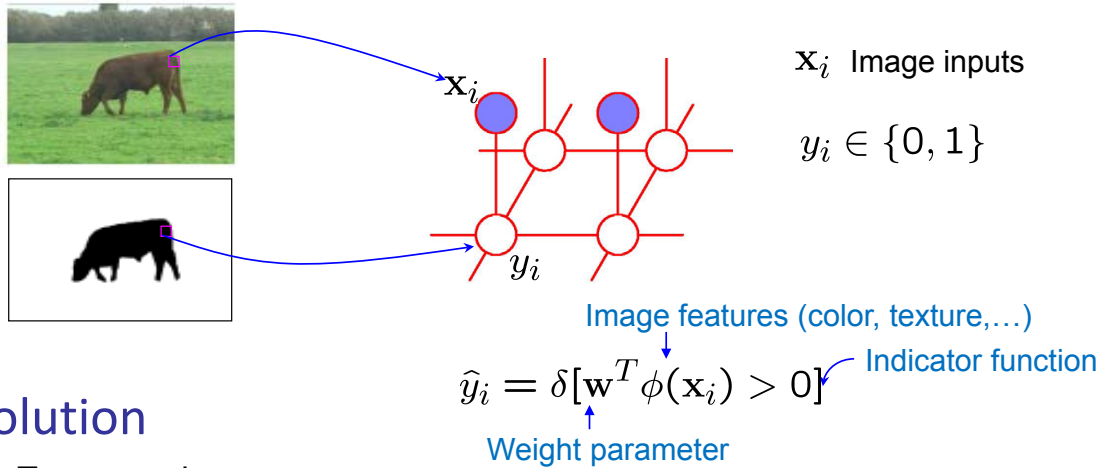
$$A \perp\!\!\!\perp B | C$$

Markov Blanket



An example – foreground object

- Binary segmentation



- A “local” solution

Toy example:

$$\begin{aligned}\phi(\mathbf{x}_i) &= [\text{green}(\mathbf{x}_i), \text{brown}(\mathbf{x}_i)]^T \\ \mathbf{w} &= [-1, 1]^T\end{aligned}$$

An example cont'd

- A score maximization view

$$\begin{aligned}\hat{y}_i = \delta[\mathbf{w}^T \phi(\mathbf{x}_i) > 0] &\iff \hat{y}_i = \arg \max_{y_i} y_i \mathbf{w}^T \phi(\mathbf{x}_i) \\ &= \arg \max_{y_i} \underbrace{\mathbf{w}^T \tilde{\phi}(\mathbf{x}_i, y_i)}_{\text{Score function}}\end{aligned}$$

- Predicted label has a higher score.

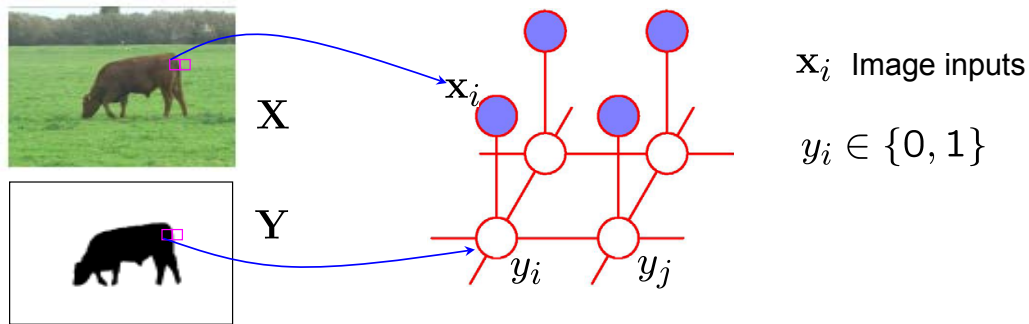
- Problem?



(Shotton et al, ECCV 2006)

An example cont'd

- Incorporating spatial context
 - Labels are generally spatially smooth

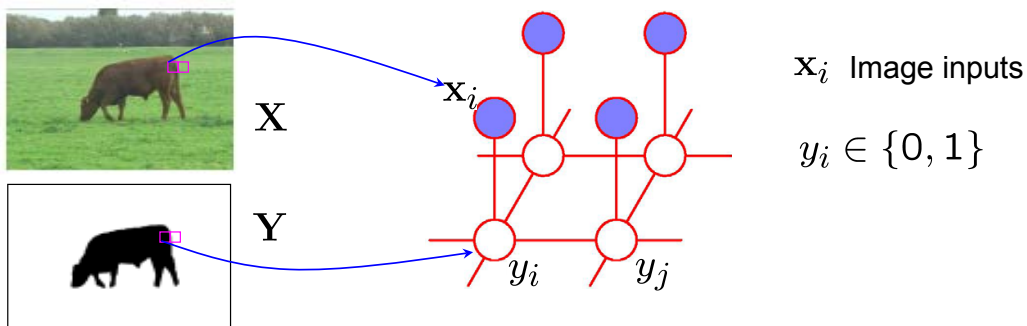


$$F(X, Y; W) = \sum_i w^T \phi(y_i, x_i)$$

“Local” image cues

An example cont'd

- A simple smooth model



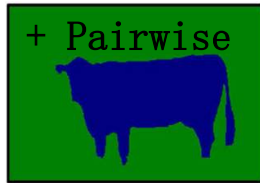
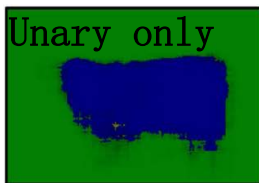
$$\psi(y_i, y_j, |\mathbf{x}_i - \mathbf{x}_j|) = \delta[y_i = y_j] e^{\{-|\mathbf{x}_i - \mathbf{x}_j|\}}$$

- Same labeling for neighboring pixels unless an intensity gradient exists

An example cont'd

- Inferring the scene properties (i.e., foreground mask) globally

$$\begin{aligned}\hat{\mathbf{Y}} &= \arg \max_{\mathbf{Y}} F(\mathbf{X}, \mathbf{Y}; \mathbf{W}) \\ &= \arg \max_{\mathbf{Y}} \sum_i \mathbf{w}^T \phi(y_i, \mathbf{x}_i) + \alpha \sum_{i,j} \psi(y_i, y_j, |\mathbf{x}_i - \mathbf{x}_j|)\end{aligned}$$



Structured prediction framework

- Input $\mathbf{X} = \{x_i\}_{i=1}^n, \quad x_i \in \mathbf{R}^d$
- Output $\mathbf{Y} = \{y_i\}_{i=1}^n, \quad y_i \in \mathbf{L}, \mathbf{L} = \{1, \dots, K\}$
- Structured prediction model

$$\hat{\mathbf{Y}} = \arg \max_{\mathbf{Y}} F(\mathbf{X}, \mathbf{Y}, \mathbf{W})$$

$$\begin{aligned} F(\mathbf{X}, \mathbf{Y}, \mathbf{W}) = & \sum_i \phi(x_i, y_i; \mathbf{w}_u) && \text{Unary potential} \\ & + \sum_{i,j} \psi(\mathbf{x}_{ij}, y_i, y_j; \mathbf{w}_p) && \text{Pairwise potential} \\ & + \sum_c \psi_c(\mathbf{x}_c, \mathbf{y}_c; \mathbf{w}_c) && \text{Higher-order potential} \end{aligned}$$

- Examples: surface contour, object class, depth, pose, ...

Structured prediction framework

- A probabilistic view – (conditional) random field

- Conditional probability

$$P(\mathbf{Y}|\mathbf{X}; \mathbf{W}) = \frac{1}{Z_{\mathbf{X}, \mathbf{W}}} \exp\{F(\mathbf{X}, \mathbf{Y}, \mathbf{W})\}$$

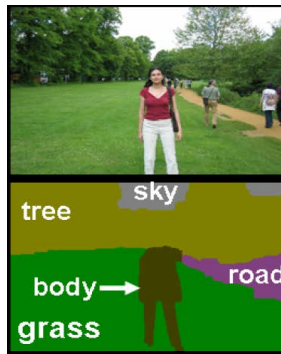
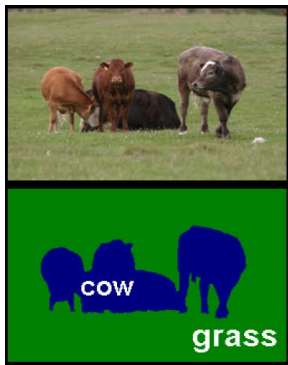
- Label prediction: MAP estimation

- Main question in scene modeling

- What are the potential functions?
- Hand-crafted features, deep neural networks, ...

Multiclass scene labeling

- **TextronBoost CRF** (Shotton et al., ECCV 2006)
 - Simultaneous recognition and segmentation
 - Explain every pixel (dense features)



Model output

Model overview – TextonBoost CRF

- What are useful cues for object classification?
 - Appearance (color, texture,...)
 - Shape
 - Object location
 - Spatial context
- Incorporating those factors into a score function:

$$F = \text{shape-texture term (A)} + \text{color term (B)} \\ + \text{location term (C)} + \text{spatial context term (D)}$$

A. Shape-texture potential

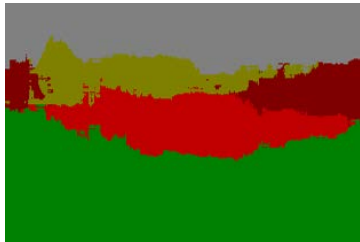
shape-texture potentials

$$F(\mathbf{X}, \mathbf{Y}, \boldsymbol{\theta}) = \sum_i \psi_i(y_i, \mathbf{x}; \boldsymbol{\theta}_\psi)$$

jointly across all pixels



- Shape-texture potentials
 - broad intra-class appearance distribution
 - log boosted classifier
 - parameters $\boldsymbol{\theta}_\psi$ learned offline



shape-texture potentials

B. Color potential

$$F(\mathbf{X}, \mathbf{Y}, \boldsymbol{\theta}) = \sum_i \psi_i(y_i, \mathbf{x}; \boldsymbol{\theta}_\psi) + \overbrace{\pi(y_i, \mathbf{x}_i; \boldsymbol{\theta}_\pi)}^{\text{colour potentials}}$$

- Colour potentials
 - compact appearance distribution
 - Gaussian mixture model

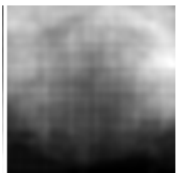


intra-class
appearance variations

C. Location potential

$$F(\mathbf{X}, \mathbf{Y}, \boldsymbol{\theta}) = \sum_i \psi_i(y_i, \mathbf{x}; \boldsymbol{\theta}_\psi) + \pi(y_i, \mathbf{x}_i; \boldsymbol{\theta}_\pi) + \overbrace{\lambda(y_i, i; \boldsymbol{\theta}_\lambda)}^{\text{location potentials}}$$

- Capture prior on absolute image location



tree



sky



road

D. Spatial context

$$F(\mathbf{X}, \mathbf{Y}, \boldsymbol{\theta}) = \sum_i \psi_i(y_i, \mathbf{x}; \boldsymbol{\theta}_\psi) + \pi(y_i, \mathbf{x}_i; \boldsymbol{\theta}_\pi) + \lambda(y_i, i; \boldsymbol{\theta}_\lambda) \\ + \sum_{(i,j) \in \mathcal{E}} \underbrace{\phi(y_i, y_j, \mathbf{g}_{ij}(\mathbf{x}); \boldsymbol{\theta}_\phi)}_{\text{edge potentials}}$$

sum over
neighbouring
pixels \rightarrow

- Potts model

- encourages neighbouring pixels to have same label

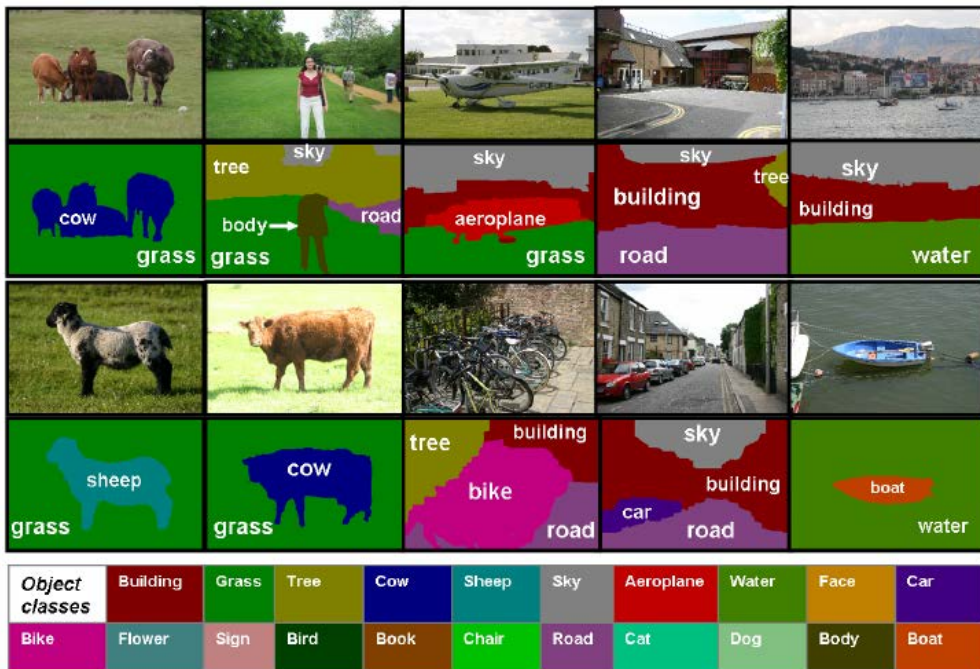
- Contrast sensitivity

- encourages segmentation to follow image edges



image edge map

Good Results



Graphical Models

- A **graphical model** is a probabilistic model for which a graph expresses conditional dependence between random variables
 - Bayesian networks: directed acyclic graph
 - Markov networks: undirected graph
 - Factor graphs, conditional random fields, etc.

Converting Directed to Undirected Graphs (1)



$$p(\mathbf{x}) = \underbrace{p(x_1)p(x_2|x_1)} \underbrace{p(x_3|x_2)} \cdots p(x_N|x_{N-1})$$

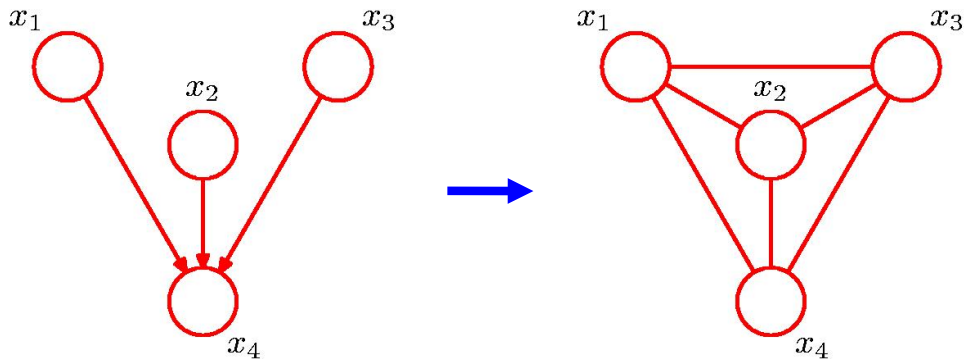
$$p(\mathbf{x}) = \frac{1}{Z} \psi_{1,2}(x_1, x_2) \underbrace{\psi_{2,3}(x_2, x_3)} \cdots \psi_{N-1,N}(x_{N-1}, x_N)$$

blanket



Converting Directed to Undirected Graphs (2)

- Additional links (moralization)



$$\begin{aligned} p(\mathbf{x}) &= p(x_1)p(x_2)p(x_3)p(x_4|x_1, x_2, x_3) \\ &= \frac{1}{Z} \psi(x_1, x_2, x_3, x_4) \end{aligned}$$

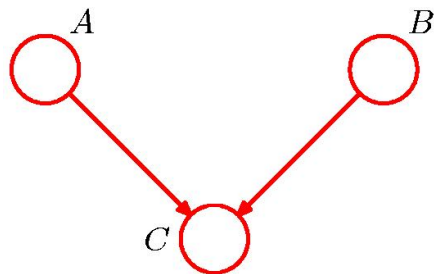
Bayesian Network \rightarrow Markov Network

- Steps

1. Moralization
2. Construct potential functions from CPTs

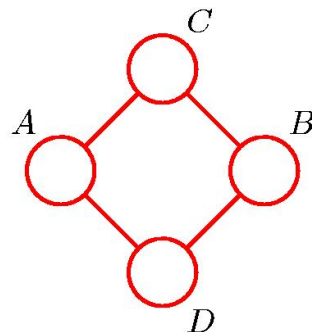
- The BN and MN encode the same distribution
- Do they encode the same set of conditional independence?

Encoding Conditional Independence



$$A \perp\!\!\!\perp B \mid \emptyset$$

$$A \not\perp\!\!\!\perp B \mid C$$



$$A \not\perp\!\!\!\perp B \mid \emptyset$$

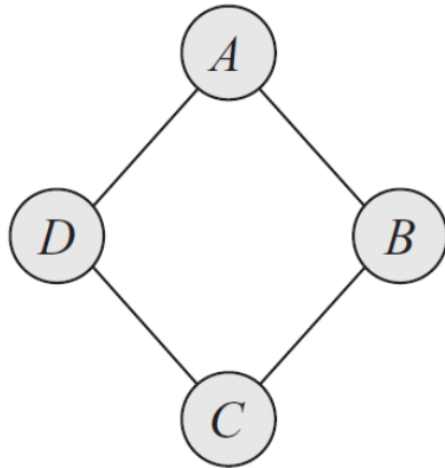
$$A \perp\!\!\!\perp B \mid C \cup D$$

$$C \perp\!\!\!\perp D \mid A \cup B$$

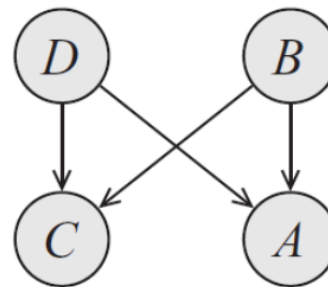
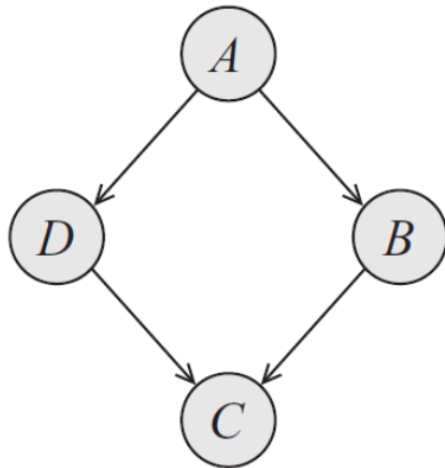
How

问题 8

For four random variables, there exists a Markov Network to represent it as:

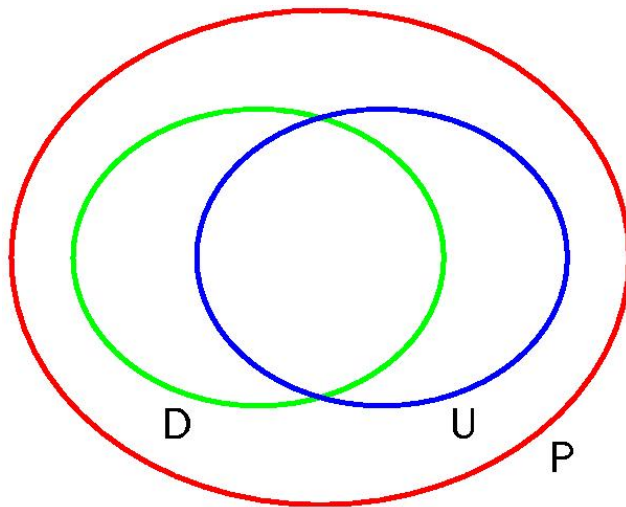


Please choose the Bayesian Network that can precisely (no more, no less) represent the distribution of this Markov Network from the two models:



- ☐ the first model
- ☐ the second model
- ☐ both of them
- ☒ neither of them

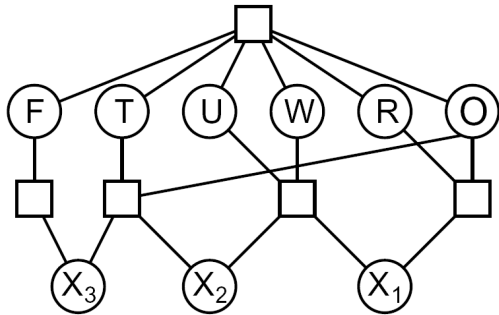
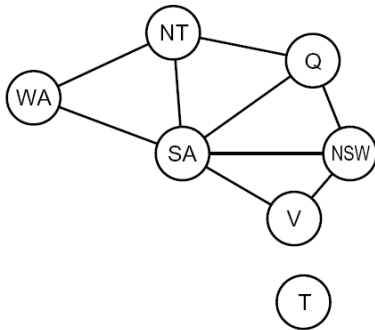
Encoding Conditional Independence



The set of distributions whose conditional independence can be exactly (i.e., no more, no less) represented by a **directed/undirected** graph

Markov networks vs. Constraint graphs

- Constraint graphs can be seen as Markov networks with 0/1 potentials



BN/MN vs. Logic

- Which logic is BN/MN more similar to: PL? FOL?
 - Boolean nodes represent propositions
 - No explicit representation of objects, relations, quantifiers
- BN/MN can be seen as a probabilistic extension of PL
- PL can be seen as BN/MN with deterministic CPTs/potentials