Lecture 16. PGM Representation

COMP90051 Statistical Machine Learning

Semester 2, 2019
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Next Lectures

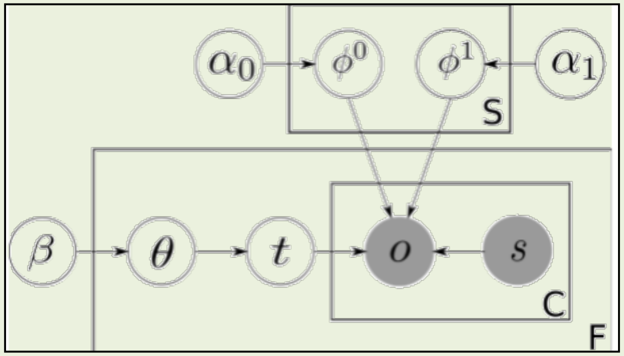
- Representation of joint distributions
- Conditional/marginal independence
  * Directed vs undirected
- Probabilistic inference
  * Computing other distributions from joint
- Statistical inference
  * Learn parameters from (missing) data

Probabilistic Graphical Models

Marriage of graph theory and probability theory.
Tool of choice for Bayesian statistical learning.

We'll stick with easier discrete case,
ideas generalise to continuous.

Motivation by practical importance



- **Many applications**
  - Phylogenetic trees
  - Pedigrees, Linkage analysis
  - Error-control codes
  - Speech recognition
  - Document topic models
  - Probabilistic parsing
  - Image segmentation
  - …
- **discovered algorithms**
  - HMMs
  - Kalman filters
  - Mixture models
  - LDA
  - MRFs
  - CRF
  - Logistic, linear regression
  - …

Motivation by way of comparison

Bayesian statistical learning

- Model joint distribution of X's,Y and parameter r.v.'s
  - "Priors": marginals on parameters
- Training: update prior to posterior using observed data
- Prediction: output posterior, or some function of it (MAP)

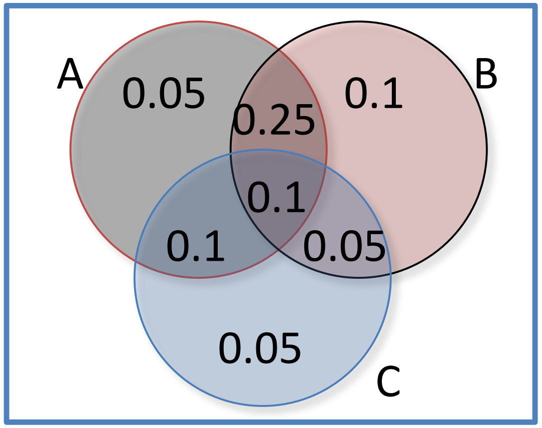
PGMs aka "Bayes Nets"

- Efficient joint representation
  - Independence made explicit
  - Trade-off between expressiveness and need for data, easy to make
  - Easy for practitioners to model
- Algorithms to fit parameters, compute marginals, posterior

Everything Starts at the Joint Distribution

- All joint distributions on discrete r.v.'s can be represented as tables
- #rows grows exponentially with #r.v.'s
- Example: Truth Tables
  - M Boolean r.v.'s require 2^M-1 rows
  - Table assigns probability per row

A	B	C	Prob
0	0	0	0.30
0	0	1	0.05
0	1	0	0.10
0	1	1	0.05
1	0	0	0.05
1	0	1	0.10
1	1	0	0.25
1	1	1	?



The Good: What we can do with the joint

- **Probabilistic inference** from joint on r.v.'s
  - Computing any other distributions involving our r.v.'s
- Pattern: want a distribution, have joint; use: Bayes rule + marginalisation
- Example: **naïve Bayes classifier**
  - Predict class y of instance $\boldsymbol{x}$ by maximising

$$\Pr(Y=y|\boldsymbol{X}=\boldsymbol{x}) = \frac{\Pr(Y=y,\boldsymbol{X}=\boldsymbol{x})}{\Pr(\boldsymbol{X}=\boldsymbol{x})} = \frac{\Pr(Y=y,\boldsymbol{X}=\boldsymbol{x})}{\sum_y \Pr(\boldsymbol{X}=\boldsymbol{x},Y=y)}$$

Recall: *integration (over parameters)* continuous equivalent of sum (both referred to as marginalisation)

The Bad & Ugly: Tables *waaaaay* too large*!!*

- **The Bad**: Computational complexity
  - Tables have exponential number of rows in number of r.v.'s
  - Therefore → poor space & time to marginalise
- **The Ugly**: Model complexity
  - Way too flexible
  - Way too many parameters to fit
    → need lots of data OR will overfit
- Antidote: assume independence!

A	B	C	Prob
0	0	0	0.30
0	0	1	0.05
0	1	0	0.10
0	1	1	0.05
1	0	0	0.05
1	0	1	0.10
1	1	0	0.25
1	1	1	?

Example: You're late!

- Modeling a tardy lecturer. Boolean r.v.'s
  - T: Ben teaches the class
  - S: It is sunny (o.w. bad weather)
  - L: The lecturer arrives late (o.w. on time)
- Assume: Ben sometimes delayed by bad weather, Ben more likely late than other lecturers
  - $\Pr(S|T) = \Pr(S)$, $\Pr(S) = 0.3$, $\Pr(T) = 0.6$
- Lateness not independent on weather, lecturer
  - Need $\Pr(L|T = t, S = s)$ for all combinations
- Need just 6 parameters

$\Pr(L = true \mid \ldots)$		T: False	T: True
S	False	0.1	0.2
	True	0.05	0.1

$\Pr(T)$

$\Pr(L|T,S)\ \Pr(T|S)\ \Pr(S) \Leftarrow$ joint

Independence: not a dirty word

Lazy Lecturer Model	Model details	# params
Our model with S, T independence	$\Pr(S,T)$ factors to $\Pr(S)\Pr(T)$	2
	$\Pr(L \mid T, S)$ modelled in full	4
Assumption-free model	$\Pr(L, T, S)$ modelled in full	7

- Independence assumptions
  - Can be reasonable in light of domain expertise
  - Allow us to factor → Key to tractable models

Factoring Joint Distributions

- Chain Rule: for any ordering of r.v.'s can always factor:

$$\Pr(X_1, X_2, \ldots, X_k) = \prod_{i=1}^{k} \Pr(X_i | X_{i+1}, \ldots, X_k)$$

- Model's independence assumptions correspond to
  - Dropping conditioning r.v.'s in the factors!
  - Example unconditional indep.: $\Pr(X_1|X_2) = \Pr(X_1)$
  - Example conditional indep.: $\Pr(X_1|X_2, X_3) = \Pr(X_1|X_2)$
- Example: independent r.v.'s $\Pr(X_1, \ldots, X_k) = \prod_{i=1}^{k} \Pr(X_i)$
- Simpler factors: speed up inference and avoid overfitting

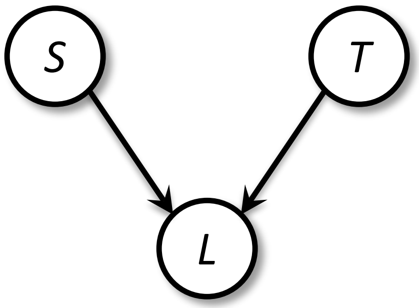
Directed PGM

- Nodes
- Edges (acyclic)

- Random variables
- Conditional dependence
  - Node table: $\Pr(child|parents)$
  - Child directly depends on parents
- Joint factorisation

$$\Pr(X_1, X_2, \dots, X_k) = \prod_{i=1}^{k} \Pr\left(X_i | X_j \in parents(X_i)\right)$$

Tardy Lecturer Example

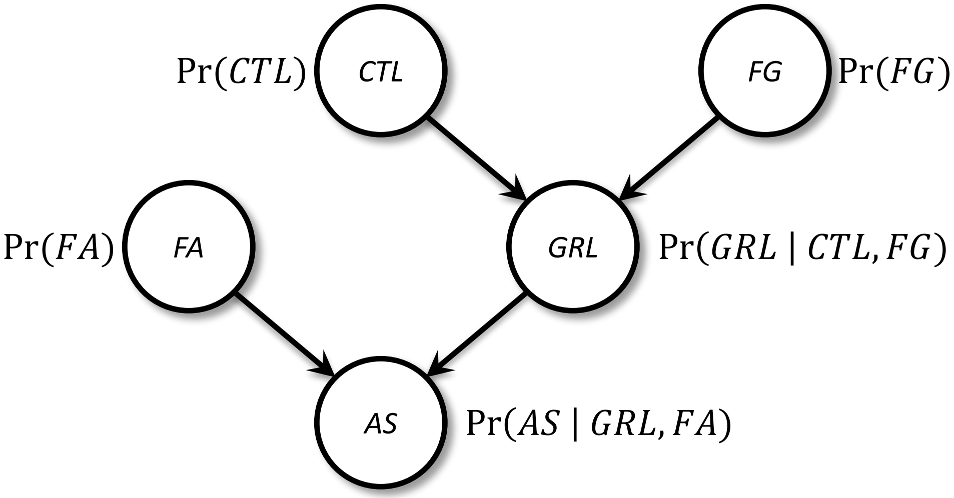


$\Pr(S)$ $\Pr(T)$

$\Pr(L|S,T)$

Example: Nuclear power plant

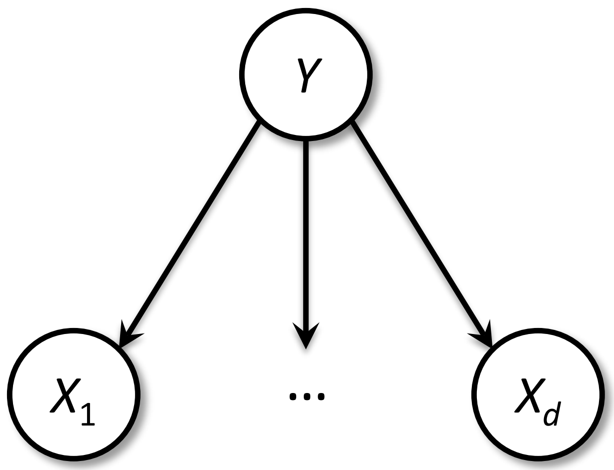
- Core temperature
  → Temperature Gauge
  → Alarm
- Model uncertainty in monitoring failure
  * GRL: gauge reads low
  * CTL: core temperature low
  * FG: faulty gauge
  * FA: faulty alarm
  * AS: alarm sounds
- PGMs to the rescue!



Joint $\Pr(CTL, FG, FA, GRL, AS)$ given by

$$\Pr(AS|FA, GRL)\Pr(FA)\Pr(GRL|CTL, FG)\Pr(CTL)\Pr(FG)$$

Naïve Bayes



$Y \sim \mathrm{Bernoulli}(\theta)$

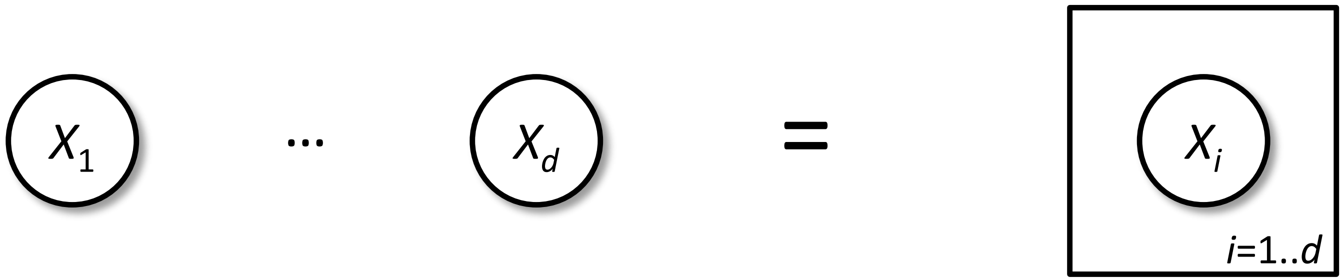
Aside: Bernoulli is just Binomial with count=1

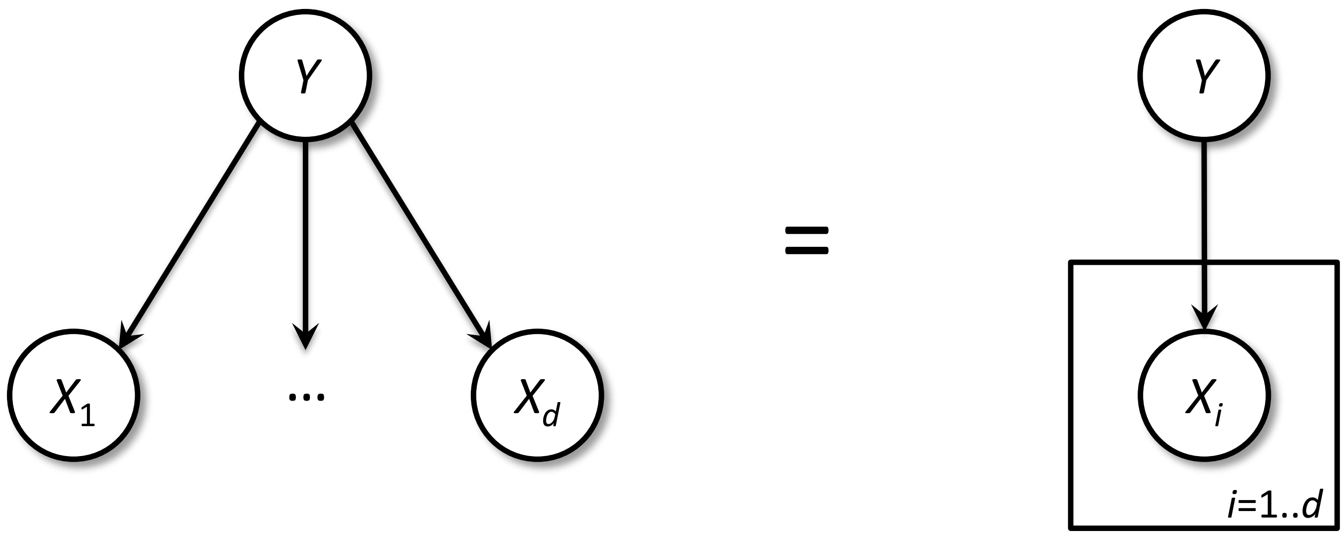
$X_j | Y \sim \mathrm{Bernoulli}(\theta_{j,Y})$

$$
\begin{aligned}
&\Pr(Y, X_1, \dots, X_d) \\
&\quad = \Pr(X_1, \dots, X_d, Y) \\
&\quad = \Pr(X_1|Y)\Pr(X_2|X_1,Y)\dots\Pr(X_d|X_1,\dots,X_{d-1},Y)\Pr(Y) \\
&\quad = \Pr(X_1|Y)\Pr(X_2|Y)\dots\Pr(X_d|Y)\Pr(Y)
\end{aligned}
$$

Prediction: predict label maximising $\Pr(Y|X_1, \dots, X_d)$

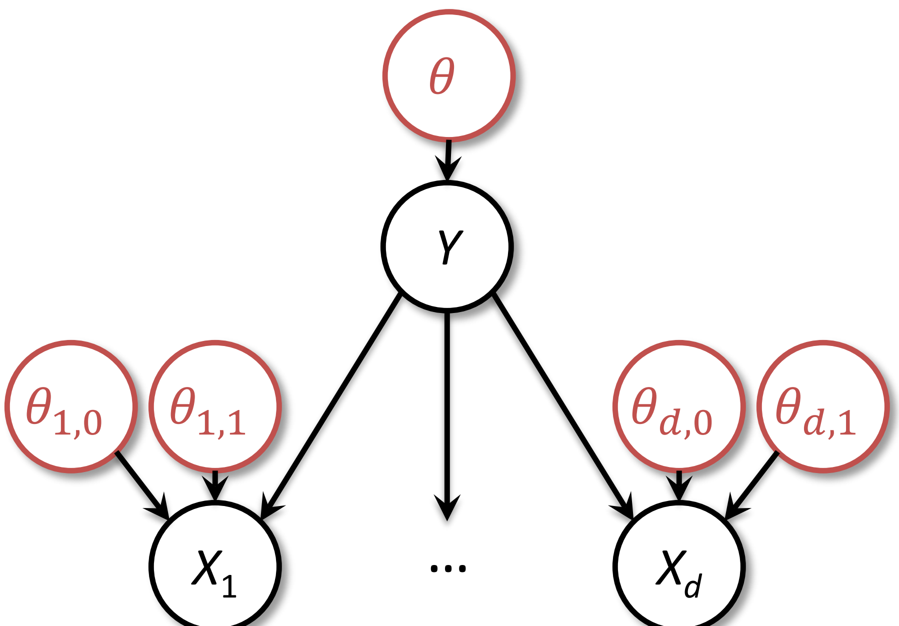
Short-hand for repeats: Plate notation





PGMs frequentist OR Bayesian…

- PGMs represent joints, which are central to Bayesian
- Catch is that Bayesians add: node per parameters, with table being the parameter's prior



$Y \sim \mathrm{Bernoulli}(\theta)$

$X_j | Y \sim \mathrm{Bernoulli}(\theta_{j,Y})$

$\theta's \sim Beta$

Undirected PGMs

Undirected variant of PGM, parameterised by arbitrary positive valued functions of the variables, and global normalisation.

A.k.a. Markov Random Field.

Undirected vs directed

Undirected PGM

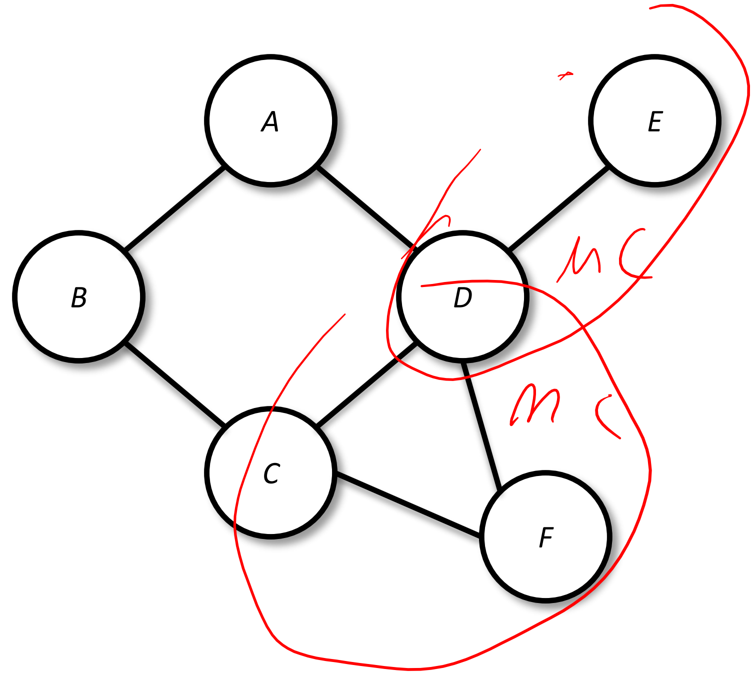
- Graph
  * Edges undirected
- Probability
  * Each node a r.v.
  * Each clique C has "factor" $\psi_C(X_j : j \in C) \geq 0$
  * Joint $\propto$ product of factors

Directed PGM

- Graph
  * Edged directed
- Probability
  * Each node a r.v.
  * Each node has conditional $p(X_i | X_j \in parents(X_i))$
  * Joint $=$ product of cond'ls

Key difference = normalisation

Undirected PGM formulation



- Based on notion of
  - *Clique: a set of fully connected nodes (e.g., A-D, C-D, C-D-F)*
  - *Maximal clique: largest cliques in graph (not C-D, due to C-D-F)*
- Joint probability defined as

$$P(a,b,c,d,e,f) = \frac{1}{Z}\psi_1(a,b)\psi_2(b,c)\psi_3(a,d)\psi_4(d,c,f)\psi_5(d,e)$$

  - where ψ is a positive function and Z is the normalising 'partition' function

$$Z = \sum_{a,b,c,d,e,f} \psi_1(a,b)\psi_2(b,c)\psi_3(a,d)\psi_4(d,c,f)\psi_5(d,e)$$

Directed to undirected

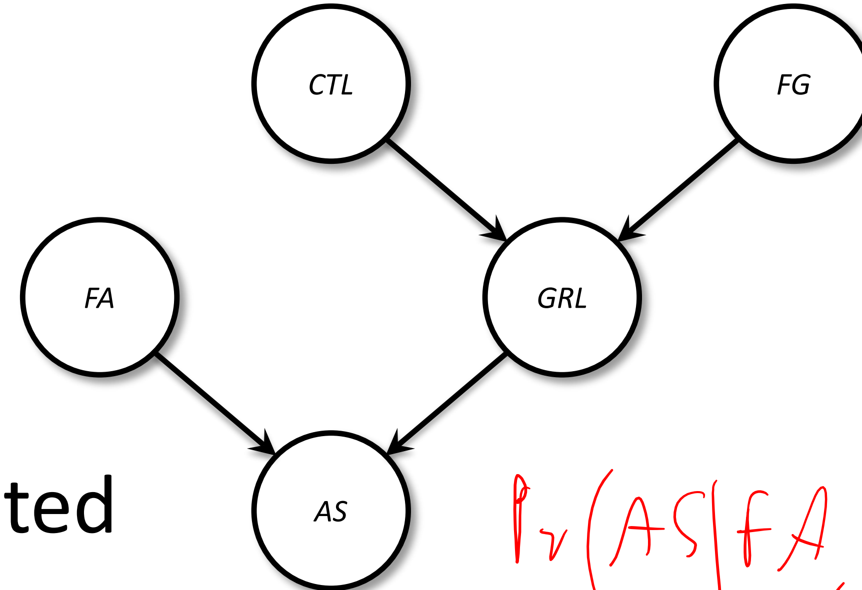
- Directed PGM formulated as

$$P(X_1, X_2, \ldots, X_k) = \prod_{i=1}^{k} Pr(X_i | X_{\pi_i})$$

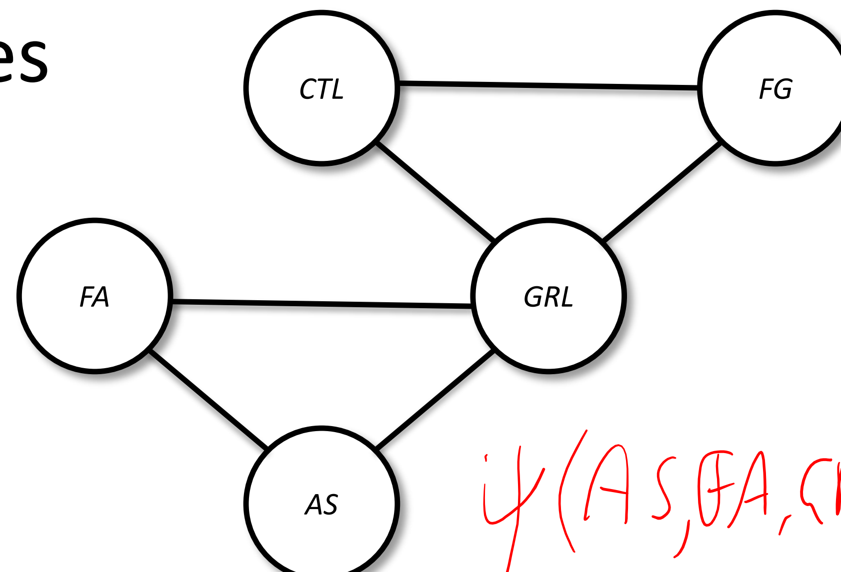
where **π** indexes parents.

- Equivalent to U-PGM with
  * each conditional probability term is included in one factor function, ψ_c
  * clique structure links *groups of variables,* i.e., $\{\{X_i\} \cup X_{\pi_i}, \forall i\}$
  * normalisation term trivial, Z = 1

1. copy nodes
2. copy edges, undirected
3. 'moralise' parent nodes



$Pr(AS|FA,GRL)$



$\psi(AS,FA,GRL)$

Why U-PGM?

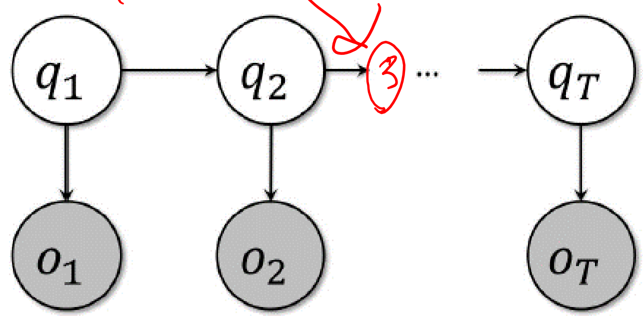
- Pros
  - generalisation of D-PGM
  - simpler means of modelling without the need for per-factor normalisation
  - general inference algorithms use U-PGM representation (supporting both types of PGM)
- Cons
  - (slightly) weaker independence
  - calculating global normalisation term (Z) intractable in general (but tractable for chains/trees, e.g., CRFs)

Example PGMs

The hidden Markov model (HMM);
lattice Markov random field (MRF);
Conditional random field (CRF)

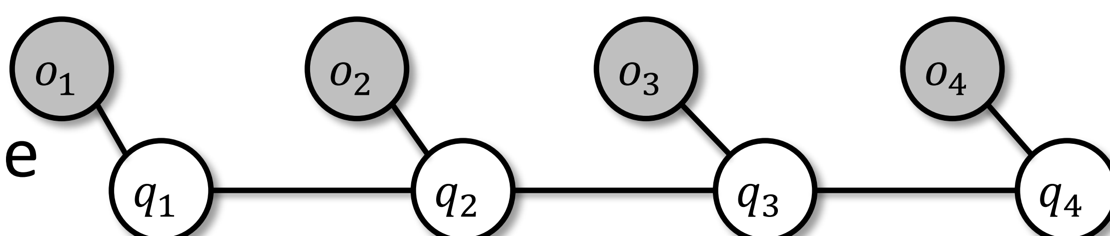
The HMM (and Kalman Filter)

- Sequential observed ~~outputs~~ from hidden state



$A = \{a_{ij}\}$	transition probability matrix; $\forall i : \sum_j a_{ij} = 1$
$B = \{b_i(o_k)\}$	output probability matrix; $\forall i : \sum_k b_i(o_k) = 1$
$\Pi = \{\pi_i\}$	the initial state distribution; $\sum_i \pi_i = 1$

- The Kalman filter same with continuous Gaussian r.v.'s
- A CRF is the undirected analogue

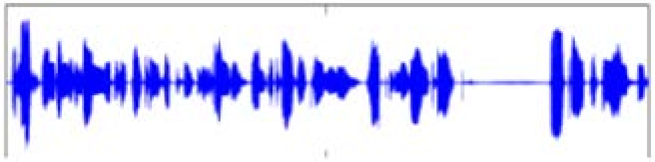


HMM Applications

- NLP – part of speech tagging: given words in sentence, infer hidden parts of speech

  "I love Machine Learning" → noun, verb, noun, noun

- Speech recognition: given waveform, determine phonemes



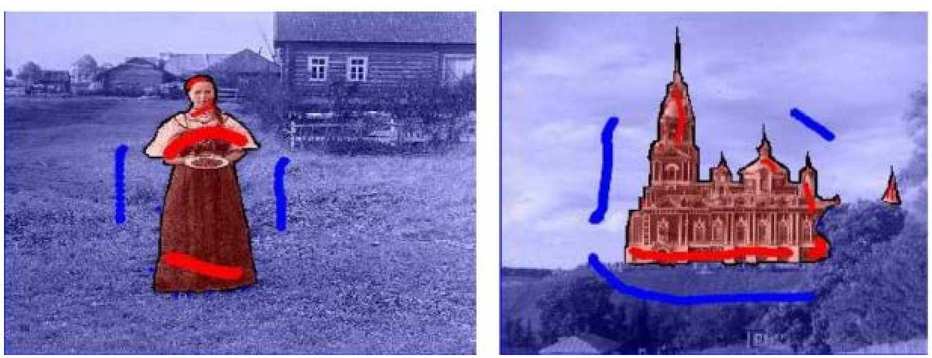
- Biological sequences: classification, search, alignment
- Computer vision: identify who's walking in video, tracking

Fundamental HMM Tasks

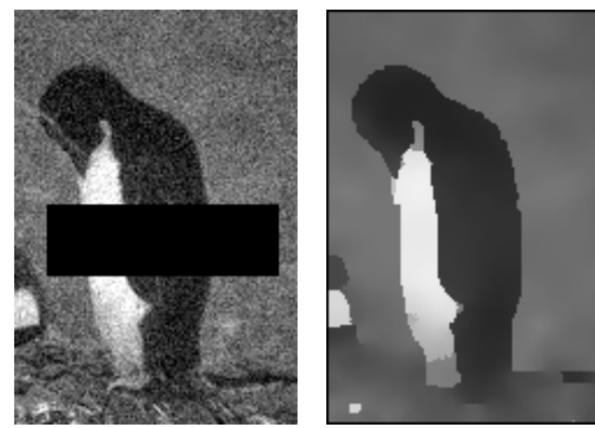
HMM Task	PGM Task
Evaluation. Given an HMM μ and observation sequence O, determine likelihood $\Pr(O\|\mu)$	Probabilistic inference
Decoding. Given an HMM μ and observation sequence O, determine most probable hidden state sequence Q	MAP point estimate
Learning. Given an observation sequence O and set of states, learn parameters A, B, Π	Statistical inference

Pixel labelling tasks in Computer Vision

Semantic labelling (Gould et al. 09)



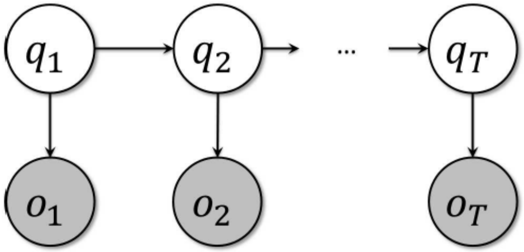
Interactive figure-ground segmentation (Boykov & Jolly 2011)



Denoising (Felzenszwalb & Huttenlocher 04)

What these tasks have in common

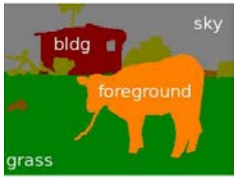
- Hidden state representing semantics of image
  - Semantic labelling: Cow vs. tree vs. grass vs. sky vs. house
  - Fore-back segment: Figure vs. ground
  - Denoising: Clean pixels
- Pixels of image
  - What we observe of hidden state
- Remind you of HMMs?



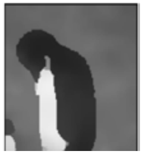
A hidden square-lattice Markov random field

- Hidden states: square-lattice model
  - Boolean for two-class states

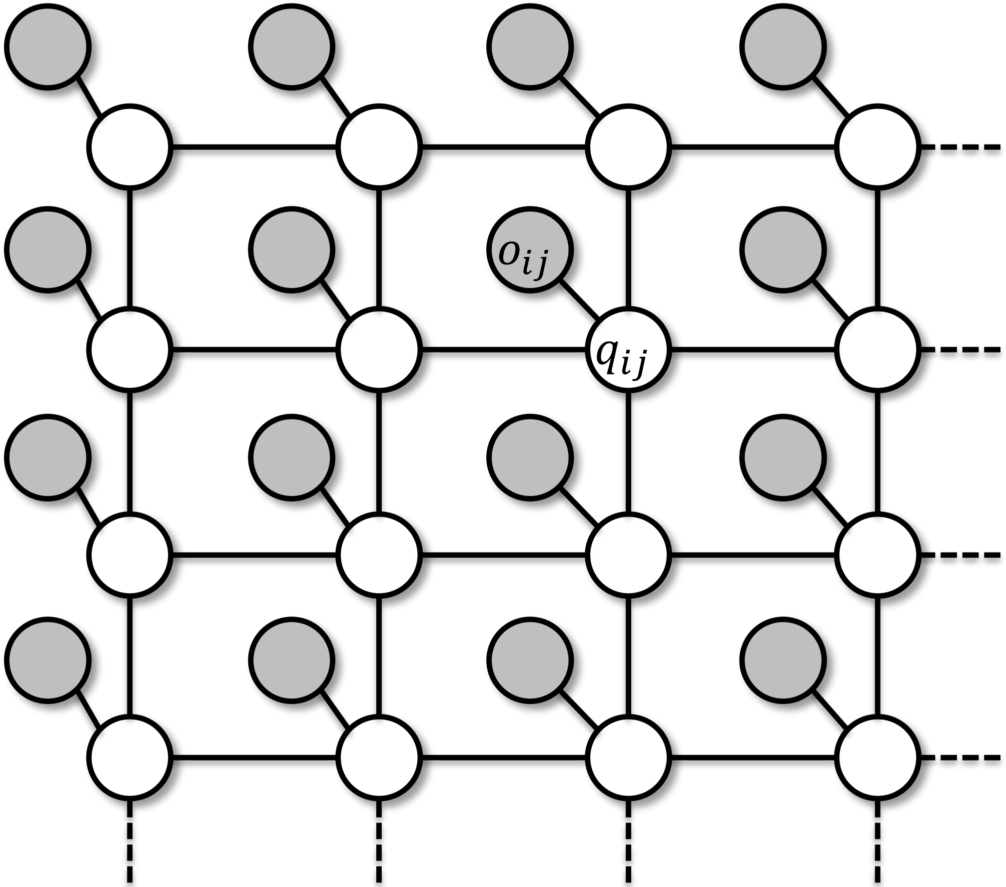
  - Discrete for multi-class



  - Continuous for denoising

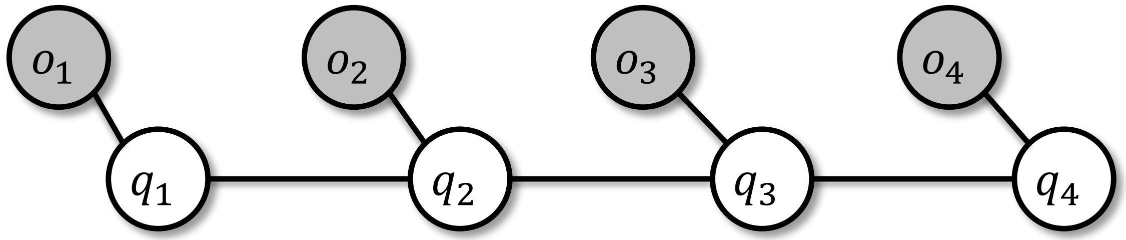


- Pixels: observed outputs
  - Continuous e.g. Normal



Application to sequences: CRFs

- Conditional Random Field: Same model applied to sequences
  - observed outputs are words, speech, amino acids etc
  - states are tags: part-of-speech, phone, alignment…
- CRFs are discriminative, model *P(Q|O)*
  - versus HMM's which are generative, *P(Q,O)*
  - undirected PGM more general and expressive



Summary

- Probabilistic graphical models
  - Motivation: applications, unifies algorithms
  - Motivation: ideal tool for Bayesians
  - Independence lowers computational/model complexity
  - PGMs: compact representation of factorised joints
  - U-PGMs
- Example PGMs and applications
- Next time: elimination for probabilistic inference