

(1) - Introduction

Jordan (2004):

- (W): I don't understand the significance of kernels in the DGM specification
- (W): It is not fully specified how the assertions of conditional independence in directed and undirected graphs differ (i.e. arrows/edge)
- (W): I don't fully understand how we move from the formalism for cliques $C \rightarrow$ formalism for factors
(undirected graph) (factor graph)
- (W): Conversion of directed \rightarrow undirected formalism; work with (2) i.e.

* 3.1 Exact algorithms

- Not entirely sure how/needs investigation of distributive law for marginalisation of $p(x_i)$ i.e. how

$$p(x_1) = \sum_{x_2} \sum_{x_3} \sum_{x_4} \dots \sum_{x_6} \frac{1}{Z} \psi(x_1, x_2) \psi(x_1, x_3) \psi(x_2, x_4) \psi(x_3, x_5) \psi_2(x_2, x_5, x_6)$$

is simplified

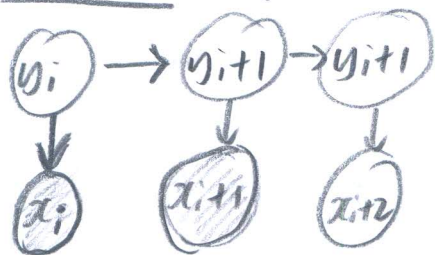
- (W): Key terminology: - elimination order, triangulation algorithm, tree width
- (W): At a high level; what is stated in this algorithm is an efficient way of reducing the computational complexity of marginalising a joint probability distri
- Rest is details, machinery for doing so. (exact elimination algorithm)
- Elimination algorithm \rightarrow sum-product \rightarrow junction-tree algorithm.

• To run; determine how 'loaded' die is.

Inference/learning: QB - How loaded is the die; how fair is the die, how often does the regime switch.

These are 'layman' questions; think in terms of variable-structure-prob.

Let's formalise: - remember r.v.s denote events (Knowledge Engineering)



(GM that reflects our story; but not exhaustively)

(one way of setting up)

HMM ✓

shaded \rightarrow observed; so observation x_i is observed; y_i latent
(shown face of a die) (110 fair die)

$x_i \in [1, 2, 3, 4, 5, 6]$

$y_i \in [0, 1]$

structure: causal, generative, coupling

There are many ways to of 'cutting the cake' for an observe-relative specification e.g. specification of params. / r.v.s. etc.; but here to deal appropriately with requisite complexity

need sequential evolution: add (y_{i+1}, x_{i+1})

How about selecting loaded, die - independent; or dependent event?

If we keep choice of fair/loaded depended on previous choice of die; ☹

then we have about GM structure $(i+1)$ $(i-1)$

Markovian property: 1st order; immediate future independent of immediate past given present (i).

HMM very widely used for modelling dependencies (Blackjack?)

Ex: Begin with joint distri:- $p(x, y)$

A sequence $x = (x_1, \dots, x_T)$ and parse $y = (y_1, \dots, y_T)$

$p(x, y) = p(x_1, \dots, x_T, y_1, \dots, y_T)$ - use Factorisation using arg, cond. for parts
 $= p(y_1) p(x_1 | y_1) \dots p(y_T | y_{T-1}) p(x_T | y_T)$