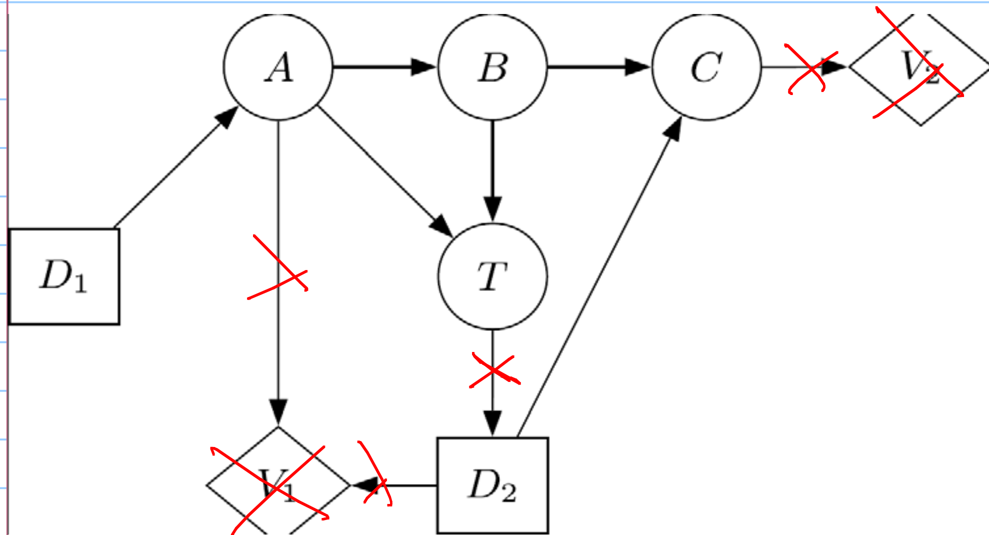
Note Title 4/13/2009



For the purpose of d-separation,

- remove utility nodes
- remove the edges (information links) into decision nodes

$$\underbrace{\{\}}_{\mathcal{I}_0} < D_1 < \underbrace{\{T\}}_{\mathcal{I}_1} < D_2 < \underbrace{\{A, B, C\}}_{\mathcal{I}_2}$$

Ex. C is d-separated from T by B

C is d-separated from A by B

A and T are d-separated from D_2.

Proposition 10.1 Let $A \in \mathcal{I}_i$ and let D_j be a decision variable with $i < j$. Then

(i) A and D_j are d-separated, and hence

$$P(A \mid D_j) = P(A)$$

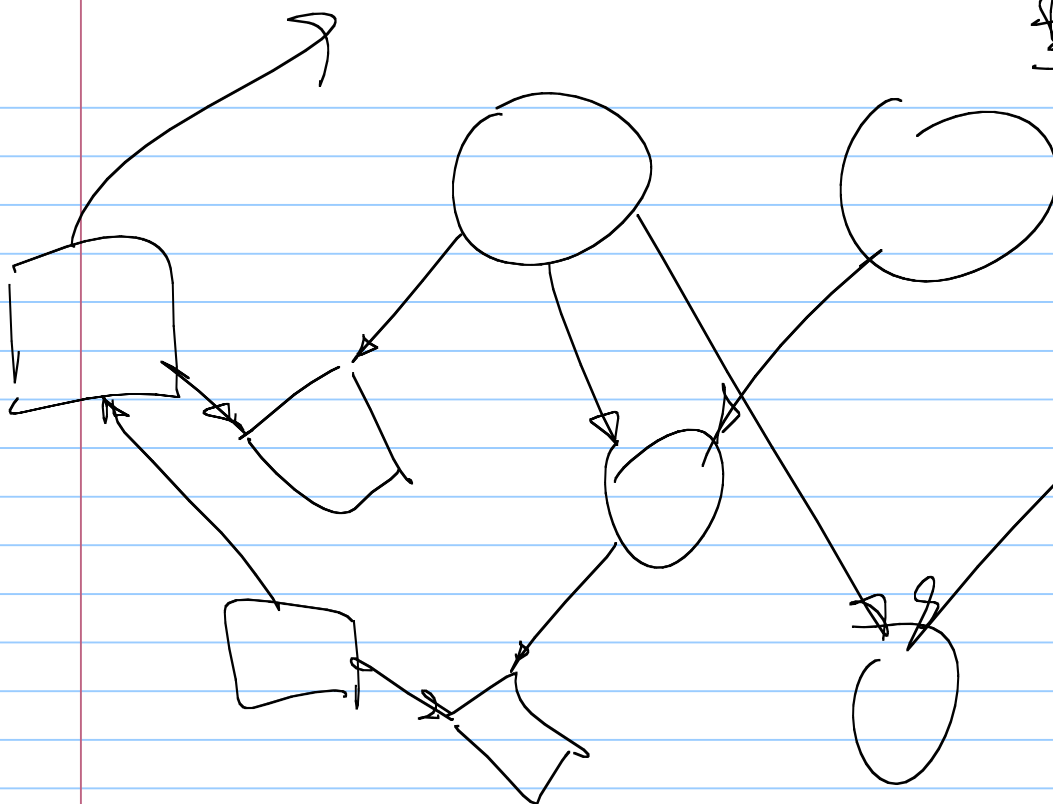
(ii) Let W be any set of variables prior to D_j in the temporal ordering. Then A and D_j are d-separated given W and hence

$$P(A \mid D_j, W) = P(A \mid W)$$

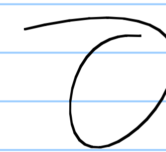
The Chain Rule for Influence Diagrams

Let ID be an influence diagram with universe $U = U_C \cup U_D$. Then

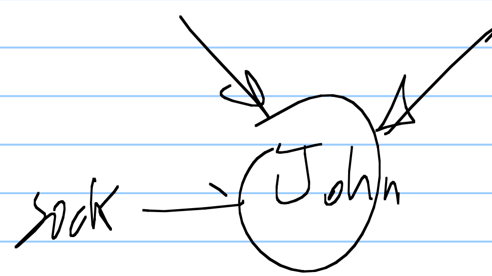
$$P(U_C \mid U_D) = \prod_{X \in U_C} P(X \mid pa(X))$$



Ex. 9.5 – add one utility & decision node for each horse.



Remember to link the decision nodes in a directed path.



10.2 Variable Elimination for IDs.

You can compute the MEU of a decision node by variable elimination, similarly to the way this is done for posterior probability (belief) computation in BNs.

However, in an ID, you have $\underbrace{\text{chance variables}}_{\text{as variables in BNs}}$ and decision variables.

Variables are eliminated in the reverse order of their appearance in the information order

$$\mathcal{J}_0 < D_1 < \mathcal{J}_1 < \dots < \mathcal{J}_i < D_{i+1} < \dots < \mathcal{J}_n$$

D_i is a single decision variable

$\mathcal{J}_i$ is a set of variables known to the decision maker between decision i and decision $i+1$.

There are two kinds of marginalization, one for chance variables, and one for decision variables.

Algorithm 10.1

Two sets of potentials, Φ, set of probability potentials

Ψ, set of utility potentials.

When variable X is eliminated, the potential sets are modified in the following way:

1. $\Phi_X := \{ \varphi \in \Phi \mid X \in \mathrm{dom}(\varphi) \}$

$\Psi_X := \{ \psi \in \Psi \mid X \in \mathrm{dom}(\psi) \}$

2. If X is a chance variable, then

$$\varphi_X := \sum_X \prod \phi_X$$

$$\psi_X := \sum_X \prod \phi_X \left(\sum \psi_X\right)$$ [New]

If X is decision variable

$$\varphi_X := \max_X \prod \phi_X$$

$$\psi_X := \max_X \prod \phi_X \left(\sum \Psi_X\right)$$

3.

$$\Phi := \left(\Phi \setminus \Phi_X\right) \cup \{\varphi_X\}$$

$$\Psi := \left(\Psi \setminus \Psi_X\right) \cup \left\{\frac{\psi_X}{\varphi_X}\right\}$$

?! read 10.1 !

Next: strong junction trees
(e.g. j.t. for BNs)

Strong: respect the ordering

$\mathcal{I}_0 < D_1 < \mathcal{I}_1, \ldots$!