

Bayesian networks:

In naive Bayes:

$$P(x_1, x_2, \dots, x_N) = P(x_1)P(x_2) \dots P(x_N)$$

More generally

$$P(x_1, x_2) = P(x_2 | x_1) P(x_1)$$

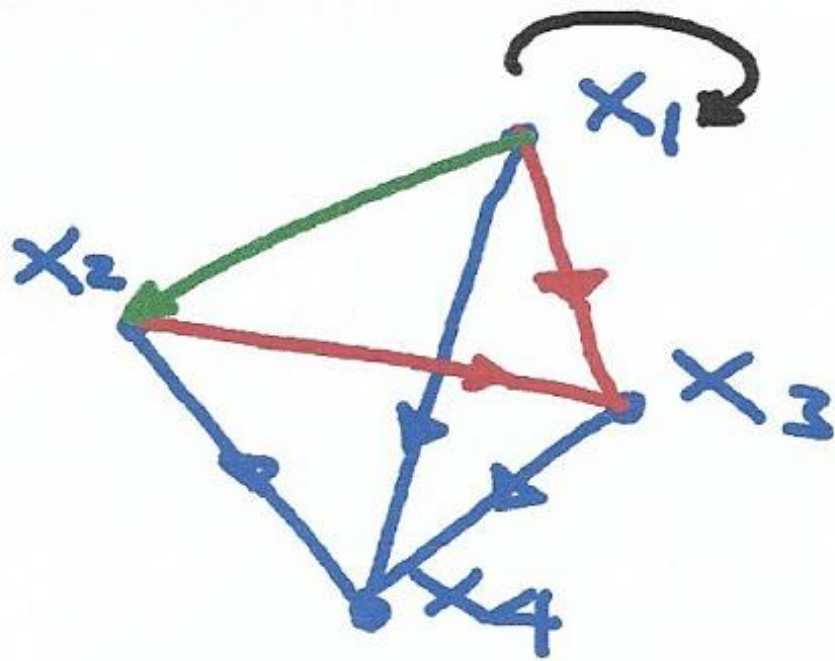
$$P(x_1, x_2, x_3) = P(x_3 | x_2, x_1) \cdot P(x_1, x_2)$$

$$= P(x_3 | x_2, x_1) P(x_2 | x_1) P(x_1)$$

$$P(x_1, x_2, x_3, x_4) = P(x_4 | x_3, x_2, x_1) P(x_1, x_2, x_3)$$

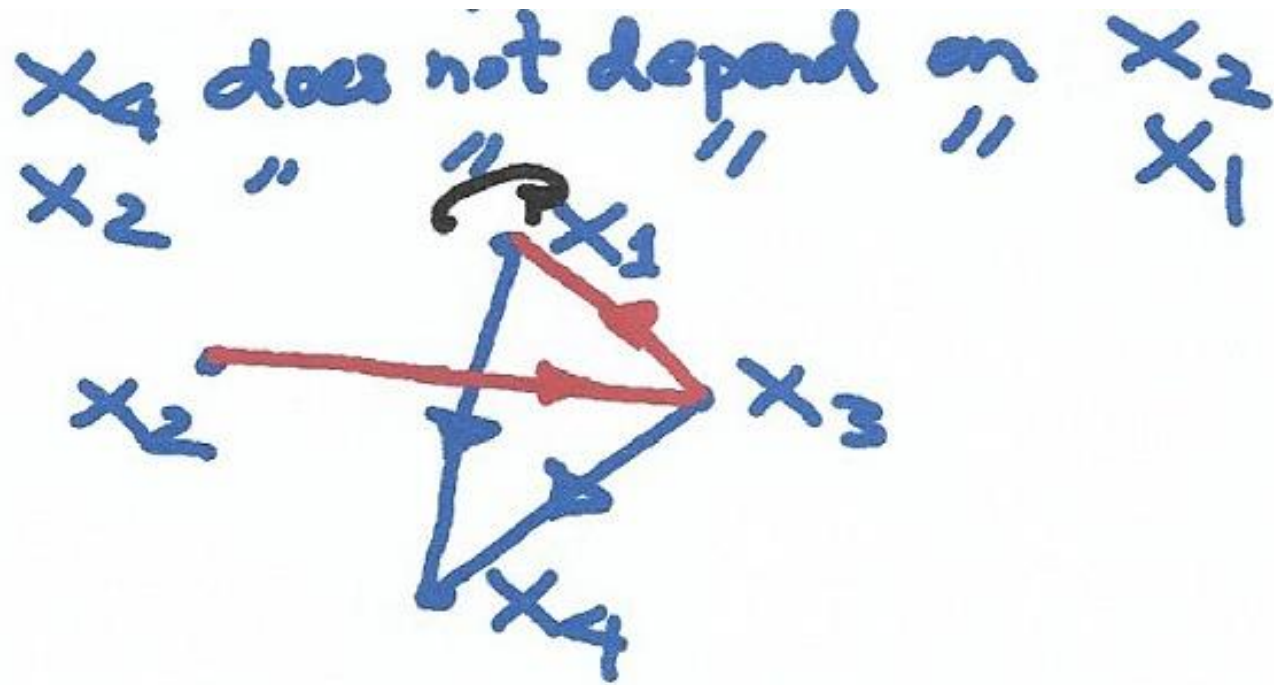
$$= P(x_4 | x_3, x_2, x_1) P(x_3 | x_2, x_1) P(x_2 | x_1) P(x_1)$$

$$P(x_1, x_2, \dots, x_N) = P(x_N | x_{N-1}, \dots, x_1) \cdot P(x_{N-1} | x_{N-2}, \dots, x_1) \dots P(x_2 | x_1) P(x_1)$$

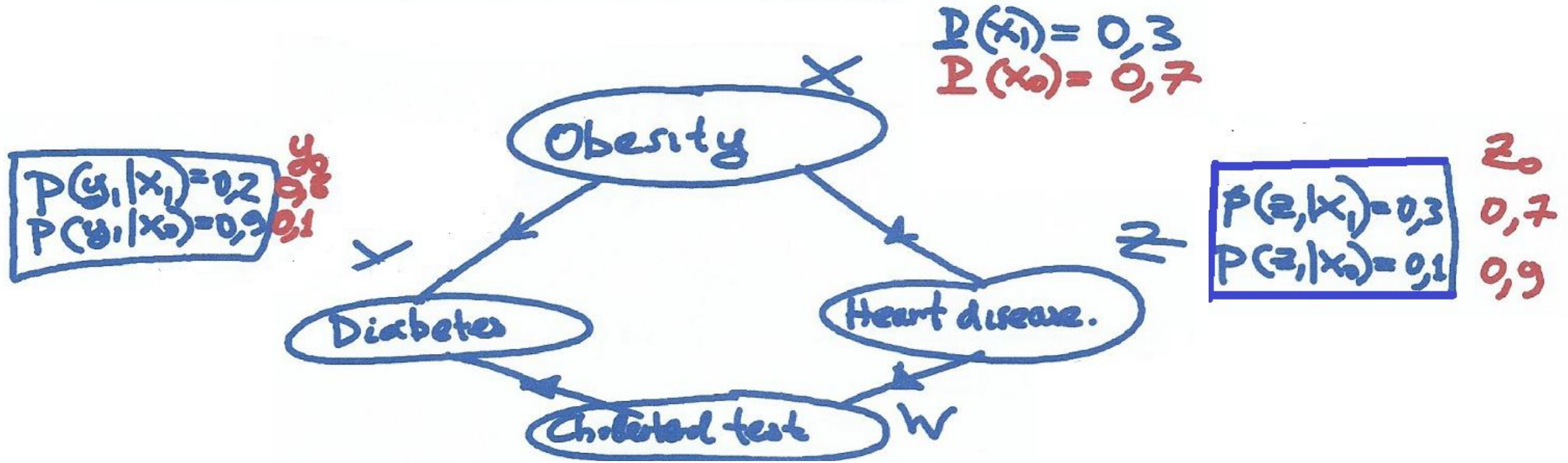


x_1, x_2, x_3, x_4

Knowledge (particular to the problem):



Bayesian network example:



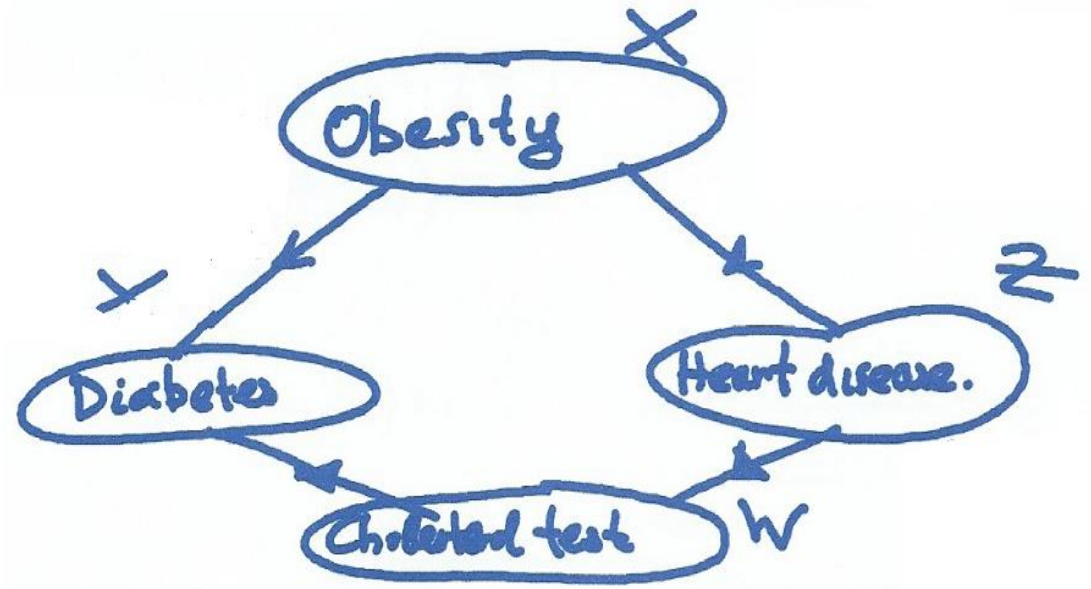
$P(W_1 Y_1, Z_1) = 0,9$	W_0
$P(W_1 Y_1, Z_0) = 0,6$	0,1
$P(W_1 Y_0, Z_1) = 0,3$	0,4
$P(W_1 Y_0, Z_0) = 0,1$	0,7
	0,9

$$P(\text{Positive test} | \text{Obese})$$

↓
Evidence.

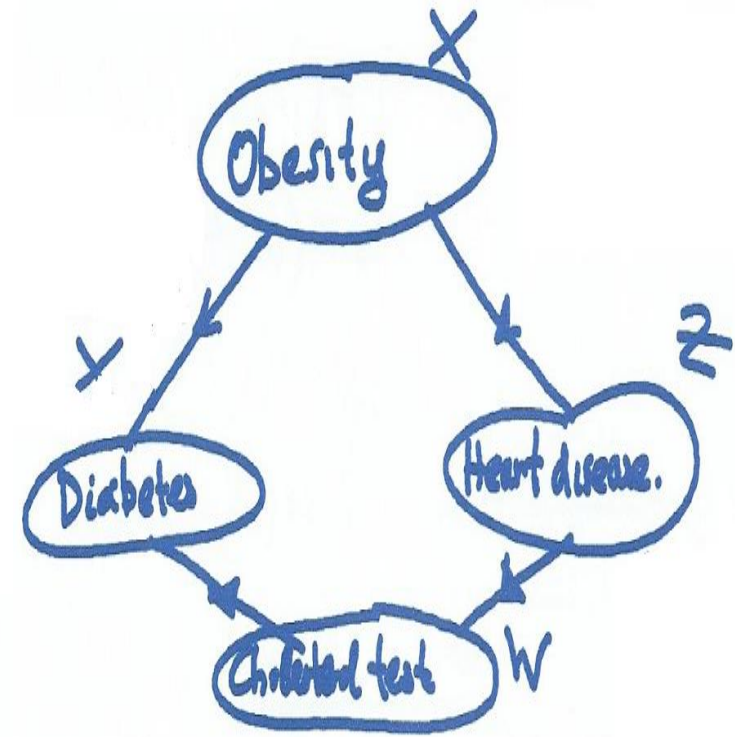
$$= P(w_i | x_i)$$

Pearl's algorithm.



$$\textcircled{1} \quad P(w, |x_1) = \frac{P(x_1, w_1)}{P(x_1)}$$

$$\begin{aligned} \textcircled{2} \quad P(w, |x_1) &= \sum_{y, z} P(w_1, y, z, x_1) = \\ &= P(w_1, y_1, z_1, x_1) + P(w_1, y_1, z_0, x_1) \\ &\quad + P(w_1, y_0, z_1, x_1) + P(w_1, y_0, z_0, x_1). \end{aligned}$$



$$\textcircled{3} \quad P(w, |y, z, x_1) = P(w, |y_1, z_1) P(y_1 | x_1) P(z_1 | x_1) \cdot P(x_1)$$

$$\textcircled{3} P(\omega_1, y_1, z_1, x_1) = P(\omega_1 | y_1, z_1) P(y_1 | x_1) P(z_1 | x_1) \cdot P(x_1)$$

$$0,0162$$

$$P(\omega_1, y_1, z_0, x_1) = P(\omega_1 | y_1, z_0) P(y_1 | x_1) P(z_0 | x_1) P(x_1)$$

$$0,0168$$

$$P(\omega_1, y_0, z_0, x_1) = 0,0216$$

$$P(\omega_1, y_0, z_1, x_1) = 0,0168$$

$$P(\omega_1, x_1) = 0,0714$$

$$P(\omega_1 | x_1) = \frac{P(x_1, \omega_1)}{P(x_1)} = \frac{0,0714}{0,3} = 0,238.$$

Backward inference:

$$P(x_1 | w_1) = \frac{P(x_1, w_1)}{P(w_1)}$$

$$= \frac{P(x_1, w_1)}{\sum_{x, y, z} P(w_1, x, y, z)} \quad \text{8 situations}$$

Ex. $P(w_1, x_1, y_1, z_1) = P(w_1 | y_1, z_1) P(y_1 | x_1)$
 $\cdot P(z_1 | x_1) P(x_1)$

Hopfield network example.

5 neurons
3 patterns

$$z_1 = \begin{bmatrix} 1 \\ -1 \\ -1 \\ -1 \\ 1 \end{bmatrix} \quad z_2 = \begin{bmatrix} 1 \\ -1 \\ -1 \\ 1 \\ -1 \end{bmatrix} \quad z_3 = \begin{bmatrix} 1 \\ 1 \\ -1 \\ -1 \\ -1 \end{bmatrix}$$

$$w_{13} = \frac{1 \cdot 1 + 1 \cdot (-1) + 1 \cdot 1}{5} = \frac{1}{5}$$

$$w_{25} = \frac{1 \cdot 1 + (-1) \cdot 1 + 1 \cdot (-1)}{5} = -\frac{1}{5}$$

$$W = \frac{1}{5} \begin{bmatrix} 3 & 1 & 1 & -1 & 1 \\ 1 & 3 & 3 & 1 & -1 \\ 1 & 3 & 3 & 1 & -1 \\ -1 & 1 & 1 & 3 & 1 \\ 1 & -1 & -1 & 1 & 3 \end{bmatrix}$$

Input $z_1 \rightarrow$ output $\text{sign}[Wz_1]$

$$Wz_1 = W \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = \frac{1}{5} \begin{bmatrix} 5 \\ 7 \\ 7 \\ 5 \\ 3 \end{bmatrix} \xrightarrow{\text{sign}} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = z_1$$

$$z_2 \rightarrow z_3' = \begin{bmatrix} 1 \\ 1 \\ -1 \\ -1 \end{bmatrix} \rightarrow \text{flipped.}$$

Output: $\text{sign}[W \cdot z_3']$

$$W \cdot z_3' = W \cdot \begin{bmatrix} 1 \\ 1 \\ -1 \\ -1 \end{bmatrix} = \frac{1}{5} \begin{bmatrix} 3 \\ 1 \\ 1 \\ -5 \\ -3 \end{bmatrix} \xrightarrow{\text{sign}} \begin{bmatrix} 1 \\ 1 \\ -1 \\ -1 \end{bmatrix} = z_3.$$

