

CSC321 T4

ex 1

Conditional probability table (CPT)

$X = M/F$. $Y = \text{Smoker / non-smoker}$

		Y	
		S	NS
X	M	P_1	P_2
	F	P_3	P_4

eg. $P_1 = P(X=M, Y=\text{smoker})$

$$P_1 + P_2 + P_3 + P_4 = 1$$

a.

$$P(Y=S) = P(Y=S, X=M) + P(Y=S, X=F)$$

b.

$$P(Y=S | X=M)$$

$$= \frac{P(Y=S, X=M)}{P(X=M)}$$

$$= \frac{P(Y=S, X=M)}{P(X=M, Y=S) + P(X=M, Y=NS)}$$

$$= \frac{P_1}{P_1 + P_2}$$

ex 2

Conditional independence

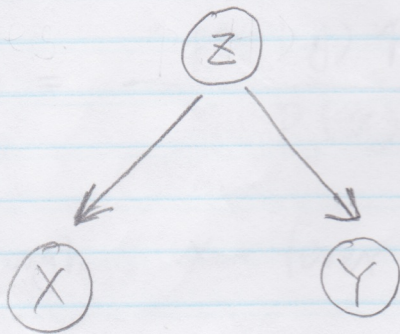
Toss Coin $X = H$ or T Coin $Y = H$ or T

$X \perp\!\!\!\perp Y$

$$P(X=H, Y=H) = P(X=H)P(Y=H)$$

$$P(Y=H | X=H) = P(Y=H)$$

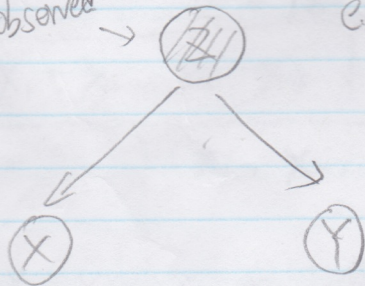
Given Z : biased toward H or T



$X \not\perp\!\!\!\perp Y$

$$P(Y=H | X=H) > P(Y=H)$$

observed \rightarrow



es. 0.6 H, 0.4 T

$X \perp\!\!\!\perp Y | Z$

$$P(X=H, Y=H | Z) = P(X=H | Z) P(Y=H | Z)$$

$$= P(H) P(H)$$

OE D) for D variables

x3

Bayes rule: $P(Y|X) P(X) = P(X, Y) = P(X|Y) P(Y)$

Example: $X = \text{cough}$

$Y = \text{lung cancer}$

$P(Y|X) = ?$ not known

Assume we know:

$P(X|Y), P(X), P(Y)$

Diagnosis:

$$P(Y|X) = \frac{P(X|Y) P(Y)}{P(X)}$$

ex b.

$X_1 = \text{cough}, X_2 = \text{fever}, X_3 = \text{smoke}, X_4 = \text{air pollution}$

$Y = \text{lung cancer}$

$P(Y|X_1, X_2, X_3, X_4) = ?$
 $2^4 = 16$ possibilities

$$= \frac{P(X_1, X_2, X_3, X_4 | Y) P(Y)}{P(X_1, X_2, X_3, X_4)}$$

$\propto P(X_1, X_2, X_3, X_4 | Y) P(Y)$

$O(2^D)$ for D variables

Naive Bayes Assumption:

$X_1 \perp\!\!\!\perp X_2 | Y$

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$$\cong P(X_1|Y) P(X_2|Y) P(X_3|Y) P(X_4|Y) P(Y)$$

$$= P(Y) \prod_k P(X_k|Y) \quad O(D) \text{ for } D \text{ variables}$$

	X_1	X_2	X_3	X_4	Y
1	1	1	1	1	
2	0	1	1	1	
3	1	0	1	1	
4	1	1	0	1	
...					
16	0	0	0	0	

ex 4. Maximum likelihood (ML) of Gaussian mean

$$P(X | \mu, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma^2} \exp\left\{-\frac{1}{2\sigma^2}(X-\mu)^2\right\}$$

$$P(x_1, x_2, \dots, x_N | \mu, \sigma^2) \stackrel{i.i.d.}{=} \prod_{i=1}^N P(x_i | \mu, \sigma^2)$$

i.i.d.: ^① independent
^② identically distributed

$$\begin{aligned} L = \log P(\vec{X} | \mu, \sigma^2) &= \log \prod_{i=1}^N P(x_i | \mu, \sigma^2) \\ &= \sum_{i=1}^N \log P(x_i | \mu, \sigma^2) \\ &= \sum_{i=1}^N \left(-\frac{1}{2\sigma^2}(x_i - \mu)^2\right) + \text{const} \end{aligned}$$

$$\frac{\partial L}{\partial \mu} = \frac{1}{\sigma^2} \sum_{i=1}^N (x_i - \mu)$$

$$= \frac{1}{\sigma^2} \left(\sum_{i=1}^N x_i - N\mu\right)$$

$$\frac{\partial L}{\partial \mu} = 0 \quad \text{and solve for } \mu$$

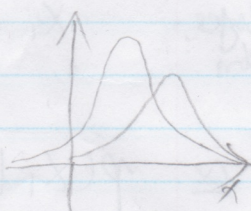
$$\frac{1}{\sigma^2} \left(\sum_{i=1}^N x_i - N\mu\right) = 0$$

$$\mu_{ML} = \frac{1}{N} \sum_{i=1}^N x_i$$

i.i.d

Violation of ^②: Gaussian mixture model.

es. two classes



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^①: hard problem. possible solution: hidden Markov model

e.g. ^① switching b/w biased & unbiased coin.
^② virus outbreak

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