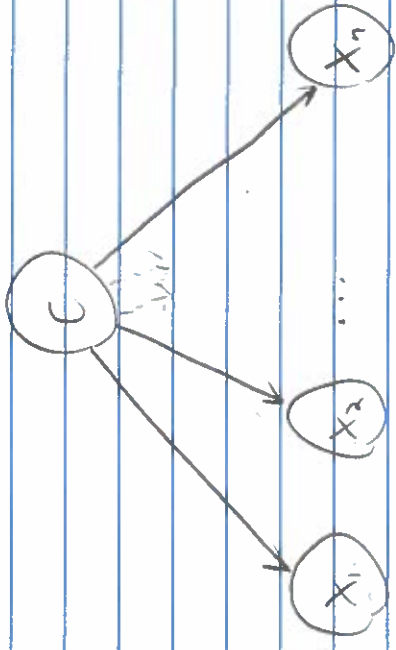


### 3) Expectation Maximization in a Naive Bayes Model



Class Variable  $C$ , discrete evidence Variables  $x_1, \dots, x_n$

CPDs parametrized:  $P(C=c) = \Theta_c$ ,  $P(x_i = x_i | C=c) = \Theta_{x_i, c}$  for  $i=1, \dots, n$   
and for all assignments  $x_i \in \text{Val}(x_i)$ , classes  $c \in \text{Val}(C)$

Given dataset  $D = \{x[1], \dots, x[M]\}$  each  $x[l]$  assigned to  $x_1, \dots, x_n$   
 $C$  not observed

E-Step 1:  $X[M] = (x_1, x_2, \dots, x_n)_{C=c_i}$   
Expand  $x[M]$  into  $\text{Val}(C)$  datapoints, one for each  $c \in C$

$$U = \frac{1}{2} \Theta_c \prod_{i=1}^n \Theta_{x_i, c} = \frac{1}{2} \cdot \frac{1}{|\text{Val}(C)|} \cdot \prod_{i=1}^n \frac{1}{|\text{Val}(x_i)|}$$

$$Z = \sum_{j=1}^{|\text{Val}(C)|} \frac{1}{|\text{Val}(C)|} \cdot \prod_{i=1}^n \frac{1}{|\text{Val}(x_i)|} = \prod_{i=1}^n \frac{1}{|\text{Val}(x_i)|}$$

$$W = \frac{\frac{1}{|\text{Val}(C)|} \cdot \prod_{i=1}^n \frac{1}{|\text{Val}(x_i)|}}{\prod_{i=1}^n \frac{1}{|\text{Val}(x_i)|}} = \frac{1}{|\text{Val}(C)|}$$

Weight  $w$  is same for all datapoints

Aa-Step 1:  $\Theta_c = \frac{\sum_{\text{data}} \frac{1}{|\text{Val}(C)|}}{M \cdot |\text{Val}(C)|} = \frac{1}{|\text{Val}(C)|}$

$\Theta_{x_i = x_i | C=c} = \frac{u \cdot M \cdot \frac{1}{|\text{Val}(C)|}}{M \cdot \frac{1}{|\text{Val}(C)|}} = \frac{u}{M}$ ,  $u \leq M \rightarrow u \rightarrow +$

E-Step 2:  $w = \frac{1}{2} \cdot \frac{1}{|\text{Val}(C)|} \cdot \prod_{i=1}^n \frac{1}{|\text{Val}(x_i)|} = \frac{1}{2} \cdot \frac{1}{|\text{Val}(C)|} \cdot \prod_{i=1}^n \frac{1}{|\text{Val}(x_i)|}$

$Z = |\text{Val}(C)| \cdot \frac{1}{|\text{Val}(C)|} \cdot \prod_{i=1}^n \frac{1}{|\text{Val}(x_i)|} = \prod_{i=1}^n \frac{1}{|\text{Val}(x_i)|}$

$= \frac{1}{|\text{Val}(C)|} \cdot \prod_{i=1}^n \frac{1}{|\text{Val}(x_i)|}$

$\rightarrow U = \frac{\frac{1}{|\text{Val}(C)|} \cdot \prod_{i=1}^n \frac{1}{|\text{Val}(x_i)|}}{\prod_{i=1}^n \frac{1}{|\text{Val}(x_i)|}} = \frac{1}{|\text{Val}(C)|}$