

$$P = P(X=x_i, Y=y_i) = P(X=x_i|Y=y_i) \cdot P(Y=y_i) \quad \theta_1, \dots, \theta_k$$

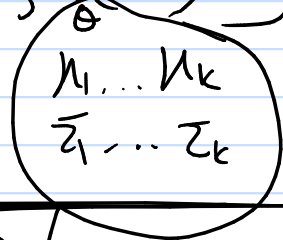
θ
 n_1, \dots, n_k
 \sum_1, \dots, \sum_k

$$= \prod_{y=1}^k \left[P(X=x_i|Y=y) \cdot P(Y=y) \right]^{\mathbb{1}[y=y_i]}$$

$$\log P = \sum_{y=1}^k \mathbb{1}[y=y_i] \cdot (\log P_{x_i|y} + \log \theta_y)$$

$$\hat{\theta}_1 = \frac{1}{N} \sum \mathbb{1}[y_i=1]$$

$$\max_{\theta} \sum_{i=1}^N \log P(x_i)$$



$$P(y_i = y | \text{Data})$$

E ✓

$$\{x_i, y_i\} \rightarrow \max_{\alpha} \sum_{i=1}^N P_{\alpha}(x_i, y_i)$$

M

$(x_1, \dots, x_N) = \text{Data}$

marginal likelihood



$$\sum_x \log p = \log \left(\exp \left(\sum w_i f_i(x) \right) \right) - \log Z$$

$$\frac{\partial}{\partial w_j} = \sum_{i=1}^J w_i f_i(x) - \log Z(w_1, \dots, w_J)$$

$$\sum_{k=1}^J f_k(x)$$