



Figure 2.3. Conditional probability distributions. (a) $P(y|x)$: Each *row* shows the conditional distribution of the second letter, y , given the first letter, x , in a bigram xy . (b) $P(x|y)$: Each *column* shows the conditional distribution of the first letter, x , given the second letter, y .

that the first letter x is **q** are **u** and **-**. (The space is common after **q** because the source document makes heavy use of the word **FAQ**.)

The probability $P(x|y=\mathbf{u})$ is the probability distribution of the first letter x given that the second letter y is a **u**. As you can see in figure 2.3b the two most probable values for x given $y=\mathbf{u}$ are **n** and **o**.

Rather than writing down the joint probability directly, we often define an ensemble in terms of a collection of conditional probabilities. The following rules of probability theory will be useful. (\mathcal{H} denotes assumptions on which the probabilities are based.)

Product rule – obtained from the definition of conditional probability:

$$P(x, y | \mathcal{H}) = P(x | y, \mathcal{H})P(y | \mathcal{H}) = P(y | x, \mathcal{H})P(x | \mathcal{H}). \quad (2.6)$$

This rule is also known as the chain rule.

Sum rule – a rewriting of the marginal probability definition:

$$P(x | \mathcal{H}) = \sum_y P(x, y | \mathcal{H}) \quad (2.7)$$

$$= \sum_y P(x | y, \mathcal{H})P(y | \mathcal{H}). \quad (2.8)$$

Bayes' theorem – obtained from the product rule:

$$P(y | x, \mathcal{H}) = \frac{P(x | y, \mathcal{H})P(y | \mathcal{H})}{P(x | \mathcal{H})} \quad (2.9)$$

$$= \frac{P(x | y, \mathcal{H})P(y | \mathcal{H})}{\sum_{y'} P(x | y', \mathcal{H})P(y' | \mathcal{H})}. \quad (2.10)$$

Independence. Two random variables X and Y are *independent* (sometimes written $X \perp Y$) if and only if

$$P(x, y) = P(x)P(y). \quad (2.11)$$



Exercise 2.2.^[1, p.40] Are the random variables X and Y in the joint ensemble of figure 2.2 independent?