s. With probability  $\frac{1}{2}$ , we choose the value of s to be 1. Otherwise, we choose the value of s to be -1. We can then generate a random variable y by assigning y = sx. Clearly, x and y are not independent, because x completely determines the magnitude of y. However, Cov(x, y) = 0.

The **covariance matrix** of a random vector  $\boldsymbol{x} \in \mathbb{R}^n$  is an  $n \times n$  matrix, such that

$$Cov(\mathbf{x})_{i,j} = Cov(\mathbf{x}_i, \mathbf{x}_j). \tag{3.14}$$

The diagonal elements of the covariance give the variance:

$$Cov(x_i, x_i) = Var(x_i). (3.15)$$

## 3.9 Common Probability Distributions

Several simple probability distributions are useful in many contexts in machine learning.

## 3.9.1 Bernoulli Distribution

The **Bernoulli** distribution is a distribution over a single binary random variable. It is controlled by a single parameter  $\phi \in [0,1]$ , which gives the probability of the random variable being equal to 1. It has the following properties:

$$P(\mathbf{x} = 1) = \phi \tag{3.16}$$

$$P(x = 0) = 1 - \phi \tag{3.17}$$

$$P(x = x) = \phi^{x} (1 - \phi)^{1 - x}$$
(3.18)

$$\mathbb{E}_{\mathbf{x}}[\mathbf{x}] = \phi \tag{3.19}$$

$$Var_{x}(x) = \phi(1 - \phi) \tag{3.20}$$

## 3.9.2 Multinoulli Distribution

The **multinoulli** or **categorical** distribution is a distribution over a single discrete variable with k different states, where k is finite. The multinoulli distribution is

<sup>&</sup>quot;Multinoulli" is a term that was recently coined by Gustavo Lacerdo and popularized by Murphy (2012). The multinoulli distribution is a special case of the **multinomial** distribution. A multinomial distribution is the distribution over vectors in  $\{0, \ldots, n\}^k$  representing how many times each of the k categories is visited when n samples are drawn from a multinoulli distribution. Many texts use the term "multinomial" to refer to multinoulli distributions without clarifying that they refer only to the n = 1 case.