

where the expectation is over the data (seen as samples from a random variable) and θ is the true underlying value of θ used to define the data generating distribution. An estimator $\hat{\theta}_m$ is said to be **unbiased** if $\text{bias}(\hat{\theta}_m) = \mathbf{0}$, which implies that $\mathbb{E}(\hat{\theta}_m) = \theta$. An estimator $\hat{\theta}_m$ is said to be **asymptotically unbiased** if $\lim_{m \rightarrow \infty} \text{bias}(\hat{\theta}_m) = \mathbf{0}$, which implies that $\lim_{m \rightarrow \infty} \mathbb{E}(\hat{\theta}_m) = \theta$.

Example: Bernoulli Distribution Consider a set of samples $\{x^{(1)}, \dots, x^{(m)}\}$ that are independently and identically distributed according to a Bernoulli distribution with mean θ :

$$P(x^{(i)}; \theta) = \theta^{x^{(i)}} (1 - \theta)^{(1-x^{(i)})}. \quad (5.21)$$

A common estimator for the θ parameter of this distribution is the mean of the training samples:

$$\hat{\theta}_m = \frac{1}{m} \sum_{i=1}^m x^{(i)}. \quad (5.22)$$

To determine whether this estimator is biased, we can substitute equation 5.22 into equation 5.20:

$$\text{bias}(\hat{\theta}_m) = \mathbb{E}[\hat{\theta}_m] - \theta \quad (5.23)$$

$$= \mathbb{E} \left[\frac{1}{m} \sum_{i=1}^m x^{(i)} \right] - \theta \quad (5.24)$$

$$= \frac{1}{m} \sum_{i=1}^m \mathbb{E} [x^{(i)}] - \theta \quad (5.25)$$

$$= \frac{1}{m} \sum_{i=1}^m \sum_{x^{(i)}=0}^1 \left(x^{(i)} \theta^{x^{(i)}} (1 - \theta)^{(1-x^{(i)})} \right) - \theta \quad (5.26)$$

$$= \frac{1}{m} \sum_{i=1}^m (\theta) - \theta \quad (5.27)$$

$$= \theta - \theta = 0 \quad (5.28)$$

Since $\text{bias}(\hat{\theta}) = 0$, we say that our estimator $\hat{\theta}$ is unbiased.

Example: Gaussian Distribution Estimator of the Mean Now, consider a set of samples $\{x^{(1)}, \dots, x^{(m)}\}$ that are independently and identically distributed according to a Gaussian distribution $p(x^{(i)}) = \mathcal{N}(x^{(i)}; \mu, \sigma^2)$, where $i \in \{1, \dots, m\}$.