

Markov's Inequality:

Let $u(X)$ be a non-negative function of the random variable X .

If $E[u(X)]$ exists, then, for every positive constant c ,

$$P(u(X) \geq c) \leq \frac{E[u(X)]}{c}.$$

Chebyshev's Inequality:

Let X be any random variable with mean μ and variance σ^2 . For any $\varepsilon > 0$,

$$P(|X - \mu| \geq \varepsilon) \leq \frac{\sigma^2}{\varepsilon^2}$$

or, equivalently,

$$P(|X - \mu| < \varepsilon) \geq 1 - \frac{\sigma^2}{\varepsilon^2}$$

Setting $\varepsilon = k\sigma$, $k > 1$, we obtain

$$P(|X - \mu| \geq k\sigma) \leq \frac{1}{k^2}$$

or, equivalently,

$$P(|X - \mu| < k\sigma) \geq 1 - \frac{1}{k^2}$$

That is, for any $k > 1$, the probability that the value of any random variable will be within k standard deviations of its mean is at least $1 - \frac{1}{k^2}$.

Example 1: Suppose $\mu = E(X) = 17$, $\sigma = SD(X) = 5$.

Consider interval $(9, 25) = (17 - 8, 17 + 8)$. $\Rightarrow k = \frac{8}{5} = 1.6$.

$$\Rightarrow P(9 < X < 25) = P(|X - \mu| < 1.6\sigma) \geq 1 - \frac{1}{1.6^2} = \mathbf{0.609375}.$$

Example 2: Suppose $\mu = E(X) = 17$, $\sigma = SD(X) = 5$.

Suppose also that the distribution of X is symmetric about the mean.

Consider interval $(10, 30) = (17 - 7, 17 + 13) = (\mu - 1.4 \sigma, \mu + 2.6 \sigma)$.

$$P(10 < X < 24) = P(|X - \mu| < 1.4 \sigma) \geq 1 - \frac{1}{1.4^2} \approx 0.490.$$

$$P(4 < X < 30) = P(|X - \mu| < 2.6 \sigma) \geq 1 - \frac{1}{2.6^2} \approx 0.852.$$

Since the distribution of X is symmetric about the mean,

$$P(10 < X < 17) \geq \frac{0.490}{2} = 0.245, \quad P(17 < X < 30) \geq \frac{0.852}{2} = 0.426.$$

$$\Rightarrow P(10 < X < 30) \geq 0.245 + 0.426 = \mathbf{0.671}.$$

Example 3: Consider a discrete random variable X with p.m.f.

$$P(X = -1) = \frac{1}{2}, \quad P(X = 1) = \frac{1}{2}.$$

Then $\mu = E(X) = 0$, $\sigma^2 = \text{Var}(X) = E(X^2) = 1$.

$$\Rightarrow P(|X - \mu| \geq \sigma) = P(|X| \geq 1) = 1. \quad (k = 1)$$

$$P(|X - \mu| < \sigma) = P(|X| < 1) = 0.$$

Example 4: (Chebyshev's Inequality cannot be improved)

Let $a > 0$, $0 < p < \frac{1}{2}$. Consider a discrete random variable X with p.m.f.

$$P(X = -a) = p, \quad P(X = 0) = 1 - 2p, \quad P(X = a) = p.$$

Then $\mu = E(X) = 0$, $\sigma^2 = \text{Var}(X) = E(X^2) = 2pa^2$.

Let $k = \frac{1}{\sqrt{2p}} > 1$. Then $k\sigma = a$.

$$\Rightarrow P(|X - \mu| \geq k\sigma) = P(|X| \geq a) = 2p = \frac{1}{k^2}.$$

$$P(|X - \mu| < k\sigma) = P(|X| < a) = 1 - 2p = 1 - \frac{1}{k^2}.$$

Jensen's Inequality:

If g is convex on an open interval I and X is a random variable whose support is contained in I and has finite expectation, then

$$E[g(X)] \geq g[E(X)].$$

If g is strictly convex then the inequality is strict, unless X is a constant random variable.

$$\Rightarrow E(X^2) \geq [E(X)]^2 \quad \Leftrightarrow \quad \text{Var}(X) \geq 0$$

$$\Rightarrow E(e^{tX}) \geq e^{tE(X)} \quad \Rightarrow \quad M_X(t) \geq e^{t\mu}$$

$$\Rightarrow E\left(\frac{1}{X}\right) \geq \frac{1}{E(X)} \quad \text{for a positive random variable } X$$

$$\Rightarrow E[\ln X] \leq \ln E(X) \quad \text{for a positive random variable } X$$