

§ 4.4 Markov's and Chebyshev's Inequalities

Thm 4.7.5 (Markov's Inequality)

If X is a r.v. with mean μ and pdf $f(x)$ with $f(x) = 0$ for $x < 0$, then for any positive constant a ,

$$P(X \geq a) \leq \frac{\mu}{a}$$

Pf. (Cts case - discrete is similar).

$$P(X \geq a) = \int_a^{\infty} f(x) dx$$

$$\leq \int_a^{\infty} \frac{x}{a} f(x) dx$$

as $\frac{x}{a} f(x) \geq f(x)$
when $x \geq a$!

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$$\begin{aligned}
&= \frac{1}{a} \int_a^{\infty} x f(x) \\
&\leq \frac{1}{a} \int_0^{\infty} x f(x) \\
&= \frac{1}{a} \int_{-\infty}^{\infty} x f(x) \quad \text{as } f(x) = 0 \text{ when } x < 0 \\
&= \frac{1}{a} E(X) \\
&= \frac{1}{a} \mu. \quad \square
\end{aligned}$$

Ex. For the r.v. X we had earlier with pdf.

$$f(x) = \begin{cases} \frac{4}{\pi(1+x^2)}, & 0 < x < 1 \\ 0 & \text{elsewhere} \end{cases}$$

use Markov to estimate $P(X \geq \frac{1}{2})$.

Soln. Had $\mu = \frac{\ln 4}{\pi} \approx .4413$ from earlier

By Markov $P(X \geq \frac{1}{2}) \leq \frac{\mu}{\frac{1}{2}} \approx .8826$

This illustrates the first main use of Markov's Inequality, namely that the estimates from Markov are often easier to calculate than the actual probabilities $P(X \geq a)$, especially if we already know μ .

The second main use of Markov is as an aid in proving Chebyshev's Inequality, which shows us how σ or σ^2 are indicative of the spread or dispersion of a r.v.

Theorem 4.8 (Chebyshev's Inequality)

If μ and σ are the mean and std. deviation (resp.) of the r.v. X , then for any positive constant k

$$P(|X - \mu| \geq k\sigma) \leq \frac{1}{k^2}, \quad \sigma \neq 0$$

or

$$P(|X - \mu| < k\sigma) \geq 1 - \frac{1}{k^2}, \quad \sigma \neq 0.$$

Pf. Note that the second statement follows immediately from the first as we are dealing with complementary events.

To show the first, let Y be the r.v.
 $Y = (X - \mu)^2$.

Then since Y can only take on values ≥ 0 , if we let g denote the pdf of y , then clearly $g(x) = 0$ for $x < 0$ (or, to be more exact, we can require that this be so).

Also, if we let ν be the mean of Y , then

$$\begin{aligned} \nu &= E(Y) = E((X - \mu)^2) \\ &= \sigma^2 \quad (\text{by defn of } \sigma^2). \end{aligned}$$

We now apply Markov to Y with $a = k^2 \sigma^2$
to get.

$$P(|X - \mu| \geq k\sigma)$$

$$= P((X - \mu)^2 \geq k^2 \sigma^2) \quad (\text{same event!})$$

$$= P(Y \geq k^2 \sigma^2)$$

$$\leq \frac{\gamma}{k^2 \sigma^2}$$

$$= \frac{\sigma^2}{k^2 \sigma^2}$$

$$= \frac{1}{k^2} \quad \text{as } \sigma \neq 0. \quad \square$$

One way of stating the second part of Chebyshev is that for any positive const k , the prob is at least $1 - \frac{1}{k^2}$ that X will take on a value within k standard deviations of the mean.

Ex. If X is a cts. r.v. with pdf

$$f(x) = \begin{cases} 630x^4(1-x)^4, & 0 < x < 1 \\ 0 & \text{elsewhere.} \end{cases}$$

find the prob. that it will take on a value within 2 std deviations of the mean and compare this with the lower bound given by Chebyshev.

Solⁿ. Integration shows that $\mu = \frac{1}{2}$
and $\sigma^2 = \frac{1}{44}$ so $\sigma = \sqrt{\frac{1}{44}} \approx 0.15$.

Hence the prob. that X will take on a value within 2 std. deviations of the mean is (approx)

$$\begin{aligned} &P\left(\left[\frac{1}{2} - 2 \times 0.15, \frac{1}{2} + 2 \times 0.15\right]\right) \\ &= P([0.2, 0.8]) = \int_{0.2}^{0.8} 630x^4(1-x)^4 dx \approx 0.96 \end{aligned}$$

On the other hand, Chebyshev. gives

$$P(|X - 0.5| > 2 \times 0.15) \geq 1 - \frac{1}{2^2}$$

$$= 0.75.$$