

MEDIAN-MEAN INEQUALITY

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Prove that the median is no more than one standard deviation away from the mean, i.e.,

$$|\text{median}(X) - \text{mean}(X)| \leq \text{std}(X)$$

The definition of the median of a random variable is given by [1]

For any probability distribution on the real line with cumulative distribution function F , regardless of whether it is any kind of continuous probability distribution, in particular an absolutely continuous distribution (and therefore has a probability density function), or a discrete probability distribution, a median m satisfies the inequalities

$$\mathbb{P}(X \leq m) \geq \frac{1}{2} \wedge \mathbb{P}(X \geq m) \geq \frac{1}{2}$$

or

$$\int_{-\infty}^m dF(x) \geq \frac{1}{2} \wedge \int_m^{\infty} dF(x) \geq \frac{1}{2}$$

For an absolutely continuous probability distribution with probability density function f , we have

$$\mathbb{P}(X \leq m) = \mathbb{P}(X \geq m) = \int_{-\infty}^m f(x)dx = \frac{1}{2}.$$

The above claim can be proved using Chebyshev inequality.

Proof. WLOG, suppose $\text{median}(X) > \text{mean}(X)$, if $\text{median}(X) - \text{mean}(X) > \text{std}(X)$, i.e., $\text{median}(X) > \text{mean}(X) + \text{std}(X)$, then based on one tailed Chebyshev inequality,

$$\frac{1}{2} \leq \mathbb{P}(X \geq \text{median}(X)) < \mathbb{P}(X \geq \text{mean}(X) + \text{std}(X)) \leq \frac{\text{var}(X)}{\text{std}(X)^2 + \text{var}(X)} = \frac{1}{2}$$

A contradiction is already arrived. It is similar for $\text{median}(X) < \text{mean}(X)$ case using the other version of one tailed Chebyshev inequality. \square

The one-tailed Chebyshev inequality

$$\mathbb{P}(X - \text{mean}(X) \geq t) \leq \frac{\text{var}(X)}{t^2 + \text{var}(X)}$$

where $t > 0$ can be proved by the following arguments.

Proof.

$$\begin{aligned} \text{var}(X) &= \mathbb{E}[X^2] - \mathbb{E}^2[X] \\ &= \mathbb{E}[\mathbb{E}[X^2|A]] - (\mathbb{E}[\mathbb{E}[X|A]])^2 \\ &= \mathbb{E}[\mathbb{E}[X^2|A] - \mathbb{E}^2[X|A]] + \mathbb{E}[\mathbb{E}^2[X|A]] - (\mathbb{E}[\mathbb{E}[X|A]])^2 \\ &= \mathbb{E}[\text{var}(X|A)] + \text{var}(\mathbb{E}[X|A]) \end{aligned}$$

Let p, q, r denote the probability for $X > t, X = t, X < t$, respectively and let A be the indicator random variable accordingly with the following definition

$$A = \begin{cases} 1 & X > t \\ 0 & X = t \\ -1 & X < t \end{cases}$$

Hence WLOG,

$$\mathbb{E}[X] = p\mathbb{E}[X|A=1] + q\mathbb{E}[X|A=0] + r\mathbb{E}[X|A=-1] = 0$$

since $\text{var}(X+s) = \text{var}(X)$ where s is a constant so the one tailed Chebyshev inequality is equivalent to prove the X with $\mathbb{E}[X] = 0 = \mathbb{E}[\mathbb{E}[X|A]]$.

Notice that

$$\begin{aligned} \text{var}(X) &= \mathbb{E}[\text{var}(X|A)] + \text{var}(\mathbb{E}[X|A]) \\ &\geq \text{var}(\mathbb{E}[X|A]) \\ &= \mathbb{E}[(\mathbb{E}[X|A])^2] \\ &\geq pt^2 + qt^2 + r(\mathbb{E}[X|A=-1])^2 \end{aligned}$$

Keep in mind that

$$\begin{aligned} 0 &= p\mathbb{E}[X|A=1] + q\mathbb{E}[X|A=0] + r\mathbb{E}[X|A=-1] \\ &\geq pt + qt + r\mathbb{E}[X|A=-1] \end{aligned}$$

Hence

$$(\mathbb{E}[X|A=-1])^2 \geq \frac{(1-r)^2 t^2}{r^2}$$

so

$$\text{var}(X) \geq (1-r)t^2 + \frac{(1-r)^2 t^2}{r} = t^2(1-r) \left(\frac{r+1-r}{r} \right) = \frac{t^2(1-r)}{r} = \frac{t^2 s}{1-s}$$

where

$$s = 1-r = p+q$$

Hence

$$\text{var}(X) \geq s(t^2 + \text{var}(X))$$

Therefore

$$\frac{\text{var}(X)}{t^2 + \text{var}(X)} \geq s = \mathbb{P}(X \geq t)$$

□

It is worth checking out the following two articles about the proof for Chebyshev inequality and connection with the mode, median and mean of a random variable. [2, 3]

REFERENCES

- [1] Median @ <http://en.wikipedia.org/wiki/Median>
- [2] Chebyshev's Inequalities @ <http://www.mcdowella.demon.co.uk/Chebyshev.html>
- [3] Chebyshev's inequality and a one-tailed version @ <http://www.btinternet.com/~se16/hgb/cheb.htm>