

Strong Law of Large Numbers (SLLN)

Let X_1, X_2, \dots be a sequence of IID random variables with $E[X_i] = \mu < \infty$. Then

$$P\left[\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n X_i = \mu\right] = 1.$$

Weak Law of Large Numbers (WLLN)

For any $\epsilon > 0$, $\lim_{n \rightarrow \infty} P\left[\left|\frac{1}{n} \sum_{i=1}^n X_i - \mu\right| \geq \epsilon\right] = 0$.

Differences: Additional assumptions in the proof in the text:

$$\text{WLLN} : \text{Var}[X_i] = \sigma^2 < \infty$$

$$\text{SLLN} : E[X_i^4] < \infty.$$

Furthermore:

$$\text{SLLN} \Rightarrow \text{WLLN}.$$

Additional Inequalities

We may be interested in estimating

$P[X - \mu \geq a]$, when only $E[X] = \mu$
and $\text{Var}[X] = \sigma^2$ are known, (for $a > 0$)

Trivially, since $X - \mu \geq a \Rightarrow |X - \mu| \geq a$,
we can immediately apply Chebyshev's Inequality:

$$P[X - \mu \geq a] \leq P[|X - \mu| \geq a] \leq \frac{\sigma^2}{a^2} \quad \text{for } a > 0.$$

Proposition One-sided Chebyshev Inequality:

$$\text{If } E[X] = 0, \quad P[X \geq a] \leq \frac{\sigma^2}{\sigma^2 + a^2} \leq \frac{\sigma^2}{a^2}.$$

Proof: Let $b > 0$ and note that

$X \geq a$ is equivalent to $X + b \geq a + b$,

$$\begin{aligned} \Rightarrow P[X \geq a] &= P[X + b \geq a + b] \\ &\leq P[(X + b)^2 \geq (a + b)^2] \\ &\leq \frac{E[(X + b)^2]}{(a + b)^2} = \frac{\sigma^2 + b^2}{(a + b)^2} \end{aligned}$$

Set $b = \sigma^2/a$ (which minimizes $\frac{\sigma^2 + b^2}{(a + b)^2}$)

$$\Rightarrow P[X \geq a] \leq \frac{\sigma^2}{\sigma^2 + a^2}.$$

Jensen's Inequality

If f is a convex function, i.e., $f''(x) \geq 0$ for all x ,

then $E[f(X)] \geq f(E[X])$,

assuming $E[f(X)]$, $E[X]$ exist and are finite

Proof :

$$\text{Write } f(x) = f(\mu) + f'(\mu)(x-\mu) + \frac{f''(\xi)(x-\mu)^2}{2}$$

$\mu = E[X]$ $\xi \in [x, \mu]$

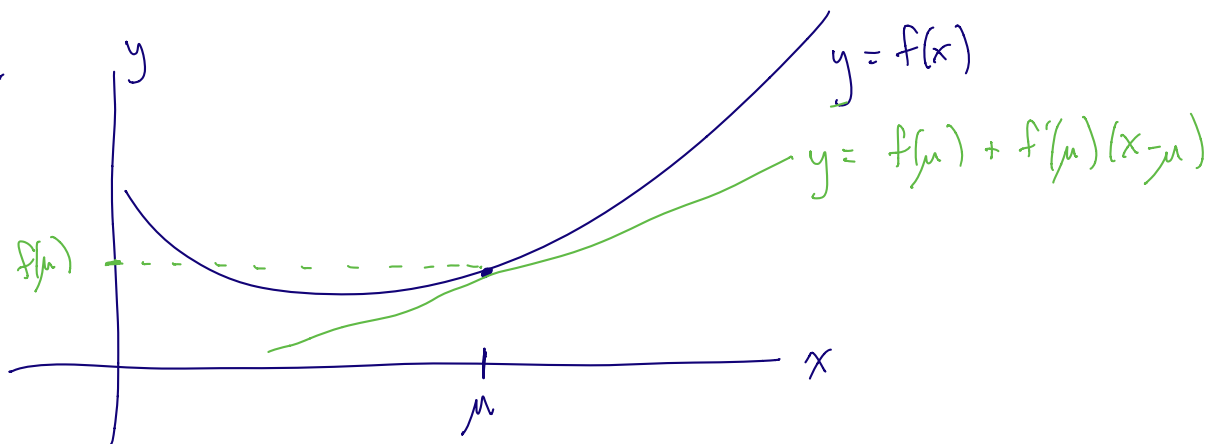
Since $f''(\xi) \geq 0$,

$$f(x) \geq f(\mu) + f'(\mu)(x-\mu)$$

$$\Rightarrow f(X) \geq f(\mu) + f'(\mu)(X-\mu)$$

$$\begin{aligned} \Rightarrow E[f(X)] &\geq E[f(\mu) + f'(\mu)(X-\mu)] \\ &= f(\mu) + f'(\mu) \cancel{E[X-\mu]} = 0 \\ &= f(E[X]). \quad \checkmark \end{aligned}$$

Idea:



The line $y = f(\mu) + f'(\mu)(x-\mu)$ is always below the curve $y = f(x)$

$$\Rightarrow f(x) \geq f(\mu) + f'(\mu)(x-\mu).$$