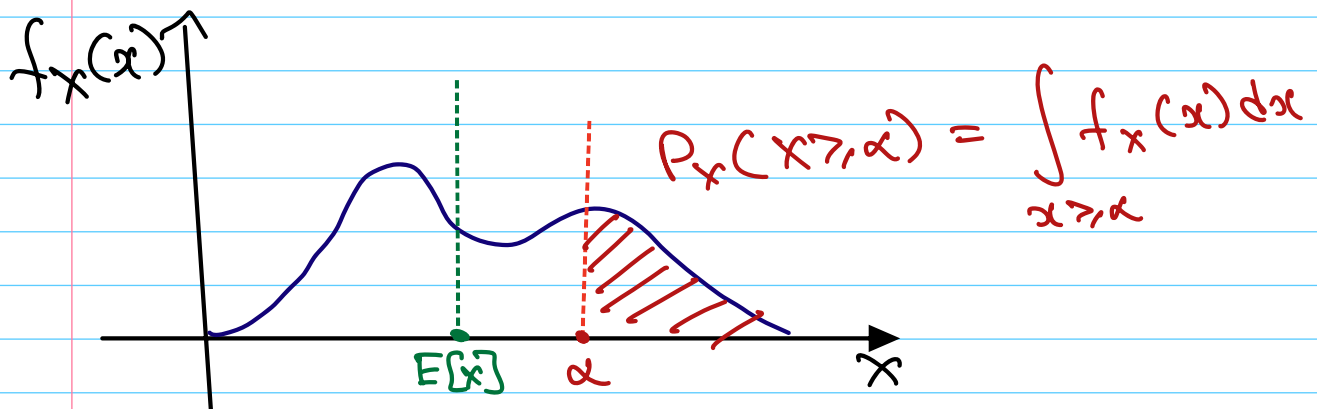


## MARKOV Inequality:

$$P_X(X \geq \alpha) \leq \frac{E[X]}{\alpha}$$

- \* The Markov inequality is useful for bounding the probability of exceeding threshold values.
- \* It is defined only on non-negative random variables.

The purpose of Markov inequality is to bound the prob of r.v exceed's some sort of threshold.



① define a new r.v  $Z(\omega)$  which is discrete

$$Z(\omega) = \begin{cases} \alpha & ; X(\omega) \geq \alpha \\ 0 & ; \text{o.w} \end{cases}$$

②  $E[Z(\omega)] \leq E[X(\omega)]$

Order Preservation:

$$\left( \alpha Z(\omega) \leq X(\omega) \right) \\ \forall \omega \in \Omega$$

③  $E[Z(\omega)]$   
 $= \alpha P_X(X \geq \alpha) + 0 P(X < \alpha)$

④  $\alpha P_X(X \geq \alpha) \leq E[X]$

$$\Rightarrow P_X(X \geq \alpha) \leq \frac{E[X]}{\alpha}$$

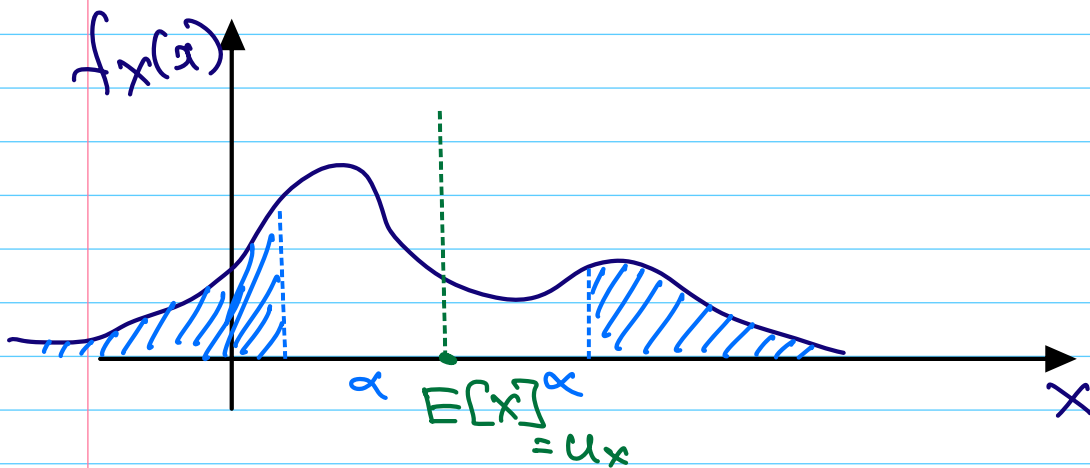
This is meaningful only when  $\alpha > E[X]$

$\Rightarrow$  if  $E[X] > \alpha$  then  $\frac{E[X]}{\alpha} > 1$  then

$P(X > \alpha) \leq 1$  (which is always true)

## Chebyshev Inequality

$\Rightarrow$  The Chebyshev inequality bounds the probability of a random variable deviating from its mean  $\mu_x$



$$P_X(|X - \mu_x| \geq \alpha) \leq \frac{\text{Var}(X)}{\alpha^2}$$

①  $Y = \left( \frac{|X - \mu_x|}{\alpha} \right)^2$  : Positive r.v

② use Markov inequality.

$$P_Y(Y \geq 1) \leq E[Y]$$

③  $P\left(\left(\frac{|X - \mu_x|}{\alpha}\right)^2 \geq 1\right) \leq E\left[\left(\frac{X - \mu_x}{\alpha}\right)^2\right]$

$$\Rightarrow P((X - \mu_X)^2 > c^2) \leq \frac{E[(X - \mu_X)^2]}{c^2}$$

$$\Rightarrow P(|X - \mu_X| > c) \leq \frac{\text{var}(X)}{c^2}$$

• if  $c$  is a big number. The Prob of being more than  $c$  away from the mean is going to be smaller number  $\left(\frac{\sigma^2}{c^2}\right)$

• if the variance is small, The distribution is not very wide, and that when  $\sigma^2$  is small, The Prob of being far away is small.

# JENSON'S Inequality

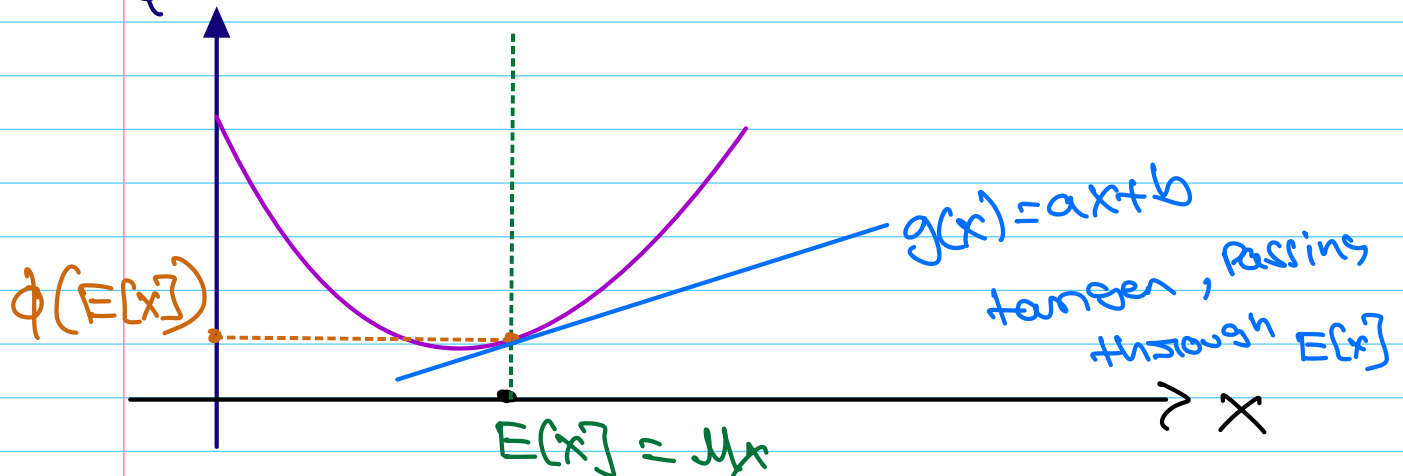
Jenson's inequality allows us to bound a function of the expectation by the expectation of a function

$$\phi(E[x]) \leq E[\phi(x)]$$

$\phi(\cdot)$  convex function

$$\lambda \phi(x) + (1-\lambda) \phi(y) \geq \phi(\lambda x + (1-\lambda)y)$$

$\phi(x)$  : convex where  $\lambda \in [0, 1]$



①  $g(x) = ax + b$       $x^* = E[x]$

tangent to  $\phi(x)$  @  $x^*$

② Since  $\phi(x)$  is convex  $\Rightarrow g(x) \leq \phi(x)$

$$E[g(x)] \leq E[\phi(x)]$$

$$E[ax+b] \leq E[\phi(x)]$$

$$aE[x] + b \leq E[\phi(x)]$$

③ Since  $g(x)$  is Linear

$$E[g(x)] = g(E[x])$$

$$\Rightarrow g(E[x]) = aE[x] + b$$

Since  $g(x)$  is a tangent to  $\phi(x)$   
at  $E[x]$

$$g(E[x]) = \phi(E[x])$$

$$\Rightarrow g(E[x]) = E[g(x)] = \phi(E[x])$$

④ and we know

$$E[g(x)] \leq E[\phi(x)]$$

$$\Rightarrow \phi(E[x]) \leq E[\phi(x)]$$