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$E(X)$  is known as the First Moment

**Moments:** For each integer  $n$ , the  $n$ th moment of an r.v.  $X$  is:  $E(X^n)$

The  $n$ th central moment is:  $E(X - E(X))^n$

Variance is 2nd central moment:  $\text{Var}(X) = E(X - E(X))^2$

**Properties of  $\text{Var}(X)$ :**

$$\text{Var}(ax + b) = a^2 \text{Var}(X)$$

$$\text{Var}(X) = E(X^2) - [E(X)]^2$$

$$\text{Ex. } X \sim \text{INV. GAMMA } (\alpha, \beta) \quad f(x) = \frac{1}{\Gamma(\alpha) \beta^\alpha} x^{-(\alpha+1)} e^{-\frac{1}{\beta}x}$$

$$\text{From last class: } E(X) = \frac{1}{(\alpha-1)\beta}$$

$$E(X^2) = \int_0^\infty x^2 \frac{1}{\Gamma(\alpha)\beta^\alpha} x^{-(\alpha+1)} e^{-\frac{1}{\beta}x} dx = \frac{1}{\Gamma(\alpha)\beta^\alpha} \int_0^\infty x^{-(\alpha-2+1)} e^{-\frac{1}{\beta}x} dx = \frac{1}{\Gamma(\alpha)\beta^\alpha} \cdot \Gamma(\alpha-2) \beta^{\alpha-2}$$

WITH  $\Gamma(\alpha) = (\alpha-1) \Gamma(\alpha-1)$

$$\therefore = \frac{1}{(\alpha-2)(\alpha-1)\beta^2}$$

$$\therefore \text{Var}(X) = E(X^2) - E(X)^2 = \frac{1}{(\alpha-2)(\alpha-1)\beta^2} - \left( \frac{1}{(\alpha-1)\beta} \right)^2 = \frac{1}{(\alpha-2)(\alpha-1)^2\beta^2}$$

Let's say instead of  $E(X)$  we are interested in  $E(Y)$  where  $Y = g(X)$ . Want to know:  $E(g(x)) = g(E(X))$

This holds under very restrictive conditions, and often those are not met. However, we can usually compare

**Jensen's inequality:** a function  $g(x)$  is convex if  $g(\lambda x + (1-\lambda)y) \leq \lambda g(x) + (1-\lambda)g(y)$   
 $\lambda \in [0,1], x, y \in \mathbb{R}$

$g(x)$  is concave if  $-g(x)$  is convex

$$\text{If } \lambda = \frac{1}{2}: \quad g\left(\frac{x+y}{2}\right) \leq \frac{1}{2}(g(x) + g(y))$$

How to determine if concave

- DRAW IT
- SECOND DERIVATIVE: If  $g''(x) > 0$ , CONVEX

**THEOREM: 4.7.7**

If  $g(x)$  is convex,  $E(g(x)) \geq g(E(x))$

If  $g(x)$  is concave,  $E(g(x)) \leq g(E(x))$

$$\text{Ex. } g(x) = x^2: \text{ CONVEX} \quad \therefore E(x^2) \geq E(x)^2$$

$$g(x) = e^x: \text{ CONVEX} \quad \therefore E(e^x) \geq e^{E(x)}$$

$$g(x) = \ln(x): \text{ CONCAVE} \quad \therefore E(\ln(x)) \leq \ln(E(x))$$

Ex. DIRE MEANS OF POS. NUMS.

$$\alpha_A = \frac{1}{n} (a_1 + a_2 + \dots + a_n)$$

$$\alpha_H = \frac{1}{n} (a_1 + a_2 + \dots + a_n)^{\frac{1}{n}}$$

$$\text{PROVE: } \alpha_H \leq \alpha_G \leq \alpha_A$$

X IS R.V. WITH SUPPORT  $(a_1, a_2, \dots, a_n)$  &  $P(X = a_i) = \frac{1}{n}$

$$\begin{aligned} E(X) &= \sum_{i=1}^n a_i p(X=a_i) = \frac{1}{n} \sum_{i=1}^n a_i \\ \log(\alpha_H) &= \frac{1}{n} \sum_{i=1}^n \log(a_i) = E(\log(X)) \leq \log(E(X)) = \log\left(\frac{1}{n} \sum_{i=1}^n a_i\right) = \log(\alpha_A) \Rightarrow \alpha_H \leq \alpha_A \\ \log\left(\frac{1}{n} \sum_{i=1}^n a_i\right) &= \log\left(\frac{1}{n} \sum_{i=1}^n a_i\right) \geq E(\log(X)) = -E(\log(X)) = -\log(\alpha_G) = \log\left(\frac{1}{n} \sum_{i=1}^n a_i\right) \\ \therefore \frac{1}{n} \sum_{i=1}^n a_i &\geq \frac{1}{n} \sum_{i=1}^n a_i \therefore \alpha_H \leq \alpha_G \end{aligned}$$

Moment Generating Function (MGF)

X IS R.V. WITH CDF  $F_X(x)$ , THE MGF OF X IS.

$$M_X(t) = E(e^{tx}) = \begin{cases} \int_{-\infty}^{\infty} e^{tx} F_X(x) dx & X \text{ IS CONT.} \\ \sum_{x \in X} e^{tx} f_X(x) & X \text{ DISCRETE} \end{cases}$$

This holds if the expectation exists for  $t$  in the neighborhood of 0. That is, there exists an  $h > 0$  such that  $E(e^{tx})$  exists for all  $-h < t < h$

Thm: If X HAS MGF:  $M_X(t)$ , THEN  $E(X^n) = M_X^{(n)}(0) = \frac{d^n}{dt^n} M_X(t) \Big|_{t=0}$

Proof: (start with assumption that we can bring the derivative inside the integral, see section 2.4 in CB)

$$\begin{aligned} \frac{d^n}{dt^n} M_X(t) \Big|_{t=0} &= \left[ \frac{d^n}{dt^n} \int e^{tx} f_X(x) dx \right] \Big|_{t=0} = \left[ \int \underbrace{\frac{d^n}{dt^n} e^{tx}}_{x^n e^{tx}} f_X(x) dx \right] \Big|_{t=0} \\ &= \left[ \int x^n e^{tx} f_X(x) dx \right] \Big|_{t=0} = E(x^n e^{tx}) \Big|_{t=0} = E(x^n) \end{aligned}$$

Ex. X IS EXP. R.V. WI  $f(x) = \frac{1}{\theta} e^{-x/\theta}$   $x > 0$

$$\begin{aligned} M_X(t) = E(e^{tx}) &= \int_0^{\infty} e^{tx} \frac{1}{\theta} e^{-x/\theta} dx = \frac{1}{\theta} \int_0^{\infty} e^{-x(\frac{1}{\theta} - t)} dx = \frac{1}{\theta} \int_0^{\infty} e^{-x(\frac{1-t\theta}{\theta})} dx \\ &= \frac{1}{\theta} \frac{1}{\frac{1-t\theta}{\theta}} = \frac{1}{1-t\theta} \end{aligned}$$

$$E(X) = M_X'(0) \Rightarrow \frac{d}{dt} \frac{1}{1-t\theta} = \frac{d}{dt} (1-t\theta)^{-1} = \frac{\theta}{(1-t\theta)^2} \therefore E(X) = M_X'(0) \cdot \frac{\theta}{(1-\theta)^2} = \theta$$

$$E(X^2) = M_X''(0) \quad \frac{d^2}{dt^2} \frac{1}{1-t\theta} = \frac{2\theta^2}{(1-t\theta)^3} \therefore E(X^2) = 2\theta^2$$

$$\therefore \text{VAR}(X) = E(X^2) - E(X)^2 = 2\theta^2 - \theta^2 = \theta^2$$