Larson and Marx Section 3.6

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Definition: Suppose a discrete random variable *X* has probability density function $p_X(k)$.

The variance of X, denoed by Var(X) or σ^2 is given by:

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all $_k$

The sum is taken over all values k that the random variable can assume.

Definition: Suppose a continuous random variable *Y* has pdf $f_Y(y)$. The **variance** of *Y*, denoed by Var(Y) or σ^2 is given by:

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Equivalently, integral may also be taken over the subset of the real line where f_Y has support.

The Variance

The variance of a discrete random variable X is **undefined** if

 $E(X^2)$ is not finite.

The Variance

The variance of a continuous random variable Y undefined if

 $E(Y^2)$ is not finite.

The Standard Deviation

In applications, the measure of dispersion most commonly used is called the **standard deviation**, and is defined for a discrete random variable *X* by:

$$\sigma = \sqrt{Var(X)} = \sqrt{\sigma^2} = \sqrt{\sum_{k=1}^{\infty} (k-\mu)^2 \cdot p_X(k)}$$
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For a continuous random variable Y, the standard deviation is defined to be:

$$\sigma = \sqrt{Var(Y)} = \sqrt{\sigma^2} = \sqrt{\int_{-\infty}^{\infty} (y - \mu)^2 \cdot f_Y(y) \, dy}$$

Relationship of Mean and Variance

Theorem: Suppose *W* is a random variable with mean μ for which

 $E(W^2)$ is finite

then

 $Var(W) = \sigma^2 = E(W^2) - [E(W)]^2 = E(W^2) - \mu^2$

Higher Moments

Definition: Suppose *W* is a random variable with pdf $f_W(w)$. For any positive integer *r*, $p_Y(y)$ and g(Y) is a function of *Y*.

The r^{th} moment about the origin μ_r is given by:

$$\mu_r = E(W^r)$$

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The r^{th} moment about the mean μ'_r is given by:

$$\mu_r' = E[(W - \mu)^r]$$

provided the expectation on the right hand side is finite.