

**Variance**

# Variance

**Definition 4.6.1** (Variance and standard deviation). The **variance** of an r.v.  $X$  is  $\text{Var}(X) = E(X - EX)^2$

Square root of the variance is called the **standard deviation** (SD):

$$\text{SD}(X) = \sqrt{\text{Var}(X)}$$

Recall that by  $E(X - EX)^2$  we mean expectation of r.v.  $(X - EX)^2$ , **not**  $(E(X - EX))^2$  (which is 0 by linearity).

Variance measures the “spread” – hence squaring the deviation from the mean,  $X - EX$ , (so negative deviations don’t cancel positive ones).

Why not take  $E(|X - EX|)$ ? This measure of “spread” also exists (called MAD) but it’s not so nice, since  $|x|$  is not diff. at  $x = 0$ .

# Variance

**Theorem 4.6.2** For any r.v.  $X$ ,  $\text{Var}(X) = E(X^2) - (EX)^2$

**Proof:** Let  $\mu = EX$ . Expanding  $(X - \mu)^2$  and using linearity,  
$$E(X - \mu)^2 = E(X^2 - 2\mu X + \mu^2) = E(X^2) - 2\mu EX + \mu^2 = E(X^2) - \mu^2$$

Variance has the following properties:

- 1)  $\text{Var}(X + c) = \text{Var}(X)$  for any constant  $c$
- 2)  $\text{Var}(cX) = c^2 \text{Var}(X)$  for any constant  $c$  ( $\text{Var}$  is **not** linear!)
- 3) If  $X$  and  $Y$  – independent, then  $\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y)$

In general, there's an inequality ( $\geq$ ), in the extreme case  $Y = X$ :

$$\text{Var}(X + Y) = \text{Var}(2X) = 4\text{Var}(X) > 2\text{Var}(X) = \text{Var}(X) + \text{Var}(Y)$$

- 4)  $\text{Var}(X) \geq 0$ , with  $=$  iff  $P(X = a) = 1$  for some constant  $a$

# Variance

**Example 4.6.4** (Geometric and Negative Binomial).  $X \sim \text{Geom}(p)$  – we know  $E(X) = q/p$ . By LOTUS,

$$E(X^2) = \sum_{k=0}^{\infty} k^2 P(X = k) = \sum_{k=0}^{\infty} k^2 p q^k = \sum_{k=1}^{\infty} k^2 p q^k = ?$$

Let's use the trick with differentiating  $\sum_{k=0}^{\infty} q^k = \frac{1}{1-q}$  w.r.t.  $q$ :

$$\sum k q^{k-1} = \frac{1}{(1-q)^2} \text{ – now } \cdot q, \text{ so } \sum k q^k = \frac{q}{(1-q)^2}, \text{ diff. again:}$$

$$\sum k^2 q^{k-1} = \frac{1+q}{(1-q)^3}, \text{ so } E(X^2) = p q \frac{1+q}{(1-q)^3} = \frac{q(1+q)}{p^2}$$

Finally,  $\text{Var}(X) = E(X^2) - (EX)^2 = q(1+q)/p^2 - (q/p)^2 = q/p^2$

For  $Y \sim \text{NBin}(r, p)$ ,  $Y = (\Sigma \text{ of } r \text{ i.i.d. Geom}(p))$ , so  $\text{Var}(Y) = r q / p^2$

# Variance

**Example 4.6.5** (Binomial variance).  $X \sim \text{Bin}(n, p)$ . With  $X = I_1 + I_2 + \dots + I_n$ ,  $I_k =$  (indicator of  $k$ -th trial being success). Each  $\text{Var}(I_k) = E(I_k^2) - (EI_k)^2 = p - p^2 = p(1 - p)$

Since all  $I_k$  are ***independent***,

$$\text{Var}(X) = \text{Var}(I_1) + \dots + \text{Var}(I_n) = np(1 - p)$$

Alternatively, one can find  $E(X^2)$  by first finding  $E(\# \text{ of } \mathbf{pairs} \text{ of successful trials})$ : with  $I_k$  for each,  $E \binom{X}{2} = \binom{n}{2} p^2$

So  $n(n - 1)p^2 = E(X(X - 1)) = E(X^2) - E(X) = E(X^2) - np$   
and  $\text{Var}(X) = E(X^2) - (EX)^2 = \dots = np(1 - p)$