

Proof: Why variances of independently varying distributions add

Expected values are summations: $E(X \pm Y) = E(X) + E(Y)$

First, we'll prove a 'Lemma' (a side results that we need to prove the main result):

Lemma: $Var(X) = E(x^2) - \mu^2$

Proof: $Var(X) = E((x - \mu)^2)$ where $E(X)$ means $\sum (x_i - \mu)^2 P(x_i)$

$$\begin{aligned} &= E(x^2 - 2x\mu + \mu^2) \\ &= E(x^2) + E(-2x\mu) + E(\mu^2) \\ &= E(x^2) - 2\mu E(x) + E(\mu^2) \quad \text{but } E(X) = \mu \\ &= E(x^2) - 2\mu\mu + E(\mu^2) \quad \mu \text{ is a constant, so } E(\mu^2) = \mu^2 \\ &= E(x^2) - 2\mu\mu + \mu^2 \\ &= E(x^2) - \mu^2 \end{aligned}$$

Now we can prove the theorem: If X and Y are independent: $Var(X \pm Y) = Var(X) + Var(Y)$

Proof: $Var(X \pm Y) = E((x + y)^2) - (\mu_{x \pm y})^2$ using the Lemma

$$\begin{aligned} &= E((x + y)^2) - (\mu_x \pm \mu_y)^2 \quad \text{because } \mu \text{ is a constant} \\ &= E(x^2 \pm 2xy + y^2) - (\mu_x^2 \pm 2\mu_x\mu_y + \mu_y^2) \\ &= E(x^2) \pm 2E(xy) + E(y^2) - \mu_x^2 \mp 2\mu_x\mu_y - \mu_y^2 \\ &= E(x^2) - \mu_x^2 \left[\pm 2E(xy) \mp 2\mu_x\mu_y \right] + E(y^2) - \mu_y^2 \\ &= E(x^2) - \mu_x^2 \pm 2 \underbrace{\left[E(xy) - \mu_x\mu_y \right]} + E(y^2) - \mu_y^2 \end{aligned}$$

$E(xy)$ is sum of terms $x_i y_j \cdot P(x_i \cap y_j)$

$\mu_x \mu_y$ is sum of terms $x_i P(x_i) \cdot y_j P(y_j)$

if X and Y are independent, probabilities multiply

and $P(x_i \cap y_j) = P(x_i) \cdot P(y_j)$

so middle term is zero if independent

$$Var(X \pm Y) = E(x^2) - \mu_x^2 + E(y^2) - \mu_y^2$$

$$Var(X \pm Y) = Var(X) + Var(Y)$$

This proof is from the website below, which provides even more background...

http://apcentral.collegeboard.com/apc/members/courses/teachers_corner/50250.html