Math 340: Lec 12 Big Ideas Journal (Variance)

Asa Royal (ajr74)

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Definition 1 (Variance). For a random variable X, the variance of X is

$$Var(X) = \mathbb{E}[X^2] - \mathbb{E}[X]^2 \tag{1}$$

or alternatively, if $\mathbb{E}[X] = \mu$,

$$Var(X) = \mathbb{E}[(X - \mu)^2] \tag{2}$$

Remark. We can think of variance as quantifying deviation from or closeness to the mean.

Properties of variance

- 1. $Var(x) \ge 0$
- 2. Var(X) can be ∞ even if $\exists [X] < \infty$
- 3. $Var(X) < \infty \iff \mathbb{E}[X^2] < \infty$
- 4. Scaling: For any $\alpha, \beta \in \mathbb{R}$, $Var(\alpha X + \beta) = \alpha^2 Var(X)$

Variance of an indicator variable

Proposition 2. Let $A \subset \Omega$ be any event. Consider $X = \chi_A$. $Var(X) \leq 1/4$

Proof. Generally, $Var(X) = \mathbb{E}[X^2] - \mathbb{E}[X]^2$. Because X is an indicator variable, $X^2 = X$ and $\mathbb{E}[X] = \mathbb{P}(X)$. Thus $Var(X) = \mathbb{P}(X) - \mathbb{P}(X)^2 = \mathbb{P}(X)[1 - \mathbb{P}(X)]$. Var(X) is clearly maximized when $\mathbb{P}P(X) = 1/2$, so $Var(X) \le 1/4$.

Covariance

Definition 3 (Covariance). The covariance of two random variables X and Y is defined as

$$Cov(X,Y) = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y] = \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])]$$
(3)

Correlation is a normalized measure of covariance.

Proposition 4. Cov is bilinear because it is an inner product on certain vector spaces (see endof notes). Thus

- 1. Cov(cX, Y) = cCov(X, Y)
- 2. Cov(X, Y + Z) = Cov(X, Y) + Cov(X, Z)
- 3. Cov(X, X) = Var(X)
- 4. $\operatorname{Cov}(\sum_{i=1}^{m} a_i X_i, \sum_{j=1}^{n} b_j Y_j) = \sum_{i,j} a_i b_j \operatorname{Cov}(X_i, Y_j)$

 $\textit{Proof.} \ \operatorname{Cov}(X,Y+Z) = \mathbb{E}[X(Y+Z)] - \mathbb{E}[X]\mathbb{E}[Y+Z] = \mathbb{E}[XY] + \mathbb{E}[XZ] - \mathbb{E}[X]\mathbb{E}[Y] - \mathbb{E}[X]\mathbb{E}[Z] = \operatorname{Cov}(X,Y) + \operatorname{Cov}(X,Z) \quad \Box$

Variance of sums

Proposition 5.

$$Var(X_1 + X_2 + \dots + X_n) = \sum_{i=1}^n Var(X_i) + 2\sum_{i \le k} Cov(X_i, X_k)$$
(4)

Remark. Note that

$$Var(X_1 + X_2) = Cov(X_1 + X_2, X_1 + X_2)$$

$$= Cov(X_1, X_1) + Cov(X_1, X_2) + Cov(X_2, X_1) + Cov(X_2, X_2)$$

$$= Var(X_1) + Var(X_2) + 2Cov(X_1, X_2)$$

Proof. Applying prop 4.4,

$$Var(X_1 + \dots + X_n) = Cov(X_1 + \dots + X_n, X_1 + \dots + X_n)$$

$$= Cov(X_1 + X_1) + Cov(X_2 + X_2) + \dots + Cov(X_n + X_n) + Cov(X_1, X_2) + Cov(X_2, X_1) + \dots$$

$$= \sum_{i=1}^n Var(X_i) + 2\sum_{j < k} Cov(j, k)$$

Corollary 6. If X_1, \ldots, X_n are independent (or just uncorrelated)

$$\operatorname{Var}(X_1 + \ldots + X_n) = \sum_{i=1}^n \operatorname{Var}(X_i)$$

Vector spaces of random variables

Remark. Given Ω, \mathbb{P} , let S be the set of all random variables X on Ω s.t. $\mathbb{E}[X] = 0$ and $\mathbb{E}[X^2] < \infty$ (which means $\mathrm{Var}(X) < \infty$). Then S is a vector space. Thus, $X_1, X_2 \in S \implies \alpha X_1 + \beta X_2 \in S$ for any $\alpha, \beta \in R$.

Remark. We can think of Cov as an inner product on S. $||X_1|| = \text{Cov}(X_1, X_1) = \sqrt{\text{Var}(X)}$, so $||X_1||^2 = \text{Var}(X)$.

Remark. Independent vectors in S are orthogonal to each other, so for independent vectors $X_1, X_2, ||X_1 + X_2|| = ||X_1|| + ||X_2||$. This makes sense, because the $\cos \theta$ term we'd see when calculating out $||X_1 + X_2||$ would be obliterated for orthogonal vectors.