## **CMPT 210:** Probability and Computing

Lecture 20

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**Variance**: Standard way to measure the deviation from the mean. For r.v. X,  $Var[X] = \mathbb{E}[(X - \mathbb{E}[X])^2] = \sum_{x \in Range(X)} (x - \mu)^2 Pr[X = x]$ , where  $\mu := \mathbb{E}[X]$ . **Alternate Definition**:  $Var[X] = \mathbb{E}[X^2] - (\mathbb{E}[X])^2$ .

**Standard Deviation**: For r.v. X, the standard deviation of X is defined as  $\sigma_X := \sqrt{\operatorname{Var}[X]} = \sqrt{\mathbb{E}[X^2] - (\mathbb{E}[X])^2}.$ 

For constants a, b and r.v. R,  $Var[aR + b] = a^2 Var[R]$ .

**Pairwise Independence**: Random variables  $R_1, R_2, R_3, ..., R_n$  are pairwise independent if for any pair  $R_i$  and  $R_j$ , for  $x \in \text{Range}(R_i)$  and  $y \in \text{Range}(R_j)$ ,  $\Pr[(R_i = x) \cap (R_j = y)] = \Pr[R_i = x] \Pr[R_j = y].$ 

Linearity of variance for pairwise independent r.v's: If  $R_1, \ldots, R_n$  are pairwise independent,  $Var[R_1 + R_2 + \ldots R_n] = \sum_{i=1}^n Var[R_i].$ 

### Covariance

For two random variables R and S, the covariance between R and S is defined as:

 $\operatorname{Cov}[R, S] := \mathbb{E}[(R - \mathbb{E}[R])(S - \mathbb{E}[S])] = \mathbb{E}[RS] - \mathbb{E}[R]\mathbb{E}[S]$ 

 $Cov[R, S] = \mathbb{E}[(R - \mathbb{E}[R]) (S - \mathbb{E}[S])]$ =  $\mathbb{E}[RS - R \mathbb{E}[S] - S \mathbb{E}[R] + \mathbb{E}[R] \mathbb{E}[S]]$ =  $\mathbb{E}[RS] - \mathbb{E}[R \mathbb{E}[S]] - \mathbb{E}[S \mathbb{E}[R]] + \mathbb{E}[R] \mathbb{E}[S]$  $\implies Cov[R, S] = \mathbb{E}[RS] - \mathbb{E}[R] \mathbb{E}[S] - \mathbb{E}[S] \mathbb{E}[R] + \mathbb{E}[R] \mathbb{E}[S] = \mathbb{E}[RS] - \mathbb{E}[R] \mathbb{E}[S]$ 

Covariance generalizes the notion of variance to multiple random variables.

 $\operatorname{Cov}[R, R] = \mathbb{E}[R R] - \mathbb{E}[R] \mathbb{E}[R] = \operatorname{Var}[R]$ 

If R and S are independent r.v's,  $\mathbb{E}[RS] = \mathbb{E}[R]\mathbb{E}[S]$  and Cov[R, S] = 0.

The covariance between two r.v's is symmetric i.e. Cov[R, S] = Cov[S, R].

### Covariance

For two arbitrary (not necessarily independent) r.v's, R and S,

Var[R+S] = Var[R] + Var[S] + 2 Cov[R,S]

Recall from Lecture 19, Slide 6, where we showed that,

 $\operatorname{Var}[R+S] = \operatorname{Var}[R] + \operatorname{Var}[S] + 2(\mathbb{E}[RS] - \mathbb{E}[R]\mathbb{E}[S]) = \operatorname{Var}[R] + \operatorname{Var}[S] + 2\operatorname{Cov}[R, S].$ 

If R and S are independent, Cov[R, S] = 0 and we recover the formula for the sum of independent variables.

For R = S, Var[R + R] = Var[R] + Var[R] + 2Cov[R, R] = Var[R] + Var[R] + 2Var[R] = 4Var[R]which is consistent with our previous formula that  $Var[2R] = 2^2Var[R]$ .

Generalization to multiple random variables  $R_1, R_2, \ldots, R_n$  (Recall from Lecture 19, Slide 7):

$$\operatorname{Var}\left[\sum_{i=1}^{n} R_{i}\right] = \sum_{i=1}^{n} \operatorname{Var}[R_{i}] + 2\sum_{1 \leq i < j \leq n} \operatorname{Cov}[R_{i}, R_{j}]$$

## Covariance - Example

**Q**: If X and Y are indicator r.v's for events A and B respectively, calculate the covariance between X and Y

We know that  $Cov[X, Y] = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y]$ . Note that  $X = \mathcal{I}_A$  and  $Y = \mathcal{I}_B$ . We can conclude that  $XY = \mathcal{I}_{A \cap B}$  since XY = 1 iff both events A and B happen.

$$\implies \mathbb{E}[X] = \Pr[A] ; \mathbb{E}[Y] = \Pr[B]; \mathbb{E}[XY] = \Pr[A \cap B]$$
$$\implies \operatorname{Cov}[X, Y] = \mathbb{E}[XY] - \mathbb{E}[X] \mathbb{E}[Y] = \Pr[A \cap B] - \Pr[A] \Pr[B]$$

If  $\operatorname{Cov}[X, Y] > 0 \implies \Pr[A \cap B] > \Pr[A] \Pr[B]$ . Hence,

$$\Pr[A|B] = \frac{\Pr[A \cap B]}{\Pr[B]} > \frac{\Pr[A]\Pr[B]}{\Pr[B]} = \Pr[A]$$

If Cov[X, Y] > 0, it implies that Pr[A|B] > Pr[A] and hence, the probability that event A happens increases if B is going to happen/has happened. Similarly, if Cov[X, Y] < 0, Pr[A|B] < Pr[A]. In this case, if B happens, then the probability of event A decreases.

### Correlation

The correlation between two r.v's  $R_1$  and  $R_2$  is defined as:

$$\mathsf{Corr}[R_1, R_2] = \frac{\mathsf{Cov}[R_1, R_2]}{\sqrt{\mathsf{Var}[R_1]\,\mathsf{Var}[R_2]}}$$

 $Corr[R_1, R_2] \in [-1, 1]$  and indicates the strength of the relationship between  $R_1$  and  $R_2$ .

If  $Corr[R_1, R_2] > 0$ , then  $R_1$  and  $R_2$  are said to be positively correlated, else if  $Corr[R_1, R_2] < 0$ , the r.v's are negatively correlated.

 $=\frac{\mathbb{E}[-R^2] - \mathbb{E}[R]\mathbb{E}[-R]}{\operatorname{Var}[R]} = \frac{-\mathbb{E}[R^2] + \mathbb{E}[R]\mathbb{E}[R]}{\operatorname{Var}[R]} = \frac{-\operatorname{Var}[R]}{\operatorname{Var}[R]} = -1$ 

If 
$$R_1 = R_2 = R$$
, then,  $\operatorname{Corr}[R, R] = \frac{\operatorname{Cov}[R, R]}{\sqrt{\operatorname{Var}[R]} \operatorname{Var}[R]} = \frac{\operatorname{Var}[R]}{\operatorname{Var}[R]} = 1$ .  
If  $R_1$  and  $R_2$  are independent,  $\operatorname{Cov}[R_1, R_2] = 0$  and  $\operatorname{Corr}[R_1, R_2] = 0$ .  
If  $R_1 = -R_2 = R$ , then,  
 $\operatorname{Corr}[R, -R] = \frac{\operatorname{Cov}[R, -R]}{\sqrt{\operatorname{Var}[R]\operatorname{Var}[-R]}} = \frac{\operatorname{Cov}[R, -R]}{\sqrt{\operatorname{Var}[R](-1)^2\operatorname{Var}[R]}} = \frac{\operatorname{Cov}[R, -R]}{\operatorname{Var}[R]}$ 

# Questions?

## Tail inequalities

Variance gives us one way to measure how "spread" the distribution is.

Tail inequalities bound the probability that the r.v. takes a value much different from its mean.

*Example*: Consider a r.v. X that can take on only non-negative values and  $\mathbb{E}[X] = 99.99$ . Show that  $\Pr[X \ge 300] \le \frac{1}{3}$ .

$$Proof: \mathbb{E}[X] = \sum_{x \in \text{Range}(X)} x \Pr[X = x] = \sum_{x \mid x \ge 300} x \Pr[X = x] + \sum_{x \mid 0 \le x < 300} x \Pr[X = x]$$
  
$$\geq \sum_{x \mid x \ge 300} (300) \Pr[X = x] + \sum_{x \mid 0 \le x < 300} x \Pr[X = x]$$
  
$$= (300) \Pr[X \ge 300] + \sum_{x \mid 0 \le x < 300} x \Pr[X = x]$$

If  $\Pr[X \ge 300] > \frac{1}{3}$ , then,  $\mathbb{E}[X] > (300) \frac{1}{3} + \sum_{x|0 \le x < 300} x \Pr[X = x] > 100$  (since the second term is always non-negative). Hence, if  $\Pr[X \ge 300] > \frac{1}{3}$ ,  $\mathbb{E}[X] > 100$  which is a contradiction since  $\mathbb{E}[X] = 99.99$ .