

# CMPSCI 240: Reasoning about Uncertainty

## Lecture 13: Coupon Collecting and Correlation and Causation

Andrew McGregor

University of Massachusetts

# Outline

- 1 Review
- 2 Covariance and Correlation
- 3 Coupon Collecting
- 4 Loose Ends: Random Facts about Random Things

# Expectation and Variance Review

- The expected value  $E[X]$  of a random variable  $X$  is a probability-weighted average of the possible values of  $X$ :

$$E[X] = \sum_k k P(X = k)$$

- If  $X$  is a random variable and  $f : \mathbb{R} \rightarrow \mathbb{R}$  then  $Y = f(X)$  is also a random variable with expectation

$$E(Y) = \sum_k f(k) P(X = k)$$

- The variance quantifies how close to  $\mu = E[X]$  we expect  $X$  to be:

$$\text{var}(X) = \sum_k (k - \mu)^2 P(X = k) = E[X^2] - \mu^2.$$

and the standard deviation of  $X$  is  $\sigma_X = \sqrt{\text{var}(X)}$

# Multiple Random Variables

- Given two random variables,  $X$  and  $Y$  mapping from  $\Omega$  to  $\mathbb{R}$ , we can define events of the form

$$\{X = i, Y = j\} = \{X = i\} \cap \{Y = j\} = \{\omega \in \Omega \mid X(\omega) = i \text{ and } Y(\omega) = j\}$$

- The probabilities of these events give the **joint PMF** of  $X$  and  $Y$ :

$$P(X = i, Y = j) = P(\{X = i, Y = j\})$$

- Given the joint PMF, we can compute the **marginal** probabilities:

$$P(X = i) = \sum_j P(X = i, Y = j)$$

$$P(Y = j) = \sum_i P(X = i, Y = j)$$

# Functions of Multiple Random Variables

- Given random variables  $X_1, X_2, \dots, X_N$  and  $f : \mathbb{R} \times \mathbb{R} \times \dots \times \mathbb{R} \rightarrow \mathbb{R}$ ,

$$Z = f(X_1, X_2, \dots, X_N)$$

is a new random variable with expectation

$$E(Z) = \sum_{a_1, a_2, \dots, a_N} f(a_1, a_2, \dots, a_N) P(X_1 = a_1, X_2 = a_2, \dots, X_N = a_N)$$

- **Linearity of Expectation:** If  $Z = \sum_{i=1}^N c_i X_i$ ,

$$E(Z) = E\left(\sum_{i=1}^N c_i X_i\right) = \sum_{i=1}^N c_i E(X_i)$$

- **Linearity of Variance:** If  $Z = \sum_{i=1}^N c_i X_i$ ,

$$\text{var}(Z) = \text{var}\left(\sum_{i=1}^N c_i X_i\right) = \sum_{i=1}^N c_i^2 \text{var}(X_i)$$

if  $X_1, \dots, X_N$  are pairwise independent, i.e., for all  $i, j, a, b$

$$P(X_i = a, X_j = b) = P(X_i = a)P(X_j = b) .$$

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# Independence

- Two discrete random variables  $X$  and  $Y$  are independent if and only if  $P(X = a, Y = b) = P(X = a)P(Y = b)$  for all  $a$  and  $b$ .
- When two random variables are not independent, it's natural to want to measure how dependent they are.

# Quantifying Dependence: Covariance

- The **covariance** between  $X$  and  $Y$  is one measure of dependence that quantifies the degree to which there is a **linear relationship** between  $X$  and  $Y$ .

$$\begin{aligned}\text{cov}(X, Y) &= E[(X - E[X])(Y - E[Y])] \\ &= E[XY] - E[X]E[Y]\end{aligned}$$

- The covariance of  $X$  and  $Y$  is positive if when  $X$  is large,  $Y$  is also large. It's negative if when  $X$  is large,  $Y$  is small.
- If  $X$  and  $Y$  are independent then  $\text{cov}(X, Y) = 0$  but  $\text{cov}(X, Y) = 0$  does not necessarily imply that  $X$  and  $Y$  are independent.
- We can write  $\text{var}(X + Y) = \text{var}(X) + \text{var}(Y) + 2\text{cov}(X, Y)$ .



# Example

P(X,Y)		
X\Y	Y = 0	Y = 1
X = 0	0.4	0.1
X = 1	0.2	0.3

- $P(X = 0) = 0.5, P(X = 1) = 0.5$  and so  $E[X] = 0.5$
- $P(Y = 0) = 0.6, P(Y = 1) = 0.4$  and so  $E[Y] = 0.4$
- $E[XY]$  can be computed as follows

$$\begin{aligned}
 E[XY] &= 0 \times 0 \times P(X = 0, Y = 0) + 0 \times 1 \times P(X = 0, Y = 1) + \\
 &\quad 1 \times 0 \times P(X = 1, Y = 0) + 1 \times 1 \times P(X = 1, Y = 1) \\
 &= 0.3
 \end{aligned}$$

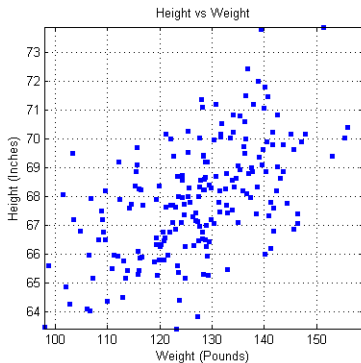
- $\text{cov}(X, Y) = E(XY) - E(X)E(Y) = 0.3 - 0.5 \times 0.4 = 0.1$

# Quantifying Dependence: Correlation

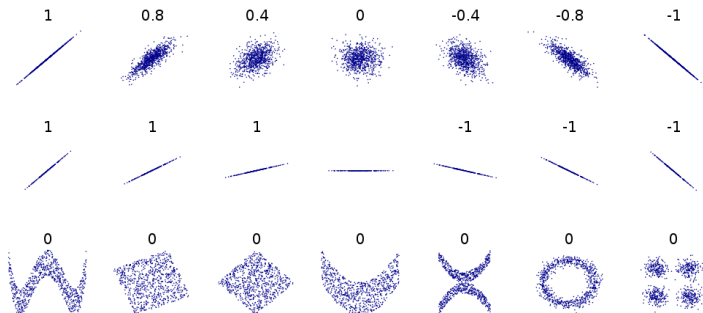
- The maximum magnitude of the covariance depends on the variance of  $X$  and the variance of  $Y$ .
- The **correlation** between  $X$  and  $Y$  is closely related to the covariance, but is normalized to the range  $[-1, 1]$ . 1 indicates maximum positive covariance and  $-1$  indicates maximum negative covariance:

$$\rho(X, Y) = \text{corr}(X, Y) = \frac{\text{cov}(X, Y)}{\sqrt{\text{var}(X)\text{var}(Y)}}$$

# Visualizing Correlations: Height vs Weight ( $\rho = 0.56$ )



# Visualizing Correlations: Linear vs Non-Linear



# Causation

- **Question:** When two random variables are correlated does this mean one random variable causes the other?
- **Example:** There are more fireman at the scene of larger fires? Do fireman cause an increase in the size of a fire.
- **Example:** More people drown on days where a lot of ice cream is sold. Does ice cream cause drowning?
- **Example:** In the height/weight example, height and weight were positively correlated. Does increasing your weight make you taller?
- **Example:** When you see a wind turbine turning it is usually windy. Do wind turbines create wind?

# Causation

Given two correlated random variables  $X$  and  $Y$ :

- $X$  might cause  $Y$  (i.e., causation)
- $Y$  might cause  $X$  (i.e., reverse causation)
- A third random variable  $Z$  might cause  $X$  and  $Y$  (i.e., common cause)
- A combination of all of these (e.g., self-reinforcement)
- The correlation might be spurious due to small sample size

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# Coupon Collecting/Shuffle Mode

- You have  $n$  songs on your phone.
- In **shuffle mode**, the player picks songs uniformly at random.
- Let  $T$  be the total number of songs played until every song is played.
- $T$  could be infinite or as small as  $n$ .
- For this section, recall that if  $X$  is a geometric random variable with parameter  $p$  then  $P(X = k) = (1 - p)^{k-1}p$  and has expectation  $1/p$ .



# What's the probability that $T = n$ ?

- What's the probability that  $T = n$ ?
- Number of possible sequences of  $n$  songs:  $n^n$
- Number of possible sequences of  $n$  songs including every song:  $n!$
- Therefore, probability is:

$$\frac{n!}{n^n} = \frac{n}{n} \times \frac{n-1}{n} \times \dots \times \frac{1}{n} \leq 2^{-n/2}$$

# Expected Value of $T$

- To analyze  $E[T]$  we define  $C_1, C_2, \dots, C_n$  where

$C_i =$  songs played after  $(i-1)$ -th new song until  $i$ -th new song is played

and note that  $T = \sum_{i=1}^n C_i$

- By linearity of expectation:

$$E[T] = \sum_{i=1}^n E[C_i]$$

- $C_i$  is a geometric random variable with

$$P(C_i = j) = p_i(1 - p_i)^{j-1} \quad \text{for } j = 1, 2, \dots$$

where  $p_i = \frac{n-i+1}{n}$

- $E[C_i] = \frac{1}{p_i} = \frac{n}{n-i+1}$

- So

$$E[T] = \frac{n}{n} + \frac{n}{n-1} + \dots + \frac{n}{1} = nH_n \approx n \ln n$$

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# Secrets of the Chebyshev Bound

## ■ Chebyshev Bound:

$$P(X \leq E(X) - c) + P(X \geq E(X) + c) = P(|X - E(X)| \geq c) \leq \text{Var}(X)/c^2$$

- The bound is useful when we are trying to bound the probability that  $X$  is much smaller or larger than its expectation.
- However, it also implies bounds on just one tail.
- For example, if  $E(X) = 10$  and  $\text{var}(X) = 2$  then

$$P(X \geq 15) = P(X \geq E(X) + 5) \leq P(|X - E(X)| \geq 5) \leq 2/25$$

# Poisson Expectation

For a Poisson random variable,  $P(X = k) = \frac{e^{-\lambda}}{k!} \lambda^k$ . Hence,

$$\begin{aligned} E[X] &= \sum_{k=0}^{\infty} k \cdot \frac{e^{-\lambda}}{k!} \lambda^k \\ &= \lambda \sum_{k=1}^{\infty} k \cdot \frac{e^{-\lambda}}{k!} \lambda^{k-1} \\ &= \lambda \sum_{k=1}^{\infty} \frac{e^{-\lambda}}{(k-1)!} \lambda^{k-1} \\ &= \lambda (P(X = 0) + P(X = 1) + P(X = 2) + \dots) \\ &= \lambda \end{aligned}$$

The last line follows because the events  $\{X = 0\}, \{X = 1\}, \{X = 2\}, \dots$  partition the sample space and hence the probabilities sum up to 1.

# Geometric Expectation

For a Geometric random variable,  $P(X = k) = (1 - p)^{k-1}p$ . You'll prove in the homework that:

- $E[X] = P(X \geq 1) + P(X \geq 2) + P(X \geq 3) \dots$
- $P(X \geq k) = (1 - p)^{k-1}$

Using these,

$$\begin{aligned} E[X] &= P(X \geq 1) + P(X \geq 2) + P(X \geq 3) \dots \\ &= 1 + (1 - p) + (1 - p)^2 + \dots \\ &= 1/p \end{aligned}$$

# Alternative Expression for Expectation

- If  $Y = f(X)$ , we can write  $E[Y] = \sum_k f(k)P(X = k)$ .
- Use the fact that  $P(Y = r) = \sum_{k:f(k)=r} P(X = k)$  and then,

$$\begin{aligned} E[Y] &= \sum_r rP(Y = r) \\ &= \sum_r r \sum_{k:f(k)=r} P(X = k) \\ &= \sum_r \sum_{k:f(k)=r} rP(X = k) \\ &= \sum_r \sum_{k:f(k)=r} f(k)P(X = k) \\ &= \sum_k f(k)P(X = k) \end{aligned}$$

# Secrets of Pairwise Independence

- Suppose we have some bernoulli random variables  $X_1, X_2, \dots, X_n$  where for all  $i < j$  the joint probabilities are given in the following table:

$X_i \backslash X_j$	0	1
0	0.25	0.25
1	0.25	0.25

- Are the variables pairwise independent? I.e., for all  $i < j$  and  $a, b \in \{0, 1\}$ ,  $P(X_i = a, X_j = b) = P(X_i = a)P(X_j = b)$ . Yes.
- Are they also three-wise independent? I.e., for all  $i < j < k$  and  $a, b, c \in \{0, 1\}$

$$P(X_i = a, X_j = b, X_k = c) = P(X_i = a)P(X_j = b)P(X_k = c)$$

- Not necessarily, e.g., let  $X_1$  and  $X_2$  be the result of tossing two independent coins and  $X_3 = X_1 + X_2 \pmod{2}$ .