CS70.

- 1. Random Variables: Brief Review
- 2. Joint Distributions.
- 3. Linearity of Expectation

Random Variables: Definitions

Definition

A random variable, X, for a random experiment with sample space Ω is a function $X : \Omega \to \Re$.

Thus, $X(\cdot)$ assigns a real number $X(\omega)$ to each $\omega \in \Omega$.

Definitions

(a) For $a \in \Re$, one defines

$$X^{-1}(a) := \{ \omega \in \Omega \mid X(\omega) = a \}.$$

(b) For $A \subset \mathfrak{R}$, one defines

$$X^{-1}(A) := \{ \omega \in \Omega \mid X(\omega) \in A \}.$$

(c) The probability that X = a is defined as

$$Pr[X = a] = Pr[X^{-1}(a)].$$

(d) The probability that $X \in A$ is defined as

$$Pr[X \in A] = Pr[X^{-1}(A)].$$

(e) The distribution of a random variable X, is

$$\{(a, Pr[X = a]) : a \in \mathscr{A}\},$$

where \mathscr{A} is the *range* of X. That is, $\mathscr{A} = \{X(\omega), \omega \in \Omega\}$.

Expectation - Definition

Definition: The **expected value** (or mean, or expectation) of a random variable X is

$$E[X] = \sum_{a} a \times Pr[X = a].$$

Theorem:

$$E[X] = \sum_{\omega} X(\omega) \times Pr[\omega].$$

Proof:

$$E[X] = \sum_{a} a \times Pr[X = a]$$

$$= \sum_{a} a \times \sum_{\omega: X(\omega) = a} Pr[\omega]$$

$$= \sum_{a} \sum_{\omega: X(\omega) = a} X(\omega) Pr[\omega]$$

$$= \sum_{\omega} X(\omega) Pr[\omega]$$

An Example

Flip a fair coin three times.

$$\Omega = \{HHH, HHT, HTH, THH, HTT, THT, TTH, TTT\}.$$

X = number of H's: $\{3, 2, 2, 2, 1, 1, 1, 0\}$.

Thus,

$$\sum_{\omega} X(\omega) Pr[\omega] = \{3 + 2 + 2 + 2 + 1 + 1 + 1 + 0\} \times \frac{1}{8}.$$

Also,

$$\sum_{a} a \times Pr[X = a] = 3 \times \frac{1}{8} + 2 \times \frac{3}{8} + 1 \times \frac{3}{8} + 0 \times \frac{1}{8}.$$

Win or Lose.

Expected winnings for heads/tails games, with 3 flips? Recall the definition of the random variable *X*:

 $\{HHH, HHT, HTH, HTT, THH, THT, TTH, TTT\} \rightarrow \{3, 1, 1, -1, 1, -1, -1, -3\}.$

$$E[X] = 3 \times \frac{1}{8} + 1 \times \frac{3}{8} - 1 \times \frac{3}{8} - 3 \times \frac{1}{8} = 0.$$

Can you ever win 0?

Apparently: expected value is not a common value, by any means.

The expected value of X is not the value that you expect! It is the average value per experiment, if you perform the experiment many times:

$$\frac{X_1+\cdots+X_n}{n}$$
, when $n\gg 1$.

The fact that this average converges to E[X] is a theorem: the Law of Large Numbers. (See later.)

Multiple Random Variables.

Experiment: toss two coins. $\Omega = \{HH, TH, HT, TT\}.$

$$X_1(\omega) = \left\{ egin{array}{ll} 1, & \mbox{if coin 1 is heads} \ 0, & \mbox{otherwise} \end{array}
ight. \quad X_2(\omega) = \left\{ egin{array}{ll} 1, & \mbox{if coin 2 is heads} \ 0, & \mbox{otherwise} \end{array}
ight.$$

Multiple Random Variables: setup.

Joint Distribution: $\{(a,b,Pr[X=a,Y=b]): a \in \mathcal{A}, b \in \mathcal{B}\}$, where $\mathcal{A}(\mathcal{B})$ is possible values of X(Y).

$$\sum_{a \in \mathscr{A}, b \in \mathscr{B}} Pr[X = a, Y = b] = 1$$

Marginal for X: $Pr[X = a] = \sum_{b \in \mathscr{B}} Pr[X = a, Y = b]$. Marginal for Y: $Pr[Y = b] = \sum_{a \in \mathscr{A}} Pr[X = a, Y = b]$.

X/Y	1	2	3	Х
1	.2	.1	.1	.4
2	0	0	.3	.3
3	.1	0	.2	.3
Υ	.3	.1	.2 .6	

Conditional Probability: $Pr[X = a | Y = b] = \frac{Pr[X = a, Y = b]}{Pr[Y = b]}$.

Review: Independence of Events

- ▶ Events A, B are independent if $Pr[A \cap B] = Pr[A]Pr[B]$.
- ► Events *A*, *B*, *C* are mutually independent if *A*, *B* are independent, *A*, *C* are independent independent.
 - and $Pr[A \cap B \cap C] = Pr[A]Pr[B]Pr[C]$.
- ▶ Events $\{A_n, n \ge 0\}$ are mutually independent if
- ► Example: $X, Y \in \{0,1\}$ two fair coin flips $\Rightarrow X, Y, X \oplus Y$ are pairwise independent but not mutually independent.
- Example: $X, Y, Z \in \{0,1\}$ three fair coin flips are mutually independent.

Independent Random Variables.

Definition: Independence

The random variables *X* and *Y* are **independent** if and only if

$$Pr[Y = b|X = a] = Pr[Y = b]$$
, for all a and b.

Fact:

X, Y are independent if and only if

$$Pr[X = a, Y = b] = Pr[X = a]Pr[Y = b]$$
, for all a and b .

Follows from $Pr[A \cap B] = Pr[A|B]Pr[B]$ (Product rule.)

Independence: Examples

Example 1

Roll two die. X, Y = number of pips on the two dice. X, Y are independent.

Indeed:
$$Pr[X = a, Y = b] = \frac{1}{36}, Pr[X = a] = Pr[Y = b] = \frac{1}{6}.$$

Example 2

Roll two die. X = total number of pips, Y = number of pips on die 1 minus number on die 2. X and Y are not independent.

Indeed:
$$Pr[X = 12, Y = 1] = 0 \neq Pr[X = 12]Pr[Y = 1] > 0$$
.

Example 3

Flip a fair coin five times, X = number of Hs in first three flips, Y = number of Hs in last two flips. X and Y are independent.

Indeed:

$$Pr[X = a, Y = b] = {3 \choose a} {2 \choose b} 2^{-5} = {3 \choose a} 2^{-3} \times {2 \choose b} 2^{-2} = Pr[X = a] Pr[Y = b].$$

Linearity of Expectation

Theorem:

$$E[X + Y] = E[X] + E[Y]$$
$$E[cX] = cE[X]$$

Proof: $E[X] = \sum_{\omega \in \Omega} X(\omega) \times P[\omega]$.

$$E[X + Y] = \sum_{\omega \in \Omega} (X(\omega) + Y(\omega))Pr[\omega]$$

$$= \sum_{\omega \in \Omega} X(\omega)Pr[\omega] + Y(\omega)Pr[\omega]$$

$$= \sum_{\omega \in \Omega} X(\omega)Pr[\omega] + \sum_{\omega \in \Omega} Y(\omega)Pr[\omega]$$

$$= E[X] + E[Y]$$

Indicators

Definition

Let A be an event. The random variable X defined by

$$X(\omega) = \begin{cases} 1, & \text{if } \omega \in A \\ 0, & \text{if } \omega \notin A \end{cases}$$

is called the indicator of the event A.

Note that Pr[X = 1] = Pr[A] and Pr[X = 0] = 1 - Pr[A].

Hence,

$$E[X] = 1 \times Pr[X = 1] + 0 \times Pr[X = 0] = Pr[A].$$

This random variable $X(\omega)$ is sometimes written as

$$1\{\omega \in A\}$$
 or $1_A(\omega)$.

Thus, we will write $X = 1_A$.

Linearity of Expectation

Theorem: Expectation is linear

$$E[a_1X_1 + \cdots + a_nX_n] = a_1E[X_1] + \cdots + a_nE[X_n].$$

Proof:

$$E[a_1X_1 + \dots + a_nX_n]$$

$$= \sum_{\omega} (a_1X_1 + \dots + a_nX_n)(\omega)Pr[\omega]$$

$$= \sum_{\omega} (a_1X_1(\omega) + \dots + a_nX_n(\omega))Pr[\omega]$$

$$= a_1\sum_{\omega} X_1(\omega)Pr[\omega] + \dots + a_n\sum_{\omega} X_n(\omega)Pr[\omega]$$

$$= a_1E[X_1] + \dots + a_nE[X_n].$$

Note: If we had defined $Y = a_1 X_1 + \cdots + a_n X_n$ has had tried to compute $E[Y] = \sum_y y Pr[Y = y]$, we would have been in trouble!

Using Linearity - 1: Pips (dots) on dice

Roll a die n times.

 X_m = number of pips on roll m.

$$X = X_1 + \cdots + X_n$$
 = total number of pips in n rolls.

$$E[X] = E[X_1 + \dots + X_n]$$

= $E[X_1] + \dots + E[X_n]$, by linearity
= $nE[X_1]$, because the X_m have the same distribution

Now,

$$E[X_1] = 1 \times \frac{1}{6} + \dots + 6 \times \frac{1}{6} = \frac{6 \times 7}{2} \times \frac{1}{6} = \frac{7}{2}.$$

Hence,

$$E[X]=\frac{7n}{2}.$$

Note: Computing $\sum_{X} xPr[X = x]$ directly is not easy!

Using Linearity - 2: Fixed point.

Hand out assignments at random to *n* students.

X = number of students that get their own assignment back.

$$X = X_1 + \cdots + X_n$$
 where $X_m = 1$ {student m gets his/her own assignment back}.

One has

$$E[X] = E[X_1 + \dots + X_n]$$

 $= E[X_1] + \dots + E[X_n]$, by linearity
 $= nE[X_1]$, because all the X_m have the same distribution
 $= nPr[X_1 = 1]$, because X_1 is an indicator
 $= n(1/n)$, because student 1 is equally likely
to get any one of the n assignments
 $= 1$.

Note that linearity holds even though the X_m are not independent (whatever that means).

Note: What is Pr[X = m]? Tricky

Using Linearity - 3: Binomial Distribution.

Flip n coins with heads probability p. X - number of heads Binomial Distibution: Pr[X = i], for each i.

$$Pr[X=i] = \binom{n}{i} p^{i} (1-p)^{n-i}.$$

$$E[X] = \sum_{i} i \times Pr[X = i] = \sum_{i} i \times \binom{n}{i} p^{i} (1 - p)^{n - i}.$$

Uh oh. ... Or... a better approach: Let

$$X_i = \left\{ egin{array}{ll} 1 & ext{ if } i ext{th flip is heads} \\ 0 & ext{ otherwise} \end{array}
ight.$$

$$E[X_i] = 1 \times Pr["heads"] + 0 \times Pr["tails"] = p.$$

Moreover $X = X_1 + \cdots + X_n$ and

$$E[X] = E[X_1] + E[X_2] + \cdots + E[X_n] = n \times E[X_i] = np.$$

Using Linearity - 4

Assume A and B are disjoint events. Then $1_{A\cup B}(\omega)=1_A(\omega)+1_B(\omega)$. Taking expectation, we get

$$Pr[A \cup B] = E[1_{A \cup B}] = E[1_A + 1_B] = E[1_A] + E[1_B] = Pr[A] + Pr[B].$$

In general, $1_{A\cup B}(\omega)=1_A(\omega)+1_B(\omega)-1_{A\cap B}(\omega)$. Taking expectation, we get $Pr[A\cup B]=Pr[A]+Pr[B]-Pr[A\cap B]$.

Observe that if $Y(\omega) = b$ for all ω , then E[Y] = b. Thus, E[X + b] = E[X] + b.

Empty Bins

Experiment: Throw *m* balls into *n* bins.

Y - number of empty bins.

Distribution is horrible.

Expectation? X_i - indicator for bin i being empty.

$$Y = X_1 + \cdots X_n$$
.

$$Pr[X_1 = 1] = (1 - \frac{1}{n})^m$$
. $\rightarrow E[Y] = n(1 - \frac{1}{n})^m$.

For
$$n = m$$
 and large n , $(1 - 1/n)^n \approx \frac{1}{e}$.

$$\frac{n}{e} \approx 0.368n$$
 empty bins on average.

Coupon Collectors Problem.

Experiment: Get random coupon from n until get all n coupons.

Outcomes: {123145...,56765...}

Random Variable: *X* - length of outcome.

Today: E[X]?

Geometric Distribution: Expectation

$$X =_D G(p)$$
, i.e., $Pr[X = n] = (1 - p)^{n-1}p, n \ge 1$.

One has

$$E[X] = \sum_{n=1}^{\infty} nPr[X = n] = \sum_{n=1}^{\infty} n(1-p)^{n-1}p.$$

Thus,

$$E[X] = p+2(1-p)p+3(1-p)^{2}p+4(1-p)^{3}p+\cdots$$

$$(1-p)E[X] = (1-p)p+2(1-p)^{2}p+3(1-p)^{3}p+\cdots$$

$$pE[X] = p+(1-p)p+(1-p)^{2}p+(1-p)^{3}p+\cdots$$
by subtracting the previous two identities

$$= \sum_{n=1}^{\infty} Pr[X=n] = 1.$$

Hence,

$$E[X] = \frac{1}{p}$$
.

Time to collect coupons

X-time to get *n* coupons.

 X_1 - time to get first coupon. Note: $X_1 = 1$. $E(X_1) = 1$.

 X_2 - time to get second coupon after getting first.

 $Pr["get second coupon"]"got milk first coupon"] = \frac{n-1}{n}$

$$E[X_2]$$
? Geometric!!! $\implies E[X_2] = \frac{1}{p} = \frac{1}{\frac{n-1}{2}} = \frac{n}{n-1}$.

 $Pr["getting ith coupon|"got i - 1 rst coupons"] = \frac{n - (i - 1)}{n} = \frac{n - i + 1}{n}$

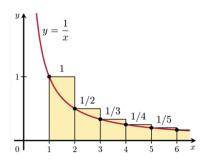
$$E[X_i] = \frac{1}{p} = \frac{n}{n-i+1}, i = 1, 2, ..., n.$$

$$E[X] = E[X_1] + \dots + E[X_n] = \frac{n}{n} + \frac{n}{n-1} + \frac{n}{n-2} + \dots + \frac{n}{1}$$
$$= n(1 + \frac{1}{2} + \dots + \frac{1}{n}) =: nH(n) \approx n(\ln n + \gamma)$$

Review: Harmonic sum

$$H(n) = 1 + \frac{1}{2} + \dots + \frac{1}{n} \approx \int_{1}^{n} \frac{1}{x} dx = \ln(n).$$

.

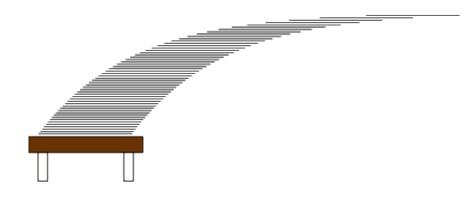


A good approximation is

 $H(n) \approx \ln(n) + \gamma$ where $\gamma \approx 0.58$ (Euler-Mascheroni constant).

Harmonic sum: Paradox

Consider this stack of cards (no glue!):



If each card has length 2, the stack can extend H(n) to the right of the table. As n increases, you can go as far as you want!

Paradox

par·a·dox

/'perə däks/

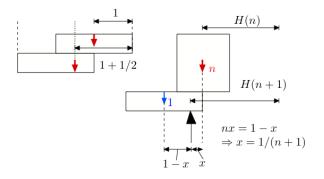
noun

a statement or proposition that, despite sound (or apparently sound) reasoning from acceptable premises, leads to a conclusion that seems senseless, logically unacceptable, or self-contradictory.

"a potentially serious conflict between quantum mechanics and the general theory of relativity known as the information paradox"

- a seemingly absurd or self-contradictory statement or proposition that when investigated or explained may prove to be well founded or true.
 "in a paradox, he has discovered that stepping back from his job has increased the rewards he gleans from it"
 synonyms: contradiction, contradiction in terms, self-contradiction, inconsistency, incongruity; More
- a situation, person, or thing that combines contradictory features or qualities.
 "the mingling of deciduous trees with elements of desert flora forms a fascinating ecological paradox"

Stacking



The cards have width 2. Induction shows that the center of gravity after n cards is H(n) away from the right-most edge. Video.

Calculating E[g(X)]

Let Y = g(X). Assume that we know the distribution of X.

We want to calculate E[Y].

Method 1: We calculate the distribution of *Y*:

$$Pr[Y = y] = Pr[X \in g^{-1}(y)]$$
 where $g^{-1}(x) = \{x \in \Re : g(x) = y\}.$

This is typically rather tedious!

Method 2: We use the following result.

Theorem:

$$E[g(X)] = \sum_{x} g(x) Pr[X = x].$$

Proof:

$$E[g(X)] = \sum_{\omega} g(X(\omega))Pr[\omega] = \sum_{x} \sum_{\omega \in X^{-1}(x)} g(X(\omega))Pr[\omega]$$
$$= \sum_{x} \sum_{\omega \in X^{-1}(x)} g(x)Pr[\omega] = \sum_{x} g(x) \sum_{\omega \in X^{-1}(x)} Pr[\omega]$$
$$= \sum_{x} g(x)Pr[X = x].$$

An Example

Let X be uniform in $\{-2, -1, 0, 1, 2, 3\}$.

Let also $g(X) = X^2$. Then (method 2)

$$E[g(X)] = \sum_{x=-2}^{3} x^{2} \frac{1}{6}$$

$$= \{4+1+0+1+4+9\} \frac{1}{6} = \frac{19}{6}.$$

Method 1 - We find the distribution of $Y = X^2$:

$$Y = \begin{cases} 4, & \text{w.p. } \frac{2}{6} \\ 1, & \text{w.p. } \frac{2}{6} \\ 0, & \text{w.p. } \frac{1}{6} \\ 9, & \text{w.p. } \frac{1}{6} \end{cases}$$

Thus,

$$E[Y] = 4\frac{2}{6} + 1\frac{2}{6} + 0\frac{1}{6} + 9\frac{1}{6} = \frac{19}{6}.$$

Summary

Probability Space: Ω , $Pr[\omega] \ge 0$, $\sum_{\omega} Pr[\omega] = 1$.

Random Variable: Function on Sample Space.

Distribution: Function $Pr[X = a] \ge 0$. $\sum_a Pr[X = a] = 1$.

Expectation: $E[X] = \sum_{\omega} Pr[\omega] = \sum_{a} Pr[X = a]$.

Many Random Variables: each one function on a sample space.

Joint Distributions: Function $Pr[X = a, Y = b] \ge 0$.

$$\sum_{a,b} Pr[X=a,Y=b]=1.$$

Linearity of Expectation: E[X + Y] = E[X] + E[Y].

Applications: compute expectations by decomposing.

Indicators: Empty bins, Fixed points.

Time to Coupon: Sum times to "next" coupon.

Y = f(X) is Random Variable.

Distribution of *Y* from distribution of *X*.