CS70

Coupon Collecting: Fun with harmonic numbers! Memoryless Property.

Law of the unconscious statistician. (Hmmm.)

Variance/ Covariance.

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.

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

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

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

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

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

Coupons: Poll

Collect *n* coupons!

What's True?

(A)
$$X_1 = \frac{n}{n} = 1$$
.

(B)
$$X_2 = \frac{n}{n-1}$$
.

(C)
$$Pr[\text{getting second}|\text{got first}] = \frac{n-1}{n}$$
.

(D)
$$E[X_2] = \frac{n}{n-1}$$
.

(E)
$$E[X_n] = n$$
.

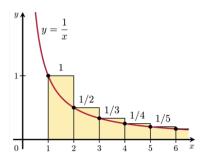
(F)
$$\sum_{i} E[X_{i}] = \sum_{i=0}^{n-1} \frac{n}{n-i}$$

(G)
$$\sum_{i} E[X_{i}] = \sum_{i=1}^{n} \frac{1}{n}$$

Review: Harmonic sum

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

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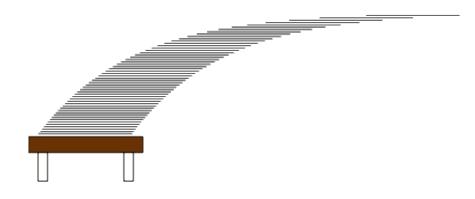


A good approximation is

 $H(n) \approx \ln(n) + \gamma$ 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/

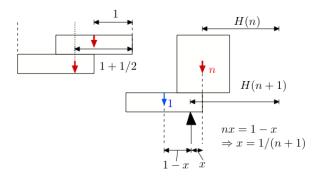
noun

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)]: LOTUS

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.

Called "Law of the unconscious statistician."

Theorem:

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

Proof:

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

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

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

Poll.

Which is LOTUS?

- (A) $E[X] = \sum_{x \in \mathsf{Range}(X)} g(x) Pr[g(X) = g(x)]$
- (B) $E[X] = \sum_{x \in \mathsf{Range}(X)} g(x) Pr[X = x]$
- (C) $E[X] = \sum_{x \in \mathsf{Range}(g)} x Pr[g(X) = x]$

Geometric Distribution.

Experiment: flip a coin with heads prob. *p.* until Heads. Random Variable *X*: number of flips.

And distribution is:

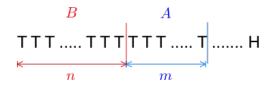
(A)
$$X \sim G(p) : Pr[X = i] = (1 - p)^{i-1}p$$
.

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

(A) Distribution of
$$X \sim G(p)$$
: $Pr[X = i] = (1 - p)^{i-1}p$.

Geometric Distribution: Memoryless - Interpretation

$$Pr[X > n + m | X > n] = Pr[X > m], m, n \ge 0.$$



$$Pr[X > n + m | X > n] = Pr[A|B] = Pr[A'] = Pr[X > m].$$

A': is m coin tosses before heads.

A|B: m'more' coin tosses before heads.

The coin is memoryless, therefore, so is X. Independent coin: Pr[H|'any previous set of coint to sees'] = p

Geometric Distribution: Memoryless by derivation.

Let *X* be G(p). Then, for $n \ge 0$,

$$Pr[X > n] = Pr[$$
 first n flips are $T] = (1 - p)^n$.

Theorem

$$Pr[X > n + m | X > n] = Pr[X > m], m, n \ge 0.$$

Proof:

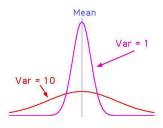
$$Pr[X > n + m | X > n] = \frac{Pr[X > n + m \text{ and } X > n]}{Pr[X > n]}$$

$$= \frac{Pr[X > n + m]}{Pr[X > n]}$$

$$= \frac{(1 - p)^{n + m}}{(1 - p)^n} = (1 - p)^m$$

$$= Pr[X > m].$$

Variance



The variance measures the deviation from the mean value.

Definition: The variance of *X* is

$$\sigma^2(X) := var[X] = E[(X - E[X])^2].$$

 $\sigma(X)$ is called the standard deviation of X.

Variance and Standard Deviation

Fact:

$$var[X] = E[X^2] - E[X]^2$$
.

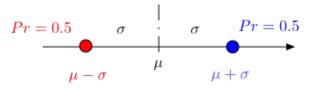
Indeed:

$$var(X) = E[(X - E[X])^2]$$

= $E[X^2 - 2XE[X] + E[X]^2)$
= $E[X^2] - 2E[X]E[X] + E[X]^2$, by linearity
= $E[X^2] - E[X]^2$.

A simple example

This example illustrates the term 'standard deviation.'



Consider the random variable X such that

$$X = \left\{ \begin{array}{ll} \mu - \sigma, & \text{ w.p. } 1/2 \\ \mu + \sigma, & \text{ w.p. } 1/2. \end{array} \right.$$

Then,
$$E[X] = \mu$$
 and $(X - E[X])^2 = \sigma^2$. Hence, $var(X) = \sigma^2$ and $\sigma(X) = \sigma$.

Example

Consider X with

$$X = \begin{cases} -1, & \text{w. p. } 0.99 \\ 99, & \text{w. p. } 0.01. \end{cases}$$

Then

$$E[X] = -1 \times 0.99 + 99 \times 0.01 = 0.$$

 $E[X^2] = 1 \times 0.99 + (99)^2 \times 0.01 \approx 100.$
 $Var(X) \approx 100 \Longrightarrow \sigma(X) \approx 10.$

Also,

$$E(|X|) = 1 \times 0.99 + 99 \times 0.01 = 1.98.$$

Thus,
$$\sigma(X) = \sqrt{E[(X - E(X))^2]} \neq E[|X - E[X]|]!$$

Exercise: How big can you make $\frac{\sigma(X)}{E[|X-E[X]|]}$?

Uniform

Assume that $Pr[X = i] = \frac{1}{n}$ for $i \in \{1, ..., n\}$. Then

$$E[X] = \sum_{i=1}^{n} i \times Pr[X = i] = \frac{1}{n} \sum_{i=1}^{n} i$$
$$= \frac{1}{n} \frac{n(n+1)}{2} = \frac{n+1}{2}.$$

Also,

$$E[X^{2}] = \sum_{i=1}^{n} i^{2} Pr[X = i] = \frac{1}{n} \sum_{i=1}^{n} i^{2}$$

$$= \frac{1}{n} \frac{(n)(n+1)(n+2)}{6} = \frac{1+3n+2n^{2}}{6}, \text{ as you can verify.}$$

This gives

$$var(X) = \frac{1+3n+2n^2}{6} - \frac{(n+1)^2}{4} = \frac{n^2-1}{12}.$$

(Sort of
$$\int_0^{1/2} x^2 dx = \frac{x^3}{3}$$
.)

Variance of geometric distribution.

X is a geometrically distributed RV with parameter *p*. Thus, $Pr[X = n] = (1 - p)^{n-1}p$ for $n \ge 1$. Recall E[X] = 1/p.

$$E[X^{2}] = p+4p(1-p)+9p(1-p)^{2}+...$$

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

$$pE[X^{2}] = p+3p(1-p)+5p(1-p)^{2}+...$$

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

$$-(p+p(1-p)+p(1-p)^{2}+...) \quad Distribution.$$

$$pE[X^{2}] = 2E[X]-1$$

$$= 2(\frac{1}{p})-1 = \frac{2-p}{p}$$

$$\implies E[X^2] = (2 - p)/p^2 \text{ and } \\ var[X] = E[X^2] - E[X]^2 = \frac{2 - p}{p^2} - \frac{1}{p^2} = \frac{1 - p}{p^2}. \\ \sigma(X) = \frac{\sqrt{1 - p}}{p} \approx E[X] \text{ when } p \text{ is small(ish)}.$$

Fixed points.

Number of fixed points in a random permutation of *n* items. "Number of student that get homework back."

$$X = X_1 + X_2 \cdots + X_n$$

where X_i is indicator variable for *i*th student getting hw back.

$$E(X^{2}) = \sum_{i} E(X_{i}^{2}) + \sum_{i \neq j} E(X_{i}X_{j}).$$

$$= n \times \frac{1}{n} + (n)(n-1) \times \frac{1}{n(n-1)}$$

$$= 1 + 1 = 2.$$

$$E(X_i^2) = 1 \times Pr[X_i = 1] + 0 \times Pr[X_i = 0]$$

$$= \frac{1}{n}$$

$$E(X_i X_j) = 1 \times Pr[X_i = 1 \cap X_j = 1] + 0 \times Pr[\text{"anything else"}]$$

$$= 1 \times \frac{(n-2)!}{n!} = \frac{1}{n(n-1)}$$

$$Var(X) = E(X^2) - (E(X))^2 = 2 - 1 = 1.$$

Poll: fixed points.

What's true?

- (A) X_i and X_j are independent.
- (B) $E[X_iX_j] = Pr[X_iX_j = 1]$
- (C) $Pr[X_i X_j] = \frac{(n-2)!}{n!}$
- (D) $X_i^2 = X_i$.

Variance: binomial.

$$E[X^2] = \sum_{i=0}^{n} i^2 \binom{n}{i} p^i (1-p)^{n-i}.$$

= Really???!!##...

Too hard!

Ok.. fine.

Let's do something else.

Maybe not much easier...but there is a payoff.

Properties of variance.

- 1. $Var(cX) = c^2 Var(X)$, where c is a constant. Scales by c^2 .
- 2. Var(X+c) = Var(X), where c is a constant. Shifts center.

Proof:

$$Var(cX) = E((cX)^{2}) - (E(cX))^{2}$$

$$= c^{2}E(X^{2}) - c^{2}(E(X))^{2} = c^{2}(E(X^{2}) - E(X)^{2})$$

$$= c^{2}Var(X)$$

$$Var(X+c) = E((X+c-E(X+c))^{2})$$

$$= E((X+c-E(X)-c)^{2})$$

$$= E((X-E(X))^{2}) = Var(X)$$

Independent random variables.

Independent: P[X = a, Y = b] = Pr[X = a]Pr[Y = b]

Fact: E[XY] = E[X]E[Y] for independent random variables.

$$E[XY] = \sum_{a} \sum_{b} a \times b \times Pr[X = a, Y = b]$$

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

$$= (\sum_{a} aPr[X = a])(\sum_{b} bPr[Y = b])$$

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

Variance of sum of two independent random variables

Theorem:

If X and Y are independent, then

$$Var(X + Y) = Var(X) + Var(Y)$$
.

Proof:

Since shifting the random variables does not change their variance, let us subtract their means.

That is, we assume that E(X) = 0 and E(Y) = 0.

Then, by independence,

$$E(XY) = E(X)E(Y) = 0.$$

Hence,

$$var(X + Y) = E((X + Y)^2) = E(X^2 + 2XY + Y^2)$$

= $E(X^2) + 2E(XY) + E(Y^2) = E(X^2) + E(Y^2)$
= $var(X) + var(Y)$.

Variance of sum of independent random variables

Theorem:

If X, Y, Z, ... are pairwise independent, then

$$var(X + Y + Z + \cdots) = var(X) + var(Y) + var(Z) + \cdots$$

Proof:

Since shifting the random variables does not change their variance, let us subtract their means.

That is, we assume that $E[X] = E[Y] = \cdots = 0$.

Then, by independence,

$$E[XY] = E[X]E[Y] = 0$$
. Also, $E[XZ] = E[YZ] = \cdots = 0$.

Hence,

$$var(X + Y + Z + \cdots) = E((X + Y + Z + \cdots)^{2})$$

$$= E(X^{2} + Y^{2} + Z^{2} + \cdots + 2XY + 2XZ + 2YZ + \cdots)$$

$$= E(X^{2}) + E(Y^{2}) + E(Z^{2}) + \cdots + 0 + \cdots + 0$$

$$= var(X) + var(Y) + var(Z) + \cdots$$

Variance of Binomial Distribution.

Flip coin with heads probability *p*. *X*- how many heads?

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

$$E(X_i^2) = 1^2 \times p + 0^2 \times (1 - p) = p.$$

$$Var(X_i) = p - (E(X))^2 = p - p^2 = p(1 - p).$$

$$p = 0 \implies Var(X_i) = 0$$

$$p = 1 \implies Var(X_i) = 0$$

$$p=1 \implies Var(X_i)=0$$

$$X = X_1 + X_2 + \dots X_n.$$

$$X_i$$
 and X_j are independent: $Pr[X_i = 1 | X_j = 1] = Pr[X_i = 1]$.

$$Var(X) = Var(X_1 + \cdots X_n) = np(1-p).$$

Poisson Distribution: Variance.

Definition Poisson Distribution with parameter $\lambda > 0$

$$X = P(\lambda) \Leftrightarrow Pr[X = m] = \frac{\lambda^m}{m!} e^{-\lambda}, m \ge 0.$$

Mean, Variance?

Ugh.

Recall that Poission is the limit of the Binomial with $p = \lambda/n$ as $n \to \infty$.

Mean: $pn = \lambda$

Variance: $p(1-p)n = \lambda - \lambda^2/n \rightarrow \lambda$.

$$E(X^2)$$
? $Var(X) = E(X^2) - (E(X))^2$ or $E(X^2) = Var(X) + E(X)^2$.

$$E(X^2) = \lambda + \lambda^2.$$

Covariance

Definition The covariance of *X* and *Y* is

$$cov(X, Y) := E[(X - E[X])(Y - E[Y])].$$

Fact

$$cov(X,Y) = E[XY] - E[X]E[Y].$$

Proof:

Think about E[X] = E[Y] = 0. Just E[XY].

□ish.

For the sake of completeness.

$$E[(X - E[X])(Y - E[Y])] = E[XY - E[X]Y - XE[Y] + E[X]E[Y]]$$

= $E[XY] - E[X]E[Y] - E[X]E[Y] + E[X]E[Y]$
= $E[XY] - E[X]E[Y]$.

Correlation

Definition The correlation of X, Y, Cor(X, Y) is

$$corr(X, Y) : \frac{cov(X, Y)}{\sigma(X)\sigma(Y)}.$$

Theorem: $-1 \le corr(X, Y) \le 1$.

Proof: Idea: $(a-b)^2 > 0 \rightarrow a^2 + b^2 \ge 2ab$.

Simple case: E[X] = E[Y] = 0 and $E[X^2] = E[Y^2] = 1$.

$$Cor(X, Y) = E[XY].$$

$$E[(X - Y)^2] = E[X^2] + E[Y^2] - 2E[XY] = 2(1 - E[XY]) \ge 0$$

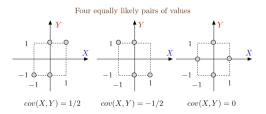
 $\to E[XY] \le 1$.

$$E[(X+Y)^2] = E[X^2] + E[Y^2] + 2E[XY] = 2(1+E[XY]) \ge 0$$

 $\to E[XY] \ge -1$.

Shifting and scaling doesn't change correlation.

Examples of Covariance



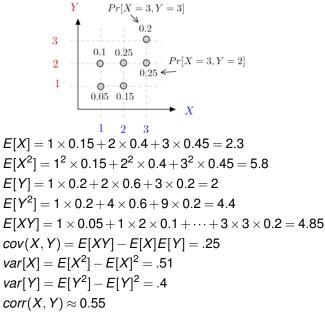
Note that E[X] = 0 and E[Y] = 0 in these examples. Then cov(X, Y) = E[XY].

When cov(X, Y) > 0, the RVs X and Y tend to be large or small together. X and Y are said to be positively correlated.

When cov(X, Y) < 0, when X is larger, Y tends to be smaller. X and Y are said to be negatively correlated.

When cov(X, Y) = 0, we say that X and Y are uncorrelated.

Examples of Covariance



Properties of Covariance

$$cov(X, Y) = E[(X - E[X])(Y - E[Y])] = E[XY] - E[X]E[Y].$$

Fact

- (a) var[X] = cov(X, X)
- (b) X, Y independent $\Rightarrow cov(X, Y) = 0$
- (c) cov(a+X,b+Y) = cov(X,Y)
- (d) $cov(aX + bY, cU + dV) = ac \cdot cov(X, U) + ad \cdot cov(X, V) + bc \cdot cov(Y, U) + bd \cdot cov(Y, V).$

Proof:

- (a)-(b)-(c) are obvious.
- (d) In view of (c), one can subtract the means and assume that the RVs are zero-mean. Then,

$$cov(aX + bY, cU + dV) = E[(aX + bY)(cU + dV)]$$

$$= ac \cdot E[XU] + ad \cdot E[XV] + bc \cdot E[YU] + bd \cdot E[YV]$$

$$= ac \cdot cov(X, U) + ad \cdot cov(X, V) + bc \cdot cov(Y, U) + bd \cdot cov(Y, V).$$

Summary

Variance

- ► Variance: $var[X] := E[(X E[X])^2] = E[X^2] E[X]^2$
- Fact: $var[aX + b]a^2var[X]$
- ▶ Sum: X, Y, Z pairwise ind. $\Rightarrow var[X + Y + Z] = \cdots$

Random Variables so far.

Probability Space: Ω , $Pr : \Omega \to [0,1]$, $\sum_{\omega \in \Omega} Pr(w) = 1$.

Random Variables: $X : \Omega \rightarrow R$.

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

X and Y independent \iff all associated events are independent.

Expectation: $E[X] = \sum_{a} aPr[X = a] = \sum_{\omega \in \Omega} X(\omega)Pr(\omega)$.

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

Variance: $Var(X) = E[(X - E[X])^2] = E[X^2] - (E(X))^2$ For independent X, Y, Var(X + Y) = Var(X) + Var(Y).

Also: $Var(cX) = c^2 Var(X)$ and Var(X + b) = Var(X).

Poisson: $X \sim P(\lambda) \ E(X) = \lambda$, $Var(X) = \lambda$.

Binomial: $X \sim B(n,p) E(X) = np$, Var(X) = np(1-p)

Uniform: $X \sim U\{1,...,n\}$ $E[X] = \frac{n+1}{2}$, $Var(X) = \frac{n^2-1}{12}$.

Geometric: $X \sim G(p) \ E(X) = \frac{1}{p}, \ Var(X) = \frac{1-p}{p^2}$