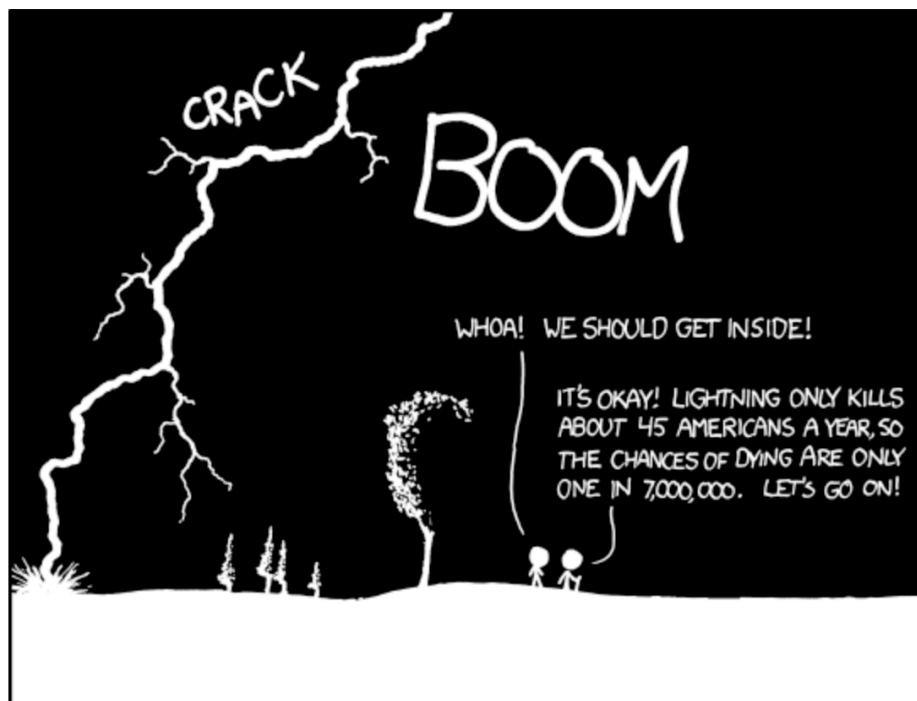


# Stat 88: Probability & Math. Statistics in Data Science



THE ANNUAL DEATH RATE AMONG PEOPLE  
WHO KNOW THAT STATISTIC IS ONE IN SIX.

<https://xkcd.com/795/>

Lecture 16: 2/26/2021

Conditional expectation and expectation by conditioning

# Agenda

- Example 5.7.11
- Example from 5.5
- 5.6: Expectation by conditioning

## Example: (5.7.11)

A data scientist believes that a randomly picked student at his school is twice as likely not to own a car as to own one car. He knows that no student has three cars, though some students do have two cars. He therefore models the probability distribution for the number of cars owned by a random student as follows. The model involves an unknown positive parameter  $\theta$ .

Each  $X_k$  has the den:

# of cars	0	1	2
Probability	$2\theta$	$\theta$	$1 - 3\theta$

(a) Find  $E(X_k) = E(X_k) = \sum_x x P(X_k=x) = 0 \cdot 2\theta + 1 \cdot \theta + 2(1-3\theta) = 2-5\theta$

(b) Let  $X_1, X_2, \dots, X_n$  be the numbers of cars owned by  $n$  random students picked independently of each other. Assuming that the data scientist's model is good, use the entire sample to construct an unbiased estimator of  $\theta$ .

$$E(\bar{X}) = 2 - 5\theta \quad \star = ? \quad 5\theta = 2 - E(\bar{X})$$

$$\theta = \frac{2 - E(\bar{X})}{5}$$

$$E(\star) = \theta, \quad E\left(\frac{2 - \bar{X}}{5}\right) = \frac{2 - E(\bar{X})}{5} = \theta \quad \star = \frac{2 - \bar{X}}{5}$$

Example: (5.7.11)

We know that

$$\theta = \frac{2 - E(\bar{X})}{5} = E\left(\frac{2 - \bar{X}}{5}\right)$$

$$E\left(\frac{2 - \bar{X}}{5}\right) = \theta$$

$\frac{2 - \bar{X}}{5}$  is an unbiased

estimator of  $\theta$ .

UNBIASED

"On average, the estimator hits its target"

means  $E(S) = \theta$

i.i.d = "independent & identically distributed"

## Conditional Expectation: An example

- Let  $X$  and  $Y$  be iid rvs with the distribution described below, and let  $S = X + Y$ :

x	1	2	3
$P(X=x)$	$1/4$	$1/2$	$1/4$

$$S = X + Y$$

- Let's write down the joint distribution of  $X$  and  $S$ :

$$S = X + Y, X = 2 \\ 2 = 2 + Y$$

$S \backslash X$	1	2	3	marg. dsn of $S$ $f_S(z)$
2	$\frac{1}{4} \cdot \frac{1}{4} = \frac{1}{16}$	0	0	$\frac{1}{16} = P(S=2)$
3	$\frac{1}{4} \cdot \frac{1}{2} = \frac{1}{8}$	$\frac{1}{8}$	0	$\frac{1}{4} = \frac{2}{16} = P(S=3)$
4	$\frac{1}{4} \cdot \frac{1}{4} = \frac{1}{16}$	$\frac{1}{4} (= \frac{1}{2} \cdot \frac{1}{2})$	$\frac{1}{16} P(X=3, Y=1)$	$\frac{6}{16} = P(S=4)$
5	0	$X=2, Y=3$ $\frac{1}{2} \cdot \frac{1}{4} = \frac{1}{8}$	$\frac{1}{8}$	$\frac{4}{16}$
6	0	0	$\frac{1}{16} X=Y=3$	$\frac{1}{16}$
marginal dsn of $X$ $f_X(x) \rightarrow$	$\frac{4}{16}$	$\frac{8}{16}$	$\frac{4}{16}$	

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Note that  $S, X$

are NOT indep.

## Conditional Expectation: An example

Given  $S=3$ , what is  $P(X=1)$

	$P(X=1)$	$P(X=2)$	$P(X=3)$	$f_S(3)$
$S=3$	$\frac{1}{8}$ $P(X=1, S=3)$	$\frac{1}{8}$	0	$\frac{4}{16}$

$$\text{Need } P(X=1 | S=3) = \frac{P(X=1, S=3)}{P(S=3)} = \frac{\frac{1}{8}}{\frac{4}{16}} = \frac{\frac{1}{8}}{\frac{1}{2}} = \frac{1}{4} \cdot 2 = \frac{1}{2}$$

Conditional distribution of  $X$  given  $S=3$

$X:$	1	2	3
	$\frac{1}{2}$	$\frac{1}{2}$	0

} conditioned on  $S=3$

Do this for each value of  $S$ . (get the conditional distn of  $X$ )

Given	$P(X=1)$	$P(X=2)$	$P(X=3)$	Conditional Expectation $E(X S=s)$
$S=2$	1	0	0	1
$S=3$	$\frac{1}{2}$	$\frac{1}{2}$	0	$\frac{3}{2} = 1.5$
$S=4$	$\frac{1}{6}$ <small><math>= P(X=1, S=4) / P(S=4)</math></small>	$\frac{4}{6}$	$\frac{1}{6}$	$1 \cdot \frac{1}{6} + 2 \cdot \frac{4}{6} + 3 \cdot \frac{1}{6} = \frac{12}{6} = 2$
$S=5$	0	$\frac{1}{2}$ <small><math>\frac{P(X=2, S=5)}{P(S=5)}</math></small>	$\frac{1}{2}$	$\frac{5}{2} = 2 \cdot \frac{1}{2} + \frac{3}{2}$
$S=6$	0	0	1	$3 - 1 = 3$

function of  $S \rightarrow E(X|S=1) = 1 \quad E(X|S=3) = 3 \quad \dots$

$$P(X=1|S=4) = \frac{P(X=1, S=4)}{P(S=4)} = \frac{\frac{1}{6}}{\frac{6}{6}} = \frac{1}{6}$$

In general,  $V, W$  are 2 random variables on the same outcome space.

If we fix the value of  $W$  to be  $W=w$

conditional distribution of  $V|W=w$

is the probabilities  $P(V=v|W=w)$  over all the possible values of  $V$ .

Given  $V, W$ . Construct a joint distribution

$V \backslash W$	$w_1$	$w_2$	...	$w_m$	$f_V(v)$
$v_1$					$f_V(v_1)$
$\vdots$					
$v_n$					
	$f_W(w)$				$f(w, v)$

From the joint distribution we can get the marginal dsns and the conditional dsns.

$$f(v, w) = P(V = v, W = w)$$

$$f_V(v) = \sum_w f(v, w)$$

$$f_W(w) = \sum_v f(v, w)$$

$A, B$ $P(A \cap B) = P(A)P(B)$ $f(x, y) = P(X=x, Y=y)$ $P(X=x, Y=y) = \underbrace{P(X=x)}_{f_X(x)} P(Y=y)$ $f(x, y) = f_X(x) \cdot f_Y(y)$
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$$f(v, w) = f_V(v) \cdot f_W(w) \text{ for every}$$

choice of  $v, w$  then  $V, W$  are independent.

Further, can compute the conditional distribution



## Expectation by Conditioning

- In the example we just worked out, once we fix a value  $s$  for  $S$ , then we have a distribution for  $X$ , and can compute its expectation using that distribution that depends on  $s$ :  $E(X | S = s) = \sum_x x P(X = x | S = s)$ , with the sum over all values of  $X$ .
- Note that  $E(X | S = s)$  is a *function of  $s$* . We can think of  $E(X | S)$  as a rv.  
*changes with diff values of  $s$ .*  $E(X | S)$
- This means that if we want to compute  $E(X)$ , we can just take a weighted average of these conditional expectations  $E(X | S = s)$ :

$$E(X) = \sum_s E(X | S = s) P(S = s)$$

- This is the *law of iterated expectation*

$$E(E(X | S)) = E(X)$$

## Law of iterated expectation

- Note that  $E(X | S = s)$  is a function of  $s$ . That is, if we change the value of  $s$  we get a different value. (It is not a function of  $x$ , though.)
- Therefore we can define the function  $g(s) = E(X | S = s)$ , and the random variable  $g(S) = E(X | S)$ .
- In general, recall that  $E(g(S)) = \sum_s g(s)f(s) = \sum_s g(s)P(S = s)$ .
- How can we use this to find the expected value of the rv  $g(S)$ ?