

Probability and Expectation

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Outline

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- 2 Preliminaries
 - Sample Space and Events
 - Defining Probabilities on Events

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Note

Discrete Probability combines aspects of logic, set theory, combinatorics and inference.

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- (i) Suppose that the experiment consists of tossing a coin. Then, $S = \{H, T\}$.
- (ii) Suppose that the experiment consists of tossing a die.

Then, $S = \{1, 2, 3, 4, 5, 6\}$.

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Then, $S = [0, \infty)$.

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Then, $S = \{1, 2, 3, 4, 5, 6\}$.
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Then, $S = \{HH, HT, TH, TT\}$.
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Then, $S = [0, \infty)$.

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Any subset of the sample space S is called an event.

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Remember that events are sets when reasoning about them.

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The above three conditions are called the axioms of probability theory.

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In this case,

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Let E denote the event that the first coin turns up heads and F denote the event that the second coin turns up heads.

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What is the probability that either the first or the second coin turns up heads?

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$P(E | F)$ is equal to $\frac{P(EF)}{P(F)}$, assuming $P(F) > 0$.

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Observe that $P(F) = \frac{1}{2}$ and $P(EF) = \frac{1}{4}$.

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Observe that $P(F) = \frac{1}{2}$ and $P(EF) = \frac{1}{4}$.

Hence, $P(E \mid F) =$

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In the previously discussed coin tossing example, let E denote the event that both coins turn up heads and F denote the event that the first coin turns up heads.

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Notice that $P(E) = \frac{1}{4} \neq P(E | F)$.

Some more examples

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Assume that the sample space is $S = \{(b, g), (b, b), (g, b), (g, g)\}$

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Assume that the sample space is $S = \{(b, g), (b, b), (g, b), (g, g)\}$ and that all outcomes are equally likely.

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Two balls are chosen from this urn, one after the other, without replacement and at random.

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One more example

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Assume that a patient has responded positively to compound A.

What is the probability that the patient also responded positively to compound B?

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Let X denote the event that the patient responded positively to compound A.

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Consider the experiment of tossing two fair dice.

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Are E_1 and F independent?

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How about E_2 and F ?

Bayes' Formula

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Thus, the probability of an event E occurring can be computed as the weighted average of its conditional probability on an arbitrary event F .

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Consider two urns.

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Urn 1 has 2 white balls and 7 black balls.

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A fair coin is tossed.

If the coin turns up heads, a ball is drawn from Urn 1, otherwise, a ball is drawn from Urn 2.

Given that the ball drawn was white, what is the conditional probability that it was drawn from Urn 1?

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Let W denote the event that a white ball was drawn and let H denote the event that the coin turned up heads.

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Accordingly, we have, $P(H) = \frac{1}{2}$ and $P(W | H) = \frac{2}{9}$.

We are interested in the quantity $P(H | W)$.

Example (contd.)

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Solution

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From conditional probability, we know that, $P(H | W) = \frac{P(HW)}{P(W)}$.

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From conditional probability, we know that, $P(H | W) = \frac{P(HW)}{P(W)}$.

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From conditional probability, we know that, $P(H | W) = \frac{P(HW)}{P(W)}$.

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As per Bayes' formula,

$$P(W) = P(W | H) \cdot P(H) + P(W | H^c)(1 - P(H))$$

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From conditional probability, we know that, $P(H | W) = \frac{P(HW)}{P(W)}$.

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As per Bayes' formula,

$$\begin{aligned} P(W) &= P(W | H) \cdot P(H) + P(W | H^c)(1 - P(H)) \\ &= \frac{2}{9} \cdot \frac{1}{2} + \frac{5}{11} \cdot \frac{1}{2} \end{aligned}$$

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From conditional probability, we know that, $P(H | W) = \frac{P(HW)}{P(W)}$.

Now, $P(HW) = P(W | H) \cdot P(H) = \frac{2}{9} \cdot \frac{1}{2} = \frac{1}{9}$.

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$$\begin{aligned} P(W) &= P(W | H) \cdot P(H) + P(W | H^c)(1 - P(H)) \\ &= \frac{2}{9} \cdot \frac{1}{2} + \frac{5}{11} \cdot \frac{1}{2} \\ &= \frac{67}{198}. \end{aligned}$$

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Therefore, $P(H | W) = \frac{\frac{1}{9}}{\frac{67}{198}}$

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Therefore, $P(H | W) = \frac{\frac{1}{9}}{\frac{67}{198}} = \frac{22}{67}$,

Example (contd.)

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From conditional probability, we know that, $P(H | W) = \frac{P(HW)}{P(W)}$.

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As per Bayes' formula,

$$\begin{aligned}P(W) &= P(W | H) \cdot P(H) + P(W | H^c)(1 - P(H)) \\&= \frac{2}{9} \cdot \frac{1}{2} + \frac{5}{11} \cdot \frac{1}{2} \\&= \frac{67}{198}.\end{aligned}$$

Therefore, $P(H | W) = \frac{\frac{1}{9}}{\frac{67}{198}} = \frac{22}{67}$, i.e., the conditional probability that the ball was drawn from Urn 1, given that it is white, is $\frac{22}{67}$.

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For instance, in the experiment of tossing two dice, we could be interested in knowing whether or not the the sum of the upturned faces is 7.

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We may not care whether the actual outcome is $(1, 6)$, $(6, 1)$, or

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We may not care whether the actual outcome is $(1, 6)$, $(6, 1)$, or \dots

A variable which records the values of the function of interest is called a random variable.

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For instance, in the experiment of tossing two dice, we could be interested in knowing whether or not the the sum of the upturned faces is 7.

We may not care whether the actual outcome is $(1, 6)$, $(6, 1)$, or

A variable which records the values of the function of interest is called a random variable.

In other words, a random variable is a function $X : S \rightarrow E$, where S is the sample space and E is a measurable space.

Random Variables

Motivation

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An example

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Let X denote the random variable that is defined as the sum of two fair dice.

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What are the values that X can take?

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Discrete Random Variable

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A random variable that can take on only a countable number of possible values is said to be *discrete*.

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For a discrete random variable X , the probability mass function (pmf) $p(a)$ is defined as:

$$p(a) = P\{X = a\}.$$

The Bernoulli Random Variable

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Main idea

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Consider an experiment which has exactly two outcomes; one is labeled a “success” and the other a “failure”.

If we let the random variable X assume the value 1, if the experiment was a success and 0, if the experiment was a failure, then X is said to be a Bernoulli random variable.

The Bernoulli Random Variable

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Assume that the probability that the experiment results in a success is p .

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The probability mass function of X is given by:

$$p(i) = P\{X = i\} = C(n, i) \cdot p^i \cdot (1 - p)^{n-i}, \quad i = 0, 1, 2, \dots, n.$$

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What is the probability that you will get two heads and two tails?

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Accordingly, we are interested in the probability of getting exactly two successes in four Bernoulli trials.

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As discussed previously,

$$\begin{aligned} p(2) &= C(4, 2) \cdot \left(\frac{1}{2}\right)^2 \cdot \left(1 - \frac{1}{2}\right)^2 \\ &= \frac{3}{8}. \end{aligned}$$

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The probability mass function of X is given by:

$$p(i) = P\{X = i\} = (1 - p)^{i-1} \cdot p, \quad i = 1, 2, \dots$$

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Let X denote a discrete random variable with probability mass function $p(x)$.

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Example

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What is $E[X]$?

Expectation of a Bernoulli Random Variable

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Let X denote a Bernoulli Random Variable with p denoting the probability of success.

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Solution

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Solution

$$E[X] = 1 \cdot p$$

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Let X denote a Bernoulli Random Variable with p denoting the probability of success. Compute $E[X]$.

Solution

$$E[X] = 1 \cdot p + 0 \cdot (1 - p)$$

Expectation of a Bernoulli Random Variable

Bernoulli Random Variable

Let X denote a Bernoulli Random Variable with p denoting the probability of success. Compute $E[X]$.

Solution

$$\begin{aligned} E[X] &= 1 \cdot p + 0 \cdot (1 - p) \\ &= p. \end{aligned}$$

Expectation of a Binomial Random Variable

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Let X denote a Binomial Random Variable with parameters n and p .

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Solution

$$E[X] = \sum_{i=0}^n i \cdot p(i), \text{ by definition}$$

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Let X denote a Binomial Random Variable with parameters n and p .

Compute $E[X]$.

Solution

$$\begin{aligned} E[X] &= \sum_{i=0}^n i \cdot p(i), \text{ by definition} \\ &= \sum_{i=0}^n i \cdot C(n, i) \cdot p^i \cdot (1-p)^{n-i} \end{aligned}$$

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Expectation of a Binomial Random Variable (contd.)

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Solution

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Expectation of a Binomial Random Variable (contd.)

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$$\begin{aligned} E[X] &= \sum_{i=1}^n i \cdot \frac{n!}{i! \cdot (n-i)!} \cdot p^i \cdot (1-p)^{n-i} \\ &= \sum_{i=1}^n \frac{n!}{(i-1)! \cdot (n-i)!} \cdot p^i \cdot (1-p)^{n-i} \\ &= n \cdot p \cdot \sum_{i=1}^n \frac{(n-1)!}{(i-1)! \cdot (n-i)!} \cdot p^{i-1} \cdot (1-p)^{n-i} \end{aligned}$$

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Solution

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Solution

Substituting $k = (i - 1)$, we get,

$$E[X] =$$

Expectation of a Binomial Random Variable (contd.)

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Substituting $k = (i - 1)$, we get,

$$E[X] = n \cdot p \cdot \sum_{k=0}^{n-1} \frac{(n-1)!}{k! \cdot (n-k-1)!} \cdot p^k \cdot (1-p)^{n-k-1}$$

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Expectation of a Binomial Random Variable (contd.)

Solution

Substituting $k = (i - 1)$, we get,

$$\begin{aligned} E[X] &= n \cdot p \cdot \sum_{k=0}^{n-1} \frac{(n-1)!}{k! \cdot (n-k-1)!} \cdot p^k \cdot (1-p)^{n-k-1} \\ &= n \cdot p \cdot \sum_{k=0}^{n-1} \frac{(n-1)!}{k! \cdot ((n-1)-k)!} \cdot p^k \cdot (1-p)^{(n-1)-k} \\ &= n \cdot p \cdot \sum_{k=0}^{n-1} C(n-1, k) \cdot p^k \cdot (1-p)^{(n-1)-k} \\ &= n \cdot p \cdot [p + (1-p)]^{n-1}, \text{ recall the Binomial theorem} \\ &= n \cdot p \cdot 1 \end{aligned}$$

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Substituting $k = (i - 1)$, we get,

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$$E[X] = \sum_{i=1}^{\infty} i \cdot p(i), \text{ by definition}$$

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Expectation of a Geometric Random Variable (contd.)

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Solution

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Note that linearity of expectation holds even when the random variables are **not** independent.

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Note that $E[X | Y]$ is itself a random variable.

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