

## Probability

Before, we defined probability as the number of 'good' outcomes (size of an event) divided by the total number of outcomes. We do this more formally as: let  $S$  be a (countable) sample space. A *probability distribution* is a function  $p : S \rightarrow \mathbb{R}$  such that:

1.  $0 \leq p(s) \leq 1$  for all  $s \in S$  (all probabilities should be nonnegative and less than 1)
2.  $\sum_{s \in S} p(s) = 1$  (the sum of all probabilities should be 1)

We call  $p(s)$  the probability of an outcome  $s \in S$ . For an event  $E \subset S$ , we define the probability as  $p(E) = \sum_{s \in E} p(s)$ .

### Exercises

For the following, let  $S$  be a sample space, and  $p$  a probability distribution on  $S$ .

1. For any event  $E \subset S$ , show that  $p(\overline{E}) = 1 - p(E)$ .

$$p(\overline{E}) + p(E) = \sum_{s \in \overline{E}} p(s) + \sum_{s \in E} p(s) = \sum_{s \in S} p(s) = 1$$

The second equality is because  $E$  and  $\overline{E}$  are disjoint and their union is the whole sample space. The last equality is from the definition of a probability distribution.

2. For any events  $E_1, E_2 \subset S$ , show that  $p(E_1 \cup E_2) = p(E_1) + p(E_2) - p(E_1 \cap E_2)$ .

$$p(E_1) + p(E_2) = \sum_{s \in E_1} p(s) + \sum_{s \in E_2} p(s) = \sum_{s \in E_1 \cup E_2} p(s) + \sum_{s \in E_1 \cap E_2} p(s) = p(E_1 \cup E_2) + p(E_1 \cap E_2)$$

The second equality is because  $|E_1 \cup E_2| = |E_1| + |E_2| - |E_1 \cap E_2|$  (inclusion exclusion).

3. For any pairwise disjoint events  $E_1, E_2, \dots \subset S$ , show that  $p(\cup_i E_i) = \sum_i p(E_i)$ .

Since the events  $E_i$  are disjoint, we know that  $s \in \cup_i E_i \iff s \in E_i$  for exactly one  $i$ . Therefore:

$$p(\cup_i E_i) = \sum_{s \in \cup_i E_i} p(s) = \sum_i \sum_{s \in E_i} p(s) = \sum_i p(E_i)$$

4. We say that events  $E_1, E_2 \subset S$  are *independent* if  $p(E_1 \cap E_2) = p(E_1)p(E_2)$ . Under what situation can two disjoint events  $E_1, E_2 \subset S$  be independent?

If  $E_1 \cap E_2 = \emptyset$ , then  $p(E_1 \cap E_2) = p(\emptyset) = 0$ . The only way for a product of two real numbers to be 0 is if at least one is zero. Hence at least one of  $p(E_1)$  and  $p(E_2)$  must be 0. (So usually, disjoint events will not be independent!)

## Conditional Probability

### Exercises

1. Prove that if  $p(E | F) = p(E)$ , then  $E$  and  $F$  are independent events.

$$p(E | F) = \frac{p(E \cap F)}{p(F)} = p(E) \implies p(E \cap F) = p(E)p(F)$$

2. A *Bernoulli trial* is an experiment with two outcomes, one (“success”) with fixed probability  $p$  and the other (“failure”) with probability  $1-p$ . Prove that the probability of  $k$  successes in  $n$  independent Bernoulli trials is  $\binom{n}{k}p^k(1-p)^{n-k}$ . What is the sum  $\sum_{k=0}^n \binom{n}{k}(p^k)(1-p)^{n-k}$  in terms of a simple expression?

Think of  $n$  independent (it is important that they are independent!) Bernoulli trials as a string of  $n$  letters which are either S (success) or F (failure). The the number of ways to get  $k$  successes in  $n$  trials is the number of strings with  $k$  S’s and  $n-k$  F’s. The probability of getting such a string is  $\binom{n}{k}p^k(1-p)^{n-k}$  because we also need to account for the probability of success ( $p$ ) and the probability of failure ( $q = 1-p$ ).

$$\sum_{k=0}^n \binom{n}{k} (p^k)(1-p)^{n-k} = 1$$

Two ways to prove this are: (1) this is the sum of all probabilities in a probability distribution, so must be equal to 1. (2) Using the binomial theorem, this is the expansion of  $(p + (1-p))^n = 1^n = 1$ .

## Bayes’ Theorem

### Exercises

1. Show that  $p(F | E)p(E) + p(F | \bar{E})p(\bar{E}) = p(F)$ . Hence we can also write Bayes’ Theorem as  $p(E | F) = \frac{p(F|E)p(E)}{p(F)}$ . Prove this form of Bayes’ Theorem using the definition of conditional probability.

$$\begin{aligned} p(F | \bar{E})p(\bar{E}) + p(F | E)p(E) &= \frac{p(F \cap \bar{E})}{p(\bar{E})}p(\bar{E}) + \frac{p(F \cap E)}{p(E)}p(E) \\ &= p(F \cap \bar{E}) + p(F \cap E) = p(F) \end{aligned}$$

and this proves the alternative form of Bayes’ theorem.

The last equality is from using problem 3 on the previous side since  $F \cap \bar{E}$  and  $F \cap E$  are disjoint (since  $E$  and  $\bar{E}$  are) and  $F \cap \bar{E} \cup F \cap E = F$ .

(Often it will be more convenient to use one form over another for computations. For example, some cases may give  $p(F)$  directly whereas other cases may cause computing the larger expression  $p(F | E)p(E) + p(F | \bar{E})p(\bar{E})$  to be more intuitive.)