## ECE 361 Probability for Engineers (Fall, 2016) Lecture 1b

## Some background for homework 1

Homework 1 problem 1 asks to find the probability of each outcome of the following experiment.

Consider flipping a *fair* coin. The coin is repeatedly flipped until a head occurs, and the outcome of the experiment is the number of times the coin is flipped.

A straightforward argument establishes  $p_n$ , the probability that n flips are required, is  $(1/2)^n$ . But problem 2 is significantly harder, and requires more thought. As a help with problem 2, consider the following alternative approach to problem 1.

Define the event  $A_n$  (for  $n \in \mathbb{N}$ ) as consisting of all outcomes where *strictly* more than n flips are required, which means the first n flips were tails. Then  $\mathbb{P}(A_n) = (1/2)^n$ . Now consider  $A_n^c$ , the complement of  $A_n$ , which has probability  $\mathbb{P}(A_n^c) = 1 - (1/2)^n$ . In words,  $A_n^c$  is the event that n or fewer flips are required.

Define the event  $B_n$  (for  $n \in \mathbb{N}$ ) as the outcome where exactly n flips are required. Thus  $p_n = \mathbb{P}(B_n)$  is the quantity of interest in the problem. But observe the following fundamental facts:

$$A_n^c = B_n \cup A_{n-1}^c, \ B_n \cap A_{n-1}^c = \emptyset.$$
 (1)

In words, i) the event that n or fewer flips are required equals the union of the events that exactly n flips are required with the event that n-1 or fewer flips are required, and ii) the event that exactly n flips are required and the event that n-1 or fewer flips are required are disjoint. The truth of these two statements is self-evident. Also observe  $A_1^c \subset A_2^c \subset A_3^c \subset \cdots$ , as is also self-evident when the symbols are translated into English. The point is that, by the additivity axiom, we can compute:

$$\mathbb{P}(A_n^c) = \mathbb{P}(B_n) + \mathbb{P}(A_{n-1}^c) 
p_n = \mathbb{P}(A_n^c) - \mathbb{P}(A_{n-1}^c) 
= (1 - (1/2)^n) - (1 - (1/2)^{n-1}) 
= (1/2)^{n-1} - (1/2)^n 
= (1/2)^{n-1}(1 - 1/2) 
= (1/2)^n$$
(2)

The logic in this argument is standard in probability, and can be used to solve problem 2.

## §1.2 Probabilistic models

### Properties of probability laws

Many further results follow from the probability axioms. Here are some examples involving one event:

•  $\mathbb{P}(\emptyset) = 0$ . Proof:

$$1 = \mathbb{P}(\Omega) = \mathbb{P}(\Omega \cup \emptyset) = \mathbb{P}(\Omega) + \mathbb{P}(\emptyset) = 1 + \mathbb{P}(\emptyset). \tag{3}$$

•  $\mathbb{P}(A^c) = 1 - \mathbb{P}(A)$ . Proof: note that  $A \cap A^c = \emptyset$  and  $A \cup A^c = \Omega$ .

$$1 = \mathbb{P}(\Omega) = \mathbb{P}(A \cup A^c) = \mathbb{P}(A) + \mathbb{P}(A^c). \tag{4}$$

•  $\mathbb{P}(A) \leq 1$ . Proof: use the above result and non-negativity axiom.

$$\mathbb{P}(A) = 1 - \mathbb{P}(A^c) \le 1. \tag{5}$$

Here are some examples involving two events:

• If  $A \subset B$  then  $\mathbb{P}(A) \leq \mathbb{P}(B)$ . Proof:

$$\mathbb{P}(B) = \mathbb{P}(A \cup (B \setminus A)) = \mathbb{P}(A) + \mathbb{P}(B \setminus A) \ge \mathbb{P}(A). \tag{6}$$

•  $\mathbb{P}(A \cup B) = \mathbb{P}(A) + \mathbb{P}(B) - \mathbb{P}(A \cap B)$  for all events A, B. Proof: there are two steps. First step: observe  $B = (A \cap B) \cup (B \setminus A)$ , where  $A \cap B$  and  $B \setminus A$  are disjoint. Thus

$$\mathbb{P}(B) = \mathbb{P}((A \cap B) \cup (B \setminus A)) = \mathbb{P}(A \cap B) + \mathbb{P}(B \setminus A), \tag{7}$$

and so  $\mathbb{P}(B \setminus A) = \mathbb{P}(B) - \mathbb{P}(A \cap B)$ . Second step: observe  $A \cup B = A \cup (B \setminus A)$ , where A and  $B \setminus A$  are disjoint. Thus

$$\mathbb{P}(A \cup B) = \mathbb{P}(A \cup (B \setminus A)) = \mathbb{P}(A) + \mathbb{P}(B \setminus A) = \mathbb{P}(A) + \mathbb{P}(B) - \mathbb{P}(A \cap B). \tag{8}$$

•  $\mathbb{P}(A \cup B) \leq \mathbb{P}(A) + \mathbb{P}(B)$ . Proof: use non-negativity on the above result.

These results are of fundamental importance, and so we list them again.

Basic relationships among probabilities of events. For any two events A, B:

- $\mathbb{P}(A \cup B) = \mathbb{P}(A) + \mathbb{P}(B) \mathbb{P}(A \cap B)$ .
- If  $A \subseteq B$  then  $\mathbb{P}(A) \leq \mathbb{P}(B)$ .
- If  $A \cap B = \emptyset$  (A, B are disjoint) then  $\mathbb{P}(A \cap B) = \mathbb{P}(A) + \mathbb{P}(B)$ .
- $\mathbb{P}(A \cup B) \leq \mathbb{P}(A) + \mathbb{P}(B)$ , with equality when  $A \cap B = \emptyset$ .

In fact the last three are consequences (special cases) of the first. A key generalization of the last result above is the so-called union bound:

$$\mathbb{P}\left(\bigcup_{i=1}^{n} A_i\right) \le \sum_{i=1}^{n} \mathbb{P}(A_i). \tag{9}$$

In words: the probability of a union of events is upper bounded by the sum of the probabilities of those events. Note the union bound holds with equality when the events are *disjoint*.

# §1.3 Conditional probability

Conditional probability captures partial information in a random experiment. Here are some examples:

- In rolling two dice, what is the probability the first die is a 6 given you are told the sum is 9?
- How likely is it that a person has a disease given a test is negative?

Formally, partial information is indicated by restricting the set of outcomes of the experiment – the more complete the information the more restrictive the set of outcomes. Write  $\mathbb{P}(A|B)$  to denote the probability of the event A given knowledge that the outcome will be in B. To be clear:  $\mathbb{P}(A|B) = \mathbb{P}(\omega \in A|\omega \in B)$ .

Conditional probability definition.

$$\mathbb{P}(A|B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}, \text{ for all events } B \text{ with } \mathbb{P}(B) > 0.$$
 (10)

#### Conditional probabilities specify a probability law

Conditioning on any event B with  $\mathbb{P}(B) > 0$  induces a new probability law that satisfies the probability axioms:

• Nonnegativity:  $\mathbb{P}(A|B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)} \ge 0$ .

• Additivity: Fix disjoint  $A_1, A_2$ . Then:

$$\mathbb{P}(A_1 \cup A_2 | B) = \frac{\mathbb{P}((A_1 \cup A_2) \cap B)}{\mathbb{P}(B)} = \frac{\mathbb{P}((A_1 \cap B) \cup (A_2 \cap B))}{\mathbb{P}(B)} = \frac{\mathbb{P}(A_1 \cap B) + \mathbb{P}(A_2 \cap B)}{\mathbb{P}(B)}$$

$$= \frac{\mathbb{P}(A_1 \cap B)}{\mathbb{P}(B)} + \frac{\mathbb{P}(A_2 \cap B)}{\mathbb{P}(B)} = \mathbb{P}(A_1 | B) + \mathbb{P}(A_2 | B). \tag{11}$$

• Normalization:  $\mathbb{P}(\Omega|B) = \frac{\mathbb{P}(\Omega \cap B)}{\mathbb{P}(B)} = \frac{\mathbb{P}(B)}{\mathbb{P}(B)} = 1.$ 

Since conditioning induces a valid probability law, it follows that all the consequences of the probability axioms also hold under conditioning. For example:

$$\mathbb{P}(A \cup C|B) \le \mathbb{P}(A|B) + \mathbb{P}(C|B). \tag{12}$$

Moreover, if all outcomes in  $\Omega$  are equally likely, we have the conditional discrete uniform probability law:

$$\mathbb{P}(\omega) = \frac{1}{|\Omega|} \forall \omega \in \Omega \Rightarrow \mathbb{P}(A|B) = \frac{|A \cap B|}{|B|}.$$
 (13)

Here are three examples of this law.

- 1. Toss a fair coin three times successively. What is the probability that more heads than tails come up (A) given that the first toss is a head (B)? Note  $B = \{HHH, HHT, HTH, HTT\}$  and  $A \cap B = \{HHH, HHT, HTH\}$  and thus  $\mathbb{P}(A|B) = 3/4$ .
- 2. A fair 4-sided die is tossed twice, where (X, Y) are the results of the two rolls. Find the probability the max is m(A) given the min is 2(B). Note  $B = \{(2, 2), (2, 3), (2, 4), (3, 2), (4, 2)\}$  and thus

$$\mathbb{P}(\max(X,Y) = m|B) = \begin{cases} 2/5, & m = 4\\ 2/5, & m = 3\\ 1/5, & m = 2\\ 0, & m = 1 \end{cases}$$
 (14)

Observe:

3. A conservative design team (C) and an innovative design team (N) design a new product, and each team is either successful (S) or unsuccessful (F), with the probability that C succeeds as 2/3, that N succeeds as 1/2, and that at least one succeeds as 3/4. Given exactly one successful design is produced (B), what is the probability it was by N (A)?

First write down the sample space and the events of interest:

- $\Omega = \{(CS, NS), (CS, NF), (CF, NS), (CF, NF)\}$
- $B = \{(CS, NF), (CF, NS)\}$
- $A = \{(CS, NS), (CF, NS)\}$
- $A \cap B = \{(CF, NS)\}$

Alternately expressed as:

$$\Omega = {}^{CS}_{CF} \left[ \begin{array}{cc} (CS, NS) & (CS, NF) \\ (CF, NS) & (CF, NF) \end{array} \right]$$

$$(16)$$

We have four unknowns: the probabilities of the four outcomes. We adopt a shorthand notation as follows, where right column and the bottom row are the sums of the corresponding elements:

$$\mathbb{P} = \begin{vmatrix} p_{CS,NS} & p_{CS,NF} & p_{CS} \\ p_{CF,NS} & p_{CF,NF} & p_{CF} \\ p_{NS} & p_{NF} & 1 \end{vmatrix}$$
 (17)

Here the third row and third column are the sums of their entries, and the lower right one is the sum of the four uknowns. We are given that:

$$p_{CS} = 2/3, \ p_{NS} = 1/2, \ p_{CF,NF} = 1/4.$$
 (18)

These equations can be solved to find:

$$\mathbb{P} = \begin{array}{c|c|c} 5/12 & 1/4 & 2/3 \\ \hline 1/12 & 1/4 & 1/3 \\ \hline 1/2 & 1/2 & 1 \end{array}$$
 (19)

Then:

$$\mathbb{P}(A|B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)} = \frac{1/12}{1/4 + 1/12} = 1/4. \tag{20}$$

### Using conditional probability for modeling

Often it is more natural to specify the probabilistic model in terms of the conditional probabilities  $\mathbb{P}(A|B)$ , than to specify the joint probabilities  $\mathbb{P}(A \cap B)$ . The joint probabilities may be obtained from the conditional probabilities via  $\mathbb{P}(A \cap B) = \mathbb{P}(A|B)\mathbb{P}(B)$ . This is illustrated in the following example.

**Radar detection.** If an aircraft is present (A) it may generate an alarm (B). There are four joint events of interest:

- Present and detected:  $A \cap B$
- Present and not detected:  $A \cap B^c$  (missed detection)
- Absent and detected  $A^c \cap B$  (false alarm)
- Absent and not detected  $A^c \cap B^c$

The probabilities are specified conditionally (this is the model):

probability of correct detection: 
$$P(B|A) = 0.99$$
 (implies  $P(B^c|A) = 0.01$ )  
probability of false alarm:  $P(B|A^c) = 0.10$  (implies  $P(B^c|A^c) = 0.90$ )  
probability an aircraft is present:  $P(A) = 0.05$  (implies  $P(A^c) = 0.95$ ) (21)

We are asked to find the above four probabilities using this data:

$$\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B|A) = 0.05 \times 0.99 = 0.0495 
\mathbb{P}(A \cap B^c) = \mathbb{P}(A)\mathbb{P}(B^c|A) = 0.05 \times 0.01 = 0.0005 
\mathbb{P}(A^c \cap B) = \mathbb{P}(A^c)\mathbb{P}(B|A^c) = 0.95 \times 0.1 = 0.095 
\mathbb{P}(A^c \cap B^c) = \mathbb{P}(A^c)\mathbb{P}(B^c|A^c) = 0.95 \times 0.90 = 0.855$$
(22)

Note these four sum to one. We can write the sample space as

$$\Omega = {A \atop A^c} \left[ \begin{array}{c} \text{present and detected} & \text{missed detection} \\ \text{false alarm} & \text{absent and not detected} \end{array} \right]. \tag{23}$$

Filling in the above probabilities:

$$\mathbb{P} = \begin{array}{c|cccc} 0.0495 & 0.0005 & 0.05 \\ \hline 0.0950 & 0.8550 & 0.95 \\ \hline 0.1445 & 0.8555 & 1.00 \end{array} \tag{24}$$

### References

[1] Introduction to Probability, 2nd Edition by Dimitri P. Bertsekas and John N. Tsitsiklis, Athina Scientific Press, 2008.