## $\Delta I$ can act as an upper bound on information loss

Consider the following game: person A chooses, at random, one object out of a set of objects, and person B has to guess which one was chosen by asking yes/no questions. The  $i^{th}$  object is chosen with probability  $p_i$ . Person B, however, thinks the  $i^{th}$  object is chosen with probability  $q_i$ , and will base her question-asking strategy on that wrong distribution. Cover and Thomas (mainly Chap. 5) tells us that the average number of yes/no questions person B has to ask to guess the object, denoted N(p,q), is

$$N(p,q) = -\sum_{i} p_i \log q_i = H(p) + \Delta I \tag{1}$$

where  $H(p) \equiv -\sum_i p_i \log p_i$  is the entropy of the true distribution and  $\Delta I \equiv \sum_i p_i \log p_i/q_i = D(p||q)$  is the Kullback-Leibler distance between p and q.

The quantity  $\Delta I$  that appears in Eq. (1) has a natural interpretation: it is the penalty, in yes/no questions, that person B pays for using the wrong distribution to design her question-asking strategy. We can also interpret  $\Delta I$  as an information loss, in the following sense: We can make up for the wrong distribution by supplying person B with  $\Delta I$  bits. In other words, if we give  $\Delta I$  bits to person B, on average she will do as well guessing what object is present as a person who knows the true distribution.

In fact, what we show below is stronger than that: if we give  $\Delta I$  bits to person B, she will do no worse at guessing the object than a person who knows the true distribution, and she may do better. Alternatively, if we want person B to guess the object in H(p) yes/no questions (the same number as a person who knows the true distribution), we could do that by supplying her with at most  $\Delta I$  bits, and sometimes less than that. The actual number of bits she needs depends on the distributions p and q.

When we say "give bits to person B", we have in mind the following: Person A chooses an object, and then sends a string of symbols (0s and 1s, say) to person B through a noisy channel. Those strings provide information about which object was chosen using a pretty standard coding scheme: the objects are divided into groups, and each string tells which group the object is in. For example, a coding scheme for 6 objects might be: objects 1 and 2 are labeled with the string 1, objects 3 and 4 are labeled with the string 01, and objects 5 and 6 are labeled with the string 00. If, say, object 5 is chosen, then the string 00 would be sent. Since the channel is noisy, a string different than 00 might be received.

So here's the situation. Person A chooses object i, determines that it is labeled with string k, and then sends string k to person B. Because the channel through which the string

is sent is noisy, person B receives string l. She then revises her estimate of the probability that object i is chosen. Letting P(k|l) be the probability that string k was sent given that string l was received, her new estimate of the distribution of objects, which we'll call q(i|l), is

$$q(i|l) = \frac{q_i}{Q_k} P(k|l) \tag{2}$$

where  $Q_k \equiv \sum_{i \in k} q_i$  and the notation  $i \in k$  means sum over only those i such that i is in group k. The number of yes/no questions she will have to ask to guess the object is now

$$N_I(p,q) = -\sum_l P(l) \sum_i p(i|l) \log q(i|l)$$
(3)

where the subscript I means that I bits were sent (I will be computed shortly), P(l) is the probability that person B received string l, and p(i|l) is the true probability that object i was chosen given that string l was received. Analogous to Eq. (2), this last quantity is given by

$$p(i|l) = \frac{p_i}{P_k} P(k|l) \tag{4}$$

where  $P_k \equiv \sum_{i \in k} p_i$ .

Inserting Eqs. (2) and (4) into (3), rearranging terms slightly, and using  $P_k = \sum_l P(k|l)P(l)$ , we find that

$$N_I(p,q) = N(p,q) - \sum_l P(l) \sum_k P(k|l) \log rac{P(k|l)}{P_k} - \sum_k P_k \log rac{P_k}{Q_k}$$

The second term is I(k; l), the amount of information transmitted through the noisy channel (also the average string length), and the third term is D(P||Q), the Kullback-Leibler distance between P and Q. We thus have

$$N_I(p,q) = N(p,q) - I(k;l) - D(P||Q)$$
.

Since D(P||Q) is non-negative, giving I bits to person B reduces the number of yes/no questions she has to ask by at least I. The reduction could be larger, though. To find out how much larger, we minimize  $N_I(p,q)$  with respect to q, subject to the constraint that the  $q_i$  sum to 1. When we do this, we find that the minimum value of  $N_I(p,q)$ , which

occurs when  $q_i = p_i Q_k/P_k$ , is H(p) - I(k; l). The maximum reduction in yes/no questions, N(p,q) - [H(p) - I(k; l)], is thus  $I(k; l) + \Delta I$  (see Eq. (1)). Consequently, giving I bits to person B reduces the number of yes/no questions she has to ask by an amount somewhere between I and  $I + \Delta I$ , inclusive. Alternatively,

Giving  $\Delta I$  bits **or less** to person B allows her to guess the object in exactly the same number of yes/no questions as someone who knows the true distribution.

This is our main result, and it's why we interpret  $\Delta I$  as an upper bound on information loss.

This looks sort of odd: we can, in principle, give person B an arbitrarily small amount of information and produce a potentially large reduction in the number of yes/no questions. Can this really happen? The answer is yes, as the following example shows.

Let  $p_i = 1/M$ , i = 1, ..., M,  $q_1 = 1/M - \alpha/M$ , and  $q_{i>1} = 1/M + \alpha/M(M-1)$ . For these distributions

$$\Delta I = -\frac{1}{M}\log(1-\alpha) - \frac{M-1}{M}\log\left[1 + \frac{\alpha}{M-1}\right].$$

For fixed M, we can make  $\Delta I$  arbitrarily large by letting  $\alpha$  approach 1.

Now let's inject a little information by telling person B whether or not element 1 was chosen. We'll use a lossless channel, so this results in a transmission of

$$I = -\frac{1}{M}\log\frac{1}{M} - \frac{M-1}{M}\log\frac{M-1}{M}$$

bits, which, for large M, approaches  $\log M/M$ . Thus, we can provide person B with an arbitrarily small amount of information (by letting M go to infinity), while reducing the number of yes/no questions she would have to ask by an arbitrarily large amount (by letting  $\alpha$  go to 1).