Information and Coding Theory

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As in the notes from the previous lecture, $\mathbf{x} = (x_1, \ldots, x_n)$ will denote a sequence of n elements, each drawn from a finite universe U with |U| = m. For a sequence \mathbf{x} , we use $P_{\mathbf{x}}$ to denote its type (empirical distribution). We will use \mathcal{P}_n to denote the set of all types for sequences of length n. Recall from the previous lecture that $|\mathcal{P}_n| \leq (n+1)^m$.

1 Sanov's theorem (continued)

Theorem 1.1 (Sanov) Let Π be a set of distributions on U, and m = |U|. Let

 $P^* = \operatorname{argmin}_{P \in \Pi} D(P \| Q).$

Then

$$\mathbb{P}_{Q^n}\left[P_{\mathbf{x}} \in \Pi\right] \le (n+1)^m 2^{-D(P^* \| Q)}.$$

If Π is the closure of an open set, then

$$\frac{1}{n}\log \mathbb{P}_{Q^n}\left[P_{\mathbf{x}} \in \Pi\right] \to -D(P^* \| Q).$$

We will need the following bound proved in the last lecture:

$$\mathbb{P}_{Q^n}[D(P_{\mathbf{x}}||Q) \ge \delta] \le (n+1)^m \cdot 2^{-n\delta}.$$

Let's review the proof. We have

$$\mathbb{P}_{Q^n}\left[\mathbf{x}\in\mathcal{T}_P\right]\leq 2^{-nD(P\|Q)}\,.$$

Let $C_{\delta} = \{P \in \mathcal{P}_n \mid D(P || Q) \ge \delta\}$. Then, we have

$$\mathbb{P}_{Q^{n}}\left[D(P_{\mathbf{x}} \| Q) \geq \delta\right] = \mathbb{P}_{Q^{n}}\left[\bigcup_{P \in \mathcal{C}_{\delta}} (\mathbf{x} \in \mathcal{T}_{P})\right]$$
$$\leq |\mathcal{C}_{\delta}| \cdot 2^{-n\delta}$$
$$< (n+1)^{m} \cdot 2^{-n\delta}$$

We now use this to prove Sanov's theorem.

Proof: Take $\delta = D(P^* || Q)$, so for all $P \in \Pi$ we have $D(P || Q) \ge \delta$. Then we get

$$\mathbb{P}_{Q^n} \left[P_{\mathbf{x}} \in \Pi \right] = \mathbb{P}_{Q^n} \left[P_{\mathbf{x}} \in \Pi \cap \mathcal{P}_n \right]$$
$$\leq \mathbb{P}_{Q^n} \left[D(P_{\mathbf{x}} \| Q) \ge \delta \right]$$
$$\leq (n+1)^m 2^{-n\delta}$$
$$= (n+1)^m 2^{-nD(P^* \| Q)}$$

as desired. Now let's prove the other direction. Since Π is the closure of an open set and $P^* \in \Pi$, there is an n_0 such that we can find a sequence $\{P^{(n)}\}_{n \ge n_0}$ satisfying $P^{(n)} \to P^*$ and $P^{(n)} \in \mathcal{P}_n \cap \Pi$ for each n. Then we have

$$\mathbb{P}_{Q^n} \left[P_{\mathbf{x}} \in \Pi \right] = \mathbb{P}_{Q^n} \left[P_{\mathbf{x}} \in \Pi \right]$$
$$= \mathbb{P}_{Q^n} \left[P_{\mathbf{x}} \in \Pi \cap \mathcal{P}_n \right]$$
$$\geq \mathbb{P}_{Q^n} \left[P_{\mathbf{x}} = P^{(n)} \right]$$
$$\geq \frac{1}{(n+1)^m} 2^{-nD(P^{(n)} ||Q)}$$

Thus we get

and

$$-D(P^{(n)} \| Q) - \frac{m \log(n+1)}{n} \le \frac{1}{n} \log \mathbb{P}_{Q^n} [P_{\mathbf{x}} \in \Pi] \le -D(P^* \| Q) + \frac{m \log(n+1)}{n}$$
$$\frac{1}{n} \mathbb{P}_{Q^n} [P_{\mathbf{x}} \in \Pi] \to -D(P^* \| Q).$$

Note that the upper bound on the probability in Sanov's theorem holds for any Π . However, for the lower bound we need some conditions on Π . This is necessary since if (for example) Π is a set of distributions such that all probabilities in all the distributions are irrational, then $\mathbb{P}_{Q^n}[P_{\mathbf{x}} \in \Pi] = 0$. In particular, we cannot get any lower bound on this probability for such a Π .

We now show how to compute P^* for a special family of distributions Π . Such a family is sometimes called a *linear family*.

An example: finding P^* for a linear family Π

Let $f: U \to \mathbb{R}$. Let's try to compute $\mathbb{P}_{Q^n} \left[\frac{1}{n} \sum_{i=1}^n f(x_i) \ge \alpha \right]$. Note that

$$\frac{1}{n}\sum_{i=1}^{n}f(x_i) = \sum_{a\in U}P_{\mathbf{x}}(a)f(a).$$

Let

$$\Pi = \left\{ P : \sum_{a \in U} P(a) f(a) \ge \alpha \right\}.$$

Then the probability we want is $\mathbb{P}_{Q^n}[P_{\mathbf{x}} \in \Pi]$. We have that

$$\frac{1}{n} \log \mathop{\mathbb{P}}_{Q^n} \left[P_{\mathbf{x}} \in \Pi \right] \to -D(P^* \| Q)$$

And

$$P^* = \operatorname{argmin}_{P \in \Pi} D(P \| Q)$$

(Assume that $\sum Q(a)f(a) < \alpha$.) Then we want to minimize D(P||Q) so that $\sum P(a)f(a) = \alpha$ (which must be true for P^*) and $\sum P(a) = 1$. The Lagrangian is $D(P||Q) + \lambda_1(\sum P(a)f(a) - \alpha) + \lambda_2(\sum P(a) - 1)$; we want to find stationary points of this function. The resulting constraints are

$$P^*(a) = Q(a) \cdot 2^{\lambda f(a)} \cdot c 2^{c\lambda_2}$$

and

$$P^*(a) = Q(a) \cdot 2^{\lambda f(a)} \cdot c'$$

where

$$c' = \frac{1}{\sum Q(a)2^{\lambda f(a)}}.$$

 λ is such that $\sum P^*(a)f(a) = \alpha$. Thus, we solve for λ in the equation

$$\frac{\sum Q(a)2^{\lambda f(a)}f(a)}{\sum Q(a)2^{\lambda f(a)}} = \alpha.$$

Exercise. Solve for λ if $U = \{1, 2, 3, 4\}$, $f = \{0, 1, 1/2, 1/2\}$, $Q = \{1/2, 1/6, 1/6, 1/6\}$.

2 Hypothesis testing

Setup for hypothesis testing. Null hypothesis (H_0) : true distribution is P (or, more generally, in II). Test $T: U^n \to \{0, 1\}$. 0 means that H_0 is true, and 1 means that H_0 is false. Two types of errors: type-1 (false positive: incorrectly reject H_0) has probability $\mathbb{P}_{P^n}[T(\mathbf{x}) = 1]$, type-2 (false negative: incorrectly fail to reject H_0) has probability $\mathbb{P}_{Q^n}[T(\mathbf{x}) = 0]$ if the true distribution is Q. Note that the probability of a type-2 error depends on the true distribution Q; this dependence cannot be eliminated.

The way our test will work is $T(\mathbf{x}) = 1 \iff D(P_{\mathbf{x}} || P) \ge \delta).$

Then we can compute the probability of a type-1 error as

$$\mathbb{P}_{P^n}\left[D(P_{\mathbf{x}}\|P) \ge \delta\right] \le (n+1)^m 2^{-n\delta} \le \frac{1}{n+1}$$

if we assign $\delta = \frac{(m+1)\log(n+1)}{n}$.

Then we want to find the probability of a type-2 error $\mathbb{P}_{Q^n}[T(\mathbf{x}) = 0]$. The claim is that

$$\frac{1}{n}\log \mathbb{P}_{Q^n}\left[T(\mathbf{x})=0\right] \to -D(P||Q).$$

Exercise. Try proving it.