Information and Coding Theory	**Autumn 2022**

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1 The Method of Types

For this lecture, we will take $\mathcal{X}$ to be a finite universe $|\mathcal{X}| = r$, and use $\overline{\mathbf{x}} = (x_1, x_2, \ldots, x_n)$ to denote a sequence of n elements from U.

Definition 1.1. *The* type $P_{\overline{\mathbf{x}}}$ *of* $\overline{\mathbf{x}}$*, also called the* empirical distribution *of* $\overline{\mathbf{x}}$*, is a distribution* $\hat{P}$ *on* $\mathcal{X}$*, defined as*

$$\hat{P}(a) \;:=\; \frac{|\{i : x_i = a\}|}{n} \qquad \forall a \in \mathcal{X}\,.$$

We use $\mathcal{T}_n$ *to denote the set of all types coming from sequences of length* n*. We also use* $\mathcal{C}_P$ *to denote the set of all sequences with the type* P*.* $\mathcal{C}_P$ *is called the* type class *of* P*.*

$$\mathcal{C}_P \;:=\; \{\overline{\mathbf{x}} \in \mathcal{X}^n \;\mid\; P_{\overline{\mathbf{x}}} = P\}\,.$$

Exercise 1.2. *Check that* $|\mathcal{T}_n| \;=\; \binom{n+r-1}{r-1} \;\leq\; (n+1)^r$*.*

Next, we bound the size of a given type class in terms of the entropy of that type.

Proposition 1.3. *For any type* $P \in \mathcal{T}_n$*, we have*

$$\frac{2^{n \cdot H(P)}}{(n+1)^r} \;\leq\; |\mathcal{C}_P| \;\leq\; 2^{n \cdot H(P)}\,.$$

Proof: For each $a_i \in U$, let $P(a_i) = k_i/n$. Then $|\mathcal{C}_P| = n!/(k_1!k_2!\ldots k_r!)$. We prove the lower bound by considering

$$\begin{aligned}
n^n \;=\; (k_1 + k_2 + \cdots + k_r)^n \;&=\; \sum_{j_1+\cdots+j_r=n} \frac{n!}{j_1!\ldots j_m!}(k_1^{j_1}\ldots k_m^{j_r}) \\
&\leq\; \binom{n+r-1}{r-1} \cdot \max_{j_1+\cdots+j_r=n} \frac{n!}{j_1!\ldots j_r!} \cdot (k_1^{j_1}\ldots k_m^{j_r})\,,
\end{aligned}$$

where each tuple $(j_1, \ldots, j_r)$ corresponds to a distinct type. We leave it as an exercise to check that the maximum term in the expression above is when $(j_1, \ldots, j_r) = (k_1, \ldots, k_r)$.

Exercise 1.4. *Show that*

$$\frac{n!}{j_1! \dots j_r!} \cdot (k_1^{j_1} \dots k_r^{j_r}) \;\leq\; \frac{n!}{k_1! \dots k_r!} \cdot (k_1^{k_1} \dots k_r^{k_r})$$

for all $(j_1, \dots, j_r)$ *such that* $j_1 + \dots + j_r = n$. *(Hint: if* $j_s > k_s$ *for some* s*, then* $j_t < k_t$ *for some* t*.)*

Using the above, we can now prove the lower bound.

$$n^n \;\leq\; \binom{n+r-1}{r-1} \cdot \frac{n!}{k_1! \dots k_r!} \cdot (k_1^{k_1} \dots k_r^{k_r}) \;\leq\; (n+1)^r \cdot |\mathcal{C}_P| \cdot (k_1^{k_1} \dots k_m^{k_m}) \,.$$

We get

$$\begin{aligned}
|\mathcal{C}_P| \;&\geq\; \frac{1}{(n+1)^r} \cdot \frac{n^{k_1+k_2+\dots+k_r}}{k_1^{k_1} \dots k_r^{k_r}} \\
&=\; \frac{1}{(n+1)^r} \cdot \prod_{i=1}^{r} \left(\frac{n}{k_i}\right)^{k_i} \\
&=\; \frac{1}{(n+1)^r} \cdot \prod_{i=1}^{r} 2^{k_i \cdot \log(n/k_i)} \;=\; \frac{1}{(n+1)^r} \cdot 2^{n \cdot H(P)} \,.
\end{aligned}$$

The proof of the upper bound is similar and left as an exercise. ∎

Next, we need the observation that the probability of a sequence according to a product distribution only depends on its type.

Proposition 1.5. *Let* Q *be any distribution on* U *and let* Q^n *the product distribution on* $\mathcal{X}^n$*. Let* $\overline{\mathbf{x}}, \overline{\mathbf{y}} \in \mathcal{X}^n$ *be such that* $P_{\overline{\mathbf{x}}} = P_{\overline{\mathbf{y}}}$*. Then,* $Q^n(\overline{\mathbf{x}}) = Q^n(\overline{\mathbf{y}})$*.*

Proof: Let $P = P_{\overline{\mathbf{x}}} = P_{\overline{\mathbf{y}}}$. Then we have:

$$Q^n(\overline{\mathbf{x}}) \;=\; \prod_{a \in \mathcal{X}} (Q(a))^{|\{i : x_i = 1\}|} \;=\; \prod_{a \in \mathcal{X}} (Q(a))^{n \cdot P(a)} \;=\; Q^n(\overline{\mathbf{y}}) \,.$$

∎

Now we give bounds on the probability of a certain type occurring, in terms of the KL divergence between the true distribution and the empirical distribution.

Theorem 1.6. *For any product distribution* Q^n *and type* P *on* $\mathcal{X}^n$*, we have*

$$\frac{2^{-n \cdot D(P \| Q)}}{(n+1)^r} \;\leq\; \mathop{\mathbb{P}}_{\overline{\mathbf{x}} \sim Q^n} \left[P_{\overline{\mathbf{x}}} = P\right] \;\leq\; 2^{-n \cdot D(P \| Q)} \,.$$

Proof: Let $\overline{\mathbf{x}}$ be of type $P_{\overline{\mathbf{x}}} = P$. For the lower bound, we note that

$$\frac{Q^n(\overline{\mathbf{x}})}{P^n(\overline{\mathbf{x}})} = \frac{\prod_{a\in\mathcal{X}}(Q(a))^{nP(a)}}{\prod_{a\in\mathcal{X}}(P(a))^{nP(a)}} = \prod_{a\in\mathcal{X}}\left(\frac{Q(a)}{P(a)}\right)^{nP(a)} = 2^{n\sum_{a\in\mathcal{X}}P(a)\log\left(\frac{Q(a)}{P(a)}\right)} = 2^{-n\cdot D(P\|Q)}$$

We also know from the previous proposition that for any $\overline{\mathbf{x}} \in \mathcal{C}_P$, we have

$$P^n(\overline{\mathbf{x}}) = \prod_{a\in U}(P(a))^{n\cdot P(a)} = 2^{-n\cdot H(P)}.$$

Finally, using Proposition 1.3, we get

$$\begin{aligned}
\mathop{\mathbb{P}}_{\overline{\mathbf{x}}\sim Q^n}[P_{\overline{\mathbf{x}}} = P] = \sum_{\overline{\mathbf{x}}\in\mathcal{C}_P} Q^n(\overline{\mathbf{x}}) &= \sum_{\overline{\mathbf{x}}\in\mathcal{C}_P} 2^{-n\cdot H(P)}\cdot 2^{-n\cdot D(P\|Q)} \\
&= |\mathcal{C}_P|\cdot 2^{-n\cdot H(P)}\cdot 2^{-n\cdot D(P\|Q)} \\
&\geq \frac{2^{n\cdot H(P)}}{(n+1)^r}\cdot 2^{-n\cdot H(P)}\cdot 2^{-n\cdot D(P\|Q)} \\
&= \frac{2^{-n\cdot D(P\|Q)}}{(n+1)^r}
\end{aligned}$$

The proof of the upper bound is left as an exercise. Note that It may be that $\mathrm{Supp}(Q) \subsetneq \mathrm{Supp}(P)$ i.e., $\exists a \in \mathcal{X} : Q(a) = 0, P(a) \neq 0$. Then the $\log(1/Q(a))$ term makes $D(P\|Q)$ undefined, so thinking of $D(P\|Q)$ as $+\infty$, we get $2^{-nD(P\|Q)} = \mathrm{Prob}_{Q^n}(T_P^n) = 0$. ■

2 Chernoff bounds

The above counting can be used to prove the Chernoff bound. Let $\mathcal{X} = \{0,1\}$, and let $\overline{\mathbf{x}} = (x_1, \ldots, x_n)$ be a sequence drawn from $\mathcal{X}^n$ according to Q^n, where

$$Q = \begin{cases} 0 & : \quad \text{with probability } 1/2 \\ 1 & : \quad \text{with probability } 1/2\,. \end{cases}$$

We expect there to be around $n/2$ occurrences of 1 in $\overline{\mathbf{X}}$; that is, $\mathbb{E}[\sum_{i=1}^n x_i] = n/2$. It is natural to ask how much the empirical distribution is likely to deviate from $n/2$. If we set

$$P = \begin{cases} 0 & : \quad \text{with probability } 1/2 - \varepsilon \\ 1 & : \quad \text{with probability } 1/2 + \varepsilon\,, \end{cases}$$

then we have

$$\mathop{\mathbb{P}}_{Q^n}\left[X_1 + \cdots + X_n = \frac{n}{2} + \varepsilon n\right] = \mathop{\mathbb{P}}_{\overline{\mathbf{x}}\sim Q^n}[P_{\overline{\mathbf{x}}} = P] \leq 2^{-n\cdot D(P\|Q)} = 2^{-c\cdot n\cdot\varepsilon^2},$$

by Theorem 1.6, for a constant c. This is sort of like Chernoff bounds, but we may want to know how likely we are to see *any* sufficiently large deviation, and not just the deviation exactly equal to εn.

Theorem 2.1 (Chernoff bound)**.** *For* $\overline{\mathbf{X}} = (X_1, \ldots, X_n) \sim_{Q^n} U^n$ *with* Q *the uniform distribution on* $\mathcal{X} = \{0,1\}$*, we have*

$$\underset{Q^n}{\mathbb{P}}\left[\sum_{i=1}^{n} X_i \geq \frac{n}{2} + \varepsilon n\right] \;\leq\; (n+1) \cdot 2^{-c \cdot n \cdot \varepsilon^2}\,.$$

Proof: Let $\mathcal{X} = \{0,1\}$ and note that that each type class corresponds to a unique value of $x_1 + \cdots + x_n$. From the above bound, we have that for any $\eta > 0$,

$$\underset{Q^n}{\mathbb{P}}\left[X_1 + \cdots + X_n = \frac{n}{2} + \eta n\right] \;\leq\; 2^{-c \cdot n \cdot \eta^2}\,.$$

Going over all types for all $\eta \geq \varepsilon$, and noting that the number of types is at most $n+1$, we get

$$\underset{Q^n}{\mathbb{P}}\left[\sum_{i=1}^{n} X_i \geq \frac{n}{2} + \varepsilon n\right] \;\leq\; (n+1) \cdot 2^{-c \cdot n \cdot \varepsilon^2}\,,$$

as claimed. ■

The above idea can be generalized for product distributions over arbitrary (finite) universes to prove a general large deviation result known as Sanov's theorem.

3 Sanov's theorem

We generalize the Chernoff bound to understand the probability that $P_{\overline{\mathbf{x}}} \in \Pi$ for an arbitrary set Π of distributions over U.

Theorem 3.1 (Sanov)**.** *Let* Π *be a set of distributions on* $\mathcal{X}$*, and* $|\mathcal{X}| = r$*. Then*

$$\underset{Q^n}{\mathbb{P}}\left[P_{\overline{\mathbf{x}}} \in \Pi\right] \;\leq\; (n+1)^r \cdot 2^{-n \cdot \delta}\,,$$

where $\delta = \inf_{P \in \Pi} D(P \| Q)$*. Moreover, if* Π *is the closure of an open set and*

$$P^* \;:=\; \underset{P \in \Pi}{\arg\min}\, D(P \| Q)\,,$$

then

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

Proof: For any $P \in \mathcal{T}_n$, we have by Theorem 1.6 that

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

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

$$\mathop{\mathbb{P}}_{\bar{\mathbf{x}} \sim Q^n}\left[D(P_{\bar{\mathbf{x}}}\|Q) \geq \delta\right] \;=\; \sum_{P \in \mathcal{T}_\delta} 2^{-n \cdot D(P\|Q)} \;\leq\; (n+1)^r \cdot 2^{-n\delta}.$$

We now use this to prove Sanov's theorem. Take $\delta = \inf_{P\in\Pi} D(P\|Q)$, so for all $P \in \Pi$ we have $D(P\|Q) \geq \delta$. Then we get

$$\mathop{\mathbb{P}}_{\bar{\mathbf{x}} \sim Q^n}\left[P_{\bar{\mathbf{x}}} \in \Pi\right] \;=\; \mathop{\mathbb{P}}_{Q^n}\left[P_{\bar{\mathbf{x}}} \in \Pi \cap \mathcal{T}_n\right] \;\leq\; \mathop{\mathbb{P}}_{Q^n}\left[D(P_{\bar{\mathbf{x}}}\|Q) \geq \delta\right] \;\leq\; (n+1)^r \cdot 2^{-n\delta}$$

as desired. Now let's prove the other direction. Since Π is the closure of an open set (obtained by including the limit points of all converging sequences), we can say that the limit of the sequence converging to $\inf_{P\in\Pi} D(P\|Q)$ exists in the set, and there exists $P^* \in \Pi$ such that $D(P^*\|Q) = \inf_{P\in\Pi} D(P\|Q)$. This is the distribution P^* satisfying $P^* := \arg\min_{P\in\Pi} D(P\|Q)$.

Also, there is an n_0 such that we can find a sequence $\{P^{(n)}\}_{n \geq n_0}$ satisfying $P^{(n)} \to P^*$ and $P^{(n)} \in \mathcal{T}_n \cap \Pi$ for each n. Then we have

$$\begin{aligned}
\mathop{\mathbb{P}}_{\bar{\mathbf{x}} \sim Q^n}\left[P_{\bar{\mathbf{x}}} \in \Pi\right] \;=\; \mathop{\mathbb{P}}_{\bar{\mathbf{x}} \sim Q^n}\left[P_{\bar{\mathbf{x}}} \in \Pi\right] \;&=\; \mathop{\mathbb{P}}_{\bar{\mathbf{x}} \sim Q^n}\left[P_{\bar{\mathbf{x}}} \in \Pi \cap \mathcal{T}_n\right] \\
&\geq\; \mathop{\mathbb{P}}_{\bar{\mathbf{x}} \sim Q^n}\left[P_{\bar{\mathbf{x}}} = P^{(n)}\right] \\
&\geq\; \frac{1}{(n+1)^r} \cdot 2^{-nD(P^{(n)}\|Q)}
\end{aligned}$$

Thus we get

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

which gives

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

as claimed. ∎

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 $\mathbb{P}_{Q^n}\left[P_{\bar{\mathbf{x}}} \in \Pi\right] = 0$. In particular, we cannot get any lower bound on this probability for such a Π.

Sanov's theorem can also be extended to the case when $\mathcal{X}$ is an infinite set, using the definition of KL-divergence as a supremum over all finite partitions of an infinite space.