

# Problem Set 2

Information and Coding Theory

February 12, 2021

CLAYTON SEITZ

**Problem 0.1.** Find tight upper and lower bounds on two extremely biased coins where the first coin is distributed according to

$$P = \begin{cases} 0 & \epsilon \\ 1 & 1 - \epsilon \end{cases}$$

and the second is distributed according to

$$Q = \begin{cases} 0 & 2\epsilon \\ 1 & 1 - 2\epsilon \end{cases}$$

**Solution.** I will assume that distinguishing the two coins means that, given a sequence of  $n$  flips, we can say whether it is coin  $P$  or coin  $Q$  in at least  $\frac{9}{10}n$  trials, on average. To start, we write out the KL-Divergence between the distributions  $P$  and  $Q$

$$\begin{aligned} D(P||Q) &= \epsilon \log \frac{\epsilon}{2\epsilon} + (1 - \epsilon) \log \frac{1 - \epsilon}{1 - 2\epsilon} \\ &= (1 - \epsilon) \log \frac{1 - \epsilon}{1 - 2\epsilon} - \epsilon \\ &= (1 - \epsilon) \log \left( 1 + \frac{\epsilon}{1 - 2\epsilon} \right) - \epsilon \\ &\leq (1 - \epsilon) \left( \frac{\epsilon}{1 - 2\epsilon} \right) - \epsilon \\ &= \frac{1}{2 \ln 2} \cdot \frac{\epsilon^2}{1 - 2\epsilon} \end{aligned}$$

At the same time, we know that

$$n \geq \frac{1}{2 \ln 2 \cdot D(P||Q)} \left(\frac{8}{5}\right)^2$$

given the constraint on successful predictions. Substituting for  $D(P||Q)$  gives us the lower bound on  $n$

$$n \geq \left(\frac{1}{\epsilon^2} - \frac{2}{\epsilon}\right) \left(\frac{8}{5}\right)^2$$

■

**Problem 0.2.** *Show that  $0 \leq \mathbf{JSD}(P, Q) \leq 1$*

**Solution.**

$$\mathbf{JSD}(P, Q) = \frac{1}{2}D(P||M) + \frac{1}{2}D(Q||M)$$

The lower bound must be true because  $D(P||M) \geq 0$  and  $D(Q||M) \geq 0$ . For the upper bound, consider just one of the terms

$$\begin{aligned} D(P||M) &= \frac{1}{2} \sum_{x \sim P} P(x) \log \frac{P(x)}{M(x)} \\ &= \frac{1}{2} \sum_{x \sim P} P(x) \log \frac{2P(x)}{P(x) + Q(x)} \\ &\leq \frac{1}{2} \sum_{x \sim P} P(x) \log 2 = \frac{1}{2} \end{aligned}$$

Therefore,  $\mathbf{JSD}(P, Q) \leq 1$ .

Show that  $\mathbf{JSD}(P, Q) \geq \frac{1}{8 \ln 2} \cdot ||P - Q||_1^2$

$$\begin{aligned}
\mathbf{JSD}(P, Q) &= \frac{1}{2} [D(P||M) + D(Q||M)] \\
&\geq \frac{1}{4 \ln 2} [\|P - M\|_1^2 + \|Q - M\|_1^2] \\
&= \frac{1}{4 \ln 2} \left[ \left( \sum |P - M| \right)^2 + \left( \sum |Q - M| \right)^2 \right] \\
&= \frac{1}{8 \ln 2} \left[ \left( \sum |P - Q| \right)^2 + \left( \sum |Q - P| \right)^2 \right] \\
&= \frac{1}{8 \ln 2} \cdot \|P - Q\|_1^2
\end{aligned}$$

Show that  $\mathbf{JSD}(\mathbf{P}, \mathbf{Q}) \leq \frac{1}{2} \cdot \|P - Q\|_1$

$$\begin{aligned}
\mathbf{JSD}_\lambda(P, Q) &= \frac{1}{2} [D(P||M) + D(Q||M)] \\
&= \frac{1}{2} \left[ \sum_{x \sim P} P(x) \log \frac{P(x)}{M(x)} + \sum_{x \sim Q} Q(x) \log \frac{Q(x)}{M(x)} \right] \\
&= \frac{1}{2} \sum_{x \sim \chi} \left[ P(x) \log \frac{2P(x)}{P(x) + Q(x)} + Q(x) \log \frac{2Q(x)}{P(x) + Q(x)} \right] \\
&= \frac{1}{2} \sum_{x \sim \chi} [P(x) + Q(x)] \cdot \frac{P(x)}{P(x) + Q(x)} \log \frac{2P(x)}{P(x) + Q(x)} \\
&\quad + \frac{Q(x)}{P(x) + Q(x)} \log \frac{2Q(x)}{P(x) + Q(x)} \\
&= \frac{1}{2} \sum_{x \sim \chi} [P(x) + Q(x)] \cdot |1 - H \left( \frac{P(x)}{P(x) + Q(x)}, \frac{Q(x)}{P(x) + Q(x)} \right)| \\
&\leq \sum_{x \sim \chi} |P(x) - Q(x)|
\end{aligned}$$

$$\mathbf{JSD}_\lambda(P_1 \dots P_k) = \sum_i \lambda_i D(P_i || M)$$

where  $M = \sum_i \lambda_i P_i$ . Show that

$$0 \leq \mathbf{JSD}_\lambda(P_1 \dots P_k) \leq H(\lambda)$$

As before, the lower bound must be true because  $D(P_i||M) \geq 0$  and  $\lambda$  is non-negative. As for the upper bound,

$$\begin{aligned}
\mathbf{JSD}_\lambda(P_1 \dots P_k) &= \sum_i \lambda_i D(P_i||M) \\
&= \sum_i \lambda_i P_i \log \frac{P_i}{M} \\
&= H\left(\sum_i \lambda_i P_i\right) - \sum_i \lambda_i H(P_i) \\
&= H(\lambda) - \sum_i \lambda_i H(P_i) \\
&\leq H(\lambda)
\end{aligned}$$

■

**Problem 0.3.** *Counting using the method of types*

**Solution.** Sanov's Theorem states that

$$Q^n(E) = (n+1)^r 2^{-nD(P^*||Q)}$$

where  $P^*$  is the distribution in  $E$  that is closest to  $Q$ . Since  $Q$  is a uniform distribution we have that

$$D(P^*||Q) = \log m - H(P)$$

Therefore, if we let  $H^*$  be the entropy of the distribution which has maximum entropy, Sanov's theorem becomes

$$Q^n(E) = (n+1)^r 2^{-n(\log m - H^*)}$$

$$\begin{aligned}
|S| &= m^n (n+1)^r 2^{-n(\log m - H^*)} \\
&= (n+1)^r 2^{-nH^*}
\end{aligned}$$

and therefore, in general,  $|S| \leq (n+1)^r 2^{-nH^*}$ .

■

**Problem 0.4.** *Differential entropy of the multivariate Gaussian*

$$\phi(x) = \frac{1}{(2\pi)^{n/2}|\Sigma|^{1/2}} \exp -\frac{1}{2}(x - \mu)^T \Sigma^{-1}(x - \mu)$$

**Solution.**

$$\begin{aligned} h(x) &= - \int \phi(x) \log \phi(x) dx \\ &= \int \phi(x) \left[ \frac{n}{2} \log(2\pi e) + \frac{1}{2} \log |\Sigma| + \frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) \right] dx \\ &= \frac{n}{2} \log(2\pi e) + \frac{1}{2} \log |\Sigma| + \mathbf{E} \left[ \frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) \right] \\ &= \frac{n}{2} \log(2\pi e) + \frac{1}{2} \log |\Sigma| \end{aligned}$$

■