

## Homework 02: Large Deviations for Log-Likelihood

### Problem 1: Large Deviations for Log-Likelihood

Let  $P$  and  $Q$  be two probability distributions such that  $P \ll Q$ . Let  $X_i$  be i.i.d. random variables under  $P$  and  $Y_i$  be i.i.d. random variables under  $Q$ . Define for each index  $i$

$$W_i = \log \frac{p(Y_i)}{q(Y_i)},$$
$$Z_i = \log \frac{p(X_i)}{q(X_i)}.$$

The purpose of this problem is to prove:

*Proposition I.* For any  $t \geq 0$  and any  $n \in \mathbb{N}$ , the following large-deviation bound holds:

$$\mathbb{P} \left[ \sum_{i=1}^n (W_i - Z_i) \geq nt \right] \leq \exp(-n(\alpha + \tfrac{t}{2})),$$

where

$$\mathcal{B}(P, Q) = \mathbb{E}_{Y \sim Q} \left[ \sqrt{\frac{p(Y)}{q(Y)}} \right], \quad \alpha = -2 \log \mathcal{B}(P, Q).$$

1. (Chernoff bound) Show that for all  $t \geq 0$ ,

$$\mathbb{P} \left[ \sum_{i=1}^n (W_i - Z_i) \geq nt \right] \leq \exp(-n \cdot F(t)),$$

where

$$\psi_Q(\lambda) = \log \mathbb{E}[e^{\lambda W_i}],$$
$$\psi_P(\lambda) = \log \mathbb{E}[e^{\lambda Z_i}],$$
$$F(t) = \sup_{\lambda \geq 0} \{ \lambda t - \psi_P(-\lambda) - \psi_Q(\lambda) \}.$$

2. (Value at zero) Show that

$$F(0) = -\psi_P(-\tfrac{1}{2}) - \psi_Q(\tfrac{1}{2}) = \alpha.$$

3. (Linear lower bound) Prove that for all  $t \geq 0$ ,

$$F(t) \geq F(0) + \tfrac{t}{2},$$

and conclude Proposition I.

## Solution

### 1. Chernoff Bound

Let

$$S_n = \sum_{i=1}^n (W_i - Z_i).$$

For any  $\lambda \geq 0$ , by Markov's inequality,

$$\mathbb{P}[S_n \geq nt] = \mathbb{P}[e^{\lambda S_n} \geq e^{\lambda nt}] \leq e^{-\lambda nt} \mathbb{E}[e^{\lambda S_n}] = e^{-\lambda nt} (\mathbb{E}[e^{\lambda W_1}])^n (\mathbb{E}[e^{-\lambda Z_1}])^n.$$

Define

$$\psi_Q(\lambda) = \log \mathbb{E}[e^{\lambda W_1}], \quad \psi_P(-\lambda) = \log \mathbb{E}[e^{-\lambda Z_1}].$$

Then

$$\mathbb{P}[S_n \geq nt] \leq \exp(-n(\lambda t - \psi_P(-\lambda) - \psi_Q(\lambda))).$$

Optimizing over  $\lambda \geq 0$  yields

$$\mathbb{P}[S_n \geq nt] \leq \exp(-nF(t)), \quad F(t) = \sup_{\lambda \geq 0} \{\lambda t - \psi_P(-\lambda) - \psi_Q(\lambda)\}.$$

### 2. Value at Zero

We have

$$F(0) = \sup_{\lambda \geq 0} \{-\psi_P(-\lambda) - \psi_Q(\lambda)\}.$$

Observe:

$$\begin{aligned} \psi_P(-\lambda) &= \log \mathbb{E}_P \left[ \left( \frac{p(X)}{q(X)} \right)^{-\lambda} \right] = \log \int p(x)^{1-\lambda} q(x)^\lambda dx \\ \psi_Q(\lambda) &= \log \mathbb{E}_Q \left[ \left( \frac{p(Y)}{q(Y)} \right)^\lambda \right] = \log \int p(y)^\lambda q(y)^{1-\lambda} dy. \end{aligned}$$

Now by cauchy-schwartz (or Hölder with  $p=q$ ) we have:

$$\left( \int p(x)^{1-\lambda} q(x)^\lambda dx \right) \left( \int p(y)^\lambda q(y)^{1-\lambda} dy \right) \geq \left( \int \sqrt{pq} \right)^2 = B^2(P, Q)$$

Thus by monotonicity of log we have:

$$F(0) = -\log \left[ \left( \int p(x)^{1-\lambda} q(x)^\lambda dx \right) \left( \int p(y)^\lambda q(y)^{1-\lambda} dy \right) \right] \leq -\log B^2(P, Q) = -2 \log B(P, Q) = \alpha$$

Moreover, if we set  $\lambda = \frac{1}{2}$ , we have  $F(0) = -2 \log B^2(P, Q) = \alpha$ , so we have equality condition at  $\lambda = \frac{1}{2}$ , and the proof is complete.

### 3. Linear Lower Bound

Using the candidate  $\lambda = \frac{1}{2}$  in the definition of  $F(t)$ ,

$$F(t) \geq \frac{1}{2}t - \psi_P(-\frac{1}{2}) - \psi_Q(\frac{1}{2}) = F(0) + \frac{t}{2}.$$

Therefore,

$$\mathbb{P}[S_n \geq nt] \leq \exp(-nF(t)) \leq \exp(-n(\alpha + \frac{t}{2})),$$

as claimed. □