

# Lecture 7

(1)

Review: \* Scheffé Selector

Let  $P_1, \dots, P_M$  be measures on  $\mathcal{X}$ . Given samples  $X_1, \dots, X_n$  from  $P_i$ , find  $i$  s.t.

$$d(P_i, P) \leq c \cdot \min_j d(P_j, P).$$

→ Scheffé selector for  $M=2$

Let  $A = \{x : f_1(x) \geq f_2(x)\}$ .

$$\hat{P} = \begin{cases} P_1, & \text{if } |P_1(A) - \mu_n(A)| \leq |P_2(A) - \mu_n(A)| \\ P_2, & \text{o.w.} \end{cases}$$

→ Scheffé Tournament

- Use Scheffé selector to find a winner for each "match"  $P_i$  vs  $P_j$ ,  $1 \leq i < j \leq M$ .
- Choose the winner as the  $P_i$  that wins the most matches.

→ Performance of Scheffé tournament

$$d(\hat{P}, P) \leq 9 \min_i d(P_i, P) + 8 \Delta$$

$$\text{where } \Delta = \max_{A \in \{A(f_i, f_j) : 1 \leq j \leq M\}} |P(A) - \mu_n(A)|$$

Agenda:

Estimating the mean of a Gaussian using

Scheffé selector

(2)

We modify the problem a little bit (we shall illustrate in HW that this modification is without loss of generality).

$$\epsilon(n, \delta) = \min_{\hat{\mu}} \max_{\mu} P_{\mu} \left( d(P_{\mu}, P_{\hat{\mu}}) > \delta \right).$$

New recipe

- (i) Form a list of guesses  $\mu_1, \dots, \mu_M$  using  $X^n$
- (ii) Use a Scheffé selector to find  $\hat{\mu} = \mu_i$ .

Recall that

$$d(P_{\mu}, P_{\nu}) \leq \frac{1}{2} |\mu - \nu|.$$

Step (i)

Consider  $n$  independent samples  $X_1, \dots, X_n$  from  $N(\mu, \sigma^2)$ .

Then, 
$$P \left( |X_i - \mu| > t \right) = 2Q \left( \frac{t}{\sigma} \right) \leq 2 \cdot e^{-t^2/2\sigma^2}$$

Thus,

$$\begin{aligned} P \left( \min_i |X_i - \mu| > t \right) &= P \left( |X_1 - \mu| > t \right)^n \\ &\leq 2 \cdot e^{-nt^2/2\sigma^2} = \frac{\epsilon}{2} \end{aligned}$$

if 
$$t = \frac{2\sigma}{\sqrt{n}} \log \frac{4}{\epsilon}.$$

i.e., with prob. greater than  $1 - \epsilon/2$ , there exists  $i$  s.t.

$$|X_i - \mu| \leq \frac{2\sigma}{\sqrt{n}} \log \frac{4}{\epsilon}.$$

Thus, a simple guess list is  $\{P_{X_1}, \dots, P_{X_n}\}$ .

(3)

Step(ii) We now use Scheffé tournament to find a good candidate from the guess-list. The selected  $\hat{P}$  satisfies

$$\begin{aligned} d(\hat{P}, P) &\leq 9 \min_{1 \leq i \leq n} d(P_i, P) + 8\Delta \\ &\leq \frac{9\sigma}{\sqrt{n}} \log \frac{4}{\epsilon} + 8\Delta \end{aligned}$$

with prob.  $\geq 1 - \epsilon/2$ .

Here, in the definition of  $\Delta$ , the set

$$A(\mu_i, \mu_j) = \{x: |x - \mu_i| \leq |x - \mu_j|\} = \{x: x \leq \frac{\mu_i + \mu_j}{2}\}.$$

Thus,

$$\begin{aligned} \Delta &= \max_{i,j} \left| P_\mu \left( X \leq \frac{\mu_i + \mu_j}{2} \right) - \mu_n \left( X \leq \frac{\mu_i + \mu_j}{2} \right) \right| \\ &\leq \max_{a \in \mathbb{R}} \left| P_\mu (X \leq a) - \mu_n (X \leq a) \right| \end{aligned}$$

↳ excuse the bad notation!!

Convergence of Empirical measure to the original one

Let  $\mu_n$  denote the empirical measure generated using  $n$  samples from  $\mu$  on  $\mathbb{R}$ .

Then,

$$(1) \quad \mu \left( \sup_a |\mu(X \leq a) - \mu_n(X \leq a)| > \frac{1}{\sqrt{n}} + t \right) \leq e^{-nt^2/2}$$

Using (1),

$$P_{\mu} \left( d(\hat{P}, P) > \frac{9\sigma}{\sqrt{n}} \log \frac{4}{\epsilon} + \frac{1}{\sqrt{n}} + \frac{1}{\sqrt{n}} \sqrt{2 \log \frac{2}{\epsilon}} \right) \leq \epsilon. \quad (4)$$

$$\text{Thus, } n_{\epsilon}(\delta) \leq O\left(\frac{\sigma^2}{\delta} \log \frac{1}{\epsilon}\right)$$

Proof of (1) (See lectures 6, 7 of E2207)

We use a result of Massart '90:

Kolmogorov-Smirnov Distance (for  $\mu, \nu$  on  $\mathbb{R}$ )

$$d_{KS}(\mu, \nu) = \sup_{a \in \mathbb{R}} |\mu(X \leq a) - \nu(X \leq a)|.$$

Massart '90:  $\mathbb{E}_{\mu} [d_{KS}(\mu, \mu_n)] \leq \frac{1}{\sqrt{n}}.$

Note that the function  $d_{KS}(\mu, \mu_n)$  satisfies BDD with constants  $(\frac{1}{n}, \dots, \frac{1}{n})$ . Thus, by McDiarmid's inequality

$$\begin{aligned} \mu(d_{KS}(\mu_n, \mu) > \mathbb{E}_{\mu} [d_{KS}(\mu_n, \mu)] + t) \\ \leq e^{-nt^2/2} \end{aligned}$$

$$\Rightarrow \mu(d_{KS}(\mu_n, \mu) > \frac{1}{\sqrt{n}} + t) \leq e^{-nt^2/2}. \quad \square$$

The same analysis can be extended to higher dimensions.

The guesses would be  $\{X_1, \dots, X_n\}$  and then the Scheffe selector can return the best  $i$  to be used as a proxy for  $\mu_i$ .

But now we will need  $O(d \log d)$  samples and ⑤  
the Scheffé selector will work in  $O(d^2 \log^2 d)$  steps.  
This is "comparable" with the  $O(d^2)$  steps required for  
calculating the empirical mean of  $O(d)$  samples.