

Lecture 17

(1)

Review: * monotone properties

* Influence $I_p(A)$

* Russo's Lemma:

$$\frac{d P_p(A)}{d p} = I_p(A)$$

[A] Proof of Russo's Lemma (contd.)

Proof. Let $U_1, \dots, U_n$ be iid unif $[0, 1]$. Given $\underline{p} = (p_1, \dots, p_n)$ and

$\hat{\underline{p}} = (p_1, \dots, p_i, \hat{p}_i, p_{i+1}, \dots, p_n)$, let

$$X_j = 2 \mathbb{1}_{\{U_j \leq p_j\}} - 1 \quad \text{and} \quad \hat{X}_j = 2 \mathbb{1}_{\{U_j \leq \hat{p}_j\}} - 1, \quad 1 \leq j \leq n.$$

Consider the case $\hat{p}_i > p_i$. Then, since A is monotone,

$$X \in A \Rightarrow \hat{X} \in A.$$

$$\text{Thus, } P(\hat{X} \in A) - P(X \in A)$$

$$= P(\hat{X} \in A, X \notin A)$$

$$= P(U_i \in (p_i, \hat{p}_i), X_i^+ \in A, X_i^- \notin A)$$

$$= (\hat{p}_i - p_i) \cdot P(X_i^+ \in A, X_i^- \notin A).$$

For $p_j = p$ for every $j \neq i$, we get

$$P(\hat{X} \in A) - P(X \in A) = (\hat{p}_i - p_i) I_p^i(A)$$

and similarly, when $\hat{p}_i < p_i$,

$$P(\hat{X} \in A) - P(X \in A) = -(\hat{p}_i - p_i) I_p^i(A).$$

Thus, denoting by $Q_{\underline{p}}(A)$ the prob. $X \in A$ for

$$\underline{p} = (p, \dots, p),$$

$$\frac{\partial}{\partial p_i} Q_p(A) = I_p^i(A) \quad (2)$$

which gives

$$\frac{d P_p(A)}{d p} = \sum_{i=1}^n \frac{\partial Q_p(A)}{\partial p_i} = \sum_{i=1}^n I_p^i(A) = I(A)$$

[B] Formalising the threshold phenomenon

We have already noted that for a monotone set $A \neq \emptyset$ or $\{-1, 1\}^n$, $P_0(A) = 0$, $P_1(A) = 1$. Also, for such a set A , $I_p(A) > 0$. Indeed, since $(-1, -1, \dots, -1) \in A^c$ and $(1, 1, \dots, 1) \in A$, $\exists i$ and a sequence x s.t. $x_i^- \in A^c$ and $x_i^+ \in A$. Thus, $I_p^i(A) > 0 \Rightarrow I_p(A) > 0$. We have established the following.

Corollary. For every monotone set $A \neq \emptyset$ or $\{-1, 1\}^n$, $f(p) \stackrel{\text{def}}{=} I_p(A)$ is strictly increasing and $f(0) = 0$, $f(1) = 1$.

For $0 < \epsilon < 1$, let $p_\epsilon \stackrel{\text{def}}{=} \inf \{p : P_p(A) \geq \epsilon\}$. Then, in view of the corollary above, $p_0 = 0$, $p_1 = 1$. We are interested in bounding $p_\epsilon - p_{1-\epsilon}$ for $\epsilon < 1/2$.

While we can use a version of log-Sobolev inequality for arbitrary p to lower bound $I_p(A)$, this will not do it.

[C] A strengthening of log-Sobolev inequality. (3)

Theorem (General BLSI)

Let $X_1, \dots, X_n$ be iid with $P_{X_i}(1) = 1 - P_{X_i}(-1) = p$.

Then, for every $f: \{-1, 1\}^n \rightarrow \mathbb{R}$ and $c(p) = \frac{1}{1-2p} \log \frac{1-p}{p}$,

$$\text{Ent}(f^2) \leq 2c(p) \mathcal{E}(f)$$

$$\text{where } \mathcal{E}(f) = \frac{1}{2} \sum_{i=1}^n \mathbb{E}[(f(X) - f(X_i)) ^2]$$

$$= p(1-p) \mathbb{I}_p(f)$$

$$\hookrightarrow \sum_{i=1}^n \mathbb{E}[(f(X) - f(\bar{X}^{(i)}))^2]$$

Proof. Just as in the proof of BLSI for the uniform case, it suffices to show the inequality for $n=1$. This case reduces to showing

$$pa^2 \log a^2 + (1-p)b^2 \log p^2 - (pa^2 + (1-p)b^2) \log(pa^2 + (1-p)b^2) \leq p(1-p)c(p)(|a| - |b|)^2. \quad (\text{HW!})$$

Check: $\mathbb{E}[(f(X) - f(X_i))^2] = 2p(1-p) \mathbb{E}[(f(X_i^+) - f(X_i^-))^2]$
 $\mathbb{E}[(f(X) - f(\bar{X}^{(i)}))^2] = \mathbb{E}[(f(X_i^+) - f(X_i^-))^2].$

A direct proof for the case $f = \mathbb{I}_A$ is simple.

Theorem ("Strengthened" general BLSI and Efron-Stein)

For $Z = \mathbb{I}_A$ and $S_p(A) = \max_{1 \leq i \leq n} \mathbb{I}_p^i(A)$,

$$\text{Var}(Z) \log \frac{\text{Var}(Z)}{(2p(1-p))^2 S_p(A) \mathbb{I}_p(A)} \leq p(1-p)c(p) \mathbb{I}_p(A).$$

Remark. BLSI: Bounds $P(A) \log \frac{1}{P(A)}$ (4)

BESI: Bounds $P(A)(1-P(A)) \left(\leq P(A) \log \frac{1}{P(A)} \right)$

Since there is no dependence on n in these inequalities, we can't expect them to enable a proof of the threshold phenomenon.

Proof. Step 1: Subadditivity and tensorization

$$Z_i = \mathbb{E}[Z | X^i], \quad \Delta_i = Z_i - Z_{i-1}$$

$$\left(\text{Var}(\Delta_i) = \mathbb{E} \Delta_i^2 \leq \mathbb{E} \text{Var}^{(i)}(Z) \right) : \text{ES proof}$$

$$\begin{aligned} \mathcal{E}(\Delta_j) &= \frac{1}{2} \sum_{i=1}^n \mathbb{E} [(\Delta_j(X) - \Delta_j(X^{(i)}))^2] \\ &= p(1-p) \sum_{i=1}^n \mathbb{E} [(\Delta_j(X) - \Delta_j(\bar{X}^{(i)}))^2] \end{aligned}$$

Claim: $\mathcal{E}(\Delta_j) = \mathcal{E}(Z_j) - \mathcal{E}(Z_{j-1})$

Proof: $\Delta_j(X) - \Delta_j(\bar{X}^{(i)})$

$$= \mathbb{E}_j[f(X) - f(\bar{X}^{(i)})] - \mathbb{E}_{j-1}[f(X) - f(\bar{X}^{(i)})]$$

Also, denoting $\bar{Z}_{j,i} = \mathbb{E}_j[f(\bar{X}^{(i)})]$,

$$Z_{j-1} - \bar{Z}_{j-1,i} = \mathbb{E}_{j-1}[f(X) - f(\bar{X}^{(i)})].$$

Since $\mathbb{E}_j[Y] - \mathbb{E}_{j-1}[Y] \perp \mathbb{E}_{j-1}[Y]$ for any rv Y ,

$(\Delta_j - \Delta_j(\bar{X}^{(i)}))$ is uncorrelated with $Z_{j-1} - \bar{Z}_{j-1,i}$.

Thus,

$$\begin{aligned} \mathcal{E}(\Delta_j) &= p(1-p) \sum_{i=1}^n \mathbb{E} \left[\mathbb{E}_j[(f(X) - f(\bar{X}^{(i)}))^2] - \mathbb{E}_{j-1}[f(X) - f(\bar{X}^{(i)})]^2 \right] \\ &= \mathcal{E}(Z_j) - \mathcal{E}(Z_{j-1}) \end{aligned}$$

(5)

$$\Rightarrow \mathcal{E}(f) = \sum_{j=1}^n \mathcal{E}(\Delta_j).$$

Step 2: log-Sobolev and other inequalities

$$(a) \mathcal{E}(f) \geq \mathcal{E}(|f|)$$

$$\text{Pf. } (a-b)^2 \geq (|a|-|b|)^2$$

$$(b) \mathcal{E}(|f|) \geq \frac{1}{2C(p)} \text{Ent}(f^2)$$

$$(c) \text{ For } f: \mathbb{R}^n \rightarrow \mathbb{R}_+,$$

$$\text{Ent}(f^2) \geq \mathbb{E}[f^2] \log \frac{\mathbb{E}[f^2]}{\mathbb{E}[f]^2}.$$

$$\text{Pf. } \text{Ent}(f^2) = \mathbb{E}[f^2 \log(f^2 / \mathbb{E}[f^2])]$$

$$= \mathbb{E}\left[f^2 \log \frac{f^2}{\mathbb{E}[f^2]} \cdot \mathbb{E}[f]^2\right] \\ + \mathbb{E}[f^2] \log \mathbb{E}[f^2] / (\mathbb{E}[f])^2$$

The first term on the right-side equals,

$$2 \mathbb{E}\left[f^2 \log \frac{f}{\mathbb{E}[f]} \cdot \mathbb{E}[f]\right] \geq 2 \mathbb{E}\left[f^2 \left(1 - \frac{\mathbb{E}[f]}{f \cdot \mathbb{E}[f]}\right)\right] \\ = 2 \mathbb{E}[f^2] - 2 \mathbb{E}[f^2] = 0,$$

which completes the proof. $\blacksquare$

$$(d) (\text{log-sum inequality}) \quad \sum_i a_i \log \frac{a_i}{b_i} \geq \sum_i a_i \log \frac{\sum_i a_i}{\sum_i b_i}$$

Step 3: Finally, combining everything —

⑥

$$\mathcal{E}(f) = \sum_{i=1}^n \mathcal{E}(\Delta_i) \geq \sum_{i=1}^n \mathcal{E}(|\Delta_i|) \geq \frac{1}{2c(p)} \sum_{i=1}^n \text{Ent}(\Delta_i^2)$$

$$\geq \frac{1}{2c(p)} \sum_{i=1}^n \mathbb{E}[\Delta_i^2] \log \frac{\mathbb{E}[\Delta_i^2]}{(\mathbb{E}[|\Delta_i|])^2}$$

$$\geq \frac{1}{2c(p)} \sum_{i=1}^n \mathbb{E}[\Delta_i^2] \log \frac{\sum_{i=1}^n \mathbb{E}[\Delta_i^2]}{\sum_{i=1}^n (\mathbb{E}[|\Delta_i|])^2}$$

$$= \frac{1}{2c(p)} \text{Var}(f) \log \frac{\text{Var}(f)}{\sum_{i=1}^n \mathbb{E}[|\Delta_i|]^2}$$

Finally, note for $f = \mathbb{1}_A$ at

$$\begin{aligned} \mathbb{E}[|\Delta_i|] &= \mathbb{E}[|Z_i - Z_{i-1}|] \leq \mathbb{E}[|f(X) - \mathbb{E}^{(i)} f|] \\ &= 2p(1-p) \mathbb{I}_p^i(A). \end{aligned}$$

$$\text{Thus, } \mathcal{E}(f) \geq \frac{1}{2c(p)} \text{Var}(\mathbb{1}_A) \log \frac{\text{Var}(\mathbb{1}_A)}{4p^2(1-p)^2 \sum_{i=1}^n \mathbb{I}_p^i(A)^2}$$

$$\geq \frac{1}{2c(p)} \text{Var}(\mathbb{1}_A) \log \frac{\text{Var}(\mathbb{1}_A)}{4p^2(1-p)^2 \delta_p(A) \mathbb{I}_p(A)}$$

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