

begin
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المسألة

$$B = UDU^T \Rightarrow E(e^{\lambda Q}) = U^T (e^{\lambda D}) U$$

المسألة

$$\begin{aligned} &\leq U^T e^{\frac{1}{2} \lambda \sigma^2 D^2} U \\ &= e^{\frac{1}{2} \lambda \sigma^2} U^T D^2 U \\ &= e^{\frac{1}{2} \lambda \sigma^2} B^T \quad \checkmark \end{aligned}$$

$$\|B\|_2 \leq b \Rightarrow B \leq b I_{S \times S} \Rightarrow e^{\frac{1}{2} \lambda \sigma^2 B^T} = e^{\frac{1}{2} \lambda \sigma^2 b I_{S \times S}} \quad \checkmark$$

المسألة

التي لا يمكن كتابتها على شكل

Theorem 6.15:

$$\begin{aligned} &E(e^{\frac{\gamma}{n} \sum Q_i}) = E[\lambda_{\max}(e^{\gamma S})] \leq \text{tr}(E(e^{\gamma S})) \\ &= \text{tr}(\gamma_s(\frac{\gamma}{n})) \leq \text{tr}(\exp(\sum \log \gamma_s(\frac{\gamma}{n}))) \\ &\stackrel{\text{Lemma 6.15}}{\leq} \text{tr}(\exp(\frac{\gamma}{n} \sum v_i)) \\ &\stackrel{6.25}{\leq} d e^{\frac{\gamma \sigma^2}{n} \frac{1}{n} \sum v_i} \quad \checkmark \end{aligned}$$

$$\rightarrow \gamma = \sqrt{\frac{\gamma n}{\sigma^2}} \log d \Rightarrow E(\lambda_{\max}(\frac{1}{n} \sum Q_i)) \leq \sqrt{\frac{\gamma \sigma^2}{n} \log d} \quad \checkmark$$

$$E(e^{\gamma \|\frac{1}{n} \sum Q_i\|_F}) = E(e^{\gamma \max_{S \subseteq [n]} \{ \lambda_{\max}(\frac{1}{n} \sum_{i \in S} Q_i), \lambda_{\min}(\frac{1}{n} \sum_{i \in S} Q_i) \}}) \quad (\text{سوال ٢-٢})$$

$$\leq E(e^{\gamma \lambda_{\max}(S_n)} + e^{-\gamma \lambda_{\min}(S_n)})$$

$$\leq \text{tr}(E(e^{\gamma \lambda_{\max}(S_1)})) + \text{tr}(E(e^{-\gamma \lambda_{\min}(S_1)}))$$

$$\leq d e^{\frac{\gamma \sigma^2}{2n}} + d e^{\frac{\gamma \sigma^2}{2n}} = 2d e^{\frac{\gamma \sigma^2}{2n}}$$

$$\Rightarrow \gamma = \sqrt{\frac{2 \log d}{n}} \Rightarrow E \|\frac{1}{n} \sum Q_i\|_F \leq \sqrt{\frac{2 \log d}{n}} \|\frac{1}{n} \sum Q_i\|_F \quad \checkmark$$

$$Q_i = \begin{pmatrix} 0 & A_i \\ A_i^T & 0 \end{pmatrix} \Rightarrow Q_i^2 = \begin{pmatrix} A_i A_i^T & 0 \\ 0 & A_i^T A_i \end{pmatrix}$$

سوال ٣

$$\det(Q_i^2 - \lambda I) = (A_i A_i^T - \lambda I)(A_i^T A_i - \lambda I) \Rightarrow \text{eval } Q_i^2 = \text{eval } A_i^T A_i \cup \text{eval } A_i A_i^T$$

$$\|Q_i\|_2 = \sqrt{\|A_i A_i^T\|_2} = \sqrt{A_i^T A_i} = \|A_i\|_2 \rightarrow \begin{matrix} \text{مقدار بزرگترین} \\ \text{مقدار ویژه} \\ \text{ماتریس} \end{matrix}$$

$$E(Q_i^2) \leq \frac{2!}{r} b^{2-r} \text{var}(Q)$$

↓

$$E((g_i, Q_i)^2) \leq \frac{2!}{r} (b_1 b_2)^{2-r} \text{var}(g_i, Q_i) \quad ?$$

$$\text{var}(g_i, Q_i) = \|\Sigma V(Q_i)\|_2 = \max \{ \|E(g_i A_i A_i^T g_i)\|_2, \|E(g_i^T A_i A_i g_i)\|_2 \} \approx \sigma^2 \\ = \sigma^2 \frac{r}{b_1 b_2} I$$

$$\Rightarrow E((y_i q_i)^2) \leq \frac{2!}{r} (b_i b_i)^{\frac{r}{2}} \underset{\substack{\downarrow \\ \max\{ \dots \}}}{\sigma^2 b_i^{\frac{r}{2}}} I$$

$$y_i q_i \text{ e.v. } -\lambda \iff y_i q_i \text{ e.v. } \lambda \iff \text{symmetric } b_i q_i^2 \text{ e.v. } \lambda \iff \text{ } \checkmark$$

$$\xrightarrow{\text{Jensen}} P(\| \frac{1}{n} \sum q_i \| \geq \delta) \leq \underbrace{\text{rank}(\sum v_i)}_{= d_{\text{trd}_c}} e^{\frac{-n \delta^2}{r(b_i^{\frac{r}{2}} + b_i b_i \delta)}} \quad \checkmark$$

$$\boxed{\sigma=1}$$

مردم سادی

$$x_{i,j} = \text{subg}(1), x_{i,j}^Y = \text{subg}(Y, 1) \Rightarrow \sum x_{i,j}^2 = \text{subg}(Y \sqrt{n}, \epsilon)$$

$$\Rightarrow \frac{1}{n} \sum x_{i,j}^2 = \text{subg}\left(\frac{Y \sqrt{n}}{n}, \frac{\epsilon}{n}\right)$$

$$\hookrightarrow \text{tail bound: } P(|\hat{D}_{ii} - D_{ii}| \geq t) \leq Y e^{-\eta_Y \min(t, t^2)}$$

$$\text{union bound: } P(\|\hat{D} - D\|_2 \geq t) \leq Y d e^{-\eta_Y \min(t, t^2)}$$

$$P(\|\hat{D} - D\|_2 \geq t + \epsilon) \leq Y d e^{-\eta_Y \min(t, t^2) - \frac{n}{\lambda} \epsilon^2}$$

$$\epsilon = \sqrt{\frac{\lambda \log d}{n}}, P(\|\hat{D} - D\|_2 \geq \sqrt{\frac{\lambda \log d}{n}} + t) \leq Y e^{-\eta_Y \min(t, t^2)} \checkmark$$

$n \geq \lambda \log d$

$$n < \lambda \log d, P(\|\hat{D} - D\|_2 \geq \frac{\lambda \log d}{n} + t) \leq Y e^{-\eta_Y \min(t, t^2)} \checkmark$$

حال برای سمت دوم از ناسازی مارکوف و وینر استفاده می‌کنیم:

$$\begin{aligned} P(\|\hat{D} - D\|_2 \geq \epsilon \sqrt{\frac{d_Y m}{t}}) &\leq \frac{1}{(\epsilon \delta)^m} \times \frac{n^{m_Y}}{d_Y^m} E(\max_{\frac{\partial}{\partial t}} |\hat{D} - D|_2^m) \\ &\leq \frac{1}{(\epsilon \delta)^m} \cdot \frac{n^{m_Y}}{\epsilon^m} \|\hat{D} - D\|_m^m \end{aligned}$$

$$\leq \frac{C_m}{\epsilon^m} \left(\left(\sum E((x_{ii}^Y - D_{ii})^Y) \right)^{\frac{1}{Y}} + \sum E(|x_{ii}^Y - D_{ii}|^{\frac{1}{m}}) \right)^m$$

$$\leq \frac{C_m}{h^m} \cdot (\sqrt{h} C_f + \sqrt{h} C_m)^m \leq C_m \cdot \frac{h^m}{h^{m/2}} \max(C_f, C_m)$$

$$\Rightarrow P(\|\hat{D} - D\|_F \geq \epsilon \sqrt{\frac{d_m}{n}}) \leq \frac{C_m \max(C_f, C_m) \sqrt{d_m}}{(\epsilon/2)^m}$$

$$(-\hat{w}_i, \hat{\alpha}_i, \hat{\beta}_i, \hat{\gamma}_i) \frac{\partial \mathcal{L}}{\partial \theta}$$

$$Z = \bar{R}_n - B = \frac{1}{n} \sum (R_k - E(R)) = \sum_{k=1}^n s_k$$

$$\|s_k\| \leq \frac{1}{n} (\|R_k\| + \|E(R)\|) \leq \frac{1}{n} (\|R_k\| + E\|R\|) \leq \frac{YL}{n} \quad (\|R\| \leq L)$$

$$\nu(Z) = \max \left\{ \left\| \sum E(s_k s_k^*) \right\|, \left\| \sum E(s_k s_k^*) \right\| \right\} = n \cdot \max \left\{ E\|s_1\|^2, E\|s_1^* s_1\| \right\}$$

$$0 \leq E(s_i s_i^*) = \frac{1}{n} E((R - E(R))(R - E(R))^*) \leq \frac{1}{n} (E(R R^*) - \underbrace{E(R) E(R)^*}_{=0})$$

$$\leq \frac{1}{n} E(R R^*)$$

$$\Rightarrow E(s_i s_i^*) \leq \frac{1}{n} E(R R^*)$$

$$E(s_i^* s_i) \leq \frac{1}{n} E(R^* R)$$

$$\rightarrow \nu(Z) = \frac{1}{n} \max \{ \|E(R R^*)\|, \|E(R^* R)\| \}$$

id

matrix
Bernstein

$$E\|Z\| \leq \sqrt{\nu(Z) \log(d_1 + d_2)} + \frac{1}{\mu} \log(d_1 + d_2) L \quad \checkmark$$

$$P(\|Z\| \geq t) \leq (d_1 + d_2) \exp\left(\frac{-t^2/\mu}{\nu(Z) + Lt/\mu}\right)$$

$$\Rightarrow \begin{cases} \|R_n - B\| \leq \sqrt{\frac{\nu(Z) \log(d_1 + d_2)}{n} \cdot \max\{E(R R^*), E(R^* R)\}} + \frac{YL \log(d_1 + d_2)}{en} \quad \checkmark \\ P(\|R_n - B\| \geq t) \leq (d_1 + d_2) \exp\left(\frac{-t^2/\mu}{\nu(Z) + Lt/\mu + \max\{E(R R^*), E(R^* R)\}}\right) \quad \checkmark \end{cases}$$