

**Homework 3 Solutions***Please do not distribute.***1. Gaussian graphical models (20 points)**

(a) Consider a  $p$ -dimensional Gaussian vector  $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \Sigma)$ . For any  $1 \leq u, v \leq p$ , show that

$$x_u \perp\!\!\!\perp x_v \mid \mathbf{x}_{\mathcal{V} \setminus \{u, v\}}$$

(namely,  $x_u$  and  $x_v$  are conditionally independent given all other variables) if and only if  $\Theta_{u,v} = 0$ . Here,  $\Theta = \Sigma^{-1}$ .

**Solution:**

Let

$$\mathbf{a} = \begin{bmatrix} x_u \\ x_v \end{bmatrix}, \quad \mathbf{b} = \mathbf{x}_{\mathcal{V} \setminus \{u, v\}}.$$

Then,  $\mathbf{a}, \mathbf{b}$  are jointly Gaussian as

$$\begin{bmatrix} \mathbf{a} \\ \mathbf{b} \end{bmatrix} \sim \mathcal{N} \left( \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \end{bmatrix}, \begin{bmatrix} \Sigma_{\mathbf{a}} & \Sigma_{\mathbf{ab}} \\ \Sigma_{\mathbf{ab}}^\top & \Sigma_{\mathbf{b}} \end{bmatrix} \right),$$

where covariance matrices are

$$\Sigma_{\mathbf{a}} = \mathbb{E}[\mathbf{a}\mathbf{a}^\top], \quad \Sigma_{\mathbf{ab}} = \mathbb{E}[\mathbf{a}\mathbf{b}^\top], \quad \Sigma_{\mathbf{b}} = \mathbb{E}[\mathbf{b}\mathbf{b}^\top].$$

The conditional density of  $\mathbf{a}$  given  $\mathbf{b}$  is

$$p_{\mathbf{a}|\mathbf{b}}(\mathbf{r}|\mathbf{s}) = \frac{1}{2\pi} (\det \Lambda)^{-\frac{1}{2}} \exp \left( -\frac{1}{2} (\mathbf{r} - \mathbf{w})^\top \Lambda^{-1} (\mathbf{r} - \mathbf{w}) \right)$$

where

$$\mathbf{w} = \Sigma_{\mathbf{ab}} \Sigma_{\mathbf{b}}^{-1} \mathbf{s},$$

$$\Lambda = \Sigma_{\mathbf{a}} - \Sigma_{\mathbf{ab}} \Sigma_{\mathbf{b}}^{-1} \Sigma_{\mathbf{ab}}^\top$$

In the similar way, we can have the conditional density of  $x_u$  and  $x_v$  given  $\mathbf{b}$  respectively as

$$p_{x_u|\mathbf{b}}(t|\mathbf{s}) = \frac{1}{\sqrt{2\pi\lambda_u}} \exp \left( -\frac{1}{2\lambda_u} (t - w_u)^2 \right),$$

$$p_{x_v|\mathbf{b}}(t|\mathbf{s}) = \frac{1}{\sqrt{2\pi\lambda_v}} \exp \left( -\frac{1}{2\lambda_v} (t - w_v)^2 \right),$$

where

$$\lambda_u = \Sigma_{x_u} - \Sigma_{x_u \mathbf{b}} \Sigma_{\mathbf{b}}^{-1} \Sigma_{x_u \mathbf{b}}^\top,$$

$$\lambda_v = \Sigma_{x_v} - \Sigma_{x_v \mathbf{b}} \Sigma_{\mathbf{b}}^{-1} \Sigma_{x_v \mathbf{b}}^\top,$$

$$w_u = \Sigma_{x_u \mathbf{b}} \Sigma_{\mathbf{b}}^{-1} \mathbf{s},$$

$$w_v = \Sigma_{x_v \mathbf{b}} \Sigma_{\mathbf{b}}^{-1} \mathbf{s}.$$

We have

$$\Lambda_{11} = \lambda_u, \quad \Lambda_{22} = \lambda_v, \quad \mathbf{w}_1 = w_u, \quad \mathbf{w}_2 = w_v.$$

Assume  $\Theta_{u,v} = 0$ . Using Schur complement,

$$\Theta_{u,v} = [\Sigma^{-1}]_{u,v} = \left[ (\Sigma_{\mathbf{a}} - \Sigma_{\mathbf{a}\mathbf{b}} \Sigma_{\mathbf{b}}^{-1} \Sigma_{\mathbf{a}\mathbf{b}}^{\top})^{-1} \right]_{12} = [\Lambda^{-1}]_{12} = 0. \quad (1)$$

Therefore, since  $\Lambda$  is symmetric,

$$\Lambda = \begin{bmatrix} \lambda_u & 0 \\ 0 & \lambda_v \end{bmatrix}, \quad (2)$$

and

$$p_{\mathbf{a}|\mathbf{b}}(\mathbf{r}|\mathbf{s}) = \frac{1}{2\pi} \frac{1}{\sqrt{\lambda_u \lambda_v}} \exp \left( -\frac{1}{2\lambda_u} (r_u - w_u)^2 - \frac{1}{2\lambda_v} (r_v - w_v)^2 \right) = p_{x_u|\mathbf{b}}(r_u|\mathbf{s}) p_{x_v|\mathbf{b}}(r_v|\mathbf{s}),$$

which implies that  $x_u$  and  $x_v$  are conditionally independent given  $\mathbf{b} = \mathbf{x}_{\mathcal{V} \setminus \{u,v\}}$ .

Now, prove that  $\Theta_{u,v} = 0$  if  $x_u$  and  $x_v$  are conditionally independent given  $\mathbf{b}$ . For any  $\mathbf{r} = (r_u, r_v)^{\top}$ , we have

$$(\det \Lambda)^{-\frac{1}{2}} \exp \left( -\frac{1}{2} (\mathbf{r} - \mathbf{w})^{\top} \Lambda^{-1} (\mathbf{r} - \mathbf{w}) \right) = \frac{1}{\sqrt{\lambda_u \lambda_v}} \exp \left( -\frac{1}{2\lambda_u} (r_u - w_u)^2 - \frac{1}{2\lambda_v} (r_v - w_v)^2 \right).$$

This implies that

$$\begin{aligned} \det \Lambda &= \lambda_u \lambda_v, \\ (\mathbf{r} - \mathbf{w})^{\top} \Lambda^{-1} (\mathbf{r} - \mathbf{w}) &= (\mathbf{r} - \mathbf{w})^{\top} \begin{bmatrix} \frac{1}{\lambda_u} & 0 \\ 0 & \frac{1}{\lambda_v} \end{bmatrix} (\mathbf{r} - \mathbf{w}), \end{aligned}$$

which shows that (2) and (1) are true.

(b) In graphical lasso, the objective function includes a term  $\log \det \Theta$ . Show that  $g(\Theta) := \log \det(\Theta)$  ( $\Theta \succ \mathbf{0}$ ) is a concave function.

Hint: A function  $g(\Theta)$  is concave if  $h(t) := g(\Theta + t\mathbf{V})$  is concave for all  $t$  and  $\mathbf{V}$  obeying  $\Theta + t\mathbf{V} \succ \mathbf{0}$ .

**Solution:** We have

$$\begin{aligned} h(t) &= \log \det(\Theta + t\mathbf{V}) \\ &= \log \det \left( \Theta^{\frac{1}{2}} \left( \mathbf{I} + t\Theta^{-\frac{1}{2}} \mathbf{V} \Theta^{-\frac{1}{2}} \right) \Theta^{\frac{1}{2}} \right) \\ &= \log \det \left( \mathbf{I} + t\Theta^{-\frac{1}{2}} \mathbf{V} \Theta^{-\frac{1}{2}} \right) + \log \det \Theta \\ &= \sum_{i=1}^n \log(1 + t\lambda_i) + \log \det \Theta, \end{aligned}$$

where  $\lambda_1, \dots, \lambda_n$  are the eigenvalues of  $\Theta^{-\frac{1}{2}} \mathbf{V} \Theta^{-\frac{1}{2}}$ .  $\Theta^{\frac{1}{2}}$  and  $\Theta^{-\frac{1}{2}}$  are well defined since  $\Theta \succ \mathbf{0}$ . It is shown that  $h''(t) \leq 0$ , because

$$h'(t) = \sum_{i=1}^n \frac{\lambda_i}{1 + t\lambda_i}, \quad h''(t) = -\sum_{i=1}^n \frac{\lambda_i^2}{(1 + t\lambda_i)^2}.$$

Thus,  $h(t)$  is concave in  $t$ .

## 2. Restricted isometry properties (30 points)

Recall that the restricted isometry constant  $\delta_s \geq 0$  of  $\mathbf{A}$  is the smallest constant such that

$$(1 - \delta_s)\|\mathbf{x}\|_2^2 \leq \|\mathbf{Ax}\|_2^2 \leq (1 + \delta_s)\|\mathbf{x}\|_2^2 \quad (3)$$

holds for all  $s$ -sparse vector  $\mathbf{x} \in \mathbb{R}^p$ .

(a) Show that

$$|\langle \mathbf{Ax}_1, \mathbf{Ax}_2 \rangle| \leq \delta_{s_1+s_2} \|\mathbf{x}_1\|_2 \|\mathbf{x}_2\|_2$$

for all pairs of  $\mathbf{x}_1$  and  $\mathbf{x}_2$  that are supported on disjoint subsets  $S_1, S_2 \subset \{1, \dots, n\}$  with  $|S_1| \leq s_1$  and  $|S_2| \leq s_2$ .

**Solution:** WLOG, assume  $\|\mathbf{x}_1\| = \|\mathbf{x}_2\| = 1$ . Since  $\mathbf{x}_1$  and  $\mathbf{x}_2$  have disjoint support, we get

$$\begin{aligned} |\langle \mathbf{Ax}_1, \mathbf{Ax}_2 \rangle| &= \frac{1}{4} \left| \|\mathbf{Ax}_1 + \mathbf{Ax}_2\|_2^2 - \|\mathbf{Ax}_1 - \mathbf{Ax}_2\|_2^2 \right| \\ &= \frac{1}{4} \left| \left\| \mathbf{A} \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix} \right\|^2 - \left\| \mathbf{A} \begin{bmatrix} \mathbf{x}_1 \\ -\mathbf{x}_2 \end{bmatrix} \right\|^2 \right| \\ &\leq \frac{1}{4} |2(1 + \delta_{s_1+s_2}) - 2(1 - \delta_{s_1+s_2})| \\ &\leq \delta_{s_1+s_2}. \end{aligned}$$

(b) For any  $\mathbf{u}$  and  $\mathbf{v}$ , show that

$$|\langle \mathbf{u}, (\mathbf{I} - \mathbf{A}^\top \mathbf{A})\mathbf{v} \rangle| \leq \delta_s \|\mathbf{u}\|_2 \cdot \|\mathbf{v}\|_2,$$

where  $s$  is the cardinality of  $\text{support}(\mathbf{u}) \cup \text{support}(\mathbf{v})$ .

**Solution:** Let  $\mathcal{S} = \text{support}(\mathbf{u}) \cup \text{support}(\mathbf{v})$ .

$$\begin{aligned} |\langle \mathbf{u}, (\mathbf{I} - \mathbf{A}^\top \mathbf{A})\mathbf{v} \rangle| &= |\langle \mathbf{u}, \mathbf{v} \rangle - \langle \mathbf{Au}, \mathbf{Av} \rangle| \\ &= |\langle \mathbf{u}_{\mathcal{S}}, \mathbf{v}_{\mathcal{S}} \rangle - \langle \mathbf{A}_{\mathcal{S}} \mathbf{u}_{\mathcal{S}}, \mathbf{A}_{\mathcal{S}} \mathbf{v}_{\mathcal{S}} \rangle| \\ &= |\langle \mathbf{u}_{\mathcal{S}}, (\mathbf{I} - \mathbf{A}_{\mathcal{S}}^\top \mathbf{A}_{\mathcal{S}}) \mathbf{v}_{\mathcal{S}} \rangle| \\ &\leq \|\mathbf{u}_{\mathcal{S}}\|_2 \|\mathbf{I} - \mathbf{A}_{\mathcal{S}}^\top \mathbf{A}_{\mathcal{S}}\|_{\text{op}} \|\mathbf{v}_{\mathcal{S}}\|_2, \end{aligned}$$

where  $\|\cdot\|_{\text{op}}$  denotes the operator norm of a matrix as

$$\|\mathbf{A}\|_{\text{op}} = \max_{\|\mathbf{x}\|_2=1} \|\mathbf{Ax}\|_2.$$

By the definition of the restricted isometry constant,

$$|\langle (\mathbf{A}_{\mathcal{S}}^\top \mathbf{A}_{\mathcal{S}} - \mathbf{I})\mathbf{x}, \mathbf{x} \rangle| = |\langle \mathbf{A}_{\mathcal{S}} \mathbf{x}, \mathbf{A}_{\mathcal{S}} \mathbf{x} \rangle - \langle \mathbf{x}, \mathbf{x} \rangle| = |\|\mathbf{A}_{\mathcal{S}} \mathbf{x}\|_2^2 - \|\mathbf{x}\|_2^2| \leq \delta_s \|\mathbf{x}\|_2^2.$$

Therefore,

$$\|\mathbf{I} - \mathbf{A}_{\mathcal{S}}^\top \mathbf{A}_{\mathcal{S}}\|_{\text{op}} \leq \delta_s$$

and

$$|\langle \mathbf{u}, (\mathbf{I} - \mathbf{A}^\top \mathbf{A}) \mathbf{v} \rangle| \leq \delta_s \|\mathbf{u}_S\|_2 \|\mathbf{v}_S\|_2 = \delta_s \|\mathbf{u}\|_2 \|\mathbf{v}\|_2.$$

(c) Suppose that each column of  $\mathbf{A}$  has unit norm. Show that  $\delta_2 = \mu(\mathbf{A})$ , where  $\mu(\mathbf{A})$  is the mutual coherence of  $\mathbf{A}$ .

**Solution:** Given that

$$|\langle (\mathbf{A}_S^\top \mathbf{A}_S - \mathbf{I}) \mathbf{x}, \mathbf{x} \rangle| = |\langle \mathbf{A}_S \mathbf{x}, \mathbf{A}_S \mathbf{x} \rangle - \langle \mathbf{x}, \mathbf{x} \rangle| = ||\mathbf{A}_S \mathbf{x}\|^2 - \|\mathbf{x}\|^2 \leq \delta_s \|\mathbf{x}\|^2,$$

$\delta_s$  is the same as

$$\delta_s = \max_{|S| \leq s} \|\mathbf{A}_S^\top \mathbf{A}_S - \mathbf{I}\|_{\text{op}}.$$

When  $s = 2$ ,

$$\delta_2 = \max_{i \neq j} \left\| \begin{bmatrix} \mathbf{a}_i & \mathbf{a}_j \end{bmatrix}^\top \begin{bmatrix} \mathbf{a}_i & \mathbf{a}_j \end{bmatrix} - \mathbf{I} \right\|_{\text{op}}.$$

The eigenvalues of the following matrix

$$\begin{bmatrix} \mathbf{a}_i & \mathbf{a}_j \end{bmatrix}^\top \begin{bmatrix} \mathbf{a}_i & \mathbf{a}_j \end{bmatrix} - \mathbf{I} = \begin{bmatrix} 1 & \langle \mathbf{a}_i, \mathbf{a}_j \rangle \\ \langle \mathbf{a}_i, \mathbf{a}_j \rangle & 1 \end{bmatrix} - \mathbf{I} = \begin{bmatrix} 0 & \langle \mathbf{a}_i, \mathbf{a}_j \rangle \\ \langle \mathbf{a}_i, \mathbf{a}_j \rangle & 0 \end{bmatrix}$$

are  $\pm \langle \mathbf{a}_i, \mathbf{a}_j \rangle$ , and accordingly

$$\delta_2 = \max_{i \neq j} |\langle \mathbf{a}_i, \mathbf{a}_j \rangle| = \mu(\mathbf{A}).$$

**3. Statistical dimension (10 points)** Recall that for any convex cone  $\mathcal{K}$ , its statistical dimension and Gaussian width are defined respectively as

$$\text{stat-dim}(\mathcal{K}) := \mathbb{E}[\|\mathcal{P}_{\mathcal{K}}(\mathbf{g})\|_2^2]$$

and

$$w(\mathcal{K}) := \mathbb{E} \left[ \sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2=1} \langle \mathbf{z}, \mathbf{g} \rangle \right],$$

where  $\mathbf{g} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$  and  $\mathcal{P}_{\mathcal{K}}$  denotes the projection to  $\mathcal{K}$  as

$$\mathcal{P}_{\mathcal{K}}(\mathbf{g}) = \arg \min_{\mathbf{z} \in \mathcal{K}} \|\mathbf{g} - \mathbf{z}\|_2.$$

(a) Prove that  $w^2(\mathcal{K}) \leq \text{stat-dim}(\mathcal{K})$ .

**Solution:**

$$w^2(\mathcal{K}) = \left( \mathbb{E} \left[ \sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2=1} \langle \mathbf{z}, \mathbf{g} \rangle \right] \right)^2 \tag{4}$$

$$\leq \left( \mathbb{E} \left[ \sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 \leq 1} \langle \mathbf{z}, \mathbf{g} \rangle \right] \right)^2 \tag{5}$$

$$\leq \mathbb{E} \left[ \left( \sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 \leq 1} \langle \mathbf{z}, \mathbf{g} \rangle \right)^2 \right], \tag{6}$$

where (5) holds because  $\{\mathbf{z} : \mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 = 1\} \subset \{\mathbf{z} : \mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 \leq 1\}$ , and (6) holds by Jensen's inequality. Further, the statistical dimension can be represented as

$$\text{stat-dim}(\mathcal{K}) = \mathbb{E} \left[ \left( \sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 \leq 1} \langle \mathbf{z}, \mathbf{g} \rangle \right)^2 \right],$$

since

$$\sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 \leq 1} \langle \mathbf{z}, \mathbf{g} \rangle = \sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 \leq 1} \langle \mathbf{z}, \mathcal{P}_{\mathcal{K}}(\mathbf{g}) + \mathcal{P}_{\mathcal{K}^\circ}(\mathbf{g}) \rangle \leq \sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 \leq 1} \langle \mathbf{z}, \mathcal{P}_{\mathcal{K}}(\mathbf{g}) \rangle = \left\langle \frac{\mathcal{P}_{\mathcal{K}}(\mathbf{g})}{\|\mathcal{P}_{\mathcal{K}}(\mathbf{g})\|_2}, \mathcal{P}_{\mathcal{K}}(\mathbf{g}) \right\rangle = \|\mathcal{P}_{\mathcal{K}}(\mathbf{g})\|_2,$$

where

$$\mathcal{K}^\circ = \{\mathbf{u} : \langle \mathbf{u}, \mathbf{x} \rangle \leq 0 \quad \forall \mathbf{x} \in \mathcal{K}\}, \quad \mathbf{g} = \mathcal{P}_{\mathcal{K}}(\mathbf{g}) + \mathcal{P}_{\mathcal{K}^\circ}(\mathbf{g}), \quad \langle \mathcal{P}_{\mathcal{K}}(\mathbf{g}), \mathcal{P}_{\mathcal{K}^\circ}(\mathbf{g}) \rangle = 0,$$

and

$$\sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\| \leq 1} \langle \mathbf{z}, \mathbf{g} \rangle \geq \left\langle \frac{\mathcal{P}_{\mathcal{K}}(\mathbf{g})}{\|\mathcal{P}_{\mathcal{K}}(\mathbf{g})\|_2}, \mathbf{g} \right\rangle = \|\mathcal{P}_{\mathcal{K}}(\mathbf{g})\|_2.$$

Therefore,  $w^2(\mathcal{K}) \leq \text{stat-dim}(\mathcal{K})$ .

(b) (Optional (10 bonus points)) Prove the reverse inequality  $\text{stat-dim}(\mathcal{K}) \leq w^2(\mathcal{K}) + 1$ .  
*hint:* Let  $f(\cdot)$  be a function that is Lipschitz with respect to the Euclidean norm:

$$|f(\mathbf{u}) - f(\mathbf{v})| \leq M \|\mathbf{u} - \mathbf{v}\|_2 \quad \forall \mathbf{u}, \mathbf{v}.$$

Then,  $\text{Var}(f(\mathbf{g})) \leq M^2$ .

**Solution:** It was shown before that

$$\text{stat-dim}(\mathcal{K}) = \mathbb{E} \left[ \left( \sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 \leq 1} \langle \mathbf{z}, \mathbf{g} \rangle \right)^2 \right],$$

and it is enough to show that

$$\mathbb{E} \left[ \left( \sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 \leq 1} \langle \mathbf{z}, \mathbf{g} \rangle \right)^2 \right] \leq w^2(\mathcal{K}) + 1.$$

For any  $\mathbf{g} \notin \mathcal{K}^\circ$ , we have

$$\sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 \leq 1} \langle \mathbf{z}, \mathbf{g} \rangle = \sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 = 1} \langle \mathbf{z}, \mathbf{g} \rangle.$$

Also, if  $\mathbf{g} \in \mathcal{K}^\circ$ , then

$$\sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 \leq 1} \langle \mathbf{z}, \mathbf{g} \rangle = \langle \mathbf{0}, \mathbf{g} \rangle = 0,$$

because  $\langle \mathbf{z}, \mathbf{g} \rangle \leq 0$  for all  $\mathbf{z} \neq \mathbf{0}, \mathbf{z} \in \mathcal{K}$ . Therefore,

$$\left( \sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 \leq 1} \langle \mathbf{z}, \mathbf{g} \rangle \right)^2 = \left( \sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 = 1} \langle \mathbf{z}, \mathbf{g} \rangle \right)^2 \mathbf{1}\{\mathbf{g} \notin \mathcal{K}^\circ\},$$

$$\mathbb{E} \left[ \left( \sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 \leq 1} \langle \mathbf{z}, \mathbf{g} \rangle \right)^2 \right] \leq \mathbb{E} [f^2(\mathbf{g})],$$

where  $f(\cdot)$  defined as

$$f(\mathbf{g}) = \sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|_2 = 1} \langle \mathbf{z}, \mathbf{g} \rangle.$$

This function  $f(\cdot)$  is 1-Lipschitz function because

$$\begin{aligned} |f(\mathbf{u})| &\leq \|\mathbf{u}\|_2 \quad \forall \mathbf{u}, \\ |f(\mathbf{u}) - f(\mathbf{v})| &\leq \|\mathbf{u}\|_2 - \|\mathbf{v}\|_2 \leq \|\mathbf{u} - \mathbf{v}\|_2 \quad \forall \mathbf{u}, \mathbf{v}. \end{aligned}$$

Using the hint,

$$\mathbb{E} [f^2(\mathbf{g})] - w^2(\mathcal{K}) = \text{Var}(f(\mathbf{g})) \leq 1.$$

Thus, we have proven  $\text{stat-dim}(\mathcal{K}) \leq w^2(\mathcal{K}) + 1$ .