Topic 16: Graphical Network Inference

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Key points:

Disclaimer: *The note is built on Prof. Jinchi Lv's lectures of the course at USC, DSO 607, High-Dimensional Statistics and Big Data Problems.*

16.1 Motivation

Consider a classic question: For n observations of dimension p, how can we capture the statistical relationships between the variables of interest? Consider the example of the multivariate Gaussian distribution:

> **Example 16.1.1: Multivariate Gaussian Distribution**
>
> Suppose we have n observations of dimension p, $\mathbf{x} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$. let $\mathbf{S}$ be the empirical covariance matrix. Then the probability density
>
> $$f(\mathbf{x}) = \frac{1}{(2\pi)^{p/2} \det(\boldsymbol{\Sigma})^{1/2}} \exp\left\{-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right\}$$
>
> define the **inverse covariance matrix** or **precision matrix** as $\boldsymbol{\Omega} = \boldsymbol{\Sigma}^{-1}$, then we have
>
> $$f_{\mu,\Omega} = \exp\left\{\boldsymbol{\mu}'\boldsymbol{\Omega}x - \left\langle \boldsymbol{\Omega}, \frac{1}{2}\mathbf{x}\mathbf{x}'\right\rangle - \frac{p}{2}\log(2\pi) + \frac{1}{2}\log\det(\boldsymbol{\Omega}) - \frac{1}{2}\boldsymbol{\mu}'\boldsymbol{\Omega}\boldsymbol{\mu}\right\}$$
>
> where $\langle \mathbf{A}, \mathbf{B} \rangle = \mathrm{tr}(\mathbf{A}\mathbf{B})$.

In this example, we know that **every** multivariate Gaussian distribution can be represented by a pairwise **Gaussian Markov Random Field (GMRF)**, which an **undirected graph** $G = (V, E)$

- representing the collection of variables $\mathbf{x}$ by a vertex set $\mathcal{V} = \{1, \cdots, p\}$
- encoding correlations between variables by a set of edges $\mathcal{E} = \{(i, j) \in \mathcal{V} \mid i = \neq j, \Omega_{ij} \neq 0\}$

For simplicity, we normalize $\boldsymbol{\mu} = \mathbf{0}$. If we draw n i.i.d. samples $\mathbf{x}_1, \cdots, \mathbf{x}_n \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma})$, then the log-likelihood is

$$\mathcal{L}(\boldsymbol{\Omega}) = \frac{1}{n}\sum_{i=1}^{n} \log f(\mathbf{x}_i) = \frac{1}{2}\log\det(\boldsymbol{\Omega}) - \frac{1}{2n}\sum_{i=1}^{n} \mathbf{x}_1' \boldsymbol{\Theta} \mathbf{x}_i$$

$$= \frac{1}{2}\log\det(\boldsymbol{\Omega}) - \frac{1}{2}\left\langle \boldsymbol{\Omega}, \frac{1}{n}\sum_{i=1}^{n} \mathbf{x}_i'\mathbf{x}_i\right\rangle$$

What's the goal?   We want to estimate a **sparse** graph structure given $n \ll p$ i.i.d. observations. But what does sparsity means in this context? A sparse graph is **equivalent** to a sparse precision matrix: the precision

matrix should have many 0s.

Sparse precision matrix   for the Gaussian vector mentioned above $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma})$, we have $\forall u, v$

$$x_u \perp x_v \mid \mathbf{x}_{\mathcal{V} \setminus \{u,v\}} \Leftrightarrow \Omega_{u,v} = 0$$

that is, sparsity of the precision matrix is equivalent to **conditional independence**[1]. Consider a graph, where x_1 and x_4 are only connected through other nodes, that is x_1 and x_4 are conditional independent, then we can have the precision matrix be something like:

$$\mathbf{\Theta} = \begin{bmatrix} * & * & 0 & 0 & * & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 & * & * & 0 \\ 0 & 0 & * & 0 & * & 0 & 0 & * \\ 0 & 0 & 0 & * & 0 & 0 & * & 0 \\ * & 0 & * & 0 & * & 0 & 0 & * \\ 0 & * & 0 & 0 & 0 & * & 0 & 0 \\ 0 & * & 0 & * & 0 & 0 & * & 0 \\ 0 & 0 & * & 0 & * & 0 & 0 & * \end{bmatrix}$$

where 0 captures precisely the conditional independence.
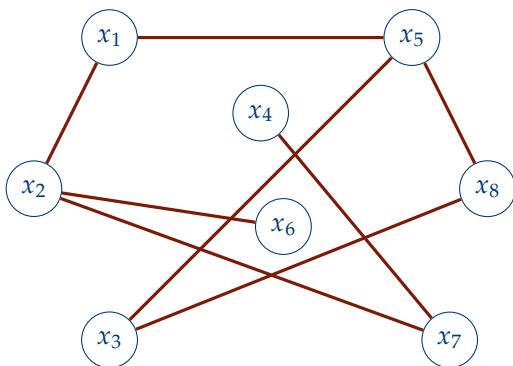
x_1 and x_4 **are** *connected* x_1 and x_4 **are** *NOT connected*, **conditionally**

Intuitively, a sparse graph is much simpler, which is why conditional independence is desired. So how to achieve sparsity? We can again use a L-1 regularization when maximizing the log-likelihood $\mathcal{L}(\mathbf{\Omega})$. Denote the sample covariance matrix as $\mathbf{S} = \frac{1}{n} \sum_{i=1}^{n} \mathbf{x}_i \mathbf{x}_i'$, then the problem becomes the so-called **Graphical Lasso**

$$\max_{\mathbf{\Omega} \geq 0} \log \det(\mathbf{\Omega}) - \text{tr}(\mathbf{S}\mathbf{\Omega}) - \rho \, \|\mathbf{\Omega}\|_1$$

which is equivalent to

$$\min_{\mathbf{\Omega} \geq 0} -\log \det(\mathbf{\Omega}) + \text{tr}(\mathbf{S}\mathbf{\Omega}) + \rho \, \|\mathbf{\Omega}\|_1$$

16.2   Graphical Lasso

The graphical lasso method is developed by (Friedman et al., 2008). For the optimization problem

$$\min_{\mathbf{\Omega} \geq 0} -\log \det(\mathbf{\Omega}) + \text{tr}(\mathbf{S}\mathbf{\Omega}) + \rho \, \|\mathbf{\Omega}\|_1 \tag{16.1}$$

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[1]Meanwhile, for independence: $\Sigma_{u,v} = 0 \Leftrightarrow x_u \perp x_v$

The first-order optimality condition gives

$$0 \in \Omega^{-1} - S - \lambda \Gamma$$

where Γ is a matrix of component-wise signs of Ω

$$\Gamma = \partial \|\Omega\|_1 \Rightarrow \gamma_{jk} \begin{cases} = \text{sign}(\omega_{jk}), & \omega_{jk} \neq 0 \\ \in [-1, 1], & \omega_{jk} = 0 \end{cases}$$

since in a graph, we always have that, following the global stationarity conditions, $\omega_{jj} > 0$, which implies that

$$w_{ii} = s_{ii} + \lambda \qquad\qquad\qquad i = 1, \cdots, p \qquad\qquad (16.2)$$

where we denote a working version of Ω^{-1} as W.

The idea is to repeatedly cycle through all columns-rows and in each step optimize only a single column-row. Consider the following partition where all matrices are partitioned into one column/row versus the rest

$$\Omega = \begin{pmatrix} \Omega_{11} & \omega_{12} \\ \omega'_{12} & \omega_{22} \end{pmatrix} \qquad S = \begin{pmatrix} S_{11} & s_{12} \\ s'_{12} & s_{22} \end{pmatrix} \qquad W = \begin{pmatrix} W_{11} & w_{12} \\ w'_{12} & w_{22} \end{pmatrix} \qquad \Gamma = \begin{pmatrix} \Gamma_{11} & \gamma_{12} \\ \gamma'_{12} & \gamma_{22} \end{pmatrix}$$

apply this partition to the optimality condition, get

$$\Omega^{-1} = S - \lambda \Gamma$$

$$\begin{pmatrix} W_{11} & w_{12} \\ w'_{12} & w_{22} \end{pmatrix} = \begin{pmatrix} S_{11} & s_{12} \\ s'_{12} & s_{22} \end{pmatrix} + \lambda \begin{pmatrix} \Gamma_{11} & \gamma_{12} \\ \gamma'_{12} & \gamma_{22} \end{pmatrix}$$

where Ω_{11} is $(p-1) \times (p-1)$, ω_{12} is $(p-1) \times 1$, ω_{22} is a scalar.

Consider a **blockwise** step: suppose we fix all but the last row/column, then using properties of inverses of block-partitioned matrices, we have

$$\begin{pmatrix} W_{11} & w_{12} \\ w'_{12} & w_{22} \end{pmatrix} = \begin{pmatrix} \left(\Omega_{11} - \frac{\omega_{12}\omega'_{12}}{\omega_{22}}\right)^{-1} & -W_{11}\frac{\omega_{12}}{\omega_{22}} \\ & \frac{1}{\omega_{22}} - \frac{\omega'_{12}W_{11}\omega_{12}}{\omega_{22}^2} \end{pmatrix}$$

$$= \begin{pmatrix} \Omega_{11}^{-1} + \frac{\Omega_{11}^{-1}\omega_{12}\omega'_{12}\Omega_{11}^{-1}}{\omega_{22} - \omega'_{12}\Omega_{11}^{-1}\omega_{12}} & -\frac{\Omega_{11}^{-1}\omega_{12}}{\omega_{22} - \omega'_{12}\Omega_{11}^{-1}\omega_{12}} \\ & \frac{1}{\omega_{22} - \omega'_{12}\Omega_{11}^{-1}\omega_{12}} \end{pmatrix}$$

then, by the partitioned optimality condition, we have[2]:

$$0 = -w_{12} + s_{12} + \lambda\gamma_{12} = W_{11}\frac{\omega_{12}}{\omega_{22}} + s_{12} + \lambda\gamma_{12} \qquad\qquad (16.3)$$

$$0 = \frac{\Omega_{11}^{-1}\omega_{12}}{\omega_{22} - \omega'_{12}\Omega_{11}^{-1}\omega_{12}} + s_{12} + \lambda\gamma_{12} = w_{22}\Omega_{11}^{-1}\omega_{12} + s_{12} + \lambda\gamma_{12} \qquad\qquad (16.4)$$

The graphic Lasso algorithm them solves Eq.16.3 for $\beta = \omega_{12}/\omega_{12}$, that is

$$W_{11}\beta + s_{12} + \lambda\gamma_{12} = 0$$

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[2]For Eq.16.4, by Eq.16.2, we know that $w_{22} = s_{22} + \lambda$, which is fixed.

where $\boldsymbol{\gamma}_{12} \in \text{sign}(\boldsymbol{\beta})$ since $\omega_{22} > 0$, which is essentially solving:

$$\min_{\boldsymbol{\beta} \in \mathbb{R}^{p-1}} \left\{ \frac{1}{2} \boldsymbol{\beta}' \mathbf{W}_{11} \boldsymbol{\beta} + \boldsymbol{\beta}' \mathbf{s}_{12} + \lambda \left\| \boldsymbol{\beta} \right\|_1 \right\}$$

and $\mathbf{W}_{11} > 0$ is assumed to be fixed.

This problem is analogous to a lasso regression problem of the **last variable** on **the rest**, but the cross-product matrix $\mathbf{S}_{11}$ is replaced by its **current estimation** $\mathbf{W}_{11}$. It is relatively easier to solve using elementwise coordinate descent, then

$$\mathbf{w}_{12} = -\mathbf{W}_{11} \frac{\boldsymbol{\omega}_{12}}{\omega_{22}} \qquad\qquad\qquad \Rightarrow \hat{\mathbf{w}}_{12} = -\mathbf{W}_{11} \hat{\boldsymbol{\beta}} \qquad\qquad \text{Step 1}$$

$$w_{22} = \frac{1}{\omega_{22}} - \frac{\boldsymbol{\omega}_{12}' \mathbf{W}_{11} \boldsymbol{\omega}_{12}}{\omega_{22}^2} \qquad\qquad \Rightarrow \frac{1}{\hat{\omega}_{22}} = w_{22} - \hat{\boldsymbol{\beta}}' \hat{\mathbf{w}}_{12} \qquad\qquad \text{Step 2}$$

$$\boldsymbol{\omega}_{12} = -\mathbf{W}_{11}^{-1} \mathbf{w}_{12} \omega_{22} \qquad\qquad \Rightarrow \hat{\boldsymbol{\omega}}_{12} = -\mathbf{W}_{11}^{-1} \hat{\mathbf{w}}_{12} \hat{\omega}_{22} \qquad\qquad \text{Step 3}$$

notice that after solving for $\boldsymbol{\beta}$ and updating $\mathbf{w}_{12}$ in Step 1, the graphic Lasso procedure can move onto the next block, that is, only Step 1 is used in the loop, Step 2 and 3 can be done at the end. The algorithm can be summarized as:

Algorithm 16.2.1: Graphical Lasso algorithm

1 Initialize $\mathbf{W} = \mathbf{S} + \lambda \mathbf{I}$
- Cycle around the columns repeatedly, performing the following steps till convergence:
  a rearrange the rows/columns so that the target column is **the last** (implicitly)
  b solve the lasso problem, starting the solution from the previous round for this column
  c update the row/column (***off-diagonal***) of the covariance using $\hat{\mathbf{w}}_{12}$
  d save $\hat{\boldsymbol{\beta}}$ for this column in the matrix $\mathbf{B}$
3 after convergence, for every row/column, compute the diagonal entries $\hat{\omega}_{jj}$, and covert the $\mathbf{B}$ matrix to $\boldsymbol{\Omega}$

16.3   What Is GLasso Solving?

Again, consider the optimization problem

$$\min_{\boldsymbol{\Omega} \geq 0} -\log \det(\boldsymbol{\Omega}) + \text{tr}(\mathbf{S}\boldsymbol{\Omega}) + \rho \left\| \boldsymbol{\Omega} \right\|_1$$

and its stationarity condition

$$0 = \boldsymbol{\Omega}^{-1} - \mathbf{S} - \lambda \boldsymbol{\Gamma}$$

rewrite the stationarity condition

$$0 = \boldsymbol{\Omega}^{-1} - \mathbf{S} - \lambda \boldsymbol{\Gamma} = \boldsymbol{\Omega} - (\mathbf{S} + \lambda \boldsymbol{\Gamma})^{-1}$$

since $\boldsymbol{\Gamma} = \text{sign}(\boldsymbol{\Omega})$, write $\tilde{\boldsymbol{\Gamma}} = \lambda \boldsymbol{\Gamma}$, we have $\left\| \tilde{\boldsymbol{\Gamma}} \right\|_\infty \leq \lambda$. Denote the element-wise absolute value matrix of $\boldsymbol{\Omega}$ as $\text{abs}(\boldsymbol{\Omega})$, then let $\tilde{\boldsymbol{\Gamma}} = \lambda \boldsymbol{\Gamma}$, $\mathbf{P} = \text{abs}(\boldsymbol{\Omega})$, we have

$$0 = \boldsymbol{\Omega} - (\mathbf{S} + \lambda \boldsymbol{\Gamma})^{-1}$$
$$= \mathbf{P} \circ \text{sign}(\tilde{\boldsymbol{\Gamma}}) - (\mathbf{S} + \tilde{\boldsymbol{\Gamma}})^{-1}$$

and mechanically, we also have

$$\mathbf{P} \circ \left(\text{abs}(\tilde{\boldsymbol{\Gamma}}) - \lambda \mathbf{1}_p \mathbf{1}_p' \right) = \mathbf{0}$$

$$\left\| \tilde{\boldsymbol{\Gamma}} \right\|_\infty \leq \lambda$$

together, these are just hte KKT optimality condition for the following box-constrained SDP

$$\max_{\tilde{\boldsymbol{\Gamma}}: \left\| \tilde{\boldsymbol{\Gamma}} \right\|_\infty \leq \lambda} g(\tilde{\boldsymbol{\Gamma}}) := \log \det(\mathbf{S} + \tilde{\boldsymbol{\Gamma}}) + p \tag{16.5}$$

with the transformation $\mathbf{S} + \tilde{\boldsymbol{\Gamma}} = \boldsymbol{\Omega}^{-1}$. Essentially, this is the dual problem of the initial optimization problem, both of them are solved by the GLasso algorithm.

Issues of GLasso method :

- the non-monotonic behavior of Glasso in minimizing $f(\boldsymbol{\Omega})$
    - $\boldsymbol{\theta}_{12}$ is entangled in $\mathbf{W}_{11}$, which is *incorrectly* treated as a constant
    - after updating $\boldsymbol{\theta}_{12}$, the entire (working) covariance matrix $\mathbf{W}$ changes, but Glasso algorithm only updates $\mathbf{w}_{12}$ and $\mathbf{w}_{12}'$
- high dimesnionality problems
    - not computationally efficient when p is ultra-large
    - $\boldsymbol{\Sigma}^{-1}$ doesn't exist when $p > n$
    - method is not scalable

Next, we address these issues by introducing some modifications.

16.4 Graphical Lasso: Modifications

16.4.1 Primal GLasso

Consider the optimality condition in Eq.16.4:

$$0 = \frac{\boldsymbol{\Omega}_{11}^{-1} \boldsymbol{\omega}_{12}}{\omega_{22} - \boldsymbol{\omega}_{12}' \boldsymbol{\Omega}_{11}^{-1} \boldsymbol{\omega}_{12}} + \mathbf{s}_{12} + \lambda \boldsymbol{\gamma}_{12} = w_{22} \boldsymbol{\Omega}_{11}^{-1} \boldsymbol{\omega}_{12} + \mathbf{s}_{12} + \lambda \boldsymbol{\gamma}_{12}$$

Here, the dependence of the covariance submatrix $\mathbf{W}_{11}$ on $\boldsymbol{\Omega}_{12}$ is *explicit*. Let $\boldsymbol{\alpha} = \boldsymbol{\omega}_{12} w_{22}$ with fixed $w_{22} \geq 0$[3], then this optimality condition is essentially solving

$$\min_{\boldsymbol{\alpha} \in \mathbb{R}^{p-1}} \left\{ \frac{1}{2} \boldsymbol{\alpha}' \boldsymbol{\Omega}_{11}^{-1} \boldsymbol{\alpha} + \boldsymbol{\alpha}' \mathbf{s}_{12} + \lambda \left\| \boldsymbol{\alpha} \right\|_1 \right\}$$

the minimizer of this problem $\hat{\boldsymbol{\alpha}}$ can then be used to derive the estimation for $\boldsymbol{\omega}_{12}$:

$$\hat{\boldsymbol{\omega}}_{12} = \frac{\hat{\boldsymbol{\alpha}}}{w_{22}}$$

, then we can update ω_{22} as before via

$$\hat{\omega}_{22} = \frac{1}{w_{22}} + \hat{\boldsymbol{\omega}}_{12}' \boldsymbol{\Theta}_{11}^{-1} \hat{\boldsymbol{\omega}}_{12}$$

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[3]$w_{22} = 1/(\omega_2 2 - \boldsymbol{\omega}_{12}' \boldsymbol{\Omega}_{11}^{-1} \boldsymbol{\omega}_{12})$

with $w_{22} = s_{22} + \lambda$. Another problem is how to obtain $\mathbf{\Omega}_{11}^{-1}$: as the iterations proceed, maintain $\mathbf{W} = \mathbf{\Omega}^{-1}$, and $\mathbf{\Omega}_{11}^{-1}$ can be derived from

$$\mathbf{\Omega}_{11}^{-1} = \mathbf{W}_{11} - \frac{\mathbf{w}_{12}\mathbf{w}_{12}'}{w_{22}}$$

once ω_{12} is updated, the *entire* working covariance matrix $\mathbf{W}$ is updated using $\mathbf{\Omega}_{11}^{-1}$. This procedure, the so-called primal graphical lasso, can be represented in the following algorithm:

Algorithm 16.4.1: P-GLasso Algorithm

1 Initialize $\mathbf{W} = \mathrm{diag}(\mathbf{S}) + \lambda\mathbf{I}$ and $\mathbf{\Omega} = \mathbf{W}^{-1}$

2 Cycle around the columns repeatedly, performing the following steps till convergence:

   a rearrange the rows/columns so that the target column is the last (implicitly)

   b compute $\mathbf{\Omega}_{11}^{-1}$ using $\mathbf{\Omega}_{11}^{-1} = \mathbf{W}_{11} - \frac{\mathbf{w}_{12}\mathbf{w}_{12}'}{w_{22}}$

   c solve $\min_{\alpha \in \mathbb{R}^{p-1}} \left\{ \frac{1}{2}\alpha'\mathbf{\Omega}_{11}^{-1}\alpha + \alpha'\mathbf{s}_{12} + \lambda\,\|\alpha\|_1 \right\}$ for α, using as warm starts the solution from the previous round of row/column updates. Then update $\hat{\omega}_{12} = \hat{\alpha}/w_{22}$ and $\hat{\omega}_{22}$

   d update $\mathbf{\Omega}$ and $\mathbf{W}$, ensuring that $\mathbf{\Omega}\mathbf{W} = \mathbf{I}_p$

3 output the solution: precision matrix $\mathbf{\Omega}$ and its exact inverse, covariance matrix $\mathbf{W}$

16.4.2 Innovated Scalable Efficient Estimation

Now, we try to tackle the high-dimesnionality issues: $\mathbf{\Sigma}^{-1}$ does **not** exist when $p > n$. Again,

$$\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma})$$

consider a linear transformation where $\tilde{\mathbf{x}} = \mathbf{\Omega}\mathbf{x}$ ($\mathbf{\Omega}$ is still the precision matrix $\mathbf{\Sigma}^{-1}$), and

$$\mathrm{cov}(\tilde{\mathbf{x}}) = \mathbf{\Omega}\mathrm{cov}(\mathbf{x})\mathbf{\Omega} = \mathbf{\Omega}\mathbf{\Sigma}\mathbf{\Omega} = \mathbf{\Omega}$$

But $\mathbf{\Omega}$ is unknown and to be estimated. To get around this, we **break** the long vector $\tilde{\mathbf{x}}$ into small sub-vectors and then estimate each one.

Notation   for subsets $A, B \subset \{1, \cdots, p\}$, let $\mathbf{x}_A$ denote a sub-vector of $\mathbf{x}$ formed by its components with indices in A, and the sub-(precision)-matrix is $\mathbf{\Omega}_{A,B} = \left(\omega_{jk}\right)_{j \in A, k \in B}$, $\mathbf{\Omega}_A := \mathbf{\Omega}_{A,A}$ for simplicity. Then define

$$\tilde{\mathbf{x}}_A = \mathbf{\Omega}_A \eta_A$$

where $\eta_A = \mathbf{x}_A + \mathbf{\Omega}_A^{-1}\mathbf{\Omega}_{A,A^C}\mathbf{x}_{A^C}$, and $A^C := \{1, \cdots, p\} \setminus A$. With this definition, we have the following proposition:

Proposition 16.4.2: Conditional Distribution of Sub-vectors

Conditional distribution $\mathbf{x}_A \mid \mathbf{x}_B \sim \mathcal{N}\left(\mu_{A|B}, \mathbf{\Sigma}_{A|B}\right)$, where

$$\mu_{A|B} = \mu_A + \mathbf{\Sigma}_{A,B}\mathbf{\Sigma}_B^{-1}\left(\mathbf{x}_B - \mu_B\right)$$
$$\mathbf{\Sigma}_{A|B} = \mathbf{\Sigma}_A - \mathbf{\Sigma}_{A,B}\mathbf{\Sigma}_B^{-1}\mathbf{\Sigma}_{B,A}$$

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and when $\mathbf{x}_B = \mathbf{x}_{A^C}$, we have

$$\mathbf{x}_A \mid \mathbf{x}_{A^C} \sim \mathcal{N}\left(-\Omega_A^{-1}\Omega_{A,A^C}\mathbf{x}_{A^C}, \Omega_A^{-1}\right)$$

Prop.16.4.2 gives a multivariate linear regression model:

$$\mathbf{x}_A = \mathbf{C}_A'\mathbf{x}_{A^C} + \boldsymbol{\eta}_A$$

where $\mathbf{C}_A = -\Omega_{A^C,A}\Omega_A^{-1}$ is the coefficient matrix, and $\boldsymbol{\eta}_A$ is model errors with Gaussian distribution $\mathcal{N}(\mathbf{0}, \Omega_A^{-1})$. Then we can have the following algorithm to solve this problem:

> **Algorithm 16.4.3: ISEE Algorithm**
>
> 1 Let $(A_l)_{l=1}^L$ be a partition of index set $\{1, \cdots, p\}$, s.t. $\bigcup_{l=1}^L A_l = \{1, \cdots, p\}$
> 2 estimate $\boldsymbol{\eta}_{A_l}$ and then obtain estimated $\tilde{\mathbf{x}}_{A_l}$
> 3 stack all estimated sub-vectors $\tilde{\mathbf{x}}_{A_l}$ together to obtain $\tilde{\mathbf{x}}$

ISEE algorithm breaks large-scale precision estimation into **small-scale linear regression problems**, each of which is computationally efficient and effective.

Estimation   for the $n \times p$ data matrix $\mathbf{X} = (\mathbf{x}_1, \cdots, \mathbf{x}_n)'$, we construct the linear transformation

$$\tilde{\mathbf{X}} = (\tilde{\mathbf{x}}_1, \cdots, \tilde{\mathbf{x}}_n) = \mathbf{X}\Omega$$

then the multivariate linear regression model by matrix notation is

$$\mathbf{X}_A = \mathbf{X}_{A^C}\mathbf{C}_A + \mathbf{E}_A$$

and the corresponding sub-matrix $\tilde{\mathbf{X}}_A$ can be written as

$$\tilde{\mathbf{X}}_A = (\mathbf{X}\Omega)_A = \mathbf{X}_A\Omega_A + \mathbf{X}_{A^C}\Omega_{A^C,A} = \left(\mathbf{X}_A + \mathbf{X}_{A^C}\Omega_{A^C,A}\Omega_A^{-1}\right)\Omega_A = \mathbf{E}_A\Omega_A$$

Sparsity is achieved bia scaled Lasso: for each node j in index set A,

$$\mathbf{X}_j = \mathbf{A}^C\boldsymbol{\beta}_j + \mathbf{E}_j$$

where $\boldsymbol{\beta}_j$ is the column of $\mathbf{C}_A$ corresponds to node j. The estimation is then done in the following steps:

- run the PLS

$$\left(\hat{\boldsymbol{\beta}}_j, \hat{\theta}_j^{1/2}\right) = \arg\min_{\boldsymbol{\beta}\in\mathbf{R}^{p-|A|}, \sigma\geq 0} \left\{ \frac{\|\mathbf{X}_j - \mathbf{X}_{A^C}\boldsymbol{\beta}\|_2^2}{2n\sigma} + \frac{\sigma}{2} + \lambda \|\boldsymbol{\beta}_*\|_1 \right\}$$

  where $\boldsymbol{\beta}_*$ is component-wise product of $\boldsymbol{\beta}$ and $\left(\frac{1}{\sqrt{n}}\|\mathbf{X}_k\|_2\right)_{k\in A^C}$, and the penalizing factor is $\lambda = C\left(\frac{2\log p}{n}\right)$.

- after obtaining $\hat{\boldsymbol{\beta}}_j$, get the estimation of the precision matrix $\hat{\Omega}_A$

$$\hat{\Omega}_A = \left(\frac{1}{n}\hat{\mathbf{E}}_A'\hat{\mathbf{E}}_A\right)^{-1}$$

where $\hat{\mathbf{E}}_j = \mathbf{X}_j - \mathbf{X}_{A^C}\hat{\boldsymbol{\beta}}_j$

References

Jerome Friedman, Trevor Hastie, and Robert Tibshirani. Sparse inverse covariance estimation with the graphical lasso. *Biostatistics*, 9(3):432–441, 2008.