

Vignette of Variance Components Model

CAI Mingxuan

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This package contains three approaches for estimating variance components of linear model [1]: the parameter expanded EM (PX-EM) algorithm [2, 3], Minorization-Maximization (MM) algorithm [4] and the Method of Moments (MoM) [5].

Variance components model

Suppose we have dataset $\{\mathbf{X}, \mathbf{Z}, \mathbf{y}\}$ where $\mathbf{X} \in \mathbb{R}^{n \times p}$ is the design matrix whose columns are normalized with mean 0 and variance $1/p$, $\mathbf{y} \in \mathbb{R}^n$ is the response vector and $\mathbf{Z} \in \mathbb{R}^{n \times c}$ is the covariate matrix of fixed effects. The linear mixed model links \mathbf{y} with \mathbf{X} and \mathbf{Z} :

$$\mathbf{y} = \mathbf{Z}\boldsymbol{\omega} + \mathbf{X}\boldsymbol{\beta} + \mathbf{e}, \quad \boldsymbol{\beta} \sim \mathcal{N}(0, \sigma_\beta^2 \mathbf{I}_p), \quad \mathbf{e} \sim \mathcal{N}(0, \sigma_e^2 \mathbf{I}_n), \quad (1)$$

where $\boldsymbol{\beta} \in \mathbb{R}^p$ is the random effect, $\boldsymbol{\omega} \in \mathbb{R}^c$ is the fixed effect and σ_β^2 and σ_e^2 are model parameters. This linear mixed model can also be re-written as a variance components model:

$$\mathbf{y} = \mathcal{N}(\mathbf{Z}\boldsymbol{\omega}, \sigma_\beta^2 \mathbf{K} + \sigma_e^2 \mathbf{I}_n), \quad (2)$$

where $\mathbf{K} = \mathbf{X}\mathbf{X}^T$. Since \mathbf{X} has been normalized with mean 0 and variance $1/p$, $\text{tr}(\mathbf{K}) = \text{tr}(\mathbf{I}_n) = n$. The goal is to estimate the variance components $\boldsymbol{\theta} = \{\sigma_\beta^2, \sigma_e^2\}$ [1]. This package provides three approaches to estimate the parameters: PX-EM algorithm, MM algorithm and the method of moments. The first two are based on maximum likelihood (MLE) approach and the third one adopts the moment matching approach.

PX-EM algorithm

The PX-EM algorithm is an extension of classical EM algorithm with faster speed [2, 3]. We first consider the parameter expanded version of (1):

$$\mathbf{y} = \mathbf{Z}\boldsymbol{\omega} + \delta \mathbf{X}\boldsymbol{\beta} + \mathbf{e},$$

where $\delta \in \mathbb{R}^1$ is the expanded parameter. The complete-data log-likelihood is given as

$$\begin{aligned} \mathcal{L} &= \log \Pr(\mathbf{y}, \boldsymbol{\beta} | \boldsymbol{\theta}; \mathbf{Z}, \mathbf{X}) \\ &= -\frac{n}{2} \log(2\pi\sigma_e^2) - \frac{1}{2\sigma_e^2} \|\mathbf{y} - \mathbf{Z}\boldsymbol{\omega} - \delta \mathbf{X}\boldsymbol{\beta}\|^2 \\ &\quad - \frac{p}{2} \log(2\pi\sigma_\beta^2) - \frac{1}{2\sigma_\beta^2} \|\boldsymbol{\beta}\|^2, \end{aligned} \quad (3)$$

from which we can easily recognize that the terms involving $\boldsymbol{\beta}$ are of a quadratic form:

$$\boldsymbol{\beta}^T \left(-\frac{\delta^2}{2\sigma_e^2} \mathbf{X}^T \mathbf{X} - \frac{1}{2\sigma_\beta^2} \mathbf{I}_p \right) \boldsymbol{\beta} + \frac{\delta}{\sigma_e^2} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega})^T \mathbf{X}\boldsymbol{\beta} + \text{Constant}.$$

Therefore, the posterior distribution of β is Gaussian $\mathcal{N}(\beta|\mu, \Sigma)$, where

$$\begin{aligned}\Sigma^{-1} &= \frac{\delta^2}{\sigma_e^2} \mathbf{X}^T \mathbf{X} + \frac{1}{\sigma_\beta^2} \mathbf{I}_p, \\ \mu &= \left(\frac{\delta^2}{\sigma_e^2} \mathbf{X}^T \mathbf{X} + \frac{1}{\sigma_\beta^2} \mathbf{I}_p \right)^{-1} \frac{\delta}{\sigma_e^2} \mathbf{X}^T (\mathbf{y} - \mathbf{Z}\omega).\end{aligned}$$

Now in the E-step, we evaluate the Q -function by taking the expectation of the complete-data log-likelihood with respect to the posterior $\mathcal{N}(\beta|\mu, \Sigma)$. Specifically, the quadratic terms involving β are evaluated as following:

$$\begin{aligned}\mathbb{E}[||\tilde{\mathbf{y}} - \delta \mathbf{X}\beta||^2] &= \mathbb{E}[\tilde{\mathbf{y}}^T \tilde{\mathbf{y}} - 2\delta \tilde{\mathbf{y}}^T \mathbf{X}\beta + \delta^2 \beta^T \mathbf{X}^T \mathbf{X}\beta] \\ &= \tilde{\mathbf{y}}^T \tilde{\mathbf{y}} - 2\delta \tilde{\mathbf{y}}^T \mathbf{X}\mu + \delta^2 \mu^T \mathbf{X}^T \mathbf{X}\mu + \delta^2 \text{tr}(\mathbf{X}^T \mathbf{X}\Sigma), \\ \mathbb{E}[||\beta||^2] &= \mu^T \mu + \text{tr}(\Sigma),\end{aligned}$$

where $\tilde{\mathbf{y}} = \mathbf{y} - \mathbf{Z}\omega$. Then the Q -function given the current parameter estimates θ_{old} is obtained as:

$$\begin{aligned}\mathcal{Q}(\theta|\theta_{old}) &= -\frac{n}{2} \log(2\pi\sigma_e^2) - \frac{p}{2} \log(2\pi\sigma_\beta^2) \\ &\quad - \frac{1}{2\sigma_e^2} ||\mathbf{y} - \mathbf{Z}\omega - \delta \mathbf{X}\mu||^2 - \frac{1}{2\sigma_\beta^2} \mu^T \mu \\ &\quad - \text{tr} \left(\left(\frac{\delta^2}{2\sigma_e^2} \mathbf{X}^T \mathbf{X} + \frac{1}{2\sigma_\beta^2} \mathbf{I}_p \right) \Sigma \right).\end{aligned}\tag{4}$$

In the M-step, the new estimates of parameter θ is obtained by setting the derivative of Q -function to be zero. The resulting updates are given as follows:

$$\begin{aligned}\delta &= \frac{(\mathbf{y} - \mathbf{Z}\omega)^T \mathbf{X}\mu}{\mu^T \mathbf{X}^T \mathbf{X}\mu + \text{tr}(\mathbf{X}^T \mathbf{X}\Sigma)}, \\ \omega &= (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T (\mathbf{y} - \delta \mathbf{X}\mu), \\ \sigma_e^2 &= \frac{1}{n} [||\mathbf{y} - \mathbf{Z}\omega - \delta \mathbf{X}\mu||^2 + \delta^2 \text{tr}(\mathbf{X}^T \mathbf{X}\Sigma)], \\ \sigma_\beta^2 &= \frac{1}{p} [\mu^T \mu + \text{tr}(\Sigma)].\end{aligned}$$

To check the convergence of PX-EM algorithm, we evaluate the lower bound after each E-step, when the incomplete-data log-likelihood is exactly equal to the lower bound (i.e. the bound is tight).

This PX-EM algorithm is summarized in Algorithm 1. After convergence, the posterior mean and variance of $\mathcal{N}(\beta|\mu, \Sigma)$ can be evaluated given the obtained parameter estimates $\hat{\theta} = \{\hat{\sigma}_e^2, \hat{\sigma}_\beta^2\}$ and $\hat{\omega}$:

$$\begin{aligned}\Sigma^{-1} &= \frac{1}{\hat{\sigma}_e^2} \mathbf{X}^T \mathbf{X} + \frac{1}{\hat{\sigma}_\beta^2} \mathbf{I}_p, \\ \mu &= \left(\frac{1}{\hat{\sigma}_e^2} \mathbf{X}^T \mathbf{X} + \frac{1}{\hat{\sigma}_\beta^2} \mathbf{I}_p \right)^{-1} \frac{1}{\hat{\sigma}_e^2} \mathbf{X}^T (\mathbf{y} - \mathbf{Z}\hat{\omega}).\end{aligned}\tag{5}$$

Algorithm 1 PX-EM algorithm for model (1)

Initialization: Parameters are initialized by setting $\boldsymbol{\omega} = (\mathbf{Z}^T \mathbf{Z})^{-1} \mathbf{Z}^T \mathbf{y}$, $\sigma_e^2 = \sigma_\beta^2 = \text{Var}(y - \mathbf{Z}\boldsymbol{\omega})/2$.

repeat

E-step: At the t -th iteration, evaluate the posterior $\mathcal{N}(\boldsymbol{\beta}|\boldsymbol{\mu}, \boldsymbol{\Sigma})$ given the current parameter estimates $\boldsymbol{\theta}^{(t)} = \{(\sigma_e^{(t)})^2, (\sigma_\beta^{(t)})^2\}$, $\boldsymbol{\omega}^{(t)}$ and set $\delta^{(t)} = 1$:

$$\boldsymbol{\Sigma}^{-1} = \frac{(\delta^{(t)})^2}{(\sigma_e^{(t)})^2} \mathbf{X}^T \mathbf{X} + \frac{1}{(\sigma_\beta^{(t)})^2} \mathbf{I}_p,$$

$$\boldsymbol{\mu} = \left(\frac{(\delta^{(t)})^2}{(\sigma_e^{(t)})^2} \mathbf{X}^T \mathbf{X} + \frac{1}{(\sigma_\beta^{(t)})^2} \mathbf{I}_p \right)^{-1} \frac{(\delta^{(t)})^2}{(\sigma_e^{(t)})^2} \mathbf{X}^T (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)}),$$

$$ELBO^{(t)} = \mathcal{Q}(\boldsymbol{\theta}^{(t)}) + \frac{1}{2} \log |2\pi \boldsymbol{\Sigma}|, \text{ where } \mathcal{Q} \text{ is defined in Equation(4).}$$

M-step: Update the model parameters by

$$\delta^{(t+1)} = \frac{(\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)})^T \mathbf{X} \boldsymbol{\mu}}{\boldsymbol{\mu}^T \mathbf{X}^T \mathbf{X} \boldsymbol{\mu} + \text{tr}(\mathbf{X}^T \mathbf{X} \boldsymbol{\Sigma})},$$

$$\boldsymbol{\omega}^{(t+1)} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T (\mathbf{y} - \delta \mathbf{X} \boldsymbol{\mu}),$$

$$(\sigma_e^{(t+1)})^2 = \frac{1}{n_r} [||\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)} - \delta \mathbf{X} \boldsymbol{\mu}||^2 + \delta^2 \text{tr}(\mathbf{X}^T \mathbf{X} \boldsymbol{\Sigma})],$$

$$(\sigma_\beta^{(t+1)})^2 = \frac{1}{p} [\boldsymbol{\mu}^T \boldsymbol{\mu} + \text{tr}(\boldsymbol{\Sigma})].$$

Reduction-step: Rescale $(\sigma_\beta^{(t+1)})^2 = (\delta^{(t+1)})^2 (\sigma_\beta^{(t+1)})^2$ and reset $\delta^{(t+1)} = 1$.

until the incomplete-data log-likelihood ($ELBO^{(t)}$) stop increasing or maximum iteration reached

In practice. We can avoid frequently inverting the $p \times p$ matrix Σ by conducting a single eigen-decomposition on $\mathbf{X}\mathbf{X}^T$ or $\mathbf{X}^T\mathbf{X}$, depending on the relative sizes of p and n . If $n \geq p$, we conduct the eigen-decomposition $\mathbf{X}^T\mathbf{X} = \mathbf{V}\mathbf{Q}\mathbf{V}^T$ before the iteration, where $\mathbf{Q} \in \mathbb{R}^{p \times p}$ is a diagonal matrix of eigenvalues q_j and $\mathbf{V} \in \mathbb{R}^{p \times p}$ is a matrix whose columns are corresponding eigenvectors of q_j . The resulting algorithm is shown in Algorithm 2.

Algorithm 2 PX-EM algorithm for model (1) when $n \geq p$

Initialization: $\omega = (\mathbf{Z}^T\mathbf{Z})^{-1}\mathbf{Z}^T\mathbf{y}$, $\sigma_e^2 = \sigma_\beta^2 = \text{Var}(y - \mathbf{Z}\omega)/2$; conduct eigen-decomposition $\mathbf{X}^T\mathbf{X} = \mathbf{V}\mathbf{Q}\mathbf{V}^T$.

repeat

E-step: At the t -th iteration, evaluate the posterior $\mathcal{N}(\beta|\mu, \Sigma)$ given the current parameter estimates $\theta^{(t)} = \{(\sigma_e^{(t)})^2, (\sigma_\beta^{(t)})^2\}$, $\omega^{(t)}$ and set $\delta^{(t)} = 1$:

$$\begin{aligned}\tilde{q}_j &= q_j/(\sigma_e^{(t)})^2 + 1/(\sigma_\beta^{(t)})^2, \quad \text{diag}(\tilde{\mathbf{Q}}) = \tilde{q} = [\tilde{q}_1, \dots, \tilde{q}_p] \\ \mu &= \frac{1}{(\sigma_e^{(t)})^2} \mathbf{V}[\mathbf{V}^T\mathbf{X}^T(\mathbf{y} - \mathbf{Z}\omega^{(t)}) \odot 1/\tilde{q}] \\ ELBO^{(t)} &= -\frac{n}{2} \log(2\pi(\sigma_e^{(t)})^2) - \frac{p}{2} \log(2\pi(\sigma_\beta^{(t)})^2) - \frac{1}{2(\sigma_e^{(t)})^2} \|\mathbf{y} - \mathbf{Z}\omega^{(t)} - \delta\mathbf{X}\mu\|^2 \\ &\quad - \frac{1}{2(\sigma_\beta^{(t)})^2} \mu^T \mu - \frac{1}{2} \sum_j^p \log \tilde{q}_j.\end{aligned}$$

M-step: Update the model parameters by

$$\begin{aligned}\delta^{(t+1)} &= \frac{(\mathbf{y} - \mathbf{Z}\omega^{(t)})^T \mathbf{X}\mu}{\mu^T \mathbf{X}^T \mathbf{X} \mu + \sum_j^p q_j/\tilde{q}_j}, \\ \omega^{(t+1)} &= (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T (\mathbf{y} - \delta\mathbf{X}\mu), \\ (\sigma_e^{(t+1)})^2 &= \frac{1}{n_r} [\|\mathbf{y} - \mathbf{Z}\omega^{(t)} - \delta\mathbf{X}\mu\|^2 + \delta^2 \sum_j^p q_j/\tilde{q}_j], \\ (\sigma_\beta^{(t+1)})^2 &= \frac{1}{p} [\mu^T \mu + \sum_j^p 1/\tilde{q}_j].\end{aligned}$$

Reduction-step: Rescale $(\sigma_\beta^{(t+1)})^2 = (\delta^{(t+1)})^2 (\sigma_\beta^{(t+1)})^2$ and reset $\delta^{(t+1)} = 1$.

until the incomplete-data log-likelihood ($ELBO^{(t)}$) stop increasing or maximum iteration reached

If $p > n$, we conduct the eigen-decomposition $\mathbf{X}\mathbf{X}^T = \mathbf{U}\mathbf{D}\mathbf{U}^T$ before the iteration, where $\mathbf{D} \in \mathbb{R}^{n \times n}$ is a diagonal matrix of eigenvalues d_i and $\mathbf{U} \in \mathbb{R}^{n \times n}$ is a matrix whose columns are corresponding eigenvectors of d_i . The resulting algorithm is shown in Algorithm 3.

MM algorithm

Unlike the PX-EM algorithm, the MM algorithm maximize the incomplete-data log-likelihood by considering the variance components model (2) [4]. The incomplete-data log-likelihood is given as

$$\log \Pr(\mathbf{y}|\theta; \mathbf{Z}, \mathbf{K}) = -\frac{1}{2} \log |\Omega| - \frac{1}{2} (\mathbf{y} - \mathbf{Z}\omega)^T \Omega (\mathbf{y} - \mathbf{Z}\omega), \quad (6)$$

where $\Omega = \sigma_\beta^2 \mathbf{K} + \sigma_e^2 \mathbf{I}_n$. The MM algorithm updates ω and θ alternatively by iteratively maximizing the

Algorithm 3 PX-EM algorithm for model (1) when $p > n$

Initialization: $\boldsymbol{\omega} = (\mathbf{Z}^T \mathbf{Z})^{-1} \mathbf{Z}^T \mathbf{y}$, $\sigma_e^2 = \sigma_\beta^2 = \text{Var}(y - \mathbf{Z}\boldsymbol{\omega})/2$; conduct eigen-decomposition $\mathbf{X}\mathbf{X}^T = \mathbf{U}\mathbf{D}\mathbf{U}^T$.

repeat

E-step: At the t -th iteration, evaluate the posterior $\mathcal{N}(\boldsymbol{\beta}|\boldsymbol{\mu}, \boldsymbol{\Sigma})$ given the current parameter estimates $\boldsymbol{\theta}^{(t)} = \{(\sigma_e^{(t)})^2, (\sigma_\beta^{(t)})^2\}$, $\boldsymbol{\omega}^{(t)}$ and set $\delta^{(t)} = 1$:

$$\begin{aligned} \tilde{d}_i &= d_i/(\sigma_e^{(t)})^2 + 1/(\sigma_\beta^{(t)})^2, \quad \text{diag}(\tilde{\mathbf{D}}) = \tilde{\mathbf{d}} = [\tilde{d}_1, \dots, \tilde{d}_n] \\ \boldsymbol{\mu} &= \frac{1}{(\sigma_e^{(t)})^2} \mathbf{X}^T \mathbf{U} [\mathbf{U}^T (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)}) \odot \mathbf{1}/\tilde{\mathbf{d}}] \\ ELBO^{(t)} &= -\frac{n}{2} \log(2\pi(\sigma_e^{(t)})^2) - \frac{p}{2} \log(2\pi(\sigma_\beta^{(t)})^2) - \frac{1}{2(\sigma_e^{(t)})^2} \|\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)} - \delta \mathbf{X}\boldsymbol{\mu}\|^2 \\ &\quad - \frac{1}{2(\sigma_\beta^{(t)})^2} \boldsymbol{\mu}^T \boldsymbol{\mu} - \frac{1}{2} \sum_i^n \log \tilde{d}_i + \frac{p-n}{2} \log(\sigma_\beta^{(t)})^2. \end{aligned}$$

M-step: Update the model parameters by

$$\begin{aligned} \delta^{(t+1)} &= \frac{(\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)})^T \mathbf{X}\boldsymbol{\mu}}{\boldsymbol{\mu}^T \mathbf{X}^T \mathbf{X}\boldsymbol{\mu} + \sum_i^n d_i/\tilde{d}_i}, \\ \boldsymbol{\omega}^{(t+1)} &= (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T (\mathbf{y} - \delta \mathbf{X}\boldsymbol{\mu}), \\ (\sigma_e^{(t+1)})^2 &= \frac{1}{n_r} [\|\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)} - \delta \mathbf{X}\boldsymbol{\mu}\|^2 + \delta^2 \sum_i^n d_i/\tilde{d}_i], \\ (\sigma_\beta^{(t+1)})^2 &= \frac{1}{p} [\boldsymbol{\mu}^T \boldsymbol{\mu} + \sum_i^n 1/\tilde{d}_i + (n-p)(\sigma_\beta^{(t)})^2]. \end{aligned}$$

Reduction-step: Rescale $(\sigma_\beta^{(t+1)})^2 = (\delta^{(t+1)})^2 (\sigma_\beta^{(t+1)})^2$ and reset $\delta^{(t+1)} = 1$.

until the incomplete-data log-likelihood ($ELBO^{(t)}$) stop increasing or maximum iteration reached

lower bound of incomplete-data log-likelihood. Given $\boldsymbol{\theta}^{(t)}$, the updata of $\boldsymbol{\omega}$ is simply a weighted least square problem

$$\boldsymbol{\omega}^{(t)} = (\mathbf{Z}^T \boldsymbol{\Omega}^{(t)} \mathbf{Z})^{-1} \mathbf{Z}^T (\boldsymbol{\Omega}^{(t)})^{-1} \mathbf{y}. \quad (7)$$

The update of $\boldsymbol{\theta}$ given $\boldsymbol{\omega}$ depends on two minorizations. First,

$$-(\mathbf{y} - \mathbf{Z}\boldsymbol{\omega})^T (\boldsymbol{\Omega}^{(t)})^{-1} \left(\frac{(\sigma_\beta^{(t)})^4}{\sigma_\beta^2} \mathbf{K} + \frac{(\sigma_e^{(t)})^4}{\sigma_e^2} \right) (\boldsymbol{\Omega}^{(t)})^{-1} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}) \leq -\frac{1}{2} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega})^T \boldsymbol{\Omega} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}), \quad (8)$$

which separates the variance components in the quadratic term of the likelihood (6). Second, the convexity of function $-\log |\boldsymbol{\Omega}|$ implies that

$$-\log |\boldsymbol{\Omega}^{(t)}| - \text{tr}((\boldsymbol{\Omega}^{(t)})^{-1} (\boldsymbol{\Omega} - \boldsymbol{\Omega}^{(t)})) \leq -\frac{1}{2} \log |\boldsymbol{\Omega}|, \quad (9)$$

which separates the variance components in the log determinant of the likelihood (6). Combining (8) and (9), the overall minorization is given as

$$\begin{aligned} \mathcal{G}(\boldsymbol{\theta} | \boldsymbol{\theta}_{old}) &= -\log |\boldsymbol{\Omega}^{(t)}| - \frac{1}{2} \text{tr}((\boldsymbol{\Omega}^{(t)})^{-1} \boldsymbol{\Omega}) - \frac{1}{2} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)})^T (\boldsymbol{\Omega}^{(t)})^{-1} \left(\frac{(\sigma_\beta^{(t)})^4}{\sigma_\beta^2} \mathbf{K} + \frac{(\sigma_e^{(t)})^4}{\sigma_e^2} \right) (\boldsymbol{\Omega}^{(t)})^{-1} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)}) \\ &= -\log |\boldsymbol{\Omega}^{(t)}| - \frac{\sigma_\beta^2}{2} \text{tr}((\boldsymbol{\Omega}^{(t)})^{-1} \mathbf{K}) - \frac{1}{2} \frac{(\sigma_\beta^{(t)})^4}{\sigma_\beta^2} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)})^T (\boldsymbol{\Omega}^{(t)})^{-1} \mathbf{K} (\boldsymbol{\Omega}^{(t)})^{-1} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)}) \\ &\quad - \frac{\sigma_e^2}{2} \text{tr}((\boldsymbol{\Omega}^{(t)})^{-1}) - \frac{1}{2} \frac{(\sigma_e^{(t)})^4}{\sigma_e^2} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)})^T (\boldsymbol{\Omega}^{(t)})^{-2} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)}). \end{aligned} \quad (10)$$

By setting the derivative of \mathcal{G} -function to be zero, the resulting updates are given as follows:

$$\begin{aligned} (\sigma_\beta^{(t+1)})^2 &= (\sigma_\beta^{(t)})^2 \sqrt{\frac{(\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)})^T (\boldsymbol{\Omega}^{(t)})^{-1} \mathbf{K} (\boldsymbol{\Omega}^{(t)})^{-1} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)})}{\text{tr}((\boldsymbol{\Omega}^{(t)})^{-1} \mathbf{K})}} \\ (\sigma_e^{(t+1)})^2 &= (\sigma_e^{(t)})^2 \sqrt{\frac{(\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)})^T (\boldsymbol{\Omega}^{(t)})^{-2} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)})}{\text{tr}((\boldsymbol{\Omega}^{(t)})^{-1})}}. \end{aligned}$$

The convergence of MM algorithm is checked by evaluating the log-likelihood at each iteration. The resulting algorithm is summarized in Algorithm 4.

To avoid frequently inverting $\boldsymbol{\Omega}$ in the iterations, we can conduct eigen-decomposition on $\mathbf{K} = \mathbf{U}\mathbf{D}\mathbf{U}^T$ before the algorithm, where $\mathbf{D} \in \mathbb{R}^{n \times n}$ is a diagonal matrix of eigenvalues d_i and $\mathbf{U} \in \mathbb{R}^{n \times n}$ is a matrix whose columns are corresponding eigenvectors of d_i . The resulting procedure is summarized in Algorithm 5.

Standard errors of variance components for MLE methods

For MLE methods including MM and PX-EM, the covariance matrix of variance components estimates are calculated from inverse of Fisher Information Matrix (FIM). $FIM = -\mathbb{E} \left[\frac{\partial^2 \mathcal{L}}{\partial \boldsymbol{\theta}^2} \right] = -\mathbb{E} \left[\frac{\partial^2}{\partial \boldsymbol{\theta}^2} - \frac{1}{2} \log |\boldsymbol{\Omega}| - \frac{1}{2} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega})^T \boldsymbol{\Omega}^{-1} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}) \right]$. The first derivatives are:

Algorithm 4 MM algorithm for model (2)

Initialization: Parameters are initialized by setting $\boldsymbol{\omega} = (\mathbf{Z}^T \mathbf{Z})^{-1} \mathbf{Z}^T \mathbf{y}$, $\sigma_e^2 = \sigma_\beta^2 = \text{Var}(y - \mathbf{Z}\boldsymbol{\omega})/2$.
repeat

$$\begin{aligned}\boldsymbol{\Omega}^{(t)} &= (\sigma_\beta^{(t)})^2 \mathbf{K} + (\sigma_e^{(t+1)})^2 \mathbf{I}_n, \\ \boldsymbol{\omega}^{(t)} &= (\mathbf{Z}^T \boldsymbol{\Omega}^{(t)} \mathbf{Z})^{-1} \mathbf{Z}^T (\boldsymbol{\Omega}^{(t)})^{-1} \mathbf{y}, \\ \text{evaluate } \mathcal{L}^{(t)}(\boldsymbol{\Omega}^{(t)}, \boldsymbol{\omega}^{(t)}) &\text{ from Equation (6),} \\ (\sigma_\beta^{(t+1)})^2 &= (\sigma_\beta^{(t)})^2 \sqrt{\frac{(\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)})^T (\boldsymbol{\Omega}^{(t)})^{-1} \mathbf{K} (\boldsymbol{\Omega}^{(t)})^{-1} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)})}{\text{tr}((\boldsymbol{\Omega}^{(t)})^{-1} \mathbf{K})}}, \\ (\sigma_e^{(t+1)})^2 &= (\sigma_e^{(t)})^2 \sqrt{\frac{(\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)})^T (\boldsymbol{\Omega}^{(t)})^{-2} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega}^{(t)})}{\text{tr}((\boldsymbol{\Omega}^{(t)})^{-1})}}.\end{aligned}$$

until the incomplete-data log-likelihood ($\mathcal{L}^{(t)}$) stop increasing or maximum iteration reached

Algorithm 5 Efficient MM algorithm for model (2)

Initialization: $\mathbf{K} = \mathbf{U} \mathbf{D} \mathbf{U}^T$, $\bar{\mathbf{Z}} = \mathbf{U}^T \mathbf{Z}$, $\bar{\mathbf{y}} = \mathbf{U}^T \mathbf{y}$, $\boldsymbol{\omega} = (\bar{\mathbf{Z}}^T \bar{\mathbf{Z}})^{-1} \bar{\mathbf{Z}}^T \bar{\mathbf{y}}$, $\sigma_e^2 = \sigma_\beta^2 = \text{Var}(y - \mathbf{Z}\boldsymbol{\omega})/2$.
repeat

$$\begin{aligned}\tilde{d}_i &= d_i / (\sigma_e^{(t)})^2 + 1 / (\sigma_\beta^{(t)})^2, \quad \text{diag}(\tilde{\mathbf{D}}) = \tilde{d} = [\tilde{d}_1, \dots, \tilde{d}_n] \\ \boldsymbol{\omega}^{(t)} &= (\bar{\mathbf{Z}}^T \tilde{\mathbf{D}} \bar{\mathbf{Z}})^{-1} \bar{\mathbf{Z}}^T (\bar{\mathbf{y}} \odot \tilde{d}), \\ \mathcal{L}^{(t)}(\boldsymbol{\Omega}^{(t)}, \boldsymbol{\omega}^{(t)}) &= -\frac{1}{2} \sum_i^n \log \tilde{d}_i - \frac{n}{2} \log \sigma_\beta^2 - \frac{n}{2} \log \sigma_e^2 - \frac{n}{2} \log 2\pi - \frac{1}{2} \sum_i^n [(\bar{\mathbf{y}}_i - \bar{\mathbf{Z}}_i^T \boldsymbol{\omega}^{(t)})^2 / \tilde{d}_i] \\ (\sigma_\beta^{(t+1)})^2 &= \frac{\sigma_\beta^{(t)}}{\sigma_e^{(t)}} \sqrt{\frac{\sum_i^n [(\bar{\mathbf{y}}_i - \bar{\mathbf{Z}}_i^T \boldsymbol{\omega}^{(t)})^2 d_i / \tilde{d}_i^2]}{\sum_i^n d_i / \tilde{d}_i}}, \\ (\sigma_e^{(t+1)})^2 &= \frac{\sigma_e^{(t)}}{\sigma_\beta^{(t)}} \sqrt{\frac{\sum_i^n [(\bar{\mathbf{y}}_i - \bar{\mathbf{Z}}_i^T \boldsymbol{\omega}^{(t)})^2 / \tilde{d}_i^2]}{\sum_i^n 1 / \tilde{d}_i}}.\end{aligned}$$

until the incomplete-data log-likelihood ($\mathcal{L}^{(t)}$) stop increasing or maximum iteration reached

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \sigma_g^2} &= \frac{1}{2} \text{tr} [-\mathbf{\Omega}^{-1} \mathbf{K} + (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega})^T \mathbf{\Omega}^{-1} \mathbf{K} \mathbf{\Omega}^{-1} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega})], \\ \frac{\partial \mathcal{L}}{\partial \sigma_e^2} &= \frac{1}{2} \text{tr} [-\mathbf{\Omega}^{-1} + (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega})^T \mathbf{\Omega}^{-2} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega})];\end{aligned}$$

and the second derivatives are given as

$$\begin{aligned}\frac{\partial^2 \mathcal{L}}{\partial (\sigma_g^2)^2} &= \frac{1}{2} \text{tr} [(\mathbf{\Omega}^{-1} \mathbf{K})^2 - 2(\mathbf{\Omega}^{-1} \mathbf{K})^2 \mathbf{\Omega}^{-1} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega})(\mathbf{y} - \mathbf{Z}\boldsymbol{\omega})^T], \\ \frac{\partial^2 \mathcal{L}}{\partial (\sigma_e^2)^2} &= \frac{1}{2} \text{tr} [\mathbf{\Omega}^{-2} - 2\mathbf{\Omega}^{-3} (\mathbf{y} - \mathbf{Z}\boldsymbol{\omega})(\mathbf{y} - \mathbf{Z}\boldsymbol{\omega})^T], \\ \frac{\partial^2 \mathcal{L}}{\partial \sigma_g^2 \partial \sigma_e^2} &= \frac{1}{2} \text{tr} [\mathbf{\Omega}^{-1} \mathbf{K} \mathbf{\Omega}^{-1} - (\mathbf{\Omega}^{-1} \mathbf{K} \mathbf{\Omega}^{-2} + \mathbf{\Omega}^{-2} \mathbf{K} \mathbf{\Omega}^{-1})(\mathbf{y} - \mathbf{Z}\boldsymbol{\omega})(\mathbf{y} - \mathbf{Z}\boldsymbol{\omega})^T].\end{aligned}$$

Since the only random variable is \mathbf{y} , and $\mathbb{E}[(\mathbf{y} - \mathbf{Z}\boldsymbol{\omega})(\mathbf{y} - \mathbf{Z}\boldsymbol{\omega})^T] = \mathbf{\Omega}$, the FIM is

$$\begin{aligned}FIM &= -\frac{1}{2} \begin{bmatrix} \text{tr}[(\mathbf{\Omega}^{-1} \mathbf{K})^2] - 2\text{tr}[(\mathbf{\Omega}^{-1} \mathbf{K})^2] & \text{tr}(\mathbf{\Omega}^{-1} \mathbf{K} \mathbf{\Omega}^{-1}) - 2\text{tr}(\mathbf{\Omega}^{-1} \mathbf{K} \mathbf{\Omega}^{-1}) \\ \cdot & \text{tr}[\mathbf{\Omega}^{-2}] - 2\text{tr}[\mathbf{\Omega}^{-2}] \end{bmatrix} \\ &= \frac{1}{2} \begin{bmatrix} \text{tr}[(\mathbf{\Omega}^{-1} \mathbf{K})^2] & \text{tr}(\mathbf{\Omega}^{-1} \mathbf{K} \mathbf{\Omega}^{-1}) \\ \cdot & \text{tr}[\mathbf{\Omega}^{-2}] \end{bmatrix}.\end{aligned}$$

Inverting the FIM leads to the covariance matrix of $\hat{\boldsymbol{\theta}}$.

When handling the FIM, we can again make use of the pre-calculated eigenvectors and eigenvalues to avoid inverting $\mathbf{\Omega}$. For MM algorithm and PX-EM algorithm with $p \geq n$ case, we can evaluate $\mathbf{\Omega}^{-1}$ using the identity $\mathbf{\Omega}^{-1} = \mathbf{U} \mathbf{\tilde{D}} \mathbf{U}^T$ with \mathbf{U} , $\mathbf{\tilde{D}}$ from Algorithm 3 and 5. For PX-EM algorithm with $n > p$, we first define $\mathbf{\Lambda}^{-1} = (\sigma_e^2 \mathbf{I}_p + \sigma_\beta^2 \mathbf{X}^T \mathbf{X})^{-1}$. Then using the matrix inverse lemma, we have $\mathbf{X}^T \mathbf{\Omega}^{-1} = \mathbf{\Lambda}^{-1} \mathbf{X}^T$. Therefore, we can express the FIM using the dual form:

$$\begin{aligned}\text{tr}[(\mathbf{\Omega}^{-1} \mathbf{K})^2] &= \text{tr}(\mathbf{\Omega}^{-1} \mathbf{X} \mathbf{X}^T \mathbf{\Omega}^{-1} \mathbf{X} \mathbf{X}^T) = \text{tr}(\mathbf{\Lambda}^{-1} \mathbf{X}^T \mathbf{X} \mathbf{\Lambda}^{-1} \mathbf{X}^T \mathbf{X}) \\ \text{tr}[\mathbf{\Omega}^{-1} \mathbf{K} \mathbf{\Omega}^{-1}] &= \text{tr}[\mathbf{\Omega}^{-1} \mathbf{X} \mathbf{X}^T \mathbf{\Omega}^{-1}] = \text{tr}(\mathbf{\Lambda}^{-2} \mathbf{X}^T \mathbf{X}) \\ \text{tr}[\mathbf{\Omega}^{-2}] &= n \left(\frac{1}{\sigma_e^2}\right)^2 - 2 \frac{\sigma_\beta^2}{(\sigma_e^2)^2} \text{tr}[\mathbf{\Lambda}^{-1} \mathbf{X}^T \mathbf{X}] + \left(\frac{\sigma_\beta^2}{\sigma_e^2}\right)^2 \text{tr}[\mathbf{\Lambda}^{-1} \mathbf{X}^T \mathbf{X} \mathbf{\Lambda}^{-1} \mathbf{X}^T \mathbf{X}],\end{aligned}$$

where $\mathbf{\Lambda}^{-1} = \mathbf{V} \tilde{\mathbf{Q}} \mathbf{V}^T$ with \mathbf{V} and $\tilde{\mathbf{Q}}$ from Algorithm 2.

Method of Moments

While the MM algorithm and PX-EM algorithm adopts the MLE, MoM estimator is obtained by first multiplying Equation (2) by the projection matrix $\mathbf{M} = \mathbf{I}_n - \mathbf{Z}(\mathbf{Z}^T \mathbf{Z})^{-1} \mathbf{Z}^T$ and then solving the following ordinary least squares (OLS) problem [5]:

$$\text{argmin}_{\sigma_\beta^2, \sigma_e^2} \|(\mathbf{M}\mathbf{y})(\mathbf{M}\mathbf{y})^T - (\sigma_\beta^2 \mathbf{M} \mathbf{K} \mathbf{M} + \sigma_e^2 \mathbf{M})\|_F^2. \quad (11)$$

Using the fact that $\|\mathbf{A}\|_F = \sqrt{\text{tr}(\mathbf{A} \mathbf{A}^T)}$, the OLS problem in (11) can be re-written as

$$\operatorname{argmin}_{\sigma_\beta^2, \sigma_e^2} \operatorname{tr}[(\mathbf{M}\mathbf{y})(\mathbf{M}\mathbf{y})^T - (\sigma_\beta^2 \mathbf{M}\mathbf{K}\mathbf{M} + \sigma_e^2 \mathbf{M})(\mathbf{M}\mathbf{y})(\mathbf{M}\mathbf{y})^T - (\sigma_\beta^2 \mathbf{M}\mathbf{K}\mathbf{M} + \sigma_e^2 \mathbf{M})^T],$$

which leads to the normal equation

$$\mathbf{S}\boldsymbol{\theta} = \mathbf{q}, \quad (12)$$

with $\mathbf{S} = \begin{bmatrix} \operatorname{tr}(\mathbf{M}\mathbf{K}\mathbf{M}\mathbf{K}) & \operatorname{tr}(\mathbf{M}\mathbf{K}) \\ \operatorname{tr}(\mathbf{M}\mathbf{K}) & n - c \end{bmatrix}$, $\boldsymbol{\theta} = \begin{bmatrix} \sigma_\beta^2 \\ \sigma_e^2 \end{bmatrix}$, $\mathbf{q} = \begin{bmatrix} \mathbf{y}^T \mathbf{M}\mathbf{K}\mathbf{M}\mathbf{y} \\ \mathbf{y}^T \mathbf{M}\mathbf{y} \end{bmatrix}$.

The MoM estimates of $\boldsymbol{\theta}$ is then given by $\hat{\boldsymbol{\theta}} = \mathbf{S}^{-1}\mathbf{q}$. The covariance matrix of MoM estimators are given by the sandwich estimator: $\boldsymbol{\Sigma}_\theta = \mathbb{E} \left[\frac{\partial B}{\partial \boldsymbol{\theta}} \right]^{-1} \operatorname{Cov}(B) \mathbb{E} \left[\frac{\partial B}{\partial \boldsymbol{\theta}} \right]^{-1}$, where B is the normal equation $\mathbf{q} - \mathbf{S}\boldsymbol{\theta}$. Specifically,

$$\mathbb{E} \left[\frac{\partial B}{\partial \boldsymbol{\theta}} \right]^{-1} = \mathbf{S}^{-1}, \quad (13)$$

and

$$\operatorname{Cov}(B) = \operatorname{Cov} \left(\begin{bmatrix} \mathbf{y}^T \mathbf{M}\mathbf{K}\mathbf{M}\mathbf{y} \\ \mathbf{y}^T \mathbf{M}\mathbf{y} \end{bmatrix} \right) = \begin{bmatrix} \operatorname{Var}(\mathbf{y}^T \mathbf{M}\mathbf{K}\mathbf{M}\mathbf{y}) & \operatorname{Cov}(\mathbf{y}^T \mathbf{M}\mathbf{K}\mathbf{M}\mathbf{y}, \mathbf{y}^T \mathbf{M}\mathbf{y}) \\ \operatorname{Cov}(\mathbf{y}^T \mathbf{M}\mathbf{K}\mathbf{M}\mathbf{y}, \mathbf{y}^T \mathbf{M}\mathbf{y}) & \operatorname{Var}(\mathbf{y}^T \mathbf{M}\mathbf{y}) \end{bmatrix}, \quad (14)$$

where the elements are calculated by $\operatorname{Var}(\mathbf{y}^T \mathbf{M}\mathbf{K}\mathbf{M}\mathbf{y}) = 2\operatorname{tr}([\mathbf{M}\mathbf{K}\mathbf{M}\boldsymbol{\Omega}]^2)$, $\operatorname{Var}(\mathbf{y}^T \mathbf{M}\mathbf{y}) = 2\operatorname{tr}([\mathbf{M}\boldsymbol{\Omega}]^2)$, $\operatorname{Cov}(\mathbf{y}^T \mathbf{M}\mathbf{K}\mathbf{M}\mathbf{y}, \mathbf{y}^T \mathbf{M}\mathbf{y}) = 2\operatorname{tr}(\mathbf{M}\mathbf{K}\mathbf{M}\boldsymbol{\Omega}\mathbf{M}\boldsymbol{\Omega})$.

Example

```
library(VCM)
n <- 1000
d <- 1000

sb2 <- 0.1
se2 <- 1
X <- matrix(rnorm(n*d), n, d)
X <- scale(X)/sqrt(d)

w <- c(rnorm(d, 0, sqrt(sb2)))
y0 <- X%*%w

y <- y0 + sqrt(se2)*rnorm(n)

fit_PXEM <- linRegPXEM(X=X, y=y, tol = 1e-6, maxIter = 500, verbose=F)
fit_MM <- linRegMM(X=X, y=y, tol=1e-6, maxIter = 500, verbose=F)
fit_MoM <- linReg_MoM(X=X, y=y)

c(fit_PXEM$se2, fit_PXEM$sb2)

## [1] 0.95707590 0.09875113
c(fit_MM$se2, fit_MM$sb2)

## [1] 0.95697922 0.09886609
```

```
c(fit_MoM$se2,fit_MoM$sb2)
```

```
## [1] 0.9624150 0.0942761
```

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