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# Robust Causal Estimation in the Large-Sample Limit without Strict Faithfulness

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## Appendix A Recovering $\mathbf{B}$ and $\mathbf{V}$ from $\hat{\Sigma}$

$$\Sigma = \mathbf{V}^{\frac{1}{2}}(\mathbf{I} - \tilde{\mathbf{B}})^{-1}(\mathbf{I} + \tilde{\mathbf{C}}\tilde{\mathbf{C}}^T)(\mathbf{I} - \tilde{\mathbf{B}})^{-T}\mathbf{V}^{\frac{1}{2}}. \quad (1)$$

We propose a procedure to recover the parameters over the observed variables  $(\mathbf{B}, \mathbf{V})$  from Equation 1 when given the covariance matrix  $\hat{\Sigma}$  and the structural coefficients  $\mathbf{C}$ .

The procedure is as follows:

1.  $\mathbf{Q} = \text{chol}(\hat{\Sigma})$
2.  $\mathbf{L} = \text{chol}(\mathbf{I} + \tilde{\mathbf{C}}\tilde{\mathbf{C}}^T)$
3. After plugging in the Cholesky decompositions into Equation 1, we obtain:

$$\mathbf{Q} = \mathbf{V}^{\frac{1}{2}}(\mathbf{I} - \tilde{\mathbf{B}})^{-1}\mathbf{L} \implies \mathbf{V}^{\frac{1}{2}}(\mathbf{I} - \tilde{\mathbf{B}})^{-1} = \mathbf{Q}\mathbf{L}^{-1}$$

4. Since  $(\mathbf{I} - \tilde{\mathbf{B}})^{-1}$  is a term with ones on the diagonal, it follows that  $\mathbf{V}^{\frac{1}{2}} = \text{diag}(\mathbf{Q}\mathbf{L}^{-1})$ .
5. Finally, we recover  $\tilde{\mathbf{B}} = \mathbf{I} - \mathbf{L}\mathbf{Q}^{-1}\mathbf{V}^{\frac{1}{2}}$  and  $\mathbf{B} = \mathbf{V}^{\frac{1}{2}}\tilde{\mathbf{B}}\mathbf{V}^{-\frac{1}{2}} = \mathbf{I} - \mathbf{V}^{\frac{1}{2}}\mathbf{L}\mathbf{Q}^{-1}$ .

## Appendix B Hessian

Here we compute the Hessian matrix of the log-likelihood per data point w.r.t.  $\Theta = (\mathbf{B}, \mathbf{V})$  evaluated at the maximum likelihood solution. With covariance matrix  $\Sigma$  and  $\mathbf{K} = \Sigma^{-1}$ , we have:

$$\frac{1}{N}\partial_{\alpha,\beta}^2 \log \mathcal{L} = \mathbf{H}_{\alpha,\beta} = -\frac{1}{2} \sum_{i,j,k,l} \Sigma_{ik}\Sigma_{jl}\partial_{\alpha}\mathbf{K}_{ij}\partial_{\beta}\mathbf{K}_{kl}.$$

With  $\Delta \equiv \mathbf{I} - \tilde{\mathbf{B}}$  and  $\Omega \equiv \mathbf{I} + \tilde{\mathbf{C}}\tilde{\mathbf{C}}^T$ , we can write

$$\Sigma_{ij} = \sqrt{v_i v_j}(\Delta^{-1}\Omega\Delta^{-T})_{ij} \equiv \sqrt{v_i v_j}\tilde{\Sigma}_{ij}$$

and

$$\mathbf{K}_{ij} = \frac{1}{\sqrt{v_i v_j}}(\Delta^T\Omega^{-1}\Delta)_{ij} \equiv \frac{1}{\sqrt{v_i v_j}}\tilde{\mathbf{K}}_{ij},$$

so that

$$\frac{\partial \mathbf{K}_{ij}}{\partial b_{pq}} = -\frac{1}{\sqrt{v_i v_j}}[\mathbf{Z}_{pi}\delta_{qj} + \mathbf{Z}_{pj}\delta_{qi}],$$

with  $\mathbf{Z} \equiv \Omega^{-1}\Delta = \Delta^{-T}\tilde{\mathbf{K}}$ , and

$$\frac{\partial \mathbf{K}_{ij}}{\partial v_r} = -\frac{\mathbf{K}_{ij}}{2v_r}[\delta_{ri} + \delta_{rj}].$$

Some bookkeeping yields

$$-\frac{\partial^2 \log \mathcal{L}}{\partial b_{pq}\partial b_{rs}} = \tilde{\Sigma}_{qs}(\Omega^{-1})_{pr} + (\Delta^{-1})_{sp}(\Delta^{-1})_{qr},$$

and

$$-\frac{\partial^2 \log \mathcal{L}}{\partial v_r \partial v_s} = \frac{1}{4v_r v_s}[\delta_{rs} + \tilde{\Sigma}_{rs}\tilde{\mathbf{K}}_{rs}],$$

and

$$-\frac{\partial^2 \log \mathcal{L}}{\partial b_{pq}\partial v_r} = \frac{1}{2v_r}[\tilde{\Sigma}_{rq}(\tilde{\mathbf{K}}\Delta^{-1})_{rp} + \delta_{rq}(\Delta^{-1})_{rp}].$$

Or, in terms of  $\mathbf{Q} = \text{chol}(\hat{\Sigma})$  and  $\mathbf{L} = \text{chol}(\mathbf{I} + \tilde{\mathbf{C}}\tilde{\mathbf{C}}^T)$ ,

$$-\frac{\partial^2 \log \mathcal{L}}{\partial b_{pq}\partial b_{rs}} = \frac{1}{\sqrt{v_q v_s}}[(\mathbf{Q}\mathbf{Q}^T)_{qs}(\mathbf{L}^{-T}\mathbf{L}^{-1})_{pr} + (\mathbf{Q}\mathbf{L}^{-1})_{sp}(\mathbf{Q}\mathbf{L}^{-1})_{qr}],$$

and

$$-\frac{\partial^2 \log \mathcal{L}}{\partial v_r \partial v_s} = \frac{1}{4v_r v_s}[\delta_{rs} + (\mathbf{Q}\mathbf{Q}^T)_{rs}(\mathbf{Q}^{-T}\mathbf{Q}^{-1})_{rs}],$$

and

$$-\frac{\partial^2 \log \mathcal{L}}{\partial b_{pq}\partial v_r} = \frac{1}{2v_r \sqrt{v_q}}[(\mathbf{Q}\mathbf{Q}^T)_{rq}(\mathbf{Q}^{-T}\mathbf{L}^{-1})_{rp} + \delta_{rq}(\mathbf{Q}\mathbf{L}^{-1})_{rp}].$$