

They have latent variables \mathbf{w} and

$$\mathbf{w} = \mathbf{X}\boldsymbol{\beta} + \sum_{k=1}^q \mathbf{Z}_k \mathbf{r}_k + \boldsymbol{\epsilon}$$

Assuming something about the errors this means

$$\mathbf{w}|\mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\Sigma}_\theta \sim N(\mathbf{X}\boldsymbol{\beta}, \boldsymbol{\Sigma}_\theta)$$

or equivalently

$$f(\mathbf{w}|\mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\Sigma}_\theta) = (2\pi)^{-n/2} |\boldsymbol{\Sigma}_\theta|^{-1/2} \exp \left\{ -\frac{1}{2} (\mathbf{w} - \mathbf{X}\boldsymbol{\beta})^T \boldsymbol{\Sigma}_\theta^{-1} (\mathbf{w} - \mathbf{X}\boldsymbol{\beta}) \right\}$$

where

$$\boldsymbol{\Sigma}_\theta = \sum_{k=1}^q \mathbf{Z}_k \mathbf{V}_k \mathbf{Z}_k^T + \sigma_0^2 \mathbf{I}$$

The joint density

$$[\mathbf{y}, \mathbf{w}|\phi, \mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\Sigma}_\theta] = [\mathbf{y}|\mathbf{g}^{-1}(\mathbf{w}), \phi] [\mathbf{w}|\mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\Sigma}_\theta]$$

where $[\mathbf{y}|\mathbf{g}^{-1}(\mathbf{w}), \phi]$ is the data model and $[\mathbf{w}|\mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\Sigma}_\theta]$ is the process model. We have

$$\begin{aligned} [\mathbf{y}|\phi, \boldsymbol{\theta}] &= \int_{\mathbf{w}} \int_{\boldsymbol{\beta}} [\mathbf{y}, \mathbf{w}|\phi, \mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\Sigma}_\theta] d\boldsymbol{\beta} d\mathbf{w} \\ &= \int_{\mathbf{w}} [\mathbf{y}|\mathbf{g}^{-1}(\mathbf{w}), \phi] \left\{ \int_{\boldsymbol{\beta}} [\mathbf{w}|\mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\Sigma}_\theta] d\boldsymbol{\beta} \right\} d\mathbf{w} \end{aligned}$$

We have

$$\int_{\boldsymbol{\beta}} [\mathbf{w}|\mathbf{X}, \boldsymbol{\beta}, \boldsymbol{\Sigma}_\theta] d\boldsymbol{\beta} = \int_{\boldsymbol{\beta}} (2\pi)^{-n/2} |\boldsymbol{\Sigma}_\theta|^{-1/2} \exp \left\{ -\frac{1}{2} \underbrace{(\mathbf{w} - \mathbf{X}\boldsymbol{\beta})^T \boldsymbol{\Sigma}_\theta^{-1} (\mathbf{w} - \mathbf{X}\boldsymbol{\beta})}_{A_1} \right\} d\boldsymbol{\beta}$$

where

$$\begin{aligned} A_1 &= (\mathbf{w} - \mathbf{X}\boldsymbol{\beta})^T \boldsymbol{\Sigma}_\theta^{-1} (\mathbf{w} - \mathbf{X}\boldsymbol{\beta}) \\ &= \mathbf{w}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{w} + \boldsymbol{\beta}^T \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X} \boldsymbol{\beta} - 2\boldsymbol{\beta}^T \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{w} \\ &= \left(\boldsymbol{\beta} - [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{w} \right)^T \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X} \left(\boldsymbol{\beta} - [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{w} \right) \\ &\quad - \mathbf{w}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X} [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{w} + \mathbf{w}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{w} \end{aligned}$$

Then

$$\begin{aligned}
[w|X, \Sigma_\theta] &= \int_{\beta} [w|X, \beta, \Sigma_\theta] d\beta \\
&= (2\pi)^{-n/2} |\Sigma_\theta|^{-1/2} \\
&\quad \int_{\beta} \exp \left\{ -\frac{1}{2} \left(\beta - [X^T \Sigma_\theta^{-1} X]^{-1} X^T \Sigma_\theta^{-1} w \right)^T X^T \Sigma_\theta^{-1} X \left(\beta - [X^T \Sigma_\theta^{-1} X]^{-1} X^T \Sigma_\theta^{-1} w \right) \right\} d\beta \\
&\quad \times \exp \left\{ -\frac{1}{2} w^T \left[\Sigma_\theta^{-1} - \Sigma_\theta^{-1} X [X^T \Sigma_\theta^{-1} X]^{-1} X^T \Sigma_\theta^{-1} \right] w \right\} \\
&= (2\pi)^{-(n-p)/2} |\Sigma_\theta|^{-1/2} |X^T \Sigma_\theta^{-1} X|^{-1/2} \\
&\quad \underbrace{\int_{\beta} (2\pi)^{-p/2} |X^T \Sigma_\theta^{-1} X|^{1/2} \exp \left\{ -\frac{1}{2} \left(\beta - [X^T \Sigma_\theta^{-1} X]^{-1} X^T \Sigma_\theta^{-1} w \right)^T [X^T \Sigma_\theta^{-1} X] \left(\beta - [X^T \Sigma_\theta^{-1} X]^{-1} X^T \Sigma_\theta^{-1} w \right) \right\} d\beta}_{=1} \\
&\quad \times \exp \left\{ -\frac{1}{2} w^T \left[\Sigma_\theta^{-1} - \Sigma_\theta^{-1} X [X^T \Sigma_\theta^{-1} X]^{-1} X^T \Sigma_\theta^{-1} \right] w \right\} \\
&= (2\pi)^{-(n-p)/2} |\Sigma_\theta|^{-1/2} |X^T \Sigma_\theta^{-1} X|^{-1/2} \\
&\quad \times \exp \left\{ -\frac{1}{2} w^T \left[\Sigma_\theta^{-1} - \Sigma_\theta^{-1} X [X^T \Sigma_\theta^{-1} X]^{-1} X^T \Sigma_\theta^{-1} \right] w \right\}
\end{aligned}$$

Then the marginal

$$\begin{aligned}
[y|\phi, \theta] &= \int_w [y|g^{-1}(w), \phi] [w|X, \Sigma_\theta] dw \\
&\quad \int_w [y|g^{-1}(w), \phi] \left\{ \int_{\beta} [w|X, \beta, \Sigma_\theta] d\beta \right\} dw \\
&= (2\pi)^{-(n-p)/2} |\Sigma_\theta|^{-1/2} |X^T \Sigma_\theta^{-1} X|^{-1/2} \\
&\quad \int_w [y|g^{-1}(w), \phi] \exp \left\{ -\frac{1}{2} w^T \left[\Sigma_\theta^{-1} - \Sigma_\theta^{-1} X [X^T \Sigma_\theta^{-1} X]^{-1} X^T \Sigma_\theta^{-1} \right] w \right\} dw
\end{aligned}$$

Try what they say, i.e., replaying β in $[w|X, \beta, \Sigma_\theta]$ by the maximum likelihood estimator $\hat{\beta} = [X^T \Sigma_\theta^{-1} X]^{-1} X^T \Sigma_\theta^{-1} w$. Then

$$\begin{aligned}
[w|X, \Sigma_\theta] &= \frac{1}{C_n} \exp \left\{ \left(w - X\hat{\beta} \right)^T \Sigma_\theta^{-1} \left(w - X\hat{\beta} \right) \right\} \\
&= \frac{1}{C_n} \exp \left\{ \underbrace{\left(w - [X^T \Sigma_\theta^{-1} X]^{-1} X^T \Sigma_\theta^{-1} w \right)^T \Sigma_\theta^{-1} \left(w - [X^T \Sigma_\theta^{-1} X]^{-1} X^T \Sigma_\theta^{-1} w \right)}_{B_1} \right\}
\end{aligned}$$

where

$$\begin{aligned}
B_1 &= \left(\mathbf{I}\mathbf{w} - [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{w} \right)^T \boldsymbol{\Sigma}_\theta^{-1} \left(\mathbf{I}\mathbf{w} - [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{w} \right) \\
&= \left(\left\{ \mathbf{I} - [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \right\} \mathbf{w} \right)^T \boldsymbol{\Sigma}_\theta^{-1} \left(\left\{ \mathbf{I} - [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \right\} \mathbf{w} \right) \\
&= \mathbf{w}^T \left\{ \mathbf{I} - [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \right\} \boldsymbol{\Sigma}_\theta^{-1} \left\{ \mathbf{I} - [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \right\} \mathbf{w} \\
&= \mathbf{w}^T \left\{ \boldsymbol{\Sigma}_\theta^{-1} + [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \boldsymbol{\Sigma}_\theta^{-1} [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} - 2 [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \right\} \mathbf{w}
\end{aligned}$$

$$\begin{aligned}
B_1 &= \left(\mathbf{I}\mathbf{w} - [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{w} \right)^T \boldsymbol{\Sigma}_\theta^{-1} \left(\mathbf{I}\mathbf{w} - [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{w} \right) \\
&= \mathbf{w}^T \left\{ \mathbf{I} - (\boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}) [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \right\} \boldsymbol{\Sigma}_\theta^{-1} \left\{ \mathbf{I} - (\boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}) [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \right\} \mathbf{w} \\
&= \mathbf{w}^T \left\{ \boldsymbol{\Sigma}_\theta^{-1} + \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X} [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \boldsymbol{\Sigma}_\theta^{-1} [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} - 2 \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X} [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \boldsymbol{\Sigma}_\theta^{-1} \right\} \mathbf{w} \\
&= \mathbf{w}^T \left\{ \boldsymbol{\Sigma}_\theta^{-1} + \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X} [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \left(\boldsymbol{\Sigma}_\theta^{-1} [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} - 2 \boldsymbol{\Sigma}_\theta^{-1} \right) \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \right\} \mathbf{w}
\end{aligned}$$

Same as Lukas.

Let

$$\begin{aligned}
\ell(\mathbf{w}, \cdot) &= \log \{ [\mathbf{y} | \mathbf{g}^{-1}(\mathbf{w}), \phi] [\mathbf{w} | \mathbf{X}, \boldsymbol{\Sigma}_\theta] \} \\
&= \log \{ [\mathbf{y} | \mathbf{g}^{-1}(\mathbf{w}), \phi] \} - \frac{1}{2} \mathbf{w}^T \left[\boldsymbol{\Sigma}_\theta^{-1} - \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X} [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \right] \mathbf{w}
\end{aligned}$$

And (again)

$$[\mathbf{y} | \phi, \boldsymbol{\theta}] = \int_{\mathbf{w}} \exp \{ \ell(\mathbf{w}, \cdot) \} d\mathbf{w}$$

Using $\hat{\mathbf{w}} = \arg \max_{\mathbf{w}} \ell(\mathbf{w}, \cdot)$ and approximate

$$\begin{aligned}
\ell(\mathbf{w}, \cdot) &\approx \ell(\hat{\mathbf{w}}) + \frac{1}{2} (\mathbf{w} - \hat{\mathbf{w}})^T \underbrace{\frac{\partial^2 \ell(\mathbf{w}, \cdot)}{\partial \mathbf{w} \partial \mathbf{w}^T} \bigg|_{\mathbf{w}=\hat{\mathbf{w}}}}_{\mathbf{H}} (\mathbf{w} - \hat{\mathbf{w}}) \\
&= \ell(\hat{\mathbf{w}}) - \frac{1}{2} (\mathbf{w} - \hat{\mathbf{w}})^T [-\mathbf{H}] (\mathbf{w} - \hat{\mathbf{w}})
\end{aligned}$$

Then

$$\begin{aligned}
[\mathbf{y}|\boldsymbol{\phi}, \boldsymbol{\theta}] &= \int_{\mathbf{w}} \exp \{ \ell(\mathbf{w}, \cdot) \} d\mathbf{w} \\
&\approx \int_{\mathbf{w}} \exp \left\{ \ell(\hat{\mathbf{w}}) - \frac{1}{2} (\mathbf{w} - \hat{\mathbf{w}})^T [-\mathbf{H}] (\mathbf{w} - \hat{\mathbf{w}}) \right\} d\mathbf{w} \\
&= (2\pi)^{n/2} |-\mathbf{H}|^{-1/2} \exp \{ \ell(\hat{\mathbf{w}}) \} \underbrace{\int_{\mathbf{w}} (2\pi)^{-n/2} [-\mathbf{H}]^{1/2} \exp \left\{ -\frac{1}{2} (\mathbf{w} - \hat{\mathbf{w}})^T [-\mathbf{H}] (\mathbf{w} - \hat{\mathbf{w}}) \right\} d\mathbf{w}}_1 \\
&= (2\pi)^{n/2} |-\mathbf{H}|^{-1/2} \exp \{ \ell(\hat{\mathbf{w}}) \}
\end{aligned}$$

And its log

$$\begin{aligned}
\log [\mathbf{y}|\boldsymbol{\phi}, \boldsymbol{\theta}] &= \frac{n}{2} \log (2\pi) + \ell(\hat{\mathbf{w}}) - \frac{1}{2} \log |-\mathbf{H}| \\
&= \frac{n}{2} \log (2\pi) + \log [\mathbf{y}|\mathbf{g}^{-1}(\hat{\mathbf{w}}), \boldsymbol{\phi}] + \log [\hat{\mathbf{w}}|\mathbf{X}, \boldsymbol{\Sigma}_\theta] - \frac{1}{2} \log |-\mathbf{H}|
\end{aligned}$$

where

$$\begin{aligned}
\log [\hat{\mathbf{w}}|\mathbf{X}, \boldsymbol{\Sigma}_\theta] &= -\frac{n-p}{2} \log (2\pi) - \frac{1}{2} |\boldsymbol{\Sigma}_\theta| - \frac{1}{2} \log |\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}| \\
&\quad - \frac{1}{2} \underbrace{\hat{\mathbf{w}}^T \left[\boldsymbol{\Sigma}_\theta^{-1} - \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X} [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \right] \hat{\mathbf{w}}}_{C_1}
\end{aligned}$$

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Compare to them with replacing C_1 above to be (with $\hat{\boldsymbol{\beta}} = [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \hat{\mathbf{w}}$)

$$\begin{aligned}
C_1 &= \left(\hat{\mathbf{w}} - \mathbf{X} \hat{\boldsymbol{\beta}} \right)^T \boldsymbol{\Sigma}_\theta^{-1} \left(\hat{\mathbf{w}} - \mathbf{X} \hat{\boldsymbol{\beta}} \right) \\
&= \left(\hat{\mathbf{w}} - [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \hat{\mathbf{w}} \right)^T \boldsymbol{\Sigma}_\theta^{-1} \left(\hat{\mathbf{w}} - [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \hat{\mathbf{w}} \right) \\
&= \hat{\mathbf{w}}^T \{ \mathbf{I} - \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X} [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \} \boldsymbol{\Sigma}_\theta^{-1} \{ \mathbf{I} - \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X} [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \} \hat{\mathbf{w}} \\
&= \hat{\mathbf{w}}^T \{ \boldsymbol{\Sigma}_\theta^{-1} - 2 \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X} [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} + \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X} [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X} [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \} \hat{\mathbf{w}}
\end{aligned}$$

#####Don't get it

#####Try myself

$$\ell(\hat{\mathbf{w}}) = \log \{ [\mathbf{y}|\mathbf{g}^{-1}(\hat{\mathbf{w}}), \boldsymbol{\phi}] \} - \frac{1}{2} \hat{\mathbf{w}}^T \left[\boldsymbol{\Sigma}_\theta^{-1} - \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X} [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \right] \hat{\mathbf{w}}$$

and

$$\frac{\partial \ell(\mathbf{w}, \cdot)}{\partial \mathbf{w}} = \frac{\partial}{\partial \mathbf{w}} \log \{ [\mathbf{y}|\mathbf{g}^{-1}(\mathbf{w}), \boldsymbol{\phi}] \} - \left[\boldsymbol{\Sigma}_\theta^{-1} - \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X} [\mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \boldsymbol{\Sigma}_\theta^{-1} \right] \mathbf{w}$$

and

$$\frac{\partial^2 \ell(\mathbf{w}, \cdot)}{\partial \mathbf{w} \partial \mathbf{w}^T} = \frac{\partial^2}{\partial \mathbf{w} \partial \mathbf{w}^T} \log \{ [\mathbf{y} | \mathbf{g}^{-1}(\mathbf{w}), \phi] \} - \left[\Sigma_\theta^{-1} - \Sigma_\theta^{-1} \mathbf{X} [\mathbf{X}^T \Sigma_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \Sigma_\theta^{-1} \right]$$

Hence,

$$\left. \frac{\partial^2 \ell(\mathbf{w}, \cdot)}{\partial \mathbf{w} \partial \mathbf{w}^T} \right|_{\mathbf{w}=\hat{\mathbf{w}}} = \underbrace{\left. \frac{\partial^2 \log \{ [\mathbf{y} | \mathbf{g}^{-1}(\mathbf{w}), \phi] \}}{\partial \mathbf{w} \partial \mathbf{w}^T} \right|_{\mathbf{w}=\hat{\mathbf{w}}}}_{D_\phi} - \underbrace{\left[\Sigma_\theta^{-1} - \Sigma_\theta^{-1} \mathbf{X} [\mathbf{X}^T \Sigma_\theta^{-1} \mathbf{X}]^{-1} \mathbf{X}^T \Sigma_\theta^{-1} \right]}_{P_\theta}$$

Hm... I get the same gradient and Hessian as they...