

$$\hat{\Lambda} = \frac{1}{n} \sum_{i=1}^n \nabla f_i (\nabla u)^T \nabla u$$

$$\nabla u \in \mathbb{R}^n \text{ i.e. } \begin{pmatrix} \vdots \\ u \\ \vdots \end{pmatrix}_{n \times 1}$$

$$\Lambda \in \mathbb{R}^{n \times n}$$

$$R_n = \underbrace{y_n - \hat{\mu}_n}_{\substack{\uparrow \\ 0}} = \underline{u_i}$$

$$\nabla u (\nabla u)^T$$

y_n y_i there would be then it would be fine!
 $\hat{\sigma}(n)$ $\hat{\sigma}(i) \rightarrow$ ie calculated without i

~~$$R_n = y_n - \hat{\mu}_n$$~~

$$\int (\det \Lambda(s))^{1/2} ds$$

~~$$y_n - \hat{\mu}_n \perp \hat{\sigma}_n \mid y_n$$~~

$$\sum_{v \in V} \int (\det \Lambda(v))^{1/2} dv$$

volume 1 voxels

~~$$\text{As such } \mathbb{E}[(\nabla R_i)(\nabla R_i)^T]$$~~

$$= \int \frac{1}{V} \sum_{v \in V} (\det \Lambda(v))^{1/2} dv$$

~~$$= \mathbb{E}[\mathbb{E}[(\nabla R_i)(\nabla R_i)^T \mid y_i]] \neq$$~~

$R_i, \nabla R_i$ are independent still as R_i is variance
 so maybe the proof still holds