Euclid summer school: Parameter estimation for a polynomial model

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## 1 Analytical solution

1)

$$\mathcal{L}(\{d_{i}\}|\{a_{k}\}) = \frac{1}{(2\pi)^{N/2}\sqrt{\det\Sigma}}\exp{-\frac{1}{2}\left[\sum_{ij}\left(d_{i}-\sum_{k=0}^{M}a_{k}(z_{i}-z_{c})^{k}\right)\Sigma_{ij}^{-1}\left(d_{j}-\sum_{\ell=0}^{M}a_{\ell}(z_{j}-z_{c})^{\ell}\right)\right]} \\
= \frac{1}{(2\pi)^{N/2}\sqrt{\det\Sigma}}\exp{-\frac{1}{2}\left[\left(\mathbf{d}-\mathcal{P}\mathbf{a}\right)^{T}\Sigma^{-1}\left(\mathbf{d}-\mathcal{P}\mathbf{a}\right)\right]} \tag{1}$$

5)

$$\ln \mathcal{L}(\boldsymbol{d}|\boldsymbol{a}) = -\frac{N}{2}\ln(2\pi) - \frac{1}{2}\ln(\det(\Sigma)) - \frac{1}{2}\left[(\boldsymbol{d} - \mathcal{P}\boldsymbol{a})^{T}\Sigma^{-1}(\boldsymbol{d} - \mathcal{P}\boldsymbol{a})\right]$$

$$\frac{\partial \ln \mathcal{L}(\boldsymbol{d}|\boldsymbol{a})}{\partial a_{\gamma}} = -\frac{1}{2}\sum_{ij}\left[\left(\sum_{\alpha}\mathcal{P}_{i\alpha}\delta_{\alpha\gamma}\right)(\Sigma^{-1})_{ij}(\boldsymbol{d}_{j} - \sum_{\beta}\mathcal{P}_{j\beta}\boldsymbol{a}_{\beta}) + (\boldsymbol{d}_{i} - \sum_{\alpha}\mathcal{P}_{i\alpha}\boldsymbol{a}_{\alpha})(\Sigma^{-1})_{ij}\sum_{\beta}\mathcal{P}_{j\beta}\delta_{\beta\gamma}\right]$$

$$= -\frac{1}{2}\sum_{ij}\left[\left(\mathcal{P}_{i\gamma}\right)(\Sigma^{-1})_{ij}(\boldsymbol{d}_{j} - \sum_{\beta}\mathcal{P}_{j\beta}\boldsymbol{a}_{\beta}) + (\boldsymbol{d}_{i} - \sum_{\alpha}\mathcal{P}_{i\alpha}\boldsymbol{a}_{\alpha})(\Sigma^{-1})_{ij}\mathcal{P}_{j\gamma}\right]$$

$$= -\sum_{ij}(\mathcal{P}_{i\gamma})(\Sigma^{-1})_{ij}(\boldsymbol{d}_{j} - \sum_{\beta}\mathcal{P}_{j\beta}\boldsymbol{a}_{\beta})$$
(2)

Where we used the fact that the covariance matrix is symmetric

$$\nabla_{\mathbf{a}} \ln \mathcal{L}(\mathbf{d}|\mathbf{a}) = -\mathcal{P}^{T} \Sigma^{-1} (\mathbf{d} - \mathcal{P}\mathbf{a}) = 0$$

$$\mathcal{P}^{T} \Sigma^{-1} \mathcal{P} \hat{\mathbf{a}} = \mathcal{P}^{T} \Sigma^{-1} \mathbf{d}$$

$$\hat{\mathbf{a}} = (\mathcal{P}^{T} \Sigma^{-1} \mathcal{P})^{-1} \mathcal{P}^{T} \Sigma^{-1} \mathbf{d}$$
(4)

6)

$$\langle \hat{\boldsymbol{a}} \rangle = (\mathcal{P}^T \Sigma^{-1} \mathcal{P})^{-1} \mathcal{P}^T \Sigma^{-1} \langle \boldsymbol{d} \rangle = (\mathcal{P}^T \Sigma^{-1} \mathcal{P})^{-1} \mathcal{P}^T \Sigma^{-1} \langle \mathcal{P} \boldsymbol{a} + \boldsymbol{n} \rangle = \boldsymbol{a}$$
 (5)

since  $\langle \boldsymbol{n} \rangle = 0$ 

$$\langle \hat{\boldsymbol{a}} \hat{\boldsymbol{a}}^{T} \rangle = (\mathcal{P}^{T} \Sigma^{-1} \mathcal{P})^{-1} \mathcal{P}^{T} \Sigma^{-1} \langle \boldsymbol{d} \boldsymbol{d}^{T} \rangle \Sigma^{-1} \mathcal{P} (\mathcal{P}^{T} \Sigma^{-1} \mathcal{P})^{-1} 
= (\mathcal{P}^{T} \Sigma^{-1} \mathcal{P})^{-1} \mathcal{P}^{T} \Sigma^{-1} \langle (\mathcal{P} \boldsymbol{a} + \boldsymbol{n}) (\mathcal{P} \boldsymbol{a} + \boldsymbol{n})^{T} \rangle \Sigma^{-1} \mathcal{P} (\mathcal{P}^{T} \Sigma^{-1} \mathcal{P})^{-1} 
= (\mathcal{P}^{T} \Sigma^{-1} \mathcal{P})^{-1} \mathcal{P}^{T} \Sigma^{-1} \mathcal{P} \boldsymbol{a} \boldsymbol{a}^{T} \mathcal{P}^{T} \Sigma^{-1} \mathcal{P} (\mathcal{P}^{T} \Sigma^{-1} \mathcal{P})^{-1} 
+ (\mathcal{P}^{T} \Sigma^{-1} \mathcal{P})^{-1} \mathcal{P}^{T} \Sigma^{-1} \Sigma \Sigma^{-1} \mathcal{P} (\mathcal{P}^{T} \Sigma^{-1} \mathcal{P})^{-1} 
= \boldsymbol{a} \boldsymbol{a}^{T} + (\mathcal{P}^{T} \Sigma^{-1} \mathcal{P})^{-1} 
\operatorname{Cov}(\hat{\boldsymbol{a}}) = (\mathcal{P}^{T} \Sigma^{-1} \mathcal{P})^{-1}$$
(6)