S2 Text: Fisher Information

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Fisher Information

If the log likelihood is $R = \log p(y|w)$ then the Fisher score is the gradient

$$g = \frac{\partial R}{\partial w} \tag{1}$$

The Fisher information matrix is then the covariance of the score

$$F = \operatorname{Cov}[g]$$

$$= E_{p(y|w)}[gg^{T}]$$
(2)

where the second line follows as the expected score is zero.

For multivariate Gaussian likelihoods (with precision Γ) about predictions f(t) we have

$$g(t) = S_t^T \Gamma[y(t) - f(t)]$$

$$g = \sum_{t=1}^T g(t)$$
(3)

where t indexes the observation, and S_t is the sensitivity matrix, or derivative of the predictions with respect to the parameters. The Fisher Information can then be computed by taking expectations, giving

$$F = \sum_{t=1}^{T} S_t^T \Gamma S_t \tag{4}$$

A sample-based or 'observed' Fisher information matrix can be computed as

$$F^{obs} = \sum_{t=1}^{T} g(t)g(t)^{T}$$

$$\tag{5}$$

The Fisher Information matrix can also be written as the expected curvature of the likelihood

$$F = -E_{p(y|w)} \left[\frac{\partial^2 R}{\partial w^2} \right] \tag{6}$$

A general expression for the observed Fisher Information [1] is

$$F^{obs} = -H \tag{7}$$

where H is the Hessian (matrix of second order partial derivatives) of R. This can be evaluated numerically and is used when analytic expressions for F are unavailable. A drawback of this approach is that it is expensive computationally, with evaluation time being quadratic in the number of model parameters. A concern with the observed Fisher Information is that it is not necessarily positive definite, however, this is ameliorated in a Bayesian setting where the prior precision is added to it before matrix inversion.

References

1. Efron B, Hinkley D. Assessing the accuracy of the maximum likelihood estimator: Observed versus expected Fisher Information. Biometrika. 1978;65.