

Exercise: BIC for Gaussians

(Source: Jaakkola.)

The Bayesian information criterion (BIC) is a penalized log-likelihood function that can be used for model selection. It is defined as

$$BIC = \log p(\mathcal{D}|\hat{\theta}_{ML}) - \frac{d}{2} \log(N) \quad (1)$$

where d is the number of free parameters in the model and N is the number of samples. In this question, we will see how to use this to choose between a full covariance Gaussian and a Gaussian with a diagonal covariance. Obviously a full covariance Gaussian has higher likelihood, but it may not be “worth” the extra parameters if the improvement over a diagonal covariance matrix is too small. So we use the BIC score to choose the model.

We can write

$$\log p(\mathcal{D}|\hat{\Sigma}, \hat{\mu}) = -\frac{N}{2} \text{tr}(\hat{\Sigma}^{-1} \hat{S}) - \frac{N}{2} \log(|\hat{\Sigma}|) \quad (2)$$

$$\hat{S} = \frac{1}{N} \sum_{i=1}^N (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})^T \quad (3)$$

where \hat{S} is the scatter matrix (empirical covariance), the trace of a matrix is the sum of its diagonals, and we have used the trace trick.

1. Derive the BIC score for a Gaussian in D dimensions with full covariance matrix. Simplify your answer as much as possible, exploiting the form of the MLE. Be sure to specify the number of free parameters d .
2. Derive the BIC score for a Gaussian in D dimensions with a *diagonal* covariance matrix. Be sure to specify the number of free parameters d . Hint: for the diagonal case, the ML estimate of Σ is the same as $\hat{\Sigma}_{ML}$ except the off-diagonal terms are zero:

$$\hat{\Sigma}_{diag} = \text{diag}(\hat{\Sigma}_{ML}(1,1), \dots, \hat{\Sigma}_{ML}(D,D)) \quad (4)$$