Bayesian Data-Analysis Toolbox
Release 4.23, Manual Version 3

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September 18, 2018

Chapter 22

Enter Ascii Model Selection

The Enter Ascii Model Selection Package allows you to load one or more Ascii model and then use Bayesian probability theory to compute the posterior probability for the loaded model, thus allowing you to determine which model best accounts for the data.[1] To use this package you do not have to have Fortran or C installed on your server. However, if you do not have Fortran or C installed, you must use the system models. Consequently, installing both Fortran and C is strongly recommended. The interface to this package is shown in Fig. 22. To use this package, you must do the following:

Select the "Enter Ascii Model Selection" package from the Package menu.

Load one or more Fortran or C model using the "System" or "User" buttons in the "Load And Build Model" widget group.

Load one or more Ascii data sets using the Files menu. When a data set is successfully loaded the data is plotted in the Ascii Data viewer. The format of the Ascii data that must be loaded is dependent on the model. Usually the data are two column Ascii, however, in general this package takes multicolumn Ascii data with a multicolumn abscissas. See Appendix A for a detailed description of the Ascii data files used by the Bayesian Analysis software.

Build the model using the "Build" button would normally be the next step. However, in this package it is assumed that you have previously compiled and tested each Ascii model, so this package does not have a "Build" button.

Check the Find Outliers box if you suspect outliers are present in the data.

Review the prior probabilities for the loaded model using the Prior Viewer would normally be the next step. However, because multiple models are loaded and thus multiple parameter sets are loaded, we require the user to test his models prior to running this package. So there is no review of the prior probabilities in this package. You can test your models using either the Enter Ascii Model Package or the Test Ascii Model package and you can review and update the prior information using those packages.

[1] I would like to build a system library of predefined models. If you have models that you think would be of general use, I would like to hear from you. To have one of your models included, I would need the source code, the parameter file, a brief description of the model equations and data requirements.

Figure 22.1: The Enter Ascii Model Selection Package Interface

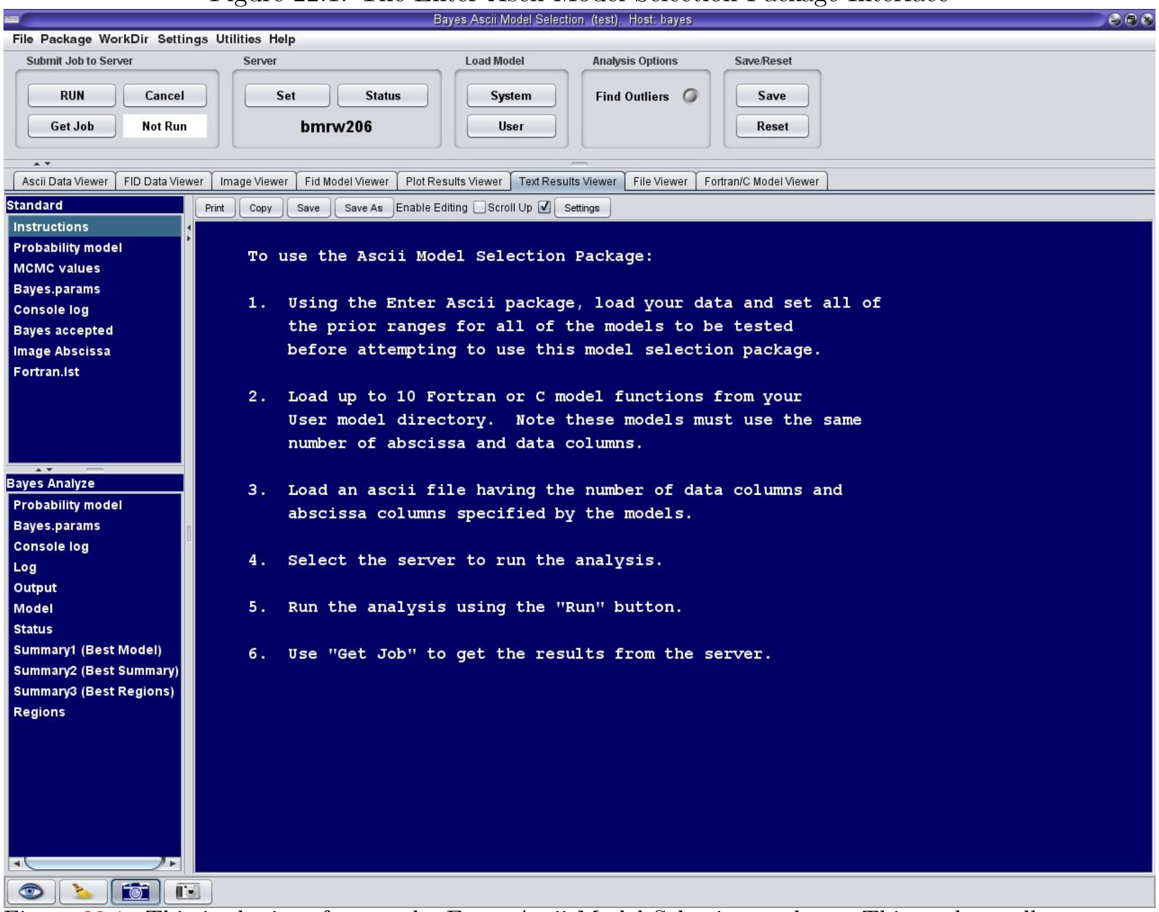

Figure 22.1: This is the interface to the Enter Ascii Model Selection package. This package allows you to load multiple Fortran or C models and then run the the model selection calculation using these models. The program will select the best model from withing the set of loaded models. For more on the actual calculations and the widgets see the text.

Select the server that is to process the analysis.

Check the status of the selected server to determine if the server is busy, change to another server if the selected server is busy.

Run the the analysis on the selected server by activating the Run button.

Get the the results of the analysis by activating the Get Job button. If the analysis is running, this button will return the Accepted report containing the status of the current run. Otherwise, it will fetch and display the results from the current analysis.

22.1 The Bayesian Calculations

In the model selection calculation done by the Enter Ascii Model Selection package, it assumes one has a set of models, $U_j \equiv \{U_1, \ldots, U_m\}$, and one wishes to compute the posterior probability for each of the U_j models. These models can be loaded from the System directory or they can be loaded from the user directory. They don't need to have common parameters, but they do need to have common data requirements. Each of these models will have a set of parameters associated it and these parameters will be designated as Ω_j. The subscript j indicating that these are the parameters associated with model U_j. The equation that relates model U_j to the data is given by

$$d_k(t_i) = U_j(t_i, \Omega_j) + n_k(t_i) \tag{22.1}$$

where $d_k(t_i)$ represents a data item in the kth data set, sampled at abscissa value t_i. The t_i may be vector valued or it may be a single column of numbers. However, it must have the same number of columns in all loaded models. The noise is represented symbolically by $n_k(t_i)$ and is the noise value in the kth data set sampled at abscissa value t_i.

The posterior probability for each model U_j is given by Bayes' theorem:

$$P(U_j|DI) = \frac{P(U_j|I)P(D|U_jI)}{P(D|I)} \tag{22.2}$$

where $P(U_j|DI)$ is the posterior probability for model U_j given the data and the prior information, $P(U_j|I)$ is the prior probability for model U_j given only the prior information, $P(D|U_jI)$ is the marginal direct probability for all of the data given the model U_j and the prior information. This term was called a direct probability because it is a probability for the data and it is a marginal probability because none of the parameters from model U_j appear, so they have been marginalized out. $P(D|I)$ is a normalization constant that ensures the probabilities sum to one:

$$\sum_{j=1}^{m} P(U_i|DI) = 1, \tag{22.3}$$

so

$$\sum_{j=1}^{m} \frac{P(U_j|I)P(D|U_jI)}{P(D|I)} = 1, \tag{22.4}$$

and

$$\sum_{j=1}^{m} P(U_j|I)P(D|U_jI) = P(D|I). \tag{22.5}$$

Equation (22.2) cannot be computed in this form because the marginal direct probability, $P(D|U_jI)$, cannot be assigned. However, the prior probability for the models, $P(U_j|I)$ can be assigned and in this calculation it is assigned as a uniform prior:

$$P(U_j|I) = \frac{1}{m}. \tag{22.6}$$

The marginal direct probability for the data given the model, $P(D|U_jI)$, can be computed if we reintroduce the model parameters Ω_j and then use the sum rule of probability theory to marginalize out these parameters

$$P(D|U_jI) = \int P(D\Omega_j|U_jI)d\Omega_j. \tag{22.7}$$

The probability on the right-hand side of this equation is the joint prior probability for the data and the Ω_j parameters given the model U_j and the prior information I. Applying the product rule to factor the right-hand side of this equation, one obtains

$$P(D|U_jI) = \int P(\Omega_j|I)P(D|\Omega_jU_jI)d\Omega_j \tag{22.8}$$

where $P(D|\Omega_jU_jI)$ is the direct probability for the data given the parameters and the model, this direct probability is also called a likelihood and $P(\Omega_j|I)$ is the joint prior probability for the Ω_j parameters.

In the Bayesian Analysis software that implements this calculation, there are two types of Ascii models: those that do not use marginalization to remove the amplitudes and those that do. The functional form of the Ascii model is very different between these two types of Fortran/C codes. Consequently, the calculation for the marginal direct probability for the data given the model, $P(D|U_jI)$, must be split into two separate calculations: one that uses amplitude marginalization and one that does not.

22.1.1 The Direct Probability With No Amplitude Marginalization

In this subsection it will be assumed that the input model is one that has not defined any amplitudes and consequently there is no amplitude marginalization in the posterior probability for the parameters. So in this calculation the Ω_j parameters are given by $\Omega_j \in \{\omega_{j1}, \ldots, \omega_{j\nu_j}\}$ where ν_j is the number of parameters. The individual Ascii model parameters are designated by ω_{jk} and these parameters may include amplitudes, but if it does, the program that implements the calculation has no knowledge of them. Assuming logical independence of the parameters, i.e., knowing the value of one parameter would not help us in making inferences about the other parameters, then the joint prior probability for the Ω_j parameters can be factored into an independents prior probability for each parameter,

$$P(\Omega_j|I) = \prod_{k=1}^{\nu_j} P(\omega_{jk}|\Omega_jI) \tag{22.9}$$

where $P(\omega_{jk}|\Omega_j I)$ is the prior probability for the k parameter in the jth model. The model Ω_j was include in the prior information because what prior we assign to the parameters will definitely be dependent on the model.

The likelihood, $P(D|\Omega_j U_j I)$, is the likelihood function for all of the data D. However, the data D is made up of multiple data sets, $D \equiv \{D_1, \ldots, D_n\}$, where n is the input number of data sets, and each data set consists of N_j data values, so $D_j \equiv \{d_j(t_1), \ldots, d_j(t_{N_j})\}$, where $d_j(t_i)$ is a data item in the jth data set sampled at abscissa value t_i. The number of data values in a given data set, N_j, need not be the same from one data set to another. Assuming logical independence of the various data sets, the joint direct probability for the data, $P(D|\Omega U_j I)$, can be written as

$$P(D|\Omega_j U_j I) = \prod_{k=1}^{n} P(D_k|\Omega_j U_j I). \tag{22.10}$$

Each of the probabilities, $P(D_k|\Omega_j U_j I)$, is a direct probability or likelihood for the data in the kth data set given the model, the parameters, and the prior information. Such direct probabilities are usually assigned using a Gaussian prior probability for the noise, then the likelihood for a single data set becomes

$$P(D_k|\sigma_k \Omega_j U_j I) = (2\pi\sigma_k^2)^{-\frac{N_k}{2}} \exp\left\{-\frac{Q_{jk}^2}{2\sigma_k^2}\right\} \tag{22.11}$$

where the standard deviations have been added to $P(D_k|\Omega_j U_j I)$ because the right-hand side of this equation cannot be computed unless the standard deviations are known. The total squared residual, Q_{jk}^2, is defined as:

$$Q_{jk}^2 \equiv \sum_{i=1}^{N_k} [d_k(t_i) - U_j(t_i, \Omega_j)]^2 \tag{22.12}$$

in the kth data set given the jth model and its parameters Ω_j. Substituting Eq. (22.11) into Eq. (22.10) one obtains

$$P(D|\sigma_1 \cdots \sigma_n \Omega_j U_j I) = \prod_{k=1}^{n} (2\pi\sigma_k^2)^{-\frac{N_k}{2}} \exp\left\{-\frac{Q_{jk}^2}{2\sigma_k^2}\right\} \tag{22.13}$$

as the direct probability for all of the data, where we have modified the notation to indicate that all of the σ_j must be given. Finally, substituting Eq. (22.13), Eq. (22.9) and Eq. (22.6) into Eq. (22.2) one obtains

$$P(U_j|\sigma_1 \cdots \sigma_n DI) \propto \int \frac{1}{m} \left[\prod_{k=1}^{\nu_j} P(\omega_{jk}|I)\right] \left[\prod_{k=1}^{n} (2\pi\sigma_k^2)^{-\frac{N_k}{2}} \exp\left\{-\frac{Q_{jk}^2}{2\sigma_k^2}\right\}\right] d\Omega_j \tag{22.14}$$

as the marginal posterior probability for model U_j. In the package that processes this analysis, the prior probabilities are specified by the user. And because the prior probability for the model was assigned as uniform, it will cancel when this probability density function is normalized. A Markov chain Monte Carlo simulation is used to numerically integrate this equation and thus obtain the posterior probability for the models.

Often the standard deviation of the noise prior probability are not known, so Eq. (22.14) cannot be used. When the standard deviation are not known, one can remove the standard deviations using the rules of probability theory:

$$P(U_j|DI) = \int P(\sigma_1 \cdots \sigma_n U_j|DI) d\sigma_1 \cdots d\sigma_n d\Omega_j. \tag{22.15}$$

Factoring the right-hand side using the product rule of probability theory, one obtains

$$P(U_j|DI) = \int P(\sigma_1 \cdots \sigma_n|I) P(U_j|\sigma_1 \cdots \sigma_n DI) d\sigma_1 \cdots d\sigma_n d\Omega_j. \tag{22.16}$$

Assuming logical independence, the joint prior probability for the standard deviations can be factored to obtain:

$$P(U_j|DI) = \int \left[\prod_{k=1}^{n} P(\sigma_j|I)\right] P(U_j|\sigma_1 \cdots \sigma_n DI) d\sigma_1 \cdots d\sigma_n d\Omega_j. \tag{22.17}$$

Substituting Eq. (22.14) into Eq. (22.17) one obtains

$$P(U_j|DI) \propto \frac{1}{m} \int \left[\prod_{k=1}^{\nu_j} P(\omega_{jk}|I)\right] \left[\prod_{k=1}^{n} (2\pi\sigma_k)^{-\frac{N_k+1}{2}} \exp\left\{-\frac{Q_{jk}^2}{2\sigma_k^2}\right\}\right] d\sigma_1 \cdots d\sigma_n d\Omega_j \tag{22.18}$$

as the posterior probability for model U_j given the data and the prior information. The integrals of the standard deviations of the noise prior probability are gamma function integrals. We address those integrals in the next section when we consider the same calculation but with marginalization over the amplitudes. Here we are just going to give the result of marginalizing over the σ_k:

$$P(U_j|DI) \propto \frac{1}{m} \int \left[\prod_{k=1}^{\nu_j} P(\omega_{jk}|I)\right] \prod_{k=1}^{n} \left[\frac{1}{2}\Gamma\left(\frac{N_k}{2}\right) Q_{jk}^{-\frac{N_k}{2}}\right] d\Omega_j. \tag{22.19}$$

For the details of how this integration is performed see subsection 22.1.2.2. When the standard deviation for the noise prior probability is known Eq. (22.18) is used in the numerical simulation that implements this calculation. Knowledge of the standard deviation of the noise prior probability usually comes about in image processing applications because in those applications it is possible to directly sample the noise. However, more often than not, no information is available about the standard deviation of the noise prior probability, then the posterior probability for the model independent of the standard deviations of the noise prior probability, Eq. (22.19), is used. The functional form of this equation is that of a Student's t-distribution. The Markov chain Monte Carlo simulation that is used to evaluate the remaining integrals targets either Eq. (22.18) or Eq. (22.19) using a Monte Carlo simulation to draw samples from this posterior probability and then uses Monte Carlo integration to evaluate the posterior probability for the models.

22.1.2 The Direct Probability With Amplitude Marginalization

The above calculation assumes the amplitudes are not analytically marginalized out. However, the Bayesian Analysis software uses two types of models. One that does not explicitly marginalize out the amplitudes and one that does. The functional form of these models that marginalize out the amplitudes is a special subset of the from assumed above. The models that do not marginalize out the amplitudes may contain amplitudes, but they are not identified as such in the parameter file associated with the Fortran/C model; rather the amplitudes are just lumped in with the other nonlinear parameters. However, when the amplitudes are marginalized out, the amplitudes are made explicit in the Fortran/C model parameter file and the functional form of the Fortran/C model is different. Consequently, the calculation for the marginal posterior probability for the model is a bit different for these models.

The signal model used in the calculation when the amplitudes are marginalized out, starts out similar to the calculation where no marginalization occurs. The data are related to the jth model U_j by

$$d_k(t_i) = U_j(t_i, \mathcal{B}_j, \Omega_j) + n_k(t_i) \tag{22.20}$$

where $d_k(t_i)$ represents a data item in the kth data set that was sampled at abscissa value t_i, $n_k(t_i)$ represents the noise in the kth data set sampled at abscissa value t_i, $\mathcal{B}_j$ is the set of all amplitudes appearing in the jth model, and Ω_j is the set of all nonamplitude parameters, $\Omega_j \in \{\omega_{j1}, \ldots, \omega_{j\nu_j}\}$ and ν_j is the number of nonamplitude parameters in the jth data set. These parameters will be referred to as the nonlinear parameters because they almost always appear in the model in a nonlinear fashion. The model, $U_j \in \{U_1, \ldots, U_m\}$, is one from the set of models that are being analyzed. When the amplitudes are marginalized out, it is assumed that the $U_j(t_i, \mathcal{B}_j, \Omega_j)$ have the following functional form:

$$U_j(t_i, \mathcal{B}_j, \Omega_j) = \sum_{\ell=1}^{u_j} B_{jk\ell} G_{j\ell}(t_i, \Omega_j) \tag{22.21}$$

where $B_{jk\ell}$ is the ℓth amplitude of the jth model in the kth data set, and $G_{j\ell}(t_i, \Omega_j)$ is the ℓth subcomponent of the jth model. Note that the $G_{j\ell}(t_i, \Omega_j)$ do not depend on the amplitudes in any way; and in this model the only dependence on the amplitudes is a linear dependence. To given an example of this, suppose we are estimating a sum of u_j sinusoids, the model $U_j(t_i, \mathcal{B}_j, \Omega_j)$ would be given by

$$U_j(t_i, \mathcal{B}_j, \Omega_j) = \sum_{\ell=1}^{u_j} B_{jk\ell} \cos(2\pi\omega_{j\ell} t_i + \theta_{j\ell}) \tag{22.22}$$

and each submodel component, the $G_{j\ell}(t_i, \Omega_j)$ are given by

$$G_{j\ell}(t_i, \Omega_j) = \cos(2\pi\omega_j t + \theta_{j\ell}). \tag{22.23}$$

In this sinusoidal model, the sinusoids depend on the data sets through the amplitude and phase while the frequencies are common to all data sets.

22.1.2.1 Marginalizing the Amplitudes

To compute the posterior probability for the model when the amplitudes are marginalized out, we note that that the calculation begins where the previous calculation ends with Eq. (22.14). Rewriting Eq. (22.14) so as to separate out the amplitudes integrals from the integrals over the nonlinear parameters, one obtains

$$P(U_j|DI) \propto \frac{1}{m} \int \left[\prod_{\ell=1}^{v_j} P(\omega_{j\ell}|I) \right] \left[\prod_{k=1}^{n} \left(\prod_{z=1}^{u_j} P(B_{jkz}|I) \right) (2\pi\sigma_k)^{-\frac{N_k}{2}} \exp\left\{ -\frac{Q_{jk}^2}{2\sigma_k^2} \right\} \right] dB_j d\Omega_j \tag{22.24}$$

where u_j is the number of amplitudes in the jth model. The prior probability for the lth nonlinear parameter in the jth model is designated by $P(\omega_{jl}|I)$. Finally, $P(B_{jkz}|I)$ is the prior probability for the zth amplitude in the jth model of the kth data set. Substituting the model, Eq. (22.21), into the definition of Q^2_{jk}, Eq. (22.12), we can obtain

$$\begin{aligned} Q^2_{jk} &\equiv \sum_{i=1}^{N_k} [d_k(t_i) - U_k(t_i, \mathcal{B}_j, \Omega_j)]^2 \\ &= \sum_{i=1}^{N_k} \left[d_k(t_i) - \sum_{\ell=1}^{u_j} B_{jk\ell} G_{j\ell}(t_i, \Omega_j) \right]^2 . \end{aligned} \tag{22.25}$$

Multiplying out the brackets one obtains

$$Q^2_{jk} = d_k(t_i) \cdot d_k(t_i) - 2 \sum_{\ell=1}^{u_j} B_{jk\ell} d_k(t_i) \cdot G_{j\ell}(t_i) + \sum_{\ell=1}^{u_j} \sum_{v=1}^{u_j} B_{jk\ell} B_{jkv} G_{j\ell}(t_i) \cdot G_{jv}(t_i) \tag{22.26}$$

where we are using the "$\cdot$" notation to mean sum over time, so

$$d_k(t_i) \cdot G_{j\ell} = \sum_{i=1}^{N_k} d_k(t_i) G_{j\ell}(t_i). \tag{22.27}$$

And to compress the notation still further, we define

$$d^2_k = d_k(t_i) \cdot d_k(t_i), \tag{22.28}$$

$$T_{jk\ell} = d_k(t_i) \cdot G_{j\ell}(t_i) \tag{22.29}$$

and

$$g_{j\ell v} = G_{j\ell}(t_i) \cdot G_{jv}(t_i) \tag{22.30}$$

so Eq. (22.26) becomes

$$Q^2_{jk} = d^2_k - 2 \sum_{\ell=1}^{u_j} B_{jk\ell} T_{jk\ell} + \sum_{\ell=1}^{u_j} \sum_{v=1}^{u_j} B_{jk\ell} B_{jkv} g_{j\ell v}. \tag{22.31}$$

To evaluate the integrals in Eq. (22.24), we must assign a prior probability for the amplitudes. A zero-mean Gaussian prior probability will be assigned for each amplitudes. This Gaussian prior probability is given by

$$P(B_{jku}|I) \propto \left(\frac{2\pi\sigma^2_j}{\gamma^2 g_{juu}} \right)^{-\frac{1}{2}} \exp\left\{ -\frac{B^2_{jku} \gamma^2 g_{juu}}{2\sigma^2_j} \right\} \tag{22.32}$$

where γ is used to control the width of this prior probability, σ_j is the standard deviation of the noise prior probability in the jth data set, and g_{jku} was defined in Eq. (22.30). The reason for this particular form is that it allows one to evaluate the integrals over the amplitudes in a concise functional form that aids in doing the numerical calculations.

Substituting Eq. (22.32) and Eq. (22.31) into the posterior probability for the model, Eq. (22.24), one obtains

$$\begin{aligned}
P(U_j|DI) &= \frac{1}{m}\int\left[\prod_{l=1}^{v_j} P(\omega_{jl}|I)\right] \\
&\times \prod_{k=1}^{n}\left[\frac{1}{\sigma_k}\prod_{\beta=1}^{u_{jk}}\left(\frac{2\pi\sigma_k^2}{\gamma^2 g_{j\beta\beta}}\right)^{-\frac{1}{2}}\exp\left\{-\frac{B_{jk\beta}^2\gamma^2 g_{j\beta\beta}}{2\sigma_k^2}\right\}\right. \\
&\times \left.(2\pi\sigma_k^2)^{-\frac{N_k}{2}}\exp\left\{-\frac{1}{2\sigma_k^2}\left[d_k(t_i)^2 - 2\sum_{\ell=1}^{u_j} B_{jk\ell}T_{jk\ell} + \sum_{\ell=1}^{u_j}\sum_{v=1}^{u_j} B_{jk\ell}B_{jkv}g_{j\ell v}\right]\right\}\right] \\
&\times dB_{jk1}\cdots dB_{jku_j}d\sigma_k d\Omega_j
\end{aligned} \tag{22.33}$$

as the posterior probability for model U_j. Expanding the product over β, and simplifying this equation somewhat, one obtains

$$\begin{aligned}
P(U_j|DI) &\propto \int\left[\prod_{l=1}^{v_j} P(\omega_{jl}|I)\right]\prod_{k=1}^{n}\left[\frac{1}{\sigma_k}\left(2\pi\sigma_k^2\right)^{\frac{-N_k+u_j}{2}}\gamma^{u_j}g_{j11}\cdots g_{ju_ju_j}\right. \\
&\times \left.\exp\left\{-\frac{1}{2\sigma_k^2}\left[d_k(t_i)^2 - 2\sum_{\ell=1}^{u_j} B_{jk\ell}T_{jk\ell} + \sum_{\ell=1}^{u_j}\sum_{v=1}^{u_j} B_{jk\ell}B_{jkv}g'_{j\ell v}\right]\right\}\right] \\
&\times dB_{jk1}\cdots dB_{jku_j}d\sigma_1\cdots d\sigma_n d\Omega_j
\end{aligned} \tag{22.34}$$

where

$$g'_{j\ell v} = g_{j\ell v}\left(1+\delta_{lv}\gamma^2\right) \tag{22.35}$$

and δ_{lv} is the Kronecker delta function. The Kronecker delta function is zero if $l \neq v$ and its one if $l = v$. In order to evaluate the amplitude integrals a change of variables and functions will be made. The $g'_{j\ell v}$ matrix is positive definite and of rank u_j. Let $e_{\ell v}$ represent the vth component of the ℓth normalized eigenvector of $g'_{j\ell v}$, then

$$\sum_{v=1}^{u_j} g'_{j\beta v}e_{\ell v} = \lambda_\ell e_{\ell\beta} \tag{22.36}$$

where λ_ℓ is the ℓth eigenvalue of $g_{j\ell v}$. The functions $H_{j\ell}(t_i)$, defined as

$$H_{j\ell}(t_i) = \frac{1}{\sqrt{\lambda_\ell}}\sum_{v=1}^{u_j} e_{\ell v}G_{jv}(t_i), \tag{22.37}$$

are orthonormal, i.e.,

$$\sum_{i=1}^{N_j} H_{j\ell}(t_i)H_{jv}(t_i) = \delta_{\ell v} \tag{22.38}$$

where $\delta_{\ell v}$ is the Kronecker delta function and it is these H_j functions that will be used in the calculation. The model Eq. (22.21) can be rewritten in terms of these orthonormal functions as

$$U_j(t_i, \mathcal{A}_j, \Omega_j) = \sum_{\ell=1}^{u_j} A_{jk\ell}H_{j\ell}(t_i) \tag{22.39}$$

and it is these $A_{jk\ell}$ that will be used in a change of variables. The amplitudes $B_{jk\ell}$ are linearly related to the $A_{jk\ell}$ by

$$B_{jk\ell} = \sum_{\beta=1}^{u_j} \frac{A_{jk\beta} e_{\beta\ell}}{\sqrt{\lambda_\beta}} \quad \text{and} \quad A_{jk\ell} = \sqrt{\lambda_\ell} \sum_{\beta=1}^{u_\beta} B_{jk\beta} e_{\ell\beta}. \tag{22.40}$$

The volume elements in the kth data set is given by

$$\begin{aligned} dB_{jk1} \cdots dB_{jku_j} &= \left| \frac{e_{\ell v}}{\sqrt{\lambda_v}} \right| dA_{jk1} \cdots dA_{jku_j} \\ &= \lambda_1^{-\frac{1}{2}} \cdots \lambda_{u_j}^{-\frac{1}{2}} dA_{jk1} \cdots dA_{jku_j}. \end{aligned} \tag{22.41}$$

The Jacobin is a function of the Ω_j parameters but it is a constant as long as we are not integrating over the Ω_j parameters. At the end of the calculation the linear relations between the A's and B's can be used to calculate the expected values of the B's from the expected value of the A's,

$$E(B_{jk\ell}|\Omega_j DI) = \langle B_{jk\ell} \rangle = \sum_{\beta=1}^{u_j} \frac{\langle A_{jk\beta} \rangle e_{\beta\ell}}{\sqrt{\lambda_\beta}} \tag{22.42}$$

and the same is true of the second posterior moments:

$$E(B_{jk\ell} B_{jkl}|\Omega_j DI) = \langle B_{jk\ell} B_{jkl} \rangle = \sum_{\beta=1}^{u_j} \sum_{v=1}^{u_j} \frac{e_{\beta\ell} e_{vl} \langle A_{jk\beta} A_{jkv} \rangle}{\sqrt{\lambda_\beta \lambda_v}} \tag{22.43}$$

where $E(B_{jk\ell}|\Omega_j DI)$ means the expected value of the ℓth amplitude $B_{jk\ell}$ in the jth model of the kth data set given the nonlinear Ω_j parameters, the data D and the prior information I. Substituting, Eq. (22.40) into Eq. (22.34) and using the definition of the H_{jl} functions, Eq. (22.37) one can rewrite the posterior probability for the model as:

$$\begin{aligned} P(U_j|DI) \quad &\propto \quad \int \left[\prod_{l=1}^{v_{jk}} P(\omega_{jkl}|I) \right] \prod_{k=1}^{n} \left[\frac{1}{\sigma_k} \left(2\pi\sigma_k^2 \right)^{-\frac{N_k+u_j}{2}} \gamma^{u_j} \frac{g_{j11} \cdots g_{ju_j u_j}}{\lambda_1^{-\frac{1}{2}} \cdots \lambda_{u_j}^{-\frac{1}{2}}} \right. \\ &\times \quad \left. \exp\left\{ -\frac{1}{2\sigma_k^2} \left(d_k^2 - 2\sum_{\ell=1}^{u_j} A_{jk\ell} h_{jk\ell} + \sum_{v=1}^{u_j} A_{jk\ell}^2 \right) \right\} \right] \\ &\times \quad dA_{jk1} \cdots dA_{jku_j} d\sigma_1 \cdots d\sigma_n d\Omega_j \end{aligned} \tag{22.44}$$

where

$$h_{jk\ell} = \sum_{i=1}^{N_j} d_{jk}(t_i) H_{j\ell}(t_i). \tag{22.45}$$

Completing the square in Eq. (22.44), one obtains:

$$\begin{aligned} P(U_j|DI) \quad &\propto \quad \int \left[\prod_{l=1}^{v_{jk}} P(\omega_{jkl}|I) \right] \prod_{k=1}^{n} \left[\frac{1}{\sigma_k} \left(2\pi\sigma_k^2 \right)^{\frac{-N_k+u_j}{2}} \gamma^{u_j} \frac{g_{j11} \cdots g_{ju_j u_j}}{\lambda_1^{-\frac{1}{2}} \cdots \lambda_{u_j}^{-\frac{1}{2}}} \right. \\ &\times \quad \left. \exp\left\{ -\frac{1}{2\sigma_k^2} \left[d_k^2 - h_{jk\ell}^2 + \sum_{\ell=1}^{u_j} \left(A_{jk\ell} - h_{jk\ell} \right)^2 \right] \right\} \right] \\ &\times \quad dA_{jk1} \cdots dA_{jku_j} d\sigma_1 \cdots d\sigma_n d\Omega_j. \end{aligned} \tag{22.46}$$

Designating the integral over the amplitudes as I_j and isolating it, Eq. (22.46) can be written as:

$$\begin{aligned} P(U_j|DI) \quad &\propto \quad \int \prod_{k=1}^{n} \left[\frac{1}{\sigma_k} \left(2\pi\sigma_k^2\right)^{-\frac{N_k+u_j}{2}} \gamma^{u_j} \frac{g_{j11}\cdots g_{ju_ju_j}}{\lambda_1^{-\frac{1}{2}}\cdots\lambda_{u_j}^{-\frac{1}{2}}} \left[\prod_{l=1}^{v_j} P(\omega_{jl}|I) \right] \right. \\ &\times \quad \left. \exp\left\{ \frac{1}{2\sigma_k^2} \left[d_k^2 - h_{jk\ell}^2 \right] \right\} \times I_j d\sigma_1 \cdots d\sigma_n d\Omega_j \right] \end{aligned} \tag{22.47}$$

where the amplitude integral is given by:

$$I_j \equiv \prod_{k=1}^{n} \int \exp\left\{ -\frac{1}{2\sigma_k^2} \sum_{\ell=1}^{u_j} \left(A_{jk\ell} - h_{jk\ell}\right)^2 \right\} dA_{jk1}\cdots dA_{jku_j}. \tag{22.48}$$

Introducing a change of variables

$$z_{jk\ell} = \frac{1}{\sqrt{2}\sigma_k}(A_{jk\ell} - h_{jk\ell}) \tag{22.49}$$

with volume element given by

$$\sqrt{2}\sigma_k dz_{jk\ell} = dA_{jk\ell} \tag{22.50}$$

the integral I_j becomes

$$\begin{aligned} I_j \quad &\equiv \quad \int_{-\infty}^{\infty} \exp\left\{ -\sum_{\ell=1}^{u_j} z_{jk\ell}^2 \right\} \sqrt{2}\sigma_k dz_{jk1}\cdots\sqrt{2}\sigma_k dz_{jku_j} \\ &= \quad \left(\sqrt{2}\sigma_k\right)^{u_j} \int_{-\infty}^{\infty} \exp\left\{ -\sum_{\ell=1}^{z_j} z_{jk\ell}^2 \right\} dz_{jk1}\cdots dz_{jku_j} \\ &= \quad \left(\sqrt{2}\sigma_k\right)^{u_j} \left(\sqrt{\pi}\,\right)^{u_j} \\ &= \quad \left(\sqrt{2}\sigma_k\sqrt{\pi}\,\right)^{u_j} \\ &= \quad \left(2\pi\sigma_k^2\right)^{\frac{u_j}{2}}. \end{aligned} \tag{22.51}$$

Inserting I_j back into Eq. (22.47), the posterior probability for model U_j is given by

$$\begin{aligned} P(U_j|DI) \quad &\propto \quad \int \prod_{k=1}^{n} \left[\frac{1}{\sigma_k} \left(2\pi\sigma_k^2\right)^{-\frac{N_k}{2}} \gamma^{u_j} \frac{g_{j11}\cdots g_{ju_ju_j}}{\lambda_1^{-\frac{1}{2}}\cdots\lambda_{u_j}^{-\frac{1}{2}}} \left[\prod_{l=1}^{v_j} P(\omega_{jl}|I) \right] \right. \\ &\times \quad \left. \exp\left\{ -\frac{1}{2\sigma_k^2} \left[d_k^2 - h_{jk\ell}^2 \right] \right\} d\sigma_1 \cdots d\sigma_n d\Omega_j \right]. \end{aligned} \tag{22.52}$$

The reason for the unusual functional form for the prior probability for the amplitudes, Eq. (22.32), is that all of the pesky little values of 2π drop out and leave one with a much cleaner functional form for the posterior probability for the model.

22.1.2.2 Marginalizing The Noise Standard Deviation

To evaluate the integrals over the σ_k, the integrand must be rearranged to isolate the integral:

$$\begin{aligned} P(U_j|DI) \quad &\propto \quad \int \prod_{k=1}^{n} \left[\gamma^{u_j} \frac{g_{j11} \cdots g_{ju_ju_j}}{\lambda_1^{-\frac{1}{2}} \cdots \lambda_{u_j}^{-\frac{1}{2}}} \left[\prod_{l=1}^{v_j} P(\omega_{jl}|I) \right] \right. \\ &\times \quad \left. \int_0^\infty \frac{1}{\sigma_k} \left(2\pi\sigma_k^2\right)^{-\frac{N_k}{2}} \exp\left\{ -\frac{1}{2\sigma_k^2} \left[d_k^2 - h_{jk\ell}^2 \right] \right\} \right] d\sigma_1 \cdots d\sigma_n d\Omega_j. \end{aligned} \tag{22.53}$$

All of the integrals over the σ_k have the same functional form, so we can evaluate one of these integrals and then use the results to evaluate the remaining integrals. Evaluating the integral over σ_k one has

$$I_{\sigma_k} \equiv \int_0^\infty \frac{1}{\sigma_k} \left(2\pi\sigma_k^2\right)^{-\frac{N_k}{2}} \exp\left\{ -\frac{1}{2\sigma_k^2} \left[d_k^2 - h_{jk\ell}^2 \right] \right\} d\sigma_k \tag{22.54}$$

and introducing the notation

$$Q_{jk} \equiv \frac{1}{2} \left[d_k^2 - h_{jk\ell}^2 \right] \tag{22.55}$$

and I_{σ_k} becomes

$$I_{\sigma_k} \equiv (2\pi)^{-\frac{N_k}{2}} \int_0^\infty \sigma_k^{-(N_k+1)} \exp\left\{ -\frac{Q_{jk}}{\sigma_k^2} \right\} d\sigma_k \tag{22.56}$$

This integral can be transformed into a Gamma function. A gamma function is defined as:

$$\Gamma(z) = \int_0^\infty t^{z-1} \exp\{-t\} dz \tag{22.57}$$

so a simple change of variables and a little algebra and the integral I_{σ_k} is then given by

$$I_{\sigma_k} \equiv \left[\frac{1}{2} \Gamma\left(\frac{N_k}{2} \right) (2\pi Q_{jk})^{-\frac{N_k}{2}} \right] \tag{22.58}$$

Inserting Eq. (22.58) into Eq. (22.53) one obtains

$$P(U_j|DI) \propto \int \left[\prod_{l=1}^{v_j} P(\omega_{jl}|I) \right] \prod_{k=1}^{n} \left\{ \left[\gamma^{u_j} \frac{g_{j11} \cdots g_{ju_ju_j}}{\lambda_1^{-\frac{1}{2}} \cdots \lambda_{u_j}^{-\frac{1}{2}}} \right] \left[\Gamma\left(\frac{N_k}{2} \right) (2\pi Q_{jk})^{-\frac{N_k}{2}} \right] \right\} d\Omega_j. \tag{22.59}$$

as the posterior probability for the model where we dropped the factor of one half, because it is exactly the same for all of the $P(U_j|DI)$ and so cancels when this distribution is normalized.

This equation is correct, but not very computationally convenient because it requires an eigenvalue decomposition every time one evaluates the posterior probability. Fortunately, there are a few modifications that can be done that improve computational efficiency significantly without making approximations. First, note the presence of the eigenvalues, they are simply the determinant of the g_{jlm} matrix and can be computed with a matrix inverse. Making this substitution one obtains

$$P(U_j|DI) \propto \int \left[\prod_{l=1}^{v_j} P(\omega_{jl}|I) \right] \prod_{k=1}^{n} \left[\gamma^{u_j} g_{j11} \cdots g_{ju_ju_j} \left| g_{jlm} \right|^{-\frac{1}{2}} \right] Q_{jk}^{-\frac{N_k}{2}} d\Omega_j. \tag{22.60}$$

Next the function Q_{jk} can be computed using a matrix inverse instead of an eigenvalue decomposition, thus supplying the determinate mentioned earlier as well as allowing evaluation of the Q_{jk} function. The integral over an amplitude in a Gaussian quadrature integral, just constrains the amplitudes to their maximum posterior probability values. Consequently, we can write

$$Q_{jk} \equiv \sum_{i=1}^{N_j} \left[d_k(t_i) - \sum_{\ell=1}^{u_j} \hat{B}_{j\ell} G_{j\ell}(t_i, \Omega_j) \right]^2 \tag{22.61}$$

and its mathematically the same as doing the eigenvalue decomposition. The amplitudes in this equation, the $\hat{B}_{j\ell}$, are given by the solution to

$$\sum_{k=1}^{\nu} g_{jk\ell} \hat{B}_{j\ell} = T_{j\ell}. \tag{22.62}$$

The right-hand side of this equation is the projection of the data onto the model components and is given by

$$T_{j\ell} = \sum_{i=1}^{N_j} d_j(t_i) G_{j\ell}(t_i). \tag{22.63}$$

See [2], and [11] for more on how the integrals over the amplitudes are evaluated.

Equation 22.60 is the joint posterior probability for the nonlinear parameters and is targeted by the Markov chain Monte Carlo simulations used to evaluate the remaining integrals. These simulations only vary the nonlinear parameters, the amplitudes simply do not appear in the posterior probability. However, the amplitudes are output from the simulation. The output amplitudes are given by Eq. (22.62). Because these amplitudes are estimated for each value of the nonlinear parameters, there is as many samples from the distributions of the amplitudes as there is for each of the nonlinear parameters. Consequently, the model that use marginalization do output density functions for the amplitudes.

22.2 Outputs Form The Enter Ascii Model Package

The Text outputs files from the Enter Ascii Model Selection packages consist of: "Bayes.prob.model," "BayesModelAscii.mcmc.values," "Bayes.params," "Console.log," "Bayes.accepted" and a condensed file "Bayes.Condensed.File." These output files can be viewed using the Text Viewer or they can be viewed using File Viewer by navigating to the current working directory and then selecting the files. The format of the mcmc.values report is discussed in Appendix D and the other reports are discussed in Chapter ??. Additionally, the "Plot Results Viewer" can be used to view the output probability density functions. In addition to the standard data, model and residual plots there are probability density functions for each parameter in the currently loaded Fortran/C model. These output probability density functions are named

```
ModelFileName.ParamName
```

where `ModelFileName` is the name of the currently loaded model. For example, if you have a model named `MyFunnyExp` model, and it has a decay rate named `FunnyRate` the output file containing the posterior probability for `FunnyRate` would be named:

```
MyFunnyExp.FunnyRate.
```

This naming convention also applies to derived parameters. So, if in addition to generating samples for `FunnyRate`, you also generated samples from a derived inverse decay rate, which was called `FunnyDecayTime` then there would also be an output file named

```
MyFunnyExp.FunnyDecayTime
```

containing the posterior probability for the decay time. For more on writing Ascii models in either Fortran or C, see Appendix E.

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