Bayesian Analysis Users Guide
Release 4.00, Manual Version 1

G. Larry Bretthorst
Biomedical MR Laboratory
Washington University School Of Medicine,
Campus Box 8227
Room 2313, East Bldg.,
4525 Scott Ave.
St. Louis MO 63110
http://bayes.wustl.edu
Email: larry@bayes.wustl.edu

October 21, 2016
# Contents

Manual Status 16

1 An Overview Of The Bayesian Analysis Software 19
   1.1 The Server Software 19
   1.2 The Client Interface 22
      1.2.1 The Global Pull Down Menus 24
      1.2.2 The Package Interface 24
      1.2.3 The Viewers 27

2 Installing the Software 29

3 the Client Interface 33
   3.1 The Global Pull Down Menus 35
      3.1.1 the Files menu 35
      3.1.2 the Packages menu 40
      3.1.3 the WorkDir menu 45
      3.1.4 the Settings menu 46
      3.1.5 the Utilities menu 50
      3.1.6 the Help menu 50
   3.2 The Submit Job To Server area 51
   3.3 The Server area 52
   3.4 Interface Viewers 52
      3.4.1 the Ascii Data Viewer 53
      3.4.2 the fid Data Viewer 53
      3.4.3 Image Viewer 59
         3.4.3.1 the Image List area 59
         3.4.3.2 the Set Image area 62
         3.4.3.3 the Image Viewing area 62
         3.4.3.4 the Grayscale area on the bottom 63
         3.4.3.5 the Pixel Info area 63
         3.4.3.6 the Image Statistics area 64
      3.4.4 Prior Viewer 65
      3.4.5 Fid Model Viewer 68
         3.4.5.1 The fid Model Format 70
4 An Introduction to Bayesian Probability Theory

4.1 The Rules of Probability Theory ........................................... 99
4.2 Assigning Probabilities ....................................................... 102
4.3 Example: Parameter Estimation ............................................. 109
  4.3.1 Define The Problem .................................................... 110
  4.3.1.1 The Discrete Fourier Transform ................................. 110
  4.3.1.2 Aliases ............................................................. 113
  4.3.2 State The Model—Single-Frequency Estimation .................. 114
  4.3.3 Apply Probability Theory ............................................. 115
  4.3.4 Assign The Probabilities ............................................ 118
  4.3.5 Evaluate The Sums and Integrals .................................. 120
  4.3.6 How Probability Generalizes The Discrete Fourier Transform 123
  4.3.7 Aliasing ............................................................... 126
  4.3.8 Parameter Estimates ................................................ 132
4.4 Summary and Conclusions .................................................. 136

5 Given Exponential Model ..................................................... 137

5.1 The Bayesian Calculation ................................................... 139
5.2 Outputs From The Given Exponential Package .......................... 141

6 Unknown Number of Exponentials ........................................ 143

6.1 The Bayesian Calculations ................................................ 145
6.2 Outputs From The Unknown Number of Exponentials Package ....... 148

7 Inversion Recovery ............................................................ 151

7.1 The Bayesian Calculation ................................................... 153
7.2 Outputs From The Inversion Recovery Package ........................ 154
14 Magnetization Transfer 265  
14.1 The Bayesian Calculation ........................................ 267  
14.2 Using The Package ............................................. 271  

15 Magnetization Transfer Kinetics 275  
15.1 The Bayesian Calculation ........................................ 277  
15.2 Using The Package ............................................. 281  

16 Given Polynomial Order 285  
16.1 The Bayesian Calculation ........................................ 287  
16.1.1 Gram-Schmidt .................................................. 287  
16.1.2 The Bayesian Calculation .................................... 288  
16.2 Outputs From the Given Polynomial Order Package .......... 290  

17 Unknown Polynomial Order 293  
17.1 Bayesian Calculations ........................................... 295  
17.1.1 Assigning Priors ................................................ 296  
17.1.2 Assigning The Joint Posterior Probability ................. 297  
17.2 Outputs From the Unknown Polynomial Order Package ....... 299  

18 Errors In Variables 303  
18.1 The Bayesian Calculation ........................................ 305  
18.2 Outputs From The Errors In Variables Package ............... 308  

19 Behrens-Fisher 311  
19.1 Bayesian Calculation ........................................... 311  
19.1.1 The Four Model Selection Probabilities ....................... 314  
19.1.1.1 The Means And Variances Are The Same ................. 315  
19.1.1.2 The Mean Are The Same And The Variances Differ ....... 317  
19.1.1.3 The Means Differ And The Variances Are The Same .... 318  
19.1.1.4 The Means And Variances Differ .......................... 319  
19.1.2 The Derived Probabilities .................................... 320  
19.1.3 Parameter Estimation ......................................... 321  
19.2 Outputs From Behrens-Fisher Package ......................... 322  

20 Enter Ascii Model 329  
20.1 The Bayesian Calculation ........................................ 331  
20.1.1 The Bayesian Calculations Using Eq. (20.1) ............... 331  
20.1.2 The Bayesian Calculations Using Eq. (20.2) ............... 332  
20.2 Outputs Form The Enter Ascii Model Package ................. 335  

22 Enter Ascii Model Selection 341  
22.1 The Bayesian Calculations ...................................... 343  
22.1.1 The Direct Probability With No Amplitude Marginalization .. 344  
22.1.2 The Direct Probability With Amplitude Marginalization ... 346  
22.1.2.1 Marginalizing the Amplitudes ............................ 347  
22.1.2.2 Marginalizing The Noise Standard Deviation .......... 352
List of Figures

1.1 The Start Up Window ......................................................... 23
1.2 Example Package Exponential Interface ..................................... 25

2.1 Installation Kit For The Bayesian Analysis Software ...................... 31

3.1 The Start Up Window .......................................................... 34
3.2 The Files Menu ...................................................................... 35
3.3 The Files/Load Image Submenu ................................................ 37
3.4 The Packages Menu ............................................................. 41
3.5 The Working Directory Menu .................................................. 46
3.6 The Working Directory Information Popup ..................................... 47
3.7 The Settings Pull Down Menu ................................................ 47
3.8 The McMC Parameters Popup ................................................... 48
3.9 The Edit Server Popup ........................................................... 49
3.10 The Submit Job Widgets ......................................................... 51
3.11 The Server Widgets Group .................................................... 52
3.12 The Ascii Data Viewer .......................................................... 54
3.13 The Fid Data Viewer ............................................................. 55
3.14 Fid Data Display Type .......................................................... 56
3.15 Fid Data Options Menu ......................................................... 58
3.16 The Image Viewer ............................................................... 60
3.17 The Image Viewer Right Mouse Popup Menu ............................... 61
3.18 The Prior Probability Viewer ................................................... 66
3.19 The Fid Model Viewer .......................................................... 69
3.20 The Plot Results Viewer ........................................................ 72
3.21 Plot Information Popup ......................................................... 73
3.22 The Text Results Viewer ........................................................ 75
3.23 The Bayes Condensed File ..................................................... 78
3.24 Data, Model, And Resid Plot ................................................... 81
3.25 The Parameter Posterior Probabilities ....................................... 82
3.26 The Maximum Entropy Histograms ......................................... 84
3.27 The Parameter Samples Plot ................................................... 85
3.28 Posterior Probability Vs Parameter Value .................................... 86
3.29 Posterior Probability Vs Parameter Value, A Skewed Example ........... 87
3.30 The Expected Value Of The Logarithm Of The Likelihood ............... 89
List of Tables

8.1 Multiplet Relative Amplitudes ........................................... 165
8.2 Bayes Analyze Models ......................................................... 181
8.3 Bayes Analyze Short Descriptions ....................................... 195
Enter Ascii Model

The Enter Ascii Model Package allows you to enter a model of your own and then use Bayesian probability theory to analyze that model. To use this package you do not have to have either Fortran or C installed on your server. However, if you do not have either Fortran or C installed, the only models you will be able to use are the system models. Consequently, installing both Fortran and C is strongly recommended. The interface to this package is shown in Fig. 20.1 To use this package, you must do the following:

Select the “Enter Ascii Model” package from the Package menu.

Load a 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 abscissa. 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.

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

Review the prior probabilities for the loaded model using the Prior Viewer.

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.

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 20.1: Enter Ascii Model Package Interface

To use the Enter Ascii package:

1. Load the Fortran or C model function from the System or User Models directory.
2. For non-system models, build the model using the “Build” button.
3. Load an ascii file having the number of abscissa specified by the model parameter file.
4. Review the prior range information, and make appropriate changes.
5. Select the server to run the analysis.
6. Run the analysis using the “Run” button.
7. Use “Get Job” to get the results from the server.

Figure 20.1: All packages that allow the user to load a Fortran or C model have the buttons titled “Load and Build Model.” These buttons allow you to load a model from either the system directory or from your user directory. They allow you to compile a model and save the current prior settings. Additionally, using the “Fortran/C Model Viewer” you can edit, modify and create models, see Appendix E for more on creating Fortran and C models.
Get 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.

20.1 The Bayesian Calculation

The calculation done by Enter Ascii Model Package is a parameter estimation calculation. However, there are two distinct functional forms for the model that are used: one using marginalization over the amplitudes, and one that does not. The model function that does not use marginalization is given by:

\[ d_j(t_i) = U_j(t_i, r_1, r_2, \ldots) + n_j(t_i) \] (20.1)

where \( d_j(t_i) \) represents a data item in the \( j \)th data set at abscissa value \( t_i \) and \( t_i \) may be vector valued. \( U_j(t_i, r_1, r_2, \ldots) \) is the model function. \( r_j \) are the various parameters appearing in the model including any amplitudes that may be present, and \( n_j(t_i) \) represents noise in the \( j \)th data set at abscissa \( t_i \). Because, this model does not marginalize out the amplitudes, it is possible to restrict the amplitudes ranges using the prior probabilities.

The other model used by this package assumes the amplitudes are to be marginalized from the joint posterior probability for the parameters. The model equation that uses marginalization is similar

\[ d_j(t_i) = \sum_{\ell=1}^{m} A_{jk} G_{j\ell}(t_i, r_1, r_2, \ldots) + n_j(t_i) \] (20.2)

where the amplitudes are labeled \( A_{jk} \) meaning the \( k \)th amplitude in the \( j \)th data set, the sum is over all of the amplitudes in the model, \( G_{j\ell}(t_i, r_1, r_2, \ldots) \) is the \( \ell \)th model function in the \( j \)th data set evaluated at abscissa \( t_i \) and this model equation implicitly assumes that each data set contains same number of amplitudes.

20.1.1 The Bayesian Calculations Using Eq. (20.1)

To compute the marginal posterior probability for each parameter using Eq. (20.1), a Markov chain Monte Carlo simulation is run targeting the joint posterior probability for all of the parameters. This joint posterior probability is represented symbolically by \( P(r_1 r_2 \ldots DI) \). The joint posterior probability for the parameters is factored using Bayes’ theorem to obtain

\[ P(r_1 r_2 \ldots DI) \propto P(r_1 r_2 \ldots I)P(D|r_1 r_2 \ldots I) \] (20.3)

where \( D \) stands for all of the data in all of the data sets, \( P(r_1 r_2 \ldots \sigma_1 \ldots I) \), is factored into independent prior probabilities for each parameter:

\[ P(r_1 r_2 \ldots DI) \propto \prod_{j=1}^{m} P(r_j|I) P(D|r_1 r_2 \ldots I) \] (20.4)

where \( m \) is the total number of parameters in the model. The priors, \( P(r_j|I) \), are specified in the input parameter file that describes the model. These prior are either the defaults, if you loaded the model from the system directory, or they are the priors set using the interface. Because we don’t
know the functional form of these priors, we are going to leave them in symbolic form. Factoring the
direct probability for the data into an independent direct probability for each data set, one obtains

$$P(r_1 r_2 \ldots | DI) \propto \prod_{l=1}^{m} P(r_l|I) \prod_{j=1}^{n} P(D_j|r_1 r_2 \ldots I)$$  \hspace{1cm} (20.5)

as the joint posterior probability for the parameters. The direct probability for the data is a marginal
likelihood, because the standard deviation of the noise prior probability is not present. Introducing
a standard deviation of the noise prior probability, \( \sigma_j \), for each data set, and using the rules of
probability theory to remove these parameters, one obtains:

$$P(r_1 r_2 \ldots | DI) \propto \prod_{l=1}^{m} P(r_l|I) \prod_{j=1}^{n} \left[ \int P(\sigma_j|I)P(D_j|\sigma_j r_1 r_2 \ldots I) d\sigma_j \right].$$  \hspace{1cm} (20.6)

We have reached the point in this calculation where one has no other choice than to assign proba-
bilities to represent each of these probabilities and then to perform the indicated integrals. Assign
a Jeffreys’ prior to the prior probability for the noise standard deviation:

$$P(\sigma_j|I) \propto \frac{1}{\sigma_j},$$  \hspace{1cm} (20.7)

and assigning the direct probability for the data using a Gaussian of standard deviation \( \sigma_j \) one
obtains

$$P(r_1 r_2 \ldots | DI) \propto \prod_{l=1}^{m} P(r_l|I) \prod_{j=1}^{n} \left[ \int \sigma_j^{-(N_j+1)} \exp \left\{ -\frac{Q_j(t_i, r_1, r_2, \ldots)}{2\sigma_j^2} \right\} d\sigma_j \right].$$  \hspace{1cm} (20.8)

as the joint posterior probability for the parameters, where \( Q_j(t_i, r_1, r_2, \ldots) \) is given by:

$$Q_j(t_i, r_1, r_2, \ldots) = \sum_{i=1}^{N_j} \left[ d_j(t_i) - U_j(t_i, r_1, r_2, \ldots) \right]^2,$$  \hspace{1cm} (20.9)

and is the total squared residual and is essentially \( \chi^2 \). Evaluating the integral over the standard
deviation of the noise, one obtains

$$P(r_1 r_2 \ldots | DI) \propto \prod_{l=1}^{m} P(r_l|I) \prod_{j=1}^{n} \left[ \frac{Q_j(t_i, r_1, r_2, \ldots)}{2} \right]^{-\frac{N_j}{2}}$$  \hspace{1cm} (20.10)

as the joint posterior probability for the parameters, where we have dropped a number of constants
that make no difference in this parameter estimation problem.

### 20.1.2 The Bayesian Calculations Using Eq. (20.2)

To compute the marginal posterior probability for each parameter using Eq. (20.2), a Markov chain
Monte Carlo simulation is run targeting the joint posterior probability for all of the nonlinear
parameters. In this context, nonlinear means all of the parameters appearing in the model in a
nonlinear fashion, i.e., all of the parameters except the amplitudes. This joint posterior probability is represented symbolically by \( P(\{ r_j \}_{k=1}^m | D) \). The joint posterior probability for the nonlinear parameters is factored using Bayes’ theorem to obtain

\[
P(\{ r_j \}_{k=1}^m | D) \propto P(\{ r_j \}_{k=1}^m | I_1) P(D | \{ r_j \}_{k=1}^m ) I_1
\]

(20.11)

where \( D \) stands for all of the data in all of the data sets, the prior probability for all of the nonlinear parameters is represented by, \( P(\{ r_j \}_{k=1}^m \sigma \sigma \sigma \sigma | I_1) \), and we will factor it into independent prior probabilities for each parameter. Consequently, the joint posterior probability for all of the nonlinear parameters is given by

\[
P(\{ r_j \}_{k=1}^m | D) \propto \prod_{j=1}^{m} P(\{ r_j \}_{k=1}^m | I_1) \prod_{j=1}^{n} P(\{ D_j \}_{j=1}^{n} | \{ r_j \}_{k=1}^m I_1)\prod_{n=1}^{j} P(\{ D_j \}_{j=1}^{n} | \{ r_j \}_{k=1}^m I_1)
\]

(20.12)

where \( m \) is the total number of nonlinear parameters in the model. The priors, \( P(\{ r_j \}_{k=1}^m | I_1) \), are specified in the input parameter file that describes the model. These prior are either the defaults, if you loaded the model from the system directory, or they are the priors set using the interface. Because we don’t know the functional form of these priors, we are going to leave them in symbolic form. Factoring the direct probability for the data into an independent direct probability for each data set, one obtains

\[
P(\{ r_j \}_{k=1}^m | D) \propto \prod_{l=1}^{m} P(\{ r_l \}_{k=1}^m | I_1) \prod_{j=1}^{n} P(\{ D_j \}_{j=1}^{n} | \{ r_j \}_{k=1}^m I_1)\prod_{n=1}^{j} P(\{ D_j \}_{j=1}^{n} | \{ r_j \}_{k=1}^m I_1)
\]

(20.13)

as the joint posterior probability for the nonlinear parameters.

The direct probability for the data is a marginal likelihood, because neither the standard deviation of the noise prior probability nor the amplitudes are present. To proceed with this calculation, these parameters must be reintroduced into the joint posterior probability for the nonlinear parameters. Representing the standard deviation of the noise prior probability for each data set as \( \sigma_j \) and \( \{ A \}_{j} \) as all of the amplitudes in the \( j \)th data set, one obtains

\[
P(\{ r_j \}_{k=1}^m | D) \propto \prod_{l=1}^{m} P(\{ r_l \}_{k=1}^m | I_1) \prod_{j=1}^{n} \int P(\{ D_j \}_{j=1}^{n} | \{ r_j \}_{k=1}^m I_1) d\sigma_j d\{ A \}_{j}
\]

(20.14)

as the joint posterior probability for the parameters. Factoring the right-hand side of this equation, one obtains

\[
P(\{ r_j \}_{k=1}^m | D) \propto \prod_{l=1}^{m} P(\{ r_l \}_{k=1}^m | I_1) \prod_{j=1}^{n} \int P(\sigma_j | I_1) P(\{ A \}_{j} | I_1) P(\{ D_j \}_{j=1}^{n} | \{ r_j \}_{k=1}^m I_1) d\sigma_j d\{ A \}_{j}
\]

(20.15)

where \( P(\sigma_j | I_1) \) is the prior probability for the standard deviation of the noise prior probability in the \( j \)th data set. Similarly, \( P(\{ A \}_{j} | I_1) \) is the joint prior probability for the amplitudes in the \( j \)th data set. If we assume the amplitudes are logically independent, then the joint prior probability for the amplitudes, \( P(\{ A \}_{j} | I_1) \), can be factored into a product of prior probabilities for each amplitude:

\[
P(\{ r_j \}_{k=1}^m | D) \propto \prod_{l=1}^{m} P(\{ r_l \}_{k=1}^m | I_1) \prod_{j=1}^{n} \int P(\sigma_j | I_1) \prod_{k=1}^{n} P(\{ A \}_{j} | I_1) P(\{ D_j \}_{j=1}^{n} | \{ r_j \}_{k=1}^m I_1) d\sigma_j d\{ A \}_{j}
\]

(20.16)
where \( P(A_{jk}|I) \) is the prior probability for the \( k \)th amplitude in the \( j \)th data set, and \( \nu \) is the number of data sets. We will assign a zero-mean Gaussian prior probability for each amplitudes. This Gaussian prior probability is given by

\[
P(A_{jk}|I) \propto \left( \frac{2\pi \sigma^2_j}{\gamma^2 g_{jkk}} \right)^{-\frac{1}{2}} \exp \left\{ -\frac{A_{jk}^2 \gamma^2 g_{jkk}}{2\sigma^2_j} \right\} \tag{20.17}
\]

where

\[
g_{jkl} \equiv \sum_{i=1}^{N_j} G_{jk}(t_i)G_{j\ell}(t_i) \tag{20.18}
\]

and \( \gamma \) is used to control the width of this prior probability. The reason for this particular functional 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 the prior probability for the amplitudes, Eq. (20.17), into the joint posterior probability for the parameters, Eq. 20.16,

\[
P(r_1 r_2 \ldots | DI) \propto \left[ \prod_{l=1}^{m} P(r_l|I) \right] \times \prod_{j=1}^{n} \left[ \int \left( \frac{1}{\sigma_j} \left( \frac{2\pi \sigma^2_j}{\gamma^2 g_{j11} \cdots g_{j\nu\nu}} \right)^{-\frac{1}{2}} \right. \right. \exp \left\{ -\frac{\sum_{k=1}^{\nu} A_{jk}^2 \gamma^2 g_{jkk}}{2\sigma^2_j} \right\} \times P(D_j|\sigma_j \{ A_j \}, r_1 r_1 \ldots I) \right] d\sigma_j d\{ A_j \} \tag{20.19}
\]

and assigning a Gaussian for the direct probability for the data, \( P(D_j|\sigma_j \{ A_j \}, r_1 r_2 \ldots I) \), one obtains:

\[
P(r_1 r_2 \ldots | DI) \propto \left[ \prod_{l=1}^{m} P(r_l|I) \right] \times \prod_{j=1}^{n} \left[ \int \left( \frac{1}{\sigma_j} \left( \frac{2\pi \sigma^2_j}{\gamma^2 g_{j11} \cdots g_{j\nu\nu}} \right)^{-\frac{1}{2}} \right. \right. \exp \left\{ -\frac{\sum_{k=1}^{\nu} A_{jk}^2 \gamma^2 g_{jkk}}{2\sigma^2_j} \right\} \times \left. \left. \left( 2\pi \sigma^2_j \right)^{-\frac{N_j}{2}} \right. \exp \left\{ -\sum_{i=1}^{N_j} \frac{(d_{ji} - \sum_{k=1}^{\mu} A_{jk} G_{jk}(t_i, r_1 \cdots))^2}{2\sigma_j} \right\} \right] d\sigma_j d\{ A_j \} \tag{20.20}
\]

After evaluating the integrals over the amplitudes, one obtains

\[
P(r_1 r_2 \ldots | DI) \propto \left[ \prod_{l=1}^{m} P(r_l|I) \right] \prod_{j=1}^{n} \left( \frac{\gamma^2}{g_{j11} \cdots g_{j\nu\nu}} \right)^{-\frac{1}{2}} \left[ Q_j(r_1 r_2 \ldots) \right]^{-\frac{N_j}{2}} \tag{20.21}
\]
with
\[ Q_j(r_1 r_2 \ldots) \equiv \sum_{i=1}^{N_j} \left[ d_{ji} - \sum_{\ell=1}^{\nu} \hat{A}_{j\ell} G_{j\ell}(t_i r_1 r_2 \ldots) \right]^2, \]  
(20.22)

\(|g_{jkl}|\) is the magnitude of the determinate of the \(g_{jkl}\) matrix defined in Eq. (20.18) and the amplitudes \(\hat{a}_{j\ell}\) are given by the solution to

\[ \sum_{k=1}^{\nu} g_{jkl} \hat{A}_{j\ell} = T_{j\ell} \]  
(20.23)

with the right-hand side of this equation given by:

\[ T_{j\ell} = \sum_{i=1}^{N_j} d_{j}(t_i) G_{j\ell}(t_i). \]  
(20.24)

See [2], and [11] for more on how the integrals over the amplitudes are evaluated. Equation 20.21 is the joint posterior probability for the nonlinear parameters that is targeted by the Markov chain Monte Carlo simulations. 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. (20.23). 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.

## 20.2 Outputs Form The Enter Ascii Model Package

The Text outputs files from the Enter Ascii Model packages consist of: “Bayes.prob.model,” “BayesModelAscii.mcmc.values,” “Bayes.params,” “Console.log,” “Bayes.accepted” and a “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 3. 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

\[ MyFunnyExp.FunnyDecayTime. \]
THE PACKAGES

MyFunnyExp.FunnyDecayTime

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


[45] Nicholas Metropolis, Arianna W. Rosenbluth, Marshall N. Rosenbluth, Augusta H. Teller, and Edward Teller (1953), “Equation of State Calculations by Fast Computing Machines,” Journal of Chemical Physics. The previous link is to the American Institute of Physics and if you do not have access to Science Sitations you many not be able to retrieve this paper.


