Contents

Manual Status 14

1 An Overview Of The Bayesian Analysis Software 17
  1.1 The Server Software .................................................. 17
  1.2 The Client Interface .................................................... 20
    1.2.1 The Global Pull Down Menus ................................... 22
    1.2.2 The Package Interface ........................................... 22
    1.2.3 The Viewers ...................................................... 25

2 Installing the Software .................................................. 27

3 the Client Interface ....................................................... 29
  3.1 The Global Pull Down Menus ........................................ 31
    3.1.1 the Files menu .................................................. 31
    3.1.2 the Packages menu ............................................. 36
    3.1.3 the WorkDir menu ............................................... 41
    3.1.4 the Settings menu ............................................... 42
    3.1.5 the Utilities menu ............................................... 46
    3.1.6 the Help menu ................................................... 47
  3.2 The Submit Job To Server area ...................................... 47
  3.3 The Server area ....................................................... 48
  3.4 Interface Viewers ..................................................... 49
    3.4.1 the Ascii Data Viewer .......................................... 49
    3.4.2 the fid Data Viewer ............................................ 51
    3.4.3 Image Viewer .................................................... 56
      3.4.3.1 the Image List area ........................................ 56
      3.4.3.2 the Set Image area ........................................ 58
      3.4.3.3 the Image Viewing area ................................... 58
      3.4.3.4 the Grayscale area on the bottom ......................... 60
      3.4.3.5 the Pixel Info area ........................................ 60
      3.4.3.6 the Image Statistics area ................................ 60
    3.4.4 Prior Viewer ..................................................... 62
    3.4.5 fid Model Viewer ................................................ 65
      3.4.5.1 The fid Model Format ....................................... 65
# List of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>The Start Up Window</td>
<td>21</td>
</tr>
<tr>
<td>1.2</td>
<td>Example Package Interface</td>
<td>23</td>
</tr>
<tr>
<td>3.1</td>
<td>The Start Up Window</td>
<td>30</td>
</tr>
<tr>
<td>3.2</td>
<td>The Files Menu</td>
<td>31</td>
</tr>
<tr>
<td>3.3</td>
<td>The Load Image Selection Menu</td>
<td>33</td>
</tr>
<tr>
<td>3.4</td>
<td>The Packages Menu</td>
<td>37</td>
</tr>
<tr>
<td>3.5</td>
<td>The Working Directory Pull Down Menu</td>
<td>42</td>
</tr>
<tr>
<td>3.6</td>
<td>The Working Directory Po pup</td>
<td>43</td>
</tr>
<tr>
<td>3.7</td>
<td>The Settings Pull Down Menu</td>
<td>44</td>
</tr>
<tr>
<td>3.8</td>
<td>The McMC Parameters Po pup</td>
<td>44</td>
</tr>
<tr>
<td>3.9</td>
<td>The Edit Server Popup</td>
<td>45</td>
</tr>
<tr>
<td>3.10</td>
<td>The Submit Job Widget Group</td>
<td>48</td>
</tr>
<tr>
<td>3.11</td>
<td>The Server Widget Group</td>
<td>49</td>
</tr>
<tr>
<td>3.12</td>
<td>the Ascii Data viewer</td>
<td>50</td>
</tr>
<tr>
<td>3.13</td>
<td>the fid Data viewer</td>
<td>52</td>
</tr>
<tr>
<td>3.14</td>
<td>The Fid Data Viewer Display Type</td>
<td>53</td>
</tr>
<tr>
<td>3.15</td>
<td>The Fid Data Viewer the Options Menu</td>
<td>54</td>
</tr>
<tr>
<td>3.16</td>
<td>The Image Viewer</td>
<td>57</td>
</tr>
<tr>
<td>3.17</td>
<td>The Image Viewer Right Mouse Menu</td>
<td>58</td>
</tr>
<tr>
<td>3.18</td>
<td>The Prior Viewer</td>
<td>63</td>
</tr>
<tr>
<td>3.19</td>
<td>The Fid Model Viewer</td>
<td>66</td>
</tr>
<tr>
<td>3.20</td>
<td>The Data Model and Residuals</td>
<td>69</td>
</tr>
<tr>
<td>3.21</td>
<td>The Plot Information popup</td>
<td>70</td>
</tr>
<tr>
<td>3.22</td>
<td>The Posterior Probabilities</td>
<td>71</td>
</tr>
<tr>
<td>3.23</td>
<td>The Posterior Probabilities Vs Parameter Value</td>
<td>73</td>
</tr>
<tr>
<td>3.24</td>
<td>The Posterior Probabilities Vs Parameter Value a Skewed Example</td>
<td>74</td>
</tr>
<tr>
<td>3.25</td>
<td>The Expected Log Likelihood</td>
<td>76</td>
</tr>
<tr>
<td>3.26</td>
<td>The Scatter Plots</td>
<td>77</td>
</tr>
<tr>
<td>3.27</td>
<td>The Log Probability Plot</td>
<td>79</td>
</tr>
<tr>
<td>3.28</td>
<td>The Text Results Viewer</td>
<td>81</td>
</tr>
<tr>
<td>3.29</td>
<td>The Bayes Condensed File</td>
<td>84</td>
</tr>
<tr>
<td>3.30</td>
<td>Fortran/C Model Viewer</td>
<td>87</td>
</tr>
<tr>
<td>3.31</td>
<td>Fortran/C Model Viewer</td>
<td>88</td>
</tr>
</tbody>
</table>
11.1 the Find Resonances interface ........................................... 230
12.1 Diffusion Tensor Interface ................................................. 238
12.2 Diffusion Tensor Parameter Estimates .................................. 246
12.3 Diffusion Tensor Posterior Probability For The Model ................. 246
13.1 The Big Magnetization Package Interface ............................... 250
13.2 Big Magnetization Transfer Example Fid ................................. 253
13.3 Big Magnetization Transfer Expansion .................................. 253
13.4 Big Magnetization Transfer Peak Pick .................................. 254
14.1 Magnetization Transfer Interface .......................................... 256
14.2 Magnetization Transfer Peak Pick ........................................ 262
14.3 Magnetization Transfer Example Data ................................... 263
14.4 Magnetization Transfer Example Spectrum .............................. 264
15.1 Magnetization Transfer Kinetics Interface ............................... 268
15.2 Magnetization Transfer Kinetics Arrhenius Plot ....................... 274
15.3 Magnetization Transfer Kinetics Water Viscosity Table ............... 275
16.1 Given Polynomial Order Package Interface .............................. 278
16.2 Given Polynomial Order Scatter Plot ................................... 284
17.1 Unknown Polynomial Order Interface ..................................... 286
17.2 The Distribution of Models ................................................ 290
17.3 Unknown Polynomial Order Package Posterior Probability ............ 292
18.1 Errors In Variables Interface .............................................. 296
18.2 Errors In Variables McMC Values File .................................. 302
19.1 the Behrens-Fisher interface .............................................. 304
19.2 Behrens-Fisher Hypotheses Tested ....................................... 305
19.3 Behrens-Fisher Console Log .............................................. 315
19.4 Behrens-Fisher Status Listing ............................................ 316
19.5 Behrens-Fisher McMC Values File, The Preamble ...................... 317
19.6 Behrens-Fisher McMC Values File, The Middle ....................... 318
19.7 Behrens-Fisher McMC Values File, The End ............................ 319
20.1 Enter Ascii Model Interface ................................................ 322
21.1 Test Your Own Ascii Model Interface .................................... 330
22.1 Ascii Model Selection Interface .......................................... 332
26.1 Absorption Model Images .................................................. 346
26.2 Bayes Phase Interface ...................................................... 347
26.3 Bayes Phase Listing ......................................................... 353
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>27.1</td>
<td>Nonlinear Phasing Example</td>
<td>356</td>
</tr>
<tr>
<td>27.2</td>
<td>Nonlinear Phasing Interface</td>
<td>360</td>
</tr>
<tr>
<td>28.1</td>
<td>Image Pixels Example</td>
<td>362</td>
</tr>
<tr>
<td>A.1</td>
<td>Ascii Data File Format</td>
<td>368</td>
</tr>
<tr>
<td>D.1</td>
<td>The McMC Values Report Header</td>
<td>386</td>
</tr>
<tr>
<td>D.2</td>
<td>McMC Values Report, The Middle</td>
<td>387</td>
</tr>
<tr>
<td>D.3</td>
<td>The McMC Values Report, The End</td>
<td>388</td>
</tr>
<tr>
<td>E.1</td>
<td>Writing Models A Fortran Example</td>
<td>392</td>
</tr>
<tr>
<td>E.2</td>
<td>Writing Models A C Example</td>
<td>393</td>
</tr>
<tr>
<td>E.3</td>
<td>Writing Models, The Parameter File</td>
<td>395</td>
</tr>
<tr>
<td>E.4</td>
<td>Writing Models Fortran Declarations</td>
<td>399</td>
</tr>
<tr>
<td>E.5</td>
<td>Writing Models Fortran Example</td>
<td>402</td>
</tr>
<tr>
<td>E.6</td>
<td>Writing Models The Parameter File</td>
<td>403</td>
</tr>
<tr>
<td>G.1</td>
<td>The FD File Header</td>
<td>409</td>
</tr>
<tr>
<td>H.1</td>
<td>the Posterior Probability for the Number of Outliers</td>
<td>412</td>
</tr>
<tr>
<td>H.2</td>
<td>The Data, Model and Residual Plot With Outliers</td>
<td>414</td>
</tr>
</tbody>
</table>
List of Tables

8.1 Multiplet Relative Amplitudes .................................................. 157
8.2 Bayes Analyze Models .............................................................. 173
8.3 Bayes Analyze Short Descriptions ............................................. 186
Chapter 18

Errors In Variables

The “Errors in Variables” package fits polynomials to data when you have errors in both the abscissa $X$ and the data value $Y$. The interface to this package is shown in Fig. 18.1. This interface is used to configure the Errors In Variables Package by setting both the polynomial order and by indicating what errors are known or given. Additionally, depending on the settings of the “Given Errors In” widget, the interface will load two, three or four column Ascii data. To use this package, you must do the following:

Select the Errors In Variables Package from the Package menu.

Using “Given Errors In” pull down menu select the type of Errors In Variables problem you wish to solve. Your choices are:

1. “Not Given” solves the Errors In Variables problem when the errors in both $X$ and $Y$ are not given. This option requires two column Ascii data, see Section 18.2 for a description of these files.

2. “$X$ and $Y$” solves the Errors In Variables problem when the errors in $X$ and $Y$ are given. This option requires four column Ascii data.

3. “$X$ Only” solves the Errors In Variables problem when the errors in $X$ are given. This option requires three column Ascii data.

4. “$Y$ Only” solves the Errors In Variables problem when the errors in $Y$ are given. This option requires three column Ascii data.

Load one data set appropriate to the selected problem. Only “Not Given” uses standard two column Ascii data. Consequently, when this option is selected both Bayes Analyze and a Peak Pick can server as input. All of the other options require input of either three or four column Ascii files which can only be loaded using the “Files/Load Ascii/Files” menu. When you have successfully loaded a data set it will be plotted in the Ascii Data Viewer. However, the plot is a simple XY plot and no attempt is made by the interface to show the error bars in either $X$ or $Y$.

Using the “Order” pull down menu, set the order of the polynomial to fit to the data.
Figure 18.1: The Errors In Variables Package solves the problem of fitting polynomials when there are errors in both $X$ and $Y$ where $X$ is an abscissa and $Y$ is some function of $X$. Here this function is assumed to be a polynomial of a given order.

To use the Errors In Variables package:

1. Indicate which errors are known using the “Given Errors In:” combo box.
2. Load an Ascii file having 2, 3 or four columns as indicated.
3. Select the polynomial order you wish to analyze.
4. Select the server to run the analysis.
5. Run the analysis using the “Run” button.
6. Use “Get Job” to get the results from the server.
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 analysis on the selected server by activating the Run button.

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.

18.1 The Bayesian Calculation

The problem we are considering is one in which the data consists of measured pairs of numbers, \((\hat{x}_i, \hat{y}_i)\), where both the measured abscissa data value, \(\hat{x}_i\), and the measured ordinate, \(\hat{y}_i\), contain errors, i.e., noise, and we wish to fit a polynomial to these measured data pairs. If we designate the “true” but unknown values of \((\hat{x}_i, \hat{y}_i)\) as \((x_i, y_i)\) then the polynomial one would normally fit is given by

\[
y = F(x) = \sum_{j=0}^{m} B_j H_j(x) \tag{18.1}
\]

where the polynomial, \(F(x)\), is evaluated at the true value of \(x\) giving a true value of \(y\), \(B_j\) is the amplitude of the polynomial \(H_j(x)\). These polynomials are the same polynomials discussed in Chapter 16 and are the Gram-Schmidt polynomials generated from \(x^j\). Unfortunately, neither the \(y\) values nor the \(x\) values are known. An abscissa data value, \(\hat{x}_i\), is related to the unknown true abscissa, \(x_i\), by

\[
\hat{x}_i = x_i + e_i \tag{18.2}
\]

where \(e_i\) is the error in the measured abscissa. Similarly, a measured ordinate value, \(\hat{y}_i\), is related to the unknown true ordinate, \(y_i\), by

\[
\hat{y}_i = y_i + n_i \tag{18.3}
\]

where \(n_i\) is the error in the measured ordinate.

In the following calculation we will assume that the errors in the abscissa and ordinate are both unknown. We do this for the simple reason that it is the harder, i.e., more interesting calculation. However, in some cases one or both of these errors are actually known and the computer program that implements this package implements four different cases: 1) errors in both abscissa and ordinate known, 2) errors in the abscissa know but the ordinate error is unknown, etc.

If we Taylor expand the polynomial, \(F(x)\), around \(\hat{x}_i\), then

\[
F(x_i) \approx F(\hat{x}_i) + F'(\hat{x}_i)(\hat{x}_i - x_i) \tag{18.4}
\]

where

\[
F'(\hat{x}_i) = \frac{dF(\hat{x}_i)}{d\hat{x}_i} \tag{18.5}
\]

This first order Taylor expansion will gives a reasonable approximation to \(F(x)\) if the errors in the unknown abscissa are not large, i.e., if the polynomial is approximately linear over the likely error in
the abscissa. We make the Taylor expansion because, now the unknown true values of \( x_i \) appear in the model in a linear fashion and consequently we will be able to remove them by marginalization.

The probabilities we want to compute are the marginal posterior probabilities for the amplitudes of the polynomials and standard deviations of the noise prior probabilities. To calculate these, the numerical simulations must target the joint posterior probability for the amplitudes, \( \{B_0, \ldots, B_m\} \), and the noise standard deviations, \( \sigma_x \) and \( \sigma_y \) given the abscissa and ordinate data. This joint posterior probability is represented symbolically by \( P(B_0 \cdots B_m \sigma_x \sigma_y | \hat{x} \hat{y} I) \), where \( \hat{x} \) and \( \hat{y} \) represent the abscissa and ordinate data.

The joint posterior probability for the amplitudes and the noise standard deviations targeted by the Markov chain Monte Carlo simulation, \( P(B_0 \cdots B_m \sigma_x \sigma_y | \hat{x} \hat{y} I) \), is a marginal probability:

\[
P(B_0 \cdots B_m \sigma_x \sigma_y | \hat{x} \hat{y} I) = \int P(B_0 \cdots B_m \sigma_x \sigma_y \{x\} | \hat{x} \hat{y} I) d\{x\}
\]

where the integrals are over all of the unknown abscissa values. To compute this posterior probability, one factors the right-hand side of this equation using Bayes’ theorem and the product rule to obtain

\[
P(B_0 \cdots B_m \sigma_x \sigma_y \{x\} | \hat{x} \hat{y} I) \propto P(\sigma_y | I) \prod_{j=0}^{m} P(B_j | I)
\]

\times \prod_{i=1}^{N} P(x_i | I)
\]

\times \prod_{i=1}^{N} P(\hat{x}_i | x_i \sigma_x I)
\]

\times \prod_{i=1}^{N} P(\hat{y}_i | x_i B_0 \cdots B_m \sigma_y I).
\]

The prior probability for the standard deviation of the noise for the abscissa data, \( P(\sigma_x | I) \), will be assigned as a bound Jeffreys’ prior

\[
P(\sigma_x | I) = \begin{cases} 
\frac{1}{R_x \sigma_x} & \text{if } \sigma_{x_L} \leq \sigma_x \leq \sigma_{x_H} \\
0 & \text{otherwise}
\end{cases}
\]

(18.8)

where \( \sigma_{x_L} \) and \( \sigma_{x_H} \) are a lower and upper bound on \( \sigma_x \). The normalization constant \( R_x \) is given by

\[
R_x = \int_{\sigma_{x_L}}^{\sigma_{x_H}} \frac{d\sigma_x}{\sigma_x} = \log(\sigma_{x_H} / \sigma_{x_L}).
\]

(18.9)

The bounds, \( \sigma_{x_L} \) and \( \sigma_{x_H} \), are set rather pragmatically within the program that implements this package. The program computes the mean-square deviation, \( \langle \bar{x}^2 - \bar{x}^2 \rangle \), using the \( \hat{x} \) data, and then sets the lower and upper bounds

\[
\sigma_{x_L} = \frac{\langle \bar{x}^2 - \bar{x}^2 \rangle}{10} \quad \text{and} \quad \sigma_{x_H} = 10 \langle \bar{x}^2 - \bar{x}^2 \rangle,
\]

(18.10)

which restricts \( \sigma_x \) to a two order of magnitude variation. Similarly, \( P(\sigma_y | I) \), will be assigned

\[
P(\sigma_y | I) = \begin{cases} 
\frac{1}{R_y \sigma_y} & \text{if } \sigma_{y_L} \leq \sigma_y \leq \sigma_{y_H} \\
0 & \text{otherwise}
\end{cases}
\]

(18.11)
where the normalization constant, $R_y$, and the lower and upper bounds are computed analogously to corresponding abscissa values. The prior probability for the amplitudes, $P(B_j|I)$, is assigned a bounded zero mean Gaussian. The bounds are set at plus and minus ten times the largest projection of the model onto the data:

$$P(B_j|I) = \begin{cases} 
(2\pi\sigma_B^2)^{-1/2} \exp\left\{-\frac{B_j^2}{2\sigma_B^2}\right\} & \text{if } B_L \leq B_j \leq B_H \\
0 & \text{otherwise}
\end{cases} \quad (18.12)$$

with $B_L = -B_H$ and $B_H = \max(\text{abs}[\sum_{i=1}^{N} \hat{y}_i H_j(\hat{x}_i)])$. The standard deviation of this prior is $\sigma_B = B_H/3$. So the interval, $B_H - B_L$, represents a 6 standard deviation interval and the prior serves as little more than a way to keep the amplitudes from wandering into an unphysical region of the parameter space.

In this problem the unknown true values, the $x_i$, are parameters and one must assign a prior probability to all such parameters. The prior probability for the $x_i$, the $P(x_i|I)$, are assigned as unbounded Gaussians having mean equal to $\tilde{x}_i$ and standard deviation, $\sigma_p$:

$$P(x_i|I) = (2\pi\sigma_p^2)^{-1/2} \exp\left\{-\frac{(\tilde{x}_i - x_i)^2}{2\sigma_p^2}\right\} \quad (18.13)$$

where $\tilde{x}_i$ is the sampling point we thought we were measuring, and we set $\sigma_p$ equal to the average $x$ interval. We did this because it greatly simplified the formulas that must be programmed and so makes for a faster program, without changing the results to within the error bars.

The likelihood for a measured $\hat{x}_i$ data value, $P(\hat{x}_i|x_i\sigma_x I)$, was assigned a Gaussian

$$P(\hat{x}_i|x_i\sigma_x I) = (2\pi\sigma_x^2)^{-1/2} \exp\left\{-\frac{(\hat{x}_i - x_i)^2}{2\sigma_x^2}\right\} \quad (18.14)$$

and the likelihood for a measured $\hat{y}_i$ data value, $P(\hat{y}_i|\{A\}\sigma_y I)$, was assigned a Gaussian likelihood of the form:

$$P(\hat{y}_i|B_0 \cdots B_m\sigma_y I) = (2\pi\sigma_y^2)^{-1/2} \exp\left\{-\frac{\left(\hat{y}_i - F(\hat{x}_i) - F'(\hat{x}_i)[\hat{x}_i - x_i]\right)^2}{2\sigma_y^2}\right\}. \quad (18.15)$$

If we now accumulate all of the priors, Eqs. (18.8,18.11,18.13), and likelihoods, Eqs.(18.14,18.15),
and substitute them into Eq. (18.6) one obtains

\[
P(B_0 \cdots B_m \sigma_x \sigma_y | \hat{x} \hat{y}) \propto \int_{-\infty}^{+\infty} dx_1 \cdots dx_N \frac{1}{R_x \sigma_x R_y \sigma_y} \times (2\pi \sigma_B^2)^{-\frac{m+1}{2}} \exp \left\{ -\sum_{j=0}^{m} \frac{B_j^2}{2\sigma_B^2} \right\} \times (2\pi \sigma_p^2)^{-\frac{N}{2}} \exp \left\{ -\sum_{i=1}^{N} \frac{(\hat{x}_i - x_i)^2}{2\sigma_p^2} \right\} \frac{1}{\sigma_x \sigma_y} \exp \left\{ -\sum_{i=1}^{N} \left( \hat{y}_i - F(\hat{x}_i) + F'(\hat{x}_i)[\hat{x}_i - \bar{x}_i] \right)^2 \frac{\sigma_x^2 + \sigma_p^2}{2\sigma_y^2} \right\} \frac{N}{\prod_{i=1}^{N} \left( \frac{\sigma_x \sigma_y}{\sigma_i} \right)} \exp \left\{ -\frac{Q_i}{2\sigma_x^2} \right\} \] 

(18.17)

where we have dropped some constants that cancel when this probability density function is normalized. The function, \(Q_i\), is given by

\[
Q_i \equiv \left[ \hat{y}_i - F(\hat{x}_i) \right]^2 \left[ \sigma_p^2 + \sigma_x^2 \right] - 2F'(\hat{x}_i) \sigma_x^2 [\hat{x}_i - \bar{x}_i] [\hat{y}_i - F(\hat{x}_i)] + [F'(\hat{x}_i)]^2 \sigma_x^2 + \sigma_y^2 [\hat{x}_i - \bar{x}_i]^2
\]

(18.18)

where

\[
\sigma_i \equiv \sqrt{\sigma_x^2 \sigma_y^2 + \sigma_p^2 \sigma_x^2 + F'(\hat{x}_i)^2 \sigma_x^2 \sigma_y^2}.
\]

(18.19)

In the special case that the Errors In Variables package implements, \(\bar{x}_i = \hat{x}_i\), \(\hat{Q}_i\) simplifies and one obtains

\[
P(B_0 \cdots B_m \sigma_x \sigma_y | \hat{x} \hat{y}) \propto \frac{1}{\sigma_x \sigma_y} \exp \left\{ -\sum_{j=0}^{m} \frac{B_j^2}{2\sigma_B^2} \right\} \frac{N}{\prod_{i=1}^{N} \left( \frac{\sigma_x \sigma_y}{\sigma_i} \right)} \exp \left\{ -\frac{[\hat{y}_i - F(\hat{x}_i)]^2 [\sigma_p^2 + \sigma_x^2]}{2\sigma_i^2} \right\}.
\]

(18.20)

Computationally, this special case is simpler to calculate, so the program runs faster without given up the ability to estimate both \(\sigma_x\) and \(\sigma_y\) and it is this probability density function that is targeted by the Markov chain Monte Carlo simulation.

### 18.2 Outputs From The Errors In Variables Package

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 the decay rate constants, decay times, the amplitudes for each data set for each exponential and finally there are probability density functions for the standard deviation of the noise in each data set.

The only thing the least bit unusual about this package is the Ascii data that is required. In most Ascii packages the data are two columns, an abscissa and an ordinate. However, here there are four different file formats:

1. When the errors in both the abscissa and ordinate are unknown, two column Ascii data is required. Column one is the abscissa and column two is the ordinate. These data may be generated and or loaded using the files menu.

2. When the errors are known in the abscissa but not in the ordinate, three column Ascii data is required. Column one is the abscissa, column two is the ordinate, and column three is the error in the abscissa. This input can only be loaded using the “Files/Load Ascii/File” menu.

3. When the errors are known in the ordinate but not in the abscissa, three column Ascii data is required. Column one is the abscissa, column two is the ordinate, and column three is the error in the ordinate. This input can only be loaded using the “Files/Load Ascii/File” menu.

4. When the errors are known in both the abscissa and the ordinate, four column Ascii data is required. Column one is the abscissa, column two is the ordinate, column three is the error in the abscissa and column four is the error in the ordinate. This input can only be loaded using the ‘Files/Load Ascii/File’ menu.

There are four test data sets located in the “Bayes.test.data/ErrorsInVariables” directory that may be used for testing. These four data sets are named: ErrInVar\_given\_x.dat, ErrInVar\_given\_xy.dat, ErrInVar\_given\_y.dat, and ErrInVar\_not\_given.dat respectively. An example of the McMC values report generated by the Errors In Variables package is shown in Fig. 18.2. This report was generated using the “ErrInVar\_given\_xy.dat” data. The top section of the report contains some configuration information followed by information about the priors. This is followed by some averages over the various probabilities including the posterior probability for the model. This is followed by the parameters that maximized the joint marginal posterior probability for the parameters. Finally, the mean and standard deviation estimates of the amplitudes of the polynomials are given. For more on the general layout of the McMC value file, see Appendix D.

In addition to the McMC values file there are the standard Data, Model and Residual plots which can be viewed using the Plot Results Viewer. There are posterior probability density functions for the uncertainty in the abscissa data values, this plot is named “Sigma X” and there is a posterior probability density for the uncertainty in the ordinate, named “Sigma Y.” Additionally, there is one output probability density function for each amplitude in the polynomial being analyzed. So if you are analyzing a 6th order polynomial, there are seven output probability density functions. Finally, there are the output plots that come at the end of the plot list. These include the expected logarithm of the likelihood as a function of the annealing parameter, the scatter plots and the logarithm of the posterior probability for each simulation as a function of repeat number.
The Parameter File Listing for the Errors in Variables Package

! BayesErrInVarsGiven Package
! Created 10-Feb-2012 10:11:27 by larry
!

Output Dir = BayesOtherAnalysis
Number Of Abscissa = 1
Number Of Columns = 1
Number Of Sets = 1
File Name = BayesOtherAnalysis/ErrInVar_given_xy.dat
McMC Simulations = 48
McMC Repeats = 21
Minimum Annealing Steps = 21
Histogram Type = Binned
Outlier Detection = Disabled
Number Of Priors = 0
Package Parameters = 2
Total Mcmc Samples = 1008
Kill Count = 4

McMC Values Report for the Errors In Variables package

<table>
<thead>
<tr>
<th>Param Desc</th>
<th>Low</th>
<th>Mean</th>
<th>High</th>
<th>Sigma</th>
<th>Norm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coef 0.1</td>
<td>-1.504E+03</td>
<td>0.000E+00</td>
<td>1.504E+03</td>
<td>4.513E+02</td>
<td>-3.626E+00</td>
</tr>
<tr>
<td>Coef 1.1</td>
<td>-1.504E+03</td>
<td>0.000E+00</td>
<td>1.504E+03</td>
<td>4.513E+02</td>
<td>-3.626E+00</td>
</tr>
<tr>
<td>X 1.1</td>
<td>-5.445E-02</td>
<td>-4.785E-03</td>
<td>4.488E-02</td>
<td>9.933E-03</td>
<td>-3.222E+00</td>
</tr>
<tr>
<td>X 101.1</td>
<td>9.488E-01</td>
<td>9.985E-01</td>
<td>1.048E+00</td>
<td>9.933E-03</td>
<td>-3.222E+00</td>
</tr>
</tbody>
</table>

Avg.       | 194.0262  | 122.93507 |
SD.        |          |          |

The Average Log Posterior Probability: 194.0262 122.93507
The Average Log Prior Params: -9.0257 0.00079
The Average Log Likelihood: 4.06109543E+02 1.37923E+00
The Log Posterior Probability For The Model: 3.74864004E+02

The parameters that maximized the posterior probability are:

- Parameter Description: Parameter
- Std Dev in X: 4.65331682E-04
- Std Dev in Y: 1.10193610E+00
- Coef 0.1: 1.01151226E+01
- Coef 1.1: 9.68326780E+00

The expected parameter values (mean value of the probability distributions):

- Parameter Description: Mean Value  Std. Dev.  Peak Value
- Sigma X: 1.09472E-03  5.34846E-04  4.65332E-04
- Sigma Y: 1.09118E+00  7.44062E-02  1.0194E+00
- Coef 1.0: 1.01672E+01  2.01540E-01  1.01151E+01
- Coef 1.1: 9.59826E+00  3.49706E-01  9.68327E+00

Figure 18.2: This is the ErrInVarsGiven.mcmc.values file. It is the primary printed output from the Errors In Variables package. This report was generated using test data found in Bayes.test.data, the ErrorsInVariables subdirectory, the data file was ErrInVar_given_xy.dat. The top section of the report contains some configuration information followed by information about the priors. This is followed by some averages over the various probabilities including the posterior probability for the priors. This is followed by the parameters that maximized the joint marginal posterior probability. Finally, the mean and standard deviation estimates of the amplitudes of the polynomials are given.
Bibliography


[43] Metropolis, Nicholas, 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.


