Title
Bayesian Model Checking with Applications to Hierarchical Models

Permalink
https://escholarship.org/uc/item/8x4578js

Author
R. E. Weiss

Publication Date
2011-10-25
Introduction

The paper introduces a general approach to Bayesian model checking. It presents a method to evaluate the plausibility of a model given the observed data. The approach is implemented in a hierarchical random effects model, which allows for the assessment of the uncertainty in the parameters. The posterior distribution of the parameters is obtained through Bayesian inference, and the model checking is performed by simulating from this distribution. The results are used to assess the fit of the model to the data. The paper also discusses applications of this approach in various fields, including epidemiology and social sciences.

August 13, 1996

Robert E. Weiss
2 Full Prior Predictive Model Checking

In a Bayesian model, the prior distribution plays a crucial role in specifying prior beliefs about the parameters. The posterior distribution, which combines the prior with the likelihood of the data, is then used to make inferences about the parameters and make predictions about future data. The choice of the prior is critical, as it can influence the posterior distribution and, consequently, the conclusions drawn from the analysis.

The prior predictive distribution, obtained by simulating data from the posterior predictive distribution, is a useful tool for assessing the fit of the model to the data. It can be used to compare the observed data with the expected distribution under the model, providing a way to evaluate the adequacy of the model.

Bayesian model checking involves comparing the observed data with the expected distribution under the model. This comparison can be performed through various methods, such as checking the fit of the model to a subset of the data, using posterior predictive checks, or employing goodness-of-fit tests.

The choice of a prior is often driven by subject matter knowledge or previous research. However, it is important to be aware of the impact that the prior can have on the posterior distribution and the conclusions drawn from the analysis. Therefore, sensitivity analyses and checks for the robustness of the model are essential to ensure that the results are reliable and valid for the data at hand.

In summary, Bayesian model checking is a crucial step in the analysis process. It allows for an assessment of the model's fit to the data, which is essential for obtaining reliable and valid results. The choice of the prior is a critical aspect of Bayesian model checking, as it can influence the posterior distribution and the conclusions drawn from the analysis.
where \( D \) is the column of \( \phi \), is a linear combination of the \( \phi \) vector, actually, \( \phi D = \phi \) taken as evidence that the observation \( \phi \) is outlying. However, since \( \phi \) is not a

the prior mean of zero, double is cast upon the model. This has empirically been

the order classical analyst. Consider the second \( \phi \) of \( \phi \) when \( \phi \) is far from

appreciated and classical residual analysis and Bayes analysis improve on

a simple but key example shows how the difference between this Bayesian

and this distribution can double upon the model.

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]

\[ \theta \]

\[ \phi \]

\[ (X^T X)^{-1} (X^T Y) = (\phi^T \theta) \]
the model. For this section, the model is the linear model of the previous section. I have outlined and we wish to check for the

ability to adapt to the covariance to

produce a Bayesian lack of priors. The table is for when a known covariance has
debates are included. In this situation, a lack of priors may be useful and I
discuss is for the situation where model misspecification is suspected but
and diagnostic is for the situation where model misspecification is suspected but
actually important. Subsection 3.1 presents a check for over-diagnostic. The use
of practical experience. Priors in Bayesian practice are often quite diffuse if not
c the applications of the methodology developed so far. Possibility due to a lack
of diagnostic measures which are spec-

This section illustrates three novel Bayesian diagnostic measures which are spec-

3 Three Diagnostic Measures.
If we were fully observed, \( q \) is the number of outcomes at the level of a prior,

\[
\{ z/2 \leq \text{df} \} \cup \left\{ \frac{\text{SS}}{\text{df}} = (\tilde{y})^2 \right\}
\]

than an additional choice of \( q = 0 \) or \( 0.1 \). Define then \( \text{df} \geq z/2 \). An additional choice is that the prior may have been derived from

the data. For example, if the prior is not a representation of the data, then a prior belief may have been derived from the prior mean. Another possibility is that the prior mean is not equal to the posterior mean. This suggests that the prior is too random relative with a decrease of freedom. Thus suggests that the prior is too large even for \( q = 0 \). The small, where \( X \) is the posterior mean, will be approximately zero, and a posterior with \( \text{df} \geq z/2 \) is a posterior, while however when the posterior of \( \alpha \) are not large, an influence is ranked by the prior to a conventional influence, or alternatively an influence is compared by the output. Otherwise the question of \( \alpha \) are taken to be larger than is actually believed, so as to

\[
(\tilde{y})^{2/2} \sim \text{Ch}(\text{df}^{2/2}, \text{SS}^{2/2}) - V(X, Y)^{2/2} = \text{df}^{2/2}
\]

A common conjugate prior for the regression coefficients is

\[
(\tilde{y})^{2/2} \sim \text{Ch}(\text{df}^{2/2}, \text{SS}^{2/2})
\]
there is a function of X, and a suitable log-linear model. The
number of parameters of the model is

Next, we summarize the points qualitatively after reading
the readability case. We then summarize the points qualitatively after reading
an excerpt sample from the predictor distribution of C. Dynamic
graphs indicate that it would be helpful to plot a regression model. To see if it could be a useful addition to the model,
let M be a known π, n times with certainty M Li represents a set of coefficients

3.3. Omitted Predictors

predictors

predictors

predictors

predictors

predictors

predictors

predictors

predictors
In simple case we can explore the posterior distribution of \( \phi \) by using
\[
\psi = \psi_0 \Rightarrow \mathcal{L}(\psi_0, \mathbf{X}) = \mathcal{L}(\psi) \Rightarrow \mathcal{L}(\mathbf{X}) = \mathcal{L}(\psi_0, \mathbf{X}) = \mathcal{L}(\psi) \Rightarrow \mathcal{L}(\psi_0, \mathbf{X}) = \mathcal{L}(\psi)
\]

Sometimes we have more than one predictor \( \phi \) in our model. For example, we might be interested in the model
\[
\mathcal{L}(\psi_0, \mathbf{X}) = \mathcal{L}(\psi) \Rightarrow \mathcal{L}(\mathbf{X}) = \mathcal{L}(\psi_0, \mathbf{X}) = \mathcal{L}(\psi) \Rightarrow \mathcal{L}(\psi_0, \mathbf{X}) = \mathcal{L}(\psi)
\]

Prop. 109. (1) The posterior distribution of the best linear predictor \( \hat{\phi} = \hat{\phi}_0 \) is the same as the posterior distribution of the model \( \mathcal{L}(\psi_0, \mathbf{X}) = \mathcal{L}(\psi) \).

**Proof:**

By the normal equation, the posterior distribution of \( \psi \) is a normal distribution with mean \( \mathbf{X}^T \mathbf{X} \psi \) and variance \( \mathbf{X}^T \mathbf{X} \), which is the same as the posterior distribution of the model \( \mathcal{L}(\psi_0, \mathbf{X}) = \mathcal{L}(\psi) \).

We can investigate the posterior distribution of \( \hat{\phi} = \hat{\phi}_0 \) through the appropriate posterior summaries. One summary is

\[
\mathbb{E}[\mathbf{X}^T \mathbf{X}^{-1}(\mathbf{X}^T \mathbf{X}^{-1} \mathbf{X})^{-1}] = \frac{\mathbf{X}^T \mathbf{X}^{-1}}{\mathbf{X}^T \mathbf{X}^{-1} \mathbf{X}^{-1}} \mathbf{X} \\
= \mathbf{X} \mathbf{X}^T \mathbf{X}^{-1} = \mathbf{I}
\]

with \( \mathbb{E}[\mathbf{X}^T \mathbf{X}^{-1}] = \mathbf{I} \).

From this distribution, we can derive the prior distribution of \( \psi \) as

\[
\psi \sim \mathcal{N}(\mathbf{0}, \mathbf{I})
\]

and

\[
\mathbb{E}[\mathbf{X}^T \mathbf{X}^{-1}] = \mathbf{I}
\]
Given the data, I assume that samples 
are

\[ y_i = f(x_i; \theta) + \epsilon_i \]

where \( y_i \) is a sample from the distribution of the parameters \( \theta \).

Csiszar, I., Klir, G., Wang, Y. (1997). \textit{Qualitative Measure, and Computational}\n
Ressources Statistiques and Simult 1996. Alger and

The graph shows a red line with a slope of 1 and an intercept of 0.

The basic RNN is

\[ X \sim \mathcal{N}(0, \Sigma) \]

\[ Z \sim \mathcal{N}(0, \Sigma) \]

\[ b + \mathcal{N}(X, \Sigma) = Y \]

4.1 The Model and Notation

will be considered and compared.

The proposed model is equivalent to the missing data model proposed in

Here I illustrate the proposed distributions in a hierarchical random effects model

4 Weight Loss Data.

For a variable outcome, if \( \text{var}(X) < \text{var}(M) \), then we detect

when \( \text{var}(X) < \text{var}(M) \), we detect

where \( \text{var}(X) \) is the variance of the outcome and \( \text{var}(M) \) is the variance of the missing variable.
Consider a prior for the fixed effects $\eta$, where $\eta = \frac{\eta_{t, \theta}}{D}$. This distribution $N(0, \psi_2)$ is assigned for the model $\eta$, with $\psi_2$ depends on $D$, the prior distribution normal distribution on $\psi_2$ and $D$. This is the prior distribution, even if and $D$, is also a possible prior for $\eta$. The prior distribution is a normal distribution, since the prior conditional distribution $N(0, \psi_2)$ is distributed $N(\psi_2, D)$. Our best estimate for overall difference is the distribution $N(\psi_2, D)$.

4.2 Data Description

Simple sample from $p(\phi)$ calculations are based on Gibbs samples of sizes 1000.

The data set contains up to 8 weekly observations per person at times $t = 1, 2, \ldots, 8$.
\[
\begin{align*}
\{(g - I) \chi \leq \beta \} \sum_{j} & = (g) \Phi \\
\{(g - I) \chi \geq \beta \} \sum_{j} & = (g) \Phi \\
\{|z_{j} - \mu| > \omega \} \sum_{j} & = (g) \Phi \\
\end{align*}
\]

Following sums of outer indicator statistics can treat the residuals as either univariate or multivariate residuals. Define the following in general of discovery problems, so I don't consider the \( g \) anymore. We can consider in case of discovery problems to consider the \( g \) and \( \Phi \) separately to partial isolated test hypotheses separately. By investigating the \( g \) residuals and the \( \Phi \) residuals, we can investigate the hypotheses separately. By investigating only the \( g \) from the model, we can investigate can consider goodness-of-fit based on a marginal model. There are several ways to extend the goodness-of-fit check to multivariate here.

4.4 Goodness of Fit Checks
Based on Gibbs samples of size 2000 and 10000 respectively, the number of outcomes conditional on that model. The symbol ° indicates the proportion of outcomes falling below the critical value of 0.05.
The second two sections of Table 1 check for an excess of multivariate outliers.

Including the 0.90 inspection, both models had one or more outliers, and the number of outliers is not unusual, and we see that 2 models 1 and 2 have one or more outliers. Also at the 0.90 inspection of model 1, the proportion of 2 models with one or more outliers is 99.30% and the proportion of 2 models with one or more outliers is 99.80%.

A few points to remember in any lack of fit analysis is that with 0.90 inspection and a number of outliers 0.90 = 0.90. For example with the bimodal distribution, where 0.90 = 0.90 and 0.90 = 0.90. The row labeled p gives the proportion of multivariate outliers for 0.90 and 0.90 = 0.90. We use the proportion of 0.90 inspection of 0.90 and 0.90.

The fourth two sections of Table 1 check for an excess of multivariate outliers.

Notice the increase of 0.90 in a way that the multivariate statistic, the multivariate statistic (0.90) and 0.90 are not the multivariate statistics for 0.90 and 0.90. Each of these statistics leads to a different conclusion of whether 0.90 = 0.90 and the 0.90 is smaller than the 0.90. The statistics are not the same. The 0.90 is the diagonal element of 0.90 and 0.90 is the proportion of 0.90.
and thus, that the model does not fit.

Finally, we see that the observations are not distributed like a $N(0,1)$.

Furthermore, the points at the bottom are close to 0, and those at the top are large. For a host of reasons, the model is not a good fit.

We see several very large outliers making up the right of the plot. Figure 1 also shows a single representative of several plots. We see for model 1 and 2. In Figure 1, we see a possible single outlier at the upper left corner of the plot.

Figure 1 shows a representative of a normal distribution.

Assume that we could sample from a standard normal distribution

$((\frac{\theta}{\rho^2})_{\sigma^2}, \tau_1 - \phi_1, \tau_2 - \phi_2, \cdots, \tau_n - \phi_n)$

Thus, we plot ordered values of $\theta$ with $\beta = 0.05$.

For a host of reasons, we also map to the standard normal distribution with $\beta = 0.05$.

The distribution and the cell for the distribution with $\beta = 0.05$.

$((\frac{\theta}{\rho^2})_{\sigma^2}, \tau_1 - \phi_1, \tau_2 - \phi_2, \cdots, \tau_n - \phi_n)$

The position of $\theta$ with $\beta = 0.05$.

For example, we could draw a single sample from $\theta$ with $\beta = 0.05$.

Each goodness of fit statistic has a quantile-quantile plot associated with it.
In the linear model, the contrast is a model-specific contrast. The
controversy over the nature of the contrast lies in the contrast
being a linear function of the parameters. In contrast, the
contrast is a linear function of the parameters. In the contrast,
the intercept is missing a linear term and the effect is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
and the intercept is non-linear. For the contrast, the intercept is non-
linear. The model is linear, the linear terms are in the contrast,
\[(\alpha_j \cdot \theta_i < \beta_k) \cdot \delta = (\alpha_j \cdot \theta_i) \cdot \delta\]

and

\[(\alpha_j \cdot \theta_i < \beta_k) \cdot \delta = (\alpha_j \cdot \theta_i) \cdot \delta\]

The two columns are orthogonal and span the space of any predictions in the model. The next model has already been included in the model and approximately equals \(\beta_k\). The mean square is the model and approximately equals \(\beta_k\). The second column includes the current column, and \(\delta\) is approximately 2. The mean square is the model and approximately equals \(\beta_k\).

### Table 1

<table>
<thead>
<tr>
<th>(200^\circ)</th>
<th>(0\circ)</th>
<th>(60^\circ)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(1)</td>
<td>(67.2^\circ)</td>
<td>(3)</td>
</tr>
<tr>
<td>(1)</td>
<td>(1)</td>
<td>(28.7^\circ)</td>
<td>(2)</td>
</tr>
<tr>
<td>(1)</td>
<td>(1)</td>
<td>(8.4^\circ)</td>
<td>(1)</td>
</tr>
</tbody>
</table>

**Gebra**

<table>
<thead>
<tr>
<th>(200^\circ)</th>
<th>(130^\circ)</th>
<th>(16^\circ)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0)</td>
<td>(0\circ)</td>
<td>(12.2^\circ)</td>
<td>(3)</td>
</tr>
<tr>
<td>(0)</td>
<td>(0\circ)</td>
<td>(13.1^\circ)</td>
<td>(2)</td>
</tr>
<tr>
<td>(0)</td>
<td>(0\circ)</td>
<td>(19^\circ)</td>
<td>(1)</td>
</tr>
</tbody>
</table>

**Cube**

<table>
<thead>
<tr>
<th>(200^\circ)</th>
<th>(110^\circ)</th>
<th>(96^\circ)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(0)</td>
<td>(066^\circ)</td>
<td>(95.9^\circ)</td>
<td>(3)</td>
</tr>
<tr>
<td>(0)</td>
<td>(086^\circ)</td>
<td>(72.2^\circ)</td>
<td>(2)</td>
</tr>
<tr>
<td>(0)</td>
<td>(269^\circ)</td>
<td>(3.82^\circ)</td>
<td>(1)</td>
</tr>
</tbody>
</table>

**Quadrate**

<table>
<thead>
<tr>
<th>(100^\circ)</th>
<th>(290^\circ)</th>
<th>(91.9^\circ)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(200^\circ)</td>
<td>(410^\circ)</td>
<td>(100.1^\circ)</td>
<td>(3)</td>
</tr>
<tr>
<td>(200^\circ)</td>
<td>(850^\circ)</td>
<td>(96^\circ)</td>
<td>(2)</td>
</tr>
<tr>
<td>(1)</td>
<td>(1)</td>
<td>(10/8^\circ)</td>
<td>(1)</td>
</tr>
</tbody>
</table>

**Square**

\[(\alpha_j \cdot \theta_i) \cdot \delta \] and \((\alpha_j \cdot \theta_i) \cdot \delta \]

Chaloner, K. and Brant, R. (1988). A Bayesian approach to outlier detection and

*New York: John Wiley & Sons*, 114-137.

models in regression of longitudinal (repeated) P, R. Prognosis and A, P, M. Smith,


*Biometrika*, 78, 637-641.


A. A. 143, 383-410.


Regression models. *Biometrika*, 72, 71-75.


References

can be compared.

Tobit results have a small sample distribution with which the asymptotic results

but no exact results are approximation because closed and levels, but now these asympto-

With our approach, classical residual checks and hypothesis tests with asymptotic

to check the model. The challenge is to choose useful functions for model checking.

With the current approach, any function of the parameters and data can be used

**Discussion**

effect is apparent but not an outlier for any model.
American Statistical Association, 70, 138-141.


Report 94-009.

to describe and compare adaptations of the model to the real world. Discrete optimization.

model. Some algebra and geometry for hierarchical models, applied

costs. A. W. van der Eijk and S. M. Huard (1996), Posterior predictive assessment of

costs. A. W. van der Eijk and S. M. Huard (1996), Posterior predictive assessment of
multivariate $\varepsilon_i$ residuals.