Title

bayestest model — Hypothesis testing using model posterior probabilities

Description

`bayestest model` computes posterior probabilities of Bayesian models fit using the `bayesmh` command. These posterior probabilities can be used to test hypotheses about model parameters. The command reports marginal likelihoods, prior probabilities, and posterior probabilities for all tested models.

Quick start

Compute posterior probabilities of models corresponding to previously saved estimation results `M1` and `M2`

```
bayestest model M1 M2
```

As above, but specify prior probabilities for models

```
bayestest model M1 M2, prior(0.3 0.7)
```

Menu

Statistics > Bayesian analysis > Hypothesis testing using model posterior probabilities

Syntax

`bayestest model` [*namelist*] [, *options*]

where *namelist* is a name, a list of names, `_all`, or `*`. A name may be `.`, meaning the current (active) estimates. `_all` and `*` mean the same thing.

options	Description
Main	
`prior(`*numlist*`)`	specify prior probabilities for tested models; default is all models are equally likely
Advanced	
`marglmethod(`*method*`)`	specify marginal-likelihood approximation method; default is to use Laplace–Metropolis approximation, `lmetropolis`; rarely used

method	Description
`lmetropolis`	Laplace–Metropolis approximation; default
`hmean`	harmonic-mean approximation

Options

Main

`prior(`*numlist*`)` specifies prior probabilities for models. By default, all models are assumed to be equally likely. You may specify probabilities for all tested models, in which case the probabilities must sum to one. Alternatively, you may specify probabilities for all but the last model, in which case the sum of the specified probabilities must be less than one, and the probability for the last model is computed as one minus this sum.

Advanced

`marglmethod(`*method*`)` specifies a method for approximating the marginal likelihood. *method* is either `lmetropolis`, the default, for Laplace–Metropolis approximation or `hmean` for harmonic-mean approximation. This option is rarely used.

Remarks and examples

stata.com

Remarks are presented under the following headings:

Introduction

In this entry, we describe hypothesis testing by computing model posterior probabilities, probabilities of Bayesian models given observed data. For interval hypothesis testing, see [BAYES] **bayestest interval**.

The `bayestest model` command computes posterior probabilities for specified models. The computed probabilities can be used to compare which model is more likely among considered models given observed data. You can compare models that differ only in several covariates or models with completely different regression functions, such as linear and nonlinear models. You can compare models with different outcome distributions or with different prior distributions or both. The only requirements are that the considered models have proper posterior distributions and that the same data are used to fit the models. If MCMC is used to approximate posterior distributions, convergence of MCMC should also be verified before model comparison.

The results reported by `bayestest model` are related to Bayes factors; see [BAYES] **bayesstats ic** to compute Bayes factors.

To use `bayestest model`, you must store estimation results after each `bayesmh` model of interest. You can use `estimates store` (see [R] **estimates store**) to store estimation results after `bayesmh`, as you can with other estimation commands, provided you also saved simulation results from `bayesmh` using the `saving()` option. See *Storing estimation results after bayesmh* in [BAYES] **bayesmh postestimation** for details.

Testing nested hypotheses

Consider the following Bayesian regression model for `auto.dta`,

$$\texttt{mpg} = \beta_0 + \beta_1\texttt{weight1} + \beta_2\texttt{length1} + \epsilon$$

where `weight1` and `length1` are the original `weight` and `length` variables rescaled to have similar scale as `mpg`.

We assume that errors are normally distributed: $\epsilon \sim \text{normal}(0, \sigma^2)$. We also assume a noninformative Jeffreys prior for the parameters: $(\boldsymbol{\beta}, \sigma^2) \sim 1/\sigma^2$. Suppose that we are interested in testing whether there is a relationship between mileage and weight and length of cars. We will consider four models: the mean-only model, the model with weight only, the model with length only, and the full model with both covariates.

In a frequentist setting, the four models correspond to the following hypotheses: H_0: $\beta_1 = 0$, $\beta_2 = 0$, H_0: $\beta_1 = 0$, and H_0: $\beta_2 = 0$. In a Bayesian setting, we cannot formulate point hypotheses for parameters with continuous distributions; see [BAYES] **bayestest interval** for examples. However, we can compute probabilities of how likely each of the four models is given the observed data.

Let's load auto.dta and generate rescaled versions of weight and length.

```
. use http://www.stata-press.com/data/r14/auto
(1978 Automobile Data)
. generate weight1 = weight/100
. generate length1 = length/10
```

Next, we fit the four models using bayesmh. We use the saving() option to save the simulation datasets so that we can store estimation results of each model for later use with bayestest model.

The first model we fit is the mean-only model. We store its estimation results as meanonly.

```
. set seed 14
. bayesmh mpg, likelihood(normal({var}))
> prior({mpg:}, flat) prior({var}, jeffreys)
> saving(meanonly_simdata) burnin(3500)
note: adaptation option maxiter() changed to 35
Burn-in ...
Simulation ...
Model summary
------------------------------------------------------------------------------
Likelihood:
  mpg ~ normal({mpg:_cons},{var})
Priors:
  {mpg:_cons} ~ 1 (flat)
        {var} ~ jeffreys
------------------------------------------------------------------------------

Bayesian normal regression                       MCMC iterations  =     13,500
Random-walk Metropolis-Hastings sampling         Burn-in          =      3,500
                                                 MCMC sample size =     10,000
                                                 Number of obs    =         74
                                                 Acceptance rate  =      .2627
                                                 Efficiency:  min =       .105
                                                              avg =      .1064
Log marginal likelihood = -234.64617                          max =      .1078

------------------------------------------------------------------------------
             |                                                Equal-tailed
             |      Mean   Std. Dev.     MCSE     Median  [95% Cred. Interval]
-------------+----------------------------------------------------------------
mpg          |
       _cons |  21.29355   .6768607   .020887   21.28059   20.00132   22.61904
-------------+----------------------------------------------------------------
         var |  34.80707   5.963995   .181615   34.23247    24.9129    47.6883
------------------------------------------------------------------------------
file meanonly_simdata.dta saved
. estimates store meanonly
```

To accommodate the Jeffreys prior for the parameters, we specify suboption flat within the prior() option for coefficients to request the flat prior with the density of 1 and suboption jeffreys within prior() for the variance parameter to request a Jeffreys prior. We also specify a longer burn-in period to improve convergence of MCMC samples for all examples. (Remember to use bayesgraph to check convergence of MCMC.)

We fit the second model containing only covariate `length1` and store its results as `length`:

```
. set seed 14
. bayesmh mpg length1, likelihood(normal({var}))
> prior({mpg:}, flat) prior({var}, jeffreys)
> saving(length_simdata) burnin(3500)
note: adaptation option maxiter() changed to 35
Burn-in ...
Simulation ...
Model summary
------------------------------------------------------------------------------
Likelihood:
  mpg ~ normal(xb_mpg,{var})
Priors:
  {mpg:length1 _cons} ~ 1 (flat)                                           (1)
              {var} ~ jeffreys
------------------------------------------------------------------------------
(1) Parameters are elements of the linear form xb_mpg.
Bayesian normal regression                       MCMC iterations  =     13,500
Random-walk Metropolis-Hastings sampling         Burn-in          =      3,500
                                                 MCMC sample size =     10,000
                                                 Number of obs    =         74
                                                 Acceptance rate  =      .2865
                                                 Efficiency:  min =      .0771
                                                              avg =     .07938
Log marginal likelihood =  -198.7678                          max =     .08286
```

	Mean	Std. Dev.	MCSE	Median	Equal-tailed [95% Cred.	Interval]
mpg						
length1	-2.069861	.1882345	.006539	-2.068094	-2.44718	-1.706264
_cons	60.20346	3.562119	.127411	60.20927	53.34306	67.22423
var	12.88852	2.273808	.081887	12.62042	9.169482	18.16685

```
file length_simdata.dta saved
. estimates store length
```

We fit the third model containing only covariate `weight1` and store its results as `weight`:

```
. set seed 14

. bayesmh mpg weight1, likelihood(normal({var}))
> prior({mpg:}, flat) prior({var}, jeffreys)
> saving(weight_simdata) burnin(3500)
note: adaptation option maxiter() changed to 35
Burn-in ...
Simulation ...

Model summary
------------------------------------------------------------------------------
Likelihood:
  mpg ~ normal(xb_mpg,{var})

Priors:
  {mpg:weight1 _cons} ~ 1 (flat)                                          (1)
                {var} ~ jeffreys
------------------------------------------------------------------------------
(1) Parameters are elements of the linear form xb_mpg.

Bayesian normal regression                       MCMC iterations  =     13,500
Random-walk Metropolis-Hastings sampling         Burn-in          =      3,500
                                                 MCMC sample size =     10,000
                                                 Number of obs    =         74
                                                 Acceptance rate  =      .1735
                                                 Efficiency:  min =      .0463
                                                              avg =     .06694
Log marginal likelihood = -198.20751                          max =     .07989

------------------------------------------------------------------------------
             |                                                Equal-tailed
             |      Mean   Std. Dev.     MCSE     Median  [95% Cred. Interval]
-------------+----------------------------------------------------------------
mpg          |
     weight1 | -.6014409   .0506121   .001791  -.6013071  -.6996976    -.50121
       _cons |  39.45934   1.574673   .057646   39.49735   36.31386   42.33547
-------------+----------------------------------------------------------------
         var |  12.13997   2.141741   .099534   11.87332   8.883221   17.14041
------------------------------------------------------------------------------

file weight_simdata.dta saved

. estimates store weight
```

Finally, we fit the last model containing both covariates and store its results as `full`:

```
. set seed 14
. bayesmh mpg weight1 length1, likelihood(normal({var}))
> prior({mpg:}, flat) prior({var}, jeffreys)
> saving(full_simdata) burnin(3500)
note: adaptation option maxiter() changed to 35
Burn-in ...
Simulation ...
Model summary
------------------------------------------------------------------------------
Likelihood:
  mpg ~ normal(xb_mpg,{var})
Priors:
  {mpg:weight1 length1 _cons} ~ 1 (flat)                                  (1)
                        {var} ~ jeffreys
------------------------------------------------------------------------------
(1) Parameters are elements of the linear form xb_mpg.
Bayesian normal regression                       MCMC iterations  =     13,500
Random-walk Metropolis-Hastings sampling         Burn-in          =      3,500
                                                 MCMC sample size =     10,000
                                                 Number of obs    =         74
                                                 Acceptance rate  =      .2323
                                                 Efficiency:  min =     .05455
                                                              avg =     .06647
Log marginal likelihood = -196.86195                          max =     .08085
```

	Mean	Std. Dev.	MCSE	Median	Equal-tailed [95% Cred.	Interval]
mpg						
weight1	-.3977027	.1580411	.005558	-.401646	-.6965175	-.0721332
length1	-.7599159	.5546754	.021944	-.7502182	-1.907818	.3106868
_cons	47.5913	6.132597	.262563	47.5656	35.89593	60.18002
var	11.81753	1.96315	.07608	11.59273	8.729182	16.14065

```
file full_simdata.dta saved
. estimates store full
```

▷ Example 1: Computing posterior probabilities of models

We now use `bayestest model` to compute posterior probabilities of the four models.

```
. bayestest model meanonly length weight full
Bayesian model tests
```

	log(ML)	P(M)	P(M|y)
meanonly	-234.6462	0.2500	0.0000
length	-198.7678	0.2500	0.1055
weight	-198.2075	0.2500	0.1848
full	-196.8619	0.2500	0.7097

```
Note: Marginal likelihood (ML) is computed using
      Laplace-Metropolis approximation.
```

The mean-only model is very unlikely compared with other models. The length and weight models are somewhat likely with the respective posterior probabilities of 0.11 and 0.18, and the full model has the highest posterior probability of 0.71.

◁

▷ Example 2: Specifying prior probabilities of models

If we have some prior knowledge about each of the models, we can use the `prior()` option to specify prior probabilities for each model. For example, suppose that we have prior knowledge that the weight model is much more likely than the full model so that the prior probabilities are 0.1 for the mean-only model and the length model, 0.6 for the weight model, and only 0.2 for the full model.

```
. bayestest model meanonly length weight full, prior(0.1 0.1 0.6 0.2)
Bayesian model tests
```

	log(ML)	P(M)	P(M|y)
meanonly	-234.6462	0.1000	0.0000
length	-198.7678	0.1000	0.0401
weight	-198.2075	0.6000	0.4210
full	-196.8619	0.2000	0.5389

```
Note: Marginal likelihood (ML) is computed using
      Laplace-Metropolis approximation.
```

Under the specified prior, posterior probabilities of the weight and full models are now more similar: 0.42 and 0.54, respectively, but the full model is still preferable.

The above is equivalent to the following prior specification:

```
. bayestest model meanonly length weight full, prior(0.1 0.1 0.6)
  (output omitted)
```

◁

Using our results, we conclude that `mpg` is related to both `weight` and `length` and would proceed with the full model.

After your analysis, remember to erase the saved simulation datasets you no longer need. For example, we erase all of them by typing

```
. erase meanonly_simdata.dta
. erase weight_simdata.dta
. erase length_simdata.dta
. erase full_simdata.dta
```

Comparing models with different priors

In the previous section, we used `bayestest model` to compare nested hypotheses about which covariates to include in the regression function. We can use `bayestest model` to compare models with not only different covariates but also different outcome distributions and priors for parameters.

We continue our analysis of `auto.dta`, but for simplicity, we now consider the mean-only model for `mpg`. Let's compare models with two slightly different informative priors. We use an informative normal–inverse-gamma prior for both models,

$$(\beta_0|\sigma^2) \sim N(\mu_0, \sigma^2/n_0)$$
$$\sigma^2 \sim \text{InvGamma}(\nu_0/2, \nu_0\sigma_0^2/2)$$

with $\mu_0 = 25$, $n_0 = 10$, and $\sigma_0^2 = 30$, but we consider two different values for the degrees of freedom: $\nu_0 = 5$ and $\nu_0 = 1$.

We use bayesmh to fit our models. Following the formulas, we specify a normal() prior for the constant {mpg:_cons} (mean parameter) and an inverse-gamma prior igamma() for the variance parameter {var}. We specify an expression for the variance of the normal prior distribution in parentheses.

We fit the first model with $\nu_0 = 5$ and store its estimation results as informative1.

```
. set seed 14

. bayesmh mpg, likelihood(normal({var}))
> prior({mpg:}, normal(25,{var}/10))
> prior({var}, igamma(2.5,75)) saving(inf1_simdata)
Burn-in ...
Simulation ...

Model summary
------------------------------------------------------------------------------
Likelihood:
  mpg ~ normal({mpg:_cons},{var})

Priors:
  {mpg:_cons} ~ normal(25,{var}/10)
        {var} ~ igamma(2.5,75)
------------------------------------------------------------------------------

Bayesian normal regression                       MCMC iterations  =     12,500
Random-walk Metropolis-Hastings sampling         Burn-in          =      2,500
                                                 MCMC sample size =     10,000
                                                 Number of obs    =         74
                                                 Acceptance rate  =      .2548
                                                 Efficiency:  min =     .09065
                                                              avg =      .1049
Log marginal likelihood = -238.55856                          max =      .1192

------------------------------------------------------------------------------
             |                                                Equal-tailed
             |      Mean   Std. Dev.     MCSE     Median  [95% Cred. Interval]
-------------+----------------------------------------------------------------
mpg          |
       _cons |  21.71853   .6592655   .019091   21.69554   20.44644   23.04896
-------------+----------------------------------------------------------------
         var |  35.47405   5.823372   .193417   34.72454   25.84419     48.228
------------------------------------------------------------------------------

file inf1_simdata.dta saved

. estimates store informative1
```

We fit the second model with $\nu_0 = 1$ and store its estimation results as `informative2`.

```
. set seed 14
. bayesmh mpg, likelihood(normal({var}))
> prior({mpg:}, normal(25,{var}/10))
> prior({var}, igamma(0.5,15)) saving(inf2_simdata)
Burn-in ...
Simulation ...
Model summary
------------------------------------------------------------------------------
Likelihood:
  mpg ~ normal({mpg:_cons},{var})
Priors:
  {mpg:_cons} ~ normal(25,{var}/10)
        {var} ~ igamma(0.5,15)
------------------------------------------------------------------------------
Bayesian normal regression                       MCMC iterations  =     12,500
Random-walk Metropolis-Hastings sampling         Burn-in          =      2,500
                                                 MCMC sample size =     10,000
                                                 Number of obs    =         74
                                                 Acceptance rate  =      .2261
                                                 Efficiency:  min =      .0941
                                                              avg =       .109
Log marginal likelihood =  -239.4049                          max =      .1239
```

	Mean	Std. Dev.	MCSE	Median	Equal-tailed [95% Cred.	Interval]
mpg						
_cons	21.7175	.6539814	.021319	21.7295	20.47311	23.02638
var	35.89504	6.288571	.178665	35.17056	25.86084	50.21624

```
file inf2_simdata.dta saved
. estimates store informative2
```

▷ Example 3: Comparing models with informative priors

We now use `bayestest model` to compare our models with two different informative priors.

```
. bayestest model informative1 informative2
Bayesian model tests
```

	log(ML)	P(M)	P(M|y)
informative1	-238.5586	0.5000	0.6998
informative2	-239.4049	0.5000	0.3002

```
Note: Marginal likelihood (ML) is computed using
      Laplace-Metropolis approximation.
```

Assuming that both models are equally likely a priori, the posterior probability of the `informative1` stored results, 0.70, is much higher than the probability of the `informative2` stored results, 0.3.

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▷ Example 4: Comparing a model with noninformative prior

A note of caution regarding comparing models with informative and noninformative priors—models with noninformative priors will often win because they are typically in most agreement with the observed data. For models with noninformative priors, most of the information about parameters is contained in a likelihood. As such, any model with an informative prior that is not in perfect agreement with the data will not fit data as well as a model with a noninformative prior.

For example, let's fit our constant-only model using a noninformative Jeffreys prior for the parameters.

```
. set seed 14
. bayesmh mpg, likelihood(normal({var}))
> prior({mpg:}, flat) prior({var}, jeffreys)
> saving(jeffreys_simdata)
Burn-in ...
Simulation ...
Model summary
------------------------------------------------------------------------------
Likelihood:
  mpg ~ normal({mpg:_cons},{var})
Priors:
  {mpg:_cons} ~ 1 (flat)
        {var} ~ jeffreys
------------------------------------------------------------------------------

Bayesian normal regression                       MCMC iterations  =     12,500
Random-walk Metropolis-Hastings sampling         Burn-in          =      2,500
                                                 MCMC sample size =     10,000
                                                 Number of obs    =         74
                                                 Acceptance rate  =      .2668
                                                 Efficiency:  min =     .09718
                                                              avg =      .1021
Log marginal likelihood =   -234.645                          max =      .1071
```

	Mean	Std. Dev.	MCSE	Median	Equal-tailed [95% Cred.	Interval]
mpg						
_cons	21.29222	.6828864	.021906	21.27898	19.99152	22.61904
var	34.76572	5.91534	.180754	34.18391	24.9129	47.61286

```
file jeffreys_simdata.dta saved
. estimates store jeffreys
```

Let's now compare this model with our two informative models.

```
. bayestest model informative1 informative2 jeffreys
Bayesian model tests
```

	log(ML)	P(M)	P(M|y)
informative1	-238.5586	0.3333	0.0194
informative2	-239.4049	0.3333	0.0083
jeffreys	-234.6450	0.3333	0.9723

```
Note: Marginal likelihood (ML) is computed using
      Laplace-Metropolis approximation.
```

The posterior probability of the Jeffreys model is 0.97.

◁

Finally, at the end of our analysis, we erase all the simulation datasets we no longer need. We erase all of them by typing

```
. erase inf1_simdata.dta
. erase inf2_simdata.dta
. erase jeffreys_simdata.dta
```

Stored results

`bayestest model` stores the following in `r()`:

Macros

`r(names)`	names of estimation results used
`r(marglmethod)`	method for approximating marginal likelihood: `lmetropolis` or `hmean`

Matrices

`r(test)`	test results for parameters in `r(names)`

Methods and formulas

Suppose we have r models M_j for $j = 1, \ldots, r$ with prior probabilities $P(M_j)$ such that $\sum_{j=1}^{r} p(M_j) = 1$. Then, posterior probability for model J is

$$P(M_j|\mathbf{y}) = \frac{P(\mathbf{y}|M_j)P(M_j)}{P(\mathbf{y})}$$

where $P(\mathbf{y}|M_j) = m_j(y)$ is the marginal likelihood of M_j with respect to $\mathbf{y}$, and $P(\mathbf{y}) = \sum_{j=1}^{r} P(\mathbf{y}|M_j)P(M_j)$. See *Methods and formulas* in [BAYES] **bayesmh** for details about computing marginal likelihood.

Also see

[BAYES] **bayesmh** — Bayesian regression using Metropolis–Hastings algorithm

[BAYES] **bayesmh postestimation** — Postestimation tools for bayesmh

[BAYES] **bayesstats ic** — Bayesian information criteria and Bayes factors

[BAYES] **bayesstats summary** — Bayesian summary statistics

[BAYES] **bayestest interval** — Interval hypothesis testing