**Gibbs sampling**

Suppose we have two parameters in the model, a and b, and data .

We get the **likelihood** from the model + distributional assumption:

We specify a **prior** for a and b:

This gives the ***joint* posterior**:

We want the ***marginal* posteriors**:

We can **use MCMC** to do this:

1. Write down the conditional posteriors (which involves just taking the joint posterior and “plugging in” the value for the other parameter(s).
2. It can be shown that, under remarkably general conditions, if we iterate over these conditional distributions, we get draws from the marginal distributions!

**Algorithm** is:

Given some starting value, say (pick a starting value for b), for j = 1,2, …, M,

1. Draw
2. Draw

This gives an MCMC “chain” for draws for and , j from 1 to M.

Drop some values at the beginning of the chain, to allow time for convergence (we can check if it appears to have converged) – the “burn-in” sample. The remainder are draws from the marginal posterior distributions!

If we can recognize the form of the distribution we must draw from, we can draw directly from that distribution (e.g. suppose we recognize that is a Normal distribution, we can draw from that Normal). This is Gibbs sampling.

Example

Suppose we have a Normal likelihood, with unknown mean and precision (inverse of the variance),

We specify either an uninformative prior, or a Normal-Gamma prior for the parameters,

or Uniform

or Jeffreys

Joint posterior is a Normal-Gamma

So it easy to show that the conditional distributions are:

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Linear regression examples:

See **Bayeslinerg-nopackage.R** for example not using a package (looking ‘under the hood’)

See **gibbsegch3.R** for example using bayesm

glmhetersked.R for example with heterosked error (and for slow convergence example)

GSlinreg.R another example of Gibbs sampler for linear regression

gsreg.R = function using bayesm