**Overview**

What are doing?

Bayes’ rule: (should condition on any background information, I as well)

Posterior is proportional to likelihood x prior

“likelihood” = sampling distribution for the data, conditional on the model and parameters of the model.

a constant.

For example, if , where = number of success in trials from Bernoulli trials.

We know that this gives us a binomial likelihood.

[In this case ]

If we choose a prior with a similar functional form, then the math is much easier.

Beta prior: ,

The Beta distribution is flexible enough to represent a lot of different shaped distributions.

The posterior will be proportional to

Posterior:

Let and , then we have another Beta distribution!

We can choose ANY prior (any functional form) and ANY likelihood we think makes sense. The math may be complicated though (and analytically intractable), but it is NOT numerically intractable!

There are generic methods to use for any specification of prior and likelihood, e.g. Metropolis-Hasting algorithm. For most common situations we come across, there are sensible specifications and specific algorithms we can use that are easier and/or more efficient.

**Use “posterior simulation**” instead of trying to do everything analytically as it is much simpler.

Now we want some summary statistics:

Mean(

var(

Instead, draw (with large) pseudo-random draws from the posterior density.

Then compute sample statistics using the pseudo-random sample. These will approximate the exact analytical answer. The larger , the closer the approximation.

Law of large numbers, LLN:

for ANY function f of draw of from for