10: Introduction to Bayesian Computation

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Introduction

This chapter gives an overview for how to approximate intractable quantities such as posterior expectations and predictions.

Definitions

Numerical integration methods approximate integrals.

These methods can be loosely categorized as either **stochastic** or **deterministic** (e.g. quadrature methods).

Deterministic Methods

Deterministic methods don't draw samples, and instead approximate the integral by summing up approximate volumes:

$$E[h(\theta) \mid y] = \int h(\theta)p(\theta \mid y)\mathrm{d}\theta \approx \frac{1}{S}\sum_{s=1}^{S} w_s h(\theta^s)p(\theta^s \mid y)$$

Stochastic Methods

Stochastic methods involve sample averages of simulated draws from some distribution. There are many ways to do this, but generally

$$E[h(\theta) \mid y] = \int h(\theta) p(\theta \mid y) \mathrm{d}\theta \approx \frac{1}{S} \sum_{s=1}^{S} h(\theta^s)$$

with $\theta^s \sim p(\theta \mid y)$, or

$$E[h(\tilde{y}) \mid y] = \int h(\tilde{y}) p(\tilde{y} \mid y) \mathrm{d}\tilde{y} \approx \frac{1}{S} \sum_{s=1}^{S} h(\tilde{y}^s)$$

with $\tilde{y} \sim p(\tilde{y} \mid y)$

Stochastic Methods

Drawing $\tilde{y}$ samples can be done in a two-stage way:

1. draw $\theta^s \sim p(\theta \mid y)$
2. draw $\tilde{y}^s \sim p(\tilde{y} \mid \theta^s)$

Stochastic Methods

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If it's available, you should probably use a Rao-Blackwellized procedure, though:

$$E[h(\tilde{y}) \mid y] = E[E\left(h(\tilde{y}) \mid \theta\right) \mid y] \approx \frac{1}{S}\sum_{s=1}^{S} E\left(h(\tilde{y}) \mid \theta^s\right)$$

with $\theta^s \sim p(\theta \mid y)$

Approximating the posterior on a grid

We used this method earlier for the rat tumor example!

Given that we can evaluate the unnormalized target $p(\theta, y) = p(y \mid \theta)p(\theta)$, we choose a nonrandom grid of points (think seq) $\theta_1, \ldots, \theta_S$, and then we approximate the the continuous posterior with a discrete random variable with pmf equal to

$$\tilde{p}(\theta_j \mid y) = \frac{p(y \mid \theta_j)p(\theta_j)}{\sum_{s=1}^{S} p(y \mid \theta_s)p(\theta_s)}$$

for any $\theta_j \in \{\theta_1, \ldots, \theta_s\}$

Approximating the posterior on a grid

From now on we will write the posterior in terms of an unnormalized density $q(\theta \mid y)$. In other words:

$$p(\theta \mid y) = \frac{q(\theta \mid y)}{\int q(\theta \mid y) \mathrm{d}\theta}$$

Most (maybe all) of the sampling techniques will assume that we can't evaluate $p(\theta \mid y)$, but that we can evaluate $q(\theta \mid y)$

Rejection Sampling aka Accept-Reject sampling

Setup

1. $p(\theta \mid y)$ the target, posterior
2. $q(\theta \mid y) = p(y \mid \theta)p(\theta)$ the unnormalized target
3. $g(\theta)$ the "instrumental" or "proposal" distribution
4. need $q(\theta \mid y)/g(\theta) \leq M$ uniformly
5. $g \gg q$ the proposal "dominates" your target (won't divide by 0)

We are free to choose our own $g(\theta)$. For the time being, we assume that $\int g(\theta)\mathrm{d}\theta = 1$.

Rejection Sampling aka Accept-Reject sampling

To (potentially) produce one draw:

1. propose the draw $\theta^s \sim g(\theta)$
2. draw $U \sim \text{Uniform}(0, 1]$
3. accept θ^s if $U < q(\theta^s \mid y)/\{q(\theta^s)M\}$

Rejection Sampling aka Accept-Reject sampling

$$
\begin{aligned}
P\left(\theta \le t \,\middle|\, U \le \frac{q(\theta \mid y)}{Mg(\theta)}\right) &= \frac{P\left(\theta \le t, U \le \frac{q(\theta|y)}{Mg(\theta)}\right)}{P\left(U \le \frac{q(\theta|y)}{Mg(\theta)}\right)} \\
&= \frac{\int_{-\infty}^{t} \int_{0}^{\frac{q(\theta|y)}{Mg(\theta)}} g(\theta) 1 \mathrm{d}u \mathrm{d}\theta}{\int_{-\infty}^{\infty} \int_{0}^{\frac{q(\theta|y)}{Mg(\theta)}} g(\theta) 1 \mathrm{d}u \mathrm{d}\theta} \\
&= \frac{\int_{-\infty}^{t} g(\theta) \frac{q(\theta|y)}{Mg(\theta)} \mathrm{d}\theta}{\int_{-\infty}^{\infty} g(\theta) \frac{q(\theta|y)}{Mg(\theta)} \mathrm{d}\theta} \\
&= \frac{\int_{-\infty}^{t} q(\theta \mid y) \mathrm{d}\theta}{\int_{-\infty}^{\infty} q(\theta \mid y) \mathrm{d}\theta} \\
&= p(\theta \le t \mid y).
\end{aligned}
$$

Example 1

Assume $y \sim \text{Normal}(\theta, 1)$, and $p(\theta) = \frac{1}{\pi(1+\theta^2)}$. Our goal is to draw from

$$
\begin{aligned}
p(\theta \mid y) &\propto q(\theta \mid y) \\
&= p(y \mid \theta) p(\theta) \\
&= \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{1}{2}(y-\theta)^2\right] \frac{1}{\pi(1+\theta^2)} \\
&\propto \exp\left[-\frac{(\theta-y)^2}{2} - \log(1+\theta^2)\right],
\end{aligned}
$$

Example 1

Let's assume that we want to use our prior distribution as a proposal: $g(\theta) = p(\theta)$. Then we have to find M:

$$\begin{aligned}
\frac{q(\theta \mid y)}{g(\theta)} &= \frac{p(y \mid \theta)p(\theta)}{p(\theta)} \\
&= p(y \mid \theta) \\
&= \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{1}{2}(y-\theta)^2\right] \\
&\leq \frac{1}{\sqrt{2\pi}} \stackrel{\text{def}}{=} M
\end{aligned}$$

Our acceptance probability for draw θ^s is then

$$q(\theta^s \mid y)/\{q(\theta^s)M\} = p(y \mid \theta^s)/M = \exp\left[-\frac{1}{2}(y-\theta^s)^2\right]$$

Rejection Sampling aka Accept-Reject sampling

Generally a good strategy is work with logarithms, and then exponentiate as late as possible.

```
y <- 2 # fake data
num_trials <- 1000
theta_proposals <- rt(num_trials, 1)
us <- runif(num_trials, min = 0, max = 1)
log_accept_prob <- function(theta){
  -.5*(y - theta)^2
}
probs <- exp(log_accept_prob(theta_proposals))
accepts <- ifelse(us < probs, TRUE, FALSE)
hist(theta_proposals[accepts]) # only the accepted draws
#hist(theta_proposals) # all draws!
```

Importance Sampling

importance sampling also involves ratios like the previous algorithm. However, instead of using those ratios to either accept or discard samples, it uses the ratios to weight samples.

Pros: it runs in a nonrandom amount of time, and it doesn't require us to calculate an M.

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4. $g \gg q$ the proposal dominates your target

We are free to choose our own $g(\theta)$. For the time being, we assume that $\int g(\theta)\mathrm{d}\theta = 1$.

Importance Sampling

Algorithm:

1. for all s, draw $\theta^s \sim g(\theta)$
2. for all s, calculate unnormalized weight $\tilde{w}(\theta^s) = \frac{q(\theta^s|y)}{g(\theta^s)}$
3. for all s, calculate normalized weights $w(\theta^s) = \tilde{w}(\theta^s) / \sum_r \tilde{w}(\theta^r)$
4. $E_q[h(\theta) \mid y] \approx \sum_s w(\theta^s) h(\theta^s)$

Importance Sampling

Motivation:

$$\begin{aligned} E_q[h(\theta) \mid y] &= \int h(\theta) p(\theta \mid y) \mathrm{d}\theta \\ &= \frac{\int h(\theta) q(\theta \mid y) \mathrm{d}\theta}{\int q(\theta \mid y) \mathrm{d}\theta} \\ &= \frac{\int h(\theta) \frac{q(\theta|y)}{g(\theta)} g(\theta) \mathrm{d}\theta}{\int \frac{q(\theta|y)}{g(\theta)} g(\theta) \mathrm{d}\theta} \end{aligned}$$

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So first:

$$\frac{1}{S} \sum_{s=1}^{S} \frac{q(\theta^s \mid y)}{g(\theta^s)} \to E_g\left[\frac{q(\theta \mid y)}{g(\theta)}\right] = \int \frac{q(\theta \mid y)}{g(\theta)} g(\theta) \mathrm{d}\theta = \int q(\theta \mid y) \mathrm{d}\theta$$

Importance Sampling

1. $E_q[h(\theta) \mid y] = \frac{\int h(\theta)q(\theta|y)\mathrm{d}\theta}{\int q(\theta|y)\mathrm{d}\theta}$
2. $\frac{1}{S}\sum_{s=1}^{S} \frac{q(\theta^s|y)}{g(\theta^s)} \to \int q(\theta \mid y)\mathrm{d}\theta$ (for the denominator)

And second:

$$\frac{1}{S}\sum_{s=1}^{S} h(\theta^s)\frac{q(\theta^s \mid y)}{g(\theta^s)} \to E_g\left[h(\theta)\frac{q(\theta \mid y)}{g(\theta)}\right] = \int h(\theta)q(\theta \mid y)\mathrm{d}\theta$$

which converges to the numerator

1. $E_q[h(\theta) \mid y] = \frac{\int h(\theta)q(\theta|y)\mathrm{d}\theta}{\int q(\theta|y)\mathrm{d}\theta}$
2. $\frac{1}{S}\sum_{s=1}^{S} \frac{q(\theta^s|y)}{g(\theta^s)} \to \int q(\theta \mid y)\mathrm{d}\theta$
3. $\frac{1}{S}\sum_{s=1}^{S} h(\theta^s)\frac{q(\theta^s|y)}{g(\theta^s)} \to \int h(\theta)q(\theta \mid y)\mathrm{d}\theta$

So finally

$$\sum_{i=1}^{S} w(\theta^s)h(\theta^s) = \frac{\sum_{s=1}^{S} h(\theta^s)\frac{q(\theta^s|y)}{g(\theta^s)}}{\sum_{r=1}^{S} \frac{q(\theta^r|y)}{g(\theta^r)}} = \frac{\frac{1}{S}\sum_{s=1}^{S} h(\theta^s)\frac{q(\theta^s|y)}{g(\theta^s)}}{\frac{1}{S}\sum_{r=1}^{S} \frac{q(\theta^r|y)}{g(\theta^r)}} \to E[h(\theta) \mid y]$$

where $w(\theta^s) = \frac{q(\theta^s|y)}{g(\theta^s)} \Big/ \sum_{r=1}^{S} \frac{q(\theta^r|y)}{g(\theta^r)}$ are the self-normalized weights

Example 2

Assume $y \sim \text{Normal}(\theta, 1)$, and $p(\theta) = \frac{1}{\pi(1+\theta^2)}$. Approximate $E_q[\theta \mid y]$ using proposal $g(\theta) = p(\theta)$.

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If we sample from $g(\theta) = p(\theta) = \frac{1}{\pi(1+\theta^2)}$ then the unnormalized weights are

$$\begin{aligned}
\tilde{w}(\theta^s) &= \frac{q(\theta^s \mid y)}{g(\theta^s)} \\
&= p(y \mid \theta^s) \\
&= \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{1}{2}(y - \theta^s)^2\right]
\end{aligned}$$

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&= \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{1}{2}(y - \theta^s)^2\right]
\end{aligned}$$

then normalize these...

Example 2

```
y <- 2 # fake data
num_samples <- 1000000
theta_draws <- rt(num_samples , 1)
log_unnorm_weight <- function(theta){
  # sqrt(2pi) because it will cancel out
  -.5*(y - theta)^2
}
lunws <- log_unnorm_weight(theta_draws)
norm_weights <- exp(lunws)/sum(exp(lunws))
mean(norm_weights * theta_draws)
#hist(norm_weights)
```

Example 2

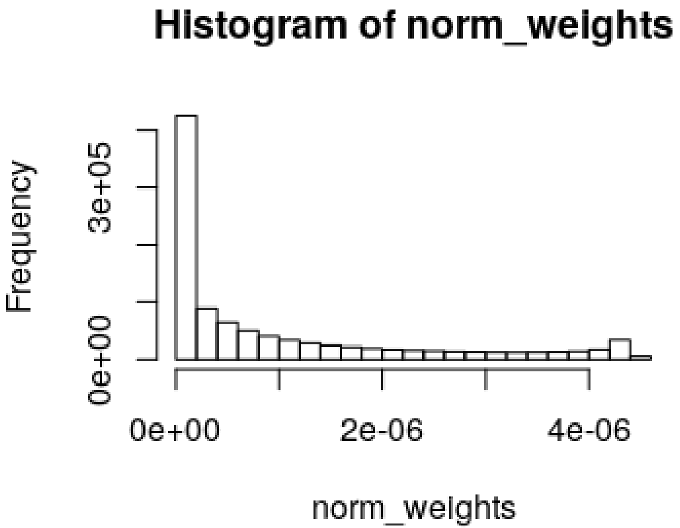
Beware of bad proposal distributions!

We can estimate the standard error using the Delta method:

$$\mathrm{Var}_g\left(\sum_{i=1}^{S} w(\theta^s)h(\theta^s)\right) \approx \frac{1}{s}E_g\left[\underbrace{\tilde{w}^2(\theta)}_{!!!}(h(\theta) - E_q[h(\theta)])^2\right] \Big/ (E_g[\tilde{w}(\theta)])^2$$

Details: `https://stats.stackexchange.com/questions/250934/var-self-normalised-sampling-estimator/250972#250972`

Example 2


Histogram of norm_weights
Frequency
0e+00
3e+05
0e+00
2e-06
4e-06
norm_weights

Example 2

Beware of bad proposal distributions!

A sample estimator of this approximate variance is

$$\sum_{s=1}^{S} w(\theta^s) \left(h(\theta^s) - \hat{E}[h(\theta)] \right)^2$$

where $\hat{E}[h(\theta)] = \sum_s w(\theta^s) h(\theta^s)$.

Note the weights aren't uniform like a "standard" estimation of the sample variance.

Example 2

```
y <- 2 # fake data
log_unnorm_weight <- function(theta){
  # sqrt(2pi) because it will cancel out
  -.5*(y - theta)^2 }
getISEstimator <- function(num_samples){
  theta_draws <- rt(num_samples , 1)
  lunws <- log_unnorm_weight(theta_draws)
  norm_weights <- exp(lunws)/sum(exp(lunws))
  estimator <- sum(norm_weights * theta_draws)
  list("estimate" = estimator,
       "approx_var" = sum( norm_weights*(theta_draws - estimat
# two ways to calculate standard errors
num_samps_per_estimate <- 10
sqrt(getISEstimator(num_samps_per_estimate)$approx_var)
sd(replicate(1000,
    getISEstimator(num_samps_per_estimate)$estimate))
```