

Rejection sampling

Computational Statistics

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Simulate from unnormalized density q

- ▶ Find unnormalized density p and $\alpha > 0$ such that $\alpha q \leq p$
- ▶ Draw values $U \sim \text{Unif}(0, 1)$ and $Y \sim p$.
 - ▶ If $U > \alpha q(Y)/p(Y)$ reject Y and try again.
 - ▶ Otherwise, take Y as a simulated value from q .

Specific problem

$$q(y) = \prod_{i=1}^{100} \exp(yz_i x_i - \exp(yx_i)), \quad y \geq 0,$$
$$p(y) = \exp(-y^2/2).$$

Due to the size of q , I will work on log-scale.

`log_p_over_q(uniroot(ddy_log, c(0, 2), tol = 1e-20))`
(where `ddy_log` calculates $\frac{d}{dy} \log \frac{p(y)}{q(y)}$) gives

$$\alpha_{\log} = \inf_{y \geq 0} \log \frac{p(y)}{q(y)} \approx 92.38.$$

Simple loop implementation

```
1  sum_xz <- sum(dat$x * dat$z)
2
3  log_q_over_p_single <- function(y)
4    y^2 / 2 + y * sum_xz - sum(exp(y * x))
5
6  not_rejected_log_single <- function(y,
7    alpha_log = alpha_log_gauss,
8    log_q_over_p = log_q_over_p_single)
9    log(runif(1)) <= alpha_log + log_q_over_p(y)
10
11 r_abs_norm <- function(n)
12   abs(rnorm(n))
13
14 sim_loop <- function(n,
15   r_proposal = r_abs_norm,
16   not_rejected = not_rejected_log_single)
17 {
18   y <- numeric(n)
19   count <- 1
20   while (count <= n) {
21     y_proposal <- r_proposal(1)
22     if (not_rejected(y_proposal)) {
23       y[count] <- y_proposal
24       count <- count + 1
25     }
26   }
27   y
28 }
```

Profiling: 10^6 simulations.

log_q_over_p_single <- function(y)	260	
{		
sum_exp_yx <- sum(exp(y * x))	14350	
y^2 / 2 + y * sum_xz - sum_exp_yx	1680	
}		
not_rejected_log_single <- function(y,	160	
alpha_log = alpha_log_gauss,		
log_q_over_p = log_q_over_p_single)		
{		
u <- runif(1)	17320	
log_q_over_p_y <- log_q_over_p(y)	17400	
log(u) <= alpha_log + log_q_over_p_y	1540	
}		
r_abs_norm <- function(n)	170	
{		
normal_sim <- rnorm(n)	18650	
abs(normal_sim)	1380	
}		
sim_loop <- function(n,		
r_proposal = r_abs_norm,		
not_rejected = not_rejected_log_single)		
{		
y <- numeric(n)		
count <- 1		
while (count <= n) {	330	
y_proposal <- r_proposal(1)	21860	
if (not_rejected(y_proposal)) {	39980	
y[count] <- y_proposal	140	
count <- count + 1	10	
}		
}		
y		
}		

Bottlenecks

- ▶ Simulating uniform variables and proposals are bottlenecks.
- ▶ Idea: Simulate more values at once.

Simulate several proposals at once

```
1 log_q_over_p_more <- Vectorize(log_q_over_p_single)
2
3 not_rejected_more <- function(y,
4                               alpha_log = alpha_log_gauss,
5                               log_q_over_p = log_q_over_p_more)
6   log(runif(length(y))) <= alpha_log + log_q_over_p(y)
7
8 ## Tries to simulate n values by estimating the probability of rejection based
9 ## on the total number of accepted and rejected proposals so far.
10 sim_approx <- function(n,
11                        total_accepted,
12                        total_rejected,
13                        r_proposal = r_abs_norm,
14                        not_rejected = not_rejected_more)
15 {
16   if (total_accepted == 0)
17     n_proposal <- n
18   else
19     n_proposal <- n * (total_accepted + total_rejected) / total_accepted
20   y <- r_proposal(n_proposal)
21   accepted <- y[not_rejected(y)]
22   n_accepted <- length(accepted)
23   list(
24     accepted = accepted,
25     n_accepted = n_accepted,
26     n_rejected = n_proposal - n_accepted
27   )
28 }
29
```

... wrapped up.

```
1  sim_smart <- function(n,  
2                                r_proposal = r_abs_norm,  
3                                not_rejected = not_rejected_more)  
4  {  
5    y <- numeric(n)  
6    total_accepted <- 0  
7    total_rejected <- 0  
8    while (total_accepted < n) {  
9      sim <- sim_approx(n,  
10                           total_accepted,  
11                           total_rejected,  
12                           r_proposal,  
13                           not_rejected)  
14      if (sim$n_accepted > 0) {  
15        y[(1 + total_accepted):(total_accepted + sim$n_accepted)] <-  
16          sim$accepted  
17        total_accepted <- total_accepted + sim$n_accepted  
18      }  
19      total_rejected <- total_rejected + sim$n_rejected  
20    }  
21    y[1:n]  
22  }
```


Profiling: 10^6 simulations.

Only `sim_approx` takes time (of course).

```
sim_smart <- function(n,  
                      r_proposal = r_abs_norm,  
                      not_rejected = not_rejected_more)  
{  
  y <- numeric(n)  
  total_accepted <- 0  
  total_rejected <- 0  
  while (total_accepted < n) {  
    sim <- sim_approx(n,  
                      total_accepted,  
                      total_rejected,  
                      r_proposal,  
                      not_rejected)  
    if (sim$n_accepted > 0) {  
      y[(1 + total_accepted):(total_accepted + sim$n_accepted)] <-  
        sim$accepted  
      total_accepted <- total_accepted + sim$n_accepted  
    }  
    total_rejected <- total_rejected + sim$n_rejected  
  }  
  y[1:n]  
}
```

30070	
10	
10	

Profiling: r_proposal no longer a bottleneck!

```
sim_approx <- function(n,  
                        total_accepted,  
                        total_rejected,  
                        r_proposal = r_abs_norm,  
                        not_rejected = not_rejected_more)  
{  
  if (total_accepted == 0)  
    n_proposal <- n  
  else  
    n_proposal <- n * (total_accepted + total_rejected) / total_accepted  
  y <- r_proposal(n_proposal)  
  not_rejected_y <- not_rejected(y)  
  accepted <- y[not_rejected_y]  
  n_accepted <- length(accepted)  
  list(  
    accepted = accepted,  
    n_accepted = n_accepted,  
    n_rejected = n_proposal - n_accepted  
  )  
}
```

560

29480

20

Profiling: runif no longer a bottleneck!

```
not_rejected_more <- function(y,  
                               alpha_log = alpha_log_gauss,  
                               log_q_over_p = log_q_over_p_more)  
{  
  unif_sim <- runif(length(y))  
  log_q_over_p_y <- log_q_over_p(y)  
  log(unif_sim) <= alpha_log + log_q_over_p_y  
}
```



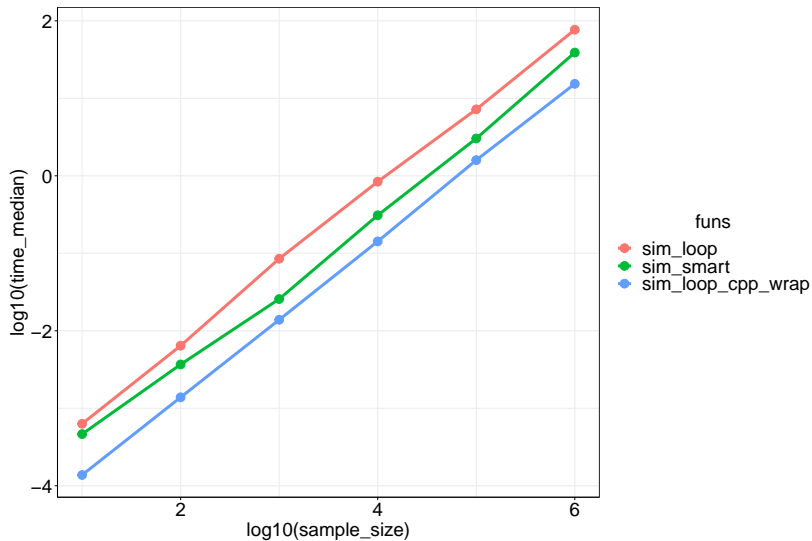
250
28280
960

- ▶ Only bottleneck now is `log_q_over_p`.
- ▶ Idea: Do loop implementation in Rcpp.

Rcpp version of simple loop implementation

```
1  double
2  log_q_over_p_cpp(double y, const NumericVector& x, double sum_xz)
3  {
4      unsigned long long n = x.length();
5      double result = y * y / 2 + y * sum_xz;
6
7      for (unsigned long long i = 0; i < n; i++)
8          result -= exp(y * x[i]);
9      return result;
10 }
11
12 // [[Rcpp::export]]
13 NumericVector
14 sim_loop_cpp(unsigned long long n, double alpha_log,
15              const NumericVector& x, double sum_xz)
16 {
17     NumericVector y(n);
18     double y_norm;
19     unsigned long long count = 0;
20
21     while (count < n) {
22         y_norm = R::rnorm(0,1);
23         if (log(R::runif(0,1)) <= alpha_log + log_q_over_p_cpp(y_norm, x, sum_xz))
24             y[count++] = y_norm;
25     }
26     return y;
27 }
```

Benchmarking: order as expected



Adaptive envelopes

- ▶ Assume log-concave density
- ▶ log-affine envelope

$$f(y) \leq \exp \left(\sum_{i=1}^m (a_i y + b_i) 1_{I_i}(y) \right)$$

where

$$a_i = (\log f(t_i))', \quad b_i = \log f(t_i) - a_i t_i.$$

- ▶ Knots $t_1 < \dots < t_m$ and grid $I_i = (z_i, z_{i+1}]$ with $z_{i+1} = \frac{b_{i+1} - b_i}{a_i - a_{i+1}}$ such that $a_i z_{i+1} + b_i = a_{i+1} z_{i+1} + b_{i+1}$ (so the envelope changes log-affine function where they intersect).
- ▶ More knots \Rightarrow fewer rejections, but more computations per proposal.
- ▶ Fewer knots \Rightarrow more rejections, but fewer computations per proposal.

Simulating from adaptive envelope

With

$$F_i(y) = \int_{z_i}^y e^{a_i z + b_i} dz = \frac{1}{a_i} e^{b_i} (e^{a_i y} - e^{a_i z_i})$$

and $Q_i = \sum_{k=1}^{i-1} F_i(z_k)$ for $i = 1, \dots, m+1$, and $c = Q_{m+1}$, the piecewise log-affine adaptive envelope density leads to the CDF

$$F(y) = \frac{Q_i + F_i(y)}{c}, \quad \text{for } y \in I_i.$$

Hence, we can simulate from F by drawing a uniform $q \in (0, 1)$ and solving

$$F_i(y) = cq - Q_i, \quad \text{where } Q_i < cq \leq Q_{i+1},$$

that is,

$$y = \frac{1}{a_i} \log \left(a_i e^{-b_i} (cq - Q_i) + e^{a_i z_i} \right).$$

Where to place the knots t ?

- ▶ Choose reasonable end-knots.
 - ▶ Plot unnormalized density q and eyeball reasonable values.
 - ▶ Or: use other envelope to simulate initial values and find, e.g., 10% and 90% empirical quantiles.
- ▶ Place knots equidistantly between the two end points.
- ▶ Or: place knots at equidistant empirical quantiles between 10% and 90%.

I use five knots at empirical quantiles of 10^6 simulated values.

```
1 simulations <- sim_loop_cpp_wrap(10^6)
2 knots <- quantile(simulations, seq(0.1, 0.9, length.out = 5))
```


Implementation: highest level.

```
1  sim_adapt_more <- function(n, t)
2  {
3      a <- dlogf(t)
4      b <- logf(t) - a * t
5      z <- get_z(a, b)
6      Q_and_c <- get_Q_and_c(a, b, z)
7      replicate(n, get_accepted_proposal(a, b, Q_and_c$c, z, Q_and_c$Q))
8  }
9
10 get_accepted_proposal <- function(a, b, c, z, Q)
11 {
12     reject <- TRUE
13     while(reject) {
14         cu <- c * runif(1)
15         i <- findInterval(cu, Q)
16         proposal <- log(a[i] * exp(-b[i]) * (cu - Q[i]) +
17                         exp(a[i] * z[i])) / a[i]
18         reject <- log(runif(1)) > logf(proposal) - a[i] * proposal - b[i]
19     }
20     proposal
21 }
```

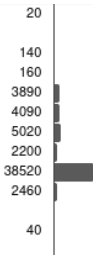
Implementation: z , Q , and c .

```
1  get_z <- function(a, b)
2  {
3      N <- length(a)
4      c(
5          0,
6          (b[2:N] - b[1:(N-1)]) / (a[1:(N-1)] - a[2:N]),
7          1
8      )
9  }
10
11 get_Q_and_c <- function(a, b, z)
12 {
13     N <- length(a)
14     Qc <- cumsum(c(0,
15                   exp(b[1:N]) * (exp(a[1:N] * z[2:(N+1)])
16                     - exp(a[1:N] * z[1:N])) / a[1:N]))
17     list(
18         Q = Qc[1:N],
19         c = Qc[N+1]
20     )
21 }
```

Profiling 10^6 simulations

- logf is the largest bottleneck.

```
get_accepted_proposal <- function(a, b, c, z, Q)
{
  reject <- TRUE
  while(reject) {
    cu <- c * runif(1)
    i <- findInterval(cu, Q)
    proposal <- log(a[i] * exp(-b[i]) * (cu - Q[i]) + exp(a[i] * z[i])) / a[i]
    unif_random <- runif(1)
    logf_proposal <- logf(proposal)
    reject <- log(unif_random) > logf_proposal - a[i] * proposal - b[i]
  }
  proposal
}
```



Line Number	Approximate Relative Time
20	10
21	10
22	10
23	10
24	10
25	10
26	10
27	10
28	10
29	10
30	10
31	10
32	10
33	10
34	10
35	10
36	10
37	10
38	38
39	10
40	10

Not much to do about it in R:

```
1 logf <- function(y)
2   y * sum_xz - sum(exp(y * x))
```

Rcpp implementation of adaptive envelope

```
1  // [[Rcpp::export]]
2  NumericVector
3  sim_adapt_more_cpp(unsigned long long n, const NumericVector& t,
4                      const NumericVector& x, double sum_xz)
5  {
6      unsigned long long n_t = t.length();
7      double *a = get_a(t, n_t, x, sum_xz);
8      double *b = get_b(a, t, n_t, x, sum_xz);
9      double *z = get_z(a, b, n_t);
10     double *Q_and_c = get_Q_and_c(a, b, z, n_t);
11     double c = *(Q_and_c + n_t);
12     NumericVector simulations(n);
13     for (unsigned long long i = 0; i < n; i++)
14         simulations[i] = get_accepted_proposal(a, b, c, z, Q_and_c,
15                                                n_t, x, sum_xz);
16     return simulations;
17 }
```

Rcpp implementation of adaptive envelope

```
1  double
2  get_accepted_proposal(double *a, double *b, double c,
3                       double *z, double *Q, unsigned long long n_ab,
4                       const NumericVector& x, double sum_xz)
5  {
6      double cu, proposal;
7      unsigned long long i;
8
9      do {
10         cu = c * R::runif(0, 1);
11         i = find_interval(cu, Q, n_ab);
12         proposal = log(*(a + i) * exp(-(b + i)) * (cu - *(Q + i))
13                      + exp(*(a + i) * *(z + i))) / *(a + i);
14     } while (log(R::runif(0, 1)) >
15             logf(proposal, x, sum_xz) - *(a + i) * proposal - *(b + i));
16
17     return proposal;
18 }
```

Rcpp implementation of adaptive envelope

```
1  double
2  logf(double y, const NumericVector& x, double sum_xz)
3  {
4      unsigned long long n = x.length();
5      double result = y * sum_xz;
6
7      for (unsigned long long i = 0; i < n; i++)
8          result -= exp(y * x[i]);
9      return result;
10 }
11
12 double
13 dlogf(double y, const NumericVector& x, double sum_xz)
14 {
15     unsigned long long n = x.length();
16     double result = sum_xz;
17
18     for (unsigned long long i = 0; i < n; i++)
19         result -= x[i] * exp(y * x[i]);
20     return result;
21 }
```

Rcpp implementation of adaptive envelope

```
1  double *
2  get_a(const NumericVector& t, unsigned long long n_t, const NumericVector& x, double sum_xz)
3  {
4      double *a = (double *) malloc(n_t * sizeof(double));
5
6      for (unsigned long long i = 0; i < n_t; i++)
7          *(a + i) = dlogf(t[i], x, sum_xz);
8      return a;
9  }
10
11 double *
12 get_b(double *a, const NumericVector& t, unsigned long long n_t,
13        const NumericVector& x, double sum_xz)
14 {
15     double *b = (double *) malloc(n_t * sizeof(double));
16     for (unsigned long long i = 0; i < n_t; i++)
17         *(b + i) = logf(t[i], x, sum_xz) - *(a + i) * t[i];
18     return b;
19 }
20
21 double *
22 get_z(double *a, double *b, unsigned long long n_ab)
23 {
24     double *z = (double *) malloc((n_ab + 1) * sizeof(double));
25
26     *z = 0;
27     for (unsigned long long i = 1; i < n_ab; i++)
28         *(z + i) = (*(b + i) - *(b + i - 1)) / (*(a + i - 1) - *(a + i));
29     *(z + n_ab) = 1;
30     return z;
31 }
```

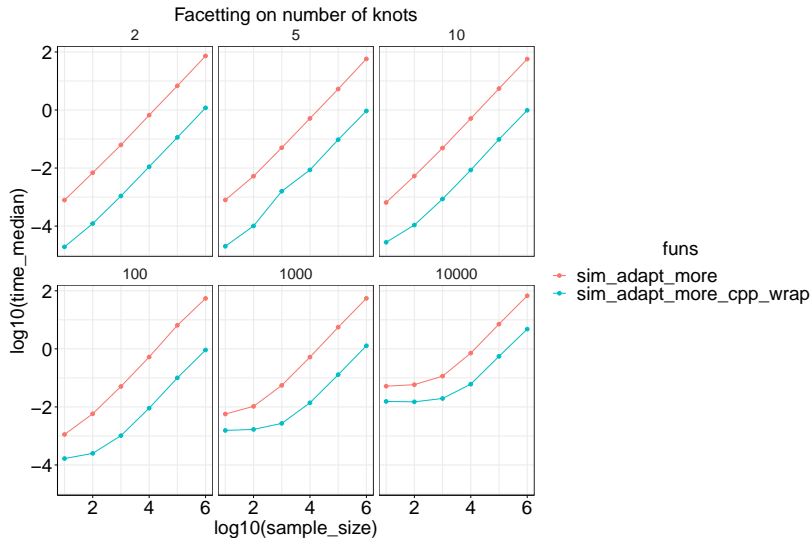
Rcpp implementation of adaptive envelope

```
1  /* Replaces contents of array with the cumulative sum */
2  void
3  replace_with_cumsum(double *array, unsigned long long array_length)
4  {
5      for (unsigned long long i = 1; i < array_length; i++)
6          *(array + i) += *(array + i - 1);
7  }
8
9  /* Returns pointer to array of length n_ab where element 0 is  $Q_0 = 0$ ,
10     element 1 is  $Q_1$ , and so on, until element n_ab which is  $Q_m = c$  */
11  double *
12  get_Q_and_c(double *a, double *b, double *z, unsigned long long n_ab)
13  {
14      double *Q_and_c = (double *) malloc((n_ab + 1) * sizeof(double));
15
16      *Q_and_c = 0;
17      for (unsigned long long i = 0; i < n_ab; i++)
18          *(Q_and_c + i + 1) = exp(*(b + i))
19              * (exp(*(a + i) * *(z + i + 1))
20                  - exp(*(a + i) * *(z + i))) / *(a + i);
21      replace_with_cumsum(Q_and_c, n_ab + 1);
22      return Q_and_c;
23  }
```

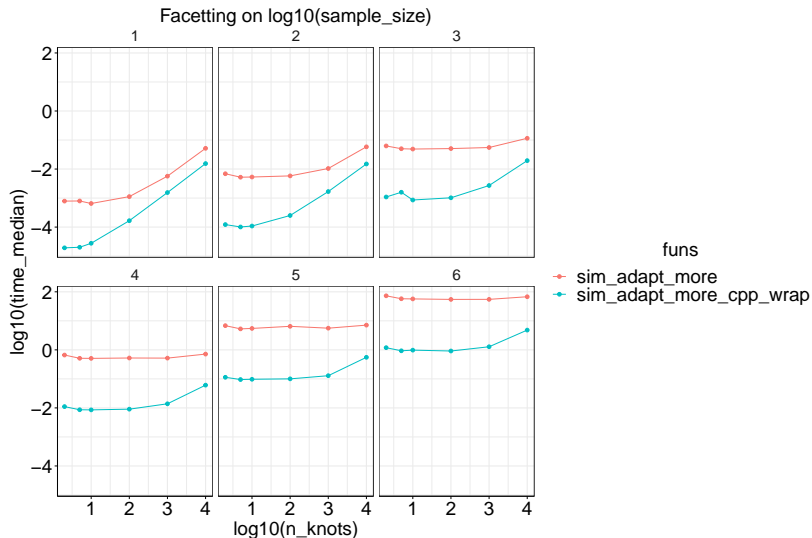

Rcpp implementation of adaptive envelope

```
1  unsigned long long
2  find_interval(double point, double *grid, unsigned long long n_grid)
3  {
4      if (*(grid + n_grid - 1) < point)
5          return n_grid - 1;
6
7      for (unsigned long long i = 0; i < n_grid - 1; i++)
8          if (*(grid + i) < point && point <= *(grid + i + 1))
9              return i;
10
11     return -1;                                /* Error code */
12 }
```

Benchmarking



Benchmarking



f is posterior in a Poisson regression with flat prior

If $Z_i \stackrel{\text{iid}}{\sim} \text{Poisson}(\lambda_i)$ where

$$\log \lambda_i = yx_i$$

then the likelihood is

$$\begin{aligned} p(z \mid x, y) &= \prod_{i=1}^n \frac{\exp(yx_i)^{z_i}}{(yx_i)!} \exp(-\exp(yx_i)) \\ &\propto \prod_{i=1}^n \exp(z_i yx_i - \exp(yx_i)) \end{aligned}$$

so with a flat prior $p(y) \propto 1$ the posterior for Y is

$$p(y \mid z, x) \propto p(z \mid x, y)p(y) \propto p(z \mid x, y).$$

Simulating from posterior with Stan

► Writing model in Stan:

```
data {  
  int<lower = 0> N;  
  int<lower = 0> z[N];  
  real x[N];  
}  
parameters {  
  real y;  
}  
model {  
  z ~ poisson_log(y * x);  
}
```

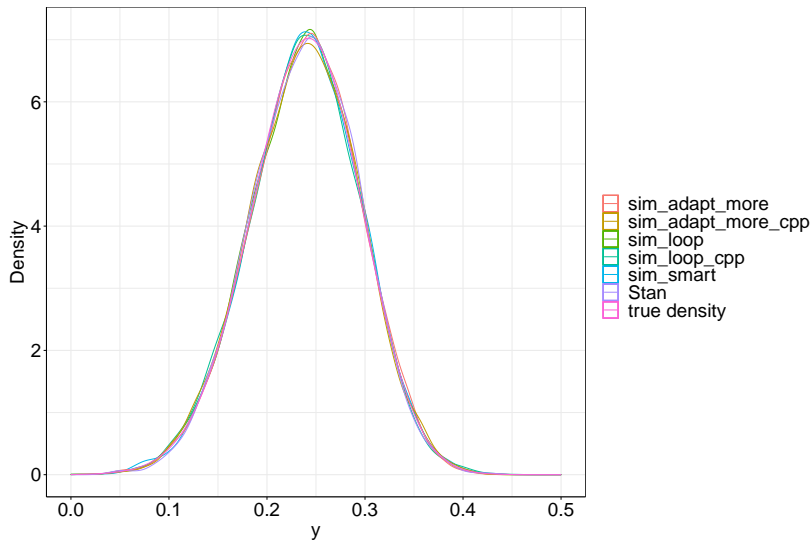
► Simulating from Posterior:

```
1 stan_sim <- rstan::stan(file = "model.stan",  
2                        data = list(N = nrow(dat),  
3                                    z = dat$z,  
4                                    x = dat$x),  
5                        chains = 4, cores = 4, iter = 1e4 * 2 / 4)  
6 y_stan_sim <- rstan::extract(stan_sim)$y
```

Comparing simulated values to true density

Density estimates for 10^4 simulated values.

The true density is q normalized by its numerical integral.



What else could be done?

- ▶ Adaptive choice of knots for the log-affine envelope (each time a proposal is rejected, add a knot at the proposed value) (notes 3 slides from now).
- ▶ Explore rejection rates depending on number- and placement of knots (fun but not essential when our primary interest is runtime).

Other slides

- ▶ Use binary search instead of brute force search for large number of knots? (1 slide from now).
- ▶ Generic implementation for other densities. (2 slides from now).
- ▶ Check Stan convergence (4 slides from now)

Binary search instead of brute force

```
1  unsigned long long
2  find_interval_binary_search(double point, double *grid,
3                             unsigned long long n_grid)
4  {
5      unsigned long long i_min = 0;
6      unsigned long long i_max = n_grid - 1;
7      unsigned long long i;
8
9      if (*(grid + i_max) <= point)
10         return i_max;
11
12     while (i_max - i_min > 1) {
13         i = floor((i_max + i_min) / 2);
14         if (*(grid + i) == point)
15             return i;
16         else if (*(grid + i) > point)
17             i_max = i;
18         else
19             i_min = i;
20     }
21
22     return i_min;
23 }
```

Slower than brute force for small grids (benchmarked).

Generic implementation for other densities

```
1  ## The user has to supply logf.
2  ## This only applies to get_accepted_proposal and sim_adapt_more.
3  get_accepted_proposal_generic <- function(a, b, c, z, Q, logf)
4  {
5    reject <- TRUE
6    while(reject) {
7      cu <- c * runif(1)
8      i <- findInterval(cu, Q)
9      proposal <- log(a[i] * exp(-b[i]) * (cu - Q[i]) + exp(a[i] * z[i])) / a[i]
10      reject <- log(runif(1)) > logf(proposal) - a[i] * proposal - b[i]
11    }
12    proposal
13  }
14
15  ## dlogf is an optional argument.
16  ## If it is NULL, then we use numerical differentiation.
17  sim_adapt_more_generic <- function(n, t, logf, dlogf = NULL)
18  {
19    if (is.null(dlogf))
20      a <- numDeriv::grad(logf, t, method = "simple")
21    else
22      a <- dlogf(t)
23    b <- logf(t) - a * t
24    z <- get_z(a, b)
25    Q_and_c <- get_Q_and_c(a, b, z)
26    replicate(n, get_accepted_proposal(a, b, Q_and_c$c, z, Q_and_c$Q, logf))
27  }
```

Adaptive knots in

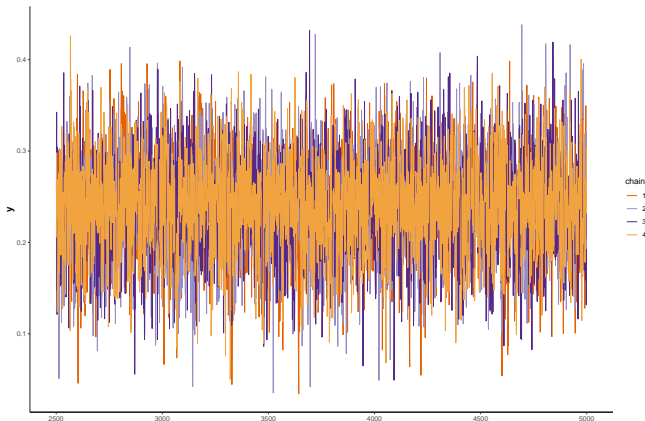
R

- ▶ Easy to add new knots in the middle of vector.

C++

- ▶ Linked list of knots should make it easy/cheap to add new knots adaptively.

Checking Stan



The trace plot shows good mixing and we get $\hat{R} \approx 1$, which indicates convergence of the chains.

The effective sample size for Y is 3930 (out of 10000 post-warmup draws in total).