

# STAT 243 Final Project: Adaptive Rejection Sampling

*Jonathan Morrell, Ziyang Zhou, Vincent Zijlmans*

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## Introduction

In this project we implement the adaptive rejection sampling algorithm proposed by Gilks et al. (1995), a method for rejection sampling from any univariate log-concave probability density function  $f(x)$ . This method is particularly useful in situations where the density function is computationally expensive to evaluate, as it uses successive evaluations of  $h(x) = \log(f(x))$  to improve the approximation of a rejection envelope  $u(x)$  and squeezing function  $l(x)$ , which are (theoretically) much simpler to compute and sample from than the original density function.

The R package, **ars**, containing our solution can be found using the following link:

<https://github.com/jtmorrell/ars>

Or, can be installed using devtools:

```
devtools::install_github('jtmorrell/ars')
```

## Methodology

Our implementation consists of one function, **ars**, which takes as arguments the univariate log-concave density function  $f(x)$ , the number of samples desired  $N$ , the initial points  $x_0$  used to approximate  $h(x) = \log(f(x))$  (default: `c(-1, 1)`), and optionally the bounds of the density function.

To demonstrate the implementation of **ars** we will go through the example of sampling  $N = 100,000$  points from the normal distribution.

```
## Normally inputs to ars()
f <- dnorm
N <- 100000
x0 <- c(-1.0, 1.0)
bounds <- c(-Inf, Inf)
```

First we check the inputs.

```
## Input sanity check
if (!is.function(f)) {
  stop('f is not a function.')
}

if (length(bounds) != 2) {
  stop('Length of bounds must be 2! (upper and lower bounds required)')
}

if (bounds[1] == bounds[2]) {
  warning('Same upper and lower bounds, replacing them by default: bounds=c(-Inf, Inf)')
  bounds <- c(-Inf, Inf)
}
```

```
## Ensure bounds are c(lower, upper)
if (bounds[1] > bounds[2]) {
  warning('Bounds should be in order c(lower, upper)')
  bounds <- sort(bounds)
}

if (!all((x0 > bounds[1]) & (x0 < bounds[2]))) {
  stop('Bad inputs: x0 must be inside bounds.')
}
```

Then we'll initialize some helper variables.

```
## define h(x) = log(f(x))
h <- function(x) {
  return (log(f(x)))
}

## helper variables
dx <- 1E-8 # mesh size for finite difference approximation to h'(x)
eps <- 1E-7 # tolerance for non-log-concavity test
max_iters <- 10000 # prevent infinite loop
current_iter <- 0
bds_warn <- FALSE # Flag for boundary warning in main while loop
```

Because the derivative of the log-density function  $h'(x)$  is required in our calculation, we need to approximate it using a finite-difference method. We'll use a forward differencing approximation, as we only need to evaluate  $h(x)$  one additional time to calculate  $h'(x)$ . The forward difference method uses the following Taylor expansion

$$f(x_0 + h) = f(x_0) + f'(x_0)h + \frac{1}{2}f''(x_0)h^2 + \mathcal{O}(h^3)$$

to approximate the first derivative as

$$f'(x_0) \approx \frac{f(x_0 + h) - f(x_0)}{h}$$

where  $h$  is a small number, often called the mesh spacing in numerical methods.

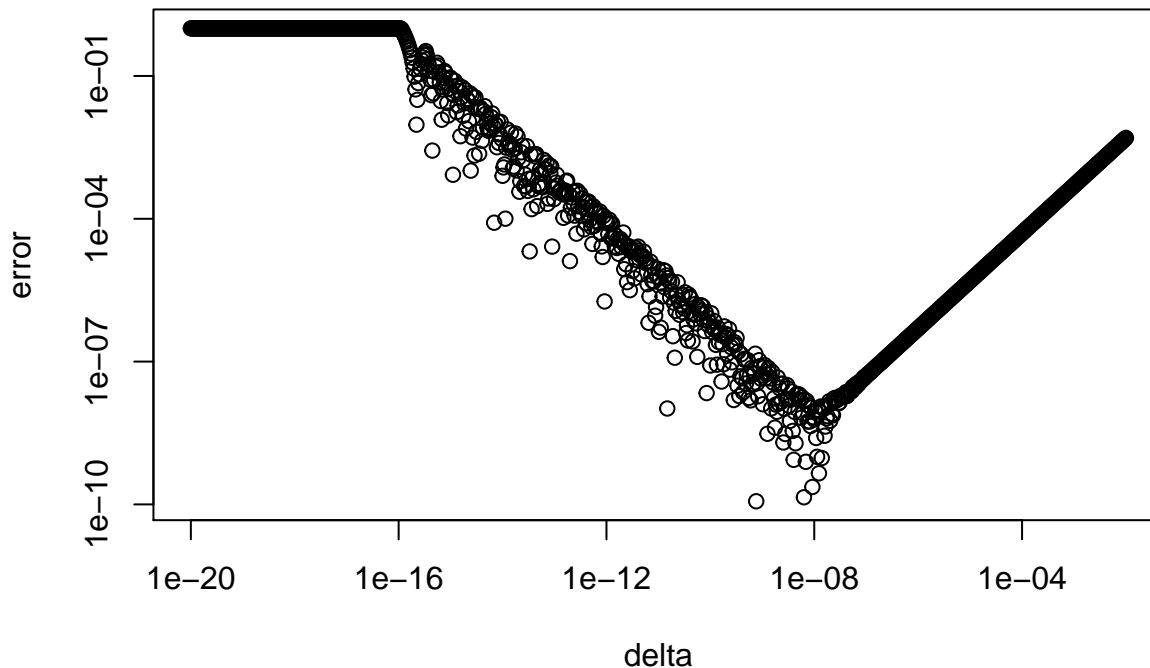
This approximation ignores higher order corrections, which means it will have first order truncation error:

$$\epsilon = \frac{1}{2}f''(x_0)h + \mathcal{O}(h^2)$$

Therefore, we want to choose our mesh spacing  $h$  as small as possible. However, because we are performing these computations on double-precision floating point computers there is a limit to how small we can make  $h$  before machine precision impacts the precision of this approximation. Looking at how we will compute the approximation of the derivative, we see that the numerator  $f(x_0 + h) - f(x_0)$  requires the subtraction of two very similar numbers. Assuming  $\mathcal{O}(f'(x)) \approx 1$ , the difference will be  $\approx \mathcal{O}(h)$ . However the numbers we're subtracting have 16 digits of accuracy, so if  $h$  were  $10^{-10}$  the difference would only have 6 digits of accuracy! (The numerator and denominator are of similar order, so we expect only a small loss of precision in the division operation). Therefore we expect the mesh spacing with the highest accuracy to be around  $10^{-8}$ .

If we consider the simple example of  $f(x) = x^2$  we can see that this is approximately correct.

```
## vector of possible mesh spacings
delta <- 10**seq(-20, -2, length = 1000)
## example function x^2
quad <- function(x) x**2
## approximate derivative using forward difference
h_prime <- (quad(1.0 + delta) - quad(1.0))/delta
## Difference from true value of 2
error <- abs(h_prime - 2.0)/2.0
plot(delta, error, log = 'xy')
```



Continuing on with the ARS algorithm

```
## initialize vectors
x0 <- sort(x0) # Ensures x0 is in ascending order
x_j <- c() # evaluated x values
h_j <- c() # evaluated h(x) values
dh_j <- c() # evaluated h'(x) values
x <- c() # accepted sample vector

## Evaluate h(x0)
h0 <- h(x0)
## Finite difference approximation to h'(x)
dh0 <- (h(x0 + dx) - h0)/dx

## Check for NaNs and infinities
isnum <- is.finite(h0)&is.finite(dh0)
x0 <- x0[isnum]
h0 <- h0[isnum]
dh0 <- dh0[isnum]

## Error if no good x0 values
if (length(h0) == 0) {
  stop('h(x0) either infinite or NaN.')
```

```

}

## ARS requires either finite bounds or at least
## one positive and one negative derivative
if (!(dh0[1] > 0 || is.finite(bounds[1]))) {
  stop('dh(x0)/dx must have at least one positive value, or left bound must be
    greater than -infinity.')
}

if (!(dh0[length(dh0)] < 0 || is.finite(bounds[2]))) {
  stop('dh(x0)/dx must have at least one negative value, or right bound must be
    less than infinity.')
}

```

The first step specified by Wilks is to initialize our functions  $u_k(x)$ ,  $l_k(x)$ ,  $s_k(x)$  and to pre-compute the intercepts of  $u_k(x)$  ( $z_k$ ). To do this we will write helper functions to calculate the coefficients of the piecewise linear functions as specified by Wilks.

```

##### HELPER FUNCTIONS #####

calc_z_j <- function (x, h, dh, bounds) {
  ## Calculate intercepts of piecewise u_j(x)
  ##
  ## Arguments
  ## x, h, dh: evaluated x, h(x) and h'(x)
  ## bounds: bounds of distribution h(x)
  ##
  ## Value
  ## intercepts (bounds) of piecewise u_j(x)

  L <- length(h)
  z <- (h[2:L] - h[1:L-1] - x[2:L]*dh[2:L] + x[1:L-1]*dh[1:L-1])/(dh[1:L-1] - dh[2:L])

  return (append(bounds[1], append(z, bounds[2])))
}

calc_u <- function (x, h, dh) {
  ## Calculate slope/intercept for piecewise u_j(x)
  ##
  ## Arguments
  ## x, h, dh: evaluated x, h(x), and h'(x)
  ##
  ## Value (list)
  ## m, b: slope/intercept of u(x)

  return (list(m = dh, b = h - x*dh))
}

calc_l <- function (x, h) {
  ## Calculate slope/intercept for piecewise l_j(x)
  ##
  ## Arguments
  ## x, h: evaluated x, and h(x)

```

```
##
## Value (list)
## m, b: slope/intercept of l(x)

L <- length(h)
m <- (h[2:L] - h[1:L-1])/(x[2:L] - x[1:L-1])
b <- (x[2:L]*h[1:L-1] - x[1:L-1]*h[2:L])/(x[2:L] - x[1:L-1])

return (list(m = m, b = b))
}
```

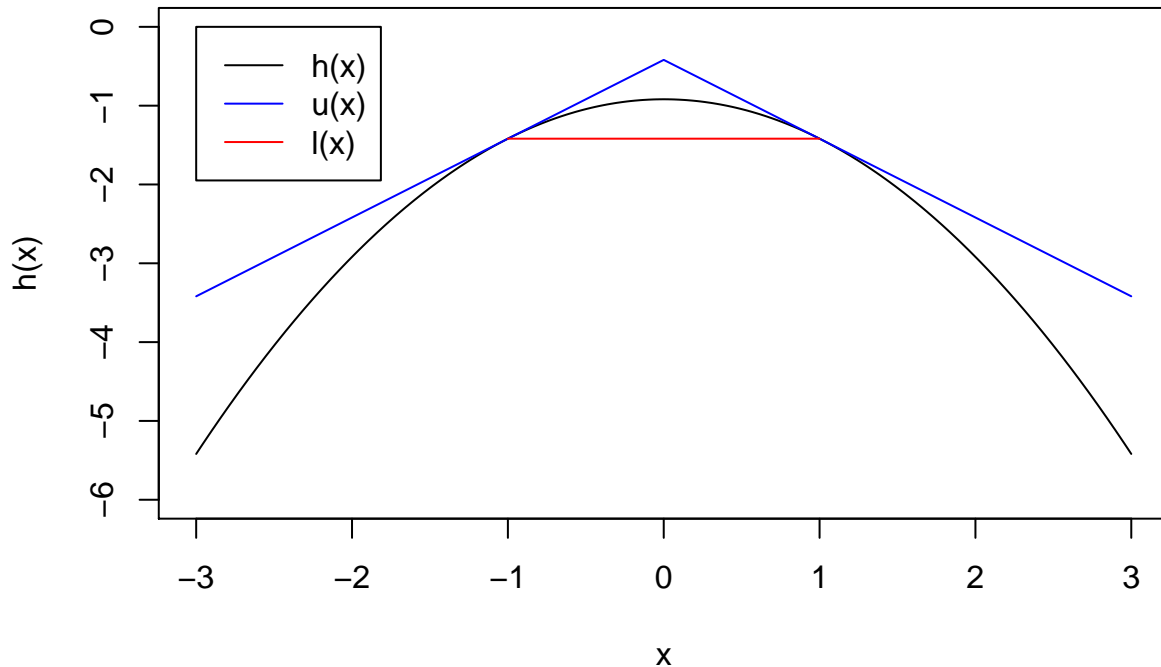
We see that already with only two points we have a good approximation to the rejection envelope  $u_k(x)$  and squeezing function  $l_k(x)$ .

```
u <- calc_u(x0, h0, dh0)
u <- c(-3*u$m[1] + u$b[1], u$b[1], 3*u$m[2] + u$b[2])

l <- calc_l(x0, h0)
l <- l$m*x0 + l$b

x <- seq(-3, 3, length = 1000)
plot(x, h(x), ylim = c(-6, 0), type = 'l', col = 'black')

lines(c(-3, 0, 3), u, col = 'blue')
lines(x0, l, col = 'red')
legend(-3, 0, legend = c('h(x)', 'u(x)', 'l(x)'),
      col = c('black', 'blue', 'red'), lty = 1)
```



For the function

$$s_k(x) = \exp u_k(x) / \int_D \exp u(x') dx'$$

from which we'll sample  $x$ , instead of computing the function we will compute coefficients which will allow us to sample easily. To do this we'll re-define  $s_k(x)$  as

$$s_k(x) = e^{u_k(x)} / \int_D e^{u(x')} dx' = \frac{e^{b_k} e^{m_k x}}{\sum_{j=1}^K \int_{z_j}^{z_{j+1}} e^{b_j} e^{m_j x'} dx'} = \frac{e^{b_k} e^{m_k x}}{\sum_{j=1}^K I_j} \equiv \beta_k e^{m_k x}$$

where  $I_j$  is  $\frac{e^{b_j}}{m_j}(e^{m_j z_{j+1}} - e^{m_j z_j})$  for  $m_j \neq 0$ , or  $e^{b_j}(z_{j+1} - z_j)$  for  $m_j = 0$ .

To sample  $x$ , we will first use weighted random sampling to determine which segment to sample from, where the weights used are the area of each segment

$$w_j = \int_{z_j}^{z_{j+1}} \beta_j e^{m_j x'} dx' = \frac{\beta_j}{m_j} (e^{m_j z_{j+1}} - e^{m_j z_j})$$

where  $m_j \neq 0$ , or

$$w_j = \beta_j (z_{j+1} - z_j)$$

for  $m_j = 0$ .

Then we will use inverse CDF sampling to sample  $x$  from segment  $j$ :

$$S_j(x) = \mathcal{U}(0, 1) = u = \frac{1}{w_j} \int_{z_j}^x s_j(x') dx' = \frac{\beta_j}{w_j m_j} (e^{m_j x} - e^{m_j z_j})$$

giving us

$$x = \frac{1}{m_j} \log\left(\frac{w_j m_j}{\beta_j} u + e^{m_j z_j}\right)$$

for  $m_j \neq 0$ , and  $x = z_j + \frac{w_j}{\beta_j} u$  for  $m_j = 0$ .

```
calc_s_j <- function (m, b, z) {
  ## Calculate beta values and weights
  ##   needed to sample from u(x)
  ##
  ## Arguments
  ## m, b: slope/offset for piecewise u_j(x)
  ## z: bounds z_j for piecewise function u_j(x)
  ##
  ## Value (list)
  ## beta: amplitude of each piecewise segment in u(x)=beta*exp(m*x)
  ## w: area of each segment

  L <- length(z)
  eb <- exp(b) # un-normalized betas
  eb <- ifelse(is.finite(eb), eb, 0.0) # Inf/Nan -> 0

  ## treat m=0 case
  nz <- (m != 0.0)
  nz_sum <- sum((eb[nz]/m[nz])*(exp(m[nz]*z[2:L][nz]) - exp(m[nz]*z[1:L-1][nz])))
  z_sum <- sum(eb[!nz]*(z[2:L][!nz] - z[1:L-1][!nz]))
}
```

```

## Ensure integral of s(x) > 0
if (nz_sum + z_sum <= 0.0) {
  stop('Area of s(x)=exp(u(x)) <= 0')
}

## Normalize beta
beta <- eb/(nz_sum + z_sum)
## Calculate weights for both m!=0 and m=0 cases
w <- ifelse(nz, (beta/m)*(exp(m*z[2:L]) - exp(m*z[1:L-1])), beta*(z[2:L] - z[1:L-1]))

return (list(beta = beta, w = ifelse((w > 0) & is.finite(w), w, 0.0)))
}

draw_x <- function (N, beta, m, w, z) {
  ## Sample from distribution u(x), by selecting segment j
  ## based on segment areas (probabilities), and then sample
  ## from exponential distribution within segment using
  ## inverse CDF sampling.
  ##
  ## Arguments
  ## N: number of samples
  ## beta, m, w: parameters of u_j(x)
  ## z: intercepts (bounds) of u_j(x)
  ##
  ## Value (list)
  ## x: samples from u(x)
  ## J: segment index j of each sample

  ## choose random segments with probability w
  J <- sample(length(w), N, replace = TRUE, prob = w)
  u <- runif(N) # uniform random samples
  ## Inverse CDF sampling of x
  x <- ifelse(m[J] != 0, (1.0/m[J])*log((m[J]*w[J]/beta[J])*u + exp(m[J]*z[J])),
             z[J] + w[J]*u/beta[J])

  return (list(x = x, J = J))
}

```

For the main loop we'll sample x in chunks that will grow until either the full number of samples is reached or until the chunk size equals N.

```

##### MAIN LOOP #####

## Loop until we have N samples (or until error)
while (length(x) < N) {

  ## Track iterations, 10000 is arbitrary upper bound
  current_iter <- current_iter + 1

  if (current_iter > max_iters) {
    stop('Maximum number of iterations reached.')
  }

  ## Vectorized sampling in chunks

```

```

## Chunk size will grow as square of iteration,
## up until it is the size of the sample (N)
## This ensures small samples at first, while
## u(x) is a poor approximation of h(x), and
## large samples when the approximation improves.
chunk_size <- min(c(N, current_iter**2))

##### INITIALIZATION AND UPDATING STEP #####

## only re-initialize if there are new samples
if (length(x0) > 0) {

  ## Update with new values
  x_j <- append(x_j, x0)
  h_j <- append(h_j, h0)
  dh_j <- append(dh_j, dh0)
  x0 <- c()
  h0 <- c()
  dh0 <- c()

  ## Sort so that x_j's are in ascending order
  srted <- sort(x_j, index.return = TRUE)
  x_j <- srted$x
  h_j <- h_j[srted$ix]
  dh_j <- dh_j[srted$ix]

  L <- length(dh_j)

  ## Check for duplicates in x and h'(x)
  ## This prevents discontinuities when
  ## computing z_j's

  if (L > 1) {
    while (!all((abs(dh_j[1:L-1] - dh_j[2:L]) > eps) & ((x_j[2:L] - x_j[1:L-1]) > dx))) {

      ## Only keep values with dissimilar neighbors
      ## Always keep first index (one is always unique)
      dup <- append(TRUE, ((abs(dh_j[1:L-1] - dh_j[2:L]) > eps)
                          & ((x_j[2:L] - x_j[1:L-1]) > dx)))

      x_j <- x_j[dup]
      h_j <- h_j[dup]
      dh_j <- dh_j[dup]

      L <- length(dh_j)
      if (L == 1) {
        break
      }
    }

    if (L > 1) {
      ## Ensure log-concavity of function
      if(!all((dh_j[1:L-1] - dh_j[2:L]) >= eps)) {

```



```

        stop('Input function f not log-concave.')
    }
}

## pre-compute z_j, u_j(x), l_j(x), s_j(x)
z_j <- calc_z_j(x_j, h_j, dh_j, bounds)

u_j <- calc_u(x_j, h_j, dh_j)
m_u <- u_j$m
b_u <- u_j$b

l_j <- calc_l(x_j, h_j)
m_l <- l_j$m
b_l <- l_j$b

s_j <- calc_s_j(m_u, b_u, z_j)
beta_j <- s_j$beta
w_j <- s_j$w
}

##### SAMPLING STEP #####

## draw x from exp(u(x))
draws <- draw_x(chunk_size, beta_j, m_u, w_j, z_j)
x_s <- draws$x
J <- draws$J

## random uniform for rejection sampling
w <- runif(chunk_size)

## Warn if samples were outside of bounds
## This happens if bounds given don't reflect
## the actual bounds of the distribution
if (!all((x_s > bounds[1]) & (x_s < bounds[2]))) {

    ## Flag so warning only happens once
    if (!bds_warn) {
        warning('Sampled x* not inside bounds...please check bounds.')
        bds_warn <- TRUE
    }

    ## Only keep x values within bounds
    ibd <- ((x_s > bounds[1]) & (x_s < bounds[2]))
    J <- J[ibd]
    x_s <- x_s[ibd]
    w <- w[ibd]
}

## Index shift for l_j(x)
J_l <- J - ifelse(x_s < x_j[J], 1, 0)
## only use x-values where l_j(x) > -Inf

```

```

ibd <- (J_1 >= 1) & (J_1 < length(x_j))

## Perform first rejection test on u(x)/l(x)
y <- exp(x_s[ibd]*(m_l[J_1[ibd]] - m_u[J[ibd]])) + b_l[J_1[ibd]] - b_u[J[ibd]])
acc <- (w[ibd] <= y)

## Append accepted values to x
x <- append(x, x_s[ibd][acc])
## Append rejected values to x0
x0 <- append(x_s[!ibd], x_s[ibd][!acc])

if (length(x0) > 0) {

  ## Evaluate h(x0)
  h0 <- h(x0)
  ## Finite difference approximation to h'(x)
  dh0 <- (h(x0 + dx) - h0)/dx

  ## Check for NaNs and infinities
  isnum <- is.finite(h0)&is.finite(dh0)
  x0 <- x0[isnum]
  h0 <- h0[isnum]
  dh0 <- dh0[isnum]

  w <- append(w[!ibd], w[ibd][!acc])[isnum]
  J <- append(J[!ibd], J[ibd][!acc])[isnum]

  ## Perform second rejection test on u(x)/h(x)
  acc <- (w <= exp(h0 - x0*m_u[J] - b_u[J]))
  ## Append accepted values to x
  x <- append(x, x0[acc])
}
}

## Only return N samples (vectorized operations makes x sometimes larger)
x <- x[1:N]

```

We will now briefly discuss the performance of the algorithm. We see that the number of function evaluations goes approximately as  $3n^{1/3}$ .

```
print(length(x_j))
```

```
## [1] 128
```

```
print(3*N**(1/3))
```

```
## [1] 139.2477
```

This is consistent with the description of the efficiency of the method from Wilks.

Plotting this for many sample sizes shows us the general trend.

```
library('ars')
```

```

N_evals <- 0
f <- function (x) {
  N_evals <- N_evals + 1

```

```

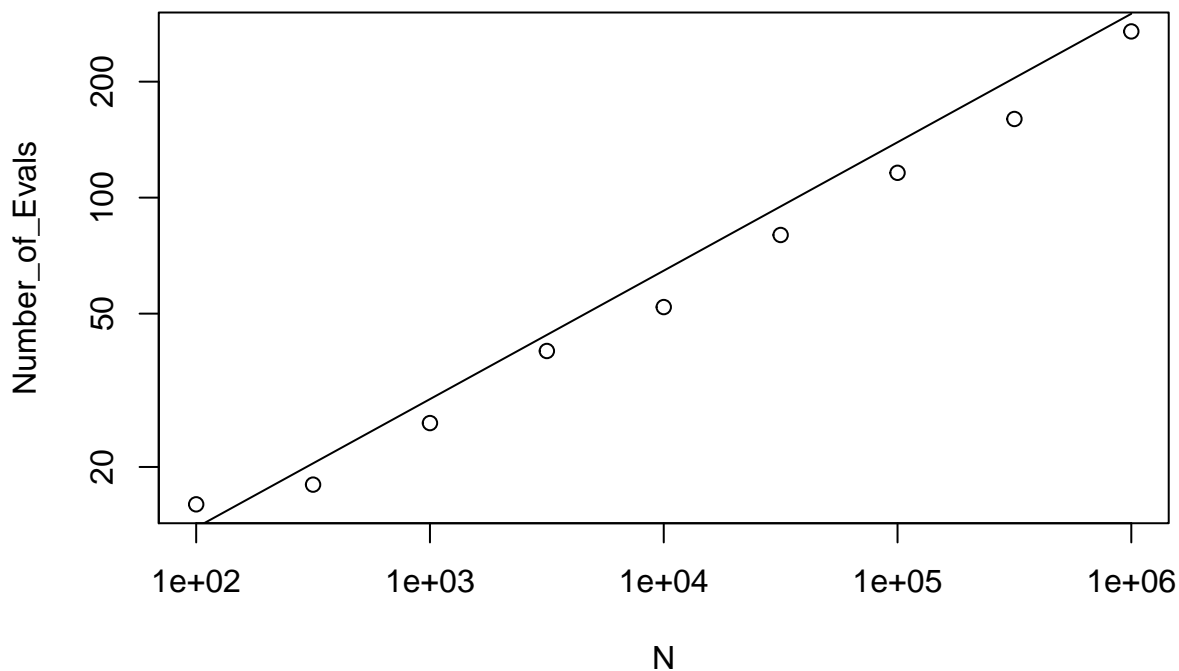
    return (dnorm(x))
}

Number_of_Evals <- c()
N <- 10**seq(2, 6, 0.5)

for (n in N) {
  x <- ars(f, n)
  Number_of_Evals <- append(Number_of_Evals, N_evals)
  N_evals <- 0
}

plot(N, Number_of_Evals, log = 'xy')
lines(N, 3*N**(1/3))

```



## Testing

As part of our function we have developed a `test_that` script that can be called with `test_package('ars')` or `devtools::test()`. We include 25 tests in total, which can be divided into two types: input tests and output tests.

### *Input Tests*

If the user provides invalid input, we want to make sure that our function returns an error (as opposed to returning invalid output values). Therefore, in our `test_that` script we run the following scenarios:

1. the user specifies more than two boundary points;
2. the starting points  $x_0$  fall outside of the boundary points;
3. the input density  $f(x)$  is not a function;
4. the input density  $f(x)$  is not log-concave (e.g. Student's t, F, Pareto, etc.)

### *Output Tests*

We also want to ensure that the function provides the right solution. In other words, we want to confirm that the output sample is close enough to the target density. To do this, we compute  $N = 1000$  data points for many well-known log-concave distributions (e.g. Normal, Exponential, Gamma, Beta, Chi-Square, etc.). We then use the Kolmogorov-Smirnov (KS) statistic to test the null hypothesis that the empirical CDF  $F_n(x)$  is equal to the target CDF  $F(x)$ . The KS statistic is defined as:

$$D_n = \sup_x |F_n(x) - F(x)|$$

Under  $H_0$ , as  $n \rightarrow \infty$ ,  $\sqrt{n}D_n \rightarrow K$ , where  $K$  is the Kolmogorov distribution. `test_that` returns an error if the KS p-value is below 5%.

Below is the underlying code for our `test_that` script:

```
test_that("check if the input density is function", {
  ## std. normal dist
  expect_equal(length(ars(dnorm, 100)), 100)

  ## exp. dist
  expect_equal(length(ars(dexp, 100, c(0.5), c(0, Inf))), 100)

  ## gamma dist
  expect_equal(length(ars(dgamma, 100, x0=c(10), bounds=c(0.0, Inf), shape=3.0, rate=2.0)), 100)

  ## case when the input density is not a function
  expect_error(ars(1, 100))
})

test_that("check if the bound is of length 2", {
  ## length 2 case
  expect_equal(length(ars(dnorm, 100, bounds = c(-100, 100))), 100)

  ## case when length not equal to 2
  expect_error(ars(dnorm, 100, bounds = c(-1, 0, 1)))
})

test_that("check if the upper bound and the lower bound are equal", {
  expect_warning(ars(dnorm, 100, bounds = c(100, 100)))
})

test_that("check if x_0 is between bounds", {
  ## when x_0 is at the left side of bounds
  expect_error(ars(dnorm, 100, x0 = c(-1), bounds = c(0, 1)))

  ## when x_0 is at the right side of bounds
  expect_error(ars(dnorm, 100, x0 = c(2), bounds = c(0, 1)))

  ## when x_0 is in between bounds
  expect_equal(length(ars(dnorm, 100, x0 = c(0.5), bounds = c(0, 1))), 100)
})

test_that("check if the sampling distribution is close enough to the original distribution", {
  # Note we perform Kolmogorov-Smirnov Test with the null
  # hypothesis that the samples are drawn from the same
  # continuous distribution

```

```

## std. normal
expect_equal(ks.test(ars(dnorm, 1000), rnorm(1000))$p.value > 0.05, T)

## exp(1)
expect_equal(ks.test(ars(dexp, 1000, x0 = 5, bounds = c(0, Inf)),
  rexp(1000))$p.value > 0.05, T)

## gamma(3,2)
expect_equal(ks.test(ars(dgamma, 1000, x0 = 5, bounds = c(0, Inf), shape = 3, scale = 2),
  rgamma(1000, shape = 3, scale = 2))$p.value > 0.05, T)

## unif(0,1)
expect_equal(ks.test(ars(dunif, 1000, x0 = 0.5, bounds = c(0,1)),
  runif(1000))$p.value > 0.05, T)

## logistics
expect_equal(ks.test(ars(dlogis, 1000, x0 = 0, bounds = c(-10,10)),
  rlogis(1000))$p.value > 0.05, T)

## beta(3,2)
expect_equal(ks.test(ars(dbeta, 1000, x0 = 0.5, bounds = c(0, 1), shape1 = 3, shape2 = 2),
  rbeta(1000, shape1 = 3, shape2 = 2))$p.value > 0.05, T)

## laplace
library(rmutil)
expect_equal(ks.test(ars(dlaplace, 1000, x0 = 0, bounds = c(-5,5)),
  rlaplace(1000))$p.value > 0.05, T)

## chi(2)
expect_equal(ks.test(ars(dchisq, 1000, x0 = 1, bounds = c(0, Inf), df = 2),
  rchisq(1000, df = 2))$p.value > 0.05, T)

## weibull(2,1)
expect_equal(ks.test(ars(dweibull, 1000, shape = 2, x0 = 1, bounds = c(0, Inf)),
  rweibull(1000, shape = 2))$p.value > 0.05, T)
})

test_that("check for non-log-concavity", {

  ## simple exponential exp(x^2)
  de = function(x) {
    return (exp(x^2))
  }
  expect_error(ars(de, 1000, x0 = 0, bounds = c(-5, 5)))

  ## student t(2)
  expect_error(ars(dt, 1000, x0 = 1, bounds = c(-5, 5), df = 2))

  ## cauchy
  expect_error(ars(dcauchy, 1000, x0 = 0, bounds = c(-5, 5)))

  ## pareto(1,2)
  expect_error(ars(dpareto, 1000, x0 = 3, bounds = c(1, Inf), m = 1, s = 2))

```

```
## lognormal
expect_error(ars(dlnorm, 1000, x0 = 1, bounds = c(0, Inf)))

## F dist (1,1)
expect_error(ars(stats::df, 1000, x0 = 1, bounds = c(0, Inf), df1 = 1, df2 = 2))
})
```

We can run this using `devtools::test()` and view a summary of all test cases that passed.

```
devtools::test()

## Loading ars
## Invalid DESCRIPTION:
## Malformed Depends or Suggests or Imports or Enhances field.
## Offending entries:
##   testthat
## rmutil
## Entries must be names of packages optionally followed by '<=' or
## '>=', white space, and a valid version number in parentheses.
##
## See section 'The DESCRIPTION file' in the 'Writing R Extensions'
## manual.

## Testing ars

## ✓ | OK F W S | Context
##
/ | 0      | Input Checks
- | 1      | Input Checks
\ | 2      | Input Checks
| | 3      | Input Checks
/ | 4      | Input Checks
- | 5      | Input Checks
\ | 6      | Input Checks
| | 7      | Input Checks
/ | 8      | Input Checks
- | 9      | Input Checks
\ | 10     | Input Checks
✓ | 10     | Input Checks [0.3 s]
##
/ | 0      | Output Checks
- | 1      | Output Checks
\ | 2      | Output Checks
| | 3      | Output Checks
/ | 4      | Output Checks
- | 5      | Output Checks
\ | 6      | Output Checks
| | 7      | Output Checks
/ | 8      | Output Checks
- | 9      | Output Checks
\ | 10     | Output Checks
| | 11     | Output Checks
/ | 12     | Output Checks
- | 13     | Output Checks
\ | 14     | Output Checks
```

```
| | 15      | Output Checks
√ | 15      | Output Checks
```

```
##
```

```
## == Results =====
```

```
## Duration: 0.4 s
```

```
##
```

```
## OK:      25
```

```
## Failed:  0
```

```
## Warnings: 0
```

```
## Skipped: 0
```

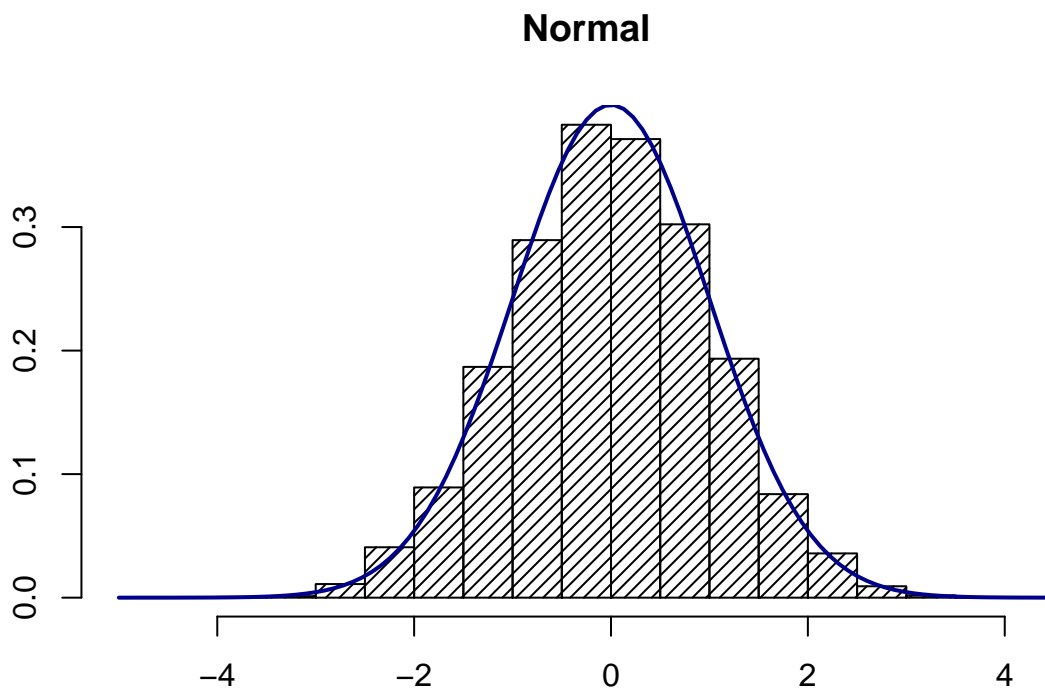
## Appendix: Contributions from each group member

Jonathan Morrell: Responsible for `ars` function (`ars.R`) and assembling R package. Contributed to methodology section of report (`ars.Rmd`).

Ziyang Zhou: Responsible for test cases (`test_ars.R`). Contributed to test cases portion of report and `ars` function (helper functions).

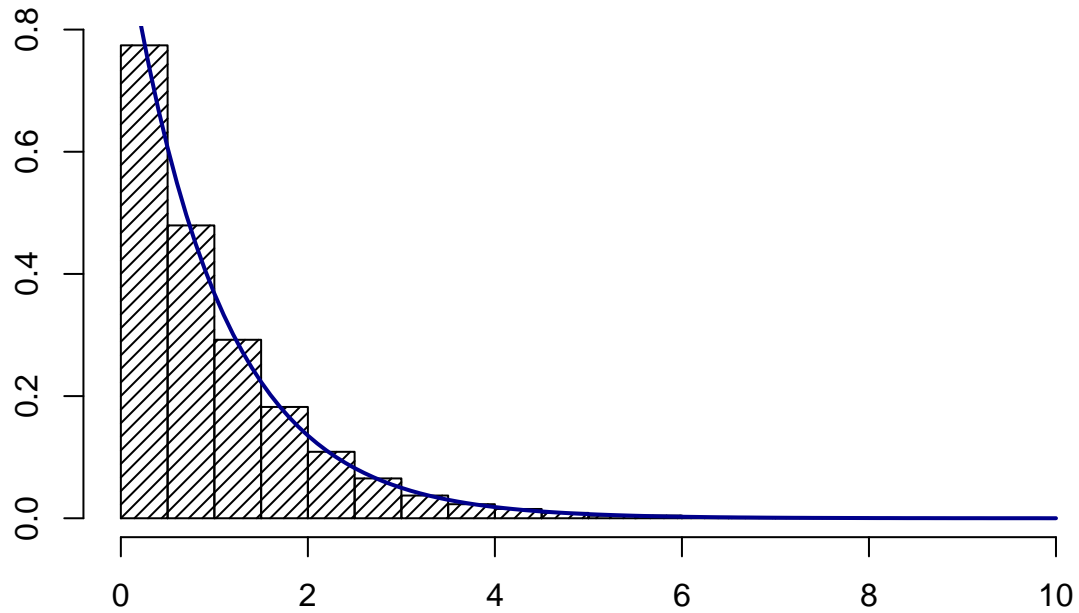
Vincent Zijlmans: Responsible for report. Contributed to test cases and wrote examples. Corrected bugs in `ars` function.

## Appendix: Examples



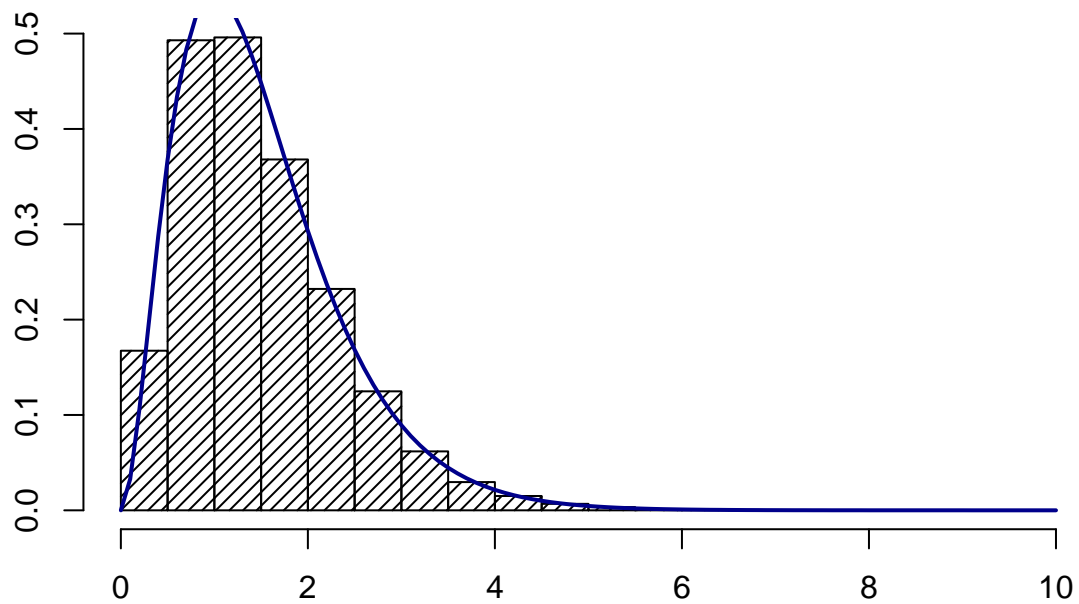


## Exponential

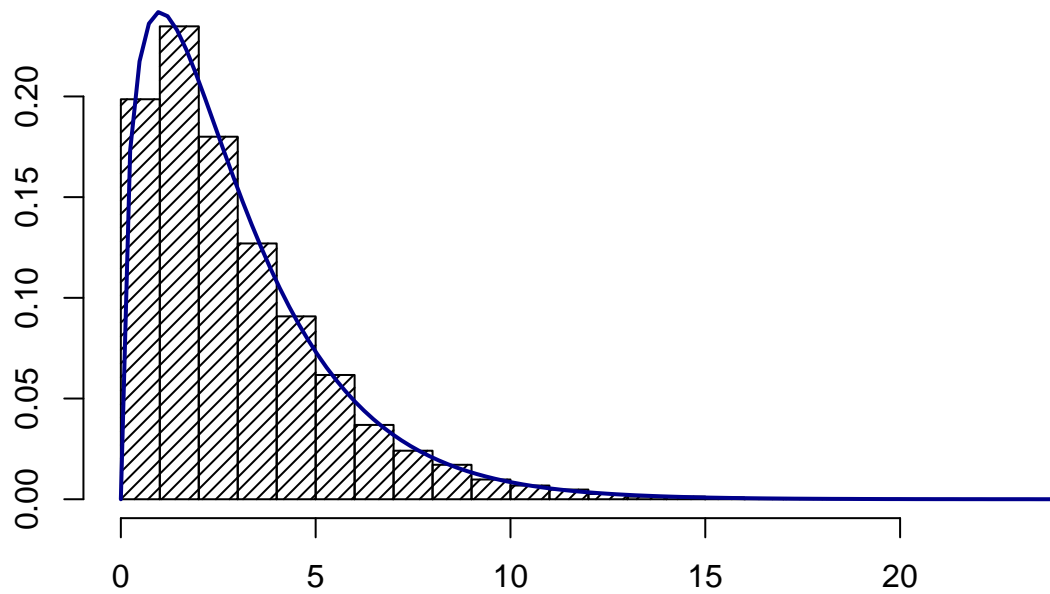


## Appendix: Examples (cont'd)

## Gamma

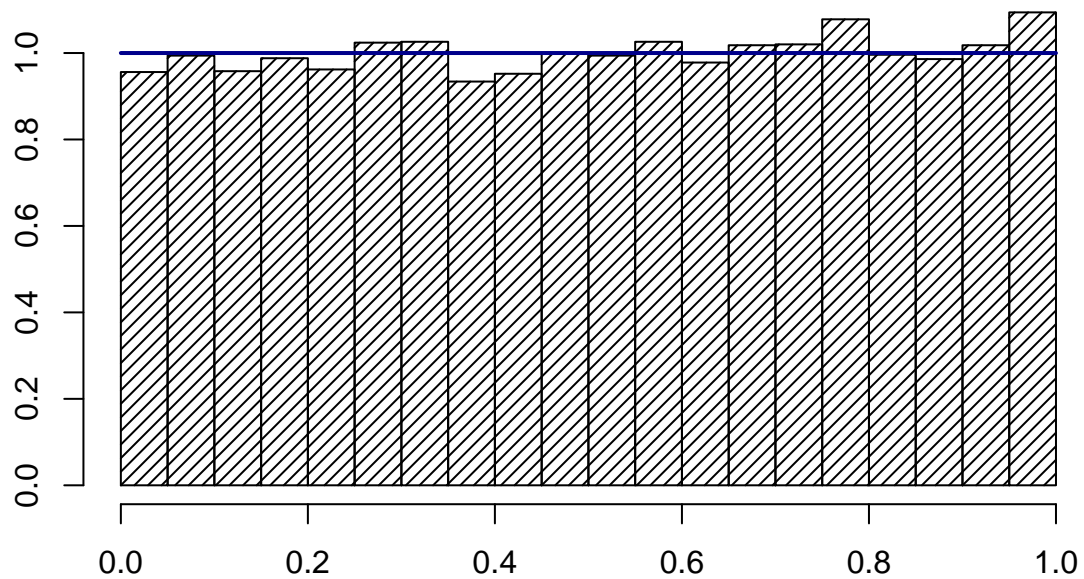


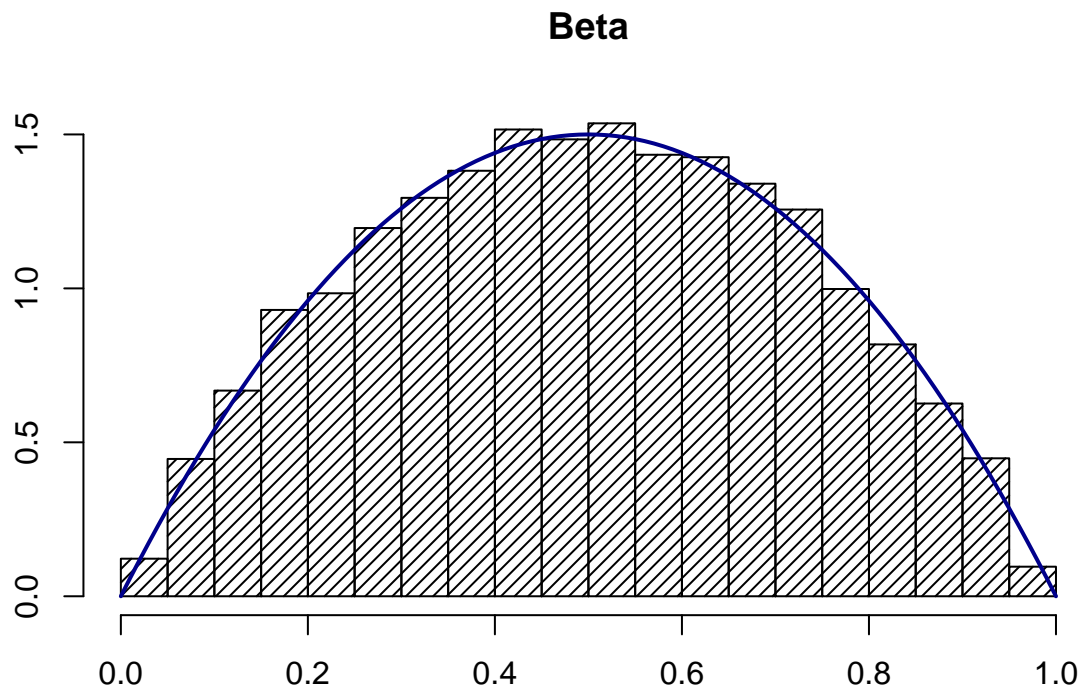
## Chi Square



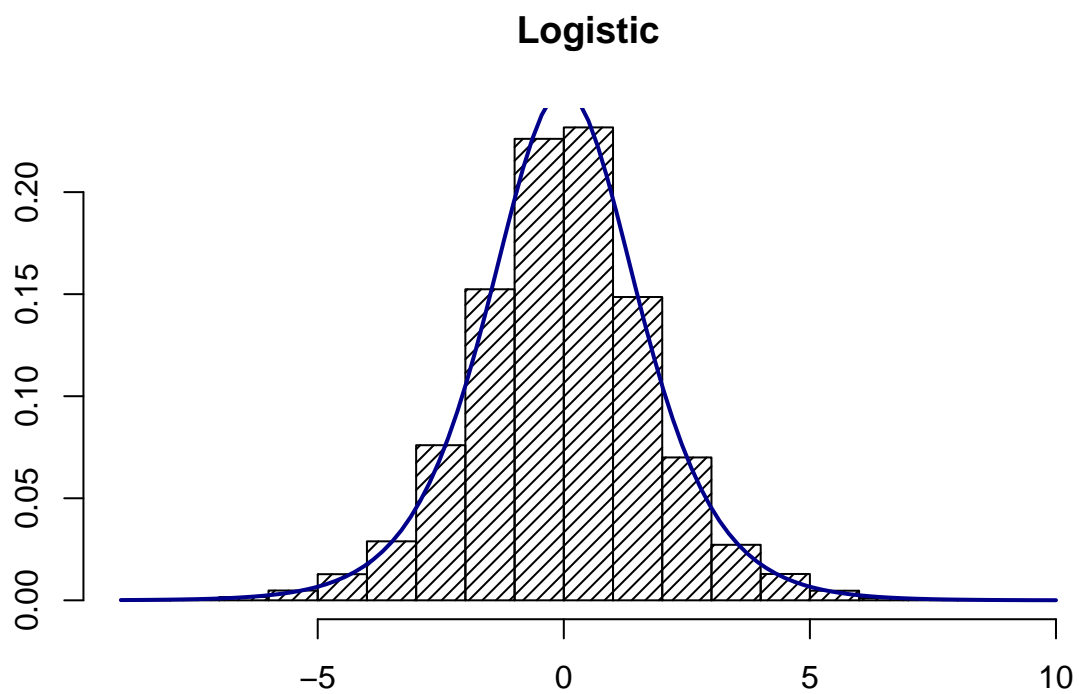
## Appendix: Examples (cont'd)

### Uniform





## Appendix: Examples (cont'd)



## Weibull

