

## ST3456 Modern statistical methods II

Lab 7 - 20/11/18

Bernardo Nipoti

### Lab 7: Metropolis-Hastings for continuous distributions

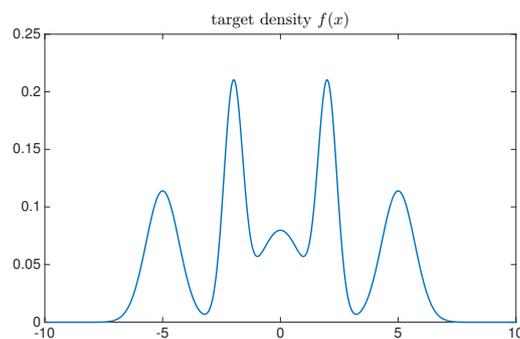
Download the files `ST3456_lab7.R` and `ST3456_lab7_solutions.R` from the course webpage

[http://www.bernardonipoti.com/teaching/st3456\\_1819](http://www.bernardonipoti.com/teaching/st3456_1819)

We want to use the Metropolis-Hastings algorithm to simulate from the target distribution  $f$ , displayed below and defined as

$$f(x) = \frac{1}{5}f_N(x; -5, 0.7) + \frac{1}{5}f_N(x; -2, 0.4) + \frac{1}{5}f_N(x; 0, 1) + \frac{1}{5}f_N(x; 2, 0.4) + \frac{1}{5}f_N(x; 5, 0.7),$$

where  $f_N(x; \mu, \sigma)$  denotes the density of a normal random variable with mean  $\mu$  and standard deviation  $\sigma$ .



The function `target()` allows  $f$  to be evaluated.

#### Part 1. Independent Metropolis-Hastings

- 1a. Write a function `iMH()` to implement the independent M-H algorithm with normal proposal  $g(x)$  with mean 0 and variance  $S^2$ . Recall that the probability of accepting a generated value is given by

$$\alpha(x, y) = \min \left\{ \frac{f(y)g(x)}{f(x)g(y)}, 1 \right\}$$

Specifically `iMH()` should have, as input,  $N$  (number of iterations),  $x_0$  (initial state) and  $S$  (st. dev. of the proposal), and return the generated sample and the acceptance rate.

- 1b. Set  $N = 10\,000$ ,  $x_0 = 0$  and  $S = 3$ . Generate a sample by using `iMH()` and use it to estimate mean (=0) variance (=12.06) of  $f$  and to build a histogram approximating the true distribution  $f$ .
- 1c. Study the effect of parameter  $S$  on the histogram you obtain (and related estimates for mean and variance). Specifically, consider  $S = 1$  (too small?) and  $S = 20$  (too large?).

## Part 2. Random walk Metropolis-Hastings

- 2a. Write a function `rwMH()` to implement a random walk M-H algorithm with normal distribution for the jumps of the random walk. That is, given that the chain is at state  $x$ , a new value  $y$  is obtained by simulating  $Y = x + \varepsilon$ , where  $\varepsilon \sim N(0, S^2)$ . Recall that the probability of accepting a generated value is given by

$$\alpha(x, y) = \min \left\{ \frac{f(y)}{f(x)}, 1 \right\}$$

Specifically `rwMH()` should have, as input,  $N$  (number of iterations),  $x_0$  (initial state) and  $S$  (st. dev. of  $\varepsilon$ ), and return the generated sample and the acceptance rate.

- 2b. Set  $N = 10\,000$ ,  $x_0 = 0$  and  $S = 3$ . Generate a sample by using `rwMH()` and use it to estimate mean (=0) and variance (=12.06) of the true distribution and to build a histogram approximating the true distribution  $f$ .
- 2c. Visualise the traceplot of generated values to qualitatively assess the mixing of the chain.
- 2d. Repeat parts 2b and 2c with  $S = 0.1$  (too small?).
- 2e. Tuning of the parameter  $S$ . Study how the acceptance rate changes with  $S$  and identify a value  $S^*$  which gives an acceptance rate approximately equal to 50%.

## Part 3. Comparison via simulation study

- 3a. Compare the performance of independent M-H (with  $S = 3$ ) and random walk M-H (with  $S = S^*$ , as found in part 2e). For each generated sample, the comparison is made by estimating the variance (=12.06) of  $f$ . Repeat 20 times and, for each method, compute the mean absolute deviation, given by

$$\text{m.a.d.}(\hat{V}) = \frac{1}{20} \sum_{i=1}^{20} |\hat{V}_i - 12.06|,$$

where  $\hat{V}_i$  is the estimate obtained at the  $i$ th replicate. You should see that the two algorithms have pretty similar performances.