

# Brownian Motion

## Brownian Motion Context

We say that a stochastic process  $(W_t)_{t \geq 0}$  is a standard Brownian Motion if:

- $W_0 = 0$
- $t \rightarrow W_t$  are continuous
- The increments are independent:  $\forall 0 \leq s \leq t$ ,  $W_t - W_s$  is independent of  $W_s$ 
  - same with  $t_1 \leq t_2 \leq \dots \leq t_k$ ,  $(W_{t_i+x} - W_{t_i})_{x \in [1, k]}$  are independent
- The law of  $W_t - W_s$  is  $\mathcal{N}(0, t - s)$ .

## Simulating Brownian Motions

### GOAL

We are interested in implementing a Brownian Motion process model using two different algorithms.

### METHOD

#### Simulation method 1:

We simulate a Brownian Motion trajectory by:

1. Introducing a time length  $n$  and a time step  $t_i$ ,  $\forall i \in [0, n]$  such that  $t_i = \eta \cdot i$  with  $\eta$  a fixed, discretization timestep
2. We set  $W_0 = 0$
3. We set  $W_{t_1} = \sqrt{t_1} \cdot \mathcal{N}(0, 1)$
4. Then,  $\forall i \in [2, \frac{T_{max}}{\eta}]$ ,  $W_{t_i} = W_{t_{i-1}} + \sqrt{t_i - t_{i-1}} \cdot \mathcal{N}(0, 1)$

#### Simulation method 2:

We can also rely on Donsker's Theorem ([https://en.wikipedia.org/wiki/Donsker%27s\\_theorem](https://en.wikipedia.org/wiki/Donsker%27s_theorem)):

1. Let  $X_1, X_2, \dots$  be a sequence of IID random variable with mean 0 and variance 1 (in our case,  $\forall i \in \{1, 2, \dots\}$ ,  $X_i \in \{-1, 1\}$  and  $P(X_i = 1) = P(X_i = -1) = \frac{1}{2}$ ).
2. Let  $n \in \mathbb{N}$ ,  $S_n = \sum_{i=1}^n X_i$  be the stochastic process known as a random walk
3. Let the diffusively rescaled random walk (partial sum process)  $W^{(n)}(t)$  such that:

$$W^{(n)}(t) = \frac{1}{\sqrt{n}} \cdot S_{[nt]}, t \in [0, 1]$$

#### Function implementations:

```

standard_simulation <- function(n, eta, graph=F) {
  ### Simulate a brownian motion using an iterative process
  timesteps = seq(0, n, eta)
  # Initializes the brownian motion
  w0 = 0
  w1 = sqrt(eta) * rnorm(1)
  brownian_motion = c(w0, w1)
  # Populates the brownian motion
  for (i in timesteps[3:length(timesteps)]) { # !! R is 1-valued
    new_step = brownian_motion[length(brownian_motion)] + sqrt(eta) * rnorm(1)
    brownian_motion = c(brownian_motion, new_step)
  }
  if (graph) {
    plot(timesteps, brownian_motion, type="l",
         main="Simulated brownian motion",
         xlab="n", ylab="W_t")
  }
  brownian_motion
}

donsker_simulation <- function(n, eta, graph=F) {
  ### Simulate a brownian motion based on donsker's theorem
  timesteps = seq(0, 1, eta)
  # Computes the steps of a donsker-based brownian motion
  X = sample(c(-1, 1), n, T, prob = c(1/2, 1/2))
  S = cumsum(X)
  W = unlist(apply(matrix(timesteps), 1, function(x) {1/sqrt(n)*S[round(n*x)]}))
  if (graph) {
    par(mar=c(2.5,2.5,2.5,2.5)) # deals with margin error
    plot(timesteps, c(0, W), type="l",
         main="Simulated brownian motion via Donsker's Theorem",
         xlab="n", ylab="W_t")
  }
  c(0, W)
}

simulate <- function (simulation_function, n_simulations, time_length, timestep, dons
ker_n=NULL) {
  ### Simulate a set of brownian motions and display the results given a
  ### simulation method.
  time_range = seq(0, time_length, timestep)
  simulations = c()
  # Computes the simulations
  for (sim in 1:n_simulations) {
    if (simulation_function == "standard") {
      s = standard_simulation(time_length, timestep)
      title = "simulated Brownian Motions"
    } else {
      if (is.null(donsker_n)) {
        donsker_n = time_length/timestep
      }
    }
  }
}

```

```

    s = donsker_simulation(donsker_n, timestep)
    title = "Brownian Motions (simulated via Donsker's Theorem)"
  }
  simulations = c(simulations, s)
}
simulations = t(matrix(simulations, ncol=n_simulations))
# Plots
ylim = c(min(simulations), max(simulations))
plot(time_range, simulations[1,], col=2, type="l", ylim=ylim,
      xlab="n", ylab="W_t",
      main=paste("Set of", n_simulations, title,
                 "\nwith parameters n =", time_length, ", eta =", timestep))
for (sim in 2:n_simulations) {
  lines(time_range, simulations[sim,], col=sim+1)
}
simulations
}

```

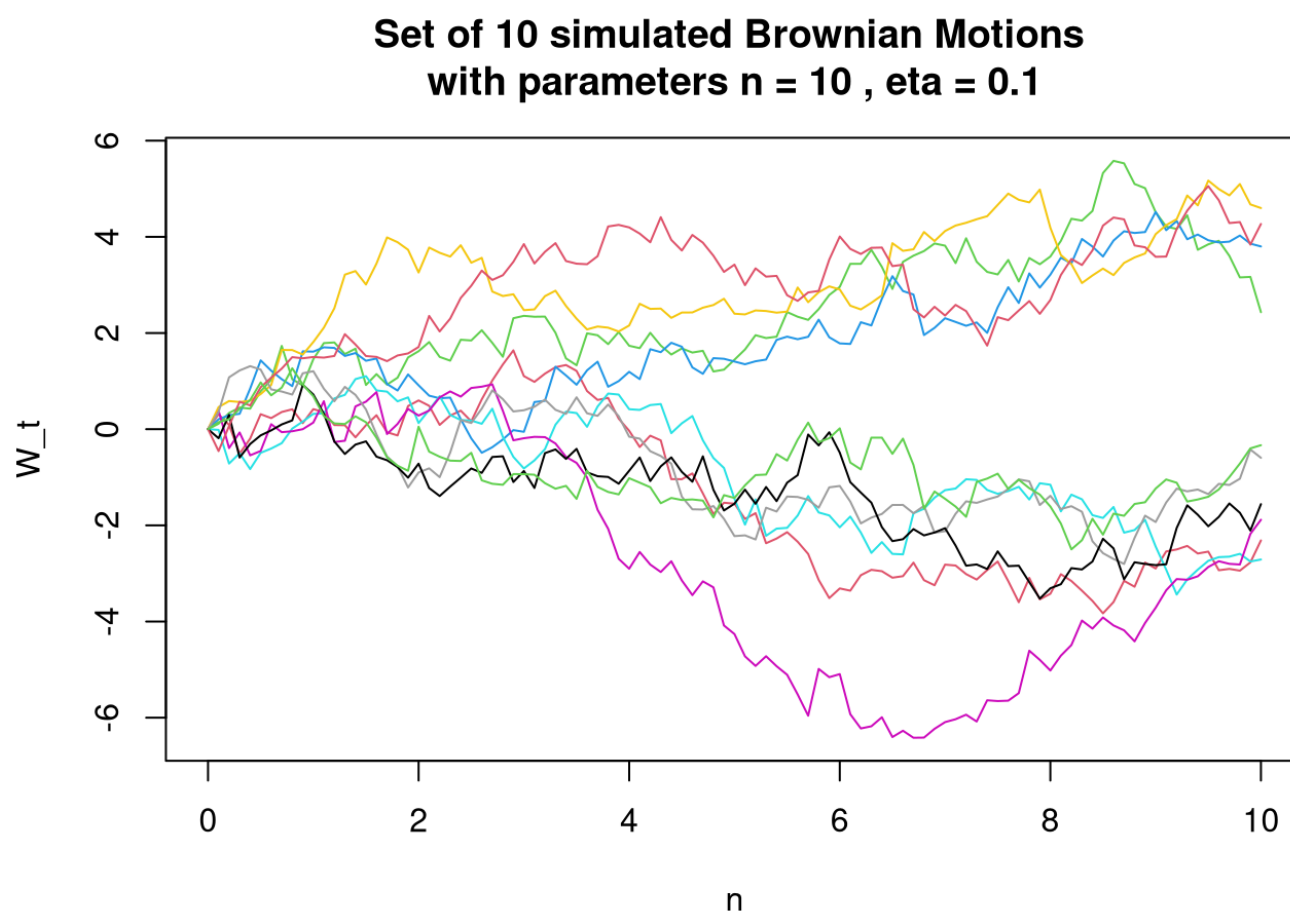
## RESULTS - Simulation with Algorithm 1

We generate 10 brownian motions with parameters  $n = 10$  and  $\eta = 0.1$ .

```

algot_simulations = simulate("standard", 10, 10, 0.1)

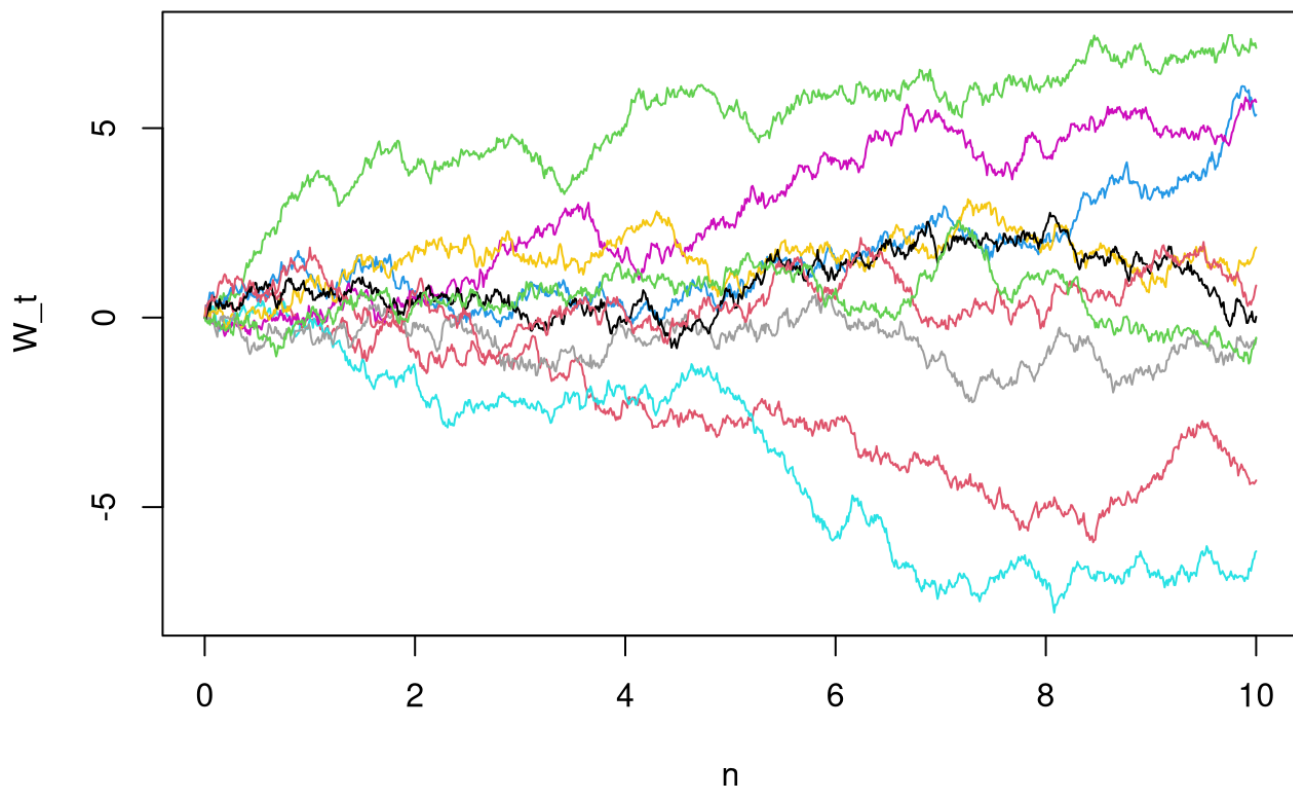
```



We generate 10 brownian motions with parameters  $n = 10$  and  $\eta = 0.01$ .

```
algo1_simulations = simulate("standard", 10, 10, 0.01)
```

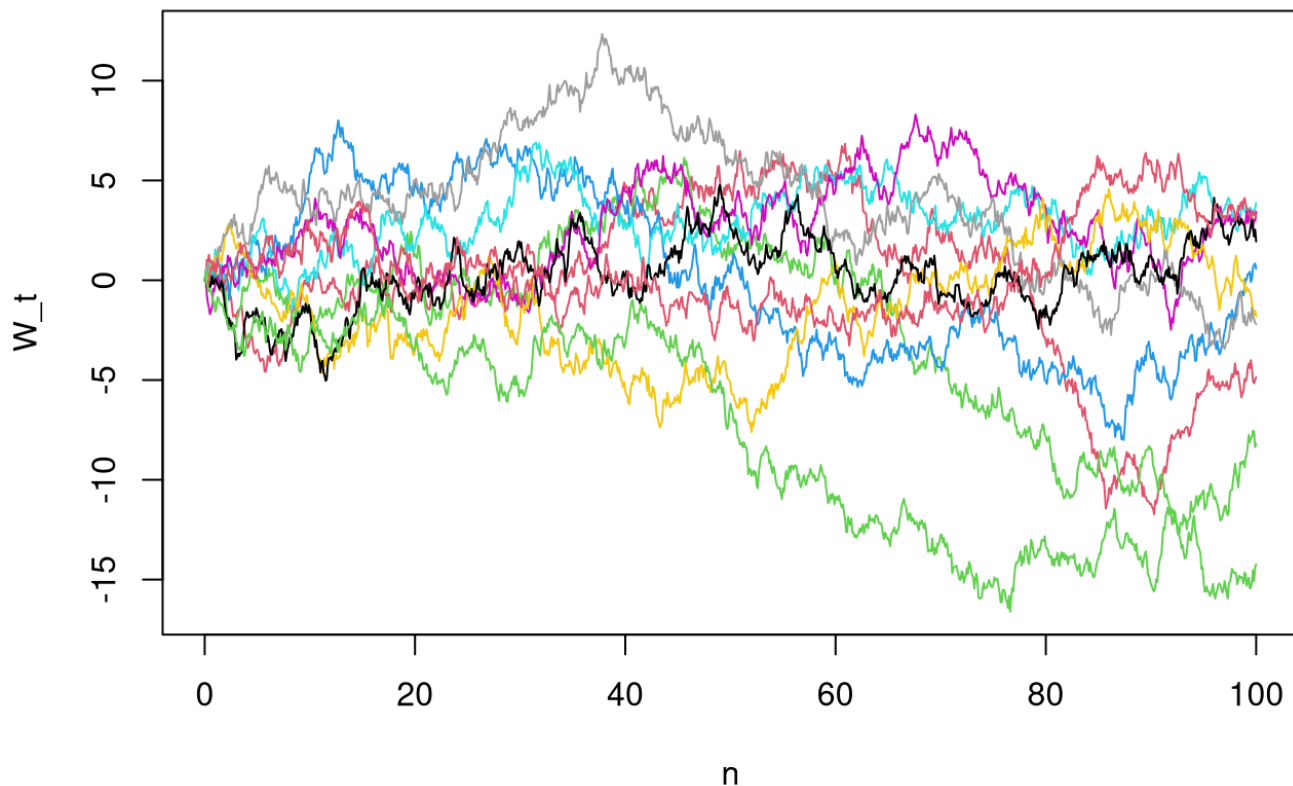
**Set of 10 simulated Brownian Motions  
with parameters  $n = 10$  ,  $\eta = 0.01$**



We generate 10 brownian motions with parameters  $n = 100$  and  $\eta = 0.1$ .

```
algo1_simulations = simulate("standard", 10, 100, 0.1)
```

### Set of 10 simulated Brownian Motions with parameters $n = 100$ , $\eta = 0.1$

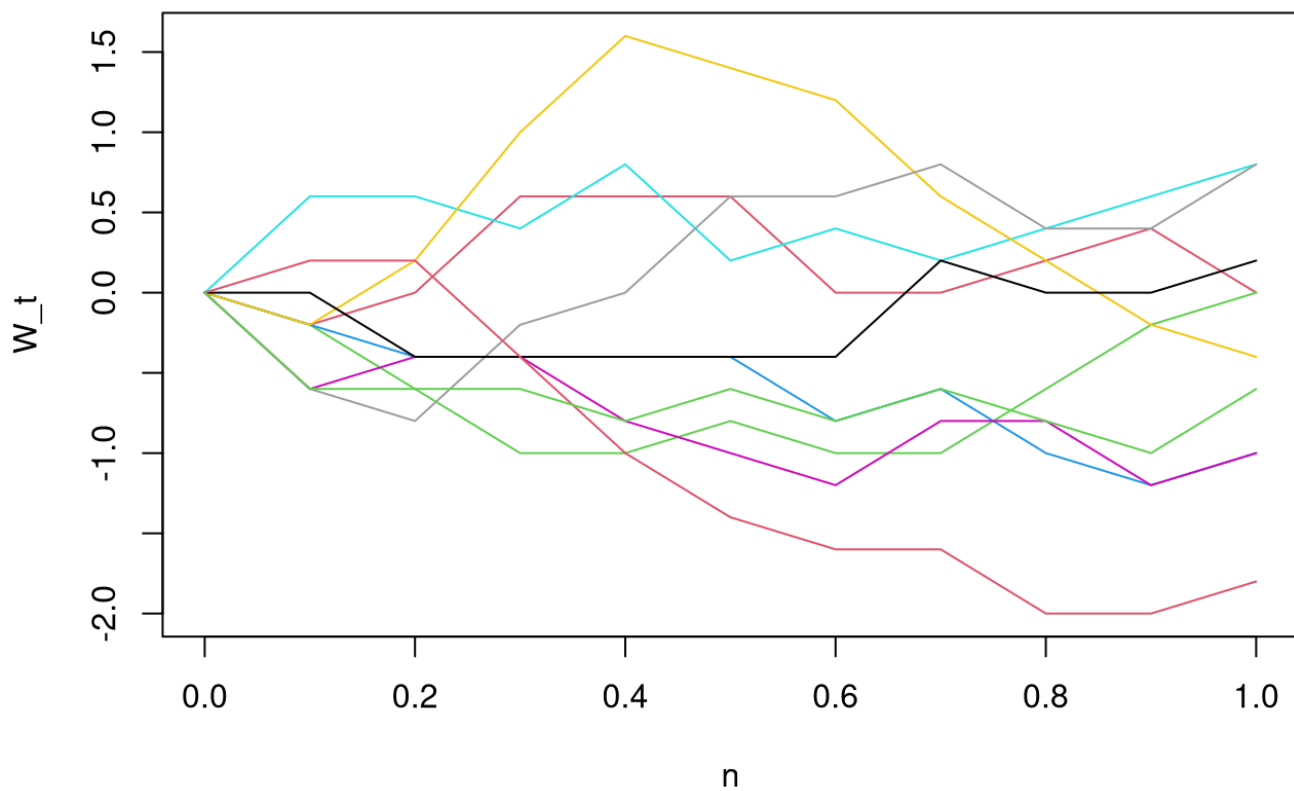


## RESULTS - Simulation with Algorithm 2

We generate 10 brownian motions with parameters  $donsker_n = 100$  and  $\eta = 0.1$ , using the Donsker's theorem.

```
# Note: by the Donsker's theorem, the time length is set to 1  
algo2_simulations = simulate("donsker", 10, time_length=1, 0.1, donsker_n=100)
```

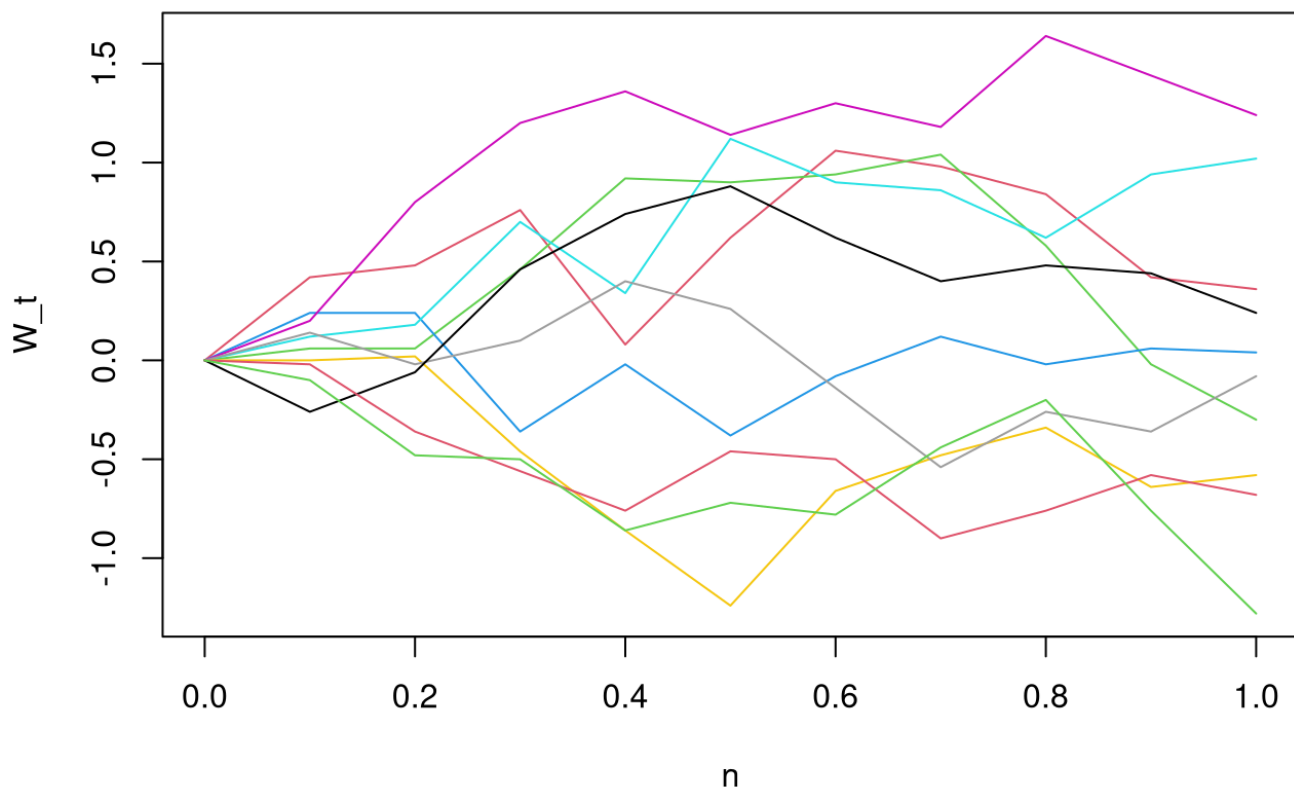
## Set of 10 Brownian Motions (simulated via Donsker's Theorem) with parameters $n = 1$ , $\eta = 0.1$



We generate 10 brownian motions with parameters  $donsker_n = 10000$  and  $\eta = 0.1$ , using the Donsker's theorem.

```
# Note: by the Donsker's theorem, the time length is set to 1
algo2_simulations = simulate("donsker", 10, time_length=1, 0.1, donsker_n=10000)
```

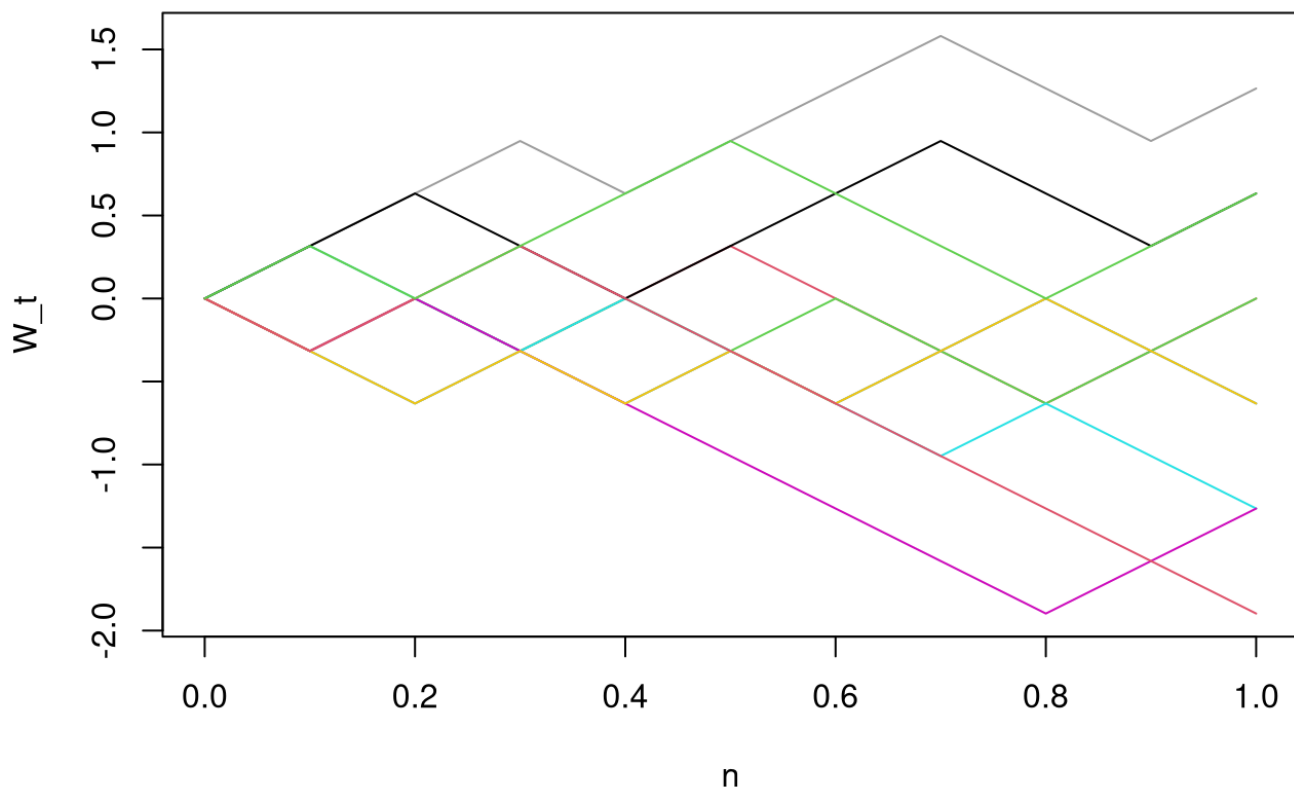
## Set of 10 Brownian Motions (simulated via Donsker's Theorem) with parameters $n = 1$ , $\eta = 0.1$



We generate 10 brownian motions with parameters  $donsker_n = 10$  and  $\eta = 0.1$ , using the Donsker's theorem.

```
# Note: by the Donsker's theorem, the time length is set to 1
algo2_simulations = simulate("donsker", 10, time_length=1, 0.1, donsker_n=10)
```

## Set of 10 Brownian Motions (simulated via Donsker's Theorem) with parameters $n = 1$ , $\eta = 0.1$

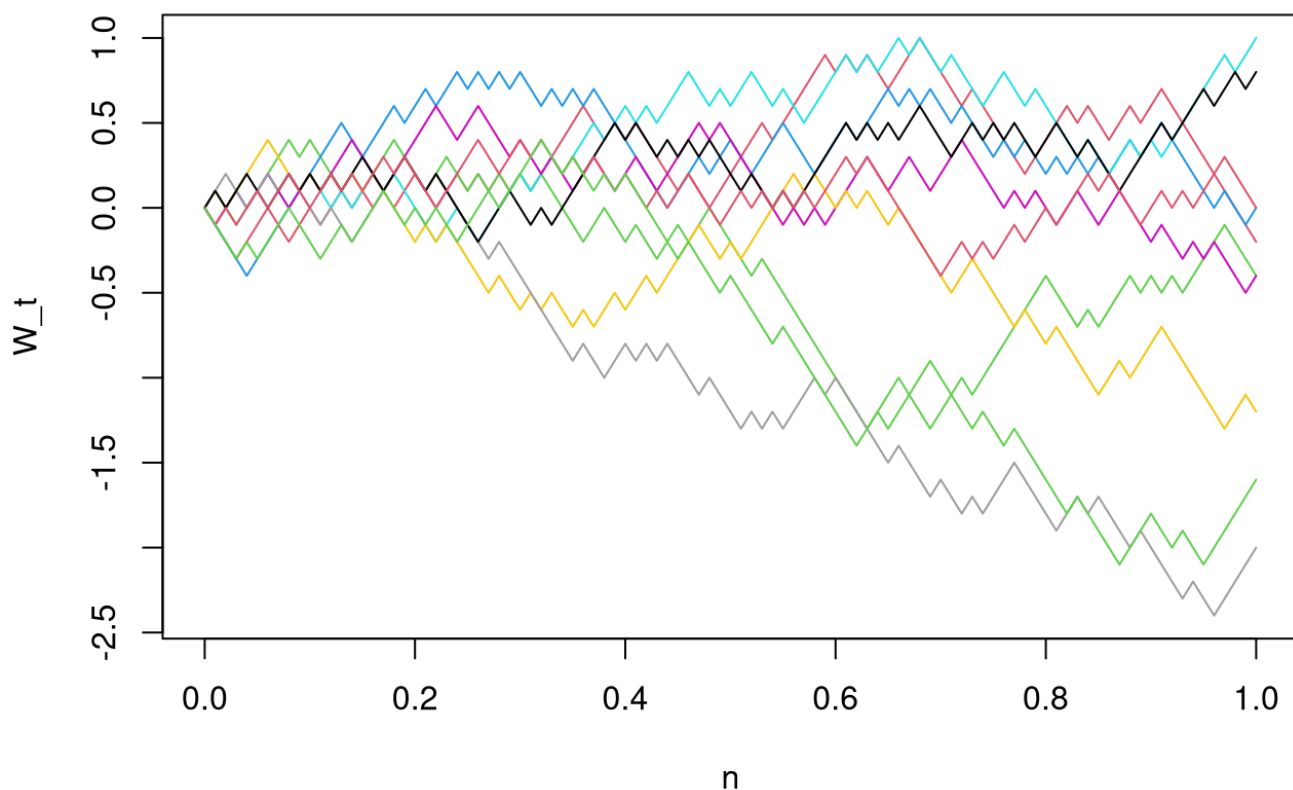


We generate 10 brownian motions with parameters  $donsker_n = 100$  and  $\eta = 0.01$ , using the Donsker's theorem.

```
# Note: by the Donsker's theorem, the time length is set to 1
algo2_simulations = simulate("donsker", 10, time_length=1, 0.01, donsker_n=100)
```



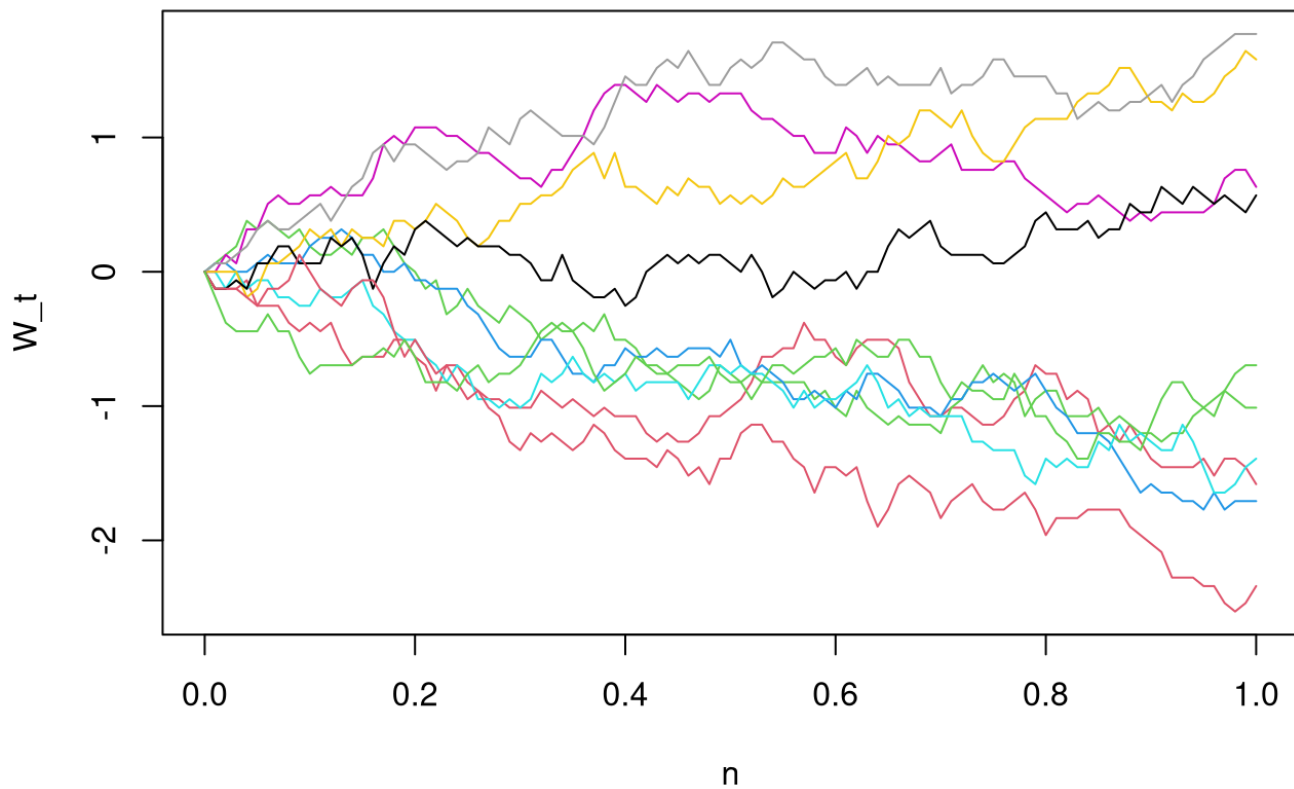
### Set of 10 Brownian Motions (simulated via Donsker's Theorem) with parameters $n = 1$ , $\eta = 0.01$



We generate 10 brownian motions with parameters  $donsker_n = 1000$  and  $\eta = 0.01$ , using the Donsker's theorem.

```
# Note: by the Donsker's theorem, the time length is set to 1  
algo2_simulations = simulate("donsker", 10, time_length=1, 0.01, donsker_n=1000)
```

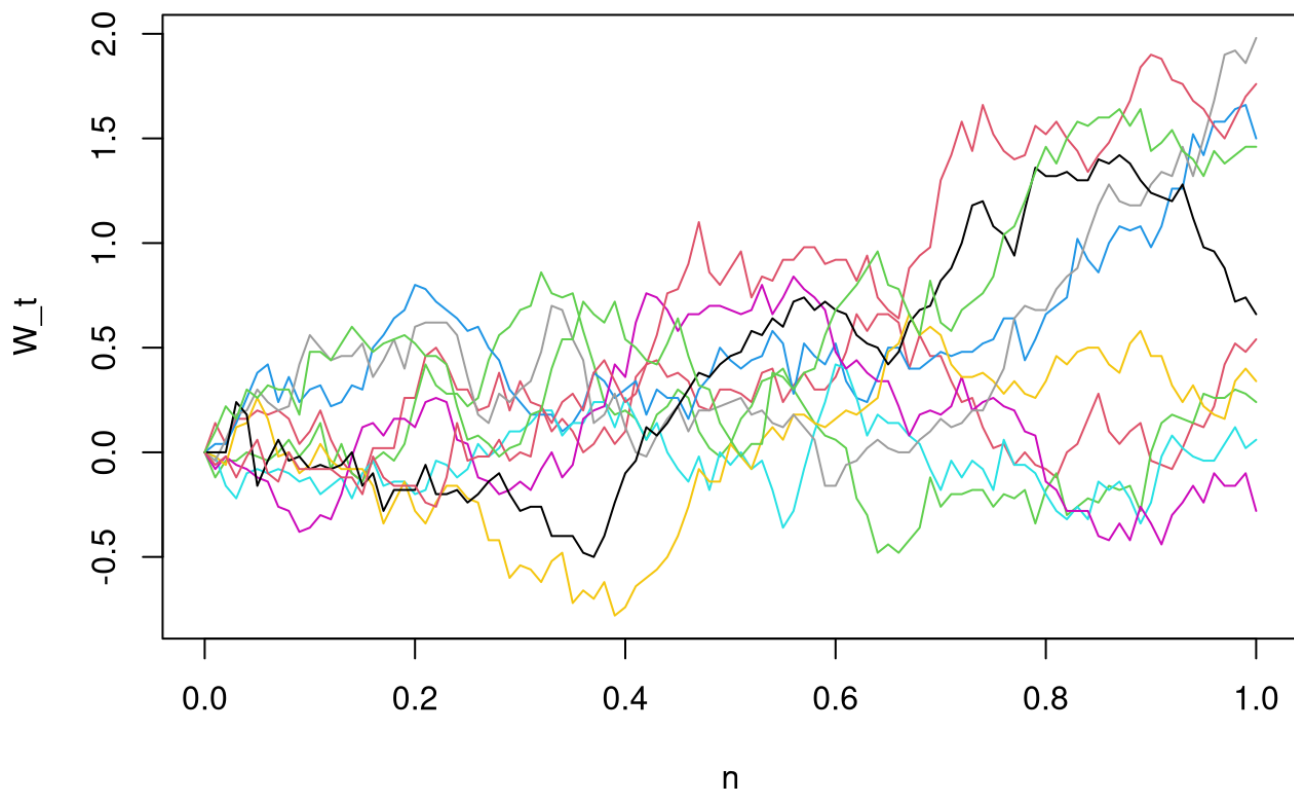
### Set of 10 Brownian Motions (simulated via Donsker's Theorem) with parameters $n = 1$ , $\eta = 0.01$



We generate 10 brownian motions with parameters  $donsker_n = 10000$  and  $\eta = 0.01$ , using the Donsker's theorem.

```
# Note: by the Donsker's theorem, the time length is set to 1  
algo2_simulations = simulate("donsker", 10, time_length=1, 0.01, donsker_n=10000)
```

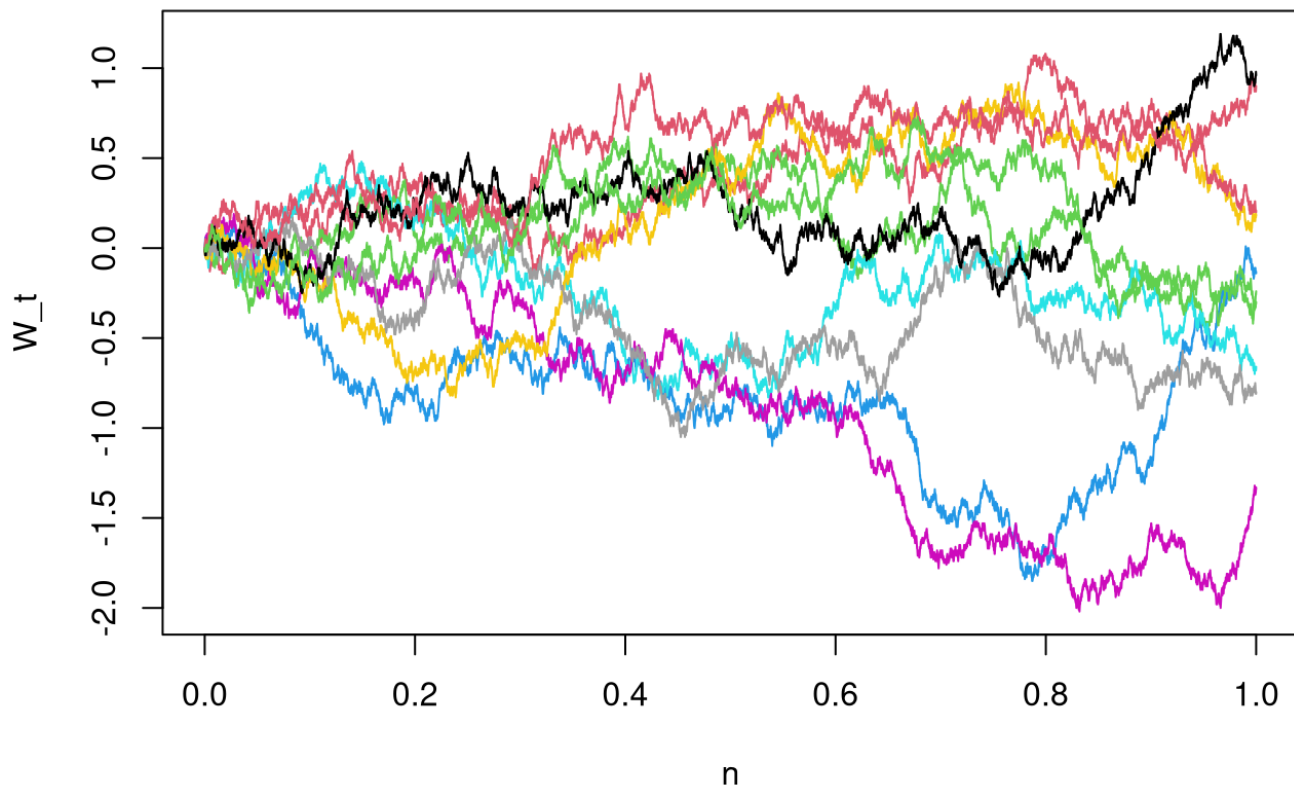
### Set of 10 Brownian Motions (simulated via Donsker's Theorem) with parameters $n = 1$ , $\eta = 0.01$



We generate 10 brownian motions with parameters  $donsker_n = 10000$  and  $\eta = 0.0001$ , using the Donsker's theorem.

```
# Note: by the Donsker's theorem, the time length is set to 1  
algo2_simulations = simulate("donsker", 10, time_length=1, 0.0001, donsker_n=10000)
```

### Set of 10 Brownian Motions (simulated via Donsker's Theorem) with parameters $n = 1$ , $\eta = 1e-04$



## COMMENTS

We have shown two ways to yield a Brownian Motion. It is interesting to note that the algorithm relying on the Donsker's Theorem only produces a Brownian Motion on the interval  $[0, 1]$  with a resulting range for  $W_t$  restricted around a mean of 0.

In order to obtain a Brownian Motion on a larger scale (e.g.  $n \in [0, 10]$ ), it is interesting to consider how to rescale the resulting simulations (whether we only scale the  $x$ -axis, or whether we should rescale both  $x$  and  $y$ -axes).