

# Ito Calculus

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## 1 Introduction

Ito integration and calculus are fundamental concepts in stochastic calculus, a branch of mathematics that extends traditional calculus to deal with stochastic processes.

Stochastic calculus is particularly important in the field of mathematical finance, where it provides a rigorous framework for modeling and analyzing financial instruments in uncertain and dynamic environments.

## 2 Stochastic Differential Equation (SDE):

Ito calculus begins with the formulation of stochastic differential equations (SDEs). An SDE is an equation that involves both deterministic differentials and stochastic differentials.

A standard form of an SDE is given by:

$$dX_t = \mu(t, X_t)dt + \sigma(t, X_t)dW_t$$

where:

- $X_t$  is the stochastic process,
- $\mu(t, X_t)$  is the drift term,
- $\sigma(t, X_t)$  is the diffusion term,
- $dt$  represents the deterministic part,
- $dW_t$  is the stochastic differential associated with a Wiener process.

### 3 Ito Integral

The Ito integral is a stochastic generalization of the Riemann-Stieltjes integral. The integral is used to solve stochastic differential equations and represents the accumulation of a stochastic process with respect to time.

The Ito integral of a process  $Y_t$  with respect to a Wiener process  $W_t$  is denoted as:

$$\int_0^t Y_s dW_s$$

### 4 Ito's Lemma

Ito's Lemma is a fundamental result in stochastic calculus that provides a formula for differentiating a function of a stochastic process.

It is a stochastic version of the chain rule and is crucial for solving SDEs and understanding the dynamics of stochastic processes.

### 5 Didactical Simulation

Here follows a simulation of a simple example of an Ito integral using Python. We'll simulate a geometric Brownian motion and calculate the Ito integral of the process.

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 # Parameters
5 mu = 0.1
6 sigma = 0.2
7 initial_value = 50.0
8 num_steps = 1000
9 total_time = 1.0
10 dt = total_time / num_steps
11
12 # Simulate Geometric Brownian Motion
13 t_values = np.linspace(0, total_time, num_steps + 1)
14 W_t = np.random.randn(num_steps) * np.sqrt(dt)
15 X_t = np.zeros(num_steps + 1)
16 X_t[0] = initial_value
17
18 for i in range(1, num_steps + 1):
19     dX = mu * X_t[i - 1] * dt + sigma * X_t[i - 1] * W_t[i - 1]
20     X_t[i] = X_t[i - 1] + dX
```

```

21
22 # Calculate Ito Integral
23 Ito_integral = np.cumsum(X_t[:-1] * W_t) * np.sqrt(dt)
24
25 # Plot the results
26 plt.figure(figsize=(12, 6))
27
28 plt.subplot(1, 2, 1)
29 plt.plot(t_values, X_t, label='Geometric Brownian Motion')
30 plt.title('Geometric Brownian Motion')
31 plt.xlabel('Time')
32 plt.ylabel('Value')
33 plt.legend()
34
35 plt.subplot(1, 2, 2)
36 plt.plot(t_values[:-1], Ito_integral, label='Ito Integral')
37 plt.title('Ito Integral of Geometric Brownian Motion')
38 plt.xlabel('Time')
39 plt.ylabel('Value')
40 plt.legend()
41
42 plt.tight_layout()
43 plt.show()
44

```

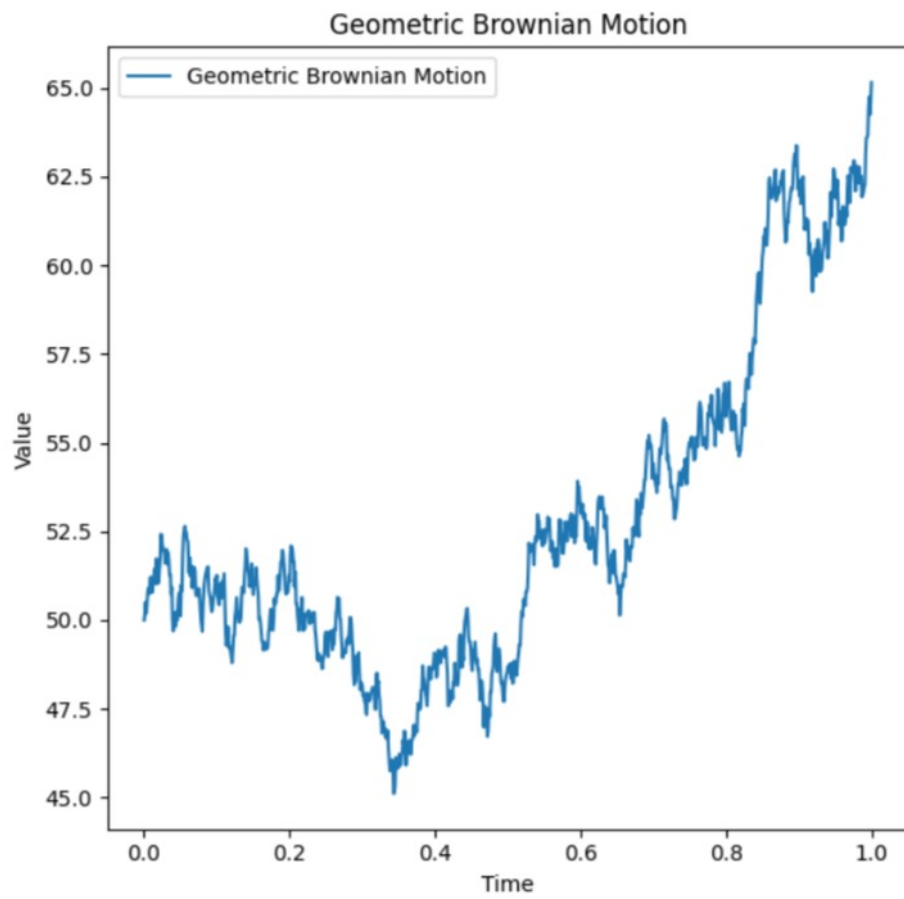


Figure 1: Geometric Brownian Motion

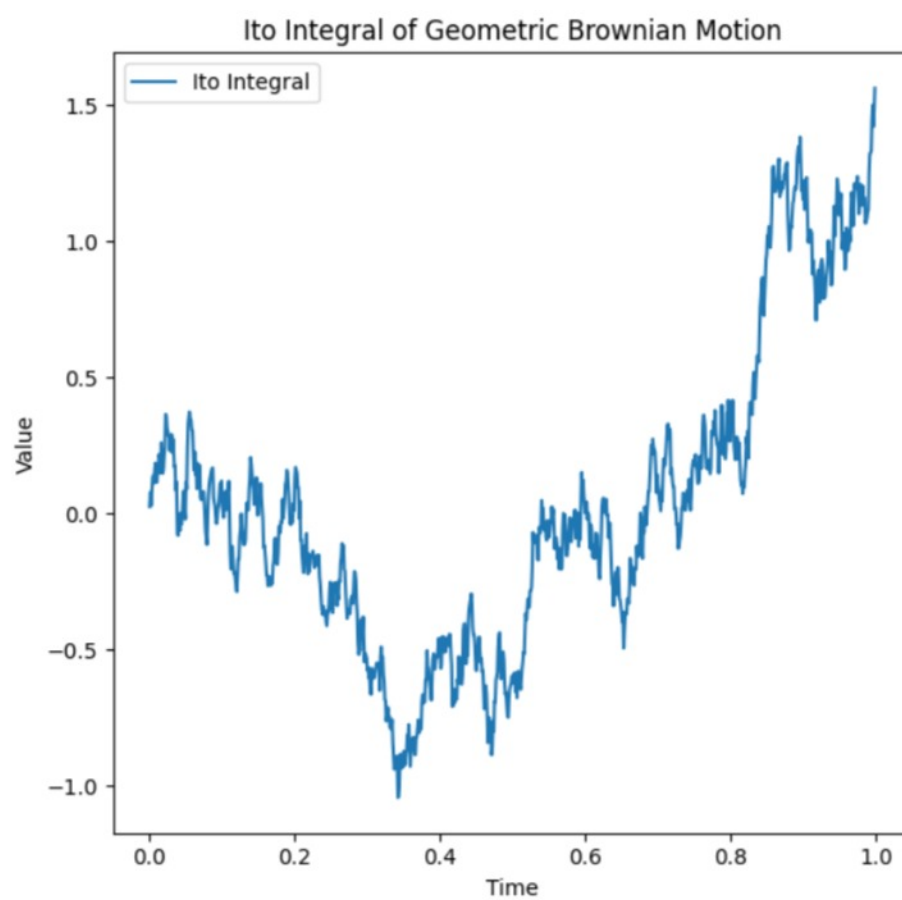


Figure 2: Ito Integral of GBM