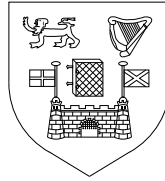


Trinity Centre for High Performance Computing



MSc in HPC course 5635b

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## An Introduction to Mathematical Finance (5635b)

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## Course Outline

- 1 Integration
- 2 Itô Integral
- 3 Itô Formula
- 4 Stochastic Differential Equations
- 5 Recap
- 6 Ito Processes and SDE's

## Itô Integral

## Integration

For an ordinary function  $f(x)$ , we can define an integral as the limit of a sum:

$$\int_0^T f(t)dt = \lim_{||\Pi|| \rightarrow 0} \sum_{j=0}^{n-1} f(t_j^*)(t_{j+1} - t_j),$$

where  $t_j^*$  is in  $[t_j, t_{j+1}]$ .



Remember:

$$||\Pi|| = \max_{k=0, \dots, n-1} (t_{k+1} - t_k)$$

[http://en.wikipedia.org/wiki/Riemann\\_integral](http://en.wikipedia.org/wiki/Riemann_integral)

## Stochastic Integral

We want to define an integral where the integrator is a Wiener process,

$$I(t) = \int_0^t \Delta(s) dW(s)$$

where  $\Delta(s)$  is square-integrable.  $\Delta(t)$  is determined based on information collected up to time  $t$  and may be stochastic.

In ordinary calculus, with differentiable function  $f(t)$  instead of  $W(t)$ , we could define

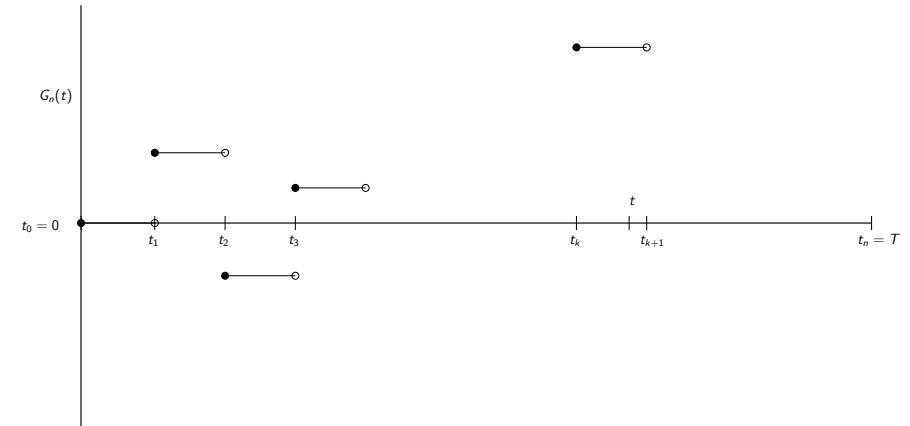
$$\int_0^t \Delta(s) df(s) = \int_0^t \Delta(s) f'(s) ds.$$

This does not work here, because  $W$  is not differentiable.

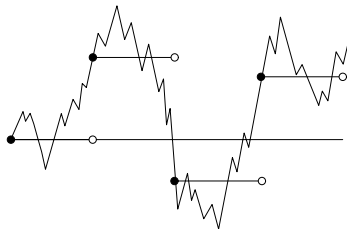
Instead we discretize, choose a partition first, define what we mean, and then shrink the mesh.

## Step Function $\Delta(t)$

For a partition  $\Pi = \{t_0, t_1, \dots, t_n\}$  of the interval  $[0, T]$ , where  $0 = t_0 < t_1 < t_2 < \dots < t_n = T$ , define a “step function”  $\Delta_n(t)$ , on  $\Pi$  to be a function which holds a constant value in each interval  $[t_j, t_{j+1})$ .



## Step function approximating general function



## Stochastic Integral, Definition

We choose a partition  $\Pi = t_0, t_1, \dots, t_n$  of the time interval  $[0, T]$ ,

$$0 = t_0 \leq t_1 \leq \dots \leq t_n = T, \quad ||\Pi|| = \max_{k=0, \dots, n-1} (t_{k+1} - t_k).$$

We then define the stochastic integral of a step function  $\Delta_n(t)$  as

$$I_n(t) = \sum_{j=0}^{n-1} \Delta_n(t_j) (W(t_{j+1}) - W(t_j)) = \int_0^T \Delta_n(t) dW(t),$$

and an integral for a general function  $\Delta(t)$ ,

$$I(T) = \int_0^T \Delta(t) dW(t) = \lim_{||\Pi|| \rightarrow 0} I_n(T),$$

where

$$\lim_{||\Pi|| \rightarrow 0, n \rightarrow \infty} \Delta_n(T) = \Delta(T).$$

$$\left[ \text{Actually: } \lim_{n \rightarrow \infty} \mathbb{E} \int_0^T |\Delta_n(t) - \Delta(t)|^2 dt = 0. \right]$$

The position in time interval  $[t_k, t_{k+1}]$  where we evaluate  $\Delta(t)$  is crucial, we obtain different values of  $I(t)$  in the limit depending on this choice:

- Left point: popular in Finance (think of  $\Delta$  as asset holdings chosen due information up to time  $t_k$  and then exposed to random movements of the price  $W$  per unit holding over the next time period). The resulting integral is called *Itô integral*, to be used in the following.
- Mid point: popular in Physics, the resulting integral is called Stratonovich integral

$$\int_0^T W(t) dW(t)$$

In ordinary calculus we have for  $f(0) = 0$

$$\int_0^T f(t) df(t) = \int_0^T f(t) f'(t) dt = \frac{1}{2} \int_0^T \frac{d}{dt}(f^2(t)) dt = \frac{1}{2} f^2(T)$$

For the Itô integral we will show that

$$I(T) = \int_0^T \Delta(t) dW(t) = \int_0^T W(t) dW(t) = \frac{1}{2} (W^2(T) - T)$$

## Approximate $W(t)$ with a step function

$$\Delta_n(t) = W_n(t) = \begin{cases} W(0) = 0 & \text{if } 0 \leq t < \frac{T}{n}, \\ W(\frac{T}{n}) & \text{if } \frac{T}{n} \leq t < \frac{2T}{n}, \\ W(\frac{2T}{n}) & \text{if } \frac{2T}{n} \leq t < \frac{3T}{n}, \\ \vdots & \\ W(\frac{(n-1)T}{n}) & \text{if } \frac{(n-1)T}{n} \leq t < T, \end{cases}$$

So,

$$\begin{aligned} \int_0^T W(t) dW(t) &= \lim_{n \rightarrow \infty} \int_0^T \Delta_n(t) dW(t) \\ &= \lim_{n \rightarrow \infty} \sum_{j=0}^{n-1} W\left(\frac{jT}{n}\right) \left[ W\left(\frac{(j+1)T}{n}\right) - W\left(\frac{jT}{n}\right) \right]. \end{aligned}$$

$$\int_0^T W(t) dW(t)$$

Letting  $W_j = W\left(\frac{jT}{n}\right)$ , consider the sum:

$$\begin{aligned} \frac{1}{2} \sum_{j=0}^{n-1} (W_{j+1} - W_j)^2 &= \frac{1}{2} \sum_{j=0}^{n-1} W_{j+1}^2 - \sum_{j=0}^{n-1} W_{j+1} W_j + \frac{1}{2} \sum_{j=0}^{n-1} W_j^2 \\ &= \frac{1}{2} W_n^2 + \frac{1}{2} \sum_{j=0}^{n-1} W_j^2 - \sum_{j=0}^{n-1} W_{j+1} W_j + \frac{1}{2} \sum_{j=0}^{n-1} W_j^2 \\ &= \frac{1}{2} W_n^2 + \sum_{j=0}^{n-1} W_j^2 - \sum_{j=0}^{n-1} W_{j+1} W_j \\ &= \frac{1}{2} W_n^2 - \sum_{j=0}^{n-1} W_j (W_{j+1} - W_j) \end{aligned}$$

$$\int_0^T W(t) dW(t)$$

Take the limit as  $\|\Pi\| \rightarrow 0$  gives:

$$\frac{1}{2}T = \frac{1}{2}W^2(T) - \int_0^T W(t)dW(t),$$

so,

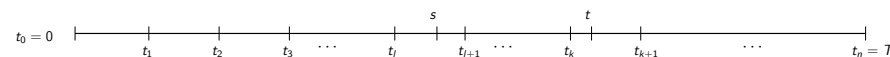
$$\int_0^T W(t)dW(t) = \frac{1}{2}W^2(T) - \frac{1}{2}T.$$

$I_\Pi(t)$  is a Martingale

In order to show  $I_\Pi(t)$  is a Martingale, we need to show that for  $0 \leq s \leq t \leq T$ ,

$$\mathbb{E}[I_\Pi(t) | \mathcal{F}(s)] = I_\Pi(s).$$

Set up a partition as follows



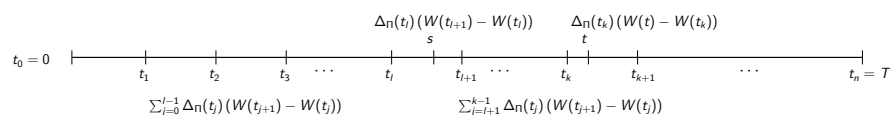
where we have  $0 \leq s < t \leq T$ , such that for  $l < k$  (i.e.,  $t_l < t_k$ ),  $s \in [t_l, t_{l+1})$  and  $t \in [t_k, t_{k+1})$ . As before, we have

$$I_\Pi(t) = \sum_{j=0}^{k-1} \Delta_\Pi(t_j)(W(t_{j+1}) - W(t_j)) + \Delta_\Pi(t_k)(W(t) - W(t_k))$$

$I_\Pi(t)$  is a Martingale (ctd)

We can split  $I_\Pi(t)$  up into four parts:

$$\begin{aligned} I_\Pi(t) &= \sum_{j=0}^{k-1} \Delta_\Pi(t_j)(W(t_{j+1}) - W(t_j)) + \Delta_\Pi(t_k)(W(t) - W(t_k)), \\ &= \sum_{j=0}^{l-1} \Delta_\Pi(t_j)(W(t_{j+1}) - W(t_j)) + \Delta_\Pi(t_l)(W(t_{l+1}) - W(t_l)) \\ &\quad + \sum_{j=l+1}^{k-1} \Delta_\Pi(t_j)(W(t_{j+1}) - W(t_j)) + \Delta_\Pi(t_k)(W(t) - W(t_k)) \end{aligned}$$



$I_\Pi(t)$  is a Martingale (ctd)

So  $\mathbb{E}[I_\Pi(t) | \mathcal{F}(s)]$  becomes

$$\begin{aligned} &\mathbb{E}\left[\sum_{j=0}^{l-1} \Delta_\Pi(t_j)(W(t_{j+1}) - W(t_j)) \middle| \mathcal{F}(s)\right] \\ &+ \mathbb{E}[\Delta_\Pi(t_l)(W(t_{l+1}) - W(t_l)) | \mathcal{F}(s)] \\ &+ \mathbb{E}\left[\sum_{j=l+1}^{k-1} \Delta_\Pi(t_j)(W(t_{j+1}) - W(t_j)) \middle| \mathcal{F}(s)\right] \\ &+ \mathbb{E}[\Delta_\Pi(t_k)(W(t) - W(t_k)) | \mathcal{F}(s)] \end{aligned}$$

By taking out what is known, this becomes:

$$\begin{aligned} &\sum_{j=0}^{l-1} \Delta_\Pi(t_j)(W(t_{j+1}) - W(t_j)) \\ &+ \Delta_\Pi(t_l)(\mathbb{E}[W(t_{l+1}) | \mathcal{F}(s)] - W(t_l)) \\ &+ \dots \end{aligned}$$

Using the fact that  $W(t)$  is a martingale ( $\mathbb{E}[W(t) | \mathcal{F}(s)] = W(s)$ ) gives

$$\sum_{j=0}^{l-1} \Delta_\Pi(t_j)(W(t_{j+1}) - W(t_j)) + \Delta_\Pi(t_l)(W(s) - W(t_l)) + \dots$$

## $I_{\Pi}(t)$ is a Martingale (ctd)

So far we have

$$\begin{aligned}\mathbb{E}[I_{\Pi}(t) | \mathcal{F}(s)] &= I_{\Pi}(s) \\ &+ \mathbb{E}\left[\sum_{j=l+1}^{k-1} \Delta_{\Pi}(t_j) (W(t_{j+1}) - W(t_j)) \middle| \mathcal{F}(s)\right] \\ &+ \mathbb{E}[\Delta_{\Pi}(t_k) (W(t) - W(t_k)) | \mathcal{F}(s)]\end{aligned}$$

## $I_{\Pi}(t)$ is a Martingale (ctd)

What is

$$\mathbb{E}\left[\sum_{j=l+1}^{k-1} \Delta_{\Pi}(t_j) (W(t_{j+1}) - W(t_j)) \middle| \mathcal{F}(s)\right] ?$$

Looking at terms individually

$$\begin{aligned}\mathbb{E}[\Delta_{\Pi}(t_j) (W(t_{j+1}) - W(t_j)) | \mathcal{F}(s)] &= \mathbb{E}[\mathbb{E}[\Delta_{\Pi}(t_j) (W(t_{j+1}) - W(t_j)) | \mathcal{F}(t_j)] | \mathcal{F}(s)] \\ &= \mathbb{E}[\Delta_{\Pi}(t_j) (\mathbb{E}[W(t_{j+1}) | \mathcal{F}(t_j)] - W(t_j)) | \mathcal{F}(s)] \\ &= \mathbb{E}[\Delta_{\Pi}(t_j) (W(t_j) - W(t_j)) | \mathcal{F}(s)] \\ &= 0,\end{aligned}$$

where we used the iterated conditioning rule along with the fact that  $s < t_j$ .  
So,

$$\mathbb{E}\left[\sum_{j=l+1}^{k-1} \Delta_{\Pi}(t_j) (W(t_{j+1}) - W(t_j)) \middle| \mathcal{F}(s)\right] = 0.$$

## $I_{\Pi}(t)$ is a Martingale (ctd)

Now we have

$$\begin{aligned}\mathbb{E}[I_{\Pi}(t) | \mathcal{F}(s)] &= I_{\Pi}(s) \\ &+ \mathbb{E}[\Delta_{\Pi}(t_k) (W(t) - W(t_k)) | \mathcal{F}(s)]\end{aligned}$$

Using a similar iterated conditioning argument to the one used on the previous slide,

$$\mathbb{E}[\Delta_{\Pi}(t_k) (W(t) - W(t_k)) | \mathcal{F}(s)] = 0$$

Therefore

$$\mathbb{E}[I_{\Pi}(t) | \mathcal{F}(s)] = I_{\Pi}(s),$$

So  $I_{\Pi}(t)$  is a Martingale.

## Itô Isometry

Since  $I_{\Pi}(t)$  is a Martingale,

$$\mathbb{E}(I_{\Pi}(t)) = I(0) = 0,$$

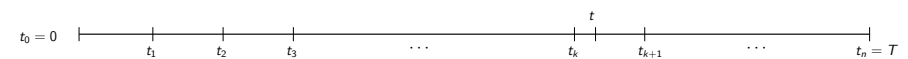
So

$$\text{Var}(I_{\Pi}(t)) = \mathbb{E}(I_{\Pi}(t)^2).$$

We will show that

$$\mathbb{E}((I_{\Pi}(t))^2) = \mathbb{E} \int_0^t (\Delta_{\Pi}(u))^2 du$$

Use a similar partition to the one used before,



So,

$$I_{\Pi}(t) = \sum_{j=0}^{k-1} \Delta_{\Pi}(t_j) (W(t_{j+1}) - W(t_j)) + \Delta_{\Pi}(t_k) (W(t) - W(t_k))$$

## Itô Isometry (ctd)

$$I_{\Pi}(t) = \sum_{j=0}^{k-1} \Delta_{\Pi}(t_j)(W(t_{j+1}) - W(t_j)) + \Delta_{\Pi}(t_k)(W(t) - W(t_k)).$$

Let  $\Delta W_j = (W(t_{j+1}) - W(t_j))$ ,  $0 \leq j < k$ , and let  $\Delta W_k = (W(t) - W(t_k))$ . Then rewrite the Itô integral as,

$$I_{\Pi}(t) = \sum_{j=0}^k \Delta_{\Pi}(t_j) \Delta W_j.$$

So,

$$\begin{aligned} \mathbb{E}((I_{\Pi}(t))^2) &= \mathbb{E} \left[ \left( \sum_{j=0}^k \Delta_{\Pi}(t_j) \Delta W_j \right) \left( \sum_{i=0}^k \Delta_{\Pi}(t_i) \Delta W_i \right) \right], \\ &= \mathbb{E} \left[ \sum_{j=0}^k (\Delta_{\Pi}(t_j))^2 \Delta W_j^2 + 2 \sum_{0 \leq i < j \leq k} \Delta_{\Pi}(t_i) \Delta_{\Pi}(t_j) \Delta W_i \Delta W_j \right], \end{aligned}$$

## Itô Isometry (ctd)

Taking the second term first

$$\begin{aligned} &\mathbb{E} \left[ 2 \sum_{0 \leq i < j \leq k} \Delta_{\Pi}(t_i) \Delta_{\Pi}(t_j) \Delta W_i \Delta W_j \right] \\ &= 2 \sum_{0 \leq i < j \leq k} \mathbb{E} [\Delta_{\Pi}(t_i) \Delta_{\Pi}(t_j) \Delta W_i \Delta W_j] \\ &= 2 \sum_{0 \leq i < j \leq k} \mathbb{E} [\Delta_{\Pi}(t_i) \Delta_{\Pi}(t_j) \Delta W_i] \underbrace{\mathbb{E} [\Delta W_j]}_{=0} \\ &= 0. \end{aligned}$$

Because

- $\Delta_{\Pi}(t_i) \Delta_{\Pi}(t_j) \Delta W_i$   $\mathcal{F}(t_j)$ -measurable
- $\Delta W_j$  independent of  $\mathcal{F}(t_j)$

## Itô Isometry (ctd)

So,

$$\mathbb{E}((I_{\Pi}(t))^2) = \mathbb{E} \left[ \sum_{j=0}^k (\Delta_{\Pi}(t_j))^2 \Delta W_j^2 \right] + 0$$

and

$$\begin{aligned} \mathbb{E} \left[ \sum_{j=0}^k (\Delta_{\Pi}(t_j))^2 \Delta W_j^2 \right] &= \sum_{j=0}^k \mathbb{E} [(\Delta_{\Pi}(t_j))^2 \Delta W_j^2] = \sum_{j=0}^k \mathbb{E} [(\Delta_{\Pi}(t_j))^2] \mathbb{E} [\Delta W_j^2] \\ &= \sum_{j=0}^{k-1} \mathbb{E} [(\Delta_{\Pi}(t_j))^2] (t_{j+1} - t_j) + \mathbb{E} [(\Delta_{\Pi}(t_k))^2] (t - t_k) \\ &= \mathbb{E} \left[ \sum_{j=0}^{k-1} (\Delta_{\Pi}(t_j))^2 (t_{j+1} - t_j) \right] + \mathbb{E} [(\Delta_{\Pi}(t_k))^2] (t - t_k) \\ &= \mathbb{E} \sum_{j=0}^{k-1} \int_{t_j}^{t_{j+1}} (\Delta_{\Pi}(u))^2 du + \mathbb{E} \int_{t_k}^t (\Delta_{\Pi}(u))^2 du \\ &= \boxed{\mathbb{E} \int_0^t (\Delta_{\Pi}(u))^2 du} \end{aligned}$$

## Quadratic variation of Itô integral

Since the Itô integral is written as

$$I(t) = \int_0^t G(u) dW(u),$$

In informal notation, this can be written as

$$dI(t) = G(t) dW(t)$$

Again informally, the quadratic variation is written,

$$dI dI = G(t) dW(t) G(t) dW(t) = (G(t))^2 dt$$

So, the quadratic variation of the Itô integral is

$$QV_I(t) = \int_0^t (G(u))^2 du$$

## Summary: Properties of Itô Integral

For an Itô integral

$$I(T) = \int_0^T G(t) dW(t),$$

- Expected Value:

$$\mathbb{E}[I(T)] = 0$$

- Variance: (Itô Isometry):

$$\text{Var}[I(T)] = \int_0^T \mathbb{E}[G^2(t)] dt,$$

- Quadratic variation:

$$QV_I(T) = \int_0^T [G^2(t)] dt,$$

- Martingale: for  $0 \leq s < t$ ,

$$\mathbb{E}[I(t)|\mathcal{F}(s)] = I(s)$$

## Chain Rule $f(W(t))$

For an expression of the form  $f(W(t))$ , if asked for

$$\frac{d}{dt} f(W(t)),$$

would normally write

$$\frac{d}{dt} f(W(t)) = \frac{df(W(t))}{dW} \frac{dW(t)}{dt}$$

or

$$df(W(t)) = \frac{df(W(t))}{dW} \frac{dW(t)}{dt} dt$$

or

$$df(W(t)) = \frac{df(W(t))}{dW} dW(t)$$

But  $\frac{dW(t)}{dt}$  does not exist

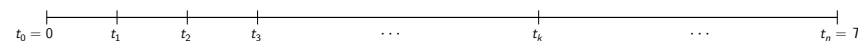
## $df(t, W(t))$

For a function  $f(t, W(t))$  of time and  $W(t)$ , we would write

$$df(t, W(t)) = \frac{\partial f(t, W(t))}{\partial t} dt + \frac{\partial f(t, W(t))}{\partial W(t)} dW(t),$$

But  $\frac{dW(t)}{dt}$  does not exist

## Partition of interval $[0, T]$





## Taylor Series

Given a differentiable function  $f(x)$  and two points  $x_j$  and  $x_{j+1}$ , then

$$f(x_{j+1}) = f(x_j) + f'(x_j)(x_{j+1} - x_j) + \frac{1}{2}f''(x_j)(x_{j+1} - x_j)^2 + \cdots,$$

where  $x_{j+1} = x_j + (x_{j+1} - x_j)$ .

For a function  $f(t, x(t))$  and points  $(t_j, x(t_j))$  and  $(t_{j+1}, x(t_{j+1}))$

$$\begin{aligned} f(t_{j+1}, x(t_{j+1})) &= f(t_j, x(t_j)) \\ &+ f_t(t_j, x(t_j))(t_{j+1} - t_j) + f_x(t_j, x(t_j))(x(t_{j+1}) - x(t_j)) \\ &+ \frac{1}{2}f_{tt}(t_j, x(t_j))(t_{j+1} - t_j)^2 \\ &+ f_{tx}(t_j, x(t_j))(t_{j+1} - t_j)(x(t_{j+1}) - x(t_j)) \\ &+ \frac{1}{2}f_{xx}(t_j, x(t_j))(x(t_{j+1}) - x(t_j))^2 \\ &+ \text{higher order terms} \cdots, \end{aligned}$$

where

$$\begin{aligned} f_t &= \frac{\partial f(t, x)}{\partial t}, & f_x &= \frac{\partial f(t, x)}{\partial x}, \\ f_{tt} &= \frac{\partial^2 f(t, x)}{\partial t^2}, & f_{tx} &= \frac{\partial^2 f(t, x)}{\partial t \partial x}, \\ f_{xx} &= \frac{\partial^2 f(t, x)}{\partial x^2}. \end{aligned}$$

## Itô's Formula for $f(t, W(t))$

The function  $f(x)$  is differentiable, so we can expand it as before

$$\begin{aligned} f(t_{j+1}, W(t_{j+1})) &= f(t_j, W(t_j)) \\ &+ f_t(t_j, W(t_j))(t_{j+1} - t_j) + f_x(t_j, W(t_j))(W(t_{j+1}) - W(t_j)) \\ &+ \frac{1}{2}f_{tt}(t_j, W(t_j))(t_{j+1} - t_j)^2 \\ &+ f_{tx}(t_j, W(t_j))(t_{j+1} - t_j)(W(t_{j+1}) - W(t_j)) \\ &+ \frac{1}{2}f_{xx}(t_j, W(t_j))(W(t_{j+1}) - W(t_j))^2 \\ &+ \text{higher order terms} \cdots, \end{aligned}$$

where

$$\begin{aligned} f_t &= \frac{\partial f(t, x)}{\partial t}, & f_x &= \frac{\partial f(t, x)}{\partial W(t)}, \\ f_{tt} &= \frac{\partial^2 f(t, x)}{\partial t^2}, & f_{tx} &= \frac{\partial^2 f(t, x)}{\partial t \partial W(t)}, \\ f_{xx} &= \frac{\partial^2 f(t, x)}{\partial W^2(t)}. \end{aligned}$$

## Itô's Formula for $f(t, W(t))$ (ctd)

Summing, we have

$$\begin{aligned} f(T, W(T)) - f(0, W(0)) &= \sum_{j=0}^{n-1} [f(t_{j+1}, W(t_{j+1})) - f(t_j, W(t_j))] \\ &= \sum_{j=0}^{n-1} f_t(t_j, W(t_j))(t_{j+1} - t_j) \\ &\quad + \sum_{j=0}^{n-1} f_x(t_j, W(t_j))(W(t_{j+1}) - W(t_j)) \\ &\quad + \sum_{j=0}^{n-1} \frac{1}{2}f_{xx}(t_j, W(t_j))(W(t_{j+1}) - W(t_j))^2 \\ &\quad + \sum_{j=0}^{n-1} \frac{1}{2}f_{tt}(t_j, W(t_j))(t_{j+1} - t_j)^2 \\ &\quad + \sum_{j=0}^{n-1} f_{tx}(t_j, W(t_j))(t_{j+1} - t_j)(W(t_{j+1}) - W(t_j)) \\ &\quad + \text{higher order terms} \cdots. \end{aligned}$$

## Itô's Formula for $f(t, W(t))$ (ctd)

$\lim_{||\Pi|| \rightarrow 0}$

In the limit as  $||\Pi|| \rightarrow 0$ , this becomes,

$$\begin{aligned} f(T, W(T)) - f(0, W(0)) &= \\ &= \int_0^T f_t(t, W(t))dt \leftarrow \left( \lim_{||\Pi|| \rightarrow 0} \sum_{j=0}^{n-1} f_t(t_j, W(t_j))(t_{j+1} - t_j) \right) \\ &\quad + \int_0^T f_x(t, W(t))dW(t) \leftarrow \left( \lim_{||\Pi|| \rightarrow 0} \sum_{j=0}^{n-1} f_x(t_j, W(t_j))(W(t_{j+1}) - W(t_j)) \right) \\ &\quad + \frac{1}{2} \int_0^T f_{xx}(t, W(t))dt \leftarrow \left( \lim_{||\Pi|| \rightarrow 0} \sum_{j=0}^{n-1} \frac{1}{2}f_{xx}(t_j, W(t_j))(W(t_{j+1}) - W(t_j))^2 \right) \\ &\quad + 0 \leftarrow \left( \lim_{||\Pi|| \rightarrow 0} \sum_{j=0}^{n-1} \frac{1}{2}f_{tt}(t_j, W(t_j))(t_{j+1} - t_j)^2 \right) \\ &\quad + 0 \leftarrow \left( \lim_{||\Pi|| \rightarrow 0} \sum_{j=0}^{n-1} f_{tx}(t_j, W(t_j))(W(t_{j+1}) - W(t_j))(t_{j+1} - t_j) \right), \end{aligned}$$

using arguments very like ones we have seen before.

## Itô's Formula for $f(t, W(t))$

So we have,

$$f(T, W(T)) - f(0, W(0)) = \int_0^T df(t, W(t)) = \int_0^T f_t(t, W(t))dt + \int_0^T f_W(t, W(t))dW(t) + \frac{1}{2} \int_0^T f_{WW}(t, W(t))dt$$

In informal differential notation,

$$df(t, W(t)) = f_t dt + f_W dW(t) + \frac{1}{2} f_{WW} dt,$$

or

$$df(t, W(t)) = \frac{\partial f}{\partial t} dt + \frac{\partial f}{\partial W} dW(t) + \frac{1}{2} \frac{\partial^2 f}{\partial W^2} dt.$$

or, if you like,

$$df(t, W(t)) = \left( \frac{\partial f}{\partial t} + \frac{1}{2} \frac{\partial^2 f}{\partial W^2} \right) dt + \frac{\partial f}{\partial W} dW(t).$$

## $\int_0^T W dW$ again

The integral can be quickly evaluated using Itô's formula

Let  $f(x) = \frac{1}{2}x^2$ . Then

$$\begin{aligned} \frac{\partial f(x)}{\partial x} &= f_x(x) = x, \\ \frac{\partial^2 f(x)}{\partial x^2} &= f_{xx}(x) = 1. \end{aligned}$$

If we replace  $x$  by  $W$ , the Itô formula gives

$$\begin{aligned} df(W) &= \underbrace{f_t}_{f_t=0} dt + f_W dW + \frac{1}{2} f_{WW} dt, \\ &= W dW + \frac{1}{2} \cdot 1 \cdot dt, \end{aligned}$$

So

$$\begin{aligned} \int_0^T df(W) &= f(W(T)) - f(W(0)) = \frac{1}{2}(W(T))^2 + \underbrace{0}_{W(0)=0} \\ &= \int_0^T W dW + \int_0^T \frac{1}{2} \cdot dt = \int_0^T W dW + \frac{1}{2} T, \end{aligned}$$

Therefore

$$\int_0^T W dW = \frac{1}{2} W^2(T) - \frac{1}{2} T.$$

## Product Rule

Let  $X(t, W(t))$  and  $Y(t, W(t))$ , so that  $X \cdot Y$  is a function of  $t$  and  $W(t)$ , too.

$$\begin{aligned} d[XY] &= \left( \frac{\partial XY}{\partial t} + \frac{1}{2} \frac{\partial^2 XY}{\partial W^2} \right) dt + \frac{\partial XY}{\partial W} dW \\ &= \dots \\ &= X dY + Y dX + \frac{\partial X}{\partial W} \frac{\partial Y}{\partial W} dt \\ &= X dY + Y dX + dX dY \end{aligned}$$

## Itô Process

An Itô process  $X(t)$  is defined

$$X(t) = X(0) + \int_0^t A(u) du + \int_0^t B(u) dW,$$

or, informally,

$$dX(t) = A(t) dt + B(t) dW.$$

Conditions are imposed on the functions  $A(t)$  and  $B(t)$

$$\begin{aligned} \mathbb{E} \int_0^t B^2(u) du &< \infty, \\ \int_0^t |A(u)| du &< \infty. \end{aligned}$$

## Quadratic Variation for $X(t)$ informally

Using the rules we have already described, the quadratic variation can be obtained informally as follows

$$\begin{aligned}
 QV_X(t) &= dX(t)dX(t) \\
 &= (A(t)dt + B(t)dW)^2 \\
 &= A^2(t)dtdt + 2A(t)B(t)dWdt + B^2(t)dWdW \\
 &= 0 + 0 + B^2(t)dWdW \\
 &= B^2(t)dt.
 \end{aligned}$$

## Integral with respect to Itô Process

We've seen Itô integrals with respect to Brownian Motion:

$$\int_0^t G(u)dW(u).$$

We can also define an integral with respect to an Itô process by splitting up the  $A(t)$  and  $B(t)$  terms

$$\int_0^t G(u)dX(u) = \int_0^t G(u)A(u)du + \int_0^t G(u)B(u)dW(u).$$

## Itô's Formula for $f(t, X(t))$ instead of $f(t, W(t))$

Proceeding as before, we have (replace  $W(t)$  by  $X(t)$ ):

$$\begin{aligned}
 f(t_{j+1}, X(t_{j+1})) &= f(t_j, X(t_{j+1})) \\
 &+ f_t(t_j, X(t_{j+1}))(t_{j+1} - t_j) + f_x(t_j, X(t_{j+1}))(X(t_{j+1}) - X(t_j)) \\
 &+ \frac{1}{2}f_{tt}(t_j, X(t_{j+1}))(t_{j+1} - t_j)^2 \\
 &+ f_{tx}(t_j, X(t_{j+1}))(t_{j+1} - t_j)(X(t_{j+1}) - X(t_j)) \\
 &+ \frac{1}{2}f_{xx}(t_j, X(t_{j+1}))(X(t_{j+1}) - X(t_j))^2 \\
 &+ \text{higher order terms} \dots,
 \end{aligned}$$

where

$$\begin{aligned}
 f_t &= \frac{\partial f(t, x)}{\partial t}, & f_x &= \frac{\partial f(t, x)}{\partial X(t)}, \\
 f_{tt} &= \frac{\partial^2 f(t, x)}{\partial t^2}, & f_{tx} &= \frac{\partial^2 f(t, x)}{\partial t \partial X(t)}, \\
 f_{xx} &= \frac{\partial^2 f(t, x)}{\partial X(t)^2}.
 \end{aligned}$$

## Itô's Formula for $f(t, X(t))$

So, for  $f(t, X(t))$ ,

$$df(t, X(t)) = f_t(t, X(t))dt + f_x(t, X(t))dX + \frac{1}{2}f_{xx}(t, X(t))dXdX,$$

where

$$dX(t)dX(t) = B^2(t)dt.$$

## Summary

Itô's Formula for  $f(t, X(t))$

For  $dX(t) = A(t)dt + B(t)dW$  and a function  $f(t, X(t))$

$$df(t, X) = f_t(t, X)dt + f_x(t, X)dX + \frac{1}{2}f_{xx}(t, X)dXdX,$$

$$df(t, X) = f_t dt + f_x dX + \frac{1}{2}f_{xx}B^2(t)dt,$$

$$df(t, X) = \frac{\partial f}{\partial t}dt + \frac{\partial f}{\partial X}dX + \frac{1}{2}\frac{\partial^2 f}{\partial X^2}B^2(t)dt.$$

$$df(t, X) = \left( \frac{\partial f}{\partial t} + \frac{1}{2}\frac{\partial^2 f}{\partial X^2}B^2(t) \right) dt + \frac{\partial f}{\partial X}dX.$$

## Stochastic Differential Equations

## Itô's Formula for $f(t, X(t))$

In terms of  $W(t)$ ...

$$\begin{aligned} df(t, X) &= f_t(t, X(t))dt + f_x(t, X(t))dX + \frac{1}{2}f_{xx}(t, X(t))B^2(t)dt, \\ &= f_t(t, X(t))dt + f_x(t, X(t))(A(t)dt + B(t)dW) + \frac{1}{2}f_{xx}(t, X(t))B^2(t)dt, \\ &= f_t(t, X(t))dt + f_x(t, X(t))A(t)dt + f_x(t, X(t))B(t)dW \\ &\quad + \frac{1}{2}f_{xx}(t, X(t))B^2(t)dt. \end{aligned}$$

## Basic Differential Equations

Reminder

### Example ( $df(t) = \mu f(t)dt$ )

Consider the differential equation

$$df(t) = \mu f(t)dt,$$

where  $\mu$  is a constant.

We can rewrite this as

$$\frac{1}{f(t)}df(t) = \mu dt,$$

Let  $f(t=0) = f_0$ . We want a formula for the value of  $f(T)$ , for  $T > 0$ , i.e., on the interval  $[0, T]$ . So again we integrate the equation:

$$\int_0^T \frac{df(t)}{f(t)} = \mu \int_0^T dt = \mu(T-0),$$

$$\begin{aligned} \int_0^T \frac{df(t)}{f(t)} &= \log f(t) \Big|_0^T \\ &= \log f(T) - \log f(0) \\ &= \log \frac{f(T)}{f(0)} = \log \frac{f(T)}{f_0} \quad (\text{using the properties of } \log x) \end{aligned}$$

## Basic Differential Equations

### Example ( $df(t) = \mu f(t)dt$ (ctd.))

From the previous slide

$$\log \frac{f(T)}{f_0} = \mu T,$$

Raising both sides to the power of  $e$  (remember  $e^x$  and  $\exp(x)$  are the same thing)

$$\exp\left(\log \frac{f(T)}{f_0}\right) = \exp(\mu T),$$

Solution:

$$f(T) = f_0 e^{\mu T},$$

because  $\exp\left(\log \frac{f(T)}{f_0}\right) = \frac{f(T)}{f_0}$ .

## Brownian Motion

First regular Brownian Motion, or SDE's of the form

$$dS = \mu(t)dt + \sigma(t)dW.$$

In fact we know the solution already, we just integrate to get

$$S(t) - S(0) = \int_0^t \mu(s)ds + \int_0^t \sigma(s)dW(s)$$

When  $\mu(t), \sigma(t)$  are constant, we have

$$S(t) - S(0) = \mu t + \sigma W(t)$$

## Geometric Brownian Motion

A special case of general SDE

Consider

$$dS = \mu(t)S(t)dt + \sigma(t)S(t)dW.$$

which is special case of

$$dS = (f(t) + \mu(t)S(t))dt + (g(t) + \sigma(t)S(t))dW.$$

with  $f(t) = g(t) = 0$

This is known as a homogeneous equation (recall from ODE's) because all the terms depend on  $S$ .

## Geometric Brownian Motion

From the previous slide

$$dS = \mu(t)S(t)dt + \sigma(t)S(t)dW(t).$$

Need to solve to obtain  $S(t)$ . Try solution of form  $S = e^f$ . Then  $f = \ln S$ .  $df(S) = ?$ .  
Apply Itô:

$$\begin{aligned} f_t &= 0, \\ f_S &= \frac{1}{S}, \\ f_{SS} &= -\frac{1}{S^2}. \end{aligned}$$

Therefore

$$\begin{aligned} df(S) &= f_S dS + \frac{1}{2} f_{SS} dS dS, \\ &= \frac{1}{S} dS - \frac{1}{2} \frac{1}{S^2} dS dS, \\ &= \frac{1}{S} (\mu(t)S(t)dt + \sigma(t)S(t)dW(t)) - \frac{1}{2} \frac{1}{S^2} \sigma^2(t)S^2 dt, \\ &= \left( \mu(t) - \frac{1}{2} \sigma(t)^2 \right) dt + \sigma(t)dW(t). \end{aligned}$$

## Geometric Brownian Motion (ctd)

From the previous slide

$$\begin{aligned}\int_0^T df(S(t)) &= f(T) - f(0) = \log(S(T)) - \log(S(0)) \\ &= \int_0^T \left( \mu(t) - \frac{1}{2}\sigma(t)^2 \right) dt + \int_0^T \sigma(t) dW(t).\end{aligned}$$

Therefore

$$S(T) = S(0) \exp \left\{ \int_0^T \left( \mu(t) - \frac{1}{2}\sigma(t)^2 \right) dt + \int_0^T \sigma(t) dW(t) \right\}$$

When  $\mu, \sigma$  are constant, this becomes

$$S(T) = S(0) \exp \left\{ \left( \mu - \frac{1}{2}\sigma^2 \right) t + \sigma W(t) \right\}$$

## An Interesting Martingale

Consider the Generalised Geometric Brownian Motion with  $\mu(t) = 0$

$$S(t) = S(0) \exp \left( -\frac{1}{2} \int_0^t \sigma^2(t') dt' + \int_0^t \sigma(t') dW(t') \right).$$

Use Ito's formula to derive the SDE for  $S(t)$ :

$$dS(t) = \sigma(t) S(t) dW(t)$$

so that

$$S(t) - S(t_0) = \int_{t_0}^t \sigma(t') S(t') dW(t')$$

and the expectation conditional on information up to  $t_0$  is

$$\mathbb{E}[S(t)|\mathcal{F}(t_0)] = \mathbb{E}[S(t_0)|\mathcal{F}(t_0)] + \mathbb{E} \left[ \int_{t_0}^t \sigma(t') S(t') dW(t') | \mathcal{F}(t_0) \right] = S(t_0).$$

$\Rightarrow S(t)$  is a Martingale – i.e., drift-free (generalised) Geometric Brownian Motion is a Martingale

## Distribution of Itô integral with deterministic integrand

An Itô integral

$$I(t) = \int_0^t G(s) dW(s),$$

where  $G(t)$  is deterministic is normally distributed with mean 0 and variance  $\int_0^t G^2(s) ds$ .

**Mean**  $I(t)$  is a martingale, so  $EI(t) = I(0) = 0$

**Variance**  $\mathbb{E}I(t) = 0$ , so

$$\text{Var}[I(t)] = \mathbb{E}I^2(t) = \mathbb{E} \int_0^t G^2(s) ds$$

**Distribution** If  $I(t)$  is normally distributed, then its moment generating function (MGF) will be of the same form as that of a normally distributed random variable  
The MGF of a normally distributed random variable,  $X$ , with mean 0 and variance  $\sigma^2$  is

$$\text{MGF}(X) = \mathbb{E} \left[ e^{uX} \right] = e^{\frac{1}{2}u^2\sigma^2}$$

If  $I(t)$  is normally distributed with mean 0 and variance  $\int_0^t I^2(s) ds$ , then it should have

$$\text{MGF}(I(t)) = \mathbb{E} \left[ e^{uI(t)} \right] = e^{\frac{1}{2}u^2 \int_0^t G^2(s) ds}$$

## Distribution of Itô integral with deterministic integrand

If

$$\mathbb{E} \left[ e^{uI(t)} \right] = e^{\frac{1}{2}u^2 \int_0^t G^2(s) ds},$$

then

$$\mathbb{E} \left[ e^{uI(t)} \right] e^{-\frac{1}{2}u^2 \int_0^t G^2(s) ds} = 1.$$

Since  $G(t)$  is deterministic, this can be written as

$$\mathbb{E} \left[ e^{uI(t)} e^{-\frac{1}{2}u^2 \int_0^t G^2(s) ds} \right] = 1,$$

or

$$\mathbb{E} \left[ e^{uI(t) - \frac{1}{2}u^2 \int_0^t G^2(s) ds} \right] = 1.$$

Writing  $\sigma(t) = uG(t)$ , and  $I(t) = \int_0^t G(s) dW(s)$ ,

$$\begin{aligned}& \mathbb{E} \left[ e^{u \int_0^t G(s) dW(s) - \frac{1}{2}u^2 \int_0^t G^2(s) ds} \right] = 1, \\ &= \mathbb{E} \left[ e^{\int_0^t uG(s) dW(s) - \frac{1}{2} \int_0^t u^2 G^2(s) ds} \right], \\ &= \mathbb{E} \left[ e^{\int_0^t \sigma(s) dW(s) - \frac{1}{2} \int_0^t \sigma^2(s) ds} \right] = 1,\end{aligned}$$

## Distribution of Itô integral with deterministic integrand

But

$$S(t) = e^{\int_0^t \sigma(s) dW(s) - \frac{1}{2} \int_0^t \sigma^2 ds},$$

is a martingale. Also  $S(0) = 1$ . Therefore

$$\mathbb{E}(S(t)) = 1,$$

as required. So  $I(t)$  is normally distributed with mean 0 and variance  $\int_0^t G^2(s) ds$ .

## Euler Method for Ordinary Differential Equations

Consider a (deterministic) initial value problem:

$$\frac{dx(t)}{dt} = a(t, x), \quad x(t_0) = x_0.$$

- It is not possible in general to find explicit solutions to such an equation
- Numerical approximations to the solution are often required
- one type of numerical approximation is a discrete time approximation
- the continuous time differential equation is replaced by a discrete time difference equation which generates values  $y_1, y_2, \dots, y_n, \dots$  which are approximations to  $x(t_1; t_0, x_0), x(t_2; t_0, x_0), \dots, x(t_n; t_0, x_0), \dots$ , at the time points  $t_0 < t_1 < t_2 < \dots < t_n < \dots$
- if the differences between the time points,  $\Delta_n = t_{n+1} - t_n$  are small enough then the method should be reasonably accurate

Euler Method:

$$y_{n+1} = y_n + a(t_n, y_n) \Delta_n,$$

where  $y_0 = x_0$ .

## Euler-Maruyama Method for Stochastic Differential Equations

Consider a SDE

$$dX(t) = a(t, X(t))dt + b(t, X(t))dW, \quad X(t_0) = X_0.$$

For  $t_0 < t_1 < t_2 < \dots < t_n < \dots$ , the Euler-Maruyama (discrete-time) approximation to the solution to this SDE is:

$$Y_{n+1} = Y_n + a(t_n, Y_n)(t_{n+1} - t_n) + b(t_n, Y_n)(W(t_{n+1}) - W(t_n)),$$

with  $Y_0 = X_0$ .

Writing  $(t_{n+1} - t_n)$  as  $\Delta_n$  and  $(W(t_{n+1}) - W(t_n))$  as  $\Delta W_n$ , this becomes

$$Y_{n+1} = Y_n + a(t_n, Y_n)\Delta_n + b(t_n, Y_n)\Delta W_n,$$

## Strong Convergence

For the SDE

$$dX(t) = a(t, X(t))dt + b(t, X(t))dW, \quad X(t_0) = X_0.$$

Let  $X(T)$  be the solution of the SDE at some time  $T > 0$ . Let  $Y(T)$  be the solution at time  $T$  obtained using the Euler-Maruyama method. Additionally assume that  $X(T)$  and  $Y(T)$  are evaluated using the same underlying Brownian Motion path. We can obtain an estimate of pathwise closeness between the actual solution and the Euler-Maruyama approximation by calculating

$$\epsilon = \mathbb{E}(|X(T) - Y(T)|).$$

The expected value is required by the presence of the Brownian motion term

## Weak Convergence

For the SDE

$$dX(t) = a(t, X(t))dt + b(t, X(t))dW, \quad X(t_0) = X_0.$$

Let  $X(T)$  be the solution of the SDE at some time  $T > 0$ . Let  $Y(T)$  be the solution at time  $T$  obtained using the Euler-Maruyama method.

We can obtain an estimate of closeness of moments of the actual solution to those of the Euler-Maruyama approximation may be obtained by calculating

$$|\mathbb{E}[X(T)] - \mathbb{E}[Y(T)]|.$$

For the Euler-Maruyama method, the order of strong convergence is generally different from the order of weak convergence

## Order of Convergence

Suppose an error  $\epsilon$  has the following form in terms of a time interval size  $\Delta$  (assuming equal interval sizes)

$$\epsilon(\Delta) = C\Delta^\gamma.$$

Then

$$\log \epsilon = \gamma \log \Delta + \log C.$$

## Review of Course Topics

- 1 Integration
- 2 Itô Integral
- 3 Itô Formula
- 4 Stochastic Differential Equations
- 5 Recap
- 6 Ito Processes and SDE's