

# Math 562 Fall 2020

Renming Song

University of Illinois at Urbana-Champaign

October 12, 2020

# Outline

# Outline

- 1 **General Info**
- 2 5.1 The Construction of Stochastic Integrals
- 3 5.2 Ito's Formula

I posted HW4 in my homepage. HW4 is due 10/16 at noon. I also set up HW4 in the course Moodle page.

# Outline

- 1 General Info
- 2 5.1 The Construction of Stochastic Integrals**
- 3 5.2 Ito's Formula

### Definition 5.7

Let  $X$  be a continuous semimartingale and let  $X = M + V$  be its canonical decomposition. If  $H$  is a locally bounded progressive process, the stochastic integral  $H \cdot X$  is the continuous semimartingale with canonical decomposition

$$H \cdot X = H \cdot M + H \cdot V$$

and we write

$$(H \cdot X)_t = \int_0^t H_s dX_s.$$

### Properties

- (i) The mapping  $(H, X) \mapsto H \cdot X$  is bilinear.
- (ii)  $H \cdot (K \cdot X) = (HK) \cdot X$  if  $H$  and  $K$  are progressive and locally bounded.

### Definition 5.7

Let  $X$  be a continuous semimartingale and let  $X = M + V$  be its canonical decomposition. If  $H$  is a locally bounded progressive process, the stochastic integral  $H \cdot X$  is the continuous semimartingale with canonical decomposition

$$H \cdot X = H \cdot M + H \cdot V$$

and we write

$$(H \cdot X)_t = \int_0^t H_s dX_s.$$

### Properties

- (i) The mapping  $(H, X) \mapsto H \cdot X$  is bilinear.
- (ii)  $H \cdot (K \cdot X) = (HK) \cdot X$  if  $H$  and  $K$  are progressive and locally bounded.

## Properties (cont)

- (iii) For every stopping time  $T$ ,  $(H \cdot X)^T = H1_{[0, T]} \cdot X = H \cdot X^T$ .
- (iv) If  $X$  is a continuous local martingale, resp. if  $X$  is a finite variation process, then the same holds for  $H \cdot X$ .
- (v) If  $H$  is of the form  $H_s(\omega) = \sum_{j=0}^{p-1} H_{(j)}(\omega) 1_{(t_j, t_{j+1}]}(s)$ , where  $0 = t_0 < t_1 < \dots < t_p$ , and, for every  $j = 0, \dots, p-1$ ,  $H_{(j)}$  is  $\mathcal{F}_{t_j}$ -measurable, then

$$(H \cdot X)_t = \sum_{j=0}^{p-1} H_{(j)}(X_{t_{j+1} \wedge t} - X_{t_j \wedge t}).$$

Property (ii) can be restated as, if  $Y_t = \int_0^t K_s dX_s$  then

$$\int_0^t H_s dY_s = \int_0^t H_s K_s dX_s.$$



## Properties (cont)

- (iii) For every stopping time  $T$ ,  $(H \cdot X)^T = H1_{[0, T]} \cdot X = H \cdot X^T$ .
- (iv) If  $X$  is a continuous local martingale, resp. if  $X$  is a finite variation process, then the same holds for  $H \cdot X$ .
- (v) If  $H$  is of the form  $H_s(\omega) = \sum_{j=0}^{p-1} H_{(j)}(\omega) 1_{(t_j, t_{j+1}]}(s)$ , where  $0 = t_0 < t_1 < \dots < t_p$ , and, for every  $j = 0, \dots, p-1$ ,  $H_{(j)}$  is  $\mathcal{F}_{t_j}$ -measurable, then

$$(H \cdot X)_t = \sum_{j=0}^{p-1} H_{(j)}(X_{t_{j+1} \wedge t} - X_{t_j \wedge t}).$$

Property (ii) can be restated as, if  $Y_t = \int_0^t K_s dX_s$  then

$$\int_0^t H_s dY_s = \int_0^t H_s K_s dX_s.$$

Properties (i)–(iv) easily follow from the results obtained when  $X$  is a continuous local martingale, resp. a finite variation process. As for property (v), we first note that it is enough to consider the case where  $X = M$  is a continuous local martingale with  $M_0 = 0$ , and by stopping  $M$  at suitable stopping times, we can even assume that  $M$  is in  $\mathbb{H}^2$ . There is a minor difficulty coming from the fact that the variables  $H_{(j)}$  are not assumed to be bounded (and therefore we cannot directly use the construction of the integral of elementary processes). To circumvent this difficulty, we set, for every  $n \geq 1$ ,

$$T_n = \inf\{t \geq 0 : |H_t| \geq n\} = \inf\{t_j : |H_{(j)}| \geq n\}.$$

It is easy to verify that  $T_n$  is a stopping time, and we have  $T_n \uparrow \infty$  as  $n \uparrow \infty$ .

Furthermore, we have for every  $n$ ,

$$H_s \mathbf{1}_{[0, T_n]}(s) = \sum_{j=0}^{p-1} H_{(j)}^n \mathbf{1}_{(t_j, t_{j+1}]}(s)$$

where the random variables  $H_{(j)}^n = H_{(j)} \mathbf{1}_{\{T_n > t_j\}}$  satisfy the same properties as the  $H_{(j)}$ 's and additionally are bounded by  $n$ . Hence  $H \mathbf{1}_{[0, T_n]}$  is an elementary process, and by the very definition of the stochastic integral with respect to a martingale of  $\mathbb{H}^2$ , we have

$$(H \cdot M)_{t \wedge T_n} = (H \mathbf{1}_{[0, T_n]} \cdot M)_t = \sum_{j=0}^{p-1} H_{(j)}^n (M_{t_{j+1} \wedge t} - M_{t_j \wedge t})$$

The desired result now follows by letting  $n$  tend to infinity.

### Proposition 5.8

Let  $X = M + V$  be the canonical decomposition of a continuous semimartingale  $X$ , and let  $t > 0$ . Let  $(H^n)_{n \geq 1}$  and  $H$  be locally bounded progressive processes, and let  $K$  be a non-negative progressive process. Assume that the following properties hold a.s.:

- (i)  $H_s^n \rightarrow H_s$  as  $n \rightarrow \infty$ , for every  $s \in [0, t]$ ;
- (ii)  $|H_s^n| \leq K_s$ , for every  $n \geq 1$  and  $s \in [0, t]$ ;
- (iii)  $\int_0^t K_s^2 d\langle M, M \rangle_s < \infty$  and  $\int_0^t K_s |dV_s| < \infty$ .

Then, as  $n \rightarrow \infty$ ,

$$\int_0^t H_s^n dX_s \rightarrow \int_0^t H_s dX_s$$

in probability.

## Remarks

- (a) Condition (iii) holds automatically if  $K$  is locally bounded.
- (b) Instead of assuming that (i) and (ii) hold for every  $s \in [0; t]$  (a.s.), it is enough to assume that these conditions hold for  $d\langle M, M \rangle_s$ -a.e.  $s \in [0, t]$  and for  $|dV_s|$ -a.e.  $s \in [0, t]$ , a.s. This will be clear from the proof.

## Proof of Proposition 5.8

The a.s. convergence

$$\int_0^t H_s^n dV_s \rightarrow \int_0^t H_s dV_s$$

follows from the usual dominated convergence theorem. So we just have to verify that  $\int_0^t H_s^n dM_s$  converges in probability to  $\int_0^t H_s dM_s$ .

## Remarks

- (a) Condition (iii) holds automatically if  $K$  is locally bounded.
- (b) Instead of assuming that (i) and (ii) hold for every  $s \in [0; t]$  (a.s.), it is enough to assume that these conditions hold for  $d\langle M, M \rangle_s$ -a.e.  $s \in [0, t]$  and for  $|dV_s|$ -a.e.  $s \in [0, t]$ , a.s. This will be clear from the proof.

## Proof of Proposition 5.8

The a.s. convergence

$$\int_0^t H_s^n dV_s \rightarrow \int_0^t H_s dV_s$$

follows from the usual dominated convergence theorem. So we just have to verify that  $\int_0^t H_s^n dM_s$  converges in probability to  $\int_0^t H_s dM_s$ .

## Proof of Proposition 5.8 (cont)

For every  $p \geq 1$ , define

$$T_p = \inf\{r \in [0, t] : \int_0^r K_s^2 d\langle M, M \rangle_s \geq p\} \wedge t.$$

Note that  $T_p = t$  for all large enough  $p$ , a.s., by assumption (iii). Then

$$\begin{aligned} & \mathbb{E} \left[ \left( \int_0^{T_p} H_s^n dM_s - \int_0^{T_p} H_s dM_s \right)^2 \right] \\ & \leq \mathbb{E} \left[ \int_0^{T_p} (H_s^n - H_s)^2 d\langle M, M \rangle_s \right] \end{aligned}$$

which tends to 0 as  $n \rightarrow \infty$ , by dominated convergence, using assumptions (i) and (ii) and the fact that  $\int_0^{T_p} K_s^2 d\langle M, M \rangle_s \leq p$ . Since  $\mathbb{P}(T_p = t) \rightarrow 1$  as  $p \rightarrow \infty$ , the desired result follows.

### Proposition 5.9

Let  $X$  be a continuous semimartingale, and let  $H$  be an adapted process with continuous sample paths. Then, for every  $t > 0$ , for every sequence  $0 = t_0^n < t_1^n < \dots < t_{p_n}^n = t$  of partitions of  $[0, t]$  with mesh tending to 0,

$$\lim_{n \rightarrow \infty} \sum_{j=0}^{p_n-1} H_{t_j^n} (X_{t_{j+1}^n} - X_{t_j^n}) \rightarrow \int_0^t H_s dX_s$$

in probability.

### Proof of Proposition 5.9

For every  $n \geq 1$ , define a process  $H_s^n$  by

$$H_s^n = \begin{cases} H_{t_j^n}, & \text{if } t_j^n < s \leq t_{j+1}^n, j = 0, \dots, p_n - 1 \\ H_0, & \text{if } s = 0 \\ 0, & \text{if } s > t. \end{cases}$$



### Proposition 5.9

Let  $X$  be a continuous semimartingale, and let  $H$  be an adapted process with continuous sample paths. Then, for every  $t > 0$ , for every sequence  $0 = t_0^n < t_1^n < \dots < t_{p_n}^n = t$  of partitions of  $[0, t]$  with mesh tending to 0,

$$\lim_{n \rightarrow \infty} \sum_{j=0}^{p_n-1} H_{t_j^n} (X_{t_{j+1}^n} - X_{t_j^n}) \rightarrow \int_0^t H_s dX_s$$

in probability.

### Proof of Proposition 5.9

For every  $n \geq 1$ , define a process  $H_s^n$  by

$$H_s^n = \begin{cases} H_{t_j^n}, & \text{if } t_j^n < s \leq t_{j+1}^n, j = 0, \dots, p_n - 1 \\ H_0, & \text{if } s = 0 \\ 0, & \text{if } s > t. \end{cases}$$

## Proof of Proposition 5.9 (cont)

Note that  $H^n$  is progressive. We then observe that all assumptions of Proposition 5.8 hold if we take

$$K_s = \max_{0 \leq r \leq s} |H_r|$$

which is a locally bounded progressive process. Hence, we conclude that

$$\int_0^t H_s^n dX_s \rightarrow \int_0^t H_s dX_s$$

in probability. This gives the desired result since

$$\int_0^t H_s^n dX_s = \sum_{j=0}^{p_n-1} H_{t_j^n} (X_{t_{j+1}^n} - X_{t_j^n}).$$

## Remark

The preceding proposition can be viewed as a generalization of the corresponding result for Lebesgue-Stieltjes integrals to stochastic integrals. However, in contrast with that lemma, it is essential in Proposition 5.9 to evaluate  $H$  at the left end of the interval  $(t_j^n, t_{j+1}^n]$ . The result will fail if we replace  $H_{t_j^n}$  by  $H_{t_{j+1}^n}$ . Here is a simple counterexample. Let  $H_t = X_t$  and we assume that the sequence of partitions  $0 = t_0^n < t_1^n < \dots < t_{p_n}^n = t$  is increasing. By the proposition, we have

$$\lim_{n \rightarrow \infty} \sum_{j=0}^{p_n-1} X_{t_j^n} (X_{t_{j+1}^n} - X_{t_j^n}) \rightarrow \int_0^t X_s dX_s$$

in probability. On the other hand, writing

$$\sum_{j=0}^{p_n-1} X_{t_{j+1}^n} (X_{t_{j+1}^n} - X_{t_j^n}) = \sum_{j=0}^{p_n-1} X_{t_j^n} (X_{t_{j+1}^n} - X_{t_j^n}) + \sum_{j=0}^{p_n-1} (X_{t_{j+1}^n} - X_{t_j^n})^2$$

**Remark (cont)**

and using Proposition 4.21, we get

$$\lim_{n \rightarrow \infty} \sum_{j=0}^{p_n-1} X_{t_{j+1}^n} (X_{t_{j+1}^n} - X_{t_j^n}) = \int_0^t X_s dX_s + \langle X, X \rangle_t$$

in probability. The resulting limit is different from  $\int_0^t X_s dX_s$  unless the martingale part of  $X$  is zero.

# Outline

- 1 General Info
- 2 5.1 The Construction of Stochastic Integrals
- 3 5.2 Ito's Formula**

Ito's formula is the most important result in stochastic calculus. It shows that, if we apply a twice continuously differentiable function to a  $p$ -tuple of continuous semimartingales, the resulting process is still a continuous semimartingale, and there is an explicit formula for the canonical decomposition of this semimartingale.

### Theorem 5.10 (Ito's formula)

Let  $X^1, \dots, X^p$  be  $p$  continuous semimartingales, and let  $F$  be a twice continuously differentiable real function on  $\mathbb{R}^p$ . Then, for every  $t \geq 0$ ,

$$F(X_t^1, \dots, X_t^p) = F(X_0^1, \dots, X_0^p) + \sum_{j=1}^p \int_0^t \frac{\partial F}{\partial x^j}(X_s^1, \dots, X_s^p) dX_s^j \\ + \frac{1}{2} \sum_{j,k=1}^p \int_0^t \frac{\partial^2 F}{\partial x^j \partial x^k}(X_s^1, \dots, X_s^p) d\langle X^j, X^k \rangle_s.$$

Ito's formula is the most important result in stochastic calculus. It shows that, if we apply a twice continuously differentiable function to a  $p$ -tuple of continuous semimartingales, the resulting process is still a continuous semimartingale, and there is an explicit formula for the canonical decomposition of this semimartingale.

### Theorem 5.10 (Ito's formula)

Let  $X^1, \dots, X^p$  be  $p$  continuous semimartingales, and let  $F$  be a twice continuously differentiable real function on  $\mathbb{R}^p$ . Then, for every  $t \geq 0$ ,

$$F(X_t^1, \dots, X_t^p) = F(X_0^1, \dots, X_0^p) + \sum_{j=1}^p \int_0^t \frac{\partial F}{\partial X^j}(X_s^1, \dots, X_s^p) dX_s^j \\ + \frac{1}{2} \sum_{j,k=1}^p \int_0^t \frac{\partial^2 F}{\partial X^j \partial X^k}(X_s^1, \dots, X_s^p) d\langle X^j, X^k \rangle_s.$$

## Proof of Theorem 5.10

We first deal with the  $p = 1$  and we write  $X = X^1$  for simplicity. Fix  $t > 0$  and consider an increasing sequence  $0 = t_0^n < t_1^n < \dots < t_{p_n}^n = t$  of partitions of  $[0, t]$  with mesh tending to zero. Then, for every  $n$ ,

$$F(X_t) = F(X_0) + \sum_{j=0}^{p_n-1} (F(X_{t_{j+1}^n}) - F(X_{t_j^n})).$$

For every  $j = 0, \dots, p_n - 1$ , we apply the Taylor-Lagrange formula to the function  $[0, 1] \ni \theta \mapsto F(X_{t_j^n} + \theta(X_{t_{j+1}^n} - X_{t_j^n}))$ , we get

$$F(X_{t_{j+1}^n}) - F(X_{t_j^n}) = F'(X_{t_j^n})(X_{t_{j+1}^n} - X_{t_j^n}) + \frac{1}{2} f_{n,j}(X_{t_{j+1}^n} - X_{t_j^n})^2,$$

where  $f_{n,j}$  can be written as  $F''(X_{t_j^n} + c(X_{t_{j+1}^n} - X_{t_j^n}))$  for some  $c \in [0, 1]$ .



## Proof of Theorem 5.10 (cont)

By Proposition 5.9 with  $H_s = F'(X_s)$ , we have

$$\lim_{n \rightarrow \infty} \sum_{j=0}^{p_n-1} F'(X_{t_j^n})(X_{t_{j+1}^n} - X_{t_j^n}) = \int_0^t F'(X_s) dX_s$$

in probability. To complete the proof of the case  $p = 1$  of the theorem, it is therefore enough to verify that

$$\lim_{n \rightarrow \infty} \sum_{j=0}^{p_n-1} f_{n,j}(X_{t_{j+1}^n} - X_{t_j^n})^2 = \int_0^t F''(X_s) d\langle X, X \rangle_s \quad (1)$$

in probability. We observe that

$$\sup_{0 \leq j \leq p_n-1} |f_{n,j} - F''(X_{t_j^n})| \leq \sup_{0 \leq j \leq p_n-1} \left( \sup_{x \in [X_{t_j^n} \wedge X_{t_{j+1}^n}, X_{t_j^n} \vee X_{t_{j+1}^n}]} |F''(x) - F''(X_{t_j^n})| \right)$$

## Proof of Theorem 5.10 (cont)

The right-hand side of the preceding display tends to 0 a.s. as  $n \rightarrow \infty$ , as a simple consequence of the uniform continuity of  $F''$  (and of the sample paths of  $X$ ) over a compact interval.

Since  $\sum_{j=1}^{p_n-1} (X_{t_{j+1}^n} - X_{t_j^n})^2$  converges in probability, it follows from the last display that

$$\left| \sum_{j=0}^{p_n-1} f_{n,j}(X_{t_{j+1}^n} - X_{t_j^n})^2 - \sum_{j=0}^{p_n-1} F''(X_{t_j^n})(X_{t_{j+1}^n} - X_{t_j^n})^2 \right| = 0$$

in probability. So the convergence (1) will follow if we can verify that

$$\lim_{n \rightarrow \infty} \sum_{j=0}^{p_n-1} F''(X_{t_j^n})(X_{t_{j+1}^n} - X_{t_j^n})^2 = \int_0^t F''(X_s) d\langle X, X \rangle_s \quad (2)$$

in probability. In fact, we will show that (2) holds a.s. along a suitable sequence of values of  $n$  (this suffices for our needs, because we can replace the initial sequence of partitions by a subsequence).

## Proof of Theorem 5.10 (cont)

To this end, we note that

$$\sum_{j=0}^{p_n-1} F''(X_{t_j^n})(X_{t_{j+1}^n} - X_{t_j^n})^2 = \int_{[0,t]} F''(X_{t_j^n}) \mu_n(ds)$$

where  $\mu_n$  is the random measure on  $[0, t]$  defined by

$$\mu_n(dr) := \sum_{j=0}^{p_n-1} (X_{t_{j+1}^n} - X_{t_j^n})^2 \delta_{t_j^n}(dr)$$

Let  $D = \{t_j^n : n \geq 1, 0 \leq j \leq p_n\} \subset [0, t]$ . As a consequence of Proposition 4.21, we get for every  $r \in D$ ,

$$\mu_n([0, r]) \rightarrow \langle X, X \rangle_r$$

in probability, as  $n \rightarrow \infty$ . Using a diagonal extraction, we can thus

### Proof of Theorem 5.10 (cont)

find a subsequence of values of  $n$  such that, along this subsequence, we have for every  $r \in D$ ,

$$\mu_n([0, r]) \rightarrow \langle X, X \rangle_r, \quad a.s.,$$

which implies that the sequence  $\mu_n$  converges a.s. to the measure  $1_{[0, t]}(r) d\langle X, X \rangle_r$ , in the sense of weak convergence of finite measures. We conclude that we have

$$\int_{[0, t]} F''(X_{t_j^n}) \mu_n(ds) \rightarrow \int_0^t F''(X_s) d\langle X, X \rangle_s, \quad a.s.$$

along the chosen subsequence. This completes the proof of the case  $p = 1$ .