

# AN INTRODUCTION TO MALLIAVIN CALCULUS

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# INTRODUCTION

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## MOTIVATION

- The Itô Representation Theorem states that, for  $F \in L^2(\mathbf{P})$ , there exists a unique adapted process  $f$  such that

$$F = \mathbf{E}[F] + \int_0^T f(t) \, dW(t)$$

- How can we find this process?

## MOTIVATION

- We'll show that

$$F = \mathbf{E}[F] + \int_0^T \mathbf{E}[D_t F \mid \mathcal{F}_t] dW(t)$$

which is known as the **Clark-Ocone Formula**.

- To do that, we need to know what is  $D_t F$ , which begs the question: how can we define a derivative for random variables?
- Notice that this derivative also allows us to study the smoothness of densities of diffusions and the regularity of densities.

## THREE APPROACHES

- **Malliavin:**  $\Omega$  as the Wiener space  $C_0([0, T])$ , with  $\omega(0) = 0$ , equipped with the uniform topology.
- **Hida:**  $\Omega$  as the space  $\mathcal{S}'$  of tempered distributions  $\omega : \mathcal{S} \rightarrow \mathbf{R}$ , where  $\mathcal{S}$  is the Schwartz space of rapidly decreasing smooth functions on  $\mathbf{R}$ , constructing a probability via the Bochner-Minlos-Sazonov theorem.
- **Wiener-Itô chaos expansion:** the one presented in the following slides.

# THE WIENER-ITÔ CHAOS EXPANSION

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## ITÔ ITERATED INTEGRALS

We define  $\hat{L}^2([0, T]^n)$  as the subspace of  $L^2([0, T]^n)$  consisting of symmetric functions.

Now consider the set

$$S_n = \{(t_1, \dots, t_n) \in [0, T]^n : 0 \leq t_1 \leq \dots \leq t_n \leq T\}$$

Notice that the set  $S_n$  occupies  $\frac{1}{n!}$  of the whole box  $[0, T]^n$ . Thus, if  $g \in \hat{L}^2([0, T]^n)$ , then  $g|_{S_n} \in L^2(S_n)$  and

$$\|g\|_{L^2([0, T]^n)}^2 = n! \int_{S_n} g^2(t_1, \dots, t_n) dt_1 \cdots dt_n = n! \|g\|_{L^2(S_n)}^2$$

## ITÔ ITERATED INTEGRALS

**Definition 1.** Let  $f$  be a deterministic function defined on  $S_n$  such that  $\|f\|_{L^2(S_n)}^2 < \infty$ . We define the  $n$ -**fold iterated Itô integral** as

$$J_n(f) = \int_0^T \int_0^{t_n} \cdots \int_0^{t_3} \int_0^{t_2} f(t_1, \dots, t_n) dW(t_1) dW(t_2) \cdots dW(t_{n-1}) dW(t_n)$$

**Remark 2.**

1. Note that each  $i$ -th Itô integral with respect to  $dW(t_i)$  is well-defined, since the integrand is an  $\mathbf{F}$ -adapted stochastic process.
2. Furthermore,  $J_n(f) \in L^2(\mathbf{P})$ .



## ITÔ ITERATED INTEGRALS

**Theorem 3.** For  $m, n \in \mathbf{Z}_{>0}$ ,

$$\mathbf{E}[J_m(g)J_n(h)] = \begin{cases} 0, & n \neq m \\ \langle g, h \rangle_{L^2(S_n)}, & n = m \end{cases}$$

In particular,

$$\|J_n(h)\|_{L^2(\mathbf{P})} = \|h\|_{L^2(S_n)}$$

For  $n = 0$  or  $m = 0$ , we define  $J_0(g) = g$ , when  $g$  is a constant, and  $\langle g, h \rangle_{L^2(S_0)} = gh$ , when  $g$  and  $h$  are constants.

*Proof.* Follows by applying Itô's isometry iteratively in two different cases:  $g \in L^2(S_m)$  and  $h \in L^2(S_n)$  with  $m < n$ , and  $g, h \in L^2(S_n)$ . □

## ITÔ ITERATED INTEGRALS

**Definition 4.** Let  $g \in \hat{L}^2([0, T]^n)$ . Then

$$I_n(g) = \int_{[0, T]^n} g(t_1, \dots, t_n) dW(t_1) \cdots dW(t_n) = n! J_n(g)$$

is also called  **$n$ -fold iterated Itô integral**.

For  $n = 0$ , we define

$$I_0(g) = \int_{\mathbf{R}^0} g dW^{\otimes 0} = g$$

## ITÔ ITERATED INTEGRALS

**Theorem 5.** *If  $\xi_1, \xi_2, \dots$  are orthonormal functions in  $L^2([0, T])$ , then*

$$I_n(\xi_1^{\otimes \alpha_1} \hat{\otimes} \dots \hat{\otimes} \xi_m^{\otimes \alpha_m}) = \prod_{k=1}^m h_{\alpha_k} \left( \int_0^T \xi_k(t) dW(t) \right)$$

*with  $\alpha_1 + \dots + \alpha_m = n$ ,  $\alpha_k \in \mathbf{N}_0$  for all  $k$ , and  $\hat{\otimes}$  is the symmetrized tensor product, which is the symmetrization of  $f \otimes g$ .*

*Proof.* See, e.g., [Itô51]. □

Using this, it is possible to prove [NN18, p. 64] that

$$\begin{aligned} I_n(g^{\otimes n}) &= n! \int_0^T \int_0^{t_n} \dots \int_0^{t_2} g(t_1)g(t_2) \dots g(t_n) dW(t_1) \dots dW(t_n) \\ &= \|g\|^n h_n \left( \frac{\int_0^T g(t) dW(t)}{\|g\|} \right) \end{aligned}$$

## THE WIENER-ITÔ CHAOS EXPANSION

**Theorem 6 (The Wiener-Itô Chaos Expansion).** Let  $\xi$  be an  $\mathcal{F}_T$ -measurable random variable in  $L^2(\mathbf{P})$ . There exists a unique sequence  $(f_n)$  of functions  $f_n \in \hat{L}^2([0, T]^n)$  such that

$$\xi = \sum_{n=0}^{\infty} I_n(f_n)$$

with convergence in  $L^2(\mathbf{P})$ . Moreover, we have the following isometry:

$$\|\xi\|_{L^2(\mathbf{P})}^2 = \sum_{n=0}^{\infty} n! \|f_n\|_{L^2([0, T]^n)}^2$$

## THE WIENER-ITÔ CHAOS EXPANSION [1]

*Proof.* Our goal is to obtain an orthogonal decomposition of  $L^2(\mathbf{P})$ . To do that, we show that a certain function  $\psi$  is orthogonal to

$$\exp \left( \int_0^T g(t) dW(t) \right)$$

which form a total set in  $L^2(\mathbf{P})$ , implying that  $\psi \equiv 0$ .

1. By the Itô's Representation Theorem, there exists an  $\mathbf{F}$ -adapted process  $\varphi_1(s_1)$ ,  $0 \leq s_1 \leq T$ , such that

$$\mathbf{E} \left[ \int_0^T \varphi_1^2(s_1) ds_1 \right] \leq \mathbf{E}[\xi^2]$$

## THE WIENER-ITÔ CHAOS EXPANSION [2]

and

$$\xi = \mathbf{E}[\xi] + \int_0^T \varphi_1(s_1) dW(s_1)$$

Define  $g_0 = \mathbf{E}[\xi]$ .

2. For almost all  $s_1 \leq T$ , we can apply the Itô's Representation Theorem to  $\varphi_1(s_1)$  and obtain an  $\mathbf{F}$ -adapted process  $\varphi_2(s_1, s_1)$ ,  $0 \leq s_2 \leq s_1$  such that

$$\mathbf{E} \left[ \int_0^{s_1} \varphi_2^2(s_2, s_1) ds_2 \right] \leq \mathbf{E}[\varphi_1^2(s_1)] < \infty$$

and

$$\varphi_1(s_1) = \mathbf{E}[\varphi_1(s_1)] + \int_0^{s_1} \varphi_2(s_2, s_1) dW(s_2)$$

## THE WIENER-ITÔ CHAOS EXPANSION [3]

3. Replacing  $\varphi_1(s_1)$  into our expression for  $\xi$  yields

$$\xi = g_0 + \int_0^T g_1(s_1) dW(s_1) + \int_0^T \int_0^{s_1} \varphi(s_2, s_1) dW(s_2) dW(s_1)$$

where  $g_1(s_1) = \mathbf{E}[\varphi_1(s_1)]$ .

4. Applying Itô's isometry,

$$\begin{aligned} & \mathbf{E} \left[ \left( \int_0^T \int_0^{s_1} \varphi_2(s_2, s_1) dW(s_2) dW(s_1) \right)^2 \right] \\ &= \int_0^T \int_0^{s_1} \mathbf{E}[\varphi_2^2(s_2, s_1)] ds_2 ds_1 \leq \mathbf{E}[\xi^2] \end{aligned}$$

## THE WIENER-ITÔ CHAOS EXPANSION [4]

5. Iterating this procedure  $n + 1$  times, we obtain a process

$\varphi_{n+1}(t_1, \dots, t_{n+1})$ ,  $0 \leq t_1 \leq \dots \leq t_{n+1} \leq T$ , and  $n + 1$  deterministic functions  $g_0, g_1, \dots, g_n$  (where  $g_0 = \mathbf{E}[\xi]$  and  $g_k(s_k, s_{k-1}, \dots, s_1) = \mathbf{E}[\varphi_k(s_k, s_{k-1}, \dots, s_1)]$  for  $1 \leq k \leq n$ ) such that

$$\xi = \sum_{k=0}^n J_k(g_k) + \int_{S_{n+1}} \varphi_{n+1} dW^{\otimes(n+1)}$$

6. Note that we have a  $(n + 1)$ -fold Iterated Itô Integral

$$\int_{S_{n+1}} \varphi_{n+1} dW^{\otimes(n+1)} =: \psi_{n+1}$$



## THE WIENER-ITÔ CHAOS EXPANSION [5]

and

$$\mathbf{E} \left[ \left( \int_{S_{n+1}} \varphi_{n+1} dW^{\otimes(n+1)} \right)^2 \right] \leq \mathbf{E}[\xi^2]$$

7. Also remark that the family  $\psi_{n+1}$  is bounded in  $L^2(\mathbf{P})$  and, from Itô's Isometry,

$$\langle \psi_{n+1}, J_k(f_k) \rangle_{L^2(\mathbf{P})} = 0$$

for  $k \leq n$  and  $f_k \in L^2([0, T]^k)$ .

8. Compute  $\|\xi\|_{L^2(\mathbf{P})}^2$  and notice that  $\sum_{k=0}^{\infty} J_k(g_k)$  is convergent in  $L^2(\mathbf{P})$ . Thus,

$$\langle J_k(f_k), \psi \rangle_{L^2(\mathbf{P})} = 0$$

## THE WIENER-ITÔ CHAOS EXPANSION [6]

9. Using that

$$I_n(g^{\otimes n}) = \|g\|^n h_n \left( \frac{\theta}{\|g\|} \right), \quad \theta = \int_0^T g(t) dW(t)$$

and Hermite polynomials, we have

$$\mathbf{E} \left[ h_n \left( \frac{\theta}{\|g\|} \right) \psi \right] = 0, \quad \mathbf{E} [\theta^k \psi] = 0, \quad \mathbf{E} [\exp \theta \cdot \psi] = \sum_{k=0}^{\infty} \frac{1}{k!} \mathbf{E} [\theta^k \psi] = 0$$

10. Since  $\{\exp \theta : g \in L^2([0, T]^n)\}$  is total in  $L^2(\mathbf{P})$  (i.e. its linear span is dense),  $\psi = 0$ . Thus, we obtain

$$\xi = \sum_{k=0}^{\infty} J_k(g_k)$$

## THE WIENER-ITÔ CHAOS EXPANSION [7]

and

$$\|\xi\|_{L^2(\mathbf{P})}^2 = \sum_{k=0}^{\infty} \|J_k(g_k)\|_{L^2(\mathbf{P})}^2$$

11. To extend  $g_n$  from  $S_n$  to  $[0, T]^n$ , we put

$$g_n(t_1, \dots, t_n) = 0, \quad (t_1, \dots, t_n) \in [0, T]^n \setminus S_n$$

and define  $f_n = \hat{g}_n$ , i.e., the symmetrization of  $g_n$ .

Then,

$$I_n(f_n) = n!J_n(f_n) = n!J_n(\hat{g}_n) = J_n(g_n)$$

and the result follows.



# THE MALLIAVIN DERIVATIVE

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## THE MALLIAVIN DERIVATIVE

1. Using the Wiener-Itô Chaos Expansion, it is quite natural to define the derivative of a random variable.
2. But for this to make sense, it is necessary to restrict the definition to a suitable context as follows.

## THE MALLIAVIN DERIVATIVE

**Definition 7.** Let  $F \in L^2(\mathbf{P})$  be  $\mathcal{F}_t$ -measurable with Wiener-Itô Chaos Expansion  $F = \sum_{n=0}^{\infty} I_n(f_n)$ .

1. We say that  $F \in \mathbf{D}_{1,2}$  if

$$\|F\|_{\mathbf{D}_{1,2}}^2 := \sum_{n=0}^{\infty} n! \|f_n\|_{L^2([0,T]^n)}^2 < \infty$$

2. If  $F \in \mathbf{D}_{1,2}$ , we define the **Malliavin derivative**  $D_t F$  of  $F$  at time  $t$  as

$$D_t F = \sum_{n=1}^{\infty} n I_{n-1}(f_n(\cdot, t)), \quad t \in [0, T]$$

in which  $I_{n-1}(f_n(\cdot, t))$  is the  $(n-1)$ -fold iterated integral of  $f_n(t_1, \dots, t_{n-1}, t)$  with respect to the first  $n-1$  variables, and  $t_n = t$  as a parameter.

## THE MALLIAVIN DERIVATIVE

The restriction to  $\mathbf{D}_{1,2}$  ensures that the Malliavin derivative is well-defined in  $L^2$ .

**Remark 8.** If  $F \in \mathbf{D}_{1,2}$ , then

$$\begin{aligned}\|D.F\|_{L^2(\mathbf{P} \times \lambda)}^2 &= \mathbf{E} \left[ \int_0^T (D_t F)^2 dt \right] = \sum_{n=1}^{\infty} \int_0^T n^2 (n-1)! \|f_n(\cdot, t)\|_{L^2([0,T]^n)}^2 dt \\ &= \sum_{n=1}^{\infty} n n! \|f_n\|_{L^2([0,T]^n)}^2 = \|F\|_{\mathbf{D}_{1,2}}^2 < \infty\end{aligned}$$

Therefore,  $D.F = D_t F$  is well-defined in  $L^2(\mathbf{P} \times \lambda)$ .

## CLOSABILITY OF THE MALLIAVIN DERIVATIVE [1]

**Theorem 9 (Closability of Malliavin Derivative).** Suppose that  $F \in L^2(\mathbf{P})$  and  $F_k \in \mathbf{D}_{1,2}$ ,  $k = 1, 2, \dots$ , satisfy

- a)  $F_k \rightarrow F$  as  $k \rightarrow \infty$  in  $L^2(\mathbf{P})$ ,
- b)  $(D_t F_k)_{k=1}^\infty$  converges in  $L^2(\mathbf{P} \times \lambda)$ .

Then  $F \in \mathbf{D}_{1,2}$  and  $D_t F_k \rightarrow D_t F$  in  $L^2(\mathbf{P} \times \lambda)$ .

*Proof.*

1. Write the Wiener-Itô Expansion of  $F_k$  and  $F$ . Let

$$F = \sum_{n=0}^{\infty} I_n(f_n), \quad F_k = \sum_{n=0}^{\infty} I_n(f_n^{(k)})$$

2. Using (a), we have that  $f_n^{(k)} \rightarrow f_n$  as  $k \rightarrow \infty$  in  $L^2(\lambda^n)$  for all  $n$ .



## CLOSABILITY OF THE MALLIAVIN DERIVATIVE [2]

3. By (b),

$$\sum_{n=1}^{\infty} nn! \|f_n^{(k)} - f_n^{(j)}\|_{L^2(\lambda^n)}^2 = \|D_t F_k - D_t F_j\|_{L^2(\mathbf{P} \times \lambda)}^2 \longrightarrow 0, \quad j, k \rightarrow \infty$$

4. Using Fatou's Lemma,

$$\lim_{k \rightarrow \infty} \sum_{n=1}^{\infty} nn! \|f_n^{(k)} - f_n\|_{L^2(\lambda^n)}^2 \leq \lim_{k \rightarrow \infty} \liminf_{j \rightarrow \infty} \sum_{n=1}^{\infty} nn! \|f_n^{(k)} - f_n^{(j)}\|_{L^2(\lambda^n)}^2 = 0$$

5. Thus,  $F \in \mathbf{D}_{1,2}$  and  $D_t F_k \rightarrow D_t F$  in  $L^2(\mathbf{P} \times \lambda)$ .



## CHAIN RULE [1]

In practice, how do we compute the Malliavin derivative? The following deduction will often help.

1. Suppose that  $f_n(t_1, \dots, t_n) = f(t_1) \cdots f(t_n)$ .
2. Let us write  $D_t I_n(f_n)$  using Hermite polynomials

$$\begin{aligned} D_t I_n(f_n) &= n I_{n-1}(f_n(\cdot, t)) \\ &= n I_{n-1}(f^{\otimes(n-1)}) f(t) \\ &= n \|f\|^{n-1} h_{n-1} \left( \frac{\theta}{\|f\|} \right) f(t) \end{aligned}$$

3. Then, using that  $h'_n(x) = n h_{n-1}(x)$ ,

$$D_t h_n \left( \frac{\theta}{\|f\|} \right) = h'_n \left( \frac{\theta}{\|f\|} \right) \frac{f(t)}{\|f\|}$$

## CHAIN RULE [2]

4. From here, we extract two useful identities. For  $n = 1$ , we have

$$D_t \int_0^T f(s) dW(s) = f(t)$$

and for  $n > 1$ , using induction,

$$D_t \left( \int_0^T f(s) dW(s) \right)^n = n \left( \int_0^T f(s) dW(s) \right)^{n-1} f(t)$$

## CHAIN RULE

Let  $\mathbf{D}_{1,2}^0$  be the set of  $F \in L^2(\mathbf{P})$  whose chaos expansion has only finitely many items.

**Theorem 10 (Product Rule).** *If  $F_1, F_2 \in \mathbf{D}_{1,2}^0$ , then  $F_1, F_2 \in \mathbf{D}_{1,2}$  and  $F_1 F_2 \in \mathbf{D}_{1,2}$  and*

$$D_t(F_1 F_2) = F_1 D_t F_2 + F_2 D_t F_1$$

*Proof.* It is clear that  $F_1, F_2 \in \mathbf{D}_{1,2}$ . To prove the second claim, notice that Gaussian random variables have finite moments.

Let  $\{\xi_i\}_{i=1}^\infty$  be an orthogonal basis of  $L^2([0, T]^n)$ . Take  $F_k^{(n)}$  as a linear combination of iterated integrals of the tensor product of  $\xi_i$ .

By the Theorem 5, we have the result for  $F_k^{(n)}$ . Choose sequence  $F_k^{(n)} \rightarrow F_k$  and  $D_t F_k^{(n)} \rightarrow D_t F_k$  by closability. □

## CHAIN RULE

**Theorem 11 (Chain Rule).** Let  $G \in \mathbf{D}_{1,2}$  and  $g \in C^1(\mathbf{R})$  with bounded derivative. Then  $g(G) \in \mathbf{D}_{1,2}$  and

$$D_t g(G) = g'(G) D_t G$$

*Proof.* Uses techniques from White Noise Theory, so we skip. □

## CONSEQUENCES

What happens when we take the conditional expectation of

1. The Itô integral of a function in  $L^2([0, T])$ ?
2. The Itô integral of an  $\mathbf{F}$ -adapted process?
3. An iterated integral?

After answering these questions, we look at what happens when we take the Malliavin derivative of a conditional expectation.

## CONSEQUENCES

**Definition 12.** Let  $G$  be a Borel set in  $[0, T]$ . We define  $\mathcal{F}_G$  to be the completed  $\sigma$ -algebra generated by all random variables of the form

$$F = \int_0^T \chi_A(t) dW(t)$$

for all Borel sets  $A \subseteq G$ .

## CONSEQUENCES [1]

**Lemma 13.** For any  $g \in L^2([0, T])$  we have

$$\mathbf{E} \left[ \int_0^T g(t) dW(t) \mid \mathcal{F}_G \right] = \int_0^T \chi_G(t) g(t) dW(t)$$

*Proof.* The first step is to prove that  $\int_0^T \chi_G(t) g(t) dW(t)$  is  $\mathcal{F}_G$ -measurable. Since continuous functions are dense in  $L^2([0, T])$ , assume that  $g$  is continuous. Then

$$\int_0^T \chi_G(t) g(t) dW(t) = \lim_{\Delta t_i \rightarrow 0} \sum_{i=0}^n g(t_i) \int_{t_i}^{t_{i+1}} \chi_G(t) dW(t)$$

with the limit in  $L^2(\mathbf{P})$ . And we can take a subsequence which converges almost surely.



## CONSEQUENCES [2]

Now we prove that

$$\mathbf{E} \left[ F \int_0^T g(t) \, dW(t) \right] = \mathbf{E} \left[ F \int_0^T \chi_G(t) g(t) \, dW(t) \right]$$

in which  $F$  is a bounded  $\mathcal{F}_G$ -measurable random variable. We may assume  $F = \int_0^T \chi_A(t) \, dW(t)$  for  $A \subseteq G$ . Applying Itô Isometry, we have the result.  $\square$

## CONSEQUENCES

**Lemma 14.** Let  $G \subseteq [0, T]$  be a Borel set and  $v(t)$  be a stochastic process such that

1.  $v(t)$  is measurable with respect to  $\mathcal{F}_t \cap \mathcal{F}_G = \mathcal{F}_{[0,t] \cap G}$  for all  $t \in [0, T]$ .
2.  $\mathbf{E} \left[ \int_0^T v^2(t) dt \right] < \infty$ .

Then the following integral is  $\mathcal{F}_G$ -measurable:

$$\int_G v(t) dW(t)$$

*Proof.* Consider  $v$  as an elementary process and integrate. The general case follows from approximation. □

## CONSEQUENCES

**Lemma 15.** Let  $u(t)$  be an  $\mathbf{F}$ -adapted stochastic process in  $L^2(\mathbf{P} \times \lambda)$ . Then

$$\mathbf{E} \left[ \int_0^T u(t) dW(t) \mid \mathcal{F}_G \right] = \int_G \mathbf{E}[u(t) \mid \mathcal{F}_G] dW(t)$$

*Proof.* By the lemma 14, we have that  $\int_G \mathbf{E}[u(t) \mid \mathcal{F}_G] dW(t)$  is  $\mathcal{F}_G$ -measurable.

Our goal is to verify

$$\mathbf{E} \left[ \int_0^T u(t) dW(t) \right] = \mathbf{E} \left[ \int_G \mathbf{E}[u(t) \mid \mathcal{F}_G] dW(t) \right]$$

for  $F = \int_A dW(t)$  and  $A \subseteq G$  Borel. Apply Itô Isometry to both sides of the equation and use a density argument.



## CONSEQUENCES

**Theorem 16.** Let  $f_n \in \hat{L}^2([0, T]^n)$ . Then  $\mathbf{E}[I_n(f_n) \mid \mathcal{F}_G] = I_n[f_n \chi_G^{\otimes n}]$ .

*Proof.* By induction on  $n$  and the lemma 15.



## CONSEQUENCES

**Theorem 17.** If  $F \in \mathbf{D}_{1,2}$ , then  $\mathbf{E}[F \mid \mathcal{F}_G] \in \mathbf{D}_{1,2}$  and

$$D_t \mathbf{E}[F \mid \mathcal{F}_G] = \mathbf{E}[D_t F \mid \mathcal{F}_G] \chi_G(t)$$

*Proof.*

- If  $F = I_n(f_n)$ , then the result follows from the Theorem 16.
- More generally, if  $F = \sum_{n=0}^{\infty} I_n(f_n) \in \mathbf{D}_{1,2}$ , we define  $F_k = \sum_{n=0}^k I_n(f_n)$ .
- Then  $F_k \rightarrow F$  in  $L^2(\Omega)$  and  $D_t F_k \rightarrow D_t F$  in  $L^2(\mathbf{P} \times \lambda)$  as  $k \rightarrow \infty$ .
- Using the previous case, we have  $D_t \mathbf{E}[F_k \mid \mathcal{F}_G] = \mathbf{E}[D_t F_k \mid \mathcal{F}_G] \chi_G(t)$  for all  $k$ . Taking the limit in  $L^2(\mathbf{P} \times \lambda)$ , we have the result.



## CONSEQUENCES

**Corollary 18.** Let  $u(s)$  be an  $\mathbf{F}$ -adapted stochastic process such that  $u(s) \in \mathbf{D}_{1,2}$  for all  $s \in [0, T]$ . Then

1.  $D_t u(s), s \in [0, T]$ , is  $\mathbf{F}$ -adapted for all  $t$ .
2.  $D_t u(s) = 0$  for  $t > s$ .

*Proof.* Apply the Theorem 17 to  $D_t u(s)$ .



# THE SKOROHOD INTEGRAL

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## THE SKOROHOD INTEGRAL

1. The Skorohod integral is an extension of the Itô integral for integrands that, not necessarily, are **F**-adapted. If the integrand is **F**-adapted, then they coincide.
2. **Duality formula:** the Malliavin derivative is the adjoint operator of the Skorohod integral, i.e.,  $\langle \delta(u), F \rangle_{L^2(\mathbf{P})} = \langle u, D.F \rangle_{L^2(\mathbf{P} \times \lambda)}$ , where  $\delta(u)$  is the Skorohod integral of  $u$ .



## THE SKOROHOD INTEGRAL

1. Take  $u(t)$  a measurable random variable from a stochastic process  $u(x, t)$  in  $L^2(\mathbf{P})$ .
2. Write the Chaos Expansion  $u(t) = \sum_{n=0}^{\infty} I_n(f_{n,t})$  for each  $t \in [0, T]$ . This gives us symmetric functions  $f_{n,t}(t_1, \dots, t_n)$ .
3. Since  $f_{n,t}(t_1, \dots, t_n)$  also depends on  $t$ , we can write  $f_n(t_1, \dots, t_n, t_{n+1})$ , with  $t_{n+1} = t$ , and take its symmetrization  $\hat{f}_n$ .
4. Define the **Skorohod Integral** as

$$\delta(u) = \int_0^T u(t) \delta W(t) = \sum_{n=0}^{\infty} I_{n+1}(\hat{f}_n)$$

## THE CLARK-OCONE FORMULA

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## THE CLARK-OCONE FORMULA [1]

**Theorem 19 (The Clark-Ocone Formula).** Let  $F \in \mathbf{D}_{1,2}$  be  $\mathcal{F}_T$ -measurable.

Then

$$F = \mathbf{E}[F] + \int_0^T \mathbf{E}[D_t F \mid \mathcal{F}_t] dW(t)$$

*Proof.* The idea is to write the Chaos Expansion of  $F$  and compute the integral on the right hand side.

Let

$$F = \sum_{n=0}^{\infty} I_n(f_n)$$

be the Wiener-Itô chaos expansion of  $F$ .

## THE CLARK-OCONE FORMULA [2]

Then

$$\begin{aligned}\int_0^T \mathbf{E}[D_t F \mid \mathcal{F}_t] dW(t) &= \int_0^T \mathbf{E} \left[ D_t \sum_{n=0}^{\infty} I_n(f_n) \mid \mathcal{F}_t \right] dW(t) \\ &= \int_0^T \mathbf{E} \left[ \sum_{n=1}^{\infty} n I_{n-1}(f_n(\cdot, t)) \mid \mathcal{F}_t \right] dW(t) \\ &= \int_0^T \sum_{n=1}^{\infty} n \mathbf{E} [I_{n-1}(f_n(\cdot, t)) \mid \mathcal{F}_t] dW(t)\end{aligned}$$

Using that  $\mathbf{E}[I_n(f_n) \mid \mathcal{F}_G] = I_n[f_n \chi_G^{\otimes n}]$  (Theorem 16), we have

## THE CLARK-OCONE FORMULA [3]

$$\begin{aligned}\int_0^T \sum_{n=1}^{\infty} n \mathbf{E} [I_{n-1}(f_n(\cdot, t)) \mid \mathcal{F}_t] dW(t) &= \int_0^T \sum_{n=1}^{\infty} n I_{n-1}(f_n(\cdot, t)) \chi_{[0,t]}^{\otimes(n-1)}(\cdot) dW(t) \\&= \int_0^T \sum_{n=1}^{\infty} n(n-1)! J_{n-1}(f_n(\cdot, t)) \chi_{[0,t]}^{\otimes(n-1)}(\cdot) dW(t) \\&= \sum_{n=1}^{\infty} n! J_n(f_n) = \sum_{n=1}^{\infty} I_n(f_n) \\&= \sum_{n=0}^{\infty} I_n(f_n) - I_0(f_0) = F - \mathbf{E}[F]\end{aligned}$$



## WHAT IF WE CHANGE THE MEASURE?

Before stating the Clark-Ocone formula under change of measure, let us recall the Girsanov theorem and Novikov's criterion. The processes  $(u_t)$ ,  $(Z_t)$  and  $(\tilde{W}_t)$  defined in them will be used throughout the section.

## WHAT IF WE CHANGE THE MEASURE?

**Theorem 20 (Girsanov).** Let  $(u_t)$  be an adapted process satisfying  $\int_0^T u_s^2 ds < \infty$  a.s. and such that the process  $(Z_t)$  given by

$$Z_t = \exp \left( - \int_0^t u_s dW_s - \frac{1}{2} \int_0^t u_s^2 ds \right)$$

is a martingale.

Then, under the probability  $Q = \mathbf{P}^Z$  with density  $Z_T$  with respect to  $\mathbf{P}$ , the process  $(\tilde{W}_t)$  defined by

$$\tilde{W}_t = W_t + \int_0^t u_s ds$$

is an  $(\mathcal{F}_t)$ -Brownian motion.

*Proof.* See, e.g., [S<sup>+</sup>04, Theorem 5.2.3].



## WHAT IF WE CHANGE THE MEASURE?

**Remark 21 (Novikov's criterion).** *If*

$$\mathbf{E} \left[ \exp \left( \frac{1}{2} \int_0^T u_t^2 \, dt \right) \right] < \infty$$

*then the  $(Z_t)$  in Girsanov theorem is a martingale.*



## WHAT IF WE CHANGE THE MEASURE?

**Theorem 22 (Clark-Ocone Formula Under Change of Measure).** Suppose that  $F \in \mathbf{D}_{1,2}$  is  $\mathcal{F}_T$ -measurable, and that the following conditions are met

1.  $\mathbf{E}_Q[|F|] < \infty$ ;
2.  $\mathbf{E}_Q \left[ \int_0^T |D_t F|^2 dt \right] < \infty$ ;
3.  $\mathbf{E}_Q \left[ |F| \int_0^T \left( \int_0^T D_t u(s) dW(s) + \int_0^T u(s) D_t u(s) ds \right)^2 dt \right] < \infty$ .

Then

$$F = \mathbf{E}_Q[F] + \int_0^T \mathbf{E}_Q \left[ \left( D_t F - F \int_t^T D_t u(s) d\tilde{W}(s) \right) \middle| \mathcal{F}_t \right] d\tilde{W}(t)$$

## WHAT IF WE CHANGE THE MEASURE?

To prove this result, we'll need the Bayes Rule and a lemma.

**Theorem 23 (Bayes Rule).** If  $G \in L^1(Q)$ , then

$$\mathbf{E}_Q[G \mid \mathcal{F}_t] = \frac{\mathbf{E}[Z(T)G \mid \mathcal{F}_t]}{Z(t)}$$

*Proof.* Let  $A \in \mathcal{F}_t$ . Then

$$\begin{aligned}\mathbf{E}_Q \left[ \chi_A \frac{\mathbf{E}[Z(T)G \mid \mathcal{F}_t]}{Z(t)} \right] &= \mathbf{E}[\chi_A \mathbf{E}[Z(T)G \mid \mathcal{F}_t]] \\ &= \mathbf{E}[\chi_A Z(T)G] = \mathbf{E}_Q[\chi_A G]\end{aligned}$$



## WHAT IF WE CHANGE THE MEASURE? [1]

### **Lemma 24.**

$$D_t(Z(T)F) = Z(T) \left[ D_t F - F \left( u(t) + \int_t^T D_t u(s) d\tilde{W}(s) \right) \right]$$

*Proof.* We use the following result

$$D_t \left( \int_0^T u(s) dW(s) \right) = \int_t^T D_t u(s) dW(s) + u(t)$$

Applying this fact and the chain rule to  $D_t Z(T)$  yields

## WHAT IF WE CHANGE THE MEASURE? [2]

$$\begin{aligned} D_t Z(T) &= Z(T) \left[ -D_t \int_0^T u(s) dW(s) - \frac{1}{2} D_t \int_0^T u^2(s) ds \right] \\ &= Z(T) \left[ - \int_t^T D_t u(s) dW(s) - u(t) - \int_0^T u(s) D_t u(s) ds \right] \\ &= Z(T) \left[ - \int_t^T D_t u(s) d\tilde{W}(s) - u(t) \right] \end{aligned}$$



## WHAT IF WE CHANGE THE MEASURE? [1]

Now we're ready to prove Theorem 22.

*Proof.* Define  $Y(t) = \mathbf{E}_Q[F \mid \mathcal{F}_t]$  and  $\Lambda(t) = Z^{-1}(t)$ . Notice that

$$\begin{aligned}\Lambda(t) &= \exp \left( \int_0^t u(s) dW_s + \frac{1}{2} \int_0^t u^2(s) ds \right) \\ &= \exp \left( \int_0^t u(s) d\tilde{W}_s - \frac{1}{2} \int_0^t u^2(s) ds \right)\end{aligned}$$

Using the corollary 23,

$$Y_t = \Lambda(t) \mathbf{E}[Z(T)F \mid \mathcal{F}_t]$$

## WHAT IF WE CHANGE THE MEASURE? [2]

Applying the Clark-Ocone formula,

$$Y_t = \Lambda(t) \left[ \mathbf{E}[\mathbf{E}[Z(T)F \mid \mathcal{F}_t]] + \int_0^T \mathbf{E}[D_s \mathbf{E}[Z(T)F \mid \mathcal{F}_t] \mid \mathcal{F}_s] dW(s) \right]$$

Simplifying and using the proposition 17,

$$Y_t = \Lambda(t) \left[ \mathbf{E}[Z(T)F] + \int_0^T \mathbf{E}[D_s(Z(T)F) \mid \mathcal{F}_s] dW(s) \right] = \Lambda(t)U(t)$$

where we defined

$$U(t) = \mathbf{E}[Z(T)F] + \int_0^T \mathbf{E}[D_s(Z(T)F) \mid \mathcal{F}_s] dW(s)$$

## WHAT IF WE CHANGE THE MEASURE? [3]

Apply Itô formula to  $\Lambda(t)$ ,

$$d\Lambda(t) = \Lambda(t)u(t) d\tilde{W}(t)$$

By the lemma 24, using the change of measure and the expression above,

$$\begin{aligned} dY(t) &= \Lambda(t)\mathbf{E} \left[ D_t(Z(T)F) \mid \mathcal{F}_t \right] dW(t) + \Lambda(t)u(t)U(t)d\tilde{W}(t) \\ &\quad + \Lambda(t)u(t)\mathbf{E} \left[ D_t(Z(T)F) \mid \mathcal{F}_t \right] dW(t)d\tilde{W}(t) \\ &= \Lambda(t)\mathbf{E} \left[ D_t(Z(T)F) \mid \mathcal{F}_t \right] d\tilde{W}(t) + u(t)Y(t)d\tilde{W}(t) \\ &= \Lambda(t) \left( \mathbf{E} \left[ Z(T)D_tF \mid \mathcal{F}_t \right] - \mathbf{E} \left[ Z(T)Fu(t) \mid \mathcal{F}_t \right] \right. \\ &\quad \left. - \mathbf{E} \left[ Z(T)F \int_t^T D_t u(s) d\tilde{W}(s) \mid \mathcal{F}_t \right] \right) d\tilde{W}(t) + u(t)Y(t)d\tilde{W}(t) \end{aligned}$$

## WHAT IF WE CHANGE THE MEASURE? [4]

Since  $Y(T) = \mathbf{E}_Q[F \mid \mathcal{F}_T] = F$  and  $Y(0) = \mathbf{E}_Q[F \mid \mathcal{F}_0] = \mathbf{E}_Q[F]$ , the result follows.





## EXTENSIONS

- Here we proved the Clark-Ocone formula only for  $\mathbf{D}_{1,2}$ .
- It is possible to extend this result to  $L^2(\mathbf{P})$  and  $\mathcal{G}^*$ .
- Nevertheless, to do that we need White Noise Theory and the Hida-Malliavin derivative, where we work in  $\Omega = \mathcal{S}'(\mathbf{R})$ .
- For a reference, see chapters five and six of [NØP08].

# FINANCIAL APPLICATION

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## FINANCIAL APPLICATION

Consider a market consisting of a riskless asset  $S_0$  with

$$\text{riskless asset} \quad \begin{cases} dS_0(t) = \rho(t)S_0(t) dt \\ S_0(0) = 1 \end{cases} \quad (1)$$

and a risky asset  $S_1$  satisfying

$$\text{risky asset} \quad \begin{cases} dS_1(t) = \mu(t)S_1(t) dt + \sigma(t)S_1(t) dW(t) \\ S_1(0) > 0 \end{cases} \quad (2)$$

where  $\rho(t)$ ,  $\mu(t)$ , and  $\sigma(t) \neq 0$  are  $\mathbf{F}$ -adapted processes.

## FINANCIAL APPLICATION

We also suppose that they satisfy the following condition

$$\mathbf{E} \left[ \int_0^T (|\rho(t)| + |\mu(t)| + \sigma^2(t)) dt \right] < \infty$$

Let  $\theta_0(t)$  and  $\theta_1(t)$  denote the number of units of  $S_0(t)$  and  $S_1(t)$ , respectively. Then the value of the portfolio  $\theta = (\theta_0, \theta_1)$  is  $V^\theta = \theta_0 S_0 + \theta_1 S_1$ . We also suppose that the portfolio is self-financing, i.e.,

$$dV^\theta(t) = \theta_0(t)dS_0(t) + \theta_1(t)dS_1(t) \tag{3}$$

## FINANCIAL APPLICATION

Substituting

$$\theta_0(t) = \frac{V^\theta(t) - \theta_1(t)S_1(t)}{S_0(t)}$$

into (3) and using (1) we have

$$dV^\theta = \rho(t)(V^\theta(t) - \theta_1(t)S_1(t))dt + \theta_1(t)dS_1 \quad (4)$$

Replacing (2),

$$dV^\theta = [\rho(t)V^\theta(t) + (\mu(t) - \rho(t))\theta_1(t)S_1(t)]dt + \sigma(t)\theta_1(t)S_1(t)dW(t) \quad (5)$$

## FINANCIAL APPLICATION

- Our goal is to find a replicating (hedging) portfolio

$$V^\theta(T) = F, \quad \mathbf{P} - a.s. \quad (6)$$

where  $F$  is  $\mathcal{F}_T$ -measurable. For an European call, for example,  
 $F = \max\{S_1 - K, 0\} = (S_1 - K)^+.$

- How much do we need to invest at time  $t = 0$  and which portfolio  $\theta(t)$  should we use? Are  $V^\theta$  and  $\theta$  unique?
- We consider  $(V^\theta(t), \theta_1(t))$  an  $\mathbf{F}$ -adapted process. The equations (4) and (6) form a **backward stochastic differential equation** (BSDE). To find an explicit solution, we can change the measure and apply Clark-Ocone.

## FINANCIAL APPLICATION

Define

$$u(t) = \frac{\mu(t) - \rho(t)}{\sigma(t)}$$

Using the change of measure, we can write

$$\begin{aligned} dV^\theta &= [\rho(t)V^\theta(t) + (\mu(t) - \rho(t))\theta_1(t)S_1(t)]dt + \sigma(t)\theta_1(t)S_1(t)d\tilde{W}(t) \\ &\quad - \sigma(t)\theta_1(t)S_1(t)\sigma^{-1}(t)(\mu(t) - \rho(t))dt \\ &= \rho(t)V^\theta(t)dt + \sigma(t)\theta_1(t)S_1(t)d\tilde{W}(t) \end{aligned} \tag{7}$$

## FINANCIAL APPLICATION

Let

$$U^\theta(t) = e^{-\int_0^t \rho(s) ds} V^\theta(t)$$

Then using (7),

$$dU^\theta(t) = e^{-\int_0^t \rho(s) ds} \sigma(t)\theta_1(t)S_1(t) d\tilde{W}(t)$$

or, equivalently,

$$e^{-\int_0^T \rho(s) ds} V^\theta(T) = V^\theta(0) + \int_0^T e^{-\int_0^t \rho(s) ds} \sigma(t)\theta_1(t)S_1(t) d\tilde{W}(t) \quad (8)$$



## FINANCIAL APPLICATION

Applying the generalized Clark-Ocone formula to

$$G = e^{-\int_0^t \rho(s) ds} F$$

we have

$$G = \mathbf{E}_Q[G] + \int_0^T \mathbf{E}_Q \left[ \left( D_t G - G \int_t^T D_t u(s) d\tilde{W}(s) \right) \middle| \mathcal{F}_t \right] d\tilde{W}(t) \quad (9)$$

Comparing (8) with (9), we have  $V^\theta(0) = \mathbf{E}_Q[G]$  by uniqueness, and the replicating portfolio is given by

$$\theta_1(t) = e^{-\int_0^t \rho(s) ds} \sigma^{-1}(t) S_1^{-1}(t) \mathbf{E}_Q \left[ \left( D_t G - G \int_t^T D_t u(s) d\tilde{W}(s) \right) \middle| \mathcal{F}_t \right] \quad (10)$$

## FINANCIAL APPLICATION

In particular, if  $\rho$  and  $\mu$  are constants, and  $\sigma(t) = \sigma \neq 0$ , then

$$u(t) = u = \frac{\mu - \rho}{\sigma}$$

is also constant, whence  $D_t u = 0$ . Then the equation (10) simplifies to

$$\theta_1(t) = e^{\rho(t-T)} \sigma^{-1} S_1^{-1}(t) \mathbf{E}_Q[D_t F \mid \mathcal{F}_t]$$

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