

# ① Properties of Brownian Motion and Markov Processes.

We now come back to Brownian Motion and discuss several important features, with generalizations to other processes where appropriate.

1) Wiener Measure on  $(C[0,\infty), \mathcal{B}(C[0,\infty)))$

using Kolmogorov-Donelli and Kolmogorov - Čentsov we established existence of B.M. on the probability space  $(\Omega^{(0,\infty)}, \mathcal{B}(\Omega^{(0,\infty)}))$  where  $\mathcal{B}(\Omega^{(0,\infty)})$  is generated by the cylinder sets.

- we can also think of Brownian Motion through its law.

(2)

Let  $C([0, \infty))$  denote the space of continuous functions on  $(0, \infty)$ .

Define the metric

$$\rho(w_1, w_0) = \sum_{n=1}^{\infty} 2^{-n} (1 \wedge \max_{x \in [0, n]} |w_1(x) - w_0(x)|)$$

facts: i)  $(C([0, \infty)), \rho)$  is a complete, separable metric space

ii) With

$$\mathcal{C} = \left\{ C = \{w \mid (w_{x_1}, \dots, w_{x_n}) \in A\} , n \geq 1, 0 \leq x_1 \leq \dots \leq x_n, A \in \mathcal{B}(\mathbb{R}^n) \right\}$$

$$\mathcal{C}_x = \{ \text{some } w \text{ but } 0 \leq x_1 \leq \dots \leq x_n \leq x \}$$

we have

$$A = \sigma(\mathcal{C}) = \mathcal{B}(C([0, \infty)), \rho)$$

$$A_x = \sigma(\mathcal{C}_x) = \mathcal{B}_x(C([0, \infty)), \rho)$$

$\uparrow$  Basic sets on  $[0, x]$ .

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Then, if  $B$  is a B.N. (one-dim) on space  $(\Omega, \mathcal{F}, P)$  then the law of  $B$  is a measure on  $(C[0, \omega], \mathcal{B}(C[0, \omega]))$  which we call Wiener measure  $P^*, P^\circ$  or  $W$ . (in various settings).

Specifically, if we consider the probability space  $(\Omega, \mathcal{F}, P) = (C[0, \omega], \mathcal{B}(C[0, \omega]), P^*)$

then with

$$X_t(\omega) = \omega_t \quad \text{"coordinate mapping"}$$

$$\mathbb{F} = \mathbb{F}^X \quad \text{"natural filtration"}$$

we have that  $X$  is a B.N. under  $P^*$ .

2) d-dim. B.N. Revisited.

Recall:  $B = (B^1, \dots, B^d)$  is a d-dim B.N. with initial distribution  $\mu$  if.

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$$1) B_0 \sim \mu$$

- 2)  $\forall 0 \leq s < t, B_t - B_s$  is  $\mathcal{N}$  of  $\sigma(B_{t-s})$   
 and b) normally distributed with mean  
 $\vec{0}$  and covariance  $(t-s)\mathbf{I}_d$ .

Constructing  $B$

- one method which will help us when we talk about Markov processes.

- a) start with  $d$  II copies of Wiener measure:

$$\mathcal{P} = C([0, \infty))^d; \quad \mathcal{F} = \mathcal{B}(C([0, \infty))^d)$$

$$P^0 = P_0 \times P_1 \times \dots \times P_d.$$

Then the coordinate mapping process  $B$  is a  $d$ -dim B.N. starting at  $0$ .

- b) fix  $x \in \mathbb{R}^d$ . Define  $P^x$  via

$$P^x(F) = P^0(\{\omega \mid \omega(\cdot) + x \in F\})$$

$$F \in \mathcal{B}(C([0, \infty))^d).$$

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Clearly: Coordinate Mapping process is a d-dim B.M. starting at  $x$ .

$$\text{e.g. } F = \{\tilde{\omega} \mid \tilde{\omega}_x - \tilde{\omega}_z \in A\}.$$

$$\Rightarrow w(\cdot) + x \in F \Rightarrow w(x) - w(z) \in A.$$

$$p^x(F) = p^x(B_x - B_z \in A) \rightarrow \text{Coordinate Mapping}_B$$

$$= p^0(B_x - B_z \in A)$$

c) For  $\mu$  a Borel measure on  $\mathbb{R}^d$ , set

$$p^\mu(F) \triangleq \int_{\mathbb{R}^d} p^x(F) \mu(dx) \quad F \in \mathcal{B}((0, \infty)^d).$$

then  $\beta$  (coordinate mapping) is a d-dim B.M. with initial dist.  $\mu$ . if

$x \mapsto p^x(F)$  is Borel map

from  $\mathbb{R}^d$  to  $[0, 1]$  for each  $F \in \mathcal{B}((0, \infty)^d)$ .

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But,  $X \mapsto p^x(F)$  is Borel mbl.

~~$$\text{e.g. } F = \{\omega \mid (\omega_{x_0} - \omega_x) \in A_n\}.$$~~

e.g.  $F = \{\omega \mid \omega_{x_0} \in \Gamma_0, \omega_1 \in \Gamma_1, \dots, \omega_n \in \Gamma_n\}$

then

$$p^x(F) = \mathbb{1}_{\Gamma_0}(x) \int_{\Gamma_1} \dots \int_{\Gamma_n} p(x_1, x, y_1) p(x_2 - x_1, y_1, y_2) \dots p(x_n - x_{n-1}, y_{n-1}, y_n) dy_n \dots dy_1.$$

$$p(x, y) = \frac{1}{(2\pi)^{1/2}} e^{-\frac{1}{2} |x-y|^2}$$

- clearly Borel mbl.

Result follows from a Dynkin system argument.

- went through this to stress measurability of  $X \mapsto p^x(F)$ .

⑦

## Martingale Property of B.M.

Basic Idea:  $B$ : 1-dm standard

B.M. wrt. some  $(\mathcal{F}_t, \mathbb{P})$ , F.

Suppose we ~~observe~~ are at time  $s$  and want to know about  $B$  at a later time  $t$ .  $B_{t+s} \rightarrow \text{ero.}$

i.e., we want to compute

$$\mathbb{E}[f(B_{t+s}) | \mathcal{F}_s]$$

Now, we know that  $B_{t+s} = B_s + B_{t+s} - B_s$  and  $B_{t+s} - B_s \perp \mathcal{F}_s$ , and that  $B_s$  is  $\mathcal{F}_s$  mbl.

 $\Rightarrow$ 

$$\mathbb{E}[f(B_{t+s}) | \mathcal{F}_s] = \mathbb{E}[f(B_{t+s} - B_s + B_s) | \mathcal{F}_s]$$

so, we should be able to do two things

1) replace  $\mathcal{F}_s$  with  $\sigma(B_s)$

$$B_{t+s} - B_s \perp \mathcal{F}_s \quad (\perp \sigma(B_s))$$

$B_s$  is knowable wrt. smaller  $\sigma$ -alg  $\sigma(B_s)$ .

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- i.e. the whole past does not matter,  
just the present value.

2) "Pretend"  $B_1$  is constant given  $\sigma(B_1)$

so

$$\begin{aligned} \mathbb{E}[f(B_{\Delta+\epsilon}) | \mathcal{B}_s] &= \mathbb{E}[f(B_{\Delta+\epsilon} - B_\Delta + B_\Delta) | \mathcal{B}_s] \\ &= \mathbb{E}[f(B_{\Delta+\epsilon} - B_\Delta + B_\Delta) | B_\Delta] \\ &= g(B_\Delta) \end{aligned}$$

where

$$\begin{aligned} g(y) &\stackrel{\Delta}{=} \mathbb{E}[f(B_{\Delta+\epsilon} - B_\Delta + y)] \\ &= \frac{1}{\sqrt{2\pi\epsilon}} \int_{-\infty}^{\infty} f(y+z) e^{-\frac{z^2}{2\epsilon}} dz. \end{aligned}$$

$$= \int_{-\infty}^{\infty} f(x) \cdot \underbrace{\frac{1}{\sqrt{2\pi\epsilon}} e^{-\frac{(x-y)^2}{2\epsilon}} dx}_{p(x,y)}.$$

$p(x,y)$ : transition density.

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This argument is made precise through the Independence Lemma.

### Independence Lemma.

$X, Y$  r.v.  $Y$  is A mbl,  $X$  is  $\perp\!\!\!\perp$  of  $A$ .

$f$ : bounded Borel mbl function.

Then

$$\begin{aligned} E[f(X+Y) | A] &= E[f(X+Y) | Y] \\ &= g(Y) \end{aligned}$$

for

$$g(y) \triangleq E[f(X+y)].$$

In particular,  $E[f(X+Y) | Y=y] = g(y)$  \* for  $PY^y \neq 0$ . s.e.  $y$  (i.e.  $P(Y \text{ s.t. } *$  does not hold) = 0).

- proof is easy building up from indicators.

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for a general process  $X$ , we say it is Markov if the above statements hold.

Def.

$(\Omega, \mathcal{F}, P^\mu)$ ,  $\mathbb{F}$  given. Say a d-dim adapted process  $X$  is a Markov process with initial dist.  $\mu$  if.

$$1) P^\mu[X_0 \in \Gamma] = \mu(\Gamma) \quad \Gamma \in \mathcal{B}(\mathbb{R}^d).$$

$$2) \text{ for } 0 \leq s < t, \quad \Gamma \in \mathcal{B}(\mathbb{R}^d)$$

$$P^\mu[X_{t+s} \in \Gamma | \mathcal{F}_s]$$

$$= P^\mu[X_{t+s} \in \Gamma | X_s] \quad P^\mu \text{ a.s.}$$

-got rid of past....

As for the second statement, we need some additional definitions. since we don't a-priori know how  $P^\mu$  was built.

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Def:  $(\Omega, \mathcal{F})$ ,  $\mathbb{F}$  given. Also, we have  $\{P^x\}_{x \in \mathbb{R}^d}$  given. Say a  $d$ -dim adapted process  $X_s$  together with the family  $\{P^x\}_{x \in \mathbb{R}^d}$  is a Markov family if.

1) for  $\forall F \in \mathcal{G}$ ,  $x \mapsto P^x(F)$  is

"Universally" measurable

- slight extension of Borel measurability needed when  $\mathcal{G}$  is larger than  $\mathcal{B}(C([0, \infty)^d))$ .

- pg 73.

2)  $P^x[X_0 = x] = 1 \quad \forall x \in \mathbb{R}^d$

3)  $x \in \mathbb{R}^d$ ,  $s \leq t$ ,  $\Pi \in \mathcal{B}(\mathbb{R}^d)$

$$P^x[X_{t+s} \in \Pi | \mathcal{F}_s] = P^x[X_{t+s} \in \Pi | X_s]$$

$P^x$  a.s.

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$$4) \quad x \in \mathbb{R}^d, \quad s \leq t, \quad \Gamma \in \mathcal{B}(\mathbb{R}^d)$$

$$P^x[X_{s+t} \in \Gamma \mid X_s = y]$$

$$= P^y[X_t \in \Gamma]$$

$$P^x X_1^{-1} \text{ a.s. } y$$

$$P^x X_1^{-1}(A) = P^x(X_1 \in A) \quad A \in \mathcal{B}(\mathbb{R}^d).$$

so, we have shown that (at least for  $d=1$ )

- 1)  $d$ -dim B.n. with initial distribution  $\mu$  is a Markov process.
- 2)  $d$ -dim B.n. with measures  $\{P^x\}$  dictating the starting point is a Markov family.

Note: often,  $\Omega = \text{closed}^d$ ,  $\mathcal{F} = \mathcal{B}(\text{closed}^d)$  and  $X_t(a) = w_t$  is the coordinate mapping process.

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Here, the markov family is the  
 measure  $\{\mu_x\}_{x \in \mathbb{N}^d}$ . So, you will often  
 read "Let  $\{\mu_x\}_{x \in \mathbb{N}^d}$  be a Markov  
 process".

- they mean the coordinate process  
 together with  $\{\mu_x\}_{x \in \mathbb{N}^d}$  is a Markov  
 family.

Notes.

i) Markov  $\not\Rightarrow$  Martingale.

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$B_t^2$  is Markov (why?) but not a  
 martingale.

Warning: to show  $B_t^2$  is Markov,  
 you must show

$$E[f(B_{t+s}^2) | \mathcal{F}_s] = g(B_s^2), \text{ not}$$

just  $g(B_s)$  which we already know.

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b) Martingale  $\Rightarrow$  Markov.

- trickier, but heuristically this holds because to get a Markov process we must verify

$$E[f(X_{t+s}) | \mathcal{F}_s] = g(X_s)$$

$\forall$  Borel mbl (bdd)  $f$ ; not just  $f(x) = x$ .

Equivalent Formulations of the Markov Property

- there are many (see p.p. 75  $\rightarrow$  79), we will give one.
  - Let  $(\Omega, \mathcal{F}, \mathbb{P})$ ,  $X$  and  $\{\mathbb{P}^x\}$  be given.
  - assume  $X \mapsto \mathbb{P}^x(f)$  is Borel mbl (or for universally mbl).
  - define, for bdd mbl  $f$
- $$U_t f(x) \triangleq E^x[f(X_t)]$$

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Note that  $U_\epsilon f$  is bdd, Basl (universally) mbl.  $\square$

Prop.

$X_s \{p_x\}$  is flatcar iff

1)  $x \mapsto p_x(f)$  is Basl (universally) mbl.

2)  $p_x[X_0 = x] = 1 \quad \forall x$

3)  $x \in \mathbb{R}^d; A \subseteq \mathbb{R}; \Gamma \in \mathcal{B}(\mathbb{R}^d)$

$$p_x[X_{t+s} \in \Gamma \mid \mathcal{B}_s] = U_\epsilon \mathbb{1}_\Gamma(X_s) \quad p_x \text{ a.s.}$$

Df (assuming  $x \mapsto p_x(f)$  is Basl).

$$p_x[X_{t+s} \in \Gamma \mid X_s = y] = U_\epsilon \mathbb{1}_\Gamma(y) \quad p_x \text{ a.s.}$$

Since  $y \mapsto U_\epsilon \mathbb{1}_\Gamma(y)$  is Basl mbl we know

$$p_x[X_{t+s} \in \Gamma \mid X_s] = U_\epsilon \mathbb{1}_\Gamma(X_s) \quad p_x \text{ a.s.}$$

so 3) holds.

$$\text{If 3) holds, } p_x[X_{t+s} \in \Gamma \mid \mathcal{B}_s] = U_\epsilon \mathbb{1}_\Gamma(X_s)$$

is Basl  $\sigma(X_s)$  mbl so  $p_x[X_{t+s} \in \Gamma \mid \mathcal{B}_s]$

$= p_x[X_{t+s} \in \Gamma \mid X_s]$  and if  $X_s = y$ , this is  $U_\epsilon \mathbb{1}_\Gamma(y)$ .  $\square$