

Lecture notes of the course  
**V3F2/F4F1 - Foundations in Stochastic Analysis**

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# 0 Topics for the oral examination

1. Stopping time, optional sampling
2. Semimartingales, quadratic variation
3. Construction of the Itô integral, Itô-Isometry
4. Itô-Formula
5. Exponential local martingales, Levy char.
6. Strong solutions of SDE
7. Time change, Dubins-Schwarz Theorem
8. Change of measure, Girsanov Theorem

Important.

# 1 Introduction to Stochastic Analysis

## Plan:

- (a) Brownian Motion: the fil rouge of the lecture
- (b) Filtration & Martingales in continuous time
- (c) Continuous semimartingales
- (d) Stochastic Integrals and the Itô Formula
- (e) Stochastic Differential Equations (SDE)
- (f) Brownian Martingale

## Examples

### 1. Population Dynamics

Let  $S_t$  the size of a population at time  $t$  (if  $S_t \gg 1$ : a continuous approximation is ok) and let  $R_t$  the growth rate at time  $t$

$$\frac{dS_t}{dt} = R_t S_t \quad (1.1)$$

If  $R_t = \bar{R}$ , where  $\bar{R}$  is a constant, then  $S_t = S_0 e^{\bar{R}t}$ . If  $R_t$  is random, e.g.

$$R_t = \underbrace{\bar{R}}_{\text{average}} + \underbrace{N_t}_{\text{noiseterm}} \quad (1.2)$$

Question: What is the law of  $S_t$ ? What is a good choice for  $N_t$ ?

### 2. Langevin Equation

$$m \frac{dv_t}{dt} = - \underbrace{\eta}_{\text{viscosity}} v_t + \underbrace{N_t}_{\text{noiseterm}} \quad (1.3)$$

### 3. Stocks

If  $S_t =$  Stockprice at time  $t$  and evolves as

$$\frac{dS_t}{dt} = (R + N_t) S_t \quad (1.4)$$

and if  $\bar{R}$  is the bond rate let  $C_0$  be the portfolio at time  $t = 0$  made by  $A_0$  stocks and  $B_0$  bonds.  
 $\Rightarrow C_t = A_t S_t + B_t e^{\bar{R}t}$ . For a self financing portfolio

$$\Rightarrow dC_t = A_t dS_t + B_t d(e^{\bar{R}t}) \quad (1.5)$$

Question: How much is the fair price of an European Call Option?

Answer: Black Scholes Formula

**But:** 1.4 is not necessarily satisfied by the market.

4. Dirichlet Problems

Let  $f$  be an harmonic function on  $D$  (bounded and regular) and  $f(x) = 0$  on  $\partial D$ .

$$\Rightarrow f(x) = E[f(B_t^x)] \tag{1.6}$$

where  $B_t^x = x + \int_0^t N_s ds$  and  $\tau$  is the time  $t$  when  $B_t^x$  reaches  $\partial D$ .

Goals:

- Understand what is  $N_t$  &  $B_t$
- Work with them

**1. Trial**  $N_t$  should be the continuous analogue of a sequence of iid random variables. We would like to have:

1.  $N_t$  should be independent of  $N_s$  for  $s \neq t$ .
2.  $N_t, t \geq 0$  should all have the same distribution  $\mu$ .
3.  $E[N_t] = 0$ .

$t \equiv$  time is in  $\mathbb{R}$ . Problem (if  $N_t \neq 0$ ): Such an object is not well defined (e.g.  $N_t$  is not measurable (in  $t$ )).

**2. Trial** In examples (1), (2) & (4) we are actually interested in the integral of  $N_t$ . Denote by

$$B_t = \int_0^t N_s ds. \tag{1.7}$$

The 3 conditions become:

(BM1) *Independent increments* For  $0 \leq t_0 < t_1 < \dots < t_n$ : the variables  $B_{t_{k+1}} - B_{t_k}$ , for  $k = 0, \dots, n-1$  are independent.

(BM2)  $B_t$  has *stationary increment*, i.e. the joint distribution of  $(B_{t_1+s} - B_{u_1+s}, \dots, B_{t_n+s} - B_{u_n+s})$  for  $u_k < t_k, k = 1, \dots, n$  is independent of  $s > 0$ .

(BM3)  $E[B_t] = 0$

(BM4) And a normalization  $Var[B_1] = E[B_1^2] = 1$ .

But: (BM1)-(BM4) are not enough to determine the process  $B_t$  uniquely. Thus we add:

(BM5)  $t \mapsto B_t$  is continuous (almost surely).

$B_t$  is called the *Wiener Process* or *Brownian Motion*.

**Lemma 1.1.**

It holds:

$$\forall \varepsilon > 0 \lim_{n \rightarrow \infty} nP(|B_{t+\frac{1}{n}} - B_t| > \varepsilon) = 0 \tag{1.8}$$

*Proof.* Let  $H_n := \sup_{1 \leq k \leq n} |B_{\frac{k}{n}} - B_{\frac{k-1}{n}}|$ . By (BM5)  $H_n$  is almost surely continuous on  $[0, 1]$ .

$$\Rightarrow \forall \varepsilon > 0 \lim_{n \rightarrow \infty} P(H_n > \varepsilon) = 0 \tag{1.9}$$

But:

$$P(H_n > \varepsilon) = 1 - P(H_n < \varepsilon) \quad (1.10)$$

$$\stackrel{BM1}{=} 1 - \prod_{k=1}^n P(|B_{\frac{k}{n}} - B_{\frac{k-1}{n}}| \leq \varepsilon) \quad (1.11)$$

$$\stackrel{BM2}{=}_{B_0=0} 1 - (P(|B_{\frac{1}{n}}| \leq \varepsilon))^n \quad (1.12)$$

$$= 1 - (1 - P(|B_{\frac{1}{n}}| > \varepsilon))^n \quad (1.13)$$

$$\geq 1 - \underbrace{e^{-nP(|B_{\frac{1}{n}}| > \varepsilon)}}_{\leq 1} \quad (1.14)$$

because  $1 - x \leq e^{-x}$ . As we take  $n \rightarrow \infty$  we get

$$\lim_{n \rightarrow \infty} nP(|B_{\frac{1}{n}}| > \varepsilon) = 0 \quad (1.15)$$

Using (BM2) we get the general result by seeing that

$$P(|B_{t+\frac{1}{n}} - B_t| > \varepsilon) = P(|B_{\frac{1}{n}}| > \varepsilon) \quad (1.16)$$

□

What is the distribution of  $B_t$ ?

**Lemma 1.2.**

It holds:

$$\forall t, s \geq 0 : P(B_{t+s} - B_t \in A) = \frac{1}{\sqrt{2\pi s}} \int_A e^{-\frac{x^2}{2s}} dx \quad \forall A \in \mathcal{B}(\mathbb{R}) \quad (1.17)$$

*Proof.* Without loss of generality we can assume  $t = 0$  (because of BM2). Define

$$B_s := \sum_{k=1}^n X_{n,k} \quad (1.18)$$

with  $X_{n,k} = B_{\frac{sk}{n}} - B_{\frac{s(k-1)}{n}}$  are iid R.V. From BM3 it follows  $E[X_{n,k}] = 0$  and from BM4  $Var[B_s] = s$ . As we use the CLT we get

$$\lim_{n \rightarrow \infty} \sum_{k=1}^n X_{n,k} \sim \mathcal{N}(0, s) \quad (1.19)$$

□

New condition:

$$(\widetilde{BM2}) \quad \forall s, t \geq 0 \forall A \in \mathcal{B}(\mathbb{R})$$

$$P(B_{s+t} - B_s \in A) = \frac{1}{\sqrt{2\pi t}} \int_A e^{-\frac{x^2}{2t}} dx \quad (1.20)$$

and  $B_0 = 0$ .

**Definition 1.3.**

A one-dimensional (standard) Brownian-Motion (BM) is a real-valued process in continuous time satisfying (BM1),  $(\widetilde{BM2})$ , (BM5).

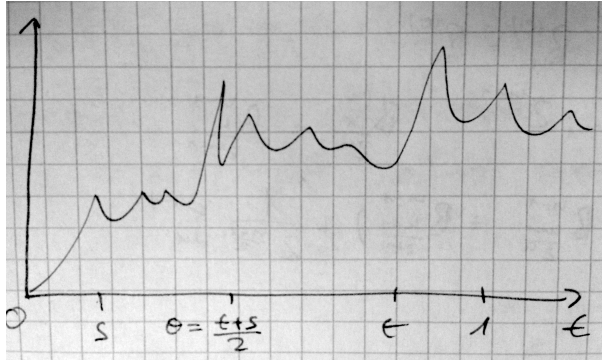
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## 2 Brownian Motion

### 2.1 Construction of the Brownian Motion

Question: Is there an object satisfying Definition 1.3? We construct  $\{B_t, t \in [0, T]\}$ . WLOG  $T = 1$ , otherwise one has to multiply time variables by  $T$  and space variables by  $\sqrt{T}$ .

**Remark:** Let's assume the Brownian Motion is constructed.



Question: Given that  $B_s = x$ ,  $B_t = z$ , what is the distribution of  $B_\theta$ ?

Answer:  $B_\theta \sim \mathcal{N}(\mu = \frac{x+z}{2}, \sigma^2 = \frac{t-s}{4})$ . Using BM1 ( $B_s, B_\theta - B_s$  and  $B_t - B_\theta$  are independent):

$$\mathbb{P}(B_s \in dx, B_\theta \in dy, B_t \in dz) = p(0, x, s)p\left(x, y, \frac{t-s}{2}\right)p\left(y, z, \frac{t-s}{2}\right) dx dy dz \quad (2.1)$$

$$\stackrel{1}{=} p(0, x, s)p(x, z, t-s) \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-\mu)^2}{2\sigma^2}} dx dy dz \quad (2.2)$$

with

$$p(x, y, \tau) := \frac{1}{\sqrt{2\pi\tau}} e^{-\frac{(x-y)^2}{2\tau}} \quad (2.3)$$

Also:

$$P(B_s \in dx, B_t \in dz) = p(0, x, s)p(x, z, t-s) dx dz \quad (2.4)$$

Which leads to

$$P(B_\theta \in dy | B_s = x, B_t = z) = \frac{P(B_\theta \in dy, B_s \in dx, B_t \in dz)}{P(B_s \in dx, B_t \in dz)} \quad (2.5)$$

$$= \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-\mu)^2}{2\sigma^2}} dy \quad (2.6)$$

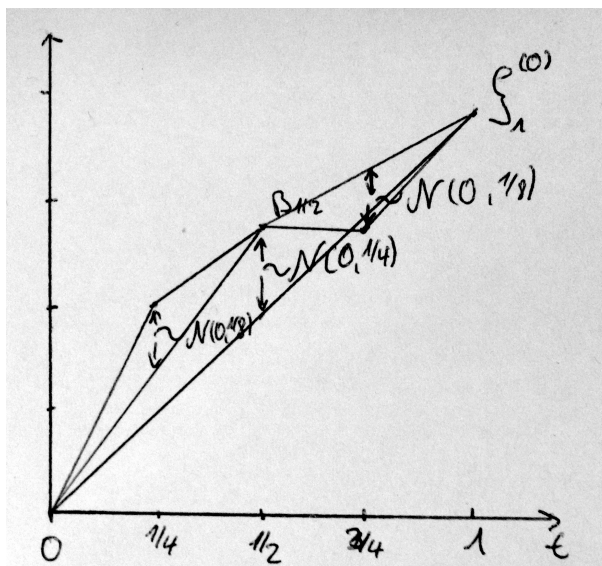
Construction: Let  $\{\xi_k^{(n)}, k \in I(n), n \geq 1\}$  independent R.V.  $\sim \mathcal{N}(0, 1)$  where  $I(n) = \{k \in \mathbb{N} : 1 \leq k \leq 2^n, k \text{ odd}\}$ .

a)  $B_0^{(n)} = 0, B_1^{(0)} = \xi_1^{(0)}$

b) For  $k = 0, \dots, 2^{n-1} : B_{\frac{k}{2^{n-1}}}^{(n)} := B_{\frac{k}{2^{n-1}}}^{(n-1)}$

<sup>1</sup>Algebra





$$c) B_t^{(n)} = \frac{1}{2} \left( B_{\frac{k-1}{2^n}}^{(n-1)} + B_{\frac{k+1}{2^n}}^{(n-1)} \right) + \frac{1}{2^{n/2}} \xi_k^{(n)}$$

Goal: Show that

$$B_t^{(n)} \xrightarrow{n \rightarrow \infty} B_t \quad (2.7)$$

uniformly in  $t$  and that  $B_t$  is almost surely continuous. First we introduce

$$H_1^{(0)} = 1 \quad (2.8)$$

$$H_k^{(n)} = \begin{cases} 2^{\frac{k-1}{2^n}} & , \frac{k-1}{2^n} \leq t < \frac{k}{2^n} \\ -2^{\frac{k-1}{2^n}} & , \frac{k}{2^n} \leq t < \frac{k+1}{2^n} \\ 0 & , \text{otherwise.} \end{cases} \quad (2.9)$$

for  $n \geq 1, k \in I(n)$ . We set

$$S_k^n(t) = \int_0^t H_k^{(n)}(u) du \quad (2.10)$$

For  $n = 0$ :

$$B_t^{(0)}(\omega) = S_1^{(0)}(t) \xi_1^{(0)}(\omega) \quad (2.11)$$

For general  $n$  (e.g. by induction):

$$B_t^{(n)}(\omega) = \sum_{m=0}^n \sum_{k \in I(m)} S_k^{(m)}(t) \xi_k^{(m)}(\omega) \quad (2.12)$$

**Lemma 2.1.**

The sequence of functions

$$\left\{ \{B_t^{(n)}(\omega), 0 \leq t \leq 1\} \right\}_{n \geq 1} \quad (2.13)$$

converges uniformly to a continuous function  $\{B_t(\omega), 0 \leq t \leq 1\}$  for almost every  $\omega$ .

*Proof.* Let  $b_n := \max_{k \in I(n)} |\xi_k^{(n)}|$ .  $\forall x > 0, k, n$  it holds

$$P\left(|\xi_k^{(n)}| > x\right) = \frac{2}{\sqrt{2\pi}} \int_x^\infty e^{-\frac{u^2}{2}} du \quad (2.14)$$

$$\leq \sqrt{\frac{2}{\pi}} \int_x^\infty \frac{u}{x} e^{-\frac{u^2}{2}} du \quad (2.15)$$

$$= \frac{\sqrt{2}}{2} \sqrt{\frac{2}{\pi}} \int_{\frac{x^2}{2}}^\infty \frac{\sqrt{2v}}{x} e^{-v} \sqrt{\frac{2}{v}} \frac{1}{2} dv \quad (2.16)$$

$$= \sqrt{\frac{2}{\pi}} \frac{1}{x} e^{-\frac{x^2}{2}} \quad (2.17)$$

$$\Rightarrow P(b_n > n) = P\left(\bigcup_{k \in I(n)} \{|\xi_k^{(n)}| > n\}\right) \quad (2.18)$$

$$\leq \sum_{k \in I(n)} P(|\xi_k^{(n)}| > n) \quad (2.19)$$

$$= \sum_{k \in I(n)} P(|\xi_1^{(n)}| > n) \quad (2.20)$$

$$\leq \sqrt{\frac{2}{\pi}} e^{-\frac{n^2}{2}} \cdot \underbrace{2^n}_{|I(n)| \leq 2^n} \quad (2.21)$$

$\Rightarrow \sum_{n \geq 1} P(b_n > n) < \infty$ . We can now use Borel-Cantelli I:

$$\exists \tilde{\Omega} \subset \Omega \text{ s.t. } P(\tilde{\Omega}) = 1 \text{ s.t. } \forall \omega \in \tilde{\Omega} \exists n_0(\omega) \text{ s.t. } \forall n \geq n_0(\omega) b_n(\omega) \leq n \quad (2.22)$$

$$\Rightarrow \sum_{n \geq n_0(\omega)} \sum_{k \in I(n)} \underbrace{S_k^{(n)}(t)}_{\leq \frac{1}{2^{\frac{n+1}{2}}}} \underbrace{|\xi_k^{(n)}(\omega)|}_{\leq n} \leq \sum_{n \geq n_0(\omega)} n \frac{1}{2^{\frac{n+1}{2}}} \quad (2.23)$$

because  $\forall t$  at most one  $k \in I(n)$  is s.t.  $S_k^{(n)}(t) > 0$ . Moreover, as  $n_0 \rightarrow \infty$

$$\sum_{n \geq n_0(\omega)} \sum_{k \in I(n)} S_k^{(n)}(t) |\xi_k^{(n)}(\omega)| \rightarrow 0 \quad (2.24)$$

$\Rightarrow \forall \omega \in \tilde{\Omega}$  it holds:  $B_t^{(n)}(\omega)$  converges uniformly in  $t \in [0, 1]$  to a limit  $B_t(\omega)$ . Due to the uniform convergence  $B_t(\omega)$  is continuous.  $\square$

**Lemma 2.2.**

The Haarfunctions  $\{H_k^{(n)}, n \geq 0, k \in I(n)\}$  are a complete orthonormal system of  $L^2([0, 1])$  with the scalarproduct

$$\langle f, g \rangle = \int_0^1 f(x)g(x)dx \quad (2.25)$$

It holds the parseval equation

$$\langle f, g \rangle = \sum_{n \geq 0} \sum_{k \in I(n)} \langle f, H_k^{(n)} \rangle \langle H_k^{(n)}, g \rangle \quad (2.26)$$

$^2u \mapsto \sqrt{2v}$

*Proof.* See exercises. □

If we take  $f = \mathbb{1}_{[0,t]}$ ,  $g = \mathbb{1}_{[0,s]}$ , (2.26) becomes

$$\begin{aligned} \min(s, t) &= \underbrace{\langle f, g \rangle}_{= \int_0^1 \mathbb{1}_{[0,s]}(x) \mathbb{1}_{[0,t]}(x) dx} = \sum_{n \geq 0} \sum_{k \in I(n)} S_k^{(n)}(t) S_k^{(n)}(s) \end{aligned} \quad (2.27)$$

**Lemma 2.3.**

Let

$$B_t := \lim_{n \rightarrow \infty} B_t^{(n)}. \quad (2.28)$$

Then  $B_t$  is a Brownian Motion on  $[0, 1]$ .

*Proof.* We have to show:  $\forall 0 = t_0 < t_1 < \dots < t_n \leq 1$  the R.V.  $B_{t_j} - B_{t_{j-1}}$ ,  $j = 1, \dots, n$  are independent and  $\sim \mathcal{N}(0, t_j - t_{j-1})$ . We will show:

$$\begin{aligned} E \left[ e^{-i \sum_{j=1}^n (\lambda_{j+1} - \lambda_j) B_{t_j}} \right] &= \prod_{j=1}^n e^{-\frac{1}{2} \lambda_j^2 (t_j - t_{j-1})} \\ &= E \left[ e^{-i \sum_{j=1}^n (\lambda_{j+1} - \lambda_j) B_{t_j}} \right] \end{aligned} \quad (2.29)$$

setting  $\lambda_{n+1} = 0 = B_0$ . Now let  $M \in \mathbb{N}$ .

$$E \left[ \exp \left( -i \sum_{j=1}^n (\lambda_{j+1} - \lambda_j) B_{t_j}^{(M)} \right) \right] = E \left[ \exp \left( -i \sum_{j=1}^n (\lambda_{j+1} - \lambda_j) \cdot \sum_{m=0}^M \sum_{k \in I(m)} S_k^{(m)}(t_j) \xi_k^{(m)} \right) \right] \quad (2.30)$$

$$= \prod_{m=0}^M \prod_{k \in I(m)} E \left[ \exp \left( -i \sum_{j=1}^n (\lambda_{j+1} - \lambda_j) S_j^{(m)}(t_j) \xi_k^{(m)} \right) \right] = \Delta \quad (2.31)$$

We use  $\xi \sim \mathcal{N}(0, 1) \Rightarrow E \left[ e^{-i \alpha \xi} \right] = e^{-\frac{1}{2} \alpha^2}$  and get

$$\Delta = \prod_{m=0}^M \prod_{k \in I(m)} \exp \left( -\frac{1}{2} \left( \sum_{j=1}^n (\lambda_{j+1} - \lambda_j) S_k^{(m)}(t_j) \right)^2 \right) \quad (2.32)$$

$$= \exp \left[ -\frac{1}{2} \sum_{m=0}^M \sum_{k \in I(m)} \sum_{j,l=1}^n (\lambda_{j+1} - \lambda_j) (\lambda_{l+1} - \lambda_l) S_k^{(m)}(t_j) S_k^{(m)}(t_l) \right] \quad (2.33)$$

$$= \exp \left[ -\frac{1}{2} \sum_{j,l=1}^n (\lambda_{j+1} - \lambda_j) (\lambda_{l+1} - \lambda_l) \sum_{m=0}^M \sum_{k \in I(m)} S_k^{(m)}(t_j) S_k^{(m)}(t_l) \right] \quad (2.34)$$

if we reconsider (2.27) this becomes

$$\xrightarrow{M \rightarrow \infty} \exp \left[ -\frac{1}{2} \sum_{j,l=1}^n (\lambda_{j+1} - \lambda_j) (\lambda_{l+1} - \lambda_l) \min(t_j, t_l) \right] \quad (2.35)$$

$$= \exp \left[ -\frac{1}{2} \sum_{j=1}^n (\lambda_{j+1} - \lambda_j)^2 t_j - \sum_{j=1}^{n-1} \sum_{l=j+1}^n (\lambda_{j+1} - \lambda_j) (\lambda_{l+1} - \lambda_l) t_j \right] \quad (2.36)$$

$$= \exp \left[ -\frac{1}{2} \sum_{j=1}^n (\lambda_{j+1} - \lambda_j)^2 t_j - \sum_{j=1}^{n-1} (\lambda_{j+1} - \lambda_j) \sum_{l=j+1}^n (\lambda_{l+1} - \lambda_l) t_j \right] = \Delta \quad (2.37)$$

the last sum is a telescoping series (and  $\lambda_{n+1} = 0$ )

$$\Delta = \exp \left[ -\frac{1}{2} \sum_{j=1}^n (\lambda_{j+1} - \lambda_j)^2 t_j + \sum_{j=1}^{n-1} (\lambda_{j+1} - \lambda_j) \lambda_{j+1} t_j \right] \quad (2.38)$$

$$= \exp \left[ -\frac{1}{2} \sum_{j=1}^n t_j (\lambda_{j+1}^2 - 2\lambda_{j+1} \lambda_j + \lambda_j^2 - 2\lambda_{j+1}^2 + 2\lambda_j \lambda_{j+1}) \right] \quad (2.39)$$

$$= \exp \left[ -\frac{1}{2} \sum_{j=1}^n t_j \lambda_j^2 \right] \cdot \exp \left[ \frac{1}{2} \sum_{j=1}^n t_j \lambda_{j+1}^2 \right] \quad (2.40)$$

$$= \exp \left[ -\frac{1}{2} \sum_{j=1}^n t_j \lambda_j^2 \right] \cdot \exp \left[ \frac{1}{2} \sum_{j=1}^n t_{j-1} \lambda_j^2 \right] \quad (2.41)$$

$$= \exp \left[ -\frac{1}{2} \sum_{j=1}^n (t_j - t_{j-1}) \lambda_j^2 \right] \quad (2.42)$$

□

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## 2.2 Trajectories of Brownian Motions

The BM has continuous trajectories, but they are very rough.

### Theorem 2.4.

The trajectories

$$t \mapsto B_t \quad (2.43)$$

- a) have an a.s. unbounded variation.
- b) and so they are nowhere differentiable.

This theorem shows why the object “ $N_t$ ” is difficult to define.

### Lemma 2.5.

Let  $0 = t_0^{(n)} < t_1^{(n)} < \dots < t_n^{(n)} = T$  a family of partitions of  $[0, T]$  s.t.

$$\lim_{n \rightarrow \infty} \max_{0 \leq j \leq n-1} |t_{j+1}^{(n)} - t_j^{(n)}| = 0. \quad (2.44)$$

Then

$$\lim_{n \rightarrow \infty} \sum_{j=0}^{n-1} (B_{t_{j+1}^{(n)}} - B_{t_j^{(n)}})^2 = T \text{ in } L^2. \quad (2.45)$$

<sup>4</sup>iid.

*Proof.* Define  $\Delta B_j := B_{t_{j+1}}^{(n)} - B_{t_j}^{(n)}$ ;  $\Delta t_j := t_{j+1}^{(n)} - t_j^{(n)}$ ,  $\delta_k := \max_j \Delta t_j$ . Calculate

$$\| \sum_j (\Delta B_j)^2 - T \|^2 = E \left[ \left( \sum_j (\Delta B_j)^2 - T \right)^2 \right] \quad (2.46)$$

$$= E \left[ \sum_{i,j} (\Delta B_j)^2 (\Delta B_i)^2 - 2T \sum_i (\Delta B_j)^2 + T^2 \right] \quad (2.47)$$

$$= \sum_i E \left[ (\Delta B_i)^4 \right] + \sum_{i \neq j} E \left[ (\Delta B_j)^2 \right] E \left[ (\Delta B_i)^2 \right] - 2T \sum_i E \left[ (\Delta B_j)^2 \right] + T^2 \quad (2.48)$$

$$= 2 \sum_j (\Delta t_j)^2 \quad (2.49)$$

$$\leq 2\Delta_n \sum_j \Delta t_j = 2\delta_n T \xrightarrow{n \rightarrow \infty} 0 \quad (2.50)$$

by using in (2.48) that we know for  $X \sim \mathcal{N}(0, \sigma^2) \Rightarrow E[X^2] = \sigma^2, E[X^4] = 3\sigma^4$   $\square$

Informally Lemma 2.5 shows with  $T = dt$

$$(dB_t)^2 \approx dt \quad (2.51)$$

$$\Rightarrow dB_t \approx \sqrt{dt} \gg dt \quad (2.52)$$

Therefore  $B_t$  will not be differentiable, since

$$\frac{dB_t}{dt} \rightarrow \infty. \quad (2.53)$$

**Lemma 2.6.**

Let  $X_1, X_2, \dots$  be a sequence of R.V. s.t

$$\lim_{n \rightarrow \infty} \mathbb{E} \left[ |X_k|^2 \right] = 0 \quad (2.54)$$

Then there exists a subsequence  $(X_{n_k})_{k \geq 1}$  s.t.  $X_{n_k} \rightarrow 0$  almost surely.

*Proof.* We choose a subsequence s.t.  $\mathbb{E} \left[ |X_{n_k}|^2 \right] < \frac{1}{k^2}$ . Then  $\sum_{k=1}^{\infty} \mathbb{E} \left[ |X_{n_k}|^2 \right] < \infty$ . By using Chebicev we get

$$\forall m \in \mathbb{N} \sum_{k=1}^{\infty} \mathbb{P} \left( |X_{n_k}| \geq \frac{1}{m} \right) \leq m^2 \mathbb{E} \left[ |X_{n_k}|^2 \right] \quad (2.55)$$

$$\Rightarrow \forall m \in \mathbb{N} \sum_{k=1}^{\infty} \mathbb{P} \left( |X_{n_k}| \geq \frac{1}{m} \right) \leq m^2 \sum_{k=1}^{\infty} \mathbb{E} \left[ |X_{n_k}|^2 \right] < \infty \quad (2.56)$$

$$\Rightarrow \forall m \in \mathbb{N} \mathbb{P} \left( |X_{n_k}| \geq \frac{1}{m} \text{ u.o.} \right) = 0 \quad (2.57)$$

$$\Rightarrow X_{n_k} \rightarrow 0 \text{ a.s.} \quad (2.58)$$

$\square$

*Proof of Theorem 2.4(a).* The previous two lemmas give:  $\exists$  subsequence  $(n_k)_{k \geq 1}$  s.t. for almost all  $\omega \in \Omega$

$$\lim_{k \rightarrow \infty} \sum_{j=1}^{n-1} \left( B_{t_{j+1}}^{(n_k)}(\omega) - B_{t_j}^{(n_k)}(\omega) \right)^2 = T. \quad (2.59)$$

<sup>5</sup>Nach Defintion der  $L^2$ -Norm

Let  $\omega \in \Omega$  be fix s.t.(2.59) holds. Let  $\varepsilon_{n_k} := \max_j |\Delta B_j| \Rightarrow \lim_{k \rightarrow \infty} \varepsilon_{n_k} = 0$  because  $t \mapsto B_t$  is uniformly continuous.

$$\Rightarrow \sum_{j=0}^{n_k-1} |\Delta B_j| \geq \sum_{j=0}^{n_k-1} \frac{1}{\varepsilon_{n_k}} |\Delta B_j|^2 \approx \frac{T}{\varepsilon_{n_k}} \rightarrow \infty \text{ as } k \rightarrow \infty \quad (2.60)$$

□

**Lemma 2.7.**

Let  $(B_t)_{0 \leq t \leq T}$  be a Brownian Motion on  $[0, T]$ . Then,  $\forall c > 0$

$$(cB_{\frac{t}{c}})_{0 \leq t \leq T} \quad (2.61)$$

is a Brownian Motion on  $[0, \frac{T}{c}]$ .

*Proof.* Exercise Sheet 1. □

*Proof of Theorem 2.4(b).* Let

$$X_{n,k} := \max_{j=k, k+1, k+2} |B_{\frac{j}{2^n}} - B_{\frac{j-1}{2^n}}| \quad (2.62)$$

$$\Rightarrow \forall \varepsilon > 0 \mathbb{P}(X_{n,k} \leq \varepsilon) = \mathbb{P}\left(|B_{\frac{1}{2^n}}| \leq \varepsilon\right)^3 \quad (2.63)$$

$$= \mathbb{P}\left(|B_1| \leq 2^{\frac{n}{2}} \varepsilon\right)^3 \quad (2.64)$$

$$\leq (2^{\frac{n}{2}} \varepsilon)^3 \quad (2.65)$$

Now let  $Y_n := \min_{k \leq 2^n T} X_{n,k}$ .

$$\Rightarrow \mathbb{P}(Y_n \leq \varepsilon) \leq T 2^n (2^{\frac{n}{2}} \varepsilon)^3 \quad (2.66)$$

Let  $A := \{\omega \in \Omega \text{ s.t. } t \mapsto B_t(\omega) \text{ is differentiable somewhere}\}$ . For an  $\omega \in A$ ,  $t \mapsto B_t(\omega)$  is in  $t_0(\omega)$  differentiable. Let  $D$  be the derivative.

$$\Rightarrow \exists \delta > 0 \text{ s.t. } \forall t \in [t_0 - \delta, t_0 + \delta] \quad |B_t - B_{t_0}| \leq (|D| + 1)|t - t_0| \quad (2.67)$$

We now choose  $n_0$  big enough s.t.

$$\delta > \frac{1}{2^{n_0-1}}, n_0 > 2(|D| + 1), n_0 > t_0 \quad (2.68)$$

Now for  $\forall n \geq n_0$  choose  $k$  s.t.

$$\frac{k}{2^n} \leq t_0 \leq \frac{k+1}{2^n}. \quad (2.69)$$

Then

$$|t_0 - \frac{j}{2^n}| < \delta \text{ for } j = k, k+1, k+2. \quad (2.70)$$

$$\Rightarrow X_{n,k}(\omega) \leq (|D| + 1) \frac{1}{2^n} \leq \frac{n}{2^n} \quad (2.71)$$

and, since  $n > t_0 > \frac{k}{2^n}$ , also  $Y_n(\omega) \leq X_{n,k}(\omega) \leq \frac{n}{2^n}$ . Therefore  $A \subset A_n := \{Y_n(\omega) \leq \frac{n}{2^n}\}$  for  $n$  large enough and hence also

$$A \subset \liminf_n A_n \quad (2.72)$$

<sup>6</sup>Lemma 2.7

But (2.66) implies

$$\sum_{n \geq 1} \mathbb{P}(A_n) \leq \sum_{n \geq 1} n 2^2 (2^{\frac{n}{2}+1} n 2^{-n})^3 < \infty \quad (2.73)$$

$$\Rightarrow \mathbb{P}\left(\liminf_{n \rightarrow \infty} A_n\right) = 0 \quad (2.74)$$

i.e.  $t \mapsto B_t(\omega)$  is a.s. not differentiable.  $\square$

[16.10.2012]  
[19.10.2012]

**Definition 2.8.**

Let

$$p(x, y, \tau) := \frac{1}{\sqrt{2\pi\tau}} \exp\left(-\frac{(x-y)^2}{2\tau}\right) \quad (2.75)$$

be the Heat-Kernel  $\forall x, y \in \mathbb{R}, \tau > 0$ . A stochastic process  $(B_t)_{0 \leq t \leq T}$  with values in  $\mathbb{R}^d$  is called a  $d$ -dimensional Brownian Motion if

- $B_0 = (0, \dots, 0)$
- The increments are independent and stationary with distribution

$$\mathbb{P}(B_t - B_s \in A) = \int_A p(0, x_1, t-s) \dots p(0, x_d, t-s) dx_1 \dots dx_n \quad (2.76)$$

$$\forall A \in \mathcal{B}(\mathbb{R}^d) \forall 0 \leq s < t \leq T.$$

- The trajectories  $t \mapsto B_t(\omega)$  are continuous for a.e.  $\omega \in \Omega$ .

## 2.3 Stochastic Processes

**Definition 2.9.**

A family  $(X_t)_{t \geq 0}$  is a stochastic process on  $(\Omega, \mathcal{F}, \mathbb{P})$  with values in a measurable space  $(E, \mathcal{S})$  if  $\forall t \geq 0$   $X_t$  is a R.V..  $t$  usually plays the role of time and  $E$  is the space where  $X$  lives (=state space). For all  $\omega \in \Omega$ ,  $t \mapsto X_t(\omega)$  is called a trajectory.

**Definition 2.10.**

Let  $X$  and  $Y$  two stochastic processes (defined on the same probability space and with the same state space). Then

- (a)  $X$  is a modification/version of  $Y$  if

$$\mathbb{P}(X_t = Y_t) = 1 \quad \forall t. \quad (2.77)$$

- (b)  $X$  and  $Y$  are indistinguishable if

$$\mathbb{P}(X_t = Y_t, \forall t \geq 0) = 1. \quad (2.78)$$

It holds  $b) \Rightarrow a)$  but not the other way round.

**Example:**  $\Omega = [0, 1], \mathbb{P}$  the Lebesguemeasure. Define

$$\begin{cases} X_t(\omega) = 0 \\ Y_t(\omega) = \mathbb{1}_{\{t=\omega\}} \end{cases} \quad (2.79)$$

Then,  $\forall t \geq 0$   $\mathbb{P}(X_t = Y_t) = \mathbb{P}(t \neq \omega) = 1$  but  $\mathbb{P}(X_t = Y_t, \forall t \in [0, 1]) = 0$ .

**Lemma 2.11.**

Let  $Y$  be a modification of  $X$ . If  $X$  and  $Y$  have a.s. right-continuous paths (trajectories). Then  $X$  and  $Y$  are indistinguishable.

*Proof.* Let  $\Omega_0 \subset \Omega$  be the set where either  $X$  or  $Y$  are not right continuous. By assumption:  $\mathbb{P}(\Omega_0) = 0$ . For  $q \in \mathbb{Q}_+$  let  $N_q = \{\omega \in \Omega | X_q(\omega) \neq Y_q(\omega)\}$ . Since  $Y$  is a modification of  $X$   $\mathbb{P}(N_q) = 0$ . As  $\mathbb{Q}_+$  is countable also  $\mathbb{P}\left(\bigcup_{q \in \mathbb{Q}_+} N_q\right) = 0 \Rightarrow \mathbb{P}(\Omega_0 \cup \underbrace{\bigcup_{q \in \mathbb{Q}_+} N_q}_{=\tilde{\Omega}}) = 0$ .

Therefore  $\forall \omega \notin \tilde{\Omega} X_t(\omega) = Y_t(\omega) \forall t \in \mathbb{Q}_+$  and as  $X_t(\omega)$  and  $Y_t(\omega)$  are rightcontinuous it holds  $X_t(\omega) = Y_t(\omega) \forall t \geq 0$  and with  $\mathbb{P}(\tilde{\Omega}^c) = 1$  the statement follows.  $\square$

## 2.4 Hölder continuity for Brownian Motion

**Definition 2.12.**

A function  $f : \mathbb{R}_+ \rightarrow \mathbb{R}$  is called  $\gamma$ -Hölder continuous in  $x \geq 0$  if  $\exists \varepsilon > 0, C < \infty$  s.t.

$$|f(x) - f(y)| \leq C|x - y|^\gamma \quad \forall y \geq 0 : |y - x| \leq \varepsilon \quad (2.80)$$

$\gamma$  is called the Hölder-exponent.

**Theorem 2.13** (Kolmogorov-Chentsov).

Let  $(X_t)_{t \geq 0}$  be a stochastic process on  $(\Omega, \mathcal{F}, \mathbb{P})$ ,  $\alpha \geq 1, \beta \geq 0, c > 0$  s.t.

$$\mathbb{E}[|X_t - X_s|^\alpha] \leq C|t - s|^{\beta+1} \quad (2.81)$$

Then there exists a version/modification  $(Y_t)_{0 \leq t \leq T}$  of  $(X_t)_{0 \leq t \leq T}$  for all  $T > 0$  s.t.  $Y$  is  $\gamma$ -Hölder continuous  $\forall \gamma \in (0, \beta/\alpha)$ .

Before we proof this theorem, we will apply it on BM. We have

$$\mathbb{E}[|B_t - B_s|^n] = \frac{(2n)!}{2^n n!} |t - s|^n \quad (2.82)$$

Therefore with  $\alpha = 2n, \beta + 1 = n$  there exists a  $\gamma$ -Hölder-continuous version  $\forall \gamma < \frac{n-1}{2n} \forall n \xrightarrow{\rightarrow \infty} \gamma < 1/2$ .

**Corollary 2.14.**

Let  $B$  be a BM. Then there exists a Version  $\tilde{B}$  s.t.  $\tilde{B}$  is  $\gamma$ -Hölder-continuous for all  $\gamma < \frac{1}{2}$  s.t.

$$\mathbb{P}\left(\sup_{0 \leq t-s \leq h(\omega), 0 \leq s, t \leq T} \frac{|B_t(\omega) - B_s(\omega)|}{|t - s|^\gamma} \leq C\right) = 1 \quad (2.83)$$

where  $h(\omega)$  is a positive R.V. (a.s.).

*Proof of Theorem 2.13.* WLOG  $T = 1$ . The proof consists of 5 claims.

1. claim  $X_s \xrightarrow{P} X_t$  when  $s \rightarrow t$ .

Proof:

$$\forall \varepsilon > 0 \mathbb{P}(|X_t - X_s| \geq \varepsilon) \leq \frac{\mathbb{E}[|X_t - X_s|^\alpha]}{\varepsilon^\alpha} \quad (2.84)$$

$$\leq C \frac{|t - s|^{\beta+1}}{\varepsilon^\alpha} \rightarrow 0 \quad (2.85)$$



2. claim  $\exists \Omega^* \subset \Omega$  with  $\mathbb{P}(\Omega^*) = 1$  s.t.  $\forall \omega \in \Omega^*$

$$\max_{1 \leq k \leq 2^n} |X_{\frac{k}{2^n}}(\omega) - X_{\frac{k-1}{2^n}}(\omega)| < 2^{-\gamma n} \forall n > n^*(\omega), \gamma \in (0, \beta/\alpha) \quad (2.86)$$

Proof: Let  $D_n = \{\frac{k}{2^n}, 0 \leq k \leq 2^n, k \in \mathbb{N}\}$  and  $D = \cup_{n \geq 1} D_n$ . Using (2.85) with  $t = \frac{k}{2^n}$ ,  $s = \frac{k-1}{2^n}$ ,  $\varepsilon = 2^{-\gamma n}$  we get

$$\mathbb{P}\left(|X_{\frac{k}{2^n}} - X_{\frac{k-1}{2^n}}| \geq 2^{-\gamma n}\right) \leq C 2^{-n(\beta+1)} 2^{\alpha \gamma n} \quad (2.87)$$

$$= C 2^{-n(\beta+1-\alpha\gamma)} \quad (2.88)$$

Let  $E_n = \{\omega : \max_{1 \leq k \leq 2^n} |X_{\frac{k}{2^n}} - X_{\frac{k-1}{2^n}}| \geq 2^{-\gamma n}\}$ .

$$\Rightarrow \mathbb{P}(E_n) \leq 2^n C 2^{-n(\beta+1-\alpha\gamma)} \quad (2.89)$$

$$\leq C 2^{-n(\beta-\alpha\gamma)} \quad (2.90)$$

$$\Rightarrow \sum_{n \geq 1} \mathbb{P}(E_n) \leq C \sum_{n \geq 1} \frac{C}{2^{n(\beta-\alpha\gamma)}} < \infty \quad (2.91)$$

whenever  $\gamma < \beta/\alpha$ . Using Borel-Cantelli we get claim 2.

3. claim: For any given  $\omega \in \Omega^*$ ,  $n > n^*(\omega)$ ,  $\forall m \geq n$

$$|X_t(\omega) - X_s(\omega)| \leq 2 \sum_{j=n+1}^m \frac{1}{2^{j\gamma}}, \forall s, t \in D_m, 0 \leq t - s \leq 2^{-n} \quad (2.92)$$

Proof (induction):  $m = n + 1 \Rightarrow t = \frac{k}{2^n}$ ,  $s = \frac{k-1}{2^n}$  follows from claim 2. Now assume that claim 3 holds for  $m = n + 1, \dots, M - 1$ . Choose  $s, t \in D_m$ ,  $s < t$  and define  $t' = \max\{u \in D_{m-1}, u \leq t\}$ ,  $s' = \min\{u \in D_{m-1}, u \geq s\}$ . Therefore  $s \leq s' \leq t' \leq t$ ,  $s' - s \leq 2^{-M}$ ,  $t - t' \leq 2^{-M}$ . Claim 2 gives

$$\Rightarrow |X_{s'}(\omega) - X_s(\omega)| \leq 2^{-\gamma M} \quad (2.93)$$

$$|X_{t'}(\omega) - X_t(\omega)| \leq 2^{-\gamma M} \quad (2.94)$$

By the induction hypothesis:

$$|X_{t'}(\omega) - X_{s'}(\omega)| \leq 2 \sum_{n+1}^{M-1} \frac{1}{2^{\gamma j}} \quad (2.95)$$

and with the triangular inequality

$$|X_s(\omega) - X_t(\omega)| \leq 2 \sum_{j=n+1}^M \frac{1}{2^{\gamma j}} \quad (2.96)$$

4. claim:  $t \mapsto X_t(\omega)$  is uniformly continuous  $\forall \omega \in \Omega^*$ .

Proof: Choose  $s, t \in D$ ,  $0 < t - s < h(\omega) := 2^{-n^*(\omega)}$  and  $n > n^*(\omega)$  s.t.  $2^{-(n+1)} \leq t - s \leq 2^{-n}$ . Then from claim 3

$$|X_t(\omega) - X_s(\omega)| \leq 2 \sum_{j=n+1}^{\infty} \frac{1}{2^{\gamma j}} \quad (2.97)$$

$$= C \frac{1}{2^{\gamma n}} \leq C |t - s|^{\gamma} \quad (2.98)$$

5. step: Define a modification:

$$\tilde{X}_t(\omega) = \begin{cases} X_t(\omega) & , \text{if } \omega \in \Omega^*, t \in D \\ 0 & , \text{if } \omega \notin \Omega^* \end{cases} \quad (2.99)$$

For  $\omega \in \Omega^*, t \notin D$  choose a sequence  $(s_n)_{n \geq 1}$  in  $D$  s.t.  $s_n \rightarrow t$ . From claim 4 we get that  $X_{s_n}$  is a convergent sequence (cauchy-sequence). So we can define

$$\tilde{X}_t(\omega) = \lim_{n \rightarrow \infty} X_{s_n}(\omega) \quad (2.100)$$

$\Rightarrow \tilde{X}_t$  is continuous and satisfies

$$|X_t(\omega) - X_s(\omega)| < C|t - s|^\gamma \quad (2.101)$$

for  $t - s$  small enough. Finally one verify that  $\tilde{X}_t$  is indeed a modification of  $X_t$ .

$$\left. \begin{array}{l} X_{s_n} \xrightarrow{a.s.} \tilde{X}_t \\ X_{s_n} \xrightarrow{P} X_t \end{array} \right\} \Rightarrow X_t \stackrel{a.s.}{=} \tilde{X}_t \quad (2.102)$$

□

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# 3 Filtrations and Stoppingtimes

## 3.1 Filtrations

From now on  $(\Omega, \mathcal{F}, \mathbb{P})$  is always a probability space.

**Definition 3.1** (Filtration).

An increasing family  $\{\mathcal{F}_t, t \geq 0\}$  of  $\sigma$ -algebras of  $\mathcal{F}$  is called a *filtration*, i.e.

$$\mathcal{F}_s \subset \mathcal{F}_t \subset \mathcal{F} \quad \forall 0 \leq s \leq t \leq \infty. \quad (3.1)$$

**Intuition:**  $\mathcal{F}_t$  contains the information, that are known until the time  $t \in [0, \infty)$ .

**Definition 3.2** (Filtered probability space).

$(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$  is called *filtered probability space*.

**Notation:** We define

$$\mathcal{F}_\infty := \sigma(\mathcal{F}_t, t \geq 0) \quad \mathcal{F}_{t+} := \bigcap_{s>t} \mathcal{F}_s \quad (3.2)$$

$$\mathcal{F}_{t-} := \sigma(\mathcal{F}_s, s < t) \text{ the past} \quad \mathcal{F}_{0-} = \{\emptyset, \Omega\} \quad (3.3)$$

Obviously it holds  $\mathcal{F}_{t-} \subset \mathcal{F}_t \subset \mathcal{F}_{t+}$ .

If we have a stochastic process  $X$  on  $(\Omega, \mathcal{F}, \mathbb{P})$  we denote by  $\mathcal{F}_t^X := \sigma(X_s, 0 \leq s \leq t)$  the natural filtration (of  $X$ )

**Definition 3.3.**

If  $\mathcal{F}_t = \mathcal{F}_{t+} \forall t \geq 0$ , then we say that  $(\mathcal{F}_t)_{t \geq 0}$  is *right-continuous*.

$(\mathcal{F}_{t+})_{t \geq 0}$  is always right-continuous.

**Definition 3.4.**

A set  $A$  is called a  $(\mathcal{F}, \mathbb{P})$ -nullset if

$$\exists \tilde{A} \in \mathcal{F} \text{ s.t. } A \subset \tilde{A} \text{ and } \mathbb{P}(\tilde{A}) = 0. \quad (3.4)$$

$(\Omega, \mathcal{F}, \mathbb{P}, (\mathcal{F}_t)_{t \geq 0})$  is called *complete*, if all  $(\mathcal{F}, \mathbb{P})$ -nullsets are in  $\mathcal{F}_0$

**Remark:** • If  $(\Omega, \mathcal{F}, \mathcal{F}_t, \mathbb{P})$  is complete, then every  $(\Omega, \mathcal{F}_t, \mathbb{P})$  is complete.

• The other direction does not hold!

• *Augmentation:* Let  $\mathcal{N} = \{(\mathcal{F}, \mathbb{P})\text{-nullsets}\}$ . Set  $\mathcal{F}' = \sigma(\mathcal{F} \cup \mathcal{N})$ ,  $\mathcal{F}'_t = \sigma(\mathcal{F}_t \cup \mathcal{N})$ . Then  $(\Omega, \mathcal{F}', \mathcal{F}'_t, \mathbb{P})$  is complete.

**Definition 3.5.**

A filtered probability space  $(\Omega, \mathcal{F}, \mathbb{P}, (\mathcal{F}_t)_{t \geq 0})$  is called *standard*, if it is complete and the filtration is right-continuous.

One can extend an filtration s.t. it becomes standard by

- Augmentation of  $\mathcal{F}_t$  and  $\mathcal{F}$ , and
- using  $\mathcal{F}_{t+}$  instead of  $\mathcal{F}_t$ .

## 3.2 Adapted processes

### Definition 3.6.

(i) Let  $X$  be a stochastic process on  $(\Omega, \mathcal{F}, \mathbb{P})$  with values in  $(E, \mathcal{E})$ .

$$\mathcal{F}_t^X := \sigma(X_s : s \leq t) \quad (3.5)$$

is called the *filtration generated by  $X$* .

(ii) A stochastic process  $(X_t)_{t \geq 0}$  is called *adapted* to the filtration  $(\mathcal{F}_t)_{t \geq 0}$  if

$$\mathcal{F}_t^X \subset \mathcal{F}_t \quad \forall t \geq 0, \quad (3.6)$$

i.e. if  $X_t$  is  $\mathcal{F}_t$ -measurable  $\forall t \geq 0$ .

**Example:** a) Let  $B_t$  a standard B; and  $\mathcal{F}_t$  the natural filtration. Then  $X_t = B_{t/2}$  is adapted to  $(\mathcal{F}_t)_{t \geq 0}$  but  $Y_t := B_{2t}$  is not adapted to  $(\mathcal{F}_t)_{t \geq 0}$ .

b) Let  $f \in L^1(\Omega, \mathcal{F}, \mathbb{P})$  and  $(\mathcal{F}_t)_{t \geq 0}$  a filtration, then  $X_t := \mathbb{E}[f | \mathcal{F}_t]$  is adapted to  $(\mathcal{F}_t)_{t \geq 0}$ .

## 3.3 Progressively measurable processes

### Definition 3.7 (Progressively measurable).

A process  $(X_t)_{t \geq 0}$  is called *progressively measurable* (or simply *progressiv*) with respect to a filtration  $(\mathcal{F}_t)_{t \geq 0}$  if  $\forall t \geq 0$  the map

$$X : [0, t] \times \Omega \rightarrow E \quad (3.7)$$

$$(s, \omega) \mapsto X_s(\omega) \quad (3.8)$$

is measurable with respect to  $\mathcal{B}([0, t]) \otimes \mathcal{F}_t$ .

**Remark:** • It holds: *progressively measurable*  $\Rightarrow$  *adapted* but not the otherway round.

- As one can see in Theorem 3.15 we need this property to ensure that the stopped process is again measurable.

### Proposition 3.8.

Let  $(X_t)_{t \geq 0}$  be a stochastic process which is adapted to  $(\mathcal{F}_t)_{t \geq 0}$ . Assume that each trajectory  $t \mapsto X_t(\omega)$  is right-continuous (or left-continuous). Then  $(X_t)_{t \geq 0}$  is progressively measurable.

**Remark:** For a BM there exists a modification that is progressively measurable.

*Proof.* Let  $t > 0$  fixed. We approximate  $X$  by  $X^{(n)}$ . So for  $k = 0, 1, \dots, 2^n - 1, 0 \leq s \leq t$ , set

$$X_s^{(n)}(\omega) := X_{\frac{(k+1)t}{2^n}}(\omega) \text{ for } \frac{kt}{2^n} < s \leq \frac{(k+1)t}{2^n} \quad (3.9)$$

and  $X_0^{(n)}(\omega) := X_0(\omega)$ . Then  $X^{(n)} : (s, \omega) \mapsto X_s^{(n)}(\omega)$  is measurable w.r.t.  $\mathcal{B}([0, t]) \otimes \mathcal{F}_t$ , since this map is equal to  $(s, \omega) \mapsto \sum_{k=0}^{2^n-1} X_{\frac{(k+1)t}{2^n}} \mathbb{1}_{\{\frac{kt}{2^n} < s \leq \frac{(k+1)t}{2^n}\}}$ . But since  $X$  is right-continuous  $\lim_{r \rightarrow \infty} X_s^{(n)}(\omega) = X_s(\omega) \forall (s, \omega) \in [0, t] \times \Omega. \Rightarrow (s, \omega) \mapsto X_s(\omega)$  is also  $\mathcal{B}([0, t]) \otimes \mathcal{F}_t$  measurable.  $\square$

### 3.4 Stopping times

**Definition 3.9** (Stopping time).

A map  $T : \Omega \rightarrow [0, \infty]$  is called a (*strong*) *stopping time* w.r.t.  $(\mathcal{F}_t)_{t \geq 0}$  if  $\forall t \geq 0$

$$\{T \leq t\} = \{\omega \in \Omega : T(\omega) \leq t\} \in \mathcal{F}_t. \quad (3.10)$$

$T$  is called a *weak stopping time* if

$$\{T < t\} \in \mathcal{F}_t. \quad (3.11)$$

If  $T$  is a (weak) stopping time, then  $T$  is measurable w.r.t.  $\mathcal{F}$ .

**Proposition 3.10.**

- Each fixed time  $T = c \geq 0$  is a stopping time.
- Each stopping time is also a weak stopping time.
- If  $(\mathcal{F}_t)_{t \geq 0}$  is a right-continuous filtration, then a weak stopping time is a stopping time.
- $T$  is a stopping time  $\Leftrightarrow X_t = \mathbb{1}_{[0, T)}$  is adapted to the filtration.
- $T$  is a weak stopping time w.r.t.  $(\mathcal{F}_t) \Leftrightarrow T$  is a stopping time w.r.t.  $(\mathcal{F}_{t+})$ .

*Proof.* **ad a)**  $A_t := \{\omega \in \Omega | c \leq t\}$  is either  $\Omega$  or  $\emptyset$ . So  $A_t \in \mathcal{F}_t \forall t$ .

**ad b)**  $\{T < t\} = \underbrace{\cup_{n \geq 1} \{T \leq t - \frac{1}{n}\}}_{\in \mathcal{F}_{t - \frac{1}{n}}} \in \mathcal{F}_t$

**ad c)** Let  $T$  be a weak stopping time. Recall that  $\mathcal{F}_t = \mathcal{F}_{t+} = \cap_{s > t} \mathcal{F}_s$ . Then

$$\forall m \geq 1 \{T \leq t\} = (\cap_{n \geq m} \underbrace{\{T < t + \frac{1}{n}\}}_{\in \mathcal{F}_{t + \frac{1}{n}} \subset \mathcal{F}_{t + \frac{1}{m}}}) \in \mathcal{F}_{t + \frac{1}{m}} \quad (3.12)$$

$$\Rightarrow \{T \leq t\} \in \mathcal{F}_{t + \frac{1}{m}} \forall m \Rightarrow \{T \leq t\} \in \mathcal{F}_{t+} \Rightarrow \{T \leq t\} \in \mathcal{F}_t \quad (3.13)$$

**ad d)**  $\{T \leq t\} = \{X_t = 0\} \in \mathcal{F}_t$  since  $X_t$  is adapted.  $\square$

**Proposition 3.11.**

- Let  $T$  be a weak stopping time and  $\vartheta > 0$  a constant  $\Rightarrow T + \vartheta$  is a stopping time.
- Let  $T, S$  be stopping times  $\Rightarrow T \wedge S, T \vee S$  and  $S + T$  are also stopping times.
- Let  $S, T$  be weak stopping times  $\Rightarrow S + T$  is a weak stopping time.
- Let  $S, T$  be weak stopping times. If  $T > 0$  and  $S > 0$  OR if  $T > 0$  and  $T$  is even a strong stopping time, then  $T + S$  is a strong stopping time.
- Let  $\{T_n\}_{n \geq 0}$  be a sequence of weak stopping times.  $\Rightarrow \sup_{n \geq 1} T_n, \inf_{n \geq 1} T_n, \limsup_{n \rightarrow \infty} T_n$  and  $\liminf_{n \rightarrow \infty} T_n$  are also weak stopping times. If the  $T_n$  are strong stopping times,  $\Rightarrow \sup_{n \geq 1} T_n$  is a strong stopping time.

**Example:** Let  $(X_t)_{t \geq 0}$  be right-continuous and adapted, with  $X_t \in \mathbb{R}^d$ . For  $A \in \mathcal{B}(\mathbb{R}^d)$ . Define

$$T_A(\omega) := \inf\{t \geq 0 | X_t(\omega) \in A\} \text{ with } \inf \emptyset = \infty \quad (3.14)$$

$$\text{is called the first entrance time of } A. \quad (3.15)$$

$$T_A^*(\omega) := \inf\{t > 0 | X_t(\omega) \in A\} \quad (3.16)$$

$$\text{is called the first hitting time.} \quad (3.17)$$

**Remark:** Each stopping time is a first entrance time ( $X_t := \mathbb{1}_{(0, T_A)}(t)$ ).

**Lemma 3.12.**

- a) If  $A$  is open  $\Rightarrow T_A$  is a weak stopping time.
- b) If  $A$  is closed and  $X_t(\omega)$  is continuous  $\Rightarrow T_A$  is a stopping time.

*Proof.* **ad a)**

$$\{T_A < t\} = \{X_s(\omega) \in A \text{ for some } 0 \leq s \leq t\} \quad (3.18)$$

$$\stackrel{\Delta}{=} \cup_{s \in \mathbb{Q}, 0 \leq s < t} \{X_s(\omega) \in A\} \in \mathcal{F}_t \quad (3.19)$$

Regarding  $\Delta$ : " $\supset$ " is clear. " $\subset$ " follows from the right-continuity of  $X_t$  and  $A$  open.

**ad b)**

$$\{T_A \leq t\}^c = \{T_A > t\} \quad (3.20)$$

$$= \{\|X_s - A\| > 0, \forall 0 \leq s \leq t\} \quad (3.21)$$

$$= \cup_{n \geq 1} \{\|X_s - A\| > \frac{1}{n}, \forall 0 \leq s \leq t\} \quad (3.22)$$

$$\stackrel{\text{continuity}}{=} \cup_{n \geq 1} \{\|X_s - A\| > \frac{1}{n}, \forall 0 \leq s \leq t, s \in \mathbb{Q}\} \quad (3.23)$$

$$= \cup_{n \geq 1} \underbrace{\cap_{s \in \mathbb{Q}, 0 \leq s \leq t} \{\|X_s - A\| > \frac{1}{n}\}}_{\in \mathcal{F}_s \subset \mathcal{F}_t} \in \mathcal{F}_t \quad (3.24)$$

□

[23.10.2012]  
[26.10.2012]

**Definition 3.13** ( $\mathcal{F}_T$ ).

Let  $T$  be a stopping time, then

$$\mathcal{F}_T := \{A \in \mathcal{F} : A \cap \{T \leq t\} \in \mathcal{F}_t, \forall t \geq 0\} \quad (3.25)$$

is called the  $\sigma$ -algebra of events determined prior to the stopping time  $T$ . Zu deutsch: Die  $\sigma$ -Algebra der  $T$ -Vergangenheit.

**Lemma 3.14.**

Let  $S$  and  $T$  be stopping times for a filtration  $(\mathcal{F}_t)$ . It holds

- a) Let  $A \in \mathcal{F}_S \Rightarrow A \cap \{S \leq T\} \in \mathcal{F}_T$ .
- b)  $S \leq T \Rightarrow \mathcal{F}_S \subset \mathcal{F}_T$
- c)  $\mathcal{F}_{T \wedge S} = \mathcal{F}_T \cap \mathcal{F}_S$
- d)  $\{\{T < S\}, \{T \leq S\}, \{T = S\}, \{T \geq S\}, \{T > S\}\} \subset \mathcal{F}_T \cap \mathcal{F}_S$ .
- e)  $\mathbb{E}[\cdot | \mathcal{F}_{T \wedge S}] = \mathbb{E}[\mathbb{E}[\cdot | \mathcal{F}_S] | \mathcal{F}_T]$ .
- f)  $\mathbb{E}[\cdot | \mathcal{F}_T] = \mathbb{E}[\cdot | \mathcal{F}_{T \wedge S}]$  a.s. on the set  $\{T \leq S\}$ .

**Theorem 3.15.**

Let  $X$  be progressively measurable w.r.t.  $(\mathcal{F}_t)_{t \geq 0}$  and  $T$  be a stopping time. Then

1.  $X_T : \{T < \infty\} \rightarrow E$ ,  $\omega \mapsto X_{T(\omega)}(\omega)$  is  $\mathcal{F}_T$ -measurable.
2. The stopped process

$$X^T : (t, \omega) \mapsto X_{T(\omega) \wedge t}(\omega) \quad (3.26)$$

is also progressively measurable w.r.t.  $(\mathcal{F}_t)_{t \geq 0}$ .

*Proof.* **ad 1)** To show (1) we have to see that  $\forall B \in \mathcal{B}(E)$  and  $\forall t \geq 0$  it holds

$$\{X_T \in B\} \cap \{T \leq t\} = \underbrace{\{X_{T \wedge t} \in B\}}_{\in \mathcal{F}_t \text{ if (2) holds}} \cap \underbrace{\{T \leq t\}}_{\in \mathcal{F}_t} \stackrel{!}{\in} \mathcal{F}_t \quad (3.27)$$

**ad 2)**

$$(s, \omega) \xrightarrow{\text{measurable being } T \text{ a r.v.}} (T(\omega) \wedge s, \omega) \mapsto X_{T(\omega) \wedge s}(\omega) \quad (3.28)$$

$$(s, \omega) \xrightarrow[\text{w.r.t. } \mathcal{B}([0, t]) \otimes \mathcal{F}_t]{\text{measurable}} X_s(\omega) \quad (3.29)$$

$\Rightarrow (s, \omega) \mapsto X_{T(\omega) \wedge s}(\omega)$  is also measurable w.r.t.  $\mathcal{B}([0, t]) \otimes \mathcal{F}_t \forall t \geq 0$ .  $\square$

**Example:** Let  $B$  be a standard BM and  $b > 0$  a constant. Let  $T_b = \inf\{t \geq 0 | B_t = b\}$ . *Question:*  $\mathbb{P}(T_b \leq t) = ?$ .

We know that for fixed  $s$ :  $B_t - B_s$  and  $B_s$  are independent (Markov property). The same holds if  $s$  is stopping time (strong markov property).

$$\mathbb{P}(T_b \leq t) = \mathbb{P}(T_b \leq t, B_t < b) + \underbrace{\mathbb{P}(T_b \leq t, B_t = b)}_{=0} + \mathbb{P}(T_b \leq t, B_t > b) \quad (3.30)$$

$$= 2\mathbb{P}(T_b \leq t, B_t > b) \quad (3.31)$$

$$= 2\mathbb{P}(B_t > b) \quad (3.32)$$

$$= 2 \frac{1}{\sqrt{2\pi t}} \int_b^\infty e^{-\frac{x^2}{2t}} dx \quad (3.33)$$

$$= \frac{2}{\sqrt{2\pi}} \int_{b/\sqrt{t}}^\infty e^{-\frac{y^2}{2}} dy \quad (3.34)$$

In particular

$$\mathbb{P}(T_b \in dt) = \frac{1}{\sqrt{2\pi t^3}} e^{-b^2/2t} |b| dt \quad (3.35)$$

---

$\frac{1}{\sqrt{t}} = y$

## 4 Continuous time martingales

From now on  $(\Omega, \mathcal{F}, \mathcal{F}_t, \mathbb{P})$  is always a filtered probability space and we have  $E = \mathbb{R}$ .

### 4.1 Conditional expectation

**Definition 4.1** (Conditional expectation).

Let  $\mathcal{G} \subset \mathcal{F}$  be a sub- $\sigma$ -algebra and  $X \in \mathcal{L}^1(\Omega, \mathcal{F}, \mathbb{P})$  a random variable. Then a random variable  $Y$  is called *conditional expectation* of  $X$  if  $\forall A \in \mathcal{G}$

$$\int_A X d\mathbb{P} = \int_A Y d\mathbb{P} \quad \text{and } Y \text{ is } \mathcal{G}\text{-measurable.} \quad (4.1)$$

and it is usually denoted by

$$Y = \mathbb{E}[X|\mathcal{G}]. \quad (4.2)$$

**Remark:**  $\mathbb{E}[X|\mathcal{G}]$  is a.s. unique.

**Properties:** •  $\mathbb{E}[\mathbb{E}[X|\mathcal{G}]] = \mathbb{E}[X]$

- If  $X$  is  $\mathcal{G}$ -measurable, then  $\mathbb{E}[X|\mathcal{G}] = X$  a.s..
- If  $Y$  is  $\mathcal{G}$ -measurable and bounded, then  $\mathbb{E}[XY|\mathcal{G}] = Y\mathbb{E}[X|\mathcal{G}]$  a.s.
- If  $X$  is  $\mathcal{G}$  independent i.e.,  $X$  independent from  $\mathbb{1}_A, \forall A \in \mathcal{G}$ , then  $\mathbb{E}[X|\mathcal{G}] = \mathbb{E}[X]$ .
- If  $\mathcal{H} \subset \mathcal{G} \subset \mathcal{F} \Rightarrow \mathbb{E}[\mathbb{E}[X|\mathcal{G}]|\mathcal{H}] = \mathbb{E}[X|\mathcal{H}]$  a.s.
- $\mathbb{E}[\alpha X + \beta Y|\mathcal{G}] = \alpha\mathbb{E}[X|\mathcal{G}] + \beta\mathbb{E}[Y|\mathcal{G}] \forall X, Y$  r.v. and  $\alpha, \beta \in \mathbb{R}$ .
- If  $X \leq Y$  a.s., then  $\mathbb{E}[X|\mathcal{G}] \leq \mathbb{E}[Y|\mathcal{G}]$  a.s.
- *Jensen:* Let  $\varphi$  be a convex function, then  $\varphi(\mathbb{E}[X|\mathcal{G}]) \leq \mathbb{E}[\varphi(X)|\mathcal{G}]$ .

Now let  $(X_n)_{n \geq 1}$  be a sequence of r.v.

- *Fatou:* If there exists a  $\mathcal{F}$ -measurable r.v.  $Y$  with  $\mathbb{E}[Y] > -\infty$  s.t.  $\forall k \geq 1, X_k \geq Y$ , then  $\mathbb{E}[\liminf_{n \rightarrow \infty} X_k|\mathcal{G}] \leq \liminf_{n \rightarrow \infty} \mathbb{E}[X_k|\mathcal{G}]$
- *Monoton convergence:* If  $\mathbb{E}[X] > -\infty$  and  $X_k \nearrow X$  a.s., then  $\mathbb{E}[X_k|\mathcal{G}] \nearrow \mathbb{E}[X|\mathcal{G}]$  a.s.
- *Dominated convergence:* If there exists a  $\mathcal{F}$ -measurable r.v.  $Y$  s.t.  $\mathbb{E}[Y] < \infty$  and  $|X_k| \leq Y$  and if  $X_k \rightarrow X$  a.s., then  $\mathbb{E}[X_k|\mathcal{G}] \rightarrow \mathbb{E}[X|\mathcal{G}]$  a.s.

### 4.2 Martingale

**Definition 4.2** (Martingale).

Let  $X$  be a stochastic process adapted to a filtration  $(\mathcal{F}_t)_{t \geq 0}$ .  $X$  is called *submartingale*, if

- $X_t \in \mathbb{R}$  with  $\mathbb{E}[X_t^+] \equiv \mathbb{E}[\max\{X_t, 0\}] < \infty$  for all  $t \geq 0$ .
- $\mathbb{E}[X_t|\mathcal{F}_s] \geq X_s$  a.s.  $\forall 0 \leq s \leq t$ .

$X$  is a *supermartingale* if  $-X$  is a submartingale.

$X$  is a *martingale* if it is both a super- and a submartingale.



**Properties:**  $\forall 0 \leq s \leq t$

$$\mathbb{E}[X_t] = \mathbb{E}[\mathbb{E}[X_t|\mathcal{F}_s]] \geq \mathbb{E}[X_s] \text{ for submartingales} \quad (4.3)$$

$$\mathbb{E}[X_t] = \mathbb{E}[\mathbb{E}[X_t|\mathcal{F}_s]] \leq \mathbb{E}[X_s] \text{ for supermartingales} \quad (4.4)$$

$$\mathbb{E}[X_t] = \mathbb{E}[\mathbb{E}[X_t|\mathcal{F}_s]] = \mathbb{E}[X_s] \text{ for martingales} \quad (4.5)$$

We will now see some examples for martingales.

**Proposition 4.3.**

Let  $B$  be a  $d$ -dimensional (standard) BM and  $\mathcal{F}_t \equiv \mathcal{F}_t^B$  the natural filtration. Then

a) For any fixed vector  $Y \in \mathbb{R}^d$

$$Y \cdot B_t = \langle Y, B_t \rangle \quad (4.6)$$

is a martingale.

b)  $|B_t|^2 - t \cdot d$  is a martingale.

c) For  $Y \in \mathbb{R}^d$

$$\exp\left(Y \cdot B_t - \frac{1}{2}|Y|^2 t\right) \quad (4.7)$$

is a martingale.

**Remark:** We will see that for any  $X$  with properties a) and b) + a.s. continuity and  $(X_0 = 0) \Rightarrow X$  is a BM. (Levy-Martingale-Characterization)

*Proof.*  $B$  is adapted, therefore the transformations are also adapted.

Integrability is easy, due to the gaussian tails of the normal distribution. We will now check  $\mathbb{E}[X_t|\mathcal{F}_s] = X_s$ .

**ad a)** Let  $0 \leq s \leq t$ .

$$\mathbb{E}[Y \cdot B_t|\mathcal{F}_s] = \sum_{k=1}^d Y_k \mathbb{E}[B_t^{(k)}|\mathcal{F}_s] \quad (4.8)$$

$$= \sum_{k=1}^d Y_k [\underbrace{\mathbb{E}[B_t^{(k)} - B_s^{(k)}|\mathcal{F}_s]}_{\text{independent of } \mathcal{F}_s} + \underbrace{\mathbb{E}[B_s^{(k)}|\mathcal{F}_s]}_{\text{measurable w.r.t. } \mathcal{F}_s}] \quad (4.9)$$

$$= \sum_{k=1}^d Y_k (\mathbb{E}[B_t^{(k)} - B_s^{(k)}] + B_s^{(k)}) \quad (4.10)$$

$$= Y \cdot B_s \quad (4.11)$$

**ad b)** Let  $0 \leq s \leq t$ .

$$\mathbb{E}[|B_t|^2|\mathcal{F}_s] = \underbrace{\mathbb{E}[|B_t - B_s|^2|\mathcal{F}_s]}_{\text{indep. of } \mathcal{F}_s} + \underbrace{\mathbb{E}[|B_s|^2|\mathcal{F}_s]}_{\mathcal{F}_s \text{ measurable}} + 2\underbrace{\mathbb{E}[\underbrace{(B_t - B_s)}_{\text{indep. of } \mathcal{F}_s} \underbrace{B_s}_{\mathcal{F}_s \text{ measurable}}|\mathcal{F}_s]}_{\mathcal{F}_s \text{ measurable}} \quad (4.12)$$

$$= \mathbb{E}[|B_t - B_s|^2] + |B_s|^2 + 2B_s \underbrace{\mathbb{E}[B_t - B_s]}_{=0} \quad (4.13)$$

$$= d(t - s) + |B_s|^2 \quad (4.14)$$

**ad c)** Let  $0 \leq s \leq t$ .

$$\mathbb{E}[e^{Y \cdot B_t}|\mathcal{F}_s] = \mathbb{E}[e^{Y(B_t - B_s)} e^{Y B_s}|\mathcal{F}_s] \quad (4.15)$$

$$= e^{Y B_s} \underbrace{\mathbb{E}[e^{Y(B_t - B_s)}|\mathcal{F}_s]}_{=\mathbb{E}[e^{Y B_{t-s}}]} \quad (4.16)$$

It holds

$$\mathbb{E} \left[ e^{YB_{t-s}} \right] = \prod_{k=1}^d \underbrace{\mathbb{E} \left[ e^{Y^{(k)}B_{t-s}^{(k)}} \right]}_{= e^{\frac{(Y^{(k)})^2}{2}(t-s)}}} = e^{\frac{t-s}{2}|Y|^2} \quad (4.17)$$

□

[26.10.12]  
[30.10.12]

**Example:** Let  $X$  be a  $L^1$  r.v. and  $(\mathcal{F}_t)_{t \geq 0}$  a filtration.  $\Rightarrow Y_t := \mathbb{E}[X|\mathcal{F}_t]$  is a martingale.

Indeed:

- adapted by def of the conditional expectation
- $L^1$  since :  $\mathbb{E}[|Y_t|] = \mathbb{E}[|\mathbb{E}[X|\mathcal{F}_t]|] \leq \mathbb{E}[\mathbb{E}[|X|\mathcal{F}_t]] = \mathbb{E}[|X|] < \infty$  by using Jensen.
- For all  $0 \leq s \leq t$  :  $\mathbb{E}[Y_t|\mathcal{F}_s] = \mathbb{E}[\mathbb{E}[X|\mathcal{F}_t]|\mathcal{F}_s] = \mathbb{E}[X|\mathcal{F}_s] = Y_s$  a.s. because  $\mathcal{F}_s \subset \mathcal{F}_t$

### 4.3 Properties and inequalities

#### Proposition 4.4.

a) Let  $X, Y$  be two martingales,  $\alpha \in \mathbb{R}$

$$X + Y, \quad X - Y, \quad \alpha X \quad (4.18)$$

are also martingales.

b) Let  $X, Y$  be two submartingales,  $\alpha \geq 0$ ,

$$X + Y, \quad \alpha X, \quad X \vee Y, \quad (4.19)$$

are also submartingales.

c) Let  $X$  be a martingale and  $\varphi$  a convex function with  $\varphi(X_t) \in L^1$  for all  $t \geq 0$ , then  $\varphi(X)$  is a submartingale.

d)  $X$  is a Martingale  $\Leftrightarrow X$  is a  $L^1$ -sub-/supermartingale and  $t \mapsto \mathbb{E}[X_t]$  is constant.

**Example:**  $|B_t|$  with  $B_t$  a BM is a submartingale.

*Proof.* ad a),b) trivial.

ad c) Let  $0 \leq s \leq t$

$$\mathbb{E}[\varphi(X_t)|\mathcal{F}_s] \stackrel{\text{Jensen}}{\geq} \varphi(\mathbb{E}[X_t|\mathcal{F}_s]) = \varphi(X_s) \quad (4.20)$$

□

**Theorem 4.5** (Doobs maximum inequality).

Let  $(X_t)_{t \geq 0}$  be a submartingale with

a) each trajectory is right-continuous and  $I = [\sigma, \tau] \subset [0, \infty)$  ( $I = [\sigma, \infty)$  also possible)

or b)  $I = \{\tau_1, \tau_2, \dots\}$  with  $\tau_k \leq \tau_{k+1}$  and  $\lim_{k \rightarrow \infty} \tau_k = \tau$

Then

1.  $\lambda \cdot \mathbb{P}(\sup_{t \in I} X_t \geq \lambda) \leq \mathbb{E}[X_\tau^+]$  with  $X_\tau^+ = \max\{X_\tau, 0\}$ ,  $\lambda > 0$ .

2. If  $X$  is even a martingale or  $X \geq 0$ , then

$$\mathbb{E} \left[ \left( \sup_{t \in I} X_t \right)^p \right] \leq \left( \frac{p}{1-p} \right)^p \mathbb{E}[|X_\tau|^p] \quad \forall p > 1 \quad (4.21)$$

*Proof.* **ad b)**  $\equiv$  discrete case  $\rightarrow$  proven in Stochastic Processes Thm 4.3.1 and 4.3.4.

**ad a)** Strategy: discrete time  $\rightarrow$  use the fact that the trajectories are rightcontinuous  $\square$

**Definition 4.6.**

The number of upcrossings of  $[a, b]$  (for  $a < b \in \mathbb{R}$ ) during the time  $I = [0, T]$  is given by

$$U_I(a, b, X(\omega)) = \sup\{n \in \mathbb{N} : \exists t_1 < t_2 < \dots < t_{2n} \leq T \text{ s.t. } X_{t_1}(\omega) < a, X_{t_2}(\omega) > b, X_{t_3}(\omega) < a, \dots\} \quad (4.22)$$

**Theorem 4.7.**

Let  $a < b \in \mathbb{R}$ ,  $X_t$  a submartingale like in Thm 4.5

$$\mathbb{E}[U_I(a, b, X)] \leq \frac{\mathbb{E}[X_T^+] + |a|}{b - a} \quad (4.23)$$

*Proof.* The proof is similar to the discrete case.  $\square$

## 4.4 Convergence

**Theorem 4.8.**

Let  $X$  be a right-continuous submartingale with

$$C := \sup_{t \geq 0} \mathbb{E}[X_t^+] < \infty \quad (4.24)$$

then there exists a r.v.  $X_\infty$  s.t.

$$X_\infty = \lim_{t \rightarrow \infty} X_t \text{ a.s.} \quad (4.25)$$

**Corollary 4.9.**

Let  $X$  be a supermartingale, right-continuous and positive.

$$X_\infty = \lim_{t \rightarrow \infty} X_t \text{ exists a.s.} \quad (4.26)$$

*Proof of the Corollary.* Trivial from Thm 4.8  $Y_t = -X_t \Rightarrow C = \sup_{t \geq 0} \mathbb{E}[Y_t^+] = 0$ .  $\square$

*Proof of the Theorem.* From Thm 4.7 we know that  $\forall n \geq 1, a < b$

$$\mathbb{E}[U_{[0,n]}(a, b, X)] \leq \frac{\mathbb{E}[X_n^+] + |a|}{b - a} \leq \frac{C + a}{b - a} \quad (4.27)$$

Taking  $n \rightarrow \infty$  gives with monoton convergence

$$E[U_{[0,\infty)}(a, b, X)] \leq \frac{C+a}{b-a} < \infty \quad (4.28)$$

$$\Rightarrow P(\underbrace{U_{[0,\infty)}(a, b, X) = \infty}_{\Lambda_{a,b}}) = 0 \forall a < b$$

$$\Rightarrow P\left(\bigcup_{a < b, a, b \in \mathbb{Q}} \Lambda_{a,b}\right) = 0 \Rightarrow P(\limsup_{t \rightarrow \infty} X_t > \liminf_{t \rightarrow \infty} X_t) = 0. \quad \square$$



**Remark:** Finally one can also verify that  $X_\infty$  is a.s. finite.

$$E[|X_\infty|] \leq \liminf_{t \rightarrow \infty} E[|X_t|] < \infty \quad (4.29)$$

by using Fatou. Regarding "??":

$$E[|X_t|] = 2E[X_t^+] - E[X_t] \leq 2C - E[X_0] < \infty \quad (4.30)$$

because  $E[X_t] \geq E[X_0]$  (since  $X_t$  is a submartingale)

In the exercise we will show

**Theorem 4.10.**

Let  $X$  be a right-continuous, positive submartingale (resp. martingale). Then we have 3 equivalent statements

1.  $\lim_{t \rightarrow \infty} X_t$  exists in  $L^1$ .
2.  $\{X_t, t \in [0, \infty)\}$  is uniformly integrable
3.  $\exists X_\infty \in L^1$  s.t.  $X_\infty = \lim_{t \rightarrow \infty} X_t$  a.s. and  $(X_t)_{t \in [0, \infty]}$  is a submartingale (resp. martingale) w.r.t.  $(\mathcal{F}_t)_{t \in [0, \infty]}$ .

**Remark:** For the case of a martingale,  $\exists X_\infty \in L^1$  s.t.  $X_t = E[X_\infty | \mathcal{F}_t]$  a.s.

**Remark** (So nicht in der Vorlesung): Es gilt:

$$\{X_t : t \in [0, \infty)\} \text{ unif. integ.} \Leftrightarrow \begin{cases} \{X_t : t \in [0, \infty)\} \text{ unif. bounded in } L^1 \text{ and} \\ \forall \varepsilon > 0 \exists \delta > 0 : \forall A \in \mathcal{F} : \mathbb{P}(A) < \delta \Rightarrow \sup_t E[|X_t| \mathbb{1}_A] < \varepsilon \end{cases} \quad (4.31)$$

Angenommen  $\sup_t E[|X_t|^p] \leq C < \infty$  für ein  $p > 1$ . Dann sind die beiden rechten Bedingungen erfüllt.

$$\sup_t E[|X_t|] \leq \sup_t E[|X_t|^p]^{1/p} < \infty \Rightarrow \sup_t E[|X_t|] < \infty \quad (4.32)$$

$$E[|X_t| \mathbb{1}_A] \stackrel{\text{Hölder}}{\leq} E[|X_t|^p]^{1/p} E[\mathbb{1}_A]^{1/p'} \leq C \cdot \mathbb{P}(A)^{1/p'} \xrightarrow{\mathbb{P}(A) \rightarrow 0} 0 \quad (4.33)$$

Somit sind die Voraussetzungen für das obige Theorem erfüllt! Tatsächlich gilt sogar  $X_t \rightarrow X_\infty$  in  $L^p$ .

## 4.5 Optional Sampling

For a submartingale  $X$  it holds

$$X_s \leq \mathbb{E}[X_t | \mathcal{F}_s] \text{ a.s.} \quad (4.34)$$

We now want a generalisation for  $s, t$  two stopping times.

**Theorem 4.11** (Optional Sampling).

Let  $X$  be a right-continuous submartingale w.r.t  $(\mathcal{F}_t)_{t \geq 0}$  and  $S, T$  two bounded stopping times satisfying  $S \leq T$ .

$$\Rightarrow X_S \leq \mathbb{E}[X_T | \mathcal{F}_S] \text{ a.s.} \quad (4.35)$$

**Remark:** To verify  $X_S \leq \mathbb{E}[X_T | \mathcal{F}_S]$  a.s. we have to show that  $\forall A \in \mathcal{F}_S$

$$\int_A X_S d\mathbb{P} \leq \int_A X_T d\mathbb{P} \stackrel{\text{def}}{=} \int_A \mathbb{E}[X_T | \mathcal{F}_S] d\mathbb{P} \quad (4.36)$$

*Proof.*  $\exists t_0$  s.t.  $S \leq T \leq t_0$ . Assume that  $X_S \leq \mathbb{E}[X_T | \mathcal{F}_S]$  holds for  $X_t \geq 0$ .  $\Rightarrow$  for  $X_t \geq -m \Rightarrow Y_t := X_t + m \geq 0$  by linearity  $\Rightarrow$  statement holds  $\forall X_t \geq -m$ .  $\Rightarrow X_t^{(m)} := X_t \vee (-m)$ . Monotone convergence gives that it is always true.

A simple bound  $\mathbb{E}[X_T] \leq \mathbb{E}[X_{t_0}] < \infty$ .

**a)** Discrete approximation.

We define

$$T_n := \frac{k+1}{2^n} \text{ if } \frac{k}{2^n} \leq T < \frac{k+1}{2^n} \text{ for a } k \geq 0. \quad (4.37)$$

Similarly define  $S_n$ . It is clear that  $T \leq T_n \forall n$  and  $T_n \geq T_{n+1} \geq \dots$ . Is  $T_n$  a stopping time?

$$\{T_n \leq t\} = \underbrace{\left\{ T < \frac{\lceil 2^n t \rceil}{2^n} \right\}}_{\in \mathcal{F}_t} \cap \underbrace{\left\{ T < \frac{\lceil 2^n t \rceil - 1}{2^n} \right\}^c}_{\in \mathcal{F}_t} \in \mathcal{F}_t \quad \checkmark \quad (4.38)$$

Also  $\forall n : T_n \geq S_n$ . Using that  $X$  is right-continuous it follows that

$$\lim_{n \rightarrow \infty} X_{S_n} = X_S \text{ and } \lim_{n \rightarrow \infty} X_{T_n} = X_T \quad (4.39)$$

**b)** Show:  $X_{T_n} \leq \mathbb{E}[X_{t_0} | \mathcal{F}_{T_n}]$ .

Take  $K_n := \lceil t_0 2^n \rceil$ .

$$\Rightarrow \mathbb{E}[X_{t_0} | \mathcal{F}_{T_n}] = \sum_{l=1}^{K_n} \mathbb{E} \left[ X_{t_0} | T_n = \frac{l}{2^n} \right] \mathbb{1}_{[T_n = \frac{l}{2^n}]} \quad (4.40)$$

$$\stackrel{\text{submart.}}{\geq} \sum_{l=1}^{K_n} X_{\frac{l}{2^n}} \mathbb{1}_{[T_n = \frac{l}{2^n}]} = X_{T_n} \quad (4.41)$$

$\Rightarrow \{X_{T_n} : n \in \mathbb{N}\}$  is uniformly integrable, since  $\{\mathbb{E}[X_{t_0} | \mathcal{F}_{T_n}] : n \in \mathbb{N}\}$  unif. integ.

$$\Rightarrow \lim_{n \rightarrow \infty} X_{T_n} = X_T \in L^1 \quad (4.42)$$

(analogue for  $S_n$ ).

**c)** Show:  $\forall A \in \mathcal{F}_{S_n}$ :

$$\int_A X_{S_n} d\mathbb{P} \leq \int_A X_{T_n} d\mathbb{P} \quad (4.43)$$

Too see this: Let

$$A_j = A \cap \{S_n = \frac{j}{2^n}\} \in \mathcal{F}_{\frac{j}{2^n}} \quad (4.44)$$

$$\Rightarrow \forall k \geq j : A_j \cap \{T_n > \frac{k}{2^n}\} \in \mathcal{F}_{\frac{k}{2^n}}$$

$$\Rightarrow \int_{A_j \cap \{T_n \geq \frac{k}{2^n}\}} X_{\frac{k}{2^n}} d\mathbb{P} \stackrel{\text{submart.}}{\leq} \int_{A_j \cap \{T_n = \frac{k}{2^n}\}} X_{T_n} d\mathbb{P} + \int_{A_j \cap \{T_n \geq \frac{k+1}{2^n}\}} X_{\frac{k+1}{2^n}} d\mathbb{P} \quad (4.45)$$

Starting with  $k = j$  and iterating:

$$\int_{A_j} X_{S_n} d\mathbb{P} = \int_{A_j \cap \{T_n \geq \frac{j}{2^n}\}} X_{\frac{j}{2^n}} d\mathbb{P} \leq \int_{A_j \cap \{T_n \geq \frac{j}{2^n}\}} X_{T_n} d\mathbb{P} \quad (4.46)$$

Now  $\sum_j \Rightarrow \mathbf{c)}$

$$\mathbf{d)} \forall A \in \mathcal{F}_S \subset \bigcap_{n \geq 1} \mathcal{F}_{S_n}$$

$$\Rightarrow \int_A X_{S_n} d\mathbb{P} \leq \int_A X_{T_n} d\mathbb{P} \quad (4.47)$$

Now take  $\lim_{n \rightarrow \infty}$

$$\Rightarrow \forall A \in \mathcal{F}_S \int_A X_S d\mathbb{P} \leq \int_A X_T d\mathbb{P} \quad (4.48)$$

□

[30.10.2012]  
[02.11.2012]

#### Corollary 4.12.

Let  $X$  a right-continuous adapted process and integrable. Then the following statements are equivalent:

- (i)  $X$  is a martingale.
- (ii) For all bounded stopping times  $T$  it holds  $\mathbb{E}[X_T] = \mathbb{E}[X_0]$ .

*Proof.* " $\Rightarrow$ " Using 2.11 with  $S = 0$  we get

$$\mathbb{E}[X_T] = \mathbb{E}[\mathbb{E}[X_T | \mathcal{F}_0]] \geq \mathbb{E}[X_0] \quad (4.49)$$

But also the other inequality holds, since  $-X_t$  is a submartingale, too.

" $\Leftarrow$ " To show  $\forall s < t, A \in \mathcal{F}_s$

$$\mathbb{E}[X_s \mathbb{1}_A] = \mathbb{E}[X_t \mathbb{1}_A] \quad (4.50)$$

Define two stopping times as follows: Let  $T(\omega) := t$  and

$$S(\omega) := \begin{cases} s & , \omega \in A \\ t & , \text{otherwise} \end{cases} \quad (4.51)$$

Let us compute

$$\mathbb{E}[X_0] \stackrel{\text{hyp}}{=} \mathbb{E}[X_T] = \mathbb{E}[X_t \mathbb{1}_A] + \mathbb{E}[X_t \mathbb{1}_{A^c}] \quad (4.52)$$

but also

$$\mathbb{E}[X_0] \stackrel{\text{hyp}}{=} \mathbb{E}[X_S] = \mathbb{E}[X_s \mathbb{1}_A] + \mathbb{E}[X_t \mathbb{1}_{A^c}] \Rightarrow \mathbb{E}[X_s \mathbb{1}_A] = \mathbb{E}[X_t \mathbb{1}_A] \forall A \in \mathcal{F}_s, s < t, \quad (4.53)$$

i.e.  $X_s = \mathbb{E}[X_t | \mathcal{F}_s]$  a.s. □

**Corollary 4.13.**

Let  $X$  be right-continuous, adapted and integrable. Then  $X$  is a submartingale  $\Leftrightarrow \forall$  bounded stopping times  $S \leq T$  it holds

$$\mathbb{E}[X_S] \leq \mathbb{E}[X_T] \quad (4.54)$$

*Proof.* " $\Rightarrow$ "

$$\mathbb{E}[X_T] \stackrel{\mathcal{F}_S \subseteq \mathcal{F}_T}{=} \mathbb{E}[\mathbb{E}[X_T | \mathcal{F}_S]] \stackrel{4.11}{\geq} \mathbb{E}[X_S] \quad (4.55)$$

" $\Leftarrow$ " Let  $s < t, A \in \mathcal{F}_s$  define  $S$  and  $T$  as in the previous proof.

$$\Rightarrow \mathbb{E}[X_S] \stackrel{hyp}{\leq} \mathbb{E}[X_T] = \mathbb{E}[X_t \mathbb{1}_A] + \mathbb{E}[X_t \mathbb{1}_{A^c}] \quad (4.56)$$

But the right side is

$$\mathbb{E}[X_S] = \mathbb{E}[X_s \mathbb{1}_A] + \mathbb{E}[X_s \mathbb{1}_{A^c}] \quad (4.57)$$

$$\Rightarrow \mathbb{E}[X_s \mathbb{1}_A] \leq \mathbb{E}[X_t \mathbb{1}_A], \forall s < t, A \in \mathcal{F}_s. \quad \square$$

**Corollary 4.14 (Optional Stopping).**

Let  $X$  be a (sub-)martingale and  $T$  a stopping time. Then,

$$X_t^T(\omega) \equiv X_{T(\omega) \wedge t}(\omega) \quad (4.58)$$

is also a (sub-)martingale.

*Proof.* Let  $s < t$ . Define  $S = s \wedge T$  and  $U = t \wedge T$ . Then by definition  $S \leq U$ . By Theorem 4.11 we get  $X_S \leq \mathbb{E}[X_U | \mathcal{F}_S]$ . If we do the same for  $-X$  we have  $X_S = \mathbb{E}[X_U | \mathcal{F}_S]$  and thus  $X_{S \wedge T} = \mathbb{E}[X_{t \wedge T} | \mathcal{F}_{s \wedge T}]$ .  $\square$

Next goal: Understand what is

$$\int_0^t f(B_s) dB_s = ? \quad (4.59)$$

with  $B$  a Brownian Motion. We will see

$$f(B_t) = f(B_0) + \int_0^t f'(B_s) dB_s + \frac{1}{2} \int_0^t f''(B_s) ds \quad (4.60)$$

where  $ds$  will be the quadratic variation of  $B$ .

# 5 Continuous semimartingales and quadratic variation

## 5.1 Semimartingales

### Definition 5.1.

- a)  $X \in \mathcal{A}^+$ : An adapted process  $X$  is called *continuous and increasing* if for almost all  $\omega \in \Omega$  the map  $t \mapsto X_t(\omega)$  is continuous and increasing.
- b)  $X \in \mathcal{A}$ : An adapted process is called *continuous with bounded variation* if for almost all  $\omega \in \Omega$ :  $t \mapsto X_t(\omega)$  is continuous and has finite variation, i.e.

$$\forall t \geq 0, S_t(\omega) \equiv S_t(X(\omega)) := \sup_{0 \leq t_0 \leq \dots \leq t_n \leq t, n \in \mathbb{N}} \sum_{k=1}^n |X_{t_{k+1}}(\omega) - X_{t_k}(\omega)| < \infty \quad (5.1)$$

- c)  $X \in \mathcal{M}$ :  $X$  is a continuous martingale.
- d)  $X \in \mathcal{M}_{loc}$ : An adapted process  $X$  is a *local, continuous martingale* if  $\exists$  a sequence of stopping times  $T_1 \leq T_2 \leq \dots$  with  $\lim_{n \rightarrow \infty} T_n = \infty$  a.s. and  $X^{T_n}$  is a martingale  $\forall n \geq 1$ .

### Lemma 5.2.

$X \in \mathcal{A} \Leftrightarrow X = Y - Z$  with  $Y, Z \in \mathcal{A}^+$ .

*Proof.* Take  $Y = \frac{S+X}{2}$  and  $Z = \frac{S-X}{2}$  where  $S$  is the variation of  $X$ . □

### Lemma 5.3.

- a)  $X \in \mathcal{M} \Rightarrow X \in \mathcal{M}_{loc}$
- b)  $X \in \mathcal{M}_{loc}, X \geq 0 \Rightarrow X$  supermartingale.
- c)  $X \in \mathcal{M}_{loc}$  and  $X$  is bounded  $\Rightarrow X \in \mathcal{M}$ .
- d)  $X \in \mathcal{M} \Leftrightarrow X \in \mathcal{M}_{loc}$  and  $\forall t \geq 0 : \{X_{T \wedge t} : T \text{ stopping time}\}$  is uniformly integrable.

**Remark:**  $\exists X \in \mathcal{M}_{loc}, X$  uniformly integrable s.t.  $X \notin \mathcal{M}$ . (ex. 3.36 in Karatzas, Shreve)

*Proof.* **ad a)** Take as sequence of stopping times

$$T_n = \infty \forall n \geq 1. \quad (5.2)$$

**ad b)**  $\forall s < t$ :

$$\mathbb{E}[X_t | \mathcal{F}_s] = \mathbb{E} \left[ \lim_{n \rightarrow \infty} X_{T_n \wedge t} | \mathcal{F}_s \right] \stackrel{Fatou}{\leq} \liminf_{n \rightarrow \infty} \mathbb{E}[X_{T_n \wedge t} | \mathcal{F}_s] \stackrel{X^{T_n} \in \mathcal{M}}{=} \liminf_{n \rightarrow \infty} X_{T_n \wedge s} = X_s \text{ a.s.} \quad (5.3)$$

<sup>1</sup>There exist  $T_n \nearrow \infty$  s.t.  $X^{T_n}$  is martingale



**ad c)** We have  $|X| \leq C < \infty$ , therefore  $C - X \geq 0, C + X \geq 0$ . Using b) we get  $C - X$  is a supermartingale and  $C + X$  is a supermartingale.  $\Rightarrow \pm X$  are both supermartingales  $\Rightarrow X$  is a martingale.

**ad d)** ” $\Rightarrow$ ”: Let  $X \in \mathcal{M}$ . From a):  $X \in \mathcal{M}_{loc}$ . Let  $T$  be any stopping time and  $t \in \mathbb{R}_+$  fixed. To show:  $\mathbb{E}[|X_{T \wedge t}|] \leq C$  uniformly in  $T$ .

$$\mathbb{E}[|X_{T \wedge t}|] \stackrel{X \in \mathcal{M}}{=} \mathbb{E}[\mathbb{E}[|X_t| | \mathcal{F}_{T \wedge t}]] \stackrel{Jensen}{\leq} \mathbb{E}[\mathbb{E}[|X_t| | \mathcal{F}_{T \wedge t}]] \leq \mathbb{E}[|X_t|] < \infty \quad (5.4)$$

The bound is uniformly in  $T$ .

” $\Leftarrow$ ”: By assumption,  $\exists$  a sequence of  $T_n \nearrow \infty$  of stopping times s.t.  $X^{T_n} \in \mathcal{M}$ . Let  $T$  be a bounded stopping time. By Cor. 4.12 we have

$$\mathbb{E}[X_{T_n \wedge T}] = \mathbb{E}[X_0] \quad (5.5)$$

$$\Rightarrow \mathbb{E}[X_0] = \lim_{n \rightarrow \infty} \mathbb{E}[X_{T_n \wedge T}] \stackrel{\text{unif. integ.}}{=} \mathbb{E}\left[\lim_{n \rightarrow \infty} X_{T_n \wedge T}\right] = \mathbb{E}[X_{T \wedge t}] \forall t \geq 0. \quad (5.6)$$

$\Rightarrow$  for all bounded  $T$  (by taking  $t > T$ )  $\mathbb{E}[X_0] = \mathbb{E}[X_T]$ .  $\stackrel{4.12}{\Rightarrow} X$  is a martingale.  $\square$

**Definition 5.4** (Semimartingale).

$X \in \mathcal{S}$ : A process  $X$  is called a *continuous semimartingale* if  $\exists M \in \mathcal{M}_{loc}$  and  $A \in \mathcal{A}$  s.t.

$$X = M + A. \quad (5.7)$$

**Theorem 5.5.**

Let  $\mathcal{M}_{loc}^0 := \{X \in \mathcal{M}_{loc} : X_0 = 0 \text{ a.s.}\}$ . Then,

$$\mathcal{M}_{loc}^0 \cap \mathcal{A} = \{0\} \quad (5.8)$$

and  $\mathcal{S} = \mathcal{M}_{loc}^0 \oplus \mathcal{A}$ .

[02.11.2012]  
[06.11.2012]

**Remark:** Recall Doob for  $p=2$ :  $\mathbb{E}\left[\sup_{t \geq 0} X_t^2\right] \leq 4\mathbb{E}[X_\infty^2]$

*Proof.* Assume that we can prove that

$$\text{if } X \in \mathcal{M}^0 \cap \mathcal{A} \Rightarrow X = 0 \text{ a.s.} \quad (5.9)$$

Then, by the definition of  $\mathcal{M}_{loc}$  there exist  $T_1 \leq T_2 \leq \dots$  stopping times with  $T_n \nearrow \infty$  a.s. s.t.  $X^{T_n} \in \mathcal{M}$ . Now let  $X \in \mathcal{M}_{loc}^0 \cap \mathcal{A} \Rightarrow X^{T_n} \in \mathcal{M}^0 \cap \mathcal{A} \stackrel{(5.9)}{\Rightarrow} X_{T_n \wedge t} = 0$  but since  $\forall t \geq 0 \lim_{n \rightarrow \infty} T_n \wedge t = t$  a.s. it holds  $X_t = 0 \forall t \geq 0$ .

We will now show, that (5.9) holds. So let  $X \in \mathcal{M}^0 \cap \mathcal{A}$ . We can also restrict ourself to processes  $X$  s.t.  $X$  is bounded and  $S_\infty(X) < \infty$ . Indeed, we can introduce stopping times

$$T'_n := \inf\{t > 0 : |X_t| > n \text{ or } S_t(x) > n\}. \quad (5.10)$$

Then  $X^{T'_n}$  is bounded with finite variation.  $\Rightarrow X^{T'_n} \in \mathcal{M}^0 \cap \mathcal{A} \forall n \stackrel{(5.9)}{\Rightarrow} X^{T'_n} = 0 \forall n \Rightarrow X = 0$ .

Now show (5.9) for  $X$  bounded and  $S_\infty(X) < \infty$ . Let  $\varepsilon > 0$ .

$$T_0 := 0 \quad (5.11)$$

$$T_{k+1} := \inf\{t \geq T_k : |X_k - X_{T_k}| > \varepsilon\}. \quad (5.12)$$

Since  $X$  is continuous and  $X \in \mathcal{A} \Rightarrow \lim_{k \rightarrow \infty} T_k = \infty$ .

$$\mathbb{E} [X_{T_n}^2] = \mathbb{E} \left[ \sum_{k=0}^{n-1} (X_{T_{k+1}}^2 - X_{T_k}^2) \right] \quad (5.13)$$

$$= \mathbb{E} \left[ \sum_{k=0}^{n-1} (X_{T_{k+1}} - X_{T_k})^2 \right] + 2 \sum_{k=0}^{n-1} \underbrace{\mathbb{E} [X_{T_k} (X_{T_{k+1}} - X_{T_k})]}_{\mathbb{E} [X_{T_k} \mathbb{E} [X_{T_{k+1}} - X_{T_k} | \mathcal{F}_{T_k}]] \stackrel{Mart.}{=} 0} \quad (5.14)$$

$$\leq \varepsilon \mathbb{E} \left[ \sum_{k=0}^{n-1} |X_{T_{k+1}} - X_{T_k}| \right] \quad (5.15)$$

$$\leq \varepsilon \cdot S_\infty(X) \rightarrow 0 \text{ as } \varepsilon \rightarrow 0 \quad (5.16)$$

$$\Rightarrow \mathbb{E} [X_{T_n}^2] = 0 \quad (5.17)$$

By taking  $n \rightarrow \infty$  we get

$$0 \leq \mathbb{E} [X_\infty^2] = \mathbb{E} \left[ \liminf_{n \rightarrow \infty} X_{T_n}^2 \right] \leq \liminf_{n \rightarrow \infty} \mathbb{E} [X_{T_n}^2] = 0 \quad (5.18)$$

and thus  $\mathbb{E} [X_\infty^2] = 0$ . Using Doob Max inequality (p=2):

$$\mathbb{E} \left[ \sup_{t \geq 0} X_t^2 \right] \leq 4 \mathbb{E} [X_\infty^2] = 0 \quad (5.19)$$

Therefore  $X = 0$  a.s.. □

## 5.2 Doob-Meyer decomposition

### Theorem 5.6.

Let  $X$  be a continuous <sup>(sub-)</sup>supermartingale, then  $\exists M \in \mathcal{M}_{loc}^0$  and  $A \in \mathcal{A}^+$  s.t.

$$X_t = M_t \overset{(+)}{-} A_t \quad (5.20)$$

Moreover,  $M$  and  $A$  are unique (up to indistinguishability).

*Hints for the proof:* **Uniqueness:** Assume  $X_t = M_t - A_t = M'_t - A'_t \Rightarrow \underbrace{M_t - M'_t}_{\in \mathcal{M}_{loc}^0} = \underbrace{A_t - A'_t}_{\in \mathcal{A}} \stackrel{5.5}{=} 0$  a.s.

**Existence** in discrete time case: Let  $(X_n)_{n \geq 1}$  be a discrete time supermartingale  $\Rightarrow Y_n := \mathbb{E} [X_n - X_{n+1} | \mathcal{F}_n] \geq 0$ . Then define  $A_n := \sum_{k=0}^{n-1} Y_k \Rightarrow$  is increasing in  $n$ , and it is  $\mathcal{F}_{n-1}$ -measurable and  $M_n = X_n + A_n$  is a Martingale. Show for the case  $m = n - 1$ :

$$\mathbb{E} [X_n + A_n | \mathcal{F}_{n-1}] = \mathbb{E} [X_n | \mathcal{F}_{n-1}] + \sum_{k=0}^{n-1} \mathbb{E} [\mathbb{E} [X_k - X_{k+1} | \mathcal{F}_k] | \mathcal{F}_{n-1}] \quad (5.21)$$

$$= \mathbb{E} [X_n | \mathcal{F}_{n-1}] + \mathbb{E} [X_{n-1} - X_n | \mathcal{F}_{n-1}] + \sum_{k=0}^{n-2} \mathbb{E} [X_k - X_{k+1} | \mathcal{F}_k] \quad (5.22)$$

$$= X_{n-1} + A_{n-1} \quad (5.23)$$

□

### Corollary 5.7.

Continuous Supermartingales (and Submartingales) are continuous semi-martingales.

*Proof.* Let  $X$  be a continuous supermartingale. By Theorem 5.6  $X = M - A$  where  $M \in \mathcal{M}_{loc}^0$  and  $A \in \mathcal{A}^+$ . By Lemma 5.2 we have  $(-A) \in \mathcal{A}$ . Therefore  $X \in \mathcal{S}$ . □

## 5.3 Quadratic Variation

**Definition 5.8** (Preliminary).

Let  $X$  be a stochastic process. Then the quadratic variation of  $X$  is defined by

$$Q_t(X)(\omega) := \lim_{\|\Delta\| \rightarrow 0} \sum_{k=1}^n |X_{t_k}(\omega) - X_{t_{k-1}}(\omega)|^2 \quad (5.24)$$

where  $\Delta = \{0 = t_0 \leq t_1 \leq \dots \leq t_n = t\}$  is a partition of  $[0, t]$  with "mesh-size"

$$\|\Delta\| = \max_{0 \leq k \leq n-1} (t_{k+1} - t_k). \quad (5.25)$$

We know that for  $X = B \equiv$  Brownian Motion:

$$Q_t(B) = t \text{ in } L^2, \quad (5.26)$$

(see Lemma 2.5)

**Theorem 5.9.**

- a)  $\forall M \in \mathcal{M}_{loc}, \exists! \langle M \rangle \in \mathcal{A}_0$  s.t.  $M^2 - M_0^2 - \langle M \rangle \in \mathcal{M}_{loc}^0$ .
- b)  $\forall M, N \in \mathcal{M}_{loc}, \exists! \langle M, N \rangle \in \mathcal{A}_0$  s.t.  $M \cdot N - M_0 \cdot N_0 - \langle M, N \rangle \in \mathcal{M}_{loc}^0$ .

(uniqueness up to indistinguishability)

*Proof.* a) Let  $M \in \mathcal{M}_{loc} \Rightarrow M^2$  is a local submartingale. By the Doob-Meyer-decomposition,  $\exists A \in \mathcal{A}_0$  s.t.  $M^2 = M' + A$  with  $M' \in \mathcal{M}_{loc}$ . We now define  $\langle M \rangle := A \Rightarrow M' = M^2 - \langle M \rangle \in \mathcal{M}_{loc}$  and since  $\langle M \rangle_0 = 0$  we also get  $M^2 - M_0^2 - \langle M \rangle \in \mathcal{M}_{loc}^0$

b) Just use the polarisation identity

$$M \cdot N = \frac{1}{4}((M + N)^2 - (M - N)^2) \quad (5.27)$$

□

**Example:** For a Brownian Motion  $B$ , we already know that

$$B_t^2 - t \quad (5.28)$$

is a martingale and  $t \mapsto t$  is in  $\mathcal{A}_0$ .  $\Rightarrow$  5.9 implies:  $\langle B \rangle_t = t$ . We also know:  $Q_t(B) = t$  and this is **not** an accident.

**Definition 5.10** (Final version of Definition 5.8).

- a)  $\langle M \rangle \equiv \langle M, M \rangle$  is called the quadratic variation of  $M$ .
- b)  $\langle M, N \rangle$  is called the covariation of  $M$  and  $N$ .

**Remark:** It holds  $\langle M, N \rangle = \frac{1}{4}(\langle M + N \rangle - \langle M - N \rangle)$

Some properties:

**Lemma 5.11.**

$\forall M, N \in \mathcal{M}_{loc}$  it holds

- a)  $\langle \cdot, \cdot \rangle$  is symmetric, bilinear, positive definit.
- b) For all stopping times  $T$  it holds  $\langle M, N \rangle^T = \langle M^T, N^T \rangle$ .
- c)  $\langle M \rangle = \langle M - M_0 \rangle$
- d)  $\langle M \rangle = 0 \Leftrightarrow M$  is a constant.

*Proof.* **ad a)** easy, use also (d).

**ad b)** Show  $\langle M \rangle^T = \langle M^T \rangle$  and use the remark before the Lemma.

$$\underbrace{(M^2 - M_0^2 - \langle M \rangle)^T}_{\in \mathcal{M}_{loc}} = (M^T)^2 - M_0^2 - \langle M \rangle^T \in \mathcal{M}_{loc} \quad (\text{Cor 4.14}) \quad (5.29)$$

but there  $\exists! \langle M^T \rangle$  s.t.

$$(M^T)^2 - M_0^2 - \langle M^T \rangle \in \mathcal{M}_{loc} \quad (5.30)$$

$$\Rightarrow \langle M^T \rangle = \langle M \rangle^T.$$

**ad c) and d)** We can assume  $M - M_0$  bounded (otherwise use  $T_n = \inf\{t > 0 : |M - M_0| > n^2\}$  and b)). Therefore (by 5.3 (c))  $M - M_0 \in \mathcal{M}$ .

**ad c)** By Theorem 5.9  $\exists! \langle M - M_0 \rangle \in \mathcal{A}_0$  s.t.  $(M - M_0)^2 - \langle M - M_0 \rangle \in \mathcal{M}^0$  but we also have

$$(M - M_0)^2 - \langle M \rangle = \underbrace{M^2 - M_0^2 - \langle M \rangle}_{\in \mathcal{M}^0} - \underbrace{2M_0(M - M_0)}_{\in \mathcal{M}^0?} \quad (5.31)$$

If  $M_0(M - M_0) \in \mathcal{M}^0$ , then  $(M - M_0) - \langle M \rangle \in \mathcal{M}^0$ . Therefore by uniqueness  $\langle M \rangle = \langle M - M_0 \rangle$ .

Regarding  $M_0(M - M_0) \in \mathcal{M}^0$ ,  $\forall 0 \leq s \leq t$ :

$$\mathbb{E}[M_0(M_t - M_0) | \mathcal{F}_s] = M_0 \mathbb{E}[M_t - M_0 | \mathcal{F}_s] \stackrel{M - M_0 \in \mathcal{M}}{=} M_0(M_s - M) \quad (5.32)$$

Therefore  $M_0(M - M_0) \in \mathcal{M}^0$ .

**ad d)** " $\Rightarrow$ ":  $\langle M \rangle = 0$  on  $[0, t] \stackrel{(c)}{\Rightarrow} (M - M_0)^2 \in \mathcal{M}$  on  $[0, t]$ , since

$$(M - M_0)^2 - \langle M - M_0 \rangle \in \mathcal{M} \quad (5.33)$$

$$\Rightarrow (M - M_0)^2 - \langle M \rangle \in \mathcal{M} \quad (5.34)$$

$$\Rightarrow (M - M_0)^2 \in \mathcal{M} \quad (5.35)$$

$$\Rightarrow \mathbb{E} \left[ \sup_{0 \leq s \leq t} (M_s - M_0)^2 \right] \stackrel{\text{Doob}}{\leq} 4 \mathbb{E} [(M_t - M_0)^2] = 0 \text{ since } (M - M_0)^2 \in \mathcal{M} \quad (5.36)$$

$\Rightarrow M$  is constant on  $[0, t]$ ,  $\forall t \geq 0 \Rightarrow M$  is constant.  $\square$

**Example:** Let  $X$  be continuous, adapted process,  $X_t \in L^2$  with independent and centered increments. Then,

a)  $X \in \mathcal{M}$  and

b)  $\langle X \rangle_t = \text{Var}(X_t - X_0) \equiv \mathbb{E}[(X_t - X_0)^2]$  a.s.

*Indeed:*

**a)**

- adapted  $\checkmark$

-  $\mathbb{E}[|X_t| < \infty]$ ,  $\forall t \geq 0$   $\checkmark$  since it even holds  $\mathbb{E}[|X_t|^2] < \infty \forall t \geq 0$ .

- For  $0 \leq s \leq t$ :  $\mathbb{E}[X_t | \mathcal{F}_s] = \mathbb{E}[X_t - X_s | \mathcal{F}_s] + X_s = \mathbb{E}[X_t - X_s] + X_s = X_s$

**b)**

- It holds

$$\mathbb{E}[X_t^2 - X_0^2 - \mathbb{E}[(X_t - X_0)^2]] = \mathbb{E}[X_t^2 - X_0^2 - \mathbb{E}[X_t^2 - X_0^2 - 2X_0(X_t - X_0)]] \quad (5.37)$$

$$= 2\mathbb{E}[X_0(X_t - X_0)] = 0 \quad (5.38)$$

since  $X_0(X_t - X_0)$  is a Martingale).  $\stackrel{a)}{\Rightarrow} X_t^2 - X_0^2 - \mathbb{E}[(X_t - X_0)^2] \in \mathcal{M}^0$ , i.e.  $\mathbb{E}[(X_t - X_0)^2] = \langle X \rangle_t$ .

[06.11.2012]  
[09.11.2012]**Definition 5.12.**

For a partition  $\Delta = \{t_0, t_1, \dots\}$  with  $t_k \rightarrow \infty$  and  $0 = t_0 \leq t_1 \leq t_2 \dots$  and a stochastic process  $X$  the *quadratic variation of  $X$  on  $\Delta$*  is defined by

$$Q_t^\Delta = \sum_{k \geq 1} |X_{t \wedge t_k} - X_{t \wedge t_{k-1}}|^2 \quad (5.39)$$

The quantity

$$\|\Delta\| := \sup_{k \geq 1} |t_k - t_{k-1}| \quad (5.40)$$

is the *mesh-size* of  $\Delta$ .

**Theorem 5.13.**

Let  $M \in \mathcal{M}_{loc}$  and  $t \geq 0$ . Then,

$$\lim_{\|\Delta\| \rightarrow 0} Q_t^\Delta = \langle M \rangle_t \text{ stochastically.} \quad (5.41)$$

i.e.,  $\forall \varepsilon > 0, \eta > 0, t \geq 0, \exists \delta > 0$  s.t.

$$\mathbb{P} \left( \sup_{0 \leq s \leq t} |Q_s^\Delta - \langle M \rangle_s| > \varepsilon \right) < \eta \quad (5.42)$$

holds  $\forall \Delta$  with  $\|\Delta\| < \delta$ .

To prove this we need one technical lemma.

**Lemma 5.14.**

a) Let  $(A_n)_{n \geq 0}$  be an increasing process with

- $A_0 = 0$
- $A_n$  is  $\mathcal{F}_n$ -measurable.

Then if  $\mathbb{E}[A_\infty - A_n | \mathcal{F}_n] \leq K, \forall n \geq 0, \Rightarrow \mathbb{E}[A_\infty^2] \leq 2K^2$ .

b) Let  $A^{(1)}$  and  $A^{(2)}$  as in a) and  $B := A^{(1)} - A^{(2)}$ . Then, if  $\exists$  a r.v.  $W \geq 0$  with  $\mathbb{E}[W^2] < \infty$  and  $|\mathbb{E}[B_\infty - B_n | \mathcal{F}_n]| \leq \mathbb{E}[W | \mathcal{F}_n]$ , there  $\exists c > 0$  s.t.

$$\mathbb{E} \left[ \sup_{n \geq 0} B_n^2 \right] \leq c \left( \mathbb{E}[W^2] + K \sqrt{\mathbb{E}[W^2]} \right) \quad (5.43)$$

*Proof.* **ad a)** Define  $a_n := A_{n+1} - A_n \geq 0$  since  $A_n$  is increasing.

$$\Rightarrow A_\infty^2 \stackrel{A_0=0}{=} \left( \sum_{n \geq 0} a_n \right)^2 = \sum_{m, n \geq 0} a_n a_m = \sum_{n \geq 0} a_n^2 + 2 \sum_{n \geq 0} \left( a_n \underbrace{\sum_{m \geq n+1} a_m}_{=A_\infty - A_{n+1} = A_\infty - A_n - a_n} \right) \quad (5.44)$$

$$= 2 \sum_{n \geq 0} a_n (A_\infty - A_n) \quad (5.45)$$

$$\mathbb{E}[A_\infty^2] \leq 2 \sum_{n \geq 0} \mathbb{E}[\mathbb{E}[a_n(A_\infty - A_n)|\mathcal{F}_n]] = 2 \sum_{n \geq 0} \mathbb{E}\left[ \underbrace{a_n \mathbb{E}[A_\infty - A_n|\mathcal{F}_n]}_{\leq K} \right] \quad (5.46)$$

$$\leq 2K \sum_{n \geq 0} \mathbb{E}[a_n] \leq 2K \mathbb{E}[A_\infty] = 2K \mathbb{E}[A_\infty - A_0] = 2K \mathbb{E}[\mathbb{E}[A_\infty - A_0|F_0]] \leq 2K^2 \quad (5.47)$$

**ad b)** Let  $b_n := B_{n+1} - B_n, a_n^{(i)} := A_{n+1}^{(i)} - A_n^{(i)}$ .

$$\mathbb{E}[B_\infty^2] \leq 2 \mathbb{E}\left[ \sum_{n \geq 0} \underbrace{\mathbb{E}[B_\infty - B_n|\mathcal{F}_n]}_{|\leq \mathbb{E}[W|\mathcal{F}_n]} b_n \right] \quad (5.48)$$

$$\stackrel{|b_n| \leq a_n^{(1)} + a_n^{(2)}}{\leq} 2 \mathbb{E}\left[ \mathbb{E}\left[ \sum_{n \geq 0} W(a_n^{(1)} - a_n^{(2)})|\mathcal{F}_n \right] \right] \quad (5.49)$$

$$= 2 \mathbb{E}[W(A_\infty^{(1)} + A_\infty^{(2)})] \quad (5.50)$$

$$\stackrel{c.s.}{\leq} 2 \mathbb{E}[W^2]^{1/2} \left( \underbrace{\mathbb{E}[(A_\infty^{(1)})^2]^{1/2}}_{\leq \sqrt{2}K} + \underbrace{\mathbb{E}[(A_\infty^{(2)})^2]^{1/2}}_{\leq \sqrt{2}K} \right) \leq 4 \sqrt{2} \mathbb{E}[W^2]^{1/2} K \quad (5.51)$$

Now we introduce the martingales

$$M_n := \mathbb{E}[B_\infty|\mathcal{F}_n] \quad (5.52)$$

and

$$W_n := \mathbb{E}[W|\mathcal{F}_n] \quad (5.53)$$

and set

$$X_n := M_n - B_n \quad (5.54)$$

Since  $|B_n|^2 \leq 2(|X_n| + |M_n|)^2$  We have to compute/bound  $|X_n|$

$$|X_n| = |\mathbb{E}[B_\infty - B_n|\mathcal{F}_n]| \quad (5.55)$$

$$\leq \mathbb{E}[W|\mathcal{F}_n] \equiv W_n \quad (5.56)$$

$$\mathbb{E}\left[ \sup_{n \geq 0} |B_n|^2 \right] \leq 2 \mathbb{E}\left[ \sup_{n \geq 0} |X_n|^2 + \sup_{n \geq 0} |M_n|^2 \right] \quad (5.57)$$

$$\leq 2 \mathbb{E}\left[ \sup_{n \geq 0} W_n^2 \right] + 2 \mathbb{E}\left[ \sup_{n \geq 0} |M_n|^2 \right] \quad (5.58)$$

$$\stackrel{\text{Doobmaxineq.}}{\leq} 8 \left( \underbrace{\mathbb{E}[W_\infty^2]}_{\mathbb{E}[W^2]} + \underbrace{\mathbb{E}[B_\infty^2]}_{\leq 2 \sqrt{2}K \mathbb{E}[W^2]^{1/2}} \right) \quad (5.59)$$

$$\leq \tilde{c}(\mathbb{E}[W^2] + K \mathbb{E}[W^2]^{1/2}) \quad (5.60)$$

□

*Proof of the theorem.* Let  $M \in \mathcal{M}_{loc}, t \geq 0$  fixed. Let  $\Delta = \{t_0, t_1, \dots\}$  a partition with  $\|\Delta\| \leq \delta$ .

**Case a)** Let  $M$  and  $\langle M \rangle$  be bounded.

Define

$$a_k^{(1)} := (M_{t_{k+1}} - M_{t_k})^2; \quad (5.61)$$

$$a_k^{(2)} := \langle M \rangle_{t_{k+1}} - \langle M \rangle_{t_k}; \quad (5.62)$$

$$b_k := a_k^{(1)} - a_k^{(2)} \quad (5.63)$$

$$\Rightarrow A_n^{(1)} := \sum_{k=0}^{n-1} a_k^{(1)} \equiv Q_{t_n}^\Delta(M); \quad (5.64)$$

$$A_n^{(2)} := \sum_{k=0}^{n-1} a_k^{(2)} \equiv \langle M \rangle_{t_n} \quad (5.65)$$

$$\Rightarrow B_n := A_n^{(1)} - A_n^{(2)} = \sum_{k=0}^{n-1} b_k = Q_{t_n}^\Delta(M) - \langle M \rangle_{t_n} \quad (5.66)$$

Define  $\mathcal{F}_n := \sigma(M_{t_{k+1}}, k \leq n) \Rightarrow a_n^{(1)}, a_n^{(2)}$  are  $\mathcal{F}_n$ -measurable and  $A_n^{(1)}, A_n^{(2)}$  are  $\mathcal{F}_{n-1}$ -measurable.

Since  $M$  and  $\langle M \rangle$  are bounded (and  $M$  is a continuous local martingale)  $\Rightarrow M$  and  $\langle M \rangle$  are uniformly continuous on the interval  $[0, t]$  (for any  $t$ )

$$W(\delta) := \sup_{0 \leq s \leq t, 0 \leq \varepsilon \leq \delta} (|M_{s+\varepsilon} - M_s|^2 + |\langle M \rangle_{s+\varepsilon} - \langle M \rangle_s|^2) \xrightarrow[\text{a.s. and also in } L^2]{\delta \rightarrow 0} 0 \quad (5.67)$$

We will now show:  $|\mathbb{E}[B_\infty - B_n | \mathcal{F}_n]| \leq \mathbb{E}[W(\delta) | \mathcal{F}_n]$  It holds

$$B_\infty - B_n = \sum_{k \geq n} b_k \quad (5.68)$$

and

$$\mathbb{E}[b_k | \mathcal{F}_n] = 0 \forall k > n \quad (5.69)$$

since  $b_k$  is independent of  $\mathcal{F}_n \forall k \geq n+1$  and  $\mathbb{E}[b_k] = 0$

$$\Rightarrow |\mathbb{E}[B_\infty - B_n | \mathcal{F}_n]| = |\mathbb{E}[b_n | \mathcal{F}_n]| = |b_n| \leq a_n^{(1)} + a_n^{(2)} = \mathbb{E}[a_n^{(1)} + a_n^{(2)} | \mathcal{F}_n] \leq \mathbb{E}[W(\delta) | \mathcal{F}_n] \quad (5.70)$$

Now apply Lemma 5.14 b)

$$\Rightarrow \mathbb{E} \left[ \sup_{n \geq 0} B_n^2 \right] \leq c(\mathbb{E}[W(\delta)^2] + \mathbb{E}[W(\delta)^2]^{1/2}) \xrightarrow{\delta \rightarrow 0} 0 \quad (5.71)$$

Finally

$$\mathbb{E} \left[ \sup_{0 \leq s \leq t} |Q_s^\Delta(M) - \langle M \rangle_s|^2 \right] \leq \mathbb{E} \left[ \left( \sup_{n \in \mathbb{N}} |Q_{t_n}^\Delta(M) - \langle M \rangle_{t_n}| + W(\delta) \right)^2 \right] \stackrel{(a+b)^2 \leq 2(a^2+b^2)}{\leq} 2\mathbb{E} \left[ \sup_{n \geq 0} B_n^2 \right] + 2\mathbb{E}[W(\delta)^2] \xrightarrow{\delta \rightarrow 0} 0 \quad (5.72)$$

**Case b)** General  $M, \langle M \rangle$ . Let  $T_n := \inf\{t \geq 0 : |M_n| \geq n \text{ or } \langle M \rangle_t \geq n\}$ .

$$\mathbb{P} \left( \sup_{0 \leq s \leq t} |Q_s^\Delta(M) - \langle M \rangle_s| > \varepsilon \right) \leq \mathbb{P} \left( \sup_{0 \leq s \leq t} |Q_s^\Delta(M^{T_n}) - \langle M^{T_n} \rangle_s| > \varepsilon \right) + \underbrace{\mathbb{P}(T_n \leq t)}_{\leq \eta/2 \text{ for } n \text{ large enough}} \quad (5.73)$$

For  $n$  large enough s.t. the right term is smaller  $\eta/2$  choose  $\delta$  small enough s.t. the left term is  $\leq \eta/2$ .  $\square$

**Corollary 5.15.**

Let  $M, N \in \mathcal{M}_{loc}$ ,  $t \geq 0$  fixed. Then,

$$\lim_{\|\Delta\| \rightarrow 0} Q_t^\Delta(M, N) = \langle M, N \rangle_t \text{ stochastically} \quad (5.74)$$

where

$$Q_t^\Delta(M, N) := \sum_{t_k \in \Delta} (M_{t_{k+1} \wedge t} - M_{t_k \wedge t})(N_{t_{k+1} \wedge t} - N_{t_k \wedge t}) \quad (5.75)$$

**Lemma 5.16.**

Let  $M \in \mathcal{M}_{loc}$ .

a) For almost all  $\omega \in \Omega$ ,  $\forall a < b$

$$\langle M \rangle_a(\omega) = \langle M \rangle_b(\omega) \Leftrightarrow M_t(\omega) = M_a(\omega), \forall t \in [a, b] \quad (5.76)$$

b) For almost all  $\omega \in \Omega$  s.t.  $\langle M \rangle_\infty(\omega) := \sup_{t \geq 0} \langle M \rangle_t(\omega) < \infty$

$$\Rightarrow \lim_{t \rightarrow \infty} M_t(\omega) \text{ exists and is finite.} \quad (5.77)$$

**Remark:** For a process  $A \in \mathcal{A}$  it holds  $\langle A \rangle = 0$ .

$$\langle A \rangle_t = \lim_{\|\Delta\| \rightarrow 0} \sum_{k \geq 1} |A_{t_k \wedge t} - A_{t_{k+1} \wedge t}|^2 \quad (5.78)$$

$$= \lim_{\|\Delta\| \rightarrow 0} \underbrace{\left[ \sup_{k \geq 1} |A_{t_k \wedge t} - A_{t_{k+1} \wedge t}| \right]}_{\rightarrow 0} \underbrace{\left[ \sum_{k \geq 1} |A_{t_k \wedge t} - A_{t_{k+1} \wedge t}| \right]}_{\leq S_t(A)} \quad (5.79)$$

For a semimartingale  $X = M + A$ ,  $M \in \mathcal{M}_{loc}$ ,  $A \in \mathcal{A}_0$ .

**Definition 5.17.**

Let  $X, \tilde{X} \in \mathcal{S}$  with  $X = M + A$ ,  $\tilde{X} = \tilde{M} + \tilde{A}$  where  $M, \tilde{M} \in \mathcal{M}_{loc}$ . We define

$$\langle X, \tilde{X} \rangle := \langle M, \tilde{M} \rangle \text{ and} \quad (5.80)$$

$$\langle X \rangle := \langle M \rangle. \quad (5.81)$$

**Theorem 5.18.**

Let  $X, X' \in \mathcal{S}$ ,  $t \geq 0$ . Then

$$\lim_{\|\Delta\| \rightarrow 0} Q_t^\Delta(X, X') = \langle X, X' \rangle \text{ stochastically} \quad (5.82)$$

*Proof.*

$$Q_t^\Delta(X, X') = \underbrace{Q_t^\Delta(M, M')}_{\rightarrow \langle M, M' \rangle =: \langle X, X' \rangle} + Q_t^\Delta(M, A') + Q_t^\Delta(A, M') + Q_t^\Delta(A, A') \quad (5.83)$$

Now check if the last 3 summands go to 0.

$$|Q_t^\Delta(M, A')| = \left| \sum_{t_k \in \Delta} (M_{t_{k+1} \wedge t} - M_{t_k \wedge t})(A'_{t_{k+1} \wedge t} - A'_{t_k \wedge t}) \right| \quad (5.84)$$

$$\leq \underbrace{\sup_{t_k \in \Delta} |M_{t_{k+1} \wedge t} - M_{t_k \wedge t}|}_{\rightarrow 0} \underbrace{\sum_{t_k \in \Delta} |A'_{t_{k+1} \wedge t} - A'_{t_k \wedge t}|}_{\leq S_t(A)} \xrightarrow{\|\Delta\| \rightarrow 0} 0 \quad (5.85)$$

Similarly:  $|Q_t^\Delta(A, M')| \xrightarrow{\|\Delta\| \rightarrow 0} 0$ ,  $|Q_t^\Delta(A, A')| \xrightarrow{\|\Delta\| \rightarrow 0} 0$ .  $\square$



**Corollary 5.19.**Let  $X, X' \in \mathcal{S}, t \geq 0$ .

$$\Rightarrow \langle X, X' \rangle_t \leq \sqrt{\langle X \rangle_t \langle X' \rangle_t} \leq \frac{1}{2}(\langle X \rangle_t + \langle X' \rangle_t) \quad (5.86)$$

*Proof.* Cauchy Schwarz and  $(ab)^{1/2} \leq \frac{a+b}{2}$  for  $a, b \geq 0$ . □

[09.11.2012]  
[13.11.2012]

**5.4  $L^2$ -bounded martingales****Definition 5.20** ( $L^2$ -bounded martingales).The space of continuous  $L^2$ -bounded martingales is defined by

$$H^2 := \{M \in \mathcal{M} : \sup_{t \geq 0} \mathbb{E}[M_t^2] < \infty\} \quad (5.87)$$

**Example:** Let  $T \in \mathbb{R}_+$  then

$$M_t := B_{t \wedge T} \quad (5.88)$$

is in  $H^2$ , since  $\mathbb{E}[B_{t \wedge T}^2] = t \wedge T \Rightarrow \sup_{t \geq 0} \mathbb{E}[B_{t \wedge T}^2] < \infty$ .

**Remark:** Let  $M \in H^2$ , then  $\{M_t, t \geq 0\}$  is uniformly integrable, i.e.

$$\sup_{t \geq 0} \mathbb{E}[|M_t| \mathbb{1}_{|M_t| > K}] \Rightarrow 0 \text{ for } K \rightarrow \infty \quad (5.89)$$

since

$$\mathbb{E}[|M_t| \mathbb{1}_{|M_t| > K}] \leq \mathbb{E}\left[\frac{|M_t|^2}{K} \mathbb{1}_{|M_t| > K}\right] \leq \frac{\sup_{t \geq 0} \mathbb{E}[|M_t|^2]}{K} \rightarrow 0 \text{ for } K \rightarrow \infty \quad (5.90)$$

From this it follows:

$$\lim_{t \rightarrow \infty} M_t = M_\infty \in L^1 \text{ exists (a.s.) and } M_t = \mathbb{E}[M_\infty | \mathcal{F}_t] \text{ a.s.} \quad (5.91)$$

Finally:  $M_\infty \in L^2$ .**Proposition 5.21.**a)  $H^2$  is a Hilbert space with respect to the norm

$$\|M\|_{H^2} := \sqrt{\mathbb{E}[M_\infty^2]} = \lim_{t \rightarrow \infty} \sqrt{\mathbb{E}[M_t^2]} \quad (5.92)$$

b) Let  $M_\infty^* := \sup_{t \geq 0} |M_t|$ . Then an equivalent norm is

$$\|M_\infty^*\|_2 \equiv \sqrt{\mathbb{E}[(M_\infty^*)^2]} \equiv \sqrt{\mathbb{E}\left[\sup_{t \geq 0} |M_t|^2\right]} \quad (5.93)$$

c) For  $M \in H_0^2 := \{X \in H^2 : X_0 = 0\}$  it holds

$$\|M\|_{H^2} = \sqrt{\mathbb{E}[\langle M \rangle_\infty]} \quad (5.94)$$

*Proof.* 1) Verify that  $\|\cdot\|_{H^2}$  is a norm: easy.

$\Rightarrow$  the associated scalar product is

$$(M, N)_{H^2} := \frac{1}{4}(\|M + N\|_{H^2}^2 - \|M - N\|_{H^2}^2) \quad (5.95)$$

2) Check b): First inequality:

$$\|M_\infty^*\|_2^2 \equiv \mathbb{E} \left[ \sup_{t \geq 0} |M_t|^2 \right] \stackrel{\text{Doob}}{\leq} 4 \sup_{t \geq 0} \mathbb{E} [M_t^2] \stackrel{M^2 \text{ submart.}}{=} 4 \lim_{t \rightarrow \infty} \mathbb{E} [M_t^2] \equiv 4\|M\|_{H^2}^2 \quad (5.96)$$

$\Rightarrow M_\infty^*$  is in  $L^2$  ( $\Rightarrow$  also in  $L^1$ ).

For the second inequality:  $M_t = \mathbb{E} [M_\infty | \mathcal{F}_t]$

$$\Rightarrow \|M\|_{H^2}^2 = \lim_{t \rightarrow \infty} \mathbb{E} [M_t^2] \stackrel{\text{submart.}}{=} \sup_{t \geq 0} \mathbb{E} [M_t^2] \leq \mathbb{E} \left[ \sup_{t \geq 0} M_t^2 \right] \equiv \|M_\infty^*\|_2^2 \quad (5.97)$$

3) Verify the completeness of  $H^2$ .

Let  $(M^n)_{n \geq 1}$  be a sequence in  $H^2$  s.t.

$$\|M^n - M^m\|_{H^2} \stackrel{m, n \rightarrow \infty}{\longrightarrow} 0 \quad (5.98)$$

$\Rightarrow \exists$  sequence  $M_\infty^n \in L^2$  s.t.

$$M_t^n \equiv \mathbb{E} [M_\infty^n | \mathcal{F}_t] \quad (5.99)$$

We know

$$\|M_\infty^n - M_\infty^m\|_{L^2} \stackrel{\text{def}}{=} \|M^n - M^m\|_{H^2} \stackrel{\text{hyp}}{m, n \rightarrow \infty} 0 \quad (5.100)$$

$\Rightarrow (M_\infty^n)_{n \geq 1}$  is Cauchy and since  $L^2$  is complete, it converges to a limit in  $L^2$ . Let us call this limit  $M_\infty$ . Define therefore the Martingale

$$M_t := \mathbb{E} [M_\infty | \mathcal{F}_t] \quad (5.101)$$

Q.: Does  $M^n \rightarrow M$ ? Yes!

$$\mathbb{E} \left[ \sup_{t \geq 0} |M_t^n - M_t|^2 \right] \stackrel{\text{Doob}}{\leq} 4 \mathbb{E} [(M_\infty^n - M_\infty)^2] = 4\|M^n - M\|_{H^2}^2 \stackrel{n \rightarrow \infty}{\longrightarrow} 0 \quad (5.102)$$

Q.: Is  $M$  a continuous Martingale? Because of (5.102) there exists a subsequence  $(n_k)_{k \geq 0}$  s.t.  $\sup_{t \geq 0} |M_t^{n_k} - M_t| \xrightarrow{k \rightarrow \infty} 0$  a.s.. We have uniformly convergence on subsequences, therefore  $t \mapsto M_t$  is continuous, i.e.  $M \in \mathcal{M}$ .

Q.: Is  $M \in H^2$ ?

$$\sup_{t \geq 0} \mathbb{E} [M_t^2] = \sup_{t \geq 0} \mathbb{E} [(\mathbb{E} [M_\infty | \mathcal{F}_t])^2] \leq \sup_{t \geq 0} \mathbb{E} [\mathbb{E} [M_\infty^2 | \mathcal{F}_t]] = \mathbb{E} [M_\infty^2] < \infty \quad (5.103)$$

$\Rightarrow M \in H^2$ .

5) Verify c): Let  $M \in H^2$  with  $M_0 = 0$ . Let  $\langle M \rangle$  be the quadratic variation of  $M$ .  $\Rightarrow M^2 - \langle M \rangle$  is a (local) martingale.  $\Rightarrow \mathbb{E} [M_t^2] - \mathbb{E} [\langle M \rangle_t] = \underbrace{\mathbb{E} [M_0^2]}_{=0} - \underbrace{\mathbb{E} [\langle M \rangle_0]}_{=0} \equiv 0 \forall t \geq 0$

$$\Rightarrow \|M\|_{H^2}^2 = \mathbb{E} [M_\infty^2] = \lim_{t \rightarrow \infty} \mathbb{E} [M_t^2] = \lim_{t \rightarrow \infty} \mathbb{E} [\langle M \rangle_t] \stackrel{\text{monot. conv.}}{=} \mathbb{E} [\langle M \rangle_\infty] \quad (5.104)$$

□

**Example:** Let  $T \in \mathbb{R}_+$  be a fixed number and  $B$  a BM.

$$\Rightarrow M_t := B_{t \wedge T} \quad (5.105)$$

$$\|M\|_{H^2} := \begin{cases} \lim_{t \rightarrow \infty} \mathbb{E} [B_{t \wedge T}^2] = \mathbb{E} [B_T^2] = T \\ \mathbb{E} [\langle B_{t \wedge T} \rangle_\infty] = \lim_{t \rightarrow \infty} t \wedge T = T \end{cases} \quad (5.106)$$

# 6 Stochastic Integration

Strategy:

- a) 6.1)-6.2) Define the Lebesgue-Stieltjes-Integral for functions, then extend to

$$\int_0^t X_s dA_s \equiv (X \cdot A)_t - (X \cdot A)_0 \quad (6.1)$$

for  $X$  locally bounded and  $A \in \mathcal{A}$ .

- b) 6.3)-6.5) Itô-Integral:

- 1) Define

$$\int_0^t X_s dM_s \quad (6.2)$$

for  $M \in H^2$  and  $X$  "elementary process".  $\rightarrow$  Itô-isometry:  $\| \underbrace{X \cdot M}_{\text{Itô-int}} \|_{H^2}^2 = \| \underbrace{X^2 \cdot \langle M \rangle}_a \|$

- 2) Extension to  $X \in L^2(M)$ , e.g.

$$\int_0^t B_s dB_s = ? \quad (6.3)$$

- 3) Extension to semi-martingales.

## 6.1 Lebesgue-Stieltjes Integral

Riemann case:  $\Delta_n = \{a = x_0 < x_1 < \dots < x_n = b\}$ . Define

$$\text{Riemann-Integral: } \lim_{\|\Delta\| \rightarrow 0} \sum_{k=0}^{n-1} f(\xi_k)(x_{k+1} - x_k) \text{ for some } \xi_k \in (x_k, x_{k+1}] \quad (6.4)$$

The limit exists e.g. when  $f$  is continuous.

$$\text{Riemann-Stieltjes: } \lim_{\|\Delta_n\| \rightarrow 0} \sum_{k=0}^{n-1} f(\xi_k)(g(x_{k+1}) - g(x_k)) \text{ for some } \xi_k \in (x_k, x_{k+1}] \quad (6.5)$$

The limit exists e.g. if  $g$  is continuous and has finite variation.

### Proposition 6.1.

Let  $g : \mathbb{R}_+ \rightarrow \mathbb{R}$  be a right-continuous function. Then the following statements are equivalent.

- a)  $g$  has finite variation.
- b)  $\exists g_1, g_2$  increasing, right-continuous s.t.  $g = g_1 - g_2$ .
- c)  $\exists$  (signed) Radon measure,  $\mu^g$ , on  $\mathbb{R}^+$  s.t.

$$g(t) = \mu^g([0, t]), \forall t \geq 0 \quad (6.6)$$

*Proof.* a  $\Leftrightarrow$  b trivial.

a, b  $\Leftrightarrow$  c: "  $\Rightarrow$  " WLOG take  $g \geq 0$ , rightcontinuous and  $S_t(g) < \infty$  (variation of  $g$  in  $[0, t]$ ) and  $g(0) = 0$ .  $\Rightarrow \mu([0, t]) := g(t) \forall t \geq 0$ .  $\Rightarrow \mu$  is a Radon-measure on  $\mathbb{R}_+$ .

"  $\Leftarrow$  " Given  $\mu$ , define  $g(t) := \mu([0, t])$ ,  $\forall t \geq 0$ . Therefore  $g$  is rightcontinuous and has finite variation.  $\square$

**Definition 6.2** (Lebesgue-Stieltjes-Integral).

Let  $g : \mathbb{R}_+ \rightarrow \mathbb{R}$  be right-continuous, with finite variation and let  $f : \mathbb{R}_+ \rightarrow \mathbb{R}$  be a locally bounded function. Then the *Lebesgue-Stieltjes-Integral* of  $f$  w.r.t.  $g$  is defined by

$$\int_{(0,t]} f(s)\mu^g(ds) \tag{6.7}$$

where  $\mu^g$  is the measure of Prop 6.1.

**Notation:** We sometimes also write

$$\int_0^t f(s)\mu^g(ds) = \int_0^t f dg = \int_0^t f(s)dg(s) = \int_0^t f(s)g(ds) \tag{6.8}$$

**Remark:** (i) If  $g \in C^1 \Rightarrow \int_0^t f(s)\mu^g(ds) = \int_0^t f(s)g'(s)ds$  where the last term means the usual Lebesgue-Integral.

(ii) If  $g$  and  $h$  are continuous and of finite variation then

$$d(gh)(s) = g(s)dh(s) + h(s)dg(s) \tag{6.9}$$

**Proposition 6.3.**

Let  $g$  be right-continuous, increasing and let  $f$  be left-continuous and locally bounded. Then  $\forall t \geq 0$

$$\lim_{\|\Delta\| \rightarrow 0} I_t^\Delta(f, g) = \int_0^t f dg \tag{6.10}$$

where

$$I_t^\Delta(f, g) := \sum_{k=0}^{n-1} f(t_k)(g(t_{k+1}) - g(t_k)) \tag{6.11}$$

and  $\Delta$  is a partition of  $[0, t]$ , i.e.  $\Delta = \{0 = t_0 < t_1 < \dots < t_n = t\}$ .

**Remark:** If  $f$  is continuous one can replace  $f(t_k)$  by  $f(t_{k+1})$ . The BM analogue will **not** satisfy this property.

*Proof.* Let  $f^\Delta := \sum_{k=0}^{n-1} f(t_k)\mathbb{1}_{(t_k, t_{k+1}]}$ . Since  $f$  is locally bounded  $\Rightarrow \sup_{s \in [0, t]} |f^\Delta(s)| \leq C < \infty$ . Also, since  $f$  is left continuous,

$$\Rightarrow \lim_{\|\Delta\| \rightarrow 0} f^\Delta(s) = f(s) \forall s \in [0, t] \tag{6.12}$$

$$I_t^\Delta(f, g) = \int_0^t f^\Delta(s)\mu^g(ds) \xrightarrow{\|\Delta\| \rightarrow 0} \int_0^t f(s)\mu^g(ds) \stackrel{def}{=} \int_0^t f dg \tag{6.13}$$

$\square$

## 6.2 Stochastic Integration w.r.t. bounded variation processes

We define " $\int_0^t X_s dA_s$ " for  $A \in \mathcal{A}$  and for

$$X \in \mathcal{B} := \{X : \text{adapted, left-continuous, the trajectories are locally bounded}\}. \quad (6.14)$$

### Definition 6.4.

Let  $A \in \mathcal{A}, X \in \mathcal{B}$  then we define the *stochastic integral of X w.r.t. A* pathwise through

$$(X \cdot A)_t = \int_0^t X dA = \int_0^t X_s dA_s : \omega \mapsto \int_0^t X_s(\omega) dA_s(\omega) \leftarrow \text{(usual Leb.-Stieltj.-Integral)} \quad (6.15)$$

**Notation:**  $X \cdot A \equiv ((X \cdot A)_{t \geq 0})$

### Properties:

### Theorem 6.5.

For  $A \in \mathcal{A}$  and  $X, Y \in \mathcal{B}$  it holds

- a)  $X \cdot A \in \mathcal{A}_0$ .
- b)  $X \cdot A$  is bilinear in  $X$  and  $A$ .
- c) For any stopping time  $T$  it holds  $(X \cdot A)^T = X \cdot A^T$ .
- d)  $X \cdot (Y \cdot A) = (XY) \cdot A$ .

*Proof.* **ad a)**  $(X \cdot A)_0 = 0$  clear. (consider the partition in 6.3)

Pathwise continuous since  $X$  is locally bounded and  $A$  is continuous.

adapted:

$$\int_0^t X_s dA_s = \lim_{\|\Delta\| \rightarrow 0} \sum_{k=0}^{n-1} X_{t_k} (A_{t_{k+1}} - A_{t_k}) \text{ meas. w.r.t } \mathcal{F}_t \quad (6.16)$$

(limit of measurable functions again measurable)

Finite variation:

$$S_t((X \cdot A)(\omega)) \leq \underbrace{\sup_{0 \leq s \leq t} |X_s(\omega)|}_{< \infty} S_t(A(\omega)) \quad (6.17)$$

**ad b)** Trivial.

**ad c)**

$$(X \cdot A)^T(\omega) = \lim_{n \rightarrow \infty} \sum_{k=0}^{n-1} X_{t_k \wedge T}(\omega) [A_{t_{k+1} \wedge T}(\omega) - A_{t_k \wedge T}] \quad (6.18)$$

$$= \lim_{n \rightarrow \infty} \sum_{k=0}^{n-1} X_{t_k}(\omega) [A_{t_{k+1} \wedge T}(\omega) - A_{t_k \wedge T}] \quad (6.19)$$

$$= (X \cdot A^T)(\omega) \quad (6.20)$$

because: if  $t_k > T \Rightarrow t_{k+1} > T \Rightarrow A_{t_{k+1} \wedge T} - A_{t_k \wedge T} = 0$ .

**ad d)**

$$(X \cdot (Y \cdot A))_t = \int_0^t X_s d((Y \cdot A)_s) \quad (6.21)$$

$$= \int_0^t X_s Y_s dA_s \equiv ((XY) \cdot A)_t \quad (6.22)$$

□

## 6.3 Itô-Integral

We will define

$$\int_0^s X_s dB_s \quad (6.23)$$

where  $B$  is a BM. If  $f, g \in C^1$  we know

$$f(g(t)) = f(g(0)) + \int_0^t f'(g(s))g'(s)ds \quad (6.24)$$

If now  $g$  is a brownian path, then  $g'$  does not exists....mmm. :(

One of the results will be for  $f \in C^2$

$$f(B_t) = f(B_0) + \underbrace{\int_0^t f'(B_s)dB_s}_{\text{Itô-Integral}} + \frac{1}{2} \int_0^t f''(B_s) \underbrace{ds}_{\equiv d\langle B \rangle_s} \quad (6.25)$$

If we try to define

$$I_n := \sum_{k=0}^{n-1} f(B_{t_k})(B_{t_{k+1}} - B_{t_k}), \quad (6.26)$$

then,  $\lim_{n \rightarrow \infty}$  (with  $\|\Delta\| \rightarrow 0$ ) does not exist pointwise in  $\Omega$  (, i.e. pathwise).  $\Rightarrow I_n$  as Lebesgue-Stieltjes-Integral can not be defined.

But one can see that the limit is fine in  $L^2$ .

Further issue: Let  $B$  be a one-dimensional standard BM. Let  $t_k := \frac{k}{n}t, 0 \leq k \leq n$ .

$$\Rightarrow \lim_{n \rightarrow \infty} \sum_{k=0}^{n-1} B_{t_k}(B_{t_{k+1}} - B_{t_k}) = \frac{B_t^2 - t}{2} \text{ in } L^2 \quad (6.27)$$

$$\lim_{n \rightarrow \infty} \sum_{k=0}^{n-1} B_{t_{k+1}}(B_{t_{k+1}} - B_{t_k}) = \frac{B_t^2 + t}{2} \text{ in } L^2 \quad (6.28)$$

Proof:

$$\sum_{k=0}^{n-1} B_{t_k}(B_{t_{k+1}} - B_{t_k}) = \underbrace{\sum_{k=0}^{n-1} \frac{1}{2}(B_{t_{k+1}}^2 - B_{t_k}^2)}_{=\frac{1}{2}B_t^2 \text{ (since } t_n=t, B_0=0)} - \frac{1}{2} \underbrace{\sum_{k=0}^{n-1} (B_{t_{k+1}} - B_{t_k})^2}_{\rightarrow t \text{ in } L^2 \text{ for } n \rightarrow \infty} \quad (6.29)$$

Itô chooses (6.27) as the definition for  $\int_0^t B_s dB_s$ .

### 6.3.1 Itô-Integral for elementary processes

#### Definition 6.6.

Let  $(\Omega, \mathcal{F}, \mathcal{F}_t, \mathbb{P})$  be a standard filtered probability space.  $X : \mathbb{R}_+ \times \Omega \rightarrow \mathbb{R}$  is called an *elementary process* if

- Exists a sequence of times  $0 = t_0 < t_1 < \dots \nearrow \infty$
- Exists a sequence of r.v.  $(\xi_n)_{n \geq 0}$  uniformly bounded (i.e.  $\sup_{n \geq 0} |\xi_n(\omega)| \leq C \forall \omega \in \Omega$ ).
- $\xi_n$  are  $\mathcal{F}_{t_n}$ -measurable.
- 

$$X_t(\omega) = \xi_0(\omega) \mathbb{1}_0(t) + \sum_{n \geq 0} \xi_n(\omega) \mathbb{1}_{(t_n, t_{n+1}]}(t), 0 \leq t < \infty, \omega \in \Omega \quad (6.30)$$

That means, that  $X$  is piecewise constant.

**Notation:**  $X \in \xi \Leftrightarrow X$  is an elementary process.

**Definition 6.7** (Itô-Integral for elementary processes).

Let  $X \in \xi, M \in H^2$ . Then we define the *stochastic integral of  $X$  w.r.t.  $M$*  pathwise by

$$\int_0^t X_s dM_s \equiv (X \cdot M)_t := \sum_{k=0}^{\infty} \xi_k (M_{t_{k+1} \wedge t} - M_{t_k \wedge t}) \quad (6.31)$$

$$= \sum_{k=0}^{n-1} \xi_k (M_{t_{k+1}} - M_{t_k}) + \xi_n (M_t - M_{t_{n-1}}) \quad (6.32)$$

where  $n$  is the unique number s.t.  $t \in (t_{n-1}, t_n]$ .

### The Itô-Isometry

**Theorem 6.8.**

Let  $M \in H^2$  and  $X \in \xi$ . Then,

- a)  $X \cdot M \in H_0^2$
- b)  $\langle X \cdot M \rangle_t = \int_0^t X_s^2 d\langle M \rangle_s \equiv (X^2 \cdot \langle M \rangle)_t$
- c) Isometry:

$$\|X \cdot M\|_{H^2}^2 \equiv \mathbb{E} \left[ \left( \int_0^\infty X_s dM_s \right)^2 \right] = \mathbb{E} \left[ \int_0^\infty X_s^2 d\langle M \rangle_s \right] \equiv \|X\|_{L^2(\mathbb{R}_+ \times \Omega, d\langle M \rangle \otimes \mathbb{P})}^2 \quad (6.33)$$

**Corollary 6.9.**

For  $M = (B_{s \wedge t})_{s \geq 0}$ , then

- a)  $X \cdot B^t \in H_0^2$ .
- b)  $\langle X \cdot B \rangle_t = \int_0^t X_s^2 ds$
- c)  $\mathbb{E} \left[ \left( \int_0^t X_s dB_s \right)^2 \right] = \mathbb{E} \left[ \int_0^t X_s^2 ds \right]$

*Proof of the Theorem.* Easy to check:  $(X \cdot M)$  is adapted,  $(X \cdot M)_0 = 0$ , Continuity.

Martingale? Let  $s < t$ , say  $s \in (t_k, t_{k+1}]$  and  $t \in (t_n, t_{n+1}]$ .

$$\mathbb{E} [(X \cdot M)_t | \mathcal{F}_s] \quad (6.34)$$

$$= \mathbb{E} \left[ (X \cdot M)_s + \xi_k (M_{t_{k+1}} - M_s) + \sum_{l=k+1}^{n-1} \xi_l (M_{t_{l+1}} - M_{t_l}) + \xi_n (M_t - M_{t_n}) | \mathcal{F}_s \right] \quad (6.35)$$

$$= (X \cdot M)_s + \xi_k \underbrace{\mathbb{E} [M_{t_{k+1}} - M_s | \mathcal{F}_s]}_{=0} + \mathbb{E} \left[ \xi_n \underbrace{\mathbb{E} [M_t - M_{t_n} | \mathcal{F}_{t_n}]}_{=0} | \mathcal{F}_s \right] + \mathbb{E} \left[ \sum_{l=k+1}^{n-1} \xi_l \underbrace{\mathbb{E} [M_{t_{l+1}} - M_{t_l} | \mathcal{F}_{t_l}]}_{=0} | \mathcal{F}_s \right] \quad (6.36)$$

$$= (X \cdot M)_s \quad (6.37)$$

since  $\mathcal{F}_s \subset \mathcal{F}_{t_n}$  and  $\xi_k$  is  $F_{t_n}$ -measurable.

$L^2$ -boundedness follows from the uniform bound of the  $\xi_k$ .

**ad b)** WLOG:  $s = t_k, t = t_{n+1}$  (otherwise add two points to  $\{t_i\}$ ). To show  $(X \cdot M)_t^2 - \int_0^t X_u^2 d\langle M \rangle_u$  is a martingale, i.e.

$$\mathbb{E} \left[ (X \cdot M)_t^2 - \int_0^t X_u^2 d\langle M \rangle_u | \mathcal{F}_s \right] \stackrel{\text{if } s < t}{=} (X \cdot M)_s^2 - \int_0^s X_u^2 d\langle M \rangle_u. \quad (6.38)$$

$$\stackrel{5.9}{\Rightarrow} \langle X \cdot M \rangle_t = \int_0^t X_u^2 d\langle M \rangle_u \equiv (X^2 \cdot \langle M \rangle)_t \quad (6.39)$$

$$\mathbb{E} \left[ (X \cdot M)_t^2 - (X \cdot M)_s^2 \middle| \mathcal{F}_s \right] \quad (6.40)$$

$$= \mathbb{E} \left[ ((X \cdot M)_t - (X \cdot M)_s)^2 \middle| \mathcal{F}_s \right] + \underbrace{2 \mathbb{E} [(X \cdot M)_s ((X \cdot M)_t - (X \cdot M)_s) \middle| \mathcal{F}_s]}_{=0 \text{ by a) since } (X \cdot M)_s \text{ } \mathcal{F}_s\text{-meas.}} \quad (6.41)$$

$$= \mathbb{E} \left[ \left( \sum_{l=k}^n \xi_l (M_{t_{l+1}} - M_{t_l}) \right)^2 \middle| \mathcal{F}_s \right] \quad (6.42)$$

$$= \mathbb{E} \left[ \sum_{l=k}^n \xi_l^2 (M_{t_{l+1}} - M_{t_l})^2 \middle| \mathcal{F}_s \right] + 2 \mathbb{E} \left[ \sum_{k \leq j < l \leq n} \xi_j \xi_l (M_{t_{l+1}} - M_{t_l})(M_{t_{j+1}} - M_{t_j}) \right] \quad (6.43)$$

$$= \mathbb{E} \left[ \sum_{l=k}^n \xi_l^2 (M_{t_{l+1}} - M_{t_l})^2 \middle| \mathcal{F}_s \right] + 2 \mathbb{E} \left[ \sum_{k \leq j < l \leq n} \xi_j \xi_l \underbrace{\mathbb{E} [(M_{t_{l+1}} - M_{t_l}) \middle| \mathcal{F}_{t_l}]}_{=0} (M_{t_{j+1}} - M_{t_j}) \right] \quad (6.44)$$

$$= \mathbb{E} \left[ \int_s^t X_u^2 d\langle M \rangle_u \middle| \mathcal{F}_s \right] \quad (6.45)$$

$\Rightarrow$  (6.38) holds

c)

$$\|X \cdot M\|_{H^2}^2 \equiv \mathbb{E} \left[ (X \cdot M)_\infty^2 \right] \stackrel{5.21}{=} \mathbb{E} [\langle X \cdot M \rangle_\infty] \stackrel{b)}{=} \mathbb{E} \left[ \int_0^\infty X_u^2 d\langle M \rangle_u \right] \quad (6.46)$$

□

[16.11.2012]  
[20.11.2012]

**Proposition 6.10** (Kunita-Watanabe).

$M, N \in H^2$ ,  $X, Y \in \xi$ .

$$a) \langle X \cdot M, Y \cdot N \rangle_t = \int_0^t X_s Y_s d\langle M, N \rangle_s \equiv ((XY) \cdot \langle M, N \rangle)_t$$

$$b) \mathbb{E} [\langle X \cdot M, Y \cdot N \rangle_\infty] \leq \mathbb{E} \left[ \int_0^\infty X_s^2 d\langle M \rangle_s \right]^{1/2} \mathbb{E} \left[ \int_0^\infty Y_s^2 d\langle N \rangle_s \right]^{1/2}$$

*Proof.* Claim:  $(X \cdot M)_t (Y \cdot N)_t - \int_0^t X_s Y_s d\langle M, N \rangle_s$  is a martingale.

We assume, that  $X$  and  $Y$  are constant on the same intervals. Otherwise one can just add the respective points.

$$(X \cdot M)_t = \sum_{l=1}^n X_{t_l} \underbrace{(M_{t_{l+1}} - M_{t_l})}_{=: \Delta M_l} \quad (6.47)$$

$$(Y \cdot N)_t = \sum_{l=1}^n Y_{t_l} \underbrace{(N_{t_{l+1}} - N_{t_l})}_{=: \Delta N_l} \quad (6.48)$$

Then

$$\mathbb{E} [(X \cdot M)_t (Y \cdot N)_t - (X \cdot M)_s (Y \cdot N)_s \middle| \mathcal{F}_s] \quad (6.49)$$

$$= \mathbb{E} \left[ \sum_{l, l'=k}^n X_{t_l} Y_{t_{l'}} \Delta M_l \Delta N_{l'} \middle| \mathcal{F}_s \right] \quad (6.50)$$

$$\stackrel{k: t_k = s}{=} \mathbb{E} \left[ \sum_{l=k}^n X_{t_l} Y_{t_l} \Delta M_l \Delta N_l \middle| \mathcal{F}_s \right] + \underbrace{\mathbb{E} \left[ \sum_{l \neq l'} \dots \right]}_{=0} \quad (6.51)$$

$$= \mathbb{E} \left[ \int_s^t X_s Y_s d\langle M, N \rangle_s \middle| \mathcal{F}_s \right] \quad (6.52)$$



b)

$$\mathbb{E} [\langle X \cdot M, Y \cdot N \rangle_\infty] \stackrel{5.19}{\leq} \mathbb{E} [\langle X \cdot M \rangle_\infty^{1/2} \langle Y \cdot N \rangle_\infty^{1/2}] \quad (6.53)$$

$$\stackrel{C.-S.}{\leq} \mathbb{E} [\langle X \cdot M \rangle_\infty]^{1/2} \mathbb{E} [\langle Y \cdot N \rangle_\infty]^{1/2} \quad (6.54)$$

□

Goal of the week

$$\int_0^t X_s dM_s \quad (6.55)$$

$X \in \xi$  (Want a larger space! : today),  $M \in H^2$  (Want the space of semimartingales: friday!)

**Definition 6.11** (Predictable  $\sigma$ -Algebra).

$\mathcal{P} = \sigma(\xi)$  smallest  $\sigma$ -algebra on  $\mathbb{R}_+ \times \Omega$  s.t.

$$(t, \omega) \mapsto X_t(\omega) \text{ measurable } \forall X \in \xi \quad (6.56)$$

A process  $X$  is called *predictable* iff  $\mathcal{P}$ -measurable.

**Proposition 6.12.**

$$\sigma(\xi) = \sigma(\{X : \mathbb{R}_+ \times \Omega \rightarrow \mathbb{R}, \text{ adapted, } X \text{ left cont. on } (0, \infty)\}) \quad (6.57)$$

$$= \sigma(\{X : \mathbb{R}_+ \times \Omega \rightarrow \mathbb{R}, \text{ adapted, } X \text{ cont. on } (0, \infty)\}) \quad (6.58)$$

*Proof.* Exercise. □

**Definition 6.13.**

Let  $M \in H^2$ . We define

$$\mathcal{L}^2(M) = \{X : \mathbb{R}_+ \times \Omega \rightarrow \mathbb{R}, \text{ predictable, } \|X\|_M < \infty\} \quad (6.59)$$

with  $\|\cdot\|_M$  defined as

$$\|X\|_M := \|X\|_{L^2(d\langle M \rangle \otimes dP)} := \mathbb{E} \left[ \int_0^\infty X_s^2 d\langle M \rangle_s \right]^{1/2} \quad (6.60)$$

$L^2(M)$  is the space of equivalence classes

$$X \sim Y \Leftrightarrow \|X - Y\|_M = 0 \quad (6.61)$$

The Itô-Isometry is now

$$\|X\|_M \equiv \mathbb{E} \left[ \int_0^\infty X_s^2 d\langle M \rangle_s \right]^{1/2} \stackrel{\text{Itô}}{\stackrel{\text{Isom}}{=}} \mathbb{E} \left[ \left( \int_0^\infty X_s dM_s \right)^2 \right]^{1/2} \equiv \|X \cdot M\|_{H^2} \quad (6.62)$$

**Proposition 6.14.**

$X \in L^2(M) \Rightarrow \exists$  a sequence of  $X^n \in L^2(M) \cap \xi$  s.t.

$$\|X^n - X\|_M \xrightarrow{n \rightarrow \infty} 0 \quad (6.63)$$

i.e.

$$\mathbb{E} \left[ \int_0^\infty |X_s - X_s^n|^2 d\langle M \rangle_s \right] \xrightarrow{n \rightarrow \infty} 0 \quad (6.64)$$

*Proof.* We give the proof only for the case  $M=B$ =Brownian Motion, i.e.  $d\langle B \rangle_s = ds$ , where  $ds$  is the Lebesgue-measure. (If  $d\langle M \rangle_s \ll \text{lebesgue}$ , then the considerations are similar. If not, then the proof is tricky (see Karatzas-Shreve, Lemma 2.7))

Let  $B$  be a BM and let  $T > 0$  arbitrary.

**Step 1:**  $Z \in L^2(B)$ , bounded, pathwise continuous.

Consider partitions

$$\Delta_n = \{t_0 = 0 < t_1^{(n)} < t_2^{(n)} < \dots < t_n^{(n)} = T\} \quad (6.65)$$

with  $\|\Delta_n\| \rightarrow 0$  for  $n \rightarrow \infty$ . Define

$$\phi_t^n(\omega) = Z_t(\omega) \mathbb{1}_{(0)}(t) + \sum_{k=1}^{n-1} Z_{t_k}(\omega) \mathbb{1}_{(t_k, t_{k+1}]}(t) \quad (6.66)$$

Then it holds, by continuity of  $t \mapsto Z_t(\omega)$  and since  $\|\Delta\|_n \rightarrow 0$ :

$$\int_0^T |\phi_t^n(\omega) - Z_t(\omega)|^2 dt \xrightarrow{n \rightarrow \infty} 0 \quad (6.67)$$

By Lebesgue (dominated convergence)

$$\mathbb{E} \left[ \int_0^T |\phi_t^n - Z_t|^2 dt \right] \rightarrow 0 \quad (6.68)$$

i.e.

$$\|\phi^n - Z\|_M \rightarrow 0 \quad (6.69)$$

**Step 2:**  $Y \in L^2(B)$ , bounded.

Let  $K$  s.t.  $|Y| \leq K$ . We are going to introduce mollifiers  $\psi_n$  s.t.,

$$\psi_n(x) \geq 0, \psi_n \text{ continuous}, \int \psi_n dx = 1, \psi_n(x) = 0 \text{ if } x \notin [0, \frac{1}{n}] \quad (6.70)$$

For  $t \leq T$  define

$$Z_t^n = \int_0^T \psi_n(t-s) Y_s ds \quad (6.71)$$

Then  $t \mapsto Z_t^n$  is continuous and bounded, i.e.  $|Z_t^n| \leq K$ .

It holds

$$\int_0^T (Z_t^n(\omega) - Y_t(\omega))^2 dt \rightarrow 0 \quad \forall \omega \in \Omega \quad (6.72)$$

and therefore by dominated convergence

$$\Rightarrow \mathbb{E} \left[ \int_0^T (Z_t^n - Y_t)^2 dt \right] \xrightarrow{n \rightarrow \infty} 0 \quad (6.73)$$

**Step 3:**  $X \in L^2(B)$ .

To make it bounded define

$$Y_t^n = \begin{cases} -n & X_t \leq -n \\ X_t & -n \leq X_t \leq n \\ n & X_t \geq n \end{cases} \quad (\text{"truncation"}) \quad (6.74)$$

$$\|X - Y^n\|_{L^2(B)} = \mathbb{E} \left[ \int_0^T (X_t - Y_t^n)^2 dt \right] \quad (6.75)$$

$$\leq \mathbb{E} \left[ \int_0^T X_t^2 \mathbb{1}_{\{|X_t| \geq n\}} dt \right] \xrightarrow{n \rightarrow \infty} 0 \quad (6.76)$$

again by dominated convergence. Note that we could use that  $X$  was bounded in the previous steps. Here we have to use the hypothesis that  $X \in L^2(B)$ .  $\square$

**Theorem 6.15.**

Let  $X \in L^2(M)$ . Then  $\exists!(X \cdot M) \in H_0^2$  s.t., if  $X^n \in \xi$  is a sequence with

$$\|X - X^n\|_M \xrightarrow{n \rightarrow \infty} 0 \quad (6.77)$$

then also

$$\|X \cdot M - X^n \cdot M\|_{H^2} \xrightarrow{n \rightarrow \infty} 0 \quad (6.78)$$

Thus

$$L^2 - \lim_{n \rightarrow \infty} (X^n \cdot M)_t = X \cdot M_t \quad (6.79)$$

uniformly in  $t$ . The map  $L^2(M) \rightarrow H_0^2, X \mapsto X \cdot M$  is an isometry, i.e.

$$\|X\|_M = \|X \cdot M\|_{H^2} \quad (6.80)$$

*Proof.* Let  $X \in L^2(M)$ .

**Step 1:** Definition of  $(X \cdot M)$ .

By Prop. 6.14:  $\exists X^n \in \xi : \|X - X^n\|_M \rightarrow 0$ . Therefore

$$\|X^n \cdot M - X^m \cdot M\|_{H^2} \stackrel{\text{Isometry}}{=} \|X^n - X^m\|_M \xrightarrow{m, n \rightarrow \infty} 0, \quad (6.81)$$

i.e.  $(X^n \cdot M)$  is a cauchy sequence in  $H^2$  which is a Hilbert space.  $\Rightarrow \lim_{n \rightarrow \infty} X^n \cdot M$  exists and is in  $H^2$ . So we can define  $X \cdot M := \lim_{n \rightarrow \infty} X^n \cdot M$ .

**Step 2:** Show that  $X \cdot M$  is independent of  $X^n$ .

Let  $Y^n$  be a second approximating sequences, i.e.

$$\|Y^n - X\|_M \rightarrow 0 \quad (6.82)$$

Then

$$\|X^n \cdot M - Y^n \cdot M\|_{H^2} = \|X^n - Y^n\|_M \xrightarrow{n \rightarrow \infty} 0 \quad (6.83)$$

Thus we have

$$\lim_{n \rightarrow \infty} X^n \cdot M = \lim_{n \rightarrow \infty} Y^n \cdot M \quad (6.84)$$

Lastly we have to check, whether  $\|X \cdot M - X^n \cdot M\|_{H^2} \rightarrow 0$ .

$$\|X \cdot M - X^n \cdot M\|_{H^2} \stackrel{\text{Doob}}{\leq} 4 \sup_t \mathbb{E} \left[ ((X^n \cdot M)_t - (X \cdot M)_t)^2 \right] \quad (6.85)$$

$$= 4 \|X^n - X\|_M \rightarrow 0 \quad (6.86)$$

□

**Definition 6.16.**

We define

$$\int_0^t X_s dM_s := (X \cdot M)_t \quad (6.87)$$

as *Itô's Integral*, where  $X \cdot M$  is the unique process from the previous Theorem.

## 6.4 Properties of Itô's Integral.

Kunita-Watanabe holds exactly as in the previous setting.

### Corollary 6.17.

Let  $M, N \in H^2$ ,  $X \in L^2(M)$ ,  $Y \in L^2(N)$ . Then

- a)  $\langle X \cdot M \rangle_t = \int_0^t X_s^2 d\langle M \rangle_s = (X^2 \cdot \langle M \rangle)_t$
- b)  $\langle X \cdot M, Y \cdot N \rangle_t = \int_0^t X_s Y_s d\langle M, N \rangle_s = ((XY) \cdot \langle M, N \rangle)_t$
- c)  $|\mathbb{E}[\langle X \cdot M, Y \cdot N \rangle_t]| \leq \mathbb{E}\left[\int_0^t |X_s| |Y_s| d\langle M, N \rangle_s\right] \leq \sqrt{\mathbb{E}\left[\int_0^t X_s^2 d\langle M \rangle_s\right]} \sqrt{\mathbb{E}\left[\int_0^t Y_s^2 d\langle N \rangle_s\right]}$

### Lemma 6.18.

Let  $X \in L^2(M)$  and  $Y \in L^2(X \cdot M)$ . Then

$$XY \in L^2(M) \quad (6.88)$$

and the associative property holds, i.e.

$$Y \cdot (X \cdot M) = (YX) \cdot M. \quad (6.89)$$

*Proof.* **Step 1:**  $XY \in L^2(M)$

It holds

$$\langle X \cdot M \rangle = X^2 \cdot \langle M \rangle \quad (6.90)$$

and thus

$$\mathbb{E}\left[\int_0^\infty Y_t^2 d\langle X \cdot M \rangle_t\right] = \mathbb{E}\left[\int_0^\infty Y_t^2 d(X^2 \cdot \langle M \rangle)_t\right] \stackrel{\text{Assoc. Stieltj.}}{=} \mathbb{E}\left[\int_0^\infty Y_t^2 X_t^2 d\langle M \rangle_t\right] \quad (6.91)$$

**Step 2:** Associativity.

Let  $N \in H^2$  arbitrary. Then

$$\langle (YX) \cdot M, N \rangle \stackrel{6.17}{=} (YX) \cdot \langle M, N \rangle \stackrel{\text{Assoc. Stieltj.}}{=} Y \cdot (X \cdot \langle M, N \rangle) \stackrel{6.17}{=} Y \cdot \langle X \cdot M, N \rangle \stackrel{6.17}{=} \langle Y \cdot (X \cdot M), N \rangle \quad (6.92)$$

Hence we have

$$\langle [(YX) \cdot M] - [Y \cdot (X \cdot M)], N \rangle = 0 \quad \forall N \in H^2 \quad (6.93)$$

and thus  $(YX) \cdot M = Y \cdot (X \cdot M)$ .  $\square$

### Proposition 6.19.

Let  $X \in L^2(M)$ ,  $T$  a stopping time. Then

$$(X \cdot M)^T = X \cdot M^T = (X \mathbb{1}_{[0, T]}) \cdot M \quad (6.94)$$

*Proof.* Follows from the Lemma above since

$$M^T = \mathbb{1}_{[0, T]} M \quad (6.95)$$

$\square$

**Lemma 6.20.**

Let  $X, Y \in L^2(M)$ ,  $0 \leq s \leq u < t$ . Then the following properties hold

- a)  $\int_s^t X_v dM_v = \int_s^u X_v dM_v + \int_u^t X_v dM_v$
- b)  $\int_s^t (\alpha X_v + \beta Y_v) dM_v = \alpha \int_s^t X_v dM_v + \beta \int_s^t Y_v dM_v$
- c)  $s < t \Rightarrow \mathbb{E} \left[ \int_s^t X_v dM_v \right] = 0$
- d)  $\mathbb{E} \left[ \int_0^t X_v dM_v | \mathcal{F}_s \right] = \int_0^s X_v dM_v$

*Proof.* **a)** and **b)** are obvious. **c)** and **d)** hold since

$$N_t := \int_0^t X_v dM_v \quad (6.96)$$

is a Martingale. □

[20.11.2012]  
[23.11.2012]

## 6.5 The Itô-Integral for continuous local semimartingales

Let  $V$  be a semimartingale. Therefore we can write  $V = M + A$  with  $M \in \mathcal{M}_{loc}$  and  $A \in \mathcal{A}$ . We already defined

$$(X \cdot A)_t = \int_0^t X_s dA_s \quad (6.97)$$

where  $X \in \mathcal{B} := \{X : \text{adapted, left-continuous, the trajectories are locally bounded}\}$ .

By definition  $M \in \mathcal{M}_{loc}$  iff  $\exists (T_n)$  stopping times  $T_n \nearrow \infty$  s.t.  $M^{T_n}$  a Martingale. We also know for a Martingale  $M$

$$(X \cdot M)^T = X \cdot M^T \quad (6.98)$$

Therefore for a local martingale  $M$  the following definition makes sense

$$X \cdot M = \lim_{n \rightarrow \infty} X \cdot M^{T_n} \quad (6.99)$$

and so for a Semimartingale  $V = M + A$

$$X \cdot V = (X \cdot M) + (X \cdot A) \quad (6.100)$$

We are now doing this calculation step by step.

**Definition 6.21.**

For  $M \in \mathcal{M}_{loc}$  we define

$$\mathcal{L}_{loc}^2(M) = \{X : X \text{ is measurable, predictable and } \forall t \in [0, \infty) : \mathbb{P} \left( \int_0^t X_s^2 d\langle M \rangle_s < \infty \right) = 1\} \quad (6.101)$$

$$L_{loc}^2(M) = \text{space of equivalence classes.} \quad (6.102)$$

**Lemma 6.22.**

Let  $M \in \mathcal{M}_{loc}$ . It holds  $X \in \mathcal{L}_{loc}^2(M) \Leftrightarrow X$  is predictable,  $\exists$  stopping times  $(T_n)_{n \in \mathbb{N}} \nearrow \infty$  s.t.

$$\mathbb{E} \left[ \int_0^{T_n} X_s^2 d\langle M \rangle_s \right] < \infty \quad \forall n \in \mathbb{N}. \quad (6.103)$$

$$(\equiv X \in \mathcal{L}^2(M^{T_n})) \quad (6.104)$$

*Proof.* "⇒": Construct  $T_n$ :

$$T_n = \inf\{t : \int_0^t X_s^2 d\langle M \rangle_s \geq n\} \nearrow \infty \quad (6.105)$$

By definition  $\int_0^{T_n} X_s^2 d\langle M \rangle_s \leq n$  and therefore

$$\mathbb{E} \left[ \int_0^{T_n} X_s^2 d\langle M \rangle_s \right] \leq n \quad (6.106)$$

"⇐": Assume  $\exists(T_n)$  s.t.  $\mathbb{E} \left[ \int_0^{T_n} X_s^2 d\langle M \rangle_s \right] < \infty$ . Then

$$\mathbb{E} \left[ \int_0^{T_n \wedge t} X_s^2 d\langle M \rangle_s \right] < \infty \quad (6.107)$$

$$\Rightarrow \mathbb{P} \left( \int_0^{T_n \wedge t} X_s^2 d\langle M \rangle_s < \infty \right) = 1 \quad (6.108)$$

$$\Rightarrow \lim_{n \rightarrow \infty} \mathbb{P} \left( \int_0^{T_n \wedge t} X_s^2 d\langle M \rangle_s < \infty \right) = 1 \quad (6.109)$$

$$\Rightarrow \mathbb{P} \left( \int_0^t X_s^2 d\langle M \rangle_s < \infty \right) = 1 \quad (6.110)$$

□

**Definition 6.23.**

Let  $M \in \mathcal{M}_{loc}$  and  $X \in L_{loc}^2(M)$ . We define the stochastic integral as

$$X \cdot M := \lim_{n \rightarrow \infty} (X \cdot M^{T_n}) \quad (6.111)$$

**Remark:** Does the limit exist?  $m \geq n, t \leq T_n$

$$(X \cdot M^{T_m})_t = (X \cdot M^{T_m})_t^{T_n} = (X \cdot M^{T_m \wedge T_n})_t = (X \cdot M^{T_n})_t \quad (6.112)$$

Therefore the sequence 'stabilizes' at a certain point ⇒ Convergence.

**Definition 6.24.**

Let  $V \in \mathcal{S}$  be a semimartingale with  $V = M + A$  where  $M \in \mathcal{M}_{loc}, A \in \mathcal{A}$ . Let  $X \in \mathcal{B}$ . We define

$$(X \cdot V) := (X \cdot M) + (X \cdot A) \quad (6.113)$$

**Proposition 6.25.**

Let  $V, W \in \mathcal{S}$  and  $X, Y \in \mathcal{B}$ .

- a)  $(X, V) \mapsto X \cdot V$  is bilinear.
- b)  $V \in \mathcal{M}_{loc} \Rightarrow X \cdot V \in \mathcal{M}_{loc}^0$   
 $V \in \mathcal{A}_0 \Rightarrow X \cdot V \in \mathcal{A}_0$
- c) Associativity  $(XY) \cdot V = X \cdot (Y \cdot V)$
- d)  $\langle X \cdot V, Y \cdot W \rangle = (XY) \cdot \langle V, W \rangle (\equiv 0 \text{ if } V \text{ or } W \in \mathcal{A})$
- e)  $(X \cdot V)^T = (X \mathbb{1}_{[0,t]} \cdot V) = (X \cdot V^T)$
- f) Let  $a, b \in \mathbb{R} \Rightarrow \mathbb{P}(X_t = 0 \text{ on } [a, b] \text{ or } V_t \text{ is const. on } [a, b]) \Rightarrow X \cdot V \text{ is const. on } [a, b] = 1$

<sup>1</sup>Limes reinziehen, da Folge von absteigenden Mengen, vergl. Ana III Satz 2.10

*Proof.* **a)** Obvious.

**b)** Let  $V \in \mathcal{M}_{loc}$ . Then  $\exists S_n \nearrow \infty$  s.t.  $V^{S_n} \in \mathcal{M}$ . Thus  $(X \cdot V^{S_n}) \in \mathcal{M}$ . But since  $(X \cdot V^{S_n}) = (X \cdot V)^{S_n}$  it follows that  $(X \cdot V) \in \mathcal{M}_{loc}$ .

For  $V \in \mathcal{A}$  see Theorem 6.5.

**c)** Theorem 6.5 and Lemma 6.18.

**d)** Corollary 6.17.

**e)** Theorem 6.5 and Proposition 6.19.

**f)** Clear for  $V \in \mathcal{A}$  by the definition of  $(X \cdot V)$  (Lebesgue-Stieltjes).

Now let  $V \in \mathcal{M}_{loc}$ . By the assumption it holds either

$$X_0(\omega) = 0 \text{ on } [a, b] \quad (6.114)$$

or

$$\langle V \rangle(\omega) \text{ constant on } [a, b]. \quad (6.115)$$

Hence

$$t \mapsto (X^2 \cdot \langle V \rangle)_t = \int_0^t X_s^2 d\langle V \rangle_s \quad (6.116)$$

is constant on  $[a, b]$ . Since  $(X^2 \cdot \langle V \rangle)_t = \langle X \cdot V \rangle_t$  we get that  $X \cdot V$  is constant on  $[a, b]$ .  $\square$

**Theorem 6.26** (Convergence of Stochastic Integrals).

Let  $V \in \mathcal{S}$ , and  $X^n, Y \in \mathcal{B}$  s.t.  $|X^n| \leq Y \forall n$ . If

$$X_t^n \xrightarrow{n \rightarrow \infty} 0 \text{ a.s., } \forall t \geq 0, \quad (6.117)$$

then

$$X^n \cdot V \rightarrow 0 \text{ } \mathbb{P}\text{-stochastically, uniformly on compacts.} \quad (6.118)$$

i.e.

$$\forall t \geq 0, \varepsilon > 0, \lim_{n \rightarrow \infty} \mathbb{P} \left( \sup_{0 \leq s \leq t} |X^n \cdot V|_s \geq \varepsilon \right) = 0. \quad (6.119)$$

*Proof.* If  $V \in \mathcal{A}_0$  then the statement follow from dominated convergence. So now let  $V \in \mathcal{M}_{loc}$  and let  $T$  be a stopping time s.t.  $V^T \in H^2$  and  $X^T$  bounded. Since  $(X^n)^T \rightarrow 0$ , we get by dominated convergence

$$\|(X^n)^T\|_{V^T} = \mathbb{E} \left[ \int_0^\infty ((X_s^n)^T)^2 d\langle V^T \rangle_s \right] \rightarrow 0 \quad (6.120)$$

Hence

$$(X^n)^T \rightarrow 0 \text{ in } L^2(V^T) \quad (6.121)$$

and the  $L^2$ -isometry (Theorem 6.15) gives

$$(X^n \cdot V)^T \rightarrow 0 \text{ in } H^2 \quad (6.122)$$

and thus

$$(X^n \cdot V)^T \rightarrow 0 \text{ uniformly on } \mathbb{R}_+ \text{ } \mathbb{P}\text{-stochastic} \quad (6.123)$$

$$\Rightarrow (X^n \cdot V) \rightarrow 0 \text{ locally uniformly } \mathbb{P}\text{-stochastic} \quad (6.124)$$

$\square$

**Theorem 6.27** (Approximation by Riemann-sums).

Let  $V \in \mathcal{S}, X \in \mathcal{B}, t > 0$ .  $\Delta_n = \{0 = t_0 < t_1 < \dots < t_n = t\}$  partitions of  $[0, t]$ , s.t.  $\|\Delta_n\| \xrightarrow{n \rightarrow \infty} 0$ . Then for

$$I_s^{\Delta_n}(X, V) := \sum_{t_k \in \Delta_n} X_{t_k} (V_{s \wedge t_{k+1}} - V_{s \wedge t_k}), \quad (6.125)$$

$I_s^{\Delta_n}(X, V)$  converges stochastically uniformly on  $[0, t)$  towards  $\int_0^s X_u dV_u$ .

*Proof.* WLOG assume  $X_0 = 0$  and  $X$  bounded (otherwise there exist  $T_n \nearrow \infty$  s.t.  $X^{T_n}$  bounded). Consider  $X_t^{\Delta_n} = \sum_{t_k \in \Delta_n} X_{t_k} \mathbb{1}_{(t_k, t_{k+1}]}$ . Since  $X$  is left-continuous  $X_t^{\Delta_n} \xrightarrow{n \rightarrow \infty} X_t$  pointwise. Thus

$$I_s^{\Delta_n}(X, V) = \int_0^s X_u^{\Delta_n} dV_u \quad (6.126)$$

$$= \underbrace{\int_0^s (X_u^{\Delta_n} - X_u) dV_u}_{\rightarrow 0 \text{ by Theorem 6.26}} + \int_0^s X_u dV_u \quad (6.127)$$

□

**Theorem 6.28** (Integration by parts).

Let  $X, Y \in \mathcal{S}$ . Then it holds

$$X_t Y_t = X_0 Y_0 + \int_0^t X_s dY_s + \int_0^t Y_s dX_s + \langle X, Y \rangle_t \quad (6.128)$$

and in particular

$$X_t^2 = X_0^2 + 2 \int_0^t X_s dX_s + \langle X \rangle_t. \quad (6.129)$$

*Proof.* We show the second statement. The general case follows from polarisation. Let  $\Delta_n$  be a partition of  $[0, t]$ .

$$\langle X \rangle_t \leftarrow \sum_{t_k \in \Delta_n} (X_{t_{k+1}} - X_{t_k})^2 = \sum_{t_k \in \Delta_n} (X_{t_{k+1}} - X_{t_k})(X_{t_{k+1}} - X_{t_k}) \quad (6.130)$$

$$= \sum_{t_k \in \Delta_n} X_{t_{k+1}} (X_{t_{k+1}} - X_{t_k}) - \underbrace{\sum_{t_k \in \Delta_n} X_{t_k} (X_{t_{k+1}} - X_{t_k})}_{= I_t^{\Delta_n}(X, X)} \quad (6.131)$$

$$= \sum_{t_k \in \Delta_n} X_{t_{k+1}}^2 - \sum_{t_k \in \Delta_n} (X_{t_{k+1}} - X_{t_k}) X_{t_k} - \sum_{t_k \in \Delta_n} X_{t_k}^2 - I_t^{\Delta_n}(X, X) \quad (6.132)$$

$$\rightarrow X_t^2 - X_0^2 - 2I_t(X, X) \quad (6.133)$$

for  $\|\Delta_n\| \rightarrow \infty$ . □

**Corollary 6.29.**

Let  $X=B=BM$ .

$$B_t^2 = 2 \int_0^t B_s dB_s + \langle B \rangle_t = 2 \int_0^t B_s dB_s + t \quad (6.134)$$

$$\int_0^t B_s dB_s = \frac{B_t^2 - t}{2} \quad (6.135)$$



If we write this in differential notation this is

$$d(XY)_t = X_t dY_t + Y_t dX_t + \langle X, Y \rangle_t \quad (6.136)$$

$$= X_t dY_t + Y_t dX_t + dX_t dY_t \quad (6.137)$$

if we define  $dX_t dY_t = d\langle X, Y \rangle_t$ . Hence

$$(dX_t)^2 = dX_t dX_t = d\langle X \rangle_t \quad (6.138)$$

If  $X \in \mathcal{A}_0$  or  $Y \in \mathcal{A}_0$  we have

$$dX_t dY_t = 0 \quad (6.139)$$

Thus  $\forall X, Y, Z \in \mathcal{S}$ :

$$(dX_t dY_t) dZ_t = dX_t (dY_t dZ_t) = 0 \quad (6.140)$$

since  $(dX_t dY_t) dZ_t = \underbrace{(d\langle X, Y \rangle)}_{\in \mathcal{A}} dZ_t$ .

Now consider a BM  $B$ . Then we have

$$B_t^2 = B_0^2 + 2 \int_0^t B_s dB_s + t \quad (6.141)$$

$$\Rightarrow dB_t^2 = 2B_t dB_t + dt \quad (6.142)$$

Rules for calculation:

$$(dB_t)^2 = dt \quad (6.143)$$

$$dB_t dt = dt dB_t = 0 \quad (6.144)$$

$$(dt)^2 = 0 \quad (6.145)$$

For  $d \geq 2$  one gets

$$dB_t^i dB_t^j = \delta_{ij} dt \quad (6.146)$$

$$dB_t^i dt = dt dB_t^i = 0 \quad (6.147)$$

$$(dt)^2 = 0 \quad (6.148)$$

Back to  $d = 1$ . When we write  $dV_t$  we should interpret it as a map from  $\{(a, b) \in \mathbb{R}^2, a < b\} \rightarrow \mathbb{R}^\Omega$ .

$$dV_t : [a, b] \mapsto \int_a^b dV_t = V_b - V_a \quad (6.149)$$

$$d(X \cdot V)_t \equiv X_t dV_t : [a, b] \mapsto \int_a^b X_t dV_t \equiv (X \cdot V)_b - (X \cdot V)_a \quad (6.150)$$

Now recall the associative property, i.e.

$$Y \cdot (X \cdot V) = (YX) \cdot V. \quad (6.151)$$

In the new notation this is

$$d(Y \cdot (X \cdot V)) = Y_t d(X \cdot V)_t = (Y_t X_t) dV_t. \quad (6.152)$$

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$$\langle X \cdot V, Y \cdot W \rangle = (XY) \cdot \langle V, W \rangle \quad (6.153)$$

$$\langle X \cdot V \rangle = X^2 \cdot \langle V \rangle \quad (6.154)$$

becomes

$$X_t dV_t Y_t dW_t = d(X \cdot V)_t d(Y \cdot W)_t = X_t Y_t dV_t dW_t \quad (6.155)$$

$$(d(X \cdot V)_t)^2 = X_t^2 (dV_t)^2. \quad (6.156)$$

**Example:** Let  $X_t = B_t^2$ . We want to get  $\langle X \rangle_t$ .

$$d\langle X \rangle_t = (dX_t)^2 \quad (6.157)$$

$$= (dB_t^2)^2 \quad (6.158)$$

$$\stackrel{6.29}{=} (2B_t dB_t + dt)^2 \quad (6.159)$$

$$= 4B_t^2 \underbrace{(dB_t)^2}_{=dt} + \underbrace{4B_t dB_t dt}_{=0} + \underbrace{(dt)^2}_{=0} \quad (6.160)$$

$$= 4B_t^2 dt \quad (6.161)$$

and hence

$$\langle X \rangle_t = \langle B^2 \rangle = 4 \int_0^t B_s^2 ds \quad (6.162)$$

Now consider the case

$$f \in C^\infty, X_t \text{ "regular function" (finite variation)} \quad (6.163)$$

Then

$$d(f(X))_t = f'(X_t)dX_t + \frac{1}{2}f''(X_t)(dX_t)^2 + \underbrace{\frac{1}{3}f'''(X_t)(dX_t)^3 + \dots}_{=0} \quad (6.164)$$

since  $(dX_t)^n = 0$  for  $n \geq 3$  (see (6.140)). In the case of a BM we get as a result

$$df(B_t) = f'(B_t)dB_t + \frac{1}{2}f''(B_t)(dB_t)^2 \quad (6.165)$$

This is Itô's-Formula!

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[23.11.2012]  
[27.11.2012]

# 7 The Itô-Formula and applications

## 7.1 The Itô-Formula

### Theorem 7.1 (Itô-Formula).

Let  $F \in C^2(\mathbb{R}^d, \mathbb{R})$  and  $X = (X^1, \dots, X^d)$  with  $X_i \in \mathcal{S}$ . Then  $F(X) \in \mathcal{S}$  and

$$F(X_t) = F(X_0) + \sum_{k=1}^d \int_0^t \partial_k F(X_s) dX_s^k + \sum_{k,l=1}^d \frac{1}{2} \int_0^t \partial_{k,l}^2 F(X_s) d\langle X^k, X^l \rangle_s, \quad (7.1)$$

**Remark:** Itô-Formula in differential form is

$$dF(X_t) = \sum_{k=1}^d \partial_k F(X_t) dX_t^k + \frac{1}{2} \sum_{k,l=1}^d \partial_{k,l}^2 F(X_t) d\langle X^k, X^l \rangle_t \quad (7.2)$$

### Corollary 7.2.

Let  $F \in C^2(\mathbb{R}^d, \mathbb{R})$ ,  $(B_t)_{t \geq 0}$  a  $d$ -dimensional BM. Then,

$$F(B_t) = F(B_0) + \int_0^t \nabla F(B_s) dB_s + \frac{1}{2} \int_0^t \Delta F(B_s) ds \quad (7.3)$$

*Proof.* We use  $\langle B^k, B^l \rangle_t = \delta_{k,l} dt$  to see this. □

### Corollary 7.3.

Let  $F \in C^2(\mathbb{R}^{d+1}, \mathbb{R})$ ,  $(B_t)_{t \geq 0}$  a  $d$ -dimensional BM. Then,

$$F(t, B_t) = F(0, B_0) + \int_0^t \nabla F(s, B_s) dB_s + \int_0^t \dot{F}(s, B_s) ds + \frac{1}{2} \int_0^t \Delta F(s, B_s) ds \quad (7.4)$$

where  $\nabla F$  is the gradient and  $\Delta$  is the Laplace-operator of  $F$  with differentials w.r.t. the space-variables and  $\dot{F}$  is the time-derivative.

**Remark:** Corollary 7.2 in differential form:

$$dF(B_s) = \nabla F(B_s) dB_s + \frac{1}{2} \Delta F(B_s) ds \quad (7.5)$$

Corollary 7.3 in differential form:

$$dF(t, B_t) = \nabla F(t, B_t) dB_t + \frac{1}{2} \Delta F(t, B_t) dt + \dot{F}(t, B_t) dt \quad (7.6)$$

*Proof of Theorem 7.1. Step 1* Prove (7.1) for  $F$  being a polynomial.

Let's see first, that (7.1) holds true for  $F \equiv 1$ . Now assume that (7.1) holds for a polynomial  $F$ . We have to show that (7.1) holds for  $G(x_1, \dots, x_d) = x_m F(x_1, \dots, x_d)$ . Then Step 1 holds by induction

and linearity.

$$G(X_t) - G(X_0) = X_t^m F(X_t) - X_0^m F(X_0) \quad (7.7)$$

$$\stackrel{\substack{\text{integr.} \\ \text{by parts}}}{=} \int_0^t X_s^m dF(X_s) + \int_0^t F(X_s) dX_s^m + \langle X^m, F(X) \rangle_s \quad (7.8)$$

$$\stackrel{\substack{\text{Itô Form.} \\ \text{for } F}}{=} \sum_{l=1}^d \int_0^t X_s^m \partial_l F(X_s) dX_s^l + \sum_{l,k=1}^d \frac{1}{2} \int_0^t X_s^m \partial_{k,l}^2 F(X_s) d\langle X^k, X^l \rangle_s \quad (7.9)$$

$$+ \int_0^t F(X_s) dX_s^m \quad (7.10)$$

$$+ \sum_{l=1}^d \int_0^t \partial_l F(X_s) d\langle X^m, X^l \rangle_s \quad (7.11)$$

Where we used in the last step that

$$\langle X^m, F(X) \rangle_s = dX_s^m dF(X)_s \quad (7.12)$$

$$= dX_s^m \left( \sum_{l=1}^d \partial_l F(X_s) dX_s^l + \sum_{k,l=1}^d \frac{1}{2} \partial_{k,l} F(X_s) d\langle X^k, X^l \rangle_s \right) \quad (7.13)$$

$$= \sum_{l=1}^d \partial_l F(X_s) dX_s^m dX_s^l + \sum_{k,l=1}^d \frac{1}{2} \partial_{k,l} F(X_s) \underbrace{dX_s^m dX_s^k dX_s^l}_{=0} \quad (7.14)$$

Thus we have

$$G(X_t) - G(X_0) = \sum_{k=1}^d \int_0^t (F(X_s) \delta_{k,m} + X_s^m \partial_k F(X_s)) dX_s^k \quad (7.15)$$

$$+ \frac{1}{2} \int_0^t \sum_{k,l=1}^d \partial_{k,l}^2 F(X_s) X_s^m + \partial_k F(X_s) \delta_{l,m} d\langle X^l, X^k \rangle_s \quad (7.16)$$

$$= \sum_{k=1}^d \int_0^t \partial_k G(X_s) dX_s^k + \frac{1}{2} \sum_{k,l=1}^d \int_0^t \partial_{k,l}^2 G(X_s) d\langle X^k, X^l \rangle_s \quad (7.17)$$

**Step 2)** Extension to  $F \in C_0^2(\mathbb{R}^d, \mathbb{R})$  (with bounded support). By the Weierstrass-Approximation theorem we can get  $F$  as the limit of polynomials  $F_n$ , i.e.

$$F_n \rightarrow F \quad (7.18)$$

$$\partial_k F_n \rightarrow \partial_k F \quad (7.19)$$

$$\partial_k \partial_l F_n \rightarrow \partial_k \partial_l F \quad (7.20)$$

$\Rightarrow$  Itô-Formula holds for  $F_n \Rightarrow$  also for  $F \in C_0^2(\mathbb{R}^d, \mathbb{R})$ .

**Step 3)** Extension to  $F \in C^2(\mathbb{R}^d, \mathbb{R})$ .

Let  $K_n = [-n, n]^d$  and

$$T_n = \inf\{t > 0 : X_t \notin K_n\} \quad (7.21)$$

Then  $T_n \nearrow \infty$  as  $n \rightarrow \infty$ . Now consider  $F_n = F \mathbb{1}_{K_n} \in C_0^2(\mathbb{R}^d, \mathbb{R})$ . We know that the formula holds for  $F_n$ . Therefore it holds for all  $\{\omega \in \Omega : T_n(\omega) > t\}$ . But as  $n \rightarrow \infty$   $T_n(\omega) > t \forall \omega \in \Omega \forall t \geq 0$ . Therefore the formula holds for all  $\Omega$ .  $\square$

**Corollary 7.4.**

Let  $X = X_0 + M + A$ ,  $M \in \mathcal{M}_{loc}^0$ ,  $A \in \mathcal{A}_0$  and  $F \in C^2(\mathbb{R}, \mathbb{R})$ . Then

$$F(X_t) = F(X_0) + \tilde{M}_t + \tilde{A}_t \quad (7.22)$$

with

$$\tilde{M} \in \mathcal{M}_{loc}^0 \text{ and } \tilde{A} \in \mathcal{A}_0 \quad (7.23)$$

where

$$\tilde{M}_t = \int_0^t F'(X_s) dM_s \quad (7.24)$$

$$\tilde{A}_t = \int_0^t F'(X_s) dA_s + \frac{1}{2} \int_0^t F''(X_s) d\langle M \rangle_s \quad (7.25)$$

Let us compute e.g. the quadratic variation of  $F(X_t)$ .

**Corollary 7.5.**

Let  $X \in \mathcal{S}^d$ ,  $F \in C^2(\mathbb{R}^d, \mathbb{R})$ . Then

$$\langle F(X) \rangle_t = \sum_{k,l=1}^d \int_0^t \partial_k F(X_s) \partial_l F(X_s) d\langle X^k, X^l \rangle_s \quad (7.26)$$

In particular, if  $X = B$  is a BM

$$\langle F(B) \rangle_t = \sum_{k=1}^d \int_0^t (\partial_k F(B_s))^2 ds = \int_0^t (\nabla F(B_s))^2 ds \quad (7.27)$$

*Proof.* The differential form to be proven is

$$d\langle F(X) \rangle_t = \sum_{k,l=1}^d \partial_k F(X_t) \partial_l F(X_t) d\langle X^k, X^l \rangle_t \quad (7.28)$$

Remember:  $d\langle X, Y \rangle_t \equiv dX_t dY_t$ . Therefore

$$d\langle F(X) \rangle_t \equiv (dF(X_t))^2 \stackrel{\text{Itô}}{=} \left( \sum_{k=1}^d \partial_k F(X_t) dX_t^k + \frac{1}{2} \sum_{k,l=1}^d \partial_k \partial_l F(X_t) d\langle X^k, X^l \rangle_t \right)^2 \quad (7.29)$$

$$\stackrel{dX_t^k dX_t^l dX_t^m = 0}{=} \sum_{k,l=1}^d \partial_k F(X_t) \partial_l F(X_t) \underbrace{dX_t^k dX_t^l}_{=d\langle X^k, X^l \rangle_t} \quad (7.30)$$

The statement for the BM follows from

$$d\langle B^k, B^l \rangle_s = \delta_{k,l} ds. \quad (7.31)$$

□

Remember one exercise: If  $M_t := \exp(\alpha B_t - \frac{1}{2} \alpha^2 t) \in \mathcal{M}$  and  $B_t$  is a continuous process with  $B_0 = 0$ . Then  $B$  is a BM.  $M_t$  is an example for a so called 'exponential martingale' and will later be the 'Levy characterization'.

**Proposition 7.6.**

a) Let  $B$  be a  $d$ -dimensional BM,  $f \in C^2(\mathbb{R}^{d+1}, \mathbb{R})$  and

$$Af := \frac{1}{2}\Delta f + \frac{\partial f}{\partial t} \quad (7.32)$$

Then,

$$M_t := f(t, B_t) - f(0, B_0) - \int_0^t Af(s, B_s)ds \in \mathcal{M}_{loc}^0 \quad (7.33)$$

In particular, if  $Af = 0$ , then

$$(f(t, B_t))_{t \geq 0} \in \mathcal{M}_{loc}^0 \quad (7.34)$$

b) If  $f \in C^2(\mathbb{R}^d)$ , then

$$M_t := f(B_t) - f(B_0) - \frac{1}{2} \int_0^t \Delta f(B_s)ds \in \mathcal{M}_{loc}^0 \quad (7.35)$$

In particular if  $f$  is harmonic on  $\mathbb{R}^d$ , i.e.  $\Delta f = 0$ , then  $(f(B_t))_{t \geq 0} \in \mathcal{M}_{loc}$  (is a local martingale).

c) Let  $D \subset \mathbb{R}^d$  and  $T = \inf\{t \geq 0 : B_t \notin D\}$ . Then, if  $f$  is harmonic on  $D$ ,

$$f(B^T) - f(B_0) \in \mathcal{M}_{loc}^0. \quad (7.36)$$

*Proof.* **ad a)** Follows from Cor. 7.3:

$$M_t = f(t, B_t) - f(0, B_0) - \int_0^t (Af)(s, B_s)ds = \int_0^t (\nabla f)(s, B_s)dB_s \in \mathcal{M}_{loc} \quad (7.37)$$

**ad b)** Follows similarly from Cor. 7.2.

**ad c)** Take  $B^T$  in b). Then one will get  $M_t^T$  is  $\mathcal{M}_{loc}^0$ . Important: We need at least  $f \in C^2(D')$  for an  $D'$  s.t.  $\bar{D} \subset D'$ .  $\square$

**Lemma 7.7.**

Let  $M_t$  as in Prop. 7.6 a). Then

$$\langle M \rangle_t = \int_0^t |\nabla f(s, B_s)|^2 ds \quad (7.38)$$

*Proof.*

$$dM_t = (\nabla f)(s, B_s)dB_s \quad (7.39)$$

$$\Rightarrow d\langle M \rangle_t = (dM_t)^2 = (\nabla f(t, B_t))^2 dt \quad (7.40)$$

$\square$

A generalisation:

**Proposition 7.8.**

Let  $B$  be a  $d$ -dimensional BM.  $\sigma(x) := (\sigma_{i,j}(x))_{1 \leq i,j \leq d}$  a Matrix with continuous coefficients and let  $X$  be a continuous, adapted  $d$ -dimensional process with

$$X_t^k = X_0^k + \sum_{l=1}^d \int_0^t \sigma_{lj}(X_s) dB_s^l \quad (7.41)$$

Then,

- a)  $X^k$  is a local martingale.
- b) For all  $f \in C^2(\mathbb{R}_+ \times \mathbb{R}^d)$ , let

$$M_t^f := f(t, X_t) - f(0, X_0) - \int_0^t Af(s, X_s) ds \quad (7.42)$$

with

$$Af(t, x) = \frac{\partial}{\partial t} f(t, x) + \frac{1}{2} \sum_{k,l=1}^d a_{kl}(x) \partial_{k,l}^2 f(t, x) \quad (7.43)$$

and  $a_{kl} = \sum_{m=1}^d \sigma_{km} \sigma_{lm} (\equiv (\sigma \sigma^T)_{kl})$ . Then  $M_t^f$  is a local martingale.

[27.11.2012]  
[30.11.2012]

*Proof.* **a)** Follows since  $B$  is a martingale.

**b)** We compute first:

$$d\langle X^k, X^l \rangle_t \equiv dX_t^k dX_t^l \stackrel{\text{hyp}}{=} \sum_{i,j=1}^d \sigma_{k,j}(X_t) \sigma_{l,i}(X_t) \underbrace{dB_t^j dB_t^i}_{=d\langle B^j, B^i \rangle_t = \delta_{ij} dt} \quad (7.44)$$

$$= \sum_{i=1}^d \sigma_{ki} \sigma_{li} dt = a_{kl} dt \quad (7.45)$$

Thus

$$f(t, X_t) \stackrel{\text{It\^o Form.}}{=} f(0, X_0) + \int_0^t \partial_s f(s, X_s) ds + \sum_{k=1}^d \int_0^t \partial_k f(s, X_s) dX_s^k + \frac{1}{2} \sum_{k,l=1}^d \int_0^t \partial_{k,l} f(s, X_s) \underbrace{d\langle X^k, X^l \rangle_s}_{=a_{k,l}(X_s) ds} \quad (7.46)$$

And therefore

$$M_t^f = \sum_{k=1}^d \int_0^t \partial_k f(s, X_s) dX_s^k \in \mathcal{M}_{loc} \quad (7.47)$$

□

## 7.2 Exponential Martingales

**Lemma 7.9.**

Let  $F \in C^2(\mathbb{R}_+ \times \mathbb{R}, \mathbb{R})$ , s.t.  $\partial_t F + \frac{1}{2} \partial_{xx}^2 F = 0$  and  $M \in \mathcal{M}_{loc}$ .

$$\Rightarrow \tilde{M}_t := F(\langle M \rangle_t, M_t) \in \mathcal{M}_{loc} \quad (7.48)$$

*Proof.*

$$d\tilde{M}_t = \frac{\partial F}{\partial t} d\langle M \rangle_t + \frac{\partial F}{\partial x} dM_t + \frac{1}{2} \partial_{xx}^2 F \cdot d\langle M \rangle_t + \underbrace{\frac{1}{2} \partial_{tt}^2 (d\langle M \rangle)^2}_{=0} \quad (7.49)$$

$$\stackrel{\text{Hyp}}{=} \frac{\partial F}{\partial x} (\langle M \rangle_t, M_t) dM_t \in \mathcal{M}_{loc} \quad (7.50)$$

□

**Definition 7.10.**

Let  $\lambda \in \mathbb{C}, M \in \mathcal{M}$ , then

$$\mathcal{E}_\lambda(M)_t := e^{\lambda M_t - \frac{1}{2} \lambda^2 \langle M \rangle_t} \quad (7.51)$$

is called *exponential local martingale*.

**Lemma 7.11.**

$\lambda \in \mathbb{C}, M \in \mathcal{M}_{loc}$ .

$$\Rightarrow \mathcal{E}_\lambda(M) \in \mathcal{M}_{loc} + i\mathcal{M}_{loc} \equiv \mathbb{C}\mathcal{M}_{loc} \quad (7.52)$$

*Proof.* Take  $F(t, x) := e^{\lambda x - \frac{1}{2} \lambda^2 t}$  and apply Lemma 7.9. □

**Example:** Choose  $\lambda = i$ .

$$\Rightarrow \cos(M_t) e^{\frac{1}{2} \langle M \rangle_t} \in \mathcal{M}_{loc} \quad (7.53)$$

$$\sin(M_t) e^{\frac{1}{2} \langle M \rangle_t} \in \mathcal{M}_{loc} \quad (7.54)$$

$$(7.55)$$

*Example for a BM.*  $X_t = F(t, B_t) = e^{\lambda B_t - \frac{1}{2} \lambda^2 t}, \lambda \in \mathbb{R}$ .

$$dX_t = d(F(X)) = \partial_x F(B_t) dB_t + \underbrace{\frac{1}{2} \Delta_x F(t, B_t) dt + \partial_t F(t, B_t) dt}_{=0} = \lambda X_t dB_t \quad (7.56)$$

Hence  $dX_t = \lambda X_t dB_t$ . Therefore

$$X_t - X_0 = \int_{=1}^t dX_s = \lambda \int_0^t X_s dB_s \quad (7.57)$$

$$\Rightarrow X_t = 1 + \lambda \int_0^t X_s dB_s \quad (7.58)$$

Q.: Is  $\mathcal{E}_\lambda(M) \in \mathcal{M}$ , i.e. a real, not just a local martingale?

A.: In general no!

**Theorem 7.12.**

$\mathcal{E}_\lambda(M) \in \mathbb{C}\mathcal{M}$  if at least one of the following conditions are satisfied:

- $M$  is bounded and  $\lambda \in \mathbb{R}$ .
- $\langle M \rangle$  is bounded and  $\lambda \in i\mathbb{R}$ .
- $M_0 = 0, \mathbb{E}[\mathcal{E}_\lambda(M)_t] = 1, \forall t \geq 0$ , and  $\lambda \in \mathbb{R}$ .



*Proof.* **a)**

$$|\mathcal{E}(M)| \leq \underbrace{|\exp(\lambda M_t) \exp(-\frac{\lambda^2}{2} \langle M \rangle_t)|}_{\leq 1} \leq \underbrace{|\exp(\lambda M_t)|}_{\text{bounded}} \quad (7.59)$$

Thus  $\mathcal{E}(M)$  is bounded hence a martingale.

**b)**

$$|\mathcal{E}(M)| \leq \underbrace{|\exp(i|\lambda|M_t)|}_{\leq 1} \exp(\frac{|\lambda|^2}{2} \langle M \rangle_t) \quad (7.60)$$

$$\leq \underbrace{|\exp(\frac{|\lambda|^2}{2} \langle M \rangle_t)|}_{\text{bounded}} \quad (7.61)$$

Thus  $\mathcal{E}(M)$  is bounded hence a martingale.

**ad c)**  $\mathcal{E}_\lambda(M)_t = e^{\lambda M_t - \frac{1}{2} \lambda^2 \langle M \rangle_t} \geq 0$ . By Lemma 5.3 we know that  $\mathcal{E}_\lambda(M)$  is a supermartingale.

$$\Rightarrow 1 \stackrel{\text{hyp.}}{=} \mathbb{E}[\mathcal{E}_\lambda(M)_t] \geq \mathbb{E}[\mathcal{E}_\lambda(M)_0] \equiv 1 \quad (7.62)$$

$\Rightarrow \mathcal{E}_\lambda(M) \in \mathcal{M}$ . (see Remark below.) □

**Remark:** Let  $M_t$  be a super-martingale s.t.  $\mathbb{E}[M_t] = c$  for all  $t$ . Claim:  $M_t$  is a martingale!

$$\mathbb{E}[X_t | \mathcal{F}_s] - X_s \leq 0 \quad (7.63)$$

but

$$\mathbb{E}[\mathbb{E}[X_t | \mathcal{F}_s] - X_s] = \mathbb{E}[X_t] - \mathbb{E}[X_s] = 0 \quad (7.64)$$

hence

$$\mathbb{E}[X_t | \mathcal{F}_s] = X_s \text{ a.e.} \quad (7.65)$$

Let  $B$  be a 2-dimensional BM.

$$\Rightarrow f(B_t) = f(B_0) + \int_0^t \nabla f(B_s) dB_s + \frac{1}{2} \int_0^t \Delta f(B_s) ds \quad (7.66)$$

Q.: If  $f$  is harmonic on  $\mathbb{R}^2$ , does it follow that

$$f(B) \in \mathcal{M} \quad (7.67)$$

Is  $\nabla f \in L^2(B)$ ?

Answer: In general not. Counterexample: Take  $f(x, y) = e^{x^2 - y^2} \cos(2xy)$ .

$$\frac{\partial f(x, y)}{\partial x} = 2xe^{x^2 - y^2} \cos(2xy) - e^{x^2 - y^2} \sin(2xy) 2y \quad (7.68)$$

$$\frac{\partial f(x, y)}{\partial y} = -2yxe^{x^2 - y^2} \cos(2xy) - e^{x^2 - y^2} \sin(2xy) 2x \quad (7.69)$$

$$\Rightarrow \frac{\partial^2 f(x, y)}{\partial x^2} + \frac{\partial^2 f(x, y)}{\partial y^2} = 0 \quad (7.70)$$

$\Rightarrow f$  is harmonic, but  $f(B)$  is not a martingale for all  $t$ . The problem is that e.g.  $\nabla f \notin L^2(B)$  or  $f(B_t) \notin L^1$  for  $t$  large enough, because:

$$\mathbb{E}[f(B_t)] = \int_{\mathbb{R}^2} f(x, y) \frac{1}{2\pi t} e^{-\frac{x^2 + y^2}{2t}} dx dy \quad (7.71)$$

which is not good for  $t > 1/2$ .

### 7.3 Levy characterization of the BM

**Theorem 7.13** (Levy).

Let  $X$  be a  $d$ -dimensional, adapted and continuous stochastic process with  $X_0 = 0$ . Then the following statements are equivalent.

- a)  $X$  is a  $d$ -dimensional BM w.r.t.  $\mathcal{F}_t$ .
- b)  $X \in \mathcal{M}_{loc}^0$  and  $\langle X^k, X^l \rangle_t = \delta_{k,l} \cdot t, \forall 1 \leq k, l \leq d$ .
- c)  $X \in \mathcal{M}_{loc}^0$  and for all  $f = (f_1, \dots, f_d)$  with  $f_k \in L^2(\mathbb{R}_+, \mathbb{R})$ ,

$$M_t := \exp \left[ i \sum_{k=1}^d \int_0^t f_k(s) dX_s^k + \frac{1}{2} \sum_{k=1}^d \int_0^t f_k^2(s) ds \right] \in \mathcal{M} + i\mathcal{M} (\equiv \mathbb{C}\mathcal{M}) \quad (7.72)$$

*Proof.* "a $\Rightarrow$ b": is already known.

"b $\Rightarrow$ c":

$$d(f \cdot X)_t = \sum_{k=1}^d f_k(s) dX_s^k \quad (7.73)$$

$$\Rightarrow (f \cdot X)_t = \underbrace{(f \cdot X)_0}_{=0} + \sum_{k=1}^d \int_0^t f_k(s) dX_s^k \text{ and} \quad (7.74)$$

$$\langle f \cdot X \rangle_t = \sum_{k,l=1}^d \int_0^t f_k(s) f_l(s) \underbrace{d\langle X^k, X^l \rangle_s}_{=\delta_{k,l} ds \text{ by hyp.}} \quad (7.75)$$

$$= \sum_{k=1}^d \int_0^t f_k^2(s) ds \quad (7.76)$$

Since  $f_k \in L^2(\mathbb{R}_+, \mathbb{R})$

$$\langle f \cdot X \rangle_t = \int_0^t \sum_{k=1}^d f_k(s)^2 ds < \infty \quad (7.77)$$

Now  $\lambda = i, N_t = \sum_{k=1}^d \int_0^t f_k(s) dX_s^k \Rightarrow M_t = \mathcal{E}_{\lambda=i}(N)_t$  and since  $\lambda \in i\mathbb{R}$  and  $\langle N \rangle_t$  bounded we have  $M_t \in \mathbb{C}\mathcal{M}$  by Theorem 7.12 .

"c $\Rightarrow$ a": Let  $z \in \mathbb{R}^d, T > 0$ . Define

$$f_k(s) = z_k \mathbb{1}_{[0,T)}(s) \quad (7.78)$$

Then,

$$\sum_{k=1}^d \int_0^t f_k(s) dX_s^k = \sum_{k=1}^d z_k X_{t \wedge T}^k \equiv (z, X_{t \wedge T}), \quad (7.79)$$

$$\sum_{k=1}^d \int_0^t f_k^2(s) ds = \sum_{k=1}^d z_k^2 (t \wedge T) \equiv \|z\|^2 \cdot (t \wedge T) \quad (7.80)$$

The assumption implies that

$$M_t = \exp[i(z, X_{t \wedge T}) + \frac{1}{2} \|z\|^2 (t \wedge T)] \in \mathbb{C}\mathcal{M} \quad (7.81)$$

$\Rightarrow$  For  $0 < s < t < T : \forall A \in \mathcal{F}_s$

$$\mathbb{E} \left[ \mathbb{1}_A e^{i(z, X_t) + \frac{1}{2} \|z\|^2 t} | \mathcal{F}_s \right] = \mathbb{1}_A e^{i(z, X_s) + \frac{1}{2} \|z\|^2 s} \quad (7.82)$$

Therefore

$$\mathbb{E} \left[ \mathbb{1}_A e^{i(z, X_t - X_s)} | \mathcal{F}_s \right] = \underbrace{\mathbb{E} \left[ \mathbb{1}_A e^{i(z, X_t - X_s)} e^{-\frac{1}{2} \|z\|^2 (t-s)} | \mathcal{F}_s \right]}_{= \mathbb{1}_A \text{ by (7.82)}} e^{-\frac{1}{2} \|z\|^2 (t-s)} \quad (7.83)$$

$$\Rightarrow \mathbb{E} \left[ \mathbb{1}_A e^{i(z, X_t - X_s)} \right] = \mathbb{E} \left[ \mathbb{E} \left[ \mathbb{1}_A e^{i(z, X_t - X_s)} | \mathcal{F}_s \right] \right] = \mathbb{E} \left[ \mathbb{1}_A e^{-\frac{1}{2} \|z\|^2 (t-s)} \right] = \mathbb{P}(A) e^{-\frac{1}{2} \|z\|^2 (t-s)} \quad (7.84)$$

$\Rightarrow \forall A \in \mathcal{F}_s : \mathbb{E} \left[ \mathbb{1}_A e^{i(z, X_t - X_s)} \right] = \mathbb{E} \left[ \mathbb{1}_A \right] e^{-\frac{1}{2} \|z\|^2 (t-s)} \Rightarrow \mathbb{E} \left[ e^{i(z, X_t - X_s)} \right] = e^{-\frac{1}{2} \|z\|^2 (t-s)}$  and  $X_t - X_s$  is independent of  $\mathcal{F}_s$  ( $\Rightarrow$  of  $X_s$ ).  $\Rightarrow X$  is a BM.  $\square$

We get some corollaries for  $d = 1$ .

**Corollary 7.14.**

Let  $X \in \mathcal{M}_{loc}^0$  with  $\langle X \rangle_t = t$ . Then  $X$  is a BM.

**Corollary 7.15.**

Let  $X \in \mathcal{M}_{loc}^0$  with

$$t \mapsto X_t^2 - t \in \mathcal{M}_{loc}^0 \quad (7.85)$$

Then  $X$  is a BM.

**Remark:** Continuity is needed! Otherwise, let  $N_t$  a Poisson Process with intensity 1, then

$$\{M_t := N_t - t\}_{t \geq 0} \quad (7.86)$$

is a martingale in continuous time with cadlag trajectories. Also  $\langle M \rangle_t = t$ , but  $M_t$  is not a BM!

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[03.12.2012]

## 7.4 Applications of Ito's Calculus

### 7.4.1 Brownian Bridge (BB)

A Brownian Bridge for  $t \in [0, 1]$  is a BM with  $X_0 = 0$  conditioned on  $X_1 = 0$ .

**Definition 7.16** (Brownian Bridge).

A *Brownian Bridge* is a continuous Gaussian Process  $(X_t, 0 \leq t \leq 1)$  (where  $0 \leq t \leq 1$  is the lifespan) s.t.

- (i)  $\mathbb{E}[X_t] = 0 \forall t \in [0, 1]$ .
- (ii)  $Cov(X_s, X_t) = s(1-t) \forall 0 \leq s \leq t \leq 1$

We can see  $X_t \sim \mathcal{N}(0, t(1-t))$ . Therefore  $X_1 \sim \mathcal{N}(0, 0)$ ,  $X_0 \sim \mathcal{N}(0, 0)$ . So the processes starts and ends at 0.

We know  $|X_t| \approx \sqrt{\mathbb{E}[X_t^2]} = \sqrt{t(1-t)}$ . So for t well inside  $[0, 1]$  we have  $\approx \sqrt{t}$ .

**Construction**

- a) Let  $B = (B_t)$  be a standard BM. Then

$$X_t = B_t - tB_1 \quad (7.87)$$

is a BB. Check:

- $X_0 = 0 = X_1 \checkmark$ ,
- $\mathbb{E}[X_t] = \mathbb{E}[B_t] - t\mathbb{E}[B_1] = 0 \checkmark$ ,
- Gaussian Process  $\checkmark$ ,
- continuous  $\checkmark$ ,
- Now let  $0 \leq s \leq t \leq 1$ .

$$\text{Cov}(X_s, X_t) = \mathbb{E}[(B_s - sB_1)(B_t - tB_1)] \quad (7.88)$$

$$= \mathbb{E}[B_s B_t] - s\mathbb{E}[B_1 B_t] - t\mathbb{E}[B_s B_1] + st\mathbb{E}[B_1^2] \quad (7.89)$$

$$= s \wedge t - st - ts + st = s(1-t) \checkmark \quad (7.90)$$

b) BB is a BM conditioned on  $\{B_1 = 0\}$ . Problem:  $\mathbb{P}(B_1 = 0) = 0$ . So for the law

$$\mathcal{L}(X_t, 0 \leq t \leq 1) = \lim_{\varepsilon \rightarrow 0} \mathbb{P}(BM | |B_1| < \varepsilon) \quad (7.91)$$

$$\Rightarrow \mathbb{P}(X_{t_1} \in \cdot, \dots, X_{t_k} \in \cdot) = \lim_{\varepsilon \rightarrow 0} \mathbb{P}(B_{t_1} \in \cdot, \dots, B_{t_k} \in \cdot | |B_1| < \varepsilon) \quad (7.92)$$

c) Let  $B$  be a BM. Then

$$X_t = \begin{cases} (1-t)B_{\frac{t}{1-t}} & 0 \leq t < 1 \\ 0 & t = 1 \end{cases} \quad (7.93)$$

is a BB. Well defined? For  $t \nearrow 1$ :  $W_{\frac{t}{1-t}} \sim \frac{1}{\sqrt{1-t}} \Rightarrow X_t \sim \sqrt{1-t} \xrightarrow{t \rightarrow 1} 0$ . Also  $t \mapsto \frac{t}{1-t}$  is monoton, goes to  $\infty$  for  $t \rightarrow 1$ . Check the other conditions:

$$\mathbb{E}[X_t] = (1-t)\mathbb{E}\left[B_{\frac{t}{1-t}}\right] = 0 \checkmark \quad (7.94)$$

$$(s \leq t) \text{Cov}(X_s, X_t) = (1-t)(1-s)\mathbb{E}\left[B_{\frac{t}{1-t}} B_{\frac{s}{1-s}}\right] = s(1-t) \checkmark \quad (7.95)$$

**Lemma 7.17.**

For a BB it holds  $(X_t, 0 \leq t \leq 1) \in \mathcal{S}$ . Furthermore  $\langle X \rangle_t = t$ , but it's not a BM, since it is not a martingale.

*Proof.* Use  $X_t = (1-t)B_{\frac{t}{1-t}}$ . Define  $B'_t = B_{\frac{t}{1-t}}$ . Then  $B'_t$  is a martingale w.r.t.  $\mathcal{F}'_t = \mathcal{F}_{\frac{t}{1-t}}$ . Choose  $F(t, x) = (1-t)x$ .

$$X_t = (1-t)B'_t = F(t, B'_t) \quad (7.96)$$

$$\Rightarrow F(t, B'_t) = \int_0^t \partial_s F(s, B'_s) ds + \int_0^t \partial_x F(s, B'_s) dB'_s + \frac{1}{2} \int_0^t \underbrace{\partial_x^2 F(s, B'_s)}_{=0} d\langle B' \rangle_s \quad (7.97)$$

$$= \underbrace{- \int_0^t B'_s ds}_{\text{finite variation}} + \underbrace{\int_0^t (1-s) dB'_s}_{\text{martingale term}} \quad (7.98)$$

Thus  $X_t$  is a semimartingale. Now for the variation:

$$\left\langle \int_0^t (1-s) dB'_s \right\rangle_t = \int_0^t (1-s)^2 d\langle B' \rangle_s \stackrel{1}{=} \int_0^t (1-s)^2 d\frac{s}{1-s} = \int_0^t (1-s)^2 \frac{(1-s) + s}{(1-s)^2} ds = t \quad (7.99)$$

Therefore by Levy  $W_t := \int_0^t (1-s) dB'_s$  is a BM! For the finite variation term we can write

$$- \int_0^t B'_s ds = - \int_0^t \frac{X_s}{1-s} ds \quad (7.100)$$

<sup>1</sup> $\langle B' \rangle_t = \frac{t}{1-t}$  since it's a time change of a BM.

Thus we get:

$$X_t = - \int_0^t \frac{X_s}{1-s} ds + W_t \quad (7.101)$$

where  $W_t$  is a BM. And in differential form

$$dX_t = -\frac{X_t}{1-t} dt + dW_t \quad (7.102)$$

□

**Remark:** *Brownian Bridge* ( $X_t, 0 \leq t \leq 1$ ):

- (i) *Gaussian process with*  $\mathbb{E}[X_t] = 0, \text{Cov}(X_s, X_t) = s(1-t)$ .
- (ii)  $X_t = B_t - tB_1$  for  $B$  a BM.
- (iii)  $X_t = (1-t)B_{\frac{t}{1-t}}$  for  $B$  a BM.
- (iv) *Solution of the SDE:*  $dX_t = -\frac{X_t}{1-t} dt + dW_t$  where  $W$  is a BM.

### 7.4.2 Ornstein-Uhlenbeck Process (OU)

**Definition 7.18.**

Let  $B = (B_t)_{t \geq 0}$  be a standard BM. Let  $\lambda > 0$ , then

$$Y_t = \frac{e^{-\lambda t}}{\sqrt{2\lambda}} B_{e^{2\lambda t}} (t \geq 0) \quad (7.103)$$

is a Ornstein-Uhlenbeck Process.

The process does not necessarily start in 0.  $Y'_t = Y_t - Y_0$  is an OU issued at 0. We can see:

$$\mathbb{E}[Y_t] = \frac{e^{-\lambda t}}{\sqrt{2\lambda}} \mathbb{E}[B_{e^{2\lambda t}}] = 0 \quad (7.104)$$

$$\mathbb{E}[Y_t^2] = \frac{e^{-2\lambda t}}{2\lambda} \mathbb{E}[B_{e^{2\lambda t}}^2] = \frac{1}{2\lambda} \quad (7.105)$$

**Lemma 7.19.**

Let  $Y$  be an OU-Process. Then it holds  $(Y_t) \in \mathcal{S}$  and  $\langle Y \rangle_t = t$ , but  $Y$  is not a martingale.

*Proof.* We set  $B'_t = B_{e^{2\lambda t}}$ , then

$$Y_t = \frac{e^{-\lambda t}}{\sqrt{2\lambda}} B'_t \quad (7.106)$$

$B'_t$  is a martingale wr.t.  $\mathcal{F}'_t = \mathcal{F}_{e^{2\lambda t}}$ . ( $t \mapsto e^{2\lambda t}$  is increasing.) Now choose  $F(t, x) = \frac{e^{-\lambda t}}{\sqrt{2\lambda}} x$ . Then  $Y_t = F(t, B'_t)$ .

$$Y_t = F(t, B'_t) = \int_0^t \partial_s F(s, B'_s) ds + \int_0^t \partial_x F(s, B'_s) dB'_s \quad (7.107)$$

$$= \underbrace{-\lambda \int_0^t \frac{e^{-\lambda s}}{\sqrt{2\lambda}} B'_s ds}_{\text{finite variation process}} + \underbrace{\int_0^t \frac{e^{-\lambda s}}{\sqrt{2\lambda}} dB'_s}_{\text{martingale part}} \quad (7.108)$$

Hence  $Y_t$  is a semimartingale. For the variation, see that

$$\left\langle \int_0^t \frac{e^{-\lambda s}}{\sqrt{2\lambda}} dB'_s \right\rangle_t = \int_0^t \frac{e^{-2\lambda s}}{2\lambda} d\langle B' \rangle_s \quad (7.109)$$

$$= \int_0^t \frac{e^{-2\lambda s}}{2\lambda} d(e^{2\lambda s}) \quad (7.110)$$

$$= \int_0^t \frac{e^{-2\lambda s}}{2\lambda} 2\lambda e^{2\lambda s} ds = t \quad (7.111)$$

$$\Rightarrow dY_t = -\lambda \frac{e^{-\lambda t}}{\sqrt{2\lambda}} B'_t dt + dW_t \quad (7.112)$$

where  $W_t$  is a BM.

$$dY_t = -\lambda Y_t dt + dW_t \quad (7.113)$$

□

So the OU is the solution of the 'easiest' linear stochastic differential equation.

**Remark:** "A particle in a Brownian Potential".

Newton:  $F = m \cdot a$ . ( $m=1$ ).  $F = ma = a = \dot{v} = -\xi v + W$  where  $W$  is a random force action of the particle.

### 7.4.3 Bessel Processes (BP)

Let  $(B_t)_{t \geq 0}$  be a  $d$ -dimensional BM, issued at  $x \neq 0$  on some probability space  $(\Omega, \mathcal{F}, \mathcal{F}_t, \mathbb{P}^x)$ . We define  $R_t := \|B_t\| = \sqrt{(B_t^1)^2 + (B_t^2)^2 + \dots + (B_t^d)^2}$

**Remark:**  $y \in \mathbb{R}^d$ ,  $\|y\| = \|x\|$ . Then there exists a rotation matrix s.t.  $y = Ox$  and  $OO^T = \mathbb{1}$ .

Since the distribution of a standard BM is symmetric around 0, the distribution of  $R_t$  solely depends on  $\|x\| = r$ . Hence from now on we will write

$$\hat{\mathbb{P}}^r = \mathbb{P}^{(r,0,\dots,0)} \quad (7.114)$$

where  $\mathbb{P}^{(r,0,\dots,0)}$  is the mass of a BM issued at  $(r, 0, \dots, 0)$ .

#### Definition 7.20.

Let  $r \geq 0$ ,  $d \geq 2$ . Then  $R_t = \|B_t\|$  on  $(\Omega, \mathcal{F}, \mathcal{F}_t, \hat{\mathbb{P}}^r)$  is a Bessel Process of dimension  $d$ .

Consider  $F : \mathbb{R}^d \rightarrow \mathbb{R}$ ,  $x = (x_1, \dots, x_n) \mapsto \sqrt{x_1^2 + \dots + x_n^2} \Rightarrow R_t = F(B_t)$  and  $\nabla F = \frac{x}{\|x\|}$ .

#### Theorem 7.21.

$B = (B_t)$  a  $d$ -dim BM,  $d \geq 2$ ,  $B_0 = x$ .  $R_t = \|B_t\|$ .

a)  $X_t := \sum_{k=1}^d X_t^k$  where  $X_t^k := \int_0^t \frac{B_s^k}{R_s} dB_s$ . Then  $(X_t)_{t \geq 0}$  is a 1-dim BM.

a)  $dR_t = \frac{d-1}{2R_t} dt + dW_t$  where  $W_t$  is a BM but  $\neq B$ .

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*Proof.* **a)**  $Leb(0 \leq s \leq t : R_s = 0) \leq Leb(0 \leq s \leq t : B_s = 0) = 0$ .

$$\langle X^k, X^l \rangle_t = \int_0^t \frac{B_s^k B_s^l}{R_s^2} \underbrace{d\langle B^k, B^l \rangle_s}_{\delta_{kl} ds} = \begin{cases} 0 & k \neq l \\ \int_0^t \frac{(B_s^k)^2}{R_s^2} ds & k = l \end{cases} \quad (7.115)$$

$$\Rightarrow \langle X \rangle_t = \sum_{k,l} \langle X^k, X^l \rangle_t = \sum_k \int_0^t \frac{(B_s^k)^2}{R_s^2} ds = \int_0^t \frac{\sum_k (B_s^k)^2}{R_s^2} ds \stackrel{\sum_k (B_s^k)^2 = R_s^2}{=} t \quad (7.116)$$

By Levy:  $X$  is a BM.

**b)**  $R_t = \|B_t\| = F(B_t), F : \mathbb{R}^d \rightarrow \mathbb{R}_+, x = (x_1, \dots, x_d) \mapsto \sqrt{(x_1)^2 + \dots + (x_d)^2}$ . Ito's Formula. Caution: singularity of  $\nabla F, \nabla^2 F$  at  $x = 0$ ! Way out:  $\forall \varepsilon > 0 : \|B_\varepsilon\| > 0, K \in \mathbb{N}, F_K \equiv F$  on  $B_{1/K}^c(0)$ .

Define  $T_{K,l} = \inf\{t \geq \frac{1}{l} : \|B_t\| \leq 1/K\} \xrightarrow{K \rightarrow \infty} \inf\{t \geq 1/l : \|B_t\| = 0\} = +\infty$ . But on  $\{(t, \omega) : T_{K,l}(\omega) \geq t \geq 1/l\}$  Ito's formula is valid for  $F_K$  and  $F_K \equiv F$ .

$$F(B_t) = F(B_{1/l}) + \int_{1/l}^t \sum_{i=1}^d \partial_i F(B_s) dB_s^i + 1/2 \int_{1/l}^t \sum_{i,j} \partial_{i,j} F(B_s) d\langle B^i, B^j \rangle_s = \Delta \quad (7.117)$$

Note:  $\partial_i F(x) = \frac{x_i}{\|x\|}, \partial_{i,j} F(x) = \frac{\delta_{ij}}{\|x\|} - \frac{x_i x_j}{\|B_s\|^2}$

$$\Delta = \dots = R_{1/l} + X_t - X_{1/l} + \frac{1}{2} \int_{1/l}^t \frac{d-1}{R_s} ds \quad (7.118)$$

Let  $K, l$  to infinity, by continuity

$$R_t = R_0 + X_t + \frac{1}{2} \int_0^t \frac{d-1}{R_s} ds \quad (7.119)$$

□

**Remark:**

$$dR_t = \underbrace{\frac{d-1}{R_t} dt}_{\text{blows up for } R_t \text{ small}} + dX_t \quad (7.120)$$

$\Rightarrow$  pushed away from 0.

**Proposition 7.22.**

Let  $d = 1, \alpha \geq 0$ .

- a)  $\mathbb{P}(\|B_t\| = \alpha \text{ for some } t) = 1 (d = 1)$
- b)  $d = 2, \alpha > 0, \mathbb{P}^x(\|B_t\| = \alpha \text{ for some } t) = 1 (x \neq 0)$
- c)  $d \geq 3, \mathbb{P}^x(\|B_t\| = \alpha \text{ for some } t) = \min\{1, \frac{\alpha}{\|x\|}\}^{d-2}$
- d)  $d \geq 2, \mathbb{P}^x(\|B_t\| = 0 \text{ for some } t > 0) = 0$
- e)  $d \geq 3, \mathbb{P}^x(\lim_{t \rightarrow \infty} \|B_t\| = +\infty) = 1$  BM in  $d \geq 3$  is transient

## 8 Stochastic differential equations

**Problem/Setting:**  $X$  is a  $d$ -dimensional stochastic process, we know its evolution, i.e.

$$(EQ1) \begin{cases} dX_t = b(t, X_t)dt + \sigma(t, X_t)dW_t \\ X_0 = \xi \end{cases} \quad (8.1)$$

where  $W$  is a BM on  $\mathbb{R}^n$ ,  $\xi$  can be a random variable or a constant.

### Definition 8.1.

We define

$$b(t, x) = [b_i(t, x)]_{1 \leq i \leq d} \text{ the drift vector.} \quad (8.2)$$

$$\sigma(t, x) = [\sigma_{i,j}(t, x)]_{1 \leq i \leq d, 1 \leq j \leq n} \text{ the dispersion matrix.} \quad (8.3)$$

From now on tacitly assume that  $W$  is a standard  $n$ -dimensional BM and that  $\xi$  is a random vector and that the two are independent.

Assumptions:  $\forall i, j$  :

$$b_i : \mathbb{R}_+ \times \mathbb{R}^d \rightarrow \mathbb{R} \quad (8.4)$$

$$\sigma_{i,j} : \mathbb{R}_+ \times \mathbb{R}^d \rightarrow \mathbb{R} \quad (8.5)$$

$$a_{ij} = (\sigma\sigma^T)_{ij} : \mathbb{R}_+ \times \mathbb{R}^d \rightarrow \mathbb{R} \quad (8.6)$$

are measurable.

Notation:

$$(a_{ij})_{1 \leq i, j \leq d} \text{ with } a_{ij} = \sum_{k=1}^n \sigma_{ik}\sigma_{jk} \quad (8.7)$$

is called *Diffusion Matrix*.

### Definition 8.2.

We define the following norms

$$\|b(t, x)\| := \sqrt{\sum_{i=1}^d b_i(t, x)^2} \quad (8.8)$$

$$\|\sigma(t, x)\| := \sqrt{\sum_{i=1}^d \sum_{j=1}^n \sigma_{i,j}^2(t, x)} \quad (8.9)$$

Q.: What do we understand under a solution of EQ1?

### 8.1 Strong solutions to SDE

Given:

- Standard filtered probability space  $(\Omega, \mathcal{F}, (\mathcal{F}_t), P)$ .
- $W, \xi$  both given



- $\mathcal{F}_t^W = \sigma(W_s, s \leq t), \mathcal{F}_t = \mathcal{F}_t^W \vee \sigma(\xi) = \sigma(W_s, 0 \leq s \leq t, \xi)$

**Definition 8.3** (Strong solution).

A strong solution to EQ1 is a  $\mathbb{R}^d$ -process  $(X_t)$  (on  $(\Omega, \mathcal{F}, \mathcal{F}_t, P)$ ) s.t.

- $X_0 = \xi$  a.s.
- $X$  is  $\mathcal{F}_t$ -adapted.
- $X$  is a continuous semimartingale s.t.  $\forall t < \infty$

$$\int_0^t \|b(s, X_s)\| + \|\sigma(s, X_s)\|^2 ds < \infty \text{ } \mathbb{P}\text{-a.s.} \quad (8.10)$$

- $X_t = X_0 + \int_0^t b(s, X_s)ds + \int_0^t \sigma(s, X_s)dW_s$   $\mathbb{P}$ -a.s. (the Ito Integral)

**Definition 8.4** (Strong uniqueness).

For (EQ1) holds *strong uniqueness* if the following holds: If  $X$  and  $\tilde{X}$  are strong solutions to (EQ1) then  $X$  and  $\tilde{X}$  are indistinguishable, i.e.

$$\mathbb{P}(X_t = \tilde{X}_t \forall t) = 1 \quad (8.11)$$

Check lecture notes for a deterministic example where uniqueness does not hold.

**Definition 8.5.**

A function  $f$  is called *locally lipschitz continuous* iff

$$\forall n \geq 1 \exists 0 < K_n < \infty \text{ s.t. } \forall x, y : \|x\| \leq n, \|y\| \leq n, \|f(x) - f(y)\| \leq K_n \|x - y\| \quad (8.12)$$

**Theorem 8.6.**

Assume  $b, \sigma$  are locally lipschitz. Then strong uniqueness for (EQ1) holds.

**Remark:** *The exact condition is*

$$\forall n \in \mathbb{N} \exists K_n < \infty \forall t \geq 0 \forall x, y \in \mathbb{R}^d : \|x\| \leq n, \|y\| \leq n : \quad (8.13)$$

$$\|b(t, x) - b(t, y)\| + \|\sigma(t, x) - \sigma(t, y)\| \leq K_n \|x - y\| \quad (8.14)$$

**Lemma 8.7** (Gronwall's Lemma).

Let  $g : [0, t] \rightarrow \mathbb{R}$  continuous,  $h : [0, T] \rightarrow \mathbb{R}$  integrable,  $\beta \geq 0$ . Then if

$$0 \leq g(t) \leq h(t) + \beta \int_0^t g(s)ds \forall t \in [0, T] \quad (8.15)$$

then

$$g(t) \leq h(t) + \beta \int_0^t h(s)e^{\beta(t-s)} ds \forall t \in [0, T] \quad (8.16)$$

**Remark:** *If  $h \equiv 0 \Rightarrow g(t) = 0 \forall t \in [0, T]$ . Therefore if  $0 \leq g(t) \leq \beta \int_0^t g(s)ds \Rightarrow g = 0!$*

*Proof.*

$$\frac{d}{dt}(e^{-\beta t} \int_0^t g(s)ds) = \dots \quad (8.17)$$

□

*Proof of the Thm.* Let  $X, \tilde{X}$  be strong solutions. Define

$$\tau_m = \inf\{t \geq 0 : \|X_t\| \geq m\}, \quad (8.18)$$

$$\tilde{\tau}_m = \inf\{t \geq 0 : \|\tilde{X}_t\| \geq m\}. \quad (8.19)$$

Easy:  $\tilde{\tau}_m, \tau_m \nearrow \infty$  as  $m \rightarrow \infty$ . Define  $S_m = \tau_m \wedge \tilde{\tau}_m$ .

$$g(t) := \mathbb{E} \left[ \|X_t^{S_m} - \tilde{X}_t^{S_m}\|^2 \right] \quad (8.20)$$

$$= \mathbb{E} \left[ \left\| \int_0^{t \wedge S_m} (b(s, X_s) - b(s, \tilde{X}_s)) + \int_0^{t \wedge S_m} (\sigma(s, X_s) - \sigma(s, \tilde{X}_s)) dW_s \right\|^2 \right] \quad (8.21)$$

$$= \sum_{i=1}^d \mathbb{E} \left[ \left( \int_0^{t \wedge S_m} \underbrace{b_i(s, X_s) - b_i(s, \tilde{X}_s)}_{=a} ds + \underbrace{\sum_{j=1}^n \int_0^{t \wedge S_m} \sigma_{ij}(s, X_s) - \sigma_{ij}(s, \tilde{X}_s) dW_s^j}_{b+c+d\dots} \right)^2 \right] \quad (8.22)$$

$$\stackrel{(a+b)^2 \leq 2a^2 + 2b^2}{\leq} C(d, n) \sum_{i=1}^d \mathbb{E} \left[ \left( \int_0^{t \wedge S_m} b_i(s, X_s) - b_i(s, \tilde{X}_s) ds \right)^2 \right] + C \sum_{i,j} \mathbb{E} \left[ \left( \int_0^{t \wedge S_m} \sigma_{ij}(s, X_s) - \sigma_{ij}(s, \tilde{X}_s) dW_s^j \right)^2 \right] \quad (8.23)$$

$$= \Delta \quad (8.24)$$

use:  $(a + b + c + \dots)^2 \leq 2a^2 + 2b^2 + 2c^2 + \dots$ . By Cauchy Schwarz  $(\int f \cdot 1 dy)^2 \leq \int f^2 ds \int 1 dx$  for the first integral, and Ito isometry for the second.

$$\Delta \leq Ct \sum_{i=1}^d \mathbb{E} \left[ \int_0^{t \wedge S_m} (b_i(s, X_s) - b_i(s, \tilde{X}_s))^2 ds \right] + C \sum_{i,j} \mathbb{E} \left[ \int_0^{t \wedge S_m} (\sigma_{ij}(s, X_s) - \sigma_{ij}(s, \tilde{X}_s))^2 ds \right] \quad (8.25)$$

$$\leq Ct \mathbb{E} \left[ \int_0^{t \wedge S_m} \sum_{i=1}^d (b_i(s, X_s) - b_i(s, \tilde{X}_s))^2 ds \right] + C \mathbb{E} \left[ \int_0^{t \wedge S_m} \sum_{i,j} (\sigma_{ij}(s, X_s) - \sigma_{ij}(s, \tilde{X}_s))^2 ds \right] \quad (8.26)$$

$$= Ct \mathbb{E} \left[ \int_0^{t \wedge S_m} \underbrace{\|b(s, X_s) - b(s, \tilde{X}_s)\|^2}_{\leq K_m^2 \|X_s - \tilde{X}_s\|^2} ds \right] + C \mathbb{E} \left[ \int_0^{t \wedge S_m} \underbrace{\|\sigma(s, X_s) - \sigma(s, \tilde{X}_s)\|^2}_{\leq \dots} ds \right] \quad (8.27)$$

$$\leq Ct K_m^2 \int_0^t \underbrace{\mathbb{E} [\|X_s^{S_m} - \tilde{X}_s^{S_m}\|^2]}_{g(s)} ds + CK_m^2 \int_0^t \underbrace{\mathbb{E} [\|X_s^{S_m} - \tilde{X}_s^{S_m}\|^2]}_{g(s)} ds \quad (8.28)$$

$$\leq CK_m^2 (1+t) \int_0^t g(s) ds \quad (8.29)$$

Now fix  $T > 0$ , then  $cK_m^2(1+t) \leq cK_m^2(1+T) =: \beta$ . Then by Gronwall  $g \equiv 0$ . But  $g(t) = \mathbb{E} [\|X_t^{S_m} - \tilde{X}_t^{S_m}\|^2] = 0 \forall t \in [0, T]$ . Therefore for all such  $t$ ,  $X_t^{S_m} = \tilde{X}_t^{S_m}$  a.s.. Let  $m \rightarrow \infty$ ,  $S_m \rightarrow \infty$ . Then  $X_t = \tilde{X}_t$  a.s.  $\forall t \in [0, T]$ . (by continuity and boundedness statement of theorem)  $\square$

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[11.12.2012]

**Theorem 8.8** (Global existence).

Assume  $\mathbb{E}[\|\xi\|^2] < \infty$  and  $\exists K > 0$  s.t.

$$\forall t \geq 0, x, y, \in \mathbb{R}^d, \quad (8.30)$$

$$\|b(t, x) - b(t, y)\| + \|\sigma(t, x) - \sigma(t, y)\| \leq K\|x - y\| \text{ (globally lipschitz)} \quad (8.31)$$

and

$$\forall t \geq 0, x \in \mathbb{R}^d \quad (8.32)$$

$$\|b(t, x)\| + \|\sigma(t, x)\| \leq K(1 + \|x\|) \text{ (linear growth)} \quad (8.33)$$

Then

a)  $\exists!$  strong solution of (EQ1)

b)  $\forall T \geq 0, \exists C > 0$  s.t.  $\forall 0 \leq t \leq T$

$$\mathbb{E}[\|X_t\|^2] \leq C(T)(1 + \mathbb{E}[\|\xi\|^2]) \quad (8.34)$$

**Remark:** The theorem also holds without the condition  $\mathbb{E}[\|\xi\|^2] < \infty$

*Proof. Idea:* Picard-Lindelöf-Iteration. Let

$$f(X_t) := \xi + \int_0^t b(s, X_s)ds + \int_0^t \sigma(s, X_s)dW_s \quad (8.35)$$

and we define

$$X_t^0 := \xi \quad (8.36)$$

$$X_t^{k+1} := f(X_t^k). \quad (8.37)$$

Hence,  $X_t^k$  is an adapted and continuous semimartingale. We want to show that  $X_t^k \xrightarrow{k \rightarrow \infty} X_t$  with  $f(X_t) = X_t$  (fixpoint), i.e.  $X_t$  is the solution of (EQ1). But first we need the following lemma.  $\square$

**Lemma 8.9.**

For all  $T > 0, \exists C > 0$  (which depends on  $K$  and  $T$ ) s.t.  $\forall k \geq 0$

$$\mathbb{E}[\|X_t^k\|^2] \leq C(1 + \mathbb{E}[\|\xi\|^2]) \quad \forall 0 \leq t \leq T. \quad (8.38)$$

*Proof.*  $k = 0$  :

$$\mathbb{E}[\|X_t^0\|^2] = \mathbb{E}[\|\xi\|^2] \leq 1 + \mathbb{E}[\|\xi\|^2] \checkmark \quad (8.39)$$

For any  $k$ :

$$\mathbb{E}[\|X_t^{k+1}\|^2] = \sum_{i=1}^d \mathbb{E}[(X_t^{k+1, i})^2] \quad (8.40)$$

$$\stackrel{X^{k+1}=f(X^k)}{\leq} \sum_{i=1}^d \mathbb{E} \left[ (\xi^i)^2 + \left( \int_0^t b_i(s, X_s^k)ds \right)^2 + \left( \sum_{j=1}^n \int_0^t \sigma_{ij}(s, X_s^k)dW_s^j \right)^2 \right] \quad (8.41)$$

$$\stackrel{\substack{\text{Hölder for } b_i \\ \text{Itô for } \sigma}}{\leq} 3\mathbb{E}[\|\xi\|^2] + 3t\mathbb{E} \left[ \underbrace{\int_0^t \|b(s, X_s^k)\|^2 ds}_{\leq K^2 2 \int_0^t (1 + \|X_s^k\|)^2 ds} \right] + 3\mathbb{E} \left[ \underbrace{\int_0^t \|\sigma(s, X_s^k)\|^2 ds}_{\leq K^2 2 \int_0^t (1 + \|X_s^k\|)^2 ds} \right] \quad (8.42)$$

$$\stackrel{0 \leq t \leq T}{\leq} 3\mathbb{E}[\|\xi\|^2] + 6K^2(T+1) \int_0^t (1 + \mathbb{E}[\|X_s^k\|^2])ds \quad (8.43)$$

Thus

$$\Rightarrow \underbrace{\mathbb{E}[\|X_t^{k+1}\|^2]}_{=:g^{k+1}(t)} \leq 3\mathbb{E}[\|\xi\|^2] + 6K^2(T+1) \int_0^t (1 + \mathbb{E}[\|X_s^k\|^2]) ds \quad (8.44)$$

Then

$$g^{k+1}(t) \leq C_1 + C_2 \int_0^t (1 + g_s^k) ds \quad (8.45)$$

$$\leq C_1 + C_2 \int_0^t 1 ds + C_2 \int_0^t ds_1 (C_1 + C_2 \int_0^{s_1} ds_2 1 + g_{s_2}^k) \quad (8.46)$$

$$\leq \dots \quad (8.47)$$

Recursively and

$$\int_0^t ds_1 \int_0^{s_1} ds_2 \dots \int_0^{s_{k-1}} ds_k 1 = \frac{t^k}{k!} \quad (8.48)$$

$$\Rightarrow \mathbb{E}[\|X_t^{k+1}\|^2] \leq C(T, K)(1 + \mathbb{E}[\|\xi\|^2]) \forall 0 \leq t \leq T \quad (8.49)$$

□

*Continuation of the proof of the theorem.*

**Step 1)** For  $X^k$  continuous, adapted and well-defined, then also  $X^{k+1}$  is continuous, adapted and well-defined.

Indeed: - Continuity and adaptedness from the definition of the integral.

- Condition c) of Def 8.2 holds:

$$\int_0^t (\|b(s, X_s^k)\| + \|\sigma(s, X_s^k)\|^2) ds \stackrel{\text{C.S. on } b}{\leq} t \int_0^t \|b(s, X_s^k)\|^2 ds + \int_0^t \|\sigma(s, X_s^k)\|^2 ds \quad (8.50)$$

$$\leq (1+t)2K^2 \int_0^t (1 + \|X_s^k\|^2) ds < \infty \forall t < \infty \quad (8.51)$$

**Step 2: Estimate  $X^{k+1} - X^k$**

For fixed  $k$  it holds

$$X^{k+1} - X^k = B + M \quad (8.52)$$

with

$$B_t = \int_0^t b(s, X_s^k) - b(s, X_s^{k-1}) ds, \quad (8.53)$$

$$M_t = \int_0^t \sigma(s, X_s^k) - \sigma(s, X_s^{k-1}) dW_s. \quad (8.54)$$

Claim: We have

$$\mathbb{E} \left[ \sup_{0 \leq s \leq t} \|X_s^{k+1} - X_s^k\|^2 \right] \leq 2\mathbb{E} \left[ \sup_{0 \leq s \leq t} \|M_s\|^2 \right] + 2\mathbb{E} \left[ \sup_{0 \leq s \leq t} \|B_t\|^2 \right] \quad (8.55)$$

Proof:

$$\|B_t\|^2 = \sum_{i=1}^d (B_t^i)^2 \quad (8.56)$$

$$= \sum_{i=1}^d \left( \int_0^t b_i(s, X_s^k) - b_i(s, X_s^{k-1}) ds \right)^2 \quad (8.57)$$

$$\stackrel{CS \text{ and } 0 \leq t \leq T}{\leq} T \sum_{i=1}^d \int_0^t (b_i(s, X_s^k) - b_i(s, X_s^{k-1}))^2 ds \quad (8.58)$$

$$= T \int_0^t \underbrace{\|b(s, X_s^k) - b(s, X_s^{k-1})\|^2}_{\leq K^2 \|X_s^k - X_s^{k-1}\|^2 \text{ by Lipschitz}} ds \quad (8.59)$$

Hence

$$\mathbb{E} \left[ \sup_{0 \leq s \leq t} \|B_s\|^2 \right] \leq K^2 T \int_0^t ds \underbrace{\mathbb{E} [\|X_s^k - X_s^{k-1}\|^2]}_{= \mathbb{E} [\sup_{0 \leq s \leq t} \|X_s^k - X_s^{k-1}\|^2]} \quad (8.60)$$

$$\mathbb{E} \left[ \sup_{0 \leq s \leq t} \|M_s\|^2 \right] = \mathbb{E} \left[ \sup_{0 \leq s \leq t} \sum_{i=1}^d (M_s^i)^2 \right] \quad (8.61)$$

$$\leq \sum_{i=1}^d \mathbb{E} \left[ \sup_{0 \leq s \leq t} (M_s^i)^2 \right] \quad (8.62)$$

$$\stackrel{Doob}{\leq} 4 \sum_{i=1}^d \mathbb{E} \left[ (M_t^i)^2 \right] \quad (8.63)$$

$$\leq 4 \sum_{i=1}^d \mathbb{E} \left[ \left( \sum_{j=1}^n \int_0^t (\sigma_{ij}(s, X_s^k) - \sigma_{ij}(s, X_s^{k-1})) dW_s^j \right)^2 \right] \quad (8.64)$$

$$\stackrel{ItoIsom}{=} 4 \sum_{i=1}^d \sum_{j=1}^n \mathbb{E} \left[ \int_0^t (\sigma_{ij}(s, X_s^k) - \sigma_{ij}(s, X_s^{k-1}))^2 ds \right] \quad (8.65)$$

$$= 4 \mathbb{E} \left[ \int_0^t ds \underbrace{\|\sigma(s, X_s^k) - \sigma(s, X_s^{k-1})\|^2}_{\leq K^2 \|X_s^k - X_s^{k-1}\|^2} \right] \quad (8.66)$$

Thus

$$\mathbb{E} \left[ \sup_{0 \leq s \leq t} \|M_s\|^2 \right] \leq 4K^2 \int_0^t \mathbb{E} \left[ \sup_{0 \leq s \leq t} \|X_u^k - X_u^{k-1}\|^2 \right] \quad (8.67)$$

$$\Rightarrow \mathbb{E} \left[ \sup_{0 \leq s \leq t} \|X_s^{k+1} - X_s^k\|^2 \right] \leq 2K^2(4+T) \int_0^t ds \mathbb{E} \left[ \sup_{0 \leq u \leq s} \|X_u^k - X_u^{k-1}\|^2 \right] \quad (8.68)$$

Iterations as in Lemma 8.9 give

$$\leq \frac{(c_1 t)^k}{k!} c_s \text{ with } c_1 = 2K^2(T+4) \text{ and} \quad (8.69)$$

$$c_2 = T \sup_{0 \leq s \leq T} \mathbb{E} \left[ \|X_s^1 - \xi\|^2 \right] < \infty \quad (8.70)$$

<sup>1</sup>Supremum wird ganz rechts bei t angenommen da integral über was positives

last  $< \infty$  since

$$\mathbb{E} \left[ \|X_s^1 - \xi\|^2 \right] \leq 2\mathbb{E} \left[ \|X_s^1\|^2 \right] + 2\mathbb{E} \left[ \|\xi\|^2 \right] \stackrel{\text{lemma}}{\leq} 2(c+1)\mathbb{E} \left[ \|\xi\|^2 \right] \quad (8.71)$$

We have

$$\mathbb{E} \left[ \sup_{0 \leq s \leq t} \|X_s^{k+1} - X_s^k\|^2 \right] \leq C_2 \frac{(C_1 t)^k}{k!} \quad (8.72)$$

**Step 3: uniform convergence on  $[0, T]$  for all fixed  $T > 0$ .**

$$\mathbb{P} \left( \sup_{0 \leq s \leq T} \|X_s^{k+1} - X_s^k\| \geq \frac{1}{2^{k+1}} \right) \stackrel{\text{Cebicevand(8.72)}}{\leq} 4c_2 \frac{(4c_1 T)^k}{k!} \quad (8.73)$$

Since  $\sum_k \sup_{0 \leq s \leq T} \|X_s^{k+1} - X_s^k\| \geq \frac{1}{2^{k+1}} < \infty$  we can use Borel Cantelli which implies

$$\exists \Omega^* : \mathbb{P}(\Omega^*) = 1 \text{ s.t. } \forall \omega \in \Omega^* \exists N = N(\omega) \text{ s.t.} \quad (8.74)$$

$$\forall k \geq N(\omega) \sup_{0 \leq s \leq T} \|X_s^{k+1} - X_s^k\| \leq \frac{1}{2^{k+1}} \quad (8.75)$$

$$\Rightarrow \forall k \geq N(\omega), m \geq 1 \sup_{0 \leq s \leq T} \|X_s^{m+k} - X_s^k\| \leq \frac{1}{2^k} \quad (8.76)$$

Hence the sequence  $\{X_t^k, 0 \leq t \leq T\}_{k \geq 1}$  converges in the sup-norm to a continuous process  $\{X_t, 0 \leq t \leq T\} \forall \omega \in \Omega^*$ .  $\Rightarrow$  But  $T$  is any positive time.

$$\Rightarrow X^k \xrightarrow{\text{unif}} X \text{ for any bounded time interval.} \quad (8.77)$$

**Step 4: Verify b)**

$$\mathbb{E} \left[ \|X_t\|^2 \right] = \mathbb{E} \left[ \lim_{k \rightarrow \infty} \|X_t^k\|^2 \right] \quad (8.78)$$

$$\leq \liminf_{k \rightarrow \infty} \mathbb{E} \left[ \|X_t^k\|^2 \right] \quad (8.79)$$

$$\stackrel{\text{Lemma}}{\leq} C(1 + \mathbb{E} \left[ \|\xi\|^2 \right]) \quad (8.80)$$

**Step 5: Check that  $X_t = \lim_{k \rightarrow \infty} X_t^k$  satisfies (EQ1)**

$$\underbrace{X_t^{k+1}}_{\rightarrow X_t} = \underbrace{\xi}_{\rightarrow X_0} + \underbrace{\int_0^t b(s, X_s^k) ds}_{\rightarrow \int_0^t b(s, X_s) ds??} + \underbrace{\int_0^t \sigma(s, X_s^k) dW_s}_{\rightarrow \int_0^t \sigma(s, X_s) dW_s??} \quad (8.81)$$

□

[11.12.2012]  
[14.12.2012]

**Recap:**

$$X_t = \frac{e^{-\lambda t}}{\sqrt{2\lambda}} B_{e^{2\lambda t}} \rightsquigarrow dX_t = -\lambda X_t dt + d\tilde{B}_t \text{ (SDE)} \quad (8.82)$$

Are there unique solutions? Yes under the right conditions.

## 8.2 Examples

### 8.2.1 Brownian Motion with drift

Let  $v \in \mathbb{R}^d$  (drift vector) and  $\sigma > 0$  a constant and  $W$  a BM. Then, the SDE

$$dX_t = vdt + \sigma dW_t \quad (8.83)$$

has a unique strong solution

$$X_t = X_0 + \int_0^t v ds + \int_0^t \sigma dW_s = X_0 + vt + \sigma W_t \quad (8.84)$$

It holds

$$\mathbb{E}[X_t] = \mathbb{E}[X_0] = vt \quad (8.85)$$

$$\text{Cov}(X_t^i, X_t^j) = \sigma^2 \text{Cov}(W_t^i, W_t^j) = \sigma^2 \delta_{ij}t \quad (8.86)$$

### 8.2.2 Ornstein-Uhlenbeck

Let  $\lambda > 0$  a constant, consider the SDE

$$dX_t = -\lambda X_t dt + dW_t \quad (8.87)$$

$\exists!$  strong solution given by

$$X_t = e^{-\lambda t} X_0 + \int_0^t e^{-\lambda(t-s)} dW_s \quad (8.88)$$

How does one get this formula? Let us set  $\frac{d \ln(X_t)}{dt} = -\lambda \Rightarrow X_t = e^{-\lambda t} X_0$ . Then

$$\Rightarrow Y_t := e^{\lambda t} X_t \quad (8.89)$$

$$\Rightarrow dY_t = e^{\lambda t} dX_t + \lambda e^{\lambda t} X_t dt \quad (8.90)$$

$$= e^{\lambda t} [-\lambda X_t dt + dW_t + \lambda X_t dt] = e^{\lambda t} dW_t \quad (8.91)$$

Hence

$$e^{\lambda t} X_t = Y_t = \int_0^t e^{\lambda s} dW_s + Y_0 \quad (8.92)$$

$$\Rightarrow X_t = e^{-\lambda t} \underbrace{X_0}_{=Y_0} + \int_0^t e^{-\lambda(t-s)} dW_s \quad (8.93)$$

Let's check if this is really a solution.

$$X_t = e^{-\lambda t} X_0 + e^{-\lambda t} \int_0^t e^{\lambda s} dW_s \quad (8.94)$$

$$\Rightarrow dX_t = -\lambda e^{-\lambda t} X_0 dt - \lambda e^{-\lambda t} dt \int_0^t e^{\lambda s} dW_s + e^{-\lambda t} e^{\lambda t} dW_s \quad (8.95)$$

$$= -\lambda \underbrace{(e^{-\lambda t} X_0 + \int_0^t e^{-\lambda(t-s)} dW_s)}_{=X_t} dt + dW_s \checkmark \quad (8.96)$$

The stationary distribution of the O.U. process is given by the initial condition

$$X_0 \sim \mathcal{N}(0, \frac{1}{2\lambda}) \quad (8.97)$$

Then  $X_t \sim \mathcal{N}(0, \frac{1}{2\lambda})$  and  $\text{Cov}(X_s, X_t) = \frac{1}{2\lambda} e^{-\lambda|t-s|}$ . The OU Process is a Gaussian process. Indeed:

**Lemma 8.10.**

Let

$$M_t = \int_0^t h(s) dW_s \quad (8.98)$$

with  $h \in L^2(\mathbb{R}_+)$ . Then it holds  $M_t = \mathcal{N}(0, \langle M \rangle_t)$ .*Proof.* Let's calculate  $\langle M \rangle_t$  first.

$$dM_t = h(t) dW_t \quad (8.99)$$

$$d\langle M \rangle_t = (h(t))^2 (dW_t)^2 = (h(t))^2 dt \quad (8.100)$$

$$\Rightarrow \langle M \rangle_t = \underbrace{\int_0^t (h(s))^2 ds}_{\text{deterministic}} < \infty \text{ by hypothesis.} \quad (8.101)$$

<sup>7.12</sup>  
 $\Rightarrow$  We know that for  $\xi \in \mathbb{R}$

$$e^{i\xi M_t + \frac{\xi^2}{2} \langle M \rangle_t} \quad (8.102)$$

is a martingale. Thus

$$\mathbb{E} \left[ e^{i\xi M_t} \right] e^{\frac{\xi^2}{2} \langle M \rangle_t} = \mathbb{E} \left[ e^{i\xi M_0} \right] e^{\frac{\xi^2}{2} \langle M \rangle_0} = 1 \quad (8.103)$$

$$\Rightarrow \mathbb{E} \left[ e^{i\xi M_t} \right] = e^{-\frac{\xi^2}{2} \langle M \rangle_t} \quad (8.104)$$

□

In our case  $h(s) = e^{-\lambda(t-s)}$ . Thus

$$\int_0^t e^{-\lambda(t-s)} dW_s \sim \mathcal{N}\left(0, \underbrace{\int_0^t e^{-2\lambda(t-s)} ds}_{= \frac{1-e^{-2\lambda t}}{2\lambda}}\right) \quad (8.105)$$

Now assume that  $X_0$  is independent of  $W$ . Then

$$e^{-\lambda t} X_0 \sim \mathcal{N}\left(0, \frac{e^{-2\lambda t}}{2\lambda}\right) \quad (8.106)$$

$$\Rightarrow X_t = e^{-\lambda t} X_0 + \int_0^t e^{-\lambda(t-s)} dW_s \stackrel{\text{indep.}}{\sim} \mathcal{N}\left(0, \frac{e^{-2\lambda t}}{2\lambda} + \frac{1-e^{-2\lambda t}}{2\lambda}\right) = \mathcal{N}\left(0, \frac{1}{2\lambda}\right) \checkmark \quad (8.107)$$

Now calculate for  $s \leq t$ 

$$\text{Cov}(X_s, X_t) = ? \quad (8.108)$$

Recall that  $X_t = e^{-\lambda t} X_0 + \int_0^t e^{-\lambda(t-u)} dW_u$ . Hence (with independence of  $X_0$  and  $W$ )

$$\text{Cov}(X_s, X_t) = e^{-\lambda t} e^{-\lambda s} \underbrace{\text{Var}(X_0)}_{\text{Cov}(X_0, X_0)} + e^{-\lambda(t+s)} \underbrace{\text{Cov}\left(\int_0^s e^{\lambda u} dW_u, \int_0^t e^{\lambda v} dW_v\right)}_{=: M_s} \quad (8.109)$$

Need to get

$$\text{Cov}(M_s, M_t) = \text{Cov}(M_s, M_s) - \underbrace{\text{Cov}(M_s, M_t - M_s)}_{=0} = \text{Var}(M_s) \quad (8.110)$$



$$\Rightarrow \text{Cov}(X_s, X_t) = e^{-2\lambda(t+s)} \frac{1}{2\lambda} + e^{-\lambda(t+s)} \mathbb{E} \left[ \left( \int_0^s e^{\lambda u} dW_u \right)^2 \right] \quad (8.111)$$

$$\stackrel{\text{It\^o Isom.}}{=} e^{-2\lambda(t+s)} \frac{1}{2\lambda} + e^{-\lambda(t+s)} \mathbb{E} \left[ \int_0^s e^{2\lambda u} du \right] \quad (8.112)$$

$$= e^{-2\lambda(t+s)} \frac{1}{2\lambda} + e^{-\lambda(t+s)} \frac{e^{2\lambda s} - 1}{2\lambda} \quad (8.113)$$

$$= \frac{e^{-\lambda(t-s)}}{2\lambda} \odot \quad (8.114)$$

**Remark:** Intuition: The drift  $b(t, x) = -\lambda x$  towards  $0 \in \mathbb{R}^d$  leads to  $X$  being stationary, i.e.

$$\mathbb{E}[X_t] \rightarrow 0 \quad (8.115)$$

$$\mathbb{E}[X_t^2] \rightarrow \frac{1}{2\lambda} \quad (8.116)$$

### 8.2.3 Geometric Brownian Motion

Let  $\sigma \neq 0$  and  $\mu \in \mathbb{R}$ . Consider the SDE

$$\begin{cases} dX_t = \mu X_t dt + \sigma X_t dW_t \\ X_0 = x > 0 \end{cases} \quad (8.117)$$

Then there exists a unique strong solution given by

$$X_t = x e^{(\mu - \frac{\sigma^2}{2})t + \sigma W_t}, \quad t \geq 0 \quad (8.118)$$

To get (8.118) we set

$$Y_t = \ln(X_t) \quad (8.119)$$

$$\Rightarrow dY_t \stackrel{\text{It\^o-Isom.}}{=} \frac{dX_t}{X_t} - \frac{1}{2} \frac{(dX_t)^2}{X_t^2} = \frac{\mu X_t dt + \sigma X_t dW_t}{X_t} - \frac{1}{2} \frac{\sigma^2 X_t^2 dt}{X_t^2} = \left( \mu - \frac{\sigma^2}{2} \right) dt + \sigma dW_t \quad (8.120)$$

$\Rightarrow Y_t$  is a BM with drift  $\mu - \frac{\sigma^2}{2}$ .

$$\ln(X_t) = Y_t = Y_0 + \left( \mu - \frac{\sigma^2}{2} \right) t + \sigma W_t \quad (8.121)$$

$$\Rightarrow X_t = e^{Y_0} e^{(\mu - \frac{\sigma^2}{2})t + \sigma W_t} \quad (8.122)$$

But since  $X_0 = x \Rightarrow e^{Y_0} = x \odot$ .

### 8.2.4 Brownian Bridge

Let  $a, b \in \mathbb{R}, T > 0$ . Then the Brownian Bridge from  $a$  at time  $t = 0$  to  $b$  at time  $t = T$  is the solution of

$$\begin{cases} dX_t = \frac{b-X_t}{T-t} dt + dW_t, & 0 \leq t \leq T \\ X_0 = a \end{cases} \quad (8.123)$$

The solution is

$$X_t = \begin{cases} a(1 - \frac{t}{T}) + \frac{bt}{T} + (T-t) \int_0^t \frac{1}{T-s} dW_s, & 0 \leq t < T \\ b, & t = T \end{cases} \quad (8.124)$$

Does  $X_t \rightarrow b$  for  $t \nearrow T$ ? Consider the case  $T = 1, a = 0 = b$ . Then:

$$X_t = (1-t)W_{\frac{t}{1-t}} \quad (8.125)$$

For  $t \nearrow 1$ :  $W_{\frac{t}{1-t}} \sim \frac{1}{\sqrt{1-t}} \Rightarrow X_t \sim \sqrt{1-t} \xrightarrow{t \rightarrow 1} 0$

### 8.2.5 Linear system (d=1)

Let us consider the case where the drift is given by

$$a(t, x) = a_1(t)x + a_2(t) \quad (8.126)$$

and the dispersion is given by

$$\sigma(t, x) = \sigma_1(t)x + \sigma_2(t) \quad (8.127)$$

with  $a_1, a_2, \sigma_1, \sigma_2$  bounded in time. Then our SDE is given by

$$dX_t = a(t, X_t)dt + \sigma(t, X_t)dW_t = X_t dY_t + dZ_t \quad (8.128)$$

$$X_0 = \xi \quad (8.129)$$

with

$$Y_t = \int_0^t a_1(s)ds + \int_0^t \sigma_1(s)dW_s \quad (8.130)$$

$$Z_t = \int_0^t a_2(s)ds + \int_0^t \sigma_2(s)dW_s \quad (8.131)$$

We know that  $\exists!$  strong solution: Let

$$\mathcal{E}_t^Y := \exp\left(Y_t - \frac{1}{2}\langle Y \rangle_t\right) \quad (8.132)$$

$\Rightarrow X_t = \mathcal{E}_t^Y(\xi + \int_0^t (\mathcal{E}_s^Y)^{-1}(dZ_s - \sigma_1(s)\sigma_2(s)ds))$ . How does one get that? We have

$$\langle Y \rangle_t = \int_0^t \sigma_1(s)^2 ds \quad (8.133)$$

$$\Rightarrow \mathcal{E}_t^Y = \exp\left[\int_0^t \left(\sigma_1(s) - \frac{\sigma_1(s)^2}{2}\right) ds + \int_0^t \sigma_1(s)dW_s\right] \quad (8.134)$$

Consider

$$Q_t := \frac{X_t}{\mathcal{E}_t^Y} = X_t[(\mathcal{E}_t^Y)^{-1}] \quad (8.135)$$

$$\Rightarrow dQ_t \stackrel{\text{Integr. by parts}}{=} \frac{dX_t}{\mathcal{E}_t^Y} + X_t d[(\mathcal{E}_t^Y)^{-1}] + dX_t d[(\mathcal{E}_t^Y)^{-1}] \quad (8.136)$$

But

$$d[(\mathcal{E}_t^Y)^{-1}] = d(e^{-Y_t + \frac{1}{2}\langle Y \rangle_t}) \quad (8.137)$$

$$\stackrel{\text{Itô Form.}}{=} (\mathcal{E}_t^Y)^{-1}(-dY_t + \frac{1}{2}d\langle Y \rangle_t + \frac{1}{2}d\langle Y \rangle_t) \quad (8.138)$$

$$= (\mathcal{E}_t^Y)^{-1}(-\underbrace{dY_t}_{a_1(t)dt} + \underbrace{d\langle Y \rangle_t}_{\sigma_1(t)^2 dt}) \quad (8.139)$$

$$\Rightarrow dQ_t = \frac{dX_t}{\mathcal{E}_t^Y} + \frac{X_t}{\mathcal{E}_t^Y}(-dY_t + d\langle Y \rangle_t) + \frac{dX_t}{\mathcal{E}_t^Y}(-dY_t + d\langle Y \rangle_t) \quad (8.140)$$

$$= (\mathcal{E}_t^Y)^{-1}(dX_t + X_t(-dY_t + d\langle Y \rangle_t) + dX_t(-dY_t + d\langle Y \rangle_t)) \quad (8.141)$$

$$= (\mathcal{E}_t^Y)^{-1}(\underbrace{X_t dY_t + dZ_t - X_t dY_t + X_t d\langle Y \rangle_t}_{\stackrel{(8.128)}{=} dX_t} + (X_t dY_t + dZ_t)(d\langle Y \rangle_t - dY_t)) \quad (8.142)$$

$$= (\mathcal{E}_t^Y)^{-1}(dZ_t + X_t d\langle Y \rangle_t - X_t d\langle Y \rangle_t - dZ_t dY_t) \quad (8.143)$$

$$= (\mathcal{E}_t^Y)^{-1}(dZ_t + \underbrace{dZ_t}_{=\sigma_2(t)dW_t} \underbrace{dY_t}_{=\sigma_1(t)W_t}) \quad (8.144)$$

$$= (\mathcal{E}_t^Y)^{-1}(dZ_t - \sigma_1(t)\sigma_2(t)dt) \quad (8.145)$$

And hence with  $Q_t = \frac{X_t}{\xi_t}$

$$\frac{X_t}{\mathcal{E}_t^Y} = \underbrace{\frac{X_0}{\mathcal{E}_0^Y}}_{=\xi} + \int_0^t (\mathcal{E}_s^Y)^{-1} (dZ_s - \sigma_1(s)\sigma_2(s)ds) \quad (8.146)$$

$$\Rightarrow X_t = \mathcal{E}_t^Y \left( \xi + \int_0^t (\mathcal{E}_s^Y)^{-1} (dZ_s - \sigma_1(s)\sigma_2(s)ds) \right) \quad (8.147)$$

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[14.12.2012]  
[18.12.2012]

## 9 Connection to PDE: The Feynman-Kac Formula

Discrete time:

$$\begin{cases} \nabla u = g & \text{on } \Omega \\ u = 0 & \text{on } \partial\Omega \end{cases} \quad (9.1)$$

↔ had a probability formula written as  $\mathbb{E}[\cdot]$  with some stopping time  $\tau_{\partial\Omega}$ .  
Today we consider the heat equation.

### 9.1 Heat equation

Let  $u(t, x)$  be the temperature in an isotropic material without dispersion at time  $t$  and position  $x \in \mathbb{R}^d$ . Let  $D$  be the diffusion constant. Then it holds

$$\frac{\partial u}{\partial t} = \frac{D}{2} \Delta u \quad (9.2)$$

This is the Heat-equation. Now we add an initial condition, and hence have

$$\begin{cases} \frac{\partial u}{\partial t} = \frac{D}{2} \Delta u \\ u(x, 0) = f(x) \end{cases} \quad (\text{EQ1})$$

More generically we have:

$$\partial_t u + \text{div} \vec{\gamma} = \sigma \text{ (loss/source of energy)} \quad (9.3)$$

$$\vec{\gamma} = -\frac{1}{2} D(x) \vec{\nabla} u \text{ (current)} \quad (9.4)$$

1) By scaling in space and time we can assume wlog  $D=1$ . One can see that

$$p_t(x, y) := \frac{e^{-\frac{(x-y)^2}{2t}}}{(\sqrt{2\pi t})^d} \quad (9.5)$$

solves (1) with  $u(x, 0) = \delta_y(x)$ . For general  $f$

$$u(x, t) := \int_{\mathbb{R}^d} p_t(x, y) f(y) dy \equiv \mathbb{E}^x[f(W_t)] \quad (9.6)$$

solves (1). Here  $W$  is a BM starting from  $x$ .

We now consider a generalisation, with an external cooling:

$$\begin{cases} \frac{\partial u}{\partial t} = \frac{1}{2} \Delta u - K(x)u \\ u(x, 0) = f(x) \end{cases} \quad (\text{EQ2})$$

Here  $K(x)$  is the cooling rate at the position  $x$ .

**Solution (Kac '49)**

$$u(x, t) = \mathbb{E}^x \left[ f(W_t) e^{-\int_0^t K(W_s) ds} \right] \quad (\text{EQ3})$$

(EQ3) is called the Feynman-Kac formula.

Paraphrase: Consider a particle with mass  $m$  in a (conservative) potential field  $V(x)$ . In Quantum-Mechanics the state of the system is given by a complex function  $\psi_t(x) \in L^2(\mathbb{R}^3)$ . Evolution: (Schrödinger eq.)

$$i\hbar\partial_t\psi = \frac{\hbar^2}{2m}\Delta\psi + V(x)\psi \tag{9.7}$$

where  $\hbar = \frac{h}{2\pi}$  is the Planck constant.

Feynman Idea (1948):

$$\psi_t(x) = \text{average over all possible trajectories of } e^{i\frac{S(y)}{\hbar}} \text{ with } S \text{ the 'action' of } y. \tag{9.8}$$

⇒ He wrote

$$\psi_t(x) = \text{Const} \int_A e^{i\frac{S(y_s)}{\hbar}} \psi_0(y(t)) \underbrace{Dy}_{\text{"}\infty\text{-dim. Leb. meas."}} \tag{9.9}$$

with  $A = \{\text{Continuous functions } y \text{ mit } y(0) = x\}$  and

$$S(y) = \int_0^t \underbrace{\frac{m}{2}(\dot{y}(s))^2}_{\text{kinetic energy}} - V(Y(s)) ds \tag{9.10}$$

This is mathematically ill-defined. Kac noticed that if you consider "purely imaginary" times ( $t \rightarrow it$ ) ⇒ the Schrödinger equation becomes (EQ2). Using the idea of Feynman he got the representation of (EQ2) above.

**Definition 9.1.**

Let  $f : \mathbb{R}^d \rightarrow \mathbb{R}$ ,  $K : \mathbb{R}^d \rightarrow \mathbb{R}_+$  be continuous functions. Assume,  $v$  is a continuous real function on  $\mathbb{R}^d \times [0, T]$ ,  $v \in C^{2,1}(\mathbb{R}^d \times [0, T])$  s.t.

$$\begin{cases} -\frac{\partial v}{\partial t} + Kv = \frac{1}{2}\Delta v & \text{on } \mathbb{R}^d \times [0, T) \\ v(x, T) = f(x) & , x \in \mathbb{R}^d \end{cases} \tag{EQ4}$$

Then  $v$  is called a solution of the Cauchy problem for the backwards heat equation (EQ4) with potential  $K$  and final condition  $f$ .

**Theorem 9.2.**

Let  $v$  as in Def 9.1. Assume that

$$\max_{0 \leq t \leq T} |v(t, x)| \leq Ce^{a\|x\|^2}, \forall x \in \mathbb{R}^d \tag{9.11}$$

for a constant  $C > 0$  and  $0 < a < \frac{1}{2Td}$ . Then  $v$  has the stochastic representation

$$(5) \quad v(x, t) = E^x(f(W_{T-t})e^{-\int_0^{T-t} K(W_s)ds}), \quad 0 \leq t \leq T, x \in \mathbb{R}^d \tag{9.12}$$

Moreover,  $v$  is unique.

**Corollary 9.3.**

By taking  $t \mapsto T - t$  one gets the stochastic representation of (2) given by

$$u(x, t) = \mathbb{E}^x \left[ f(W_t) e^{-\int_0^t K(W_s)ds} \right] \tag{9.13}$$

a

*Proof of the Theorem.* Let  $g(\vartheta) := v(W_\vartheta, t + \vartheta)e^{-\int_0^\vartheta K(W_s)ds}$ . What is  $dg(\vartheta)$ ?

$$d(e^{-\int_0^\vartheta K(W_s)ds}) = e^{-\int_0^\vartheta K(W_s)ds}(-K(W_\vartheta))d\vartheta \quad (9.14)$$

$$d(v(W_\vartheta, t + \vartheta)) = \dot{v}(W_\vartheta, t + \vartheta)d\vartheta + \nabla v(W_\vartheta, t + \vartheta)dW_\vartheta + \underbrace{\frac{1}{2}\Delta v(W_\vartheta, t + \vartheta)d\vartheta}_{\stackrel{(EQ4)}{=} -\dot{v}(W_\vartheta, t + \vartheta)d\vartheta + Kv(W_\vartheta, t + \vartheta)d\vartheta}} \quad (9.15)$$

$$= \nabla v(W_\vartheta, t + \vartheta)dW_\vartheta + Kv(W_\vartheta, t + \vartheta)d\vartheta \quad (9.16)$$

And thus

$$\Rightarrow dg \stackrel{\text{part.}}{\stackrel{\text{integ.}}{=} } -vKe^{-\int_0^\vartheta Kds}d\vartheta + e^{-\int_0^\vartheta Kds}(Kvd\vartheta + \nabla vdW_\vartheta) \quad (9.17)$$

$$= e^{-\int_0^\vartheta K(W_{s,t+s})ds}\nabla v(W_\vartheta, t + \vartheta)dW_\vartheta \quad (9.18)$$

Hence we have

$$g(\vartheta) = g(0) + \int_0^\vartheta e^{-\int_0^u K(W_{s,t+s})ds}\nabla v(W_u, t + u)dW_s \quad (9.19)$$

□

$\Rightarrow g$  is a local martingale with  $g(0) = v(W_0, t) = v(x, t)$ . Let us introduce the stopping time

$$S_n := \inf\{t \geq 0 : \|W_t\| \geq n\sqrt{d}\}, n \geq 1. \quad (9.20)$$

Let  $r \in (0, T - t)$ . Then

$$v(x, t) = \mathbb{E}^x[v(W_0, t)] = \mathbb{E}^x[g(0)] = \mathbb{E}^x[g(S_n \wedge t)] \quad (9.21)$$

$$= \underbrace{\mathbb{E}^x\left[v(W_{S_n}, t + S_n)e^{-\int_0^{S_n} K(W_s)ds} \mathbb{1}_{\{S_n \leq r\}}\right]}_{(A)} + \underbrace{\mathbb{E}^x\left[v(t + r, W_r)e^{-\int_0^r K(W_s)ds} \mathbb{1}_{\{S_n > r\}}\right]}_{(B)} \quad (9.22)$$

**ad (B)** As  $n \nearrow \infty$  and  $r \nearrow T - t$ , by dominated convergence

$$(B) \Rightarrow \mathbb{E}^x\left[v(T, W_{T-t})e^{-\int_0^{T-t} K(W_s)ds}\right] \checkmark \quad (9.23)$$

Remains to show: As  $n \nearrow \infty$  (A)  $\searrow 0$ .

$$|A| \stackrel{K \geq 0}{\leq} \mathbb{E}^x \left[ \underbrace{|v(W_{S_n}, t + S_n)|}_{\in (0, T)} \mathbb{1}_{\{S_n \leq r\}} \right] \quad (9.24)$$

$$\leq C \mathbb{E}^x \left[ e^{a\|W_{S_n}\|^2} \mathbb{1}_{S_n \leq r} \right] \quad (9.25)$$

$$\stackrel{\text{Def of } S_n}{\leq} C e^{adn^2} \mathbb{E}^x [\mathbb{1}_{S_n \leq T}] \quad (9.26)$$

$$\leq C e^{adn^2} \sum_{l=1}^d \mathbb{P}^x \left( \max_{0 \leq t \leq T} |W_t^{(l)}| \geq n \right) \quad (9.27)$$

$$\leq C e^{adn^2} \sum_{l=1}^d \mathbb{P}^x \left( \max_{0 \leq t \leq T} W_t^{(l)} \geq n \right) + \mathbb{P}^x \left( \max_{0 \leq t \leq T} -W_t^{(l)} \geq n \right) \quad (9.28)$$

$$\stackrel{\text{refl. princ.}}{=} 2C e^{adn^2} \sum_{l=1}^d \mathbb{P}^x \left( W_T^{(l)} \geq n \right) + \mathbb{P}^x \left( -W_T^{(l)} \geq n \right) \quad (9.29)$$

<sup>1</sup> $\mathbb{P}(S_n \leq T) \leq \mathbb{P}(\max_{0 \leq t \leq T} \sum (W_t^{(l)})^2 \geq n^2 d) \leq \mathbb{P}(\exists l : (W_t^{(l)})^2 \geq n^2)$

We know

$$P^x(\pm W_T^{(l)} \geq n) \leq \sqrt{\frac{T}{2\pi}} \frac{e^{-\frac{(n \mp x^{(l)})^2}{2T}}}{n \mp x^{(l)}} \stackrel{n \gg 1}{\approx} e^{-\frac{n^2}{2T}} \quad (9.30)$$

$$\Rightarrow |A| \leq \tilde{C} e^{adn^2} e^{-\frac{n^2}{2T}} \rightarrow 0 \text{ since we assumed } a < \frac{1}{2dT}.$$

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[18.12.2012]  
[08.01.2013]

# 10 Brownian Martingale

## 10.1 Time changes

**Goal:** Show the following: Let  $X \in \mathcal{M}_{loc}^0$  with  $\langle X \rangle_\infty = \infty$ , then if we set

$$\tau_t = \inf\{s > 0 : \langle X \rangle_s > t\} \quad (10.1)$$

it holds that

$$B_t := X_{\tau_t} \quad (10.2)$$

is a BM (w.r.t.  $\mathcal{F}_{\tau_t}$ ) and  $X_t = B_{\langle X \rangle_t}$ .

### Definition 10.1.

Let  $\bar{\mathbb{R}} = \mathbb{R} \cup \{\infty\}$ . Let  $f : \mathbb{R}_+ \rightarrow \mathbb{R}_+$  a monotone increasing, right-continuous function with  $f_\infty := \lim_{t \rightarrow \infty} f(t) \in \bar{\mathbb{R}}_+$ . Then the right-inverse of  $f$ , denoted by  $f^{[-1]}$ , is defined by

$$f^{[-1]}(t) := \inf\{s \geq 0 : f(s) > t\} \quad (10.3)$$

$$\equiv \sup\{s \geq 0 : f(s) \leq t\} \quad (10.4)$$

$$\equiv \text{Leb}(\mathbb{1}_{f \leq t}) \quad (10.5)$$

with  $\inf\{\emptyset\} = \infty$ .

### Lemma 10.2.

- a)  $f^{[-1]} : \mathbb{R}_+ \rightarrow \mathbb{R}_+$  is monotone increasing and right-continuous.
- b)  $(f^{[-1]})^{[-1]} = f$ .
- c)  $f(f^{[-1]}) \geq s \wedge f_\infty$ . If  $f$  is continuous (in  $t$ ) and  $f_\infty = \infty$ , then  $f(f^{[-1]}) = s$ .
- d)  $f^{[-1]}$  is constant on  $[f(t_-), f(t))$ ,  $\forall t \geq 0$ .

*Proof.* **ad a)** It's easy to see that  $f^{[-1]}$  is increasing. Now verify that  $f^{[-1]}$  is right-continuous. Since  $f^{[-1]}$  is increasing we have  $f^{[-1]}(t) \leq \lim_{\vartheta \searrow t} f^{[-1]}(\vartheta)$ . To show:  $\lim_{\vartheta \searrow t} f^{[-1]}(\vartheta) \leq f^{[-1]}(t)$ .

Let  $s := f^{[-1]}(t) \Rightarrow \forall \varepsilon > 0$  it holds  $f(s+\varepsilon) > t$  and for all  $\vartheta \in (t, f(s+\varepsilon))$  we have  $f^{[-1]}(\vartheta) \leq s+\varepsilon$  since  $f^{[-1]}(\vartheta) = \sup\{u : \underbrace{f(u) \leq \vartheta < f(s+\varepsilon)}_{\Rightarrow u < s+\varepsilon}\}$ .

Thus we now have  $\lim_{\vartheta \searrow t} f^{[-1]}(\vartheta) \leq \lim_{\varepsilon \searrow 0} s + \varepsilon = s = f^{[-1]}(t)$ .  $\square$

### Definition 10.3.

A time change  $(T_t)_{t \geq 0}$  is an increasing, right-continuous process  $T : \Omega \times \mathbb{R}_+ \rightarrow \bar{\mathbb{R}}_+$  with  $T_t$  is a stopping time  $\forall t$ .

**Example:** •  $T_t = e^{2\lambda t}$ ,  $\lambda > 0$

- $T_t = t \wedge \tau$  with  $\tau$  stopping time.
- $T_t = t + \tau$  with  $\tau$  stopping time.



•  $T_t = \inf\{s \geq 0 : A_s > t\}$  where  $A$  is an adapted, right-continuous, increasing process. (\*)  
 $\Rightarrow$  From Def 10.1:  $T_t = A_t^{[-1]}$  and we know that:  $T_t$  is a stopping time  $\Leftrightarrow A_s := \mathbb{1}_{[0, T_t)}(s)$  is adapted. Thus all time changes are of the form (\*) with  $A_t = \inf\{s \geq 0 : T_s > t\}$ .

**Definition 10.4.**

Let  $g : \mathbb{R}_+ \rightarrow \bar{\mathbb{R}}_+$  be an increasing, right-continuous function. A function  $f : \mathbb{R}_+ \rightarrow \mathbb{R}$  is called  $g$ -continuous if

$$f|_{[g(t-), g(t)]} \quad (10.6)$$

is constant  $\forall t$  (with  $g(t) < \infty$ )

**Example:** Let  $f : \mathbb{R}_+ \rightarrow \mathbb{R}_+$  continuous, increasing, then  $f$  is  $f^{[-1]}$ -continuous. Indeed:  $\forall s \in [f^{[-1]}(t-), f^{[-1]}(t)] < \infty \Rightarrow f(s) = f(f^{[-1]}(t))$ .

**Definition 10.5.**

Let  $(X_t)_{t \geq 0}$  an adapted process with  $X_t \in \bar{\mathbb{R}}$ . If either  $(T_t)_{t \geq 0}$  is a finite time change (i.e.  $T_t < \infty$  a.s.) or  $X_\infty = \lim_{t \rightarrow \infty} X_t \in \bar{\mathbb{R}}$  exists a.s., then we define the time changed process by

$$\hat{X} : \mathbb{R}_+ \times \Omega \rightarrow \bar{\mathbb{R}} \quad (10.7)$$

$$(t, \omega) \mapsto \hat{X}_t(\omega) := X_{T_t(\omega)}(\omega) \quad (10.8)$$

This process is adapted to  $\hat{\mathcal{F}}_t := \mathcal{F}_{T_t}$ .

**Remark:** If  $X \in \mathcal{M} \Rightarrow \hat{X}$  is not always a Martingale. For example:  $X = BM, T_t = \inf\{s > 0 : \max_{0 \leq u \leq s} X_u > t\}$ . By the continuity of the BM we have  $\hat{X}_t = t \notin \mathcal{M}$ .

**Definition 10.6.**

Let  $(T_t)_{t \geq 0}$  a time change. A process  $(X_t)_{t \geq 0}$  is called  $(T_t)_{t \geq 0}$ -continuous if for a.e.  $\omega : X(\omega)$  is  $T(\omega)$ -continuous, i.e.  $t \mapsto X_t(\omega)$  is constant on all intervals  $[T_{t-}(\omega), T_t(\omega)]$ .

This ensures the continuity of  $\hat{X}$ !

**Lemma 10.7.**

Let  $X \in \mathcal{M}_{loc}$  and  $T_t := \inf\{s \geq 0 : \langle X \rangle_s > t\} \equiv \langle X \rangle_t^{[-1]}$ . Then,  $X$  is  $(T_t)_{t \geq 0}$ -continuous.

*Proof.* For given  $\omega$  in a set of measure 1, and  $s \in \mathbb{R}_+$  s.t.  $(T_t)_{t \geq 0}$  has a jump at  $s$ ,

$$[T_{s-}(\omega), T_s(\omega)] = [a, b] (b > a) \quad (10.9)$$

$$\Leftrightarrow \langle X \rangle(\omega) \text{ is constant on } [a, b] \quad (10.10)$$

$$\Leftrightarrow X_s(\omega) \text{ is constant on } [a, b] \quad (10.11)$$

□

**Theorem 10.8.**

Let  $(T_t)_{t \geq 0}$  be a time change and  $X \in H^2$  with  $X$  is  $T$ -continuous.

$$\Rightarrow \hat{X} \in \hat{H}^2 := \{\text{continuous } L^2 - \text{bounded Mart. w.r.t } (\hat{\mathcal{F}}_t)_{t \geq 0}\} \quad (10.12)$$

Moreover:

$$\langle \hat{X} \rangle_t \equiv \langle X_{T_t} \rangle \stackrel{!}{=} \widehat{\langle X \rangle}_t - \widehat{\langle X \rangle}_0 \equiv \langle X \rangle_{T_t} - \langle X \rangle_{T_0} \quad (10.13)$$

*Proof (Sketch).*  $X$   $T$ -continuous  $\stackrel{\text{proof of 10.7}}{\Rightarrow} \langle X \rangle$   $T$ -continuous.  $\Rightarrow \hat{X}_t := X_{T_t}$  and  $\widehat{\langle X \rangle}_t = \langle X \rangle_{T_t}$  are continuous, since  $X$  and  $\langle X \rangle$  are constant on jumping points of  $T$ . Now since  $X \in H^2$  it holds

$$X_t = \mathbb{E}[X_\infty | \mathcal{F}_t] \quad (10.14)$$

and furthermore

$$X_{T_t} = \mathbb{E}[X_\infty | \hat{\mathcal{F}}_t]. \quad (10.15)$$

Thus  $(\hat{X}_t)_{t \geq 0}$  is a  $(\hat{\mathcal{F}}_t)_{t \geq 0}$ -Martingale and is  $L^2$ -bounded. For the latter see

$$\mathbb{E} \left[ \sup_{t \geq 0} X_{T_t}^2 \right] \leq \mathbb{E} \left[ \sup_{t \geq 0} X_t^2 \right] < \infty \quad (10.16)$$

Now let's show the formula. First one can see, that

$$|X_{T_t}^2 - \langle X \rangle_{T_t}| \leq \sup_{t \geq 0} X_t^2 + \langle X \rangle_\infty \quad (10.17)$$

The right part is in  $L^1$  since

$$X \in H^2 \Rightarrow \sup_{t \geq 0} X_t \in L^2 \quad (10.18)$$

and

$$X_\infty^2 - \langle X \rangle_\infty \in \mathcal{M}_{loc}, X_\infty^2 \in L^1 \Rightarrow \langle X \rangle_\infty \in L^1 \quad (10.19)$$

i.e. unif. integrable. Now one can stop and see

$$\rightarrow X_{T_t}^2 - \langle X \rangle_{T_t} = \mathbb{E} \left[ X_\infty^2 - \langle X \rangle_\infty | \mathcal{F}_{T_t} \right] \quad (10.20)$$

i.e.  $\hat{X}^2 - \widehat{\langle X \rangle}$  is  $\hat{\mathcal{F}}$ -Martingale.  $\Rightarrow \langle \hat{X} \rangle = \widehat{\langle X \rangle}_t - \widehat{\langle X \rangle}_0$   $\square$

[08.01.2013]  
[11.01.2013]

**Remark:** We need the term  $\widehat{\langle X \rangle}_0$ . For example if we consider a timechange  $T_t = t + c, c > 0$ .

### Corollary 10.9.

Let  $X \in \mathcal{M}_{loc}, T \equiv (T_t)_{t \geq 0}$  a finite time change, and assume that  $X$  is  $T$ -continuous. Then,

$$\hat{X} \in \hat{\mathcal{M}}_{loc} := \{\text{continuous local martingales w.r.t. } \hat{\mathcal{F}}_t\} \quad (10.21)$$

and

$$\langle \hat{X} \rangle = \widehat{\langle X \rangle} - \widehat{\langle X \rangle}_0 \quad (10.22)$$

*Proof.* WLOG  $X_0 = 0$  and let  $\sigma$  be a stopping time s.t.  $X^\sigma \in H^2$ . Define the stopping time

$$\hat{\sigma} := \inf\{s \geq 0 : T_s \geq \sigma\} \quad (10.23)$$

$$\Rightarrow \hat{X}_t^{\hat{\sigma}} \equiv \hat{X}_{\hat{\sigma} \wedge t} = X_{T_{\hat{\sigma} \wedge t}} = \begin{cases} X_{\sigma \wedge T_t} & \sigma \geq T_0 \\ X_{T_0} & \sigma < T_0 \end{cases}.$$

Thus

$$\hat{X}^{\hat{\sigma}} - X_{T_0} = \widehat{X}^{\hat{\sigma}} - X_{T_0}^\sigma \quad (10.24)$$

Similarly one gets

$$\widehat{\langle X \rangle}^{\hat{\sigma}} - \langle X \rangle_{T_0} = \widehat{\langle X^\sigma \rangle} - \langle X^\sigma \rangle_{T_0} \quad (10.25)$$

Now consider a sequence of stopping times  $(\sigma_n)_{n \geq 1}$  s.t.  $\sigma_n \nearrow \infty$  and  $X^{\sigma_n} \in H^2$  (e.g.  $\sigma_n = \inf\{t : |X_t| > n\}$ ). Then it also holds that  $\hat{\sigma}_n \nearrow \infty$ , since  $\{\hat{\sigma}_n \leq t\} = \{\sigma_n \leq T_t\} \stackrel{10.8}{\Rightarrow} \widehat{X^{\sigma_n}} \in \hat{H}^2 \stackrel{(10.24)}{\Rightarrow} \hat{X}^{\hat{\sigma}_n} \in \hat{H}^2$  and thus we have that  $\hat{X}$  is a local martingale. For the formula, one can calculate

$$\underbrace{\langle \hat{X}^{\hat{\sigma}_n} \rangle}_{=\langle \hat{X} \rangle^{\hat{\sigma}_n}} \stackrel{(10.24)}{=} \widehat{\langle X^{\sigma_n} \rangle}_t \stackrel{T_{hm}10.8}{=} \widehat{\langle X^{\sigma_n} \rangle} - \widehat{\langle X^{\sigma_n} \rangle}_0 \stackrel{(10.25)}{=} \widehat{\langle X \rangle}^{\hat{\sigma}_n} - \langle X \rangle_{T_0} \quad (10.26)$$

Taking  $n \nearrow \infty$ , since  $\hat{\sigma}_n \nearrow \infty$  a.s. we get the result

$$\langle \hat{X} \rangle_t = \widehat{\langle X \rangle}_t - \underbrace{\widehat{\langle X \rangle}_0}_{=\langle X \rangle_{T_0}} \quad (10.27)$$

□

## 10.2 Applications

### Theorem 10.12.

Let  $(X_t)_{t \geq 0}$  be a d-dimensional BM w.r.t.  $(\mathcal{F}_t)_{t \geq 0}$  and  $\tau$  a finite stopping time. Then,

$$B_t := X_{t+\tau} - X_\tau \quad (10.28)$$

is a d-dimensional BM w.r.t  $(\mathcal{F}_{\tau+t})_{t \geq 0}$ .

*Proof.* Let  $T_t := t + \tau$ . Then  $\hat{X}_t = X_{t+\tau} \stackrel{10.9 \& 10.8}{\Rightarrow} B_t$  is a Martingale w.r.t  $(\mathcal{F}_{\tau+t})_{t \geq 0} = (\hat{\mathcal{F}}_t)_{t \geq 0}$ . Moreover:

$$\langle B^i, B^j \rangle_t \stackrel{10.8}{=} \underbrace{\langle X^i, X^j \rangle_{t+\tau} - \langle X^i, X^j \rangle_\tau}_{\text{Polarisation}} = \delta_{ij}(t + \tau) - \delta_{ij}\tau = t\delta_{ij}. \quad (10.29)$$

By the Levy-characterization, B is a d-dimensional BM w.r.t.  $(\mathcal{F}_{t+\tau})_{t \geq 0}$ . □

### Theorem 10.13 (Dubins-Schwarz).

Let  $X \in \mathcal{M}_{loc}^0$  with  $\langle X \rangle_\infty = \infty$  a.s.. Then

$$B_t := X_{T_t} \quad (10.30)$$

with

$$T_t := \inf\{s \geq 0 : \langle X \rangle_s > t\} \equiv \langle X \rangle_t^{[-1]} \quad (10.31)$$

is a standard 1-dimensional BM w.r.t  $(\mathcal{F}_{T_t})_{t \geq 0}$  and

$$X_t = B_{\langle X \rangle_t} \quad (10.32)$$

*Proof.*  $T_t$  is a finite time change, because  $\langle X \rangle_\infty = \infty$  a.s.. By Lemma 10.7, we know that X is T-continuous. By Cor 10.9:  $(B_t)_{t \geq 0} \in \mathcal{M}_{loc}^0$ . It starts from 0 since  $X_0 = 0, T_0 = 0$ . Also  $\equiv \hat{X}_t$

$$\langle B \rangle_t = \widehat{\langle X \rangle}_t - \widehat{\langle X \rangle}_0 = \langle X \rangle_{T_t} - \underbrace{\langle X \rangle_{T_0}}_{=0} = \langle X \rangle_{\langle X \rangle_t^{[-1]}} \stackrel{10.2c)}{=} \underbrace{t}_{n \rightarrow \langle X \rangle_t \text{ cont., incr., } \langle X \rangle_\infty = \infty} \quad (10.33)$$

Thus  $B$  is a local martingale with  $\langle B \rangle_t = t$ . By Levy we get that  $B$  is a BM. Furthermore

$$B_{\langle X \rangle_t} = X_{T_{\langle X \rangle_t}} = X_t \quad (10.34)$$

where we use in the last "=" that

$$T_u = \inf\{s \geq 0 : \langle X \rangle_s > u\} \quad (10.35)$$

$$T_{\langle X \rangle_t} = \inf\{s \geq 0 : \langle X \rangle_s > \langle X \rangle_t\} \stackrel{\langle X \rangle_t \text{ cont.}}{=} t \quad (10.36)$$

□

**Definition 10.14.**

Let  $\tau$  be a stopping time. A process  $(B_t)_{t \geq 0}$  is called BM stopped by  $\tau$  if

$$\bullet B \in \mathcal{M}_{loc}^0 \quad (10.37)$$

$$\bullet \langle B \rangle_t = t \wedge \tau \quad (10.38)$$

**Theorem 10.15.**

Let  $X \in \mathcal{M}_{loc}^0$  with  $X_\infty(\omega) := \lim_{t \rightarrow \infty} X_t(\omega)$  exists and  $\langle X \rangle_\infty < \infty$  a.s.. Define

$$B_t := \begin{cases} X_{T_t} & \text{if } t < \langle X \rangle_\infty \\ X_\infty & \text{if } t \geq \langle X \rangle_\infty \end{cases} \quad (10.39)$$

with

$$T_t = \inf\{s \geq 0 : \langle X \rangle_s > t\}. \quad (10.40)$$

Then  $(B_t)_{t \geq 0}$  is a BM stopped by  $\langle X \rangle_\infty$

*Proof.* For given  $n$ , consider

$$T_t^{(n)} := T_t \wedge n. \quad (10.41)$$

Then  $T_t^{(n)}$  is a finite time change. Now define

$$B_t^{(n)} := X_{T_t^{(n)}}. \quad (10.42)$$

By Cor 10.9:

$$\langle B^{(n)} \rangle_t = \langle X \rangle_{T_t^{(n)}} - \underbrace{\langle X \rangle_{T_0^{(n)}}}_{=0} \quad (10.43)$$

$$= \langle X \rangle_{T_t \wedge n} \quad (10.44)$$

$$= t \wedge \langle X \rangle_n \quad (10.45)$$

Taking  $n \rightarrow \infty$  finishes the proof. □

[11.01.2013]  
[15.01.2013]

# 11 Girsanov's theorem

## 11.1 An example

Let  $Z = (Z_1, \dots, Z_n)$  be  $\mathcal{N}(0, \mathbb{1})$ -distributed on a space  $(\Omega, \mathcal{F}, \mathbb{P})$ . Let  $\mu = (\mu_1, \dots, \mu_n) \in \mathbb{R}^n$  be a fixed vector. Define a new measure by

$$\mathbb{Q}(d\omega) = e^{\sum_{k=1}^n \mu_k Z_k(\omega) - \frac{1}{2} \sum_{k=1}^n \mu_k^2} \mathbb{P}(d\omega). \quad (11.1)$$

One can compare this to the moment generating function to see, that this is still a probability measure. We now have

$$\mathbb{P}(Z_1 \in dz_1, \dots, Z_n \in dz_n) = \frac{1}{(2\pi)^{n/2}} \prod_{k=1}^n e^{-\frac{z_k^2}{2}} dz_k \quad (11.2)$$

and

$$\mathbb{Q}(Z_1 \in dz_1, \dots, Z_n \in dz_n) = \frac{1}{(2\pi)^{n/2}} \prod_{k=1}^n e^{-\frac{(z_k - \mu_k)^2}{2}} dz_k, \quad (11.3)$$

i.e.  $Z \sim \mathcal{N}(\mu, \mathbb{1})$  with respect to  $\mathbb{Q}$ . Thus  $\{\tilde{Z}_k := Z_k - \mu_k, k = 1, \dots, n\}$  are iid.  $\mathcal{N}(0, 1)$ -distributed r.v. with respect to  $\mathbb{Q}$ .

”The Girsanov Theorem extends this idea of *invariance of Gaussian finite-dimensional distributions* under appropriate translations and changes of the underlying probability measure, from the discrete to the continuous setting. Rather than beginning with an n-dimensional vector  $(Z_1, \dots, Z_n)$  of independent, standard normal random variables, we begin with a d-dimensional Brownian motion under  $\mathbb{P}$ , and then construct a new measure  $\mathbb{Q}$  under which a ”translated” process is a d-dimensional Brownian motion.” - [KS91, p. 190]

## 11.2 Change of measure

Consider a filtered standard probability space  $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$ . Let  $T \in \mathbb{R}_+$  and for all  $t \in [0, T]$  let  $\mathbb{Q}_t$  a probability measure with  $\mathbb{Q}_t \ll \mathbb{P}$ . If we take  $Z_t = \frac{d\mathbb{Q}_t}{d\mathbb{P}}$  as the Radon-Nikodym-derivative, we have

- $Z_t \geq 0$  on  $\Omega$ .
- $\mathbb{Q}_t = Z_t \mathbb{P}$ , i.e.  $\int_A d\mathbb{Q}_t = \int_A Z_t d\mathbb{P}, \forall A \in \mathcal{F}_t$ .
- $\mathbb{E}_{\mathbb{P}}[Z_t] = 1$

### Definition 11.1.

$(\mathbb{Q}_t)_{t \in [0, T]}$  is consistent, if

$$\mathbb{Q}_s = \mathbb{Q}_t \text{ on } (\Omega, \mathcal{F}_s) \forall 0 \leq s \leq t \quad (11.4)$$

If  $\mathbb{Q}$  is consistent, then  $\forall A \in \mathcal{F}_s (s < t)$

$$\int_A Z_s d\mathbb{P} \stackrel{\text{def}}{=} \int_A d\mathbb{Q}_s \stackrel{\text{consistent}}{=} \int_A d\mathbb{Q}_t \stackrel{\text{def}}{=} \int_A Z_t d\mathbb{P} \quad (11.5)$$

Thus we have  $Z_s = \mathbb{E}[Z_t | \mathcal{F}_s]$ . So  $Z$  is a martingale on  $[0, T]$ .

Viceversa: For all Martingales  $(Z_t)_{t \in [0, T]}$ , with

- $Z_t \geq 0$
- $\mathbb{E}[Z_t] = 1, \forall t \in [0, T]$

$\mathbb{Q}_t := Z_t \mathbb{P}$  is a family of consistent probability measures.

**Lemma 11.2.**

For all  $Z > 0, Z \in \mathcal{M}_{loc}, \exists! L \in \mathcal{M}_{loc}$  s.t.  $Z = \mathcal{E}^L = \exp(L - \frac{1}{2}\langle L \rangle)$ . It is given by

$$L_t = \ln(Z_0) + \int_0^t \frac{1}{Z_s} dZ_s. \quad (11.6)$$

*Proof.* Ito-Formula:

$$\ln(Z_t) = \underbrace{\ln(Z_0) + \int_0^t \frac{1}{Z_s} dZ_s}_{=L_t} - \frac{1}{2} \underbrace{\int_0^t \frac{1}{Z_s^2} d\langle Z_s \rangle}_{\stackrel{(\Delta)}{=} \langle L \rangle_t} \quad (11.7)$$

$$= L_t - \frac{1}{2} \langle L \rangle_t \quad (11.8)$$

Regarding  $(\Delta)$ :  $\langle L \rangle_t = \langle \frac{1}{Z} \cdot Z \rangle_t = (\frac{1}{Z^2} \cdot \langle Z \rangle)_t$ .

Uniqueness follows from

$$\tilde{L}_t - \frac{1}{2} \langle \tilde{L} \rangle_t = \ln(Z_t) = L_t - \frac{1}{2} \langle L \rangle_t \quad (11.9)$$

$$\Rightarrow \underbrace{L_t - \tilde{L}_t}_{\in \mathcal{M}_{loc}} = \frac{1}{2} \underbrace{(\langle \tilde{L} \rangle_t - \langle L \rangle_t)}_{\in \mathcal{A}} \quad (11.10)$$

Thus  $L_t = \tilde{L}_t$ . □

**Remark:**  $Z = \exp(L - \frac{1}{2}\langle L \rangle)$ . If  $Z_0 = 1 \Rightarrow L_0 = 0$  and from Theorem 7.12 we know that  $Z$  is a martingale (not just local!)  $\Leftrightarrow \mathbb{E}[Z_t] = 1 \forall t$ .

**Q.:** Is

$$M \in \mathcal{M} \text{ w.r.t } \mathbb{P} \Leftrightarrow M \in \mathcal{M} \text{ w.r.t. } \mathbb{Q}? \quad (11.11)$$

No! But it holds

$$S \in \mathcal{S} \text{ w.r.t } \mathbb{P} \Leftrightarrow S \in \mathcal{S} \text{ w.r.t. } \mathbb{Q} \quad (11.12)$$

$$S = M_1 + A_1 \quad S = M_2 + A_2 \quad (11.13)$$

where  $M_1$  is the martingale part w.r.t.  $\mathbb{P}$ ,  $M_2$  is the martingale part w.r.t.  $\mathbb{Q}$ .

**Q.:** How does one determine  $M_2, A_2$ ?

Consider  $Z \in \mathcal{M}$  (not only local) and  $T \in \mathbb{R}_+$  fixed. Set  $\mathbb{Q}_T := Z_T \mathbb{P}$ .

**Lemma 11.3.**

Let  $0 \leq s \leq t \leq T$  and let  $Y$  be  $\mathcal{F}_t$ -measurable with  $\mathbb{E}_{\mathbb{Q}_T}(|Y|) < \infty$ . Then,

$$\mathbb{E}_{\mathbb{Q}_T}(Y|\mathcal{F}_s) = \frac{1}{Z_s} \mathbb{E}_{\mathbb{P}}(YZ_t|\mathcal{F}_s) \text{ a.s. w.r.t. } \mathbb{Q}_T \text{ and } \mathbb{P}. \quad (11.14)$$

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

$$\int_A \frac{1}{Z_s} \mathbb{E}_{\mathbb{P}}[YZ_t | \mathcal{F}_s] \underbrace{d\mathbb{Q}_T}_{\stackrel{\text{cons.}}{=} d\mathbb{Q}_s = Z_s d\mathbb{P}} = \int_A \mathbb{E}_{\mathbb{P}}[YZ_t | \mathcal{F}_s] d\mathbb{P} \quad (11.15)$$

$$= \mathbb{E}_{\mathbb{P}}[\underbrace{\mathbb{1}_A}_{\mathcal{F}_s\text{-meas.}} \mathbb{E}_{\mathbb{P}}[YZ_t | \mathcal{F}_s]] \quad (11.16)$$

$$= \mathbb{E}_{\mathbb{P}}[\mathbb{E}_{\mathbb{P}}[\mathbb{1}_A YZ_t | \mathcal{F}_s]] \quad (11.17)$$

$$= \int_A Y \underbrace{Z_t d\mathbb{P}}_{d\mathbb{Q}_t} \quad (11.18)$$

$$\stackrel{\text{cons.}}{=} \int_A Y d\mathbb{Q}_T \quad (11.19)$$

□

**Notation:** We write

$$\mathcal{M}_{loc,T}^0 = \{\text{cont. local martingales } (M_t)_{t \in [0,T]} \text{ w.r.t. } (\Omega, \mathcal{F}_T, (\mathcal{F}_t)_{t \in [0,T]}, \mathbb{P}) : M_0 = 0\} \quad (11.20)$$

$$\tilde{\mathcal{M}}_{loc,T}^0 = \{\text{cont. local martingales } (M_t)_{t \in [0,T]} \text{ w.r.t. } (\Omega, \mathcal{F}_T, (\mathcal{F}_t)_{t \in [0,T]}, \mathbb{Q}) : M_0 = 0\} \quad (11.21)$$

**Theorem 11.4.**

Let  $M \in \mathcal{M}_{loc,T}^0$  and  $Z \in \mathcal{M}, Z_t > 0, \mathbb{E}[Z_t] = 1 \forall t$  and  $\mathbb{Q}_t = Z_t \mathbb{P}$ , then

$$\tilde{M}_t := M_t - \langle M, L \rangle_t \in \tilde{\mathcal{M}}_{loc,T}^0 \quad (11.22)$$

with

$$L_t := \ln(Z_0) + \int_0^t \frac{1}{Z_s} dZ_s \quad (11.23)$$

and it holds

$$\langle \tilde{M} \rangle_t = \langle M \rangle_t \quad (11.24)$$

on  $[0, T] \times \Omega$  a.s. w.r.t.  $\mathbb{P}$  and  $\mathbb{Q}_T$ .

*Proof.* WLOG  $M, \langle M \rangle, \langle L \rangle$  bounded in  $t$  and  $\omega$ . Then  $\tilde{M}$  is bounded because

$$\langle M, L \rangle \leq \sqrt{\langle M \rangle_t \langle L \rangle_t} \quad (11.25)$$

Now, since  $L_t := \ln(Z_0) + \int_0^t \frac{1}{Z_s} dZ_s$

$$\langle M, L \rangle_t = \langle M, \frac{1}{Z} \cdot Z \rangle_t \quad (11.26)$$

$$\stackrel{\text{Kunita}}{=} \frac{1}{Z} \cdot \langle M, Z \rangle_t \quad (11.27)$$

Using integration by parts we can now see

$$Z_t \tilde{M}_t = Z_0 \underbrace{\tilde{M}_0}_{=0} + \int_0^t Z_s d\tilde{M}_s + \int_0^t \tilde{M}_s dZ_s + \langle Z, \tilde{M} \rangle_t \quad (11.28)$$

$$= \int_0^t Z_s dM_s - \int_0^t Z_s \underbrace{d\langle M, L \rangle_s}_{\frac{1}{Z_s} d\langle M, Z \rangle_s} + \int_0^t \tilde{M}_s dZ_s + \underbrace{\langle Z, \tilde{M} \rangle_t}_{\langle Z, M \rangle_t} \quad (11.29)$$

$$= \int_0^t Z_s dM_s + \int_0^t \tilde{M}_s dZ_s \quad (11.30)$$

Thus  $Z_t \tilde{M}_t \in \mathcal{M}_{loc,T}^0 (*)$ .

But  $\forall 0 \leq s \leq t \leq T$  :

$$\mathbb{E}_{\mathbb{Q}_T}(\tilde{M}_t | \mathcal{F}_s) \stackrel{11.3}{=} \frac{1}{Z_s} \mathbb{E}_{\mathbb{P}}(\tilde{M}_t Z_t | \mathcal{F}_s) \quad (11.31)$$

$$\stackrel{(*)}{=} \frac{1}{Z_s} \tilde{M}_s Z_s \Rightarrow \tilde{M}_s \in \tilde{\mathcal{M}}_{loc,T}^0 \quad (11.32)$$

□

## 11.3 The Theorem of Girsanov

Let  $W$  be a  $d$ -dimensional BM and  $X$  a  $d$ -dimensional adapted process with

$$\mathbb{P}\left(\int_0^T (X_t^k)^2 dt < \infty\right) = 1 \forall 1 \leq k \leq d, T < \infty \quad (11.33)$$

Then define

$$L_t := (X \cdot W)_t \equiv \sum_{k=1}^d \int_0^t X_s^k dW_s^k \quad (11.34)$$

and

$$Z_t := \mathcal{E}^{L_t} = \exp\left(\sum_{k=1}^d \int_0^t X_s^k dW_s^k - \frac{1}{2} \sum_{k=1}^d \int_0^t (X_s^k)^2 ds\right) \quad (11.35)$$

$\Rightarrow (Z_t)_{t \geq 0}$  is a local cont. martingale with  $Z_0 = 1$ .

### Theorem 11.5 (Girsanov).

Assume that  $Z_t$  defined above is a martingale. Set

$$\tilde{W}_t^k = W_t^k - \int_0^t X_s^k ds, \quad k = 1, \dots, d; t \geq 0 \quad (11.36)$$

Then  $\forall T \in [0, \infty)$ , the process  $\tilde{W} = (\tilde{W}_t)_{t \in [0, T]} = (\tilde{W}_t^1, \dots, \tilde{W}_t^d)_{t \in [0, T]}$  is a  $d$ -dimensional BM w.r.t.  $(\Omega, \mathcal{F}_T, (\mathcal{F}_t)_{t \in [0, T]}, \mathbb{Q}_T)$  with  $\mathbb{Q}_T = Z_T \mathbb{P}$

[15.01.2013]  
[18.01.2013]

*Proof.* Theorem 11.4 gives us

$$W_t - \langle W, L \rangle_t \in \tilde{\mathcal{M}}_{loc,T}^0 \quad (11.37)$$

We compute

$$W_t^k - \langle W^k, L \rangle_t = W_t^k - \langle W^k, \sum_{l=1}^d (X^l \cdot W^l)_t \rangle \quad (11.38)$$

$$\stackrel{\text{Kunita}}{\equiv} \stackrel{\text{Watanabe}}{=} W_t^k - \sum_{l=1}^d (X_t^l \cdot \underbrace{\langle W^k, W^l \rangle_t}_{=\delta_{kl}}) \quad (11.39)$$

$$= W_t^k - \int_0^t X_s^k ds \quad (11.40)$$

$$= \tilde{W}_t^k \quad (11.41)$$



And thus  $\tilde{W}_t^k \in \tilde{M}_{loc,T}^0$ . Further, Theorem 11.4 implies

$$\langle \tilde{W}^k \rangle_t = \langle W^k \rangle_t = t \quad (11.42)$$

and with polarisation

$$\langle \tilde{W}^k, \tilde{W}^l \rangle_t = \langle W^k, W^l \rangle_t = \delta_{kl}t \quad (11.43)$$

Levy gives that  $\tilde{W}$  is a BM.  $\square$

**Theorem 11.6** (Novikov).

Define  $Z := \mathcal{E}^L \equiv e^{L - \frac{1}{2}\langle L \rangle}$ . If

$$\mathbb{E} \left[ e^{\frac{1}{2}\langle L \rangle_t} \right] < \infty, \forall t \geq 0 \quad (11.44)$$

then  $Z$  is a martingale.

Let  $W$  be a 1-dimensional BM w.r.t.  $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$  and for a  $b \neq 0$ , let

$$T_b := \inf\{s \geq 0 : W_s = b\} \quad (11.45)$$

**Proposition 11.7.**

- $\mathbb{P}(T_b \in dt) = \frac{|b|}{\sqrt{2\pi t^3}} e^{-\frac{b^2}{2t}} dt$
- $\mathbb{E} \left[ e^{-\alpha T_b} \right] = \exp(-|b| \sqrt{2\alpha}), \alpha > 0$

*Proof.* 1) already computed.

2)

$$\mathbb{E} \left[ e^{-\alpha T_b} \right] = \int_0^\infty e^{-\alpha t} \frac{|b|}{\sqrt{2\pi t^3}} e^{-\frac{b^2}{2t}} dt \quad (11.46)$$

$$\stackrel{t = \frac{b^2}{2u^2}}{=} \frac{2}{\sqrt{\pi}} \int_0^\infty e^{-u^2} e^{-\frac{\alpha|b|^2}{2u^2}} du \quad (11.47)$$

$$= \frac{2}{\sqrt{\pi}} e^{-\sqrt{2\alpha}|b|} \int_0^\infty e^{-(u - \frac{c}{u})^2} du \quad (11.48)$$

with  $c = \sqrt{\frac{\alpha}{2}}|b|$ .

Remains to show  $F(c) := \int_0^\infty e^{-(u - \frac{c}{u})^2} du = \sqrt{\frac{\pi}{2}}$  For  $c = 0 \checkmark$ . Then take

$$\frac{dF(c)}{dc} = \dots = 2F(c) - 2 \int_0^\infty dx e^{-(\frac{c}{x} - x)^2} = 0. \quad (11.49)$$

$\square$

Consider the process

$$\tilde{W} := (\tilde{W}_t)_{t \geq 0} = (W_t - \mu t)_{t \geq 0} \quad (11.50)$$

where  $\mu$  is a constant. Girsanov gives, that  $\tilde{W}$  is a BM w.r.t.

$$\mathbb{P}^\mu := Z_t \mathbb{P} \quad (11.51)$$

with

$$Z_t = e^{\mu W_t - \frac{1}{2}\mu^2 t}. \quad (11.52)$$

Here we have  $L_t = \mu W_t$  and  $\langle L \rangle_t = \mu^2 t$ .

$\Rightarrow W_t = \mu t + \tilde{W}_t$  is a BM with drift  $\mu$  w.r.t.  $\mathbb{P}^\mu$ . ( $\tilde{W}_t$  is a BM with drift  $-\mu$  w.r.t.  $\mathbb{P}$ .)

**Proposition 11.8.**

$$\mathbb{P}^\mu(T_b \in dt) = \frac{|b|}{\sqrt{2\pi t^3}} e^{-\frac{(b-\mu)^2}{2t}} dt \quad (11.53)$$

$$\mathbb{E}^\mu(e^{-\alpha T_b}) = \exp(\mu b - |b| \sqrt{\mu^2 + 2\alpha}), \alpha > 0 \quad (11.54)$$

*Proof.*

$$\mathbb{P}^\mu(T_b \leq t) = \mathbb{E}^\mu(\mathbb{1}_{[T_b \leq t]}) \quad (11.55)$$

$$\stackrel{\mathbb{P}^\mu = Z_t \mathbb{P}}{=} \mathbb{E}(\mathbb{1}_{[T_b \leq t]} Z_t) \quad (11.56)$$

$$= \mathbb{E}[\mathbb{E}[\mathbb{1}_{[T_b \leq t]} Z_t | \mathcal{F}_{T_b \wedge t}]] \quad (11.57)$$

$$= \mathbb{E}[\mathbb{1}_{[T_b \leq t]} \mathbb{E}[Z_t | \mathcal{F}_{T_b \wedge t}]] \quad (11.58)$$

$$\stackrel{\text{Novikov}}{=} \mathbb{E}[\mathbb{1}_{[T_b \leq t]} Z_{T_b \wedge t}] \quad (11.59)$$

$$= \mathbb{E}(\mathbb{1}_{[T_b \leq t]} \underbrace{Z_{T_b}}_{e^{\mu b - \frac{1}{2}\mu^2 T_b}}) \quad (11.60)$$

$$= \mathbb{E}[\mathbb{1}_{[T_b \leq t]} e^{-\frac{1}{2}\mu^2 T_b} e^{\mu b}] \quad (11.61)$$

$$= \int_0^t e^{-\frac{1}{2}\mu^2 s} e^{\mu b} \frac{|b|}{\sqrt{2\pi s^3}} e^{-\frac{b^2}{2s}} ds \quad (11.62)$$

Thus

$$\mathbb{P}^\mu(T_b \in dt) = \left( \frac{d}{dt} \mathbb{P}^\mu(T_b \leq t) \right) dt \quad (11.63)$$

$$= e^{-\frac{1}{2}\mu^2 t} e^{\mu b} \frac{|b|}{\sqrt{2\pi t^3}} e^{-\frac{b^2}{2t}} dt \quad (11.64)$$

$$= \frac{|b|}{\sqrt{2\pi t^3}} e^{-\frac{(b-\mu)^2}{2t}} dt \quad (11.65)$$

$$\mathbb{E}^\mu(e^{-\alpha T_b}) = \int_0^\infty e^{-\alpha s} \frac{e^{-\frac{1}{2}\frac{(b-\mu)^2}{2s}} |b|}{\sqrt{2\pi s^3}} ds \quad (11.66)$$

$$\stackrel{\tilde{\alpha} = \alpha + \frac{\mu^2}{2}}{=} e^{\mu b} \underbrace{\int_0^\infty ds \frac{e^{\tilde{\alpha} s} e^{-\frac{b^2}{2s}} |b|}{\sqrt{2\pi s^3}}}_{= \mathbb{E}[e^{-\tilde{\alpha} T_b}]} \quad (11.67)$$

$$\stackrel{\text{Prop 11.7}}{=} e^{\mu b} e^{-|b| \sqrt{2\alpha + \mu^2}} \quad (11.68)$$

□

$$\mathbb{P}^\mu(T_b \leq t) = \dots = \int_0^t e^{\mu b - \frac{\mu^2}{2}s} \mathbb{P}(T_b \in ds) = e^{\mu b} \mathbb{E} \left[ e^{-\frac{\mu^2}{2} T_b} \mathbb{1}_{[T_b \leq t]} \right] \quad (11.69)$$

**Corollary 11.9.**

$$\mathbb{P}^\mu(T_b < \infty) = \exp(\mu b - |\mu b|) \quad (11.70)$$

$$= \begin{cases} 1 & \text{if } \text{sgn}(\mu) = \text{sgn}(b) \\ \exp(-2|\mu b|) & \text{if } \text{sgn}(\mu) = -\text{sgn}(b) \end{cases} \quad (11.71)$$

*Proof.* From (11.69) we have

$$\mathbb{P}^\mu(T_b \leq t) = e^{\mu b} \mathbb{E} \left[ e^{-\frac{\mu^2}{2} T_b} \right] \quad (11.72)$$

$$\stackrel{11.8}{=} e^{\mu b} \exp(-|b| \sqrt{2 \frac{\mu^2}{2}}) \quad (11.73)$$

$$= \exp(\mu b - |\mu b|) \quad (11.74)$$

□

**Corollary 11.10.**

Let  $\mu > 0$ ,  $W_* = \inf_{t>0} W_t$ . Then

$$\mathbb{P}^\mu(-W_* \in db) = 2\mu e^{-2\mu b} db, \text{ for } b > 0 \quad (11.75)$$

$$\mathbb{P}^\mu(-W_* < 0) = 0 \quad (11.76)$$

*Proof.* Let  $b > 0$ .

$$\mathbb{P}^\mu(-W_* \leq b) = \mathbb{P}^\mu(T_{-b} < \infty) = e^{-2\mu b} \quad (11.77)$$

Then differentiate by  $b$  to see

$$\mathbb{P}^\mu(-W_* \in db) = 2\mu e^{-2\mu b} db, \text{ for } b > 0 \quad (11.78)$$

$$(11.79)$$

□

[18.01.2013]  
[22.01.2013]

# 12 Local time

Q.: If  $g \in C^2$  and  $B$  is a BM, then,

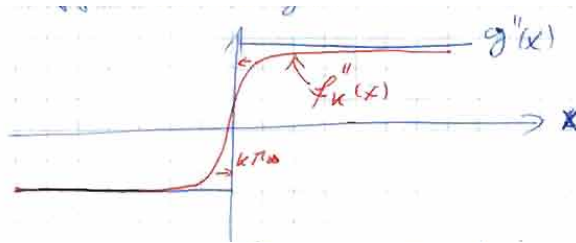
$$g(B_t) = g(B_0) + \int_0^t g'(B_s)dB_s + \frac{1}{2} \int_0^t g''(B_s)ds \quad (12.1)$$

What happens if  $g$  is not  $C^2$ , but maybe  $g \in C^2(\mathbb{R} \setminus \{z_1, \dots, z_k\})$ ?

**Lemma 12.1.**

Let  $(B_t)_{t \geq 0}$  be a 1-dimensional BM. Then, the Itô-Formula still holds for  $Y_t = g(B_t)$  if  $g$  is  $C^1$  everywhere and  $C^2$  except for finite # of points  $z_1, \dots, z_k$ , if  $g''$  is (locally) bounded for  $x \notin \{z_1, \dots, z_k\}$

*Proof.*  $C^2$  approximation as in the picture



Choose  $f_n \in C^2$  s.t.  $f_n \rightarrow g$ ,  $f_n' \rightarrow g'$  uniformly in  $n$  and  $f_n'' \rightarrow g''$  on  $\mathbb{R} \setminus \{z_1, \dots, z_k\}$  and  $|f_n''(x)| \leq M$  for  $x$  in a neighbourhood of  $\{z_1, \dots, z_k\}$  Now use Itô on  $f_n$ :

$$f_n(B_t) = f_n(B_0) + \int_0^t f_n'(B_s)dB_s + \frac{1}{2} \int_0^t f_n''(B_s)ds \quad (12.2)$$

This equation converges in  $L^2$  as  $n \rightarrow \infty$  towards

$$g(B_t) = g(B_0) + \int_0^t g'(B_s)dB_s + \frac{1}{2} \int_0^t g''(B_s)ds \quad (12.3)$$

□

**Theorem 12.2** (Tanaka).

Let  $B$  be a 1-d BM and  $\lambda$  the Lebesgue-measure. Then,

$$L_t := \lim_{\varepsilon \downarrow 0} \frac{1}{2\varepsilon} \lambda(\{s \in [0, t] : B_s \in [-\varepsilon, \varepsilon]\}) \quad (12.4)$$

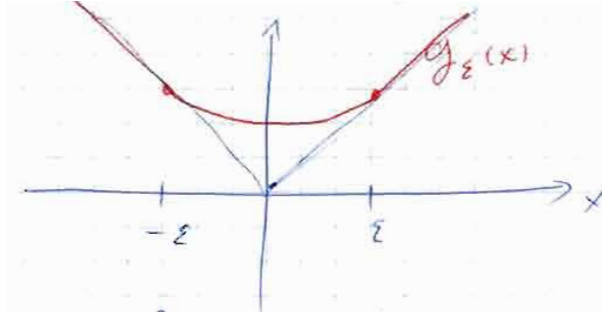
exists in  $L^2(\Omega, \mathbb{P})$  and it is given by

$$L_t = |B_t| - |B_0| - \int_0^t \text{sgn}(B_s)dB_s \quad (12.5)$$

**Remark:**  $L_t$  is called the local time of the BM at 0

*Proof.* Let us consider the function

$$g_\varepsilon(x) = \begin{cases} |x| & , |x| \geq \varepsilon \\ \frac{1}{2}(\varepsilon + \frac{x^2}{\varepsilon}) & , |x| < \varepsilon \end{cases} \quad (12.6)$$



Then we have  $g_\varepsilon \in C^2(\mathbb{R} \setminus \{-\varepsilon, \varepsilon\})$ ,  $g_\varepsilon \in C^1(\mathbb{R})$ .

$$g'_\varepsilon(x) = \begin{cases} 1 & , x > \varepsilon \\ -1 & , x < -\varepsilon \\ \frac{x}{\varepsilon} & , |x| < \varepsilon \end{cases} \quad (12.7)$$

By the previous Lemma

$$\begin{aligned} \frac{1}{2} \int_0^t g''_\varepsilon(B_s) ds &= g_\varepsilon(B_t) - g_\varepsilon(B_0) - \int_0^t g'_\varepsilon(B_s) dB_s \\ &= \frac{1}{2\varepsilon} \lambda(\{s \in [0, t] : B_s \in (-\varepsilon, \varepsilon)\}) \rightarrow L_t \end{aligned} \quad (12.8)$$

since  $g''(\varepsilon)(x) = \frac{1}{\varepsilon} \mathbb{1}_{(-\varepsilon, \varepsilon)}(x)$ ,  $x \notin \{-\varepsilon, \varepsilon\}$ .

$$g_\varepsilon(B_t) \xrightarrow{\varepsilon \rightarrow 0} |B_t|$$

$$\left\| \int_0^t (g'_\varepsilon(B_s) - \text{sgn}(B_s)) dB_s \right\|^2 = \left\| \int_0^t \mathbb{1}_{(B_s \in (-\varepsilon, \varepsilon))} \underbrace{(g'_\varepsilon(B_s) - \text{sgn}(B_s))}_{= \frac{B_s}{\varepsilon}} dB_s \right\|^2 \quad (12.9)$$

$$\stackrel{\text{Ito}}{\underset{\text{isom}}{=}} \mathbb{E} \left[ \int_0^t \mathbb{1}_{(B_s \in (-\varepsilon, \varepsilon))} \underbrace{\left( \frac{B_s}{\varepsilon} - \text{sgn}(B_s) \right)^2}_{\leq 1} ds \right] \quad (12.10)$$

$$\leq \int_0^t \mathbb{P}(B_s \in (-\varepsilon, \varepsilon)) ds \xrightarrow{\varepsilon \rightarrow 0} 0 \quad (12.11)$$

□

**Remark:** For  $f \in C^2$  :  $|f(t)| - |f(0)| - \int_0^t \text{sgn}(f(s)) f'(s) ds = 0$ , but  $d|B_t| \neq \text{sgn}(B_t) dB_t$  since

$$|B_{t+\Delta t} - B_t| \neq \text{sgn}(B_t)(B_{t+\Delta t} - B_t) \quad (12.12)$$

e.g. is  $B_t < 0$  and  $B_{t+\Delta t} > 0$ . Thus the  $L_t$  can be viewed as a correction term.

# 13 Representation of local martingale as stochastic integral

Let  $B$  be a BM and denote by  $\mathcal{F}^B$  the Brownian filtration. i.e.  $(\mathcal{F}_t^0 := \sigma(B_s, 0 \leq s \leq t))$  + rightcontinuous + complete  $\Rightarrow \mathcal{F}^B$ .

## Theorem 13.1.

Let  $(\mathcal{F}_t^B)_{t \geq 0}$  be the Brownian filtration. Then, each local  $(\mathcal{F}_t^B)_{t \geq 0}$ -martingale  $M$  has continuous version with stochastic integral representation:

$$M_t = M_0 + \int_0^t H_s dB_s \quad (13.1)$$

where  $M_0$  and  $H \in L^2(\Omega \times \mathbb{R}_+, \mathbb{P} \otimes \text{Leb})$  are uniquely determined by  $M$ . Moreover, if  $M$  is a continuous martingale, then

$$H_t = \frac{d}{dt} \langle M, B \rangle_t \quad (13.2)$$

## Remark:

$$d \langle M, B \rangle_t = dM_t dB_t \quad (13.3)$$

$$= H_t dB_t dB_t \quad (13.4)$$

$$= H_t dt \quad (13.5)$$

$$\Rightarrow \langle M, B \rangle_t = \int_0^t H_s ds \quad (13.6)$$

**Remark:**  $\exists (\mathcal{F}_t^B)_{t \geq 0}$ -martingale  $M$  s.t. the BM  $B$  can not be written as  $B_0 + \int_0^t A_s dM_t$ . Recall:  $L_t = |B_t| - |B_0| - \int_0^t \text{sgn}(B_s) dB_s$ . Let  $\beta_t := \int_0^t \text{sgn}(B_s) dB_s$ .  $\beta$  is adapted to  $\mathcal{F}^B$  ( $\beta$  has indep. incr.). What is  $\langle \beta \rangle_t$ ?

$$d\beta_t = \text{sgn}(B_t) dB_t \quad (13.7)$$

$$\Rightarrow d \langle \beta \rangle_t = (\text{sgn}(B_t))^2 d \langle B \rangle_t = dt \quad (13.8)$$

$$\Rightarrow \langle \beta \rangle_t = t \quad (13.9)$$

Thus  $\beta$  is a  $\mathcal{F}^B$ -BM. Assume that  $\exists A_t, \mathcal{F}^B$ -measurable s.t.

$$B_t = \int_0^t A_s d\beta_s \quad (13.10)$$

$\Rightarrow B_t$  is  $\mathcal{F}_t^\beta$ -measurable  $\Rightarrow \mathcal{F}_t^B \subset \mathcal{F}_t^\beta$ . Now:  $\beta_t = |B_t| - L_t$ . One can prove that  $L_t$  is a r.v. w.r.t.  $\sigma(|B_s|, 0 \leq s \leq t) \Rightarrow \beta_t \in \mathcal{F}_t^{|\beta|} \Rightarrow \mathcal{F}_t^B \subset \mathcal{F}_t^\beta \subset \mathcal{F}_t^{|\beta|}$  but this is wrong, it holds  $\mathcal{F}_t^{|\beta|} \subsetneq \mathcal{F}_t^B$

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## 14 Connection between SDE's and PDE's

$$b : \mathbb{R}^d \rightarrow \mathbb{R}^d \quad (14.1)$$

$$\sigma : \mathbb{R}^d \rightarrow \mathbb{R}^{d \times r} \text{ (Lipschitz, bounded, measurable)} \quad (14.2)$$

$a = \sigma\sigma^T$ ,  $a_{ij} = \sum_{k=1}^r \sigma_{ik}\sigma_{jk}$  Let  $(B_t)_{t \geq 0}$  be a BM. Let  $X_t^x$  be the solution of

$$\begin{cases} dX_t^x = b(X_t^x)dt + \sigma(X_t^x)dB_t \\ X_0^x = x \end{cases} \quad (14.3)$$

### Theorem 14.1.

Let  $f \in C_b(\mathbb{R}^d)$ ,  $u \in C_b([0, \infty) \times \mathbb{R}^d) \cap C_b^2((0, \infty) \times \mathbb{R}^d)$  s.t.  $u$  solves the Cauchy Problem, i.e.

$$\frac{\partial}{\partial t} u(t, x) = Au(t, x) \text{ for all } t \geq 0, x \in \mathbb{R}^d \quad (14.4)$$

$$u(0, x) = f(x) \text{ for all } x \in \mathbb{R}^d \quad (14.5)$$

where

$$Au(t, x) = \sum_{i=1}^d b_i(x) \frac{\partial}{\partial x_i} u(t, x) + \frac{1}{2} \sum_{i,j=1}^d \sigma_{ij}(x) \frac{\partial^2}{\partial x_i \partial x_j} u(t, x). \quad (14.6)$$

Then

$$u(t, x) = \mathbb{E}[f(X_t^x)] \quad (14.7)$$

*Proof.* (From now on write  $X_t = X_t^x$ .) Fix  $T > 0$  and use 'time reversal',

$$M_t = u(T - t, X_t). \quad (14.8)$$

Then, by Itô's Formula,

$$M_t = M_0 + \int_0^t \sum_{i=1}^d \frac{\partial}{\partial x_i} u(T - s, X_s) dX_s^{(i)} - \int_0^t \frac{\partial}{\partial t} u(T - s, X_s) ds + \frac{1}{2} \int_0^t \sum_{i,j=1}^d \frac{\partial^2}{\partial x_i \partial x_j} u(T - s, X_s) d\langle X^{(i)}, X^{(j)} \rangle_s \quad (14.9)$$

$$= M_0 + \int_0^t \sum_{i=1}^d b_i(X_s) \frac{\partial}{\partial x_i} u(T - s, X_s) ds + \int_0^t \sum_{i=1}^d \sum_{j=1}^r \sigma_{ij}(X_s) \frac{\partial}{\partial x_i} u(T - s, X_s) dB_s^{(j)} - \int_0^t \frac{\partial}{\partial t} u(T - s, X_s) ds + \quad (14.10)$$

$$= M_0 + \underbrace{\int_0^t \sum_{i=1}^d \sum_{j=1}^r \sigma_{ij}(X_s) \frac{\partial}{\partial x_i} u(T - s, X_s) dB_s^{(j)}}_{loc. Mart.} + \underbrace{\int_0^t (A - \frac{\partial}{\partial t}) u(T - s, X_s) ds}_{=0} \quad (14.11)$$

Use that  $d\langle X^{(i)}, X^{(j)} \rangle_s = \sum_{k,l} \sigma_{ik}\sigma_{jl} d\langle B^{(k)}, B^{(l)} \rangle_s = \sum_k \sigma_{ik}\sigma_{jk} ds = a_{ij} ds$ .

Thus we have that  $(M_t)_{t \geq 0}$  is a local martingale.  $u$  bounded  $\Rightarrow (M_t)_{0 \leq t < T}$  is bounded. Hence  $(M_t)_{0 \leq t < T}$  is a true martingale. For any  $\varepsilon > 0$

$$u(T, x) = u(T - 0, X_0^x) = M_0 = \mathbb{E}[M_0] = \mathbb{E}\left[u(\varepsilon, X_{T-\varepsilon}^x)\right] \xrightarrow{\varepsilon \rightarrow 0} \mathbb{E}\left[u(0, X_T^x)\right] = \mathbb{E}\left[f(X_T^x)\right] \quad (14.12)$$

because  $u$  is bounded continuous. Thus  $u(T, x) = \mathbb{E}\left[f(X_T^x)\right]$   $\square$

**Theorem 14.2.**

Let  $D \subset \mathbb{R}^d$  be open,  $Z = (\{0\} \times D) \cup ([0, \infty) \times \partial D)$ ,  $f \in C_b(Z)$ ,  $u \in C_b([0, \infty) \times \bar{D}) \cap C_b^2((0, \infty) \times D)$  s.t.

$$\frac{\partial}{\partial t} u = Au \text{ in } (0, \infty) \times D \quad (14.13)$$

$$u = f \text{ on } Z \quad (14.14)$$

Then

$$u(t, x) = \mathbb{E}\left[f(t - t \wedge \tau_D, X_{t \wedge \tau_D}^x)\right] \quad (14.15)$$

where  $\tau_D$  is the exit time from  $D$ ,

$$\tau_D = \inf\{t > 0 : X_t^x \notin D\} \quad (14.16)$$

*Proof.* Fix  $T > 0$ , set  $M_t = u(T - t, X_t^x)$ . As before,  $M$  is a martingale.

$$\Rightarrow M_{T \wedge \tau_D} = u(T - T \wedge \tau_D, X_{T \wedge \tau_D}^x) \quad (14.17)$$

$$= \begin{cases} u(0, X_T^x) & , T < \tau_D \\ u(T - \tau_D, X_{\tau_D}^x) & , T > \tau_D \end{cases} \quad (14.18)$$

$$= f(T - T \wedge \tau_D, X_{T \wedge \tau_D}^x) \quad (14.19)$$

$$\Rightarrow u(T, x) = \mathbb{E}[M_0] = \mathbb{E}[M_{T \wedge \tau_D}] = \mathbb{E}[f(T - T \wedge \tau_D, X_{T \wedge \tau_D}^x)] \quad \square$$

**Theorem 14.3.**

Let  $D \subset \mathbb{R}^d$  be open,  $\tau_D < \infty$  a.s.,  $f \in C_b(D)$ ,  $u \in C_b(\bar{D}) \cap C_b^2(D)$ , s.t.  $u$  solves the Dirichlet problem, i.e.

$$Au = 0 \text{ in } D \quad (14.20)$$

$$u = f \text{ on } \partial D \quad (14.21)$$

then

$$u(x) = \mathbb{E}\left[f(X_{\tau_D}^x)\right]. \quad (14.22)$$

*Proof.* Let  $v(t, x) := u(x)$  for all  $t \geq 0$ . Then  $v$  solves

$$\underbrace{\frac{\partial}{\partial t} v(t, x)}_{=0} = \underbrace{Av(t, x)}_{=0} \quad (14.23)$$

$$v = f \text{ on } [0, \infty) \times \partial D \quad (14.24)$$

$$v = u \text{ on } \{0\} \times D \quad (14.25)$$

$\Rightarrow u(x) = v(t, x) = \mathbb{E}\left[f(X_{\tau_D}^x) \mathbb{1}_{\{\tau_D < t\}}\right] + \mathbb{E}\left[f(X_{\tau_D}^x) \mathbb{1}_{\{\tau_D \geq t\}}\right]$ . Take the limit  $t \rightarrow \infty$ : since  $\tau_D < \infty$  a.s. and  $f, u$  are bounded, we get

$$u(x) = \mathbb{E}\left[f(X_{\tau_D}^x)\right] + 0 \quad (14.26)$$

$\square$



**Remark:** It is usually not trivial to check  $\tau_D < \infty$ . A sufficient condition would be:  $D$  bounded &  $\sum_{i=1}^d a_{ii} \geq \lambda > 0$  for some  $\lambda$ .

**Theorem 14.4.**

Let  $D \subset \mathbb{R}^d$  be open,  $\mathbb{E}[\tau_D] < \infty$ ,  $g \in C_b(D)$ ,  $u \in C_b(\bar{D}) \cap C_b^2(D)$  s.t.  $u$  solves the Poisson problem, i.e.

$$-Au = g \text{ in } D \tag{14.27}$$

$$u = 0 \text{ on } \partial D. \tag{14.28}$$

Then,

$$u(x) = \mathbb{E} \left[ \int_0^{\tau_D} g(X_s) ds \right]. \tag{14.29}$$

*Proof.* Consider  $M_t = u(X_t) + \int_0^t g(X_s) ds$ . For  $t < \tau_D$ : By Itô's-formula,

$$M_t = M_0 + \int_0^t \sum_{i=1}^d b_i(X_s) \frac{\partial}{\partial x_i} u(X_s) ds + \int_0^t \sum_{i=1}^d \sum_{j=1}^r \sigma_{ij}(X_s) \frac{\partial}{\partial x_i} u(X_s) dB_s^{(j)} \tag{14.30}$$

$$+ \frac{1}{2} \int_0^t \sum_{i,j=1}^d a_{ij}(X_s) \frac{\partial^2}{\partial x_i \partial x_j} u(X_s) ds + \int_0^t g(X_s) ds \tag{14.31}$$

$$= M_0 + \text{local martingale} + \underbrace{\int_0^t Au(X_s) + g(X_s) ds}_{=0(\text{by assumption})} \tag{14.32}$$

$\Rightarrow (M_t)_{0 \leq t < \tau_D}$  is a martingale.  $\Rightarrow (M_{t \wedge \tau_D})_{t \geq 0}$  is a martingale.

$$\Rightarrow (u(x) = \mathbb{E}[M_0] = \mathbb{E}[M_{\tau_D}] = \mathbb{E} \left[ u(X_{\tau_D}) + \int_0^{\tau_D} g(X_s) ds \right] = \mathbb{E} \left[ \int_0^{\tau_D} g(X_s) ds \right] \tag{14.33}$$

□

**Corollary 14.5.**

If  $-Au = g$  in  $D$ ,  $u = f$  on  $\partial D$ , then  $u(x) = \mathbb{E} \left[ f(X_{\tau_D}) + \int_0^{\tau_D} g(X_s) ds \right]$ .

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# Bibliography

[Hol00] HOLLANDER, H. M. d.: *Stochastic Analysis*. August 2000

[KS91] KARATZAS, I. ; SHREVE, S.E.: *Brownian Motion and Stochastic Calculus*. Springer, 1991 (Graduate Texts in Mathematics). [http://books.google.de/books?id=ATNy\\_Zg3PSsC](http://books.google.de/books?id=ATNy_Zg3PSsC). – ISBN 9780387976556