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Two Applications of Ito's Rule

- 1) Lévy's Characterization of Brownian Motion
- 2) Martingale Moment Inequalities.

Lévy's Characterization Result.

Amazingly useful: It says that if $X \in \mathcal{M}^{c,loc}$ and $\langle X \rangle_t = t$ then X is a B.M.

- actually, it even works in higher dimensions
- very useful way to check that a given process is a B.M.

Precise Setup and Statement.

$(\Omega, \mathcal{F}, P)$, F given (usual conditions)

Let d be an integer ≥ 1 , μ a measure on $(\mathbb{R}^d, \mathcal{B}(\mathbb{R}^d))$.

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Let $X = \{X_t\}$ be a continuous adapted process taking values in $\mathbb{R}^d$. We say X is a d -dimensional B.M. with initial dist. μ if.

1) $X_0 \sim \mu$.

2) for $0 \leq s < t$, $X_t - X_s \perp \mathcal{F}_s$
and

$$X_t - X_s \sim N(\vec{0}_d(t-s) \mathbb{1}_d)$$

$\vec{0}$: d -vector of 0's.

$\mathbb{1}_d$: $d \times d$ identity matrix.

For $\mu = \delta_0$ we can get a d -dim B.M. by putting d $\perp$ B.M. together.

$$B = (B^1, \dots, B^d) \quad \{B^i\} \perp \text{B.M.}$$

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Now, let B be a d -dim B.M.

for $1 \leq j \leq d$

$$E[B_{\lambda}^i B_{\lambda}^j | \mathcal{F}_{\lambda}]$$

$$= \begin{cases} E[B_{\lambda}^i | \mathcal{F}_{\lambda}] E[B_{\lambda}^j | \mathcal{F}_{\lambda}] & i \neq j \\ E[(B_{\lambda}^i)^2 | \mathcal{F}_{\lambda}] & i = j \end{cases}$$

$$= \begin{cases} 0 & i \neq j \\ (i-1) + (B_{\lambda}^i)^2 & i = j \end{cases}$$

$$\Rightarrow \langle B^i, B^j \rangle_{\lambda} = \begin{cases} 0 & i \neq j \\ i & i = j \end{cases}$$

- by characterization of $\langle X, Y \rangle$ as unique process of bounded variation s.t.
 $XY - \langle X, Y \rangle \in M_c^2$ for $X, Y \in M_{\lambda}^c$.

$$\therefore \langle B^i, B^j \rangle_{\lambda} = i \delta_{i=j} \quad \text{for } B \text{ a } d\text{-dim B.M.}$$

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The Levy Characterization goes in reverse!

Thm

Let $X = (X^1, \dots, X^d)$ be adapted, continuous
s.t.

$$1) M_t^i \triangleq X_t^i - X_0^i \in \mathcal{M}^{c,loc} \quad i=1, \dots, d$$

$$2) \langle M^i, M^j \rangle_t = t \delta_{i,j} \quad i, j=1, \dots, d$$

then X is a d -dim B.M. with
initial dist $\mu = \text{Law of } (X_0^1, \dots, X_0^d)$.

Next Applications

1) B : 1-dim standard B.M. (start at 0)

$$X_t \triangleq \int_0^t \text{sign}(B_s) dB_s \quad (\text{sign}(B_s) \in \mathcal{L}_B)$$

$$\Rightarrow X \in \mathcal{M}_2^c, \quad \langle X \rangle_t = \int_0^t \text{sign}^2(B_s) ds = t$$

$\therefore X$ is a B.M.!

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2) Now generally, if $\Pi \in M^{loc}$ s.t.

$$\langle \Pi \rangle_t = \langle \dot{\Pi} \rangle_t \text{ a.s.} \quad \langle \dot{\Pi} \rangle_t > 0 \text{ a.s. program.}$$

Set

$$X_t = \int_0^t \frac{1}{\langle \dot{\Pi} \rangle_s} d\Pi_s$$

Since

$$\int_0^t \frac{1}{\langle \dot{\Pi} \rangle_s} \langle \dot{\Pi} \rangle_s ds = t$$

we know $\frac{1}{\langle \dot{\Pi} \rangle} \in P_N^*$ and X is a B.M.

Proof of Lévy

Step 1: It suffices to show for $0 \leq s < t$

$$* \quad E[\exp(i\mu^T(\Pi_t - \Pi_s)) | \mathcal{F}_s] = \exp(-\frac{1}{2}|\mu|^2(t-s)) \text{ a.s.}$$

$$\mu \in \mathbb{R}^d$$

- note: if $\Pi_t - \Pi_s \perp \mathcal{F}_s$, $\Pi_t - \Pi_s \sim N(0, (t-s)Id)$
then $*$ holds.

- reverse also holds.

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- this follows using regular conditional probabilities : see Lemma 2.6.13

Showing * is easy using Ito

$$f(x) = e^{i\mu x} = \cos(\mu x) + i \sin(\mu x)$$

$$\Rightarrow f_{X_i} = \mu_i (-\sin(\mu x) + i \cos(\mu x))$$

$$\begin{aligned} f_{X_i X_j} &= -\mu_i \mu_j (\cos(\mu x) + i \sin(\mu x)) \\ &= -\mu_i \mu_j f(x) \end{aligned}$$

so, applying Ito to real/imaginary parts separately:

$$\begin{aligned} e^{i\mu T_n} &= e^{i\mu T_0} + \sum_{j=1}^d \mu_j \int_0^t (-\sin(\mu T_r) + i \cos(\mu T_r)) dW_r^j \\ &\quad - \frac{1}{2} \sum_{j,k=1}^d \mu_j \mu_k \int_0^t e^{i\mu T_r} d\langle W^j, W^k \rangle_r \end{aligned}$$

- since $|- \sin(\mu T_r) + i \cos(\mu T_r)| \leq 2$

the above local martingales are martingales

- since $\langle M^j, M^j \rangle_t = S_{jj} t$ we see that.

~~the above local martingales are martingales~~

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$\therefore \left\{ \int_0^t e^{i\pi\tau} d\pi_\tau^i \right\}_{0 \leq t \leq T}$ is bounded in L^2 ,

hence $\Rightarrow \int_0^t e^{i\pi\tau} d\pi_\tau^i$ is of class DL

Thus, multiplying the above by $e^{i\pi t} 1_A$, $A \in \mathcal{F}_T$ and taking expectations yields

$$E[e^{i\pi t} (\pi_t - \pi_0) 1_A] = P(A)$$

$$- \frac{1}{2} \sum_{i,j=1}^d \mu_i \mu_j E \left[e^{i\pi t} 1_A \int_0^t e^{i\pi\tau} d\langle \pi^i, \pi^j \rangle_\tau \right]$$

$$(\langle \pi^i, \pi^j \rangle_t = A \delta_{i,j})$$

$$= P(A) - \frac{1}{2} \sum_{i=1}^d \mu_i^2 \int_0^t E[e^{i\pi\tau} (\pi_\tau - \pi_0) 1_A] d\tau$$

Set

$$g(t) = E[e^{i\pi t} (\pi_t - \pi_0) 1_A] \quad t \geq 0.$$

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$$\Rightarrow g(x) = g(s) - \frac{1}{2}|u|^2 \int_s^x g(r) dr$$

$$\Rightarrow g(x) = g(s) e^{-\frac{1}{2}|u|^2(x-s)}$$

$$\Rightarrow E[e^{i\mu^T(\Pi_x - \Pi_s)} \mathbf{1}_A] = P(A) e^{-\frac{1}{2}|u|^2(x-s)}$$

Application: Brownian Processes.

Let $W = (W^1, \dots, W^d)$ be a d -dim B.M. starting at x .

Define R via

$$R_t = |W_t| = \sqrt{\sum_{i=1}^d (W_t^i)^2} \quad ; R_0 = |x|$$

Notes: if $|x| = |y|$ then $y = Qx$ for Q orthogonal. Since one can show

$\hat{W}_t = QW_t$ is a B.M. starting at y .

$$\stackrel{(1)}{\Rightarrow} P(R^{(x)} \in A) = P(|W_0| \in A \mid |W_0| = x)$$

$$= P(|\tilde{W}_0| \in A \mid |\tilde{W}_0| = y)$$

$$= P(R^{(y)} \in A) \quad A \in \mathcal{B}(\text{close}).$$

$\Rightarrow$ dist of R depends only upon $r = |x|$.

We say R is a Bessel process of dimension d starting at $r > 0$.

If we could use Ito on $f(x) = \sqrt{\sum_{i=1}^d (x^i)^2}$
(i.e. no problems at 0)

$$\partial_i f = \frac{x^i}{|x|} ; \quad \partial_{i,j}^2 f = \frac{\delta_{i,j}}{|x|} - \frac{x^i x^j}{|x|^3}$$

$\Rightarrow$

$$\begin{aligned} dR_x &= \sum_{i=1}^d \frac{W_x^i}{|W_x|} dW_x^i + \frac{1}{2} \sum_{i=1}^d \left(\frac{1}{|W_x|} - \frac{(W_x^i)^2}{|W_x|^3} \right) dx \\ &= \sum_{i=1}^d \frac{W_x^i}{|W_x|} dW_x^i + \frac{d-1}{2R_x} dx. \end{aligned}$$

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Now, if $\Pi_x = \sum_{i=1}^d \int_0^x \frac{w_0^i}{|w_0|} dw_0^i$ then

$$\langle \Pi \rangle_x = \sum_{i=1}^d \int_0^x \frac{w_0^i w_0^i}{|w_0|^2} d\langle w_0^i w_0^i \rangle_0$$

$$= \sum_{i=1}^d \int_0^x \frac{(w_0^i)^2}{|w_0|^2} du$$

$$= x.$$

$$\therefore \Pi_x = B_x \quad \text{or} \quad B.\Pi.$$

Thus

$$R_x = x + \int_0^x \frac{d-1}{2R_0} du + B_x. \quad *$$

Now, even though ~~$f(x) = |x|$~~ $f(x) = |x|$

has problems at 0, using an approximation argument with a function $g^\varepsilon(y)$

which is C^2 and which $\rightarrow$ ~~$f(x)$~~ $f(x)$ as

$$\varepsilon \downarrow, \text{ applied to } Y_x = \sum_{i=1}^d (w_x^i)^2.$$

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The Bessel process is interesting for many reasons

1) for $d \geq 2$, $r \geq 0$, the Bessel process R_t of dimension d , starting at r satisfies

$$1) P(R_t > 0 \quad \forall t \geq 0) = 1$$

- multi-dim B.M. never hits origin

2) With $m = \inf_{t \geq 0} R_t$:

a) if $d = 2$, $m = 0$ a.s. $\forall r > 0$

2 dim B.M. comes arbitrarily close to the origin.

b) if $d \geq 3$, $r > 0$ then

$$P(m \leq c) = \left(\frac{c}{r}\right)^{d-2} \quad 0 \leq c \leq r$$

- Beta distribution.

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c) If $d \geq 3$, $\alpha > 0$ then

$$P(\lim_{t \rightarrow \infty} R_t = \infty) = 1$$

- 3 dim B.M. moves out to infinity

d) if $d \geq 3$, $R_t \triangleq \frac{1}{R_t^{d-2}}$, $t \geq 1$ and $\alpha = 0$ then

1) M is a local martingale

$$2) \sup_{t \geq 1} E[M_t^p] < \infty \quad 0 < p < \frac{d}{d-2}$$

so M is u.i.

3) R is not a martingale

since $R_t \rightarrow 0$ a.s. R_t is u.i.

- each result follows by Ito. We will come back to these later.

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Martingale Moment Inequalities.

Motivating Example:

$$X \in \mathcal{L}_m \text{ (w. B.N.) s.t. } E\left[\int_0^T |X_u|^{2m} du\right] < \infty$$

for ~~some~~ $T > 0, m \geq 1$.

$$\Rightarrow \Pi_x = \int_0^x X_u dW_u \in M_c^2$$

$$\text{Now, } f(x) = |x|^{2m} \in C^2 \quad (0 \text{ or b/c } m \geq 1)$$

so

$$|\Pi_x|^{2m} = 2m \int_0^x |\Pi_u|^{2m-1} X_u d\Pi_u + m(2m-1) \int_0^x |\Pi_u|^{2(m-1)} X_u^2 du$$

Now, take $T_n \nearrow \infty$ so that $\Pi_x^n = \Pi_{x \wedge T_n}$

is s.t. $|\Pi_x^n| \leq n, \langle \Pi^n \rangle_x \leq n$ and $\Pi = \Pi^n$ on $x \leq T_n$.

$$\Rightarrow E[|\Pi_x^n|^{2m}] = m(2m-1) E\left[\int_0^{T_n} |\Pi_u^n|^{2(m-1)} X_u^2 du\right]$$

$$\leq m(2m-1) E\left[\int_0^x |\Pi_u^n|^{2(m-1)} X_u^2 du\right]$$

$$\leq m(2m-1) \int_0^T E[|\Pi_u^n|^{2m}]^{\frac{m-1}{m}} E[|X_u|^{2m}]^{\frac{1}{m}} du$$

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$$\begin{aligned}
 &= T^{m(m-1)} \frac{1}{T} \int_0^T E[|M_u|^{2m}]^{\frac{m-1}{m}} E[|X_u|^{2m}]^{1/m} du \\
 &\leq T^{m(m-1)} \left(\frac{1}{T} \int_0^T E[|M_u|^{2m}] du \right)^{\frac{m-1}{m}} \\
 &\quad \times \left(\frac{1}{T} \int_0^T E[|X_u|^{2m}] du \right)^{\frac{1}{m}}
 \end{aligned}$$

$\Rightarrow$

$$\begin{aligned}
 E[|M_T|^{2m}]^m &\leq T^{m-1} (m(m-1))^m \left(\frac{1}{T} \int_0^T E[|M_u|^{2m}] du \right)^{\frac{m-1}{m}} \\
 &\quad \int_0^T E[|X_u|^{2m}] du
 \end{aligned}$$

$$\leq T^{m-1} (m(m-1))^m E[|M_T|^{2m}]^{m-1} \int_0^T E[|X_u|^{2m}] du$$

$\Rightarrow$

$$E[|M_T|^{2m}] \leq T^{m-1} (m(m-1))^m \int_0^T E[|X_u|^{2m}] du$$

$\Rightarrow n \nearrow \infty$ (fatew)

$$E[|M_T|^{2m}] \leq K_m \int_0^T E[|X_u|^{2m}] du$$

upper bounds on moments of M just

(15) based upon the moments of the integrand X_u .

The Nystroms - Moment, or Burkholder - Davis - Gundy (BDG) inequalities are strengthenings of these results.

Thm.

$M \in M_{\text{cloc}}$, $M_T^* \triangleq \max_{t \leq T} |M_t|$. Then

$\forall m > 0$, $\exists$ constants, depending only on m s.t. for T a stopping time.

$$K_m E[\langle M \rangle_T^m] \leq E[(M_T^*)^m]$$

$$\leq K_m E[\langle M \rangle_T^m]$$

at $m = 1/2$, we have

$$E[M_T^*] \leq K_{1/2} E[\sqrt{\langle M \rangle_T}].$$

(16) Thus, if $E[\sqrt{\langle n \rangle_0}] < \infty \quad \forall \sigma > 0$
 then n is of class DL and
 n is a Martingale.

We first (essentially) prove this assuming
 $n, \langle n \rangle$ are bounded.

Thm.

Assume $n, \langle n \rangle$ bounded. Let T
 be a stopping time. Then

$$E[|n_T|^{2m}] \leq C_m E[\langle n \rangle_T^m] \quad m > 0$$

$$B_m E[\langle n \rangle_T^m] \leq E[|n_T|^{2m}] \quad m > 1/2$$

$$B_m E[\langle n \rangle_T^m] \leq E[(n_T^*)^{2m}] \leq C_m E[\langle n \rangle_T^m] \quad m > 1/2$$

pf.
 Ito: $Y_t = S + a \langle n \rangle_t + n_t^2 \quad S > 0, a > 0$
 $f(x) = x^m. \quad m > 0 \quad (0 \leq x \text{ b/c } Y_t \geq S > 0)$

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$$\begin{aligned}
\Rightarrow Y_t^m &= Y_0^m + m \int_0^t Y_u^{m-1} dY_u + \frac{1}{2} m(m-1) \int_0^t Y_u^{m-2} d\langle Y \rangle_u \\
&= S^m + m \int_0^t Y_u^{m-1} (a d\langle n \rangle_u + 2\pi_0 d\pi_u + d\langle n \rangle_u) \\
&\quad + \frac{1}{2} m(m-1) \int_0^t Y_u^{m-2} 4\pi_u^2 d\langle n \rangle_u \\
&= S^m + m(1+\varepsilon) \int_0^t Y_u^{m-1} d\langle n \rangle_u \\
&\quad + 2m(m-1) \int_0^t Y_u^{m-2} \pi_u^2 d\langle n \rangle_u \\
&\quad + 2m \int_0^t Y_u^{m-1} \pi_0 d\pi_u.
\end{aligned}$$

Now, $\pi_u, \langle n \rangle$ bounded imply $(Y \text{ bdd, } Y \gg 8)$

$$E\left[\int_0^t Y_u^{2(m-1)} \pi_u^2 d\langle n \rangle_u\right] \leq K_Y^{2(m-1)} K_\pi^2 K_{\langle n \rangle}$$

$$\Rightarrow \left\{ \int_0^t Y_u^{m-1} \pi_u d\pi_u \right\}_{t \geq 0} \text{ is U.I.}$$

$$\Rightarrow \text{Optional sampling: } E\left[\int_0^T Y_u^{m-1} d\pi_u\right] = 0$$

$\Rightarrow$ (18)

$$E[Y_T^m] = \delta^m + m(1+\epsilon) E\left[\int_0^T Y_u^{m-1} d\langle n \rangle_u\right] \\ + 2m(m-1) E\left[\int_0^T Y_u^{m-2} n_u^2 d\langle n \rangle_u\right]$$

or

$$E[(q\langle n \rangle_T + (\delta + n_T^2))^m]$$

$$* = \delta^m + m(1+\epsilon) E\left[\int_0^T (q\langle n \rangle_u + (\delta + n_u^2))^{m-1} d\langle n \rangle_u\right] \\ + 2m(m-1) E\left[\int_0^T (q\langle n \rangle_u + (\delta + n_u^2))^{m-2} n_u^2 d\langle n \rangle_u\right]$$

* Big Equality from which results follow.

Note

$$q=0 \Rightarrow$$

$$E[(\delta + n_T^2)^m] = \delta^m + m E\left[\int_0^T (\delta + n_u^2)^{m-1} d\langle n \rangle_u\right] \\ + 2m(m-1) E\left[\int_0^T (\delta + n_u^2)^{m-2} n_u^2 d\langle n \rangle_u\right]$$

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Too technical to do all cases, so lets focus on $m > 1$

Lower Bound.

OK to pull limit...
↓

In $\otimes$, $2m(m-1) \geq 0$ so $\alpha + \delta = 0$

$$E[(\epsilon \langle M \rangle_T + M_T^2)^m]$$

$$\geq m(1+\epsilon) E\left[\int_0^T (\epsilon \langle n \rangle_0 + n_0^2)^{m-1} d\langle n \rangle_0\right]$$

$$\geq m(1+\epsilon) \epsilon^{m-1} E\left[\int_0^T \langle n \rangle_0^{m-1} d\langle n \rangle_0\right] \quad (m > 1)$$

$$= m(1+\epsilon) \epsilon^{m-1} E[\langle n \rangle_T^m]$$

Now, $f(x) = x^m$ is convex if $m > 1$

$$\Rightarrow x^m + y^m \geq 2^{1-m} (x+y)^m$$

$$\Rightarrow \epsilon^m E[\langle n \rangle_T^m] + E[|n|_T^m]$$

$$\geq m(1+\epsilon) \epsilon^{m-1} E[\langle n \rangle_T^m] \cdot 2^{1-m}$$

$\Rightarrow$ (20)

$$E[|M|_T^{2m}] \geq \underbrace{\left((1+\epsilon) \left(\frac{\epsilon}{2}\right)^{m-1} - \epsilon^m \right)}_{B_m} E[\langle n \rangle_T^m]$$

- provided $\epsilon > 0$ small enough.

Upper Bound.

* at $\epsilon = \delta = 0$

$$\begin{aligned} E[|M|_T^{2m}] &= m E\left[\int_0^T |M_0|^{2(m-1)} d\langle n \rangle_0 \right] \\ &\quad + 2m(m-1) E\left[\int_0^T |M_0|^{2(m-1)} d\langle n \rangle_0 \right] \\ &= 2m(m-1/2) E\left[\int_0^T |M_0|^{2(m-1)} d\langle n \rangle_0 \right]. \end{aligned}$$

Using 1) $x^m + y^m \geq 2^{1-m} (x+y)^m$

$$\text{ii) } E[(\epsilon \langle n \rangle_T + (\delta + n_0^+))^m]$$

$$\geq \delta^m + m(1+\epsilon) E\left[\int_0^T (\epsilon \langle n \rangle_0 + (\delta + n_0^+))^{m-1} d\langle n \rangle_0 \right]$$

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We got

$$2^{m-1} E[\varepsilon^m \langle n \rangle_T^m + (\delta + M_T^2)^m]$$

$$\geq \delta^m + m(1+\varepsilon) E\left[\int_0^T (\varepsilon \langle n \rangle_s + (\delta + M_s^2))^{m-1} d\langle n \rangle_s\right]$$

$$\geq \delta^m + m(1+\varepsilon) E\left[\int_0^T (\delta + M_s^2)^{m-1} d\langle n \rangle_s\right]$$

at $\delta = 0$

$$2^{m-1} E[\varepsilon^m \langle n \rangle_T^m + |M_T|^{2m}]$$

$$\geq m(1+\varepsilon) E\left[\int_0^T |M_s|^{2(m-1)} d\langle n \rangle_s\right]$$

$$= \frac{m(1+\varepsilon)}{2m(m-\frac{1}{2})} E[|M_T|^{2m}]$$

$\Rightarrow$

$$E[|M_T|^{2m}] \leq \frac{2^{m-1} \varepsilon^m}{\frac{m(1+\varepsilon)}{2m(m-\frac{1}{2})} - 2^{m-1}} E[\langle n \rangle_T^m]$$

C_m provided ε ~~is~~ large enough

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Now, assumed we have B_m, C_m s.t.

$$B_m E[\langle N \rangle_T^m] \leq E[|M_T|^{2m}] \leq C_m E[\langle N \rangle_T^m]$$

consider the continuous martingale $M_{t \wedge T}$:

$\Rightarrow$

$$B_m E[\langle N \rangle_{T \wedge t}^m] \leq E[|M_{T \wedge t}|^{2m}]$$

$$\leq E[(M_{T \wedge t}^*)^{2m}]$$

$$\leq \left(\frac{2m}{2m-1}\right)^{2m} E[|M_{T \wedge t}|^{2m}] \quad (2m > 1)$$

$$X_t = |M_{T \wedge t}|$$

sub-mart.

$$\leq \underbrace{\left(\frac{2m}{2m-1}\right)^{2m}}_{C_m} C_m E[\langle M \rangle_{T \wedge t}^m]$$

$$\sup_{t \leq T} X_t = M_T^*$$

$\Rightarrow$

$$B_m E[\langle N \rangle_{T \wedge t}^m] \leq E[(M_{T \wedge t}^*)^{2m}]$$

$$\leq \left(\frac{2m}{2m-1}\right)^{2m} C_m E[\langle N \rangle_{T \wedge t}^m]$$

$$\leq C_m E[\langle N \rangle_{T \wedge t}^m]$$

as $t \nearrow \infty$ we get result by M.C.T.

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Now Assume for $n, < n$ bdd we have

$$B_m \in [\langle M \rangle_T^m] \leq E[(M_T^*)^{2m}] \leq \cancel{E} [C_m \in \langle n \rangle_T^m]$$

Let $M \in M^{cloc}$ $T_n \nearrow \infty$ s.t. $M_x^n = M_{x \wedge T_n}$

is bdd with $\langle n \rangle_{x \wedge T_n}$ bdd.

$$\max_{x \leq T \wedge T_n} \Pi_T = \max_{x \leq T \wedge T_n} \Pi_{x \wedge T_n}$$

$$\Rightarrow B_m \in [\langle M \rangle_{T \wedge T_n}^m] \leq E[(M_{T \wedge T_n}^*)^{2m}]$$

$$\leq C_m \in [\langle n \rangle_{T \wedge T_n}^m]$$

Again By NCT we can take $n \nearrow \infty$

and preserves the inequalities.

Note: Extension of results to $0 < m \leq 1/2$ is technical