

On the Convergence of Stochastic Integrals. II*

By

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Abstract

Stochastic integral converges always and it is the Riemann-Stieltjes integral defined on a probability space.

Let $(\mathcal{Q}, a, P)$ be a probability space and $\{a_t\}_{t \geq 0}$ a family of fixed increasing sub- σ -fields of a . Throughout the paper consider a probability space $(\mathcal{Q}, a, P; \{a_t\})$.

§ 1. Integral representations of a random variable, expectation and conditional expectation.

THEOREM 1 ([8]). Let X be a random variable. If X is integrable then

$$X = \int_{-\infty}^{\infty} x \, dI_{\{X \leq x\}}. \text{ Here } I_{\{X \leq x\}} \text{ denotes the indicator function of } \{X \leq x\}.$$

In fact, for $-\infty < \alpha < \beta < \infty$ the integral $\int_{\alpha}^{\beta} x \, dI_{\{X \leq x\}}$ is defined as the strong limit of the Riemann-Stieltjes sum $\sum_{j=1}^n \xi_j (I_{\{X \leq x_j\}} - I_{\{X \leq x_{j-1}\}})$ as $\max_j (x_j - x_{j-1})$ tends to 0, where

$$\alpha = x_0 < x_1 < \cdots < x_n = \beta \quad \text{and} \quad x_{j-1} \leq \xi_j \leq x_j.$$

Because,

$$\left| \int_{\alpha}^{\beta} x \, dI_{\{X \leq x\}} - \sum_{j=1}^n \xi_j (I_{\{X \leq x_j\}} - I_{\{X \leq x_{j-1}\}}) \right| \leq \max_{1 \leq j \leq n} (x_j - x_{j-1}).$$

When $\int_{\alpha}^{\beta} x \, dI_{\{X \leq x\}}$ is strongly convergent as $\alpha \rightarrow -\infty$ and $\beta \rightarrow +\infty$, the limit will be denoted by $\int_{-\infty}^{\infty} x \, dI_{\{X \leq x\}}$. If X is integrable then $X = \int_{-\infty}^{\infty} x \, dI_{\{X \leq x\}}$.

Let $E(X)$ be the expectation of X . Then

$$\begin{aligned} \textbf{THEOREM 2. } E(X) &\stackrel{\text{def.}}{=} \int_{\alpha} X \, dP \\ &= \int_{-\infty}^{\infty} x \, dP(X \leq x). \end{aligned}$$

Here $F(x) = P(X \leq x)$ is the distribution function of a random variable X .

Let $E(X/B)$ be the conditional expectation of X relative to $B \subseteq a$. Then

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THEOREM 3.

$$(i) \int_C X dP = \int_C E(X/B) dP \text{ for each } C \in B.$$

$$(ii) E(X/B) = \int_{-\infty}^{\infty} x dP(X \leq x/B).$$

Here $P(X \leq x/B) = P(X \in dx/B)$ is the conditional distribution of X relative to B . (See [3], p. 27, Theorem 9.1 and [7], p. 174.)

COROLLARY. (i) If X is measurable B , then $E(X/B) = X$ a. e. and $E(XY/B) = X \cdot E(Y/B)$

a. e.

$$(ii) P(X \leq x / \{\phi, \mathcal{Q}\}) = P(X \leq x).$$

$$(iii) E(X / \{\phi, \mathcal{Q}\}) = E(X).$$

§ 2. Convergence Theorem of Stochastic Integrals.

Let $f = \{f(t), a_t, t \geq 0\}$ be a martingale with continuous sample paths and $v = \{v(t), a_t, t \geq 0\}$ a stochastic process where $v(t)$ is measurable a_t for each t .

Let $\mathcal{A} = \{\mathcal{A}_m\}$, where $\mathcal{A}_m = \{t_{m,k} : 0 = t_{m,0} < \dots < t_{m,r} < t\}$ be a sequence of partitions of $[0, t]$ with $|\mathcal{A}| = \max_k (t_{m,k+1} - t_{m,k}) \rightarrow 0$ ($m \rightarrow \infty$) and $d(t_{m,k}) = f(t_{m,k+1}) - f(t_{m,k})$ ($r > k \geq 0$) = $f(t) - f(t_{m,r})$ ($t_{m,k} \leq t, k = r$)

denotes the increment for f . Let $\xi_{m,k} \in [t_{m,k}, t_{m,k+1}]$, $k \geq 0$. $\|f\|_1$ is the L^1 -norm of f .

LEMMA 1 ([11], [13]). For $f = \{f(s), 0 \leq s \leq t\}$, $t \geq 0$ and $\varepsilon > 0$ there exists an L^∞ martingale $f^{(\varepsilon)} = \{f^{(\varepsilon)}(s), 0 \leq s \leq t\}$ such that $\|f(s) - f^{(\varepsilon)}(s)\|_1 < \varepsilon$ for all $s, 0 \leq s \leq t$.

LEMMA 2 ([12], [13]). Let $\{A_t, a_t, t \geq 0\}$ be an increasing continuous process. For $v = \{v(t), a_t, t \geq 0\}$ and $\varepsilon > 0$ there exists a continuous (and of locally bounded variation) process $v^{(\varepsilon)} = \{v^{(\varepsilon)}(t), a_t, t \geq 0\}$ such that

$$E \left[\int_a^\beta |v(t) - v^{(\varepsilon)}(t)|^p dA_t \right] < \varepsilon \quad (p \geq 1) \text{ where } 0 \leq a \leq \beta.$$

The existence of Stochastic integrals is shown by the following theorem.

Convergence Theorem ([11], [13]). For v and f , when $m \rightarrow \infty$,

$$\theta_m = \sum_K v(\xi_{m,K}) \cdot d(t_{m,K})$$

converges in L^p and a. e. if $p > 1$ and it converges a. e. if $p = 1$. The limit θ_m defines a **stochastic integral** which will be denoted by $\int_0^t v(s) df(s)$.

PROOF. (I). Case $p > 1$. By Lemma 2 there is a continuous (so that uniformly continuous) process $v^{(\varepsilon)}(s)$ such that $E \left[\int_0^t |v(s) - v^{(\varepsilon)}(s)|^p d\langle f \rangle_s \right] < \varepsilon^p$.

Let $\theta_m^{(\varepsilon)} = \sum_K v^{(\varepsilon)}(\xi_{m,K}) \cdot d(t_{m,K})$. It may be supposed that $p = 2$.

$$\begin{aligned} (a) \quad E[E((f(t) - f(s))^2 / a_t)] &= E[(f(t) - f(s))^2] \\ &= E[E((f(t) - f(s))^2 / a_s)] \\ &= E[E(\langle f \rangle_t - \langle f \rangle_s / a_s)] \\ &= E[E(\langle f \rangle_t - \langle f \rangle_s / a_t)] \quad (t > s). \end{aligned}$$

Similarly, from $E(d(t_{m,K}) \cdot d(t_{m,l}) / a_{t_{m,l}}) = 0$ ($k > l$)

$$(b) \quad E[E(d(t_{m,K}) \cdot d(t_{m,l}) / a_{t_{m,K+1}})] = 0 \quad (k > l).$$

$$\begin{aligned}
\lim_{m \rightarrow \infty} E[|\theta_m - \theta_m^{(\varepsilon)}|^2] &= \lim_{m \rightarrow \infty} E\left[\sum_K \{v(\xi_{m,K}) - v^{(\varepsilon)}(\xi_{m,K})\}^2 \cdot d(t_{m,K})^2\right] \quad (\text{by (a), (b)}) \\
&= E\left[\int_0^t |v(s) - v^{(\varepsilon)}(s)|^2 d\langle f \rangle_s\right] < \varepsilon^2. \\
\lim_{m, n \rightarrow \infty} E[|\theta_m^{(\varepsilon)} - \theta_n^{(\varepsilon)}|^2] &= \lim_{m, n \rightarrow \infty} E\left[\sum_K \{v^{(\varepsilon)}(\xi_{m,K}) - v^{(\varepsilon)}(\xi_{n,K})\} \cdot d(t_{.,K})^2\right] \\
&\leq K \cdot \lim_{|d| \rightarrow 0} E^{1/2}[\sup |v^{(\varepsilon)}(\xi_{m,K}) - v^{(\varepsilon)}(\xi_{n,K})|^4] \quad (K > 0 \text{ is constant}) \\
&= 0 \quad (v^{(\varepsilon)}(s) \text{ is uniformly continuous}).
\end{aligned}$$

So

$$\begin{aligned}
\lim_{m, n \rightarrow \infty} E^{1/2}[|\theta_m - \theta_n|^2] &\leq \lim_{m \rightarrow \infty} 2 \cdot E^{1/2}[|\theta_m - \theta_m^{(\varepsilon)}|^2] + \lim_{m, n \rightarrow \infty} E^{1/2}[|\theta_m^{(\varepsilon)} - \theta_n^{(\varepsilon)}|^2] \\
&< 2\varepsilon + 0 \quad \text{for all } \varepsilon > 0.
\end{aligned}$$

Since θ_m converges in L^2 , θ_m converges in probability. Then, by using K. Itô's method, it is shown that θ_m converges a. e. as follows.

Since θ_m converges in probability, for sufficiently large m and n , $P(|\theta_m - \theta_n| > \varepsilon) < 1/2$ uniformly in m and n . For $\varepsilon > 0$ take a large m . For all n , by Ottaviani's inequality,

$$\begin{aligned}
P(\text{Max}_{1 \leq p \leq n} |\theta_{m+p} - \theta_m| > 2\varepsilon) &\leq 2 \cdot P(|\theta_{m+n} - \theta_m| > \varepsilon) \\
&\leq 2 \cdot \sup_n P(|\theta_{m+n} - \theta_m| > \varepsilon).
\end{aligned}$$

So

$$P(\sup_{p,q} |\theta_{m+p} - \theta_{m+q}| > 4\varepsilon) \leq 4 \cdot \sup_n P(|\theta_{m+n} - \theta_m| > \varepsilon).$$

Since θ_m converges in probability, when $m \rightarrow \infty$

$$P(\limsup_{m \rightarrow \infty} \sup_{p,q} |\theta_{m+p} - \theta_{m+q}| > 4\varepsilon) \leq 4 \cdot \sup_n P(|\theta_{m+n} - \theta_m| > \varepsilon) \rightarrow 0$$

as the desired result.

(II). Case $p=1$. By Lemma 1, for f , $t \geq 0$ and $\varepsilon > 0$ there is an L^∞ martingale $f^{(\varepsilon)}$ such that $\|f(s) - f^{(\varepsilon)}(s)\|_1 < \varepsilon^2$, $0 \leq s \leq t$.

Let $d^{(\varepsilon)}$ be the increment for $f^{(\varepsilon)}$ and let $\theta_m^{(\varepsilon)} = \sum_K v(\xi_{m,K}) \cdot d^{(\varepsilon)}(t_{m,K})$

Then, from the weak L^1 -inequality of Burkholder (See [1], [2], [10], [11]) it follows that

$$\begin{aligned}
P(\limsup_{m, n \rightarrow \infty} |\theta_m - \theta_n| > 3\varepsilon) &\leq 2 \cdot P(\sup_s \left| \sum_K v(\xi_{m,K}) \cdot [d(t_{m,K}) - d^{(\varepsilon)}(t_{m,K})] \right| > \varepsilon) + P(\limsup_{m, n \rightarrow \infty} |\theta_m^{(\varepsilon)} - \theta_n^{(\varepsilon)}| > \varepsilon) \\
&\leq 2 \cdot C \cdot \varepsilon^{-1} \cdot \|f - f^{(\varepsilon)}\|_1 + 0 \quad (C \text{ is constant}) \\
&< 2 \cdot C \cdot \varepsilon \quad \text{for all } \varepsilon > 0.
\end{aligned}$$

This completes the proof of Theorem.

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