

YUIMA SUMMER SCHOOL Brixen (June 28)

# Lecture 15

## Asymptotic expansion methods

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# Asymptotic Expansion

We will discuss:

- Introduction to asymptotic expansion
- Small diffusion and asymptotic expansion
- Asymptotic expansion by YUIMA: pricing options

# Introduction to asymptotic expansion

## What is asymptotic expansion?

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- central limit theorem  $Z_n \rightarrow^d N(0, 1) \Leftrightarrow$

$$E[f(Z_n)] - \int f(z)\phi(z)dz \rightarrow 0 \quad (n \rightarrow \infty)$$

for  $f \in C_b$ , where  $\phi$  is a normal density.

- asymptotic expansion (first order)

$$E[f(Z_n)] - \int f(z) \left\{ \phi(z) + n^{-1/2} p_1(z) \right\} dz = o(n^{-1/2})$$

uniformly in a class of measurable functions  $f$ .

## Why asymptotic expansion?

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Asymptotic expansion is one of the fundamentals in

- higher-order inferential theory
- prediction
- model selection, information criteria
- bootstrap and resampling methods
- information geometry
- stochastic numerical analysis

## Some references on the asymptotic expansion

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- independent sequences
  - Bhattacharya and Ranga Rao (1986)
- Markov chain
  - Götze and Hipp (ZW1983, AS1994)
- semimartingales
  - Mykland (AS1992) for differentiable  $f$
  - Y (PTRF1997, 2004)
  - Kusuoka and Y (PTRF2000)
- martingale expansion around a mixed normal limit Y (SPA2013, arXiv2012) (discussed in this talk)
- an exposition
  - Y (Chap 2 of “Rabi N. Bhattacharya”, Springer 2016)

## Regularity of the distribution

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- Bernoulli trials  $X_j$  ( $n \in \mathbb{N}$ ) independent,  
 $P[X_j = -1] = P[X_j = 1] = 1/2$
- $F_n$ : the distribution function of  $n^{-1/2} \sum_{j=1}^n X_j$
- For even  $n \in \mathbb{N}$ ,

$$\begin{aligned} F_n(0) - F_n(0-) &= P \left[ \sum_{j=1}^n X_j = 0 \right] \\ &= \binom{n}{n/2} \left( \frac{1}{2} \right)^n \sim C n^{-1/2} \end{aligned}$$

- For any sequence of continuous functions  $\Phi_n$ ,

$$\sup_{x \in \mathbb{R}} |F_n(x) - \Phi_n(x)| \geq c n^{-1/2}$$

- Regularity of the distribution is essential.

## Regularity of the distribution

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- Asymptotic expansion is valid for

$$Z_n = n^{-1/2} \sum_{j=1}^n (X_j - E[X_j])$$

for i.i.d. sequence if  $\mathcal{L}\{X_j\}$  has absolutely continuous part.

- Malliavin calculus ensures existence of density
- Natural to use the Malliavin calculus for functionals of semimartingales



## Small diffusion and asymptotic expansion

## What we want to do

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- pricing option
- Black-Scholes model

$$dX_t = 0.1X_t dt + \epsilon X_t dw_t, \quad X_0 = 100$$
$$\epsilon = 0.5, \quad K = 100$$

- Compute the price of Asian Call Option ( $r = 0$ )

$$C = E \left[ \left( \frac{1}{T} \int_0^T X_t dt - K \right)^+ \right]$$

- Monte Carlo method (time-consuming/iaccurate)
- asymptotic expansion (fast and fairly accurate)

$$C \sim c_0 + \epsilon c_1 + \epsilon^2 c_2 + \cdots + \epsilon^k c_k \quad (\epsilon \downarrow 0)$$

## Small diffusion: a setting

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- a diffusion process  $X^\epsilon = (X_t^\epsilon)_{t \in [0, T]}$  satisfying

$$\begin{aligned} dX_t^\epsilon &= V_0(X_t^\epsilon, \epsilon)dt + V(X_t^\epsilon, \epsilon)dw_t, \quad t \in [0, T] \\ X_0^\epsilon &= x_0, \end{aligned} \tag{1}$$

- $x_0$  is a given vector,
- $V_0 \in C_\beta^\infty(\mathbb{R}^d \times [0, 1], \mathbb{R}^d)$ ,
- $V = [V_1, \dots, V_r] \in C_\beta^\infty(\mathbb{R}^d \times [0, 1], \mathbb{R}^d \otimes \mathbb{R}^r)$ ,
- $w_t = [w_t^1, \dots, w_t^r]'$  is an  $r$ -dimensional standard Wiener process.

## Functional of $X^\epsilon = (X_t^\epsilon)$

Many statistical problems of the perturbed system (1) entail a functional of the form

$$F^\epsilon = \sum_{\alpha=0}^r \int_0^T f_\alpha(X_t^\epsilon, \epsilon) dw_t^\alpha + F(X_T^\epsilon, \epsilon). \quad (2)$$

Here

- $F, f_\alpha \in C_p^\infty(\mathbb{R}^d \times [0, 1], \mathbb{R}^k)$  ( $\alpha = 0, 1, \dots, r$ ) and  $w_t^0 = t$  by convention.
- Our setting includes time-dependent stochastic differential equations and time-dependent functions  $f_\alpha$  since we can always enlarge  $X_t$  to have the argument  $t$  if necessary.

## Example of the functional $F^\epsilon$

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- the price  $X_t^\epsilon$  of a security
- the Black-Scholes economy:

$$\begin{aligned} dX_t^\epsilon &= cX_t^\epsilon dt + \epsilon X_t^\epsilon dw_t, \quad t \in [0, T], \\ X_0^\epsilon &= x_0. \end{aligned} \tag{3}$$

- A computational problem occurs when evaluating the average option as the expected value

$$E \left[ \max \left\{ \frac{1}{T} \int_0^T X_t^\epsilon dt - K, 0 \right\} \right],$$

where  $K$  is a constant.

- The value of the option is given by composition of the smooth functional  $F^\epsilon = \int_0^T X_t^\epsilon dt / T$  and the irregular function  $f(x) = \max\{x, 0\}$ .

## Go back to the general small diffusion model

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- A diffusion process  $X^\epsilon = (X_t^\epsilon)_{t \in [0, T]}$  and a functional  $F^\epsilon$ :

$$\begin{cases} dX_t^\epsilon = V_0(X_t^\epsilon, \epsilon)dt + V(X_t^\epsilon, \epsilon)dW_t, & t \in [0, T] \\ X_0^\epsilon = x_0, \end{cases}$$

$$F^\epsilon = \sum_{\alpha=0}^r \int_0^T f_\alpha(X_t^\epsilon, \epsilon) dW_t^\alpha + F(X_T^\epsilon, \epsilon)$$

## Deterministic limit condition

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- Here we assume the deterministic limit condition

$$\text{[DL1]} \quad V_\alpha(x, 0) \equiv 0 \text{ and } f_\alpha(x, 0) \equiv 0 \text{ for } \alpha = 1, \dots, r.$$

- Under Condition [DL1], the system  $X^0$  in the limit is deterministic, described by the ordinary differential equation

$$\begin{aligned} dX_t^0 &= V_0(X_t^0, 0)dt, \quad t \in [0, T] \\ X_0^0 &= x_0. \end{aligned} \tag{4}$$

- A smooth eversion of  $X^\epsilon$  exists: w.p.1, the mapping  $(x, \epsilon) \mapsto X^\epsilon(t, x)$  is smooth.

## Derivatives of $X_t^\epsilon$

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- $D_t^0 = \partial_\epsilon X_t^\epsilon|_{\epsilon=0}$ :

$$dD_t^0 = \partial_x V_0(X_t^0, 0)[D_t^0]dt + \partial_\epsilon V_0(X_t^0, 0)dt \\ + \partial_\epsilon V(X_t^0, 0)dw_t, \quad t \in [0, T]$$

$$D_0^0 = 0.$$

- $D_t^0$  is a Gaussian process

$$D_t^0 = Y_t \int_0^t Y_s^{-1} \left\{ \partial_\epsilon V_0(X_s^0, 0)ds + \sum_{\alpha=1}^r \partial_\epsilon V_\alpha(X_s^0, 0)dw_s^\alpha \right\}.$$

where  $GL(d)$ -valued process  $Y = (Y_t)$  is a unique solution to the ODE

$$\frac{dY_t}{dt} = \partial_x V_0(X_t^0, 0)Y_t, \quad Y_0 = I_d.$$



- The second derivative  $E_t^0 = \partial_\epsilon^2 X_t^\epsilon|_{\epsilon=0}$  is a 2nd order polynomial of  $w_t$ .
- Similarly, the higher-order derivatives  $\partial_\epsilon^i X_t^\epsilon$  are a solution of a higher-order SDE, and represented by multiple Wiener integrals

$$\int \cdots \int \int * * * * * dw_{t_1}^{\alpha_1} dw_{t_2}^{\alpha_2} \cdots dw_{t_n}^{\alpha_n}$$

- On the other hand, the derivatives of the functional

$$F^\epsilon = \sum_{\alpha=0}^r \int_0^T f_\alpha(X_t^\epsilon, \epsilon) dw_t^\alpha + F(X_T^\epsilon, \epsilon)$$

are represented by  $\partial_\epsilon^i X_t^\epsilon$  ( $i = 0, 1, \dots$ ).

## Smooth stochastic expansion of $F^\epsilon$

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- Expand  $F^\epsilon$  around  $\epsilon = 0$ .
- We always take a smooth version of the solution  $X^\epsilon$ : with probability 1, the mapping  $(x, \epsilon) \mapsto X^\epsilon(t, x)$  is smooth.

- Apply the Taylor formula to obtain

$$F^\epsilon = F^0 + \epsilon F^{[1]} + \epsilon^2 F^{[2]} + \dots + \epsilon^{J-1} F^{[J-1]} + \epsilon^J R^{[J]}(\epsilon) \quad (5)$$

with

$$R^{[J]}(\epsilon) = \frac{1}{(J-1)!} \int_0^1 (1-s)^{J-1} \partial_\epsilon^J F^\epsilon|_{\epsilon=s\epsilon} ds.$$

- Here  $F^{[j]} = (j!)^{-1} \partial_\epsilon^j F^\epsilon|_{\epsilon=0}$  and  $\partial_\epsilon^j F^\epsilon$  are expressed by  $\partial_x^\nu \partial_\epsilon^n f_\alpha$ ,  $\partial_x^\nu \partial_\epsilon^n F$  and  $\partial_\epsilon^n X_t^\epsilon$ .  
Everything is a “polynomial of  $w_\alpha$ ”.

## Smooth stochastic expansion of $F^\epsilon$

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- Since

$$F^0 = \int_0^T f_0(X_t^0, 0) dt + F(X_T^0, 0) \quad (6)$$

is a deterministic number, it is more natural to deal with the normalized functional

$$\tilde{F}^\epsilon = \epsilon^{-1} \left( F^\epsilon - F^0 \right).$$

- Then  $\tilde{F}^\epsilon$  admits an expansion corresponding to (5)

$$\tilde{F}^\epsilon = \tilde{F}^{[0]} + \epsilon \tilde{F}^{[1]} + \epsilon^2 \tilde{F}^{[2]} + \dots + \epsilon^{J-1} \tilde{F}^{[J-1]} + \epsilon^J \tilde{R}^{[J]}(\epsilon), \quad (7)$$

where  $\tilde{F}^{[j]} = F^{[j+1]}$  and  $\tilde{R}^{[J]}(\epsilon) = R^{[J+1]}(\epsilon)$ .

$$\tilde{F}^\epsilon = \tilde{F}^{[0]} + \epsilon \tilde{F}^{[1]} + \epsilon^2 \tilde{F}^{[2]} + \dots$$


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- In particular, under Condition [DL1],

$$\begin{aligned} \tilde{F}^{[0]} &= \int_0^T \partial_{(x,\epsilon)} f_0(X_t^0, 0) [(D_t^0, 1)] dt + \sum_{\alpha=1}^r \int_0^T \partial_\epsilon f_\alpha(X_t^0, 0) dw_t^\alpha \\ &\quad + \partial_{(x,\epsilon)} F(X_T^0, 0) [(D_T^0, 1)], \end{aligned} \quad (8)$$

$$\begin{aligned} \tilde{F}^{[1]} &= \frac{1}{2} \int_0^T \partial_x f_0(X_t^0, 0) [E_t^0] dt + \frac{1}{2} \int_0^T \partial_{(x,\epsilon)}^2 f_0(X_t^0, 0) [(D_t^0, 1)^{\otimes 2}] dt \\ &\quad + \frac{1}{2} \sum_{\alpha=1}^r \int_0^T \{ 2\partial_x \partial_\epsilon f_\alpha(X_t^0, 0) [D_t^0] + \partial_\epsilon^2 f_\alpha(X_t^0, 0) \} dw_t^\alpha \\ &\quad + \frac{1}{2} \partial_x F(X_T^0, 0) [E_T^0] + \frac{1}{2} \partial_{(x,\epsilon)}^2 F(X_T^0, 0) [(D_T^0, 1)^{\otimes 2}] \end{aligned} \quad (9)$$

where  $D_t^0 = \partial_\epsilon X_t^0$  and  $E_t^0 = \partial_\epsilon^2 X_t^0$ , and

$$\tilde{F}^\epsilon = \tilde{F}^{[0]} + \epsilon \tilde{F}^{[1]} + \epsilon^2 \tilde{F}^{[2]} + \dots$$


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$$\begin{aligned} \tilde{F}^{[2]} = & \frac{1}{6} \int_0^T \partial_x f_0(\mathbf{X}_t^0, 0) [C_t^0] dt + \frac{1}{2} \int_0^T \partial_x^2 f_0(\mathbf{X}_t^0, 0) [D_t^0 \otimes E_t^0] dt \\ & + \frac{1}{2} \int_0^T \partial_x \partial_\epsilon f_0(\mathbf{X}_t^0, 0) [E_t^0] dt + \frac{1}{6} \int_0^T \partial_{(x,\epsilon)}^3 f_0(\mathbf{X}_t^0, 0) [(D_t^0, 1)^{\otimes 3}] dt \\ & + \sum_{\alpha=1}^r \int_0^T \left\{ \frac{1}{2} \partial_x \partial_\epsilon f_\alpha(\mathbf{X}_t^0, 0) [E_t^0] + \frac{1}{2} \partial_x^2 \partial_\epsilon f_\alpha(\mathbf{X}_t^0, 0) [D_t^0 \otimes D_t^0] \right. \\ & \left. + \frac{1}{2} \partial_x \partial_\epsilon^2 f_\alpha(\mathbf{X}_t^0, 0) [D_t^0] + \frac{1}{6} \partial_\epsilon^3 f_\alpha(\mathbf{X}_t^0, 0) \right\} dw_t^\alpha \\ & + \frac{1}{2} \partial_x^2 F(\mathbf{X}_T^0, 0) [E_T^0 \otimes D_T^0] + \frac{1}{2} \partial_x \partial_\epsilon F(\mathbf{X}_T^0, 0) [E_T^0] \\ & + \frac{1}{6} \partial_x F(\mathbf{X}_T^0, 0) [C_T^0] + \frac{1}{6} \partial_{(x,\epsilon)}^3 F(\mathbf{X}_T^0, 0) [(D_T^0, 1)^{\otimes 3}] \end{aligned} \quad (10)$$

with  $C_t^0 = \partial_\epsilon^3 \mathbf{X}_t^0$ .

## Malliavin calculus, Watanabe theory

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- smooth stochastic expansion

$$f^\epsilon \sim f^{[0]} + \epsilon f^{[1]} + \epsilon^2 f^{[2]} + \dots \quad (\epsilon \downarrow 0)$$

(i.e., every residual term and its “derivatives” with respect to  $w$  are of small order. )

- $g$ : function

$$\begin{aligned} g(f^\epsilon) &\sim \sum_j \frac{1}{j!} \partial_x^j g(f^{[0]}) (\epsilon f^{[1]} + \epsilon^2 f^{[2]} + \dots)^j \\ &= \Phi^{[0]} + \epsilon \Phi^{[1]} + \epsilon^2 \Phi^{[2]} + \dots \end{aligned}$$

In particular,

$$\begin{aligned} \Phi^{[0]} &= g(f^{[0]}) \\ \Phi^{[1]} &= \partial_x g(f^{[0]}) f^{[1]}, \dots \end{aligned}$$

- generalized expectation and asymptotic expansion

$$E[g(f^\epsilon)] \sim E[\Phi^{[0]}] + \epsilon E[\Phi^{[1]}] + \epsilon^2 E[\Phi^{[2]}] + \dots .$$

- Example.  $g(x) = \max\{x - K, 0\}$ .

$$E[\partial_x^2 g(f^{[0]}) \Psi] ?$$

- Watanabe theory formulates

$$E[T(f^\epsilon)\psi], \quad T : \text{Schwartz distribution}$$

and drives asymptotic expansion.

- formal computation

$$\begin{aligned} E[\partial_x^2 g(f^{[0]}) \Psi] &= E \left[ \partial_x^2 g(f^{[0]}) E[\Psi | f^{[0]}] \right] \\ &= \int \partial_x^2 g(x) E[\Psi | f^{[0]} = x] p^{f^{[0]}}(x) dx \\ &= \int g(x) (-\partial_x)^2 (E[\Psi | f^{[0]} = x] p^{f^{[0]}}(x)) dx \end{aligned}$$

- The (generalized) expectation of the  $j$ -th term in the expansion takes the form

$$E[\Phi^{[j]}] = \int g(x)p_j(x)dx,$$

where  $p_j(x)$  is expressed by the conditional expectation

$$E[(\text{a polynomial of } f^{[1]}, f^{[2]}, \dots) | f^{[0]} = x]$$

Therefore, this problem is reduced to the computation of

$$E \left[ \int \cdots \int \int * * * dw_{t_1}^{\alpha_1} dw_{t_2}^{\alpha_2} \cdots dw_{t_n}^{\alpha_n} \mid \int * * * dw_u = x \right].$$



## Smooth stochastic expansion of $F^\epsilon$

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Theorem 1. Suppose

- [DL1] and [DL2] (nondegeneracy condition)
- a sequence  $(H^\epsilon)_{\epsilon \in (0,1]}$  of  $k'$ -dimensional random variables admits a smooth stochastic expansion

$$H^\epsilon \sim H^{[0]} + \epsilon H^{[1]} + \epsilon^2 H^{[2]} + \dots \quad (\epsilon \downarrow 0). \quad (11)$$

- $\mathcal{G} \subset \mathcal{F}_\uparrow(\mathbb{R}^k)$

$$\sup_{g \in \mathcal{G}} \sup_x (1 + |x|^2)^{-s/2} |g(x)| < \infty \quad (12)$$

for some  $s \geq 0$ .

- Let  $q \in C_\uparrow^\infty(\mathbb{R}^{k'})$ .

Then ...

Then the expectation  $E[g(\tilde{F}^\epsilon)q(H^\epsilon)]$  has an asymptotic expansion

$$E \left[ g \left( \tilde{F}^\epsilon \right) q \left( H^\epsilon \right) \right] \sim c_0(g) + \epsilon c_1(g) + \epsilon^2 c_2(g) + \cdots \quad (\epsilon \downarrow 0),$$

where

$$c_i(g) = \int_{\mathbb{R}^k} g(z) p_i(z) dz \quad (g \in \mathcal{G})$$

for some densities  $p_i(z)$ . In particular,

$$p_0(z) = E \left[ q \left( H^{[0]} \right) \mid \tilde{F}^{[0]} = z \right] \phi(z; \mu, \Sigma)$$

$$\begin{aligned} p_1(z) = & -\partial \cdot \left( E \left[ q \left( H^{[0]} \right) \tilde{F}^{[1]} \mid \tilde{F}^{[0]} = z \right] \phi(z; \mu, \Sigma) \right) \\ & + E \left[ \partial q \left( H^{[0]} \right) [H^{[1]}] \mid \tilde{F}^{[0]} = z \right] \phi(z; \mu, \Sigma). \end{aligned}$$

and

$$\begin{aligned}
p_2(z) = & \frac{1}{2} \partial^2 \cdot \left( E \left[ (\tilde{F}^{[1]})^{\otimes 2} q(H^{[0]}) | \tilde{F}^{[0]} = z \right] \phi(z; \mu, \Sigma) \right) \\
& - \partial \cdot \left( E \left[ \tilde{F}^{[2]} q(H^{[0]}) | \tilde{F}^{[0]} = z \right] \phi(z; \mu, \Sigma) \right) \\
& - \partial \cdot \left( E \left[ \tilde{F}^{[1]} \partial q(H^{[0]}) [H^{[1]}] | \tilde{F}^{[0]} = z \right] \phi(z; \mu, \Sigma) \right) \\
& + E \left[ \partial q(H^{[0]}) [H^{[2]}] | \tilde{F}^{[0]} = z \right] \phi(z; \mu, \Sigma) \\
& + \frac{1}{2} E \left[ \partial^2 q(H^{[0]}) [(H^{[1]})^{\otimes 2}] | \tilde{F}^{[0]} = z \right] \phi(z; \mu, \Sigma).
\end{aligned}$$

This expansion is valid uniformly in  $g \in \mathcal{G}$ .

**Remark 2.** More than 900 terms are in the third order expansion. Each term is defined by a multiple integral.

**Remark 3.** Conditional expectation of a multiple Wiener integral given a Wiener integral is necessary and available.

## Asymptotic expansion by YUIMA: pricing options

## Asymptotic expansion vs. Monte Carlo method

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- YUIMA provides “asymptotic\_term” function for asymptotic expansion of a functional of a diffusion process.
- At present, asymptotic\_term is not available (out of order!) if the dimension of the diffusion process is greater than 1.
- A quite general, extended “expander” will be released soon.

## Asymptotic expansion vs. Monte Carlo method

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- Compare the values obtained by asymptotic expansion and the Monte Carlo method, both by YUIMA
- Average Price Call Option for Black-Scholes model

$$dX_t = 0.1X_t dt + \epsilon X_t dw_t, \quad X_0 = 100$$

$$\epsilon = 0.5, \quad K = 100$$

- MC ( $10^5$ )
- Results:

<i>method</i>	<i>value</i>	<i>d.r.</i>
MC	14.56604	—
asy exp (1st order)	14.6774428	0.7648314%
asy exp (2st order)	14.5997711	0.2315927%

d.r.=difference rate

## Asymptotic expansion vs. Monte Carlo method

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- Average Price Call Option for CEV model

$$dX_t = 0.1X_t dt + \epsilon \sqrt{X_t} dw_t, \quad X_0 = 100 \quad (\gamma = 1/2)$$

$$\epsilon = 0.5, \quad K = 100$$

- Results:

<i>method</i>	<i>value</i>	<i>d.r.</i>
MC	5.21069	—
asy exp (1st order)	5.2170308	0.1216788%
asy exp (2st order)	5.2170489	0.1220259%

d.r.=difference rate

## Asymptotic expansion vs. Monte Carlo method

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- Average Price Call Option for CEV model

$$dX_t = 0.1X_t dt + \epsilon \sqrt{X_t} dw_t, \quad X_0 = 100 \quad (\gamma = 2/3)$$

$$\epsilon = 0.5, \quad K = 100$$

- Results:

<i>method</i>	<i>value</i>	<i>d.r.</i>
MC	5.915403	—
asy exp (1st order)	5.91404393	−0.02298126%
asy exp (2st order)	5.9134162	−0.0335933%

d.r.=difference rate



## Asymptotic expansion vs. Monte Carlo method

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- The same method can be applied to Digital option, Basket option, Bermuda option.....
- VaR, CTE
- Control variable method

## Some references

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- Small  $\sigma$  expansion
  - Watanabe (AP1987), Kusuoka and Stroock (JFA1991)
  - Applications to statistics:
    - Y (PTRF1992,1993),
    - Dermoune and Kutoyants (Stochastics1995),
    - Sakamoto and Y (JMA1996, SISP1998),
    - Uchida and Y (SISP2004),
    - Masuda and Y (StatProbLet2004), .....

- Application to option pricing:
  - Y (JJSS1992),
  - Kunitomo and Takahashi (MathFinance2001),
  - Uchida and Y (SISP2004),
  - Takahashi and Y (SISP2004, JJSS2005),
  - Osajima (SSRN2007),
  - Takahashi and Takehara (2009,2010),
  - Andersen and Hutchings (SSRN2009),
  - Antonov and Misirpashaev (SSRN2009),
  - Chenxu Li (ColumbiaUniv2010),
  - ....

## Comments

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- Today, we did not discuss really distributional asymptotic expansions.
  - Ex. Asy exp of the distribution of an ergodic process
  - Ex. Asy exp of the realized volatility
  - Ex. Asy exp of Skorohod integrals
- The theory of asymptotic expansion is now developing.