

# Central limit theorems on Wiener chaoses

## Symposium in memory of Charles Stein

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Stein's method using kernels:  
Cacoullos-Papathanasiou-Utev  
(1994)

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- $\mu$  is a probability measure
- $\tau$  is a Borel map in  $L^1(\mu)$
- $\forall \phi \in \mathcal{C}_b^1(\mathbb{R})$ :

$$\int_{\mathbb{R}} \phi'(x) \tau(x) d\mu_x = \int_{\mathbb{R}} x \phi(x) d\mu_x$$

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$$d_{TV}(\mu, \gamma) \leq 2 \int_{\mathbb{R}} |1 - \tau(x)| d\mu_x$$

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Malliavin-Stein's method:  
Peccati-Nourdin  
(2009)

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- $(\Omega, \mathcal{F}, \mathbb{P})$  probability space
- $\Gamma$  the square field operator
- $\mathcal{L}$  the Ornstein-Uhlenbeck operator
- $\forall \phi \in \mathcal{C}_b^1(\mathbb{R}), \forall X \in \text{dom}(\Gamma)$ :  
$$\mathbb{E}(\phi'(X) \Gamma[X, -\mathcal{L}^{-1}X]) = \mathbb{E}(\phi(X)X)$$

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$$d_{TV}(X, N) \leq 2 \mathbb{E}(|1 - \Gamma[X, -\mathcal{L}^{-1}X]|)$$

# Central convergence on second Wiener chaos

## The setup:

- $F = \sum_{i,j=1}^m a_{i,j} X_i X_j$ ,
- $(X_1, \dots, X_m)$  are i.i.d.  $\mathcal{N}(0,1)$ ,
- $A = (a_{i,j})_{1 \leq i,j \leq m}$  is a real symmetric matrix,
- $\text{Diag}(A) = 0$ ,
- $\mathbb{E}(F^2) = 1$ .

Diagonalizing the matrix  $A$  leads to:

$$F = \sum_{i=1}^m \alpha_i Y_i^2$$

- $(Y_1, \dots, Y_m) = (X_1, \dots, X_m)P \sim \mathcal{N}(0, I_m)$  (since  $P \in O_m(\mathbb{R})$ )
- $(\alpha_1, \dots, \alpha_m) = \text{Spec}(A)$ .

In order to use Malliavin Lemma, we need to find  $p \geq 1$  such that  $\frac{1}{\Gamma[F, F]} \in L^p(\mathbb{P})$ .

$$\begin{aligned} \Gamma[F, F] &= \sum_{i,j=1}^m \alpha_i \alpha_j \Gamma[Y_i^2, Y_j^2] \\ &\stackrel{\text{C.R.}}{=} 4 \sum_{i,j=1}^m \alpha_i \alpha_j Y_i Y_j \Gamma[Y_i Y_j] \end{aligned}$$

$$\begin{aligned} \Gamma[Y_i, Y_j] &= \sum_{k,l=1}^m P_{k,i} P_{l,j} \Gamma[X_k, X_l] \\ &= \sum_{k=1}^m P_{k,i} P_{k,j} = [{}^t P P]_{i,j} = \underbrace{\delta_{i,j}}_{\text{Kronecker symbol}} \end{aligned}$$

$$\Gamma[F, F] = 4 \sum_{i=1}^m \alpha_i^2 Y_i^2$$

For every  $\lambda > 0$  we have

$$\begin{aligned}\mathbb{E}(\exp(-\lambda\Gamma[F, F])) &= \prod_{i=1}^m \mathbb{E}(\exp(-\lambda\alpha_i^2 Y_i^2)) \\ &= \prod_{i=1}^m \frac{1}{\sqrt{1+8\lambda\alpha_i^2}}\end{aligned}$$

On the other hand,

$$\begin{aligned}\prod_{i=1}^m (1+8\lambda\alpha_i^2) &= 1 + \sum_{j=1}^m 8^j \lambda^j S_j \\ S_j &= \sum_{1 \leq k_1 < k_2 < \dots < k_j \leq m} \alpha_{k_1}^2 \dots \alpha_{k_j}^2\end{aligned}$$

Recall that Nualart-Peccati criterion asserts that

$$\begin{aligned} F \stackrel{\text{Law}}{\approx} \mathcal{N}(0,1) &\Leftrightarrow \mathbb{E}(F^4) \approx 3 \\ &\Leftrightarrow \sum_{k=1}^m \alpha_k^4 \ll \approx 0 \\ &\Leftrightarrow \underbrace{\max_{1 \leq k \leq m} |\alpha_k|}_{\delta_F} \approx 0. \end{aligned}$$

On the other hand,

$$\begin{aligned} S_j &= \sum_{1 \leq k_1 < k_2 < \dots < k_j \leq m} \alpha_{k_1}^2 \cdots \alpha_{k_j}^2 \\ &= \frac{1}{j!} \sum_{k_1 \neq k_2 \neq \dots \neq k_j} \alpha_{k_1}^2 \cdots \alpha_{k_j}^2 \\ &\geq \frac{S_1(S_1 - \delta_F) \cdots (S_1 - (j-1)\delta_F)}{j!} \end{aligned}$$

Let us summarize:

- $F \stackrel{\text{Law}}{\approx} \mathcal{N}(0,1)$  if and only if  $\delta_F$  is small
- for all  $j \geq 2$ ,  $S_j \geq \frac{1}{j!} S_1 (S_1 - \delta_F) \cdots (S_1 - (j-1)\delta_F)$ ,
- $S_1 = \frac{1}{2} \mathbb{E}(F^2) = \frac{1}{2}$ ,
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$$\mathbb{E}(\exp(-\lambda \Gamma[F, F])) = \frac{1}{\sqrt{1 + \sum_{j=1}^m 8^j \lambda^j S_j}}.$$

Combining these facts leads to

$\forall q \geq 1, \exists \epsilon_q, C_q > 0$ , such that:

$$d_{TV}(F, \mathcal{N}(0,1)) < \epsilon_q \Rightarrow \mathbb{E}(\exp(-\lambda \Gamma[F, F])) < \frac{C_q}{\lambda^q}.$$

Assume that we have

$$\mathbb{E}(\exp(-\lambda\Gamma[F, F])) < \frac{C_q}{\lambda^q}.$$

Take  $\alpha > 0$ , one gets

$$\begin{aligned}\mathbb{P}(\Gamma[F, F] < \alpha) &= \mathbb{P}(\exp(-\lambda\Gamma[F, F]) > e^{-\lambda\alpha}) \\ &\leq e^{\lambda\alpha} \mathbb{E}(\exp(-\lambda\Gamma[F, F])) \\ &\leq \frac{C_q}{\lambda^q} e^{\lambda\alpha}\end{aligned}$$

Choosing  $\lambda = \frac{1}{\alpha}$  leads to

$$\mathbb{P}(\Gamma[F, F] < \alpha) < C_q \alpha^q \Rightarrow \frac{1}{\Gamma[F, F]} \in L^{q^-}(\mathbb{P}).$$



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Let  $F \in \text{Ker}(\mathcal{L} + 2\mathbf{I})$  which satisfies  $\mathbb{E}(F^2) = 1$ . One has, for every  $p \geq 1$ ,

$$\kappa_4(F) < \frac{24}{4^p(2p+1)!} \Rightarrow \frac{1}{\Gamma[F, F]} \in L^p(\Omega, \mathcal{F}, \mathbb{P}).$$

- What is the correct speed of "regularization"?
- Does this phenomenon extend to chaoses of higher order?

# Proof of a weaker Carbery-Wright estimate

- $P \in \mathbb{R}_d[x_1, \dots, x_m]$ ,
- $\mathbf{X} = (X_1, \dots, X_m)$  i.i.d.  $\sim \mathcal{N}(0, 1)$ ,
- $\mathbb{E}(P(\mathbf{X})^2) = 1$ .

We proceed by induction on the degree  $d$ .

$$\begin{aligned}\mathbb{P}(|P(\mathbf{X})| < \epsilon) &= \mathbb{E}(\mathbf{1}_{[-\epsilon, \epsilon]}(P(\mathbf{X}))) \\ &= \mathbb{E}\left(\mathbf{1}_{[-\epsilon, \epsilon]}(P(\mathbf{X})) \frac{\Gamma[P(\mathbf{X}), P(\mathbf{X})]}{\Gamma[P(\mathbf{X}), P(\mathbf{X})]}\right) \\ &\leq \underbrace{\frac{1}{\delta} \mathbb{E}(\mathbf{1}_{[-\epsilon, \epsilon]}(P(\mathbf{X})) \Gamma[P(\mathbf{X}), P(\mathbf{X})])}_A \\ &\quad + \underbrace{\mathbb{P}(\Gamma[P(\mathbf{X}), P(\mathbf{X})] \leq \delta)}_B\end{aligned}$$

We introduce  $\chi_\epsilon(x) = \int_0^x \mathbf{1}_{[-\epsilon, \epsilon]}(t) dt$ :

$$\begin{aligned} A &= \frac{1}{\delta} \mathbb{E} \left( \chi'_\epsilon \left( P(\mathbf{X}) \right) \overset{\text{C.R.}}{\Gamma} [P(\mathbf{X}), P(\mathbf{X})] \right) \\ &= \frac{1}{\delta} \mathbb{E} (\Gamma [\chi_\epsilon (P(\mathbf{X})), P(\mathbf{X})]) \\ &= -\mathbb{E} (\chi_\epsilon (P(\mathbf{X})) \mathcal{L} P(\mathbf{X})) \\ &\leq \frac{\epsilon}{\delta} \mathbb{E} (|\mathcal{L} P(\mathbf{X})|) \\ &\leq \frac{\epsilon}{\delta} d \sqrt{\mathbb{E} (P(\mathbf{X})^2)} \\ &= \frac{\epsilon}{\delta} d \end{aligned}$$

$$\begin{aligned} \#P(\mathbf{X}) &= \sum_{i=1}^m Y_i \frac{\partial P(\mathbf{X})}{\partial X_i} \\ &\stackrel{\text{Law}}{=} N \sqrt{\Gamma[P(\mathbf{X}), P(\mathbf{X})]} \end{aligned}$$

with  $N \sim \mathcal{N}(0,1)$  independent of  $\mathbf{X}$ . Using induction assumption, **conditionnally to  $\mathbf{Y}$**  gives:

$$\begin{aligned} \mathbb{P}\left(\left|\#P(\mathbf{X})\right| < \delta\right) &= \mathbb{P}\left(\frac{\left|\#P(\mathbf{X})\right|}{\sqrt{\mathbb{E}_{\mathbf{X}}(\#P(\mathbf{X})^2)}} < \frac{\delta}{\sqrt{\mathbb{E}_{\mathbf{X}}(\#P(\mathbf{X})^2)}}\right) \\ &\leq C_{d-1} \delta^{\alpha_{d-1}} \underbrace{\mathbb{E}_{\mathbf{Y}}\left(\frac{1}{\left(\mathbb{E}_{\mathbf{X}}(\#P(\mathbf{X})^2)\right)^{\frac{\alpha_{d-1}}{2}}}\right)}_C \end{aligned}$$

- By Poincaré inequality,  $\mathbb{E}_{\mathbf{Y}}\mathbb{E}_{\mathbf{X}}(\sharp P(\mathbf{X})^2) = \mathbb{E}(\Gamma[P(\mathbf{X}), P(\mathbf{X})]) \geq 1$ ,
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$$\begin{aligned} \mathbb{E}_{\mathbf{X}}(\sharp P(\mathbf{X})^2) &= \underbrace{\sum_{i,j=1}^m Y_i Y_j \mathbb{E} \left( \frac{\partial P(\mathbf{X})}{\partial X_i} \frac{\partial P(\mathbf{X})}{\partial X_j} \right)}_{\text{positive quadratic form of } \mathbf{Y}} \\ &\stackrel{\text{Law}}{=} \sum_{i=1}^m \underbrace{\alpha_i}_{\geq 0} Y_i^2 \Rightarrow \sum_{i=1}^m \alpha_i \geq \frac{1}{2}. \end{aligned}$$

- Computing Laplace transform one gets

$$\begin{aligned} \mathbb{P} \left( \sum_{i=1}^m \alpha_i Y_i^2 < \epsilon \right) &< \sqrt{\epsilon} \\ \Rightarrow \mathbb{E}_{\mathbf{Y}} \left( \frac{1}{\left( \mathbb{E}_{\mathbf{X}}(\sharp P(\mathbf{X})^2) \right)^{\frac{\alpha_{d-1}}{2}}} \right) &< 1 \\ \Rightarrow \mathbb{P} \left( \left| \sharp P(\mathbf{X}) \right| < \delta \right) &< C_{d-1} \delta^{\alpha_{d-1}}. \end{aligned}$$

Let summarize

- $\mathbb{P}(|P(\mathbf{X})| < \epsilon) < d \frac{\epsilon}{\delta} + \mathbb{P}(\Gamma[P(\mathbf{X}), P(\mathbf{X})] < \delta),$
- $\mathbb{P}\left(\left|\sharp P(\mathbf{X})\right| < \delta\right) < C_{d-1} \delta^{\alpha_{d-1}}$

We notice that  $\sharp P(\mathbf{X}) \stackrel{\text{Law}}{=} N \sqrt{\Gamma[P(\mathbf{X}), P(\mathbf{X})]}$  with  $N \models \Gamma[P(\mathbf{X}), P(\mathbf{X})]$ .

One can deduce that

$$\mathbb{P}(\Gamma[P(\mathbf{X}), P(\mathbf{X})] < \delta) < \frac{C_{d-1}}{\mathbb{P}(|N| < 1)} \delta^{\frac{1}{2}\alpha_{d-1}}$$

Optimization gives for  $P$  of degree  $d$  such that  $\mathbb{E}(P(\mathbf{X})^2) = 1$  that:

$$\mathbb{P}(|P(\mathbf{X})| < \epsilon) \leq \frac{1}{\mathbb{P}(|N| < 1)^2} d \epsilon^{\frac{1}{2d}}.$$