

# On Götze's multivariate central limit theorem: doubts, clarification and improvements

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# STATEMENT

- $X_1, X_2, \dots, X_n \dots$  independent  $\mathbb{R}^d$ -valued random vectors with sum  $W$
- $\mathbb{E} X_i = \mathbf{0}$ ,  $\text{Var}(W) = \mathbf{I}_d$
- $\mathcal{C}_d \dots$  the family of all measurable convex subsets of  $\mathbb{R}^d$
- $\|\cdot\| \dots$  Euclidean norm
- $\beta_3 := \sum_{i=1}^n \mathbb{E} \|X_i\|^3$

## Theorem (Götze, 1991)

*For each  $d$ , there exists  $K_d$ , such that*

$$|\mathbb{P}(W \in C) - \mathbf{N}(0, \mathbf{I}_d)\{C\}| \leq K_d \beta_3$$

*for all  $W$  and all  $C \in \mathcal{C}_d$ .*

*For  $d \geq 6$ , we have  $K_d \leq 157.85 d + 10$ .*

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**Theorem (Bhattacharya and Holmes, 2010)**

$$|\mathbb{P}(W \in C) - N(0, \mathbf{I}_d)\{C\}| \leq K d^{5/2} \beta_3$$

# STEIN'S METHOD FOR THE MULTIVARIATE NORMAL DISTRIBUTION

We have

$$\mathbb{E}[f(W)] - \mathbf{N}(0, \mathbf{I}_d)\{f\} = \mathbb{E}[\mathcal{S}g(W)],$$

where

$$\mathcal{S}g(W) = \Delta g(w) - \langle \nabla g(w), w \rangle$$

and where  $g$  solves  $\mathcal{S}g(w) = f(w) - \mathbf{N}(0, \mathbf{I}_d)\{f\}$ .

$$\begin{aligned} g(w) &= \int_0^\infty \int_{\mathbb{R}^d} \left( \mathbf{N}(0, \mathbf{I}_d)\{f\} - f(e^{-t}w + z\sqrt{1 - e^{-2t}}) \right) \phi_d(z) dz dt \\ &= \int_0^{\pi/2} \int_{\mathbb{R}^d} \left( \mathbf{N}(0, \mathbf{I}_d)\{f\} - f(w \cos \alpha + z \sin \alpha) \right) \phi_d(z) dz \tan \alpha d\alpha \end{aligned}$$

where  $\phi_d(z) = (2\pi)^{-d/2} e^{-\|z\|^2/2}$  is the standard normal density.

# SOME DIFFERENTIAL CALCULUS

Let  $w, x_1, \dots, x_r$  in  $\mathbb{R}^d$  with  $w_i = (w_1, \dots, w_d)$  and  $x_i = (x_{i1}, \dots, x_{id})$ . Define

$$\langle \nabla^r g(w), x_1 \otimes x_2 \otimes \dots \otimes x_r \rangle := \sum_{j_1, \dots, j_r=1}^d D_{j_1 j_2 \dots j_r} g(w) x_{1j_1} x_{2j_2} \dots x_{rj_r}.$$

$\nabla^r g(w)$  can be regarded as a symmetric  $r$ -fold tensor.

# EXPANSION OF STEIN'S OPERATOR

$$\mathbb{E}[f(W)] - \mathbf{N}(0, \mathbf{I}_d)\{f\} = - \int_0^{\pi/2} \mathbb{E}[\mathcal{S} \mathcal{U}_\alpha f(W)] \tan \alpha \, d\alpha,$$

where

$$\mathcal{U}_\alpha f(w) := \int_{\mathbb{R}^d} f(w \cos \alpha + z \sin \alpha) \phi_d(z) \, dz.$$

Taylor's expansion yields

$$\begin{aligned} \mathbb{E}[\mathcal{S} g(W)] \\ = \sum_{i=1}^n \mathbb{E} \left[ \left\langle \nabla^3 g(W_i + \theta X_i), X_i \otimes \tilde{X}_i^{\otimes 2} - (1 - \theta) X_i^{\otimes 3} \right\rangle \right], \end{aligned}$$

where  $W_i = W - X_i$ ,  $\tilde{X}_i$  is an independent copy of  $X_i$ ,  $\theta$  is uniformly distributed over  $[0, 1]$ , and  $\tilde{X}_i$  and  $\theta$  are independent of each other and all other variates.

# ESTIMATION OF THE DERIVATIVES (1)

Bhattacharya and Holmes estimate

$$|\langle \nabla^3 g(w), x \otimes y \otimes z \rangle| \leq \sum_{j,k,l=1}^d |D_{jkl}(w)| |x_j| |y_k| |z_l|.$$

$$\mathcal{U}_\alpha f(w) = \int_{\mathbb{R}^d} f(w \cos \alpha + z \sin \alpha) \phi_d(z) dz,$$

$$D_{jkl} \mathcal{U}_\alpha f(w) = -\cot^3 \alpha \int_{\mathbb{R}^d} f(w \cos \alpha + z \sin \alpha) D_{jkl} \phi_d(z) dz,$$

$$|\langle \nabla^3 \mathcal{U}_\alpha f(w), x \otimes y \otimes z \rangle| \leq c_3 \|f\|_\infty \sum_{j,k,l=1}^d |x_j| |y_k| |z_l| \cot^3 \alpha,$$

where

$$c_3 = \max_{j,k,l} \int_{\mathbb{R}^d} |D_{jkl} \phi_d(z)| dz = \int_{\mathbb{R}^d} |D_{111} \phi_d(z)| dz = \int_{\mathbb{R}} |\phi_1'''(z)| dz$$

# ESTIMATION OF THE DERIVATIVES (2)

$$\begin{aligned} \left| \langle \nabla^3 \mathcal{U}_\alpha f(\mathbf{w}), \mathbf{x} \otimes \mathbf{y} \otimes \mathbf{z} \rangle \right| &\leq c_3 \|f\|_\infty \sum_{j,k,l=1}^d |x_j| |y_k| |z_l| \cot^3 \alpha \\ &\leq c_3 \|f\|_\infty \cdot d^{3/2} \|\mathbf{x}\| \|\mathbf{y}\| \|\mathbf{z}\| \cot^3 \alpha. \end{aligned}$$

Can we do better?

Yes, thanks to the fact that  $\nabla^3 g(\mathbf{w})$  is a symmetric 3-tensor.

**Theorem (Banach, 1938)**

*If  $T$  is a symmetric  $r$ -tensor, then*

$$\|T\|_V := \sup_{\|x_1\|, \dots, \|x_r\| \leq 1} \left| \langle T, x_1 \otimes \dots \otimes x_r \rangle \right| = \sup_{\|x\| \leq 1} \left| \langle T, x^{\otimes r} \rangle \right|.$$

Therefore,

$$\begin{aligned} \left| \langle \nabla^3 \mathcal{U}_\alpha f(\mathbf{w}), \mathbf{x} \otimes \mathbf{y} \otimes \mathbf{z} \rangle \right| &\leq \|\nabla^3 \mathcal{U}_\alpha f(\mathbf{w})\|_V \|\mathbf{x}\| \|\mathbf{y}\| \|\mathbf{z}\| \\ &\leq c_3 \|f\|_\infty \|\mathbf{x}\| \|\mathbf{y}\| \|\mathbf{z}\| \cot^3 \alpha. \end{aligned}$$

# SMOOTHING (1)

For  $f = f_C^\downarrow := f_C - \frac{1}{2}$ , where  $f_C(w) = \mathbf{1}(w \in C)$ , we obtain

$$\left| \mathbb{E}[\mathcal{S}\mathcal{U}_\alpha f_C(W)] \right| \tan \alpha = \left| \mathbb{E}[\mathcal{S}\mathcal{U}_\alpha f_C^\downarrow(W)] \right| \tan \alpha \leq \frac{3}{4} \mathbf{c}_3 \beta_3 \cot^2 \alpha,$$

but this is not integrable with respect to  $\alpha$ .

However,

$$\begin{aligned} & \mathcal{U}_\varepsilon f_C(w) - \mathbf{N}(\mathbf{0}, \mathbf{I}_d)\{f_C\} \\ &= \int_\varepsilon^{\pi/2} (\mathbf{N}(\mathbf{0}, \mathbf{I}_d)\{f\} - \mathcal{U}_\alpha f_C(w)) \tan \alpha \, d\alpha, \\ \left| \mathbb{E}[\mathcal{U}_\varepsilon f_C(W)] - \mathbf{N}(\mathbf{0}, \mathbf{I}_d)\{f_C\} \right| &\leq \frac{3}{4} \mathbf{c}_3 \beta_3 \int_\varepsilon^{\pi/2} \cot^2 \alpha \, d\alpha \\ &\leq \frac{3}{4} \mathbf{c}_3 \beta_3 \cot \varepsilon. \end{aligned}$$

## SMOOTHING (2)

$$\left| \mathbb{E}[\mathcal{U}_\varepsilon f_C(\mathbf{w})] - \mathbf{N}(0, \mathbf{I}_d)\{f_C\} \right| \leq \frac{3}{4} \mathbf{c}_3 \beta_3 \cot \varepsilon$$

Smoothing cost:

$$\begin{aligned} & \sup_{C \in \mathcal{C}_d} \left| \mathbb{E}[f_C(W)] - \mathbf{N}(0, \mathbf{I}_d)\{f_C\} \right| \\ & \leq \frac{4}{3} \sup_{C \in \mathcal{C}_d} \left| \mathbb{E}[\mathcal{U}_\varepsilon f_C(W)] - \mathbf{N}(0, \mathbf{I}_d)\{f_C\} \right| + \frac{5}{2} \chi_{7/8;d} \gamma_d \tan \varepsilon, \end{aligned}$$

where  $\chi_{p;d}$  is the  $p$ -th quantile of the  $\chi(d)$ -distribution and where  $\gamma_d := \sup_{C \in \mathcal{C}_d} \int_{\partial C} \phi_d \, d \text{Vol}_{d-1}$ .

Optimization in  $\varepsilon$  gives

$$\sup_{C \in \mathcal{C}_d} \left| \mathbb{P}(W \in C) - \mathbf{N}(0, \mathbf{I}_d)\{C\} \right| \leq \sqrt{10} \chi_{7/8;d} \gamma_d \beta_3.$$

For  $d \geq 6$ ,  $\chi_{7/8;d} \leq 1.27 \sqrt{d}$ .

In 1991, it was only known that  $\gamma_d \leq 2\sqrt{d}$ .

# INDUCTION (1)

In order to improve the rate of convergence, we can condition the expression

$$\begin{aligned} & \mathbb{E}[\mathcal{S}g(W)] \\ &= \sum_{i=1}^n \mathbb{E} \left[ \left\langle \nabla^3 g(W_i + \theta X_i), X_i \otimes \tilde{X}_i^{\otimes 2} - (1 - \theta) X_i^{\otimes 3} \right\rangle \right], \end{aligned}$$

on  $X_i, \tilde{X}_i$ , apply independence and use the approximate normality of  $W_i$  as an induction hypothesis. Approximate normality helps because

$$\| \mathbf{N}(\mu, \Sigma) \{ \nabla^3 \mathcal{U}_\alpha f \} \|_{\vee} \leq c_3 \| f \|_{\infty} \frac{\cos^3 \alpha}{\sigma^3},$$

where  $\sigma^2$  is the smallest eigenvalue of  $\Sigma$ .

## INDUCTION (2)

Suppose that we have proved

$$\sup_{C \in \mathcal{C}_d} |\mathbb{P}(W \in C) - \mathbf{N}(0, \mathbf{I}_d)\{C\}| \leq K_d \beta_3$$

for all suitable sums  $W$  of  $n - 1$  random vectors. If  $W$  is a suitable sum of  $n$  random vectors, then

$$\left| \mathbb{E}[\mathcal{S} \mathcal{U}_\alpha f_C(W)] \right| \tan \alpha \leq \frac{\frac{3}{4} \mathbf{c}_3 \beta_3 \cos^2 \alpha \sin \alpha + \frac{3}{2} \mathbf{c}_3 \beta_3^2 \cot^2 \alpha}{\sigma^3},$$

where  $\sigma^2$  is the smallest one of all eigenvalues of  $\text{Var}(W_i)$ . Therefore,

$$\begin{aligned} & \sup_{C \in \mathcal{C}_d} |\mathbb{P}(W \in C) - \mathbf{N}(0, \mathbf{I}_d)\{C\}| \\ & \leq \frac{\frac{1}{3} \mathbf{c}_3 \beta_3 + 2 \mathbf{c}_3 K_d \beta_3^2 \cot \varepsilon}{\sigma^3} + \frac{5}{2} \chi_{7/8; d} \gamma_d \tan \varepsilon. \end{aligned}$$

$$\begin{aligned} & \sup_{C \in \mathcal{C}_d} |\mathbb{P}(W \in C) - \mathbf{N}(0, \mathbf{I}_d)\{C\}| \\ & \leq \frac{\frac{1}{3}c_3\beta_3 + 2c_3K_d\beta_3^2 \cot \varepsilon}{\sigma^3} + \frac{5}{2}\chi_{7/8;d} \gamma_d \tan \varepsilon. \end{aligned}$$

Choosing  $\tan \varepsilon = \frac{4c_3\beta_3}{\sigma^3}$ , the right hand side reduces to

$$\left( \frac{\frac{1}{3}c_3 + 10c_3\chi_{7/8;d} \gamma_d}{\sigma^3} + \frac{K_d}{2} \right) \beta_3.$$

Using  $\sigma^2 \leq 1 - \beta_3^{2/3}$  and assuming w.l.o.g. that  $\beta_3$  is sufficiently small, we can complete the induction.

For  $d \geq 6$ , we have  $\chi_{7/8;d} \gamma_d \leq 2.54 d$ .

# GAUSSIAN PERIMETERS OF CONVEX SETS

- In 1991, it was known that  $\gamma_d \leq 2\sqrt{d}$ .
- Ball (1994):  $\gamma_d \leq 4 d^{1/4}$
- Nazarov (2003):  $0.28 < \liminf_{d \rightarrow \infty} \frac{\gamma_d}{d^{1/4}} \leq \limsup_{d \rightarrow \infty} \frac{\gamma_d}{d^{1/4}} < 0.76$
- R. (2018):  $\gamma_d \leq 0.59 d^{1/4} + 0.21$

This reduces  $K_d = O(d)$  to  $K_d = O(d^{3/4})$ .

# MORE EFFICIENT SMOOTHING (1)

Senatov (1980), Bentkus (1986, 2003):

- $C^\varepsilon = \{x ; \text{dist}(x, C) \leq \varepsilon\}$ ;  $C^{-\varepsilon} = \{x ; \text{dist}(x, C^c) \geq \varepsilon\}$ ;
- $f_{C^{-\varepsilon}} \leq f_C^{-\varepsilon} \leq f_C \leq f_C^\varepsilon \leq f_{C^\varepsilon}$ ;
- $|\langle \nabla f(w) - \nabla f(z), x \rangle| \leq \frac{8\|w - z\|\|x\|}{\varepsilon^2}$  for  $f \in \{f_C^{-\varepsilon}, f_C^\varepsilon\}$ .

This allows us to bound  $\|\nabla^3 \mathcal{U}_\alpha f\|_V \leq \frac{4c_1 \cot \alpha}{\varepsilon^2}$

and we already know that  $\|\nabla^3 \mathcal{U}_\alpha f\|_V \leq \frac{1}{2} c_3 \cot^3 \alpha$ .

Combining both estimates, the induction step changes to

$$\begin{aligned} & \sup_{C \in \mathcal{C}_d} |\mathbb{P}(W \in C) - \mathbb{N}(0, \mathbf{I}_d)\{C\}| \\ & \leq \beta_3 \int_0^{\pi/2} \min \left\{ \frac{12c_1 \cos \alpha}{\varepsilon} \left( \frac{\gamma_d}{\sigma} + \frac{2K_d \beta_3}{\varepsilon \sigma^3} \right), \right. \\ & \quad \left. + 3c_3 \left( \frac{\cos^2 \alpha \sin \alpha}{4\sigma^3} + \frac{K_d \beta_3 \cot^2 \alpha}{2\sigma^3} \right) \right\} d\alpha + \gamma_d \varepsilon. \end{aligned}$$

## MORE EFFICIENT SMOOTHING (2)

$$\begin{aligned} & \sup_{C \in \mathcal{C}_d} |\mathbb{P}(W \in C) - \mathbf{N}(0, \mathbf{I}_d)\{C\}| \\ & \leq \beta_3 \int_0^{\pi/2} \min \left\{ \frac{12c_1 \cos \alpha}{\varepsilon} \left( \frac{\gamma_d}{\sigma} + \frac{2K_d \beta_3}{\varepsilon \sigma^3} \right), \right. \\ & \quad \left. + 3c_3 \left( \frac{\cos^2 \alpha \sin \alpha}{4\sigma^3} + \frac{K_d \beta_3 \cot^2 \alpha}{2\sigma^3} \right) \right\} d\alpha + \gamma_d \varepsilon. \end{aligned}$$

The last term no longer contains a factor like  $\chi_{7/8,d}$ .

Important:

$$\int_0^{\pi/2} \min\{A, B \cot^2 \alpha\} d\alpha \leq 2\sqrt{AB}.$$

This allows us to derive

$$\begin{aligned} \sup_{C \in \mathcal{C}_d} |\mathbb{P}(W \in C) - \mathbf{N}(0, \mathbf{I}_d)\{C\}| & \leq (71\gamma_d + 1)\beta_3 \\ & \leq (42d^{1/4} + 16)\beta_3. \end{aligned}$$

# EXTENSION TO DEPENDENCE?

- For dependent random vectors, we would need induction over conditional distributions.
- Conditional  $\beta_3$  can be larger than unconditional.
- It is challenging to bound the error in terms of third moments.

In particular, if  $(X_i)_{i \in \mathcal{I}}$  fit a dependence graph with maximum degree of  $D$ , is it true that

$$\sup_{C \in \mathcal{C}_d} |\mathbb{P}(W \in C) - \mathbb{N}(0, \mathbf{I}_d)\{C\}| \leq Kd^{1/4} D^2 \beta_3$$

for some universal constant  $K$ ?

# POSSIBLE STRUCTURE OF RANDOM VECTORS

- $W_\lambda$ ,  $\lambda \in \Lambda$ , defined on possibly different probability spaces;
- $\mathbb{E} W_\lambda = \mathbf{0}$ ,  $\text{Var}(W_\lambda) = \mathbf{I}_d$ ;
- $V_{\lambda\xi}$  satisfying

$$\mathbb{E}[f(W_\lambda)W_\lambda] = \int_{\Xi_\lambda} \mathbb{E}[f(V_{\lambda\xi})] \mu_\lambda(d\xi);$$

similar to the Stein coupling

$$\mathbb{E}[f(W_\lambda)W_\lambda] = \mathbb{E}[G_\lambda(f(W'_\lambda) - f(W_\lambda))]$$

( $\mu_\lambda$  are vector-valued measures);

- $\mathbb{E}[f(W_\lambda)] - \mathbb{E}[f(V_{\lambda\xi})] = \int_{\Xi_\lambda} \langle \mathbb{E}[\nabla f(V_{\lambda\eta})], \nu_{\lambda\xi}(d\eta) \rangle$   
(the total variation of the vector-valued measure  $\nu_{\lambda\xi}$  measures the proximity of  $V_{\lambda\xi}$  to  $W_\lambda$ );
- $V_{\lambda\xi} \stackrel{d}{=} Q_{\lambda\xi} W_{[\lambda,\xi]} + \nu_{\lambda\xi}$ .

THANK YOU FOR YOUR ATTENTION!