

Dyson Ornstein Uhlenbeck process

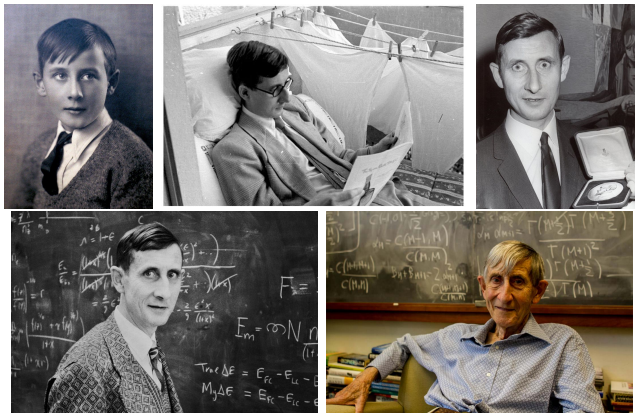
Cutoff phenomenon

Jeanne Boursier, Djalil Chafaï*, Cyril Labbé

DMA, École normale supérieure – PSL
CEREMADE, Université Paris-Dauphine – PSL

Séminaire d'analyse fonctionnelle de l'IMJ
Sorbonne Université
Jeudi 17 novembre 2022

Freeman J. Dyson (1923 – 2020)



A Brownian Motion Model for the Eigenvalues of a Random Matrix
Journal of Mathematical Physics 3 1191–1198 (1962)

Plan

The model

Non-interacting case

Random matrix case

General interacting case

Dyson Ornstein Uhlenbeck process DOU_β

- Interacting particle system $X_t^{n,1}, \dots, X_t^{n,n}$ on \mathbb{R}

$$X_0^n = x_0^n, \quad dX_t^n = \sqrt{\frac{2}{n}} dB_t - \frac{1}{n} \nabla H(X_t^n) dt$$

Dyson Ornstein Uhlenbeck process DOU_β

- Interacting particle system $X_t^{n,1}, \dots, X_t^{n,n}$ on \mathbb{R}

$$X_0^n = x_0^n, \quad dX_t^n = \sqrt{\frac{2}{n}} dB_t - \frac{1}{n} \nabla H(X_t^n) dt$$

- Configuration energy with Coulomb repulsion (singular)

$$H(x) = n \sum_{i=1}^n V(x_i) + \beta \sum_{i < j} \log \frac{1}{x_i - x_j}, \quad V(x) = \frac{x^2}{2}$$

Dyson Ornstein Uhlenbeck process DOU_β

- Interacting particle system $X_t^{n,1}, \dots, X_t^{n,n}$ on \mathbb{R}

$$X_0^n = x_0^n, \quad dX_t^n = \sqrt{\frac{2}{n}} dB_t - \frac{1}{n} \nabla H(X_t^n) dt$$

- Configuration energy with Coulomb repulsion (singular)

$$H(x) = n \sum_{i=1}^n V(x_i) + \beta \sum_{i < j} \log \frac{1}{x_i - x_j}, \quad V(x) = \frac{x^2}{2}$$

- Convergence to equilibrium $X_t^n \xrightarrow[t \rightarrow \infty]{d} P^n \propto e^{-H(x)} dx$

$$e^{-H(x)} = e^{-n \frac{|x|^2}{2}} \prod_{i < j} (x_i - x_j)^\beta$$

Dyson Ornstein Uhlenbeck process DOU_β

- Interacting particle system $X_t^{n,1}, \dots, X_t^{n,n}$ on \mathbb{R}

$$X_0^n = x_0^n, \quad dX_t^n = \sqrt{\frac{2}{n}} dB_t - \frac{1}{n} \nabla H(X_t^n) dt$$

- Configuration energy with Coulomb repulsion (singular)

$$H(x) = n \sum_{i=1}^n V(x_i) + \beta \sum_{i < j} \log \frac{1}{x_i - x_j}, \quad V(x) = \frac{x^2}{2}$$

- Convergence to equilibrium $X_t^n \xrightarrow[t \rightarrow \infty]{d} P^n \propto e^{-H(x)} dx$

$$e^{-H(x)} = e^{-n \frac{|x|^2}{2}} \prod_{i < j} (x_i - x_j)^\beta$$

- We take $\beta = 0$ or $\beta \geq 1$ (preserves order $x_n < \dots < x_1$)

Gaussian unitary invariant random matrices

- Random matrix cases $\beta \in \{1, 2, 4\}$: matrix OU

$$dM_t = \sqrt{\frac{2}{n}} dB_t - M_t dt$$

Gaussian unitary invariant random matrices

- Random matrix cases $\beta \in \{1, 2, 4\}$: matrix OU

$$dM_t = \sqrt{\frac{2}{n}} dB_t - M_t dt$$

- ▶ Symmetric/Hermitian/Symplectic $n \times n$ matrices
Real/Complex/Quaternion off-diagonal entries : \mathbb{R}^β

$$M_t \xrightarrow[t \rightarrow \infty]{d} \text{GOE/GUE/GSE} \propto e^{-n \text{Trace}(M^2)} dM$$

Gaussian unitary invariant random matrices

- Random matrix cases $\beta \in \{1, 2, 4\}$: matrix OU

$$dM_t = \sqrt{\frac{2}{n}} dB_t - M_t dt$$

- ▶ Symmetric/Hermitian/Symplectic $n \times n$ matrices
Real/Complex/Quaternion off-diagonal entries : \mathbb{R}^β

$$M_t \xrightarrow[t \rightarrow \infty]{d} \text{GOE/GUE/GSE} \propto e^{-n \text{Trace}(M^2)} dM$$

- ▶ Dyson : $(\text{spectrum}(M_t))_{t \geq 0} \stackrel{d}{=} \text{DOU}_\beta$

DOU semigroup and generator

- Markov semigroup

$$\mathbb{E}(f(X_t^n) \mid X_0^n = x) = (e^{tL}f)(x)$$

DOU semigroup and generator

- Markov semigroup

$$\mathbb{E}(f(X_t^n) \mid X_0^n = x) = (e^{tL}f)(x)$$

- Infinitesimal generator

$$L = \frac{\Delta - \nabla H \cdot \nabla}{n}$$

DOU semigroup and generator

■ Markov semigroup

$$\mathbb{E}(f(X_t^n) \mid X_0^n = x) = (e^{tL}f)(x)$$

■ Infinitesimal generator

$$\begin{aligned} L &= \frac{\Delta - \nabla H \cdot \nabla}{n} \\ &= \frac{1}{n} \sum_{i=1}^n \partial_{x_i}^2 - \sum_{i=1}^n \left[V'(x_i) - \frac{\beta}{n} \sum_{j \neq i} \frac{1}{x_i - x_j} \right] \partial_{x_i} \end{aligned}$$

DOU semigroup and generator

■ Markov semigroup

$$\mathbb{E}(f(X_t^n) \mid X_0^n = x) = (e^{tL} f)(x)$$

■ Infinitesimal generator

$$\begin{aligned} L &= \frac{\Delta - \nabla H \cdot \nabla}{n} \\ &= \frac{1}{n} \sum_{i=1}^n \partial_{x_i}^2 - \sum_{i=1}^n \left[V'(x_i) - \frac{\beta}{n} \sum_{j \neq i} \frac{1}{x_i - x_j} \right] \partial_{x_i} \\ &= \bigoplus_{i=1}^n L_{x_i}^{\text{OU}} + \frac{\beta}{2n} \sum_{j \neq i} \frac{\partial_{x_i} - \partial_{x_j}}{x_i - x_j} \end{aligned}$$

DOU semigroup and generator

- Markov semigroup

$$\mathbb{E}(f(X_t^n) \mid X_0^n = x) = (e^{tL} f)(x)$$

- Infinitesimal generator

$$\begin{aligned} L &= \frac{\Delta - \nabla H \cdot \nabla}{n} \\ &= \frac{1}{n} \sum_{i=1}^n \partial_{x_i}^2 - \sum_{i=1}^n \left[V'(x_i) - \frac{\beta}{n} \sum_{j \neq i} \frac{1}{x_i - x_j} \right] \partial_{x_i} \\ &= \bigoplus_{i=1}^n L_{x_i}^{\text{OU}} + \frac{\beta}{2n} \sum_{j \neq i} \frac{\partial_{x_i} - \partial_{x_j}}{x_i - x_j} \end{aligned}$$

- Universality wrt β : spectrum, Poincaré, log-Sobolev

Wigner theorem and semi-circle law : scaling in n

■ Empirical measure and exchangeability

$$\mu_t^n = \frac{1}{n} \sum_{i=1}^n \delta_{X_t^{n,i}} \quad \text{and} \quad \mathbb{E} \mu_\infty^n \sim \frac{1}{n} \sum_{i=1}^n P^{n,i} = P^{n,1}$$

Wigner theorem and semi-circle law : scaling in n

- Empirical measure and exchangeability

$$\mu_t^n = \frac{1}{n} \sum_{i=1}^n \delta_{X_t^{n,i}} \quad \text{and} \quad \mathbb{E} \mu_\infty^n \sim \frac{1}{n} \sum_{i=1}^n P^{n,i} = P^{n,1}$$

- Wigner theorem and semi-circle law

$$\mu_\infty^n \xrightarrow{n \rightarrow \infty} \mu_\infty = \text{SemiCircle}[-\sqrt{2\beta}, \sqrt{2\beta}]$$

Wigner theorem and semi-circle law : scaling in n

- Empirical measure and exchangeability

$$\mu_t^n = \frac{1}{n} \sum_{i=1}^n \delta_{X_t^{n,i}} \quad \text{and} \quad \mathbb{E} \mu_\infty^n \sim \frac{1}{n} \sum_{i=1}^n P^{n,i} = P^{n,1}$$

- Wigner theorem and semi-circle law

$$\mu_\infty^n \xrightarrow{n \rightarrow \infty} \mu_\infty = \text{SemiCircle}[-\sqrt{2\beta}, \sqrt{2\beta}]$$

- Long-time behavior & mean-field limit (when $\mu_0^n \xrightarrow{n \rightarrow \infty} \mu_0$)

$$\begin{array}{ccc} \mu_t^n & \xrightarrow{t \rightarrow \infty} & \mu_\infty^n \\ \Downarrow \cong & & \Downarrow \cong \\ \mu_t & \xrightarrow{t \rightarrow \infty} & \mu_\infty \end{array}$$

Mean-field limit and free probability : scaling in t

- McKean-Vlasov evolution equation

$$\partial_t \int f d\mu_t = - \int x f'(x) \mu_t(dx) + \frac{\beta}{2} \iint \frac{f'(x) - f'(y)}{x - y} \mu_t(dx) \mu_t(dy)$$

Mean-field limit and free probability : scaling in t

- McKean-Vlasov evolution equation

$$\partial_t \int f d\mu_t = - \int x f'(x) \mu_t(dx) + \frac{\beta}{2} \iint \frac{f'(x) - f'(y)}{x - y} \mu_t(dx) \mu_t(dy)$$

- Cauchy-Stieltjes transform ($\text{Im } z > 0$)

$$s_t(z) = \int \frac{\mu_t(dx)}{x - z}$$

Mean-field limit and free probability : scaling in t

- McKean-Vlasov evolution equation

$$\partial_t \int f d\mu_t = - \int x f'(x) \mu_t(dx) + \frac{\beta}{2} \iint \frac{f'(x) - f'(y)}{x - y} \mu_t(dx) \mu_t(dy)$$

- Cauchy-Stieltjes transform ($\text{Im } z > 0$)

$$s_t(z) = \int \frac{\mu_t(dx)}{x - z}$$

- Complex Burgers equation (take $f(x) = \frac{1}{x-z}$)

$$\partial_t s_t = s_t + z \partial_z s_t + \beta s_t \partial_z s_t$$

Mean-field limit and free probability : scaling in t

- McKean-Vlasov evolution equation

$$\partial_t \int f d\mu_t = - \int x f'(x) \mu_t(dx) + \frac{\beta}{2} \iint \frac{f'(x) - f'(y)}{x - y} \mu_t(dx) \mu_t(dy)$$

- Cauchy-Stieltjes transform ($\text{Im } z > 0$)

$$s_t(z) = \int \frac{\mu_t(dx)}{x - z}$$

- Complex Burgers equation (take $f(x) = \frac{1}{x-z}$)

$$\partial_t s_t = s_t + z \partial_z s_t + \beta s_t \partial_z s_t$$

- Free OU process and free Mehler formula

$$\mu_t = \text{dil}_{e^{-t}} \mu_0 \boxplus \text{dil}_{\sqrt{1-e^{-2t}}} \mu_\infty$$

Mean-field limit and free probability : scaling in t

- McKean-Vlasov evolution equation

$$\partial_t \int f d\mu_t = - \int x f'(x) \mu_t(dx) + \frac{\beta}{2} \iint \frac{f'(x) - f'(y)}{x - y} \mu_t(dx) \mu_t(dy)$$

- Cauchy-Stieltjes transform ($\text{Im } z > 0$)

$$s_t(z) = \int \frac{\mu_t(dx)}{x - z}$$

- Complex Burgers equation (take $f(x) = \frac{1}{x-z}$)

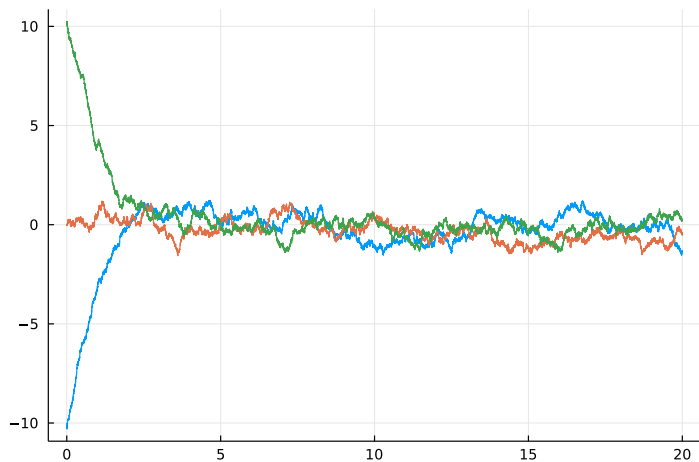
$$\partial_t s_t = s_t + z \partial_z s_t + \beta s_t \partial_z s_t$$

- Free OU process and free Mehler formula

$$\mu_t = \text{dil}_{e^{-t}} \mu_0 \boxplus \text{dil}_{\sqrt{1-e^{-2t}}} \mu_\infty$$

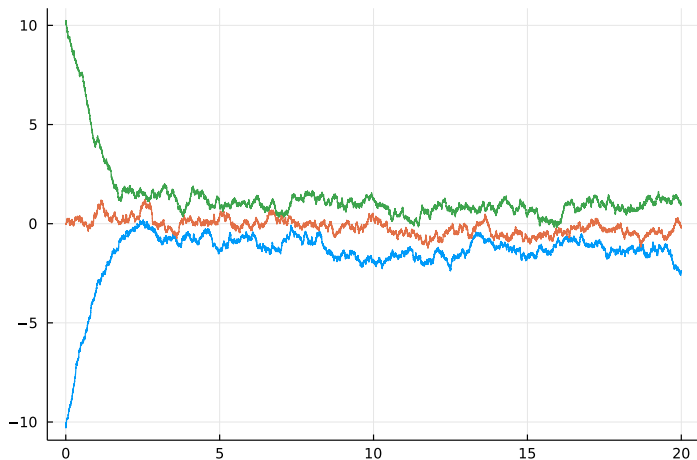
- $\mu_\infty = \text{SemiCircle}[-\sqrt{2\beta}, \sqrt{2\beta}] = \text{dil}_{\sqrt{\frac{\beta}{2}}} \text{SemiCircle}[-2, 2]$

Numerical experiments

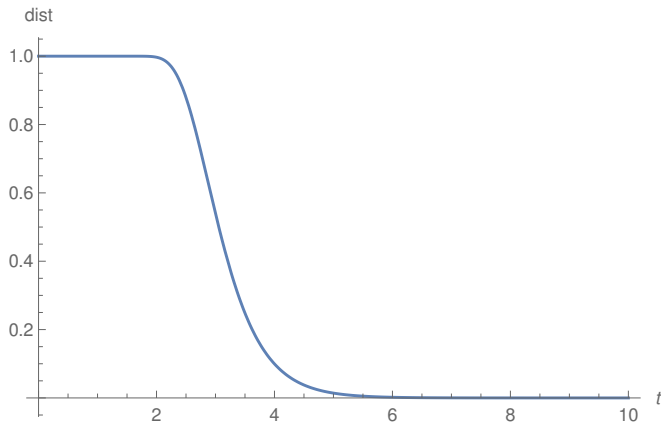


$n = 3, \beta = 0$: confinement and independence (OU)

Numerical experiments



$n = 3, \beta = 2$: confinement and repulsion (DOU)

Cutoff for OU : Hellinger distance $\text{dist}(\text{Law}(X_t^n) \mid P^n)$ 

$$n = 50, \beta = 0, \frac{|x_0^n|^2}{n} = 1, \log(50) \approx 3.91$$

Expectation : cutoff phenomenon

- For all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in S_0^n} \text{dist}(\text{Law}(X_{t_n}^n) \mid P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

Expectation : cutoff phenomenon

- For all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in S_0^n} \text{dist}(\text{Law}(X_{t_n}^n) \mid P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

- Choice of initial conditions S_0^n

Expectation : cutoff phenomenon

- For all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in S_0^n} \text{dist}(\text{Law}(X_{t_n}^n) \mid P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

- Choice of initial conditions S_0^n
- Choice of distance or divergence dist

Expectation : cutoff phenomenon

- For all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in S_0^n} \text{dist}(\text{Law}(X_{t_n}^n) \mid P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

- Choice of initial conditions S_0^n
- Choice of distance or divergence dist
- Related/Inspiring

Expectation : cutoff phenomenon

- For all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in S_0^n} \text{dist}(\text{Law}(X_{t_n}^n) \mid P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

- Choice of initial conditions S_0^n
- Choice of distance or divergence dist
- Related/Inspiring
 - ▶ Brownian motion on compact groups and on spheres

Expectation : cutoff phenomenon

- For all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in S_0^n} \text{dist}(\text{Law}(X_{t_n}^n) \mid P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

- Choice of initial conditions S_0^n
- Choice of distance or divergence dist
- Related/Inspiring
 - ▶ Brownian motion on compact groups and on spheres
 - ▶ Exclusion processes on finite sets

Expectation : cutoff phenomenon

- For all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in S_0^n} \text{dist}(\text{Law}(X_{t_n}^n) \mid P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

- Choice of initial conditions S_0^n
- Choice of distance or divergence dist
- Related/Inspiring
 - ▶ Brownian motion on compact groups and on spheres
 - ▶ Exclusion processes on finite sets
 - ▶ High dimensional OU (discrete or continuous)

Expectation : cutoff phenomenon

- For all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in S_0^n} \text{dist}(\text{Law}(X_{t_n}^n) \mid P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

- Choice of initial conditions S_0^n
- Choice of distance or divergence dist
- Related/Inspiring
 - ▶ Brownian motion on compact groups and on spheres
 - ▶ Exclusion processes on finite sets
 - ▶ High dimensional OU (discrete or continuous)
- Critical time (guess) : $c_n \asymp \log(n)$

Expectation : cutoff phenomenon

- For all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in S_0^n} \text{dist}(\text{Law}(X_{t_n}^n) \mid P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

- Choice of initial conditions S_0^n
- Choice of distance or divergence dist
- Related/Inspiring
 - ▶ Brownian motion on compact groups and on spheres
 - ▶ Exclusion processes on finite sets
 - ▶ High dimensional OU (discrete or continuous)
- Critical time (guess) : $c_n \asymp \log(n)$
- Universality with respect to β

Some distances or divergences

$$\chi^2(\nu \mid \mu) = \text{Var}_\mu \left(\frac{d\nu}{d\mu} \right) = \left\| \frac{d\nu}{d\mu} - 1 \right\|_{L^2(\mu)}^2$$

Some distances or divergences

$$\chi^2(\nu | \mu) = \text{Var}_\mu \left(\frac{d\nu}{d\mu} \right) = \left\| \frac{d\nu}{d\mu} - 1 \right\|_{L^2(\mu)}^2$$

$$\text{Kullback}(\nu | \mu) = \int \log \frac{d\nu}{d\mu} d\nu = \int \frac{d\nu}{d\mu} \log \frac{d\nu}{d\mu} d\mu$$

Some distances or divergences

$$\chi^2(\nu | \mu) = \text{Var}_\mu \left(\frac{d\nu}{d\mu} \right) = \left\| \frac{d\nu}{d\mu} - 1 \right\|_{L^2(\mu)}^2$$

$$\text{Kullback}(\nu | \mu) = \int \log \frac{d\nu}{d\mu} d\nu = \int \frac{d\nu}{d\mu} \log \frac{d\nu}{d\mu} d\mu$$

$$\text{Fisher}(\nu | \mu) = \int \left| \nabla \log \frac{d\nu}{d\mu} \right|^2 d\nu = 4 \int \left| \nabla \sqrt{\frac{d\nu}{d\mu}} \right|^2 d\mu$$

Some distances or divergences

$$\chi^2(\nu | \mu) = \text{Var}_\mu \left(\frac{d\nu}{d\mu} \right) = \left\| \frac{d\nu}{d\mu} - 1 \right\|_{L^2(\mu)}^2$$

$$\text{Kullback}(\nu | \mu) = \int \log \frac{d\nu}{d\mu} d\nu = \int \frac{d\nu}{d\mu} \log \frac{d\nu}{d\mu} d\mu$$

$$\text{Fisher}(\nu | \mu) = \int \left| \nabla \log \frac{d\nu}{d\mu} \right|^2 d\nu = 4 \int \left| \nabla \sqrt{\frac{d\nu}{d\mu}} \right|^2 d\mu$$

$$\text{Wasserstein}^2(\mu, \nu) = \inf_{(X_\mu, X_\nu)} \mathbb{E} \left(\frac{1}{2} |X_\mu - X_\nu|^2 \right) = \sup_{f \text{ BL}} \left(\int Q_1(f) d\mu - \int f d\nu \right)$$

Some distances or divergences

$$\chi^2(\nu | \mu) = \text{Var}_\mu \left(\frac{d\nu}{d\mu} \right) = \left\| \frac{d\nu}{d\mu} - 1 \right\|_{L^2(\mu)}^2$$

$$\text{Kullback}(\nu | \mu) = \int \log \frac{d\nu}{d\mu} d\nu = \int \frac{d\nu}{d\mu} \log \frac{d\nu}{d\mu} d\mu$$

$$\text{Fisher}(\nu | \mu) = \int \left| \nabla \log \frac{d\nu}{d\mu} \right|^2 d\nu = 4 \int \left| \nabla \sqrt{\frac{d\nu}{d\mu}} \right|^2 d\mu$$

$$\text{Wasserstein}^2(\mu, \nu) = \inf_{(X_\mu, X_\nu)} \mathbb{E} \left(\frac{1}{2} |X_\mu - X_\nu|^2 \right) = \sup_{f \text{ BL}} \left(\int Q_1(f) d\mu - \int f d\nu \right)$$

$$\|\mu - \nu\|_{\text{TV}} = \inf_{(X_\mu, X_\nu)} \mathbb{E}(1_{X_\mu \neq X_\nu}) = \sup_{\|f\|_\infty \leq \frac{1}{2}} \left(\int f d\mu - \int f d\nu \right)$$

Some distances or divergences

$$\chi^2(\nu | \mu) = \text{Var}_\mu \left(\frac{d\nu}{d\mu} \right) = \left\| \frac{d\nu}{d\mu} - 1 \right\|_{L^2(\mu)}^2$$

$$\text{Kullback}(\nu | \mu) = \int \log \frac{d\nu}{d\mu} d\nu = \int \frac{d\nu}{d\mu} \log \frac{d\nu}{d\mu} d\mu$$

$$\text{Fisher}(\nu | \mu) = \int \left| \nabla \log \frac{d\nu}{d\mu} \right|^2 d\nu = 4 \int \left| \nabla \sqrt{\frac{d\nu}{d\mu}} \right|^2 d\mu$$

$$\text{Wasserstein}^2(\mu, \nu) = \inf_{(X_\mu, X_\nu)} \mathbb{E} \left(\frac{1}{2} |X_\mu - X_\nu|^2 \right) = \sup_{f \in \text{BL}} \left(\int Q_1(f) d\mu - \int f d\nu \right)$$

$$\begin{aligned} \|\mu - \nu\|_{\text{TV}} &= \inf_{(X_\mu, X_\nu)} \mathbb{E}(1_{X_\mu \neq X_\nu}) = \sup_{\|f\|_\infty \leq \frac{1}{2}} \left(\int f d\mu - \int f d\nu \right) \\ &= \sup_A |\nu(A) - \mu(A)| = \frac{1}{2} \|\varphi_\mu - \varphi_\nu\|_{L^1(\lambda)} \end{aligned}$$

Some distances or divergences

$$\chi^2(\nu | \mu) = \text{Var}_\mu \left(\frac{d\nu}{d\mu} \right) = \left\| \frac{d\nu}{d\mu} - 1 \right\|_{L^2(\mu)}^2$$

$$\text{Kullback}(\nu | \mu) = \int \log \frac{d\nu}{d\mu} d\nu = \int \frac{d\nu}{d\mu} \log \frac{d\nu}{d\mu} d\mu$$

$$\text{Fisher}(\nu | \mu) = \int \left| \nabla \log \frac{d\nu}{d\mu} \right|^2 d\nu = 4 \int \left| \nabla \sqrt{\frac{d\nu}{d\mu}} \right|^2 d\mu$$

$$\text{Wasserstein}^2(\mu, \nu) = \inf_{(X_\mu, X_\nu)} \mathbb{E} \left(\frac{1}{2} |X_\mu - X_\nu|^2 \right) = \sup_{f \text{ BL}} \left(\int Q_1(f) d\mu - \int f d\nu \right)$$

$$\begin{aligned} \|\mu - \nu\|_{\text{TV}} &= \inf_{(X_\mu, X_\nu)} \mathbb{E}(1_{X_\mu \neq X_\nu}) = \sup_{\|f\|_\infty \leq \frac{1}{2}} \left(\int f d\mu - \int f d\nu \right) \\ &= \sup_A |\nu(A) - \mu(A)| = \frac{1}{2} \|\varphi_\mu - \varphi_\nu\|_{L^1(\lambda)} \end{aligned}$$

$$\text{Hellinger}^2(\mu, \nu) = \frac{1}{2} \|\sqrt{\varphi_\mu} - \sqrt{\varphi_\nu}\|_{L^2(\lambda)}^2$$

Monotonicity

- With $\nu_t = \text{Law}(X_t^n)$ and $\mu = P^n$

$$\text{dist}(\nu_t | \mu) \xrightarrow[t \rightarrow \infty]{} 0$$

Monotonicity

- With $\nu_t = \text{Law}(X_t^n)$ and $\mu = P^n$

$$\text{dist}(\nu_t | \mu) \underset{t \rightarrow \infty}{\searrow} 0$$

- Markovianity and convexity : if $\nu \ll \mu$ then

$$\text{dist}(\nu | \mu) = \int \Phi\left(\frac{d\nu}{d\mu}\right) d\mu$$

$$\Phi(u) = \begin{cases} u^2 - 1 & \text{if dist} = \chi^2 \\ u \log(u) & \text{if dist} = \text{Kullback} \\ \frac{1}{2}|u - 1| & \text{if dist} = \text{TV} \\ \frac{1}{2}(1 - \sqrt{u}) & \text{if dist} = \text{Hellinger}^2 \end{cases}$$

Monotonicity

- With $\nu_t = \text{Law}(X_t^n)$ and $\mu = P^n$

$$\text{dist}(\nu_t | \mu) \xrightarrow[t \rightarrow \infty]{} 0$$

- Markovianity and convexity : if $\nu \ll \mu$ then

$$\text{dist}(\nu | \mu) = \int \Phi\left(\frac{d\nu}{d\mu}\right) d\mu$$

$$\Phi(u) = \begin{cases} u^2 - 1 & \text{if dist} = \chi^2 \\ u \log(u) & \text{if dist} = \text{Kullback} \\ \frac{1}{2}|u - 1| & \text{if dist} = \text{TV} \\ \frac{1}{2}(1 - \sqrt{u}) & \text{if dist} = \text{Hellinger}^2 \end{cases}$$

- Fisher and Wasserstein : involve also convexity of V

Moments and cutoff

■ Moments

$$m_k(t) = \mathbb{E} \left(\frac{\sum_{i=1}^n (X_t^{n,i})^k}{n} \right) = \mathbb{E} \int u^k \mu_t^n(\mathrm{d}u)$$

Moments and cutoff

■ Moments

$$m_k(t) = \mathbb{E} \left(\frac{\sum_{i=1}^n (X_t^{n,i})^k}{n} \right) = \mathbb{E} \int u^k \mu_t^n(\mathrm{d}u)$$

■ Long-time behavior

$$m_1(\infty) = 0 \quad \text{and} \quad m_2(\infty) = \frac{1 + \frac{\beta}{2}(n-1)}{n} \sim \frac{\beta}{2}$$

Moments and cutoff

■ Moments

$$m_k(t) = \mathbb{E} \left(\frac{\sum_{i=1}^n (X_t^{n,i})^k}{n} \right) = \mathbb{E} \int u^k \mu_t^n(\mathrm{d}u)$$

■ Long-time behavior

$$m_1(\infty) = 0 \quad \text{and} \quad m_2(\infty) = \frac{1 + \frac{\beta}{2}(n-1)}{n} \sim \frac{\beta}{2}$$

■ Dynamics

$$m_1(t) = e^{-t} m_1(0) \quad \text{and} \quad m_2(t) = e^{-2t} m_2(0) + (1 - e^{-2t}) m_2(\infty)$$

Moments and cutoff

■ Moments

$$m_k(t) = \mathbb{E} \left(\frac{\sum_{i=1}^n (X_t^{n,i})^k}{n} \right) = \mathbb{E} \int u^k \mu_t^n(\mathrm{d}u)$$

■ Long-time behavior

$$m_1(\infty) = 0 \quad \text{and} \quad m_2(\infty) = \frac{1 + \frac{\beta}{2}(n-1)}{n} \sim \frac{\beta}{2}$$

■ Dynamics

$$m_1(t) = e^{-t} m_1(0) \quad \text{and} \quad m_2(t) = e^{-2t} m_2(0) + (1 - e^{-2t}) m_2(\infty)$$

■ Eigenfunctions $e^{tL} \pi_k = e^{-tk} \pi_k$

$$\pi_1(x) = \sum_{i=1}^n x_i \quad \text{and} \quad \pi_2(x) = \sum_{i=1}^n x_i^2 - (1 + \frac{\beta}{2}(n-1))$$

Moments and cutoff

■ Moments

$$m_k(t) = \mathbb{E} \left(\frac{\sum_{i=1}^n (X_t^{n,i})^k}{n} \right) = \mathbb{E} \int u^k \mu_t^n(\mathrm{d}u)$$

■ Long-time behavior

$$m_1(\infty) = 0 \quad \text{and} \quad m_2(\infty) = \frac{1 + \frac{\beta}{2}(n-1)}{n} \sim \frac{\beta}{2}$$

■ Dynamics

$$m_1(t) = e^{-t} m_1(0) \quad \text{and} \quad m_2(t) = e^{-2t} m_2(0) + (1 - e^{-2t}) m_2(\infty)$$

■ Eigenfunctions $e^{tL} \pi_k = e^{-tk} \pi_k$

$$\pi_1(x) = \sum_{i=1}^n x_i \quad \text{and} \quad \pi_2(x) = \sum_{i=1}^n x_i^2 - (1 + \frac{\beta}{2}(n-1))$$

■ $\log(n)$ cutoff for $\mathbb{E}(\pi_k(X_t))$: dimension n versus e^{-kt} decay

Cutoff for DOU : processes

- **Theorem :** Assume that $\beta = 0$ or $\beta \geq 1$ and set

$$Z_t = \sum_{i=1}^n X_t^{n,i} \quad \text{and} \quad R_t = \sum_{i=1}^n (X_t^{n,i})^2 = |X_t^n|^2$$

Then $(Z_t)_{t \geq 0} \sim \text{OU}$ and $(R_t)_{t \geq 0} \sim \text{CIR}$

Cutoff for DOU : processes

- **Theorem :** Assume that $\beta = 0$ or $\beta \geq 1$ and set

$$Z_t = \sum_{i=1}^n X_t^{n,i} \quad \text{and} \quad R_t = \sum_{i=1}^n (X_t^{n,i})^2 = |X_t^n|^2$$

Then $(Z_t)_{t \geq 0} \sim \text{OU}$ and $(R_t)_{t \geq 0} \sim \text{CIR}$

- ▶ $Z_t, R_t \xrightarrow{d} \mathcal{N}(0, 1), \text{Gamma}\left(\frac{n}{2} + \frac{\beta}{2} \frac{n(n-1)}{2}, \frac{n}{2}\right)$ as $t \rightarrow \infty$

Cutoff for DOU : processes

- **Theorem :** Assume that $\beta = 0$ or $\beta \geq 1$ and set

$$Z_t = \sum_{i=1}^n X_t^{n,i} \quad \text{and} \quad R_t = \sum_{i=1}^n (X_t^{n,i})^2 = |X_t^n|^2$$

Then $(Z_t)_{t \geq 0} \sim \text{OU}$ and $(R_t)_{t \geq 0} \sim \text{CIR}$

- ▶ $Z_t, R_t \xrightarrow{d} \mathcal{N}(0, 1), \text{Gamma}\left(\frac{n}{2} + \frac{\beta}{2} \frac{n(n-1)}{2}, \frac{n}{2}\right)$ as $t \rightarrow \infty$
- ▶ $R \stackrel{d}{=} |Z_*|^2$ with $Z_* \sim \text{OU}_{\mathbb{R}^m}$ when $m = n + \beta \frac{n(n-1)}{2} \in \mathbb{N}$

Cutoff for DOU : processes

- **Theorem** : Assume that $\beta = 0$ or $\beta \geq 1$ and set

$$Z_t = \sum_{i=1}^n X_t^{n,i} \quad \text{and} \quad R_t = \sum_{i=1}^n (X_t^{n,i})^2 = |X_t^n|^2$$

Then $(Z_t)_{t \geq 0} \sim \text{OU}$ and $(R_t)_{t \geq 0} \sim \text{CIR}$

- ▶ $Z_t, R_t \xrightarrow{d} \mathcal{N}(0, 1), \text{Gamma}(\frac{n}{2} + \frac{\beta}{2} \frac{n(n-1)}{2}, \frac{n}{2})$ as $t \rightarrow \infty$
- ▶ $R \stackrel{d}{=} |Z_*|^2$ with $Z_* \sim \text{OU}_{\mathbb{R}^m}$ when $m = n + \beta \frac{n(n-1)}{2} \in \mathbb{N}$

- **Proof** : Stroock–Varadhan local martingale

$$M_t^f = f(X_t) - f(X_0) - \int_0^t Lf(X_s) ds$$

$$\langle M \rangle_t = \int_0^t \Gamma(f)(X_s) ds, \text{ take } Lf = -\lambda f, \text{ then } f \in \{\pi_1, \pi_2\}$$

Plan

The model

Non-interacting case

Random matrix case

General interacting case

Cutoff for OU : Mean-field case

■ **Theorem** : if $\beta = 0$ and $\frac{|x_0^n|^2}{n} \asymp 1$ then for all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \text{dist}(\text{Law}(X_{t_n}^n) | P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

Cutoff for OU : Mean-field case

■ **Theorem** : if $\beta = 0$ and $\frac{|x_0^n|^2}{n} \asymp 1$ then for all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \text{dist}(\text{Law}(X_{t_n}^n) | P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

where

$$c_n = \begin{cases} \frac{1}{2} \log(n) & \text{if dist} = \text{Wasserstein} \\ \log(n) & \text{if dist} \in \{\chi^2, \text{Kullback}, \text{TV}, \text{Hellinger}\} \\ \frac{3}{2} \log(n) & \text{if dist} = \text{Fisher} \end{cases}$$

Cutoff for OU : Mean-field case

- **Theorem** : if $\beta = 0$ and $\frac{|x_0^n|^2}{n} \asymp 1$ then for all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \text{dist}(\text{Law}(X_{t_n}^n) | P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

where

$$c_n = \begin{cases} \frac{1}{2} \log(n) & \text{if dist} = \text{Wasserstein} \\ \log(n) & \text{if dist} \in \{\chi^2, \text{Kullback}, \text{TV}, \text{Hellinger}\} \\ \frac{3}{2} \log(n) & \text{if dist} = \text{Fisher} \end{cases}$$

- Other initial conditions ?

Cutoff for OU : General case

■ **Theorem** : if $\beta = 0$ and $\frac{|x_0^n|^2}{n} \asymp 1$ then for all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \text{dist}(\text{Law}(X_{t_n}^n) | P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

Cutoff for OU : General case

■ **Theorem** : if $\beta = 0$ and $\frac{|x_0^n|^2}{n} \asymp 1$ then for all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \text{dist}(\text{Law}(X_{t_n}^n) | P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

where

$$c_n = \begin{cases} \log(\sqrt{n}|x_0^n|) \vee \frac{1}{4} \log(n) & \text{if } \text{dist} \in \{\chi^2, \text{Kullback}, \text{TV}, \text{Hell.}\} \\ \log(n|x_0^n|) \vee \frac{1}{2} \log(n) & \text{if } \text{dist} = \text{Fisher} \end{cases}$$

Cutoff for OU : General case

■ **Theorem** : if $\beta = 0$ and $\frac{|x_0^n|^2}{n} \asymp 1$ then for all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \text{dist}(\text{Law}(X_{t_n}^n) | P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

where

$$c_n = \begin{cases} \log(\sqrt{n}|x_0^n|) \vee \frac{1}{4} \log(n) & \text{if } \text{dist} \in \{\chi^2, \text{Kullback}, \text{TV}, \text{Hell.}\} \\ \log(n|x_0^n|) \vee \frac{1}{2} \log(n) & \text{if } \text{dist} = \text{Fisher} \end{cases}$$

■ Bias versus variance

Cutoff for OU : General case

- **Theorem** : if $\beta = 0$ and $\frac{|x_0^n|^2}{n} \asymp 1$ then for all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \text{dist}(\text{Law}(X_{t_n}^n) | P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

where

$$c_n = \begin{cases} \log(\sqrt{n}|x_0^n|) \vee \frac{1}{4} \log(n) & \text{if dist} \in \{\chi^2, \text{Kullback}, \text{TV}, \text{Hell.}\} \\ \log(n|x_0^n|) \vee \frac{1}{2} \log(n) & \text{if dist} = \text{Fisher} \end{cases}$$

- Bias versus variance
- $\beta = 0$: $\mu_\infty^n = \mathcal{N}(0, \frac{1}{n}I_n)$, $\mu_\infty = \delta_0$

Cutoff for OU : General case

- **Theorem** : if $\beta = 0$ and $\frac{|x_0^n|^2}{n} \asymp 1$ then for all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \text{dist}(\text{Law}(X_{t_n}^n) | P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

where

$$c_n = \begin{cases} \log(\sqrt{n}|x_0^n|) \vee \frac{1}{4} \log(n) & \text{if dist} \in \{\chi^2, \text{Kullback}, \text{TV}, \text{Hell.}\} \\ \log(n|x_0^n|) \vee \frac{1}{2} \log(n) & \text{if dist} = \text{Fisher} \end{cases}$$

- Bias versus variance
- $\beta = 0$: $\mu_\infty^n = \mathcal{N}(0, \frac{1}{n}I_n)$, $\mu_\infty = \delta_0$
- Wasserstein ?

Cutoff for OU : General case (Wasserstein)

- **Theorem** : if $\beta = 0$ then for all $\varepsilon \in (0, 1)$

Cutoff for OU : General case (Wasserstein)

■ **Theorem** : if $\beta = 0$ then for all $\varepsilon \in (0, 1)$

▶ if $\lim_{n \rightarrow \infty} |x_0^n| = \infty$ then **cutoff** with $c_n = \log(|x_0^n|)$:

$$\lim_{n \rightarrow \infty} \text{Wasserstein}(\text{Law}(X_{t_n}^n), P^n) = \begin{cases} \infty & \text{if } t_n = (1 - \varepsilon) c_n \\ 0 & \text{if } t_n = (1 + \varepsilon) c_n \end{cases}$$

Cutoff for OU : General case (Wasserstein)

■ **Theorem** : if $\beta = 0$ then for all $\varepsilon \in (0, 1)$

▶ if $\lim_{n \rightarrow \infty} |x_0^n| = \infty$ then **cutoff** with $c_n = \log(|x_0^n|)$:

$$\lim_{n \rightarrow \infty} \text{Wasserstein}(\text{Law}(X_{t_n}^n), P^n) = \begin{cases} \infty & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

▶ if $\lim_{n \rightarrow \infty} |x_0^n| = \alpha \in [0, \infty)$ then **no cutoff** : for all $t > 0$,

$$\lim_{n \rightarrow \infty} \text{Wasserstein}^2(\text{Law}(X_t^n), P^n) = 1 + \frac{1}{2}(\alpha^2 - 1)e^{-2t} - \sqrt{1 - e^{-2t}}$$

Cutoff for OU : General case (Wasserstein)

■ **Theorem** : if $\beta = 0$ then for all $\varepsilon \in (0, 1)$

▶ if $\lim_{n \rightarrow \infty} |x_0^n| = \infty$ then **cutoff** with $c_n = \log(|x_0^n|)$:

$$\lim_{n \rightarrow \infty} \text{Wasserstein}(\text{Law}(X_{t_n}^n), P^n) = \begin{cases} \infty & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

▶ if $\lim_{n \rightarrow \infty} |x_0^n| = \alpha \in [0, \infty)$ then **no cutoff** : for all $t > 0$,

$$\lim_{n \rightarrow \infty} \text{Wasserstein}^2(\text{Law}(X_t^n), P^n) = 1 + \frac{1}{2}(\alpha^2 - 1)e^{-2t} - \sqrt{1 - e^{-2t}}$$

■ Reminds behavior of second moment m_2

Cutoff for OU : Proof 1/2

If $\Gamma_1 = \mathcal{N}(\mu_1, \Sigma_1)$ and $\Gamma_2 = \mathcal{N}(\mu_2, \Sigma_2)$ in \mathbb{R}^n then with $m = m_1 - m_2$:

$$\chi^2(\Gamma_1 | \Gamma_2) = \sqrt{\frac{|\Sigma_2|}{|2\Sigma_1 - \Sigma_1^2 \Sigma_2^{-1}|}} e^{\frac{1}{2} \Sigma_2^{-1} (I_n + 2\Sigma_1^{-1} \Sigma_2^{-1} - \Sigma_2^{-2}) m \cdot m} - 1$$

Cutoff for OU : Proof 1/2

If $\Gamma_1 = \mathcal{N}(\mu_1, \Sigma_1)$ and $\Gamma_2 = \mathcal{N}(\mu_2, \Sigma_2)$ in \mathbb{R}^n then with $m = m_1 - m_2$:

$$\chi^2(\Gamma_1 | \Gamma_2) = \sqrt{\frac{|\Sigma_2|}{|2\Sigma_1 - \Sigma_1^2 \Sigma_2^{-1}|}} e^{\frac{1}{2} \Sigma_2^{-1} (I_n + 2\Sigma_1^{-1} \Sigma_2^{-1} - \Sigma_2^{-2}) m \cdot m} - 1$$

$$2\text{Kullback}(\Gamma_1 | \Gamma_2) = \Sigma_2^{-1} m \cdot m + \text{Tr}(\Sigma_2^{-1} \Sigma_1 - I_n) + \log \det(\Sigma_2 \Sigma_1^{-1})$$

Cutoff for OU : Proof 1/2

If $\Gamma_1 = \mathcal{N}(\mu_1, \Sigma_1)$ and $\Gamma_2 = \mathcal{N}(\mu_2, \Sigma_2)$ in \mathbb{R}^n then with $m = m_1 - m_2$:

$$\chi^2(\Gamma_1 | \Gamma_2) = \sqrt{\frac{|\Sigma_2|}{|2\Sigma_1 - \Sigma_1^2 \Sigma_2^{-1}|}} e^{\frac{1}{2} \Sigma_2^{-1} (I_n + 2\Sigma_1^{-1} \Sigma_2^{-1} - \Sigma_2^{-2}) m \cdot m} - 1$$

$$2\text{Kullback}(\Gamma_1 | \Gamma_2) = \Sigma_2^{-1} m \cdot m + \text{Tr}(\Sigma_2^{-1} \Sigma_1 - I_n) + \log \det(\Sigma_2 \Sigma_1^{-1})$$

$$\text{Fisher}(\Gamma_1 | \Gamma_2) = |\Sigma_2^{-1} m|^2 + \text{Tr}(\Sigma_2^{-2} \Sigma_1 - 2\Sigma_2^{-1} + \Sigma_1^{-1})$$

Cutoff for OU : Proof 1/2

If $\Gamma_1 = \mathcal{N}(\mu_1, \Sigma_1)$ and $\Gamma_2 = \mathcal{N}(\mu_2, \Sigma_2)$ in \mathbb{R}^n then with $m = m_1 - m_2$:

$$\chi^2(\Gamma_1 | \Gamma_2) = \sqrt{\frac{|\Sigma_2|}{|2\Sigma_1 - \Sigma_1^2 \Sigma_2^{-1}|}} e^{\frac{1}{2} \Sigma_2^{-1} (I_n + 2\Sigma_1^{-1} \Sigma_2^{-1} - \Sigma_2^{-2}) m \cdot m} - 1$$

$$2\text{Kullback}(\Gamma_1 | \Gamma_2) = \Sigma_2^{-1} m \cdot m + \text{Tr}(\Sigma_2^{-1} \Sigma_1 - I_n) + \log \det(\Sigma_2 \Sigma_1^{-1})$$

$$\begin{aligned} \text{Fisher}(\Gamma_1 | \Gamma_2) &= |\Sigma_2^{-1} m|^2 + \text{Tr}(\Sigma_2^{-2} \Sigma_1 - 2\Sigma_2^{-1} + \Sigma_1^{-1}) \\ &\stackrel{*}{=} |\Sigma_2^{-1} m|^2 + \text{Tr}(\Sigma_2^{-2} (\Sigma_2 - \Sigma_1)^2 \Sigma_1^{-1}) \end{aligned}$$

Cutoff for OU : Proof 1/2

If $\Gamma_1 = \mathcal{N}(\mu_1, \Sigma_1)$ and $\Gamma_2 = \mathcal{N}(\mu_2, \Sigma_2)$ in \mathbb{R}^n then with $m = m_1 - m_2$:

$$\chi^2(\Gamma_1 | \Gamma_2) = \sqrt{\frac{|\Sigma_2|}{|2\Sigma_1 - \Sigma_1^2 \Sigma_2^{-1}|}} e^{\frac{1}{2} \Sigma_2^{-1} (I_n + 2\Sigma_1^{-1} \Sigma_2^{-1} - \Sigma_2^{-2}) m \cdot m} - 1$$

$$2\text{Kullback}(\Gamma_1 | \Gamma_2) = \Sigma_2^{-1} m \cdot m + \text{Tr}(\Sigma_2^{-1} \Sigma_1 - I_n) + \log \det(\Sigma_2 \Sigma_1^{-1})$$

$$\begin{aligned} \text{Fisher}(\Gamma_1 | \Gamma_2) &= |\Sigma_2^{-1} m|^2 + \text{Tr}(\Sigma_2^{-2} \Sigma_1 - 2\Sigma_2^{-1} + \Sigma_1^{-1}) \\ &\stackrel{*}{=} |\Sigma_2^{-1} m|^2 + \text{Tr}(\Sigma_2^{-2} (\Sigma_2 - \Sigma_1)^2 \Sigma_1^{-1}) \end{aligned}$$

$$2\text{Wasserstein}^2(\Gamma_1, \Gamma_2) = |m|^2 + \text{Tr}\left(\Sigma_1 + \Sigma_2 - 2\sqrt{\sqrt{\Sigma_1} \Sigma_2 \sqrt{\Sigma_1}}\right)$$

Cutoff for OU : Proof 1/2

If $\Gamma_1 = \mathcal{N}(\mu_1, \Sigma_1)$ and $\Gamma_2 = \mathcal{N}(\mu_2, \Sigma_2)$ in \mathbb{R}^n then with $m = m_1 - m_2$:

$$\chi^2(\Gamma_1 | \Gamma_2) = \sqrt{\frac{|\Sigma_2|}{|2\Sigma_1 - \Sigma_1^2 \Sigma_2^{-1}|}} e^{\frac{1}{2} \Sigma_2^{-1} (I_n + 2\Sigma_1^{-1} \Sigma_2^{-1} - \Sigma_2^{-2}) m \cdot m} - 1$$

$$2\text{Kullback}(\Gamma_1 | \Gamma_2) = \Sigma_2^{-1} m \cdot m + \text{Tr}(\Sigma_2^{-1} \Sigma_1 - I_n) + \log \det(\Sigma_2 \Sigma_1^{-1})$$

$$\begin{aligned} \text{Fisher}(\Gamma_1 | \Gamma_2) &= |\Sigma_2^{-1} m|^2 + \text{Tr}(\Sigma_2^{-2} \Sigma_1 - 2\Sigma_2^{-1} + \Sigma_1^{-1}) \\ &\stackrel{*}{=} |\Sigma_2^{-1} m|^2 + \text{Tr}(\Sigma_2^{-2} (\Sigma_2 - \Sigma_1)^2 \Sigma_1^{-1}) \end{aligned}$$

$$\begin{aligned} 2\text{Wasserstein}^2(\Gamma_1, \Gamma_2) &= |m|^2 + \text{Tr}\left(\Sigma_1 + \Sigma_2 - 2\sqrt{\sqrt{\Sigma_1} \Sigma_2 \sqrt{\Sigma_1}}\right) \\ &\stackrel{*}{=} |m|^2 + \text{Tr}((\sqrt{\Sigma_1} - \sqrt{\Sigma_2})^2) \end{aligned}$$

Cutoff for OU : Proof 1/2

If $\Gamma_1 = \mathcal{N}(\mu_1, \Sigma_1)$ and $\Gamma_2 = \mathcal{N}(\mu_2, \Sigma_2)$ in \mathbb{R}^n then with $m = m_1 - m_2$:

$$\chi^2(\Gamma_1 | \Gamma_2) = \sqrt{\frac{|\Sigma_2|}{|2\Sigma_1 - \Sigma_1^2 \Sigma_2^{-1}|}} e^{\frac{1}{2} \Sigma_2^{-1} (I_n + 2\Sigma_1^{-1} \Sigma_2^{-1} - \Sigma_2^{-2}) m \cdot m} - 1$$

$$2\text{Kullback}(\Gamma_1 | \Gamma_2) = \Sigma_2^{-1} m \cdot m + \text{Tr}(\Sigma_2^{-1} \Sigma_1 - I_n) + \log \det(\Sigma_2 \Sigma_1^{-1})$$

$$\begin{aligned} \text{Fisher}(\Gamma_1 | \Gamma_2) &= |\Sigma_2^{-1} m|^2 + \text{Tr}(\Sigma_2^{-2} \Sigma_1 - 2\Sigma_2^{-1} + \Sigma_1^{-1}) \\ &\stackrel{*}{=} |\Sigma_2^{-1} m|^2 + \text{Tr}(\Sigma_2^{-2} (\Sigma_2 - \Sigma_1)^2 \Sigma_1^{-1}) \end{aligned}$$

$$\begin{aligned} 2\text{Wasserstein}^2(\Gamma_1, \Gamma_2) &= |m|^2 + \text{Tr}\left(\Sigma_1 + \Sigma_2 - 2\sqrt{\sqrt{\Sigma_1} \Sigma_2 \sqrt{\Sigma_1}}\right) \\ &\stackrel{*}{=} |m|^2 + \text{Tr}((\sqrt{\Sigma_1} - \sqrt{\Sigma_2})^2) \end{aligned}$$

$$\text{Hellinger}^2(\Gamma_1, \Gamma_2) = 1 - \sqrt{\frac{\sqrt{\det(\Sigma_1 \Sigma_2)}}{\det\left(\frac{\Sigma_1 + \Sigma_2}{2}\right)}} \exp\left(-\frac{1}{4}(\Sigma_1 + \Sigma_2)^{-1} m \cdot m\right)$$

Cutoff for OU : Proof 1/2

If $\Gamma_1 = \mathcal{N}(\mu_1, \Sigma_1)$ and $\Gamma_2 = \mathcal{N}(\mu_2, \Sigma_2)$ in \mathbb{R}^n then with $m = m_1 - m_2$:

$$\chi^2(\Gamma_1 | \Gamma_2) = \sqrt{\frac{|\Sigma_2|}{|2\Sigma_1 - \Sigma_1^2 \Sigma_2^{-1}|}} e^{\frac{1}{2} \Sigma_2^{-1} (I_n + 2\Sigma_1^{-1} \Sigma_2^{-1} - \Sigma_2^{-2}) m \cdot m} - 1$$

$$2\text{Kullback}(\Gamma_1 | \Gamma_2) = \Sigma_2^{-1} m \cdot m + \text{Tr}(\Sigma_2^{-1} \Sigma_1 - I_n) + \log \det(\Sigma_2 \Sigma_1^{-1})$$

$$\begin{aligned} \text{Fisher}(\Gamma_1 | \Gamma_2) &= |\Sigma_2^{-1} m|^2 + \text{Tr}(\Sigma_2^{-2} \Sigma_1 - 2\Sigma_2^{-1} + \Sigma_1^{-1}) \\ &\stackrel{*}{=} |\Sigma_2^{-1} m|^2 + \text{Tr}(\Sigma_2^{-2} (\Sigma_2 - \Sigma_1)^2 \Sigma_1^{-1}) \end{aligned}$$

$$\begin{aligned} 2\text{Wasserstein}^2(\Gamma_1, \Gamma_2) &= |m|^2 + \text{Tr}\left(\Sigma_1 + \Sigma_2 - 2\sqrt{\sqrt{\Sigma_1} \Sigma_2 \sqrt{\Sigma_1}}\right) \\ &\stackrel{*}{=} |m|^2 + \text{Tr}((\sqrt{\Sigma_1} - \sqrt{\Sigma_2})^2) \end{aligned}$$

$$\text{Hellinger}^2(\Gamma_1, \Gamma_2) = 1 - \sqrt{\frac{\sqrt{\det(\Sigma_1 \Sigma_2)}}{\det\left(\frac{\Sigma_1 + \Sigma_2}{2}\right)}} \exp\left(-\frac{1}{4}(\Sigma_1 + \Sigma_2)^{-1} m \cdot m\right)$$

$$\|\mu - \nu\|_{\text{TV}} \leq \sqrt{2\text{Kullback}(\nu | \mu)}$$

Cutoff for OU : Proof 1/2

If $\Gamma_1 = \mathcal{N}(\mu_1, \Sigma_1)$ and $\Gamma_2 = \mathcal{N}(\mu_2, \Sigma_2)$ in \mathbb{R}^n then with $m = m_1 - m_2$:

$$\chi^2(\Gamma_1 | \Gamma_2) = \sqrt{\frac{|\Sigma_2|}{|2\Sigma_1 - \Sigma_1^2 \Sigma_2^{-1}|}} e^{\frac{1}{2} \Sigma_2^{-1} (I_n + 2\Sigma_1^{-1} \Sigma_2^{-1} - \Sigma_2^{-2}) m \cdot m} - 1$$

$$2\text{Kullback}(\Gamma_1 | \Gamma_2) = \Sigma_2^{-1} m \cdot m + \text{Tr}(\Sigma_2^{-1} \Sigma_1 - I_n) + \log \det(\Sigma_2 \Sigma_1^{-1})$$

$$\begin{aligned} \text{Fisher}(\Gamma_1 | \Gamma_2) &= |\Sigma_2^{-1} m|^2 + \text{Tr}(\Sigma_2^{-2} \Sigma_1 - 2\Sigma_2^{-1} + \Sigma_1^{-1}) \\ &\stackrel{*}{=} |\Sigma_2^{-1} m|^2 + \text{Tr}(\Sigma_2^{-2} (\Sigma_2 - \Sigma_1)^2 \Sigma_1^{-1}) \end{aligned}$$

$$\begin{aligned} 2\text{Wasserstein}^2(\Gamma_1, \Gamma_2) &= |m|^2 + \text{Tr}\left(\Sigma_1 + \Sigma_2 - 2\sqrt{\sqrt{\Sigma_1} \Sigma_2 \sqrt{\Sigma_1}}\right) \\ &\stackrel{*}{=} |m|^2 + \text{Tr}((\sqrt{\Sigma_1} - \sqrt{\Sigma_2})^2) \end{aligned}$$

$$\text{Hellinger}^2(\Gamma_1, \Gamma_2) = 1 - \sqrt{\frac{\sqrt{\det(\Sigma_1 \Sigma_2)}}{\det\left(\frac{\Sigma_1 + \Sigma_2}{2}\right)}} \exp\left(-\frac{1}{4}(\Sigma_1 + \Sigma_2)^{-1} m \cdot m\right)$$

$$\|\mu - \nu\|_{\text{TV}} \leq \sqrt{2\text{Kullback}(\nu | \mu)}$$

$$\text{Hellinger}^2(\mu, \nu) \leq \|\mu - \nu\|_{\text{TV}} \leq \text{Hellinger}(\mu, \nu) \sqrt{2 - \text{Hellinger}(\mu, \nu)^2}$$

Cutoff for OU : Proof 2/2

If $\beta = 0$ and $X_0^n = x_0^n$ then $X_t^n \sim \mathcal{N}(x_0^n e^{-t}, \frac{1}{n}(1 - e^{-t})I_n)$ and

Cutoff for OU : Proof 2/2

If $\beta = 0$ and $X_0^n = x_0^n$ then $X_t^n \sim \mathcal{N}(x_0^n e^{-t}, \frac{1}{n}(1 - e^{-t})I_n)$ and

$$\chi^2(\text{Law}(X_t^n) | P^n) = \frac{1}{(1 - e^{-4t})^{n/2}} \exp\left(n|x_0^n|^2 \frac{e^{-2t}}{1 + e^{-2t}}\right) - 1$$

$$\text{Kullback}(\text{Law}(X_t^n) | P^n) = \frac{1}{2} \left(n|x_0^n|^2 e^{-2t} - n e^{-2t} - n \log(1 - e^{-2t}) \right)$$

$$\text{Fisher}(\text{Law}(X_t^n) | P^n) = n^2 |x_0^n|^2 e^{-2t} + n^2 \frac{e^{-4t}}{1 - e^{-2t}}$$

$$\text{Hellinger}^2(\text{Law}(X_t^n), P^n) = 1 - \exp\left(-\frac{n}{4} \frac{|x_0^n|^2 e^{-2t}}{2 - e^{-2t}} + \frac{n}{4} \log\left(4 \frac{1 - e^{-2t}}{(2 - e^{-2t})^2}\right)\right)$$

$$\text{Wasserstein}^2(\text{Law}(X_t^n), P^n) = 1 + \frac{1}{2} (|x_0^n|^2 - 1) e^{-2t} - \sqrt{1 - e^{-2t}}$$

Cutoff for OU : Proof 2/2

If $\beta = 0$ and $X_0^n = x_0^n$ then $X_t^n \sim \mathcal{N}(x_0^n e^{-t}, \frac{1}{n}(1 - e^{-t})I_n)$ and

$$\chi^2(\text{Law}(X_t^n) | P^n) = \frac{1}{(1 - e^{-4t})^{n/2}} \exp\left(n|x_0^n|^2 \frac{e^{-2t}}{1 + e^{-2t}}\right) - 1$$

$$\text{Kullback}(\text{Law}(X_t^n) | P^n) = \frac{1}{2} \left(n|x_0^n|^2 e^{-2t} - ne^{-2t} - n \log(1 - e^{-2t}) \right)$$

$$\text{Fisher}(\text{Law}(X_t^n) | P^n) = n^2|x_0^n|^2 e^{-2t} + n^2 \frac{e^{-4t}}{1 - e^{-2t}}$$

$$\text{Hellinger}^2(\text{Law}(X_t^n), P^n) = 1 - \exp\left(-\frac{n}{4} \frac{|x_0^n|^2 e^{-2t}}{2 - e^{-2t}} + \frac{n}{4} \log\left(4 \frac{1 - e^{-2t}}{(2 - e^{-2t})^2}\right)\right)$$

$$\text{Wasserstein}^2(\text{Law}(X_t^n), P^n) = 1 + \frac{1}{2} (|x_0^n|^2 - 1) e^{-2t} - \sqrt{1 - e^{-2t}}$$

Melted **noise** and **dimension** : $dX_t^n = \sqrt{\frac{2}{n}} dB_t - X_t^n dt$ in \mathbb{R}^n

Cutoff for OU : Proof 2/2

If $\beta = 0$ and $X_0^n = x_0^n$ then $X_t^n \sim \mathcal{N}(x_0^n e^{-t}, \frac{1}{n}(1 - e^{-t})I_n)$ and

$$\chi^2(\text{Law}(X_t^n) | P^n) = \frac{1}{(1 - e^{-4t})^{n/2}} \exp\left(n|x_0^n|^2 \frac{e^{-2t}}{1 + e^{-2t}}\right) - 1$$

$$\text{Kullback}(\text{Law}(X_t^n) | P^n) = \frac{1}{2} \left(n|x_0^n|^2 e^{-2t} - n e^{-2t} - n \log(1 - e^{-2t}) \right)$$

$$\text{Fisher}(\text{Law}(X_t^n) | P^n) = n^2 |x_0^n|^2 e^{-2t} + n^2 \frac{e^{-4t}}{1 - e^{-2t}}$$

$$\text{Hellinger}^2(\text{Law}(X_t^n), P^n) = 1 - \exp\left(-\frac{n}{4} \frac{|x_0^n|^2 e^{-2t}}{2 - e^{-2t}} + \frac{n}{4} \log\left(4 \frac{1 - e^{-2t}}{(2 - e^{-2t})^2}\right)\right)$$

$$\text{Wasserstein}^2(\text{Law}(X_t^n), P^n) = 1 + \frac{1}{2} (|x_0^n|^2 - 1) e^{-2t} - \sqrt{1 - e^{-2t}}$$

Melted **noise** and **dimension** : $dX_t^n = \sqrt{\frac{2}{n}} dB_t - X_t^n dt$ in \mathbb{R}^n

$\log(n)$ cutoff for $\text{dist}(\text{Law}(X_t^n) | P^n)$: n versus e^{-t}

Plan

The model

Non-interacting case

Random matrix case

General interacting case

Cutoff for DOU: Random matrix case

- **Theorem :** Assume that $\beta \in \{1, 2, 4\}$. Let (a_n) be such that $\inf(a_n) > 0$. Then for all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in [-a_n, a_n]^n} \text{dist}(\text{Law}(X_{t_n}^n) | P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

Cutoff for DOU: Random matrix case

- **Theorem** : Assume that $\beta \in \{1, 2, 4\}$. Let (a_n) be such that $\inf(a_n) > 0$. Then for all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in [-a_n, a_n]^n} \text{dist}(\text{Law}(X_{t_n}^n) \mid P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

where

$$c_n = \begin{cases} \log(\sqrt{n}a_n) & \text{if dist} = \text{Wasserstein} \\ \log(na_n) & \text{if dist} \in \{\text{Kullback, TV, Hellinger}\} \end{cases}$$

Cutoff for DOU: Random matrix case

- **Theorem :** Assume that $\beta \in \{1, 2, 4\}$. Let (a_n) be such that $\inf(a_n) > 0$. Then for all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in [-a_n, a_n]^n} \text{dist}(\text{Law}(X_{t_n}^n) \mid P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

where

$$c_n = \begin{cases} \log(\sqrt{n}a_n) & \text{if dist = Wasserstein} \\ \log(na_n) & \text{if dist} \in \{\text{Kullback, TV, Hellinger}\} \end{cases}$$

- **Proof :** OU sandwich (trace Z , matrix M) + dist contract.

Cutoff for DOU: Random matrix case

- **Theorem :** Assume that $\beta \in \{1, 2, 4\}$. Let (a_n) be such that $\inf(a_n) > 0$. Then for all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in [-a_n, a_n]^n} \text{dist}(\text{Law}(X_{t_n}^n) \mid P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

where

$$c_n = \begin{cases} \log(\sqrt{n}a_n) & \text{if dist = Wasserstein} \\ \log(na_n) & \text{if dist} \in \{\text{Kullback, TV, Hellinger}\} \end{cases}$$

- Proof : OU sandwich (trace Z , matrix M) + dist contract.
- Cutoff should be controlled by $|x_0^n - \rho^n|$ instead of $|x_0^n|$

Plan

The model

Non-interacting case

Random matrix case

General interacting case

Cutoff for DOU: general case

- **Theorem :** Assume that $\beta = 0$ or $\beta \geq 1$. Let (a_n) be such that $\inf(a_n) > 0$. Then for all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in [-a_n, a_n]^n} \text{dist}(\text{Law}(X_{t_n}^n) | P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

Cutoff for DOU: general case

- **Theorem :** Assume that $\beta = 0$ or $\beta \geq 1$. Let (a_n) be such that $\inf(a_n) > 0$. Then for all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in [-a_n, a_n]^n} \text{dist}(\text{Law}(X_{t_n}^n) \mid P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

where

$$c_n = \begin{cases} \log(\sqrt{n}a_n) & \text{if dist} = \text{Wasserstein} \\ \log(na_n) & \text{if dist} \in \{\text{TV}, \text{Hellinger}\} \end{cases}$$

Cutoff for DOU: general case

- **Theorem :** Assume that $\beta = 0$ or $\beta \geq 1$. Let (a_n) be such that $\inf(a_n) > 0$. Then for all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in [-a_n, a_n]^n} \text{dist}(\text{Law}(X_{t_n}^n) \mid P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

where

$$c_n = \begin{cases} \log(\sqrt{n}a_n) & \text{if dist} = \text{Wasserstein} \\ \log(na_n) & \text{if dist} \in \{\text{TV}, \text{Hellinger}\} \end{cases}$$

- Lower bound : Contraction to OU Z

Cutoff for DOU: general case

- **Theorem :** Assume that $\beta = 0$ or $\beta \geq 1$. Let (a_n) be such that $\inf(a_n) > 0$. Then for all $\varepsilon \in (0, 1)$

$$\lim_{n \rightarrow \infty} \sup_{x_0^n \in [-a_n, a_n]^n} \text{dist}(\text{Law}(X_{t_n}^n) \mid P^n) = \begin{cases} \max & \text{if } t_n = (1 - \varepsilon)c_n \\ 0 & \text{if } t_n = (1 + \varepsilon)c_n \end{cases}$$

where

$$c_n = \begin{cases} \log(\sqrt{n}a_n) & \text{if dist} = \text{Wasserstein} \\ \log(na_n) & \text{if dist} \in \{\text{TV}, \text{Hellinger}\} \end{cases}$$

- Lower bound : Contraction to OU Z
- Upper bound : LSI, regularization, coupling (\sim exclusion)

Cutoff for DOU : Proof for general case (1/2)

- Optimal log-Sobolev inequality

$$\text{Kullback}(\nu | P^n) \leq \frac{1}{2n} \text{Fisher}(\nu | P^n)$$

Cutoff for DOU : Proof for general case (1/2)

- Optimal log-Sobolev inequality

$$\text{Kullback}(\nu | P^n) \leq \frac{1}{2n} \text{Fisher}(\nu | P^n) = -\frac{1}{2} \int \log(f) Lf dP^n$$

- Exponential entropy decay

$$\text{Kullback}(\text{Law}(X_t^n) | P^n) \leq e^{-2t} \text{Kullback}(\text{Law}(X_0^n) | P^n)$$

Cutoff for DOU : Proof for general case (1/2)

- Optimal log-Sobolev inequality

$$\text{Kullback}(\nu | P^n) \leq \frac{1}{2n} \text{Fisher}(\nu | P^n) = -\frac{1}{2} \int \log(f) Lf dP^n$$

- Exponential entropy decay

$$\text{Kullback}(\text{Law}(X_t^n) | P^n) \leq e^{-2t} \text{Kullback}(\text{Law}(X_0^n) | P^n)$$

- Regularization Y^n of X^n (smoothed $Y_0^{n,i} \geq X_0^{n,i} = x_0^{n,i}$)

$$\text{Kullback}(\text{Law}(Y_t^n) | P^n) \leq C(n|x_0^n|^2 + n^2 \log(n))e^{-2t}$$

Cutoff for DOU : Proof for general case (2/2)

- Coalescent coupling preserving order $Y_t^{n,i} \geq X_t^{n,i}$

$$\begin{aligned}\|\text{Law}(Y_t^n) - \text{Law}(X_t^n)\|_{\text{TV}} &\leq \mathbb{P}(Y_t^n \neq X_t^n) \\ &\leq \mathbb{P}(\inf\{s \geq 0 : A_s^n = 0\} > t)\end{aligned}$$

Cutoff for DOU : Proof for general case (2/2)

- Coalescent coupling preserving order $Y_t^{n,i} \geq X_t^{n,i}$

$$\begin{aligned}\|\text{Law}(Y_t^n) - \text{Law}(X_t^n)\|_{\text{TV}} &\leq \mathbb{P}(Y_t^n \neq X_t^n) \\ &\leq \mathbb{P}(\inf\{s \geq 0 : A_s^n = 0\} > t)\end{aligned}$$

- “Area” $A_t = \sum_{i=1}^n (Y_t^{n,i} - X_t^{n,i})$ is an AR sort of OU

$$dA_t = -A_t dt + dM_t$$

Cutoff for DOU : Proof for general case (2/2)

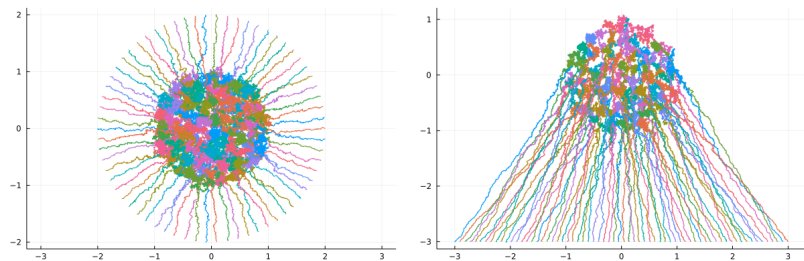
- Coalescent coupling preserving order $Y_t^{n,i} \geq X_t^{n,i}$

$$\begin{aligned} \|\text{Law}(Y_t^n) - \text{Law}(X_t^n)\|_{\text{TV}} &\leq \mathbb{P}(Y_t^n \neq X_t^n) \\ &\leq \mathbb{P}(\inf\{s \geq 0 : A_s^n = 0\} > t) \end{aligned}$$

- “Area” $A_t = \sum_{i=1}^n (Y_t^{n,i} - X_t^{n,i})$ is an AR sort of OU

$$dA_t = -A_t dt + dM_t$$

- Submartingale in $[0, 1]$ $e^{-\lambda A - \frac{\lambda^2}{2} \langle A \rangle}$



julia

$\mathbb{C}^n, -\log|\cdot|$

spectrum, eigenfunctions

Poincaré, log-Sobolev, cutoff at $\log(n)$

Open problems & Selected bibliography

- Problems

Open problems & Selected bibliography

■ Problems

- ▶ V : Exactly solvable cases (Hermite/Laguerre/Jacobi)

Open problems & Selected bibliography

■ Problems

- ▶ V : Exactly solvable cases (Hermite/Laguerre/Jacobi)
- ▶ V : General strong convex case (Bakry-Émery or KLS)

Open problems & Selected bibliography

■ Problems

- ▶ V : Exactly solvable cases (Hermite/Laguerre/Jacobi)
- ▶ V : General strong convex case (Bakry-Émery or KLS)
- ▶ Better initial conditions (ρ^n), other distances (Fisher, ...)

Open problems & Selected bibliography

■ Problems

- ▶ V : Exactly solvable cases (Hermite/Laguerre/Jacobi)
- ▶ V : General strong convex case (Bakry-Émery or KLS)
- ▶ Better initial conditions (ρ^n), other distances (Fisher, ...)
- ▶ Non-convex interactions (such as planar DOU dynamics)

Open problems & Selected bibliography

■ Problems

- ▶ V : Exactly solvable cases (Hermite/Laguerre/Jacobi)
- ▶ V : General strong convex case (Bakry-Émery or KLS)
- ▶ Better initial conditions (ρ^n), other distances (Fisher, ...)
- ▶ Non-convex interactions (such as planar DOU dynamics)
- ▶ Concentration around profile (Aldous, Salez)

Open problems & Selected bibliography

■ Problems

- ▶ V : Exactly solvable cases (Hermite/Laguerre/Jacobi)
- ▶ V : General strong convex case (Bakry-Émery or KLS)
- ▶ Better initial conditions (ρ^n), other distances (Fisher, ...)
- ▶ Non-convex interactions (such as planar DOU dynamics)
- ▶ Concentration around profile (Aldous, Salez)

■ Bibliography

Open problems & Selected bibliography

■ Problems

- ▶ V : Exactly solvable cases (Hermite/Laguerre/Jacobi)
- ▶ V : General strong convex case (Bakry-Émery or KLS)
- ▶ Better initial conditions (ρ^n), other distances (Fisher, ...)
- ▶ Non-convex interactions (such as planar DOU dynamics)
- ▶ Concentration around profile (Aldous, Salez)

■ Bibliography

- ▶ Dyson, Anderson-Guionnet-Zeitouni, Erdős-Yau

Open problems & Selected bibliography

■ Problems

- ▶ V : Exactly solvable cases (Hermite/Laguerre/Jacobi)
- ▶ V : General strong convex case (Bakry-Émery or KLS)
- ▶ Better initial conditions (ρ^n), other distances (Fisher, ...)
- ▶ Non-convex interactions (such as planar DOU dynamics)
- ▶ Concentration around profile (Aldous, Salez)

■ Bibliography

- ▶ Dyson, Anderson-Guionnet-Zeitouni, Erdős-Yau
- ▶ Voiculescu, Rogers-Shi, Biane

Open problems & Selected bibliography

■ Problems

- ▶ V : Exactly solvable cases (Hermite/Laguerre/Jacobi)
- ▶ V : General strong convex case (Bakry-Émery or KLS)
- ▶ Better initial conditions (ρ^n), other distances (Fisher, ...)
- ▶ Non-convex interactions (such as planar DOU dynamics)
- ▶ Concentration around profile (Aldous, Salez)

■ Bibliography

- ▶ Dyson, Anderson-Guionnet-Zeitouni, Erdős-Yau
- ▶ Voiculescu, Rogers-Shi, Biane
- ▶ Lassalle, Baker-Forrester

Open problems & Selected bibliography

■ Problems

- ▶ V : Exactly solvable cases (Hermite/Laguerre/Jacobi)
- ▶ V : General strong convex case (Bakry-Émery or KLS)
- ▶ Better initial conditions (ρ^n), other distances (Fisher, ...)
- ▶ Non-convex interactions (such as planar DOU dynamics)
- ▶ Concentration around profile (Aldous, Salez)

■ Bibliography

- ▶ Dyson, Anderson-Guionnet-Zeitouni, Erdős-Yau
- ▶ Voiculescu, Rogers-Shi, Biane
- ▶ Lassalle, Baker-Forrester
- ▶ Lachaud, Barrera-Jara

Open problems & Selected bibliography

■ Problems

- ▶ V : Exactly solvable cases (Hermite/Laguerre/Jacobi)
- ▶ V : General strong convex case (Bakry-Émery or KLS)
- ▶ Better initial conditions (ρ^n), other distances (Fisher, ...)
- ▶ Non-convex interactions (such as planar DOU dynamics)
- ▶ Concentration around profile (Aldous, Salez)

■ Bibliography

- ▶ Dyson, Anderson-Guionnet-Zeitouni, Erdős-Yau
- ▶ Voiculescu, Rogers-Shi, Biane
- ▶ Lassalle, Baker-Forrester
- ▶ Lachaud, Barrera-Jara
- ▶ Ané et al, Bakry-Gentil-Ledoux, Villani

Open problems & Selected bibliography

■ Problems

- ▶ V : Exactly solvable cases (Hermite/Laguerre/Jacobi)
- ▶ V : General strong convex case (Bakry-Émery or KLS)
- ▶ Better initial conditions (ρ^n), other distances (Fisher, ...)
- ▶ Non-convex interactions (such as planar DOU dynamics)
- ▶ Concentration around profile (Aldous, Salez)

■ Bibliography

- ▶ Dyson, Anderson-Guionnet-Zeitouni, Erdős-Yau
- ▶ Voiculescu, Rogers-Shi, Biane
- ▶ Lassalle, Baker-Forrester
- ▶ Lachaud, Barrera-Jara
- ▶ Ané et al, Bakry-Gentil-Ledoux, Villani
- ▶ Saloff-Coste, Méliot, Lacoïn

Open problems & Selected bibliography

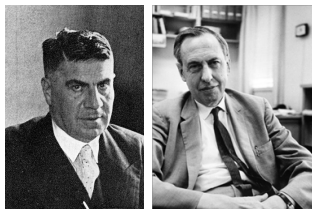
■ Problems

- ▶ V : Exactly solvable cases (Hermite/Laguerre/Jacobi)
- ▶ V : General strong convex case (Bakry-Émery or KLS)
- ▶ Better initial conditions (ρ^n), other distances (Fisher, ...)
- ▶ Non-convex interactions (such as planar DOU dynamics)
- ▶ Concentration around profile (Aldous, Salez)

■ Bibliography

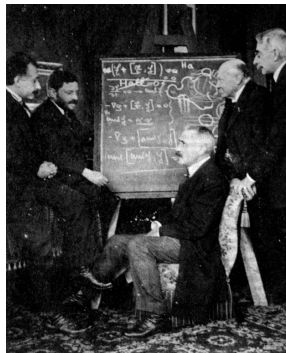
- ▶ Dyson, Anderson-Guionnet-Zeitouni, Erdős-Yau
- ▶ Voiculescu, Rogers-Shi, Biane
- ▶ Lassalle, Baker-Forrester
- ▶ Lachaud, Barrera-Jara
- ▶ Ané et al, Bakry-Gentil-Ledoux, Villani
- ▶ Saloff-Coste, Méliot, Lacoïn
- ▶ C.-Lehec, Bolley-C.-Fontbona, Lu-Mattingly

Leonard Salomon Ornstein (1880 – 1941)
George Eugene Uhlenbeck (1900 – 1988)



On the theory of Brownian Motion
Physical Reviews 36 (5) 823–841 (1930)

Paul Langevin (1872 – 1946)



Sur la théorie du mouvement brownien
Comptes-rendus de l'Académie des sciences (9 mars 1908)