

INTRODUCTION TO STOCHASTIC PROCESSES

1. From microscopic to macroscopic: role of fluctuations and randomness -

• Microscopic classical system:  $N$  particles of positions  $\{\vec{x}_i^{mic}\} 1 \leq i \leq N$

\* Evolution in time: Newton's law  $m_i \ddot{\vec{x}}_i^{mic} = \vec{F}_i(\{\vec{x}_j^{mic}\})$

forces ruling interactions between particles and with the environment

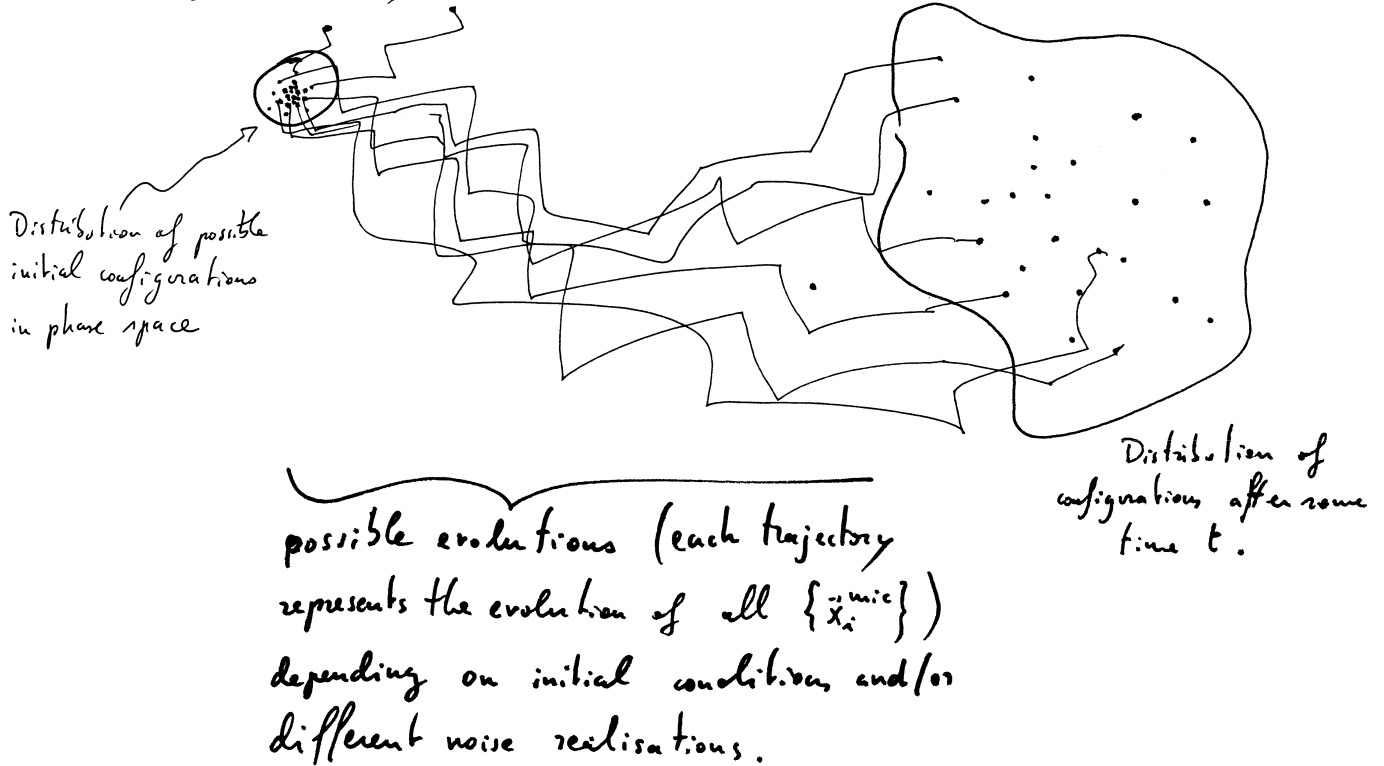
Deterministic equations

\* Very difficult to solve in general. Yet one would like to understand how things work!

\* Even if a solution is available

- high sensitivity to initial conditions (Chaos) (Think of billiards or of the baker transformation)

- high sensitivity to noise



→ Idea: Focus on distributions rather than on individual trajectories (which also helps to smooth out microscopic details)

• 1st solution: equilibrium thermodynamics (Boltzmann, Gibbs)

- x microcanonical ensemble: all configurations with the same energy are equiprobable
- x canonical ensemble: equilibration with a thermostat of temperature  $\beta^{-1}$  (or other global conserved quantity)

$$\text{Prob (configuration)} \propto \exp \{ -\beta \text{Energy (configuration)} \}$$

↳ Applies

- x to determine the mean value of observables
- x in the limit of very large system size
- x at equilibrium (no currents) and for static properties

This provides a very generic framework, but is unsuitable to catch

- x full distributions of observables (not only the mean value)
- x non-equilibrium (currents or time evolutions) dynamics
- x generic effects of finite system size

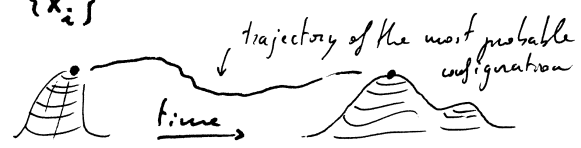
These effects are less generic (they depend on some microscopic features)

• 2nd solution: adopt a mesoscopic point of view (i.e. including fluctuations)

Focus on some mesoscopic degrees of freedom  $\{\vec{x}_i\}$

Two complementary descriptions:

- x evolution of the distribution  $P(\{\vec{x}_i\}, t)$

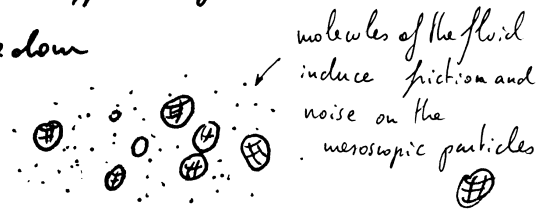


- x (effective) evolution of stochastic trajectories

$$\text{e.g. } \boxed{m_i \ddot{\vec{x}}_i = \underbrace{-\gamma_i \dot{\vec{x}}_i}_{\text{friction}} + \underbrace{\vec{F}_i(\{\vec{x}_j\}, t)}_{\text{noise}} + \underbrace{\vec{\eta}_i}_{\text{noise}}}$$

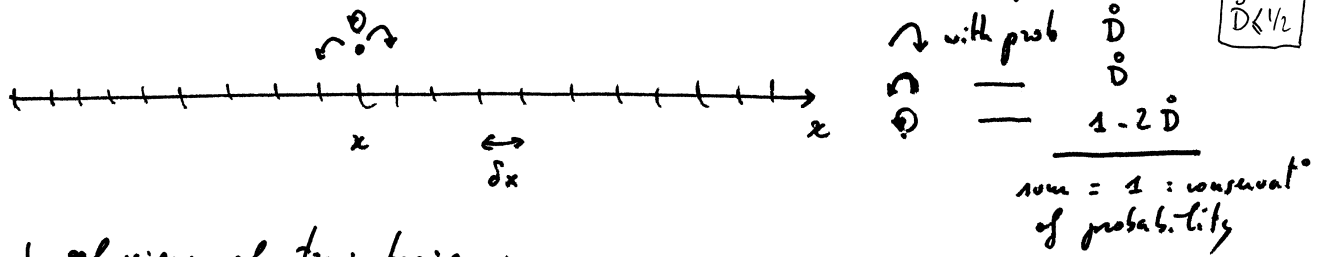
Both effectively accounting for the effect of microscopic degrees of freedom

→ traditional example: particles in a fluid  
However: much more general framework



## 2. Archetypal Example: Random Walk and Diffusion in 1D

Between  $t$  and  $t+\delta t$  a particle can jump symmetrically to its left or its right on a lattice, or stay at the same place



### Point of view of trajectories:

initial condition:  $x_0 = 0$

evolution:  $x_{t+\delta t} = x_t + \overset{\circ}{\eta}_t$ , noise  $\overset{\circ}{\eta}_t = \begin{cases} +\delta x & \text{with prob. } \overset{\circ}{D} \\ -\delta x & \text{--- } \overset{\circ}{D} \\ 0 & \text{--- } 1-2\overset{\circ}{D} \end{cases}$

Each occurrence of the noise  $\overset{\circ}{\eta}_t$  is independent of the previous ones and following

This describes the distribution of probability of the noise (The distribution does not depend on time)

How can one take a continuum space limit? ( $\delta t \rightarrow 0, \delta x \rightarrow 0$ )

This is not a trivial question:

$\frac{x_{t+\delta t} - x_t}{\delta t} = \frac{\overset{\circ}{\eta}_t}{\delta t}$  depending on how  $\delta t \rightarrow 0$  &  $\delta x \rightarrow 0$  it is not obvious to catch how  $\overset{\circ}{\eta}$  (i.e.  $\overset{\circ}{D}$ ) should be tuned so as the limit to be well-defined (i.e. not vanishing nor exploding)



### Point of view of distributions:

$\overset{\circ}{P}(x, t)$  = probability that the particle is in  $x$  at time  $t$  (over all possible realizations of the noise  $\overset{\circ}{\eta}$ )

$\triangle$   $x$  in  $\overset{\circ}{P}(x, t)$  is a dummy variable (do not write  $\overset{\circ}{P}(x_t)$ )

normalisation:  $\forall t, \sum_x \overset{\circ}{P}(x, t) = 1$

initial condition:  $\overset{\circ}{P}(x, 0) = \delta_{x0} = \begin{cases} 1 & x=0 \\ 0 & \text{otherwise} \end{cases}$

evolution:

$$\overset{\circ}{P}(x, t+\delta t) = \overset{\circ}{D} \overset{\circ}{P}(x-\delta x, t) + \overset{\circ}{D} \overset{\circ}{P}(x+\delta x, t) + (1-2\overset{\circ}{D}) \overset{\circ}{P}(x, t)$$

one was in  $x \pm \delta x$  at time  $t$

one was already in  $x$  at time  $t$ .

"Master equation"

The continuous limit is now easier to tackle: the master equation (1.4)  
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Complex System  
2012  
rewrites:

$$\frac{\dot{P}(x, t + \delta t) - \dot{P}(x, t)}{\delta t} = \frac{\dot{D}}{\delta t} \left[ \dot{P}(x - \delta x, t) + \dot{P}(x + \delta x, t) - 2\dot{P}(x, t) \right] \quad (*)$$

One introduces a probability density  $P(x, t)$  of the continuous variables  $x, t$

$$\boxed{P(x, t) = \frac{1}{\delta x} \dot{P}(x, t)}$$
 in the limit  $\delta x \rightarrow 0, \delta t \rightarrow 0$

with normalisation condition  $\int dx P(x, t) \stackrel{\forall t}{=} 1$  (arising from  $\sum_x \dot{P}(x, t) = 1$ )

and initial condition  $P(x, 0) = \delta(x)$  (Dirac delta; arising from

[Remark: normalizing probabilities is very important!]  $P(x, 0) = \lim_{\delta x \rightarrow 0} \frac{\delta_{0x}}{\delta x} = \delta(x)$ )

Expanding (\*) for small  $\delta t$  and small  $\delta x$  one obtains:

$$\partial_t P(x, t) = \frac{\dot{D}}{\delta t} \left[ \underbrace{P(x, t) + P(x, t) - 2P(x, t)}_{=0 \text{ (conservation of probability)}} + \underbrace{(-\partial_x P + \partial_x P) \delta x}_{=0 \text{ (symmetry of the noise)}} + \underbrace{\left(\frac{1}{2} + \frac{1}{2}\right) \delta x^2 \partial_x^2 P(x, t)}_{\text{first non-trivial term of the expansion}} \right]$$

$$\partial_t P(x, t) = \frac{\dot{D} \delta x^2}{\delta t} \partial_x^2 P(x, t)$$

One thus obtains a non-trivial and well defined limit provided  $\boxed{D = \frac{\dot{D} \delta x^2}{\delta t}}$  is finite

$$\boxed{\partial_t P(x, t) = D \partial_x^2 P(x, t)} \quad (**)$$

This is the diffusion equation. (Occurs in a lot of contexts!)

Solution by scaling:  $P(x, t) \stackrel{?}{=} D t^{-\zeta} \hat{P}(x t^{-\zeta})$  with  $1 = \int dx P(x, t) = \int d(x t^{-\zeta}) \hat{P}(x t^{-\zeta}) = \int d\hat{x} \hat{P}(\hat{x})$

with  $\hat{x} = x t^{-\zeta}$ ,  $(**) \Leftrightarrow -\zeta t^{-1-\zeta} (\hat{P}(\hat{x}) + \hat{x} \hat{P}'(\hat{x})) = D t^{-3\zeta} \hat{P}''(\hat{x})$

The Partial Differential Equation (PDE) then reduces to an Ordinary Differential Equation (ODE)  $\hat{P}$  normalized to 1  
↓

$$\hat{P}(\hat{x}) + \hat{x} \hat{P}'(\hat{x}) + 2D \hat{P}''(\hat{x}) = 0$$

A (unnormalized) solution is  $\boxed{\hat{P}(\hat{x}) = \frac{1}{\sqrt{4\pi D}} e^{-\frac{1}{2} \frac{\hat{x}^2}{2D}}}$

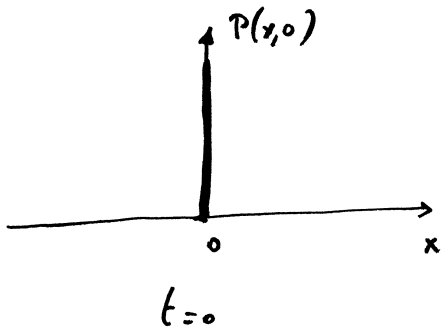
### 3. Analysis of the solution and continuum limit for trajectories:

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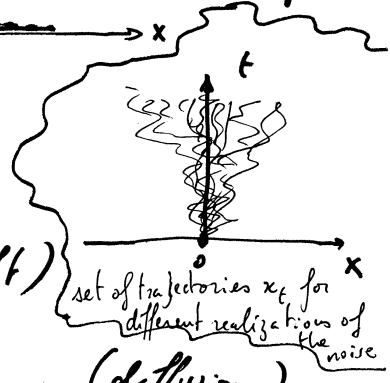
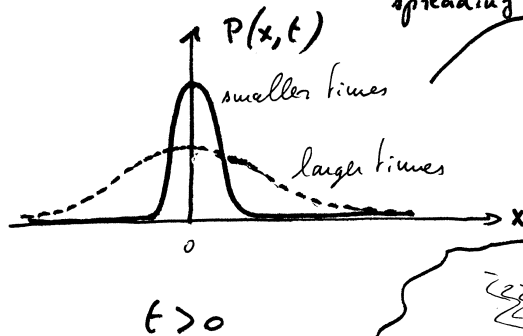
One then finds

$$P(x, t) = \frac{1}{\sqrt{4\pi Dt}} e^{-\frac{1}{2} \frac{x^2}{2Dt}}$$

this describes the spreading of trajectories as time increases in a space-time representation



$\rightsquigarrow$   
 $t > 0$



The average  $\langle x(t) \rangle = 0$  is always zero (no drift)

The variance  $\langle x^2(t) \rangle = 2Dt$  is increasing linearly with time (diffusion)

What is the continuum limit of the noise?

Let us recall the discrete evolution

$$\frac{x_{t+\delta t} - x_t}{\delta t} = \frac{\eta_t}{\delta t}$$

with  $\eta_t = \begin{cases} +\delta x & \text{prob. } \bar{D} \\ -\delta x & \text{prob. } \bar{D} \\ 0 & \text{prob. } 1-2\bar{D} \end{cases}$

one has found that: keeping our aim is to give a meaning to average of the noise:

where  $D = \frac{\bar{D} \delta x^2}{\delta t}$  finite is the "correct" continuum limit. the equation  $\partial_t x = \eta(t)$  where  $\eta(t) = \frac{\eta_t}{\delta t}$  the "correct" limit of the noise.

$$\langle \eta(t) \rangle = \langle \partial_t x \rangle = \partial_t \langle x \rangle = \partial_t \int dx x P(x, t) = 0$$

jump from averaging on trajectories to averaging with the distribution  $P(x, t)$

Hopefully, this is compatible with the discrete-time

$$\langle \eta_t \rangle = \delta x \bar{D} - \delta x \bar{D} + 0 \cdot (1-2\bar{D}) = 0$$

variance of the noise: determining  $\langle \eta(t_1) \eta(t_2) \rangle$  would require to know the two-point distribution  $P(x_2, t_2; x_1, t_1)$ .

One has in fact:  $P(x_2, t_2 | x_1, t_1) = \frac{1}{\sqrt{4\pi D(t_2-t_1)}} e^{-\frac{1}{2} \frac{(x_2-x_1)^2}{2D(t_2-t_1)}}$  for  $t_2 > t_1$

let's first determine the correlator  $C_2(t_2, t_1) = \langle (x(t_2) - x(t_1))^2 \rangle$  of the integral  $x(t) = \int_0^t \eta(\tau) d\tau$  which is a more regular quantity than  $\eta(t)$ .

[Indeed determining  $\langle \eta(t_1) \eta(t_2) \rangle$  directly may lead to inconsistencies.]

One has: for  $t_2 > t_1$ ,

$$C_2(t_1, t_2) = \langle (x(t_2) - x(t_1))^2 \rangle = \int dx_1, dx_2 (x_2 - x_1)^2 \underbrace{P(x_2, t_2 | x_1, t_1)}_{\text{allows to follow the evolution of the distribution up to time } t_2} \underbrace{P(x_1, t_1)}_{\text{and to sample } x_1 = x(t_1)}$$

allows to sample the position  $x_2 = x(t_2)$  at time  $t_2 > t_1$ , knowing that one had  $x(t_1) = x_1$

allows to follow the evolution of the distribution up to time  $t_2$  and to sample  $x_1 = x(t_1)$

The computation is a matter of Gaussian integrals. One finds:

$$C_2(t_1, t_2) = 2D(t_2 - t_1) \quad \text{and similarly if } t_1 > t_2 \quad C_2(t_1, t_2) = 2D(t_1 - t_2)$$

Finally:  $C_2(t_1, t_2) = \langle (x(t_2) - x(t_1))^2 \rangle = 2D |t_2 - t_1| \quad (*)$

This absolute value is (although unnoticeably) extremely important.

Formal Remark: link between  $\langle (x(t_2) - x(t_1))^2 \rangle$  and  $\langle \eta(t_2) \eta(t_1) \rangle$ :

Using  $x(t) - x(0) = \int_0^t dt' \eta(t')$   $\equiv C_2(t_1, t_2) \equiv C(t_2 - t_1) \equiv R_2(t_1, t_2) \equiv R(t_2 - t_1)$

One has:  $C''(t) = \partial_t^2 \langle (x(t) - x(0))^2 \rangle = \partial_t^2 \int_0^t dt' \int_0^t dt'' \underbrace{\langle \eta(t') \eta(t'') \rangle}_{R(t' - t'')} = \dots = R(t) + R(-t)$

Thus, using the parity  $R(t) = R(-t)$  [arising from  $\langle \eta(t) \eta(0) \rangle = \langle \eta(0) \eta(-t) \rangle$  by invariance of the distribution of  $\eta$  by translation along time]

One finally gets:  $R(t) = \frac{1}{2} C''(t) \quad \text{i.e.} \quad \langle \eta(t) \eta(0) \rangle = \partial_t^2 \langle (x(t) - x(0))^2 \rangle$

Finally: one gets the variance of  $\eta(t)$  from (\*)

$$\langle \eta(t_2) \eta(t_1) \rangle = 2D \delta(t_2 - t_1)$$

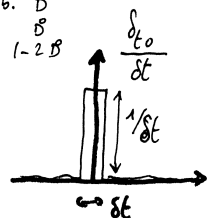
Dirac - delta correlations

Remark: this corresponds to a naive argument on  $\dot{\eta}_t$ : (with  $\eta(t) = \int_0^t \dot{\eta}_t dt$ )  
 if  $t_1 \neq t_2$ ,  $\langle \eta(t_1) \eta(t_2) \rangle = \frac{1}{\delta t^2} \langle \dot{\eta}_{t_1} \dot{\eta}_{t_2} \rangle = 0$  since for  $t_1 \neq t_2$ ,  $\dot{\eta}_{t_1}$  and  $\dot{\eta}_{t_2}$  are uncorrelated  
 if  $t_1 = t_2 = t$ ,  $\langle \eta(t) \eta(t) \rangle = \frac{1}{\delta t^2} \langle \dot{\eta}_t^2 \rangle = \frac{1}{\delta t^2} (\delta x^2 \bar{D} + \delta x^2 \bar{D} + 0 \cdot (1 - 2\bar{D}))$

$$= 2 \frac{\bar{D} \delta x^2}{\delta t} \frac{1}{\delta t}$$

where  $D = \frac{\bar{D} \delta x^2}{\delta t}$

Hence:  $\langle \eta(t_1) \eta(t_2) \rangle = 2D \frac{\delta_{t_1, t_2}}{\delta t} \xrightarrow{\delta t \rightarrow 0} 2D \delta(t_2 - t_1)$



• Remark: regularity of the function  $x(t)$

One has  $\langle (x(t+\delta t) - x(t))^2 \rangle = \delta t$

Hence  $|x(t+\delta t) - x(t)| \sim \sqrt{\delta t}$  which is much larger than  $\delta t$   
 (one would have  $x(t+\delta t) - x(t) \sim \delta t$  for a differentiable/regular-enough function)

⚠ Note that from the discrete equation  $x_{t+\delta t} = x_t + \dot{x}_t \delta t$  this behaviour is not obvious as long as one has not determined the correct  $\delta x \rightarrow 0$  limit.

- the evolution of the distribution is very simple (a Gaussian)
- the trajectories are non-trivial 'processes'.

#### 4. Determination of the distribution of trajectories: the Brownian motion

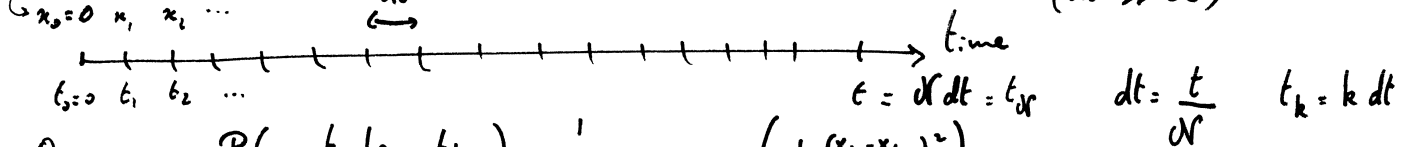
• After having determined  $\langle \eta(t) \rangle = 0, \langle \eta(t)\eta(t') \rangle = 2D \delta(t-t')$  through  $x(t) = \int_0^t dt' \eta(t')$   
 or equivalently  $\langle x(t) \rangle = 0, \langle [x(t) - x(t')]^2 \rangle = 2D |t-t'|$

let us now determine the full distribution of the processes  $\{\eta(t')\}_{0 \leq t' \leq t}, \{x(t')\}_{0 \leq t' \leq t}$

• This is not direct, since  $P(x, t) = \frac{1}{\sqrt{4\pi Dt}} e^{-\frac{1}{2} \frac{x^2}{2Dt}}$  gives only the distribution at final time.

#### • Let us discretize time, keeping $x$ continuous

values of the positions  $x_k = x(t_k)$  at different times  $t_k$ .



One uses  $P(x_k, t_k | x_{k-1}, t_{k-1}) = \frac{1}{\sqrt{4\pi D dt}} \exp\left(-\frac{1}{2} \frac{(x_k - x_{k-1})^2}{2D dt}\right)$

To write  $P(x_N, t_N | x_{N-1}, t_{N-1}, \dots | x_0, t_0) = (4\pi D dt)^{\frac{N}{2}} \exp\left(-\frac{1}{2} \sum_{k=1}^N \frac{(x_k - x_{k-1})^2}{2D dt}\right)$

This represents the probab. dens. of the history  $x_0, t_0, \dots, x_N, t_N$ , allowing to compute any mean-value of observables  $O(x_0, \dots, x_N)$  as

$$\langle O(x_0 \dots x_N) \rangle = \int dx_0 \dots dx_N O(x_0 \dots x_N) P(x_N, t_N | x_{N-1}, t_{N-1} | \dots | x_0, t_0) \underbrace{P_0(x_0)}_{\text{(arbitrary) initial distribution at time } t_0}$$

(1.8)  
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Going to continuous notations,  $\sum_{k=1}^N \frac{(x_k - x_{k-1})^2}{2D \Delta t} = \sum_{k=1}^N \Delta t \frac{1}{2D} \left( \frac{dx_k}{dt} \right)^2 \underset{\Delta t \rightarrow 0}{\approx} \int_0^t \frac{dx}{2D} \left( \frac{dx}{dt} \right)^2$

and denoting : Prob[x] the probability density of the history  $[x(\tau)]_{0 \leq \tau \leq t}$   
 $O[x]$  the observable depending on the whole history  
 $Dx = \frac{dx_0 \dots dx_N}{(4\pi D \Delta t)^{N/2}}$  the precise weighted measure on trajectories

One may write:  $\int$  Represents an integration over trajectories.

note :  $x = x$   
sorry for the variation of notation

$$\langle O[x] \rangle = \int Dx O[x] \text{Prob}[x] P_0(x(0))$$

$$\text{Prob}[x] = \exp \left\{ -\frac{1}{2} \int_0^t d\tau \frac{(\dot{x}(\tau))^2}{2D} \right\}$$

Note that the normalization is hidden in  $Dx$  through  $\int Dx \text{Prob}[x] P_0(x(0)) = 1$

With the notation above,  $\langle 1 \rangle = 1$  : the integral  $\int Dx$  is normalized.

Remark : in most cases, this integration over trajectories does not depend on the number of time slices  $N$  as  $N \rightarrow \infty$ . In case of doubt: check explicitly!

In the limit  $N \rightarrow \infty$ , the process  $[x(\tau)]_{0 \leq \tau \leq t}$  is called a Brownian motion.

\* it has zero mean and variance  $\langle (x(t_2) - x(t_1))^2 \rangle = 2D |t_2 - t_1|$

\* it has a Gaussian distribution

• In terms of  $\eta$  : the white noise in discrete:  $x_{k+1} - x_k = \eta_k \Delta t$

Similarly :

$$\text{in discrete time } P(\eta_N, t_N | \dots | \eta_0, t_0) = \exp \left( -\frac{1}{2} \frac{1}{2D} \sum_{k=0}^N \Delta t \eta_k^2 \right) \times \frac{1}{(4\pi D \Delta t)^{N/2}}$$

$$\text{in continuous time } \text{Prob}[\eta] = \exp \left( -\frac{1}{2} \frac{1}{2D} \int_0^t d\tau \eta^2(\tau) \right)$$

$\eta(\tau)$  has zero mean and variance  $\langle \eta(t_1) \eta(t_2) \rangle = 2D \delta(t_2 - t_1)$

Its distribution is Gaussian.

Rq : note the difference of indexation. The amount of information in  $(x_N, \dots, x_0)$  is the same as in  $(\eta_{N-1}, \dots, \eta_0; x_0)$ .



Remark: the writing

$$P(\eta_0, t_0 | \dots | \eta_0, t_0) = \prod_{k=0}^N \frac{1}{\sqrt{4\pi D dt}} e^{-\frac{1}{2} \frac{\eta_k^2}{2D dt}}$$

makes it clear that the  $\eta_i$ 's are independent and uncorrelated -

Remark: the generalisation to other correlation writes:

x for a  $N \times N$  invertible matrix, if:

$$A \text{ with } A^T = A$$

$$P(\eta_0, \dots, \eta_N) = \sqrt{\det \frac{A}{2\pi}} e^{-\frac{1}{2} \eta^T A \eta}$$

(For  $\eta$ ,  $A = \frac{1}{2D} \mathbb{1}$ , where  $\mathbb{1}$  is the identity matrix)

$$\text{then } \langle \eta_i \eta_j \rangle = (A^{-1})_{ij}$$

x for a functional operator  $\mathcal{R}(t_1, t_2)$ :

(which is symmetric:  $\mathcal{R}(t_1, t_2) = \mathcal{R}(t_2, t_1)$ )

$$\text{Prob}[\eta] = \exp\left(-\frac{1}{2} \int dt_1 dt_2 \eta(t_1) \mathcal{R}(t_1, t_2) \eta(t_2)\right)$$

$$\langle \eta(t_1) \eta(t_2) \rangle = \mathcal{R}^{-1}(t_1, t_2)$$

$\mathcal{R}^{-1}$  = functional inverse of  $\mathcal{R}$

$$\int dt \mathcal{R}^{-1}(t_2, t) \mathcal{R}(t, t_1) = \delta(t_2 - t_1)$$

## 5. Physical interpretation and generalizations

• Overdamped dynamics:  $\dot{x} = \eta$  rewrites as

$$\underbrace{m \ddot{x}}_{\text{with zero mass}} = \underbrace{-\gamma \dot{x}}_{\text{friction}} - \underbrace{V'(x)}_{\text{and no}} + \underbrace{\eta(t)}_{\text{noise potential}}$$

with friction coefficient  $\gamma = 1$

As a first generalization, one may consider the overdamped Langevin dynamics

$$\dot{x} = -V'(x) + \eta(t)$$

$V(x)$  being a potential of corresponding force  $-V'(x)$

in details:  $\partial_t x(t) = -V'(x(t)) + \eta(t)$

$$\text{or: } \dot{x} = F(x) + \eta(t)$$

for a generic force

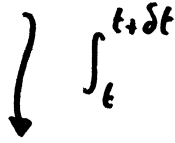
Equation of evolution for the probability density  $P(x,t)$ :

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"deterministic force" "stochastic force"

$$\dot{x}(t) = F(x(t), t) + \eta(t)$$

$F(x,t)$  is assumed to be regular enough



$$\int_t^{t+\Delta t} F(x(\tau), \tau) d\tau \approx \Delta t F(x(t), t)$$

$$\eta \Delta t = \int_t^{t+\Delta t} \eta(\tau) d\tau = B(t+\Delta t) - B(t)$$

$B(t) = \int_0^t \eta(\tau) d\tau$  : Brownian motion

we have seen that  $\langle \eta_\epsilon \eta_\epsilon \rangle = \langle (B(t+\Delta t) - B(t))^2 \rangle = C(\Delta t) = 2D \Delta t$  \*

↳ when expanding,  $\eta_\epsilon$  is of order  $\sqrt{\Delta t}$ .

$$x_{t+\Delta t} - x_t = \Delta t F(x_t, t) + \eta_\epsilon$$

Remark: one could take for  $\eta_\epsilon$ :  $\begin{cases} +\delta x & \text{prob } \frac{D}{2} \\ -\delta x & \text{prob } \frac{D}{2} \\ 0 & 1-2D \end{cases}$

As for the free case ( $F=0$ ) one could take the limit  $\frac{\delta x \rightarrow 0}{\delta t \rightarrow 0} \frac{\delta x^2}{\delta t} = \text{free}$

1<sup>st</sup> try: directly expand  $P(x, t+\Delta t)$

$$P(x, t+\Delta t) = \int dx_2 P(x_2, t) P(x, t+\Delta t | x_2, t)$$

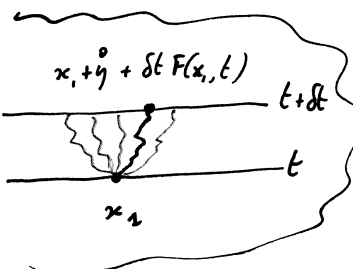
$$P(x, t+\Delta t) - P(x, t) = \int dx_2 P(x_2, t) [P(x, t+\Delta t | x_2, t) - \delta(x-x_2)]$$

a small  $\Delta t$  expansion would be difficult (it is difficult to expand around a Dirac delta)   
 ⇒ in such situations, integrate over a "test function":

2<sup>nd</sup> try: consider the time-evolution of the average of an observable  $\varphi(x)$ :

Consider an observable  $\varphi(x)$ , vanishing at  $|x| \rightarrow \infty$  (a "test function", for mathematicians)

$$\langle \varphi(x) \rangle_{t+\Delta t} = \int dx_2 \underbrace{\int d\eta P(\eta)}_{\text{average over the noise } \eta} \underbrace{P(x_2, t)}_{\text{distribution at time } t} \underbrace{\varphi(x_2 + \eta + \Delta t F(x_2, t))}_{\text{"of order } \sqrt{\Delta t} \text{"}}$$



$\langle \eta \rangle = 0, \langle \eta^2 \rangle = 2D \Delta t$  see \*

the expansion at small  $\Delta t$  is now easier

$$\approx \varphi(x_2) + \eta \varphi'(x_2) + \Delta t F(x_2, t) \varphi'(x_2) + \frac{1}{2} \eta^2 \varphi''(x_2) + O(\Delta t^{3/2})$$

of order  $\Delta t$  after averaging, see \*

$$\langle \varphi(x) \rangle_{t+\Delta t} = \int dx_2 P(x_2, t) \left\{ \varphi(x_2) + \Delta t F(x_2, t) \varphi'(x_2) + D \Delta t \varphi''(x_2) \right\} + O(\Delta t^{3/2})$$

$$\langle \varphi(x) \rangle_{t+\Delta t} = \langle \varphi(x) \rangle_t + \Delta t \left\langle F(x, t) \varphi'(x) + D \varphi''(x) \right\rangle_t + O(\Delta t^{3/2})$$

One can now take the limit  $\delta t \rightarrow 0$  by isolating  $\frac{\langle \varphi(x) \rangle_{t+\delta t} - \langle \varphi(x) \rangle_t}{\delta t}$  (1.11)

which yields  $\partial_t \langle \varphi(x) \rangle_t = \langle F(x,t) \varphi'(x) + D \varphi''(x) \rangle_t$  (\*)

Lecture on Complex System 2012

Remark: from the Langevin equation  $\partial_t x = F(x,t) + \eta$   
 one is tempted to write  $\partial_t \varphi(x_t) = \partial_t x_t \varphi'(x_t) = (F(x_t,t) + \eta_t) \varphi'(x_t)$   
 and to average as  $\partial_t \langle \varphi(x) \rangle_t = \underbrace{\langle F(x,t) \varphi'(x) \rangle_t}_{\text{"deterministic term"}} + \underbrace{\langle \eta \varphi'(x) \rangle_t}_{\text{"stochastic term"}}$

the "deterministic term" is the first term of (\*) and is easy to see.  
 the "stochastic term"  $\langle \eta \varphi'(x) \rangle_t$  is not easy to determine and is equal to  $D \langle \varphi''(x) \rangle_t$  (see (\*)).  
 $\rightarrow$  this is due to the fact that  $\eta(t)$  is a very irregular function "white noise".

Remark: (\*) is also true without averaging.

This is the Ito formula  $\partial_t [\varphi(x,t)] = \partial_t \varphi(x,t) + F(x,t) \partial_x \varphi(x,t) + D \partial_x^2 \varphi(x,t)$

Remark: Time-derivative of averages: points of view of trajectories and distributions,

From the point of view of trajectories: difference of values of the function  $\varphi$  on the same trajectory  $x_t$

$$\langle \varphi(x_{t+\delta t}) - \varphi(x_t) \rangle = \int dx P(x, t+\delta t) \varphi(x) - \int dx P(x, t) \varphi(x)$$

Here  $x$  is a dummy variable and represents all possible values of  $x$  at time  $t+\delta t$ , of probability  $P(x, t+\delta t)$  ← same as at time  $t$

$$\langle \varphi(x_{t+\delta t}) - \varphi(x_t) \rangle = \int dx [P(x, t+\delta t) - P(x, t)] \varphi(x)$$

$\downarrow \delta t \rightarrow 0$

$$\partial_t \langle \varphi(x) \rangle_t = \int dx \partial_t P(x, t) \varphi(x)$$

Viewpoint of trajectories (see computation p 10-11) or viewpoint of distributions, depending on what is useful.

Viewpoint of probability distributions

Equation on the probability distribution:

$$\forall \varphi \quad \partial_t \langle \varphi(x) \rangle_t = \langle F(x,t) \varphi'(x) + D \varphi''(x) \rangle_t$$

$$\int dx \partial_t P(x,t) \varphi(x) = \int dx \left\{ P(x,t) F(x,t) \varphi'(x) + D P(x,t) \varphi''(x) \right\}$$

$$\int dx \partial_t P(x,t) \varphi(x) = \int dx \left\{ -\partial_x [P(x,t) F(x,t)] + D \partial_x^2 P(x,t) \right\} \varphi(x)$$

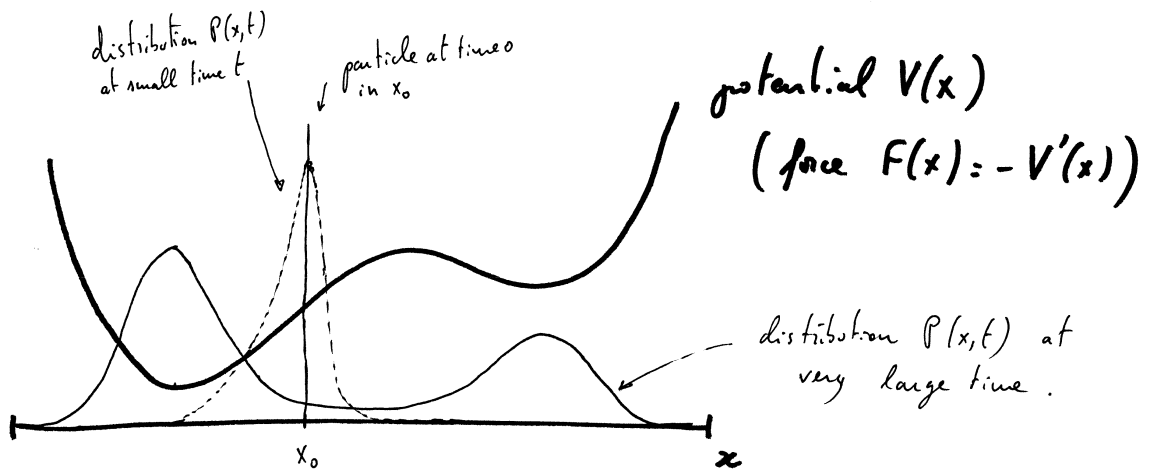
integrations by part, using  $|\varphi| \xrightarrow{x \rightarrow \infty} 0$

This equation is valid for all functions  $\varphi(x)$  decreasing fast enough at infinity

Hence:  $\partial_t P(x,t) = -\partial_x [F(x,t) P(x,t)] + D \partial_x^2 P(x,t)$

This is the Fokker-Planck equation for a 1D particle in a force  $F(x,t)$ .

Example:



Steady state: limit distribution  $P_{st}(x) = \lim_{t \rightarrow \infty} P(x,t)$  if it exists

It verifies  $0 = \partial_x [-F(x) P_{st}(x) + D \partial_x P_{st}(x)]$  for a time-independent force  $F(x,t)$

Remark: for the free particle ( $F=0$ ) one has  $\partial_t P = D \partial_x^2 P$  (diffusion equation)

on the real line:  $P(x,t) = \frac{1}{\sqrt{4Dt}} e^{-\frac{x^2}{4Dt}} \xrightarrow{t \rightarrow \infty} 0$  there is no steady state  
[long-time properties are caught here through scaling:  $P(x,t) \sim \frac{1}{\sqrt{t}} \hat{P}(x/\sqrt{t})$ ]

on an interval  $[a,b]$ : the steady state verifies  $\partial_x^2 P_{st}(x) = 0$   
 $\partial_x P_{st}|_a = \partial_x P_{st}|_b = 0$ : no current on boundaries  
uniform distribution

(for an isolated system)  $P_{st}(x) = \frac{1}{b-a}$

• Equilibrium steady state:

in a potential  $V(x)$   
at temperature  $T$

(1.13)  
Lecture on  
Complex Systems

\* remark: if  $P(x) \propto e^{-\frac{1}{T}V(x)}$  (Boltzmann distribution)

one has  $T \partial_x P_{eq}(x) = -V'(x) P_{eq}(x)$

hence: The Boltzmann distribution  $P_{eq}(x) \propto e^{-\frac{1}{T}V(x)}$  is a steady-state solution of the Fokker-Planck equation  $\partial_x [ +V'(x) P_{eq}(x) + T \partial_x P_{eq}(x) ] = 0$

This provides a link between thermodynamics (Boltzmann canonical ensemble)

where  $D = T$  (hence the interpretation of  $\eta(t)$  as a thermal noise)  
stochastic dynamics (Langevin dynamics)

\* interpretation in terms of a probability current

The FP equation writes  $\partial_t P + \partial_x J(P) = 0$  with  $J(P) = FP - D \partial_x P$

A steady-state distribution verifies  $\partial_x J(P) = 0 \Rightarrow J(P) \equiv j$  (constant) [specific of 1D]

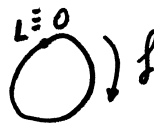
An equilibrium st. st. distribution —  $J(P) = 0$   
when  $j \neq 0$ , we speak of a non-equilibrium steady state NESS  $j = 0$

\* mean velocity in the system: the example of  $V = -fx$  i.e.  $F(x) = f$

①  $\langle \partial_t x \rangle = \langle f + \eta \rangle \Rightarrow \langle \partial_t x \rangle \equiv v = f$

② for distribution and for the NESS:

one considers periodic boundary conditions



$\langle \partial_t x \rangle = \int dx x \partial_t P(x,t) = - \int dx x \partial_x J(P)$  from Fokker-Planck

iff  $\int dx J(P)$  but  $J(P) = j$  is a constant  $j$

Hence: the velocity is  $v \equiv \langle \partial_t x \rangle = j = f$

The system is in a true NESS ( $j \neq 0$ ) iff  $f \neq 0$ .

It is not obvious to determine  $P_{st}(x)$  for  $f \neq 0$ . See exercises.

↳ indeed a try as  $P_{st}(x) \propto e^{-\frac{1}{T}fx}$  does not respect boundary conditions

- "Equilibrium dynamics" and reversibility: independent of time  
↑  
(Lecture on Complex Systems (1.14)  
2012)
  - if there exists a potential  $V(x)$  such that  $F(x) = -V'(x)$  and that  $P_{eq}(x) = \frac{1}{Z} e^{-\frac{1}{T} V(x)}$ ,  $Z = \int dx e^{-\frac{1}{T} V(x)}$  is the stationary distribution [ $J(P) = 0$ ]
  - then we say that the dynamics is an "equilibrium dynamics" and that  $P_{eq}(x)$  is an "equilibrium steady state" (or "reversible measure")
  - otherwise, the dynamics is a "non-equilibrium dynamics". [ $J(P_{st}) \neq 0$ ]

→ There is a physical interpretation in terms of reversibility. Let us fix the final time  $t$  and consider all trajectories  $x(\tau)$  for  $0 \leq \tau \leq t$ .

• probability density of a trajectory  $(x(\tau))_{0 \leq \tau \leq t}$ :

simplest way of obtaining it:

$$\text{Prob}[x(\tau)] = \int \mathcal{D}\eta \delta(\partial_t x - F(x) - \eta) e^{-\frac{1}{4T} \int_0^t d\tau \eta(\tau)^2}$$

This is justified e.g. from the expansion of the average of an observable depending on  $\langle O[x(\tau)] \rangle = \int \mathcal{D}x O[x(\tau)] \text{Prob}[x]$

$$\text{Prob}[x(\tau)] = \exp\left\{-\frac{1}{4T} \int_0^t d\tau (\partial_t x - F(x))^2\right\}$$

• time-reversed trajectory: one defines  $x^R(\tau) = x(t - \tau)$  ( $0 \leq \tau \leq t$ )

which verifies  $x^R(t) = x(0)$ ,  $x^R(0) = x(t)$ ,  $\partial_t x^R(t-\tau) = -\partial_t x(\tau)$

• joint probability of history & initial condition in the equilibrium dynamics:

$$P_{eq}(x(0)) \text{Prob}[x(\tau)] = e^{-\frac{1}{T} V(x(0))} \exp\left\{-\frac{1}{4T} \int_0^t d\tau (\partial_t x + V'(x))^2\right\}$$

$x \mapsto x^R$   
 $\tau \mapsto t - \tau$

$$= e^{-\frac{1}{T} V(x^R(t))} \int_0^t d\tau (-\partial_t x^R + V'(x^R))^2 = \int_0^t d\tau \left[ (\partial_t x^R + V'(x^R))^2 - 4 \partial_t x^R V'(x^R) \right]$$

no as to recover a +  $\partial_t(V(x^R))$

$$= -4 \left( \underbrace{V(x^R(t)) - V(x^R(0))}_{\text{these two terms cancel}} \right) + \int_0^t d\tau (\partial_t x^R + V'(x^R))^2$$

this one remains

$$\propto e^{-\frac{1}{T} V(x^R(0))} \exp\left\{-\frac{1}{4T} \int_0^t d\tau (\partial_t x^R + V'(x^R))^2\right\}$$

These is an equivalence btw

- $J(P) = 0$  (no prob. current)
- $P(x) \propto e^{-\frac{1}{T} V(x)}$
- reversibility in that sense

Hence:  $P_{eq}(x(0)) \text{Prob}[x(\tau)] = P_{eq}(x^R(0)) \text{Prob}[x^R(\tau)]$ , i.e.

otherwise not. there is reversibility (trajectories and their time-reversed have the same probability, including initial eq. distrib.) when the dynamics is an "equilibrium dynamics".

• Reversible dynamics, Doob transform and Schrödinger equation

Lecture on (L15)  
Complex Systems  
D = T from now on

Consider the "equilibrium dynamics" (also termed "reversible dyn.")

$$\partial_t x = -V'(x) + \eta \quad (\Leftrightarrow) \quad \partial_t P(x,t) = +\partial_x [V'(x) P(x,t)] + T \partial_x^2 P(x,t)$$

This equation for  $P(x,t)$  is linear, first-order in time, and looks like Schrödinger's equation  $-i \partial_t \Psi(x,t) = [\partial_x^2 - V_{\text{quant}}(x)] \Psi(x,t)$  on the wavefunction  $\Psi$  without however taking the same form.

Let's introduce  $P_{\text{sym}}(x,t) = e^{\frac{1}{2T} V(x)} P(x,t) = P_{\text{eq}}^{-1/2}(x) P(x,t)$  (this is the Doob transform)

One easily checks that the Fokker-Planck equation is equivalent to:

$$\partial_t P_{\text{sym}}(x,t) = [T \partial_x^2 - V_{\text{eff}}(x)] P_{\text{sym}}(x,t)$$

$$V_{\text{eff}}(x,t) = \frac{1}{4T} (V'(x))^2 - \frac{1}{2} V''(x) \quad \text{effective potential}$$

Hence: the FP equation for  $P_{\text{sym}}$  is equivalent to a [imaginary time] Schrödinger equation for  $P_{\text{sym}}$  in a potential  $V_{\text{eff}}(x)$

Again, this only works for "equilibrium dynamics".

Such a correspondence can be established in a much more general context, see later.

• Remark: correct form of the probability density of trajectories

The (quantum-like) Feynman path-integral would yield for the probability of histories:

$$P_{\text{sym}}(x,t) = \frac{1}{Z} e^{-\frac{1}{2T} V(x(t))} e^{-\frac{1}{4T} \int_0^t dt \left\{ \underbrace{(\partial_\tau x)^2 + (V'(x))^2}_{\text{up to time-boundary terms, corresponds to } (\partial_\tau x + V'(x))^2} - \underbrace{2TV''(x)}_{\text{this term is absent from the expression p. 14}} \right\}}$$

→ This comes from a different choice of time-discretization of the Langevin equation (Itô vs Stratonovitch) →  $e^{V''}$  can be seen as a Jacobian.

See A.W.C. Lau & T.C. Lubensky PRE 76 011123 (2007) for details

• Generalization to several interacting particles:

$x_i(t)$  each of them in a noise  $\eta_i(t)$   $1 \leq i \leq N$   
global interactions  $F_i(\{x_j\}, t)$

$$\partial_t x_i = F_i(\{x_j\}, t) + \eta_i(t)$$

$$\langle \eta_i(t) \eta_j(t') \rangle = 2 \Delta_{ij} \delta(t-t')$$

with  $\{\eta_j(t)\}$  white noises  
 $\Delta_{ij}$  invertible symmetric matrix  
 $\eta_j$ 's are uncorrelated if  $\Delta_{ij} = D \delta_{ij}$

Gaussian distribution of the noise:

$$\text{Prob}[\{\eta_j(t)\}] = \exp\left(-\frac{1}{2} \int_0^t d\tau \sum_{ij} \eta_i(\tau) ((2\Delta)^{-1})_{ij} \eta_j(\tau)\right)$$

if  $\Delta_{ij} = D \delta_{ij}$

$$= \exp\left(-\frac{1}{4D} \int_0^t d\tau \sum_i \eta_i(\tau)^2\right)$$

\* Fokker-Planck equation: notation  $\partial_i = \partial_{x_i} = \frac{\partial}{\partial x_i}$

$$\partial_t P(\{x_j\}, t) = - \sum_i \partial_i (F_i(x, t) P(x, t)) + \sum_{ij} \Delta_{ij} \partial_i \partial_j P(x, t)$$

deterministic contribution (uncorrelated) diffusive contribution  
in matrix notations:

$$\partial_t P = - \vec{\nabla} \cdot (\vec{F}(x, t) P(x, t)) + \vec{\nabla} \cdot (\Delta \vec{\nabla} P(x, t))$$

if the noise is uncorrelated ( $\Delta_{ij} = D \delta_{ij}$ )

$$\partial_t P = - \vec{\nabla} \cdot (\vec{F}(x, t) P(x, t)) + D \vec{\nabla}^2 P(x, t)$$

\* Itô formula:

$$\partial_t \varphi(x, t) = \sum_i F_i(x, t) \partial_i \varphi(x, t) + \sum_{ij} \Delta_{ij} \partial_i \partial_j \varphi(x, t)$$



\* Equilibrium:

$$\text{When } \forall i, \underbrace{F_i(x, t)} = - \underbrace{\partial_i V(x)}$$

forces acting on  
particle  $i$

common potential to all particles  
↑  
describing interactions between particles  
and also with the environment

i.e. when "forces are conservative"

i.e. when "forces derive from a potential"

then the Boltzmann-Gibbs measure is an equilibrium steady state

① For non-correlated noises  $\langle \eta_i \eta_j \rangle = 2D \delta_{ij} \delta(t-t')$ ; denoting  $\boxed{D=T}$

$$\boxed{P_{eq}(x) = \frac{1}{Z} e^{-\frac{1}{T} V(x)}}$$

$$\text{with } Z = \int dx e^{-\frac{1}{T} V(x)}$$

verifier  $\partial_i P_{eq}(x) = -\frac{1}{T} \partial_i V(x) P_{eq}(x)$  hence  $\frac{\partial V}{\partial x} P_{eq} + T P_{eq} = 0$

but the FP equation writes  $\partial_t P = + \sum_i \partial_i \left[ \frac{\partial V}{\partial x} P + T P \right]$

hence  $P_{eq}(x)$  is an equilibrium distribution all components of the current are 0

② For correlated noises  $\langle y_i(t) y_j(t') \rangle = 2 \Delta_{ij} \delta(t-t')$ :

$$P_{eq}(x) = \frac{1}{Z} \exp(-W(x)) \Rightarrow \partial_i P_{eq} = -\partial_i W P_{eq}$$

searching for a solution of  $\partial_i V P_{eq} + \sum_j \Delta_{ij} \partial_j P_{eq} = 0$  is equivalent to

$$\forall i, \partial_i V = \sum_j \Delta_{ij} \partial_j W \quad \text{ie } \forall i, \boxed{\partial_j W = \sum_i (\Delta^{-1})_{ij} \partial_i V}$$

A necessary and sufficient condition for this equation to have a solution

(using Poincaré's lemma) is:  $\forall i, j, \sum_k (\Delta^{-1})_{ki} \partial_k V = \sum_k (\Delta^{-1})_{kj} \partial_k V$

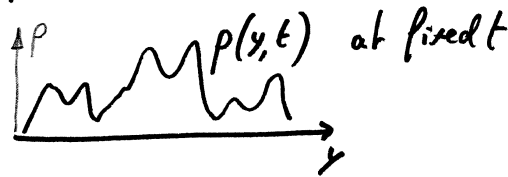
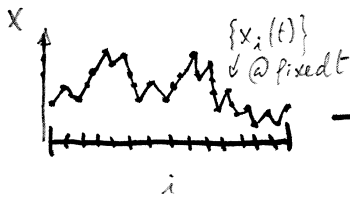
A possible solution is for quadratic potentials:  $V = \sum_{ij} \Delta_{ij} x_i x_j$

|| But otherwise there is no generic  
characterisation of equilibrium with correlated noise.

• Generalisation to several coupled noises: continuum

$$x_i(t) \longrightarrow p(y, t) \quad \begin{matrix} x \equiv p \\ y \equiv i \end{matrix}$$

$$\eta_i(t) \longrightarrow \eta(y, t)$$



one will call  $p(y, t)$  a "profile", but the description holds in generality

$$\langle \eta_i(t) \eta_j(t') \rangle = 2D_{ij} \delta(t-t') \longrightarrow \langle \eta(y, t) \eta(y', t') \rangle = \underbrace{R(y'-y)}_{\text{describes correlations in direction } y} \delta(t-t')$$

[ $R(y) = 2D \delta(y'-y)$  for uncorrelated noise]

$P(x, t) \longrightarrow P[p, t]$  (functional) probability density of the profile  $p(y)$ , at time  $t$

\* Langevin equation: from  $\partial_t x_i = F_i(x, t) + \eta_i$  (see p. 1.16) one goes to

$$\partial_t p(y, t) = \mathcal{F}[p; y, t] + \eta(y, t)$$

\* Fokker-Planck equation: from  $\partial_t P(x, t) = - \sum_i \partial_i (F_i(x, t) P(x, t)) + \sum_{ij} \Delta_{ij} \partial_i \partial_j P(x, t)$  makes

$$\partial_t P[p, t] = - \int dy \frac{\delta}{\delta p(y)} \left( \mathcal{F}[p; y, t] P[p, y] \right) + \frac{1}{2} \int dy dy' R(y'-y) \frac{\delta^2 P[p, t]}{\delta p(y) \delta p(y')}$$

\* Itô formula:

$$\partial_t (\varphi(p, t)) \stackrel{p(y,t)}{=} \partial_t \varphi[p, t] + \int dy \mathcal{F}[p; y, t] \frac{\delta \varphi[p, t]}{\delta p(y)} + \frac{1}{2} \int dy dy' R(y'-y) \frac{\delta^2 \varphi[p, t]}{\delta p(y) \delta p(y')}$$

\* Example of "equilibrium (i.e. reversible) dynamics":  $\mathcal{F}[p; y, t] = \frac{\delta \mathcal{H}[p]}{\delta p(y)}$

Then for an uncorrelated noise  $R(y) = 2T \delta(y)$

$P_{eq}[p] \propto \exp\left(-\frac{1}{T} \mathcal{H}[p]\right)$  is a solution of the FP equation, with 0 current:

$$- \mathcal{F}[p; y, t] P_{eq}[p] + \frac{1}{2T} \frac{\delta P_{eq}[p]}{\delta p(y)} = 0$$

• Generalization to position-dependent noise:

1.19  
Lecture on  
Complex Systems  
2012

Ball writing:

$$D(x,t) > 0$$

$$\boxed{\partial_t x = F(x,t) + \sqrt{2D(x,t)} \eta(t)} \quad \text{with } \langle \eta(t) \eta(t') \rangle = \delta(t-t')$$

Fokker-Planck:  $\text{Prob}[x(t)] = \exp\left(-\frac{1}{2} \int_0^t dt \frac{(\partial_x x - F(x,t))^2}{2D(x,t)}\right)$

$$\boxed{\partial_t P(x,t) = -\partial_x (F(x,t) P(x,t)) + \partial_x^2 (D(x,t) P(x,t))}$$

• With several coupled noises:

$$\boxed{\partial_t x_i = F_i(x,t) + \sqrt{2D(x,t)} \eta_i(t)} \quad \langle \eta_i(t) \eta_j(t') \rangle = \Delta_{ij} \delta(t-t')$$

$$\boxed{\partial_t P(x,t) = -\sum_i \partial_i (F_i(x,t) P(x,t)) + \sum_{ij} \partial_i^2 \partial_j^2 (\Delta_{ij} D(x,t) P(x,t))}$$

• Generalization to fields:

$$x_i(t) \mapsto \rho(y,t)$$

$$\partial_t \rho(y,t) = F(\rho(y,t), t) + \sqrt{2D(\rho(y,t))} \eta(y,t) \quad \langle \eta(y,t) \eta(y',t') \rangle = R(y-y') \delta(t-t')$$

$$\partial_t P[\rho(y), t] = -\int dy \frac{\delta}{\delta \rho(y)} \left( F(\rho(y), t) P[\rho(y), t] \right) + \int dy dy' \frac{\delta^2}{\delta \rho(y) \delta \rho(y')} \left[ R(y-y') P[\rho, t] \right] \times D(\rho(y))$$

Remark: Backward Fokker-Planck equation:

(1.10)  
Lecture on  
Complex Systems  
2012

We have seen that  $P(x, t | x_0, t_0) = P(x, t)$  verifies the forward FP equation

$$\partial_t P(x, t) = -\partial_x (F(x, t) P(x, t)) + D \partial_x^2 P(x, t)$$

We might be interested in the derivatives  $\partial_{x_0}, \partial_{t_0}$  w.r.t. the initial conditions (e.g. to tackle 1<sup>st</sup> passage problems).

As on page 110, we integrate the Langevin equation  $\dot{x} = +F(x, t) + \eta$   $\delta t > 0$   
between  $t_0 - \delta t$  and  $t_0$  to write  $\underbrace{x(t_0)}_{\equiv x_0} = \underbrace{x(t_0 - \delta t)}_{\equiv x_{-1}} + \delta t F(x_{-1}, t - \delta t) + \underbrace{\int_{t_0 - \delta t}^{t_0} d\tau \eta(\tau)}_{\equiv \eta^0}$   
with  $\eta^0$  Gaussian,  $\langle \eta^0 \rangle = 0$   $\langle \eta^0{}^2 \rangle = 2D \delta t$

Then, for any function  $f(x)$  one has:

$$x_{-1} = x_0 - \delta t F(x_0, t) - \eta^0$$

$$\int dx f(x) P(x, t | x_0, t_0) = \int dx f(x) \int d\eta^0 P(\eta^0) \underbrace{P(x, t | x_0 - \eta^0 - \delta t F(x_0, t), t_0 - \delta t)}_{\text{or } F(x_{-1}, t - \delta t) \text{ but this is the same at the order } \delta t \text{ we are interested in}}$$

we perform the average  $\int d\eta^0 P(\eta^0)$  through  $\langle \eta^0 \rangle = 0, \langle \eta^0{}^2 \rangle = 2D \delta t$

$$\approx P(x, t | x_0, t_0 - \delta t) - \eta^0 \partial_{x_0} P(x, t | x_0, t_0) - \delta t \partial_{x_0}^2 P(x, t | x_0, t_0) - \frac{1}{2} \eta^0{}^2 \partial_{x_0}^2 P(x, t | x_0, t_0) + O(\delta t^{3/2})$$

↑ one has to expand up to order  $\delta t$

Collecting:

$$\lim_{\delta t \rightarrow 0} \frac{\partial_{t_0} P(x, t | x_0, t_0)}{\delta t} = \int dx f(x, t) \left[ -F(x_0, t) \partial_{x_0} P(x, t | x_0, t_0) - D \partial_{x_0}^2 P(x, t | x_0, t_0) \right]$$

And finally:

Note the change of sign & the position of  $\partial_{x_0}$

$$-\partial_{t_0} P(x, t | x_0, t_0) = F(x_0, t) \partial_{x_0} P(x, t | x_0, t_0) + D \partial_{x_0}^2 P(x, t | x_0, t_0)$$

This is the backward Fokker-Planck equation, which describes the variations of the probability density with respect to its initial conditions.

$$P(x, t | x_0, t_0) = e^{(t-t_0) \mathcal{L}} P_0(x_0)$$

↑ indep. of time

For homogeneous processes where  $P(x, t | x_0, t_0)$  is a function of  $t - t_0$  only, e.g. of  $F(x, t) = F(x)$  one has  $\partial_{t_0} = -\partial_t$  and hence

$$\partial_t P(x, t | x_0, t_0) = F(x_0) \partial_{x_0} P(x, t | x_0, t_0) + D \partial_{x_0}^2 P(x, t | x_0, t_0)$$