

## Basic properties of stochastic processes

Now that we have gained a little intuition about stochastic processes and discussed different methods to analyze their properties, we will further formalize the discussion of stochastic processes.

So far we always looked at individual microscopic realizations of the stochastic process and subsequently performed averages over the ensemble of all possible microscopic realizations.

Now instead, we will look directly at the ensemble of all microscopic realizations as described by

probability distribution  $p_i(t, v)$

Such that

$$\langle v(t) \rangle = \int dv v p_i(t, v)$$

or more generally a set of

n-point probability distributions  $p_n(t_1, v_1, \dots, t_n, v_n)$

such that

$$\langle v(t_1) \dots v(t_n) \rangle = \int dv_1 \dots dv_n (v_1 \dots v_n) p_n(t_1, v_1, \dots, t_n, v_n)$$

where in analogy to n-body phase space distributions, the lower order distributions can be obtained by marginalizing over one of the variables

$$p_{n-1}(t_1, v_1, \dots, t_{n-1}, v_{n-1}) = \int dv_n p_n(t_1, v_1, \dots, t_n, v_n)$$

Now in addition to the probability distributions  $p_n$  that describe state of the system at different times, we are interested in the dynamics of the system as described by conditional probability distributions

$$P_{n|n-m}(t_1, v_1, \dots, t_n, v_n | t_{m+1}, v_{m+1}, \dots, t_n, v_n)$$

which describe the probability for  $t_1, v_1, \dots, t_n, v_n$   
 knowing  $t_{n-1}, v_{n-1}, \dots, t_1, v_1$ , such that  
 the likelihood  $p_n(t_1, v_1, \dots, t_n, v_n)$  that  
 all values are taken is given by

$$p_n(t_1, v_1, \dots, t_n, v_n) = p_{n|n-1}(t_1, v_1, \dots, t_n, v_n | t_{n-1}, v_{n-1}, \dots, t_1, v_1) \times \\ p_{n-1}(t_{n-1}, v_{n-1}, \dots, t_1, v_1)$$

// and to a certain extent  $p_{n|n-1}$  describe  
 the dynamics of the stochastic process

## Markov processes

Now in principle the dynamics of a stochastic  
 process can be arbitrarily complicated, however  
 there is an important class of processes  
 called "Markov processes" which has some  
 nice features and is particularly relevant  
 for many physical applications

Stochastic process is Markovian, if and only if for  $t_1 < t_2 < \dots < t_n < t_{n+1}$

$$P_{11n}(t_{n+1}, v_{n+1} | t_1, v_1, \dots, t_n, v_n) \\ = P_{111}(t_{n+1}, v_{n+1} | t_n, v_n)$$

i.e. the evolution of the probability distribution is completely determined by  $p_{111}$  and the last known state of the system  $t_n, v_n$  and there is no memory of the past evolution

It follows immediately that for Markov process and  $t_1 < t_2 < \dots < t_n < t_{n+1}$

$$P_n(t_1, v_1, \dots, t_n, v_n) = p_{111}(t_n, v_n | t_{n-1}, v_{n-1}) \dots p_{111}(t_2, v_2 | t_1, v_1) p_1(t_1, v_1)$$

such that only  $p_1$  and  $p_{111}$  are needed as the descriptors



Moreover for a Markov process the transition probabilities  $P_{ij}$  satisfy a composition relation, known as the Chapman-Kolmogorov relation, which can easily be derived as follows

Consider  $t_1 < t_2 < t_3$  such that

$$a) P_2(t_1, v_1, t_3, v_3) = P_{111}(t_3, v_3 | t_1, v_1) P_1(t_1, v_1)$$

but also

$$b) P_2(t_1, v_1, t_3, v_3) = \int dv_2 P_3(t_1, v_1, t_2, v_2, t_3, v_3)$$

$$\text{with } P_3(t_1, v_1, t_2, v_2, t_3, v_3) = P_{111}(t_3, v_3 | t_2, v_2) P_{111}(t_2, v_2 | t_1, v_1) P_1(t_1, v_1)$$

By comparison of a) and b)

$$P_{111}(t_3, v_3 | t_1, v_1) = \int dv_2 P_{111}(t_3, v_3 | t_2, v_2) P_{111}(t_2, v_2 | t_1, v_1)$$

which allows to split an arbitrary time interval  $t_3 - t_1$  into many small pieces

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## Brownian motion as a Markov process

Now generally speaking Brownian motion is not a Markov process, as a finite set of conditions of the stochastic force implies a memory of the past evolution of the system.

However on macroscopic scales  $t \gg \tau_{\text{coll}}$  the forces are uncorrelated, and the Brownian motion can be treated as a Markov process in the spirit of coarse grained description.

Now in order to determine the evolution of the  $n$ -point probability distributions for we need the conditional probabilities  $P_{||}$  for Brownian motion on macroscopic time scales

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We consider the evolution of  $P_i$  for  $\Delta t \gg \tau_{coll}$

$$P_i(t+\Delta t, v) = \int dv' f_{||1}(t+\Delta t, v|t, v') P_i(t, v')$$

$$\text{setting } v - v' = \Delta v$$

$$= \int d\Delta v f_{||1}(t+\Delta t, v+\Delta v-\Delta v | t, v-\Delta v) P_i(t, v-\Delta v)$$

we can expand this into a Taylor series in  $\Delta v$ , anticipating that for  $\Delta t \ll \frac{1}{\gamma}$  the typical change  $\Delta v$  is small compared to gradients of  $P_i(t, v)$  w.r.t  $v$

$$= \int d\Delta v \sum_{n=0}^{\infty} \frac{(-1)^n}{n!} \Delta v^n \frac{\partial^n}{\partial v^n}$$

$$P_{||1}(t+\Delta t, v+\Delta v | t, v) P_i(t, v)$$

Now we recognize that the  $\Delta v$  dependence only appears in  $P_{||1}$  and we can take moments

$$M_n(t, t+\delta t, v) = \int d^3v' v'^n p_{III}(t+\delta t, v+\delta v | t, v)$$

where in particular for  $n=0$ , we

have

$$M_0(t, t+\delta t, v) = \int d^3v' p_{III}(t+\delta t, v+\delta v | t, v) = 1$$

due to probability conservation.

Splitting this term off the sum, we obtain

$$p_I(t+\delta t, v) - p_I(t, v) = \sum_{n=1}^{\infty} \frac{(-1)^n}{n!} \frac{\partial^n}{\partial v^n} M_n(t, t+\delta t, v) p_I(t, v)$$

Now if we divide by  $\delta t$  and take the limit  $\delta t \rightarrow 0$ , the LHS shows a derivative with respect to  $t$ , while on the RHS, we only need to worry about terms for which the limit

$$\lim_{\Delta t \rightarrow 0} \frac{M_n(t, t+\Delta t, v)}{\Delta t} = M_n(t, v)$$

$\Rightarrow$  non-zero, i.e. the moments increase linearly with  $\Delta t$  for sufficiently small  $\Delta t$

Collecting everything, we obtain the

Itô-Stratonovich expansion

$$\partial_t p_i(t, v) = \sum_{n=1}^{\infty} \frac{(-1)^n}{n!} \frac{\delta^n}{\delta v^n} (M_n(t, v) p_i(t, v))$$

In particular if only  $M_1$  and  $M_2$  are non-zero, one obtains

Fokker-Planck equation:

$$\partial_t p_i(t, v) = - \frac{\partial}{\partial v} (M_1(t, v) p_i(t, v)) + \frac{1}{2} \frac{\delta^2}{\delta v^2} (M_2(t, v) p_i(t, v))$$

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Now let's calculate the moments for Brownian motion, where based on the definition

$$M_n(t, v) = \lim_{\Delta t \rightarrow 0} \int ds dv dv^n \frac{P_{||}(t+\Delta t, v+\Delta v | t, v)}{\Delta t}$$

we can calculate

$$M_n(t, v(t)) = \lim_{\Delta t \rightarrow 0} \left\langle \frac{(v(t+\Delta t) - v(t))^n}{\Delta t} \right\rangle_{\text{Noise}}$$

with

$$v(t+\Delta t) = e^{-\gamma \Delta t} v(t) + \frac{1}{M} \int_t^{t+\Delta t} ds e^{-\gamma(t+\Delta t-s)} F_c(s)$$

Now for the one-point function  $\langle F_c(s) \rangle_{\text{Noise}} = 0$

$$M_1(t, v(t)) = \lim_{\Delta t \rightarrow 0} \frac{e^{-\gamma \Delta t} - 1}{\Delta t} v(t) = -\gamma v(t)$$

Similarly we can evaluate the two point function

$$M_2(t, v(t)) = \lim_{\Delta t \rightarrow 0} \left[ \underbrace{\left( \frac{e^{-\gamma \Delta t} - 1}{\Delta t} \right)^2}_{\rightarrow 0} v(t)^2 + \frac{1}{M^2} \int_t^{t+\Delta t} \int_t^{t+\Delta t} \frac{e^{-\gamma(t+\Delta t-s)} e^{-\gamma(t+\Delta t-s')}}{\Delta t} \underbrace{\langle F_L(s) F_L(s') \rangle_{N_{\text{obs}}}}_{= 2 D_v M^2 \delta(s-s')} \right]$$

So upon performing integrals and taking limits

$$M_2(t, v(t)) = 2 D_v$$

Since it can easily be shown that all higher order moments vanish in this particular case, we obtain a Fokker-Planck equation for the evolution of the probability distribution.

$$\frac{dP_1(t, v)}{dt} = \gamma \frac{d}{dv} (v P_1(t, v)) + D_v \frac{d^2}{dv^2} P_1(t, v)$$

where we can directly attribute the different terms on the RHS to the physical effects of Drag ( $\gamma$ ) and velocity diffusion ( $D_v$ )

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Similarly if we look at the Brownian motion in phase-space  $(t, x, v)$  this is described by SDE

$$\frac{d}{dt} \begin{pmatrix} x(t) \\ v(t) \end{pmatrix} = \begin{pmatrix} v(t) \\ -\gamma v(t) + \frac{1}{m} F_{ext}(t) \end{pmatrix} + \begin{pmatrix} 0 \\ \frac{1}{m} F_C(t) \end{pmatrix}$$

and the associated Fokker-Planck equation for the probability distribution  $p_i(t, x, v) = f(t, x, v)$

$$\left( \frac{\partial}{\partial t} + v \frac{\partial}{\partial x} + F_{ext} \frac{\partial}{\partial v} \right) f(t, x, v) = \gamma \frac{\partial}{\partial v} v f(t, x, v) + D_v \frac{\partial^2}{\partial v^2} f(t, x, v)$$

takes the form of a Boltzmann type equation with the collision integral approximated by (constant) diffusion approximation

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## Property & Solution of Fokker-Planck equation

Since FPE is an evolution equation for the probability, we expect the conserved value of probability to manifest itself at the level of FPE

$$\frac{d}{dt} p_i(t, v) = \gamma \frac{d}{dv} (v p_i(t, v)) + D_v \frac{d^2}{dv^2} p_i(t, v)$$

$$= \frac{d}{dv} \gamma \left[ v p_i(t, v) + \frac{D_v}{\gamma} \frac{d}{dv} p_i(t, v) \right]$$

Can express as continuity equation

$$\frac{d}{dt} p_i(t, v) + \frac{d}{dv} J_v(t, v) = 0$$

with probability current  $J_v$

$$\mathcal{J}_v(t, v) = -\gamma \left[ v p_i(t, v) + \frac{D_v}{\gamma} \frac{d}{dv} p_i(t, v) \right]$$

in velocity space.

Based on FPE, we can also read off the equilibrium solution for the probability distribution, obtained by

$$\mathcal{J}_v(t, v) = 0 \Rightarrow \frac{d}{dv} p_i^{eq}(t, v) = -\frac{\gamma}{D_v} v p_i^{eq}(t, v)$$

such that  $p_i^{eq}(v) = \sqrt{\frac{\gamma}{2\pi D_v}} e^{-\frac{\gamma}{2D_v} v^2}$

where the prefactor is determined by the normalization condition.

Since  $\frac{D_v}{\gamma} = \frac{k_B T}{m}$  this corresponds to

the Maxwell-Boltzmann distribution

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Now let's have a look at two independent solutions of FPE.

$$\frac{df_i(t,v)}{dt} = \gamma \frac{d}{dv}(v p_i(t,v)) + D_v \frac{d^2}{dv^2} p_i(t,v)$$

Since FPE is a linear PDE, the general solution can be constructed as linear superposition of elementary solutions and we will consider for simplicity

$$p_i(t=0, v) = \delta(v-v_0)$$

Next in order to eliminate derivatives w.r.t to  $v$ , we perform a Fourier transform

$$\tilde{p}_i(t, k) = \int_{-\infty}^{\infty} dv p_i(t, v) e^{ikv}$$

such that the initial conditions are given by

$$\tilde{p}_i(t=0, k) = e^{ikv_0}$$

and a Fourier transform of the FPE  
results in the replacements

$$\frac{\partial}{\partial v} \rightarrow -ik, \quad v \rightarrow -i \frac{\partial}{\partial k}$$

such that

$$\frac{\partial}{\partial t} \tilde{\rho}_1(t, k) = \left( -\gamma k \frac{\partial}{\partial k} - D v k^2 \right) \tilde{\rho}_1(t, k)$$

which is now a linear first order PDE.

Even though this equation is not obvious  
at this point, linear first order PDEs  
can be solved in general using  
the method of characteristics.

We first re-express the equation as

$$\left( \frac{\partial}{\partial t} + \gamma k \frac{\partial}{\partial h} \right) \tilde{\rho}_i(t, h) = - D \nu h^2 \tilde{\rho}_i(t, h)$$

dragging all derivatives to the LHS.

Now the basic idea is to introduce a new variable  $s$ , describing a trajectory

$t(s), h(s)$  in order to re-write the LHS as a total derivative w.r.t to  $s$ .

$$\begin{aligned} \frac{d}{ds} \tilde{\rho}_i(t(s), h(s)) &= \frac{dt}{ds} \frac{\partial}{\partial t} \tilde{\rho}_i(t(s), h(s)) \\ &+ \frac{dh}{ds} \frac{\partial}{\partial h} \tilde{\rho}_i(t(s), h(s)) \end{aligned}$$

Such that by comparison, we infer

$$\frac{dt}{ds} = 1 \quad \Rightarrow \quad s = t \quad (\text{+ const set to zero})$$

$$\frac{dh}{ds} = \gamma k(s) \Rightarrow k(s) = k(s=0) e^{\gamma s}$$

and the PDE becomes

$$\frac{d}{ds} \tilde{\rho}_i(t(s), k(s)) = -D_v k(s)^2 \tilde{\rho}_i(t(s), k(s))$$

Since  $k(s)$  is already known from matching of two differentials, we can now infer the solution as

$$\tilde{\rho}_i(t(s), k(s)) = \exp\left(-D_v \int_0^s ds' k(s')^2\right) \tilde{\rho}_i(t(s=0), k(s=0))$$

Now performing the integral

$$\int_0^s ds' k(s=0)^2 e^{2\gamma s'} = \frac{k(s=0)^2}{2\gamma} (e^{2\gamma s} - 1)$$

we get

$$\tilde{\rho}_i(\underline{t}(s), \underline{k}(s)) = \exp\left(-\frac{D_0 v k^2(s=0)}{2\gamma} (e^{2\gamma s} - 1)\right) \tilde{\rho}_i(\underline{t}(s=0), \underline{k}(s=0))$$

where  $\underline{t}(s) = s$  and  $\underline{k}(s) = \underline{k}(s=0) e^{\gamma s}$ , so

to obtain the solution for general  $k$ , we have to invert the relation and determine

$$\underline{k}(s=0) = e^{-\gamma s} \underline{k}(s) \text{ as a function of } \underline{k}(s)$$

on the LHS. Doing this  $\underline{t}(s) = t$ ,  $\underline{k}(s) = k$

$$\tilde{\rho}_i(t, k) = \exp\left(-\frac{D_0 v k^2}{2\gamma} (1 - e^{-2\gamma t})\right) \tilde{\rho}_i(t=0, k e^{-\gamma t})$$

$$= \exp\left(-\frac{D_0 v k^2}{2\gamma} (1 - e^{-2\gamma t})\right) + i k e^{-\gamma t} v_0$$

Now to obtain the final result we simply need to perform the inverse Fourier transformation

$$\begin{aligned}
 P_1(t, v) &= \int_{-\infty}^{+\infty} \frac{dk}{2\pi} \tilde{P}_1(t, k) e^{-ikv} \\
 &= \sqrt{\frac{\gamma}{2\pi D_V (1 - e^{-2\gamma t})}} \exp\left(-\frac{\gamma}{2D_V} \frac{(v - v_0 e^{-\gamma t})^2}{1 - e^{-2\gamma t}}\right)
 \end{aligned}$$

yielding a Gaussian probability distribution  
with mean

$$\langle v(t) \rangle = v_0 e^{-\gamma t}$$

and variance

$$\sigma_v^2(t) = \frac{D_V}{\gamma} (1 - e^{-2\gamma t})$$

In line with our previous analysis of  
the stochastic differential equation

Based on the probability  $P_1(t, v)$  distribution and  
the conditional probability  $P_{111}(t, v)$  or respectively  
its moments, one can then compute all equal  
and unequal time correlation functions