

4. ANOMALOUS DIFFUSION

4.1 Introduction

We have in previous chapters seen that the hallmark of diffusion processes, $x(t)$, is the linear time dependence of the mean square displacement

$$\langle x^2(t) \rangle \sim Dt \quad (*)$$

This eq. signals that the underlying transport mechanism is described by Fick's second law.

The scaling relation (*) is a direct consequence of:

- 1) The central limit theorem
- 2) The Markovian nature of $x(t)$

Lifting any of these two properties will make (*) invalid. That is, anomalous diffusion will result.

Def: Anomalous diffusion

A stochastic process, $x(t)$, where the mean square displacement no longer is linear in time

$$\langle x^2(t) \rangle \neq \text{lin}(t)$$

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Several functional forms are popular for $\langle x^2(t) \rangle$ in the anomalous case, in particular the power-law

$$\langle x^2(t) \rangle \sim D_\alpha t^\alpha \quad \alpha \neq 1 \quad (**)$$

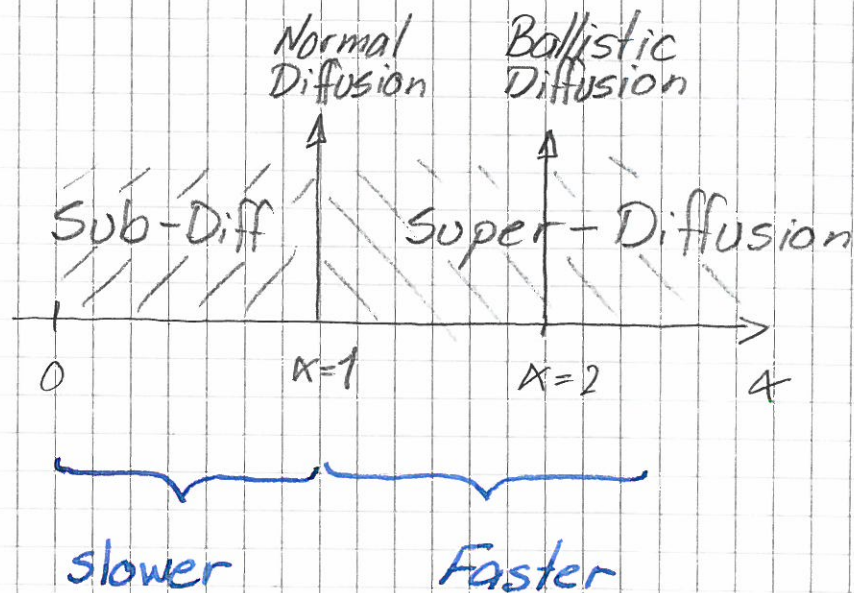
(or the logarithmic).

We will follow common practice and focus on the power-law form.

Note that D_α , the anomalous diff. const., now has dimension

$$[D_\alpha] = \frac{\text{m}^2}{\text{s}^\alpha}$$

The exponent α is known as the anomalous diffusion exponent.



Note:

Anomalous diffusion

\Rightarrow Non-Fickian transport
"anomalous transport"

The anomalous diffusion behaviour manifested by

$$\langle x^2(t) \rangle \sim D_\alpha t^\alpha$$

is intimately connected with the breakdown of the central limit theorem caused by either

- 1) broad distributions ($\sigma < \infty$)
- 2) long-range correlations

Anomalous diffusion rests on the validity of the so-called Lévy-Gnedenko generalized central limit theorem for such situations where not all moments of the underlying elementary transport events exist.

The broad spatial jump or waiting time distributions lead to non-Gaussian propagators (fundamental solutions) and a possibly non-Markovian time evolution (manifestation of non-local temporal phenomena).

4.2 Lévy Flights

We will now give a first example of anomalous diffusion — the so-called Lévy Flights.

LFs are random walks where the increments are drawn from a "fat-tailed" distribution, i.e. a distribution of diverging moments (2nd or 1st.).

$$x(t) = \sum_{i=1}^t \xi_i \quad \text{IID}$$

One familiar example of such a distribution is the Cauchy-Lorentz distr., but there are many others as we will see.

Show some plots.

4.2.1 The Lévy Distribution

The mathematicians call it the α -stable distribution.

Consider

$$x = \xi_1 + \xi_2$$

where ξ_i are IID random variables.

If $\xi_i = N(0,1)$ we know that x also will be Gaussian (Normally) distributed.

One says that the Normal dist. is stable under addition.

French math. P. Lévy asked ~~the question~~ of what is the largest class, ^{having this} property. _{of distributions}

This class is today known as the Lévy distribution (physics) or α -stable dist. (math.).

We will also see that this dist. is intimately related with the generalized central limit theorem.

The Levy Distribution is defined by a characteristic function

NB $\hat{L}_\alpha(k; a) = \exp(-a|k|^\alpha)$

i.e. a stretched exponential.

Hence, we recall, that the distribution is given by the Fourier transform:

$$L_\alpha(x; a) = \frac{1}{2\pi} \int_{-\infty}^{\infty} dk e^{ikx - a|k|^\alpha}$$

(because of symmetry)

$$= \frac{1}{\pi} \int_0^{\infty} dk \cos(kx) e^{-a k^\alpha}$$

In general this integral can not be evaluated analytically. However, two noticeable exceptions do exist:

$\alpha = 2$: The Gaussian distr.

$\alpha = 1$: Cauchy-Lorentz ; $\frac{1}{\pi} \frac{a}{x^2 + a^2}$

Technical comment:

Above we have only given the symmetric case. Strictly speaking the full class of Lévy dist. do also include non-symmetric distributions. One writes

$$L_{\alpha\beta}(x; a)$$

where β is related to the asymmetry (actually the skewness). The symmetric case corresponds to $\beta = 0$.

Some plots ; e.g. Wikipedia.

* Large x expansion of $L_\alpha(x; a)$

$$L_\alpha(x; a) = \frac{1}{\pi} \int_0^\infty dk \underbrace{\cos kx}_{u'} \underbrace{e^{-ak^\alpha}}_v$$

(Integration by part)

$$\frac{d}{dk} e^{-ak^\alpha} = -e^{-ak^\alpha} a\alpha k^{\alpha-1}$$

$$= \frac{a\alpha}{\pi} \int_0^\infty dk \frac{\sin k|x|}{|x|} e^{-ak^\alpha} k^{\alpha-1}$$

$$\xi = k|x| \quad d\xi = dk |x|$$

$$= \frac{a\alpha}{\pi |x|^{1+\alpha}} \int_0^\infty d\xi \xi^{\alpha-1} \sin \xi \exp\left\{-\frac{a\xi^\alpha}{|x|^\alpha}\right\}$$

$$\underset{x \rightarrow \infty}{\sim} \frac{a\alpha}{\pi |x|^{1+\alpha}} \int_0^\infty d\xi \xi^{\alpha-1} \sin \xi$$

$$\sim \frac{a\alpha \Gamma(\alpha) \sin(\frac{\pi\alpha}{2})}{\pi |x|^{1+\alpha}}$$

\therefore A power-law tail
inverse

$$L_\alpha(x; a) \underset{x \rightarrow \pm\infty}{\sim} \frac{A_\pm}{|x|^{\alpha+1}}$$

— " —

$$\Gamma(x) = \int_0^\infty dt \, t^{x-1} e^{-t} \quad (\text{generalized } n!)$$

$$\Gamma(n+1) = n!$$

* Small x expansion of $L_\alpha(x; a)$

$$L_\alpha(x; a) = \frac{1}{\pi} \int_0^\infty dk \cos kx e^{-ak^\alpha}$$

Taylor expansion

$$= \frac{1}{\pi} \int_0^\infty dk \sum_{n=0}^{\infty} \frac{(-1)^n (kx)^{2n}}{(2n)!} e^{-ak^\alpha}$$

$$w = ak^\alpha \Rightarrow dw = \alpha a k^{\alpha-1} dk \\ = \alpha a \left(\frac{w}{a}\right)^{\frac{\alpha-1}{\alpha}} dk$$

$$= \frac{1}{\pi} \sum_{n=0}^{\infty} \frac{(-1)^n}{(2n)!} \int_0^\infty \frac{dw}{\alpha a \left(\frac{w}{a}\right)^{\frac{\alpha-1}{\alpha}}} \frac{x^{2n}}{(2n)!} \left(\frac{w}{a}\right)^{\frac{2n}{\alpha}} e^{-w}$$

$$= \frac{1}{\pi} \sum_{n=0}^{\infty} \frac{(-1)^n}{(2n)!} \frac{x^{2n}}{(2n)!} \int_0^\infty dw \frac{1}{\alpha a} \underbrace{\left(\frac{w}{a}\right)^{\frac{2n}{\alpha} - \frac{\alpha-1}{\alpha}}}_{\frac{e^{-w}}{\left(\frac{w}{a}\right)^{\frac{\alpha-1-2n}{\alpha}}}} e^{-w}$$

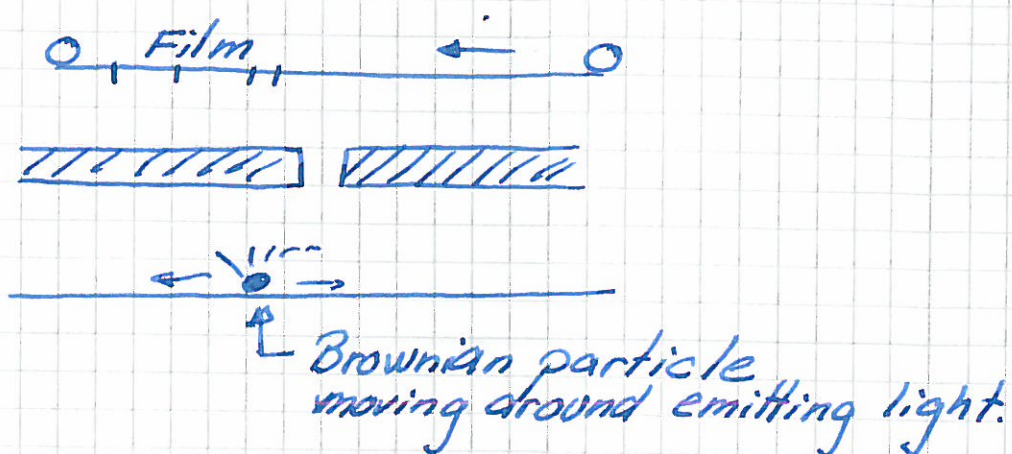
$x \rightarrow 0$ is the interesting limit

$$= \frac{1}{\pi} \sum_{n=0}^{\infty} \frac{(-1)^n}{(2n)!} \frac{x^{2n}}{\alpha a^{\frac{2n+1}{\alpha}}} \Gamma\left(\frac{2n+1}{\alpha}\right)$$

$$\sim \frac{1}{\pi} \frac{\Gamma\left(\frac{1}{\alpha}\right)}{\alpha a^{1/\alpha}}$$

Increases as $\alpha \rightarrow 0$

Ex : Roaming Brownian Particle



Each time the roaming particle passes the slit a mark is put on the film.

The distribution of time intervals between consecutive marks is given by the one-sided distribution:

$$L_{\frac{1}{2}, -\frac{1}{2}}(x) = \frac{1}{2\sqrt{\pi}} x^{-3/2} e^{-\frac{1}{4x}} \quad x > 0$$
$$0 \quad x < 0$$

Application : Single molecule spectroscopy.

Ex : The Holtzmark distribution

$L_{\alpha\beta}(x)$ with $\alpha = 3/2$ and $\beta = 0$

This symmetric dist. is of some use in cosmology.

Holtzmark was Prof. of physics at NTH (and UiO).

4.2.2 Lévy-Gnedenko Generalized Central Limit Theorem

Theorem

Define

$$X_N = \sum_{i=1}^N \xi_i$$

where $\{\xi_i\}$ are IID random variables.

If the distribution of X_N , with an appropriate normalization, converges to some distribution $P(x_N)$ in the limit $N \rightarrow \infty$, $P(x_N)$ is stable.

In particular, if its variance is finite, $P(x_N)$ is Gaussian and obeys the Central Limit Theorem.

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Q : Given a distribution for $\{\xi_i\}$, which one of the stable distributions $L_{\alpha\beta}(x;a)$ does the distribution of X_N satisfy?

A : If the distribution $p(\xi)$ satisfies

$$p(\xi) \sim \frac{A_{\pm}}{|\xi|^{\alpha+1}} \quad \xi \rightarrow \pm \infty$$

$$\beta = \frac{A_+ - A_-}{A_+ + A_-}$$

Then $p(x_N)$ when $N \rightarrow \infty$ be $L_{\alpha\beta}(x;a)$

The parameter σ_N is like the σ_N in the Gaussian case; a measure of the spread.

Note: If the variance of Ξ , $\sigma_\Xi^2 < \infty$, then the limiting dist. is the Gaussian.

4.2.3 Scaling and Superdiffusion

We once more consider the random walk where

$$X_N = \sum_{n=1}^N \Xi_n$$

where $\{\Xi_n\}$ are IID random variables.

If the second moment of the distribution of Ξ , $p(\Xi)$, is finite ($\sigma_\Xi < \infty$) then we know that $p(X_N)$ is Gaussian (for sufficiently large N) and that the width

$$\sigma_N = \langle X_N^2 \rangle^{1/2} \sim N^{1/2}$$

How is the corresponding scaling for Lévy Flights?

Hence, consider $p(\xi) = L_{\alpha,0}(\xi, a)$.

Previously, we showed (Chapter 1) that the

$$P_N(x_N) = \frac{1}{2\pi} \int_{-\infty}^{\infty} dk \hat{P}_N(k) e^{ikx_N}$$

↑
characteristic func.

Where

$$\begin{aligned}\hat{P}_N(k) &= [\exp(-a|k|^{\alpha})]^N \\ &= e^{-aN|k|^{\alpha}}\end{aligned}$$

Therefore, one gets

$$P_N(x_N) = \frac{1}{2\pi} \int_{-\infty}^{\infty} dk e^{-aN|k|^{\alpha}} e^{ikx_N}$$

$$w^{\alpha} = N k^{\alpha}$$

$$\Rightarrow k = N^{-1/\alpha} w \Rightarrow dk = N^{-1/\alpha} dw$$

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} \frac{dw}{N^{1/\alpha}} e^{-a|w|^{\alpha}} e^{i w \left(\frac{x_N}{N^{1/\alpha}} \right)}$$

$$= \frac{1}{N^{1/\alpha}} \underbrace{\frac{1}{2\pi} \int_{-\infty}^{\infty} dw e^{-a|w|^{\alpha}} e^{i w \left(\frac{x_N}{N^{1/\alpha}} \right)}}_{L_{\alpha} \left(\frac{x_N}{N^{1/\alpha}}; a \right)}$$

$$L_{\alpha} \left(\frac{x_N}{N^{1/\alpha}}; a \right)$$

$$P_N(x_N) = \frac{1}{N^{1/4}} L_x\left(\frac{x_N}{N^{1/4}}; a\right)$$

Thus, the width scales as $N^{1/4}$.

4.3 Continuous Time Random Walks (CTRW)

This model was introduced by Weiss and Montroll (1965).

The main difference from the classic Random Walk model is that the time-interv. between jumps now also is a stochastic variable

The CTRW model introduces the jump pdf $\Psi(x, t)$ (joint prob. dist.) for jumps of size x and waiting time t between consecutive jumps.

From the joint probability $\Psi(x, t)$, the marginal distributions for jump size and waiting time may be defined.

They read

$$\lambda(x) = \int_0^{\infty} dt \Psi(x, t)$$

for the jump size (or length) pdf, and

$$w(t) = \int_{-\infty}^{\infty} dx \Psi(x, t)$$

for the waiting time pdf.

If the jump size and waiting time are independent

$$\psi(x,t) = \lambda(x)w(t)$$

Otherwise they are coupled

$$\psi(x,t) = p(x|t)w(t) = \underbrace{p(t|x)}_{\text{jumps of a certain size involves a time cost.}} \lambda(x)$$

jumps of a certain size involves a time cost.

Different CTRW processes can be categorized by

$$T = \langle t \rangle = \int_0^{\infty} dt \, t w(t)$$

the characteristic waiting time, and

$$\Sigma^2 = \langle x^2 \rangle = \int_{-\infty}^{\infty} dx \, x^2 \lambda(x)$$

the characteristic jump size variance.

We will see what matters is if these variables, T and Σ^2 , are finite or not.

Ultimately, we want to know the fundamental solution — the propagator $W(x,t)$ which satisfies the init. cond. $W(x,t_0) \equiv W_0(x)$.

Note when $W_0(x) = \delta(x)$, one has that $W(x,t) \equiv P(x,t|x_0,t_0)$.

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It can be shown that in the Fourier - Laplace space the propagator can be expressed in terms of $\psi(x,t)$ like (Phys. Rev. A 35, 3081 (1987))

$$\hat{W}(k,u) = \frac{1 - \hat{W}(u)}{u} \frac{\tilde{W}_0(k)}{1 - \hat{\psi}(k,u)} \quad (*)$$

In the following we will consider a decoupled joint prob.

$$\hat{\psi}(k,u) = \tilde{\chi}(k) \hat{W}(u)$$

4.3.1 Brownian Motion: $T < \infty$, $\Sigma^2 < \infty$

We will now consider the case where both $T = \langle t \rangle < \infty$ and $\Sigma^2 = \langle x^2 \rangle < \infty$ are finite. This means that both $w(t)$ and $\lambda(x)$ will have to decay sufficiently fast, but otherwise be arbitrary.

This decay implies the following behaviour in Laplace and Fourier space

$$\left. \begin{aligned} \hat{w}(u) &\sim 1 - \tau u + O(u^2) \\ \text{and} \\ \tilde{\lambda}(k) &\sim 1 - \sigma^2 k^2 + O(k^4) \end{aligned} \right\} \begin{array}{l} \text{Universal} \\ \text{behavior} \\ \text{when } T \text{ and } \Sigma^2 \\ \text{are finite} \end{array}$$

when $(t, u) \rightarrow (0, 0)$ [corresponding to $(|x|, t) \rightarrow (\infty, \infty)$].

Here we have that

$$T \propto \tau$$

$$\text{and } \Sigma^2 \propto \sigma^2$$

The prefactors depend on the dist.

Installing these results into (*) gives

$$\begin{aligned}
 \hat{\tilde{W}}(k, u) &= \frac{\tau u + \dots}{u} \frac{\tilde{W}_0(k)}{1 - (1 - \sigma^2 k^2 + \dots)(1 - \tau u + \dots)} \\
 &= \tau \frac{\tilde{W}_0(k)}{1 - (1 - \tau u - \sigma^2 k^2 + \dots)} \\
 &= \frac{\tilde{W}_0(k)}{u + \frac{\sigma^2}{\tau} k^2} + \dots \\
 &\equiv \frac{\tilde{W}_0(k)}{u + K_1 k^2} \quad K_1 = \frac{\sigma^2}{\tau}
 \end{aligned}$$

We will now go back to (x, t) -coordinates

$$\begin{aligned}
 (u + K_1 k^2) \hat{\tilde{W}}(k, u) &= \tilde{W}_0(k) \\
 \underbrace{u \hat{\tilde{W}}(k, u) - \tilde{W}_0(k)}_{\mathcal{L}[\partial_t \tilde{W}(k, t)]} + \underbrace{K_1 k^2 \hat{\tilde{W}}(k, u)}_{\mathcal{F}[-\partial_x^2 \hat{W}(x, u)]} &= 0
 \end{aligned}$$

Hence, the classic DE

$$\partial_t W(x, t) = K_1 \partial_x^2 W(x, t)$$

results after applying $\mathcal{L}^{-1} \mathcal{F}^{-1}$.

Notice that we did not specify $\psi(x,t)$ in order to obtain this result, only did we require that $\langle t \rangle$ and $\langle x^2 \rangle$ were finite.

Hence, the results are generally valid, and any choice of $w(t)$ and $\lambda(x)$ will result in Brownian Motion (i.e. classic Diffusion) if the first and second moments, respect., are finite.

Note: The Diffusion Constant K , defined as

$$K = \frac{\sigma^2}{\tau}$$

is coming from the ^{ratio of the} prefactors of the $(k,u) \rightarrow (0,0)$ expansion prop. to u and k^2

This result is rather general we will see.

4.3.2 Sub-Diffusion; "Long Rests" $T=\infty, \Sigma^2 < \infty$

We will now consider the situation where the waiting time distribution $w(t)$ is so "fat-tailed" that $\langle t \rangle = \infty$, and at the same time the jump size dist. gives $\langle x^2 \rangle < \infty$.

In this case we have $(w(t) \sim A_\alpha (t/t)^{\alpha+1})$

$$\hat{w}(u) \sim 1 - (tu)^\alpha + \dots$$

and as before

$$\hat{\chi}(k) \sim 1 - \sigma^2 k^2 + \dots$$

Then from (*) it follows that:

$$\hat{\hat{w}}(k, u) = \frac{\hat{w}_0(k)}{u + K_\alpha u^{1-\alpha} k^2}; \quad K_\alpha = \frac{\sigma^2}{\Gamma \alpha}$$

[in the limit $(k, u) \rightarrow (0, 0)$]

Show this!

As in the BM case, we would like to make the inversion to (x, t) -space.

However, this is not so easy due to the $u^{1-\alpha}$ -term.

To this end, we will use that

$$\mathcal{L} [{}_0 D_t^{-p} W(x, t)] = u^{-p} \hat{W}(x, u) \quad p \geq 0$$

where ${}_0 D_t^{-p}$ is related to the Riemann-Liouville operator

$${}_0 D_t^{1-p} = \frac{\partial}{\partial t} {}_0 D_t^{-p}, \quad 0 < p < 1$$

that can be defined as

$${}_0 D_t^{1-\alpha} W(x, t) = \frac{1}{\Gamma(\alpha)} \frac{\partial}{\partial t} \int_0^t dt' \frac{W(x, t')}{(t-t')^{1-\alpha}}$$

It has the property (

$${}_0D_t^q t^p = \frac{\Gamma(1+p)}{\Gamma(1+p-q)} t^{p-q}$$

valid for any real q .

Notice in particular the special case $p=0$:

$${}_0D_t^q 1 = \frac{1}{\Gamma(1-q)} t^{-q}$$

Compare this to $\partial^n 1$ where n is an integer. (the special case $q=n$ is included in the above expressions for ${}_0D_t^q 1$ via the poles of the Γ -functions. ($q = 1, 2, \dots$)).

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So back to the expression for the propagator (in the Fourier-Laplace domain)

$$\hat{\tilde{W}}(k, u) = \frac{\tilde{W}_0(k)}{u + K_\alpha u^{1-\alpha} k^2} ; K_\alpha = \frac{\sigma^2}{\Gamma^\alpha}$$

Proceeding like before:

$$(u + K_\alpha u^{1-\alpha} k^2) \hat{\tilde{W}}(k, u) = \tilde{W}_0(k)$$

$$\underbrace{u \hat{\tilde{W}}(k, u) - \tilde{W}_0(k)}_{\mathcal{L}[\partial_t \tilde{W}(k, t)]} + \underbrace{K_\alpha u^{1-\alpha} k^2 \hat{\tilde{W}}(k, u)}_{k^2 \mathcal{L}[_0 D_t^{1-\alpha} \tilde{W}(k, t)]} = 0$$

Inv. Laplace transform:

$$\partial_t \tilde{W}(k, t) + K_\alpha k^2 {}_0 D_t^{1-\alpha} \tilde{W}(k, t) = 0$$

Now performing the inverse Fourier transf. gives the final result:

$$\partial_t W(x, t) = {}_0 D_t^{1-\alpha} K_\alpha \partial_x^2 W(x, t)$$

This is the Fractional Diffusion Eq for sub-Diffusion

Note that the long-range kernel $H(t) \propto 1/t^{1-\alpha}$ of the Riemann-Liouville fractional operator is responsible for the non-Markovian nature of sub-diffusion ("fat-tailed" waiting time dist.)

How to calculate the mean square displacement $\langle x^2(t) \rangle$?

- 1] Solving the FDE and calculating the 2nd moment. Difficult. (Fox functions)
- 2] Inferring it from the $(k, u) \rightarrow (0, 0)$ limit of the propagator $\tilde{W}(k, u)$ (in Fourier-Laplace space)

This can be achieved from

$$\langle x^2(t) \rangle = \lim_{k \rightarrow 0} (-\partial_k^2) \tilde{W}(k, u)$$

and then making the inverse Laplace transform.

The result is :

$$\langle x^2(t) \rangle = \frac{2K\alpha}{\Gamma(1+\alpha)} t^\alpha$$

3] The ^{last} option (that we will present) is to integrate FDE over

$$\int_{-\infty}^{\infty} dx \, x^2$$

resulting in

$$\begin{aligned} \partial_t \langle x^2(t) \rangle &= {}_0 D_t^{1-\alpha} 2K_\alpha \\ &= \frac{2K_\alpha t^{\alpha-1}}{\Gamma(\alpha)} \end{aligned}$$

The solution of this eq. is as given before.

Note : In the limit $\alpha \rightarrow 1$ the FDE reduces to Ficks second law (ordinary DE), as it should.

4.3.3 Super-Diffusion; "Long Jumps" Lévy Flights; $T < \infty$ $\Sigma^2 = \infty$

In this case one has:

$$\hat{W}(u) \sim 1 - u\tau + O(u^2)$$

and (Lévy jump size)

$$\tilde{\lambda}(k) \sim 1 - \sigma^\mu |k|^\mu, \quad 0 < \mu < 2$$

From (*) it follows that

$$\tilde{\tilde{W}}(k, u) = \frac{\tilde{W}_0(k)}{u + K^\mu |k|^\mu}$$

Inverting this propagator to (x, t) -space gives:

$$\partial_t W(x, t) = K^\mu {}_{-\infty}D_x^\mu W(x, t)$$

where ${}_{-\infty}D_x^\mu$ is another fractional derivative, known as the Weyl operator.

It is defined via the property

$$\mathcal{F} [{}_{-\infty}D_x^\mu f(x)] = -|k|^\mu \tilde{f}(k).$$

One may also check that in the limit $\mu \rightarrow 2$ the classic DE results.

Moreover, from the general solution of the above FDE, — the Fox functions — one obtains that

$$W(x,t) \sim \frac{K^\mu t}{|x|^{1+\mu}}, \quad \mu < 2$$

(typical for Lévy distributions).

Due to this property, it follows that

$$\langle x^2(t) \rangle \rightarrow \infty$$

"Instead" one has a finite moment of the form

$$\langle |x|^\delta \rangle \propto t^{\delta/\mu}, \quad 0 < \delta < \mu < 2.$$

Notice: The above process is called Lévy Flights.

Due to the finite value of T the process is Markovian.

Notice since the jumps can be quite large, and the waiting time is finite, that the speed can be arbitrarily large. (and ~~be~~ higher than speed of light.)

This has caused the introduction of a related process — the Lévy walk — where the speed is constant (or at least smaller than c). This implies that long jumps have a "time-cost."

This cost can be introduced via a spatiotemporal coupling, usually through the δ -coupling

$$\psi(x,t) = \frac{1}{2} w(t) \delta(|x| - vt)$$

where v is the propagation speed of the walker.

4.3.4. Competition between "Long Rest" and "Long Jumps"; $T \rightarrow \infty$ $\Sigma^2 = \infty$

In this case both the waiting time PDF and the jump size PDF have fat-tails.

In this case the process can be both sub- and super-diffusive.

The relevant Fractional DE is

$$\partial_t W(x,t) = {}_0 D_t^{1-\alpha} K_{\alpha}^{\mu} D_x^{\mu} W(x,t)$$

$$\hat{W}(\omega) \sim 1 - (\omega \tau)^{\alpha} \quad K_{\alpha}^{\mu} = \frac{\sigma^{\mu}}{\tau^{\alpha}}$$

$$\tilde{W}(k) \sim 1 - \sigma^{\mu} |k|^{\mu}$$

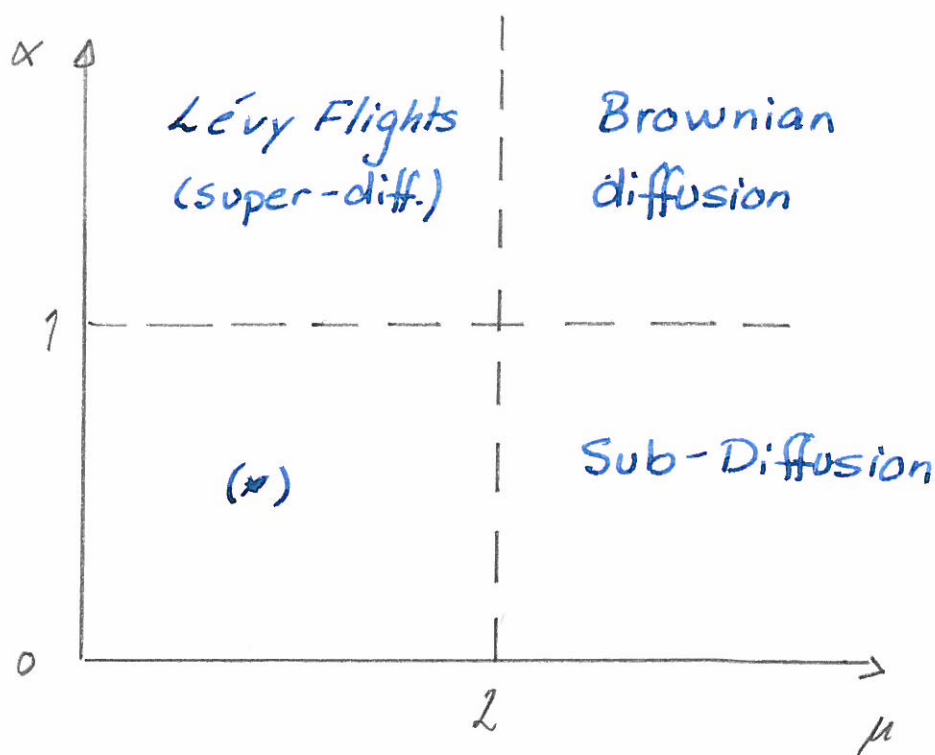
4.3.5 Summary Anomalous Diffusion

Assume, that asymptotically one has

$$\hat{w}(\omega) \sim 1 - (u\tau)^\alpha$$

$$\tilde{\chi}(k) \sim 1 - \sigma^\mu |k|^{-\mu}$$

Then one has



(*) A non-Markovian process where the single modes decay like a stretched exponential (Mittag-Leffler function).