

$$\dot{x} = -\lambda k x + \alpha \eta(t) \quad x(t=0) = x_0$$

We can solve this equation in a standard fashion

Homogeneous eq: $\dot{x} = -\lambda k x \quad x = A e^{-\lambda k t}$

Now, we take A t -dependent

$$x(t) = A(t) e^{-\lambda k t}$$

$$\dot{x}(t) = \dot{A} e^{-\lambda k t} - \lambda k A e^{-\lambda k t} = \dot{A} e^{-\lambda k t} + \lambda k x(t)$$

⇓ Substitution in the equation

$$\dot{A} e^{-\lambda k t} - \lambda k x = -\lambda k x + \alpha \eta(t)$$

$$\dot{A} = \alpha e^{\lambda k t} \eta(t)$$

$$A(t) = \alpha \int_0^t ds e^{\lambda k s} \eta(s) + k$$

Solution

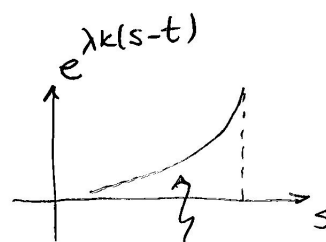
$$x(t) = \left[\alpha \int_0^t ds e^{\lambda k s} \eta(s) + k \right] e^{-\lambda k t}$$

$$x(0) = x_0 \Rightarrow k = x_0$$

$$x(t) = x_0 e^{-\lambda k t} + \alpha \int_0^t e^{\lambda k(s-t)} \eta(s) ds$$

initial conditions
are irrelevant

for $t \gg \tau = \frac{1}{\lambda k}$



memory on scales

$$\tau = 1/\lambda k$$

(2)

Note that $x(t)$ is a Gaussian variable as it is a "sum" of Gaussian variables (η)

$$\begin{aligned}\langle x(t) \rangle &= x_0 e^{-\lambda kt} + \alpha \int_0^t ds e^{\lambda k(s-t)} \langle \eta(s) \rangle \\ &= x_0 e^{-\lambda kt}\end{aligned}$$

$$\langle x(t)^2 \rangle = \left\langle \left[x_0 e^{-\lambda kt} + \alpha \int_0^t ds e^{\lambda k(s-t)} \eta(s) \right]^2 \right\rangle =$$

$$= \left\langle \left(x_0 e^{-\lambda kt} \right)^2 + 2\alpha x_0 e^{-\lambda kt} \int_0^t ds e^{\lambda k(s-t)} \eta(s) + \alpha^2 \int_0^t ds_1 e^{\lambda k(s_1-t)} \int_0^t ds_2 e^{\lambda k(s_2-t)} \eta(s_1) \eta(s_2) \right\rangle$$

this term vanishes when averaged

$$= \langle x(t) \rangle^2 + \alpha^2 \int_0^t ds_1 e^{\lambda k(s_1-t)} \int_0^t ds_2 e^{\lambda k(s_2-t)} \delta(s_1 - s_2)$$

$$\begin{aligned}\langle x(t)^2 \rangle - \langle x(t) \rangle^2 &= \alpha^2 \int_0^t ds e^{2\lambda k(s-t)} \\ &= \frac{\alpha^2}{2\lambda k} (1 - e^{-2\lambda kt}) = \sigma^2(t)\end{aligned}$$

$$P(x(t) = y) = \frac{1}{\sqrt{2\pi} \sigma(t)} \exp\left(-\frac{1}{2\sigma^2(t)} (y - x_0 e^{-\lambda kt})^2\right)$$

For t large

$$P(x(t) = y) \propto \exp\left(-\frac{\lambda k}{\alpha^2} y^2\right)$$

$$\begin{aligned} x(t + \Delta t) &= x(t) - \lambda k \Delta t x(t) + \alpha \sqrt{\Delta t} \rho(t) \\ &= (1 - \lambda k \Delta t) x(t) + \alpha \sqrt{\Delta t} \rho(t) \end{aligned}$$

Let us solve it iteratively

$$x(\Delta t) = (1 - \lambda k \Delta t) x_0 + \alpha \sqrt{\Delta t} \rho(0)$$

$$\begin{aligned} x(2\Delta t) &= (1 - \lambda k \Delta t) x(\Delta t) + \alpha \sqrt{\Delta t} \rho(\Delta t) \\ &= (1 - \lambda k \Delta t)^2 x_0 + \alpha \sqrt{\Delta t} [(1 - \lambda k \Delta t) \rho(0) + \rho(\Delta t)] \end{aligned}$$

$$\begin{aligned} x(3\Delta t) &= (1 - \lambda k \Delta t) x(2\Delta t) + \alpha \sqrt{\Delta t} \rho(2\Delta t) \\ &= (1 - \lambda k \Delta t)^3 x_0 + \alpha \sqrt{\Delta t} [(1 - \lambda k \Delta t)^2 \rho(0) + \\ &\quad + (1 - \lambda k \Delta t) \rho(\Delta t) + \rho(2\Delta t)] \end{aligned}$$

Generalization

$$\begin{aligned} x(N\Delta t) &= (1 - \lambda k \Delta t)^N x_0 + \\ &\quad + \alpha \sqrt{\Delta t} \sum_{j=0}^{N-1} (1 - \lambda k \Delta t)^j \rho((N-1-j)\Delta t) \end{aligned}$$

It follows [remember $\langle \rho(t) \rangle = 0$]

$$\langle x(N\Delta t) \rangle = (1 - \lambda k \Delta t)^N x_0$$

If $t = N\Delta t$

$$\langle x(t) \rangle = \left(1 - \lambda k \frac{t}{N}\right)^N x_0$$

We recover the continuum result if we take $N \rightarrow \infty$ at t fixed (i.e. $N \rightarrow \infty, \Delta t \rightarrow 0$ at fixed $N\Delta t = t$)

$$\langle x(t) \rangle \rightarrow e^{-\lambda k t} x_0$$

We can also compute the variance

$$V = \langle x(N\Delta t)^2 \rangle - \langle x(N\Delta t) \rangle^2 = \alpha^2 \Delta t \sum_{j_1=0}^{N-1} (1-\lambda k \Delta t)^{j_1} \sum_{j_2=0}^{N-1} (1-\lambda k \Delta t)^{j_2} \langle \rho[(N-1-j_1)\Delta t] \times \rho[(N-1-j_2)\Delta t] \rangle$$

Now

$$\langle \rho[(N-1-j_1)\Delta t] \rho[(N-1-j_2)\Delta t] \rangle = \delta_{j_1 j_2}$$

$$V = \alpha^2 \Delta t \sum_{j=0}^{N-1} (1-\lambda k \Delta t)^{2j} = \alpha^2 \Delta t \frac{1 - (1-\lambda k \Delta t)^{2N}}{1 - (1-\lambda k \Delta t)^2} = \frac{\alpha^2}{2\lambda k} \frac{1 - (1-\lambda k \Delta t)^{2N}}{1 - \lambda k \Delta t / 2}$$

$$\sum_{j=0}^M x^j = \frac{1-x^{M+1}}{1-x}$$

Instability if $1 - \lambda k \Delta t / 2 < 0$ $\Delta t > \frac{2}{\lambda k}$

$\downarrow N \rightarrow \infty, \Delta t \rightarrow 0, t = N\Delta t$

$$= \frac{\alpha^2}{2\lambda k} (1 - e^{-2\lambda k t})$$