

Autocovariance:

$$\begin{aligned} C_{xx}(t_1, t_2) &= E[(X(t_1) - \mu_{t_1})(X(t_2) - \mu_{t_2})] \\ &= E[X(t_1)X(t_2)] - \mu_{t_1}\mu_{t_2} \end{aligned}$$

Autocorrelation:

$$R_{xx}(t_1, t_2) = \frac{C_{xx}(t_1, t_2)}{\sigma_{t_1}\sigma_{t_2}}$$

If  $\tau = t_2 - t_1$

$$R(\tau) = \frac{E[(X(t_1) - \mu)(X(t_2) - \mu)]}{\sigma^2}$$

$X(t_1) \rightarrow$  random variable at time  $t_1$   
 $X(t_2) \rightarrow$  " " " "  $t_2$

Measured by a quantity called correlation time, the time scale for the process

Consider

$$\int_0^{\infty} R(\tau) d\tau = \begin{cases} \text{finite} \\ \text{infinite} \\ \text{indeterminate} \end{cases}$$

(Indeterminate might correspond to, e.g.,

$$\int_0^T R(\tau) d\tau, T \rightarrow \infty, = 0 \text{ or } 1 \text{ depending on value of } T)$$

When integral is finite, we define

$$\tau_c = \int_0^{\infty} R(\tau) d\tau$$

↑ correlation time for process

Examples:

$$(a) \quad R(\tau) = \exp(-\tau/\tau_c) \quad \left. \begin{array}{l} \\ \end{array} \right\} \text{exponential}$$

$$\int_0^{\infty} \exp(-\tau/\tau_c) d\tau = \tau_c$$

For our Brownian particle,

$$S(f) = \int_{-\infty}^{\infty} \sigma^2 e^{-\tau/\tau_c} e^{-2i\pi f\tau} d\tau$$

$$\text{Power spectrum} = \frac{2\sigma^2\tau_c}{1+(2\pi f\tau_c)^2}$$

↓

$$|S(f)|^2$$

Use Cauchy residue theorem to find  $S(f)$

When  $f \ll 1/2\pi\tau_c$ , power spectrum is basically frequency-independent. So for time windows

$\Delta T \gg \tau_c$  stochastic process is basically white noise.

Integral of white noise is called a "Wiener

Process", a non-stationary process

characterized by a power-law power

spectrum  $S(f) \sim \frac{1}{f^2}$

↗

"fingerprint" of short range stochastic process

## Long-Range Correlations

- Power law  $S(f) \Rightarrow$  long-range correlations
- Such autocorrelation functions are seen in physics, biology, social science & economic systems

So Consider

$$S(f) = \frac{\text{const.}}{|f|^\eta} \quad \text{with} \quad 0 < \eta < 2$$

- (i)  $\eta = 0 \Rightarrow$  white noise
- (ii)  $\eta = 2 \Rightarrow$  Wiener process

When  $\eta \neq 1$ , stochastic process with this spectral density is called  $1/f$  noise or "flicker noise".

$1/f$  noise seen in diodes, transistors, traffic flow, etc.

Stochastic processes like this are non-stationary

## Markov processes.

Suppose a time scale  $\tau_c$  exists and is defined.

Then for intervals  $\Delta t > \tau_c$ , we have

$$f(x_1, x_2, \dots, x_{n-1}; t_1, t_2, \dots, t_{n-1} \mid x_n; t_n)$$

preceeding state
}
current or next state

$$= f(x_{n-1}; t_{n-1} \mid x_n; t_n)$$

i.e., the pdf or state for the next value depends only the immediate last state

As a corollary:

$$f(x_1, x_2, x_3; t_1, t_2, t_3)$$

$$= f(x_1, t_1) f(x_2; t_2 \mid x_1; t_1) f(x_3; t_3 \mid x_2; t_2)$$

For a generalized Markov process, pdf depends on a finite number of preceeding states (not just 1)

6-11

## Noises & Walks

Noise: Reverts to mean

Walks: Diffusion process fBm  
Fractional Brownian motion

Time Series:  $\Delta t = t_2 - t_1$

$$V(t): \langle \Delta V \rangle^2 = \langle V(t_2) - V(t_1) \rangle^2$$

For fBm

$$\langle \Delta V \rangle^2 \sim \Delta t^{2H} \quad H: \text{Hausdorff dimension}$$

Define a fractal Dimension  $D$ :

$$D = 2 - H$$

For Wiener process,  $H = \frac{1}{2}$  (from a white noise)

Also  $H > \frac{1}{2}$  persistence  
 $H < \frac{1}{2}$  anti persistence (pink noise)

equal power at all frequencies

Spectral exponent

$$\eta = 2H + 1$$