

①

Sections 5.1-5.4 in Hsu

also called stochastic process

SES

Def A random process is a family $\{X(t) = X(t, \omega)\}_{\omega \in \Omega}$ of random variables indexed by time $t \in T$

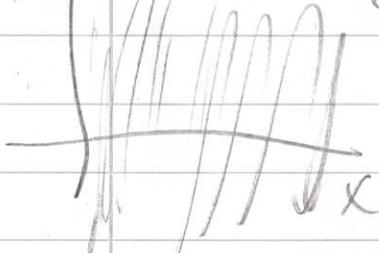
The time parameter set T is either discrete
 $T = \mathbb{N}, \mathbb{Z}, \{0, \dots, n\}$ etc or continuous
 $T = \mathbb{R}, \mathbb{R}^+, [a, b]$ etc.

As the CDF $F_x(x)$ is used to study r.v.'s
one might believe the CDF $F_{X(t), X_1}(x)$ of a random process $X(t)$ at each time t
says a lot about the process.

This is not true.

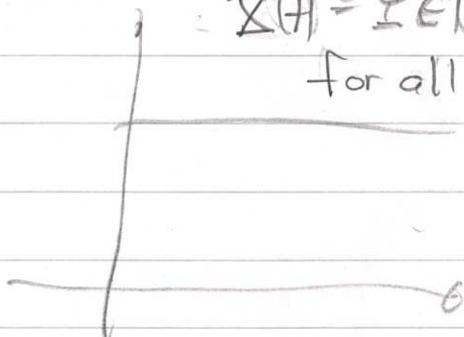
Ex 1

$X(t)$ all $X(t)$ independent
of $N(0, 1)$ -distributed



Ex 2

$X(t) = Y \in N(\mu_t, \sigma_t)$
for all t



Both the above processes have CDF
 $F_{X(t), X_1}(x) = \Phi(x)$ for each $t \in T$ but
are totally different in behavior.

(2)

Def The mean function $M_{\bar{X}(t)} = E(\bar{X}(t))$

The autocorrelation function $R_{\bar{X}}(t_1, t_2) = E(\bar{X}(t_1)\bar{X}(t_2))$

The autocovariance function $K_{\bar{X}}(t_1, t_2) = \text{Cov}(\bar{X}(t_1), \bar{X}(t_2))$

Crosscorrelation function $R_{\bar{X}, \bar{Y}}(t_1, t_2) = E(\bar{X}(t_1)\bar{Y}(t_2))$

Crosscovariance function $K_{\bar{X}, \bar{Y}}(t_1, t_2) = \text{Cov}(\bar{X}(t_1), \bar{Y}(t_2))$

Example For $\bar{X}(t) = U \cos(\omega t) + V \sin(\omega t)$

where U and V are zero mean uncorrelated
with variance σ^2 we have $M_{\bar{X}(t)} = 0$ and

$$\begin{aligned} R_{\bar{X}}(s, t) &= C_{\bar{X}, \bar{X}}(s, t) = E(U^2) \cos(\omega s) \cos(\omega t) \\ &\quad + E(V^2) \sin(\omega s) \sin(\omega t) \\ &= \sigma^2 \cos(\omega(s-t)) \end{aligned}$$

(cosine-process)

Example For $\bar{X}(t) = \alpha(\sin \omega t + \Theta)$ with Θ

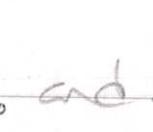
uniformly distributed over $[0, 2\pi]$ we have

$$M_{\bar{X}(t)} = 0 \text{ and}$$

$$\begin{aligned} R_{\bar{X}}(s, t) &= C_{\bar{X}, \bar{X}}(s, t) = \alpha^2 E(\sin(\omega s + \Theta) \sin(\omega t + \Theta)) \\ &= \alpha^2 E\left(\frac{1}{2} \cos(\omega s - \omega t) + \frac{1}{2} \cos(\omega s + \omega t + 2\Theta)\right) \\ &= \frac{1}{2} \alpha^2 \cos(\omega s - \omega t) \end{aligned}$$

Def $X(t)$ is (strictly) stationary if $F_{X(t), \dots, X(t_n)}(x_1, \dots, x_n) =$

$$F_{X(t+h), \dots, X(t+n)}(x_1, \dots, x_n)$$

Example The processes  and  are both stationary.

(3)

Def $X(t)$ is ^{weak} wide sense stationary WSS if
 $\{M_X(t) = \mu_X\}$
 $\{R_{XX}(t, t+z)\}$ does not depend on t .
Thm stationary \Rightarrow WSS

Notation For $X(t)$ WSS we write $R_X(t, t+z) = R_X(z)$.

Example Both trigonometric processes we saw earlier are WSS as are \sin and \cos .

Properties of autocorrelation for WSS $X(t)$

* $|R_X(z)| \leq R_X(0)$ and $(E(X(t)X(t+z)))^2 \leq (E(X(t)^2))(E(X(t+z)^2))$

since $E\left(\frac{(X(t))^2}{R_{XX}(0)} + \frac{R(t+z)^2}{R_{XX}(0)}\right) \geq 0$

* $R_X(z) = R_X(-z)$ * $R_X(0) = E(X(t)^2)$

Def A random process $X(t)$ is Gaussian if $\sum_{i=1}^n a_i X(t_i)$ is normal for all a_i and t_i .

Note $X(t)$ Gaussian \Rightarrow each $X(t)$ -value normal but it is not the other way around!

Ex $X(t) = U \cos(\omega t) + V \sin(\omega t)$ with $U, V \in N(0, \sigma^2)$ independent is Gaussian.

(4)

Fact A Gaussian process is probabilistically determined entirely by its mean function and autocorrelation function.

Proof $\Phi_{X(t_1), \dots, X(t_n)}(w_1, \dots, w_n) = E\left(e^{j \sum_{i=1}^n w_i X(t_i)}\right)$

where $u = E\left(\sum_{i=1}^n w_i X(t_i)\right) = \sum_{i=1}^n w_i u_X(t_i)$ and $\sigma^2 = \text{Var}\left(\sum_{i=1}^n w_i X(t_i)\right) = \sum_{i=1}^n \sum_j w_i w_j K_X(t_i, t_j)$. \checkmark

Fact A Gaussian process is stationary if WSS.

Proof If WSS it has same u_X and R_{XX} as stationary and therefore is stationary as determined by those. \checkmark

Fact Two Gaussian process values $X(s)$ and $X(t)$ are independent if uncorrelated.

Proof If uncorrelated they have same u_X and $R_{XX}(s, t)$ as if independent and thus are independent since determined by those. \checkmark

Example Find $\Pr(X(1) + 2X(2) \geq 3)$ for cosine-process with U and V Gaussian/normal.

Solution $X(1) + 2X(2)$ is $N(0, \Sigma^2)$ with

$$\begin{aligned}\Sigma^2 &= \text{Var}(X(1) + 2X(2)) = \text{Var}(X(1)) + 4\text{Cov}(X(1), X(2)) + 4\text{Var}(X(2)) \\ &= \sigma^2 + 4\sigma^2 \cos(1) + 4\sigma^2\end{aligned}$$

so

$$\Pr(X(1) + 2X(2) \geq 3) = 1 - \Pr(N(0, \Sigma^2) \leq 3)$$

$$= 1 - \Phi\left(\frac{3 - 0}{\sqrt{\sigma^2 + 4\sigma^2 \cos(1)}}\right).$$

We do not discuss subsection 5.4.C about independent processes as uninteresting.
 (This was one of our first examples of a random process.)

We discuss discrete valued Markov processes called Markov chains in Section 5.5 so we jump subsection 5.4-E as well.

We do not discuss subsection 5.4-G on ergodic processes as better suited to cover in second more advanced random process course.

Subsection 5.4.D

[Def]

A random process $\{X(t)\}_{t \geq 0}$ has stationary independent increments (also called Lévy process) if

- * $X(0) = 0$
- * the probability distribution of $X(t+s) - X(s)$ depends on t only but not on s for $0 \leq s \leq t+s$
- * $X(t) - X(s)$ is independent of $\{X(r)\}_{r \in [0,s]}$ of $0 \leq s \leq t$

[Ex]

The two most important stationary independent increment processes the Poisson process and the Wiener process we meet in Sections 5.6-5.7.