

6 Introduction to Stochastic Processes

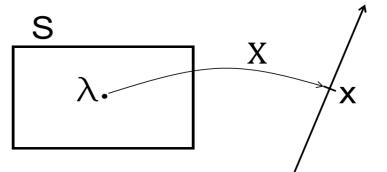
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Agenda for Today

- Repetition from last time
 - Random Variables
- Stochastic Processes
 - Definition
 - Stationarity (WSS, SSS)
 - Ergodic Processes

Stochastic Random Variables

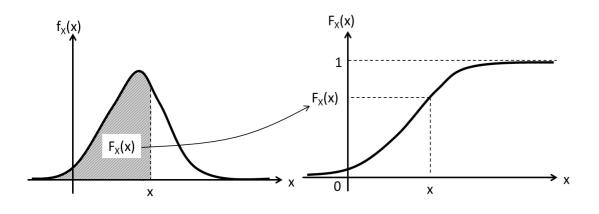
- A random variable tells something important about a stochastic experiment.
- Can be discrete or continous



Probability density function (pdf):

$$Pr(a \le X \le b) = \int_a^b f_X(x) \, dx \qquad f_X(x) \ge 0 \qquad \int_{-\infty}^\infty f_X(x) dx = 1$$

Cumulative distribution function (cdf):



$$F_X(x) = \int_{-\infty}^x f_X(u) \ du = Pr(X \le x)$$

$$0 \le F_X(x) \le 1$$

$$\lim_{x \to -\infty} F_X(x) = 0 \qquad \lim_{x \to \infty} F_X(x) = 1$$

Two Simultaneous Continuous Random Variables

$$f_{X,Y}(x,y) \ge 0$$

Joint (Simultaneous) pdf:
$$f_{X,Y}(x,y) \ge 0$$

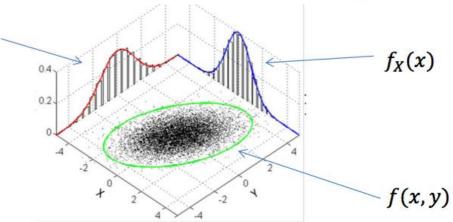
$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x,y) dx dy = 1$$

$$Pr((a \le X \le b) \cap (c \le Y \le d)) = \int_{c}^{d} \int_{a}^{b} f_{X,Y}(x,y) dxdy$$

Marginals:
$$f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) \ dy$$

$$f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) \ dx$$
 $f_Y(y)$





Cumulative Distribution Function cdf:

$$cdf \quad F_{X,Y}(x,y) = \int_{-\infty}^{y} \int_{-\infty}^{x} f_{X,Y}(x,y) dx dy = Pr(X \le x \land Y \le y)$$

$$pdf f_{X,Y}(x,y) = \frac{\partial^2 F_{X,Y}(x,y)}{\partial x \partial y}$$

Two Random Variables

Two random variables: X and Y

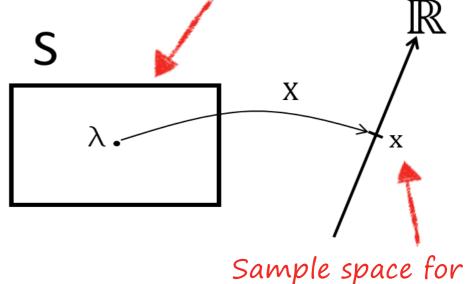
- Simultaneous pdf: $f_{X,Y}(x,y) \rightarrow f_X(x) \cdot f_Y(y)$ if independent
- Marginal pdf: $f_X(x)$ and $f_Y(y)$
- Conditional pdf: $f_{X|Y}(x|y)$ and $f_{Y|X}(y|x) \rightarrow$ Bayes rule
- Simultaneous cdf: $F_{X,Y}(x,y) = Pr(X \le x \land Y \le y)$
- Correlation: corr(X,Y) = E[XY]
- Covariance: cov(X,Y) = E[XY] E[X]E[Y]
- Correlation coefficient: $\rho = \frac{E[XY] E[X]E[Y]}{\sigma_X \cdot \sigma_Y}$
- Sum: $Z = X + Y \rightarrow f_Z(z) = f_X(z) * f_Y(z)$ if independent
- Expectation: E[Z] = E[X] + E[Y]
- Variance: Var[Z] = Var[X] + Var[Y] if independent
 - Var[Z] = Var[X] + Var[Y] + 2cov(X, Y) if <u>dependent</u>

Stochastic Processes

Stochastic Variables

Sample space for stochastic experiment

Sample space for stochastic experiment



stochastic variable

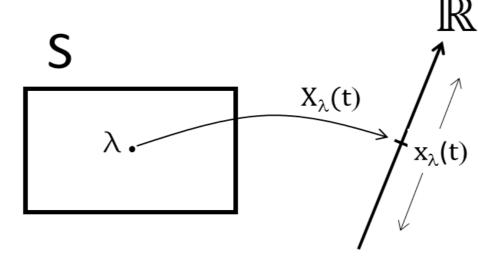
Time dependent

Stochastic Processes (signals)

- Sample space for stochastic experiment
- Random events that develops in time

iat develops in time

Sample space for stochastic experiment

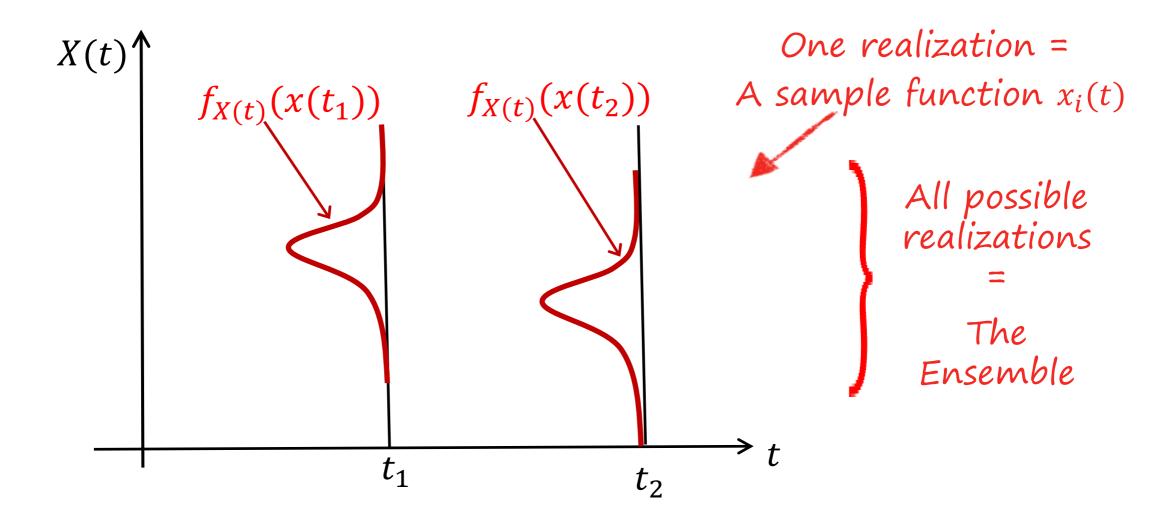


Sample space for stochastic proces

Stochastic Processes

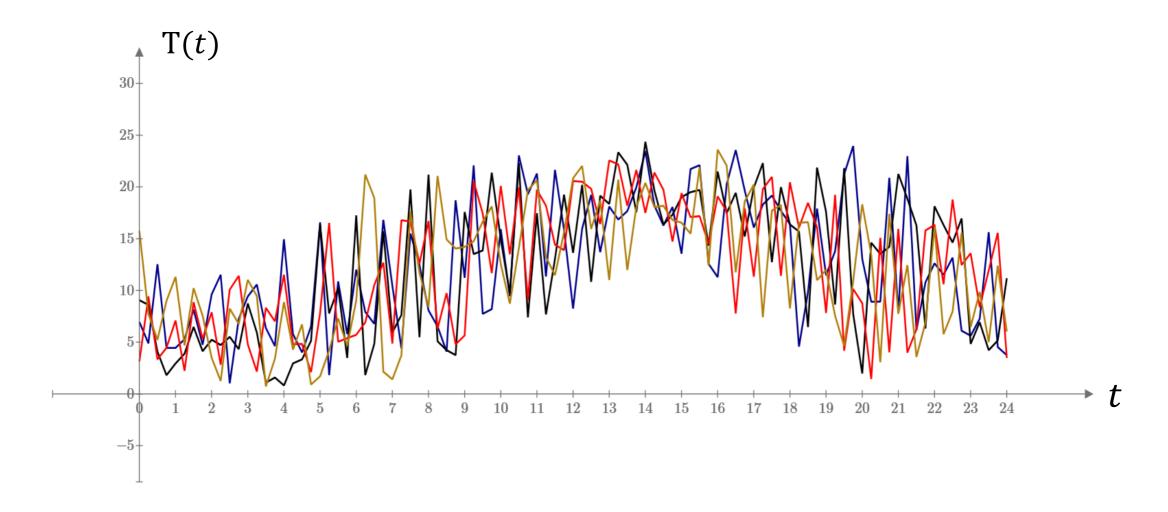
A stochastic process X:

- a collection of time-dependent random (continuous or discrete-valued) variables $x_i(t)$
- at a fixed time $X(t_1)$ is a random variable with a cdf: $f_{X(t)}(x(t_1))$



Stochastic Processes – Outdoor Temperature

- \triangleright Outdoor temperature T(t)
 - Continuous-valued: $T(t) \in [-100, 100]$
 - Continuous-time: $t \in [0, 24]$

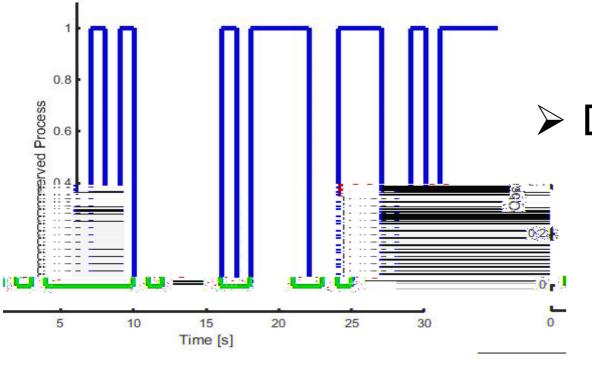


Stochastic Processes – Random Binary (digital) Signal

- Bernoulli process (flip a coin)
- A random sequence of H (1) and T (0): THHTHTT...
- A sequence of i.i.d. Bernoulli trials



One realization of a Bernoulli Proces = A sample function x(t)



Digital noise X(t)

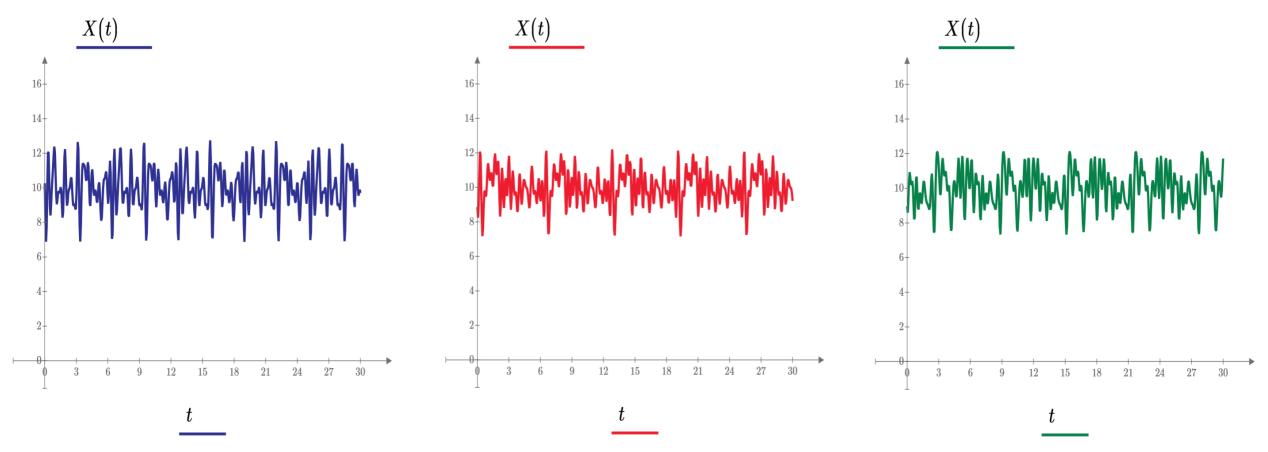
- Discrete-valued: $X(t) \in \{0,1\}$
- Discrete-time: $t \in \{0, \Delta T, 2\Delta T, ..., n\Delta T, ...\}$

Stochastic Processes – Random Signals

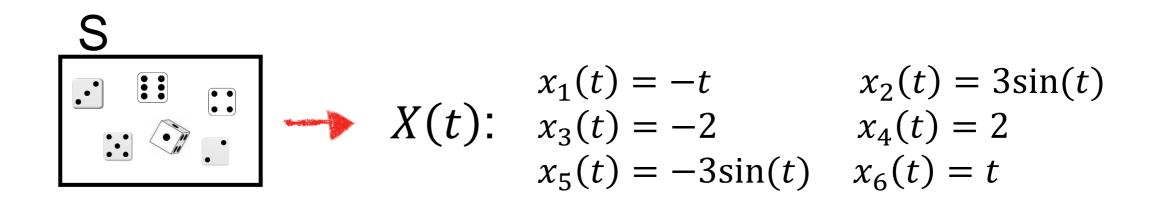
Additive Noisemodel

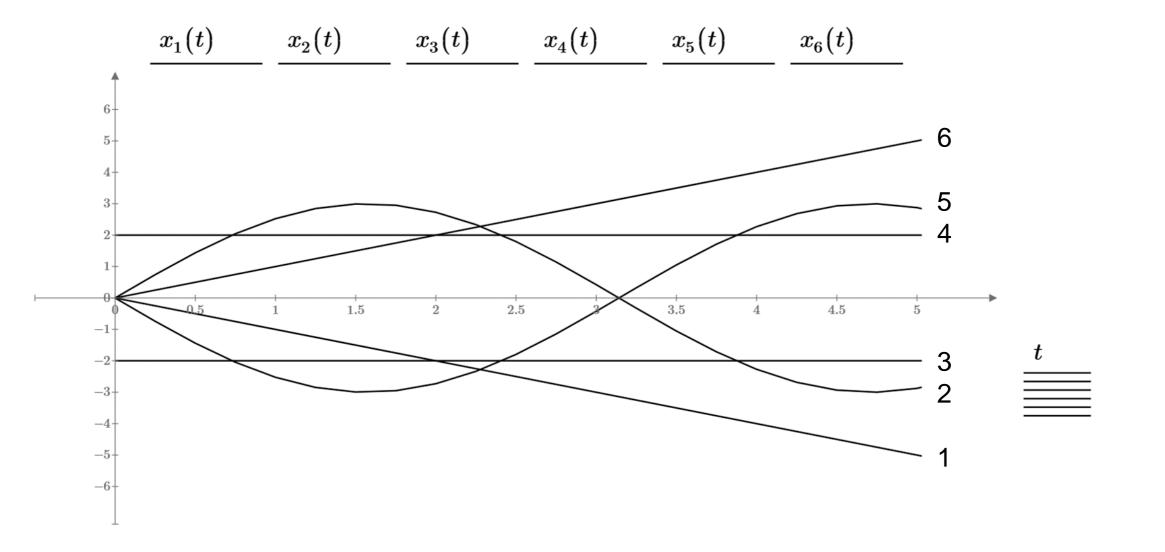
 $observed\ signal = signal\ +\ noise$

Three Realizations of the Stochastic Process



Stochastic Processes – Example



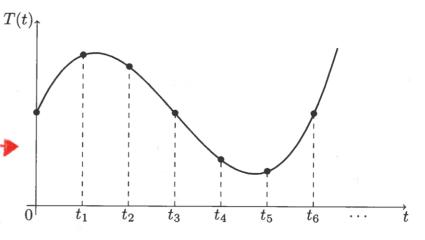


Stochastic Processes



A stochastic process is a time dependent stochastic variable:

Continuous-time



Sampling

A discrete stochastic process is given by:

$$X[n] = X(nT)$$

where n is an integer. Discrete-time

Notice:

When we measure/sample a signal from a stochastic process, we observe only one realization of the process

Sample Functions – Realizations – Ensemble

Definition:

- A Sample Function x(t) is a <u>realization</u> of a stochastic process X
- The Ensemble of the Stochastic Process is the collection of all possible realizations x(t) of the Stochastic Process X

Example:

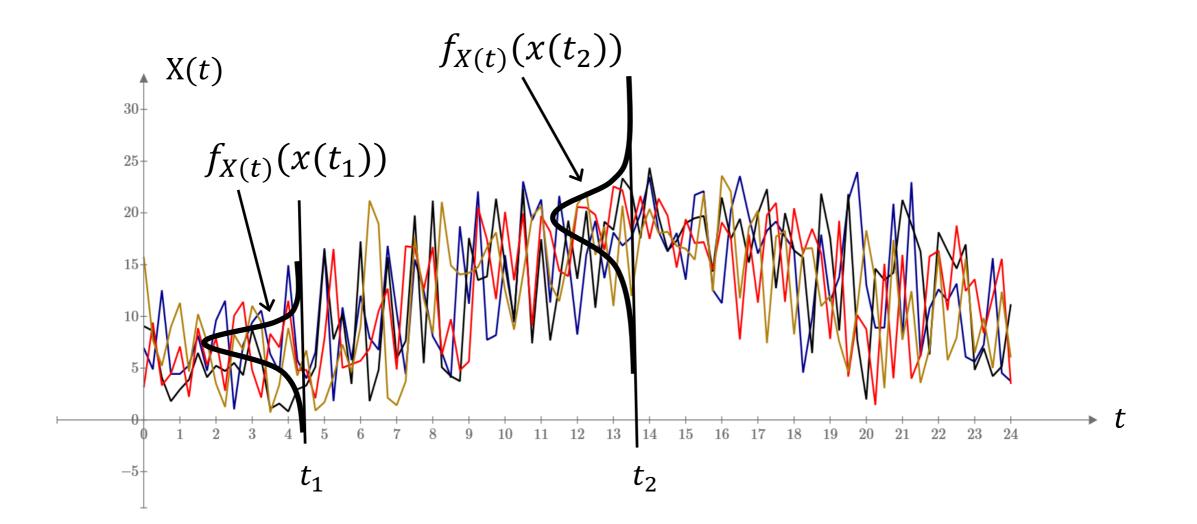
- A coin is thrown every minute: H = head, T = tail
- One realization of the stochastic signal is: HTHT
- The Ensemble of the stochastic signals is: HTHT, HHTT, TTHH, THTH, THHT, TTHT, HHHH...



Time Dependent Probability Functions

- Probability density function (pdf): $f_{X(t)}(x(t))$
- Cumulative distribution function (cdf):

$$F_{X(t)}(x(t)) = Pr(X(t) \le x(t)) = \int_{-\infty}^{x(t)} f_{X(t)}(x(t)) dx(t)$$

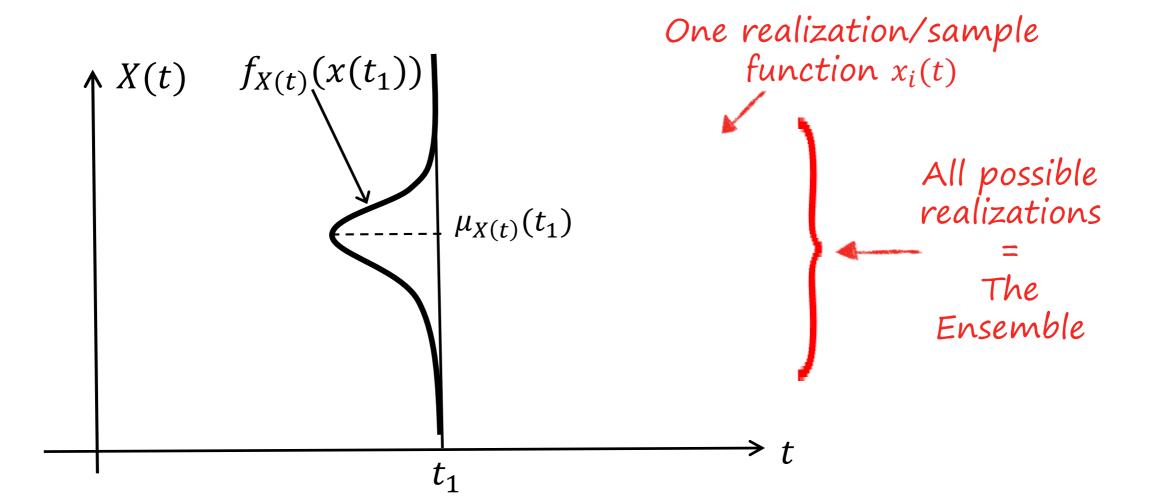


Ensemble mean

The mean value function:

$$\mu_{X(t)}(t) = E[X(t)] = \int_{-\infty}^{\infty} x(t) f_{X(t)}(x(t)) dx(t)$$

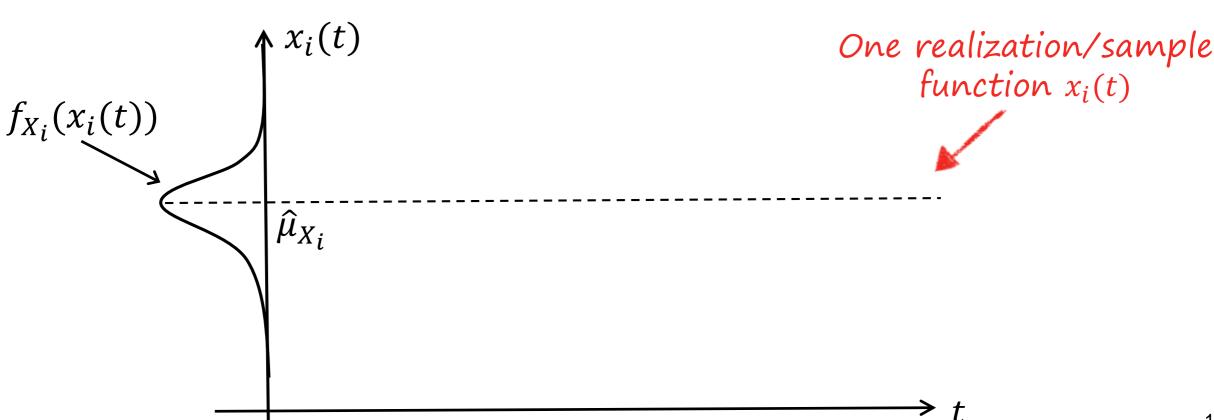
The mean of <u>all possible realizations</u> to time t



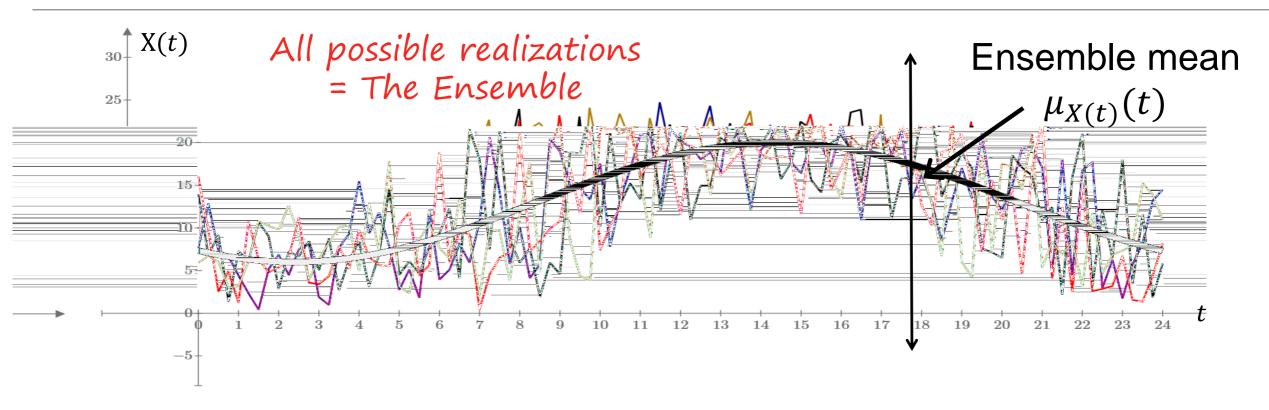
Temporal Mean

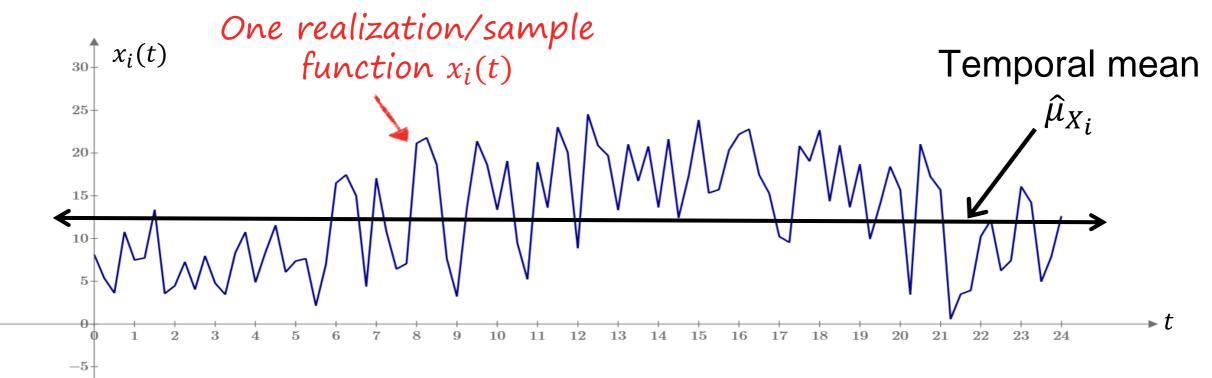
- The time average for <u>one realization</u> of the stochastic process
- The temporal mean can differ from the ensemble mean

$$\hat{\mu}_{X_i} = \langle X_i \rangle_T = \lim_{T \to \infty} \frac{1}{T} \int_{-T/2}^{T/2} x_i(t) \ dt \quad \left(\text{or } \lim_{T \to \infty} \frac{1}{T} \int_0^T x_i(t) \ dt \right)$$



Stochastic Processes – Ensemble/Temporal Mean



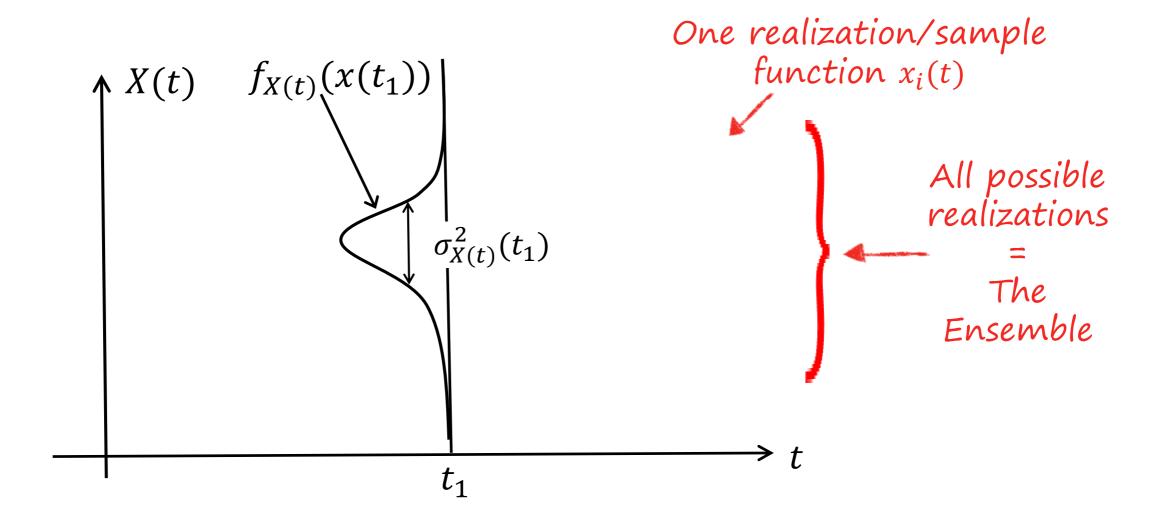


Ensemble Variance

The variance function:

$$Var(X(t)) = \sigma_{X(t)}^2(t) = E[\left(X(t) - \mu_{X(t)}(t)\right)^2]$$

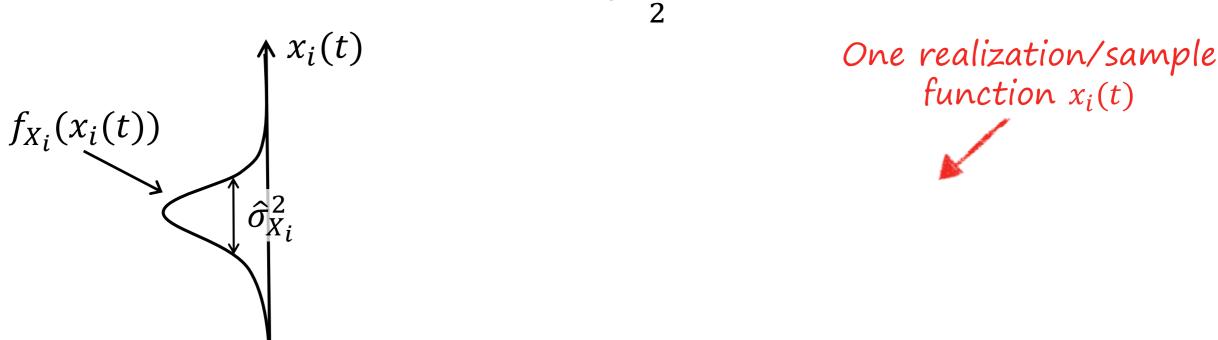
The variance of <u>all possible realizations</u> to time t



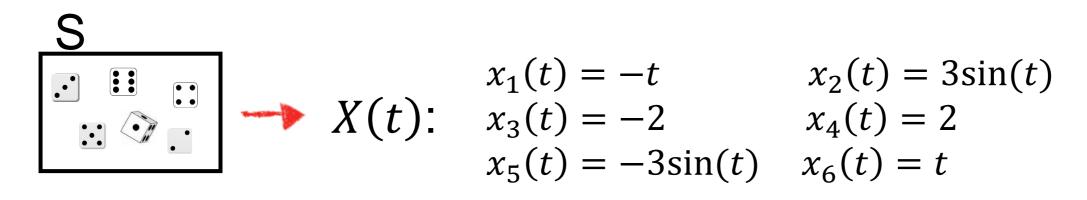
Temporal Variance

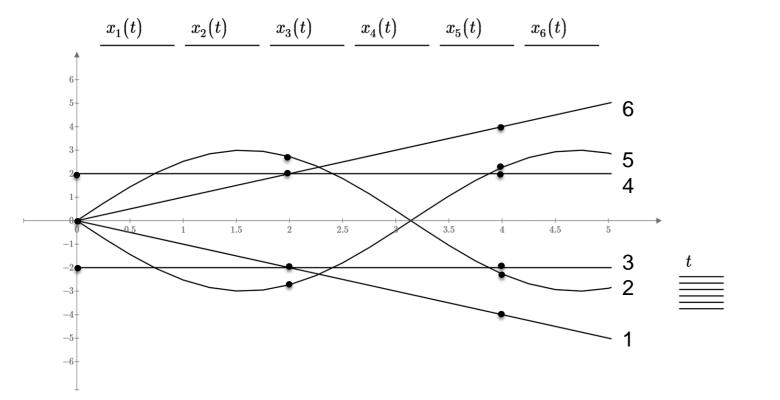
- The variance over time for <u>one realization</u> of the stochastic process
- The temporal variance can differ from the ensemble variance

$$\hat{\sigma}_{X_i}^2 = \langle X_i^2 \rangle_T - \langle X_i \rangle_T^2 = \lim_{T \to \infty} \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} (x_i(t)^2 - \hat{\mu}_{X_i}^2) dt = Var(X_i)$$



Stochastic Processes – Example





$$X(0) = \{-2, 0, 2\}$$

 $X(2) = \{-2.7, -2, 2, 2.7\}$
 $X(4) = \{-4, -2.3, -2, 2, 2.3, 4\}$
 $Pr(X(0) = 0) = 2/3$
 $Pr(X(2) = 2) = 1/3$
 $Pr(X(4) = -4) = 1/6$

Ensemble:
$$\mu_{X(t)}(t) = E[X(t)] = 0$$

$$Var(X(t)) = \sigma_{X(t)}^{2}(t) = \frac{1}{3}(t^{2} + 9sin^{2}(t) + 4)$$

$$\hat{\mu}_{X_2} = 0$$

$$\hat{\mu}_{X_2} = 0$$
 $\hat{\mu}_{X_3} = -2$

$$\hat{\sigma}_{X_2}^2 = 4.5 \qquad \hat{\sigma}_{X_3}^2 = 0$$

$$\hat{\sigma}_{X_3}^2 = 0$$

Stationarity in the Strict Sense (SSS)

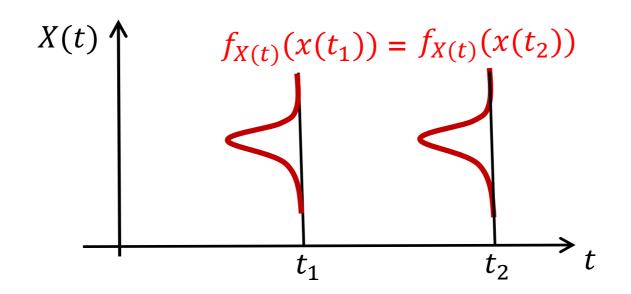
Difficult to test in reality

- The density function $f_{X(t)}(x(t))$ do not change with time
 - For all choices of t_1 and Δt_1 , the marginal pdf:

$$f_{X(t_1)}(x(t_1)) = f_{X(t_1 + \Delta t_1)}(x(t_1 + \Delta t_1))$$

– For all choices of t_1 , t_2 and Δt , the simultaneous pdf:

$$f_{X(t_1),X(t_2)}(x(t_1),x(t_2)) = f_{X(t_1+\Delta t),X(t_2+\Delta t)}(x(t_1+\Delta t),x(t_2+\Delta t))$$



Stationarity in the Wide Sense (WSS)

Can be tested

Ensemble mean is a constant

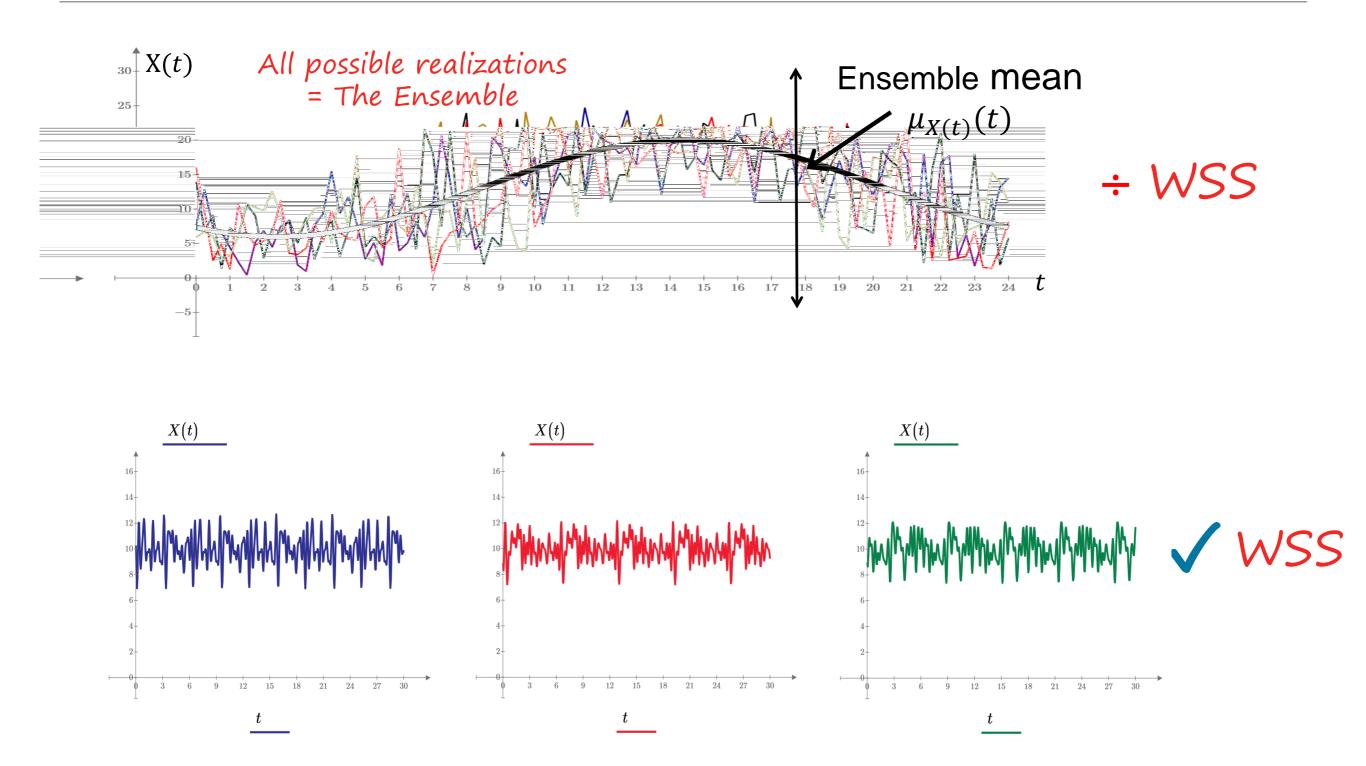
$$\mu_X(t) = E[X(t)] = \mu_X$$
 - independent of time

Ensemble variance is a constant

$$\sigma_X^2(t) = E[X(t)^2] - E[X(t)]^2 = \sigma_X^2$$
 - independent of time

Autocorrelation depends only on the time difference $\tau = t_2 - t_1$ $R_{XX}(t, t + \tau) = E[X(t)X(t + \tau)] = R_{XX}(\tau) \quad \text{- independent of time}$

Wide Sense Stationary (WSS) – Examples



Ergodicity

 We can say something about the properties of the stochastic process in general <u>based on one sample</u> <u>function</u> (realization), as long as we have observed it for long enough.

Example:

An i.i.d Gaussian noise stream

Ergodicity

If ensemble averaging is equivalent to temporal averaging:

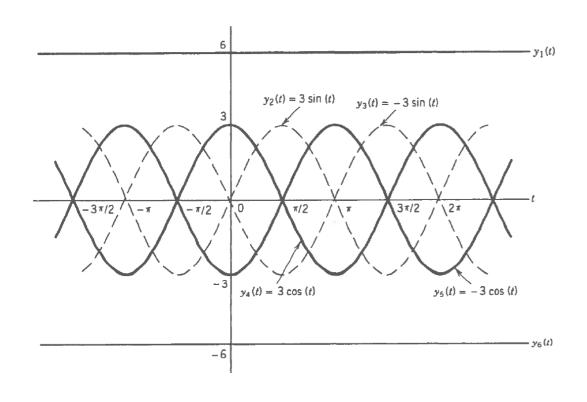
$$\mu_X(t) = \bar{X}(t) = \int_{-\infty}^{\infty} x(t) f_X(x(t)) \ dx(t) = \lim_{T \to \infty} \frac{1}{T} \int_{-T/2}^{T/2} x_i(t) \ dt = \langle X_i \rangle_T = \hat{\mu}_{X_i}$$

In practice: n=2 (Variance) For any moment:

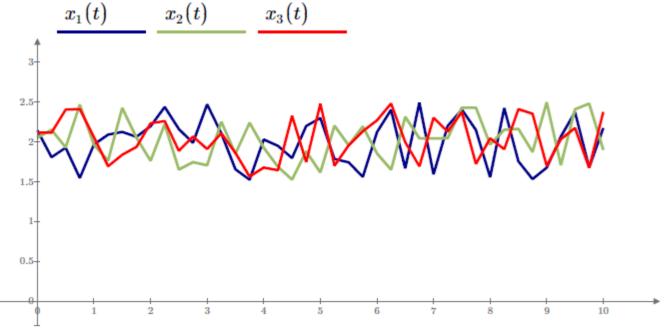
$$\overline{X^n} = \int_{-\infty}^{\infty} x^n f_X(x) \ dx = \lim_{T \to \infty} \frac{1}{T} \int_{-T/2}^{T/2} x_i^n \ (t) \ dt$$

One (any) realization Ensemple (WSS) $\hat{\mu}_{X_i} = \mu_X \\ \hat{\sigma}_{X_i}^2 = \sigma_X^2 \\ \end{pmatrix} \rightarrow Ergodic \qquad \text{All information is achieved with one measurement (realization)}$

WSS and Ergodicity – Examples



- ÷ SSS
- ✓ WSS
- ÷ Ergodic



$$X_n(t) = 2 + w_n(t)$$

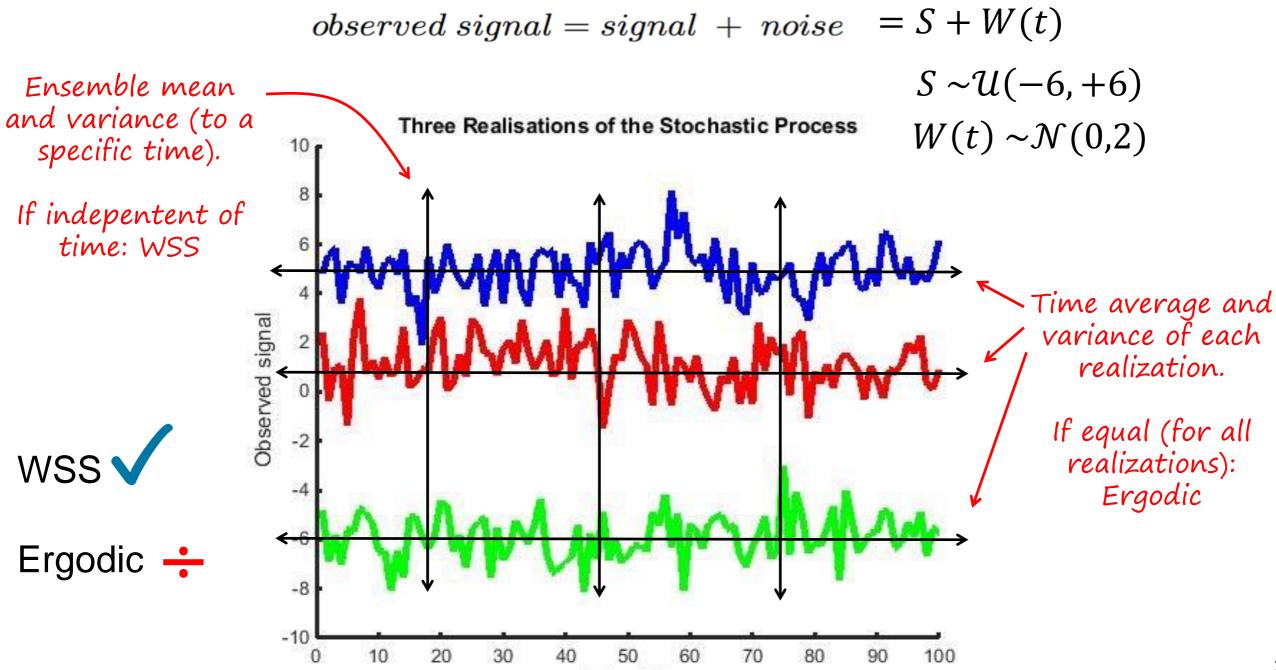
 $w_n(t) \sim \mathcal{U}(-0.5; 0.5)$

- ✓ WSS
- ✓ Ergodic



Stochastic Processes (signals)

Additive Noisemodel



Time [s]

Discrete stochastic process:

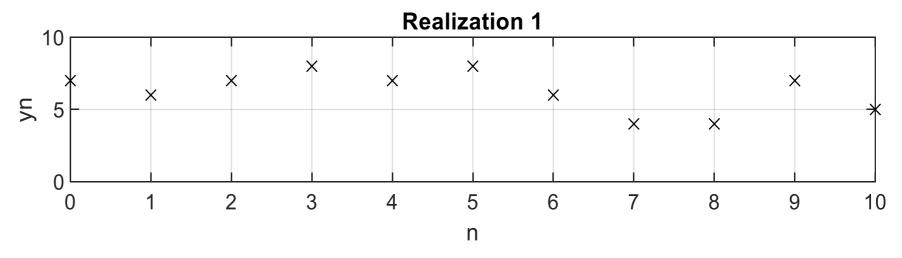
$$Y(n) = X + W(n);$$

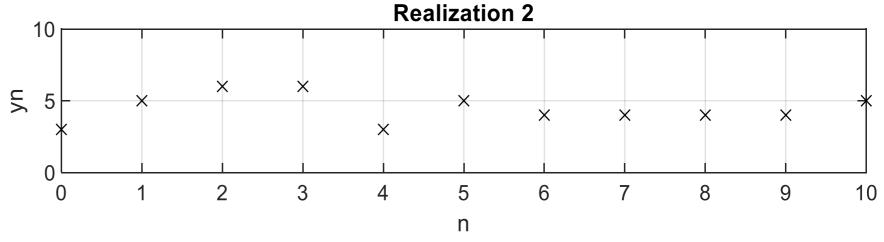
 $X \sim \mathcal{B}(10,0.5)$ $W(n) \sim \mathcal{U}[-2,2]$

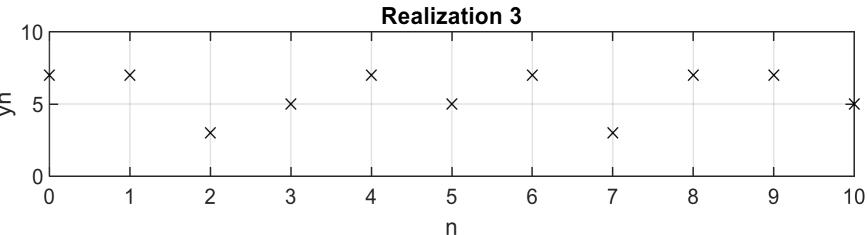
3 realizations 11 samples (n=0,..,10)



Ergodic +







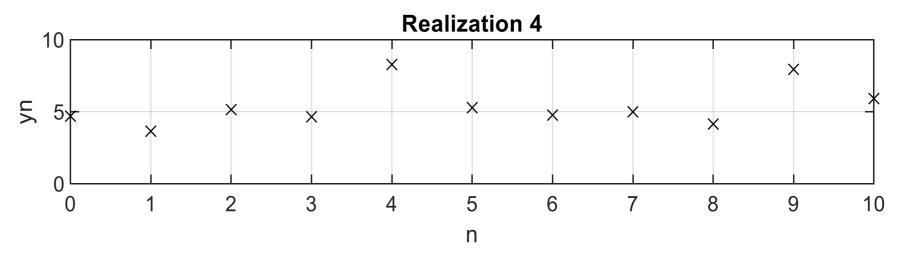
Discrete stochastic process:

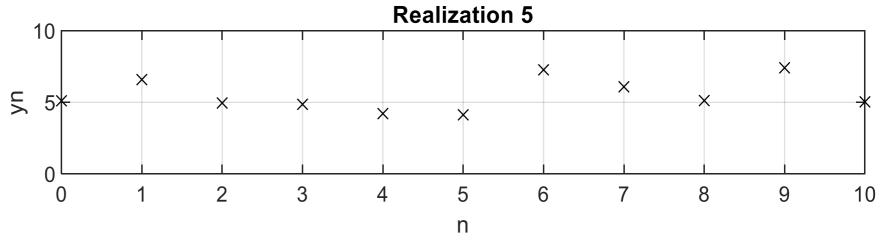
$$Y(n) = W(n);$$

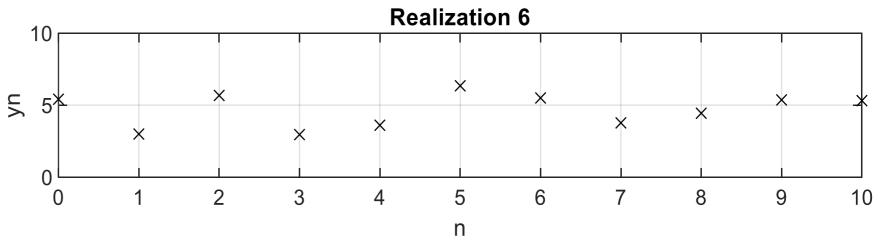
$$W(n) \sim \mathcal{N}(5,2)$$

3 realizations 11 samples (n=0,..,10)









Continuous stochastic process:

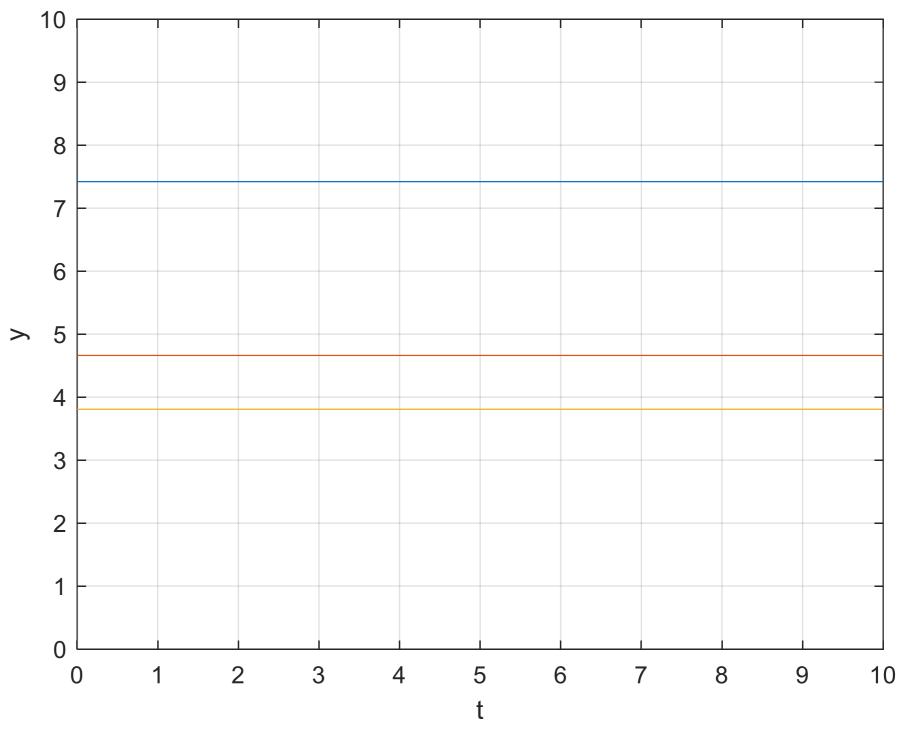
$$Y(t) = W;$$

 $W \sim \mathcal{N}(5,2)$

3 realizations $0 \le t \le 10$



Ergodic 🕂



Continuous stochastic process:

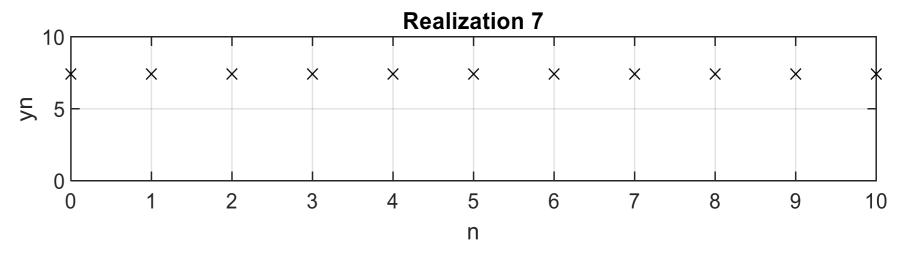
$$Y(t) = W;$$

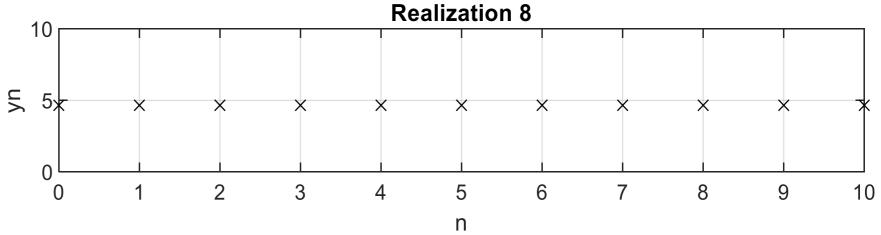
 $W \sim \mathcal{N}(5,2)$

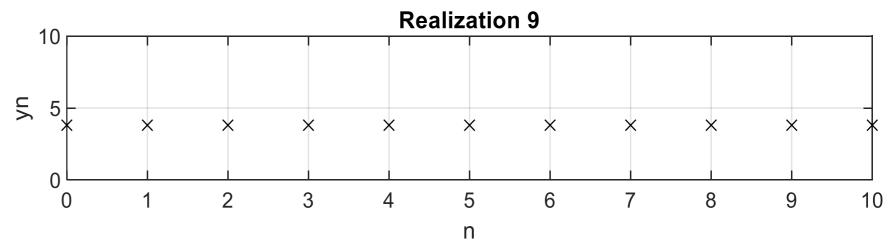
3 realizations 11 samples (n=0,..,10)



Ergodic ÷







Continuous stochastic process:

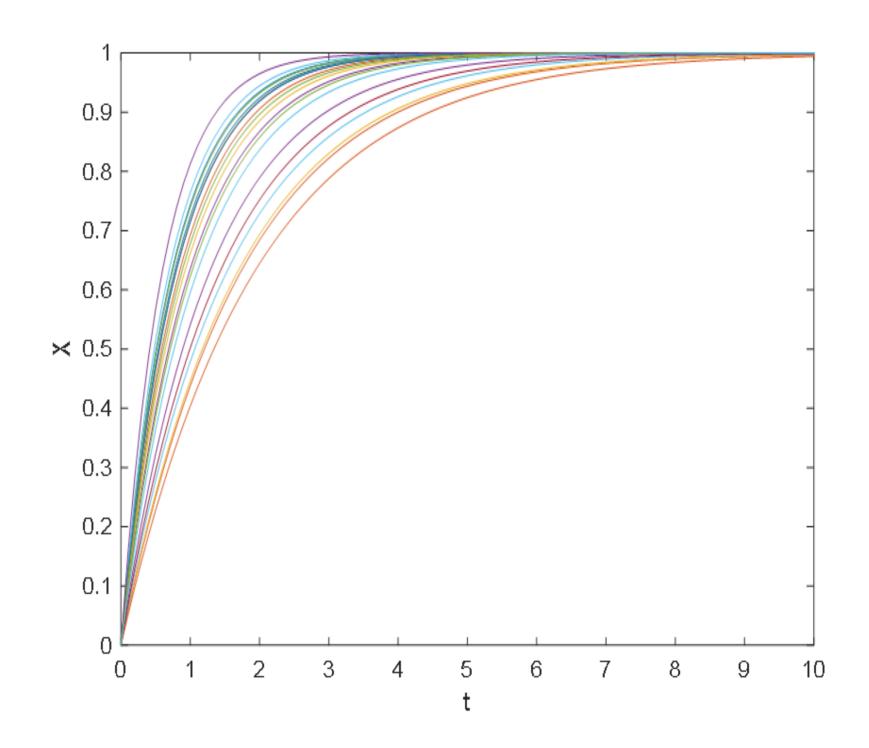
$$X(t) = A(1 - e^{-k \cdot t});$$

$$A = 1$$
; $k \sim \mathcal{N}(1,0.4)$

20 realizations $0 \le t \le 10$

WSS ÷

Ergodic +



Continuous stochastic process:

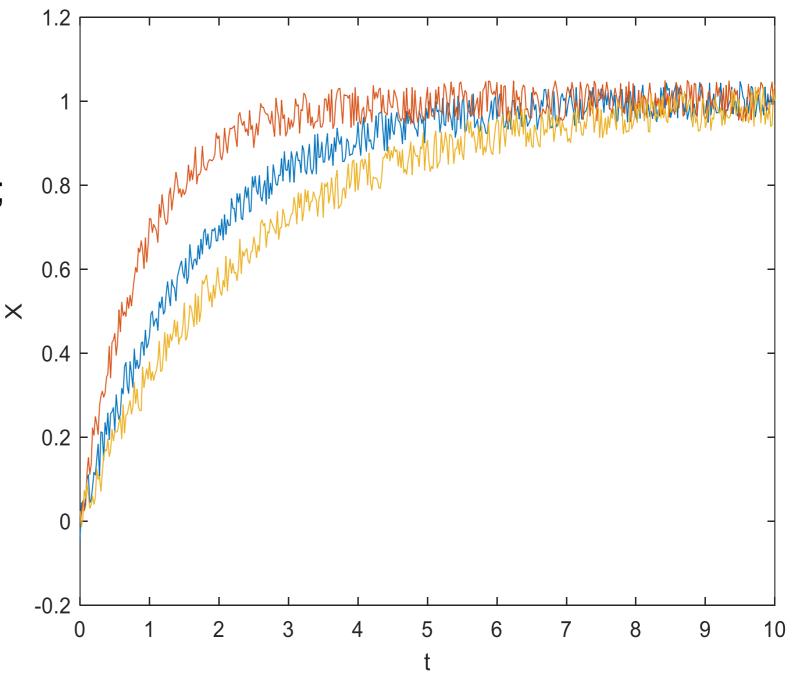
$$X(t) = A(1 - e^{-k \cdot t}) + w(t);$$

 $A = 1; k \sim \mathcal{N}(1,0.4);$
 $w(t) \sim \mathcal{U}(-0.1,0.1)$

3 realizations $0 \le t \le 10$

WSS ÷

Ergodic +



Continuous stochastic process:

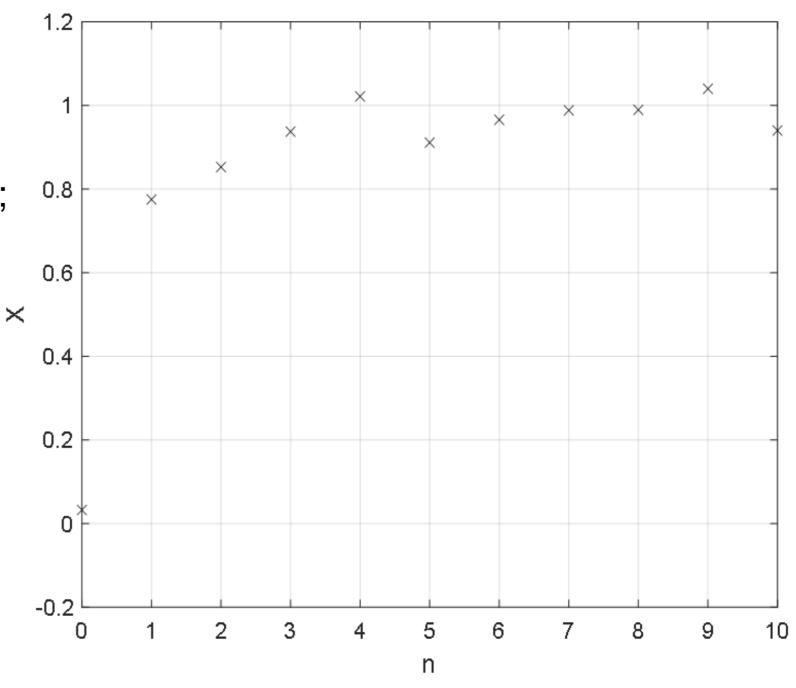
$$X(t) = A(1 - e^{-k \cdot t}) + w(t);$$

 $A = 1; k \sim \mathcal{N}(1,0.4);$
 $w(t) \sim \mathcal{U}(-0.1,0.1)$

1 realization 11 samples (n=0,..,10)

WSS ÷

Ergodic ÷



Words and Concepts to Know

Stochastic Processes

SSS

Ensemple variance

Temporal variance

Random signal

Stationarity

Descrete-time

Continuous-valued

Ensemple mean

WSS

Ergodicity

Continuous-time

Strict Sense Stationary

Descrete-valued

Realization

Temporal mean

Wide Sense Stationary