

# Time Series and Sequence Learning

Stationarity, Empirical ACF

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### Stationary time series

**Def.** A stochastic process  $\{y_t\}_{t\geq 1}$  is said to be **strictly stationary** if, for all  $t_1, \ldots, t_n$  and all  $h \geq 0$ 

$$p(y_{t_1}, \ldots, y_{t_n}) = p(y_{t_1+h}, \ldots, y_{t_n+h}).$$

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**Def.** A stochastic process  $\{y_t\}_{t\geq 1}$  is said to be (weakly) stationary if, for all t,

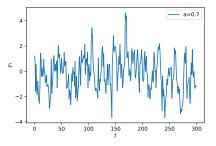
- 1.  $Var(y_t) < \infty$ ,
- 2.  $\mu(t) = \text{const.}$
- 3. The autocovariance function depends only on the time lag,

$$\gamma(t, t+h) =: \gamma(h)$$
 for all  $h$ .

ex) A first-order AR model  $y_t = ay_{t-1} + \varepsilon_t$  is (weakly) stationary iff

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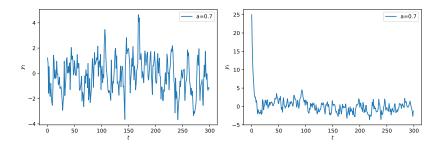
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(1) = 0 and  $\gamma$ (1,1) =  $\frac{\sigma_{\varepsilon}^2}{1-a^2}$ 



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 and  $\gamma(1,1) = \frac{\sigma_{\varepsilon}^2}{1-a^2}$ 



**N.B.** If the second requirement is not fulfilled, the process will still converge to stationarity for large *t*.

**ex)** For a first-order AR model  $y_t = ay_{t-1} + \varepsilon_t$  with

$$y_1 \sim \mathcal{N}\left(0, \frac{\sigma_{\varepsilon}^2}{1-\alpha^2}\right), \qquad \qquad \varepsilon_t \overset{iid}{\sim} \mathcal{N}\left(0, \sigma_{\varepsilon}^2\right),$$

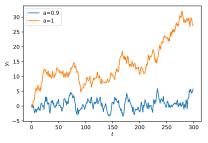
all marginal distributions are Gaussian.

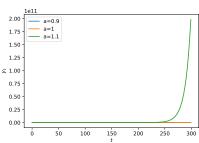
If |a| < 1, then the process is strictly stationary.

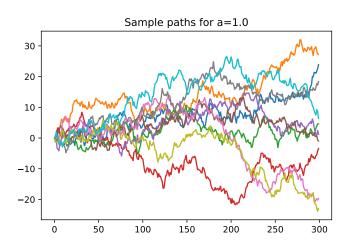
If  $|a| \ge 1$ , then the variance of the process grows without bound at a rate which is

- Linear if |a| = 1,
- Exponential if |a| > 1.

Such a process is said to be unstable!







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$$\widehat{\gamma}(h) = \frac{1}{n} \sum_{t=1}^{n-n} (y_{t+h} - \widehat{\mu})(y_t - \widehat{\mu})$$

where 
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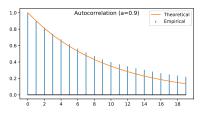
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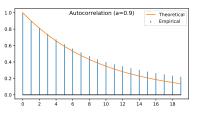
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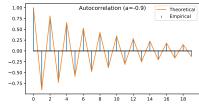
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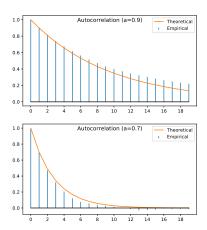


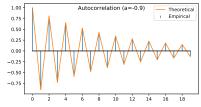
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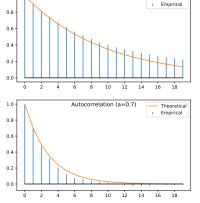


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Theoretical

ex) For a stationary AR(1) model,  $\rho(h) = a^h$ 



Autocorrelation (a=0.9)

