

# Time Series and Sequence Learning

A closer look at AR(1)

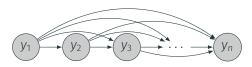
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### Stochastic process

A fundamental approach to time series analysis is to model the data as a **stochastic process**,

$${y_t: t = 1, 2, \dots}$$

#### Probabilistic graphical model:



#### Mean and autocovariance functions

A complete **probabilistic description** of a stochastic process is given by the *joint probability density function* 

$$p(y_{1:n}) = p(y_1, y_2, \dots, y_n).$$

#### Derived quantities of interest:

- 1. Marginal distributions,  $p(y_t)$ , t = 1, ..., n
- 2. Mean function,  $\mu(t) := \mathbb{E}[y_t]$
- 3. Autocovariance function,

$$\gamma(s,t) := \operatorname{Cov}(y_s, y_t) = \mathbb{E}[(y_s - \mu(s))(y_t - \mu(t))]$$

And, of particular interest, the autocorrelation function (ACF).

$$\rho(s,t) := \frac{\gamma(s,t)}{\sqrt{\gamma(s,s)\gamma(t,t)}}$$

### **Properties of WN**

Let 
$$y_{\varepsilon} = \mathcal{E}_{\varepsilon}$$
,  $\mathcal{E}_{\varepsilon} \stackrel{iid}{\sim} N(0, \sigma_{\varepsilon}^{2})$ 

$$\mu(t) = \mathbb{E}[y_{\varepsilon}] = 0 \quad \forall \quad t$$

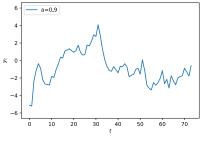
$$\gamma(s,t) = \mathbb{E}[y_{s}y_{t}] = \begin{cases} \mathbb{E}[y_{\varepsilon}^{2}] = \sigma_{\varepsilon}^{2} & t=s \\ \mathbb{E}[y_{s}] & \mathbb{E}[y_{t}] = 0 \end{cases} \quad t \neq s$$

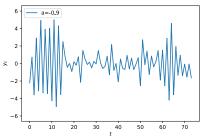
$$\rho(s,t) = \begin{cases} 1 & \text{if } s=t \\ 0 & \text{if } s \neq t \end{cases}$$

#### First-order AR

**ex)** AR(1):  $y_t = ay_{t-1} + \varepsilon_t$ 

Intuitively:  $Corr(y_{t-1}, y_t) = \rho(t-1, t) = a$ 





$$Y_{k} = \alpha Y_{k-1} + E_{k}, \quad E_{k} \stackrel{iid}{\sim} N(0, \sigma_{k}^{2})$$

$$\mu(k) = \mathbb{E}[Y_{k}] = \mathbb{E}[\alpha Y_{k-1} + E_{k}] = \alpha \mathbb{E}[Y_{k-1}] + \mathbb{E}[S_{k}]$$

$$\vdots \quad \mu(k) = \alpha \mu(k-1)$$

$$- \text{ If } \mu(1) = 0, \quad \text{then } \mu(k) = 0 \quad \forall \ t$$

$$- \text{ If } |\alpha| < 1, \quad \text{then } \mu(k) \Rightarrow 0 \quad \text{(exponentially fast)}$$

$$= \alpha^{2} \gamma(t-1, t-1) + 2\alpha \mathbb{E}[\gamma_{\epsilon-1}] \mathbb{E}[\xi_{\epsilon}] + \mathbb{E}[\xi_{\epsilon}^{2}]$$

$$= \alpha^{2} \gamma(t-1, t-1) + \sigma_{\epsilon}^{2} \otimes$$

- If 
$$|a| \ge 1$$
, then the variance increases to infinity as topo - IF  $|a| < 1$ , then  $B$  has a fixed-point solution 
$$\gamma(t-1,t-1) = \gamma(t,t) = \frac{\sigma_{\varepsilon}^2}{1-a^2}$$

Assume 
$$\mathbb{E}[y_1] = \mu(1) = 0$$
  
 $\mathbb{E}[y_1] = \mu(1) = 0$   
 $\mathbb{E}[y_2] = \mu(1) = 0$   
 $\mathbb{Var}(y_1) = \mu(1) = 0$   
 $\mathbb{Var}(y_2) = \mu(1) = 0$   
 $\mathbb{Var}(y_1) = \mu(1) = 0$ 

"Lag 1": 
$$y(t, t+1) = \mathbb{E}[y_{\epsilon}(ay_{\epsilon+1}] = \mathbb{E}[y_{\epsilon}(ay_{\epsilon+1})]$$

$$= a \operatorname{Var}(y_{\epsilon}) = a \frac{\sigma_{\epsilon}^{2}}{1-a^{2}}$$
independent of t!

Lag 2": 
$$\gamma(t, t+2) = \mathbb{E}[\gamma_t \gamma_{t+2}] = \mathbb{E}[\gamma_t(\alpha \gamma_{t+1} + \varepsilon_{t+2})]$$

= 
$$\alpha \mathbb{E}[y_t y_{t+1}] = \alpha \gamma(t, t+1) = \alpha^2 \frac{\sigma_t^2}{1-\alpha^2}$$

"Lag h": 
$$\gamma(t,t+h) = \mathbb{E}[\gamma_t \gamma_{t+h}] = \dots = a^h \frac{\sigma_t^2}{1-a^2}$$

### Properties of AR(1) - summary

For a first-order AR model  $y_t = ay_{t-1} + \varepsilon_t$  with |a| < 1:

### Assume that,

- $\mathbb{E}[y_1] = \mu(1) = 0$ , and
- $\operatorname{Var}(y_1) = \gamma(1,1) = \frac{\sigma_{\varepsilon}^2}{1-a^2}$

### We then have, for all $t \ge 1$ .

- $\mathbb{E}[y_t] = \mu(t) = 0$ , and
- $\operatorname{Var}(y_t) = \gamma(t, t) = \frac{\sigma_{\varepsilon}^2}{1 a^2}$
- · Cov $(y_t, y_{t+h}) = \gamma(t, t+h) = a^h \frac{\sigma_{\varepsilon}^2}{1-a^2}$