

Master in Applied Econometrics  
and Forecasting

# Time Series Analysis and Forecasting

**Class #4: White Noise and  
Autoregressive (AR) Models**

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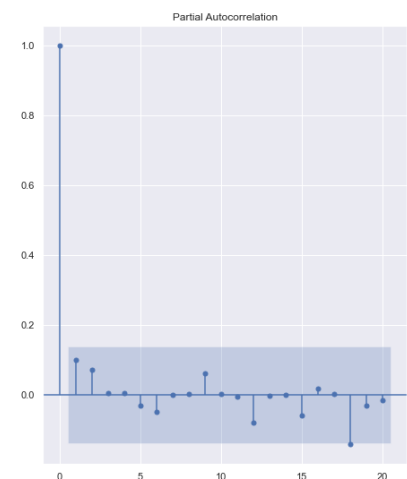
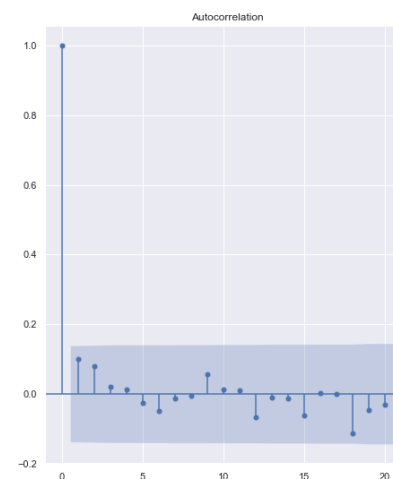
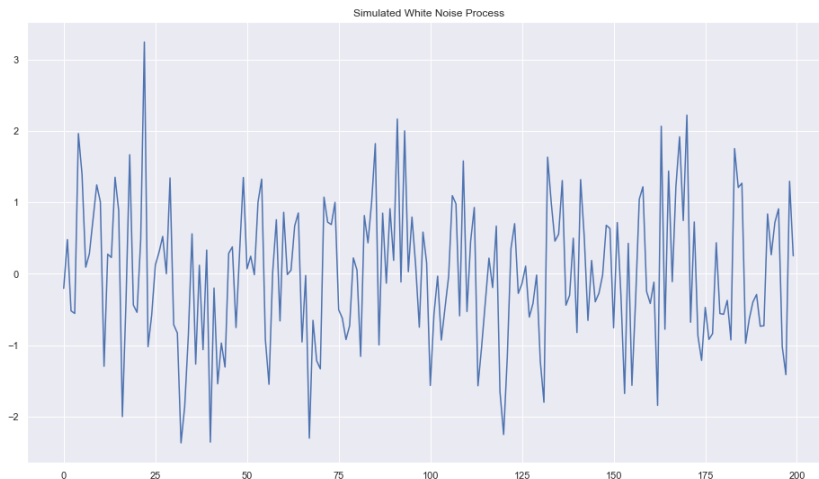
# White Noise and Autoregressive (AR) Models

## White Noise Process

A process is called a “white noise” process if it is a sequence of uncorrelated random variables:

$$X_t = a_t,$$

where  $a_t$  has constant mean  $E(a_t) = \mu_a$  (usually assumed to be 0), constant variance  $Var(a_t) = \sigma_a^2$  and null covariance  $Cov(a_t, a_{t-k}) = 0$  for all  $k \neq 0$ . The ACF and PACF of a white noise process are null for all  $k \neq 0$ .



Simulation of a white noise process with zero mean and unit variance

# White Noise and Autoregressive (AR) Models

## Autoregressive (AR) Representation

In time series analysis, there is a useful representation of a stationary time series or stochastic process  $X_t$ . The process  $X_t$  can be written in terms of an infinite autoregressive representation:

$$X_t = \pi_1 X_{t-1} + \pi_2 X_{t-2} + \cdots + a_t = \sum_{j=1}^{\infty} \pi_j X_{t-j} + a_t,$$

or, equivalently,

$$\pi(B)X_t = a_t,$$

where  $\pi(B) = 1 - \pi_1 B - \pi_2 B^2 - \cdots = 1 - \sum_{j=1}^{\infty} \pi_j B^j$  and  $1 + \sum_{j=1}^{\infty} |\pi_j| < \infty$ .

Box-Jenkins (1976) call a “process invertible” if it can be written in this form.

# White Noise and Autoregressive (AR) Models

## AR( $p$ ) Model

The autoregressive model of order  $p$  is given by

$$X_t = \phi_1 X_{t-1} + \dots + \phi_p X_{t-p} + a_t,$$

where  $a_t$  is a zero mean white noise series. Because  $\sum_{j=1}^{\infty} |\pi_j| = \sum_{j=1}^p |\phi_j| < \infty$ , the process is always invertible. To be stationary, the roots of  $(1 - \phi_1 B - \dots - \phi_p B^p) = 0$  must be outside of the unit circle.

## AR(1) Model

The first-order autoregressive model or AR(1) model is given by

$$X_t = \phi_1 X_{t-1} + a_t,$$

where  $a_t$  is a zero mean white noise series. As mentioned above, because  $|\phi_1| < \infty$ , the process is always invertible. To be stationary, the root of  $(1 - \phi_1 B) = 0$ ,  $B = 1/\phi_1$ , must be outside of the unit circle. That is,  $|\phi_1| < 1$  is the stationary condition.

# White Noise and Autoregressive (AR) Models

## ACF and PACF of an AR(1) Model

Assuming, without loss of generality, that  $E(X_t) = 0$ , the ACF of an AR(1) model can be deduced by multiplying both sides of AR(1) model by  $X_{t-k}$  and then taking expectations:

$$\begin{aligned} E(X_{t-k}X_t) &= \phi_1 E(X_{t-k}X_{t-1}) + E(X_{t-k}a_t) \\ \gamma_k &= \phi_1 \gamma_{k-1}, \quad k \geq 1 \end{aligned}$$

Thus, the ACF becomes

$$\rho_k = \phi_1 \rho_{k-1} = \phi_1^k, \quad k \geq 1$$

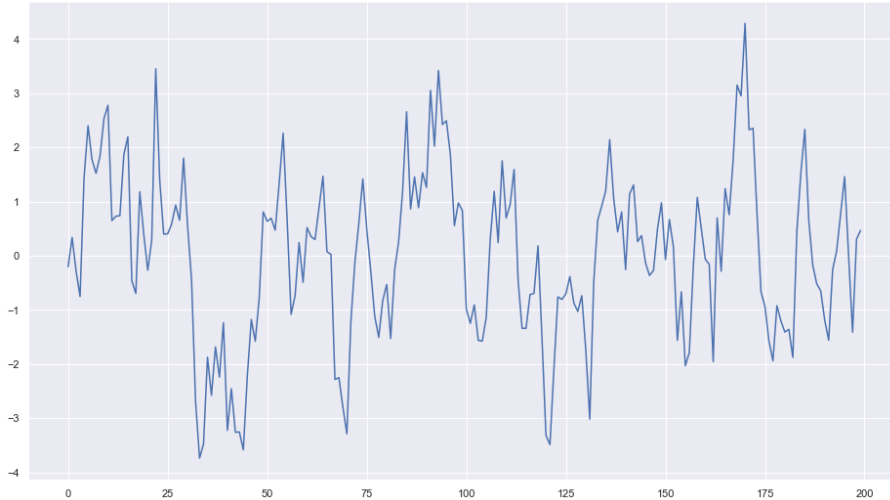
If  $-1 < \phi_1 < 0$  the ACF decays exponentially to zero, while if  $0 < \phi_1 < 1$  the ACF decays in an oscillating pattern (or damped sine wave) to zero, as shown in the next slide.

The PACF of the AR(1) model exhibits a positive or negative (depending on the sign of  $\phi_1$ ) spike at lag 1 and then cuts off after lag 1:

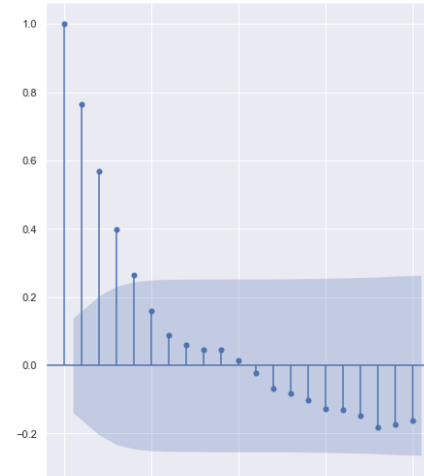
$$\phi_{kk} = \begin{cases} \rho_1 = \phi_1, & k = 1 \\ 0, & k \geq 2 \end{cases}$$

# White Noise and Autoregressive (AR) Models

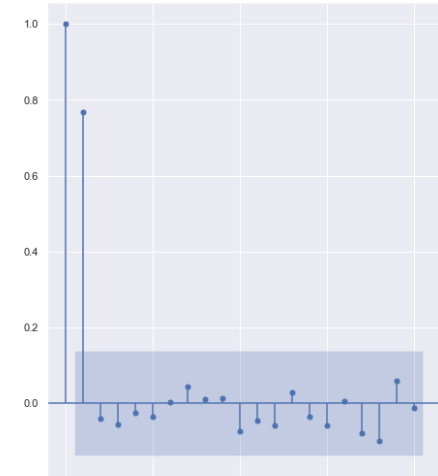
Simulated AR(1) with  $\phi=0.7$



Autocorrelation



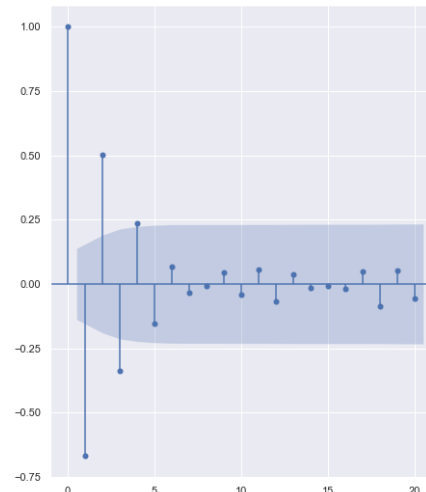
Partial Autocorrelation



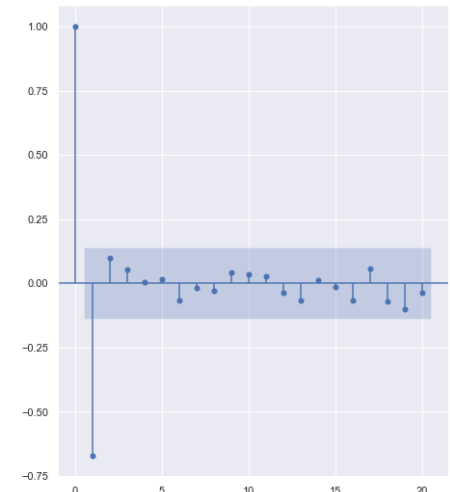
Simulated AR(1) with  $\phi=-0.7$



Autocorrelation



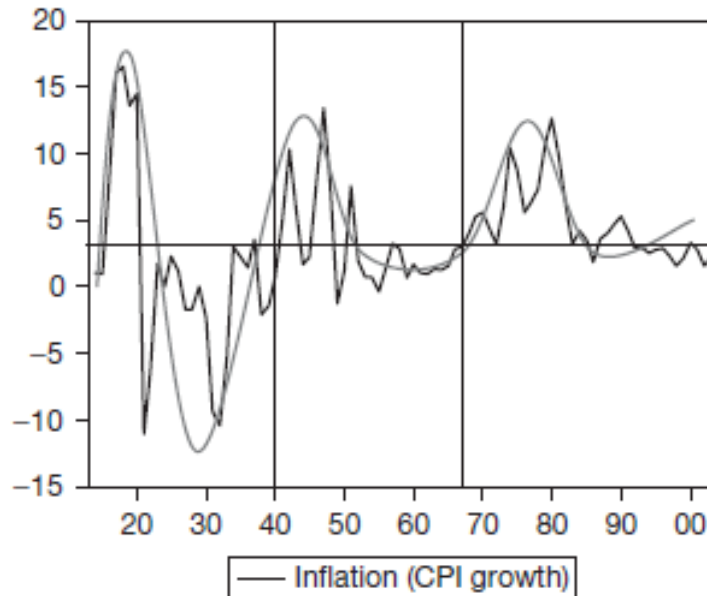
Partial Autocorrelation



Time Series, ACF and PACF of the simulated AR(1) models with  $\phi=0.7$  and  $\phi=-0.7$

# White Noise and Autoregressive (AR) Models

**Example:** Inflation Rate in US, 1913-2003



Sample: 1913 2003  
Included observations: 90

Autocorrelation	Partial Correlation	AC	PAC
		1	0.639
		2	0.259
		3	0.117
		4	0.066
		5	0.144
		6	0.181
		7	0.115
		8	0.039
		9	0.039
		10	0.035
		11	-0.047
		12	-0.174
		13	-0.280
		14	-0.303
		15	-0.306
		16	-0.184
		17	-0.032
		18	-0.075
		19	-0.161
		20	-0.208
		21	-0.155
		22	-0.008
		23	0.073

**Source:** Gloria Gonzalez-Rivera, *Forecasting for Economics and Business*, Pearson, 2013



# White Noise and Autoregressive (AR) Models

## AR(2) model

The second-order autoregressive AR(2) models is

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + a_t,$$

or

$$\phi(B)X_t = a_t,$$

where  $\varepsilon_t$  is a zero mean white noise series. To be stationary, the roots of  $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 = 0$  must be outside of the unit circle. Thus, we have the following necessary and sufficient conditions for stationarity:

$$\phi_1 + \phi_2 < 1, \phi_2 - \phi_1 < 1, -1 < \phi_2 < 1.$$

The ACF tails off as an exponential decay or a damped sine waves depending on the roots of  $\phi(B) = 0$ , and the PACF cuts off after lag 2,  $\phi_{kk} = 0$  for  $k \geq 3$ .

## AR models of order $p \geq 3$

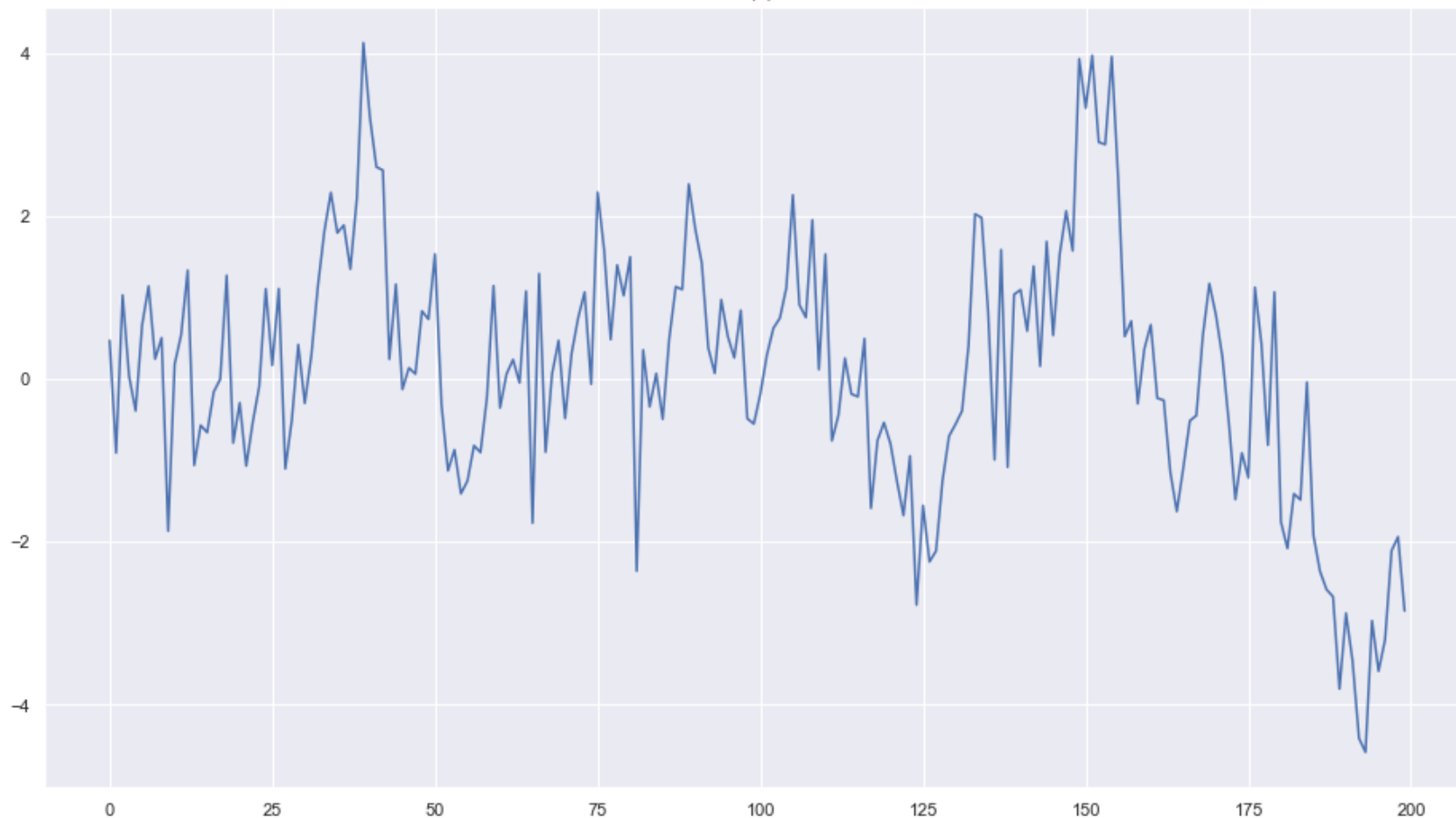
More complicated conditions hold for AR( $p$ ) models with  $p \geq 3$ .

Econometric software (EViews, Python, Stata, among others) takes care of this.



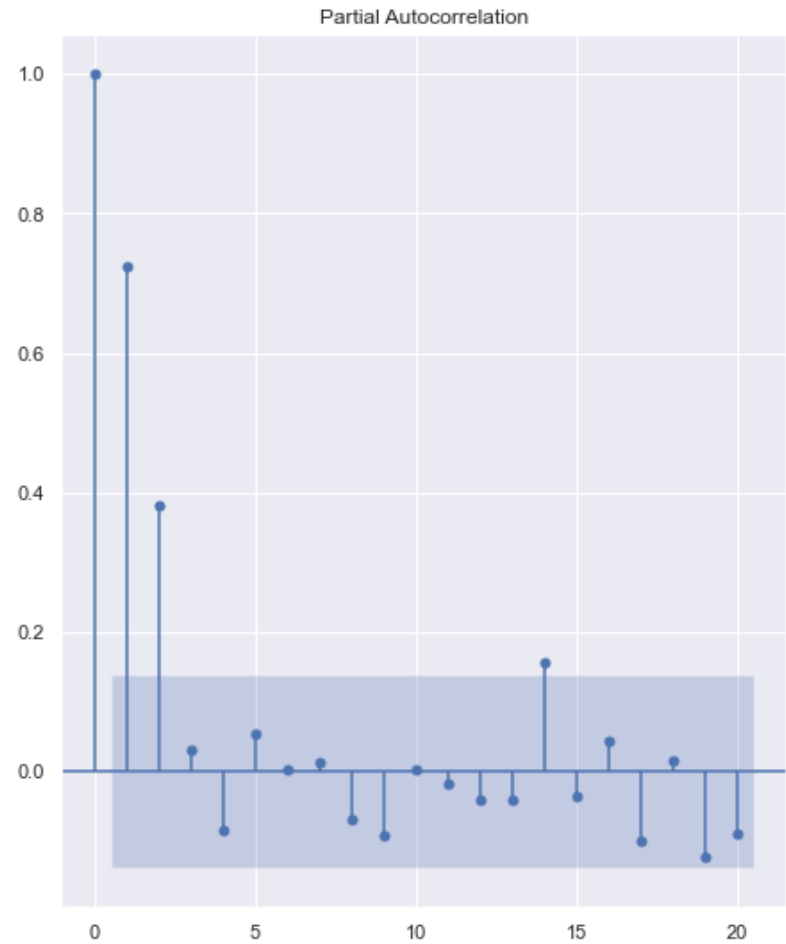
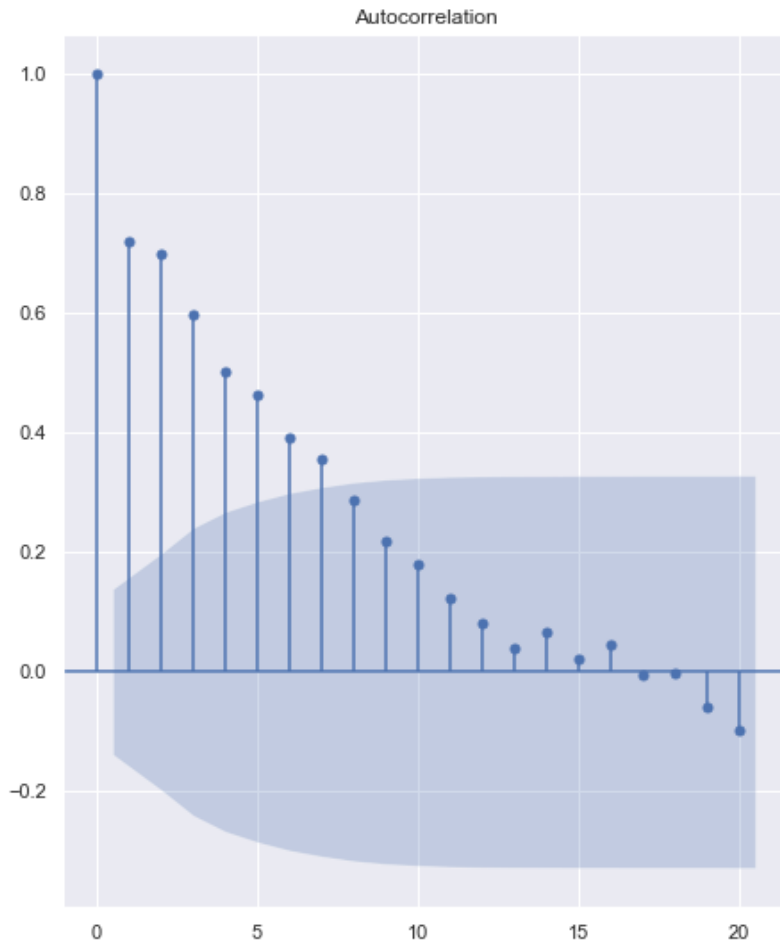
# White Noise and Autoregressive (AR) Models

Simulated AR(2) Time Series



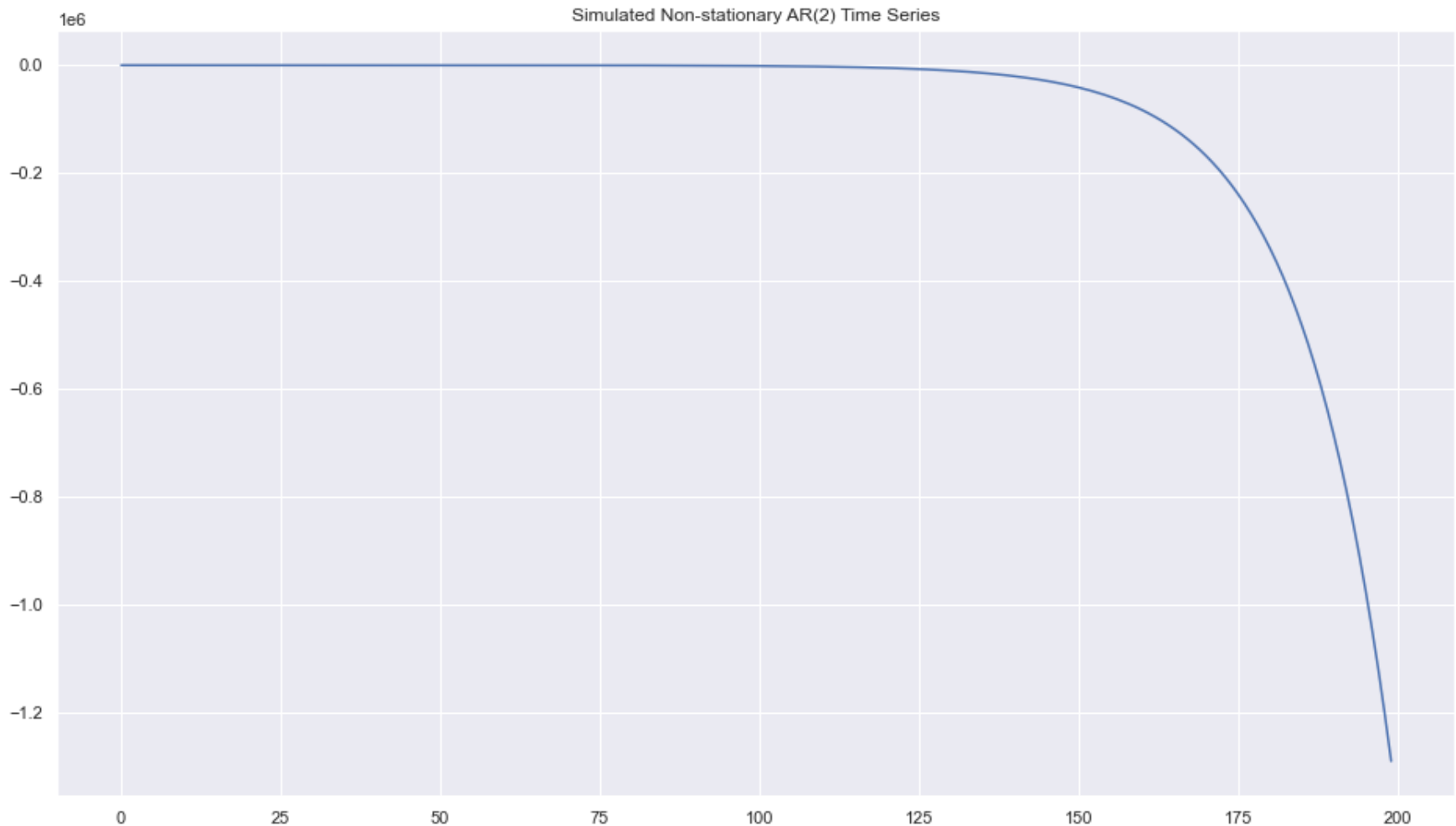
Simulated stationary AR(2) model:  $X_t = 0.6X_{t-1} + 0.3X_{t-2} + a_t$

# White Noise and Autoregressive (AR) Models



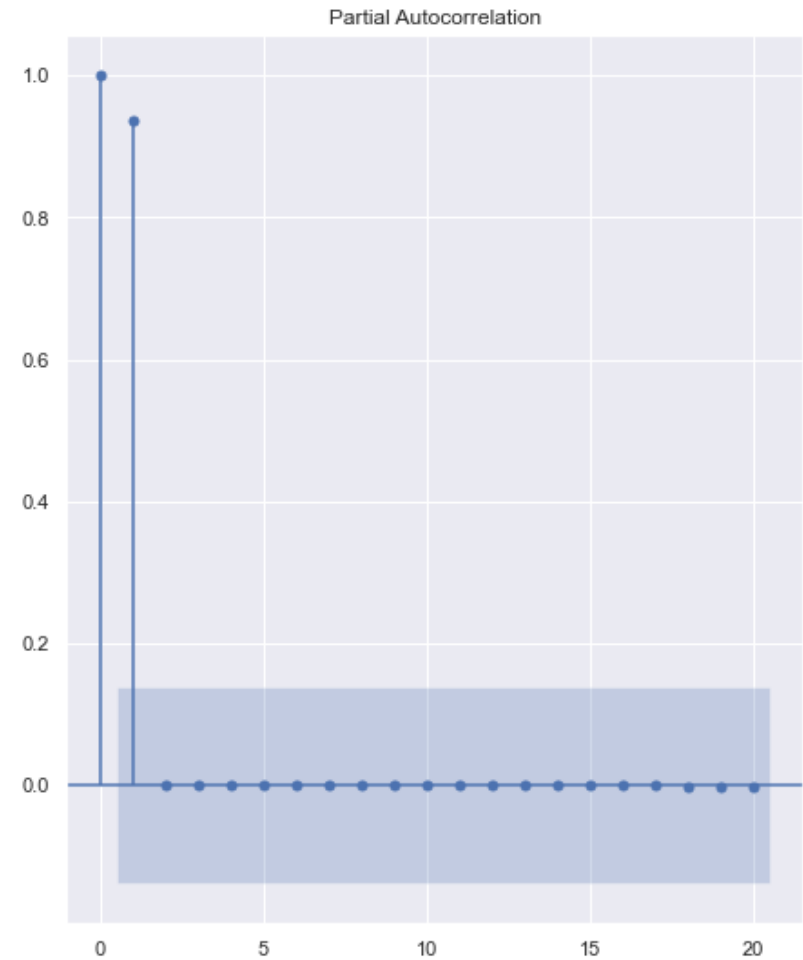
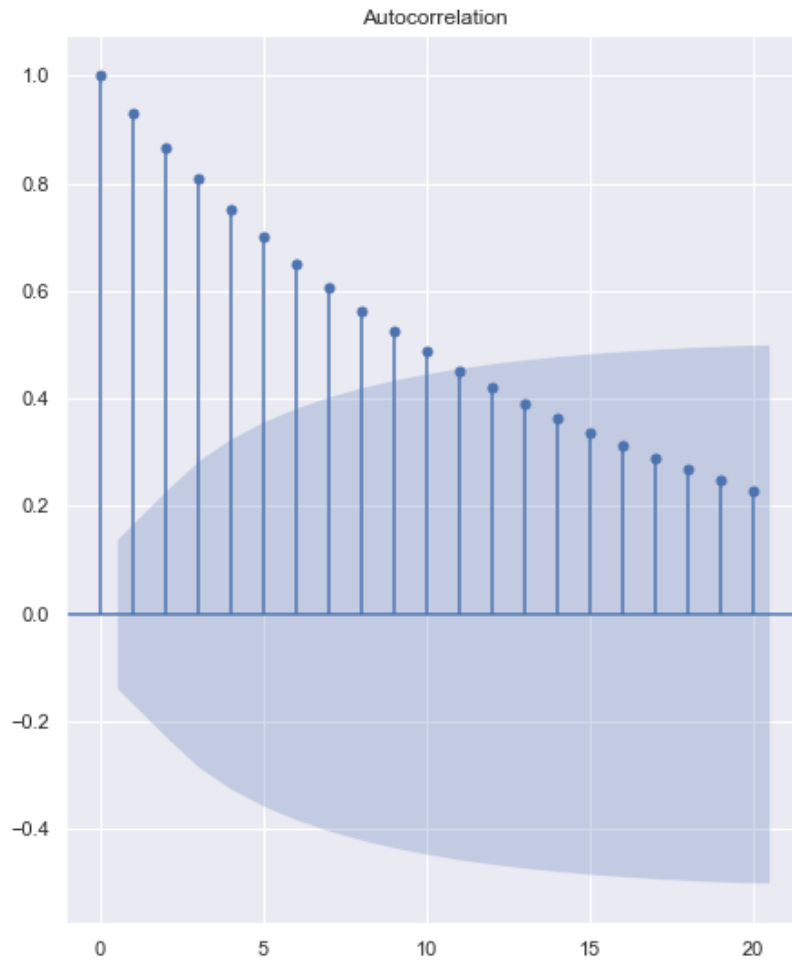
ACF and PACF of a simulated stationary AR(2) model:  $X_t = 0.6X_{t-1} + 0.3X_{t-2} + a_t$

# White Noise and Autoregressive (AR) Models



Simulated non-stationary AR(2) model:  $X_t = 0.7X_{t-1} + 0.4X_{t-2} + a_t$

# White Noise and Autoregressive (AR) Models



ACF and PACF of a simulated non-stationary AR(2) model:  $X_t = 0.7X_{t-1} + 0.4X_{t-2} + a_t$

# White Noise and Autoregressive (AR) Models

## AR(2) Model Estimation Output (Python)

ARMA Model Results						
=====						
Dep. Variable:	y	No. Observations:	200			
Model:	ARMA(2, 0)	Log Likelihood	-279.390			
Method:	csm-mle	S.D. of innovations	0.976			
Date:	Sun, 13 Dec 2020	AIC	566.779			
Time:	18:08:25	BIC	579.973			
Sample:	0	HQIC	572.118			
=====						
	coef	std err	z	P> z	[0.025	0.975]
-----						
const	-0.0114	0.408	-0.028	0.978	-0.810	0.787
ar.L1.y	0.4505	0.065	6.894	0.000	0.322	0.579
ar.L2.y	0.3857	0.066	5.874	0.000	0.257	0.514
Roots						
=====						
	Real	Imaginary	Modulus	Frequency		
-----						
AR.1	1.1288	+0.0000j	1.1288	0.0000		
AR.2	-2.2968	+0.0000j	2.2968	0.5000		
-----						

AR(2) Model:  $(1 - \phi_1 B - \phi_2 B^2)(X_t - c) = \varepsilon_t$

$$(1 - 0.45B - 0.39B^2)(X_t + 0.0114) = \varepsilon_t$$

# White Noise and Autoregressive (AR) Models

## Problems

1. Consider the AR(2) models:

(i)  $(1 - 1.4B + 0.6X_tB^2) X_t = a_t$

(ii)  $(1 - 0.6B - 0.3X_tB^2) X_t = a_t$

- a) Simulate a series of 100 observations from each of the models with  $\sigma_a^2 = 1$ . Plot the series.
- b) For each simulated series, calculate and study the sample ACF and PACF for the lags 1, 2, ..., 20.

2. Consider the AR(2) model:  $(1 - 0.3B - 0.6X_tB^2) X_t = a_t$ .

- a) Find the ACF
- b) Find the PACF