

# The autoregressive model

TIME SERIES ANALYSIS IN R



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# The autoregressive model - I

The Autoregressive (AR) recursion:

$$Today = Constant + Slope * Yesterday + Noise$$

Mean centered version:

$$(Today - Mean) =$$

$$Slope * (Yesterday - Mean) + Noise$$

# The autoregressive model - II

$$(Today - Mean) =$$

$$Slope * (Yesterday - Mean) + Noise$$

More formally:

$$Y_t - \mu = \phi(Y_{t-1} - \mu) + \epsilon_t$$

where  $\epsilon_t$  is mean zero white noise (WN).

- The mean  $\mu$
- The slope  $\phi$
- The WN variance  $\sigma^2$

# AR processes - I

$$Y_t - \mu = \phi(Y_{t-1} - \mu) + \epsilon_t$$

- If slope  $\phi = 0$  then:  $Y_t = \mu + \epsilon_t$  and

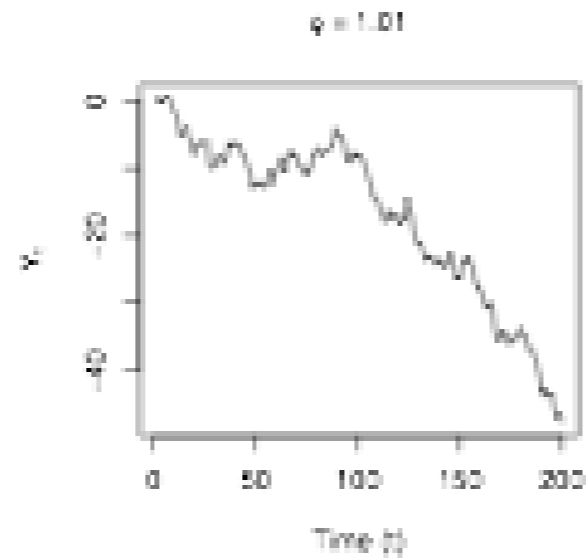
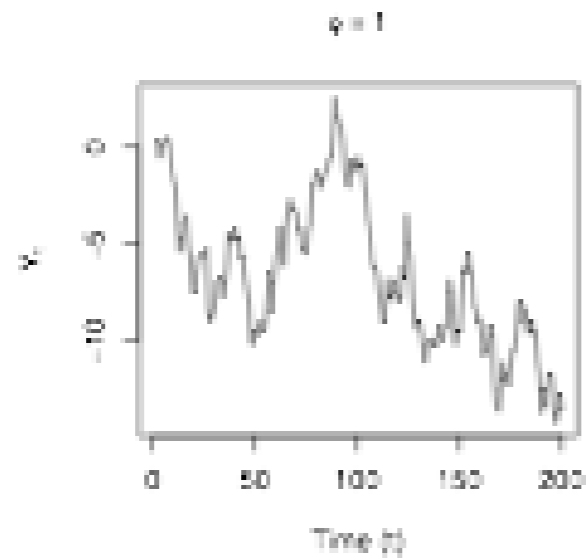
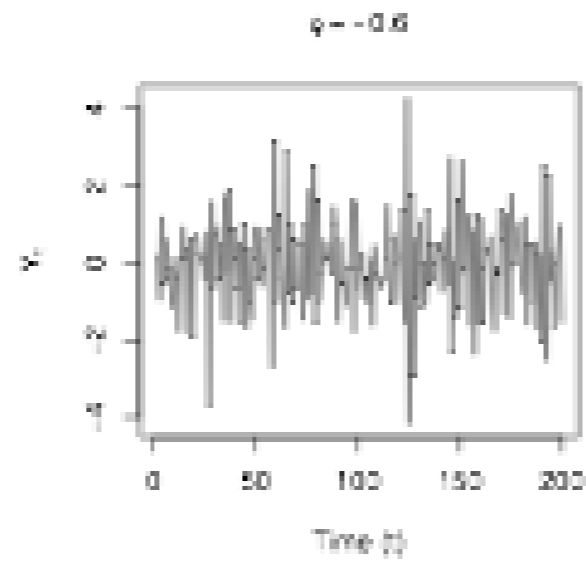
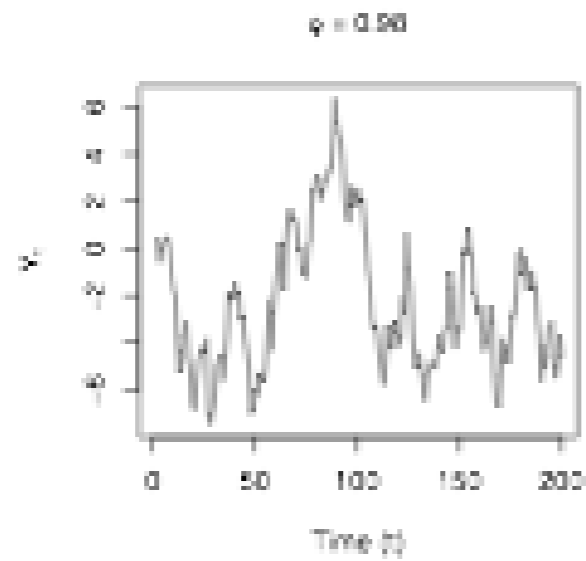
And  $Y_t$  is white noise:  $(\mu, \sigma_\epsilon^2)$

- If slope  $\phi \neq 0$  then:  $Y_t$  depends on both  $\epsilon_t$  and  $Y_{t-1}$

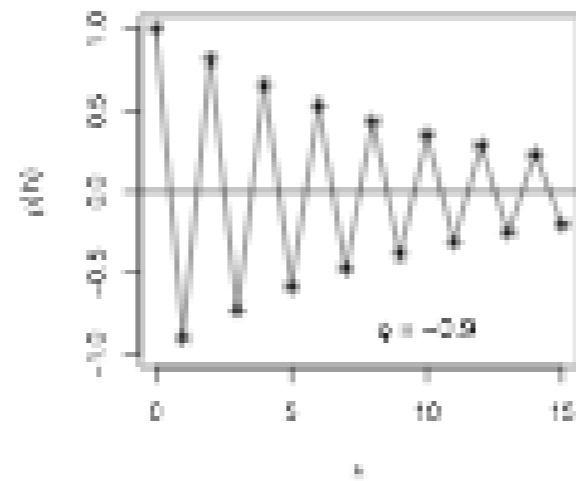
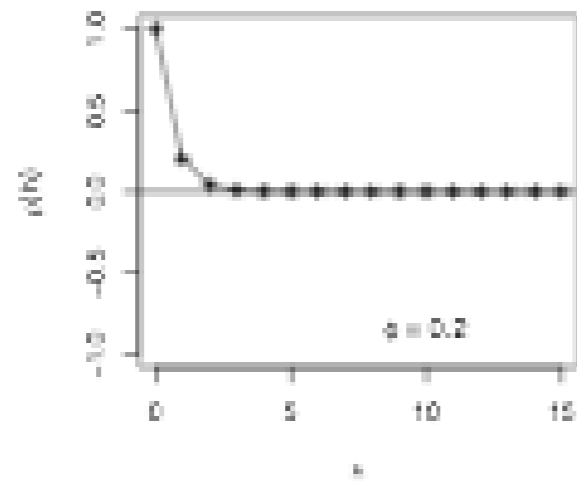
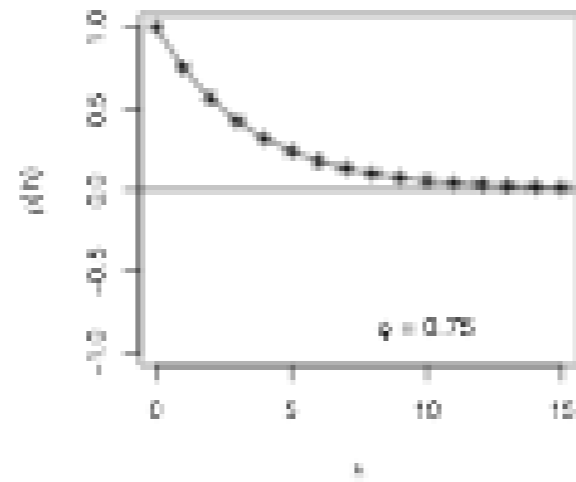
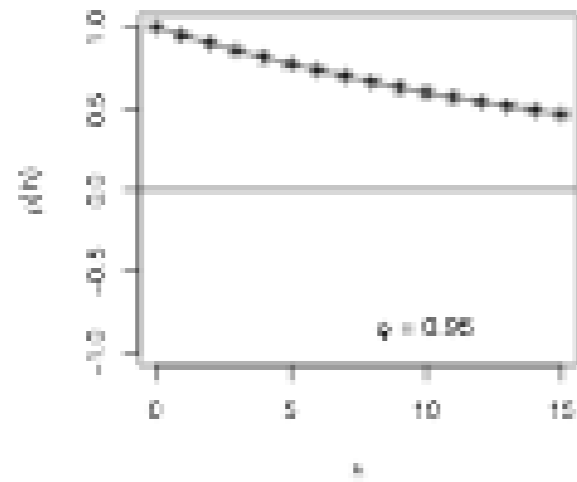
And the process  $\{Y_t\}$  is autocorrelated

- Large values of  $\phi$  lead to greater autocorrelation
- Negative values of  $\phi$  result in oscillatory time series

# AR examples



# Autocorrelations



# Random walk

If  $\mu = 0$  and slope  $\phi = 1$ , then:

$$Y_t = Y_{t-1} + \epsilon_t$$

Which is:

*Today = Yesterday + Noise*

But this is a **random walk**.

And  $\{Y_t\}$  is **not** stationary in this case.

# Let's practice!

TIME SERIES ANALYSIS IN R



# AR model estimation and forecasting

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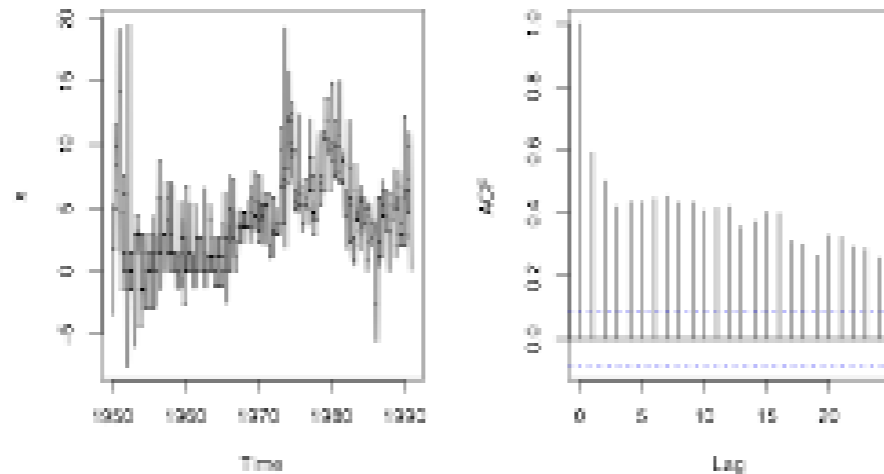
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# AR processes: inflation rate

- One-month US inflation rate (in percent, annual rate).
- Monthly observations from 1950 through 1990

```
data(Mishkin, package = "Ecdat")  
inflation <- as.ts(Mishkin[, 1])  
ts.plot(inflation) ; acf(inflation)
```



$(Today - Mean) = Slope * (Yesterday - Mean) + Noise$

$$Y_t - \mu = \phi(Y_{t-1} - \mu) + \epsilon_t$$

$$\epsilon_t \text{ WhiteNoise}(0, \sigma_\epsilon^2)$$

```
AR_inflation <- arima(inflation, order = c(1, 0, 0))  
print(AR_inflation)
```

Coefficients:

	ar1	intercept
	0.5960	3.9745
s.e.	0.0364	0.3471
sigma^2 estimated as 9.713		

$$\text{ar1} = \hat{\phi}, \text{intercept} = \hat{\mu}, \text{sigma}^2 = \hat{\sigma}_\epsilon^2$$

# AR processes: fitted values - I

- AR fitted values:

$$\widehat{Today} = \widehat{Mean} + \widehat{Slope} * (Yesterday - \widehat{Mean})$$

$$\hat{Y}_t = \hat{\mu} + \hat{\phi}(Y_{t-1} - \hat{\mu})$$

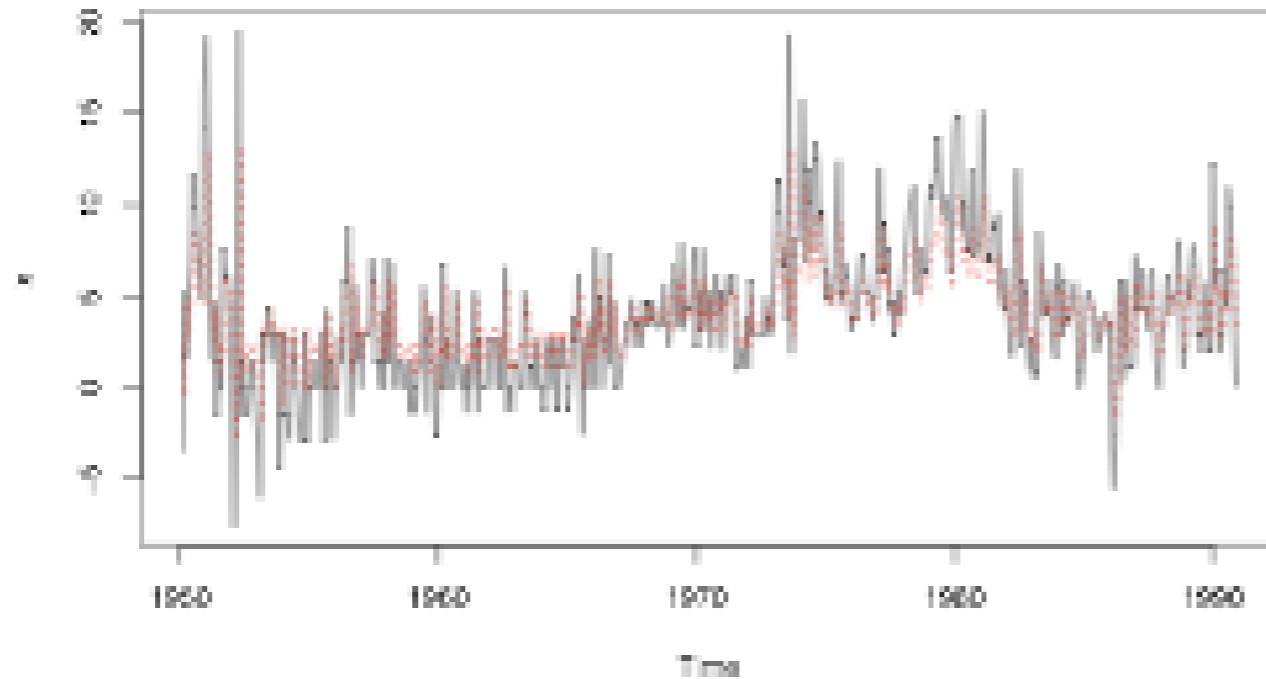
- Residuals =

$$Today - \widehat{Today}$$

$$\hat{\epsilon}_t = Y_t - \hat{Y}_t$$

# AR processes: fitted values - II

```
ts.plot(inflation)
AR_inflation_fitted <- inflation - residuals(AR_inflation)
points(AR_inflation_fitted, type = "l",
      col = "red", lty = 2)
```



# Forecasting

- 1-step ahead forecasts

```
predict(AR_inflation)$pred
```

```
Jan  
1991 1.605797
```

```
predict(AR_inflation)$se
```

```
Jan  
1991 3.116526
```

# Forecasting (cont.)

- h-step ahead forecasts

```
predict(AR_inflation, n.ahead = 6)$pred
```

	Jan	Feb	Mar	Apr	May	Jun
1991	1.605797	2.562810	3.133165	3.473082	3.675664	3.796398

```
predict(AR_inflation, n.ahead = 6)$se
```

	Jan	Feb	Mar	Apr	May	Jun
1991	3.116526	3.628023	3.793136	3.850077	3.870101	3.877188

# Let's practice!

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