



INTRODUCTION TO TIME SERIES ANALYSIS

# **The Simple Moving Average Model**

# The Simple Moving Average Model

The simple moving average (MA) model:

$$Today = Mean + Noise + Slope * (Yesterday's Noise)$$

More formally:  $Y_t = \mu + \epsilon_t + \theta\epsilon_{t-1}$

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

Three parameters:

- The mean  $\mu$
- The slope  $\theta$
- The WN variance

# MA Processes - I

*Today = Mean + Noise + Slope \* (Yesterday's Noise)*

$$Y_t = \mu + \epsilon_t + \theta\epsilon_{t-1}$$

- If slope  $\theta$  is zero then:

$$Y_t = \mu + \epsilon_t$$

And  $Y_t$  is White Noise  $(\mu, \sigma_\epsilon^2)$

# MA Processes - II

*Today = Mean + Noise + Slope \* (Yesterday's Noise)*

$$Y_t = \mu + \epsilon_t + \theta\epsilon_{t-1}$$

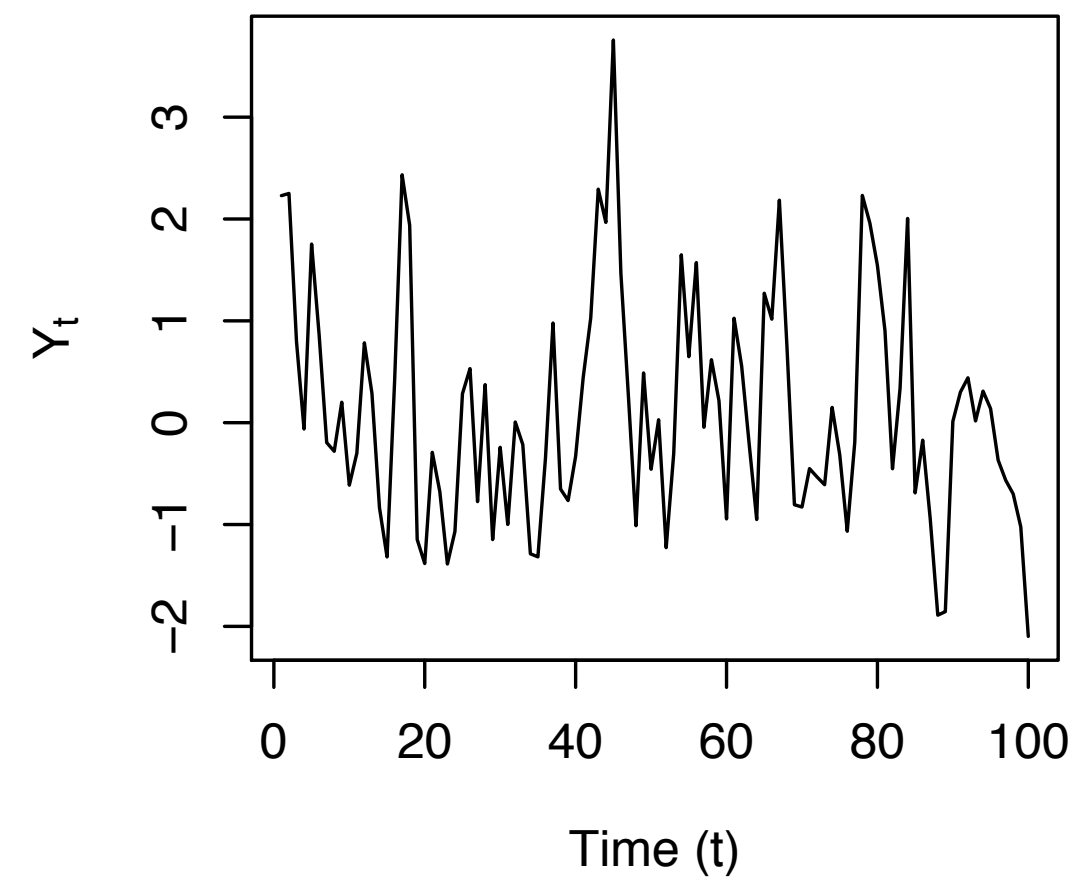
- If slope  $\theta$  is not zero then  $Y_t$  depends on both  $\epsilon_t$  and  $\epsilon_{t-1}$

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

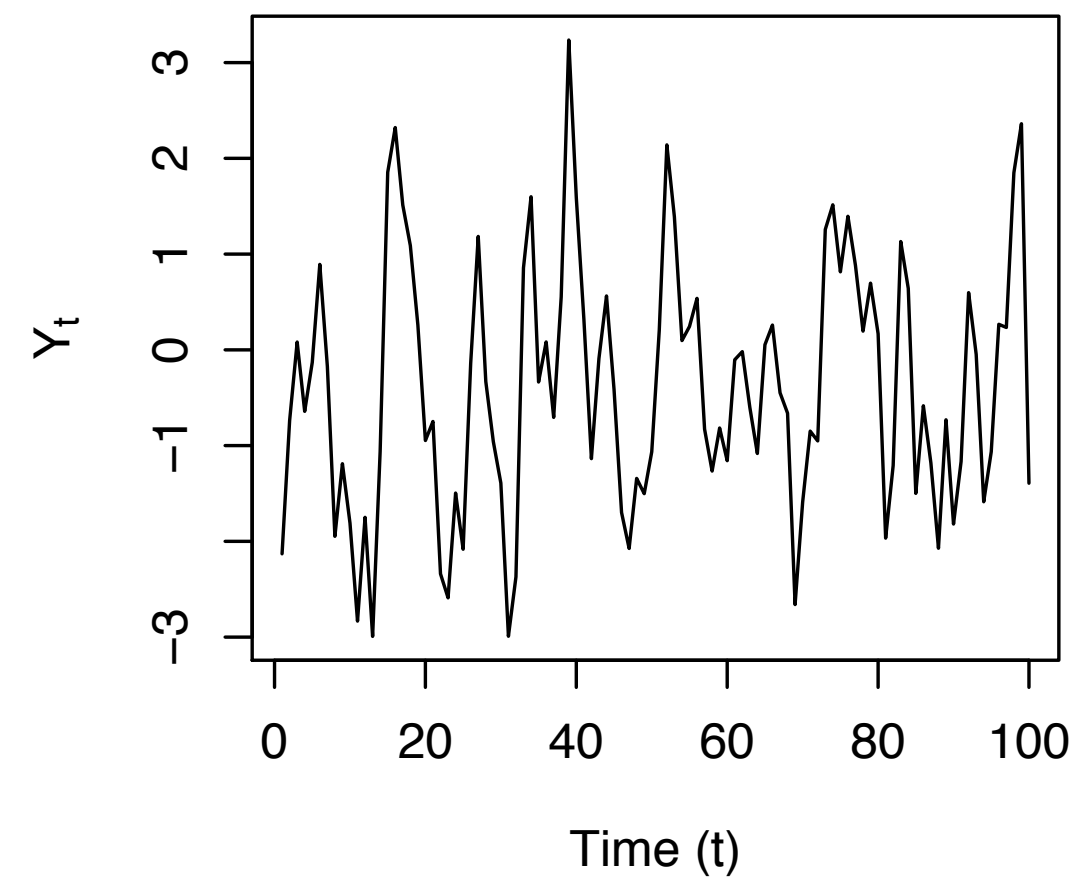
- Large values of  $\theta$  lead to greater autocorrelation
- Negative values of  $\theta$  result in oscillatory time series

# MA Examples

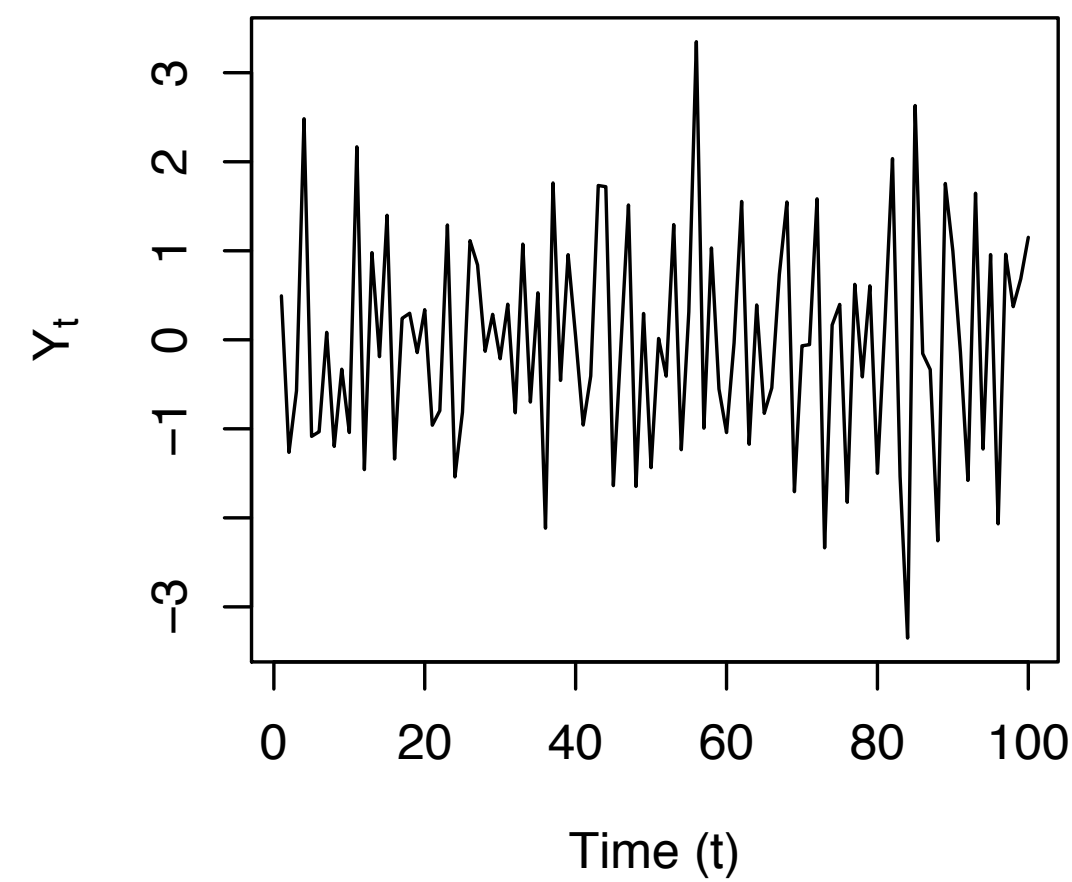
$\theta = 0.5$



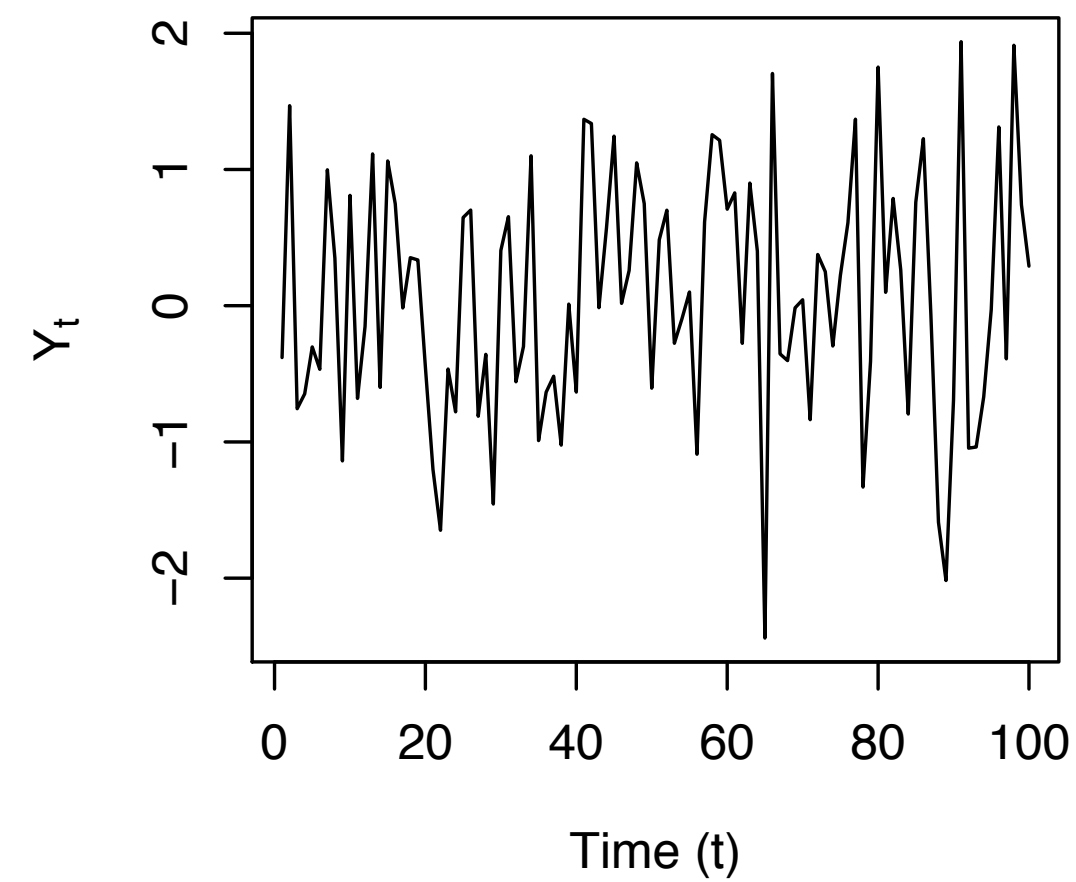
$\theta = 0.9$



$\theta = -0.5$

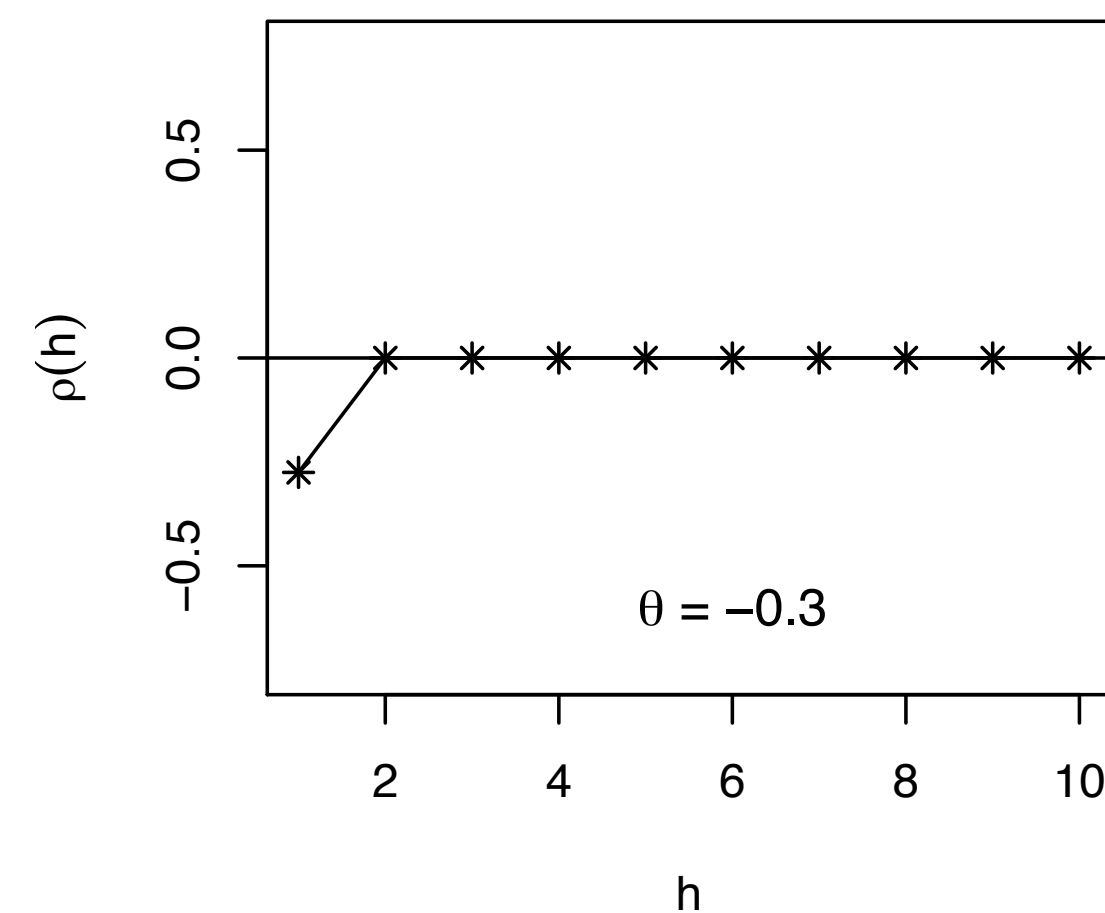
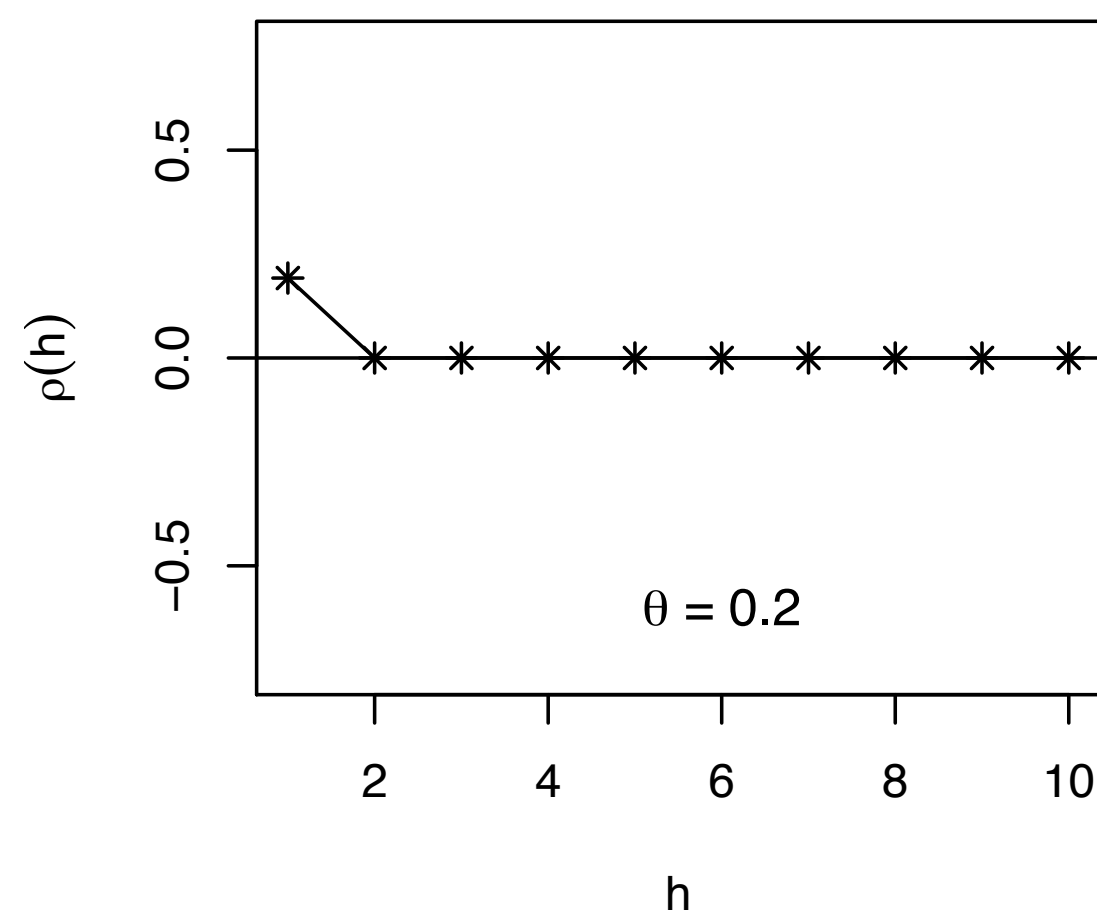
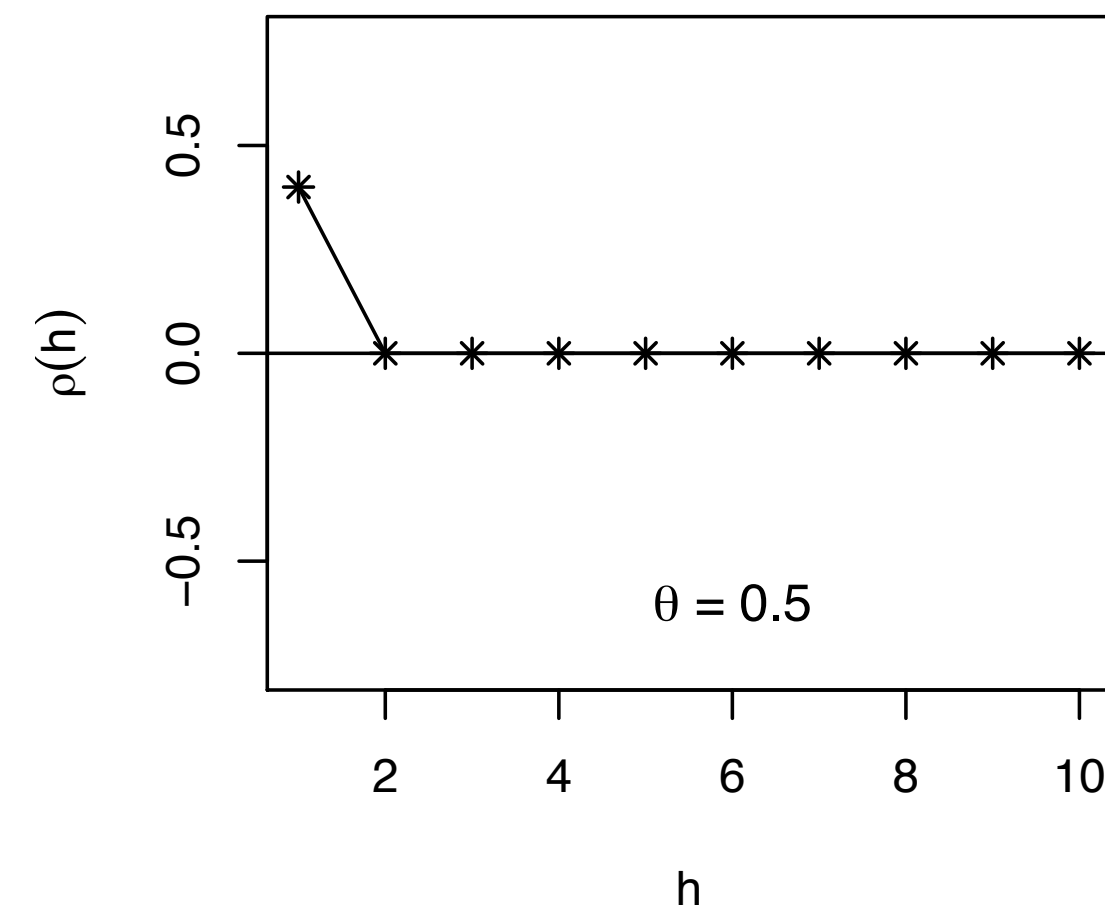
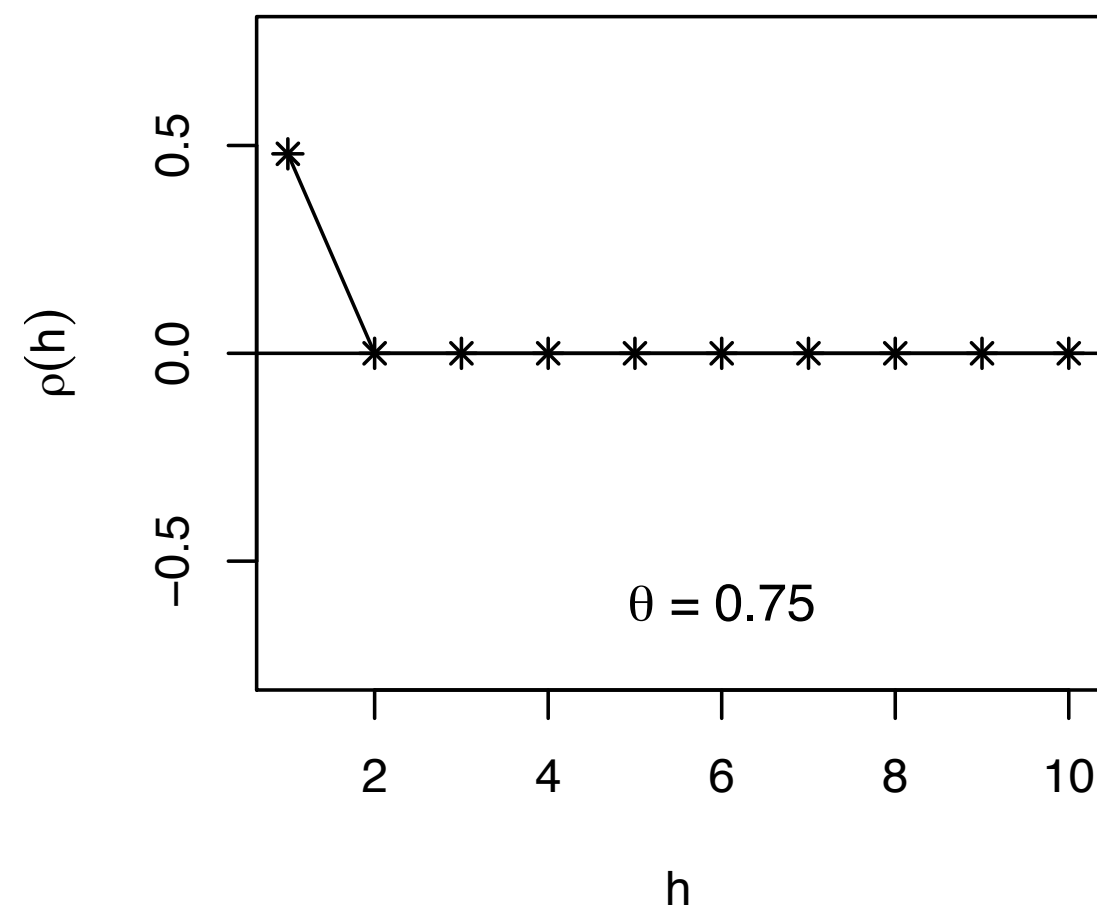


$\theta = 0$



# Autocorrelations

Only lag 1 autocorrelation non-zero for the MA model.





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# Let's practice!



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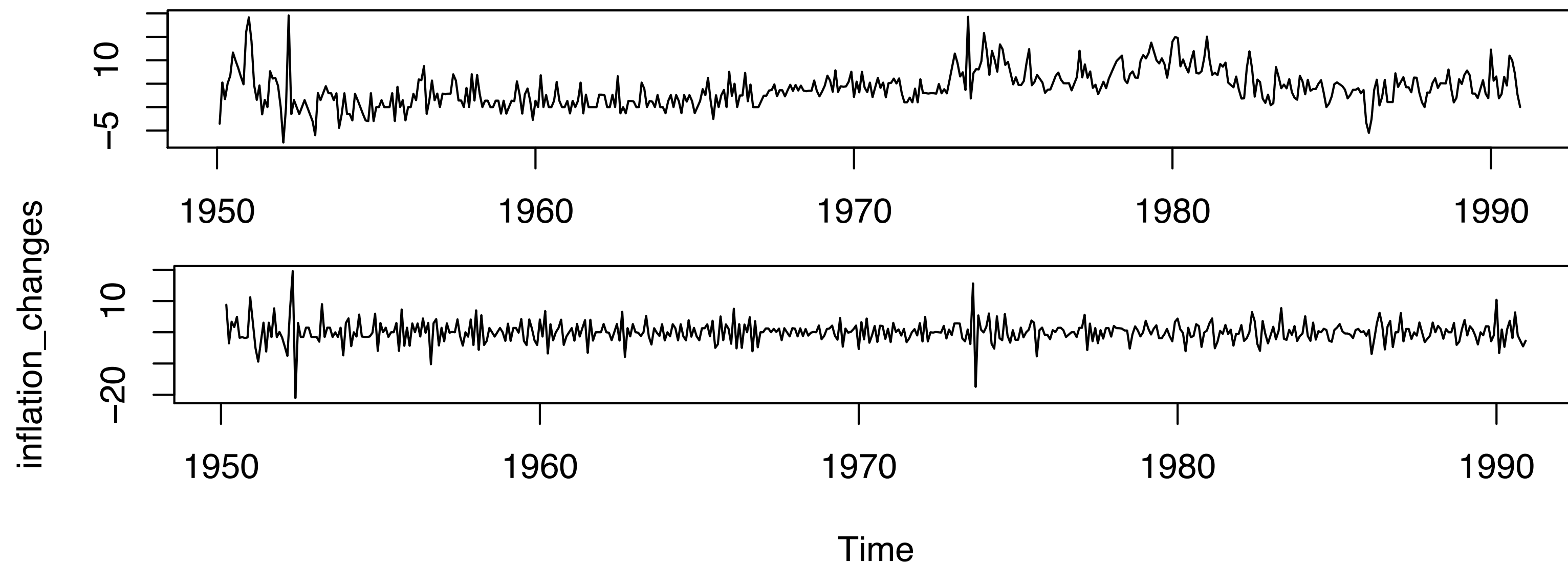
# **MA Model Estimation and Forecasting**



# MA Processes: Changes in Inflation Rate - I

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

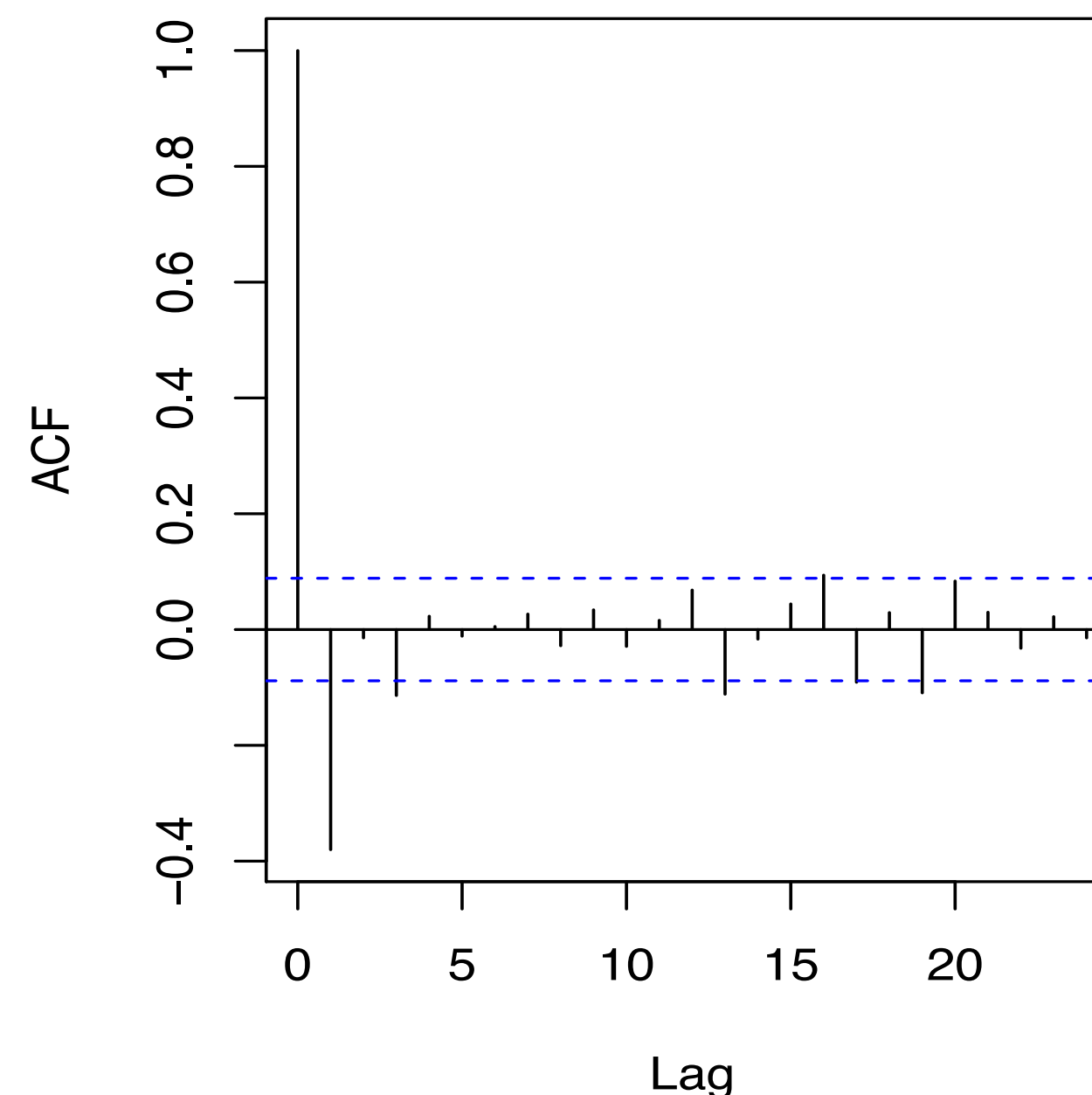
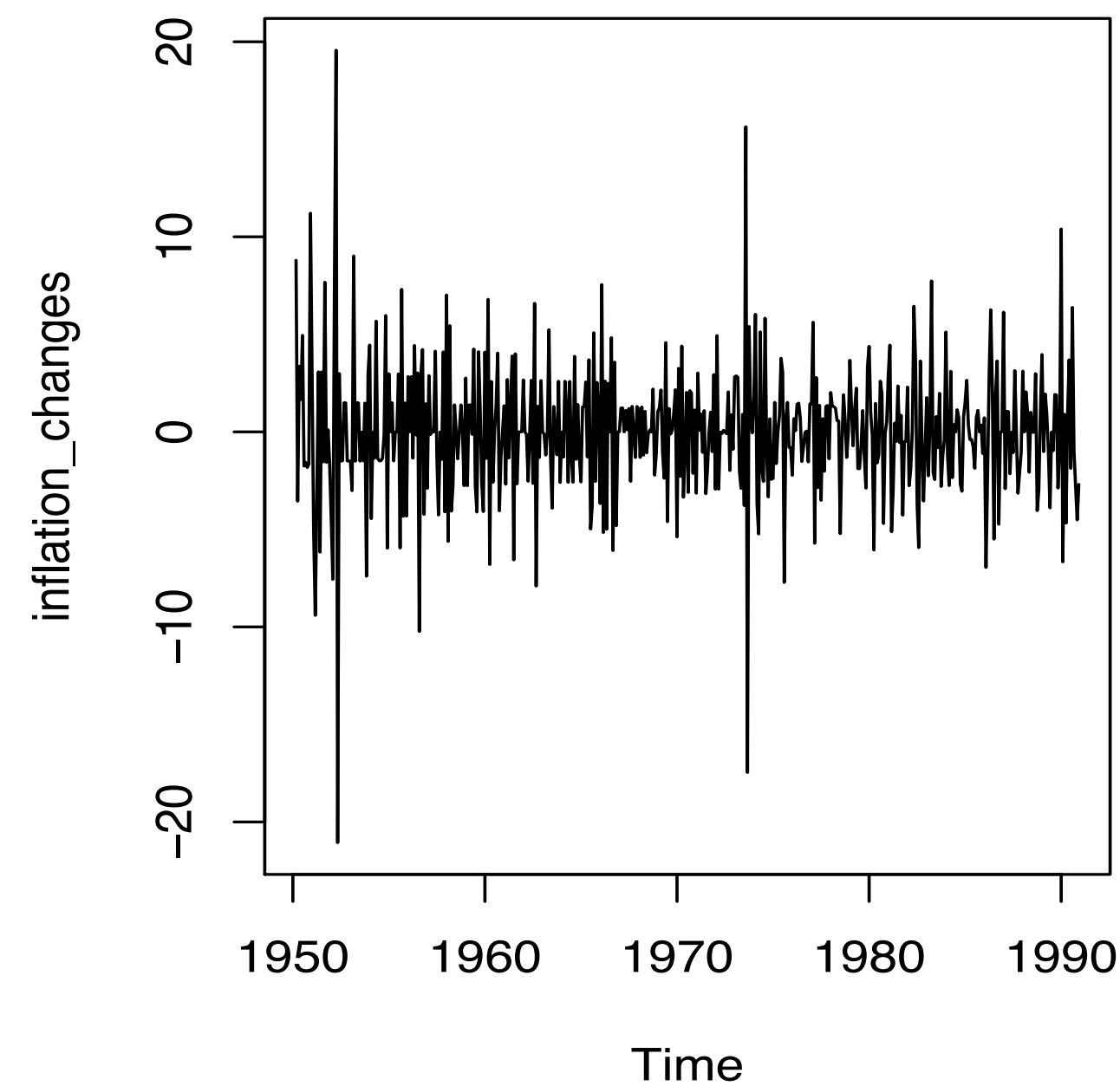
```
> data(Mishkin, package = "Ecdat")  
> inflation <- as.ts(Mishkin[, 1])  
> inflation_changes <- diff(inflation)  
> ts.plot(inflation) ; ts.plot(inflation_changes)
```



# MA Processes: Changes in Inflation Rate - II

- Inflation\_changes: changes in one-month US inflation rate
- Plot the series and its sample ACF:

```
> ts.plot(inflation_changes)
> acf(inflation_changes, lag.max = 24)
```



# MA Processes: Changes in Inflation Rate - III

*Today = Mean + Noise + Slope \* (Yesterday's Noise)*

$$Y_t = \mu + \epsilon_t + \theta\epsilon_{t-1}$$

$$\epsilon_t \sim WhiteNoise(0, \sigma_\epsilon^2)$$

```
> MA_inflation_changes <- arima(inflation_changes, order = c(0, 0, 1))  
> print(MA_inflation_changes)
```

Coefficients:

	ma1	intercept
	-0.7932	0.0010
s.e.	0.0355	0.0281
sigma^2 estimated as	8.882	

$$\text{ma1} = \hat{\theta}, \text{intercept} = \hat{\mu}, \text{sigma}^2 = \hat{\sigma}_\epsilon^2$$

# MA Processes: Fitted Values - I

- MA fitted values:  $\widehat{Today} = \widehat{Mean} + \widehat{Slope} * \widehat{Yesterday's Noise}$

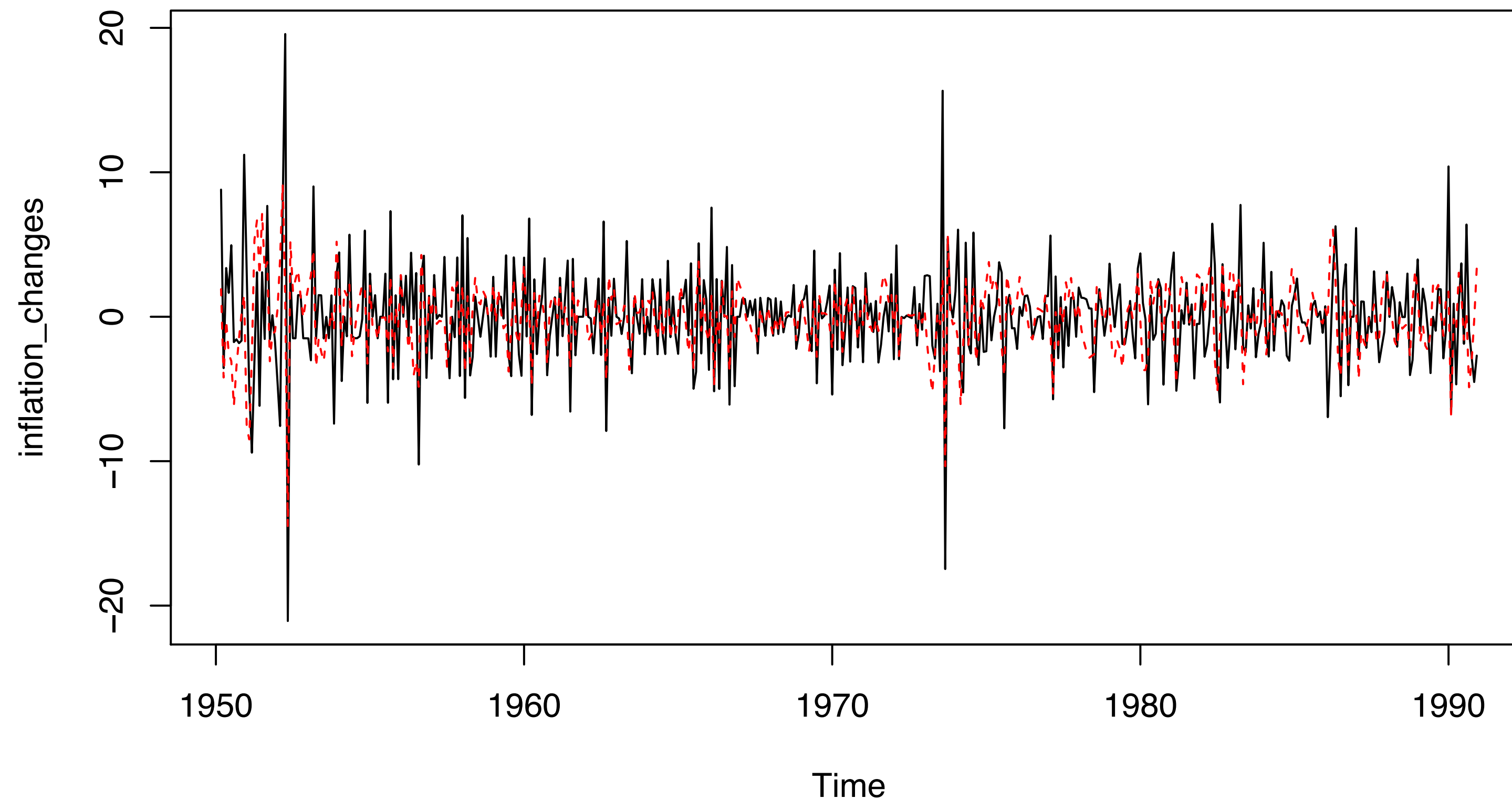
$$\hat{Y}_t = \hat{\mu} + \hat{\theta}\epsilon_{t-1}$$

- Residuals=  $Today - \widehat{Today}$

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

# MA Processes: Fitted Values - II

```
> ts.plot(inflation_changes)
> MA_inflation_changes_fitted <- inflation_changes - residuals(MA_inflation_changes)
> points(MA_inflation_changes_fitted, type = "l", col = "red", lty = 2)
```



# Forecasting

- 1-step ahead forecasts:

```
> predict(MA_inflation_changes)
$pred
      Jan
1991 4.831632

$se
      Jan
1991 2.980203
```

- h-step ahead forecasts:

```
> predict(MA_inflation_changes, n.ahead = 6)
$pred
      Jan      Feb      Mar      Apr      May      Jun
1991 4.831632 0.001049 0.001049 0.001049 0.001049 0.001049

$se
      Jan      Feb      Mar      Apr      May      Jun
1991 2.980203 3.803826 3.803826 3.803826 3.803826 3.803826
```



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# Let's practice!





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# **Compare the AR and MA models**



# MA and AR processes

- MA model:

$$Today = Mean + Noise + Slope * (Yesterday's Noise)$$

$$Y_t = \mu + \epsilon_t + \theta \epsilon_{t-1}$$

- AR model:

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

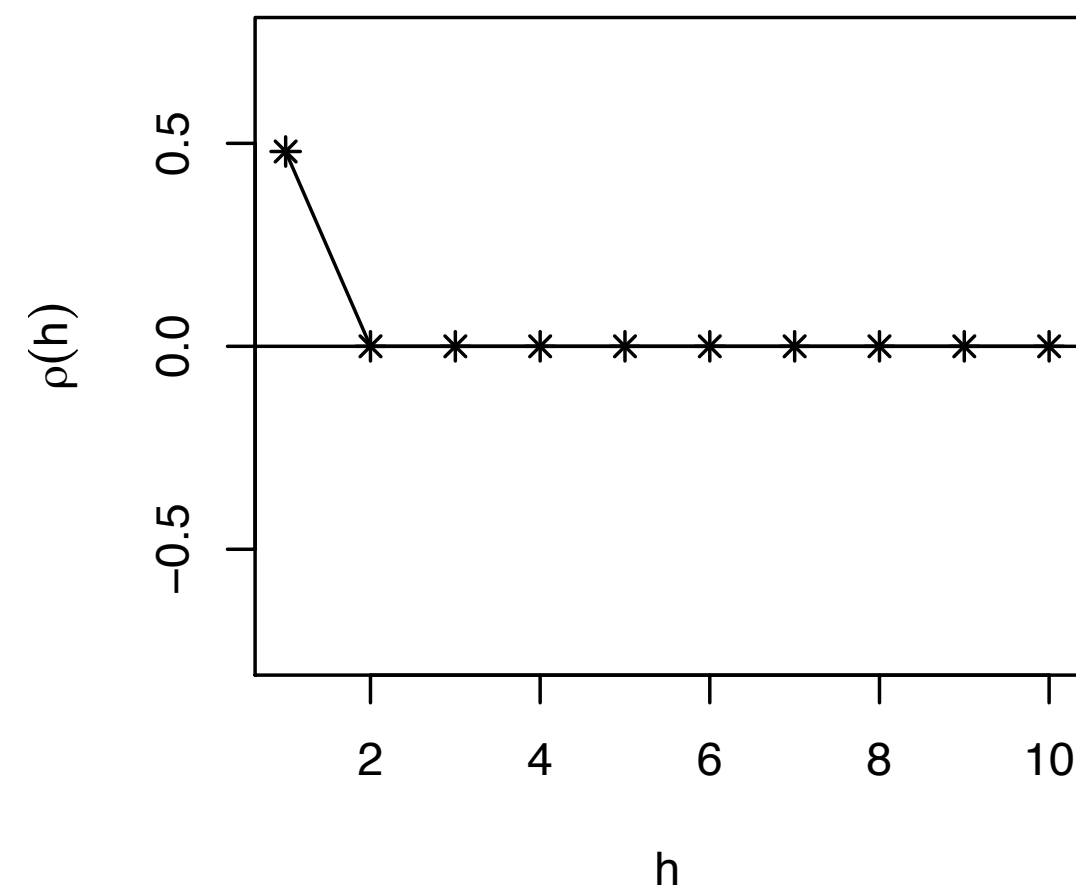
$$Y_t - \mu = \phi(Y_{t-1} - \mu) + \epsilon_t$$

- Where:

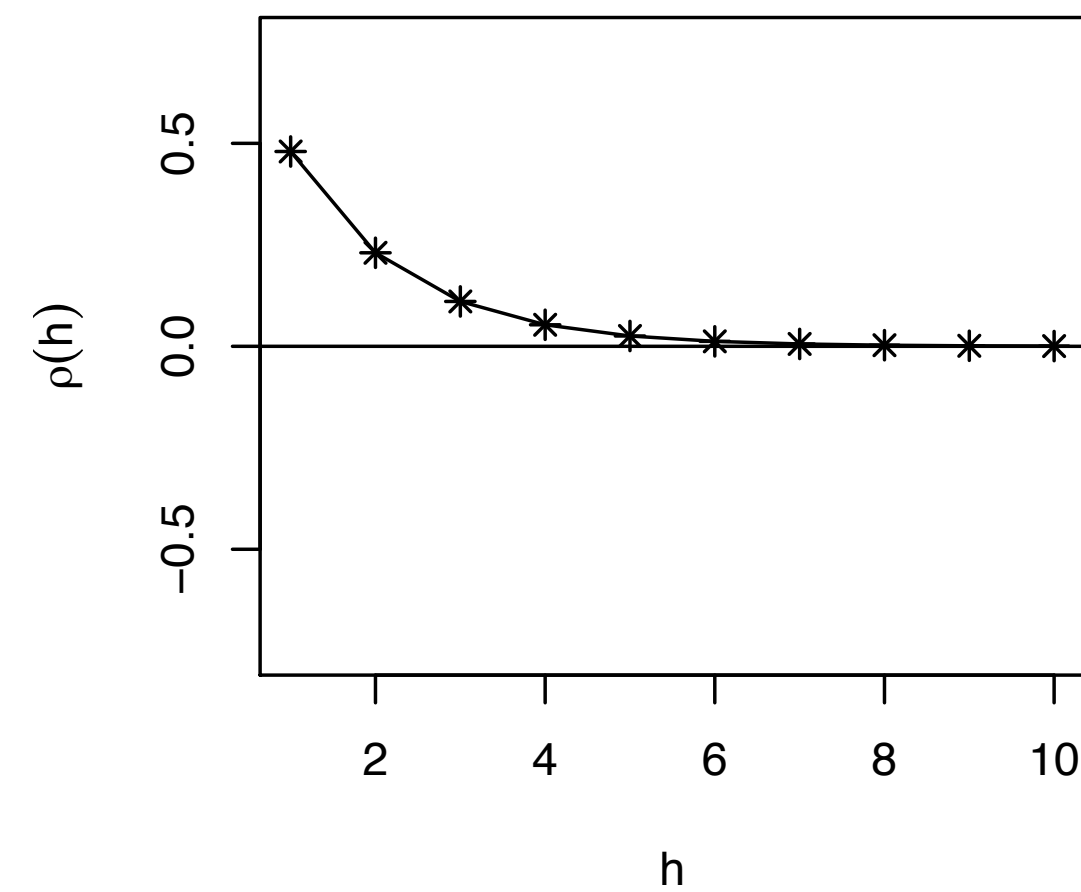
$$\epsilon_t \sim WhiteNoise(0, \sigma_\epsilon^2)$$

# MA and AR Processes: Autocorrelations

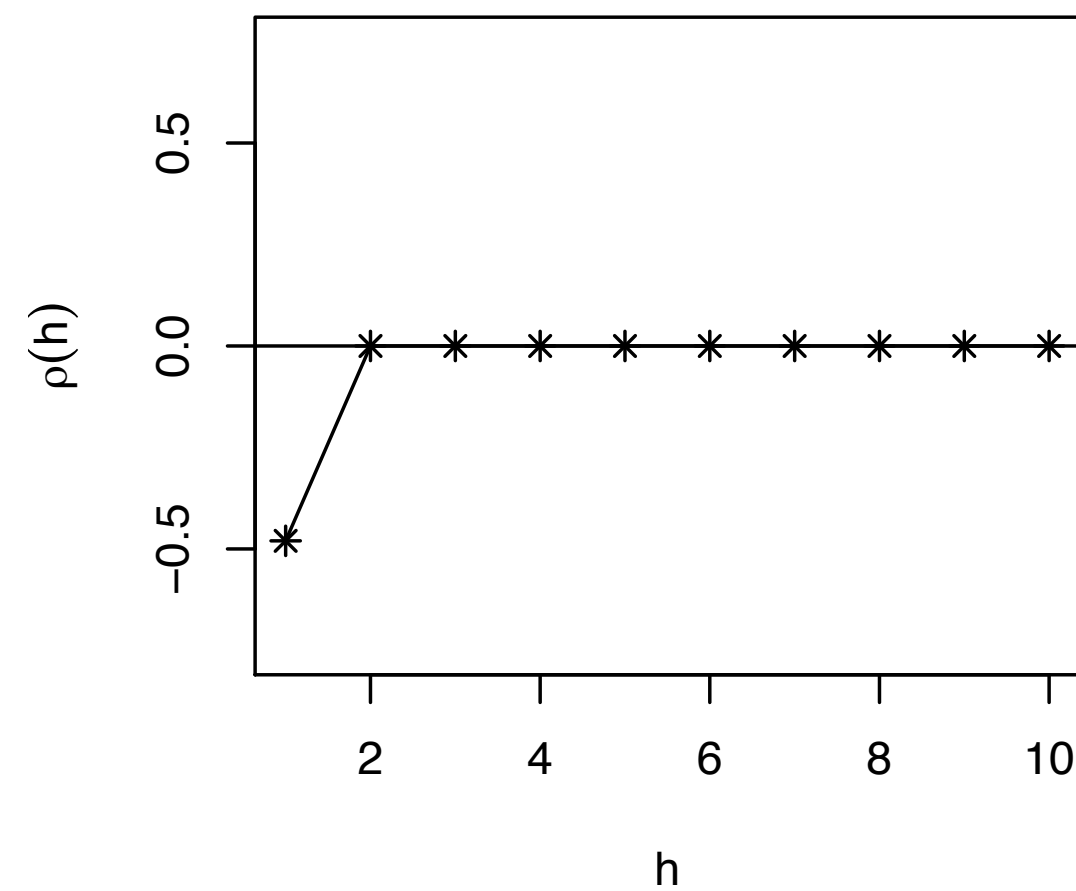
MA:  $\theta = 0.75$



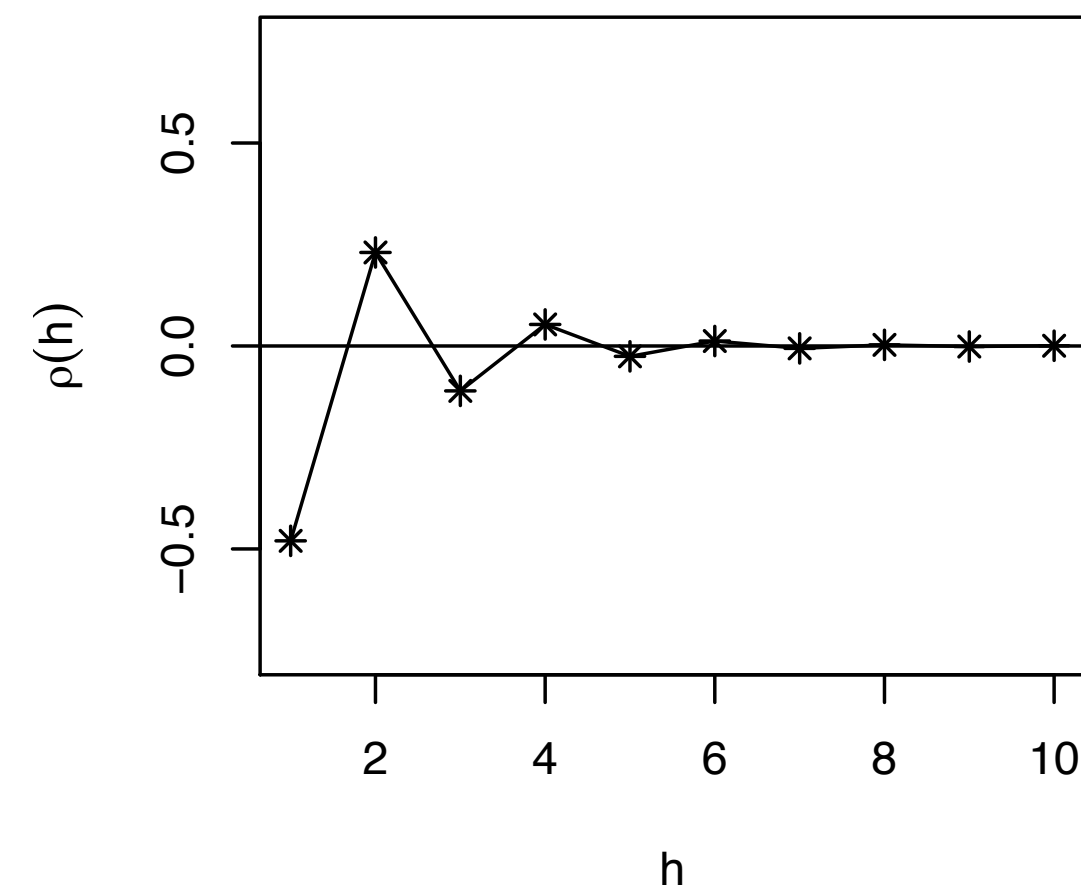
AR:  $\phi = 0.48$



MA:  $\theta = -0.75$

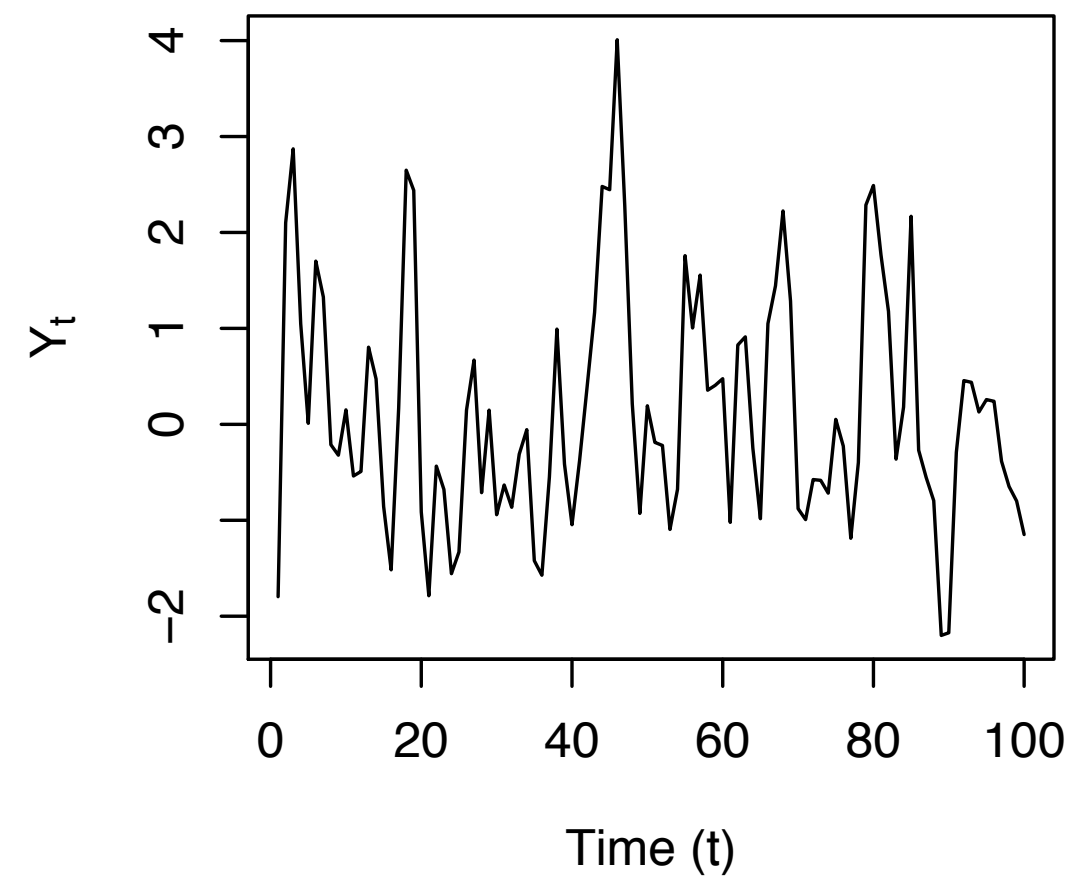


AR:  $\phi = -0.48$

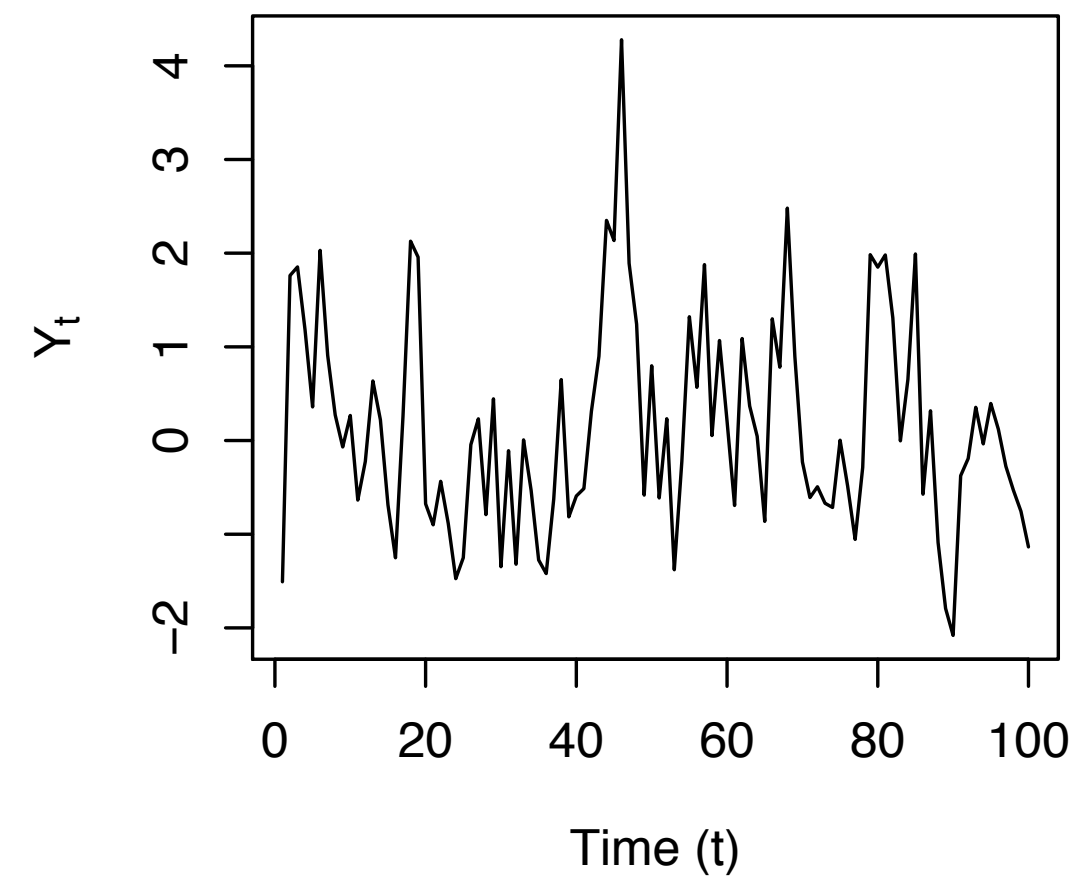


# MA and AR Processes: Simulations

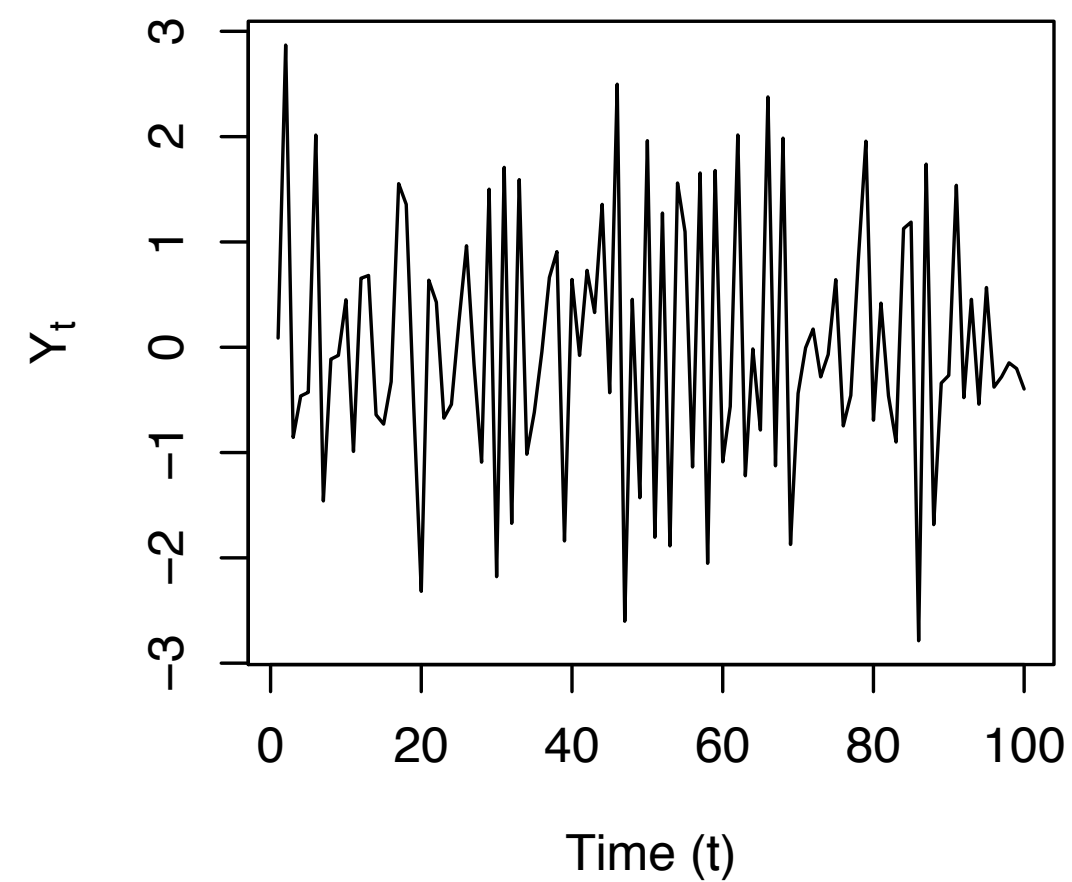
MA:  $\theta = 0.75$



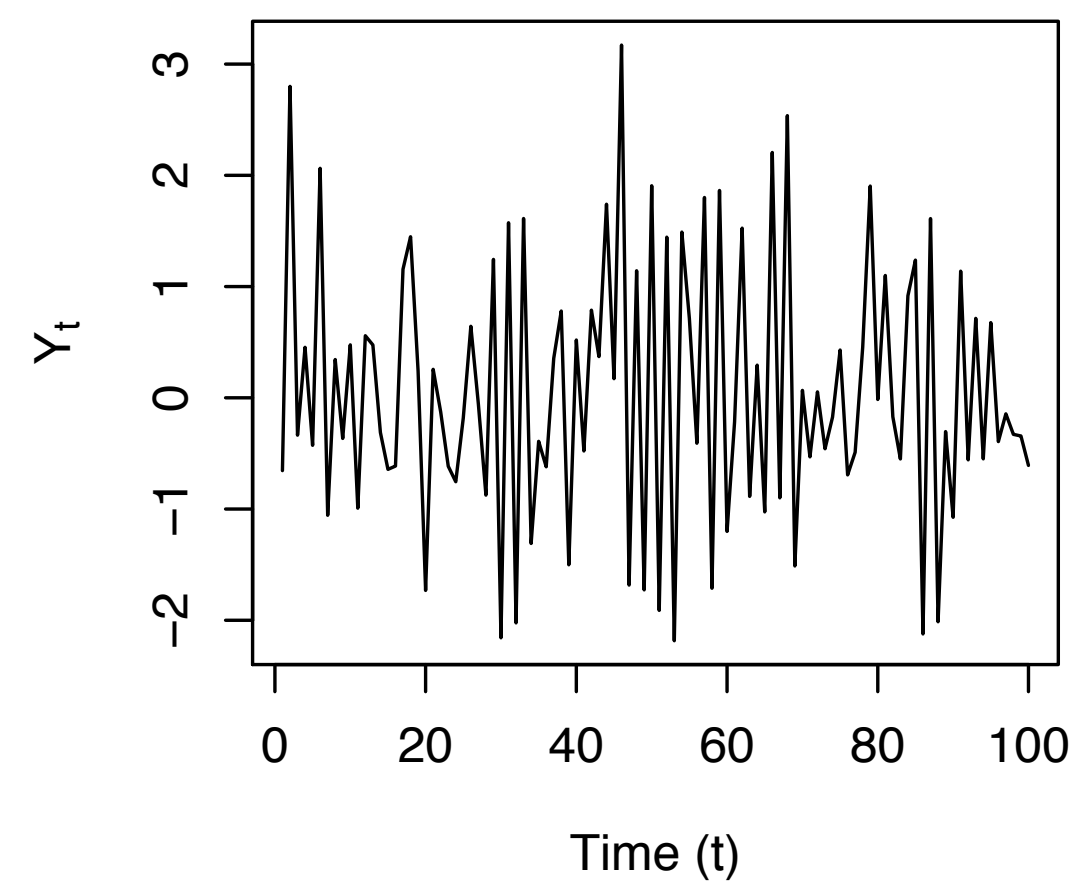
AR:  $\phi = 0.48$



MA:  $\theta = -0.75$

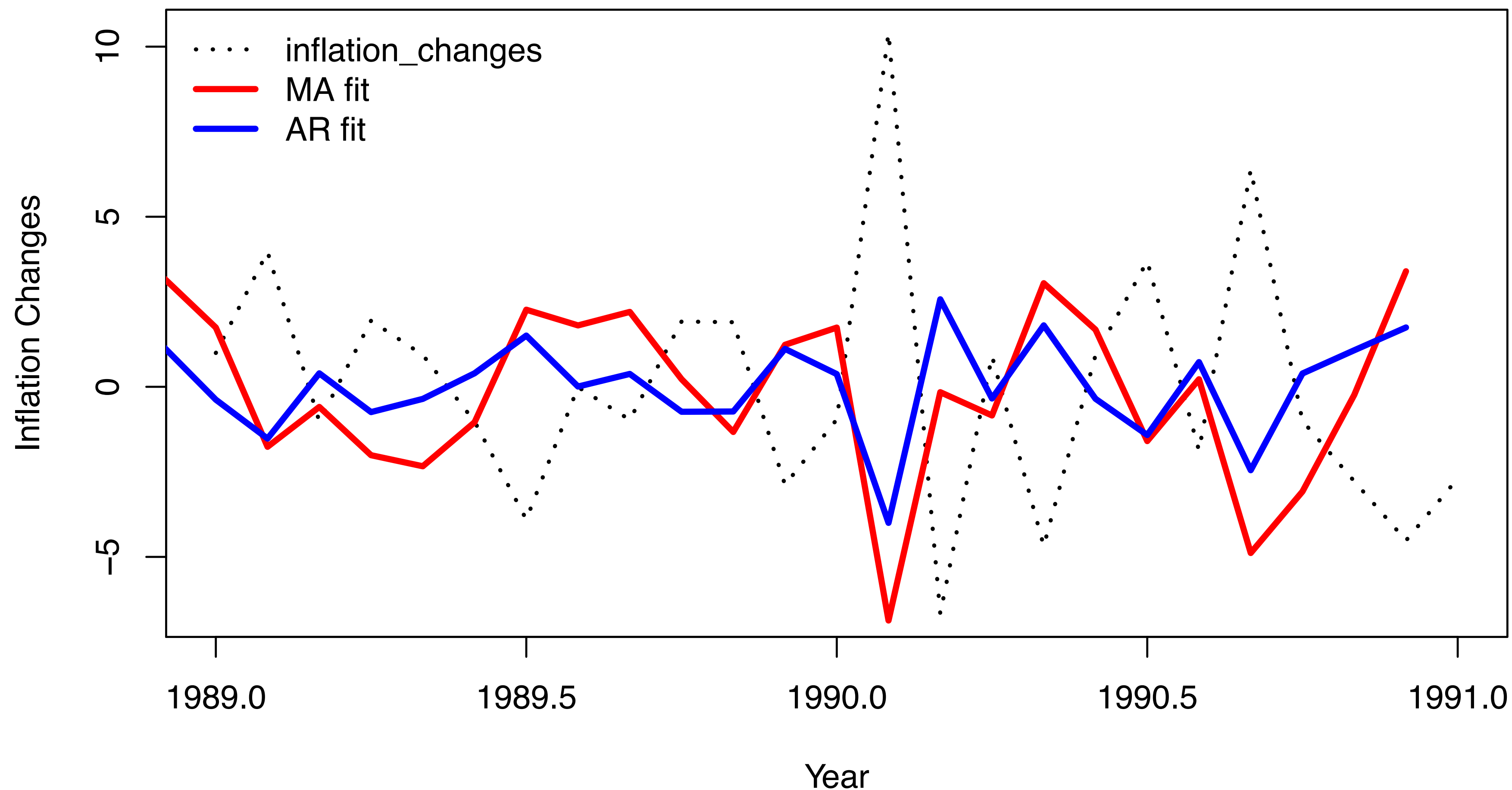


AR:  $\phi = -0.48$



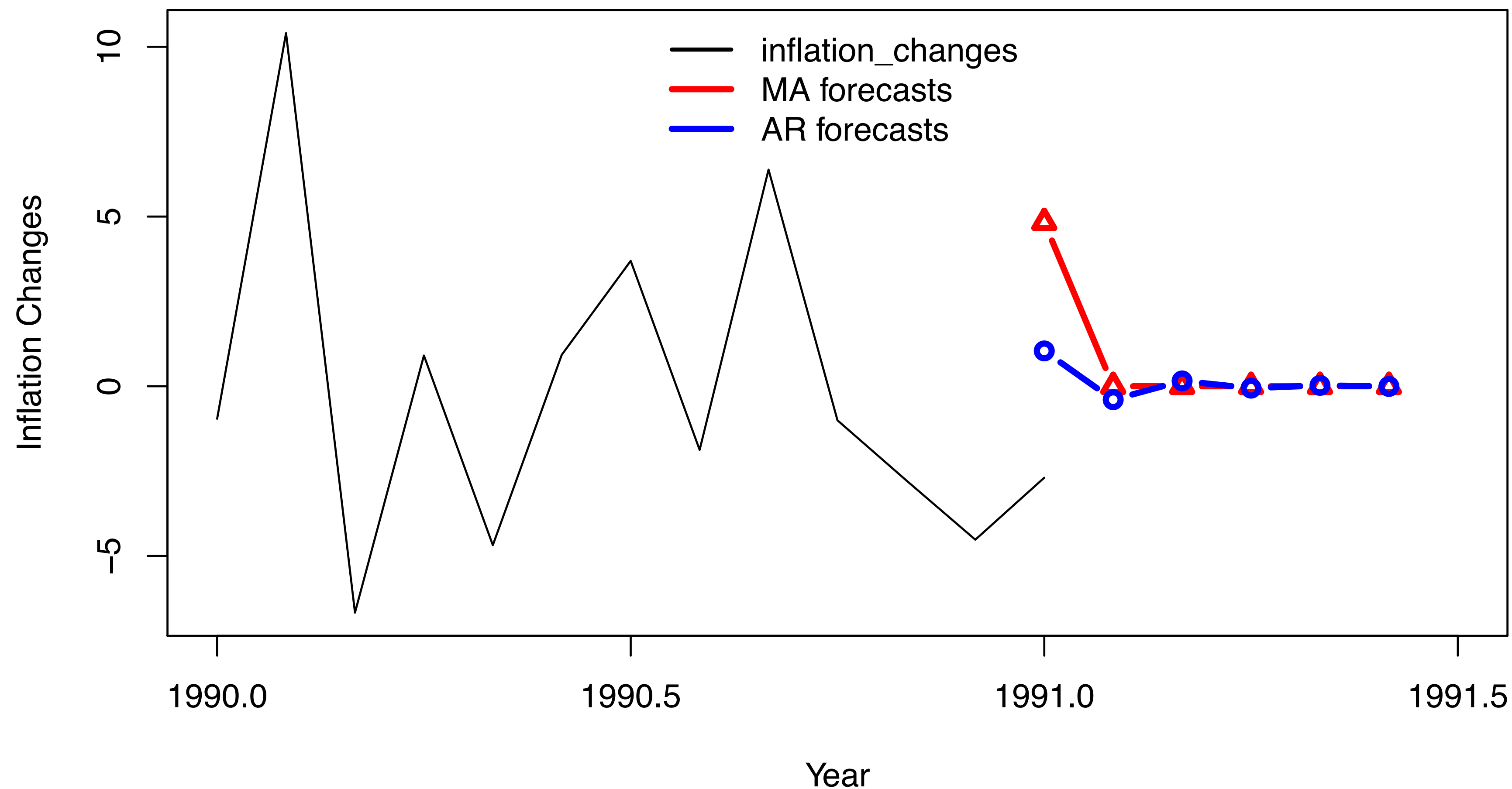
# MA and AR Processes: Fitted Values

- Changes in one-month US inflation rate



# MA and AR Processes: Forecasts

- Changes in one-month US inflation rate



# Forecasting

Akaike Information Criterion

Bayesian Information Criterion

```
> MA_inflation_changes <- arima(inflation_changes, order = c(0,0,1))
      ma1 intercept
      -0.7932    0.0010
s.e.   0.0355    0.0281
sigma^2 estimated as 8.882: log likelihood = -1230.85, aic = 2467.7
> AIC(MA_inflation_changes)
2467.703
> BIC(MA_inflation_changes)
2480.286
```

```
> AR_inflation_changes <- arima(inflation_changes, order = c(1,0,0))
      ar1 intercept
      -0.3849    0.0038
s.e.   0.0420    0.1051
sigma^2 estimated as 10.37: log likelihood = -1268.34, aic = 2542.68
> AIC(AR_inflation_changes)
2542.679
> BIC(AR_inflation_changes)
2555.262
```



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# Let's practice!



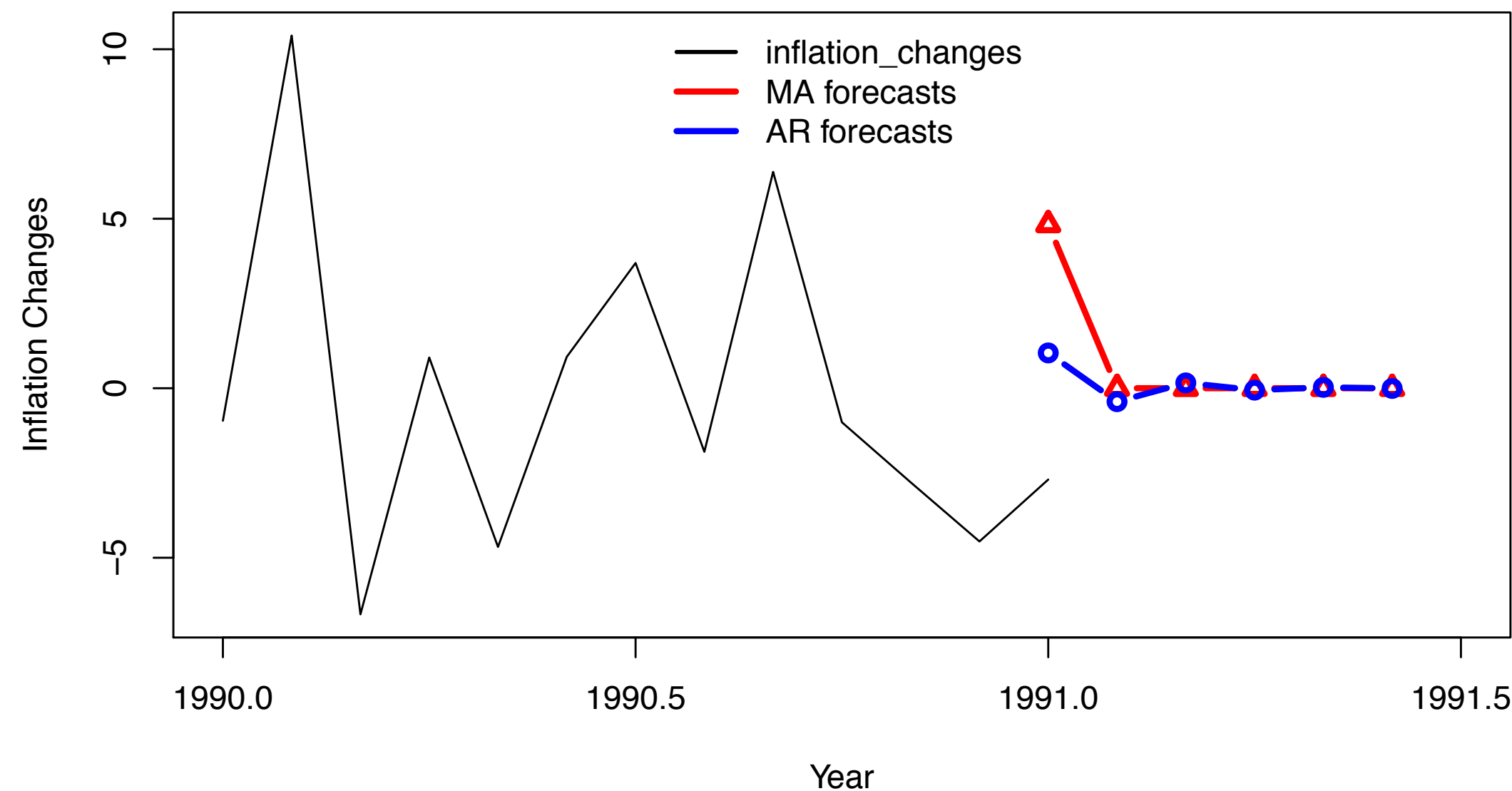
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# Congratulations!



# What you've learned

- Manipulating `ts` objects, including `log()` and `diff()`
- Time series models: white noise, random walk, autoregression, simple moving average
- Time series simulation (`arima.sim`), fitting (`arima`), and forecasting (`predict`)





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# Thank you!