Time Series

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Time Series

$$X_t = \alpha_1 X_{t-1} + \epsilon_t$$

- t represents the time.

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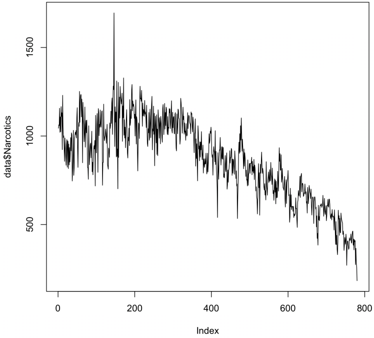
- Example: Crime related to Narcotics in Chicago
  data = read.table("data.txt", header = TRUE)
  data$Narcotics
  plot(data$Narcotics, type="l")



Time Series

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- Another example: ?AirPassengers
  data(AirPassengers)
  plot.ts(AirPassengers)

  What do we see in this time series? Trends? Seasonal trends? Increasing Variance?

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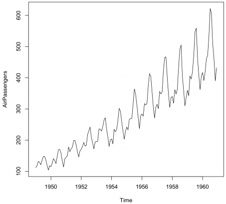
  abline(reg=lm(AirPassengers time(AirPassengers)))



Time Series

- Let's take a look at the cycles of this series

  boxplot(AirPassengers cycle(AirPassengers))

  Box plot across months gives us a sense on seasonal effect

Time Series

- With the dependence in the past, using the simple model

$$X_t = \alpha_1 X_{t-1} + \epsilon_t$$

may not be appropriate, since the series does not depend only on the previous day, but it depends on seasons ago!

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- General model

$$X_t = \alpha_1 X_{t-1} + \ldots + \alpha_p X_{t-p} + \epsilon_t$$

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$$X_t = \alpha_1 X_{t-1} + \ldots + \alpha_p X_{t-p} + \epsilon_t$$

- This is called AR(d) - Auto Regressive of order p

Time Series

- Example: Random Walk with Drift

$$X_t = \delta + X_{t-1} + \epsilon_t$$

with $X_0 = 0$ and ϵ_t white noise (Gaussian).

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- Let's generate this in R.

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with $X_0 = 0$ and ϵ_t white noise (Gaussian).

- Let's generate this in R.
- Note that $X_t = \delta t + \sum_{j=1}^{t} \epsilon_t$

Time Series

- Example: Signal in Noise

$$X_t = 2\cos\left(2\pi\frac{(t+15)}{50}\right) + \epsilon_t$$

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$$X_t = \beta_1 \epsilon_{t-1} + \ldots + \beta_q \epsilon_{t-q} + \epsilon_t$$

- This is called MA(p) - Moving Average of order q

Time Series

- Can we combine AR(p) with MA(q)?

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  ARMA(p,q)

$$X_t = \alpha_1 X_{t-1} + \ldots + \alpha_p X_{t-p} + \beta_1 \epsilon_{t-1} + \ldots + \beta_q \epsilon_{t-q} + \epsilon_t$$

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Time Series

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  Mean Function of a Random Walk with Drift

$$X_t = \delta + X_{t-1} + \epsilon_t = \delta t + \sum_{j=1}^{t} \epsilon_t$$

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Time Series

- **Definition:** The autocovariance function is defined as

$$\gamma(s,t) = cov(X_t, X_s) = E((X_t - \mu_t)(X_s - \mu_s))$$

- If $t = s$, the autocovariance reduces to the (assumed finite) variance

$$\gamma(s,t) = cov(X_t, X_t) = Vat(X_t)$$

Time Series

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- Recall White Noise $X_t = \epsilon_t$.
- So

$$\gamma(s,t) = cov(\epsilon_t, \epsilon_s) =$$

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$$\gamma(s,t) = cov(\epsilon_t, \epsilon_s) = \begin{cases} \sigma_\epsilon^2 \text{ if } s = t, \\ 0 \text{ otherwise} \end{cases}$$

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- Consider MA: $X_t = (1/3)\epsilon_{t-1} + (1/3)\epsilon_t + (1/3)\epsilon_{t+1}$.
- So

$$\begin{aligned}\gamma(t,s) &= cov((1/3)(\epsilon_{t-1} + \epsilon_t + \epsilon_{t+1}), (1/3)(\epsilon_{s-1} + \epsilon_s + \epsilon_{s+1})) \\ &= \end{aligned}$$

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Time Series

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

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Time Series

- **Definition** A **strictly stationary** time series is one for which the probabilistic behavior of every collection of values

$$\{x_{t_1}, x_{t_2}, \ldots, x_{t_k}\}$$

is identical to that of the time shifted set

$$\{x_{t_1+h}, x_{t_2+h}, \ldots, x_{t_k+h}\}$$

Time Series

- **Definition** A **weakly stationary** time series is a finite variance process such that
  (i) the mean value function is constant and does not depend on time t, and
  (ii) the autocovariance function, $\gamma(s, t)$ depends on s and t only through their difference $|s - t|$.

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  (i) the mean value function is constant and does not depend on time t, and
  (ii) the autocovariance function, $\gamma(s, t)$ depends on s and t only through their difference $|s - t|$.
  People use the term **stationary** to mean weakly stationary.

Time Series

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$$\gamma(h) = cov(x_{t+h}, x_t)$$

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- **Definition** The autocorrelation function (ACF) of a stationary time series will be written as

$$\rho(h) = \frac{\gamma(t+h, t)}{\sqrt{\gamma(t,t)\gamma(t+h, t+h)}} = \frac{\gamma(h)}{\gamma(0)}$$

Time Series

- **Example** Stationarity of White Noise
- Mean $= 0$ and

$$\gamma_\epsilon(h) = cov(\epsilon_{t+h}, \epsilon_t) = \begin{cases} \sigma_\epsilon^2 \text{ if } s = t, \\ 0 \text{ otherwise} \end{cases}$$

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&= \begin{cases} (3/9)\sigma_\epsilon^2 \text{ if } s=t, \\ (2/9)\sigma_\epsilon^2 \text{ if} |s-t|=1 \\ (1/9)\sigma_\epsilon^2 \text{ if} |s-t|=2 \\ 0 otherwise \end{cases}
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Time Series

- How do I make my time series stationary? Differencing

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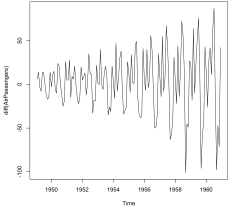
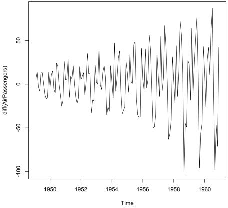
library(tseries)
plot.ts(AirPassengers)
plot.ts(diff(AirPassengers))

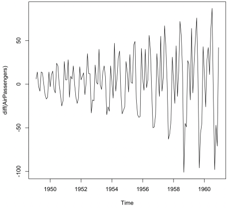


Time Series



- Variance is increasing!

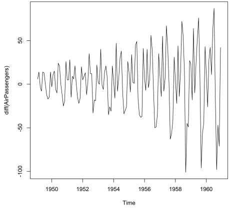
Time Series



- Variance is increasing!

- To fix increasing variance use transformation: log

Time Series



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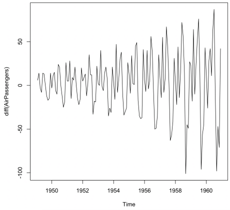
  logdata = log(AirPassengers)
  plot.ts(diff(logdata))

Time Series



- Variance is increasing!

- To fix increasing variance use transformation: log

  logdata = log(AirPassengers)

  plot.ts(diff(logdata))

  Now, check for stationarity:

  adf.test(diff(log(AirPassengers)), alternative="stationary", k=0)

  p-value is small => stationary!

Time Series

- **Definition** The **sample autocovariance** function is defined as

$$\hat{\gamma}(h) = \frac{1}{n}\sum_{t=1}^{n-h}(x_{t+h} + \bar{x})(x_t + \bar{x})$$

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- **Definition** The **sample autocorrelation** function is defined, analogously as

$$\hat{\rho}(h) = \hat{\gamma}(h)/\hat{\gamma}(0)$$

Time Series

- **Definition** An autoregressive model of order p, abbreviated AR(p), is of the form

$$X_t = \phi_1 X_{t-1} + \ldots + \phi_p X_{t-p} + \epsilon_t,$$

where X_t is stationary, $\epsilon_t \sim N(0, \sigma_\epsilon^2)$, and $\phi_1, \ldots, \phi_p$ are constants.

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where X_t is stationary, $\epsilon_t \sim N(0, \sigma_\epsilon^2)$, and $\phi_1, \ldots, \phi_p$ are constants.

- **Definition** The moving average model of order q, or MA(q) model, is defined to be

$$X_t = \theta_1 \epsilon_{t-1} + \ldots + \theta_q \epsilon_{t-q} + \epsilon_t,$$

where $\epsilon_t \sim N(0, \sigma_\epsilon^2)$, and $\phi_1, \ldots, \phi_p$ are constants.

Time Series

- **Definition** A time series X_t is ARMA(p, q) if it is stationary and

$$X_t = \phi_1 X_{t-1} + \ldots + \phi_p X_{t-p} + \theta_1 \epsilon_{t-1} + \ldots + \theta_q \epsilon_{t-q} + \epsilon_t,$$

Time Series

The Partial Autocorrelation Function (PACF)

Time Series

- **Definition** The partial autocorrelation function (PACF) of a stationary process X_t is

$$\begin{aligned} \phi_{11} &= corr(X_{t+1}, X_t) = \rho(1) \\ \phi_{hh} &= corr(X_{t+h} - \hat{X}_{t+h}, X_t - \hat{X}_t) \text{ for } h \geq 2 \end{aligned}$$

Time Series

Consider the PACF of the AR(1) process given by $x_t = \phi x_{t-1} + w_t$, with $|\phi| < 1$. By definition, $\phi_{11} = \rho(1) = \phi$. To calculate ϕ_{22}, consider the regression of x_{t+2} on x_{t+1}, say, $\hat{x}_{t+2} = \beta x_{t+1}$. We choose β to minimize

$$E(x_{t+2} - \hat{x}_{t+2})^2 = E(x_{t+2} - \beta x_{t+1})^2 = \gamma(0) - 2\beta\gamma(1) + \beta^2\gamma(0).$$

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Taking derivatives with respect to β and setting the result equal to zero, we have $\beta = \gamma(1)/\gamma(0) = \rho(1) = \phi$. Next, consider the regression of x_t on x_{t+1}, say $\hat{x}_t = \beta x_{t+1}$. We choose β to minimize

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This is the same equation as before, so $\beta = \phi$. Hence,

$$\begin{aligned}\phi_{22} &= \text{corr}(x_{t+2} - \hat{x}_{t+2}, x_t - \hat{x}_t) = \text{corr}(x_{t+2} - \phi x_{t+1}, x_t - \phi x_{t+1}) \\ &= \text{corr}(w_{t+2}, x_t - \phi x_{t+1}) = 0\end{aligned}$$

by causality. Thus, $\phi_{22} = 0$. In the next example, we will see that in this case, $\phi_{hh} = 0$ for all $h > 1$.

Time Series

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Time Series

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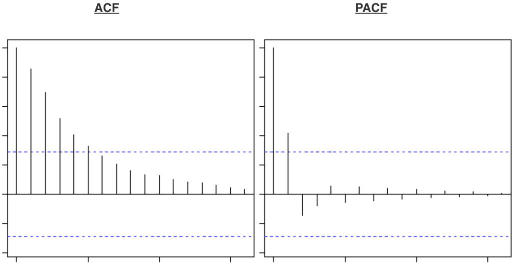
  If they look like this:



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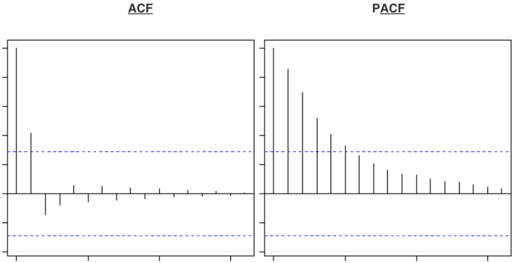

  Use an MA(2)

Time Series

- Choose ARMA when both ACF and PACF tail off

Time Series

	AR(p)	MA(q)	ARMA(p, q)
ACF	Tails off	Cuts off after lag q	Tails off
PACF	Cuts off after lag p	Tails off	Tails off

Time Series

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```
logdata = log(AirPassengers)
acf(diff(logdata))
pacf(diff(logdata))
```

Time Series

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  1. We can use the differentiation inside the command ARIMA
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  where d is the number of differences necessary

  ?arima

Time Series

- fit <- arima(log(AirPassengers), c(0, 1, 1),seasonal = list(order = c(0, 1, 1), period = 12))

  pred <- predict(fit, n.ahead = 36)

  ts.plot(AirPassengers,2.718^pred$pred, log = "y", lty = c(1,3))

Time Series

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  pred <- predict(fit, n.ahead = 36)

  ts.plot(AirPassengers,2.718^pred$pred, log = "y", lty = c(1,3))

  tsdiag(fit, gof.lag = 30)

Time Series

- How about predicting the future observations with confidence bounds?

Time Series

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  pm <- forecast(fit, h=10*12)

Time Series

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  ```
  pm <- forecast(fit, h=10*12)

  plot(pm)
  ```

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- How far in the past should we look? What's p, q, and d?

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  fit <- arima(USDCHF, c(0, 1, 0))

  AIC(fit)

  -634191.6

	MA(0)	MA(1)	MA(2)	MA(3)
AR(0)	-634191.6	-634213.6	**-634219.3**	-634218.4
AR(1)	-634214.1	-634211.9	-634217.3	-634216.4
AR(2)	**-634219.4**	-634217.3	-634215.3	-634214.4
AR(3)	-634218.3	-634216.3	-634214.3	-634212.3

Time Series

- Your turn

  Run a time series analysis with the Robberies data

Time Series

Exercises:
https://www.r-exercises.com/2018/06/06/intro-to-time-series-analysis-part-1/
https://www.r-exercises.com/2018/06/20/intro-to-time-series-analysis-part-2-exercises/
https://www.r-exercises.com/2017/04/10/forecasting-time-series-exploration-exercises-part-1/