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## Error in library(broman): there is no package called 'broman'
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# Analysis of Time Series

## Chapter 2: Time series models, trend and autocovariance

Edward L. Ionides

### Contents

## 1 Overview

### Objectives

1. Set up general notation for working with time series data and time series models.
2. Define the trend function for a time series model, and discuss its estimation from data.
3. Discuss the properties of least square estimation of the trend.
4. Define the autocovariance and autocorrelation functions and their standard estimators.

### Definition: Time series data and time series models

- A time series is a sequence of numbers, called **data**. In general, we will suppose that there are  $N$  numbers,  $y_1, y_2, \dots, y_N$ , collected at an increasing sequence of times,  $t_1, t_2, \dots, t_N$ .
- We write  $1:N$  for the sequence  $\{1, 2, \dots, N\}$  and we write the collection of numbers  $\{y_n, n = 1, \dots, N\}$  as  $y_{1:N}$ .
- We keep  $t$  to represent continuous time, and  $n$  to represent the discrete sequence of observations. This will serve us well later, when we fit continuous time models to data.
- A time series model is a collection of jointly defined random variables,  $Y_1, Y_2, \dots, Y_N$ .
- We write this collection of random variables as  $Y_{1:N}$ .
- Like all jointly defined random variables, the distribution of  $Y_{1:N}$  is defined by a joint density function, which we write as

$$f_{Y_{1:N}}(y_1, \dots, y_N | \theta).$$

- Here,  $\theta$  is a vector of parameters.
- Our notation for densities generalizes. We write  $f_Y(y)$  for the density of a random variable  $Y$  evaluated at  $y$ , and  $f_{YZ}(y, z)$  for the joint density of the pair of random variables  $(Y, Z)$  evaluated at  $(y, z)$ . We can also write  $f_{Y|Z}(y|z)$  for the conditional density of  $Y$  given  $Z$ .
- For discrete data, such as count data, our model may also be discrete and we interpret the density function as a probability mass function. Expectations and probabilities are integrals for continuous models, and sums for discrete models. Otherwise, everything remains the same. We will write formulas only for the continuous case. You should be able to swap integrals for sums, if necessary, to work with discrete models.
- Scientifically, we postulate that  $y_{1:N}$  are a realization of  $Y_{1:N}$  for some unknown value of  $\theta$ .

**Review: Random variables**

**Question 2.1.** What is a random variable?

**Question 2.2.** What is a collection of jointly defined random variables?

**Question 2.3.** What is a probability density function? What is a joint density function? What is a conditional density function?

**Question 2.4.** What does it mean to say that “ $\theta$  is a vector of parameters?”

There are different answers to these questions, but you should be able to write down an answer that you are satisfied with.

**Review: Expectation**

Random variables usually have an expected value, and in this course they always do. We write  $\mathbb{E}[X]$  for the expected value of a random variable  $X$ .

**Question 2.5.** Review question: What is expected value? How is it defined? How can it fail to exist for a properly defined random variable?

**Definition: The mean function, or trend**

- We define the **mean function**, for  $n \in 1:N$ , by

$$\mu_n = \mathbb{E}[Y_n] = \int_{-\infty}^{\infty} y_n f_{Y_n}(y_n) dy_n$$

- We use the words “mean function” and “trend” interchangeably.
- We say “function” since we are thinking of  $\mu_n$  as a function of  $n$ .
- Sometimes, it makes sense to think of time as continuous. Then, we write  $\mu(t)$  for the expected value of an observation at time  $t$ . We only make observations at the discrete collection of times  $t_{1:N}$  and so we require  $\mu(t_n) = \mu_n$ .
- A time series may have measurements evenly spaced in time, but our notation does not insist on this. In practice, time series data may contain missing values or unequally spaced observations.

- $\mu_n$  may depend on  $\theta$ , the parameter vector. We can write  $\mu_n(\theta)$  to make this explicit.
- We write  $\hat{\mu}_n(y_{1:N})$  to be some estimator of  $\mu_n$ , i.e., a map which is applied to the data to give an estimate of  $\mu_n$ . An appropriate choice of  $\hat{\mu}_n$  will depend on the data and the model.
- Usually, applied statistics courses do not distinguish between estimators (functions that can be applied to any dataset) and estimates (an estimator evaluated on the actual data). For thinking about model specification and diagnosing model misspecification it is helpful to bear this in mind.
- For example, the estimate of the mean function is the value of the estimator when applied to the data. Here, we write this as

$$\hat{\mu}_n = \hat{\mu}_n(y_{1:N}).$$

- We call  $\hat{\mu}_n$  an **estimated mean function** or **estimated trend**.
- For example, sometimes we suppose a model with  $\mu_n = \mu$ , so the mean is assumed constant. In this case, the model is called **mean stationary**. Then, we might estimate  $\mu$  using the mean estimator,

$$\hat{\mu}(y_{1:N}) = \frac{1}{N} \sum_{k=1}^N y_k.$$

- We write  $\hat{\mu}$  for  $\hat{\mu}(y_{1:N})$ , the sample mean.
- We can compute the sample mean,  $\hat{\mu}$ , for any dataset. It is only a reasonable estimator of the mean function when a mean stationary model is appropriate.
- Notice that trend is a property of the model, and the estimated trend is a function of the data.
- Formally, we should not talk about the trend of the data. People do, but we should try not to.
- Similarly, data cannot be mean stationary. A model can be mean stationary.

**Question 2.6.** Properties of models vs properties of data.

Consider these two statements. Does it matter which we use?

1. “The data look mean stationary.”
2. “A mean stationary model looks appropriate for these data.”

**Definition: The autocovariance function**

- We will assume that variances and covariances exist for the random variables  $Y_{1:N}$ . We write

$$\gamma_{m,n} = \mathbb{E}[(Y_m - \mu_m)(Y_n - \mu_n)].$$

This is called the **autocovariance** function, viewed as a function of  $m$  and  $n$ .

- We may also write  $\Gamma$  for the matrix whose  $(m, n)$  entry is  $\gamma_{m,n}$ .
- If the covariance between two observations depends only on their time difference, the time series model is **covariance stationary**. For observations equally spaced in time, the autocovariance function is then a function of a lag,  $h$ ,

$$\gamma_h = \gamma_{n,n+h}.$$

- For a covariance stationary model, and some mean function estimator  $\hat{\mu}_n = \hat{\mu}_n(y_{1:N})$ , a common estimator for  $\gamma_h$  is

$$\hat{\gamma}_h(y_{1:N}) = \frac{1}{N} \sum_{n=1}^{N-h} (y_n - \hat{\mu}_n) (y_{n+h} - \hat{\mu}_{n+h}).$$

- The corresponding estimate of  $\gamma_h$ , known as the **sample autocovariance function**, is

$$\hat{\gamma}_h = \hat{\gamma}_h(y_{1:N}).$$

**Definition: The autocorrelation function**

- Dividing the autocovariance by the variance gives the **autocorrelation function**  $\rho_h$  given by

$$\rho_h = \frac{\gamma_h}{\gamma_0}.$$

We can analogously construct the standard autocorrelation estimator,

$$\hat{\rho}_h(y_{1:N}) = \frac{\hat{\gamma}_h(y_{1:N})}{\hat{\gamma}_0(y_{1:N})},$$

which leads to an estimate known as the **sample autocorrelation**,

$$\hat{\rho}_h = \hat{\rho}_h(y_{1:N}) = \frac{\hat{\gamma}_h}{\hat{\gamma}_0}.$$

- It is common to use ACF as an acronym for any or all of the autocorrelation function, sample autocorrelation function, autocovariance function, and sample autocovariance function. **If you use the acronym ACF, you are expected to define it, to remove the ambiguity.**

**Sample statistics exist without a model**

- The sample autocorrelation and sample autocovariance functions are statistics computed from the data. They exist, and can be computed, even when the data are not well modeled as covariance stationary. However, in that case, it does not make sense to view them as estimators of the autocorrelation and autocovariance functions (which exist as functions of a lag  $h$  only for covariance stationary models).
- Formally, we should not talk about the correlation or covariance of data. These are properties of models. We can talk about the sample autocorrelation or sample autocovariance of data.

## Estimating a trend by least squares

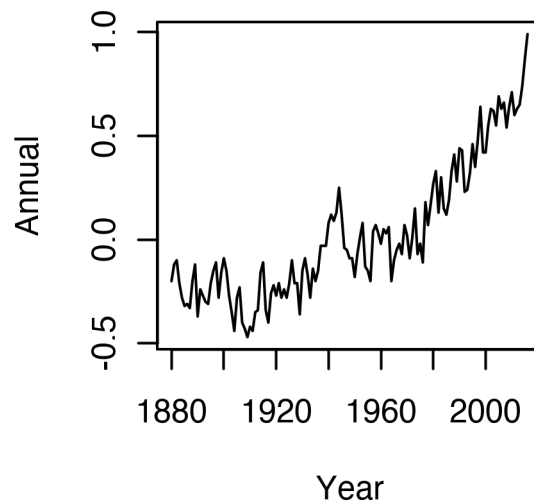
Let's analyze a time series of global mean annual temperature downloaded from [climate.nasa.gov/system/internal\\_resources/details/original/647\\_Global\\_Temperature\\_Data\\_File.txt](https://climate.nasa.gov/system/internal_resources/details/original/647_Global_Temperature_Data_File.txt). These data are in degrees Celsius measured as an anomaly from a 1951-1980 base. This is climatology jargon for saying that the sample mean of the temperature over the interval 1951-1980 was subtracted from all time points.

```
global_temp <- read.table("Global_Temperature.txt",header=TRUE)
str(global_temp)

'data.frame': 137 obs. of 3 variables:
 $ Year      : int  1880 1881 1882 1883 1884 1885 1886 18..
 $ Annual    : num -0.2 -0.12 -0.1 -0.21 -0.28 -0.32 -0...
 $ Moving5yrAverage: num -0.13 -0.16 -0.19 -0.21 -0.24 -0.26 -..
```

```
plot(Annual~Year,data=global_temp,ty="l")
```

## Mean global temperature anomaly, degrees C



- These data should make all of us pause for thought about the future of our planet.
- Understanding climate change involves understanding the complex systems of physical, chemical and biological processes driving climate.
- It is hard to know if gigantic models that attempt to capture all important parts of the global climate processes are in fact a reasonable description of what is happening.
- There is value in relatively simple statistical analysis, which can at least help to tell us what evidence there is for how things are, or are not, changing.
- Here is a quote from *Science* (18 December 2015, volume 350, page 1461; I've added some emphasis).

“Scientists are still debating whether—and, if so, how—warming in the Arctic and dwindling sea ice influences extreme weather events at midlatitudes. **Model limitations, scarce data** on the warming Arctic, and the **inherent variability** of the systems make answers elusive.”

### Fitting a least squares model with a quadratic trend

Perhaps the simplest trend model that makes sense looking at these data is a quadratic trend,

$$\mu(t) = \beta_0 + \beta_1 t + \beta_2 t^2.$$

To write the least squares estimate of  $\beta_0$ ,  $\beta_1$  and  $\beta_2$ , we set up matrix notation. Write

$$\mu = (\mu_1, \mu_2, \dots, \mu_N)^T$$

for the column vector describing the mean function, and similarly,

$$\beta = (\beta_0, \beta_1, \beta_2)^T.$$

Then, defining

$$Z = \begin{pmatrix} 1 & 1880 & 1880^2 \\ 1 & 1881 & 1881^2 \\ 1 & 1882 & 1882^2 \\ \vdots & \vdots & \vdots \end{pmatrix},$$

we can write

$$\mu = Z\beta.$$

We write the data  $y_{1:N}$  as a column vector,

$$y = (y_1, y_2, \dots, y_N)^T.$$

The ordinary least squares (OLS) estimator of  $\beta$  is

$$\hat{\beta}_{OLS}(y_{1:N}) = (Z^T Z)^{-1} Z^T y,$$

with corresponding OLS estimate

$$\hat{\beta} = \hat{\beta}_{OLS}(y_{1:N}) = (Z^T Z)^{-1} Z^T y.$$

We can carry out this computation in R by

```
lm_fit <- lm(Annual~Year+I(Year^2),data=global_temp)
```

where `I()` is a function that tells R to construct `Year2` as a variable, and inhibits interpretation in the R model formula notation.

```
summary(lm_fit)
```

Call:

```
lm(formula = Annual ~ Year + I(Year^2), data = global_temp)
```

Residuals:

Min	1Q	Median	3Q	Max
-0.27092	-0.08638	0.00613	0.07481	0.38067

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	2.959e+02	2.681e+01	11.04	<2e-16 ***
Year	-3.111e-01	2.753e-02	-11.30	<2e-16 ***
I(Year^2)	8.168e-05	7.067e-06	11.56	<2e-16 ***

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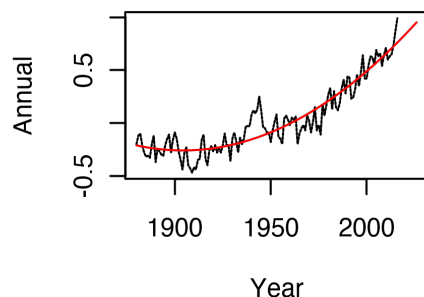
Residual standard error: 0.1157 on 134 degrees of freedom

Multiple R-squared: 0.8766, Adjusted R-squared: 0.8748

F-statistic: 476.1 on 2 and 134 DF, p-value: < 2.2e-16

We can check visually how well this model fits the data.

```
yr <- 1880:2026
Z <- cbind(1, yr, yr^2)
beta <- coef(lm_fit)
prediction <- Z%*%beta
plot(Annual~Year, data=global_temp, ty="l", xlim=range(yr),
     ylim=range(c(global_temp$Annual, prediction), na.rm=TRUE),
     lty="dashed")
lines(x=yr, y=prediction, col="red")
```



- The overall estimated trend seems a reasonable fit for the data.
- If we want to attach uncertainty to our parameter estimates, and consequently to our forecast, we need a time series model  $Y_{1:N}$ , which we write in column vector form as

$$Y = (Y_1, Y_2, \dots, Y_N)^T.$$

- The usual model behind OLS is the independent error model, known in time series analysis as the **white noise** error model:

$$[L1] \quad Y = Z\beta + \epsilon,$$

where  $\epsilon = \epsilon_{1:N}$  is a vector of independent, identically distributed random variables with mean zero and constant variance,  $\mathbb{E}[\epsilon_n] = 0$ ,  $\text{Var}[\epsilon_n] = \sigma^2$ . Standard linear model software, such as `lm` in R, provides confidence intervals based on this model.

- Under model L1, the estimator  $\hat{\beta}_{OLS}(y_{1:N})$  is unbiased. This can be checked:

$$\begin{aligned} \mathbb{E}[\hat{\beta}_{OLS}(Y_{1:N})] &= \mathbb{E}[(Z^T Z)^{-1} Z^T Y] \\ &= \mathbb{E}[(Z^T Z)^{-1} Z^T \{Z\beta + \epsilon\}] \\ &= (Z^T Z)^{-1} Z^T \{Z\beta + \mathbb{E}[\epsilon]\} \\ &= (Z^T Z)^{-1} (Z^T Z) \beta \\ &= \beta \end{aligned}$$

- A result for linear models is that  $\hat{\beta}_{OLS}(y_{1:N})$  is the minimum variance unbiased estimator for model L1.

### Variance/covariance for the white noise error model

- The variance/covariance matrix of  $\hat{\beta}_{OLS}(Y_{1:N})$  under this model is

$$\text{Cov}[\hat{\beta}_{OLS}(Y_{1:N})] = \sigma^2 (Z^T Z)^{-1},$$



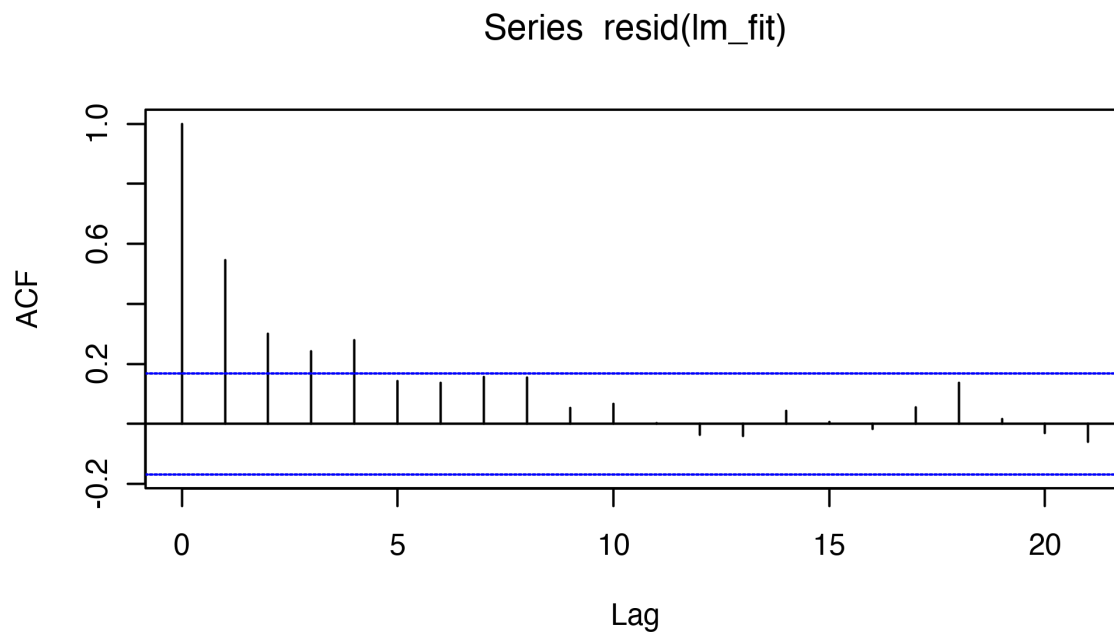
which is estimated using an estimator for  $\sigma$  of

$$\hat{\sigma}_{OLS}(y_{1:N}) = \sqrt{\frac{1}{N-d} (y - Z\hat{\beta}_{OLS})^T (y - Z\hat{\beta}_{OLS})},$$

where  $d$  is the number of covariates, i.e., the number of columns of  $Z$ .

Let's look at the residuals to assess how appropriate this model is here.

```
acf(resid(lm_fit))
```



### Context for Homework 1

- The horizontal dashed lines on the graph of the sample autocorrelation function (ACF) give a measure of chance variation under the null hypothesis that the residuals are IID.
- At each lag  $h$ , the chance that the estimated ACF falls within this band is approximately 95
- Thus, under the null hypothesis, one expects a fraction of 1/20 of the lags of the sample ACF to fall outside this band.
- Here, the sample ACF confirms what we can probably see from the plot of the fitted model: the variation around the fitted model is clustered in time, so the sample ACF of the residuals is not consistent with a model having independent error terms.

**Question 2.7.** How does R construct these horizontal dashed lines?