

Signal vs. Noise

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Lecture 0b

Announcements

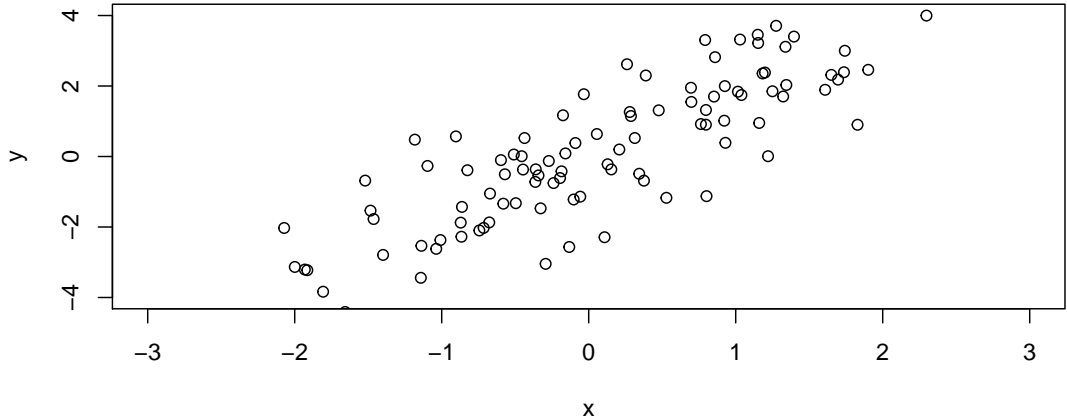
- ▶ “Practice Homework 0” has been posted. **This is not graded!** But it will give a chance to those who want to practice turning something in before turning in a “real” assignment. It also reviews pre-requisite material.
- ▶ Homework 0 is “due” January 27, but it’s not graded so it’s fine if it’s late too. Again, it’s for practice if you want.
- ▶ Must be submitted as a PDF on Gradescope.

Accommodations and Schedule Conflicts

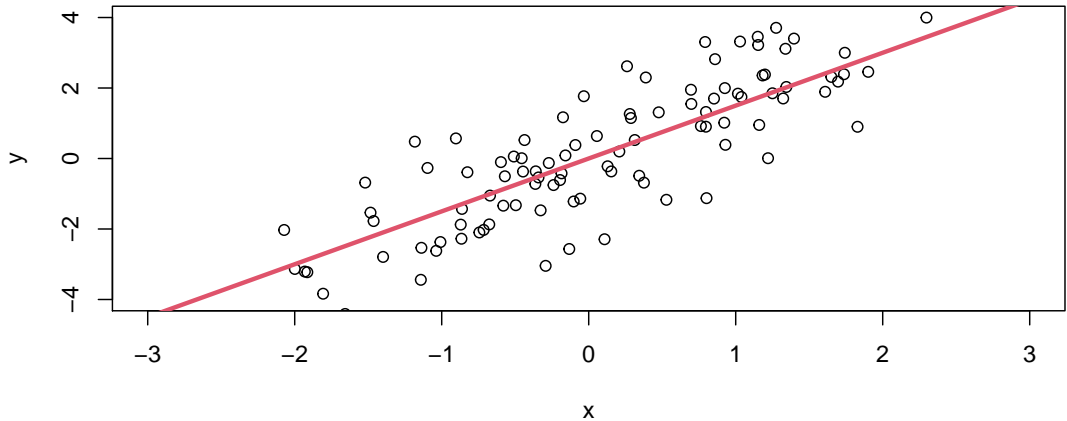
- ▶ Please let me know of any conflicts or accommodations (religious, DSP, or otherwise) as soon as possible.

Parallels between Ideas behind Time Series and Regression

Regression



Regression

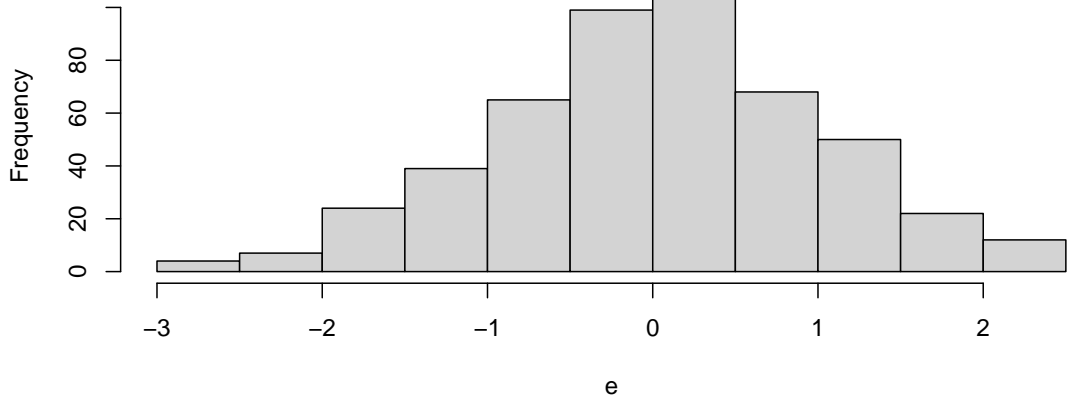


Regression = Signal + Noise

- ▶ $y_i = f(\mathbf{x}_i) + \epsilon_i$
- ▶ $f(\mathbf{x}_i) \Rightarrow$ “Signal”
- ▶ $\epsilon_i \Rightarrow$ “Noise”
- ▶ Often $\epsilon_i \sim N(0, \sigma^2)$

Gaussian Errors

Histogram of e

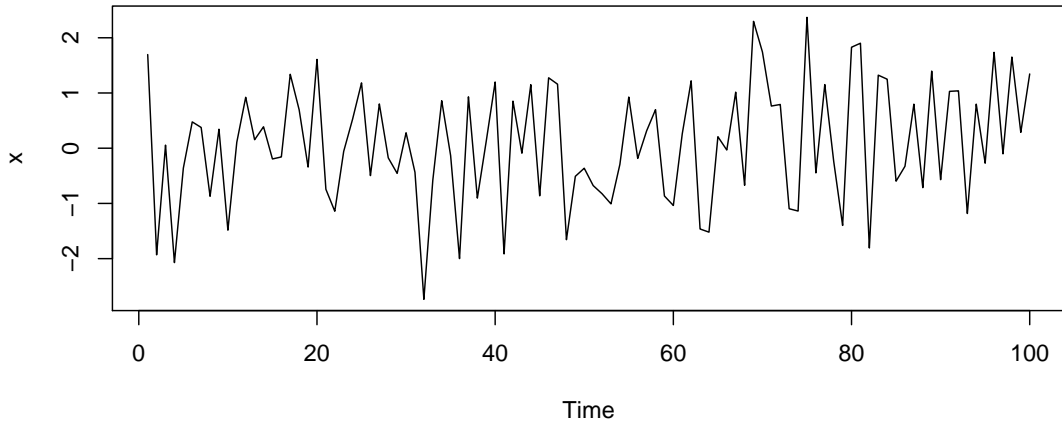


But...

- ▶ In this class, we don't have data on n subjects at 1 point in time, we will have data on 1 subject at n points in time...
- ▶ So, instead think of the model as $y_t = f(t) + \epsilon_t$, and now view the ϵ 's over time
- ▶ Or, with no signal: $y_t = \epsilon_t$

Gaussian Errors, over time

```
plot.ts(x)
```



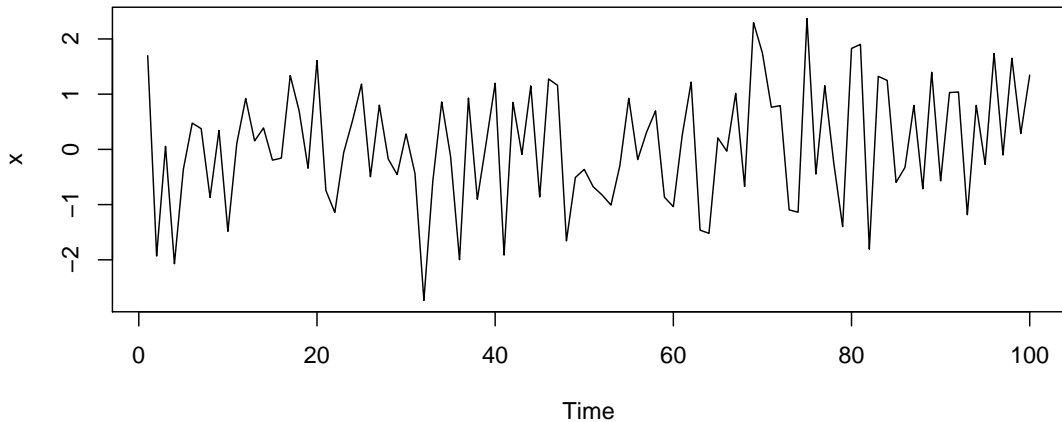
We call this “Gaussian noise”

Definitions (TSA4e Example 1.8)

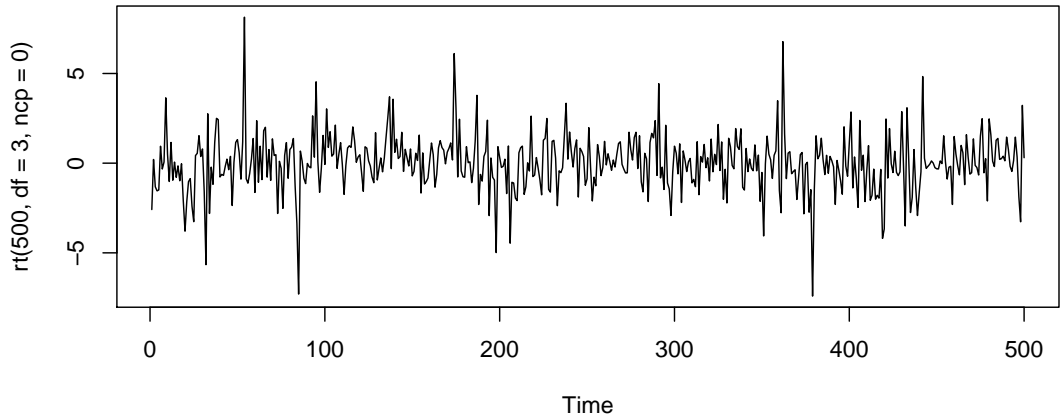
Random variables X_1, \dots, X_n will be denoted as

- ▶ White noise: if they have mean zero, variance σ^2 , and are uncorrelated
- ▶ IID noise: if they are white noise AND are independent and identically distributed (IID).
- ▶ Gaussian [white] noise: if they are IID noise AND are normally distributed, $X_i \sim N(0, \sigma^2)$

Gaussian Noise



IID Noise (T distribution)



But wait!

- ▶ Didn't we say that this class is about things that are correlated over time?
- ▶ White noise has no varying structure over time, so for most time series data it's not a good model
- ▶ BUT it is the basis for many time series models
- ▶ So how do we check to see if white noise is an appropriate model?

Tools we'll need

- ▶ Autocovariance (Definition 1.2):

$$\begin{aligned}\gamma_x(s, t) &= \text{cov}(X_s, X_t) \\ &= E[(X_s - E[X_s])(X_t - E[X_t])]\end{aligned}$$

- ▶ [mental aside: let $s > t$ and $h = s - t$. h is the number of “lags”]
- ▶ Sample autocovariance (Definition 1.14):

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

Tools we'll need

- ▶ Autocorrelation function “ACF” (Definition 1.3):

$$\begin{aligned}\rho(s, t) &= \frac{\gamma_x(s, t)}{\sqrt{\gamma_x(s, s)\gamma_x(t, t)}} \\ &= \frac{\text{cov}(X_s, X_t)}{\sqrt{\text{var}(X_s)\text{var}(X_t)}}\end{aligned}$$

- ▶ Sample autocorrelation (Definition 1.15):

$$\begin{aligned}r_h &= \frac{\hat{\gamma}(h)}{\hat{\gamma}(0)} \\ &= \frac{\sum_{t=1}^{n-h} (x_t - \bar{x})(x_{t+h} - \bar{x})}{\sum_{t=1}^n (x_t - \bar{x})^2}\end{aligned}$$

A note:

- ▶ The book uses $\hat{\rho}$. I'll accept either r or $\hat{\rho}$ for sample correlations.

Properties of White noise

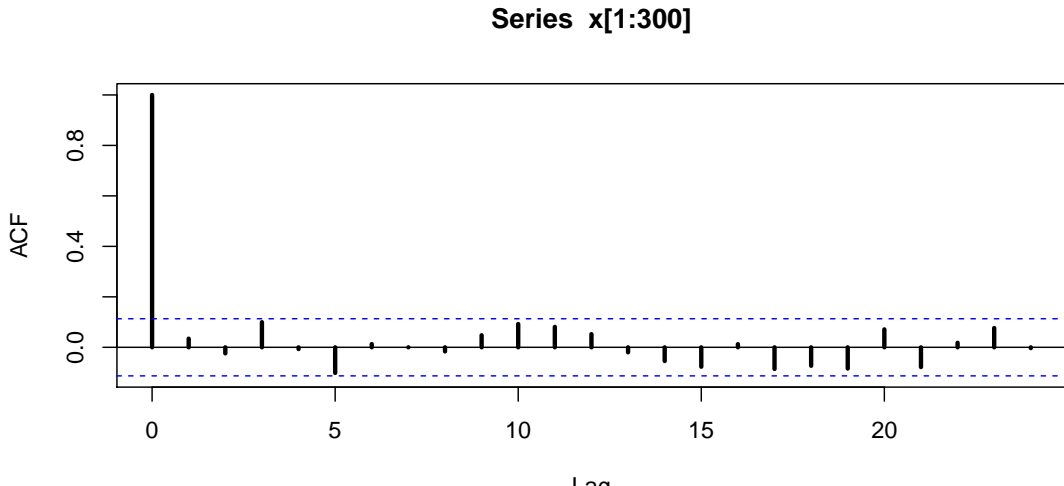
- ▶ $E(X_t) = 0$
- ▶ $\text{var}(X_t) = \sigma^2$ (constant)
- ▶ $\rho(s, t) = 0$ for all $s \neq t$
- ▶ $\rho(t, t) = 1$ (by obvious)
- ▶ How do we check if white noise is a reasonable model for a time series?

Evaluating White noise

- ▶ How do we check if white noise is a reasonable model for a time series?
- ▶ Is the average effectively 0?
- ▶ Is the variance constant?
- ▶ $r_k \approx \rho(k) = 0$ for all $k \neq 0$?

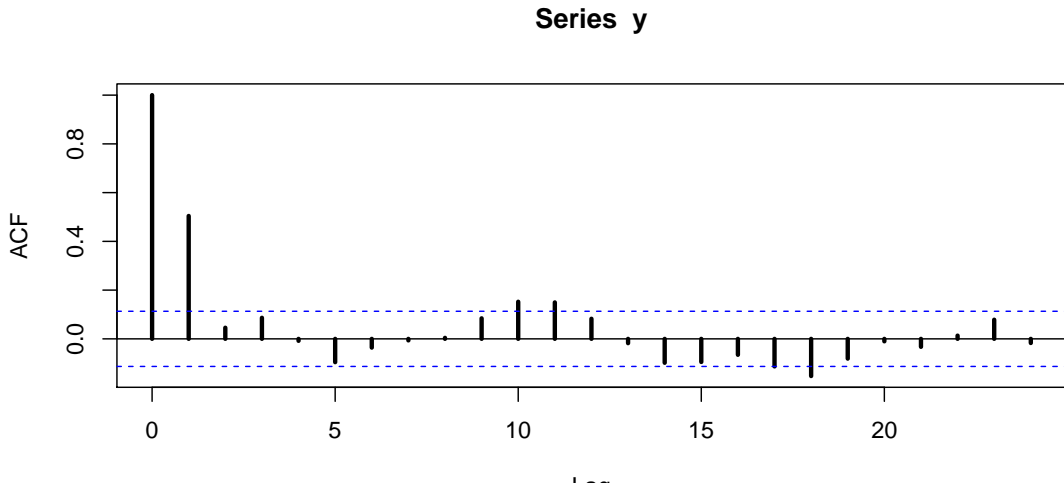
ACF plot

```
x = rnorm(301)  
acf(x[1:300], lwd=3)
```



ACF plot - simple Moving Average

```
y = .5*(x[1:300] + x[2:301])  
acf(y,lwd=3)
```



CI for Sample Correlations

- ▶ Wouldn't it be great if those dashed blue lines were the appropriate confidence interval?

Simplified Theorem A.7 (see Property 1.2)

- ▶ Under general conditions, if x_t is white noise, then for n large, and with arbitrary but fixed H , then the sample autocorrelations

$$r_1, \dots, r_H \stackrel{iid}{\sim} N(0, 1/n)$$

- ▶ In other words

$$\sqrt{n} \begin{pmatrix} r_1 \\ \vdots \\ r_H \end{pmatrix} \rightarrow N(0, I) \quad \text{as } n \rightarrow \infty$$

- ▶ Key takeaway: $\text{var}(r_h) = 1/n$ (Equation 1.38)

Confidence Interval

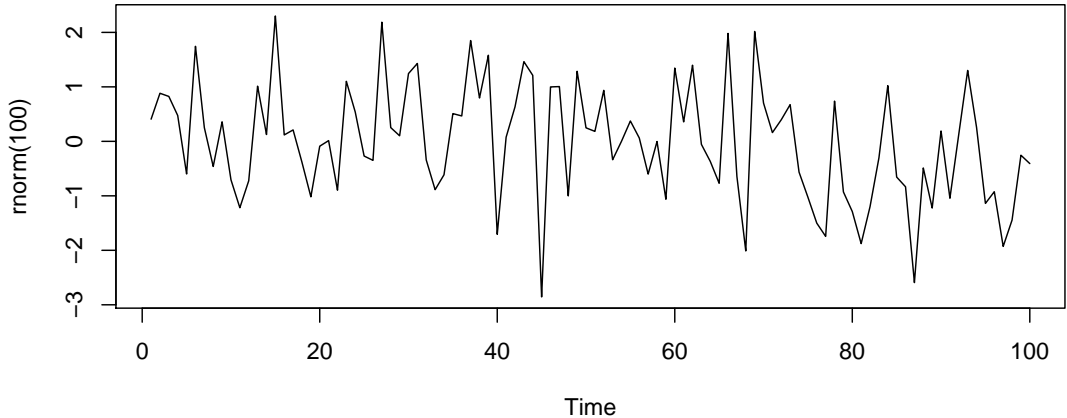
- ▶ For white noise $r_1, \dots, r_H \stackrel{iid}{\sim} N(0, 1/n)$, for

$$P\left(|r_h| > 1.96n^{-\frac{1}{2}}\right) \approx P(|N(0, 1)| > 1.96) = 5\%$$

- ▶ So for $n = 100$, $1.96n^{-\frac{1}{2}} = 1.96/\sqrt{100} = .196$

Gaussian Noise

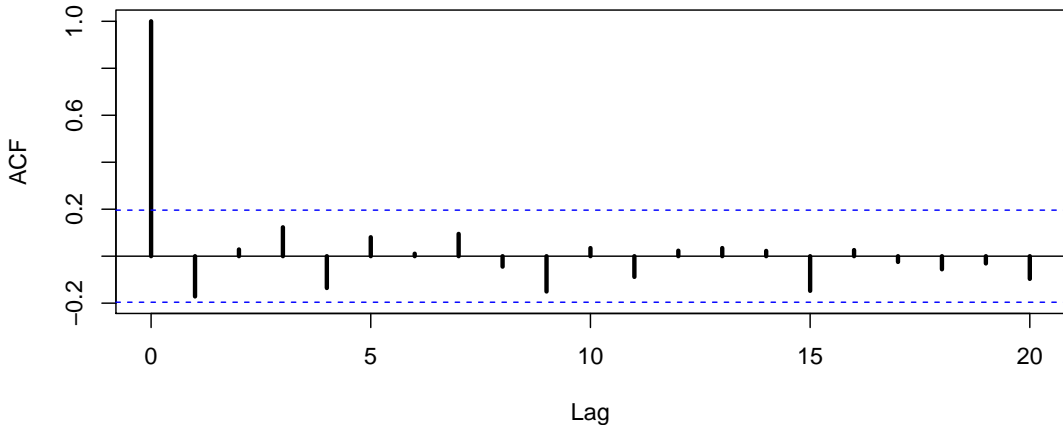
```
plot.ts(rnorm(100))
```



ACF plot - Dashes at .196?

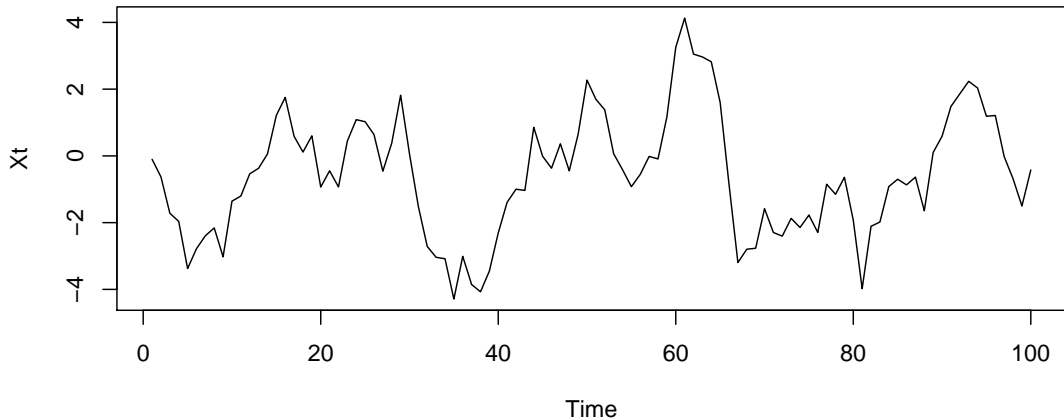
```
acf(rnorm(100),lwd=3)
```

Series rnorm(100)

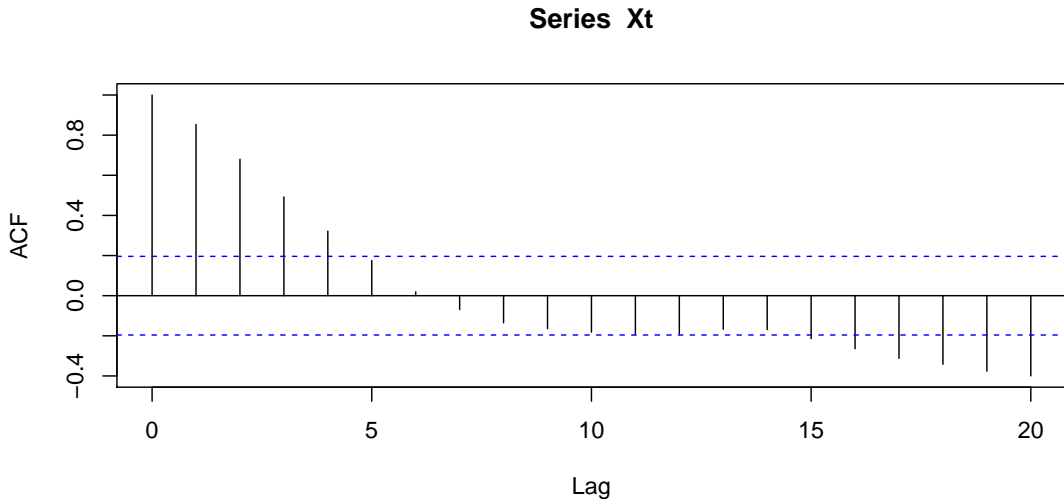


AR(1) Process (we'll learn about later)

```
Xt = arima.sim(model=list(ar=.9),n=100)  
plot.ts(Xt)
```



ACF Plot of AR(1)

`acf(Xt)`

Final Thought

- ▶ The ACF plot is called a “Correlogram”.
- ▶ We will use the correlogram of the ACF as a diagnostic to evaluate whether or not a *stationary* process can be assumed to be white noise.
- ▶ We will define “stationary” next time.

Textbook Alignment

- ▶ Section 1.1 presents time series examples
- ▶ Section 1.2 overviews the semester
- ▶ Section 1.3 defines autocovariance, etc.
- ▶ Section 1.5 defines sample autocovariance, etc.
- ▶ Remember that the textbook is intended as a reference, the readings are supplementary/optional (but probably helpful!), and some parts of the sections are beyond the scope of this course. All needed information will be in the lecture slides, lab material, etc.