

Introduction and Review

January 23, 2020

The material in this set of notes is based on Chapter 2 of S&S.

Notation

- $\mathbb{E}[x]$ refers to the expectation of x ;
- $\mathbb{V}[x]$ refers to the variance of x ;
- \mathbb{Z} refers to the set of all positive and negative integers, $\mathbb{Z} = \{0, \pm 1, \pm 2, \dots\}$;
- Bolded lowercase letters denote column vectors;
- Bolded uppercase letters denote matrices;
- $x \sim \mathcal{N}(\mu, \sigma^2)$ indicates that x is normally distributed with mean μ and variance σ^2 ;
 - Another way of writing this is $x = \sigma v + \mu$, where $v \sim \mathcal{N}(0, 1)$. I will sometimes use this notation to describe the distribution of x .
- $x \sim \mathcal{T}_k$ indicates that x is central t -distributed with k degrees of freedom;
- $x \sim \chi_k^2$ indicates that x is chi-square distributed with k degrees of freedom;
- $x \sim \mathcal{F}_{k,j}$ indicates that x is central F -distributed with k and j degrees of freedom.

- $\|\mathbf{x}\|_2^2 = \sum_{i=1}^n x_i^2$;
- $x \approx y$ denotes that x is approximately equal to y .

Basic Idea!

Most (univariate) time series analysis problems boil down to observing an $n \times 1$ vector $\mathbf{y} = (y_1, \dots, y_n) = \boldsymbol{\mu} + \boldsymbol{\epsilon}$, where $\boldsymbol{\mu}$ is a fixed but unknown mean and $\boldsymbol{\epsilon}$ are mean zero random errors, and:

- **Estimating** $\boldsymbol{\mu}$;
- **Predicting** future values y_{n+1}, \dots, y_{n+k} .

Time series analysis problems differ from classical statistical problems because elements of \mathbf{y} are ordered in time. Several examples of time series data and problems are given in Chapter 1 of S&S, pages 4-11.

Because elements of \mathbf{y} are ordered in time, consecutive elements of \mathbf{y} may be correlated and classical statistical methods may not work well. This is easiest to see via example. Suppose we assume $\mu_{x,t} = \mu$ for all $t = 1, \dots, n$, and we are interested in estimating μ . Ignoring the time series aspect of \mathbf{y} , we assume ϵ_j are independent and identically distributed with known variance σ^2 . The classical approach would be to compute a point estimate of μ , $\hat{\mu} = \sum_{t=1}^n y_t / n$ and corresponding standard error, σ^2 / n . Is this accurate?

The classical approach gives a **incorrect** standard error if elements of \mathbf{y} are correlated. What would be the correct standard error?

$$\begin{aligned} \mathbb{E} [(\hat{\mu} - \mu)^2] &= \mathbb{E} \left[\left(\sum_{t=1}^n y_t - n\mu \right)^2 / n^2 \right] \\ &= \sigma^2 / n + \sum_{t=1}^n \sum_{t'=1, t' \neq t}^n \mathbb{E} [(y_t - \mu)(y_{t'} - \mu)] / n^2. \end{aligned}$$

The correct standard error depends on covariances of elements of \mathbf{y} ,

$$\mathbb{E}[(y_t - \mu)(y_{t'} - \mu)] = \mathbb{E}[\epsilon_t \epsilon_{t'}],$$

which may be nonzero if elements of \mathbf{y} are ordered in time!

Regression Review (S&S 2.1-2.2)

Many methods for time series analysis build on **linear regression**. We perform linear regression when we are interested in expressing an $n \times 1$ response vector \mathbf{y} as a linear function of p $n \times 1$ covariate vectors $\mathbf{x}_1, \dots, \mathbf{x}_p$, i.e. we want to find regression coefficients β_1, \dots, β_p such that $\mathbf{y} \approx \beta_1 \mathbf{x}_1 + \dots + \beta_p \mathbf{x}_p$. If \mathbf{y} is a time series, then covariates might include:

- Indicators for distinct time periods different elements of \mathbf{y} belong to;
- A vector \mathbf{t} , where t_i is the time y_i was observed or the order of y_i in the sequence;
- Nonlinear functions of elements of \mathbf{t} , e.g. $z_{ij} = \sin(t)$ for some $j \in \{1, \dots, p\}$;
- Lagged values of \mathbf{y} ;
- Lagged values of a different but related time series.

We will very rarely be able to describe \mathbf{y} as an exactly linear function of $\mathbf{x}_1, \dots, \mathbf{x}_p$. Instead, we try to find the “best” way of writing \mathbf{y} as a nearly linear function of $\mathbf{x}_1, \dots, \mathbf{x}_p$ by computing the regression coefficients $\boldsymbol{\beta}$ that solve:

$$\min_{\boldsymbol{\beta}} \|\mathbf{y} - \beta_1 \mathbf{x}_1 - \dots - \beta_p \mathbf{x}_p\|_2^2. \quad (1)$$

This is easier to express concisely in matrix form. Letting $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_p]$ be the $n \times p$ matrix of regression coefficients, $\boldsymbol{\beta}$ equivalently solves:

$$\min_{\boldsymbol{\beta}} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2. \quad (2)$$

We refer to the quantity $\|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2$ as the **residual sum of squares (RSS)**, as it measures how much of the variability of \mathbf{y} remains after subtracting off a linear function of the covariates. We can minimize (2) by differentiating; the minimizing value $\hat{\boldsymbol{\beta}}$ will satisfy:

$$\mathbf{X}'\mathbf{X}\hat{\boldsymbol{\beta}} - \mathbf{X}'\mathbf{y} = \mathbf{0} \implies \mathbf{X}'\mathbf{X}\hat{\boldsymbol{\beta}} = \mathbf{X}'\mathbf{y}.$$

If the matrix \mathbf{X} is full rank with rank p , then the minimizing value is

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{y}. \quad (3)$$

If we want to say more about $\hat{\boldsymbol{\beta}}$, we need to make some more assumptions. First, note that we can always decompose the observed response \mathbf{y} into a linear part $\mathbf{X}\boldsymbol{\beta}$ and a remainder $\boldsymbol{\epsilon}$:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}. \quad (4)$$

If we assume:

- $\mathbb{E}[\boldsymbol{\epsilon}] = \mathbf{0}$, then $\hat{\boldsymbol{\beta}}$ is **unbiased**, i.e. $\mathbb{E}[\hat{\boldsymbol{\beta}}] = \boldsymbol{\beta}$.
- $\epsilon_j \stackrel{i.i.d.}{\sim} \mathcal{N}(0, \sigma^2)$, then:
 - (*) $\hat{\boldsymbol{\beta}}$ is the maximum likelihood estimator of $\boldsymbol{\beta}$;
 - (*) $\hat{\boldsymbol{\beta}} \sim \text{normal}(\boldsymbol{\beta}, \sigma_w^2 (\mathbf{X}'\mathbf{X})^{-1})$;
 - (†) $\mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}} \sim \text{normal}(\mathbf{0}, \sigma_w^2 (\mathbf{I}_n - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'))$;
 - (o) $\hat{\boldsymbol{\beta}}$ and $\mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}}$ are independent.

Time series methods rely extensively on likelihood based inference, so we pause to derive (*). If $\epsilon_j \stackrel{i.i.d.}{\sim} \text{normal}(0, \sigma^2)$ then rearranging (4) gives $\mathbf{y}_i - \mathbf{x}_i'\boldsymbol{\beta} \stackrel{i.i.d.}{\sim} \text{normal}(0, \sigma^2)$, where \mathbf{x}_i is the i -th row of \mathbf{X} . This yields the likelihood:

$$l(\mathbf{y}|\mathbf{X}, \boldsymbol{\beta}, \sigma^2) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left\{ -\frac{1}{2\sigma^2} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 \right\}.$$

Finding the value of $\boldsymbol{\beta}$ that maximizes the likelihood is equivalent to finding the value of $\boldsymbol{\beta}$ that minimizes the negative log likelihood, which corresponds to a constant plus the residual

sum of squares (2). As a side note - we can actually eliminate σ^2 from the log-likelihood by *profiling* it out, thus making the connection between maximizing the log likelihood and computing the residual sum of squares even clearer. The negative log-likelihood is given by:

$$\frac{n}{2} \log(2\pi\sigma^2) + \frac{1}{2\sigma^2} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2.$$

We want to minimize this with respect to $\boldsymbol{\beta}$ and σ^2 , and this can be achieved by *first* minimizing over σ^2 for fixed $\boldsymbol{\beta}$, and plugging in the minimizing value of σ^2 to get a minimization problem that depends on $\boldsymbol{\beta}$ alone. This takes advantage of the observation that:

$$\min_{\sigma^2, \boldsymbol{\beta}} \frac{n}{2} \log(2\pi\sigma^2) + \frac{1}{2\sigma^2} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 = \max_{\boldsymbol{\beta}} \left(\max_{\sigma^2} \frac{n}{2} \log(2\pi\sigma^2) + \frac{1}{2\sigma^2} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 \right).$$

There's a nice closed form solution to the minimization with respect to σ^2 for fixed $\boldsymbol{\beta}$. Taking derivatives with respect to σ^2 and rearranging, we get:

$$\frac{n}{2\sigma^2} - \frac{1}{2\sigma^4} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 = 0 \implies \sigma^2 = \frac{\|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2}{n}.$$

Then plugging this expression for the minimizing value of σ^2 for fixed $\boldsymbol{\beta}$, we get a minimization problem over just $\boldsymbol{\beta}$:

$$\begin{aligned} \min_{\sigma^2, \boldsymbol{\beta}} \frac{n}{2} \log(2\pi\sigma^2) + \frac{1}{2\sigma^2} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 &= \min_{\boldsymbol{\beta}} \left(\min_{\sigma^2} \frac{n}{2} \log(2\pi\sigma^2) + \frac{1}{2\sigma^2} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 \right) \\ &= \min_{\boldsymbol{\beta}} \left(\frac{n}{2} \right) \log \left(2\pi \left(\frac{\|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2}{n} \right) \right) + \frac{\|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2}{2 \left(\frac{\|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2}{n} \right)} \\ &= \min_{\boldsymbol{\beta}} \left(\frac{n}{2} \right) \log \left(2\pi \left(\frac{\|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2}{n} \right) \right) + \frac{n}{2}. \end{aligned}$$

Now only one term depends on the residual sum of squares $\|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2$, and since $\log(\cdot)$ is a strictly increasing function, this is equivalent to minimizing the residual sum of squares. This isn't very useful to us now, because the log-likelihood is already easy to maximize, and because the maximum likelihood estimate of $\boldsymbol{\beta}$ does not depend on σ^2 . However we will find the idea of profiling very useful when we start considering maximum likelihood estimation for time series models, in which elements of the error vector $\boldsymbol{\epsilon}$ are correlated and we have

more parameters to optimize over.

Returning to the claims we can make about the least squares estimate $\hat{\beta}$ when we assume that $\epsilon_j \stackrel{i.i.d.}{\sim} \mathcal{N}(0, \sigma^2)$, $(*)$, (\dagger) , and (\circ) are very useful. They allow us not only to compute standard errors and confidence intervals for $\hat{\beta}$ but also to test the null hypothesis that β_i is exactly equal to a specific value or that a subset of $p - p_1$ elements $\beta_{-1} = (\beta_{t_1}, \dots, \beta_{t_{p-p_1}})$ are jointly exactly equal to $\mathbf{0}$.

Standard practice for constructing standard errors and confidence intervals is to use $(*)$, plugging in an unbiased estimator of the variance:

$$s_w^2 = \frac{\left\| \mathbf{y} - \mathbf{X}\hat{\beta} \right\|_2^2}{n - p}. \quad (5)$$

Note that this is *not* the maximum likelihood estimate of σ^2 - the maximum likelihood estimator $\hat{\sigma}_w^2 = \left\| \mathbf{y} - \mathbf{X}\hat{\beta} \right\|_2^2 / n$ is biased.

It follows from $(*)$, (\dagger) , and (\circ) that

$$t_{n-p} = \frac{\hat{\beta}_i - \beta_i}{s_w \sqrt{(\mathbf{X}'\mathbf{X})_{ii}^{-1}}} \sim \mathcal{T}_{n-p}. \quad (6)$$

This gives us a way of testing the null hypothesis that β_i is exactly equal to a specific value because it tells us the approximate distribution of $\hat{\beta}_i$ for specific values of β_i . We call such tests **t-tests**.

Similarly, letting $\mathbf{X}_1 = [\mathbf{x}_{t_1}, \dots, \mathbf{x}_{t_{p_1}}]$ be the design matrix containing the p_1 columns corresponding to elements of β_1 and letting $\hat{\beta}_1$ be the linear regression estimate of β_1 from regressing \mathbf{y} on just the p_1 columns of \mathbf{X} contained in \mathbf{X}_1 , it follows from $(*)$, (\dagger) , and (\circ) that

$$F_{p-p_1, n-p} = \left(\frac{\left\| \mathbf{y} - \mathbf{X}_1 \hat{\beta}_1 \right\|_2^2 - \left\| \mathbf{y} - \mathbf{X} \hat{\beta} \right\|_2^2}{\left\| \mathbf{y} - \mathbf{X} \hat{\beta} \right\|_2^2} \right) \left(\frac{n-p}{p-p_1} \right) \sim \mathcal{F}_{p-p_1, n-p}. \quad (7)$$

This gives us a way of testing the null hypothesis that the $p - p_1$ elements of β_{-1} are jointly exactly equal to $\mathbf{0}$ by giving us an approximate distribution of $F_{p-p_1, n-p}$ under the null. We

call such tests ***F*-tests**.

F-tests are very useful for **model selection**, i.e. for choosing the covariates to include in our model. Model selection is especially relevant in linear regression methods for time series analysis, e.g. we may need to decide which lagged values of \mathbf{y} to include as covariates. Letting \mathbf{X}_k refer to a matrix containing k covariates and β_k and $\hat{\beta}_k$ the corresponding regression coefficients and their linear regression estimates, several popular methods for performing model selection when performing linear regression are:

(*) Perform an *F*-test comparing *nested* models with k and k' covariates.

(★) Compute **Akaike's Information Criterion (AIC)**

$$AIC = \ln \left(\frac{\left\| \mathbf{y} - \mathbf{X}_k \hat{\beta}_k \right\|_2^2}{n} \right) + \frac{n + 2k}{n} \quad (8)$$

for models with k and k' covariates, and choose the model with the lower *AIC* value.

(★) Compute **AIC, Bias Corrected (AICc)**

$$AICc = \ln \left(\frac{\left\| \mathbf{y} - \mathbf{X}_k \hat{\beta}_k \right\|_2^2}{n} \right) + \frac{n + k}{n - k - 2} \quad (9)$$

for models with k and k' covariates, and choose the model with the lower *AICc* value.

(★) Compute **Schwarz's/Bayesian Information Criterion (SIC/BIC)**

$$SIC = \ln \left(\frac{\left\| \mathbf{y} - \mathbf{X}_k \hat{\beta}_k \right\|_2^2}{n} \right) + \frac{k \log(n)}{n} \quad (10)$$

for models with k and k' covariates, and choose the model with the lower *SIC* value.

Note that (*) requires that the two models be *nested*, i.e. the columns in \mathbf{X}_k must be a subset of the columns in $\mathbf{X}_{k'}$ or vice versa. The procedures denoted with (★) are not. Whether AIC, AICc, or BIC is most appropriate for a given problem is problem-specific; AICc can

perform better than AIC when n is relatively small, and SIC/BIC can perform better than AIC when the number of covariates k is relatively large.