

POLS/CS&SS 503:
Advanced Quantitative Political Methodology
LINEAR REGRESSION ESTIMATOR

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Overview

Regression Coefficient Anatomy

Linear Regression Population Model

Sampling Distribution

Estimators and mean squared error

Gauss-Markov Theorem

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Coefficients of a simple regression

$$Y_i = A + BX_i + E_i$$

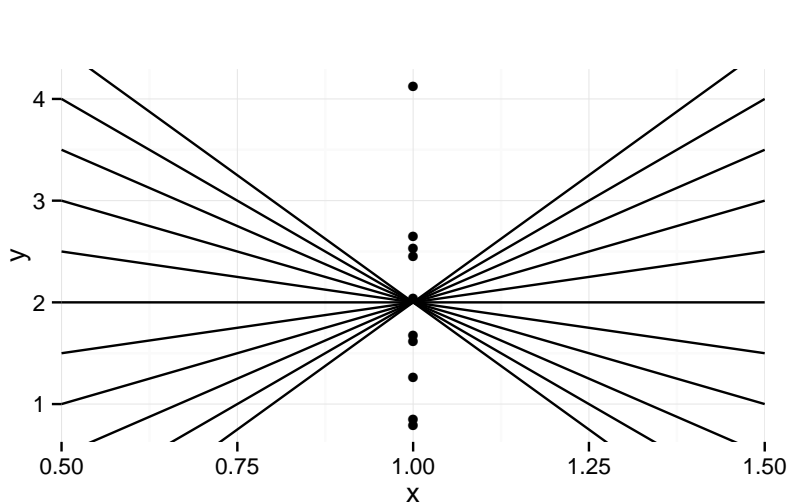
The least squares coefficients are

$$A = \bar{Y} - B\bar{X}$$

$$B = \frac{\sum_i (X_i - \bar{X})(Y_i - \bar{Y})}{\sum_i (X_i - \bar{X})^2}$$

- State B in terms of covariance of X and Y and variance?
- State B in terms of correlation of X and Y and standard deviations?
- What values can B take if $\text{SD}(X) = \text{SD}(Y) = 1$?
- What is \hat{Y} for $X = \bar{X}$?
- What happens to B as $\text{V}(X)$ decreases? $\text{V}(Y)$ decreases? If $\text{V}(X) = 0$

Least squares when $VX = 0$



Least squares coefficients are unidentified if $\forall x = 0$

- If $\forall x = 0$ then least squares solution is unidentified
- There is no unique value of A, B that $\arg \min_{A,B} \sum_i E_i^2$

```
y <- c(1, 2, 3, 4, 5)
x <- 1
ybar <- mean(y)
ybar

## [1] 3

# A = 2, B = 1
sum((y - 2 - 1 * x) ^ 2)

## [1] 10

# A = -7, B = 10
sum((y + 7 - 10 * x) ^ 2)

## [1] 10
```

Coefficients of a multiple regression

$$\vec{Y} = \mathbf{X}\mathbf{b} + \mathbf{e}$$

- $\mathbf{b} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$. *Not that intuitive!*
- Coefficient \mathbf{b}_j is

$$\mathbf{b}_k = \frac{\text{C}(\mathbf{y}, \tilde{\mathbf{x}}_j)}{\text{V}(\tilde{\mathbf{x}}_k)}$$

- Where $\tilde{\mathbf{x}}_j$ are the residuals of \mathbf{x}_j on all X_h where $h \neq j$

$$\tilde{X}_{j,i} = X_{j,i} - \tilde{A} - \sum_{h \neq j} \tilde{B}_h X_h$$

Regression example

See `multiple_regression_anatomy.R`

Least Squares coefficients are unidentified if $(X'X)^{-1}$ does not exist

- Common cases in which $(X'X)^{-1}$ does not exist:
 - Number of observations less than $k + 1$
 - X_k is constant
 - X_k is a linear function of other variables: $X_k = \sum_{j \neq k} c_j X_j$.
 - dummy variables for all categories of a categorical variable
 - variable multiplied by the constant of another variable

Which of these would be cases of collinearity and why?

- There is a variable that takes values “white”, “black”, “hispanic”, “asian”, “other”. You include a dummy variable for each category.
- GDP, GDP per capita, and population
- Log GDP, log GDP per capita, and log population
- GDP in millions of dollars; GDP in trillions of dollars
- GDP measured in nominal value; GDP measured in real terms
- Regression with 3 variables and 4 observations

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Population model in a simple regression

$$Y_i = \alpha + \beta X_i + \epsilon_i$$

Assumptions for statistical inference

1. *X is not invariant:* $V(X) > 0$
2. *Linearity.* Average value of error given x is 0. $E(\epsilon_i) = E(\epsilon_i|x_i) = 0$

$$\mu_i = E(Y_i) = E(Y|X_i) = E(\alpha + \beta X_i + \epsilon_i) = \alpha + \beta x_i$$

3. *Constant variance* Variance of the errors is the same regardless of the value of X

$$V(Y|x_i) = E(\epsilon_i^2) = \sigma_\epsilon^2$$

4. *Independence:* Observations are sampled independently. $\text{Cor}(\epsilon_i, \epsilon_j) = 0$ for all $i \neq j$.
5. Fixed X or X measured without error and independent of the error.
6. Errors are normally distributed $\epsilon_i \sim N(0, \sigma_\epsilon^2)$

Population model in a multiple regression

$$Y_i = \alpha + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \cdots + \beta_k x_{i,k} + \epsilon_i$$

Assumptions for statistical inference

1. *X is not invariant* and no X is a perfect linear function of the others.
2. *Linearity.* $E(\epsilon_i) = 0$
3. *Constant variance* $V(\epsilon_i) = \sigma_\epsilon^2$
4. *Independence Observations are sampled independently.* $\text{Cor}(\epsilon_i, \epsilon_j) = 0$ for all $i \neq j$.
5. *Fixed X or X measured without error and independent of the error*
6. *Normality* Errors are normally distributed $\epsilon_i \sim N(0, \sigma_\epsilon^2)$

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Definitions

population The observations of interest. May be theoretical

sample The data you have.

parameter A function of the population distribution

statistic A function of the sample

sampling distribution The distribution of a statistic calculated from the distribution of samples of a given size drawn from a population.

See `Sampling_Distributions.Rmd`

Sampling Distribution of Simple Regression Coefficients

The sampling distributions of A , B given $Y_i = \alpha + \beta X_i + \epsilon_i$

- expected values (linearity)

$$E(A) = \alpha$$

$$E(B) = \beta$$

- variances (linearity, constant variance, independence)

$$v(A) = \frac{\sigma_\epsilon^2}{n} \cdot \frac{\sum x_i^2}{\sum (x_i - \bar{x})^2}$$

$$v(B) = \frac{\sigma_\epsilon^2}{\sum (x_i - \bar{x})^2} = \frac{\sigma_\epsilon^2}{n v(x)}$$

- normal distribution (normal errors)

$$A \sim N(E(A), v(A))$$

$$B \sim N(E(B), v(B))$$

Coefficient sampling distributions in multiple regression

The sampling distributions of B_k given $Y_i = \alpha + \sum \beta_j X_{j,i} + \epsilon_i$

- Expected value: $E(B_K) = \beta_k$
- Variance:

$$\begin{aligned}v(B_j) &= \frac{1}{(1 - R_j^2)} \frac{\sigma_\epsilon^2}{\sum (x_{i,j} - \bar{x}_j)^2} \\&= \frac{\sigma_\epsilon^2}{\sum_i (x_{i,j} - \hat{x}_{i,j})^2}\end{aligned}$$

Where R_j^2 is R^2 from regression of X_j on other X , and \hat{x}_{ij} are fitted values from that regression.

- Normally distributed if errors are normally distributed or as $n \rightarrow \infty$.
- \mathbf{b} is multivariate normally distributed

$$\mathbf{b} \sim N\left(\boldsymbol{\beta}, \sigma_\epsilon^2 (\mathbf{X}'\mathbf{X})^{-1}\right)$$

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Let's define some things

- statistic** Function of a sample, e.g. Sample mean $\bar{x} = \frac{1}{n} \sum x_i$
- parameter** Function of the population distribution, e.g. Expected value μ of the normal distribution.
- estimator** Method to use a sample statistic (estimate) to infer a population parameter (estimand)

How to determine if an estimator is good?

- Is $\hat{\beta} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$ a good estimator for β ?
- Would another estimator be better?
- First, need criteria to by which to judge estimators

What makes an estimator good?

- Bias
- Variance
- Efficiency (mean squared error)
- Consistency

Bias and Variance

Bias

On average how far off is the estimator?

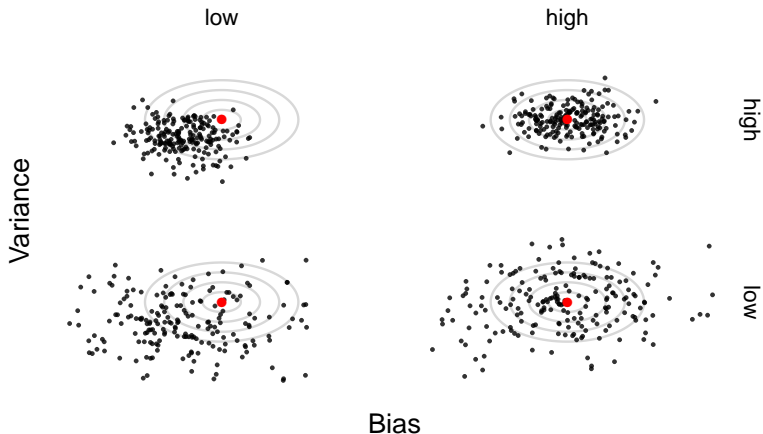
$$\text{bias}(\hat{\beta}) = E(\hat{\beta}) - \beta$$

Variance

Does the estimator give similar results in different samples?

$$v(\hat{\beta}) = E \left((\beta - E(\hat{\beta}))^2 \right)$$

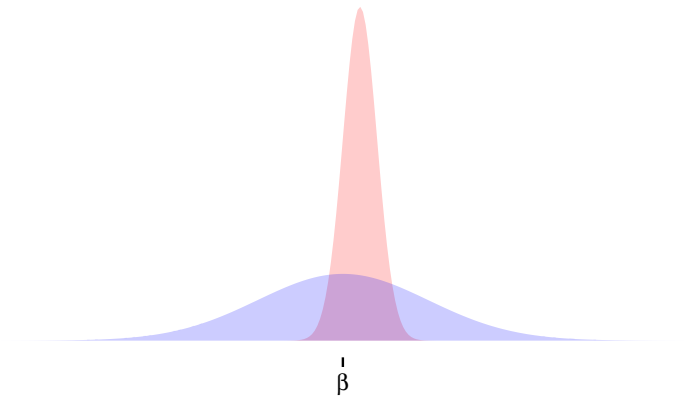
Bias and Variance Visualized



What makes an estimator good?

- Unbiased methods may still miss the truth by a large amount, just direction not systematic
- Unbiased estimates can be horrible: random draw from numbers 0-24 for time of day
- Biased estimates are not necessarily terrible: a clock that's 2 minutes fast

You may prefer a biased, low variance estimator to an unbiased, high variance estimator



Mean Squared Error (MSE)

- MSE is

$$MSE(\hat{\beta}) = \mathbb{E} \left((\hat{\beta} - \beta)^2 \right)$$

- MSE trades off bias and variance

$$\begin{aligned} MSE(\hat{\beta}) &= \mathbb{E}((\hat{\beta} - \mathbb{E}(\hat{\beta}))^2) + \mathbb{E}(\mathbb{E}(\hat{\beta}) - \beta)^2 \\ &= \mathbb{V}(\hat{\beta}) + \left(\text{bias}(\hat{\beta}, \beta) \right)^2 \end{aligned}$$

- root mean squared error (RMSE) $\sqrt{\text{MSE}}$: on average how far is an estimate from the truth
- An **efficient** estimator has the smallest MSE
- What is the MSE of an unbiased estimator?

$$MSE(\hat{\beta}) = \mathbb{V}(\hat{\beta}) + \left(\text{bias}(\hat{\beta}, \beta) \right)^2 = \mathbb{V}(\hat{\beta}) + 0 = \mathbb{V}(\hat{\beta})$$

MSE Example

- Suppose population parameter $\beta = 1$
- Consider two estimators $\hat{\beta}_1$ and $\hat{\beta}_2$.
 - $\hat{\beta}_1 \sim N(1, 1^2)$
 - $\hat{\beta}_2 \sim N(0.5, 0.5^2)$
- What are the bias, variance, and MSE of each estimator?

Consistency

- A consistent estimator converges to the parameter value as the number of observations grows

$$E(\hat{\beta} - \beta) \rightarrow 0 \quad \text{as } n \rightarrow \infty$$

- A concern of econometricians
- May not be as much a concern in finite, small sample sizes
- We will mainly be concerned with efficiency, secondarily with bias, rarely with consistency

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LS assumptions and consequences of violations

	Assumption		Consequence of violation
1	No perfect collinearity	$\text{rank}(\mathbf{X}) = k, k < n$	Coefficients unidentified
2	\mathbf{X} is exogenous	$E(\mathbf{X}\epsilon) = 0$	Biased, even as $n \rightarrow \infty$
3	Disturbances have mean 0	$E(\epsilon) = 0$	Biased, even as $n \rightarrow \infty$
4	No serial correlation	$E(\epsilon_i \epsilon_j) = 0, i \neq j$	Unbiased but ineff. Wrong se.
5	Homoskedastic errors	$E(\epsilon' \epsilon') = \sigma^2 \mathbf{I}$	Unbiased but ineff. Wrong se.
6	Normal errors	$\epsilon \sim N(0, \sigma^2)$	se wrong unless $n \rightarrow \infty$

Assumptions stronger from top to bottom, 4 and 5 could be combined

Unbiasedness of LS

- Only need assumptions 1-3 (no collinearity, \mathbf{X} exogenous, $E(\epsilon) = 0$)
- Start with

$$\begin{aligned}\hat{\beta} &= (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'(\mathbf{X}\beta + \epsilon) \\ &= \beta + (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\epsilon\end{aligned}$$

- Take the expectation

$$\begin{aligned}E(\hat{\beta}) &= E(\beta) + E(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'E(\epsilon) \\ &= E(\beta) + \mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'E(\epsilon) \\ &= E(\beta)\end{aligned}$$

- Since $E(\hat{\beta}) = E(\beta)$, LS is unbiased.

Gauss-Markov

- If make assumptions 1–5: LS is the best linear unbiased estimator (BLUE)
- LS estimator is **linear** because $\hat{\beta} = M\mathbf{y}$, where $M = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$
- **best** is best mean squared error (MSE).
- If LS is unbiased, then its mean squared error is the same as its ...?
- Could exist other non-linear unbiased estimators with smaller MSE, e.g. Robust regression when population has fat tailed errors
- If errors are Gaussian, LS is Minimum Variance Unbiased (MVU).
- MVU = for *all* estimators that are unbiased. $\hat{\beta}$ has smallest variance (and MSE).

References

- Some slides derived from Christopher Adolph *Linear Regression in Matrix Form / Properties & Assumptions of Linear Regression*. Used with permission.
<<http://faculty.washington.edu/cadolph/503/topic3.pw.pdf>>
- Material included from
 - Fox Ch 6, 9.3
 - Angrist and Pischke, Chapter 3

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