

Refresher Course in Calculus, Probability, and Statistics

Day 5a: Linear Regression

Instructor: Dr. Guillaume Wald

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Scatterplot, Sample Covariance and Sample Correlation

- ▶ What is the relationship between variables X and Y ?
- ▶ Different ways to summarise the relationship between variables:

- **Scatterplot:**

Plot of the n observations on X_i and Y_i , each represented by a point (X_i, Y_i) .

→ a good idea to begin the analysis

- **Sample covariance:**

$$\hat{\sigma}_{xy} = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y});$$

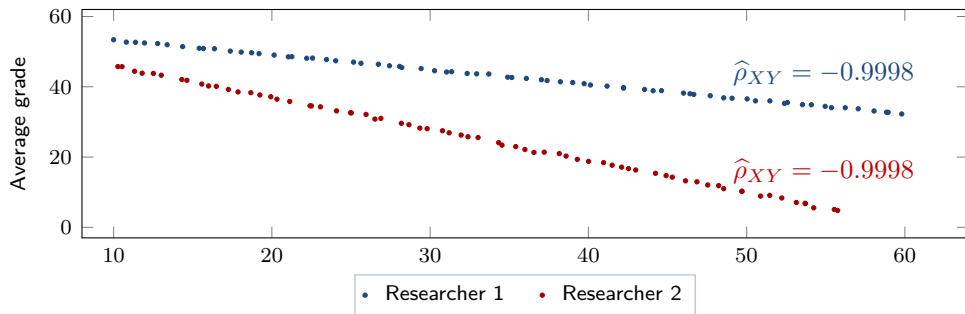
→ **Sample correlation:**

$$\hat{\rho}_{xy} = \frac{\hat{\sigma}_{xy}}{\hat{\sigma}_x \hat{\sigma}_y} \in [-1, 1],$$

A measure of the strength of the *linear* association between X and Y in the sample.

Sample Covariance and Sample Correlation

Hypothetical example: grades and student-teacher ratio.



Same correlation, despite **different slopes**:

- Correlation measures the strength and direction of *linear association*.
- = How tightly the observations follow a **straight-line relationship**, while the sign indicates the direction of the slope.

Linear Regression

Univariate model

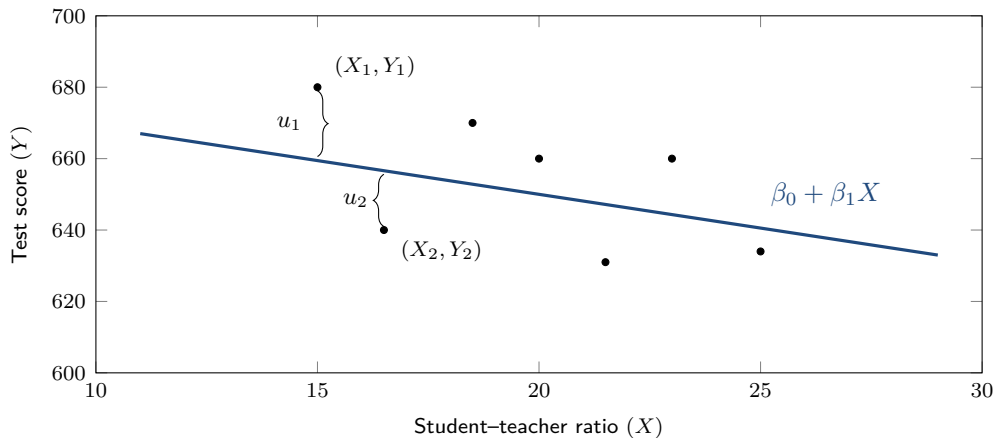
- By how much does Y change if X changes by one unit?

$$Y_i = \beta_0 + \beta_1 X_i + u_i$$

- Y_i : regressand or dependent / explained / left-hand variable;
- X_i : regressor or independent / explanatory / right-hand variable;
- β_1 : slope of the *population regression line*;
- β_0 : intercept of the *population regression line*;
- u_i : error term.

Linear Regression

Univariate model (continued)



Stock & Watson (2012)

Linear Regression

Univariate model (continued) — OLS estimator

- How are the coefficients of the linear regression model estimated?

→ In practice, β_0 & β_1 are **unknown** $\Rightarrow$ we must use data to estimate them.

- **Ordinary Least Squares (OLS) estimator:**

$$\hat{\beta}_1 = \frac{\hat{\sigma}_{XY}}{\hat{\sigma}_X^2}, \quad \hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{X}.$$

- Predicted values: $\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i$;
- Residuals: $\hat{u}_i = Y_i - \hat{Y}_i$.

- **Practical interpretation of the coefficients:**

- $\hat{\beta}_1$: average change in Y associated with a one-unit change in X ;
- $\hat{\beta}_0$: expected value of Y when X is zero.

Linear Regression

Univariate model (continued) — measures of fit

► **Measures of fit:** the R^2 .

- $R^2 \in [0, 1]$;
- interpretation: the **fraction of the variance** in the dependent variable that is **explained by the variance in the independent variable(s)**;
- an alternative measure in the multivariate case is the **adjusted** R^2 , which accounts for the number of independent variables.

Linear Regression

Univariate model (continued) — OLS output

. reg testscr str

Source	SS	df	MS	Number of obs	420
Model	7794.11004	1	7794.11004	F(1, 418)	22.58
Residual	144315.484	418	345.252353	Prob > F	0.0000
Total	152109.594	419	363.030056	R-squared	0.0512
				Adj R-squared	0.0490
				Root MSE	18.581

testscr	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
str	-2.279808	.4798256	-4.75	0.000	-3.222980 -1.336636
_cons	698.933	9.467491	73.82	0.000	680.3232 717.5428

Population model: $\text{TestScore}_i = \beta_0 + \beta_1 \text{STR}_i + u_i$

Estimated model: $\widehat{\text{TestScore}}_i = \hat{\beta}_0 + \hat{\beta}_1 \text{STR}_i = 698.93 - 2.28 \cdot \text{STR}_i$

(all other numbers are discussed in the following slides)

Linear Regression

Univariate model (continued) — hypothesis testing on $\hat{\beta}_1$

- Set up the hypotheses:

Two-sided: $H_0 : \beta_1 = c$ vs. $H_1 : \beta_1 \neq c$,

One-sided: $H_0 : \beta_1 \geq c$ vs. $H_1 : \beta_1 < c$.

or: $H_0 : \beta_1 \leq c$ vs. $H_1 : \beta_1 > c$.

- Compute the empirical t -value:

$$t_{\text{emp}} = \frac{\text{estimator} - \text{value under the null}}{\text{standard error of the estimator}} = \frac{\hat{\beta}_1 - c}{\hat{\sigma}_{\hat{\beta}_1}}.$$

- Compare it with the critical value of a t -distribution with $n - k - 1$ degrees of freedom, with k the number of regressors (slope coefficients / explanatory vars.) excluding the intercept:

→ if $|t_{\text{emp}}| > t_{\text{crit}}(\alpha)$: reject the null at significance level α (error probability $< \alpha$).

Linear Regression

Univariate model (continued) — the p -value

- ▶ OR/AND: compute the p -value, $p = \Pr_{H_0}(|t| > t_{\text{emp}})$.
- ▶ When n is large, $t_{n-k-1} \rightarrow N(0, 1)$, so with the standard normal Φ :
 - two-sided ($H_1 : \beta_1 \neq c$): $p = \Pr_{H_0}(|Z| > t_{\text{emp}}) = 2[1 - \Phi(|t_{\text{emp}}|)]$;
 - one-sided ($H_1 : \beta_1 < c$): $p = \Pr_{H_0}(Z < t_{\text{emp}}) = \Phi(t_{\text{emp}})$;
 - one-sided ($H_1 : \beta_1 > c$): $p = \Pr_{H_0}(Z > t_{\text{emp}}) = 1 - \Phi(t_{\text{emp}})$.
- ▶ Decision rule: reject H_0 if $p < \alpha$.

Linear Regression

Univariate model (continued) — confidence intervals for $\hat{\beta}_1$

► **Definition of a $(1 - \alpha)$ confidence interval:**

- the set of values that cannot be rejected by a two-sided test at significance level α ;
- an interval that contains the true value of β_1 in a fraction $1 - \alpha$ of all samples.

► **Computing the $(1 - \alpha)$ interval:**

- two-sided: $CI_{1-\alpha} = [\hat{\beta}_1 - t_{n-k-1, (\alpha/2)} \cdot \hat{\sigma}_{\hat{\beta}_1}, \hat{\beta}_1 + t_{n-k-1, (\alpha/2)} \cdot \hat{\sigma}_{\hat{\beta}_1}]$;
- one-sided ($H_1 : \beta_1 > c$): $CI_{1-\alpha} = [\hat{\beta}_1 - t_{n-k-1, \alpha} \cdot \hat{\sigma}_{\hat{\beta}_1}, +\infty)$;
- one-sided ($H_1 : \beta_1 < c$): $CI_{1-\alpha} = (-\infty, \hat{\beta}_1 + t_{n-k-1, \alpha} \cdot \hat{\sigma}_{\hat{\beta}_1}]$.

► For large n these critical values approach those of the standard normal distribution:

- 10%: 1.645
- 5%: 1.96
- 1%: 2.58.

Linear Regression

Univariate model (continued) — robust standard errors

`. reg testscr str, robust`

Number of obs	420
F(1, 418)	19.26
Prob > F	0.0000
R-squared	0.0512
Root MSE	18.581

testscr	Robust					
	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
str	-2.279808	.5194892	-4.39	0.000	-3.300945	-1.258671
_cons	698.933	10.36436	67.44	0.000	678.5602	719.3058

Estimated model (robust SEs in parentheses):

$$\widehat{\text{TestScore}}_i = \underset{(10.36)}{698.93^{***}} - \underset{(0.52)}{2.28^{***}} \cdot \text{STR}_i.$$

Linear Regression

Multivariate model

- More general, with k regressors:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + u_i, \quad i = 1, \dots, n.$$

- predicted values: $\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_{1i} + \hat{\beta}_2 X_{2i} + \cdots + \hat{\beta}_k X_{ki}$;
 - residuals: $\hat{u}_i = Y_i - \hat{Y}_i$.
- Estimation, interpretation, testing and confidence intervals extend directly from the univariate case (with $n - k - 1$ degrees of freedom).