

# Lecture 3

## Multiple Linear Regression: Inference and Prediction

Reading: Faraway, 2014 Chapters 3, 4

*DSA 8020 Statistical Methods II*

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# Agenda

Multiple Linear  
Regression:  
Inference and  
Prediction



General Linear F-Test

Prediction

Multicollinearity

1 General Linear F-Test

2 Prediction

3 Multicollinearity

## Review: T-Test and F-Test in Linear Regression

- **T-Test:** Testing one predictor

- 1 **Null/Alternative Hypotheses:**  $H_0 : \beta_j = 0$  vs.  $H_a : \beta_j \neq 0$

- 2 **Test Statistic:**  $t^* = \frac{\hat{\beta}_j - 0}{SE(\hat{\beta}_j)}$

- 3 Reject  $H_0$  if  $|t^*| > t_{1-\alpha/2, n-p}$

- **Overall F-Test:** Test of all the predictors

- 1  $H_0 : \beta_1 = \beta_2 = \dots = \beta_{p-1} = 0$

- 2  $H_a : \text{at least one } \beta_j \neq 0, 1 \leq j \leq p-1$

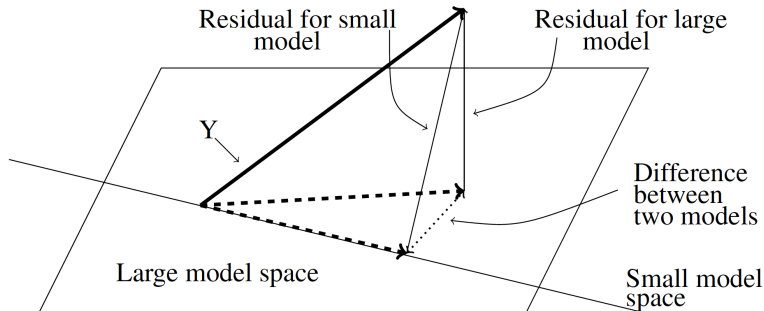
- 3 **Test Statistic:**  $F^* = \frac{MSR}{MSE}$

- 4 Reject  $H_0$  if  $F^* > F_{1-\alpha, p-1, n-p}$

Both tests are special cases of **General Linear F-Test**

- Comparison of a “full model” and “reduced model” that involves **a subset of full model predictors**
- Consider a full model with  $k$  predictors and reduced model with  $\ell$  predictors ( $\ell < k$ )
- Test statistic:  $F^* = \frac{(SSE(R) - SSE(F)) / (k - \ell)}{SSE(F) / (n - k - 1)} \Rightarrow$  Testing  $H_0$  that the regression coefficients for the extra variables are all zero
  - Example 1:  $x_1, x_2, \dots, x_{p-1}$  vs. intercept only  $\Rightarrow$  Overall F test
  - Example 2:  $x_j, 1 \leq j \leq p - 1$  vs. intercept only  $\Rightarrow$  t test for  $\beta_j$
  - Example 3:  $x_1, x_2, x_3, x_4$  vs.  $x_1, x_3 \Rightarrow H_0 : \beta_2 = \beta_4 = 0$

# Geometric Illustration of General Linear F-Test



**Source:** Faraway, *Linear Models with R*, 2014, p.34

# Species Diversity on the Galapagos Islands: Full Model

```
> summary(gala_fit2)
```

Call:

```
lm(formula = Species ~ Elevation + Area)
```

Residuals:

Min	1Q	Median	3Q	Max
-192.619	-33.534	-19.199	7.541	261.514

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	17.10519	20.94211	0.817	0.42120
Elevation	0.17174	0.05317	3.230	0.00325 **
Area	0.01880	0.02594	0.725	0.47478

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Residual standard error: 79.34 on 27 degrees of freedom

Multiple R-squared: 0.554, Adjusted R-squared: 0.521

F-statistic: 16.77 on 2 and 27 DF, p-value: 1.843e-05

# Species Diversity on the Galapagos Islands: Reduce Model

```
> summary(gala_fit1)
```

Call:

```
lm(formula = Species ~ Elevation)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-218.319	-30.721	-14.690	4.634	259.180

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	11.33511	19.20529	0.590	0.56
Elevation	0.20079	0.03465	5.795	3.18e-06 ***

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Residual standard error: 78.66 on 28 degrees of freedom

Multiple R-squared: 0.5454, Adjusted R-squared: 0.5291

F-statistic: 33.59 on 1 and 28 DF, p-value: 3.177e-06

# Performing a General Linear Test

- $H_0 : \beta_{\text{Area}} = 0$  vs.  $H_a : \beta_{\text{Area}} \neq 0$

- $F^* = \frac{(173254 - 169947)/(2-1)}{169947/(30-2-1)} = 0.5254$

- P-value:  $P[F > 0.5254] = 0.4748$ , where  $F \sim F_{\underbrace{1}_{k-\ell}, \underbrace{27}_{n-k-1}}$

```
> anova(gala_fit1, gala_fit2)
```

Analysis of Variance Table

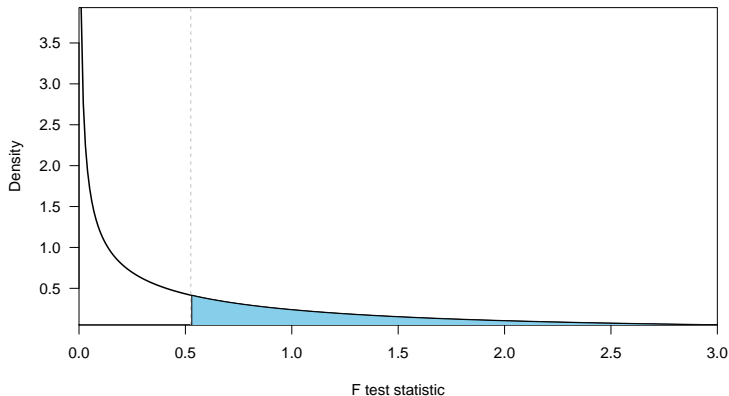
Model 1: Species ~ Elevation

Model 2: Species ~ Elevation + Area

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	28	173254				
2	27	169947	1	3307	0.5254	0.4748



# Visualizing P-value



P-value is the shaded area under the density curve of the null distribution

## Another Example of General Linear Test: Full Model

```
> full <- lm(Species ~ Area + Elevation + Nearest + Scrutz + Adjacent,  
  data = gala)  
> anova(full)
```

Analysis of Variance Table

Response: Species

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Area	1	145470	145470	39.1262	1.826e-06 ***
Elevation	1	65664	65664	17.6613	0.0003155 ***
Nearest	1	29	29	0.0079	0.9300674
Scrutz	1	14280	14280	3.8408	0.0617324 .
Adjacent	1	66406	66406	17.8609	0.0002971 ***
Residuals	24	89231	3718		

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## Another Example of General Linear Test: Reduced Model

```
> reduced <- lm(Species ~ Elevation + Adjacent)
> anova(reduced)
Analysis of Variance Table
```

Response: Species

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Elevation	1	207828	207828	56.112	4.662e-08 ***
Adjacent	1	73251	73251	19.777	0.0001344 ***
Residuals	27	100003	3704		

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# Performing a General Linear Test

- $H_0 : \beta_{\text{Area}} = \beta_{\text{Nearest}} = \beta_{\text{Scruz}}$  vs.  
 $H_a : \text{at least one of the three coefficients} \neq 0$
- $F^* = \frac{(100003 - 89231)/(5-2)}{89231/(30-5-1)} = 0.9657$
- P-value:  $P[F > 0.9657] = 0.425$ , where  $F \sim F_{3,24}$

```
> anova(reduced, full)
```

Analysis of Variance Table

Model 1: Species ~ Elevation + Adjacent

Model 2: Species ~ Area + Elevation + Nearest + Scruz + Adjacent

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	27	100003				
2	24	89231	3	10772	0.9657	0.425

Given a new set of predictors,  $\mathbf{x}_0 = (1, x_{0,1}, x_{0,2}, \dots, x_{0,p-1})^T$ , the predicted response is

$$\hat{y}_0 = \hat{\beta}_0 + \hat{\beta}_1 x_{0,1} + \dots + \hat{\beta}_{p-1} x_{0,p-1}.$$

Again, we can use matrix representation to simplify the notation

$$\hat{y}_0 = \mathbf{x}_0^T \hat{\boldsymbol{\beta}}.$$

We will use this to carry out two different kinds of predictions

## Two Kinds of Predictions

There are two kinds of predictions can be made for a given  $x_0$ :

- **Predicting a future response:**

Based on MLR, we have  $y_0 = x_0^T \beta + \varepsilon$ . Since  $E(\varepsilon) = 0$ , therefore the predicted value is

$$\hat{y}_0 = x_0^T \hat{\beta}$$

- **Predicting the mean response:**

Since  $E(y_0) = x_0^T \beta$ , there we have the predicted mean response

$$\widehat{E(y_0)} = x_0^T \hat{\beta},$$

the same predicted value as predicting a future response

Next, we need to assess the [prediction uncertainty](#)

From slides 2 page 21, we have  $\text{Var}(\hat{\beta}) = \sigma^2 (\mathbf{X}^T \mathbf{X})^{-1}$ .  
Therefore we have

$$\text{Var}(\hat{y}_0) = \text{Var}(\mathbf{x}_0^T \hat{\beta}) = \sigma^2 \mathbf{x}_0^T (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{x}_0$$

We can now construct  $100(1 - \alpha)\%$  CI for the two kinds of predictions:

- **Predicting a future response:**

$$\mathbf{x}_0^T \hat{\beta} \pm t_{n-p, \alpha/2} \hat{\sigma} \times \sqrt{\underbrace{1}_{\text{accounting for } \varepsilon} + \mathbf{x}_0^T (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{x}_0}$$

- **Predicting the mean response:**

$$\mathbf{x}_0^T \hat{\beta} \pm t_{n-p, \alpha/2} \hat{\sigma} \times \sqrt{\mathbf{x}_0^T (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{x}_0}$$

## Example: Predicting Body Fat (Taken from Faraway 2014, Linear Models with R)

```
lm(formula = brozek ~ age + weight + height + neck + chest +  
  abdom + hip + thigh + knee + ankle + biceps + forearm + wrist,  
  data = fat)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-10.264	-2.572	-0.097	2.898	9.327

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-15.29255	16.06992	-0.952	0.34225
age	0.05679	0.02996	1.895	0.05929 .
weight	-0.08031	0.04958	-1.620	0.10660
height	-0.06460	0.08893	-0.726	0.46830
neck	-0.43754	0.21533	-2.032	0.04327 *
chest	-0.02360	0.09184	-0.257	0.79740
abdom	0.88543	0.08008	11.057	< 2e-16 ***
hip	-0.19842	0.13516	-1.468	0.14341
thigh	0.23190	0.13372	1.734	0.08418 .
knee	-0.01168	0.22414	-0.052	0.95850
ankle	0.16354	0.20514	0.797	0.42614
biceps	0.15280	0.15851	0.964	0.33605
forearm	0.43049	0.18445	2.334	0.02044 *
wrist	-1.47654	0.49552	-2.980	0.00318 **

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Residual standard error: 3.988 on 238 degrees of freedom  
Multiple R-squared: 0.749, Adjusted R-squared: 0.7353  
F-statistic: 54.63 on 13 and 238 DF, p-value: < 2.2e-16

What is our prediction for the future response of a “typical” (e.g., each predictor take its median value) man?

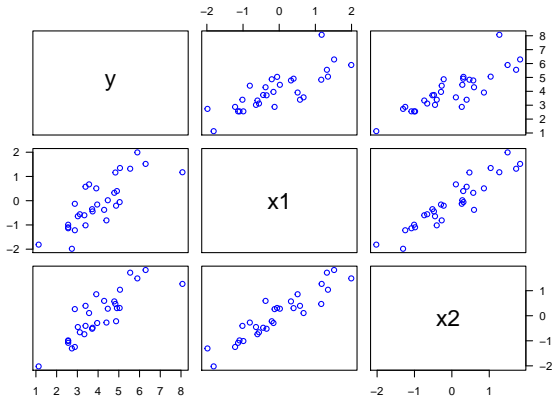


## Example: Predicting Body Fat Cont'd

- 1 Calculate the median for each predictor to get  $x_0$
- 2 Compute the predicted value  $\hat{y}_0 = x_0^T \hat{\beta}$
- 3 Quantify the prediction uncertainty

```
> X <- model.matrix(lmod)
> (x0 <- apply(x, 2, median))
(Intercept)      age      weight      height      neck      chest      abdom
      1.00      43.00      176.50      70.00      38.00      99.65      90.95
      hip      thigh      knee      ankle      biceps      forearm      wrist
      99.30      59.00      38.50      22.80      32.05      28.70      18.30
> (y0 <- sum(x0 * coef(lmod)))
[1] 17.49322
> predict(lmod, new = data.frame(t(x0)))
      1
17.49322
> predict(lmod, new = data.frame(t(x0)), interval = "prediction")
      fit      lwr      upr
1 17.49322  9.61783 25.36861
> predict(lmod, new = data.frame(t(x0)), interval = "confidence")
      fit      lwr      upr
1 17.49322 16.94426 18.04219
```

# Multicollinearity



```
> cor(sim1)
```

	y	x1	x2
y	1.0000000	0.7987777	0.8481084
x1	0.7987777	1.0000000	0.9281514
x2	0.8481084	0.9281514	1.0000000

**Multicollinearity** is a phenomenon of high inter-correlations among the predictor variables

- Numerical issue  $\Rightarrow$  the matrix  $\mathbf{X}^T \mathbf{X}$  is nearly singular
- Statistical issue
  - $\beta$ 's are not well estimated
  - Spurious regression coefficient estimates
  - $R^2$  and predicted values are usually OK

## An Simulated Example

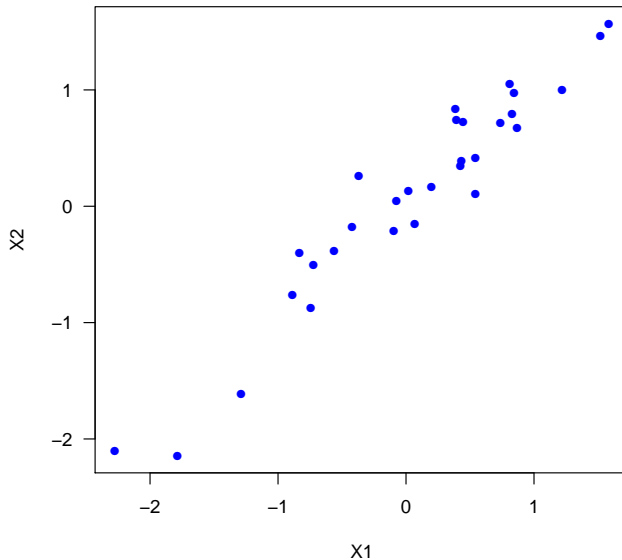
Suppose the true relationship between response  $Y$  and predictors  $(X_1, X_2)$  is

$$Y = 4 + 0.8X_1 + 0.6X_2 + \varepsilon,$$

where  $\varepsilon \sim N(0, 1)$  and  $X_1$  and  $X_2$  are positively correlated with  $\rho = 0.9$ . Let's fit the following models:

- Model 1:  $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$
- Model 2:  $Y = \beta_0 + \beta_1 X_1 + \varepsilon_1$

## Scatter Plot: $X_1$ vs. $X_2$



# Model 1 Fit

Call:

```
lm(formula = Y ~ X1 + X2)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-1.91369	-0.73658	0.05475	0.87080	1.55150

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	4.0710	0.1778	22.898	< 2e-16 ***
X1	2.2429	0.7187	3.121	0.00426 **
X2	-0.8339	0.7093	-1.176	0.24997

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9569 on 27 degrees of freedom

Multiple R-squared: 0.673, Adjusted R-squared: 0.6488

F-statistic: 27.78 on 2 and 27 DF, p-value: 2.798e-07

Call:

```
lm(formula = Y ~ X1)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.09663	-0.67031	-0.07229	0.87881	1.49739

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	4.0347	0.1763	22.888	< 2e-16 ***
X1	1.4293	0.1955	7.311	5.84e-08 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9634 on 28 degrees of freedom

Multiple R-squared: 0.6562, Adjusted R-squared: 0.644

F-statistic: 53.45 on 1 and 28 DF, p-value: 5.839e-08

## Variance Inflation Factor (VIF)

We can use the **variance inflation factor (VIF)**

$$\text{VIF}_i = \frac{1}{1 - R_i^2}$$

to quantifies the severity of multicollinearity in MLR, where  $R_i^2$  is the **coefficient of determination** when  $X_i$  is regressed on the remaining predictors

### R example code

```
> library(faraway)
> vif(sim1[, 2:3])
      x1      x2
7.218394 7.218394
```

$\sqrt{\text{VIF}}$  indicates how much larger the standard error increases compared to if that variable had 0 correlation to other predictor variables in the model.