

Inference for Multiple Linear Regression (MLR)

- Three different types of tests
 - Overall / Omnibus F test
 - Partial F test (for a *single* variable in a MLR model)
 - Multiple Partial F test (for a *group* of variables in a MLR model)
- Partial F test (Variables added in order)
 - $SS(X_2|X_1)$: “Extra Sum of Squares” for adding X_2 to $Y = \beta_0 + \beta_1 X_1$
 $SS(X_2|X_1) = SSR(X_1, X_2) - SSR(X_1)$; difference between *Regression SS*

Source	df	SS	MS	F
Regression	2	$SSR(x_1, x_2)$	$SSR(x_1, x_2) / 2$	$MSR(x_1, x_2) / MSE$
$\left\{ \begin{array}{l} X_1 \\ X_2 X_1 \end{array} \right.$	1	SSR_1		
	1	SSR_2		
Error(Residual)	$n-(2+1)$	SSE		
Total	$n-1$	SSY		

$$F(X_2 | X_1) = \frac{SS(X_2 | X_1) / 1}{MSE(X_1, X_2)}$$

- $SS(X_3|X_1, X_2)$: “Extra Sum of Squares” for adding X_3 to $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2$
 $SS(X_3|X_1, X_2) = SSR(X_1, X_2, X_3) - SSR(X_1, X_2)$

Source	df	SS	MS	F
Regression	3	$SSR(x_1, x_2, x_3)$	$SSR(x_1, x_2, x_3) / 3$	$MSR(x_1, x_2, x_3) / MSE$
$\left\{ \begin{array}{l} X_1 \\ X_2 X_1 \\ X_3 X_2, X_1 \end{array} \right.$	1	SSR_1		
	1	SSR_2		
	1	SSR_3		
Error(Residual)	$n-(k+1)$	SSE		
Total	$n-1$	SSY		

$$F(X_3 | X_1, X_2) = \frac{SS(X_3 | X_1, X_2) / 1}{MSE(X_1, X_2, X_3)}$$

- Type I SS, “Variable Added In Order” (VIO) SS → R: *anova(model)*

```

y.x1x2 <- lm(SBP~QUET+AGE)
summary(y.x1x2)
anova(y.x1x2)

```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
QUET	1	3537.9	3537.9	44.5048	2.573e-07
AGE	1	582.6	582.6	7.3293	0.01125
Residuals	29	2305.4	79.5		

```

y.x2x1 <- lm(SBP~AGE+QUET)
summary(y.x2x1) #SAME as y.x1x2
anova(y.x2x1) #DIFF from y.x1x2

```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
AGE	1	3861.6	3861.6	48.5766	1.160e-07
QUET	1	259.0	259.0	3.2576	0.08149
Residuals	29	2305.4	79.5		

Inference for Multiple Linear Regression (MLR)

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik} + \varepsilon_i, \quad \varepsilon_i \stackrel{iid}{\sim} N(0, \sigma^2) \quad i = 1, 2, \dots, n$$

- Partial F test (Variables added last)

- $SS(X^* | X_1, \dots, X_k)$: “Extra Sum of Squares” for adding X^* to $Y = \beta_0 + \beta_1 X_1 + \dots + \beta_k X_k$
 $SS(X^* | X_1, \dots, X_k) = SSR(X_1, \dots, X_k, X^*) - SSR(X_1, \dots, X_k)$

$$SS_{\text{Reg}}(\text{Full Model}) - SS_{\text{Reg}}(\text{Reduced Model})$$

- Type III SS, Type III Test, “Variable Added Last” (VAL) Test $\rightarrow$ R: `summary(model)`

- $F(X^* | X_1, \dots, X_k) = \frac{SS(X^* | X_1, \dots, X_k) / 1}{MSE(X_1, \dots, X_k, X^*)} \sim F_{1, n-k-2}$ under $H_0 : \beta_1^* = 0$

- “Variable Added Last” tests have $\text{df}(\text{numerator}) = 1 \rightarrow$ Equivalent to a T-test

$$t_s = \frac{\hat{\beta}_1^* - \beta_1^{*(0)}}{SE(\hat{\beta}_1^*)} \quad \text{when } \beta_1^{*(0)} = 0$$

- Multiple Partial F test (for a group of variables in a MLR model)

- $SS(X_1^*, \dots, X_s^* | X_1, \dots, X_q) = SSR(X_1, \dots, X_q, X_1^*, \dots, X_s^*) - SSR(X_1, \dots, X_q)$
 $= SSE(X_1, \dots, X_q) - SSE(X_1, \dots, X_q, X_1^*, \dots, X_s^*)$

- $H_0 : \beta_1^* = \beta_2^* = \dots = \beta_s^* = 0$

$$F(X_1^*, \dots, X_s^* | X_1, \dots, X_q) = \frac{SS(X_1^*, \dots, X_s^* | X_1, \dots, X_q) / s}{MSE(X_1^*, \dots, X_s^*, X_1, \dots, X_q)}$$

Inference for MLR – Confidence Intervals

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik} + \varepsilon_i, \quad \varepsilon_i \stackrel{iid}{\sim} N(0, \sigma^2) \quad i = 1, 2, \dots, n$$

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_{i1} + \hat{\beta}_2 X_{i2} + \cdots + \hat{\beta}_k X_{ik} \quad i = 1, 2, \dots, n$$

- 100(1- α)% CI for a Regression Coefficient

- $\hat{\beta}_i \pm t_{\frac{\alpha}{2}, n-(k+1)} SE(\hat{\beta}_i)$

- Estimated Variance for the regression model vs. Variance of a Fitted Value

- **SLR:** $\hat{\sigma}^2 = s_{Y|X}^2 = MSE$

- **MLR:** $\hat{\sigma}^2 = s_{Y|X_1, X_2, \dots, X_k}^2 = s_{Y|\tilde{X}=(1, X_1, X_2, \dots, X_k)}^2 = MSE$

- $s_{\hat{Y}|X_1, X_2, \dots, X_k}^2 = s_{\hat{Y}|\tilde{X}=(1, X_1, X_2, \dots, X_k)}^2 = \text{var}(\hat{Y} | \tilde{X} = (1, x_1, \dots, x_k))$ is the variance of a fitted value

- Conditional Mean of Y at $\mathbf{X}=(1, X_{1*}, X_{2*}, \dots, X_{k*})$

- CI for $\mu_{Y|\tilde{X}=(1, X_{1*}, X_{2*}, \dots, X_{k*})}$: $\hat{\mu}_{Y|\tilde{X}=(1, X_{1*}, X_{2*}, \dots, X_{k*})} \pm t_{\frac{\alpha}{2}, n-(k+1)} SE(\hat{\mu}_{Y|\tilde{X}=(1, X_{1*}, X_{2*}, \dots, X_{k*})})$

- $SE(\hat{\mu}_{Y|\tilde{X}=(1, X_{1*}, X_{2*}, \dots, X_{k*})}) = \sqrt{s_{\hat{Y}|\tilde{X}=(1, X_{1*}, X_{2*}, \dots, X_{k*})}^2} = s_{\hat{Y}|\tilde{X}=(1, X_{1*}, X_{2*}, \dots, X_{k*})}$

- $\hat{Y} | \tilde{X} = (1, x_{1*}, x_{2*}, \dots, x_{k*})$ is a linear combination of the $\hat{\beta}_i \rightarrow$

- $s_{\hat{Y}|\tilde{X}=(1, X_{1*}, X_{2*}, \dots, X_{k*})}^2$ involves variances & covariances among the $\hat{\beta}_i$

- **R:** `predict(model, x.new.df, se.fit=TRUE)` returns $s_{\hat{Y}|\tilde{X}=(1, X_{1*}, X_{2*}, \dots, X_{k*})}$ as `$se.fit`

- Prediction Interval for a new Y value at $\mathbf{X}=(1, X_{1*}, X_{2*}, \dots, X_{k*})$

- CI: $\hat{Y} | \tilde{X} = (1, x_{1*}, \dots, x_{k*}) \pm t_{\frac{\alpha}{2}, n-(k+1)} SE(\hat{Y} | \tilde{X} = (1, x_{1*}, \dots, x_{k*}))$

- $SE(\hat{Y} | \tilde{X} = (1, x_{1*}, \dots, x_{k*})) = \sqrt{s_{Y|\tilde{X}=(1, X_1, X_2, \dots, X_k)}^2 + s_{\hat{Y}|\tilde{X}=(1, X_{1*}, X_{2*}, \dots, X_{k*})}^2} = \sqrt{MSE + s_{\hat{Y}|\tilde{X}=(1, X_{1*}, X_{2*}, \dots, X_{k*})}^2}$

Inference for MLR – Confidence Intervals

```
> y.x1x2 <- lm(SBP~QUET+AGE)
anova(y.x1x2)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
QUET	1	3537.9	3537.9	44.5048	2.573e-07
AGE	1	582.6	582.6	7.3293	0.01125
Residuals	29	2305.4	79.5		

```
> predict(y.x1x2, x.new.df, interval="confidence", se.fit=T)
$fit
      fit      lwr      upr
1 131.6077 126.5475 136.668
$se.fit
[1] 2.474176
$df
[1] 29
$residual.scale
[1] 8.916038 # sqrt(MSE)

> 131.6077 - qt(1-.025,29)*sqrt(2.474176^2) # [1] 126.5481
> 131.6077 + qt(1-.025,29)*sqrt(2.474176^2) # [1] 136.6679

> predict(y.x1x2, x.new.df, interval="prediction", se.fit=T)
$fit
      fit      lwr      upr
1 131.6077 112.6833 150.5321
$se.fit
[1] 2.474176
$df
[1] 29
$residual.scale
[1] 8.916038

> 131.6077 - qt(1-.025,29)*sqrt(79.5 + 2.474176^2) # [1] 112.6828
> 131.6077 + qt(1-.025,29)*sqrt(79.5 + 2.474176^2) # [1] 150.5326
```