STA 674

Regression Analysis And Design Of Experiments
Fitting Multiple Linear Regression Models – Lecture 2

Fitting Multiple Linear Regression Models

- Last time, introduced MLR
- Now, we do inference.

Fitting Multiple Linear Regression Models

• Inference: as with SLR, we start with confidence intervals

Interval Estimate of the Regression Parameter β_k Pick 1 parameter at a time

• A $(1 - \alpha)100\%$ confidence interval for β_k has endpoints:

$$L=b_k-s_{b_k}t_{\alpha/2,\mathbf{n}-\mathbf{K}-\mathbf{1}}$$
 and $U=b_k+s_{b_k}t_{\alpha/2,\mathbf{n}-\mathbf{K}-\mathbf{1}}$ equation for CI is same as SLR...but degrees of freedom

equation for CI is same as is different - n-k-1

where s_{b_k} is the standard error of b_k .

Fitting Multiple Linear Regression Models

Example: Nuclear Power Plant Data

MLR – Output versus Cost and Date

/* Multiple linear regression model */; TITLE "3. Mwatts vs Cost and Date"; PROC REG DATA=NUCLEAR; MODEL mwatts=cost date / CLB; RUN;

Cost:

We are 95% confident that the true slope of the regression model is between 0.351 to 1.25...average output increases between 0.351 and 1.25 for each additional \$100K spent (while holding Data fixed)

Parameter Estimates								
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t	95% Confidence Limits		
Intercept	1	5920.53408	2382.75823	2.48	0.0190	1047.24632	10794	
Cost	1	0.81578	0.21243	3.84	0.0006	0.38131	1.25025	
Date	1	-79.78403	35.59545	-2.24	0.0328	-152.58490	-6.98316	

Fitting Simple Linear Regression Models

Significance test for the population slope—first, upper-tailed test

- Hypotheses: $H_0: \beta_k \leq \beta_k^* \text{ vs. } H_a: \beta_k > \beta_k^*$ H0 is equal or less than or equal...Ha is always greater than
- Test Statistic: $t = (b_k \beta_k^*)/s_{b_k}$
- Rejection Rule: Reject H_0 and conclude that $\beta_k > \beta_k^*$ at the α level of significance if $t > t_{\alpha,n-K-1}$. Otherwise, we fail to reject H_0 .
- **P-value**: Probability that t-distribution with n K 1 degrees of freedom is greater than TS t. $p = P(t_{n-K-1} > t)$

Fitting Simple Linear Regression Models

Significance test for the population slope—next, lower-tailed test

- Hypotheses: $H_0: \beta_k \ge \beta_k^* \text{ vs. } H_a: \beta_k < \beta_k^*$
- Test Statistic: $t = (b_k \beta_k^*)/s_{b_k}$
- Rejection Rule: Reject H_0 and conclude that $\beta_k < \beta_k^*$ at the α level of significance if $t < -t_{\alpha,n-K-1}$. Otherwise, we fail to reject H_0 .
- **P-value**: Probability that t-distribution with n K 1 degrees of freedom is less than TS t. $p = P(t_{n-K-1} < t)$

Fitting Simple Linear Regression Models

Significance test for the population slope—finally, two-tailed test**

- Hypotheses: $H_0: \beta_k = \beta_k^* \text{ vs. } H_a: \beta_k \neq \beta_k^*$
- Test Statistic: $t = (b_k \beta_k^*)/s_{b_k}$
- Rejection Rule: Reject H_0 and conclude that $\beta_k \neq \beta_k^*$ at the α level of significance if $t < -t_{\alpha/2,n-2}$ or $t > t_{\alpha/2,n-2}$. Otherwise, we fail to reject H_0 .
- **P-value**: Probability that t_{n-K-1} is "farther away from 0" than TS t.

$$p = 2 \times P(t_{n-K-1} > |t|)$$

**By default, this is the hypothesis SAS tests.

Fitting Multiple Linear Regression Models

Example: Nuclear Power Plant Data

H0: B2(cost) = 0, Ha: B2(cost) != 0

MLR – Output versus Cost and Date

p = 0.0328 ... or ... compare t value with test statistic

/* Multiple linear regression model */;
TITLE "3. Mwatts vs Cost and Date";
PROC REG DATA=NUCLEAR;
 MODEL mwatts=cost date / CLB;
RUN;

Reject the null hypothesis

Parameter Estimates							
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t	95% Confidence Limits	
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Cost	1	0.81578	0.21243	3.84	0.0006	0.38131	1.25025
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Fitting Multiple Linear Regression Models

Interpreting Significance Tests

- Rejecting H_0 implies that there is a statistically significant effect/positive effect/negative effect of x_k on the response after accounting for the effects of the other variables.
- E.g., if we reject H_0 : $\beta_k = 0$ then we can conclude that changing x_k while holding all of the other variables fixed changes the mean response.

Warning!

- Failing to reject H_0 : $\beta_k = 0$ does NOT mean that there is no effect of x_k on the response.
- Failing to reject H_0 : $\beta_k = 0$ implies that changing x_k while holding all of the other variables fixed does not change the mean response.

Fitting Multiple Linear Regression Models

Prediction – Fitted Values and CIs for the Mean

• The fitted value for the mean with values of the predictors $x_{m1}, x_{m2}, ..., x_{mK}$ is:

$$\hat{y}_m = b_0 + b_1 x_{1m} + b_2 x_{2m} + \dots + b_k x_{km}$$

• A $(1 - \alpha)100\%$ confidence interval for \hat{y}_m has endpoints:

$$\hat{y}_m \pm t_{\alpha/2,n-K-1} s_m$$

where s_m is the standard error of \hat{y}_m .

Fitting Multiple Linear Regression Models

Prediction – Predicted Values and Prediction Intervals for new observations

• The best prediction of a single new observation with values of the predictors $x_{p1}, x_{p2}, ..., x_{pK}$ is:

$$\hat{y}_p = b_0 + b_1 x_{1p} + b_2 x_{2p} + \dots + b_k x_{Kp} \quad \text{Same as for CN}$$

• A $(1 - \alpha)100\%$ confidence interval for \hat{y}_p has endpoints:

$$\hat{y}_p \pm t_{lpha/2,n-K-1} s_p$$
 Standard error is bigger...so bigger PI

where s_p is the standard error of \hat{y}_p .

• As in simple linear regression, $s_p = \sqrt{s_m^2 + s_e^2}$.

Fitting Multiple Linear Regression Models

Example: Nuclear Power Plant Data

• Suppose that you used the MLR model predict the output of nuclear reactors built in 1972 at a cost of \$500 hundred thousand dollars (adjusted to 1976).

TITLE "3. Mwatts vs Cost and Date";

PROC REG DATA=NUCLEAR2;

MODEL mwatts=cost date / CLB;

OUTPUT OUT=NUCLEARPRED PRED=pred LCL=ucl UCL=lcl LCLM=uclm UCLM=uclm;

RUN;

Obs	Cost	MWatts	Date	pred	uclm	uclm2	ucl	lcl
33	500		72	583.971	338.066	829.877	175.667	992.276

• Provide an interpretation of these results.

Mean output (Mw)