Regression I Midterm

Formulas

Sample Statistics

Mean $(\mu_x; \bar{x})$

$$(1) \qquad \frac{1}{n} \sum_{i=1}^{n} x_i$$

Variance $(Var(X); s_X^2; \sigma_X^2)$

(2)
$$Var(X) = E[(X - \mu)^2] = E(X^2) - \mu^2$$

(3)
$$Var(X) = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \mu_X)^2$$

Covariance $(Cov(X, Y); s_{XY}; \sigma_{XY})$

(4)
$$Cov(X,Y) = E[(X - \mu_X)(Y - \mu_Y)] = E(XY) - \mu_X \mu_Y$$

(5)
$$Cov(X,Y) = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \mu_X)(y_i - \mu_Y)$$

Correlation $(Corr(X,Y); r_{XY}; \rho_{XY})$

(6)
$$Corr(X,Y) = \frac{Cov(X,Y)}{sd(X)*sd(Y)} = \frac{\sigma_{XY}}{\sigma_X \sigma_Y}$$

Bivariate Regression Statistics

Slope (\hat{B}_1)

(7)
$$\hat{B}_1 = \frac{\sum (x_i - \mu_x)(y_i - \mu_y)}{\sum (x_i - \mu_x)^2} = \frac{Cov(X, Y)}{Var(X)}$$

Constant (\hat{B}_0)

$$\hat{B}_0 = \bar{y} - \hat{B}_1 \bar{x}$$

Standard Error of the Regression $(\hat{\sigma})$

(9)
$$\hat{\sigma}^2 = \frac{1}{(n-k-1)} \sum_{i=1}^n \hat{u}_i^2$$

$$(10) \qquad \hat{\sigma} = \sqrt{\hat{\sigma}^2}$$

Standard Error (B_1)

(11)
$$s.e.(\hat{B}_1) = \sqrt{\frac{\hat{\sigma}^2}{\sum (x_i - \mu_x)^2}}$$

Goodness of Fit

Explained ("Model") Sum of Squares (SSE)

(12)
$$SSE = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2$$

Residual Sum of Squares (SSR)

(13)
$$SSR = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 = \sum_{i=1}^{n} \hat{u}_i^2$$

Total Sum of Squares (SST)

(14)
$$SST = \sum_{i=1}^{n} (y_i - \bar{y})^2 = SSE + SSR$$

Coefficient of Determination (R^2)

(15)
$$R^2 = \frac{SSE}{SST} = 1 - \frac{SSR}{SST} = Corr(\hat{y}, y)$$

(16)
$$Adj.R^2 = 1 - \frac{SSR/(n-k-1)}{SST/(n-1)}$$

Mean Squared Error (MSE)

(17)
$$MSE = \frac{SSR}{n - k - 1}$$

(18)
$$RootMSE = \sqrt{MSE}$$

Multiple Regression Statistics

Slope (\hat{B}_1)

(19)
$$\hat{B}_1 = \left(\sum_{i=1}^n r_{i1}^2 y_i\right) / \left(\sum_{i=1}^n r_{i1}^2\right)$$

where

$$\hat{r}_{i1} = residuals(x_1 = B_0 + B_2x_2 + B_3x_3 + \dots + B_kx_k)$$

Standard Error (\hat{B}_1)

(20)
$$s.e.(\hat{B}_1) = \sqrt{\frac{\hat{\sigma}^2}{\sum (x_{i1} - \mu_{x1})^2 (1 - R_1^2)}}$$

where

$$R_1^2 = R^2(x_1 = B_0 + B_2x_2 + B_3x_3 + \dots + B_kx_k)$$

Hypothesis Testing Statistics

Test (t) statistic for \hat{B}_1 when $H_0: B_1 = 0$

(21)
$$t_{\hat{B}_1} = \hat{B}_1/s.e.(\hat{B}_1)$$

Confidence interval around \hat{B}_1

(22)
$$\hat{B}_1 \pm t_{crit} * s.e.(\hat{B}_1)$$

F Statistic, e.g.
$$H_0 := \beta_2 = 0, \beta_3 = 0, \beta_4 = 0$$

(23)
$$F = \frac{(SSR_r - SSR_u)/q}{SSR_u/(n-k-1)}$$

where

$$q = df_r - df_{ur}$$

Statistical Properties

Linear Combination Algebra

(24)
$$E(aX + b) = aE(x) + b$$

(25)
$$E(aX + bY) = aE(X) + bE(Y)$$

$$(26) Var(aX+b) = a^2 Var(x)$$

(27)
$$Var(aX + bY) = a^{2}Var(X) + b^{2}Var(Y) + 2abCov(XY)$$

OLS Estimates

(28)
$$\sum_{i=1}^{n} \hat{u}_i^2 = 0$$

(29)
$$\sum_{i=1}^{n} x_i \hat{u}_i = Cov(x_i \hat{u}_i) = 0$$

Misc.

OLS Assumptions

Gauss-Markov

- 1. Model is linear in its parameters; Y is a linear function of X and u
- 2. We have a random sample.
- 3. We have variation in X
- 4. Zero Conditional Mean; E(u) = 0; E(u|x) = 0
- 5. Homoskedasticity (Constant error variance for all Xs);

 $Var(u|x) = \sigma^2$

Note: If OLS meets GM, it is (B)est (L)inear (U)nbiased (E)stimator.

Classic Linear Model

- 6. No perfect collinearity between Xs
- 7. Normally distributed u

Extra Assumptions

- 8. No correlation between errors, i.e. $Cov(u_iu_i) = 0$
- 9. Fixed Xs across repeated samples

Properties of Estimators

- 1. Unbiasedness, $E(W) = \theta$
- 2. Efficiency, W_1 is more efficient than W_2 if $Var(W_1) \leq Var(W_2)$ Large Sample Properties
- 3. Consistency, as n gets larger, distribution of W_n becomes more concentrated around θ
- 4. Asymptotic Normality, as n gets larger, distribution \mathbb{Z}_n becomes more normal
- 5. Central Limit Theory, the sampling distribution of standardized means drawn from any shape distribution will be asymptotically normal.

Hypothesis Testing Terms

Type 1 Error (α) , probability of false rejection of H_0 Type 2 Error (β) , probability of false acceptance of H_0 Correct Acceptance of $H_0 = 1 - \alpha$ Correct Acceptance of H_0 , $(Power) = 1 - \beta$