# STAT6038 week 4 lecture 12

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### Correlation (association) & causality

Ref. Ch. 5, Faraway test

If X does cause Y ( $X \to Y$ ), then we should observe some association (not necessarily linear) between X and Y, but the converse is not necessarily true.

Correlation does not imply causation.

Theories of causality differ between disciplines but all share some common features:

- underlying theory: the "science" suggest some mechanism by which X might cause Y and also rules out alternative causes (say Z). Some times you see spurious association or correlation between X and Y, but in fact, X and Y could be both caused by Z.
- **temporal order**: X must precede Y (so that it is  $X \to Y$ , not  $Y \to X$ .)
- association:  $X \to Y$  will usually result in some correlation (linear association) between X and Y.

  note: relationship may not be linear

If we discover "associations" in observational data, and suspect that it is because  $X \to Y$ , then in the next iteration of the research process, we might try some more structured approach. (e.g. designed experiment)

# Coefficient of Determination $(R^2)$

a sample quality.

"Proportion of the variation in Y that can be explained by the model involving the  $X(\mathbf{s})$ ."

• In the R output this is Multiple R-squared; called "multiple" as it does generalize to multiple regression of Y on 2 or more X's.

$$R^2 = \frac{SS_{\text{Regression}}}{SS_{\text{Total}}} = 0.7388 \text{ or } 74\% = 1 - \frac{SS_{\text{Error}}}{SS_{\text{Total}}}$$

$$s_y^2 = \frac{1}{n-1} \sum (y_i - \bar{y})^2$$

where  $SS_{\text{Error}}$  is calculated by  $s^2 = \hat{\sigma^2} = \sum e_i^2$   $s_y^2 = \frac{1}{n-1} \sum (y_i - \bar{y})^2$  so,  $SS_{\text{Regression}} = (n-1) \cdot var(y)$  Note:  $R^2 = (r)^2$  where r is the coefficient of correlation between Y

• Adjusted  $R^2$  (adjusted for the degrees of freedom)

$$\overline{R}^2 = 1 - \frac{MS_{\text{Error}}}{MS_{\text{Total}}} = 1 - \frac{SS_{\text{Error}}/df_{\text{Error}}}{SS_{\text{Total}}/df_{\text{Total}}} = \dots = R^2 - (1 - R^2) \frac{df_{\text{Regression}}}{df_{\text{Total}}}$$

where  $(1-R^2)\frac{df_{\text{Regression}}}{df_{\text{Total}}}$  is called the adjusted factor.

- $F = \frac{MS_{\text{Regression}}}{MS_{\text{Error}}} \sim F_{k,n-p}$  overall F statistics These are all **summary** measures. But the F statistics has some advantages.
  - like  $\overline{R}^2$  it does adjust for the df. (Exercise: show you derive  $\overline{R}^2$
  - F is comparable to a known standard distribution (still have to choose X????). **HERERERERER**

#### Interpreting the regression coefficients

- Interpretation of  $\hat{\beta}_1$  (or any slope coefficient) is " the expected increase in Y as X increases by 1".
- Interpretation of  $\hat{\beta}_0$  is "the expected value of Y when X=0" (i.e. it is the intercept coefficient).
- An 95% confidence interval for  $\beta_1$  is

$$\hat{\beta}_1 \pm t_{\text{error df}}(0.975) \cdot se(\hat{\beta}_1)$$

i.e. estimate plus/minus the critical value times standard error (for SLR)

• Similarly a 95% confidence interval for  $\beta_0$  is

$$\hat{\beta}_0 \pm t_{\text{error df}(0.975)} \cdot se(\hat{\beta}_0)$$