

VARIABILITY PARTITIONING

$$y = mx + c \quad \text{correlation}(x, y) = R$$

R^2 = strength of relationship between X and Y

$R^2 \rightarrow$ how much variability in Y can be explained by X

$$y = m_1 x_1 + m_2 x_2 + \dots + c \quad \left[\begin{matrix} \underline{m_0} \underline{x_0'} \end{matrix} \right]$$

Partitioning variability of Y using x_1, x_2, x_3, \dots
[ANOVA]

sample mean

$Y = \{\text{real observed values}\}$

$Y' = \text{predictions of your linear model}$

$\sum (Y - \bar{Y})^2 = \text{total variability in } Y$

$\sum (Y - Y')^2 = \text{unexplained variability in } Y \text{ (error)}$

$$\text{explained variability} = \frac{\sum (Y - \bar{Y})^2}{\text{variability}} - \frac{\sum (Y - Y')^2}{\text{errors}}$$

$$F\text{-statistic} = \frac{\text{explained variability}}{\text{unexplained variability}}$$

ML model \rightarrow statistically significant prediction.

ADJUSTED R^2

$$y = m_1(x_1) + m_2(x_2) + \dots \quad (C)$$

$$R_{adj}^2 = 1 - \left(\frac{\text{unexplained variability}}{\text{total variability}} \times \frac{n-1}{n-k-1} \right)$$

compensates
strength of explainability
between y and $\{x_1, x_2, \dots\}$

n = number of observations
 k = predictors count

(every "variable" introduces error
every degree of freedom $(n-k-1)$ introduces error

model A $\rightarrow R_{adj}^2 = A'$

model B $\rightarrow R_{adj}^2 = B'$

$B' > A'$, choose model B over A

T-TEST: BRIEF

inferential statistic

$$\bar{x}_1 \longleftrightarrow \bar{x}_2$$

$$\hat{y} = m_1 x_1 + m_2 (x_2) \dots + c$$

$$H_0 = m_1, m_2, m_3 \dots = 0$$

$$H_A = \text{at least } m_i \neq 0$$

$$t = \frac{m_{i=2} - 0}{SE = \frac{\sigma}{\sqrt{n}}}$$

p value
for second
variable

pt

degrees of freedom
model and
 $t_{i=2}$
scipy.stats