

# Model Selection Criteria

## Four ways to estimate test performance using an approximation

Full model has  $p$  predictors

RSS is the residual sum of squares for model with  $d$  predictors

$\hat{\sigma}^2 = \text{RSS}_p / (n - p - 1)$  is an estimate of the error variance for full model

### 3. Bayesian Information Criterion (BIC)

For linear models: equivalent to Mallows's  $C_p$  (proportional to)

$$BIC = \frac{1}{n\hat{\sigma}^2} \left( \text{RSS} + \underbrace{\log(n)d\hat{\sigma}^2}_{\text{heavier penalty}} \right)$$

we are penalizing models of higher dimensionality (larger  $d$ , greater penalty)

$\implies$  choose the model which has **minimum**  $BIC$

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### 4. Adjusted R-squared value

Adjust the regular  $R^2$  by taking into account number of predictors

$$\text{Adjusted-}R^2 = 1 - \frac{\text{RSS}/(n - d - 1)}{\text{TSS}/(n - 1)}$$

$\Rightarrow$  choose the model which has **maximum** Adjusted- $R^2$