Ordinary Least Square = Maximum likelihood estimators

$$y \approx \chi \beta \qquad ||y-\chi\beta||_2^2 = \sum_{i=1}^n (y_i-x_i^{\dagger}\beta)^2$$

$$\{y_i, x_i\}_{i=1}^n$$
  $y_i \sim N(x_i^t \beta, \sigma^2)$  random variable

Likelihood = 
$$\prod_{i=1}^{n} p(y_i | x_i, B, \sigma^2)$$

$$L(\beta, \sigma^2) = \prod_{i=1}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(y_i - \chi_i^{t}\beta)^2}$$

MLE

$$\log lik(\beta, \sigma^{2}) = \sum_{i=1}^{n} -\frac{1}{2} \log \sigma^{2} - \frac{(y_{i} - x_{i} + \beta)^{2}}{2\sigma^{2}}$$

$$= -\frac{n}{2} \log \sigma^{2} - \frac{\sum_{i=1}^{n} (y_{i} - x_{i} + \beta)^{2}}{2\sigma^{2}}$$

$$\hat{\beta}_{\text{rile}} = \underset{\beta \in \mathbb{R}^{p}}{\operatorname{argmin}} \sum_{i=1}^{n} (y_{i} - x_{i}^{t} \beta)^{2}$$

$$\int_{\text{mlo}}^{2} = \frac{RSS}{n}$$

$$\int \left(\sigma^2\right) = -\frac{h}{2}\log\sigma^2 - \frac{RSS}{2\sigma^2}$$

$$\int \left(\sigma^2\right) = -\frac{h}{\sigma^2} + \frac{RSS}{(\sigma^2)^2}$$

Value of log liklihood at evaluated at MLE

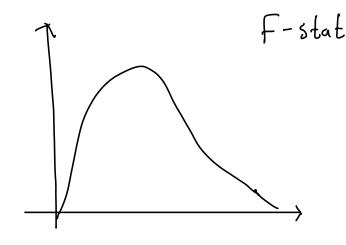
$$\begin{aligned} \log |ik(\beta, \sigma^2) &= -\frac{n}{2} \log \sigma^2 - \frac{\sum_{i=1}^{n} (y_i - x_i t_{\beta})^2}{26^2} \\ \log |ik(\hat{\beta}_{MLE}, \hat{\sigma}_{MLE}^2) &= -\frac{n}{2} \log \frac{RSS}{n} - \frac{RSS}{2 \cdot (\frac{RSS}{n})} \\ &= -\frac{n}{2} \log \frac{RSS}{n} - \frac{n}{2} = -\frac{n}{2} \left( \log \frac{RSS}{n} + 1 \right) \end{aligned}$$

$$\hat{\beta} = (\chi^T \chi)^{-1} \chi^T y$$

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projection matrix



Large F-stat means our larger model contributes significantly enough

norm\_vec[:,i] -= (enter[])

Sum += exp thing with || norm\_vec||2