Modelling

- shapiro.test( ) -> Shapiro wilke test
- MLE = OLS when $\varepsilon \sim N(0, \sigma^2)$
- $Y = \theta_0 + \theta_1 X + \varepsilon$
- If $\varepsilon_i \sim N(0, \sigma^2)$ then $Y_i | X_i \sim N(\theta_0 + \theta_1 x_i, \sigma^2)$
  Least squares used to estimate $\theta = (\theta_0, \theta_1)$
- when error term is not gaussian MLE is the more generic framework

Nonparametric (Adaptive)

- Method does not assume an underlying dist^n
- Model allowed to change with the data

KDE

$$K_h(u - x_i) = \frac{1}{h} K\left(\frac{u - x_i}{h}\right)$$

$$\hat{f}(u) = \frac{1}{N} \sum_{i=1}^{N} K_h(u - x_i)$$

-> we have kernel densities & then we take the density of the sum of those densities

Other Density Estimators

Naive Estimator

$$F_N(u) = \frac{1}{N} \sum_{i=1}^{N} \mathbb{I}_{(x_i \le u]}$$

$$f_N(u) = \frac{1}{Nh} \sum_{i=1}^{N} w\left(\frac{u - x_i}{h}\right)$$

$$w(u) = \frac{\delta(|u| < 1)}{2}$$ -> rectangular kernel

K^{th} Nearest Neighbour