

$$\text{Var}(z) = E[z^2] - (E[z])^2$$

$$\text{Var}(a+z) = \text{Var}(z)$$

$$\text{Var}(Y \pm z) = \text{Var}(Y) \pm \text{Var}(z)$$

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} = \frac{S_{xy}}{S_{xx}}$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

$$SE(\hat{\beta}_1)^2 = \frac{\sigma^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$SE(\hat{\beta}_0)^2 = \sigma^2 \left[\frac{1}{n} + \frac{\bar{x}^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \right]$$

$$[\hat{\beta}_1 - 2 \cdot SE(\hat{\beta}_1), \hat{\beta}_1 + 2 \cdot SE(\hat{\beta}_1)]$$

$$[\hat{\beta}_1 - t_{n-2, \alpha/2} \cdot SE(\hat{\beta}_1), \hat{\beta}_1 + t_{n-2, \alpha/2} \cdot SE(\hat{\beta}_1)]$$

$1-\alpha$ = level of confidence

α = level of doubt/significance

$$t = \frac{\hat{\beta}_1 - 0}{SE(\hat{\beta}_1)}$$

$$t_{n-p-1, \alpha/2}$$

$$RSS = \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

$$RSE = \sqrt{\frac{1}{n-2} RSS}$$

(Residual Standard Error)

$$TSS = \sum (y_i - \bar{y})^2$$

$$RegSS = \sum (\hat{y}_i - \bar{y})^2$$

$$TSS = RegSS + RSS$$

$$R^2 = \frac{TSS - RSS}{TSS} = 1 - \frac{RSS}{TSS}$$

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}} = \frac{S_{xy}}{S_x S_y}$$

$$F\text{-statistics} = \frac{(TSS - RSS)/p}{RSS/(n-p-1)} \sim F_{p, n-p-1}$$

(Multiple Linear Reg.)

$$p(x) = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

$$\log \left(\frac{p(x)}{1-p(x)} \right) = \beta_0 + \beta_1 x$$

case control sampling

$$\hat{\beta}_0^* = \hat{\beta}_0 + \log \frac{\pi}{1-\pi} - \log \frac{\tilde{\pi}}{1-\tilde{\pi}}$$

original fraction
of positive class

case control
sampling
fraction

$$P_{Y|X}(y|x) = \Pr(Y=y|X=x) = [p(x)]^y [1-p(x)]^{1-y}$$

$$l(\beta_0, \beta_1) = \prod_{i=1}^N [p(x_i)]^{y_i} [1-p(x_i)]^{1-y_i}$$

$$= \prod_{i=1}^N \left(\frac{e^{\beta_0 + \beta_1 x_i}}{1 + e^{\beta_0 + \beta_1 x_i}} \right)^{y_i} \left(\frac{1}{1 + e^{\beta_0 + \beta_1 x_i}} \right)^{1-y_i}$$

$$\text{cross entropy} = \sum_{i=1}^N -\{y_i \log p(x_i) + (1-y_i) \log (1-p(x_i))\}$$

$$Z = \frac{\hat{\beta}_1 - \beta}{SE(\hat{\beta}_1)} \quad \text{Rejection region: } Z > z_{\alpha/2} \text{ or } Z < -z_{\alpha/2}$$

logistic regression with
multiple classes -

$$\Pr(Y=K|X) = \frac{e^{\beta_{0K} + \beta_{1K}X_1 + \dots + \beta_{pK}X_p}}{\sum_{l=1}^K e^{\beta_{0l} + \beta_{1l}X_1 + \dots + \beta_{pl}X_p}}$$

Bayes theorem -

$$\Pr(Y=K|X=x) = \frac{\Pr(X=x|Y=K) \cdot \Pr(Y=K)}{\Pr(X=x)}$$

$$= \frac{\pi_K f_K(x)}{\sum_{l=1}^K \pi_l f_l(x)}$$

LDA Gaussian density

$$f_k(x) = \frac{1}{\sqrt{2\pi}\sigma_k} e^{-\frac{1}{2}\left(\frac{x-\mu_k}{\sigma_k}\right)^2}$$

$$p_k(x) = \frac{\pi_k f_k(x)}{\sum_{l=1}^K \pi_l f_l(x)} \quad \dots p=1$$

$$S_k(x) = \log \pi_k + \frac{\mu_k x}{2\sigma_k} - \frac{\mu_k^2}{2\sigma_k^2}$$

$$\text{Sensitivity / Recall / TPR / Hit Rate} = \frac{TP}{P} = \frac{TP}{TP+FN}$$

$$\text{Specificity / TNR} = \frac{TN}{N} = \frac{TN}{TN+FP}$$

$$\text{Precision} = \text{PPV} = \frac{TP}{TP+FP}$$

$$\text{NPV} = \frac{TN}{TN+FN}$$

$$\text{PRE}_{\text{macro}} = \frac{\text{PRE}_1 + \dots + \text{PRE}_K}{K}$$

$$\text{PRE}_{\text{micro}} = \frac{TP_1 + \dots + TP_K}{TP_1 + \dots + TP_K + FP_1 + \dots + FP_K}$$

$$F = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

$$F\beta = \frac{\beta^2 + 1}{\frac{\beta^2}{\text{recall}} + \frac{1}{\text{precision}}}$$

Bootstrap -

$$\alpha = \frac{\sigma_Y^2 - \sigma_{XY}}{\sigma_X^2 + \sigma_Y^2 - 2\sigma_{XY}}$$

$$SE_{\beta}(\hat{\alpha}) = \sqrt{\frac{1}{B-1} \sum_{r=1}^B (\hat{\alpha}^{*r} - \bar{\hat{\alpha}}^*)^2}$$

$$\text{Mallow } Cp : Cp = \frac{1}{n} (RSS + 2d\hat{\sigma}^2)$$

$$\text{AIC} = -2\log L + 2d$$

$$\text{BIC} = \frac{1}{n} (RSS + \log(n)d\hat{\sigma}^2)$$

$$\text{Adjusted } R^2 =$$

$$1 - \frac{RSS/(n-d-1)}{TSS/(n-1)}$$

Ridge regression (L_2)

Minimize $RSS + \lambda \sum_{j=1}^p \beta_j^2$

$$= \sum_{i=1}^n (y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij})^2 + \lambda \sum_{j=1}^p \beta_j^2 \rightarrow \|\beta\|_2^2$$

Lasso (L_1)

minimize $RSS + \lambda \|\beta\|_1$

Elastic Net penalty: $\lambda \left[\frac{1}{2} (1-\alpha) \|\beta\|_2^2 + \alpha \|\beta\|_1 \right]$