

3. Inference for the regression parameters and model

Remark: 3.2 - 3.4, 3.8 基于假设:

① 不相关

② 正态分布

3.1 Three important distributions (正态总体下的三大抽样分布)

(a). χ^2 Distribution:

定义 1 若 $X_1, X_2, \dots, X_n \sim N(0, 1)$ 相互独立，则称

$$Y = \sum_{i=1}^n X_i^2$$

服从“自由度”(degrees of freedom) 为 n 的卡方分布，记为 $Y \sim \chi^2(n)$

(1) Y 的 p.d.f.

$$p(y) = \begin{cases} \frac{1}{\Gamma(\frac{n}{2})} \cdot (\frac{1}{2})^{\frac{n}{2}} \cdot y^{\frac{n}{2}-1} \cdot e^{-\frac{y}{2}} & y > 0 \\ 0 & y \leq 0 \end{cases}$$

$$\text{其中 } \Gamma(x) = \int_0^{+\infty} t^{x-1} e^{-t} dt \quad (x > 0)$$

$$(2) E(Y) = n$$

$$\text{var}(Y) = 2n$$

$$(3) \text{ 若 } Y_1 \sim \chi^2(n), Y_2 \sim \chi^2(m) \text{ 且 } Y_1 \perp Y_2 \text{ 则}$$

$$Y_1 + Y_2 \sim \chi^2(n+m)$$

(b). t Distribution :

定义2 若 $X \sim N(0,1)$ $Y \sim \chi^2(n)$ 且 $X \perp Y$ 则称

$$Z = \frac{X}{\sqrt{Y/n}}$$

服从“自由度”为 n 的 t 分布，记为 $Z \sim t(n)$

(1) Z 的 p.d.f.

$$p(x) = \frac{\Gamma(\frac{n+1}{2})}{\sqrt{n\pi} \cdot \Gamma(\frac{n}{2})} \cdot \left(1 + \frac{x^2}{n}\right)^{-\frac{n+1}{2}}$$

且关于 y 轴对称

(2) 当 $m \geq n$ 时， $t(n)$ 的 m 阶及高于 m 阶的原点矩、中心矩均不存在

(3) $E(Z) = 0$, $n > 1$

$$\text{var}(Z) = \frac{n}{n-2}, n > 2$$

(4) $t(1)$ 即 Cauchy 分布

$n \rightarrow \infty$ 时， $t(n)$ 逐渐接近 $N(0,1)$

(c). F Distribution

定义3 若 $X \sim \chi^2(m)$ $Y \sim \chi^2(n)$ 且 $X \perp Y$ 则称：

$$W = \frac{X/m}{Y/n}$$

服从自由度为 m, n 的 F 分布，记作 $W \sim F(m, n)$

(1) W 的 p.d.f.

$$P(x) = \begin{cases} \frac{\Gamma(\frac{m+n}{2})}{\Gamma(\frac{m}{2}) \cdot \Gamma(\frac{n}{2})} \cdot \left(\frac{m}{n}\right)^{\frac{m}{2}} x^{\frac{m}{2}-1} \cdot \left(1 + \frac{m}{n}x\right)^{-\frac{m+n}{2}} & x > 0 \\ 0 & \text{otherwise} \end{cases}$$

(2) $F(1, n) = t^2(n)$ BP

若 $Z = \frac{X}{\sqrt{Y/n}} \sim t(n)$ 则 $Z^2 = \frac{X^2}{Y/n} \sim F(1, n)$

(3) 若 $W \sim F(m, n)$ 则 $\frac{1}{W} \sim F(n, m)$

(4) $E(W) = \frac{n}{n-2}, n > 2$

$\text{var}(W) = \frac{2n^2(m+n-2)}{m(n-2)^2(n-4)}, n > 4$

定理 1 设 X_1, X_2, \dots, X_n 是来自正态总体 $N(\mu, \sigma^2)$ 的样本，样本均值和方差为：

$$\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$$

$$S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$$

则有：

(1) \bar{X} 与 S^2 相互独立

(2) $\bar{X} \sim N(\mu, \frac{\sigma^2}{n})$

(3) $\frac{(n-1)S^2}{\sigma^2} \sim \chi^2(n-1)$

$$(4) \quad \frac{\sqrt{n}(\bar{X} - \mu)}{S} \sim t(n-1)$$

定理 2 设 X_1, X_2, \dots, X_m 是来自正态总体 $N(\mu_1, \sigma_1^2)$ 的样本； Y_1, Y_2, \dots, Y_n 是来自正态总体 $N(\mu_2, \sigma_2^2)$ 的样本；且两样本相互独立。记

$$\bar{X} = \frac{1}{m} \sum_{i=1}^m X_i$$

$$\bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i$$

$$S_x^2 = \frac{1}{m-1} \sum_{i=1}^m (X_i - \bar{X})^2$$

$$S_y^2 = \frac{1}{n-1} \sum_{i=1}^n (Y_i - \bar{Y})^2$$

则有

$$F = \frac{S_x^2 / \sigma_1^2}{S_y^2 / \sigma_2^2} \sim F(m-1, n-1)$$

特别地：

$$\text{若 } \sigma_1^2 = \sigma_2^2 \text{ 则: } F = \frac{S_x^2}{S_y^2} \sim F(m-1, n-1)$$

3.2 t -test for β_1

$$H_0: \beta_1 = 0$$

$$H_1: \beta_1 \neq 0$$

$$\textcircled{1} \text{ 已知: } \hat{\beta}_1 \sim N(\beta_1, \frac{\sigma^2}{L_{xx}})$$

$$\textcircled{2} \text{ 在假设 } H_0 \text{ 为真时, } \beta_1 = 0 \text{ 故 } \hat{\beta}_1 \sim N(0, \frac{\sigma^2}{L_{xx}})$$

$\textcircled{3}$ 但 σ^2 未知 (unknown parameter), 用 σ^2 的 Unbiased Estimator :

$$\hat{\sigma}^2 = \frac{1}{n-2} \sum_{i=1}^n e_i^2$$

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

④ 由 [定理 1 (3)]

$$\frac{(n-2) \hat{\sigma}^2}{\sigma^2} \sim \chi^2(n-2) \quad \text{Remind}$$

⑤ 又因为 $\hat{\sigma}^2 \perp \hat{\beta}_1$

故在 $H_0: \beta_1 = 0$ 的假设下有：

$$t = \frac{\hat{\beta}_1 \sqrt{L_{xx}}}{\hat{\sigma}} \sim t(n-2)$$

检验：

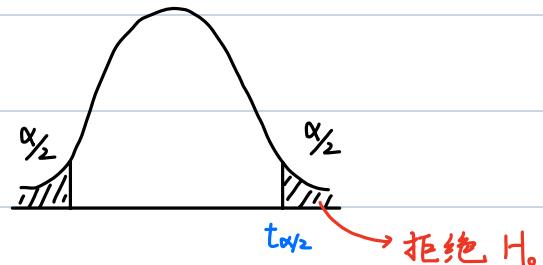
① 当原假设 $H_0: \beta_1 = 0$ 成立时， $t = \frac{\hat{\beta}_1 \sqrt{L_{xx}}}{\hat{\sigma}} \sim t(n-2)$

② 给定显著性水平 α

③ 当 $|t| > t_{\alpha/2}$ 时，拒绝 $H_0: \beta_1 = 0$

认为 β_1 显著不为 0，

y 对 x 的一元线性回归成立



p-value test:

① 当原假设 $H_0: \beta_1 = 0$ 成立时， $t = \frac{\hat{\beta}_1 \sqrt{L_{xx}}}{\hat{\sigma}} \sim t(n-2)$

② 给定显著性水平 α

③ $P(|t| > t_{\alpha/2}) = p$ 当 $p \leq \alpha$ 时，拒绝 $H_0: \beta_1 = 0$

认为 β_1 显著不为 0，

y 对 x 的一元线性回归成立

3.3 F-test for regression model

H_0 : the regression model is insignificant

H_1 : the regression model is significant

平方和分解式

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

$$SST = SSR + SSE$$

(1) Sum of Squares Total : 总离差平方和

(2) Sum of Squares Regression : 回归平方和

(3) Sum of Squares Error : 残差平方和

回归的效果

SSR占比越大，回归模型效果越佳

故，下面构造 F 检验

F-test for $\frac{SSR}{SSE}$

$$y_i \sim N(\mu, \sigma^2)$$
$$E(y_i) = \beta_0 + \beta_1 x_i$$

$$H_0: \beta_1 = 0$$

$$\textcircled{1} \quad SSE = \sum_{i=1}^n e_i^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = (n-2) \hat{\sigma}^2 \Rightarrow \beta_0 = E(y_i) = \mu$$

$$\frac{SSE}{\sigma^2} \sim \chi^2(n-2)$$

$$\textcircled{2} \quad SSR = \sum_{i=1}^n (\hat{y}_i - \bar{y})^2$$

$$\frac{SSR}{\sigma^2} \sim \chi^2(1) \quad \text{under } H_0: \beta_1 = 0$$

$$\text{or } H_1: SSR \neq 0$$

③ $SSE \perp SSR$

故构造

$$F = \frac{SSR / 1}{SSE / (n-2)} \sim F(1, n-2)$$

④ 当 $F > F_{\alpha}(1, n-2)$ 时，拒绝 H_0 ，说明回归方程显著

3.4 Significance test of the correlation coefficient 相关系数

相关系数的显著性检验

correlation coefficient 相关系数

$$\begin{aligned} r &= \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \cdot \sum_{i=1}^n (y_i - \bar{y})^2}} \\ &= \frac{L_{xy}}{\sqrt{L_{xx} \cdot L_{yy}}} \\ &= \hat{\beta}_1 \cdot \sqrt{\frac{L_{xx}}{L_{yy}}} \end{aligned}$$

Under H_0

$$\frac{\sqrt{n-2} \cdot r}{\sqrt{1-r^2}} \sim t(n-2)$$

then, 拒绝域 $|t| > t_{\alpha/2}(n-2)$

Rule of thumb 相关系数检验规则

(1) highly correlated : $|r| \geq 0.8$

(2) moderately correlated : $0.5 \leq |r| < 0.8$

(3) weakly correlated : $0.3 \leq |r| < 0.5$

(4) very weakly correlated : $|r| < 0.3$

Remark : $r \rightarrow$ only linear association

3.5 Coefficient of determination 决定系数

The proportion of the response's variation that can be explained by the regression model, that is

$$\begin{aligned} \frac{\text{SSR}}{\text{SST}} &= \frac{\sum_{i=1}^n (\hat{y}_i - \bar{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y}_i)^2} \\ &= \frac{\sum_{i=1}^n (\hat{\beta}_0 + \hat{\beta}_1 x_i - \bar{\beta}_0 - \bar{\beta}_1 \bar{x})^2}{\text{SST}} \\ &= \hat{\beta}_1^2 \cdot \frac{\text{SST}}{\text{SST}} = \frac{\text{SST}}{\text{SST}} \\ &= r^2 \end{aligned}$$

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

检验: r^2 越接近 1, 回归拟合优度好

3.6 Relationship among test and Summary 检验的关系

(1) t and r

$$t = \hat{\beta}_1 \cdot \frac{\sqrt{L_{xx}}}{\hat{\sigma}} = \frac{\sqrt{n-2} r}{\sqrt{1-r^2}}$$

(2) t and F

$$F = \frac{SSR/1}{SSE/(n-2)} = \hat{\beta}_1^2 \cdot \frac{L_{xx}}{\hat{\sigma}^2} = t^2$$

(3) SSR SST and r

$$\frac{SSR}{SST} = r^2$$

四种检验 $\{t, F, r, SSR/SST\}$ 等价

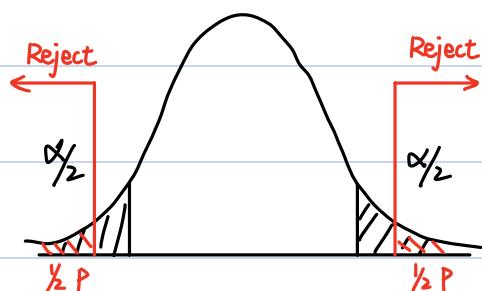
补: $\sqrt{F(1, m)} = t(m)$

3.7 P-Value P值检验

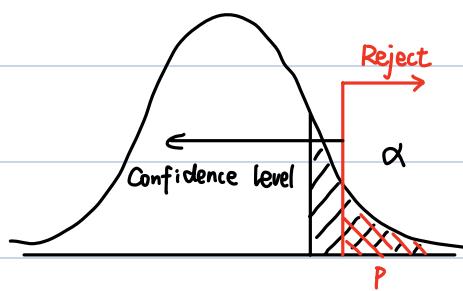
$P > \alpha$ do not reject H_0

$P \leq \alpha$ reject H_0

p-value of a two-sided test



p-value of a one-sided test



3.8 Confidence Interval 预信区间

由于 ① $\hat{\beta}_1 \sim N(\beta_1, \frac{\sigma^2}{L_{xx}})$

② $\frac{(n-2)\hat{\sigma}^2}{\sigma^2} \sim \chi^2(n-2)$

③ $\hat{\sigma}^2 \perp \hat{\beta}_1$

所以有

$$\frac{(\hat{\beta}_1 - \beta_1) \cdot \sqrt{L_{xx}}}{\hat{\sigma}} \sim t(n-2)$$

由 $P(|\frac{(\hat{\beta}_1 - \beta_1) \cdot \sqrt{L_{xx}}}{\hat{\sigma}}| < t_{1-\alpha/2}(n-2)) = 1-\alpha$

得 预信区间 $(1-\alpha) CI$ of β_1 is

$$[\hat{\beta}_1 - t_{1-\alpha/2}(n-2) \cdot \frac{\hat{\sigma}}{\sqrt{L_{xx}}}, \hat{\beta}_1 + t_{1-\alpha/2}(n-2) \cdot \frac{\hat{\sigma}}{\sqrt{L_{xx}}}]$$

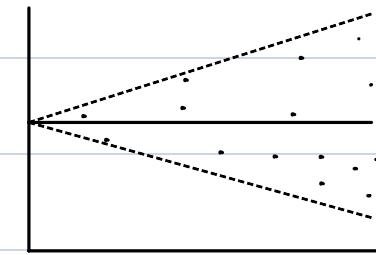
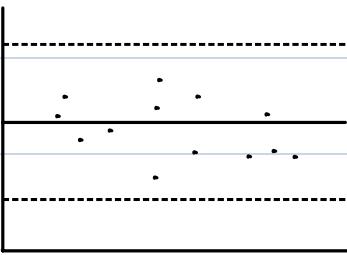
4. Residual Analysis 残差分析

4.1 Definitions of residuals and residual plots

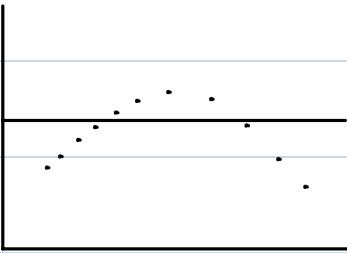
定义 残差 $e_i = y_i - \hat{y}_i$

可视为对 $\varepsilon_i = y_i - \beta_0 - \beta_1 x_i$ 的估计 (可视化, 但并不是)

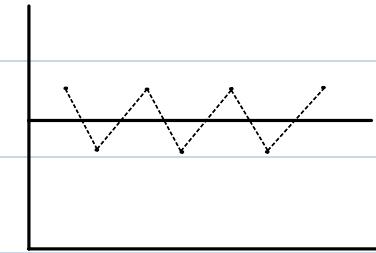
残差图 以 x_i 为横轴 (或 \hat{y}_i) , e_i 为纵轴



$\Leftrightarrow \text{var}(\varepsilon_i) = \sigma^2 \in \text{Const}$ 不变



曲线 or $\text{cov}(\varepsilon_i, \varepsilon_j) \neq 0$ 自相关



$\text{cov}(\varepsilon_i, \varepsilon_j) \neq 0$ 自相关

4.2 Properties of residuals 残差性质

(1) Expectation :

$$E(e_i) = 0$$

(2) Variance :

$$\text{var}(e_i) = (1 - h_{ii}) \sigma^2$$

$$h_{ii} = \frac{1}{n} + \frac{(x_i - \bar{x})^2}{L_{xx}} \text{ is "Leverage"}$$

当 x_i 靠近 \bar{x} , h_{ii} 越靠近 0, 残差方差越大

(3) Equation :

$$\sum_{i=1}^n e_i = 0$$

$$\sum_{i=1}^n x_i e_i = 0$$

表明残差 e_1, e_2, \dots, e_n 是相关的, 不是独立的

(4) $\hat{\sigma}^2$ is unbiased estimator

$$E(\hat{\sigma}^2) = \frac{1}{n-2} \sum_{i=1}^n E(e_i^2) = \frac{1}{n-2} \cdot \sum_{i=1}^n \text{var}(e_i) = \sigma^2$$

Proof v2) 由 $\hat{y}_i \sim N(\beta_0 + \beta_1 x_i, (\frac{1}{n} + \frac{(x_i - \bar{x})^2}{L_{xx}}) \sigma^2)$

$$\hat{\beta}_1 = \sum_{i=1}^n \frac{x_i - \bar{x}}{L_{xx}} y_i$$

$$\hat{\beta}_0 = \sum_{i=1}^n \left[\frac{1}{n} - \frac{\bar{x}(x_i - \bar{x})}{L_{xx}} \right] \cdot y_i$$

$$\therefore \text{var}(e_i) = \text{var}(y_i - \hat{y}_i)$$

$$= \text{var}(y_i) + \text{var}(\hat{y}_i) - 2 \text{cov}(y_i, \hat{y}_i)$$

$$= \sigma^2 + \left(\frac{1}{n} + \frac{(x_i - \bar{x})^2}{L_{xx}} \right) \sigma^2 - 2 \underbrace{\text{cov}(y_i, \hat{\beta}_0 + \hat{\beta}_1 x_i)}_{\textcircled{1}}$$

$$\textcircled{1} = \text{cov}(y_i, \hat{\beta}_0) + x_i \text{cov}(y_i, \hat{\beta}_1)$$

$$= \left(\frac{1}{n} - \frac{\bar{x}(x_i - \bar{x})}{L_{xx}} \right) + \frac{x_i(x_i - \bar{x})}{L_{xx}} \sigma^2$$

$$\text{故原式} = \sigma^2 + \left(\frac{1}{n} + \frac{(x_i - \bar{x})^2}{L_{xx}} \right) \sigma^2 - 2 \left(\frac{1}{n} - \frac{\bar{x}(x_i - \bar{x})}{L_{xx}} \right) + \frac{x_i(x_i - \bar{x})}{L_{xx}} \sigma^2$$

$$= \left(1 - \frac{1}{n} - \frac{(x_i - \bar{x})^2}{L_{xx}} \right) \sigma^2$$

4.3 Modified Residuals 改进的残差

标准化残差：

$$ZRE_i = \frac{e_i}{\hat{\sigma}}$$

学生化残差 (Studentized residuals)：

$$SRE_i = \frac{e_i}{\hat{\sigma} \sqrt{1 - h_{ii}}}$$

$$= \frac{e_i}{\hat{\sigma} \sqrt{1 - \frac{1}{n} - \frac{(x_i - \bar{x})^2}{L_{xx}}}}$$

判断异常值

$|SRE_i| > 3$

的观测值，视为异常值。

• $\leftarrow |SRE_i| > 3$

