

## 第九章、回归分析

### §9.1 引言

- 自变量/解释变量:  $x$ , 因变量/响应变量:  $y$ .
- 回归函数:  $f$ , 未知.
- 回归模型/方程/关系:  $y = f(x) + e$ . 其中,  $e$  是误差.
- 例:  $x =$  路程(可设定),  $y =$  耗油量.  
 $x =$  父亲身高(不可设定, 只可测量),  $y =$  儿子身高.  
关心  $f$ , 不关心自变量如何变化.  
将  $x$  视为已知参数, 将  $y, e$  视为随机变量或其取值.

- 一元线性回归(正态)模型:

$$y = b_0 + b_1x + e, \quad e \sim N(0, \sigma^2),$$

其中  $b_0, b_1, \sigma^2$  为未知参数.

- 数据  $(x_i, y_i), i = 1, \dots, n.$

$$y_i = b_0 + b_1x_i + e_i, \quad i = 1, \dots, n.$$

- $x_i$  是已知参数,

$y_i$  是随机变量(或其取值), 可观测.

$e_1, \dots, e_n$  是i.i.d. 随机变量(或其取值), 不可观测(因为 $b_0, b_1$ 是未知参数).

例1.1.  $x$  与  $y$  分别代表某个体的两个特征. 数据:  $(x_i, y_i)$ ,  
 $i = 1, \dots, n = 50$ .

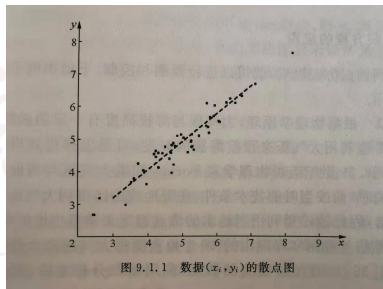
问:  $x$  与  $y$  之间什么依赖关系?

- 散点图:

- 初步判断:

$$y_i = b_0 + b_1 x_i + e_i,$$

$$i = 1, \dots, n.$$



## 回归方程的应用.

- 例1.2 (预测).  $x$  = 水的沸点,  $y$  = 大气压.

由  $n = 17$  组数据得到预测公式:

$$y = -43.131 + 0.895x + e.$$

某地测得  $x = x_0$ , 那么, 可预测  $Y_0 = \hat{b}_0 + \hat{b}_1 x_0 + e_0$ .

- 例1.3 (预测与控制).  $x$  = 某小区人口数,  $y$  = 冬季用煤量,  $z$  = 室温.

通过数据  $(x_i, y_i, z_i)$ ,  $i = 1, \dots, n$  得到回归关系:

$$y = a + bx + e, \quad z = d + fy + \varepsilon.$$

**预测:** 根据某小区人口数  $x_0$ , 预测用煤量  $Y_0 = \hat{a} + \hat{b}x_0 + e_0$ .

**控制:** 为控制  $z \in [17, 18]$ , 应该储备多少煤(反求  $y$ )?

# 回归模型与最大似然估计(§9.2)

§9.2 ~ §9.4 一元线性回归及其参数检验

$$y = b_0 + bx + e, \quad e \sim N(0, \sigma^2),$$

其中,  $\sigma^2$  未知. 数据:  $(x_i, y_i), i = 1, \dots, n$ .

- 回归模型:  $y_i = b_0 + bx_i + e_i, i = 1, \dots, n$ .

$$p_{Y_i}(y_i) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(y_i - (b_0 + bx_i))^2},$$

$x_i$ : 已知参数;  $b_0, b$ : 待估参数;  $\sigma^2$ : 讨厌参数.

- 似然函数:  $L(b_0, b, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}^n} e^{-\frac{1}{2\sigma^2} Q(b_0, b)}$ .

均方误差:  $Q(b_0, b) = \sum_{i=1}^n [y_i - (b_0 + bx_i)]^2$ .

- 定义2.1.  $Q(b_0, b)$  的最小值点  $\hat{b}_0, \hat{b}$  被称为最小二乘拟合系数, 或  $b_0$  与  $b$  的最小二乘估计.
- 最大似然估计:  $\hat{b}_0, \hat{b}, \hat{\sigma}^2 = \frac{1}{n} Q(\hat{b}_0, \hat{b})$ .

定理2.1. 假设 $x_1, \dots, x_n$  不完全相同, 则

$$\hat{b}_0 = \bar{y} - \hat{b}\bar{x}, \quad \hat{b} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} = \frac{\ell_{xy}}{\ell_{xx}}.$$

其中,  $\ell_{uv} = \sum_{i=1}^n (u_i - \bar{u})(v_i - \bar{v})$ .

- 找 $Q(a, b) = \sum_{i=1}^n [y_i - (b_0 + bx_i)]^2$  的最小值点.
- $\bar{w} = \frac{1}{n}(w_1 + \dots + w_n)$ :

$$\sum_{i=1}^n w_i^2 = \sum_{i=1}^n (w_i - \bar{w})^2 + n\bar{w}^2.$$

- $Q(a, b) = \sum_{i=1}^n [(y_i - \bar{y}) - b(x_i - \bar{x})]^2 + n(\bar{y} - (b_0 + b\bar{x}))^2$ .
- $\star = \ell_{yy} - 2b\ell_{xy} + b^2\ell_{xx}$ , 最小值点为 $\hat{b}$ .

定理2.2 & 定理3.2. 若 $x_i$  不全相等, 则 $\hat{b}_0, \hat{b}$  是最优线性无偏估计.

$$\hat{b}_0 = \bar{y} - \hat{b}\bar{x}, \quad \hat{b} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} = \frac{l_{xy}}{l_{xx}}.$$

•  $\hat{b}_0, \hat{b}$  是 $(y_1, \dots, y_n)$  的线性函数.

•  $y_i = b_0 + bx_i + e_i, \quad \bar{y} = b_0 + b\bar{x} + \bar{e},$

$$y_i - \bar{y} = b(x_i - \bar{x}) + (e_i - \bar{e}).$$

•  $E\hat{b} = b: e_1, \dots, e_n$  i.i.d., 且 $e_1 \sim N(0, \sigma^2),$

$$\hat{b} = b + \frac{1}{l_{xx}} \sum_{i=1}^n (x_i - \bar{x})(e_i - \bar{e}) = b + \frac{1}{l_{xx}} \sum_{i=1}^n (x_i - \bar{x})e_i,$$

•  $E\hat{b}_0 = b_0:$

$$\hat{b}_0 = \bar{y} - \hat{b}\bar{x} = (b_0 + b\bar{x} + \bar{e}) - \hat{b}\bar{x} = b_0 + (b - \hat{b})\bar{x} + \bar{e}.$$

## 参数检验 (§9.4)

参数:  $\theta = (b_0, b, \sigma^2)$ . 假设检验问题(2.14).

$$H_0 : b = 0 \leftrightarrow H_1 : b \neq 0.$$

- 否定  $H_0$ , 则表明  $y$  与  $x$  之间有线性依赖关系.
- $\Theta = \{\theta : b_0, b \in \mathbb{R}, \sigma^2 > 0\}$ ,  $\Theta_0 = \{\theta \in \Theta : b = 0\}$ .

- 似然函数:  $L(\theta) = \frac{1}{\sqrt{2\pi\sigma^2}^n} e^{-\frac{1}{2\sigma^2} Q(b_0, b)}$ .

$$Q(b_0, b) = \sum_{i=1}^n [y_i - (b_0 + bx_i)]^2.$$

- $\Theta$  上的最大似然估计:  $\hat{\theta} = (\hat{b}_0, \hat{b}, \hat{\sigma}^2)$ ,  $\hat{b}_0 = \bar{y} - \hat{b}\bar{x}$ ,  $\hat{b} = \frac{\ell_{xy}}{\ell_{xx}}$ ,

$$L(\hat{\theta}) = \left(\sqrt{2\pi\hat{\sigma}^2}\right)^{-n/2} e^{-\frac{n}{2}}, \quad \hat{\sigma}^2 = \frac{1}{n} Q(\hat{b}_0, \hat{b}).$$

- $\Theta_0$  上的最大似然估计:  $\check{\theta}_0 = (\check{b}_0, \check{b}, \check{\sigma}^2)$ ,  $\check{b}_0 = \bar{y}$ ,  $\check{b} = 0$ ,

$$L(\check{\theta}_0) = \left(\sqrt{2\pi\check{\sigma}_0^2}\right)^{-n/2} e^{-\frac{n}{2}}, \quad \check{\sigma}_0^2 = \frac{1}{n} Q(\check{b}_0, \check{b}).$$



$$H_0 : b = 0 \leftrightarrow H_1 : b \neq 0.$$

- $Q(b_0, b) = \sum_{i=1}^n [y_i - (b_0 + bx_i)]^2,$

$$L(\hat{\theta}) = \left(\sqrt{2\pi\hat{\sigma}^2}\right)^{-n/2} e^{-\frac{n}{2}}, \quad \hat{\sigma}^2 = \frac{1}{n} Q(\hat{b}_0, \hat{b})$$

$$L(\hat{\theta}_0) = \left(\sqrt{2\pi\check{\sigma}_0^2}\right)^{-n/2} e^{-\frac{n}{2}}, \quad \check{\sigma}_0^2 = \frac{1}{n} Q(\bar{y}, 0).$$

- $Q = Q(\hat{b}_0, \hat{b}) = \sum_{i=1}^n (y_i - \hat{y}_i)^2$ , 残差平方和;

$$Q(\bar{y}, 0) = \sum_{i=1}^n (y_i - \bar{y})^2 = l_{yy},$$

- 广义似然比:  $\lambda(\vec{y}) = L(\hat{\theta})/L(\hat{\theta}_0) = (l_{yy}/Q)^{n/2}.$

- 广义似然比否定域:

$$\mathcal{W} = \{\vec{y} : l_{yy}/Q > c_1\}.$$

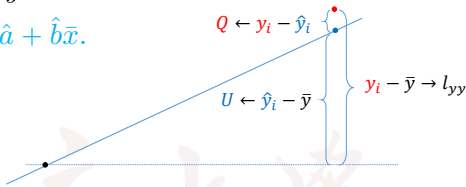
正交分解.  $\hat{a} = \bar{y} - \hat{b}\bar{x}$ ,  $\hat{b} = \frac{l_{xy}}{l_{xx}}$ . 产生直线  $\hat{f}$ :  $\hat{y} = \hat{a} + \hat{b}x$ ,

- $\hat{f}$  过点  $(\bar{x}, \bar{y})$ ,  $\bar{y} = \hat{f}(\bar{x}) = \bar{y}$ .

$$\bar{y} = \hat{a} + \hat{b}\bar{x}.$$

- 残差平方和  $Q$ :

$$\begin{aligned} Q &= \sum_{i=1}^n (y_i - (\hat{a} + \hat{b}x_i))^2 \\ &= \sum_{i=1}^n (y_i - \hat{y}_i)^2. \end{aligned}$$



- 回归平方和  $U$ :

$$U = \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 = \hat{b}^2 \sum_{i=1}^n (x_i - \bar{x})^2.$$

- 引理2.1.  $l_{yy} = \sum_{i=1}^n (y_i - \bar{y})^2 = U + Q$ .

- $\sum_{i=1}^n \underbrace{\star\star}_{(y_i - \bar{y})} \underbrace{\star\star}_{\hat{b}(x_i - \bar{x})} = \sum_{i=1}^n (y_i - \bar{y})\hat{b}(x_i - \bar{x}) - \sum_{i=1}^n \underbrace{(\hat{y}_i - \bar{y})}_{(y_i - \bar{y})}(\hat{y}_i - \bar{y})$   
 $= \hat{b}l_{xy} - \hat{b}^2l_{xx} = 0.$

- 广义似然比否定域:  $\mathcal{W} = \{\vec{y} : U/Q > c_2\}$ .

命题4.1. 残差平方和 $Q = \sum_{i=1}^n (y_i - \hat{y}_i)^2$  与回归平方和 $U = \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 = \hat{b}^2 \ell_{xx}$  相互独立, 且

$$\frac{1}{\sigma^2} Q \sim \chi^2(n-2); \quad \text{若 } b = 0, \text{ 则 } \frac{U}{\sigma^2} \sim \chi^2(1).$$

- $\hat{b}_0 = b_0 + (b - \hat{b})\bar{x} + \bar{e}, \quad \hat{b} = b + \frac{1}{\ell_{xx}} \sum_i (x_i - \bar{x})(e_i - \bar{e}).$
- $\begin{aligned} \hat{y}_i - y_i &= (\hat{b}_0 + \hat{b}x_i) - (b_0 + bx_i + e_i) \\ &= (b - \hat{b})\bar{x} + \bar{e} + (\hat{b} - b)x_i - e_i \\ &= (\hat{b} - b)(x_i - \bar{x}) - (e_i - \bar{e}). \end{aligned}$
- $\begin{aligned} (\hat{y}_i - y_i)^2 &= (\hat{b} - b)^2 (x_i - \bar{x})^2 + (e_i - \bar{e})^2 \\ &\quad - 2(\hat{b} - b)(x_i - \bar{x})(e_i - \bar{e}). \end{aligned}$
- $\begin{aligned} Q &= (\hat{b} - b)^2 \ell_{xx} + \sum_i (e_i - \bar{e})^2 - 2(\hat{b} - b) \ell_{xx} (\hat{b} - b), \\ &= \sum_i (e_i - \bar{e})^2 - \ell_{xx} (\hat{b} - b)^2. \end{aligned}$

命题4.1(续).  $Q = \sum_{i=1}^n (y_i - \hat{y}_i)^2$ . 则  $\frac{1}{\sigma^2}Q \sim \chi^2(n-2)$ .

- $Q = \sum_i (e_i - \bar{e})^2 - l_{xx}(\hat{b} - b)^2, \quad \hat{b} = b + \sum_i \frac{x_i - \bar{x}}{l_{xx}} e_i.$

- $\sum_i (e_i - \bar{e})^2:$

$$\sum_i (e_i - \bar{e})^2 = \sum_i e_i^2 - n\bar{e}^2$$

$$= \sum_i e_i^2 - \left( \sum_i \frac{1}{\sqrt{n}} e_i \right)^2 = \sum_i e_i^2 - \left( \sum_i a_{1i} e_i \right)^2.$$

- $l_{xx}(\hat{b} - b)^2:$

$$l_{xx}(\hat{b} - b)^2 = \left( \sum_i \frac{x_i - \bar{x}}{\sqrt{l_{xx}}} e_i \right)^2 = \left( \sum_i a_{2i} e_i \right)^2.$$

- 再补  $n-2$  行, 可得正交矩阵  $A = (a_{ki})_{n \times n}$ :

$$\sum_i a_{1i}^2 = \sum_i a_{2i}^2 = 1, \quad \sum_i a_{1i} a_{2i} = 0.$$

命题4.1(续).  $Q = \sum_{i=1}^n (y_i - \hat{y}_i)^2$ . 则  $\frac{1}{\sigma^2}Q \sim \chi^2(n-2)$ .

- $Q = \sum_i e_i^2 - (\sum_i a_{1i}e_i)^2 - (\sum_i a_{2i}e_i)^2.$

$A = (a_{ki})_{n \times n}$  为正交矩阵.

- $W_i = e_i/\sigma$ :  $W_1, \dots, W_n$  i.i.d.,  $W_1 \sim N(0, 1)$ , 则

$$\begin{aligned}EZ_k Z_\ell &= E \sum_i a_{ki} W_i \sum_j a_{lj} W_j \\ &= \sum_{i,j} a_{ki} a_{lj} E W_i W_j = \sum_i a_{ki} a_{li} = 1_{\{k=\ell\}}.\end{aligned}$$

$$(W_1, \dots, W_n)^T \stackrel{d}{=} (Z_1, \dots, Z_n)^T := A(W_1, \dots, W_n)^T.$$

- $Q = \sigma^2 (\sum_i Z_i^2 - Z_1^2 - Z_2^2) = \sigma^2 \sum_{i=3}^n Z_i^2.$

命题4.1(续). 回归平方和  $U = \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 = \hat{b}^2 \ell_{xx}$  与  $Q$  相互独立, 且若  $b = 0$ , 则

$$\frac{U}{\sigma^2} \sim \chi^2(1).$$

- $\hat{b}$  与  $Q = \sigma^2 \sum_{i=3}^n Z_i^2$  独立:

$$\hat{b} = b + \sum_i \frac{x_i - \bar{x}}{\ell_{xx}} e_i = b + \frac{1}{\sqrt{\ell_{xx}}} \sigma Z_2.$$

- $U = (\sqrt{\ell_{xx}} b + \sigma Z_2)^2$ . 若  $b = 0$ , 则

$$\frac{1}{\sigma^2} U = Z_2^2 \sim \chi^2(1).$$

- $Q = \sigma^2 \sum_{i=3}^n Z_i^2$ ,  $U = (\sqrt{\ell_{xx}b} + \sigma Z_2)^2$ .

- 广义似然比否定域:

$$\mathcal{W} = \left\{ \vec{y} : \frac{U}{Q} > c_2 \right\} = \left\{ \vec{y} : \frac{U}{Q/(n-2)} > \lambda \right\}.$$

- 定理4.3. 在 $H_0$ 下, 检验统计量:

$$\xi := \frac{U}{Q/(n-2)} \sim F(1, n-2).$$

因此,  $\lambda = F_{1-\alpha}(1, n-2)$ .

例2.1.  $x =$  注射后天数,  
 $y =$  金残留百分数.

- 根据散点图建立函数

$$\ln y = b_0 + bx + e.$$

- 求  $\bar{x}$ ,  $\bar{z}$ ;  $\hat{z}_i = \hat{b}_0 + \hat{b}x_i$ :

$$\hat{b} = l_{xz}/l_{xx}, \hat{b}_0 = \bar{z} - \hat{b}\bar{x};$$

- 求残差平方和:  $Q = \sum_i (z_i - \hat{z}_i)^2$   
 与回归平方和:  $U = \sum_i (\hat{z}_i - \bar{z})^2$ .

- $n = 10$ , 根据  $\lambda = F_{0.95}(1, n - 2) = F_{0.95}(1, 8) = 5.32$ .

$\frac{U}{Q/(n-2)} = 344.82 > \lambda$  否定  $H_0$ , 强烈认可  $z$  线性依赖于  $x$ .

