

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

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

$$\text{其中 } \hat{y}_i - \bar{y} = \hat{w}x_i + b - (\hat{w}\bar{x} + b) = \hat{w}(x_i - \bar{x}), \quad \hat{w} = \frac{\sum_{i=1}^n (y_i - \bar{y})(x_i - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

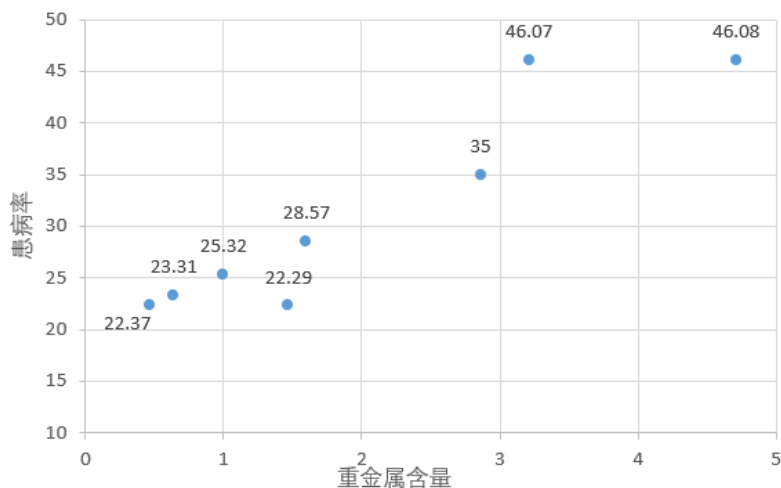
$$y_i - \hat{y}_i = y_i - \bar{y} - \hat{w}(x_i - \bar{x})$$

$$\sum_{i=1}^n (y_i - \hat{y}_i)(\hat{y}_i - \bar{y}) = \sum_{i=1}^n [\hat{w}(y_i - \bar{y})(x_i - \bar{x}) - \hat{w}^2(x_i - \bar{x})^2]$$

$$= \hat{w} \sum_{i=1}^n (y_i - \bar{y})(x_i - \bar{x}) - \hat{w} \cdot \frac{\sum_{i=1}^n (y_i - \bar{y})(x_i - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \cdot \sum_{i=1}^n (x_i - \bar{x})^2 = 0.$$

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

2. (a)



$$(b) \quad \bar{x} = \frac{0.47 + 0.64 + 1.00 + 1.47 + 1.60 + 2.86 + 3.21 + 4.71}{8}$$

$$= 1.9950$$

$$\bar{y} = \frac{22.37 + 23.31 + 25.32 + 22.29 + 28.57 + 35 + 46.07 + 46.08}{8}$$

$$= 31.1263$$

$$\hat{w} = \frac{\sum_{i=1}^8 (y_i - 31.1263)(x_i - 1.995)}{\sum_{i=1}^8 (x_i - 1.995)^2} = 6.4218$$

$$\hat{b} = \bar{y} - \hat{w}\bar{x} = 31.1263 - 6.4218 \times 1.995 = 18.3147$$

$$\text{一元线性回归方程 } \hat{y} = 6.4218x + 18.3147$$

$$r^2 = \frac{\sum_{i=1}^8 (\hat{y}_i - 31.1263)^2}{\sum_{i=1}^8 (y_i - 31.1263)^2} = 0.8718$$

3. (a) 不适用。因为最小二乘法是在自变量 $x$ 的观测值准确时移动回归直线使得对应残差的平方和最小来实现的, 而此题中自变量 $x$ 的观测值存在误差, 预测点与实际点的平方误差损失不能只用变量 $y$ 的残差平方和表示。

(b) 回归直线 $(\bar{n}, \bar{x}_0)$ .

则  $\vec{x}_i = (x_i, y_i)^T$  到回归直线的距离平方为  $[(\vec{x}_i - \vec{x}_0) \cdot \vec{n}]^2$

平方误差损失为  $\sum_{i=1}^n [(\vec{x}_i - \vec{x}_0) \cdot \vec{n}]^2$

(c) 设  $\vec{x}_0 = (x_0, y_0)^T$   $\vec{n} = (\sin \theta, -\cos \theta)^T$

$$\text{则 } \sum_{i=1}^n [(\vec{x}_i - \vec{x}_0) \cdot \vec{n}]^2 = \sum_{i=1}^n [(x_i - x_0)\sin \theta - (y_i - y_0)\cos \theta]^2 = D$$

$$\left| \frac{\partial D}{\partial x_0} = -2 \sin \theta \sum_{i=1}^n [(x_i - x_0)\sin \theta - (y_i - y_0)\cos \theta] \right.$$

$$\left\{ \begin{aligned} &= -2n(\bar{x}-x_0)\sin^2\theta + n(\bar{y}-y_0)\sin 2\theta = 0. \end{aligned} \right.$$

$$\left\{ \begin{aligned} \frac{\partial D}{\partial y_0} &= 2\cos\theta \sum_{i=1}^n [(x_i-x_0)\sin\theta - (y_i-y_0)\cos\theta] \\ &= n(\bar{x}-x_0)\sin\theta - 2n(\bar{y}-y_0)\cos^2\theta = 0. \end{aligned} \right.$$

$$\left\{ \begin{aligned} \frac{\partial D}{\partial \theta} &= 2 \sum_{i=1}^n [(x_i-x_0)\sin\theta - (y_i-y_0)\cos\theta] [(x_i-x_0)\cos\theta + (y_i-y_0)\sin\theta] \\ &= \left[ \sum_{i=1}^n (x_i-x_0)^2 - \sum_{i=1}^n (y_i-y_0)^2 \right] \sin 2\theta - 2 \sum_{i=1}^n (x_i-x_0)(y_i-y_0) \cos 2\theta = 0. \end{aligned} \right.$$

$$\text{则 } x_0 = \bar{x} \quad y_0 = \bar{y} \quad \tan 2\theta = \frac{2S_{xy}}{S_{xx} - S_{yy}}.$$

$$\theta = \frac{1}{2} \arctan \frac{2S_{xy}}{S_{xx} - S_{yy}}.$$

当  $\vec{x}_0 = (x_0, y_0)^T$  和  $\vec{n} = (\sin\theta, -\cos\theta)^T$  取如上值时平方损失表达式值最小。