

ML hw1 Report

學號：B05705001 系級：資管四 姓名：黃意芹

請實做以下兩種不同feature的模型，回答第 (1) ~ (2) 題：

1. 記錄誤差值 (RMSE)(根據kaggle public+private分數)，討論兩種feature的影響

(1) 抽全部9小時內的污染源feature當作一次項(加bias)

RMSE

(2) 抽全部9小時內pm2.5的一次項當作feature(加bias)

RMSE	全部9小時內的污染源當作feature	全部9小時內pm2.5當作feature
private	5.65158	5.72749
public	6.02616	5.99585
average	5.83887	5.86167

由得到的RMSE可知，抽全部9小時內的污染源feature當作一次項的表現會比抽全部9小時內pm2.5的一次項當作feature更好，不過差距不是很大。原因可能是因為PM2.5跟其他污染源有關聯，所以增加更多feature對於預測PM2.5會有所幫助。不過因為PM2.5本身就算是最主要的特徵，且其他資料可能有摻雜許多雜亂、異常的值，所以增加其他特徵的進步幅度沒有非常大。

2. 解釋什麼樣的data preprocessing 可以improve你的training/testing accuracy，e

x. 你怎麼挑掉你覺得不適合的data points。請提供數據(RMSE)以佐證你的想法。

RMSE	全部9小時內的污染源當作feature 且有清除掉異常pm2.5	全部9小時內的污染源當作feature 沒有清除掉異常pm2.5
private	5.69725	5.65158
public	5.54239	6.02616
average	5.61982	5.83887

除了 NR皆設為0，還有把在字尾的其他符號去除只留數字，我還有做資料清理方法為：先把pm2.5的極端值挑出 ($pm2.5 < 2$ or $pm2.5 \geq 100$)，之後算出pm2.5的平均和標準差，將平均 ± 3.6 *標準差以外的training data丟掉。在predict時，若testing data有pm2.5的值在平均 ± 3.8 *標準差以外，則取代成平均值進行預測。會

這麼做的原因在於，pm2.5本身為最重要的特徵，然而資料有一些異常值，所以先清除掉再訓練出的model會比較準確。而testing data因為沒辦法丟掉資料，所以就將異常值取代為平均值進行預測。

從上表RMSE可觀察到，有去除異常pm2.5的model表現明顯較好。這是因為訓練與預測時不會被異常值誤導，所以結果也會比較準確。

3. Refer to math problem

1.

1-(a)

$$L(w, b) = \frac{1}{2 \times 5} \sum_{i=1}^5 (y_i - (w^T x_i + b))^2$$

$$w' = \arg \min_w L(w, b)$$

$$\text{when } \frac{\partial L(w, b)}{\partial w} = 0$$

$$w' = \frac{\sum_{i=1}^5 (y_i - \bar{y})(x_i - \bar{x})}{\sum_{i=1}^5 (x_i - \bar{x})^2}$$

$$\bar{x} = \frac{\sum_{i=1}^5 x_i}{5} = 3$$

$$\bar{y} = \frac{\sum_{i=1}^5 y_i}{5} = 3.36$$

$$= \frac{(1.2 - 3.36)(1 - 3) + (2.4 - 3.36)(2 - 3) + (3 - 3.36)(3 - 3) + (4.1 - 3.36)(4 - 3) + (5.6 - 3.36)(5 - 3)}{2^2 + 1^2 + 0^2 + 1^2 + 2^2}$$

$$= \frac{(-2.16) \cdot (-2) + (-0.96) \cdot (-1) + 0 + (0.74) \cdot (1) + (2.24) \cdot (2)}{10}$$

$$= \frac{1}{10} [4.32 + 0.96 + 0.74 + 4.48] = \frac{10.5}{10} = 1.05$$

$$b' = \bar{y} - w\bar{x} = 3.36 - 1.05 \times 3 = 3.36 - 3.15 = 0.21$$

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1-(b) To find w, b that minimize $L(w, b)$

$$\Rightarrow \frac{\partial L(w, b)}{\partial w} = 0 \Rightarrow \frac{\partial \frac{1}{2N} \sum_{i=1}^N (y_i - b - wx_i)^2}{\partial w} = 0$$

$$\Rightarrow \frac{\partial}{\partial w} \frac{1}{2N} \sum_{i=1}^N (y_i - b - wx_i)^2 = 0 \Rightarrow \sum_{i=1}^N (y_i - b - wx_i) x_i = 0$$

$$\Rightarrow \sum_{i=1}^N y_i x_i - \sum_{i=1}^N wx_i^2 - \sum_{i=1}^N bx_i = 0$$

$$\Rightarrow \sum_{i=1}^N y_i x_i - \sum_{i=1}^N (\bar{y} - b\bar{x}) x_i - w \sum_{i=1}^N x_i^2 = 0$$

$$\Rightarrow \sum_{i=1}^N y_i x_i - \sum_{i=1}^N \bar{y} x_i + \sum_{i=1}^N w \bar{x} x_i - w \sum_{i=1}^N x_i^2 = 0$$

$$\Rightarrow w \sum_{i=1}^N x_i (\bar{x} - x_i) + \sum_{i=1}^N x_i (y_i - \bar{y}) = 0$$

$$\Rightarrow w = \frac{\sum_{i=1}^N x_i (y_i - \bar{y})}{\sum_{i=1}^N x_i (\bar{x} - x_i)} = \frac{\sum_{i=1}^N x_i y_i - \bar{y} \sum_{i=1}^N x_i}{\sum_{i=1}^N x_i^2 - \bar{x} \sum_{i=1}^N x_i}$$

$$= \frac{\sum_{i=1}^N xy - N\bar{x}\bar{y} - N\bar{x}\bar{y} + N\bar{x}\bar{y}}{\sum_{i=1}^N x_i^2 - N\bar{x}^2}$$

$$= \frac{\sum xy - \sum x_i \bar{y} - \sum \bar{x} y_i + \sum \bar{x} \bar{y}}{\sum x_i^2 - 2N\bar{x}^2 + N\bar{x}^2}$$

$$\therefore w = \frac{\sum (x_i y_i - x_i \bar{y} - \bar{x} y_i + \bar{x} \bar{y})}{\sum (x_i - \bar{x})^2} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

$$b = \bar{y} - \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2} \bar{x}$$

1-(C)

$$L_2(w, b) = \frac{1}{2N} \sum_{i=1}^N (y_i - (w^T x_i + b))^2 + \frac{\lambda}{2} \|w\|^2$$

$$\frac{\partial L_2(w, b) + \frac{\lambda}{2} \|w\|^2}{\partial w} = \frac{1}{N} \sum_{i=1}^N (y_i - b - w^T x_i) x_i + \frac{\partial \frac{\lambda}{2} \|w\|^2}{\partial w} = 0$$

$$\Rightarrow -\frac{1}{N} \sum (y_i x_i - b x_i - w^T x_i^2) + \lambda w = 0$$

$$\Rightarrow -(\sum y_i x_i - \sum w x_i^2 - \sum b x_i) + \lambda N w = 0$$

$$\Rightarrow -\sum y_i x_i + \sum (\bar{y} - w^T \bar{x}) x_i + \sum w x_i^2 + \lambda N w = 0$$

$$\Rightarrow -\sum y_i x_i + \sum \bar{y} x_i - w^T \bar{x} \sum x_i + w^T \sum x_i^2 + \lambda N w = 0$$

$$\Rightarrow -\sum y_i x_i + \sum \bar{y} x_i + w^T (\sum x_i (x_i - \bar{x}) + \lambda N) = 0$$

$$\Rightarrow w = \frac{\sum y_i x_i - \sum \bar{y} x_i}{\sum x_i (x_i - \bar{x}) + \lambda N} = \frac{\sum (y_i - \bar{y}) (x_i - \bar{x})}{\sum (x_i - \bar{x})^2 + \lambda N}$$

$$b = \bar{y} - w^T \bar{x}$$

3.

$$(a) \text{ Let } A = \sum_{i=1}^N g_k(x_i) y_i$$

$$e_k = \frac{1}{N} \left[\sum_{i=1}^N (g_k(x_i) - y_i)^2 \right] = \frac{1}{N} \left(\sum_{i=1}^N (g_k(x_i))^2 - 2 \sum_{i=1}^N g_k(x_i) \cdot y_i + \sum_{i=1}^N y_i^2 \right)$$

$$= \frac{1}{N} (N s_k - 2 \cdot A + N e_0) \Rightarrow N \cdot e_k = N s_k - 2A + N e_0$$

$$\Rightarrow A = \frac{N(s_k - e_k + e_0)}{2} \quad \text{NaK}$$

$$(b) \text{ Let } F = \frac{1}{N} \sum_{i=1}^N \left(\sum_{k=1}^K a_k g_k(x_i) - y_i \right)^2 \quad \sum_{i=1}^N a_k g(x_i)$$

$$\frac{\partial F}{\partial a} = \frac{1}{N} \sum_{i=1}^N \left[2 \cdot \left(\sum_{k=1}^K a_k g_k(x_i) - y_i \right) \cdot \sum_{k=1}^K g_k(x_i) \right] = 0$$

$$\rightarrow \sum_{i=1}^N \left[\left(\sum_{k=1}^K a_k g_k(x_i) \right) \cdot \sum_{k=1}^K g_k(x_i) - \sum_{k=1}^K g_k(x_i) \cdot y_i \right] = 0$$

$$\rightarrow \sum_{k=1}^K \left[\left(\sum_{i=1}^N a_k g_k(x_i) \right) \cdot \sum_{i=1}^N g_k(x_i) - \sum_{i=1}^N g_k(x_i) \cdot y_i \right] = 0$$

$$\rightarrow \sum_{k=1}^K \left(a_k N s_k - \frac{N}{2} (s_k - e_k + e_0) \right) = 0$$

$$\rightarrow a_k = \frac{N \sum_{k=1}^K (s_k - e_k + e_0)}{\sum_{k=1}^K N s_k}$$