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請實做以下兩種不同feature的模型,回答第(1)~(3)題:

- (1) 抽全部9小時內的污染源feature的一次項(加bias)
- (2) 抽全部9小時內pm2.5的一次項當作feature(加bias) 備註:
 - a. NR請皆設為0,其他的數值不要做任何更動
 - b. 所有 advanced 的 gradient descent 技術(如: adam, adagrad 等) 都是可以用的
- 1. (2%)記錄誤差值 (RMSE)(根據kaggle public+private分數),討論兩種feature的影響

<u>cost_sq</u>rt: 6.50423323304

一開始我是用(1)的model,可是似乎在public set的成績不太好, 後來改用第二種才改善。 但用正確答案算出rmse,發現其實第一種model 好像error比較小,可能是pm2.5相對來說data比較少的關係。

cost_sqrt: 6.5962445333

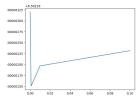
2. (1%)將feature從抽前9小時改成抽前5小時,討論其變化

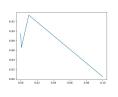
cost_sgrt: 26.4400626784

改成抽前五小時,雖然在training的error可以降到3,但是出來的結果並不好,應該是發生overfitting

cost_sqrt: 26.7351554608

3. (1%)Regularization on all the weight with λ =0.1、0.01、0.001、0.0001 ,並作圖





(1%)在線性回歸問題中,假設有 N 筆訓練資料,每筆訓練資料的特徵 (feature) 為一向量 x_n ,其標註(label)為一存量 y_n ,模型參數為一向量w (此處忽略偏權值 b),則線性回歸的損失函數(loss function)為 $\sum\limits_{n=1}^{N}(y_n-x_n\cdot w)_2$ 。若將所有訓練資料的特徵值以矩陣

 $X = [x_1 x_2 ... x_N]_T$ 表示,所有訓練資料的標註以向量 $y = [y_1 y_2 ... y_N]_T$ 表示,請問如何以 X 和 y 表示可以最小化損失函數的向量 w ?請寫下算式並選出正確答案。(其中 $X_T X$ λ invertible)

$$(c) (X TX) - 1 X TY$$

$$(d) (X TX) -2 X TY$$

$$\int_{[a]} (y_1 - x_1^T b_1)^2 \\
= (y_1 - x_1)^T (y_1 - x_2 b_1) \\
= (y_1^T - (x_1 b_1)^T) (y_1 - x_2 b_1) \\
= (x_1 b_1^T (x_1 b_1) - y_1^T (x_2 b_1) - (x_2 b_1)^T y_1 + y_1^T y_1 \\
= b_1^T x_1^T x_1 b_1 - 2(x_1 b_1)^T y_1 + y_1^T y_1 \\
= b_1^T x_1^T x_2 b_1 - 2(x_1 b_1)^T y_1 + y_1^T y_2 \\
= b_1^T x_1^T x_2 b_1 - 2(x_1 b_1)^T y_1 + y_1^T y_2 \\
= b_1^T x_1^T x_2 b_1 - 2(x_1 b_1)^T y_1 + y_1^T y_2 \\
= b_1^T x_1^T x_2 b_1 - 2(x_1 b_1)^T y_1 + y_1^T y_2 \\
= b_1^T x_1^T x_2 b_1 - 2(x_1 b_1)^T y_1 + y_1^T y_2 \\
= b_1^T x_1^T x_2 b_1 - 2(x_1 b_1)^T y_1 + y_1^T y_2 \\
= b_1^T x_1^T x_2 b_1 - 2(x_1 b_1)^T y_1 + y_1^T y_2 \\
= b_1^T x_1^T x_2 b_1 - 2(x_1 b_1)^T y_1 + y_1^T y_2 \\
= b_1^T x_1^T x_2 b_1 - 2(x_1 b_1)^T y_1 + y_1^T y_2 \\
= b_1^T x_1^T x_2 b_1 - 2(x_1 b_1)^T y_1 + y_1^T y_2 \\
= b_1^T x_1^T x_2 b_1 - 2(x_1 b_1)^T y_1 + y_1^T y_2 \\
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= b_1^T x_1^T x_2 b_1 - 2(x_1 b_1)^T y_1 + y_1^T y_2 \\
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= b_1^T x_1^T x_2 b_1 - 2(x_1 b_1)^T y_1 + y_1^T y_2 \\
= b_1^T x_1^T x_1 b_1 - 2(x_1 b_1)^T y_1 + y_1^T y_2 \\
= b_1^T x_1^T x_1 b_1 + y_1^T x_2 b_1 + y_1^T x_2 b_1 + y_1^T x_2 b_1 + y_1^T y_2 b_1 + y_1^T y_1 + y_1^T y_2 b_1 + y_1^T y_2 b_1 + y_1^T y_2 b_1 + y_1^T y_1 + y_1^T y_2 b_1 + y_1^$$