

5. counter-example

$$\mathcal{H}_1 = \{h_1(x) = 1\}$$

$$\mathcal{H}_2 = \{h_2(x) = -1\}$$

$$\text{dvc}(\mathcal{H}_1) = \text{dvc}(\mathcal{H}_2) = 0$$

$$\text{dvc}(\mathcal{H}_1 \sqcup \mathcal{H}_2) = 1$$

collaborators:

B11901016 張均豪

6.

no collaborators

		g	
		+1	-1
f	+1	no error	false negative
	-1	false positive	no error

⇒

		g	
		+1	-1
f	+1	0	10
	-1	1	0

$$\Rightarrow \alpha = \frac{10}{1+10} = \underline{\underline{\frac{10}{11}}}$$

7.

Let the probability of noise is  $p$

That is,  $E_{\text{out}}^{(2)}(f) = \mathbb{E}_{\underline{x} \sim P(\underline{x}), y \sim P(y|\underline{x})} [\mathbb{I}(f(\underline{x}) \neq y)] = p$

$$E_{\text{out}}^{(2)}(h) = \frac{1}{N} \left( p \sum_n [\mathbb{I}(h(\underline{x}) = f(\underline{x}))] + (1-p) \sum_n [\mathbb{I}(h(\underline{x}) \neq f(\underline{x}))] \right)$$

$$= E_{\text{out}}^{(2)}(f) \frac{1}{N} (N - \sum_n [\mathbb{I}(h(\underline{x}) \neq f(\underline{x}))]) + (1 - E_{\text{out}}^{(2)}(f)) \frac{1}{N} \sum_n [\mathbb{I}(h(\underline{x}) \neq f(\underline{x}))]$$

$$= E_{\text{out}}^{(2)}(f) (1 - E_{\text{out}}^{(1)}(h)) + (1 - E_{\text{out}}^{(2)}(f)) E_{\text{out}}^{(1)}(h)$$

$$= E_{\text{out}}^{(2)}(f) + E_{\text{out}}^{(2)}(h) - 2E_{\text{out}}^{(2)}(f) E_{\text{out}}^{(1)}(h)$$

$$\leq E_{\text{out}}^{(2)}(h) + E_{\text{out}}^{(2)}(f) \quad \text{Q.E.D.}$$

8. From page 11 in lecture 09,

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$$\underline{W_{LIN}} = X^T y$$

$$= (X^T X)^{-1} X^T y, \text{ where}$$

$$X = \underbrace{\begin{bmatrix} 1 & - & x_1^T & - \\ 1 & - & x_2^T & - \\ & & \vdots & \\ 1 & - & x_n^T & - \end{bmatrix}}_{N \times (d+1)}, \quad y = \underbrace{\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix}}_{N \times 1}$$

Now,  $x_0 = 1 \rightarrow x_0 = 1126$

$$X' = \underbrace{\begin{bmatrix} 1126 & - & x_1^T & - \\ 1126 & - & x_2^T & - \\ & & \vdots & \\ 1126 & - & x_n^T & - \end{bmatrix}}_{N \times (d+1)} = X M, \text{ where } M = \begin{bmatrix} 1126 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix}$$

and  $M^T = M$

$$\begin{aligned} \therefore \underline{W_{LUCKY}} &= ((X')^T X')^{-1} (X')^T y \\ &= ((XM)^T (XM))^{-1} (XM)^T y \\ &= (M^T (X^T X) M)^{-1} (M^T X^T) y \\ &= M^{-1} (X^T X)^{-1} M^{-1} (M X^T) y \\ &= M^{-1} (X^T X)^{-1} X^T y \\ &= M^{-1} \underline{W_{LIN}} \end{aligned}$$

$$\Rightarrow \underline{W_{LIN}} = M \underline{W_{LUCKY}}$$

$$\therefore D = M = \underline{\underline{\begin{bmatrix} 1126 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix}}}$$

$$9. h(\underline{x}) = \frac{1}{1 + e^{-\underline{\omega}^T \underline{x}}}$$

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$$\tilde{h}(\underline{x}) = \frac{1}{2} \left( \frac{\underline{\omega}^T \underline{x}}{\sqrt{1 + (\underline{\omega}^T \underline{x})^2}} + 1 \right) \quad \theta(s) = \frac{1}{2} \left( \frac{1}{\sqrt{1 + s^{-2}}} + 1 \right)$$

$$= \frac{1}{2} \frac{1}{\sqrt{1 + (\underline{\omega}^T \underline{x})^2}} + \frac{1}{2}$$

$$\max_{\tilde{h}} \text{likelihood (logistic } \tilde{h}) \propto \prod_{n=1}^N \tilde{h}(y_n \underline{x}_n)$$

$$\Rightarrow \max_{\underline{\omega}} \text{likelihood}(\underline{\omega}) \propto \prod_{n=1}^N \theta(y_n \underline{\omega}^T \underline{x}_n)$$

$$\Rightarrow \max_{\underline{\omega}} \ln \prod_{n=1}^N \theta(y_n \underline{\omega}^T \underline{x}_n)$$

$$\Rightarrow \min_{\underline{\omega}} \frac{1}{N} \sum_{n=1}^N -\ln \theta(y_n \underline{\omega}^T \underline{x}_n)$$

$$\Rightarrow \min_{\underline{\omega}} \frac{1}{N} \sum_{n=1}^N -\ln \left( \frac{1}{2} \left( \frac{1}{\sqrt{1 + (y_n \underline{\omega}^T \underline{x}_n)^2}} + 1 \right) \right)$$

$$\Rightarrow \min_{\underline{\omega}} \frac{1}{N} \sum_{n=1}^N \left[ \ln 2 + \ln \sqrt{1 + (y_n \underline{\omega}^T \underline{x}_n)^2} - \ln(1 + \sqrt{1 + (y_n \underline{\omega}^T \underline{x}_n)^2}) \right]$$

$$\Rightarrow \min_{\underline{\omega}} \frac{1}{N} \underbrace{\sum_{n=1}^N \text{err}(\underline{\omega}, \underline{x}_n, y_n)}_{\tilde{E}_{\text{in}}(\underline{\omega})}$$

$$\text{err}(\underline{\omega}, \underline{x}, y) = \ln 2 + \ln \sqrt{1 + (y \underline{\omega}^T \underline{x})^2} - \ln(1 + \sqrt{1 + (y \underline{\omega}^T \underline{x})^2})$$

$$\tilde{E}_{\text{in}}(\underline{\omega}) = \frac{1}{N} \sum_{n=1}^N \left[ \ln 2 + \ln \sqrt{1 + (y_n \underline{\omega}^T \underline{x}_n)^2} - \ln(1 + \sqrt{1 + (y_n \underline{\omega}^T \underline{x}_n)^2}) \right]$$

$$\Rightarrow \frac{\partial \tilde{E}_{\text{in}}(\underline{\omega})}{\partial \omega_i} = \frac{1}{N} \sum_{n=1}^N \left[ \left( \frac{1}{\sqrt{1 + (y_n \underline{\omega}^T \underline{x}_n)^2}} \right) \left( \frac{-1}{(y_n \underline{\omega}^T \underline{x}_n)^3 \sqrt{1 + (y_n \underline{\omega}^T \underline{x}_n)^2}} \right) (-y_n x_{n,i}) \right. \\ \left. - \left( \frac{1}{1 + \sqrt{1 + (y_n \underline{\omega}^T \underline{x}_n)^2}} \right) \left( \frac{-1}{(y_n \underline{\omega}^T \underline{x}_n)^3 \sqrt{1 + (y_n \underline{\omega}^T \underline{x}_n)^2}} \right) (-y_n x_{n,i}) \right]$$

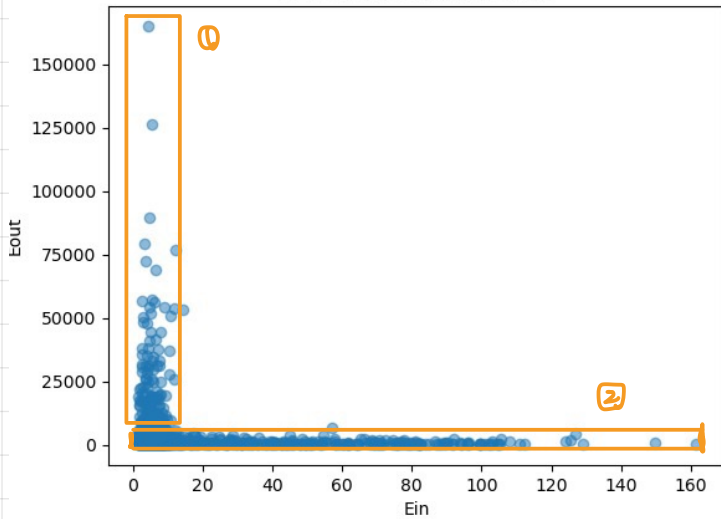
$$= \frac{1}{N} \sum_{n=1}^N \left( \frac{1}{\sqrt{1 + (y_n \underline{\omega}^T \underline{x}_n)^2}} - \frac{1}{1 + \sqrt{1 + (y_n \underline{\omega}^T \underline{x}_n)^2}} \right) \left( \frac{y_n x_{n,i}}{(y_n \underline{\omega}^T \underline{x}_n)^3 \sqrt{1 + (y_n \underline{\omega}^T \underline{x}_n)^2}} \right)$$

$$= \frac{1}{N} \sum_{n=1}^N \left( \frac{y_n x_{n,i}}{(1 + (y_n \underline{\omega}^T \underline{x}_n)^2)(1 + \sqrt{1 + (y_n \underline{\omega}^T \underline{x}_n)^2})(y_n \underline{\omega}^T \underline{x}_n)^3} \right)$$

$$\therefore \nabla \tilde{E}_{\text{in}}(\underline{\omega}) = \frac{1}{N} \sum_{n=1}^N \left( \frac{y_n \underline{x}_n}{(1 + (y_n \underline{\omega}^T \underline{x}_n)^2)(1 + \sqrt{1 + (y_n \underline{\omega}^T \underline{x}_n)^2})(y_n \underline{\omega}^T \underline{x}_n)^3} \right)$$

10.

no collaborators

Scatter plot of  $E_{in}$  vs  $E_{out}$ 

①  $E_{out}(\underline{w}_{lin})$  is far from  $E_{in}(\underline{w}_{lin})$   
and  $E_{in}(\underline{w}_{lin}) \approx 0$

②  $E_{out}(\underline{w}_{lin}) \approx E_{in}(\underline{w}_{lin})$  but  
 $E_{in}(\underline{w}_{lin})$  varies from 0 to 160  
Increase  $N$  to let  $E_{out}(\underline{w}_{lin}) \approx$   
 $E_{in}(\underline{w}_{lin})$  but  $E_{in}(\underline{w}_{lin})$  may increase.

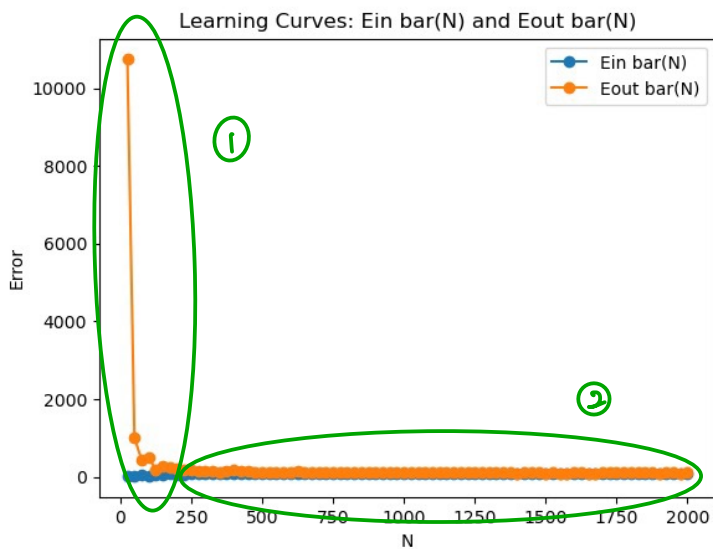
```

hw3-10.py > ...
1 > import numpy as np...
4
5 > def download_and_parse_data():...
28
29 # Linear regression
30 def linear_regression(X, y):
31     X_dagger = np.linalg.pinv(X) # pseudo-inverse of X
32     wlin = X_dagger @ y # wlin
33     return wlin
34
35 # Squared error
36 def squared_error(y_true, y_pred):
37     return np.mean((y_true - y_pred) ** 2)
38
39 # Error calculation for in-sample and out-of-sample
40 def calculate_errors(X_in, y_in, X_out, y_out, wlin):
41     y_in_pred = X_in @ wlin
42     y_out_pred = X_out @ wlin
43     Ein = squared_error(y_in, y_in_pred)
44     Eout = squared_error(y_out, y_out_pred)
45     return Ein, Eout
46
47 # Plot the results
48 > def plot_results(Ein_array, Eout_array):...
54
55 num_examples = 8192
56 N = 32
57 num_experiments = 1126
58 Ein_array = []
59 Eout_array = []
60
61 def main():
62     X, y = download_and_parse_data()
63
64     for _ in range(num_experiments):
65         indices = np.random.choice(num_examples, N, replace=False) # Randomly sample N examples for training
66         X_in = X[indices]
67         y_in = y[indices]
68         mask = np.ones(num_examples, dtype=bool)
69         mask[indices] = False
70         X_out = X[mask]
71         y_out = y[mask]
72
73         wlin = linear_regression(X_in, y_in)
74         Ein, Eout = calculate_errors(X_in, y_in, X_out, y_out, wlin)
75         Ein_array.append(Ein)
76         Eout_array.append(Eout)
77
78     plot_results(Ein_array, Eout_array)
79
80 if __name__ == '__main__':
81     main()

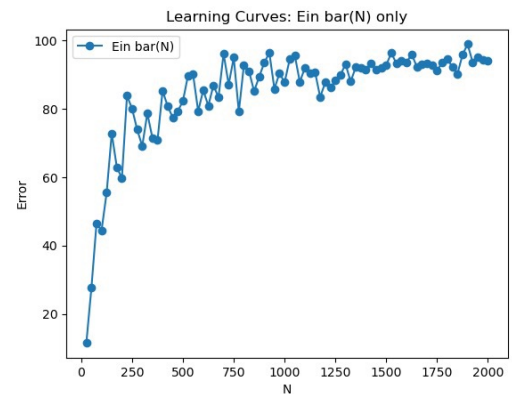
```

11.

no collaborators



- ①  $\bar{E}_{out}(N)$  are much larger than  $\bar{E}_{in}(N)$  when  $N$  is small
- ②  $\bar{E}_{out}(N) \approx \bar{E}_{in}(N)$  and  $\bar{E}_{in}(N)$  are lower than 100 auxiliary:



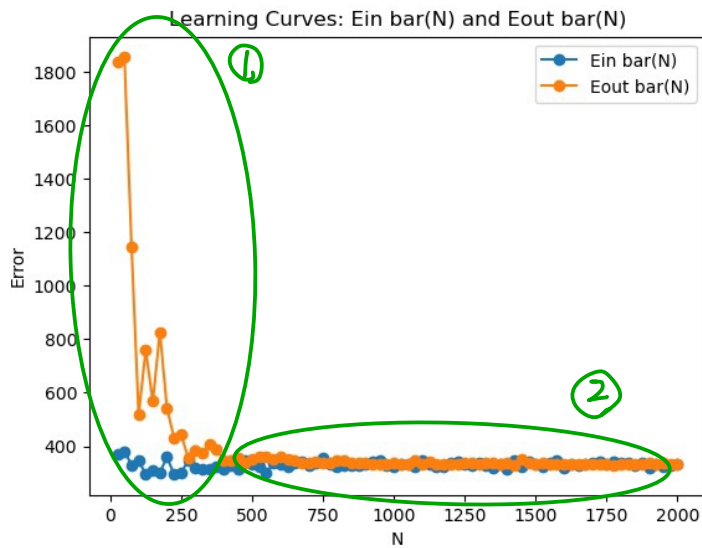
```

hw3-11.py > ...
1 > import numpy as np
4
5 > def download_and_parse_data(): ...
28
29 # Linear regression
30 > def linear_regression(X, y): ...
34
35 # Squared error
36 > def squared_error(y_true, y_pred): ...
38
39 # Error calculation for in-sample and out-of-sample
40 > def calculate_errors(X_in, y_in, X_out, y_out, wlin): ...
46 | Ctrl+L to chat, Ctrl+K to generate
47 # Plot the learning curves
48 > def plot_learning_curves(Ein_avg, Eout_avg): ...
56
57 num_examples = 8192
58 N_array = range(25, 2001, 25) # N values from 25 to 2000
59 num_experiments = 16
60
61 def main():
62     X, y = download_and_parse_data()
63     Ein_avg = []
64     Eout_avg = []
65     for N in N_array:
66         Ein_array = []
67         Eout_array = []
68         for _ in range(num_experiments):
69             indices = np.random.choice(num_examples, N, replace=False) # Randomly sample N examples for training
70             X_in = X[indices]
71             y_in = y[indices]
72             mask = np.ones(num_examples, dtype=bool)
73             mask[indices] = False
74             X_out = X[mask]
75             y_out = y[mask]
76
77             wlin = linear_regression(X_in, y_in)
78             Ein, Eout = calculate_errors(X_in, y_in, X_out, y_out, wlin)
79
80             Ein_array.append(Ein)
81             Eout_array.append(Eout)
82
83             # Calculate average Ein and Eout for the current N
84             Ein_avg.append(np.mean(Ein_array))
85             Eout_avg.append(np.mean(Eout_array))
86
87             # Plot the learning curves
88             plot_learning_curves(Ein_avg, Eout_avg)
89
90 if __name__ == '__main__':
91     main()

```

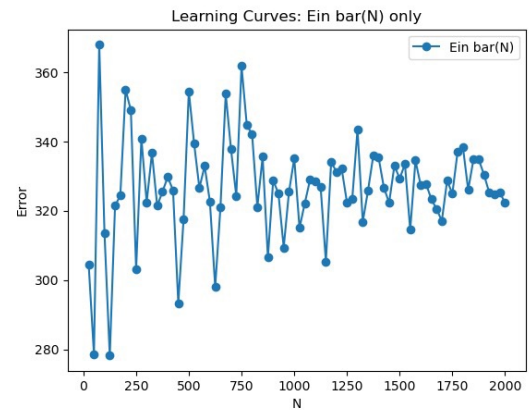


## 12. no collaborators



①  $\bar{E}_{out}(N)$  are larger than  $\bar{E}_{in}(N)$  when  $N$  is small, and both  $\bar{E}_{out}(N)$  and  $\bar{E}_{in}(N)$  oscillate with  $N$

②  $\bar{E}_{out}(N) \approx \bar{E}_{in}(N)$  and  $\bar{E}_{in}(N)$  are lower than 400 but higher than 250



```
hw3-12.py > download_and_parse_data
1 > import numpy as np
2
3
4
5 def download_and_parse_data():
6     # Downloading the dataset
7     url = 'https://www.csie.ntu.edu.tw/~cjlin/libsvmtools/datasets/regression/cpusmall_scale'
8     response = requests.get(url)
9     data = response.text
10
11     # Preprocess the data
12     lines = data.strip().split('\n')
13     labels = []
14     features = []
15     for line in lines:
16         tokens = line.split()
17         labels.append(int(tokens[0])) # The first value is the target (y)
18         feature = [1] # x0 = 1
19         for token in tokens[1:3]: # Use only the first 2 features
20             _, value = token.split(":")
21             feature.append(float(value))
22         features.append(feature)
23
24     X = np.array(features)
25     y = np.array(labels)
26
27     return X, y
28
29 # Linear regression
30 > def linear_regression(X, y): ...
31
32
33
34
35 # Squared error
36 > def squared_error(y_true, y_pred): ...
37
38
39 # Error calculation for in-sample and out-of-sample
40 > def calculate_errors(X_in, y_in, X_out, y_out, wlin): ...
41
42
43
44
45
46
47 # Plot the learning curves
48 > def plot_learning_curves(N_array, Ein_avg, Eout_avg): ...
49
50
51
52
53
54
55
56
57 # Experiment parameters
58 num_examples = 8192
59 N_array = range(25, 2001, 25) # N values from 25 to 2000
60 num_experiments = 16
61
62 > def main(): ...
63
64
65
66
67
68
69
70
71
72 if __name__ == '__main__':
73     main()
```