

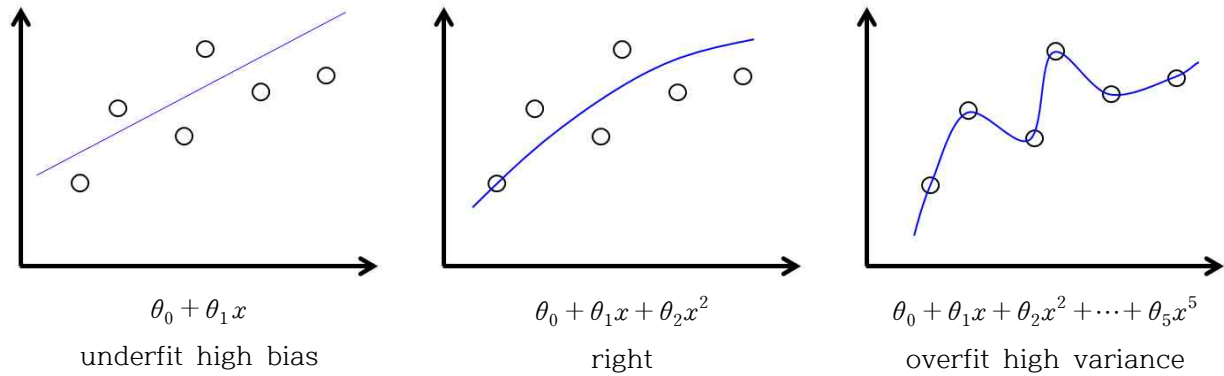
Machine Learning Lecture Note

This lecture note is based on the CS229 lecture materials from Stanford University.

Lecture 7 Bias/Variance, Regularization, Train

Bias : expected error created by using a model

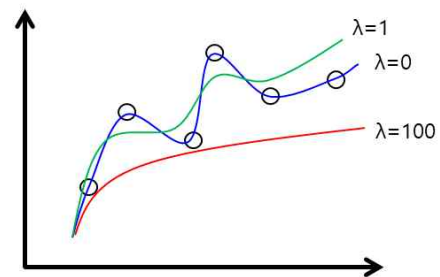
Variance : amount that predicted values would change in a different training dataset.



Regularization

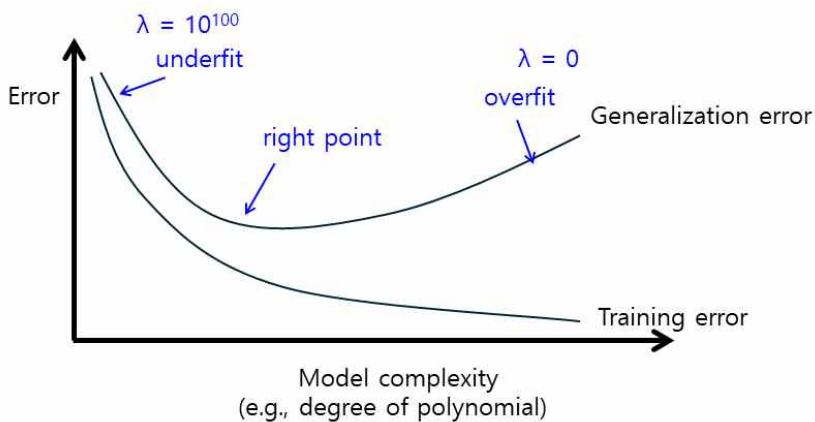
$$\min_{\theta} \frac{1}{2} \sum_{i=1}^m \|y^i - \theta^T x^i\|^2 + \frac{1}{2} \lambda \|\theta\|^2$$

$\frac{1}{2} \lambda \|\theta\|^2$: regularization term, 오버피팅되는 모델을 조정한다. λ 가 매우 큰 값을 가지면 오버피팅된 모델은 언더피팅의 효과를 가진다.



General form in logistic regression

$$\operatorname{argmax}_{\theta} \sum_{i=1}^m \log p(y^i | x^i; \theta) - \lambda \|\theta\|^2$$



Train

Data sets: $S = \{S_{train}, S_{dev}, S_{test}\}$

1) Train each model (option for the degree of polynomial) on S_{train} .

Get some hypothesis h_i

2) Measure the error on S_{dev} .

Pick a model with the lowest error on S_{dev} .

※ S_{train} 으로 학습하지 않는 이유: 복잡한 알고리즘은 항상 훈련 데이터 셋에서 더 좋은 성능을 보이기 때문에 overfit 발생 가능성이 높다.

3) Evaluate an algorithm on S_{test} .

Take training set

- historical perspective: 70% train, 30% test; 60% train, 20% dev, 20% test

대용량 데이터를 가지지 않았을 때 주로 사용하는 방법.

- modern perspective

대용량 데이터를 학습에 사용하는 경우 알고리즘간 성능을 파악하기 위해서 dev, test 데이터 셋의 비율을 줄인다. (e.g., 90% train, 5% dev, 5% test)

Small data set

m = 100 examples (70 test, 30 dev)

k-fold cross validation:

$S = \{(x^1, y^1), \dots, (x^{100}, y^{100})\}$ k=5 for illustration; k=10 is typical

divide the data set to 5 subset. so there are 20 examples in each subset.

For d=1, ..., 5 (degree of polynomial) { <- k=5 인 예제에서 다음과 같이 수행할 수 있다.

For i = 1, ..., k,

Train (fit parameters) on k-1 pieces

Test on the remaining 1 piece

Average

}

Feature selection

많은 feature가 있는 경우, overfitting을 줄이는 한가지 방법은 task에 가장 유용한 feature의 작은 subset을 찾는 것이다.

(example) 5 features: $x_1, x_2, \dots, x_5$

Start with $F = \phi$

Repeat:

1) Try adding each feature i to F , and see which single feature addition most improves the dev set performance.

2) Add that feature to F

step 1: $[\phi]$ $F = \{ \}$

step 2: $\begin{bmatrix} \phi + x_1 \\ \phi + x_2 \\ \vdots \\ \phi + x_5 \end{bmatrix}$ $F = \{x_2\}$

step 3: $\begin{bmatrix} x_2 + x_1 \\ x_2 + x_3 \\ \vdots \\ x_2 + x_5 \end{bmatrix}$ $F = \{x_2, x_4\}$