

Debugging learning algorithm

Sid

- more training examples $\rightarrow 1$
 - smaller/greater features $\rightarrow 1$
 - polynomial features $\rightarrow 2$
 - decreasing/increasing λ
 - 2
 - 1
- 1) fix high variance
2) fix high bias

ML Diagnostic

- test to gain insight to learning algorithm and how to improve performance.

Evaluate Hypothesis

- Split data into training & test set
- learn θ from training
- Compute test error $(J_{\text{test}}(\theta))$

(70%)
Training
 $(x^{(1)}, y^{(1)})$
 $(x^{(2)}, y^{(2)})$
 \vdots
 $(x^{(m)}, y^{(m)})$

(30%)
Test
 $(x_{\text{test}}^{(1)}, y_{\text{test}}^{(1)})$
 $(x_{\text{test}}^{(2)}, y_{\text{test}}^{(2)})$
 \vdots
 $(x_{\text{test}}^{(m_{\text{test}})}, y_{\text{test}}^{(m_{\text{test}})})$

- Misclassification error

$$\text{error}(h_{\theta}(x), y) = \begin{cases} 1 & h_{\theta}(x) \geq 0.5, y = 0 \\ & h_{\theta}(x) < 0.5, y = 1 \\ 0 & \text{(otherwise)} \end{cases}$$

$$\text{Test Error} = \frac{1}{m_{\text{test}}} \sum_{i=1}^{m_{\text{test}}} \text{error}(h_{\theta}(x_{\text{test}}^{(i)}), y_{\text{test}}^{(i)})$$

Model Selection:

- Training (60%) \rightarrow optimize parameters (θ) for each 'd'
- Cross Validation (20%) \rightarrow Find 'd' w/ least error ($J_{cv}(\theta)$)
- Test (20%) \rightarrow generalization error: $J_{test}(\theta^{(d)})$

$$d=1 \quad 1) \quad h_{\theta}(x) = \theta_0 + \theta_1 x \quad \rightarrow \theta^{(1)} \quad \rightarrow J_{cv}(\theta^{(1)})$$

$$d=2 \quad 2) \quad h_{\theta}(x) = \theta_0 + \theta_1 x + \theta_2 x^2 \quad \rightarrow \theta^{(2)} \quad \rightarrow J_{cv}(\theta^{(2)})$$

\vdots

$$d) \quad h_{\theta}(x) = \theta_0 + \theta_1 x + \dots + \theta_d x^d \quad \rightarrow \theta^{(d)} \quad \rightarrow J_{cv}(\theta^{(d)})$$

Bias vs Variance

- High bias (underfit)

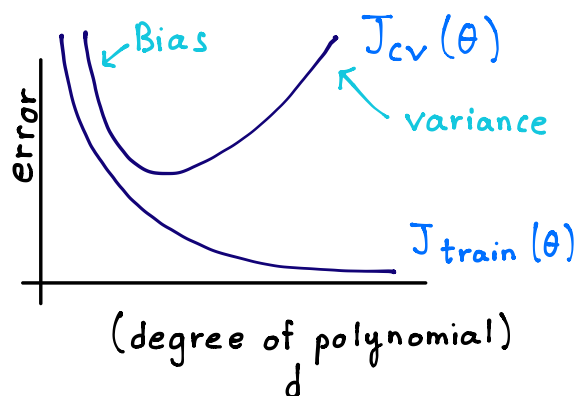
$J_{train}(\theta)$ is high

$J_{cv}(\theta) \approx J_{train}(\theta)$

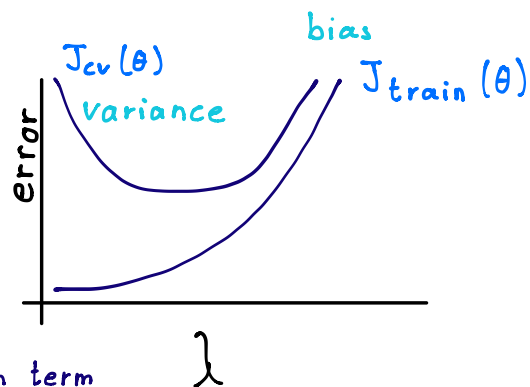
- High variance (overfit)

$J_{train}(\theta)$ is low

$J_{cv}(\theta) \gg J_{train}(\theta)$



Regularization & bias/variance (prevent overfitting)

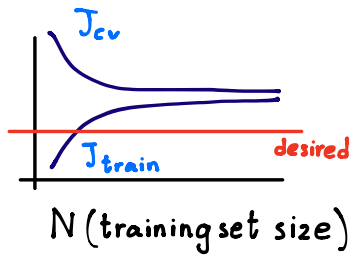


$$J(\theta) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2 + \frac{\lambda}{2m} \sum_{j=1}^n \theta_j^2$$

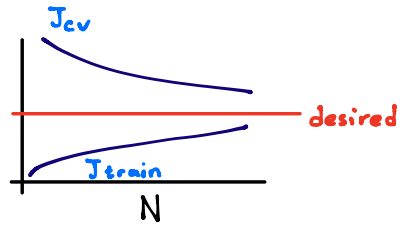
$J_{train}(\theta)$, $J_{cv}(\theta)$, $J_{test}(\theta)$: No regularization term

Learning Curve

- High Bias



- High Variance



more training data

↖ X ↗

↖ ✓ ↗