

# Evaluating a Learning Algorithm

## 1. How to improve my learning algorithm:

- Get more training examples: fix high variance
- Try smaller sets of features: fix high variance
- Try getting additional features: fix high bias
- Try add polynomial features: fix high bias
- Try decrease  $\lambda$ : fix high bias
- Try increasing  $\lambda$ : fix high variance

## 2. Learning Diagnostic:

- definition: a test you can run to gain insight what is/isn't working;

## 3. Evaluating a hypothesis:

- Split dataset into training set and test set(70%/30%, randomize ordering of data);
- Compute test error:  $J_{test}(\Theta) = \frac{1}{2m_{test}} \dots$  also the case for classification problems;
- Misclassification error(0/1 misclassification error):  $err(H_{\Theta}(x), y) = 1/0$  based on if prediction is correct or not;  $Test_{err} = 1/m \sum_{i=1}^{m_{test}} err_i$

## 4. Model selection and train/validation/test sets:

- choose different models(polynomial ) to see how the test dataset performs:

## Model selection

→  $d = \text{degree of polynomial}$  ↓

$$\begin{array}{ll}
 d=1 & 1. \rightarrow h_{\theta}(x) = \theta_0 + \theta_1 x \rightarrow \Theta^{(1)} \rightarrow J_{\text{test}}(\Theta^{(1)}) \\
 d=2 & 2. \rightarrow h_{\theta}(x) = \theta_0 + \theta_1 x + \theta_2 x^2 \rightarrow \Theta^{(2)} \rightarrow J_{\text{test}}(\Theta^{(2)}) \\
 d=3 & 3. \rightarrow h_{\theta}(x) = \theta_0 + \theta_1 x + \dots + \theta_3 x^3 \rightarrow \Theta^{(3)} \rightarrow J_{\text{test}}(\Theta^{(3)}) \\
 \vdots & \vdots \\
 d=10 & 10. \rightarrow h_{\theta}(x) = \theta_0 + \theta_1 x + \dots + \theta_{10} x^{10} \rightarrow \Theta^{(10)} \rightarrow J_{\text{test}}(\Theta^{(10)})
 \end{array}$$

Choose  $\theta_0 + \dots + \theta_5 x^5$  ←

How well does the model generalize? Report test set error  $J_{\text{test}}(\theta^{(5)})$ .

Problem:  $J_{\text{test}}(\theta^{(5)})$  is likely to be an optimistic estimate of generalization error. I.e. our extra parameter ( $d = \text{degree of polynomial}$ ) is fit to test set.

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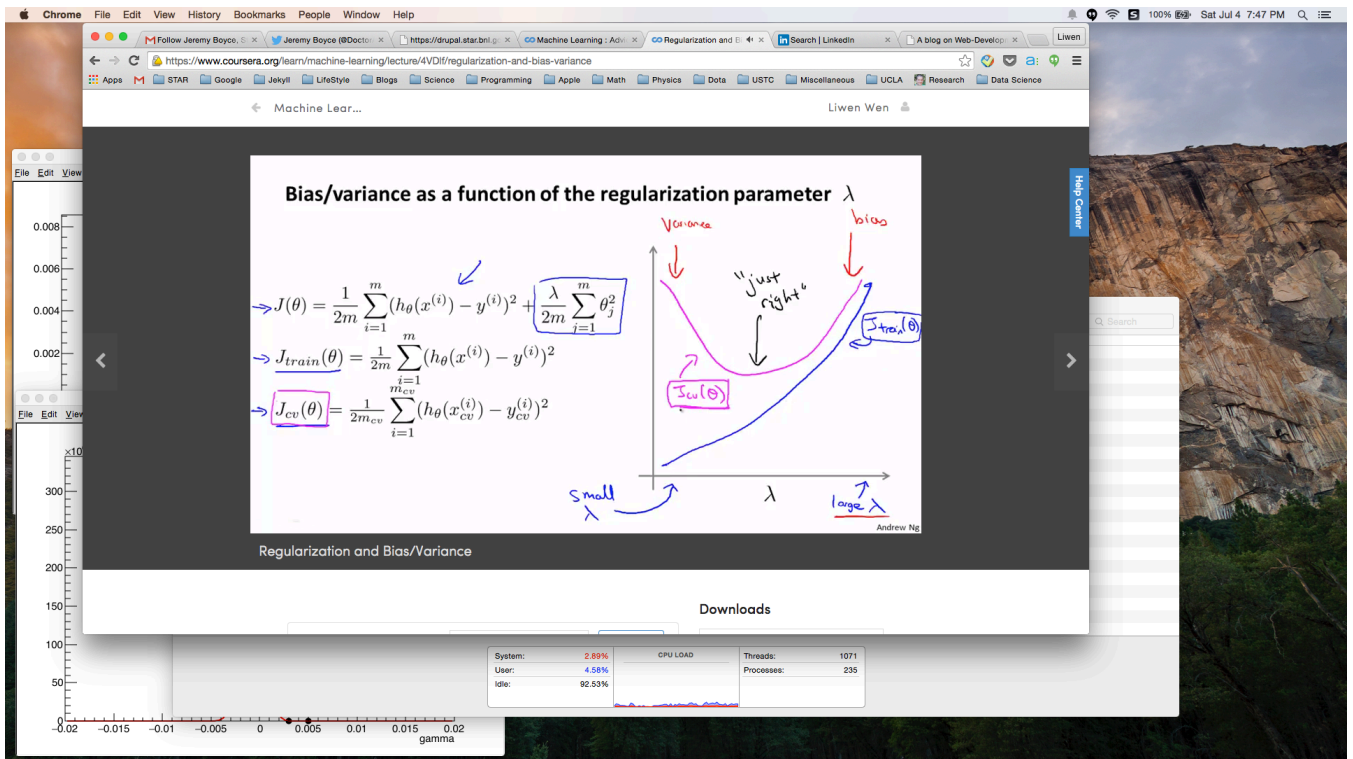
- Training/cross validation/test set(60/20/20, training error/cross validation error/ test error):
  - get hypothesis parameters;
  - apply these hypothesis on cv data set(other wise the degree of polynomial is fitted to test dataset);
  - apply the optimal hypothesis on test data set to estimate generalization error for the model selected;

## 5. Diagnosing bias vs. variance:

- plot degree of poly. vs. error:
- distinguish bias/variance:
  - bias: high-training error, high-cross validation error
  - variance: low-training error, high-cross validation error

## 6. Regularization and bias/variance:

- large  $\lambda$  : underfitting;
- intermediate  $\lambda$ : just right;
- small  $\lambda$ : overfitting;
- like in logistics regress fitting, try different  $\lambda$  from 0 to 10(for example) and follow previous procedures:



## 7. Learning curves:

- learning curves: error vs.  $m$
- high bias: converge for both training error and cv error (no help to increase the sample number)
- high variance: big gap between training error and cv error (it helps to get more samples)

## 8. How to choose neural network archetect

- small: underfitting and computationally cheap;
- large struture: overfitting and can be fixed by regularization;