



Machine Learning

Advice for applying machine learning

Deciding what to try next

Debugging a learning algorithm:

Suppose you have implemented regularized linear regression to predict housing prices.

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

However, when you test your hypothesis on a new set of houses, you find that it makes unacceptably large errors in its predictions. What should you try next?

- \rightarrow - Get more training examples
- Try smaller sets of features $x_1, x_2, x_3, \dots, x_{100}$
- \rightarrow - Try getting additional features
- Try adding polynomial features (x_1^2 , x_2^2 , $x_1 x_2$, etc.)
- Try decreasing λ
- Try increasing λ

Machine learning diagnostic:

Diagnostic: A test that you can run to gain insight what is/Isn't working with a learning algorithm, and gain guidance as to how best to improve its performance.

Diagnostics can take time to implement, but doing so can be a very good use of your time.



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Evaluating a hypothesis

Evaluating your hypothesis



→
$$h_{\theta}(x) = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$$

Fails to generalize to new examples not in training set.

x_1 = size of house

x_2 = no. of bedrooms

x_3 = no. of floors

x_4 = age of house

x_5 = average income in neighborhood

x_6 = kitchen size

\vdots

x_{100}

Evaluating your hypothesis

Dataset:

Size	Price
2104	400
1600	330
2400	369
1416	232
3000	540
1985	300
1534	315
1427	199
1380	212
1494	243

Handwritten annotations: 70% (next to training set), 30% (next to test set), Training set (bracketed next to first 7 rows), Test Set (bracketed next to last 3 rows).

$$\begin{pmatrix} x^{(1)}, y^{(1)} \\ x^{(2)}, y^{(2)} \\ \vdots \\ x^{(m)}, y^{(m)} \end{pmatrix}$$

$$\begin{pmatrix} x_{test}^{(1)}, y_{test}^{(1)} \\ x_{test}^{(2)}, y_{test}^{(2)} \\ \vdots \\ x_{test}^{(m_{test})}, y_{test}^{(m_{test})} \end{pmatrix}$$

$m_{test} = \text{no. of test example}$
 $(x_{test}^{(i)}, y_{test}^{(i)})$

Training/testing procedure for linear regression

→ - Learn parameter θ from training data (minimizing training error $J(\theta)$) 70%

- Compute test set error:

$$J_{\text{test}}(\theta) = \frac{1}{2m_{\text{test}}} \sum_{i=1}^{m_{\text{test}}} \left(\frac{h_{\theta}(x_{\text{test}}^{(i)}) - y_{\text{test}}^{(i)}}{1} \right)^2$$

Training/testing procedure for logistic regression

- Learn parameter θ from training data
- Compute test set error:

$$J_{test}(\theta) = -\frac{1}{m_{test}} \sum_{i=1}^{m_{test}} y_{test}^{(i)} \log h_{\theta}(x_{test}^{(i)}) + (1 - y_{test}^{(i)}) \log h_{\theta}(x_{test}^{(i)})$$

- Misclassification error (0/1 misclassification error):

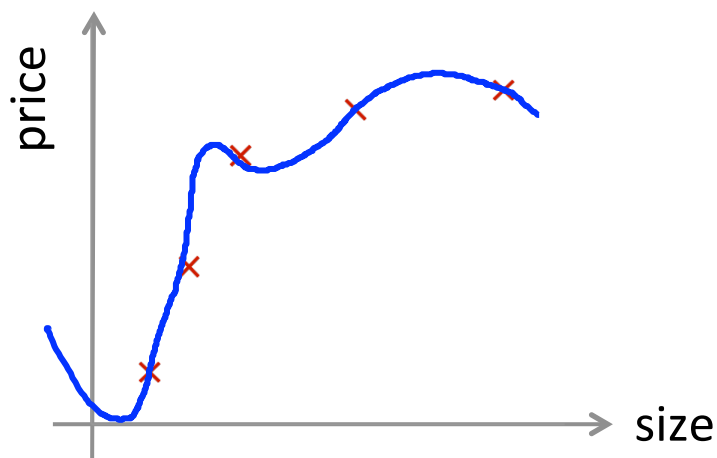


Machine Learning

Advice for applying machine learning

Model selection and
training/validation/test
sets

Overfitting example



$$h_{\theta}(x) = \underline{\theta_0} + \underline{\theta_1}x + \underline{\theta_2}x^2 + \theta_3x^3 + \theta_4x^4$$

Once parameters $\theta_0, \theta_1, \dots, \theta_4$ were fit to some set of data (training set), the error of the parameters as measured on that data (the training error $J(\theta)$) is likely to be lower than the actual generalization error.

→ $d = \text{degree of polynomial}$

Model selection

$d=1$ 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. $\rightarrow h_{\theta}(x) = \theta_0 + \theta_1 x + \dots + \theta_{10} x^{10} \rightarrow \Theta^{(10)} \rightarrow J_{\text{test}}(\Theta^{(10)})$

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

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 = degree of polynomial) is fit to test set.

$\Theta_0, \Theta_1, \dots$

Evaluating your hypothesis

Dataset:

Size	Price	
2104	400	60% Training set
1600	330	
2400	369	
1416	232	
3000	540	
1985	300	
1534	315	20% Cross validation set (cv)
1427	199	
1380	212	20% test set
1494	243	



Train/validation/test error

Training error:

$$\rightarrow J_{train}(\theta) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

$J(\theta)$

Cross Validation error:

$$\rightarrow J_{cv}(\theta) = \frac{1}{2m_{cv}} \sum_{i=1}^{m_{cv}} (h_{\theta}(x_{cv}^{(i)}) - y_{cv}^{(i)})^2$$

Test error:

$$\rightarrow J_{test}(\theta) = \frac{1}{2m_{test}} \sum_{i=1}^{m_{test}} (h_{\theta}(x_{test}^{(i)}) - y_{test}^{(i)})^2$$

Model selection

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

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

$d=3$ 3. $h_{\theta}(x) = \theta_0 + \theta_1 x + \dots + \theta_3 x^3 \rightarrow \theta^{(3)} \rightarrow J_{cv}(\theta^{(3)})$

\vdots

$d=10$ 10. $h_{\theta}(x) = \theta_0 + \theta_1 x + \dots + \theta_{10} x^{10} \rightarrow \theta^{(10)} \rightarrow J_{cv}(\theta^{(10)})$

$d=4$ \nearrow

Pick $\theta_0 + \theta_1 x + \dots + \theta_4 x^4 \leftarrow$

Estimate generalization error for test set $J_{test}(\theta^{(4)})$ \leftarrow



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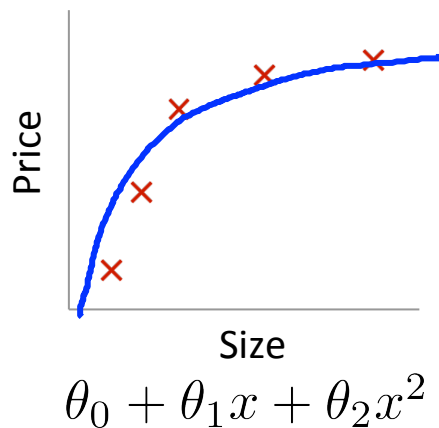
Advice for applying machine learning

Diagnosing **bias vs.** **variance**

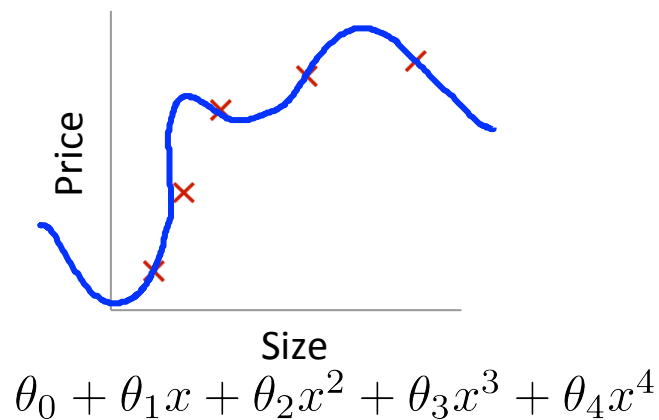
Bias/variance



High bias
(underfit)
 $d=1$



“Just right”
 $d=2$

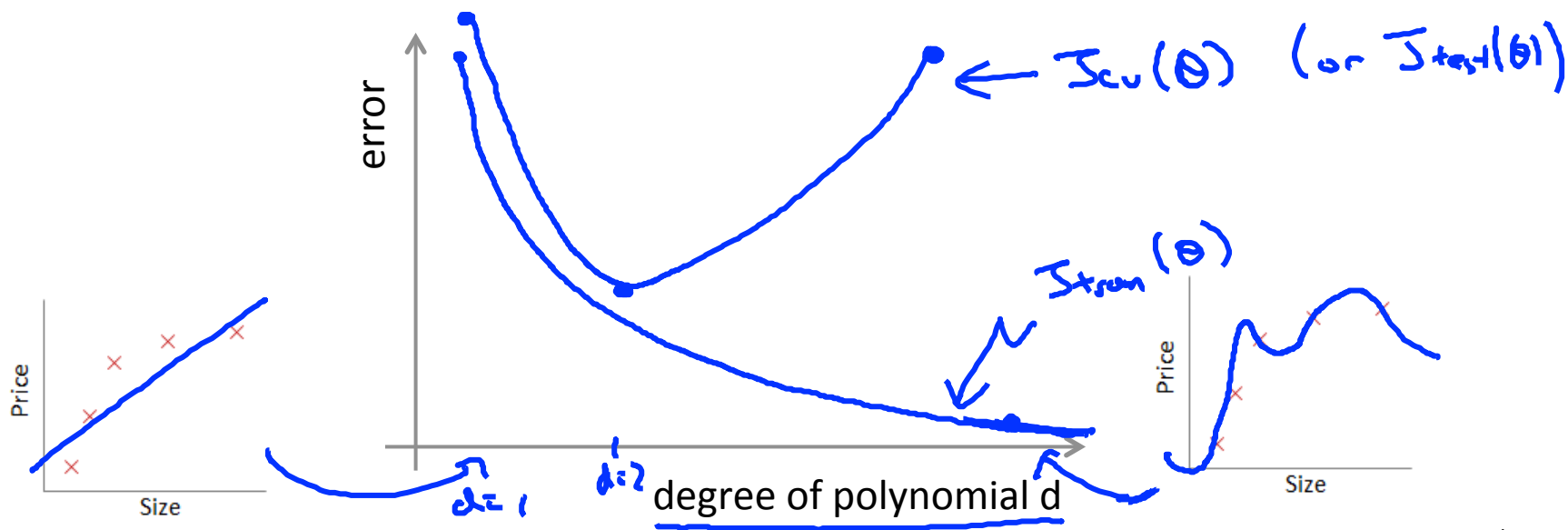


High variance
(overfit)
 $d=4$

Bias/variance

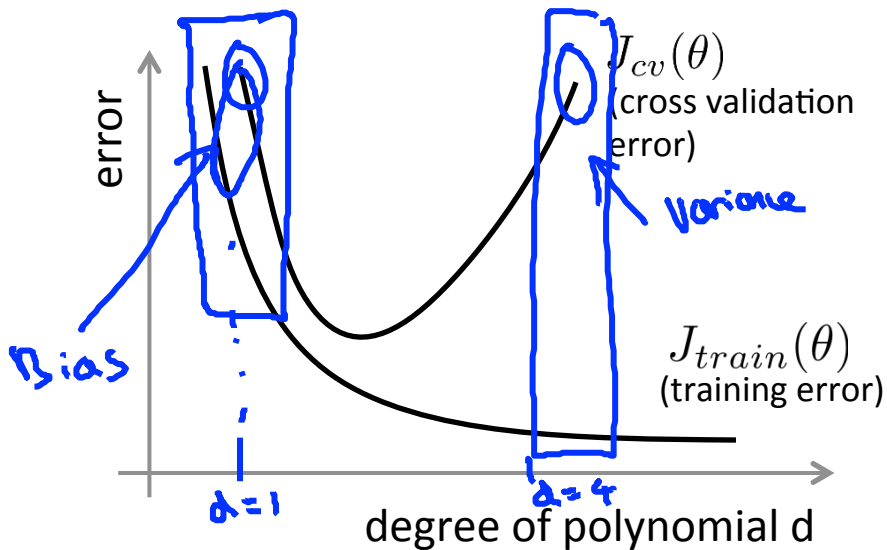
Training error: $J_{train}(\theta) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$

Cross validation error: $J_{cv}(\theta) = \frac{1}{2m_{cv}} \sum_{i=1}^{m_{cv}} (h_{\theta}(x_{cv}^{(i)}) - y_{cv}^{(i)})^2$ (or $J_{test}(\theta)$)



Diagnosing bias vs. variance

Suppose your learning algorithm is performing less well than you were hoping. ($J_{cv}(\theta)$ or $J_{test}(\theta)$ is high.) Is it a bias problem or a variance problem?



Bias (underfit):

$$\rightarrow \left. \begin{array}{l} J_{train}(\theta) \text{ will be high} \\ J_{cv}(\theta) \approx J_{train}(\theta) \end{array} \right\}$$

Variance (overfit):

$$\rightarrow \left. \begin{array}{l} J_{train}(\theta) \text{ will be low} \\ J_{cv}(\theta) \gg J_{train}(\theta) \end{array} \right\}$$

\Rightarrow



Machine Learning

Advice for applying machine learning

Regularization and bias/variance

Linear regression with regularization

Model: $h_{\theta}(x) = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$

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



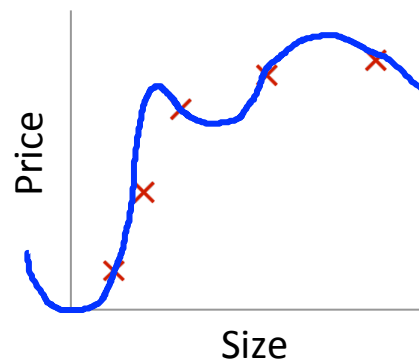
Large λ

→ High bias (underfit)

→ $\lambda = 10000$. $\theta_1 \approx 0, \theta_2 \approx 0, \dots$
 $h_{\theta}(x) \approx \theta_0$



Intermediate λ
"Just right"



→ Small λ

High variance (overfit)

→ $\lambda = 0$

Choosing the regularization parameter λ

$$h_{\theta}(x) = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4 \quad \leftarrow$$

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

$$\rightarrow J_{train}(\theta) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

$$J_{cv}(\theta) = \frac{1}{2m_{cv}} \sum_{i=1}^{m_{cv}} (h_{\theta}(x_{cv}^{(i)}) - y_{cv}^{(i)})^2$$

$$J_{test}(\theta) = \frac{1}{2m_{test}} \sum_{i=1}^{m_{test}} (h_{\theta}(x_{test}^{(i)}) - y_{test}^{(i)})^2$$

$J(\theta)$

J_{train}
 J_{cv}
 J_{test}

Choosing the regularization parameter λ

Model: $h_{\theta}(x) = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$

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

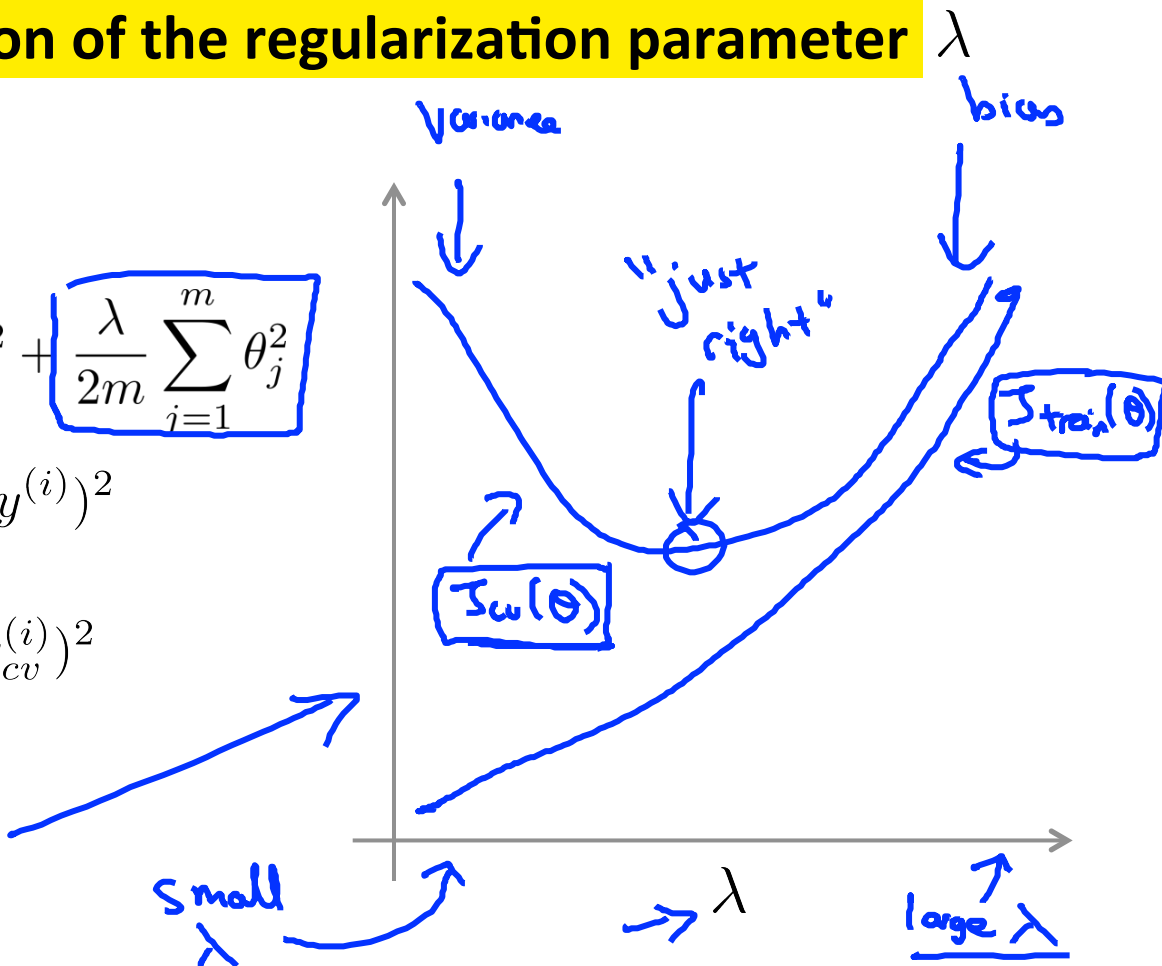
1. Try $\lambda = 0 \leftarrow \uparrow \rightarrow \min_{\theta} J(\theta) \rightarrow \theta^{(1)} \rightarrow J_w(\theta^{(1)})$
 2. Try $\lambda = 0.01$ $\rightarrow \min_{\theta} J(\theta) \rightarrow \theta^{(2)} \rightarrow J_w(\theta^{(2)})$
 3. Try $\lambda = 0.02$ $\rightarrow \theta^{(3)} \rightarrow J_w(\theta^{(3)})$
 4. Try $\lambda = 0.04$ \vdots
 5. Try $\lambda = 0.08$ $\rightarrow \theta^{(5)} \rightarrow J_w(\theta^{(5)})$
 - \vdots
 12. Try $\lambda = 10$ $\rightarrow \theta^{(12)} \rightarrow J_w(\theta^{(12)})$
 $\uparrow \quad \underline{10.24}$
- Pick (say) $\theta^{(5)}$. Test error: $J_{\text{test}}(\theta^{(5)})$

Bias/variance as a function of the regularization parameter λ

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

$$\rightarrow \underline{J_{train}(\theta)} = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

$$\rightarrow \boxed{J_{cv}(\theta)} = \frac{1}{2m_{cv}} \sum_{i=1}^{m_{cv}} (h_{\theta}(x_{cv}^{(i)}) - y_{cv}^{(i)})^2$$





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Learning curves

Learning curves

$$\rightarrow \underline{J_{train}(\theta)} = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2 \leftarrow$$

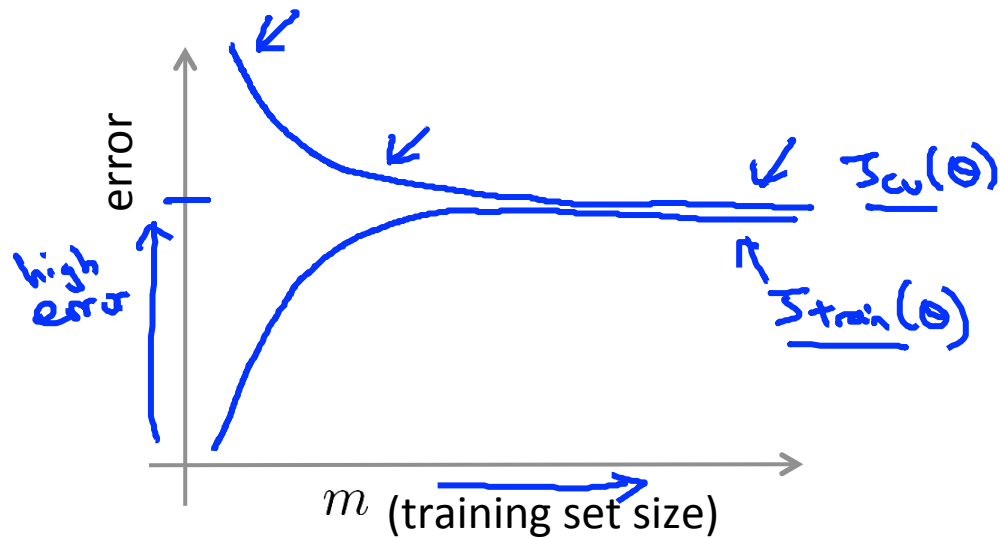
$$\rightarrow J_{cv}(\theta) = \frac{1}{2m_{cv}} \sum_{i=1}^{m_{cv}} (h_{\theta}(x_{cv}^{(i)}) - y_{cv}^{(i)})^2$$



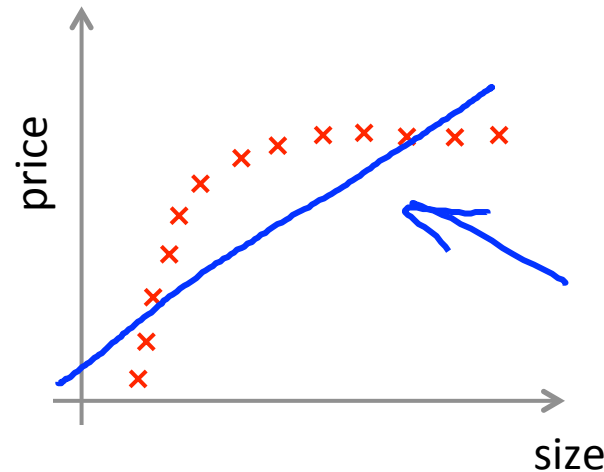
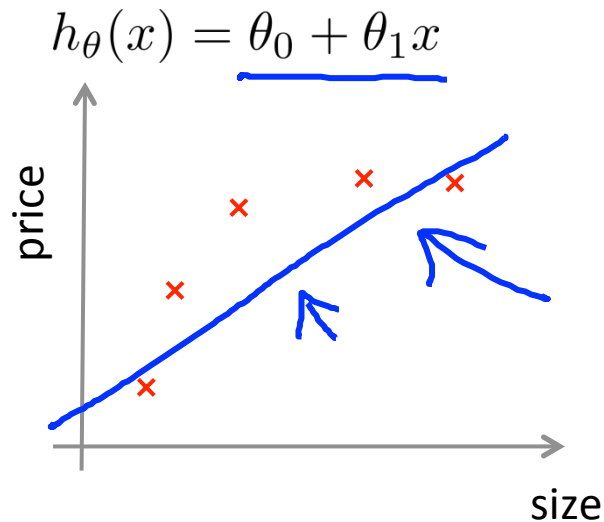
$$h_{\theta}(x) = \theta_0 + \theta_1 x + \theta_2 x^2$$



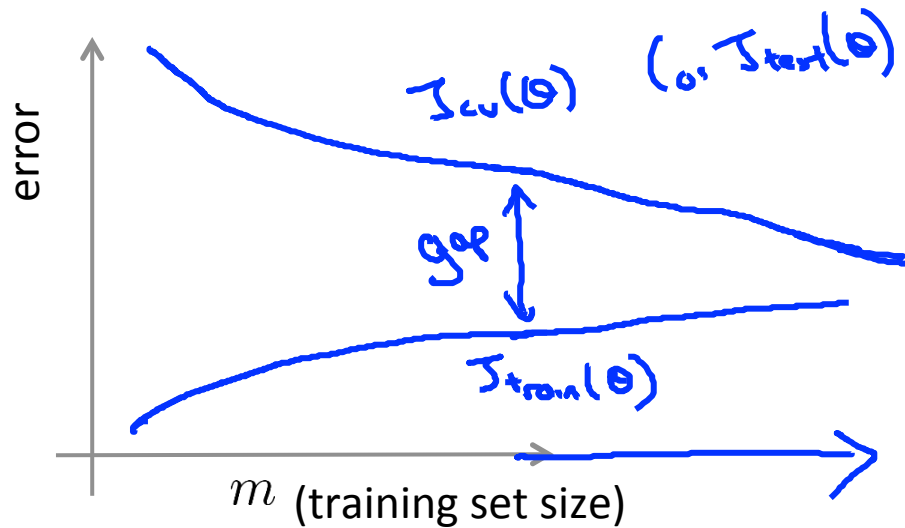
High bias



If a learning algorithm is suffering from high bias, getting more training data will not (by itself) help much.



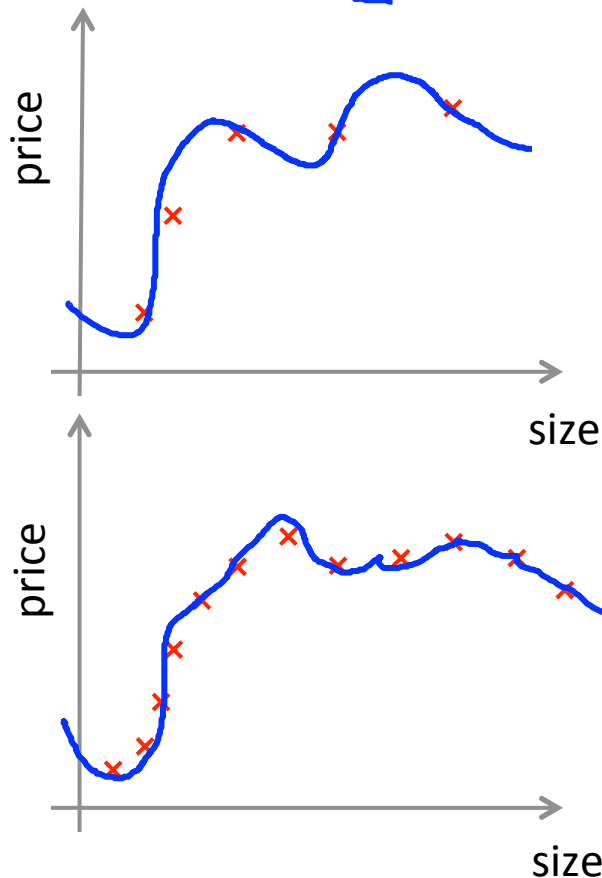
High variance



If a learning algorithm is suffering from high variance, getting more training data is likely to help. \leftarrow

$$h_{\theta}(x) = \theta_0 + \theta_1 x + \dots + \theta_{100} x^{100}$$

(and small λ) \nearrow





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Deciding what to try next (revisited)

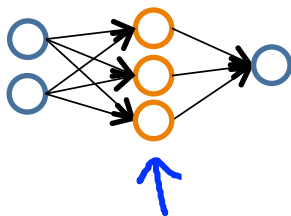
Debugging a learning algorithm:

Suppose you have implemented regularized linear regression to predict housing prices. However, when you test your hypothesis in a new set of houses, you find that it makes unacceptably large errors in its prediction. What should you try next?

- Get more training examples → fixes high variance
- Try smaller sets of features → fixes high variance
- Try getting additional features → fixes high bias
- Try adding polynomial features (x_1^2, x_2^2, x_1x_2 , etc) → fixes high bias.
- Try decreasing λ → fixes high bias
- Try increasing λ → fixes high variance

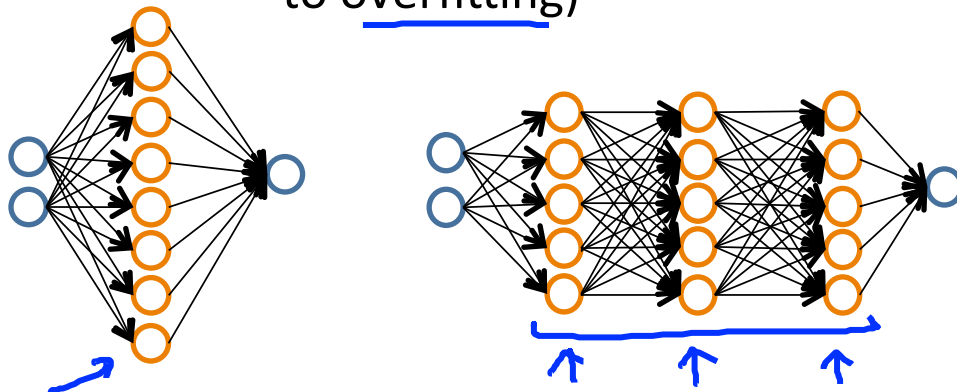
Neural networks and overfitting

→ “Small” neural network
(fewer parameters; more
prone to underfitting)



Computationally cheaper

→ “Large” neural network
(more parameters; more prone
to overfitting)



Computationally more expensive.

Use regularization (λ) to address overfitting.

$J_{co}(\theta)$ ↑