



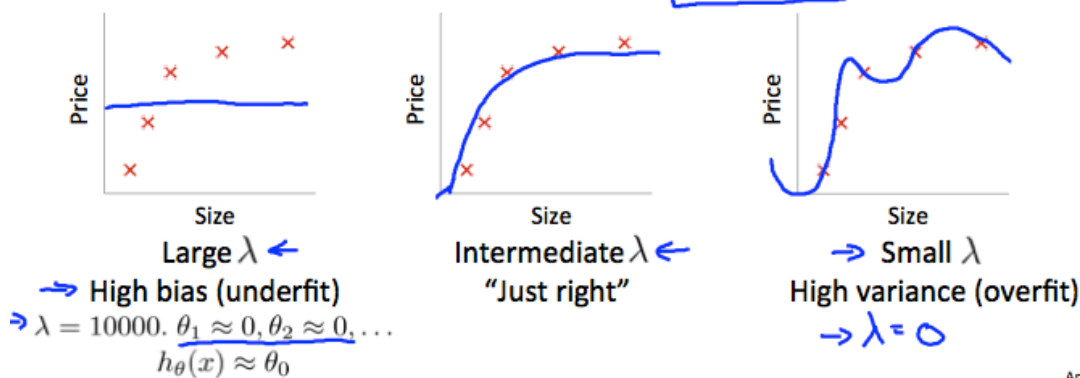
Regularization and Bias/Variance

Note: [The regularization term below and through out the video should be $\frac{\lambda}{2m} \sum_{j=1}^n \theta_j^2$ and **NOT** $\frac{\lambda}{2m} \sum_{j=1}^m \theta_j^2$]

Linear regression with regularization

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

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



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In the figure above, we see that as λ increases, our fit becomes more rigid. On the other hand, as λ approaches 0, we tend to overfit the data. So how do we choose our parameter λ to get it 'just right'? In order to choose the model and the regularization term λ , we need to:

1. Create a list of lambdas (i.e. $\lambda \in \{0, 0.01, 0.02, 0.04, 0.08, 0.16, 0.32, 0.64, 1.28, 2.56, 5.12, 10.24\}$);
2. Create a set of models with different degrees or any other variants.
3. Iterate through the λ s and for each λ go through all the models to learn some Θ .
4. Compute the cross validation error using the learned Θ (computed with λ) on the $J_{CV}(\Theta)$ **without** regularization or $\lambda = 0$.
5. Select the best combo that produces the lowest error on the cross validation set.
6. Using the best combo Θ and λ , apply it on $J_{test}(\Theta)$ to see if it has a good generalization of the problem.

[Mark as completed](#)