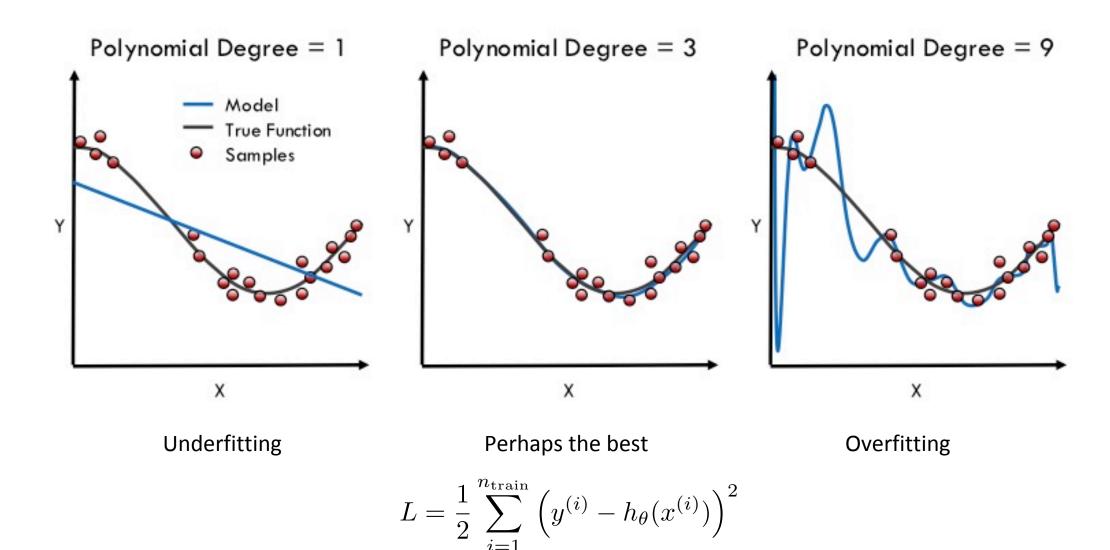
Regularization

Kookjin Lee

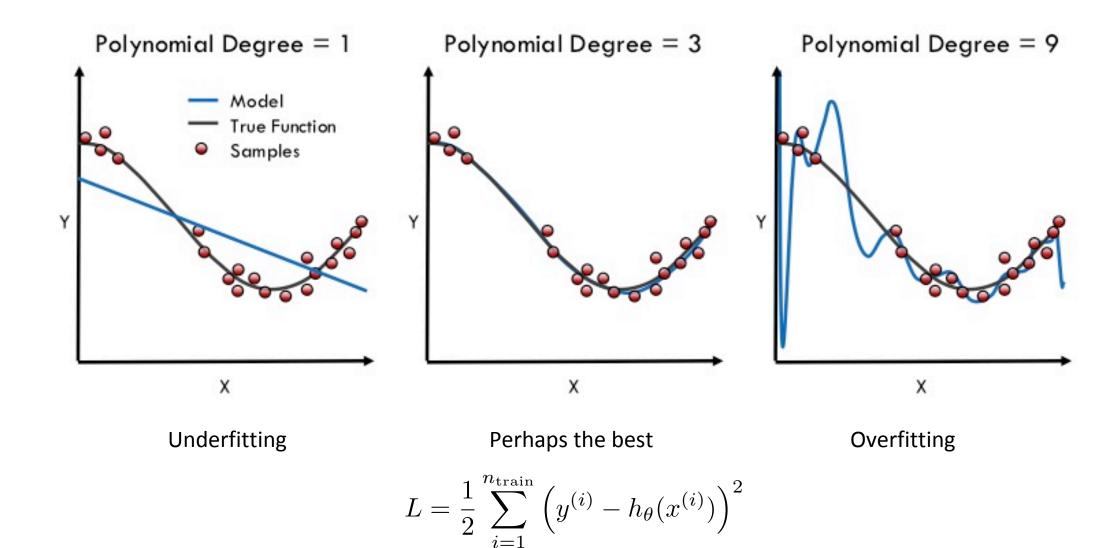
(kookjin.Lee@asu.edu)

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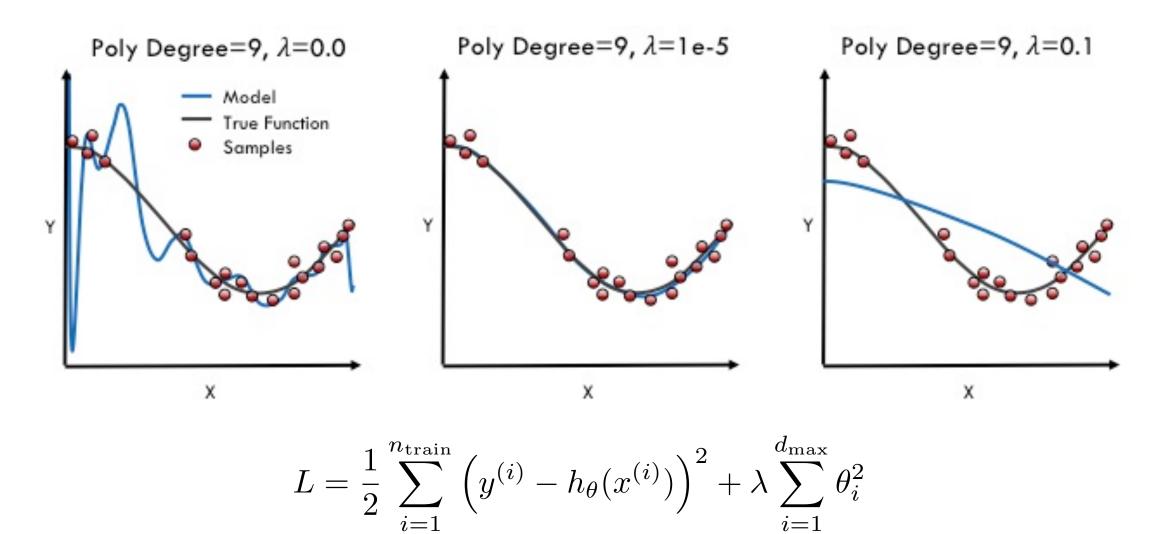
How to prevent overfitting?



Regularization



Regularization



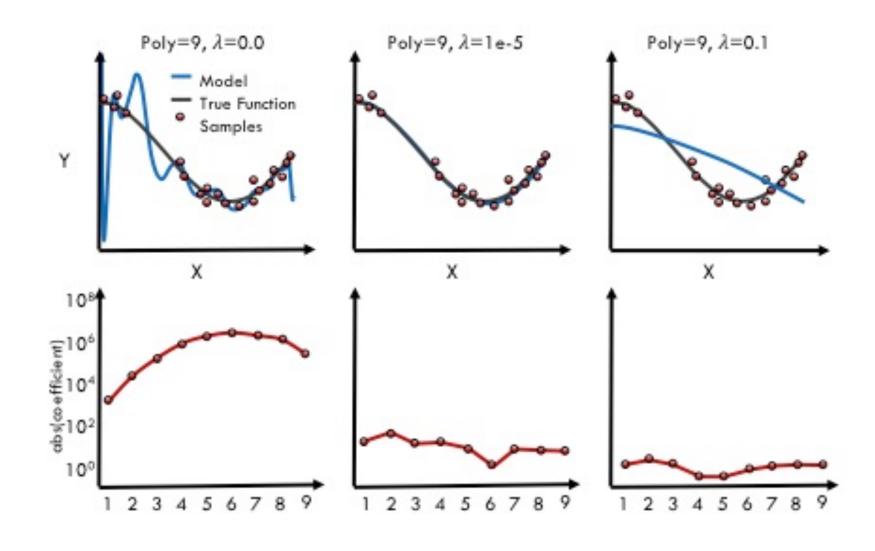
Ridge regression

L2-penalty

$$L = \frac{1}{2} \sum_{i=1}^{n_{\text{train}}} \left(y^{(i)} - h_{\theta}(x^{(i)}) \right)^{2} + \lambda \sum_{i=1}^{d_{\text{max}}} \theta_{i}^{2}$$

- Shrinks magnitude of all coefficients
- Larger coefficients strongly penalized because of the squaring

Effect of Ridge regression on parameters



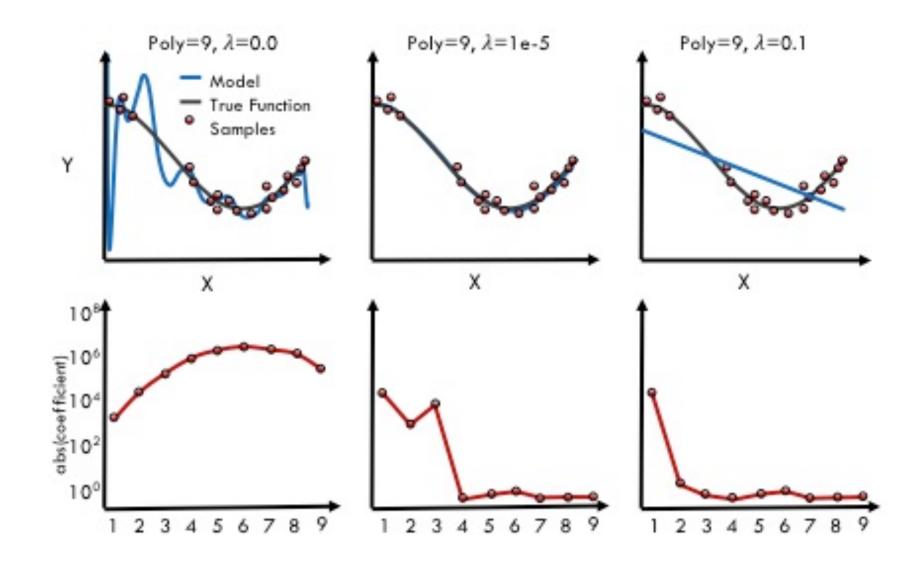
Lasso regression

L1-penalty

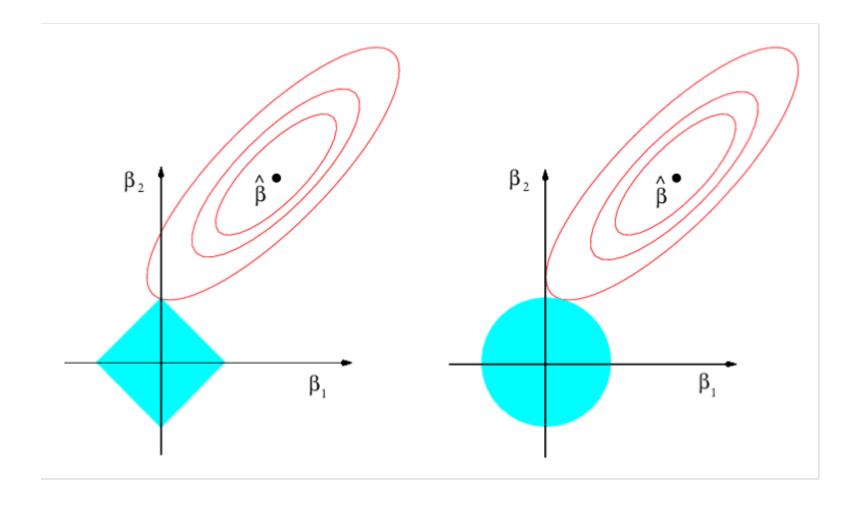
$$L = \frac{1}{2} \sum_{i=1}^{n_{\text{train}}} \left(y^{(i)} - h_{\theta}(x^{(i)}) \right)^{2} + \lambda \sum_{i=1}^{d_{\text{max}}} |\theta_{i}|$$

- Penalty selectively shrinks some coefficients
- Can be used for feature selection
- Slower convergence than Ridge regression

Effect of Lasso Regression on Parameters



L2 and L1 comparison



Elastic Net regularization

• L1 + L2

$$L = \frac{1}{2} \sum_{i=1}^{n_{\text{train}}} \left(y^{(i)} - h_{\theta}(x^{(i)}) \right)^{2} + \lambda_{1} \sum_{i=1}^{d_{\text{max}}} \theta_{i}^{2} + \lambda_{2} \sum_{i=1}^{d_{\text{max}}} |\theta_{i}|$$

- Compromise of both Ridge and Lasso regression
- Requires tuning of additional parameter that distributes regularization penalty between L1 and L2

Effect of Elastic Net Regression on Parameters

