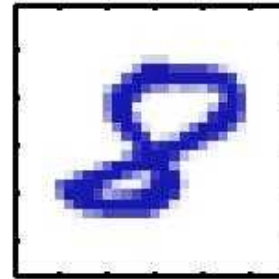
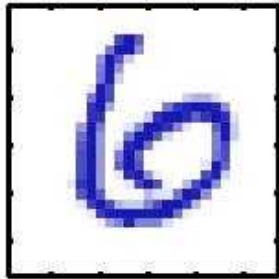
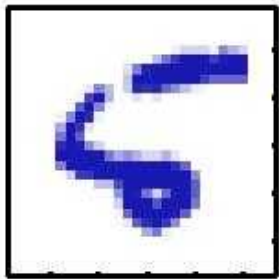
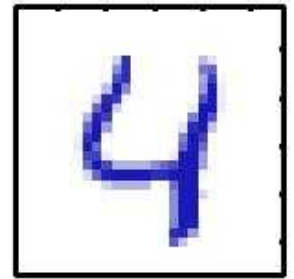
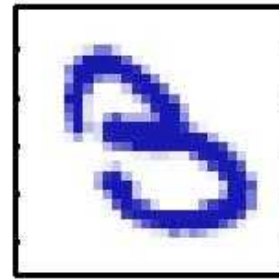
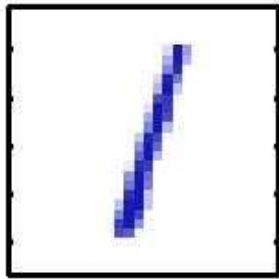
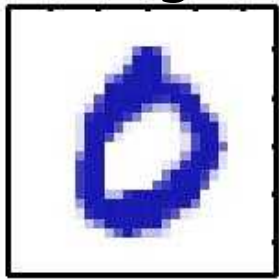




**PATTERN RECOGNITION
AND MACHINE LEARNING
CHAPTER 1: INTRODUCTION**

Example

Handwritten Digit
Recognition



What is Machine Learning?

Machine learning: branch of **artificial intelligence**

Goals

- recognize complex patterns
- make decisions based on data

Challenge

- available data (training data) is complex

(Wikipedia)

Supervised and Unsupervised

Supervised Learning:

- Divide elements into training set and test set
- Generalize from training to test
- Classification/regression

Unsupervised Learning

- No training set/test set (no target values)
 - Discover groups of similar elements
 - Clustering/density estimation
-

Supervised Machine Learning

Divide data into

- Training set (used during training/learning)
- Test set (used to test)

Key element: generalization

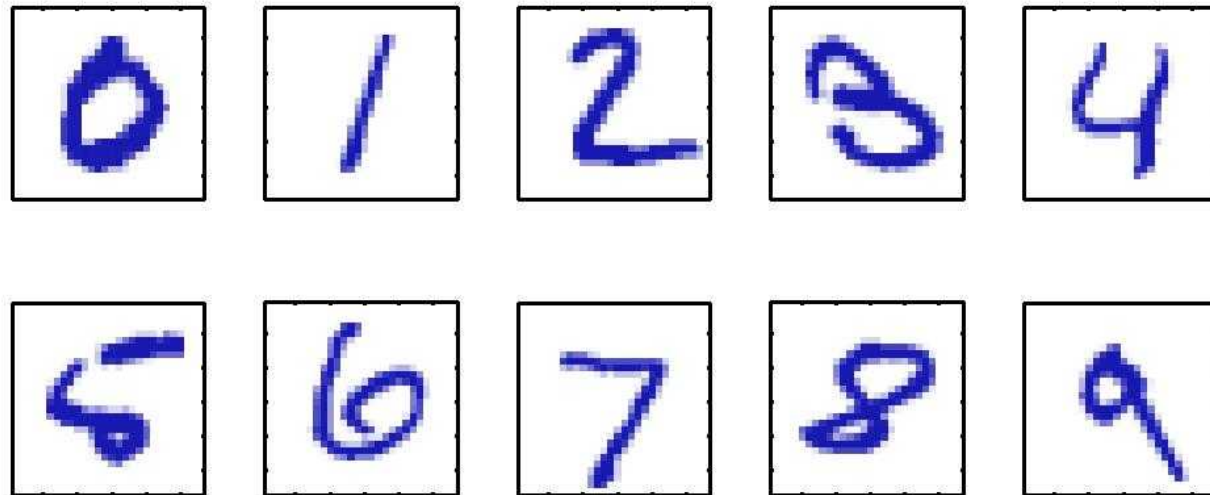
Pre-processing/feature extraction

Example of pre-processing

- Translation
- Rotation

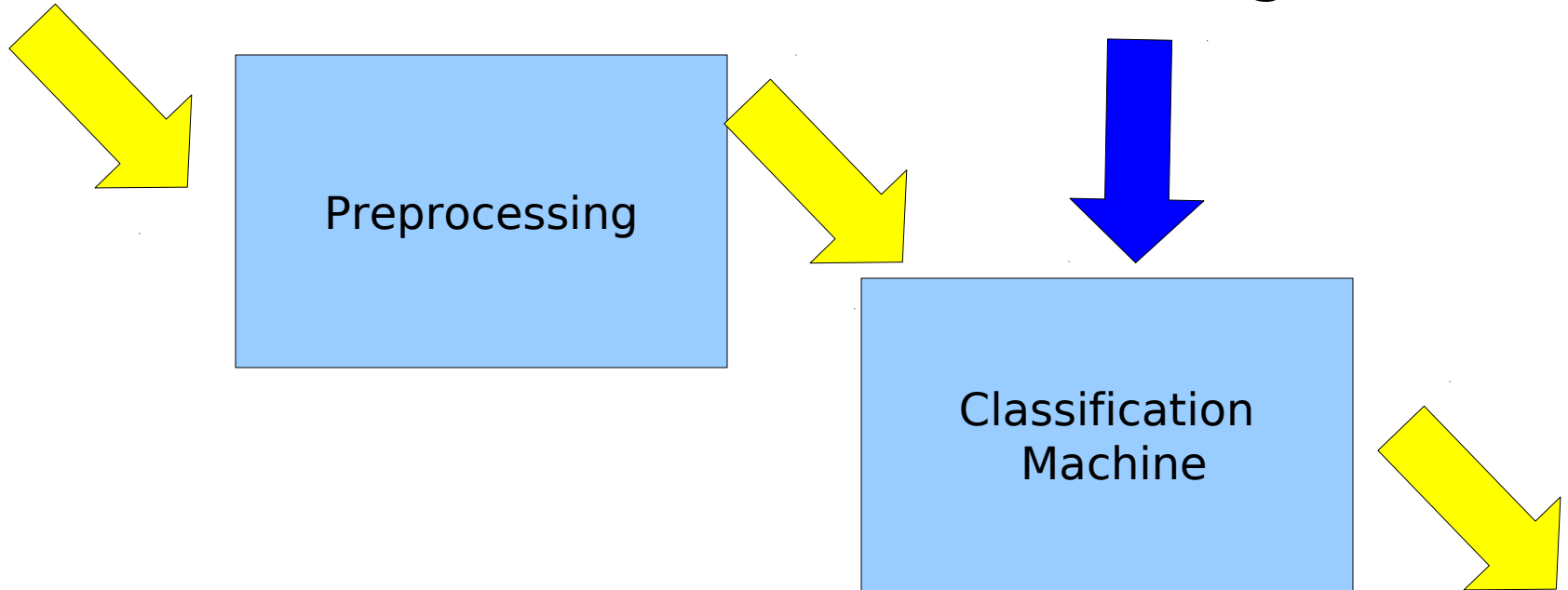
Example of feature extraction

- Get average number of black points
- Get point in the middle of the grid



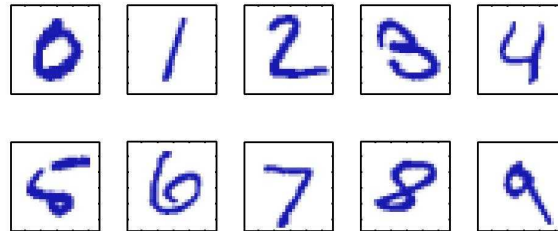
Machine Learning Methodology

| | | | | |
|---|---|---|---|---|
| 0 | 1 | 2 | 3 | 4 |
| 5 | 6 | 7 | 8 | 9 |

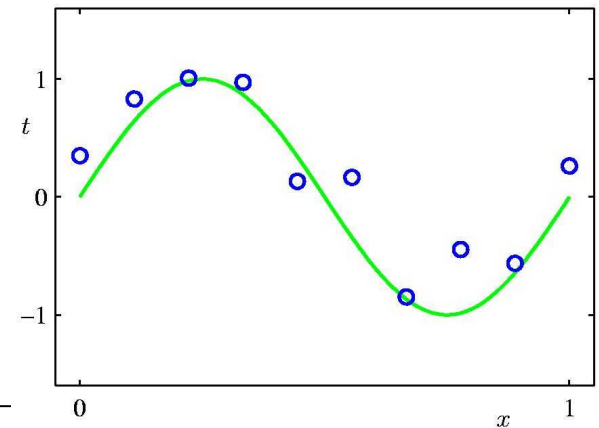


Classification and Regression

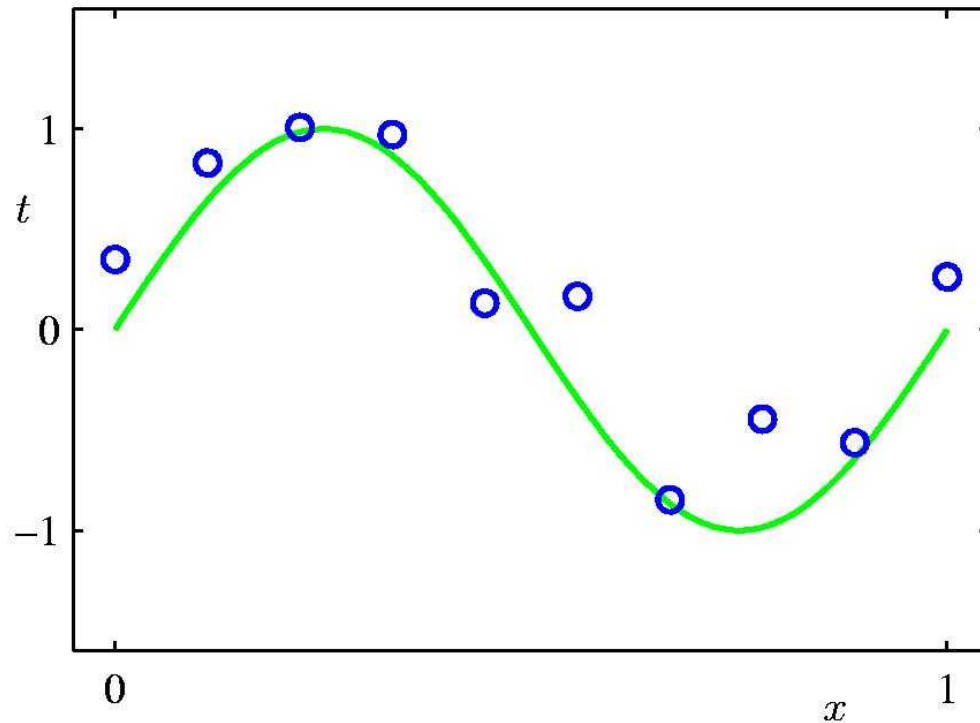
Classification: discrete categories



Regression: continuous categories

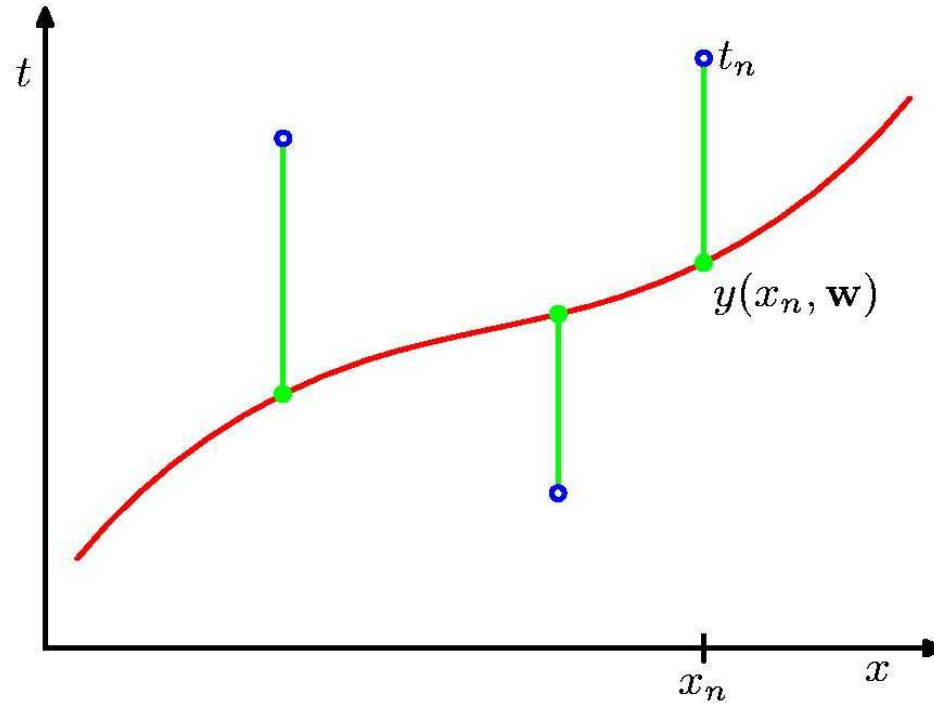


Polynomial Curve Fitting



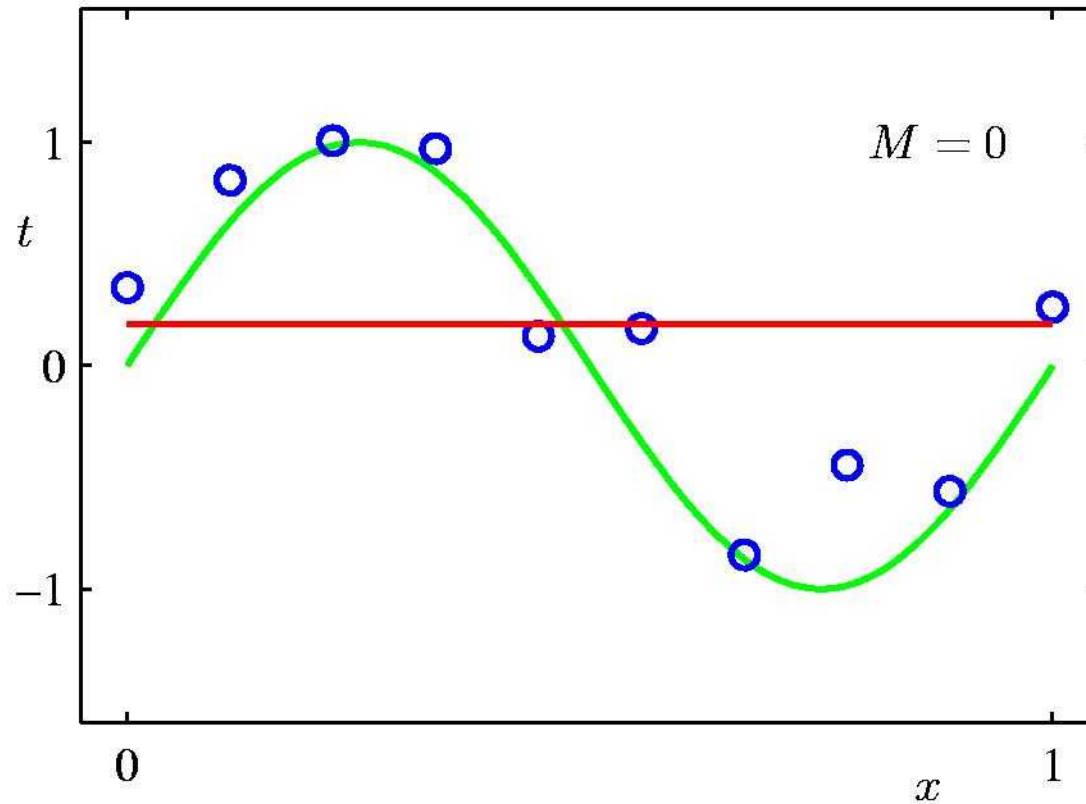
$$y(x, \mathbf{w}) = w_0 + w_1x + w_2x^2 + \dots + w_Mx^M = \sum_{j=0}^M w_jx^j$$

Sum-of-Squares Error Function

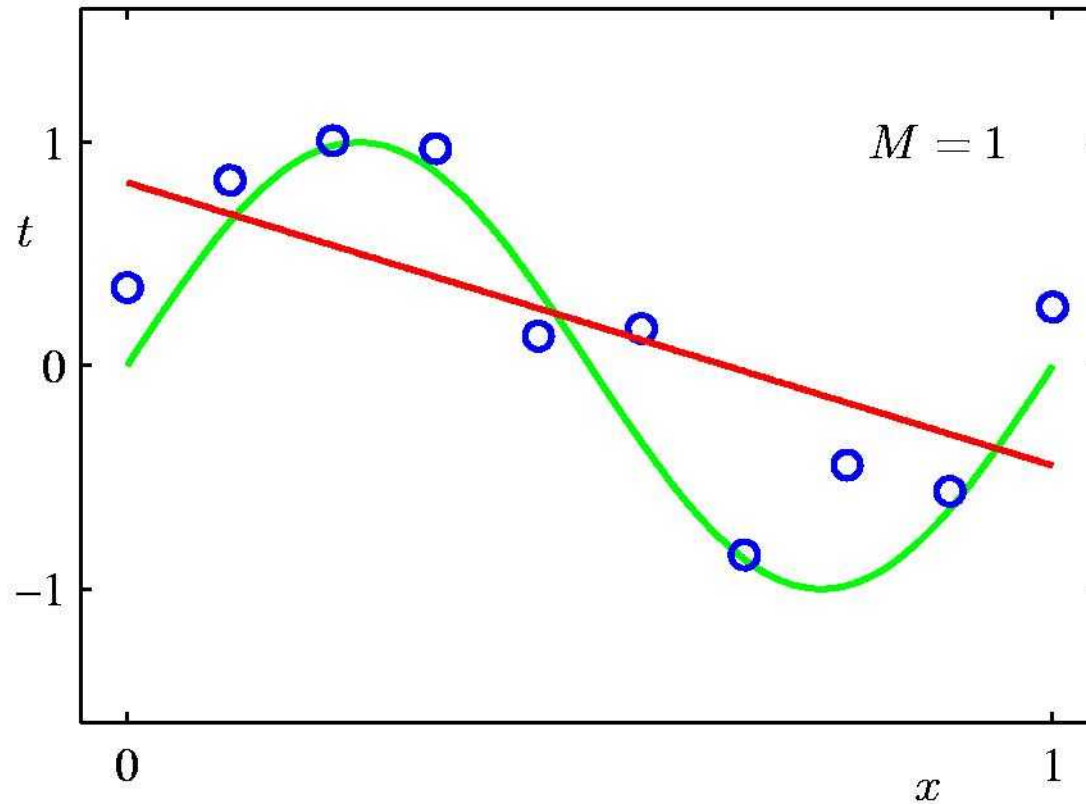


$$E(\mathbf{w}) = \frac{1}{2} \sum_{n=1}^N \{y(x_n, \mathbf{w}) - t_n\}^2$$

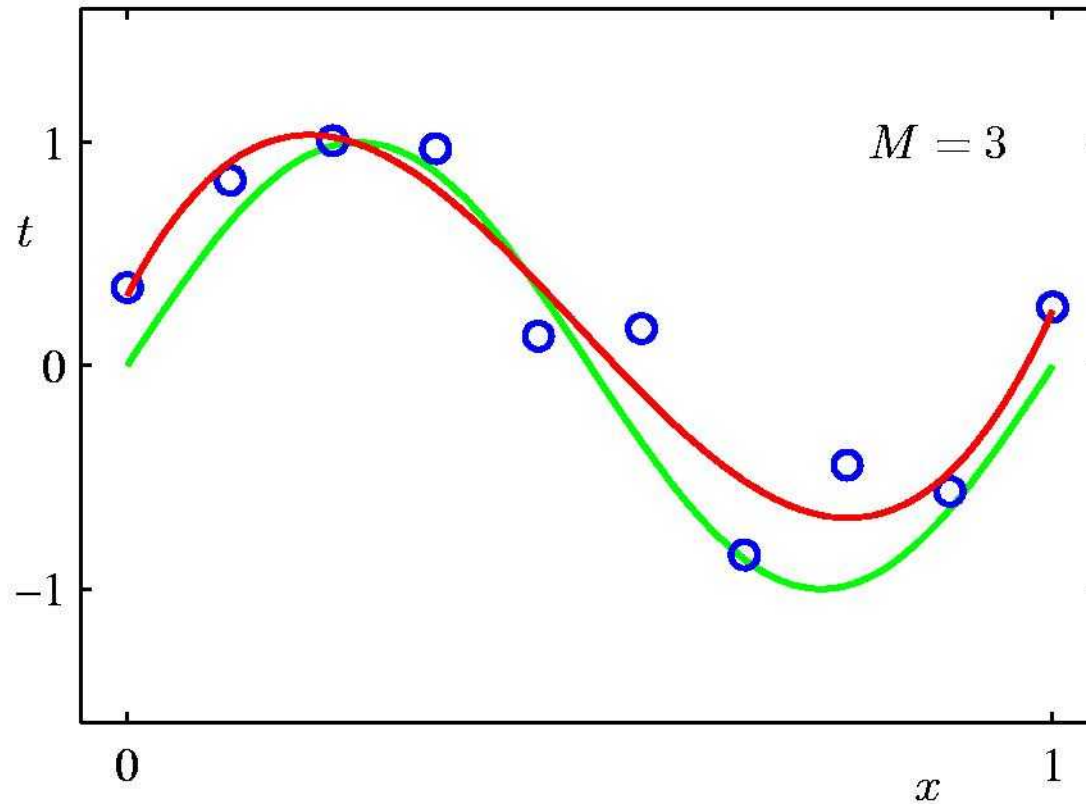
0th Order Polynomial



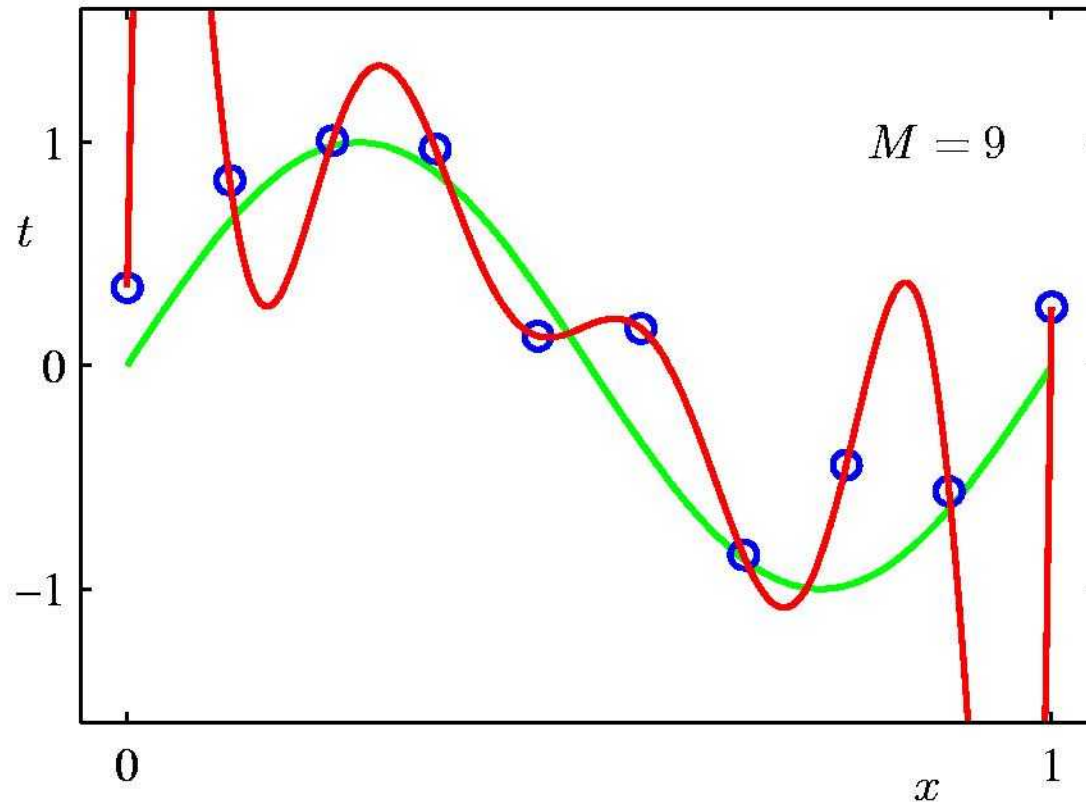
1st Order Polynomial



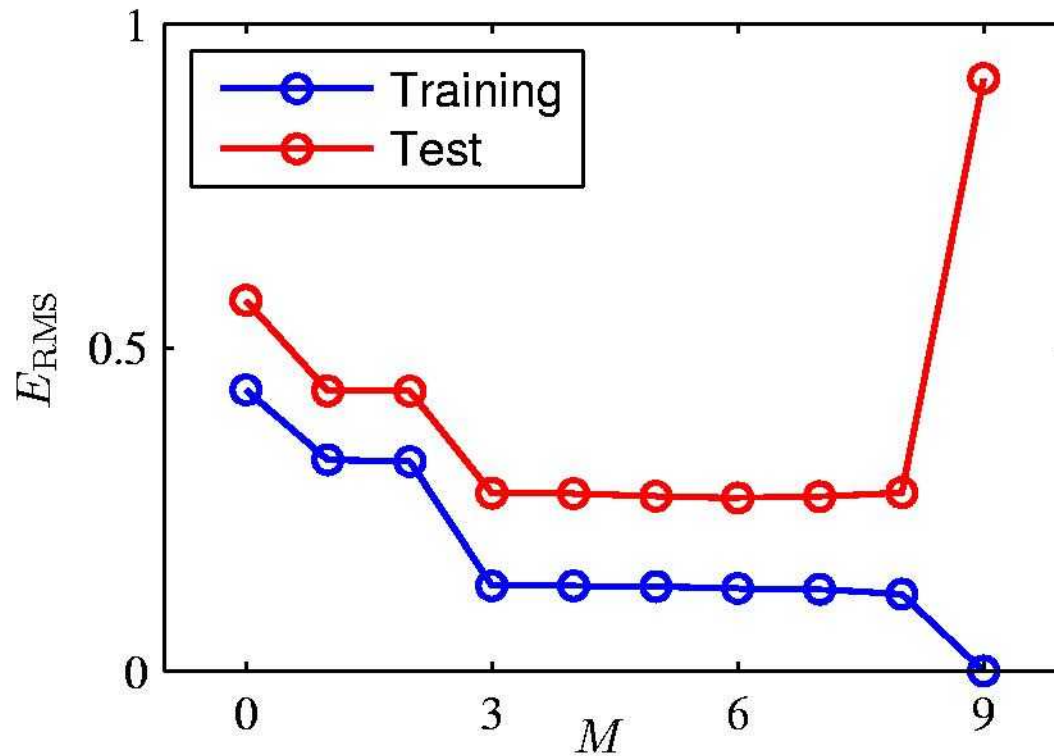
3rd Order Polynomial



9th Order Polynomial



Over-fitting



Root-Mean-Square (RMS)

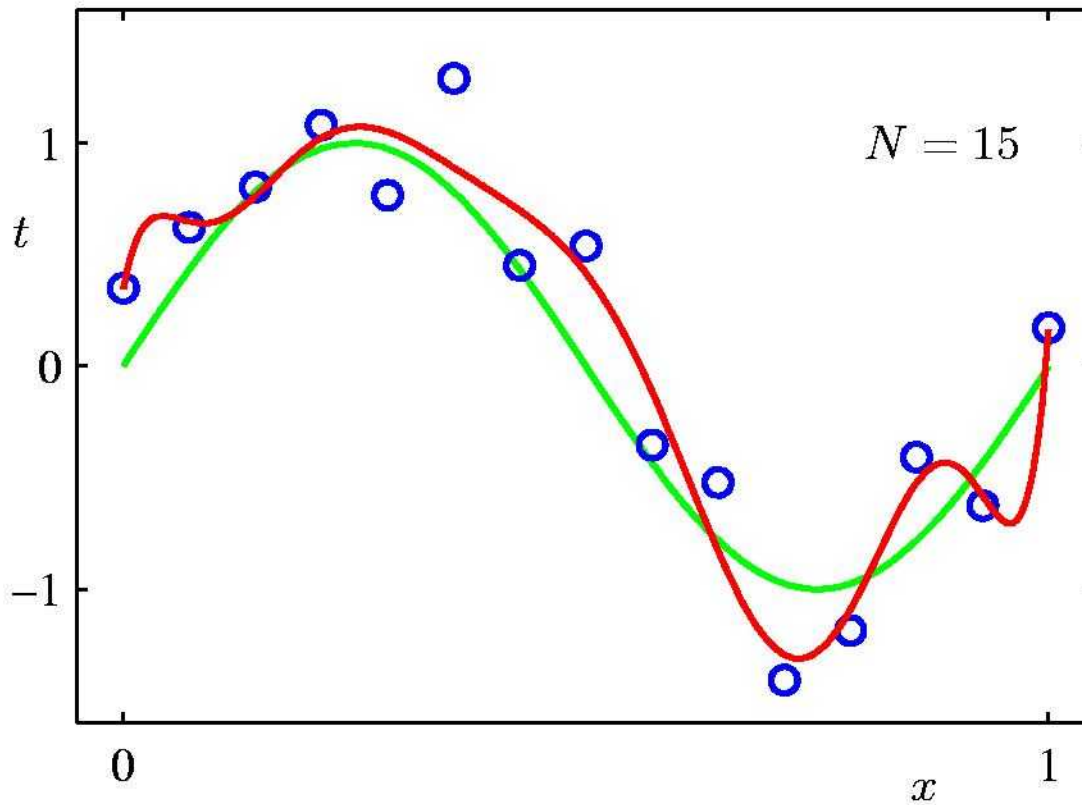
Error: $E_{\text{RMS}} = \sqrt{2E(\mathbf{w}^*)/N}$

Polynomial Coefficients

| | $M = 0$ | $M = 1$ | $M = 3$ | $M = 9$ |
|---------|---------|---------|---------|-------------|
| w_0^* | 0.19 | 0.82 | 0.31 | 0.35 |
| w_1^* | | -1.27 | 7.99 | 232.37 |
| w_2^* | | | -25.43 | -5321.83 |
| w_3^* | | | 17.37 | 48568.31 |
| w_4^* | | | | -231639.30 |
| w_5^* | | | | 640042.26 |
| w_6^* | | | | -1061800.52 |
| w_7^* | | | | 1042400.18 |
| w_8^* | | | | -557682.99 |
| w_9^* | | | | 125201.43 |

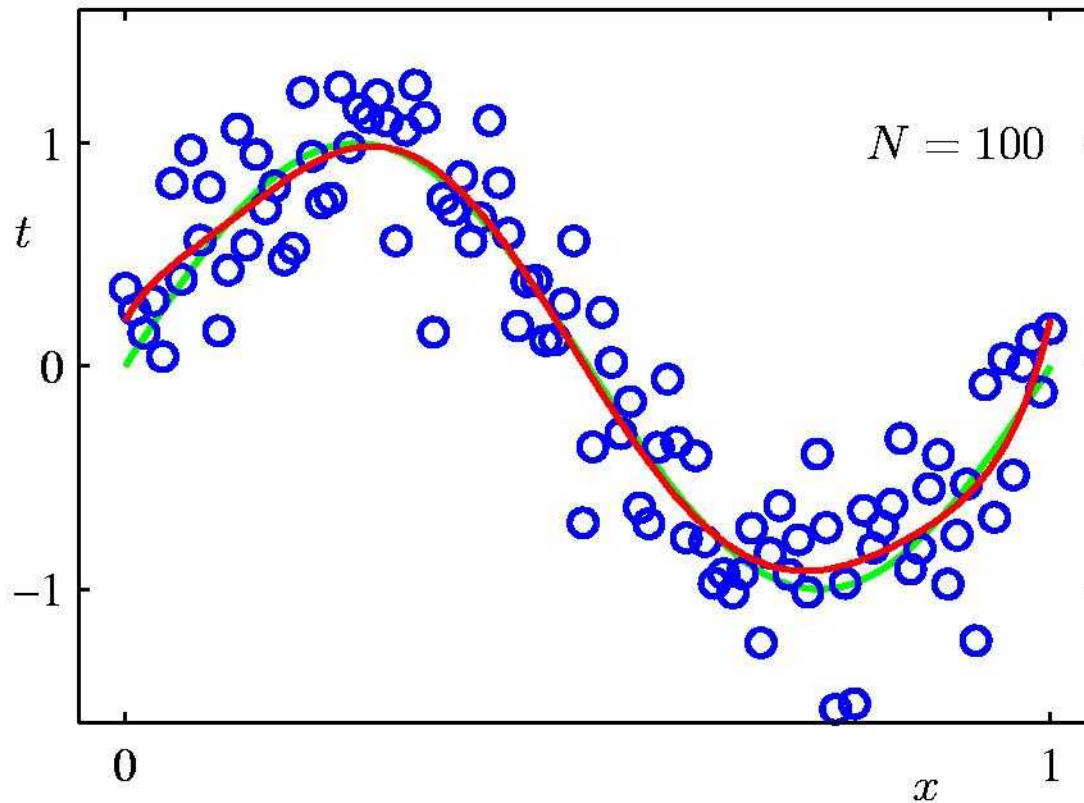
Data Set Size: $N = 15$

9th Order Polynomial



Data Set Size: $N = 100$

9th Order Polynomial

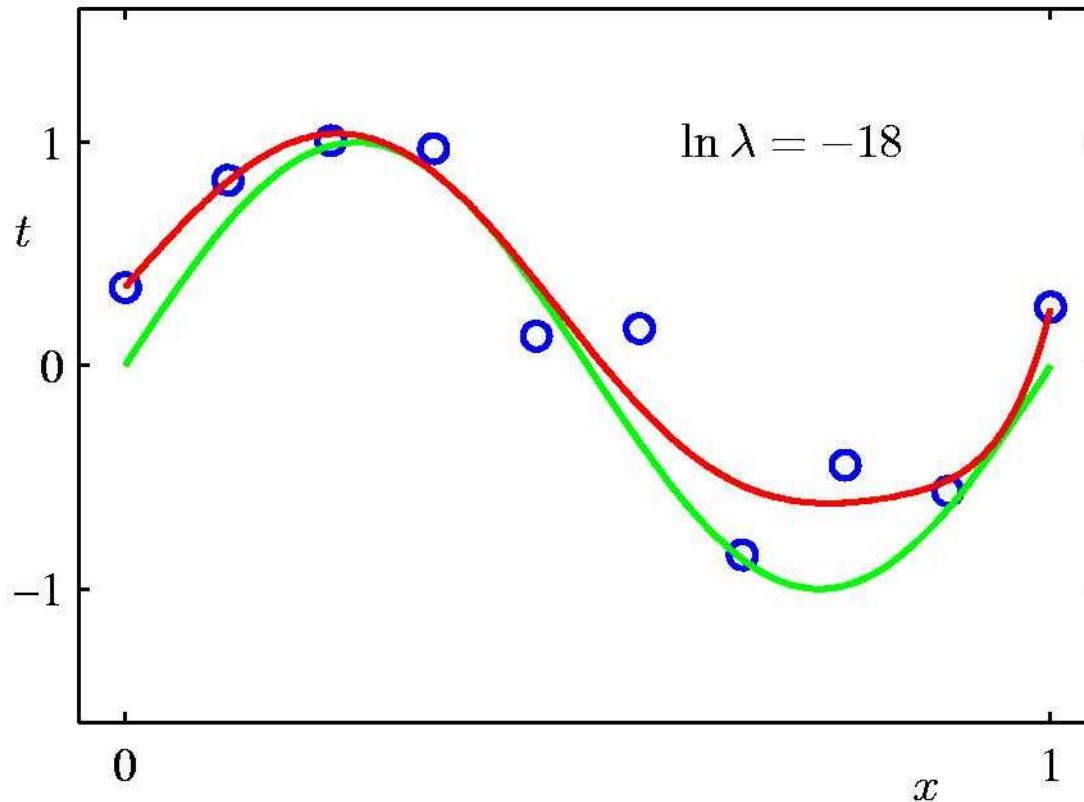


Regularization

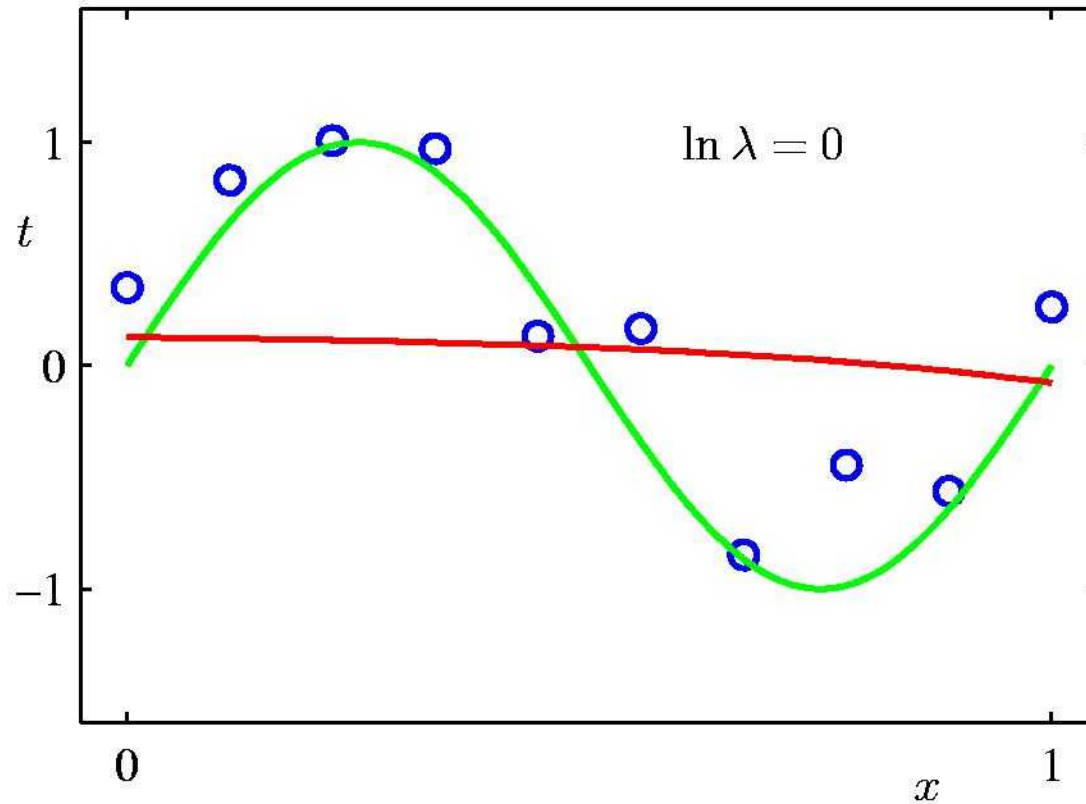
Penalize large coefficient values

$$\tilde{E}(\mathbf{w}) = \frac{1}{2} \sum_{n=1}^N \{y(x_n, \mathbf{w}) - t_n\}^2 + \frac{\lambda}{2} \|\mathbf{w}\|^2$$

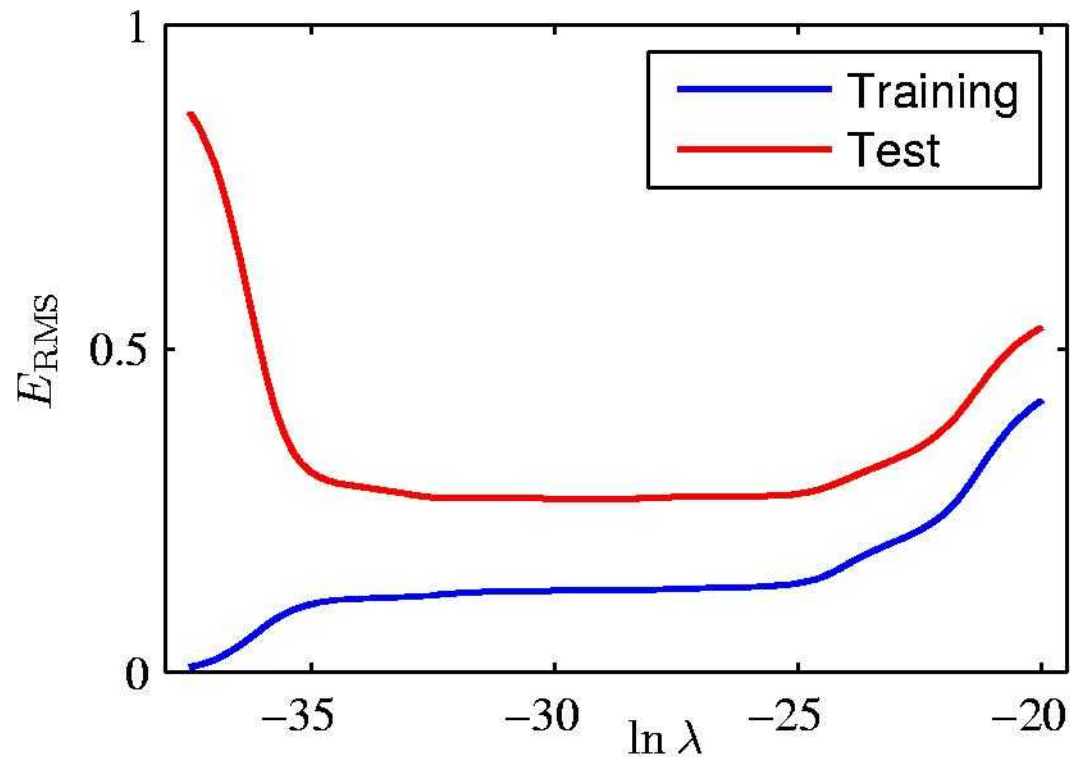
Regularization: $\ln \lambda = -18$



Regularization: $\ln \lambda = 0$



Regularization: E_{RMS} vs. $\ln \lambda$



Polynomial Coefficients

| | $\ln \lambda = -\infty$ | $\ln \lambda = -18$ | $\ln \lambda = 0$ |
|---------|-------------------------|---------------------|-------------------|
| w_0^* | 0.35 | 0.35 | 0.13 |
| w_1^* | 232.37 | 4.74 | -0.05 |
| w_2^* | -5321.83 | -0.77 | -0.06 |
| w_3^* | 48568.31 | -31.97 | -0.05 |
| w_4^* | -231639.30 | -3.89 | -0.03 |
| w_5^* | 640042.26 | 55.28 | -0.02 |
| w_6^* | -1061800.52 | 41.32 | -0.01 |
| w_7^* | 1042400.18 | -45.95 | -0.00 |
| w_8^* | -557682.99 | -91.53 | 0.00 |
| w_9^* | 125201.43 | 72.68 | 0.01 |
