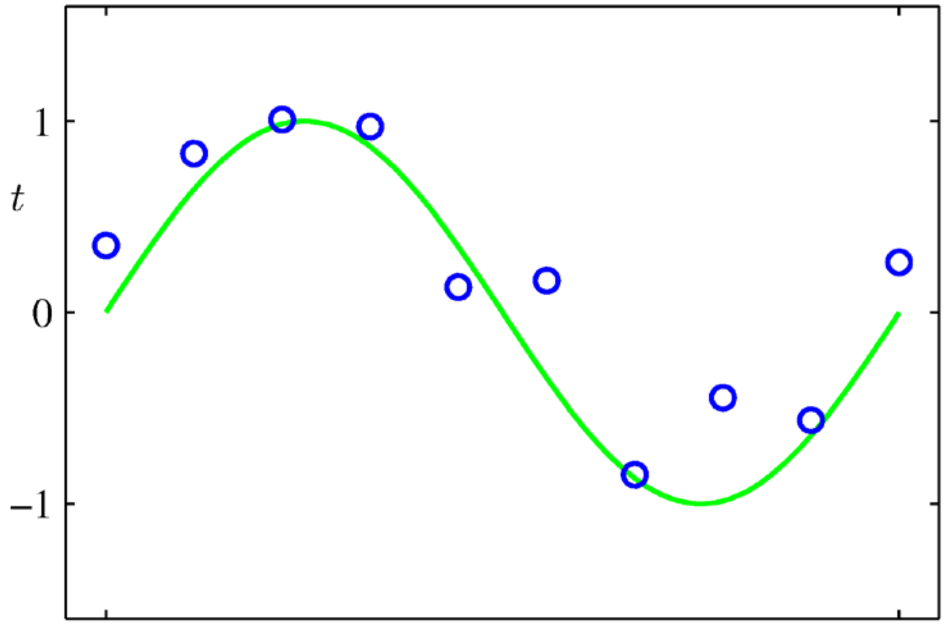
Notes on regularization

CS434

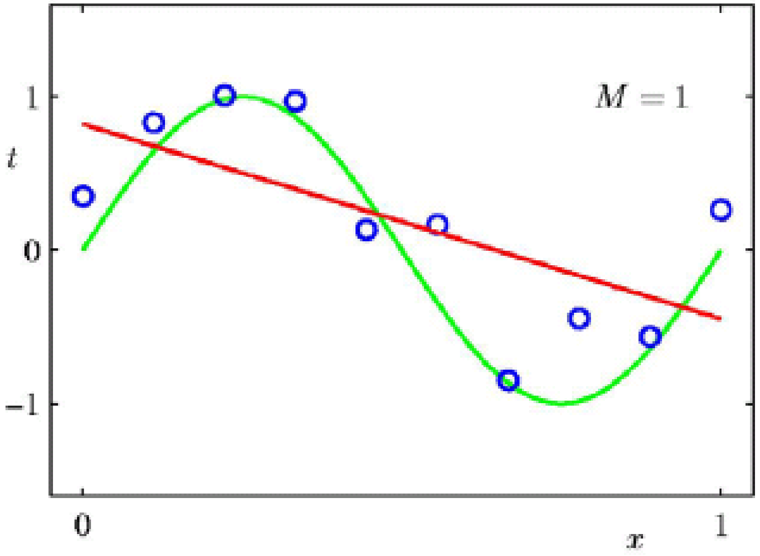
A regression example: Polynomial Curve Fitting

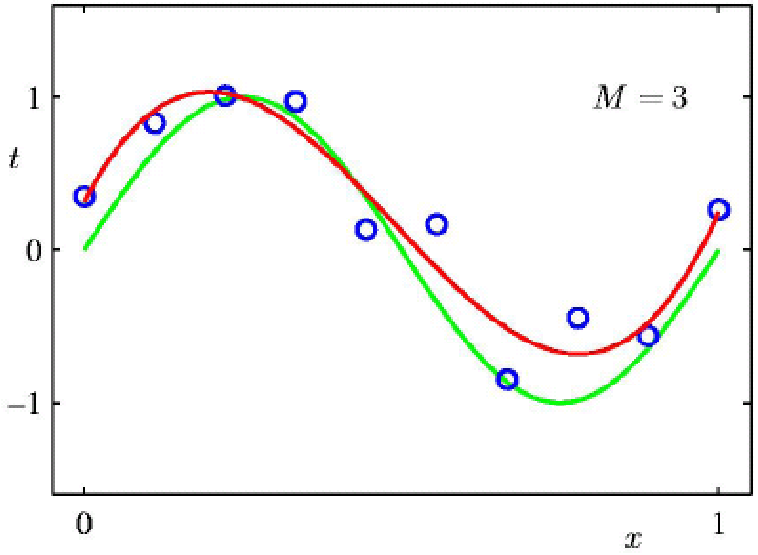


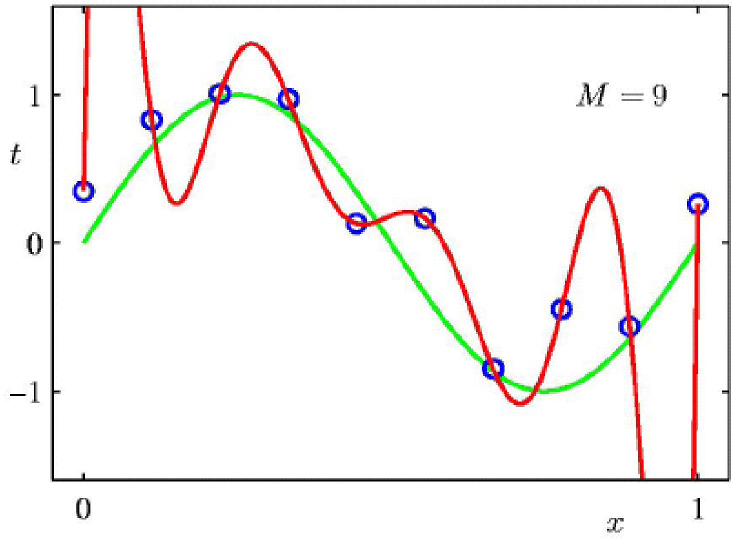
$$y(x, \mathbf{w}) = w_0 + w_1 x + w_2 x^2 + \ldots + w_M x^M = \sum_{j=0}^{M} w_j x^j$$

- In this example, there is only one feature x. We learn a function of M-order polynomial
- Alternatively, we could also view this as linear regression using $(1, x, x^2, \ldots, x^M)$ as the features.
- Note that this new feature space is derived from the original input x
- Such derived features are often referred to as the basis functions

Consider different choices for M



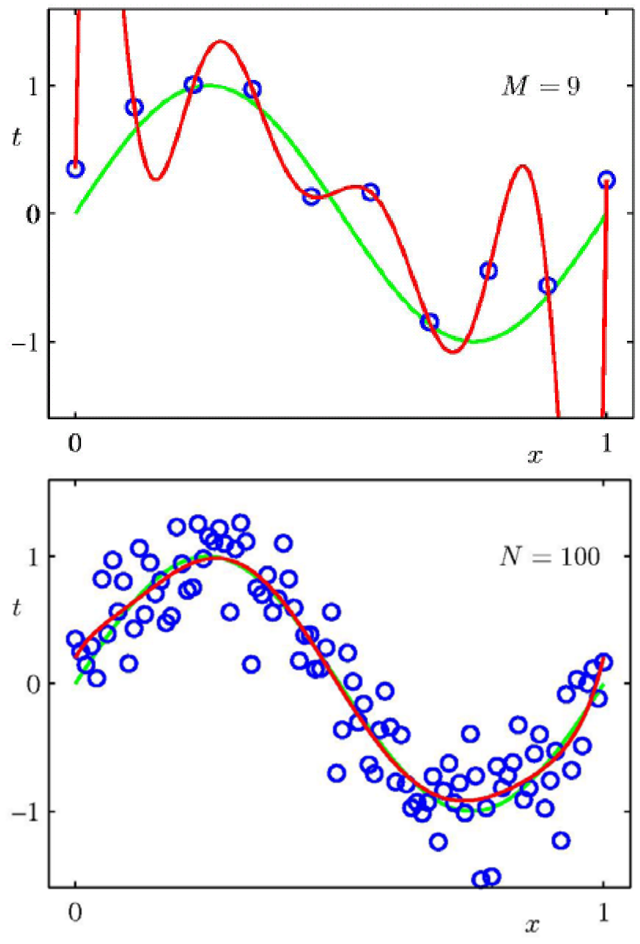




$$y(x, \mathbf{w}) = w_0 + w_1 x + w_2 x^2 + \ldots + w_M x^M = \sum_{j=0}^{M} w_j x^j$$

- Larger M leads to higher model complexity
- Given 10 data points, if M=9, we can fit the training data perfectly – severely overfitting

Over-fitting issue



- What can we do to curb over-fitting
  - Use less complex model
  - Use more training examples
  - **Regularization**

In linear regression, overfitting can often be characterized by large weights

	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

Regularized Linear Regression

- Consider the following loss function:

$$E_D(\mathbf{w}) + \lambda E_W(\mathbf{w})$$

Data term + Regularization term (penalize complex models)

$$\sum_{i=1}^{N}(y_i - \mathbf{w}^T\mathbf{x}_i)^2 + \lambda\sum_{j=0}^{M}|w_j|^q$$

Encourage small weight values

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L2 Regularized Linear Regression

- With the SSE loss and a **quadratic regularizer**, we get

$$\frac{1}{2}\sum_{i=1}^{N}(y_i - \mathbf{w}^T\mathbf{x}_i)^2 + \frac{\lambda}{2}\mathbf{w}^T\mathbf{w}$$

- which is minimized by

$$\mathbf{w} = (\lambda\boldsymbol{I} + \mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T Y$$

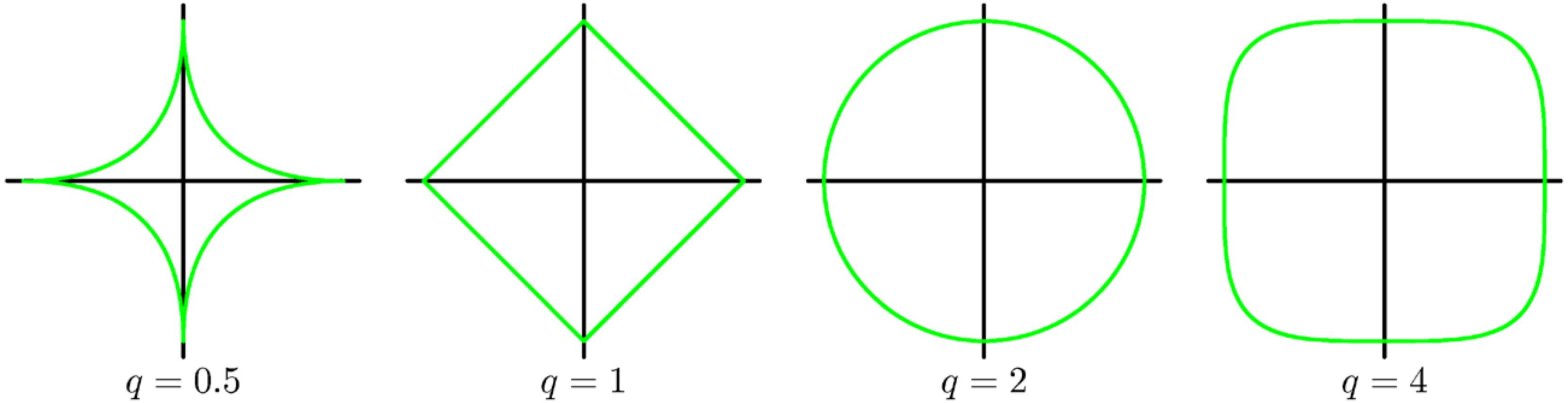
- λ: regularization coefficient, which controls the trade-off between model complexity and the fit to the data
  - Larger λ encourages simple model (driving more elements of $\mathbf{w}$ to 0)
  - Small λ encourages better fit of the data (driving SSE to zero)

More Regularizations

$$\sum_{i=1}^{N}(y_i - \mathbf{w}^T\mathbf{x}_i)^2 + \lambda \sum_{j=0}^{M}|w_j|^q$$

Equivalent to minimizing SSE subject to $\sum_{i=0}^{M}|w_i|^q \leq \epsilon$

A good explanation of this equivalence is provided here:
http://math.stackexchange.com/questions/335306/why-are-additional-constraint-and-penalty-term-equivalent-in-ridge-regression



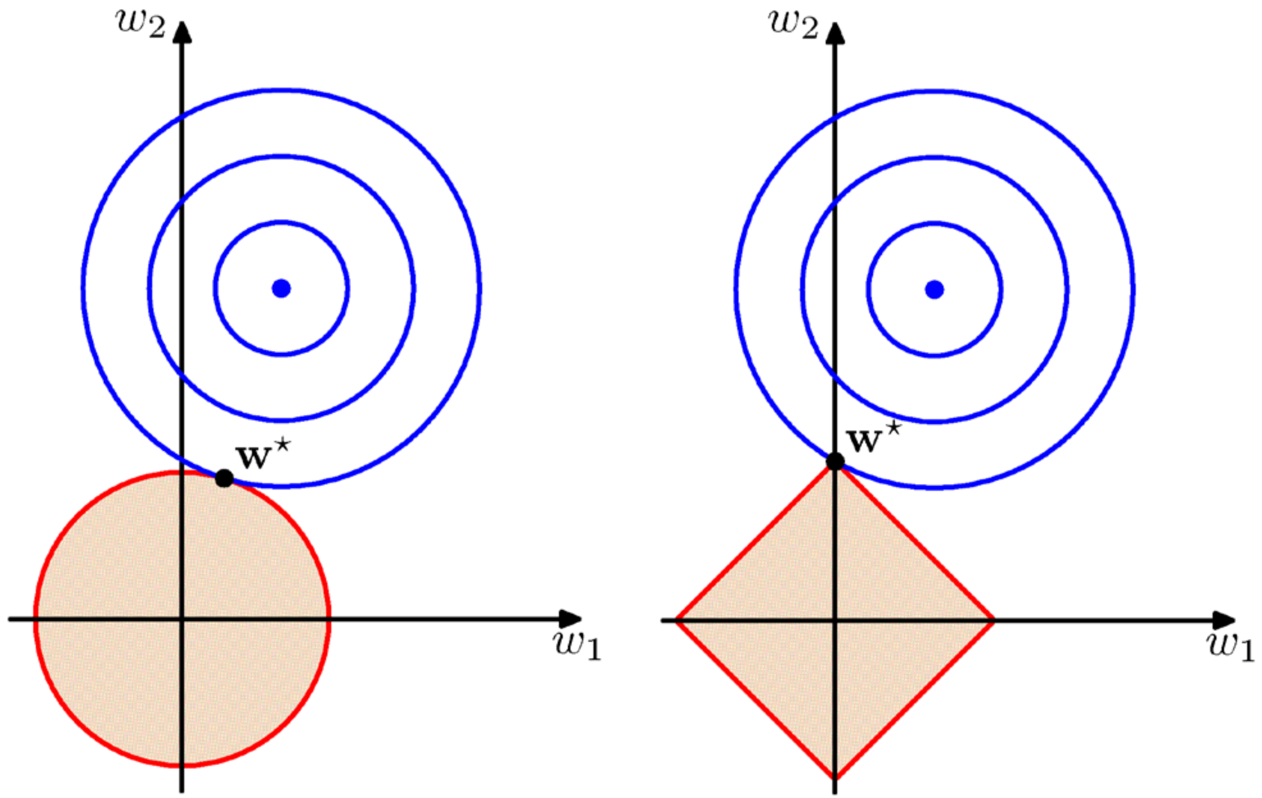
Lasso, L-1

L-2

Shape is determined by q, size determined by λ

Regularized Linear Regression

- Lasso ($q = 1$) tends to generate sparser solutions (majority of the weights shrink to zero) than a quadratic regularizer ($q = 2$, often called ridge regression).



Commonly used regularizers

- L-2 regularization $$\sum_{i=1}^{N}(y_i - \mathbf{w}^T\mathbf{x}_i)^2 + \lambda \sum_{j=0}^{M} {w_j}^2$$

  Poly-time close-form solution
  Curbs overfitting but does not produce sparse solution

- L-1 regularization $$\sum_{i=1}^{N}(y_i - \mathbf{w}^T\mathbf{x}_i)^2 + \sum_{j=0}^{M} |w_j|$$

  Poly-time approximation algorithm
  Sparse solution – potentially many zeros in $\mathbf{w}$

- L-0 regularization $$\sum_{i=1}^{N}(y_i - \mathbf{w}^T\mathbf{x}_i)^2 + \sum_{j=0}^{M} I(w_j \neq 0)$$

  Seek to identify optimal feature subset
  NP-complete problem!