

# Day 3: Overfitting and Generalization

## Summer STEM: Machine Learning

Department of Electrical and Computer Engineering  
NYU Tandon School of Engineering  
Brooklyn, New York

July 15, 2020

# Outline

- 1 Review of Day 2
- 2 Polynomial Fitting
- 3 Regularization
- 4 Non-linear Optimization

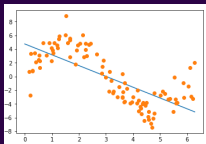
# Review

# Outline

- 1 Review of Day 2
- 2 Polynomial Fitting
- 3 Regularization
- 4 Non-linear Optimization

# Polynomial Fitting

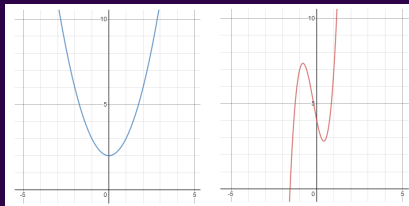
- We have been using straight lines to fit our data. But it doesn't work well every time
- Some data have more complex relation that cannot be fitted well using a straight line



- Can we use some other model to fit this data?

# Polynomial Fitting

- Can we use a polynomial to fit our data?
- Polynomial: A sum of different powers of a variable
  - Examples:  $y = x^2 + 2$ ,  $y = 5x^3 - 3x^2 + 4$



# Polynomial Fitting

- Polynomials of  $x$ :  $\hat{y} = w_0 + w_1x + w_2x^2 + w_3x^3 + \cdots + w_Mx^M$
- $M$  is called the order of the polynomial.
- The process of fitting a polynomial is similar to linearly fitting multivariate data.

# Polynomial fitting

- Rewrite in matrix-vector form

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} \approx \begin{bmatrix} 1 & x_1 & x_1^2 & \cdots & x_1^M \\ 1 & x_2 & x_2^2 & \cdots & x_2^M \\ \vdots & & \ddots & & \vdots \\ 1 & x_N & x_N^2 & \cdots & x_N^M \end{bmatrix} \begin{bmatrix} w_0 \\ w_1 \\ \vdots \\ w_M \end{bmatrix}$$

- This can still be written as

$$Y \approx X\mathbf{w}$$

- Loss  $J(\mathbf{w}) = \frac{1}{N} \|Y - X\mathbf{w}\|^2$
- The  $i$ -th row of the design matrix  $X$  is simply a transformed feature  $\phi(x_i) = (1, x_i, x_i^2, \dots, x_i^M)$



# Polynomial Fitting

- Original design matrix:
- Design matrix after feature transformation:

$$\begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_N \end{bmatrix}$$

$$\begin{bmatrix} 1 & x_1 & x_1^2 & \cdots & x_1^M \\ 1 & x_2 & x_2^2 & \cdots & x_2^M \\ \vdots & & \ddots & & \vdots \\ 1 & x_N & x_N^2 & \cdots & x_N^M \end{bmatrix}$$

- For the polynomial fitting, we just added columns of features that are powers of the original feature

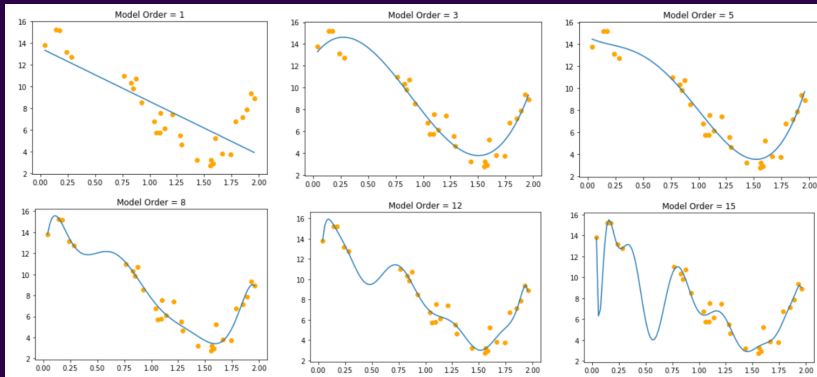
# Linear Regression

- Model  $\hat{y} = \mathbf{w}^T \phi(\mathbf{x})$
- Loss  $J(\mathbf{w}) = \frac{1}{N} \|Y - X\mathbf{w}\|^2$
- Find  $\mathbf{w}$  that minimizes  $J(\mathbf{w})$

# Overfitting

- We learned how to fit our data using polynomials of different order
- With a higher model order, we can fit the data with increasing accuracy
- As you increase the model order, at certain point it is possible find a model that fits your data perfectly (ie. zero error)
- What could be the problem?

# Overfitting



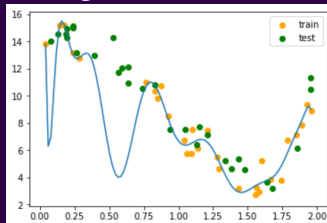
■ Which of these model do you think is the best? Why?

# Demo

Open `demo_fit_polynomial.ipynb`

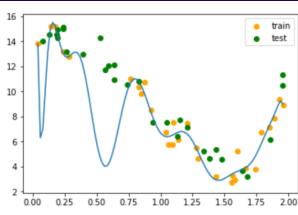
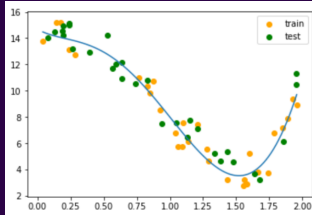
# Overfitting

- The problem is that we are only fitting our model using data that is given
- Data usually contains noise
- When a model becomes too complex, it will start to fit the noise in the data
- What happens if we apply our model to predict some data that the model has never seen before? It will not work well.
- This is called over-fitting



# Overfitting

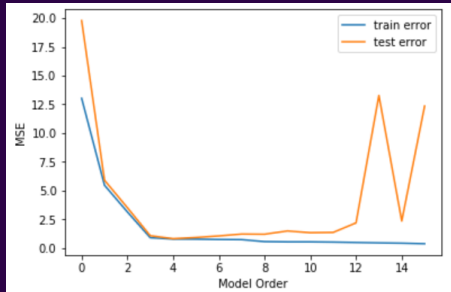
- Split the data set into a train set and a test set
- Train set will be used to train the model
- The test set will not be seen by the model during the training process
- Use test set to evaluate the model when a model is trained



- With the training and test sets shown, which one do you think is the better model now?

# Train and Test Error

- Plot of train error and test error for different model order
- Initially both train and test error go down as model order increase
- But at a certain point, test error start to increase because of overfitting





# Outline

- 1 Review of Day 2
- 2 Polynomial Fitting
- 3 Regularization
- 4 Non-linear Optimization

# How can we prevent overfitting without knowing the model order before-hand?

- **Regularization:** methods to prevent overfitting

# How can we prevent overfitting without knowing the model order before-hand?

- **Regularization:** methods to prevent overfitting
  - We just covered regularization by model order selection

# How can we prevent overfitting without knowing the model order before-hand?

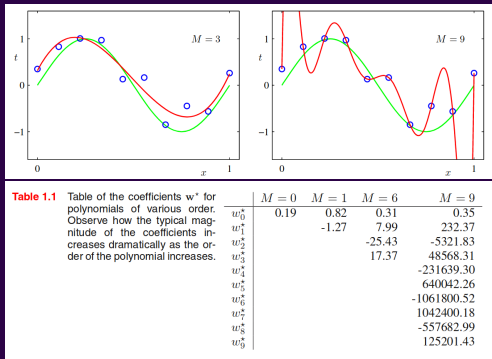
- **Regularization:** methods to prevent overfitting
  - We just covered regularization by model order selection
- Is there another way? Talk among your classmates.

# How can we prevent overfitting without knowing the model order before-hand?

- **Regularization:** methods to prevent overfitting
  - We just covered regularization by model order selection
- Is there another way? Talk among your classmates.
  - Solution: We can change our cost function.

# Weight Based Regularization

- Looking back at the polynomial overfitting
- Notice that weight-size increases with overfitting



# New Cost Function

$$J(\mathbf{w}) = \frac{1}{N} \|Y - X\mathbf{w}\|^2 + \lambda \|\mathbf{w}\|^2$$

- Penalize complexity by simultaneously minimizing weight values.
- We call  $\lambda$  a **hyper-parameter**
  - $\lambda$  determines relative importance

**Table 1.2** Table of the coefficients  $w^*$  for  $M = 9$  polynomials with various values for the regularization parameter  $\lambda$ . Note that  $\ln \lambda = -\infty$  corresponds to a model with no regularization, i.e., to the graph at the bottom right in Figure 1.4. We see that, as the value of  $\lambda$  increases, the typical magnitude of the coefficients gets smaller.

	$\ln \lambda = -\infty$	$\ln \lambda = -18$	$\ln \lambda = 0$
$w_0^*$	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

# Tuning Hyper-parameters

- Motivation: never determine a hyper-parameter based on training data
- **Hyper-Parameter**: a parameter of the algorithm that is not a model-parameter solved for in optimization.
  - Ex:  $\lambda$  weight regularization value vs. model weights ( $\mathbf{w}$ )
- Solution: split dataset into three
  - **Training set**: to compute the model-parameters ( $\mathbf{w}$ )
  - **Validation set**: to tune hyper-parameters ( $\lambda$ )
  - **Test set**: to compute the performance of the algorithm (MSE)



# Demo

Open `demo_overfitting_regularization.ipynb`

# Outline

- 1 Review of Day 2
- 2 Polynomial Fitting
- 3 Regularization
- 4 Non-linear Optimization

# Motivation

- Cannot rely on closed form solutions
  - Computation efficiency: operations like inverting a matrix is not efficient
  - For more complex problems such as neural networks, a closed-form solution is not always available
- Need an optimization technique to find an optimal solution
  - Machine learning practitioners use **gradient**-based methods

# Gradient Descent Algorithm

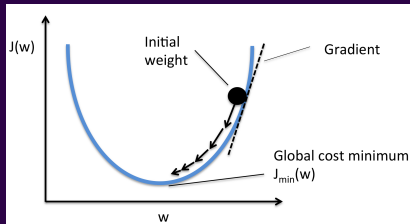
## ■ Update Rule

*Repeat*{

$$\mathbf{w}_{new} = \mathbf{w} - \alpha \nabla J(\mathbf{w})$$

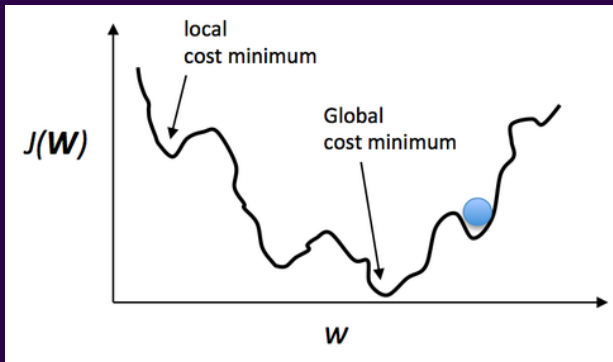
}

$\alpha$  is the learning rate

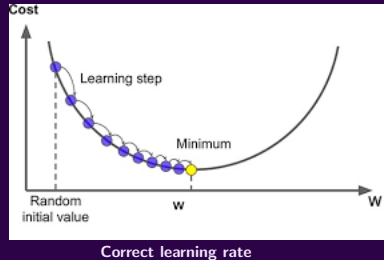
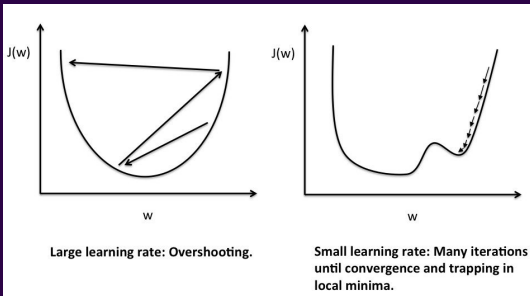


# General Loss Function Contours

- Most loss function contours are not perfectly parabolic
- Our goal is to find a solution that is very close to global minimum by the right choice of hyper-parameters



# Understanding Learning Rate



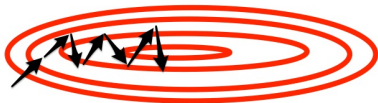
# Some Animations

- Demonstrate gradient descent animation

# Importance of Feature Normalization (Optional)

- Helps improve the performance of gradient based optimization

Without feature scaling



With feature scaling

