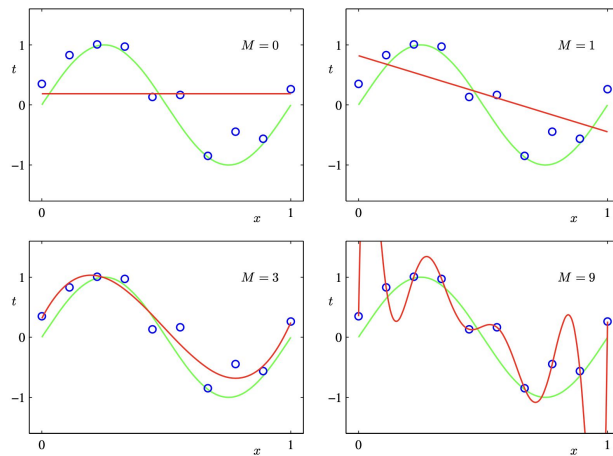




CIS 678 - Machine Learning

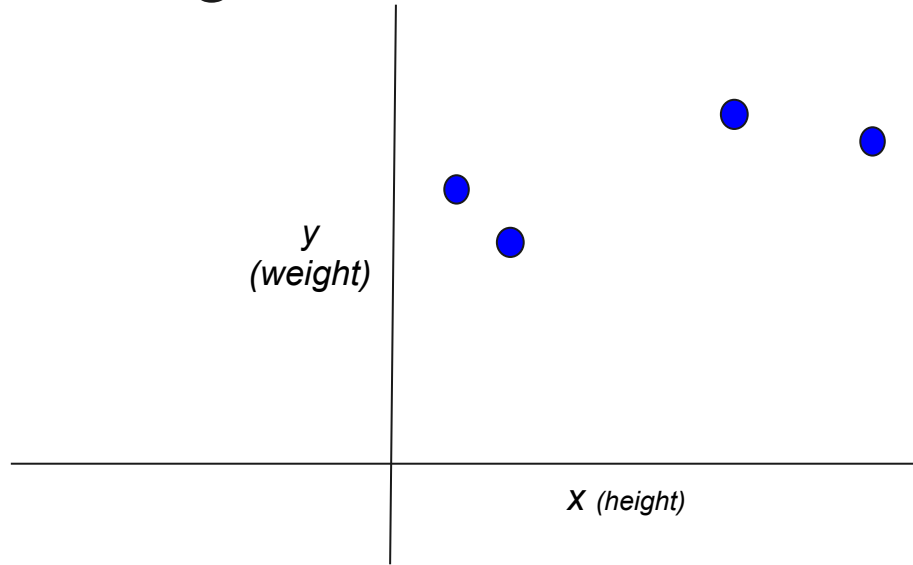
...

Linear to Polynomial Regression

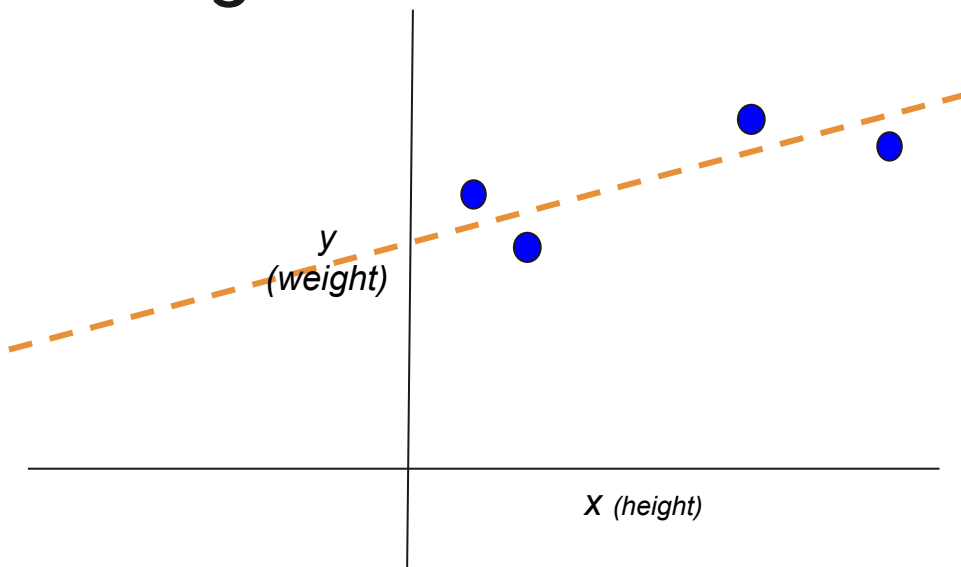




Linear Regression



Linear Regression



Model

$$\hat{y} = \beta_0 + \beta_1 x$$

$$\Theta = \{\beta_0, \beta_1\}$$

Fitting Error

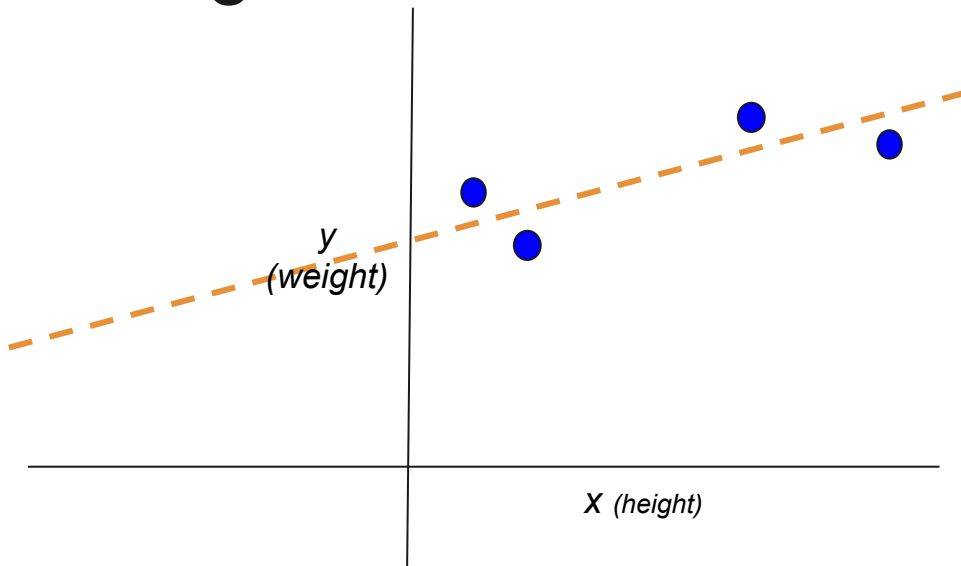
$$\epsilon = |\hat{y} - y|$$

Optimization function

$$E_{\Theta} = \frac{1}{2} \sum_{i=1}^N (\hat{y}_i - y_i)^2$$

$$\Theta^* = \operatorname{argmin}_{\Theta} E\{(x_i, y_i)\}_{i=1, \dots, N}$$

Linear Regression



So, essentially we are fitting a function; right?

Model

$$\hat{y} = \beta_0 + \beta_1 x$$

$$\Theta = \{\beta_0, \beta_1\}$$

Fitting Error

$$\epsilon = |\hat{y} - y|$$

Optimization function

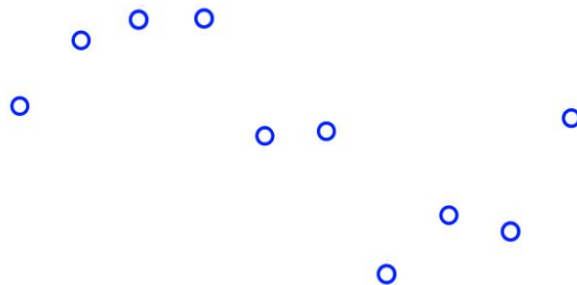
$$E_{\Theta} = \frac{1}{2} \sum_{i=1}^N (\hat{y}_i - y_i)^2$$

$$\Theta^* = \operatorname{argmin}_{\Theta} E\{(x_i, y_i)\}_{i=1, \dots, N}$$



Non linear data/function

- Does this data points seem familiar matching a known function?

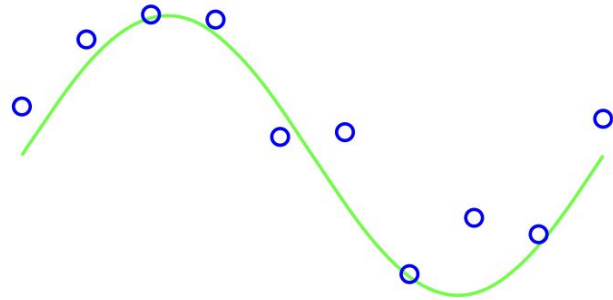


Non linear data/function

- Does this data points seem familiar matching a known function?

- A Sinusoidal function

$$y(t) = A \sin(\omega t + \varphi) = A \sin(2\pi f t + \varphi)$$

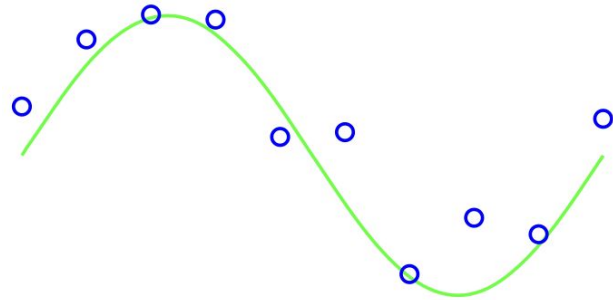


Non linear data/function

- Does this data points seem familiar matching a known function?

- A Sinusoidal function

$$y(t) = A \sin(\omega t + \varphi) = A \sin(2\pi f t + \varphi)$$

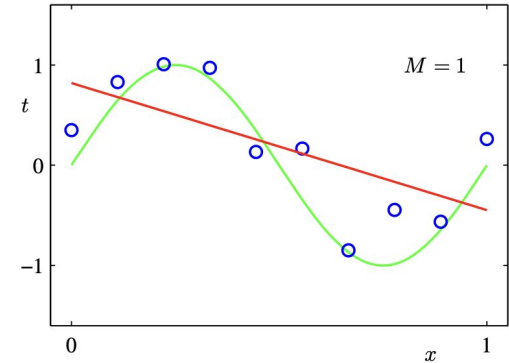
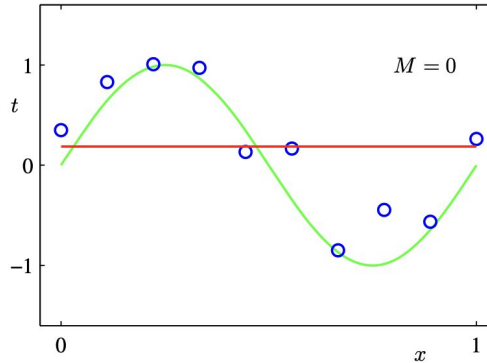


Clearly this is not a linear function; right?

Non linear data/function

- Does this data points seem familiar matching a known function?
- Can we approximate this function using LR?

$$\hat{y} = \beta_0 + \beta_1 x$$



LR will not work; right?



What no-linear functions we are aware of?

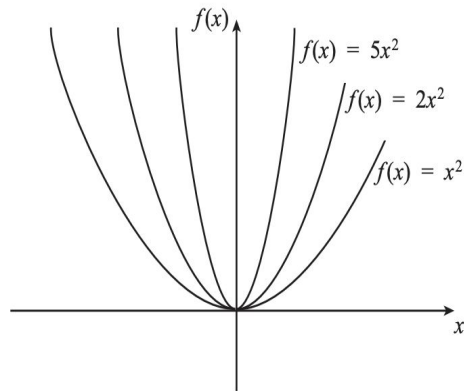
- Can you recall any nonlinear function you learned at your high school/colleges?

What no-linear functions we are aware of?

- Can you recall any nonlinear function you learned at your high school/colleges?
- **Quadratic (x^2)**

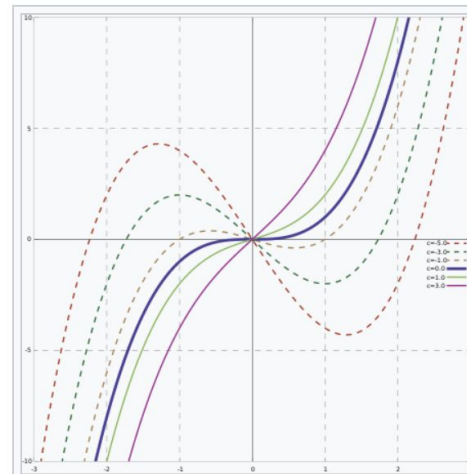
$$f(x) = x^2, \quad f(x) = 2x^2, \quad f(x) = 5x^2.$$

What is the impact of changing the coefficient of x^2 as we have done in these examples? One way to find out is to sketch the graphs of the functions.



What no-linear functions we are aware of?

- Can you recall any nonlinear function you learned at your high school/colleges?
- **Cubic (x^3)**



Cubic functions of the form

$$y = x^3 + cx.$$

The graph of any cubic function is
similar to such a curve.

What no-linear functions we are aware of?

- Can you recall any nonlinear function you learned at your high school/colleges?
- Quadratic (x^2)
- Cubic (x^3)
-

$$\hat{y} = \beta_0 + \beta_1 x$$

$$\hat{y} = \beta_0 + \beta_1 x + \beta_2 x^2$$

$$\hat{y} = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3$$

$$\hat{y} = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \dots$$

Linear (x)

Quadratic (x^2)

Cubic (x^3)

LR to Polynomial Regression

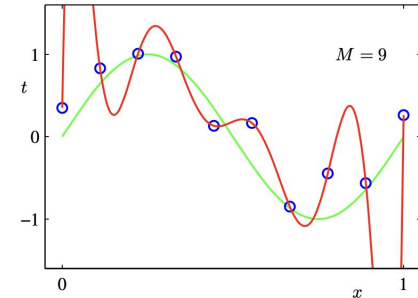
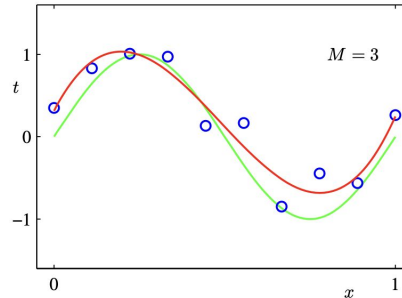
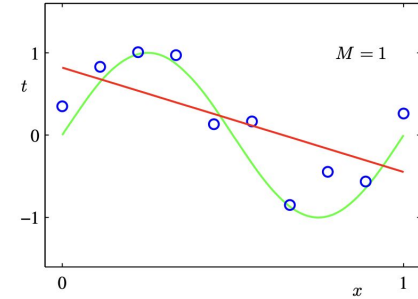
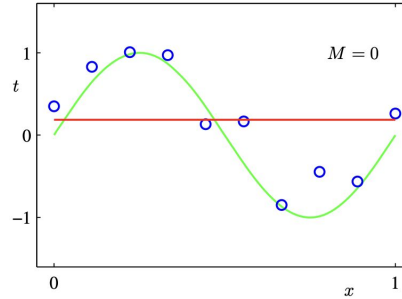
- Polynomial function
 - M is the order ..

$$\hat{y} = \beta_0 + \beta_1 x$$

$$\hat{y} = \beta_0 + \beta_1 x + \beta_2 x^2$$

$$\hat{y} = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3$$

$$\hat{y} = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \dots$$



LR to Polynomial Regression

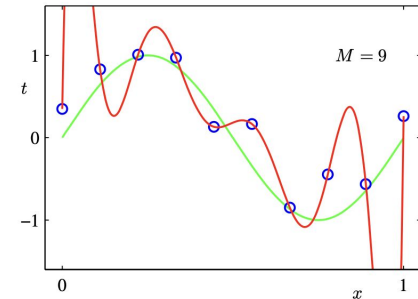
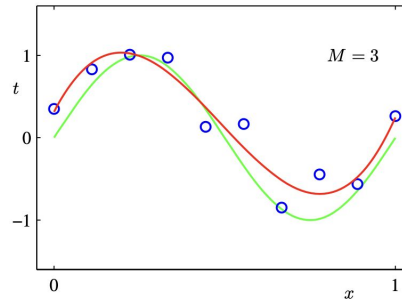
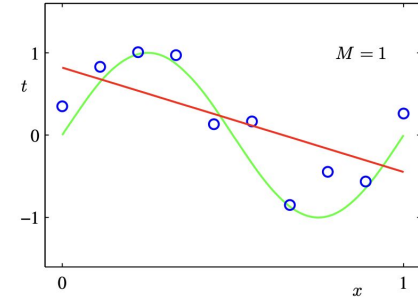
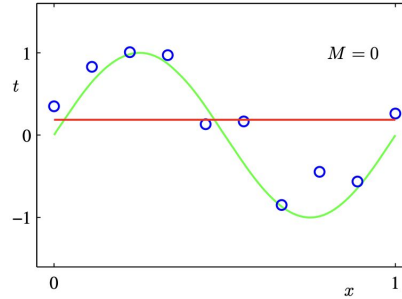
- Polynomial function
 - M is the order ..
 - **Where to stop? What is the best M?**

$$\hat{y} = \beta_0 + \beta_1 x$$

$$\hat{y} = \beta_0 + \beta_1 x + \beta_2 x^2$$

$$\hat{y} = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3$$

$$\hat{y} = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \dots$$



LR to Polynomial Regression

- Polynomial function
 - M is the order ..
 - **Where to stop? What is the best M?**

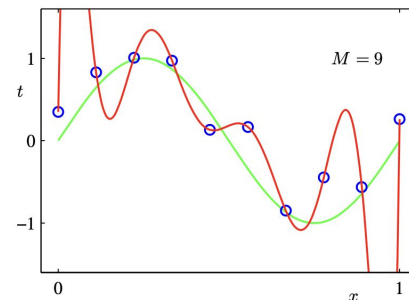
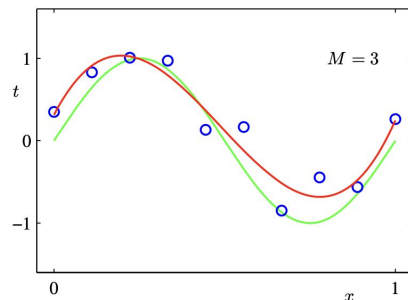
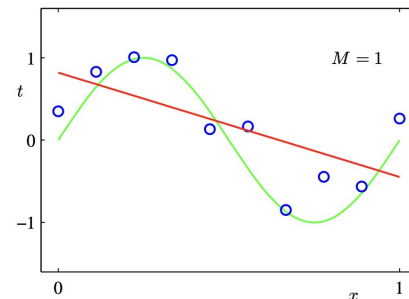
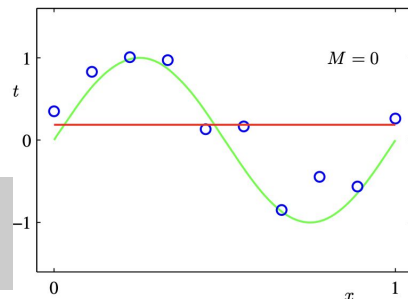
Good news is our gradient descent (iterative learning) remains the same!

$$\hat{y} = \beta_0 + \beta_1 x$$

$$\hat{y} = \beta_0 + \beta_1 x + \beta_2 x^2$$

$$\hat{y} = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3$$

$$\hat{y} = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \dots$$



LR to Polynomial Regression

- Polynomial function
 - M is the order ..
 - **Where to stop? What is the best M?**

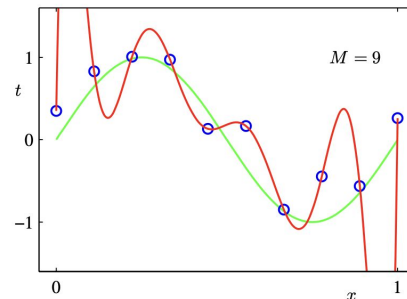
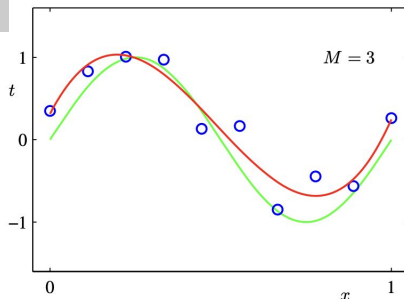
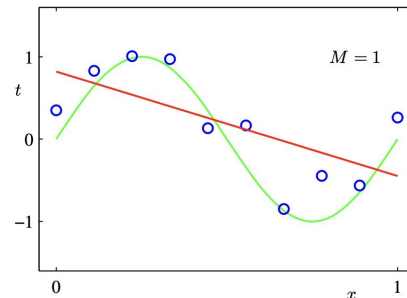
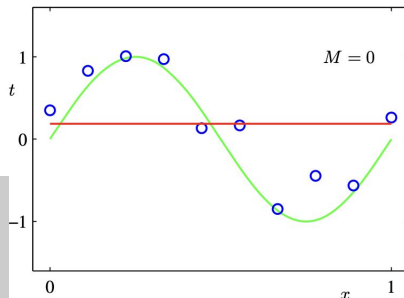
- Good news is our gradient descent (iterative learning) remains the same!
- You only need to change your objective function (from LR to Polynomial LR)

$$\hat{y} = \beta_0 + \beta_1 x$$

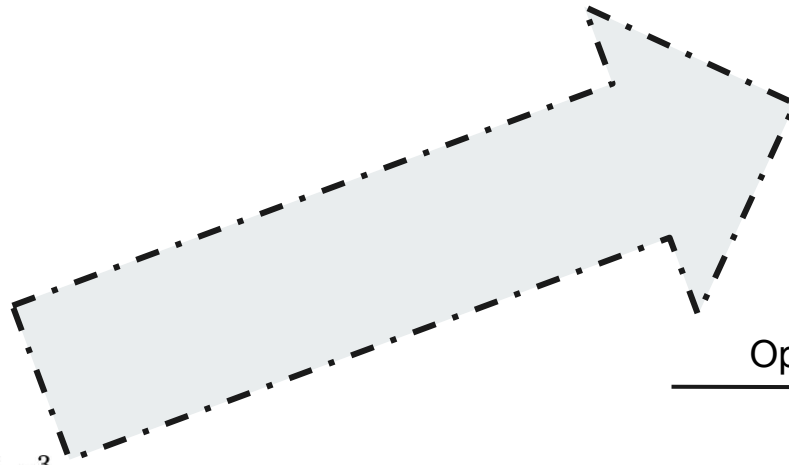
$$\hat{y} = \beta_0 + \beta_1 x + \beta_2 x^2$$

$$\hat{y} = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3$$

$$\hat{y} = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \dots$$



LR to Polynomial Regression


$$\begin{aligned}\hat{y} &= \beta_0 + \beta_1 x \\ \hat{y} &= \beta_0 + \beta_1 x + \beta_2 x^2 \\ \hat{y} &= \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_2 x^3 \\ \hat{y} &= \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_2 x^3 + \dots\end{aligned}$$

Model

$$\hat{y} = \beta_0 + \beta_1 x$$

$$\Theta = \{\beta_0, \beta_1\}$$

$$\epsilon = |\hat{y} - y|$$

Optimization function

$$E_{\Theta} = \frac{1}{2} \sum_{i=1}^N (\hat{y}_i - y_i)^2$$

$$\Theta^* = \operatorname{argmin}_{\Theta} E\{(x_i, y_i)\}_{i=1, \dots, N}$$

Our model got a little bigger: 2 params to M param



GPT

I know one of your tricks; get you soon!!



Our model today