### Curve Fitting Conceptual Expansion

In this lecture you will learn about some of the key ideas in conceptual expansion of the curve fitting

#### Fitting a Line Passing Through Origin

- y = m x
- $L(m) = \sum_{i=1}^{i=N} (y_i m x_i)^2$

• 
$$X = \begin{bmatrix} x_1 \\ \dots \\ x_N \end{bmatrix}_{N \times 1}$$
,  $Y = \begin{bmatrix} y_1 \\ \dots \\ y_N \end{bmatrix}_{N \times 1}$ ,  $W = [m]_{1 \times 1}$ 

- $L([m]) = (XW Y)^T(XW Y)$
- $\nabla L = \left[\frac{\partial L}{\partial m}\right] / / \text{It's a function}$
- $W_{(new)} = W_{(old)} \nabla L|_{W=W_{(old)}}$

Squared error typ

#### Fitting a Line – slope and intercept

• 
$$y = m \ x + c$$
  
•  $L(m) = \sum_{i=1}^{i=N} (y_i - (m \ x_i + c))^2$  •  $\nabla L = \begin{bmatrix} \frac{\partial L}{\partial m} \\ \frac{\partial L}{\partial c} \end{bmatrix} / \text{It's a function}$   
•  $X = \begin{bmatrix} x_1 & 1 \\ \dots \\ x_N & 1 \end{bmatrix}_{N \times 2}$  ,  $Y = \begin{bmatrix} y_1 \\ \dots \\ y_N \end{bmatrix}_{N \times 1}$  , •  $W_{(new)} = W_{(old)} - \nabla L|_{W = W_{(old)}}$   
•  $U = \begin{bmatrix} m \\ c \end{bmatrix}_{2 \times 1}$  •  $U = \begin{bmatrix} m \\ c \end{bmatrix}_{2 \times 1}$  •  $U = \begin{bmatrix} m \\ c \end{bmatrix}_{2 \times 1}$  •  $U = \begin{bmatrix} m \\ c \end{bmatrix}_{2 \times 1}$  •  $U = \begin{bmatrix} m \\ c \end{bmatrix}_{2 \times 1}$  •  $U = \begin{bmatrix} m \\ c \end{bmatrix}_{2 \times 1}$  •  $U = \begin{bmatrix} m \\ c \end{bmatrix}_{2 \times 1}$  •  $U = \begin{bmatrix} m \\ c \end{bmatrix}_{2 \times 1}$  •  $U = \begin{bmatrix} m \\ c \end{bmatrix}_{2 \times 1}$  •  $U = \begin{bmatrix} m \\ c \end{bmatrix}_{2 \times 1}$  •  $U = \begin{bmatrix} m \\ c \end{bmatrix}_{2 \times 1}$  •  $U = \begin{bmatrix} m \\ c \end{bmatrix}_{2 \times 1}$  •  $U = \begin{bmatrix} m \\ c \end{bmatrix}_{2 \times 1}$  •  $U = \begin{bmatrix} m \\ c \end{bmatrix}_{2 \times 1}$  •  $U = \begin{bmatrix} m \\ c \end{bmatrix}_{2 \times 1}$  •  $U = \begin{bmatrix} m \\ c \end{bmatrix}_{2 \times 1}$ 

Squared error typ

#### Fitting a Parabola?

$$\bullet \ y = a \ x^2 + b \ x + c$$

• 
$$L(a,b,c) = \sum_{i=1}^{i=N} (y_i - (a x_i^2 +$$

#### Fitting a Cubic curve?

• 
$$y = a x^3 + b x^2 + c x + d$$

• 
$$L(m) = \sum_{i=1}^{i=N} (y_i - (a x_i^3 + b x_i^2 +$$

#### Fitting a Degree-K polynomial?

• 
$$y = a_k x^k + \dots + a_0$$
  
•  $L(a_k, \dots, a_0) = \sum_{i=1}^{i=N} (y_i - \sum_{j=0}^k a_j x^j)^2$   
•  $W = \begin{bmatrix} a_k \\ \dots \\ a_0 \end{bmatrix}_{(k+1) \times 1}$   
•  $f(X) = X \times W$ 

• 
$$X = \begin{bmatrix} x_1^k \dots x_1^2 & x_1^1 & 1 \\ & \dots & \\ x_N^k \dots x_N^2 & x_N^1 & 1 \end{bmatrix}_{N \times (k+1)}$$
 •  $f(X) = X \times W$ 

• 
$$Y = \begin{bmatrix} y_1 \\ \dots \\ y_N \end{bmatrix}_{N \times 1}$$

$$\bullet \ W = \begin{bmatrix} a_k \\ \dots \\ a_0 \end{bmatrix}_{(k+1) \times 2}$$

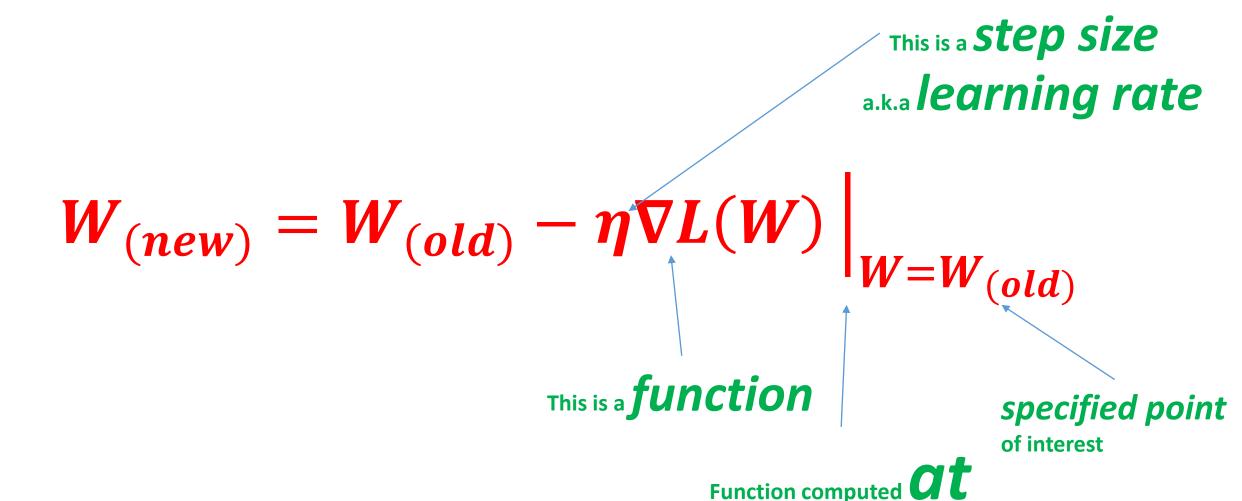
• 
$$f(X) = X \times W$$

• 
$$L(W) = (XW - Y)^T(XW - Y)$$

• 
$$\nabla L = \begin{bmatrix} \frac{\partial L}{\partial a_k} \\ \dots \\ \frac{\partial L}{\partial a_0} \end{bmatrix}$$
 //It's a function

• 
$$W_{(new)} = W_{(old)} - \eta \nabla L|_{W=W_{(old)}}$$
 squared error the squared error than the

#### Steepest Descent for Multi Variate Loss function



# Steepest Descent for Multi Variate for Squared Error Loss function

$$W_{(new)} = W_{(old)} - \eta X^{T}(XW - Y)$$
Multi Variate

Squared error type

#### What is Linear About

PARABOLA Fitting??????

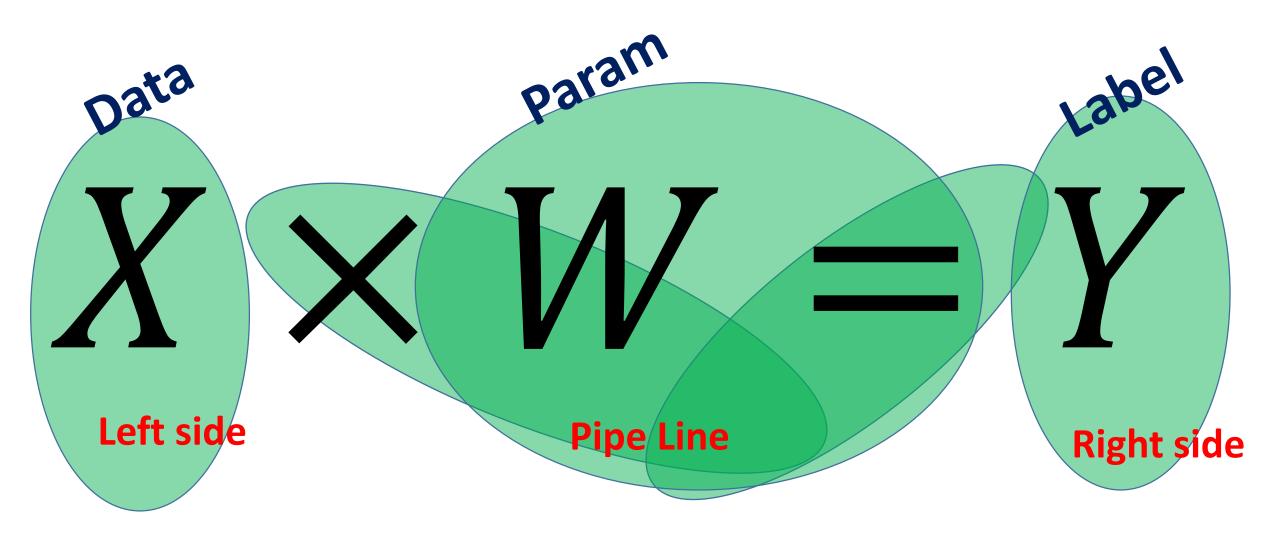
#### What is Linear About

Parabola Fitting??????

### AMBIGUOUS TERMINOLOGY NEEDS SOME CLARIFICATION

#### Expand the Concept of Curve Fitting

#### Data, Label, Parameter – Simple supervised case



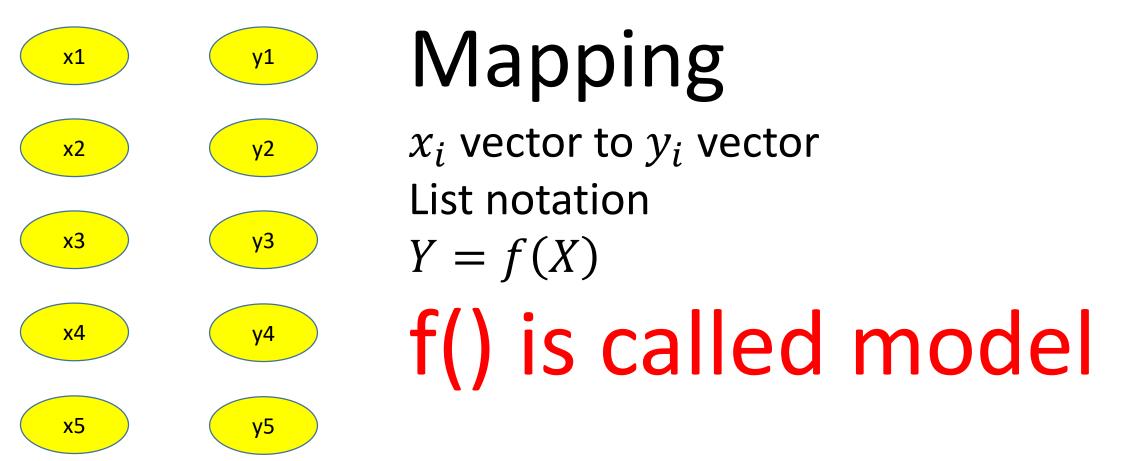
### Fitting a Degree-K polynomial? → ANY X

Fitting a Degree-K polynomial? 
$$\rightarrow$$
 All  $X$ 

•  $y = a_k x^k + \dots + a_0$ 
•  $L(m) = \sum_{i=1}^{i=N} (y_i - \sum_{j=0}^k a_j x^j)^2$ 
•  $W = \begin{bmatrix} a_0 \\ \dots \\ a_k \end{bmatrix}_{(k+1)\times 1}$ 
•  $X = \begin{bmatrix} x_1^k \dots x_1^2 & x_1^1 & 1 \\ \dots & \dots & \dots \\ x_N^k \dots x_N^2 & x_N^1 & 1 \end{bmatrix}_{N\times (k+1)}$ 
•  $V = \begin{bmatrix} y_1 \\ \dots \\ y_N \end{bmatrix}_{N\times 1}$ 
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### any... X Formulation

#### Representation



### Linear Model

• 
$$L(W) = (XW - Y)^T (XW - Y)$$
  
•  $\nabla L = \begin{bmatrix} \frac{\partial L}{\partial w_1} \\ \vdots \\ \frac{\partial L}{\partial w_k} \end{bmatrix}$  //It's a function

• 
$$W_{(new)} = W_{(old)} - \nabla L|_{W=W_{(old)}}$$

This is the Linear part of the Squared error type s

Input point x is a vector k x 1 matrix

### Linear Model

### Linear Model Multi-Variate

• where,  $g(A_{m \times m}) \rightarrow scalar$ 

$$\bullet Y_{N\times m} = \begin{bmatrix} y_{11}, y_{1,2} \dots y_{1,m} \\ \dots \\ y_{N1}, y_{N,2} \dots y_{N,m} \end{bmatrix}_{N\times m}, \qquad \bullet \nabla L_{k\times m} = \begin{bmatrix} \frac{\partial L}{\partial w_{1,1}}, \dots, \frac{\partial L}{\partial w_{1,m}} \\ \dots \\ \frac{\partial L}{\partial w_{k,1}}, \dots, \frac{\partial L}{\partial w_{k,m}} \end{bmatrix} / / \text{It's a}$$

$$\begin{bmatrix} w_{1,1} \dots w_{1,m} \\ \end{bmatrix}$$
function

• 
$$W_{(new)} = W_{(old)} - \eta \nabla L|_{W=W_{(old)}}$$

• 
$$L(W) = g((XW - Y)^T(XW - Y))$$

#### Brain storm applications...

## Depends on X and Y

- For example, Audio recording → file size prediction
- For example, Image → Cat-like-picture-ness prediction [we will see classification formulation later]
- For example, Video → A given scene-like-ness prediction [we will see classification formulation later]
- For example, Text → A given meaning-like-ness prediction [we will see classification formulation later]
- For example, Measurements  $\rightarrow$  A given *concept*-like-*ness* prediction
- For example, Housing colony data 

  House price prediction (California house price prediction)

# Depends on X and Y (multi variate)

## The whole of the deep neural networks is an extension of this concept!

- Map one image to another
- Given a set of images, *fill-in the gap* regions of an image
- Given a set of audio clips, fill in the gaps of an audio clip
- Given a sentence in one language, translate a sentence in another language
- Given an image, map it to text sentence
- Given a text label, map it to generate an image
- Hundreds of applications... so many use cases, so many domains...

...people started to think that it is the end of the world? But not!! {Refer to what is and what is not ml slides}

Given a vector map it to Another vector