# Regression

EE698V - Machine Learning for Signal Processing

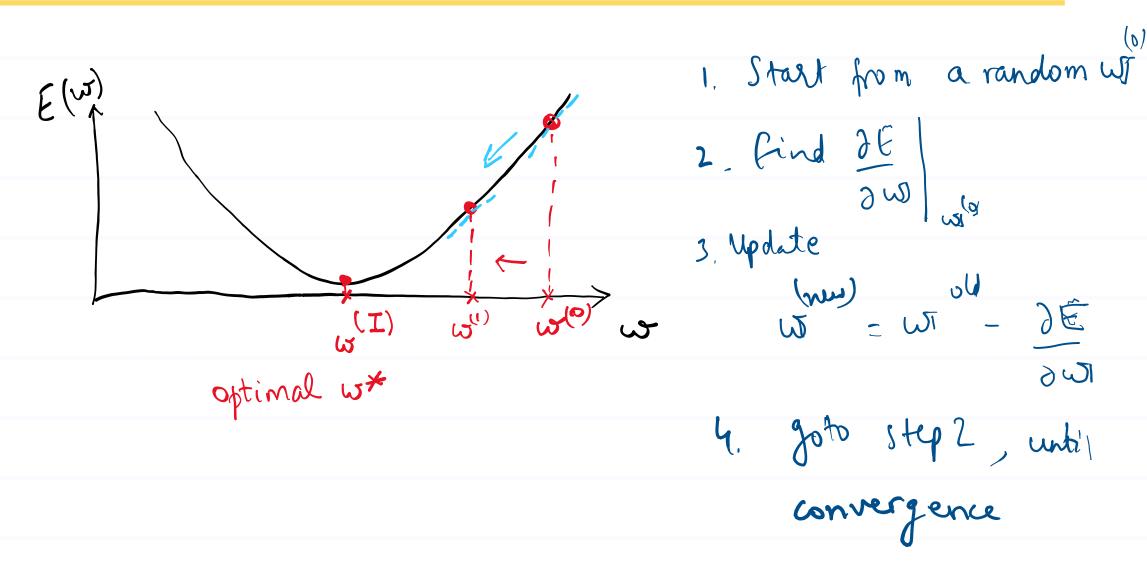
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### What if analytical solution not possible?

- This is true for most problems, e.g. neural networks
- Use iterative updates

#### Gradient Descent: scalar w



## Gradient Descent: any dimension w

$$\omega^{(T+1)} = \omega^{(z)} - \eta \partial E$$

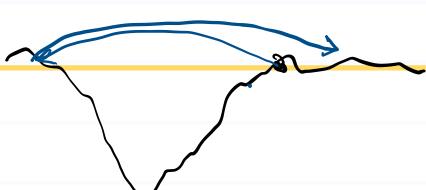
- We have already seen how to compute  $\frac{\partial E}{\partial w}$
- $\tau$  is iteration index
- $\eta$  is learning rate or step size

### Sequential Learning

- When data arriving in a stream
  - matrix inversion based solutions are difficult
  - iterative solutions are best used







- Learning depends on  $\eta$ 
  - Too small  $\eta$  : stuck in noisy bumps
  - Too large  $\eta$  : oscillates about the optimal value, or may even become unstable (explode)

#### **Data Normalization**

- If the input values vary too much, learning becomes unstable
- Good to scale to a small range (close to 0) them for better learning

$$\phi_{i}$$
  $w_{ij}$   $\Rightarrow$   $\phi_{i}$   $w_{ij}$  by substituting  $w_{ij}$ 
 $e[-100,100]$ 
 $e[-1,1]$ 
 $e[-1,1]$ 

## Non-linear Regression

Recap:  $y' = \Phi(x) W$ or  $y = \Phi(x) W$ 

1 could be a non linear function of x

y was a linear function of w.

Consider now  $yT = \sigma(\Phi(x)W_1)W_2$   $\sigma$  is sigmoid

function (element-wise operation)

This is non linear in W,

$$\mathcal{J}_{j}^{T} = \mathcal{J}(\Phi(x)W_{i})W_{2}$$

$$\mathcal{J}_{j} = \sum_{i,j} \mathcal{J}(\Sigma_{i,j}^{(x)}(x))W_{i,i,j}$$

$$\mathcal{J}_{j}^{(x)} = \sum_{i,j} \mathcal{J}(\Sigma_{i,j}^{(x)}(x))W_{i,i,j}$$

can use draw it:

#### References

- http://www.deeplearningbook.org/contents/ml.html
   (highly recommended)
- Behera, L., & Kar, I. (2010). Intelligent Systems and control principles and applications. Oxford University Press, Inc.. Chapter 2
- PRML: Chapter 5