

Levenberg-Marquardt learning

- MATLAB programming
- MLP (Multilayer Perceptrons)

MLP (multilayer perceptrons)

- Weight sum of post-tanh projections

$$F(\mathbf{x}; \theta) = \sum_{m=1}^M r_m \tanh(\mathbf{a}_m^T \mathbf{x} + b_m) + r_0$$

$$\theta = \{\mathbf{a}_m\} \cup \{b_m\} \cup \{r_m\}$$

Data Structure

● Net

- Net.a : receptive field $M \times d$
- Net.b : bias
- Net.r : posterior weights
- Net.M : number of hidden units
- Net.d : data dimension

LM_iniNet.m

```
1 - M = input('M : ');
2 - d = 2;
3 - ep = 0.001;
4 - L = M*d+2*M+1;
5 - theta = rand(1,L)*2*ep - ep;
6 % form a
7 - Net.a=reshape(theta(1:M*d),[d,M])';
8 % form b,r ??|
9 % Net.a = rand(M,d)*2*ep - ep;
10 - Net.M = M;
11 - Net.d = d;
12 % Net.b
13 % Net.r
```

Input & output

● x : $N \times d$

- N : data size
- d : data dimension

● y : $N \times 1$

● Net

[demo_LM.m](#)

```
3 - N=200;d=2;  
4 - x=rand(N,d)*2-1;  
5 - y=x(:,1)*0.5+x(:,2)+1;  
6 - Net=LM(x,y);
```

Data Structure

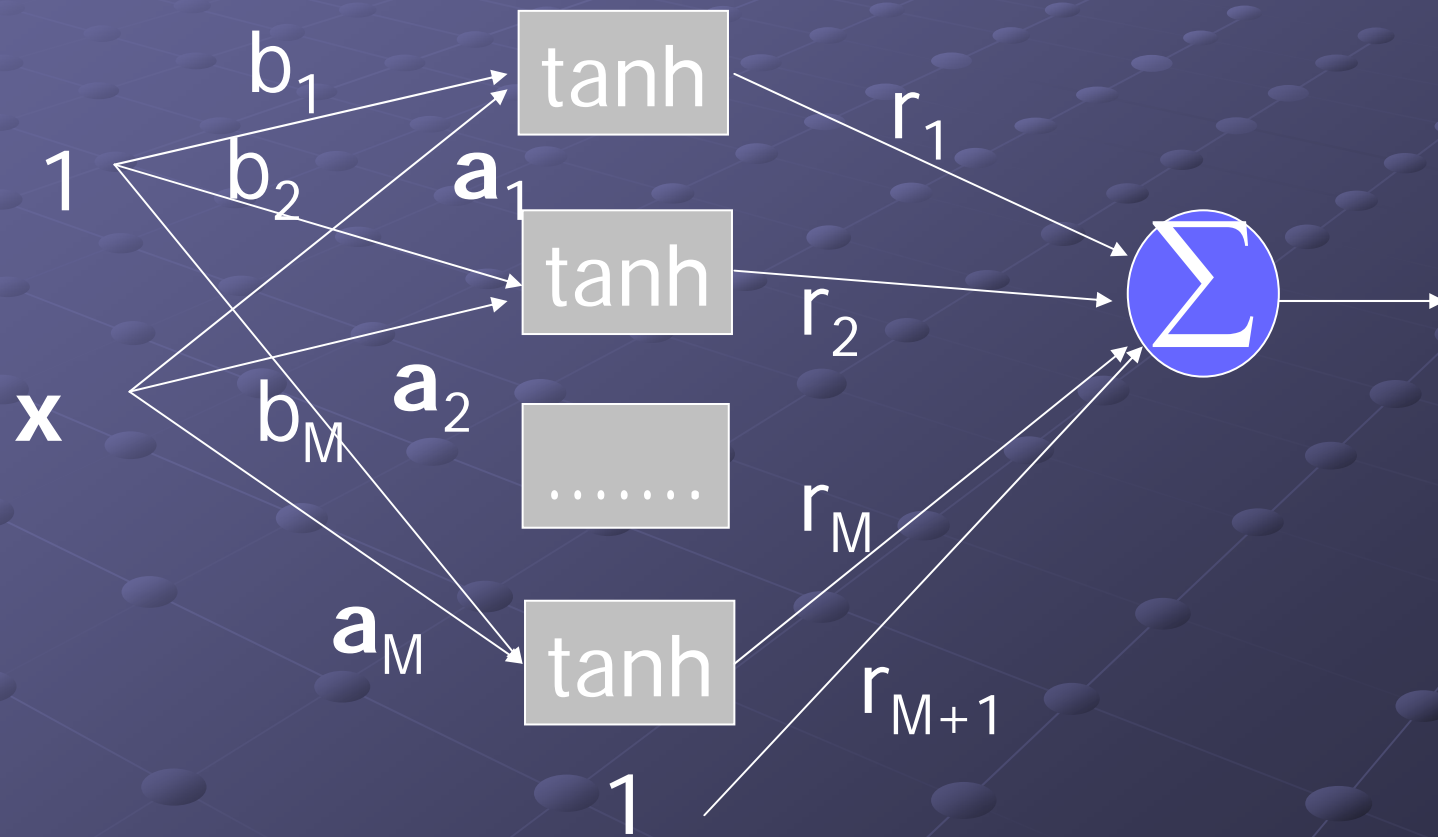
- Form a

```
a = reshape(theta(1:Net.M*Net.d),[Net.d,Net.M]);
```

- How to form b and r ?

$$\begin{aligned}\boldsymbol{\theta} &= [\mathbf{a}_1^T \ \mathbf{a}_2^T \ \cdots \ \mathbf{a}_M^T \ b_1 \ b_2 \ \cdots \ b_M \ r_0 \ r_1 \ r_2 \ \cdots \ r_M]^T \\ &= [\theta_1, \dots, \theta_{M*d+2M+1}]\end{aligned}$$

MLP



MLP Evaluation

- Form $h : N \times M$

- $x * a^T$

- Add b

- Form $v : N \times M$

- Feed to \tanh

- Multiply to r

- \hat{y} : network output, $N \times 1$

$$h_m = \mathbf{a}_m^T \mathbf{x} + b_m$$

$$v_m = \tanh(h_m)$$

Current error

- Approximating error

- $e = y - \hat{y}$
- Mean square error
 - $\text{mean}(e.^2)$

Derivative

[derivative.m](#)

```
function [gtheta]=derivative(Net,x,theta,h,v)
```

```
gtheta=[ ga gb gr ]
```

```
% gtheta : N x (Md+2M+1)
```

```
% ga : N x Md
```

```
% gb : N x M
```

```
% gr : N x ( M+1)
```

g_{θ} : $N \times (Md + 2M + 1)$

$$\varphi(t, \boldsymbol{\theta}) = \frac{dy(t|\boldsymbol{\theta})}{d\boldsymbol{\theta}}$$

$g_{\mathbf{a}}$: $N \times Md$

$$\frac{dy(t|\boldsymbol{\theta})}{d\mathbf{a}_k}$$

$$= r_k (1 - \tanh(\mathbf{a}_k^T \mathbf{x}[t] + b_k))^2 \mathbf{x}[t]$$

$$= g_{\mathbf{a}_{tk}}$$

$$ga = \begin{pmatrix} ga_{11}^T & \cdots & ga_{1k}^T & \cdots \\ \vdots & & \vdots & \\ ga_{t1}^T & \cdots & ga_{tk}^T & \cdots \\ \vdots & \vdots & \vdots & \vdots \end{pmatrix}_{N \times Md}$$

t runs from 1 to N

k runs from 1 to M

$$ga_{tk} : d \times 1$$

$$ga_{tk} = r_k (1 - \tanh(\mathbf{a}_k^T \mathbf{x}[t] + b_k))^2 \mathbf{x}[t]$$

```
[gtheta] = derivative(Net,x,theta,h,v);  
G = -(e*gtheta/Net.T)';  
R = gtheta'*gtheta/Net.T;
```

$$\nabla(\boldsymbol{\theta}_i) = \frac{-1}{N} \sum_{t=1}^N \varepsilon(t, \boldsymbol{\theta}_i) \psi(t, \boldsymbol{\theta}_i)$$

$$R(\boldsymbol{\theta}_i) = \frac{1}{N} \sum_{t=1}^N \psi(t, \boldsymbol{\theta}_i) \psi^T(t, \boldsymbol{\theta}_i)$$

LM method

LM.m

1. Initialize θ_i , $i=0$ and set λ
2. Calculate $\nabla(\theta_i)$ and $R(\theta_i)$ and $\Delta\theta_i$
3. Update network parameters

$$\theta_{i+1} = \theta_i + \Delta\theta_i$$

4. Calculate α_i

5. Update λ

(a) If $\alpha_i > 0.75$, $\lambda \leftarrow 0.5\lambda$.

(b) If $\alpha_i < 0.25$, $\lambda \leftarrow 2\lambda$.

6. If halting condition hold, exit otherwise go to step 2

- Calculate $\Delta\theta$
- Update θ

Control λ

Current parameter

Next parameter

$$\alpha_i = \frac{E_S(\boldsymbol{\theta}_i) - E_S(\boldsymbol{\theta}_i + \Delta\boldsymbol{\theta}_i)}{E_S(\boldsymbol{\theta}_i) - L_i(\boldsymbol{\theta}_i + \Delta\boldsymbol{\theta}_i)}$$

Actual cost reduction

Predicted cost reduction

Project

Learning RBF or MLP by the LM method

1. (30 pt) Derivation

$$\frac{dy(t | \theta)}{d\theta} = ?$$

2. (140 pt) Matlab codes

3. (50 pt) Testing

Derivative

$$\begin{aligned}\theta &= [\mathbf{u}_1^T \ \mathbf{u}_2^T \ \cdots \ \mathbf{u}_M^T \ \sigma_1 \ \sigma_2 \ \cdots \ \sigma_M \ w_0 \ w_1 \ w_2 \ \cdots \ w_M]^T \\ &= [\theta_1, \dots, \theta_{M*d+2M+1}]\end{aligned}$$

$$\frac{dy(t | \theta)}{d\theta} = \left[\frac{dy(t | \theta)}{d\theta_1}, \dots, \frac{dy(t | \theta)}{d\theta_{M*d+2M+1}} \right]^T$$

Derivative

$$\frac{dy(t | \theta)}{d\mathbf{u}_m} = ?$$

$$\frac{dy(t | \theta)}{d\sigma_m} = ?$$

$$\frac{dy(t | \theta)}{dw_m} = ?$$

Matlab coding

- (30 pt) Main program
- Matlab Functions
 - a. (10 pt) Calculate $E_S(\theta_i)$
 - b. (10 pt) Calculate $L_i(\theta_i)$

Matlab coding

- Matlab functions

- (10 pt) Calculate $\left. \frac{dy(t | \theta)}{d\mathbf{u}_m} \right|_{\theta=\theta_i}$

- (10 pt) Calculate $\left. \frac{dy(t | \theta)}{d\sigma_m} \right|_{\theta=\theta_i}$

- (10 pt) Calculate $\left. \frac{dy(t | \theta)}{d\mathbf{w}_m} \right|_{\theta=\theta_i}$

Matlab coding

- Matlab functions
 - (20 pt) Calculate $\nabla(\theta_i)$
 - (20 pt) Calculate $R(\theta_i)$
 - (20 pt) Calculate $G(\mathbf{x} | \theta)$

Test

- Give two examples to test your matlab codes for learning RBF or MLP networks by Levenberg-Marquardt method