Assignment 22.

Proving that MLPs having all neurons with linear transfer function are just simple 2 layer perzeptrons.

Assume the MLP is 3-layer MLP (N-H-M), we can derive output Y

$$\begin{aligned} Out_{H_{k}} &= f(net_{H_{k}}) = net_{H_{k}} = \sum_{n=1}^{N} W_{nh} \cdot X_{n} = W_{1h} \cdot X_{1} + W_{2h} \cdot X_{2} + \dots + W_{Nh} \cdot X_{N} \\ Out_{Y_{n}} &= f(net_{Y_{n}}) = net_{Y_{n}} = \sum_{h=1}^{H} U_{hm} \cdot H_{h} = U_{1m} \cdot H_{1} + U_{2m} \cdot H_{2} + \dots + U_{Hm} \cdot H_{H} \\ Out_{Y_{n}} &= U_{1m} \cdot (W_{11} \cdot X_{1} + W_{21} \cdot X_{2} + \dots + W_{N1} \cdot X_{N}) + U_{2m} \cdot (W_{12} \cdot X_{1} + W_{22} \cdot X_{2} + \dots + W_{N2} \cdot X_{N}) + \dots + U_{Hm} \cdot (W_{1H} \cdot X_{1} + W_{2H} \cdot X_{2} + \dots + W_{NH} \cdot X_{N}) \end{aligned}$$

$$Y_{m} = (U_{1m} \cdot W_{11} + U_{2m} \cdot W_{12} + \dots + U_{Hm} \cdot W_{1H}) \cdot X_{1} + (U_{1m} \cdot W_{21} + U_{2m} \cdot W_{22} + \dots + U_{Hm} \cdot W_{2H}) \cdot X_{2} + \dots + (U_{1m} \cdot W_{N1} + U_{2m} \cdot W_{N2} + \dots + U_{Hm} \cdot W_{NH}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N1} + U_{2m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N1}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N1} + U_{2m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N1}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N1} + U_{2m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N1}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N1} + U_{2m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N1}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N1} + U_{2m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N1}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N1} + U_{2m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N1}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N1} + U_{2m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N1}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N1} + U_{2m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N1}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N1} + U_{2m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N1}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N1} + U_{2m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N1} + U_{2m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m} \cdot W_{N2} + \dots + U_{Mm} \cdot W_{N2}) \cdot X_{N} + \dots + (U_{1m$$

Output Y always can be simplified in terms of Input X, where *An* includes the sum of Weights. (regardless of the structure of the network)

$$Y=A_1\cdot X_1+A_2\cdot X_2+\cdots+A_N\cdot X_N$$

This formula represents output of simple 2 layer perzeptron where A1~AN indicates weights to X to Y. What was done during the training process is factorizing *An* into various factors.

If linear transfer function will change into $f_2(z)=a^*z$, what will change?

Assume that the MLP is consist of 3-layers, then we get

$$Y_{m}=a^{2}\cdot(U_{1m}\cdot W_{11}+U_{2m}\cdot W_{12}+\cdots+U_{Hm}\cdot W_{1H})\cdot X_{1}+a^{2}\cdot(U_{1m}\cdot W_{21}+U_{2m}\cdot W_{22}+\cdots+U_{Hm}\cdot W_{2H})\cdot X_{2} + \cdots + a^{2}\cdot(U_{1m}\cdot W_{N1}+U_{2m}\cdot W_{N2}+\cdots+U_{Hm}\cdot W_{NH})\cdot X_{N}$$

The weights will increase for each additional layer,

$$Y_{m} = a^{n-1} \cdot (U_{1m} \cdot W_{11} + U_{2m} \cdot W_{12} + \dots + U_{Hm} \cdot W_{1H}) \cdot X_{1} + a^{n-1} \cdot (U_{1m} \cdot W_{21} + U_{2m} \cdot W_{22} + \dots + U_{Hm} \cdot W_{2H}) \cdot X_{2} + \dots + a^{n-1} \cdot (U_{1m} \cdot W_{N1} + U_{2m} \cdot W_{N2} + \dots + U_{Hm} \cdot W_{NH}) \cdot X_{N}$$

where n is number of layer.

So the changing of transfer function by multiplying *a* will change the weights rate for the alternative simple layer perzeptron.

1 Assignment 23

$${}^{p}\Delta w_{s} = -\eta \frac{\partial^{p} E^{**}(W_{s})}{\partial w_{s}}$$
$${}^{p}E^{**} = \frac{1}{2} \sum_{m=1}^{M} ({}^{p}\hat{Y_{m}} - {}^{p}Y_{m})^{2} + \beta \frac{1}{2} \sum_{i,j} (w_{ij})^{2}$$

1. Derivation for an output neuron m.

$$\begin{split} \frac{\partial^p E^{**}}{\partial w_{hm}} &= \frac{\partial^p E^{**}}{\partial^p net_m} \cdot \frac{\partial^p net_m}{\partial w_{hm}} \\ &\frac{\partial^p net_m}{\partial w_{hm}} = \frac{\partial}{\partial w_{ij}} \sum_{g=0}^H {}^p \widetilde{out_g} \cdot w_{gm} = ^p \widetilde{out_h} \\ \frac{\partial^p E^{**}}{\partial^p net_m} &= \frac{\partial^p E^{**}}{\partial^p y_m} \cdot \frac{\partial^p y_m}{\partial^p net_m} \\ &\frac{\partial^p y_m}{\partial^p net_m} = \frac{\partial f(^p net_m)}{\partial^p net_m} = f'(^p net_m) \\ &\frac{\partial^p E^{**}}{\partial^p y_m} = \frac{\partial}{\partial^p y_m} \frac{1}{2} \sum_{j=1}^M (^p \hat{y_j} - ^p y_j)^2 + \frac{\partial}{\partial^p y_m} \beta \frac{1}{2} \sum_{i,j} (w_{ij})^2 \\ &= \frac{1}{2} \frac{\partial}{\partial^p y_m} (^p \hat{y_m} - ^p y_m)^2 + 0 \\ &= \frac{1}{2} 2 (^p \hat{y_m} - ^p y_m) \frac{\partial}{\partial^p y_m} (-y_m) \\ &= (^p \hat{y_m} - ^p y_m) \cdot (-1) \\ &= - (^p \hat{y_m} - ^p y_m) \end{split}$$

Now, we get weight change formula - delta-rule.

$${}^{p}\Delta w_{s} = \eta \cdot ({}^{p}\hat{y_{m}} - {}^{p}y_{m}) \cdot f^{'}({}^{p}net_{m}) \cdot {}^{p}\widetilde{out_{h}}$$

$${}^{p}\Delta w_{hm} = \eta \cdot {}^{p}\delta_{m}^{**} \cdot {}^{p}\widetilde{out_{h}}$$

$$where, \quad {}^{p}\delta_{m}^{**} = -\frac{\partial^{p}E^{**}}{\partial^{p}net_{m}}$$

2. Derivation for a hidden neuron h.