

1. The sum of weights.

$$= 10 \times d^{(1)} + (d^{(1)} + 1) d^{(2)} + \dots + (d^{(L-2)} + 1) (d^{(L-1)} + 1) d^{(L)} + d^{(L-1)} \times 1$$

$$\text{s.t. } \sum_{t=1}^{L-1} d^{(t)} + 1 = 36.$$

for minimum weight number

$$\text{if } d^{(1)} = d^{(2)} = \dots = d^{(8)} = 1 \quad \text{185}$$

$$\text{min \# of weight} = 10 + 2 + \dots + 2 + 2 = 46$$

2. For maximum sum of weight numbers.

$\Rightarrow$  See program. greedy search.

$$\text{Max} = 510$$

$$3. \quad \nabla \text{err}_n(w) = \frac{\partial (x_n - w w^T x_n)^T (x_n - w w^T x_n)}{\partial w}$$

$$= 2 (x_n - w w^T x_n) \cdot \frac{\partial (x_n - w w^T x_n)}{\partial w}$$

$$= -2 (x_n - w w^T x_n) (x_n + x_n^T) w$$

$$= -2 (x_n + x_n^T) w (x_n - w w^T x_n)$$

$$= 2(x_n^T w)^2 w + 2(x_n^T w)(w^T w) x_n - 4w^T x_n x_n$$

$$4. \quad \hat{x}_n = x_n + \varepsilon_n$$

$$E(\varepsilon_n) = 0_n$$

$$\varepsilon_n \sim N(0_n, I)$$

$$E\tilde{m} = \frac{1}{N} \sum_{n=1}^N (x_n - W W^T x_n)^T (x_n - W W^T x_n)^T$$

$$= \frac{1}{N} \sum (x_n - W W^T x_n)^T (W W^T \varepsilon_n)$$

$$+ \sum (W W^T \varepsilon_n)^T (W W^T \varepsilon_n)$$

$$\Omega(w) = E \left[ \frac{1}{N} \sum (x_n - \cancel{w w^T} x_n)^T (W W^T \varepsilon_n) + \frac{1}{N} \sum (W W^T \varepsilon_n)^T (W W^T \varepsilon_n) \right]$$

$$= \frac{1}{N} \sum E [ \varepsilon_n^T W W^T W W^T \varepsilon_n ]$$

$$= W^T W \frac{1}{N} \sum E [ \varepsilon_n^T W W^T \varepsilon_n ]$$

$$= W^T W \frac{1}{N} \sum E \left[ \sum_{i=1}^d \varepsilon_{ni}^2 W_i^2 \right]$$

$$= W^T W \frac{1}{N} \sum_{n=1}^N \sum_{i=1}^d W_i^2 E(\varepsilon_{ni}^2)$$

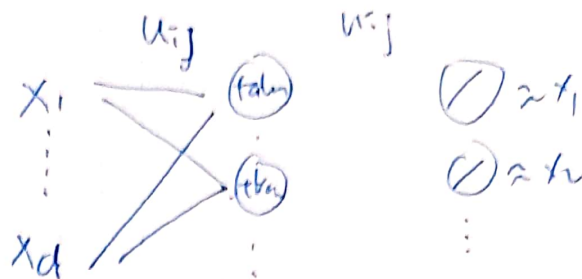
$$= W^T W \frac{1}{N} \sum_{n=1}^N \sum_{i=1}^d W_i^2 = \frac{1}{N} \sum (W^T W)^2 = \underline{(W^T W)^2}$$

5.

error function

$$= \sum_{i=1}^d (g_i(x) - x_i)^2$$

$$= \sum_{j=1}^d \left( \sum_{k=1}^{\tilde{d}} \underbrace{u_{ki}}_{w_{ji}^{(2)}} \tanh \left( \sum_{i=1}^d \underbrace{u_{ij}}_{w_{ij}^{(1)}} x_i \right) - x_j \right)^2$$



6.

$$\frac{\partial E}{\partial u_{ij}} = 2 \sum_{j=1}^d \left( \sum_{k=1}^{\tilde{d}} u_{ki} \tanh \left( \sum_{i=1}^d u_{ij} x_i \right) - x_j \right) \left[ \tanh \left( \sum_{i=1}^d u_{ij} x_i \right) + \sum_{k=1}^{\tilde{d}} u_{ki} \tanh \left( \sum_{i=1}^d u_{ij} x_i \right) \right]$$

$$\frac{\partial E}{\partial w_{ij}^{(1)}} = 2 \sum_{j=1}^d \left( \sum_{k=1}^{\tilde{d}} u_{ki} \tanh \left( \sum_{i=1}^d u_{ij} x_i \right) - x_j \right) \cdot \left( \sum_{k=1}^{\tilde{d}} u_{ki} \tanh \left( \sum_{i=1}^d u_{ij} x_i \right) \right) x_i$$

$$\frac{\partial E}{\partial w_{ij}^{(2)}} = 2 \sum_{j=1}^d \left( \sum_{k=1}^{\tilde{d}} u_{ki} \tanh \left( \sum_{i=1}^d u_{ij} x_i \right) - x_j \right) \cdot \tanh \left( \sum_{i=1}^d w_{ij}^{(1)} x_i \right)$$

$$2 \sum_{j=1}^d \left( \sum_{k=1}^{\tilde{d}} u_{ki} \tanh \left( \sum_{i=1}^d u_{ij} x_i \right) - x_j \right) \left[ \sum_{k=1}^{\tilde{d}} u_{ki} \tanh \left( \sum_{i=1}^d u_{ij} x_i \right) \tanh' \left( \sum_{i=1}^d u_{ij} x_i \right) x_i + \tanh \left( \sum_{i=1}^d w_{ij}^{(1)} x_i \right) \right]$$



7.

$$g_{LIN}(x) = \text{sign}(\|x - x_-\|^2 - \|x - x_+\|^2)$$

$$= \text{sign}((x - x_-)^T(x - x_-) - (x - x_+)^T(x - x_+))$$

$$= \text{sign}(2(x_+ - x_-)^T x + \|x_-\|^2 - \|x_+\|^2)$$

8.

$$p \cdot \tau \neq g_{RBFINZI}(x) \geq 1$$

$$\Rightarrow \beta_+ \exp(-\|x - \mu_+\|^2) + \beta_- \exp(-\|x - \mu_-\|^2) \geq 0$$

$$\Rightarrow \frac{\exp(-\|x - \mu_+\|^2)}{\exp(-\|x - \mu_-\|^2)} \geq -\frac{\beta_-}{\beta_+}$$

$$\Rightarrow \underbrace{\|x - \mu_-\|^2 - \|x - \mu_+\|^2}_{\text{as } g_{LIN}} \geq \ln\left(-\frac{\beta_-}{\beta_+}\right)$$

as  $g_{LIN}$ , using (17) solution

$$w = 2(\mu_+ - \mu_-)$$

$$b = \|\mu_-\|^2 - \|\mu_+\|^2 - \ln\left(-\frac{\beta_-}{\beta_+}\right)$$

9.

$$\sum_{n=1}^n \sum_{\substack{(x_n, r_{nm}) \\ \in D_m}} (r_{nm} - w_m^T v_n)^2$$

$$\text{FOC: } 2 \sum_{\substack{(x_n, r_{nm}) \\ \in D_m}} (r_{nm} - w_m^T v_n) v_n = 0$$

$$\Rightarrow \sum (r_{nm} - w_m^T v_n) = 0$$

$$\Rightarrow w_m = \frac{\sum_n r_{nm}}{\sum_n v_n} = \frac{\sum_n r_{nm}}{n}$$

average rating

10.

$$\max_m v_{n+1}^T v_m = \max_m \left( \frac{1}{N} \sum v_n \right)^T w_m$$

$$= \max_m \frac{1}{N} \sum v_n^T w_m = \max_m \underbrace{\frac{1}{N} \sum r_{nm}}_{\text{maximum of average rating.}}$$