

Pencil and Paper

1.

$$p(v|h, \theta) = \frac{p(v, h|\theta)}{p(h|\theta)} \quad (1)$$

$$p(h|\theta) = \sum_v p(v, h|\theta) \quad (2)$$

$$p(v|h, \theta) = \frac{p(v, h|\theta)}{\sum_v p(v, h|\theta)} \quad (3)$$

Since each node is independent, the $p(v, h|\theta)$ can be written as:

$$p(v, h|\theta) = \frac{\prod_i^n \prod_j^m e^{-W_{ij}h_i v_j - b_j v_j - c_i h_i}}{\sum_v \sum_h \prod_i^n \prod_j^m e^{-W_{ij}h_i v_j - b_j v_j - c_i h_i}} \quad (4)$$

$$= \frac{\prod_i^n \prod_j^m p(v_j, h_i|\theta)}{\sum_v \sum_h \prod_i^n \prod_j^m p(v_j, h_i|\theta)} \quad (5)$$

$$(6)$$

Then the conditional probability of v can be expressed as:

$$p(v|h, \theta) = \frac{\prod_i^n \prod_j^m p(v_j, h_i|\theta)}{\sum_v \prod_i^n \prod_j^m p(v_j, h_i|\theta)} \quad (7)$$

So for $v_j = 1$, the conditional probability is:

$$p(v_j|h, \theta) = \frac{\prod_i^n e^{-W_{ij}h_i - b_j}}{1 + \prod_i^n e^{-W_{ij}h_i - b_j}} \quad (8)$$

Again, since the nodes are independent and v can only take two values. The expectation terms can be simplified to:

$$E[v_j|h, \theta] = \frac{\prod_i^n e^{-W_{ij}h_i - b_j}}{1 + \prod_i^n e^{-W_{ij}h_i - b_j}} \quad (9)$$

$$= \text{sigmoid}\left(\sum_{i=1}^n W_{ij}h_i + b_j\right) \quad (10)$$

2.

The prove is the same as the first part. Just flip v and h :

$$p(h_i|v, \theta) = \frac{\prod_j^m e^{-W_{ij}v_j - c_i}}{1 + \prod_j^m e^{-W_{ij}v_j - c_i}} \quad (11)$$

$$E[h_i|v, \theta] = \frac{\prod_j^m e^{-W_{ij}v_j - c_i}}{1 + \prod_j^m e^{-W_{ij}v_j - c_i}} \quad (12)$$

$$= \text{sigmoid}\left(\sum_{j=1}^m W_{ij}v_j + c_i\right) \quad (13)$$

For each training token:

$$\log p(v|\theta) = \log \sum_h e^{-E(v,h)} - \log Z(\theta) \quad (14)$$

First let's find out the derivation of the first term in the RHS of eq.14:

$$\frac{-\sum_h e^{-E(v,h)} \frac{\partial E(v,h)}{\partial \theta}}{\sum_h e^{-E(v,h)}} = -\sum_h \frac{\partial E(v,h)}{\partial \theta} p(h|v) \quad (15)$$

Then for the second term:

$$\frac{1}{Z(\theta)} \frac{\partial Z(\theta)}{\partial \theta} = \frac{-\sum_h \sum_v e^{-E(v,h)} \frac{\partial E(v,h)}{\partial \theta}}{\sum_h \sum_v e^{-E(v,h)}} \quad (16)$$

$$= -\sum_h \sum_v \frac{\partial E(v,h)}{\partial \theta} p(v,h|\theta) \quad (17)$$

So the derivative can be expressed as:

$$\frac{\partial \mathcal{L}(D|\theta)}{\partial \theta} = \sum_h \sum_v \frac{\partial E(v,h)}{\partial \theta} p(v,h|\theta) - \sum_h \frac{\partial E(v,h)}{\partial \theta} p(h|v) \quad (18)$$

$$= \mathbf{E}\left[\frac{\partial E(v,h)}{\partial \theta} | \theta\right] - \mathbf{E}\left[\frac{\partial E(v,h)}{\partial \theta} | v, \theta\right] \quad (19)$$

3.

$$\frac{\partial E(v,h)}{\partial w_{ij}} = -h_i v_j \quad (20)$$

Plug the above expression into eq.19:

$$\frac{\partial \mathcal{L}(D|\theta)}{\partial w_{ij}} = -\sum_h \sum_v v_j h_i p(v,h|\theta) + \sum_h v_j h_i p(h|v) \quad (21)$$

$$= \mathbf{E}[v_j h_i | v, \theta] - \mathbf{E}[v_j h_i | \theta] \quad (22)$$

$$= v_j \text{sigmoid}\left(\sum_{j=1}^m w_{ij}v_j + c_i\right) - \mathbf{E}[v_j h_i | \theta] \quad (23)$$

for b:

$$\frac{\partial E(v, h)}{\partial b_j} = -v_j \quad (24)$$

Again plug it into eq.19:

$$\frac{\partial \mathcal{L}(D|\theta)}{\partial b_j} = - \sum_h \sum_v v_j p(v, h|\theta) + \sum_h v_j p(h|v) \quad (25)$$

$$= \mathbf{E}[v_j|v, \theta] - \mathbf{E}[v_j|\theta] \quad (26)$$

$$= v_j - \mathbf{E}[v_j|\theta] \quad (27)$$

For c:

$$\frac{\partial \mathcal{L}(D|\theta)}{\partial c_i} = - \sum_h \sum_v h_i p(v, h|\theta) + \sum_h h_i p(h|v) \quad (28)$$

$$= \mathbf{E}[h_i|v, \theta] - \mathbf{E}[h_i|\theta] \quad (29)$$

$$= \text{sigmoid}\left(\sum_{j=1}^m w_{ij}v_j + c_i\right) - \mathbf{E}[h_i|\theta] \quad (30)$$

4.

To compute the second term in (23), (27) and (30) require computing the normalization term $Z(\theta)$, which is intractable. Use Hinton approximation:

$$\mathbf{E}[v_j h_i|\theta] = \mathbf{E}[v_j|h] \mathbf{E}[h_i|v] \quad (31)$$

$$= \mathbf{E}[v_j|\mathbf{E}[h|v, \theta]] \mathbf{E}[h_i|v] \quad (32)$$

$$= \sum_{i=1}^n [w_{ij} \text{sigmoid}\left(\sum_{j=1}^m w_{ij}v_j + c_i\right)] \text{sigmoid}\left(\sum_{j=1}^m w_{ij}v_j + c_i\right) \quad (33)$$

for b:

$$\mathbf{E}[v_j|\theta] = \mathbf{E}[v_j|\mathbf{E}[h|v, \theta]] \quad (34)$$

$$= \mathbf{E}[v_j|\mathbf{E}[h|v, \theta]] \mathbf{E}[h_i|v] \quad (35)$$

$$= \sum_{i=1}^n [w_{ij} \text{sigmoid}\left(\sum_{j=1}^m w_{ij}v_j + c_i\right)] \quad (36)$$

for c:

$$\mathbf{E}[h_i|\theta] = \text{sigmoid}\left(\sum_{j=1}^m w_{ij}v_j + c_i\right) \quad (37)$$