

< Assignment 01 >

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#1-(a). Because only 0 is the position that the value is 1, and 0 everywhere else.

#1-(b).

Substituting (1) into (2), then

$$J = \log \sum_w (\exp(U_w^T v_c)) - U_0^T v_c$$

$$\text{Here, } \frac{\partial J}{\partial v_c} = -U_0 + \frac{\sum_w \exp(U_w^T v_c) \cdot U_w}{\sum_w \exp(U_w^T v_c)} = -U_0 + \sum_w \hat{y}_w U_w$$

$$[J] = \begin{bmatrix} | & | & \dots & | & \dots \\ U_1 & U_2 & \dots & U_w & \dots \\ | & | & & | & \end{bmatrix} \quad \text{and } y \text{ is one-hot vector, so } [J] y \text{ indicates } U_0$$

$$\text{Also, } [J] \hat{y} \text{ indicates } \sum_w \hat{y}_w U_w. \quad \text{Therefore, } \underline{\underline{\frac{\partial J}{\partial v_c} = [J] (\hat{y} - y)}}$$

(1) The gradient will be zero if $\hat{y} = y$.

(2) By subtracting the gradient from v_c , v_c will be adjusted to the direction that reduce the difference between predicted value and true value. In other words, v_c will be closer to the outside word vectors in its context.

#1-(c).

i) $w=0$ ($U_w=U_0$)

ii) $w \neq 0$

$$\frac{\partial J}{\partial U_w} = -v_c + \frac{\exp(U_w^T v_c) v_c}{\sum_w \exp(U_w^T v_c)} = (\hat{y}_0 - 1) v_c \quad \frac{\partial J}{\partial U_w} = \frac{\exp(U_w^T v_c) v_c}{\sum_w \exp(U_w^T v_c)} = \hat{y}_w v_c$$

#1-(d). With the answer of 1-(c), and assuming $V = |\text{Vocab}|$,

$$\frac{\partial J}{\partial U_1} = \begin{cases} (\hat{y}_1 - 1) v_c & \text{if } w=1=0 \\ \hat{y}_1 v_c & \text{if } w=1 \neq 0 \end{cases} \quad \frac{\partial J}{\partial U_2} = \begin{cases} (\hat{y}_2 - 1) v_c & \text{if } w=2=0 \\ \hat{y}_2 v_c & \text{if } w=2 \neq 0 \end{cases} \quad \dots \quad \frac{\partial J}{\partial U_V} = \begin{cases} (\hat{y}_V - 1) v_c & \text{if } w=V=0 \\ \hat{y}_V v_c & \text{if } w=V \neq 0 \end{cases}$$

1-(E).

$$\frac{d\sigma}{dx} = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x < 0 \end{cases}$$

1-(F).

$$\sigma'(x) = \frac{e^{-x}}{(1+e^{-x})^2} = \frac{1}{1+e^{-x}} \left(1 - \frac{1}{1+e^{-x}} \right) = \underline{\underline{\sigma(x)(1-\sigma(x))}}$$

1-(G). $J = -\log(\sigma(\mathbf{U}_0^T \mathbf{V}_c)) - \sum_{s=1}^K \log(\sigma(-\mathbf{U}_{w_s}^T \mathbf{V}_c))$

(i). For \mathbf{V}_c ,

$$\begin{aligned} \frac{\partial J}{\partial \mathbf{V}_c} &= - \frac{\sigma(\mathbf{U}_0^T \mathbf{V}_c)(1-\sigma(\mathbf{U}_0^T \mathbf{V}_c)) \cdot \mathbf{U}_0}{\sigma(\mathbf{U}_0^T \mathbf{V}_c)} - \sum_s \frac{\cancel{\sigma(\mathbf{U}_{w_s}^T \mathbf{V}_c)} \cdot (1-\sigma(-\mathbf{U}_{w_s}^T \mathbf{V}_c)) \cdot (-\mathbf{U}_{w_s})}{\cancel{\sigma(-\mathbf{U}_{w_s}^T \mathbf{V}_c)}} \\ &= \underline{\underline{-(1-\sigma(\mathbf{U}_0^T \mathbf{V}_c)) \mathbf{U}_0 + \sum_s (1-\sigma(-\mathbf{U}_{w_s}^T \mathbf{V}_c)) \mathbf{U}_{w_s}}} \end{aligned}$$

For \mathbf{U}_0 ,

$$\frac{\partial J}{\partial \mathbf{U}_0} = \underline{\underline{-(1-\sigma(\mathbf{U}_0^T \mathbf{V}_c)) \mathbf{V}_c}}$$

For \mathbf{U}_{w_s} ,

$$\frac{\partial J}{\partial \mathbf{U}_{w_s}} = \underline{\underline{(1-\sigma(-\mathbf{U}_{w_s}^T \mathbf{V}_c)) \mathbf{V}_c}}$$

(ii) $[\mathbf{U}_{0, \{w_1, \dots, w_K\}}^T \cdot \mathbf{V}_c] = [\mathbf{U}_0^T \mathbf{V}_c, -\mathbf{U}_{w_1}^T \mathbf{V}_c, \dots, -\mathbf{U}_{w_K}^T \mathbf{V}_c]$

Therefore, we can reuse $\underline{\underline{\sigma([\mathbf{U}_{0, \{w_1, \dots, w_K\}}^T \cdot \mathbf{V}_c)] - 1}}$,

(iii) We need lesser vectors than the naive-softmax loss.

1-(h).

$$J = -\log(\sigma(\mathbf{U}_0^T \mathbf{V}_c)) - \sum_{w_j = w_s} \log(\sigma(-\mathbf{U}_{w_j}^T \mathbf{V}_c)) - \sum_{w_j \neq w_s} \log(\sigma(-\mathbf{U}_{w_j}^T \mathbf{V}_c))$$

Assuming there are m w_s words, $\frac{\partial J}{\partial \mathbf{U}_{w_s}} = \underline{\underline{m(1-\sigma(-\mathbf{U}_{w_s}^T \mathbf{V}_c)) \mathbf{V}_c}}$

(i)

$$\frac{\partial \mathcal{J}(V_c, W_{t-m}, \dots, W_{t+m}, U)}{\partial U} = \sum_{\substack{-m \leq j \leq m \\ j \neq 0}} \frac{\partial \mathcal{J}(V_c, W_{t+j}, U)}{\partial U}$$

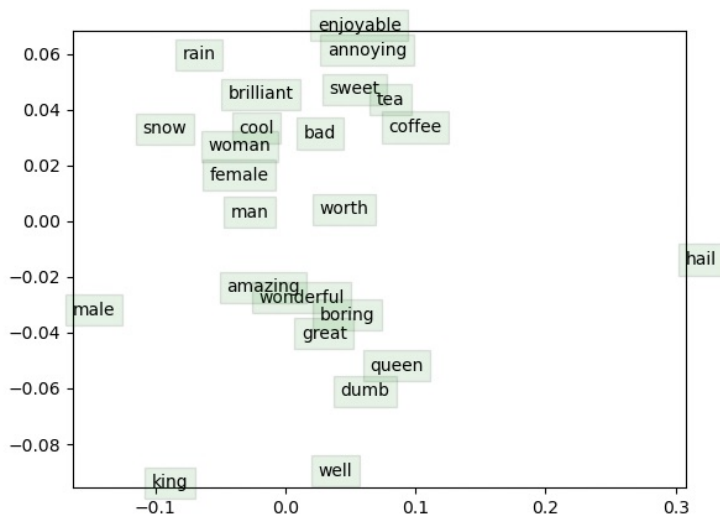
(ii)

$$\frac{\partial \mathcal{J}(V_c, W_{t-m}, \dots, W_{t+m}, U)}{\partial V_c} = \sum_{\substack{-m \leq j \leq m \\ j \neq 0}} \frac{\partial \mathcal{J}(V_c, W_{t+j}, U)}{\partial V_c}$$

(iii)

$$\frac{\partial \mathcal{J}(V_c, W_{t-m}, \dots, W_{t+m}, U)}{\partial V_w} = 0$$

#2 - (C).



There are many well-clustered words such as (amazing, wonderful, boring, great). However, there are also not well-clustered words like "hail", which should have clustered with (rain, snow). Also, in evaluation, antonyms are considered as similar, and it is shown in the cluster "great (pos) \leftrightarrow boring (neg)"