

CS 224N

Assignment 2 [Written]

Understanding Word2Vec

Given:

$$P(O=o | C=c) = \frac{\exp(u_o^T v_c)}{\sum_{\omega \in \text{Vocab}} \exp(u_\omega^T v_c)}$$

$$J_{\text{naive-softmax}}(v_c, o, U) = -\log P(O=o | C=c)$$

a) To prove:

$$-\sum_{\omega} y_{\omega} \log(\hat{y}_{\omega}) = -\log(\hat{y}_o)$$

Since, $\bar{y}_o = [0 \dots \underset{\text{o}^{\text{th}} \text{ Index}}{1} \dots 0]$

as y_{ω} is just one-hot pointing to the true output word, hence

$$y_{\omega} = \begin{cases} 0 & \text{for } \omega \neq o \\ 1 & \text{for } \omega = o \end{cases}$$

$$\begin{aligned} -\sum y_{\omega} \log(\hat{y}_{\omega}) &= 0 + 0 \dots \\ &\quad -\log(\hat{y}_o) \\ &= -\log(\hat{y}_o) \end{aligned}$$

b) To get: $\frac{\partial J_{\text{max}} - \text{softmax}}{\partial V_c}$

First, let's simplify J_{ns} a bit.

$$J_{\text{ns}} = -\log \left(\frac{\exp(u_0^T V_c)}{\sum_{\omega} \exp(u_{\omega}^T V_c)} \right)$$

$$= -u_0^T V_c + \log \left(\sum_{\omega} \exp(u_{\omega}^T V_c) \right)$$

Then, we have,

$$\frac{\partial J_{\text{ns}}}{\partial V_c} = -u_0 + \frac{1}{\sum_{\omega} \exp(u_{\omega}^T V_c)} \cdot \sum_{\omega} \exp(u_{\omega}^T V_c)$$

$$\equiv -u_0 + \frac{U \cdot \exp(U^T V_c)}{\mathbf{1} \cdot \exp(U^T V_c)}$$

$\begin{matrix} d \times m & m \times d & d \times 1 \\ U & \exp(U^T V_c) & \mathbf{1} \end{matrix}$

where $U \in \mathbb{R}^{d \times m}$
 $V_c \in \mathbb{R}^{d \times 1}$
 $\mathbf{1} = [1, 1, \dots]$

$$\equiv -U \cdot \hat{y} + U \cdot \hat{y}$$

$$= U \cdot (\hat{y} - y)$$

c) To compute: $\frac{\partial J_{ns}}{\partial \vec{u}_\omega}$

for $\omega \in \{1, \dots, m\}$

case I: $\omega \neq 0$, u_ω

$$\frac{\partial}{\partial u_\omega} \left(-u_\omega^T v_c + \log \left(\sum \exp(u_\omega^T v_c) \right) \right)$$

$$= 0 + \frac{1}{\sum \exp(u_\omega^T v_c)} \cdot \exp(u_\omega^T v_c) \cdot v_c$$

$$= \hat{y}_\omega \cdot \bar{v}_c$$

case II: $\omega = 0$

$$\frac{\partial}{\partial u_0} \left(-u_0^T v_c + \log \left(\sum \exp(u_\omega^T v_c) \right) \right)$$

$$= -v_c + \frac{1}{\sum \exp(u_\omega^T v_c)} \cdot \exp(u_0^T v_c) \cdot v_c$$

$$= -\bar{v}_c + \hat{y}_0 \cdot \bar{v}_c$$

$$= \bar{v}_c (\hat{y}_0 - \bar{y}_0)$$

$$d) \quad \frac{\partial J_{ns}}{\partial \vec{U}} = \left[\frac{\partial J}{\partial u_0} \quad \frac{\partial J}{\partial u_1} \quad \dots \quad \frac{\partial J}{\partial u_m} \right]$$

$$= \left[\hat{y}_0 \bar{v}_c, \hat{y}_1 \bar{v}_c, \dots, \bar{v}_c (\hat{y}_m - y_0), \dots, \hat{y}_m \bar{v}_c \right]$$

$$\left(\frac{\partial J_{ns}}{\partial \vec{U}} \right)_{m \times 1} = \bar{v}_c \cdot \left(\vec{\hat{y}} - \vec{y} \right)_{m \times 1}^T$$

$$e) \quad \sigma(x) = \frac{1}{1 + e^{-x}} \quad + 0 =$$

we need: $\frac{\partial \sigma(x)}{\partial x} = \frac{1}{(1 + e^{-x})^2} \cdot e^{-x}$

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

$$= \sigma(x) \left[\frac{1 + e^{-x} - 1}{1 + e^{-x}} \right]$$

$$= \sigma(x) \left[1 - \frac{1}{1 + e^{-x}} \right]$$

$$= \sigma(x) (1 - \sigma(x))$$

f)

$$J_{\text{neg-sampling}} = -\log(\sigma(u_0^T v_c)) \\ + \sum_{k=1}^K \log(\sigma(-u_k^T v_c))$$

i) To get: $\frac{\partial J_{\text{neg-sampling}}}{\partial v_c}$

$$\frac{\partial J_{\text{ns}}}{\partial v_c} = - \frac{1}{\sigma(u_0^T v_c)} (1 - \sigma(u_0^T v_c)) \cdot u_0$$

$$+ \sum_k \frac{1}{\sigma(-u_k^T v_c)} \sigma(-u_k^T v_c)$$

$$\cdot (1 - \sigma(u_k^T v_c))$$

$$= -1(1 - \sigma(u_0^T v_c)) \bar{u}_0$$

$$+ \sum \bar{u}_k (1 - \sigma(-u_k^T v_c))$$

ii) To get: $\frac{\partial J_{\text{ns}}}{\partial u_0}$

$$\frac{\partial J_{\text{ns}}}{\partial u_0} = - \frac{1}{\sigma(u_0^T v_c)} \cdot \sigma(u_0^T v_c) \cdot (1 - \sigma(u_0^T v_c)) \cdot v_c$$

$$= - (1 - \sigma(u_0^T v_c)) v_c$$

ii) To get : $\frac{\partial J_{ns}}{\partial u_k}$

$$\frac{\partial J_{ns}}{\partial u_k} = 0 - \frac{1}{\sigma(-u_k^T v_c)} \cdot \sigma(-u_k^T v_c) (1 - \sigma(-u_k^T v_c))$$

$$= \frac{1 - \sigma(-u_k^T v_c)}{\sigma(-u_k^T v_c)} v_c$$

g) In the case that the indices are distinct, the indices can be divided into two parts:

- i) One containing same index k
- ii) Other not being k

$$\Rightarrow \frac{\partial J_{ns}}{\partial u_k} = \sum_{d=1}^{d_k} \frac{1}{\sigma(-u_k^T v_c)} \cdot \sigma(-u_k^T v_c) (1 - \sigma(-u_k^T v_c))$$

$$= d_k (1 - \sigma(-u_k^T v_c)) v_c$$

where d_k are the no. of k^{th} indices in samples.

b) For skip gram, since,

$$J_{sg}(v_c, w_{t-m}, \dots, w_{t+m}, U)$$

$$= \sum_{\substack{-m \leq j \leq m \\ j \neq 0}} J(v_c, w_{t+j}, U)$$

$$i) \frac{\partial J_{sg}}{\partial U} \equiv \sum_{\substack{-m \leq j \leq m \\ j \neq 0}} \frac{\partial J}{\partial U}(v_c, w_{t+j}, U)$$

$$ii) \frac{\partial J_{sg}}{\partial v_c} \equiv \sum_{\substack{-m \leq j \leq m \\ j \neq 0}} \frac{\partial J}{\partial v_c}(v_c, w_{t+j}, U)$$

$$iii) \frac{\partial J_{sg}}{\partial v_w} = 0 \quad \left[\begin{array}{l} \text{since the term} \\ v_w \text{ doesn't occur} \\ \text{at all in the} \\ \text{expression.} \end{array} \right]$$