

Assignment 2: word2vec

1. Written: Understanding word2vec

(a) True output vector y is 1 in o^{th} position and 0 else where. So the cross-entropy
 $-\sum_{w \in Vocab} y_w \log(\hat{y}_w) = -\log(\hat{y}_o)$

(b) $J_{navie-softmax}(v_c, o, U) = -u_o^T v_c + \log \sum_{w \in Vocab} \exp(u_w^T v_c)$

$$\begin{aligned}\frac{\partial J}{\partial v_c} &= -u_o + \frac{\frac{\partial}{\partial v_c} \sum_{w \in Vocab} \exp(u_w^T v_c)}{\sum_{w \in Vocab} \exp(u_w^T v_c)} \\ &= -u_o + \frac{\sum_{w \in Vocab} \exp(u_w^T v_c) u_w}{\sum_{w \in Vocab} \exp(u_w^T v_c)} \\ &= -u_o + \sum_{\hat{w} \in Vocab} \frac{\exp(u_{\hat{w}}^T v_c)}{\sum_{w \in Vocab} \exp(u_w^T v_c)} u_{\hat{w}} \\ &= -Uy + \sum_{\hat{w} \in Vocab} u_{\hat{w}} \hat{y}_{\hat{w}} \\ &= -Uy + U\hat{y} \\ &= U(\hat{y} - y)\end{aligned}$$

where $U \in \mathbb{R}^{d \times |V|}$, $y \in \mathbb{R}^{|V| \times 1}$, $\hat{y} \in \mathbb{R}^{|V| \times 1}$

(c) $J_{navie-softmax}(v_c, o, U) = -u_o^T v_c + \log \sum_{w \in Vocab} \exp(u_w^T v_c)$

($w \neq o$)

$$\begin{aligned}\frac{\partial J}{\partial u_w} &= \frac{\frac{\partial}{\partial u_w} \sum_{w \in Vocab} \exp(u_w^T v_c)}{\sum_{w \in Vocab} \exp(u_w^T v_c)} \\ &= \frac{\exp(u_w^T v_c) v_c}{\sum_{w \in Vocab} \exp(u_w^T v_c)} \\ &= \hat{y}_w v_c\end{aligned}$$

($w = o$)

$$\begin{aligned}\frac{\partial J}{\partial u_w} &= -v_c + \frac{\frac{\partial}{\partial u_w} \sum_{w \in Vocab} \exp(u_w^T v_c)}{\sum_{w \in Vocab} \exp(u_w^T v_c)} \\ &= -v_c + \frac{\exp(u_w^T v_c) v_c}{\sum_{w \in Vocab} \exp(u_w^T v_c)} \\ &= (\hat{y}_w - 1)v_c\end{aligned}$$

$$\text{Then } \frac{\partial J(v_c, o, U)}{\partial U} = v_c(\hat{y} - y)^T$$

(d)

$$\begin{aligned}
\frac{\partial \sigma(x_i)}{\partial x_i} &= \sigma(x_i) - \frac{e^{x_i} \frac{\partial}{\partial x_i}(e^{x_i} + 1)}{(e^{x_i} + 1)^2} \\
&= \sigma(x_i) - \frac{e^{2x_i}}{(e^{x_i} + 1)^2} \\
&= \sigma(x_i) - \sigma^2(x_i)
\end{aligned}$$

$$\begin{aligned}
\frac{\sigma(x)}{\partial x} &= \left[\frac{\partial \sigma(x_j)}{\partial x_i} \right]_{d \times d} \\
&= \begin{bmatrix} \sigma'(x_1) & 0 & \cdots & 0 \\ 0 & \sigma'(x_2) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \sigma'(x_d) \end{bmatrix} \\
&= \text{diag}(\sigma'(x))
\end{aligned}$$

(e)

$$J_{neg-sample}(v_c, o, U) = -\log(\sigma(u_o^T v_c)) - \sum_{k=1}^K \log(\sigma(-u_k^T v_c))$$

Respect to v_c :

$$\begin{aligned}
\frac{\partial J}{\partial v_c} &= -\frac{\frac{\partial}{\partial v_c} \sigma(u_o^T v_c)}{\sigma(u_o^T v_c)} - \sum_{k=1}^K \frac{\frac{\partial}{\partial v_c} \sigma(-u_k^T v_c)}{\sigma(-u_k^T v_c)} \\
&= -\frac{\sigma(u_o^T v_c)(1 - \sigma(u_o^T v_c))u_o}{\sigma(u_o^T v_c)} + \sum_{k=1}^K \frac{\sigma(-u_k^T v_c)(1 - \sigma(-u_k^T v_c))u_k}{\sigma(-u_k^T v_c)} \\
&= (\sigma(u_o^T v_c) - 1)u_o + \sum_{k=1}^K \sigma(u_k^T v_c)u_k
\end{aligned}$$

Respect to u_o :

$$\begin{aligned}
\frac{\partial J}{\partial u_o} &= -\frac{\frac{\partial}{\partial u_o} \sigma(u_o^T v_c)}{\sigma(u_o^T v_c)} \\
&= (\sigma(u_o^T v_c) - 1)v_c
\end{aligned}$$

Respect to u_k :

$$\begin{aligned}
\frac{\partial J}{\partial u_k} &= -\frac{\partial}{\partial u_k} \sum_{k=1}^K \log(\sigma(-u_k^T v_c)) \\
&= (1 - \sigma(-u_k^T v_c))v_c \\
&= \sigma(u_k^T v_c)v_c, \text{ for } k = 1, 2, \dots, K
\end{aligned}$$

(f)

$$\frac{\partial J_{\text{skip-gram}}(v_c, w_{t-m}, \dots, w_{t+m}, U)}{\partial U} = \sum_{-m \leq j \leq m, j \neq 0} \frac{\partial J(v_c, w_{t+j}, U)}{\partial U}$$

$$\frac{\partial J_{\text{skip-gram}}(v_c, w_{t-m}, \dots, w_{t+m}, U)}{\partial v_c} = \sum_{-m \leq j \leq m, j \neq 0} \frac{\partial J(v_c, w_{t+j}, U)}{\partial v_c}$$

$$\frac{\partial J_{\text{skip-gram}}(v_c, w_{t-m}, \dots, w_{t+m}, U)}{\partial v_w} = 0$$

The plot of my training

