$CS224N_A1$

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1 Question 1

the cross entropy loss between the true (dicrete) probability p and another distribution q is $-\sum_{i} p_{i} log(q_{i})$ we can know that

$$y_w = 0w! = o$$

 $y_w = 1w = 0$

therefore

$$-\sum_{w=1}^{V} y_{w} log(\hat{y_{w}}) = y_{o} log(\hat{y_{0}}) = log(\hat{y_{0}})$$

(b)

$$\frac{\partial J_{naive_softmax}(v_c, o, U)}{\partial v_c} = -\frac{\partial log(P(O=0|C=c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial v_c} = -\frac{u_0^T v_c}{\partial v_c} + \frac{log(\sum_{w \in Vo$$

$$-u_o + \sum_{w=1}^{V} \frac{exp(u_w^T v_c)}{\sum_{w=1}^{V} exp(u_w^T v_c)} u_w = -u_0 + \sum_{w=1}^{V} log(P(O = w | C = c) u_w = U^T(\hat{y} - y))$$

(c)

$$\frac{\partial J_{naive_softmax}(v_c, o, U)}{\partial u_w} = -\frac{u_0^T v_c}{\partial u_w} + \frac{log(\sum_{w \in Vocab} exp(u_w^T v_c))}{\partial u_w}$$

when w = 0, we can get

$$\frac{\partial J_{naive_softmax}(v_c, o, U)}{\partial u_w} = -v_c + \frac{exp(u_o^Tv_c)}{\sum_{w=1}^V exp(u_w^Tv_c)}v_c = (P(O = w|C = c) - 1)v_c$$

when w! = 0, we have

$$\frac{\partial J_{naive_softmax}(v_c, o, U)}{\partial u_w} = \frac{exp(u_w^T v_c)}{\sum_{m=1}^{V} exp(u_m^T v_c)} v_c = (P(O = w | C = c)v_c) v_c$$

Above all, we can draw a conclusion

$$\frac{\partial J_{naive_softmax}(v_c, o, U)}{\partial u_w} = (\hat{y} - y)^T v_c$$

(d)

$$\frac{\partial \sigma(x)}{\partial x} = \sigma(x)(1 - \sigma(x))$$

(e)

$$\begin{split} \frac{\partial J_{nag-sample}(v_c, o, U)}{\partial v_c} &= -(1 - \sigma(u_o^T v_c))u_o + \sum_{k=1}^K (1 - \sigma(u_k^T v_c))u_o) \\ \frac{\partial J_{nag-sample}(v_c, o, U)}{\partial u_0} &= \frac{\partial (-log(\sigma(u_o^T v_c)))}{\partial u_o} = -(1 - \sigma(u_o^T v_c))v_c \\ \frac{\partial J_{nag-sample}(v_c, o, U)}{\partial u_k} &= \frac{\partial (-log(\sigma(u_k^T v_c)))}{\partial u_k} = (1 - \sigma(u_k^T v_c))v_c \end{split}$$

(f)

(i)

$$\partial J_{skip-gram}(v_c, w_{t-m}, ..., w_{t+m}, U)/\partial U = \sum_{-m \le j \le m, j! = 0} \frac{\partial J(v_c, w_{t+j}, U)}{\partial U}$$

(ii)

$$\partial J_{skip-gram}(v_c, w_{t-m}, ..., w_{t+m}, U) / \partial v_c = \sum_{-m < j < m, j! = 0} \frac{\partial J(v_c, w_{t+j}, U)}{\partial v_c}$$

(iii)

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

2 Question 2

- (a)
- (b)
- (c)