Stanford CS 224n Assignment 1. Softmax. a) Q. proof that $\forall n \in \mathbb{R}^n$, $\forall c \in \mathbb{R}$: Softmax(n+c) = Softmax(c) A. Softmax (n+c) = Softmax (<ni+c; nz+c; --; ni+c; --n+c>)

let Softmax (n+c); Lethe ith component of Softmax(n+c) softmax(n+c) i = ni+c Z zy+c = L. Ri 2. En (can simplify Lecourse & To to) = Project = softmax(n)i Seftmax (x+c) = softmax (n)

Nowal Network Besics

a)
$$O(x) = \frac{4}{2 + \exp(-x)}$$

$$\Rightarrow \frac{dV}{dx}(x) = \frac{0}{(1 + e^{xx})} - 1 \cdot (-e^{xx})$$

$$= \frac{e^{xx} + (1 - a)}{(1 + e^{xx})(1 + e^{xx})}$$

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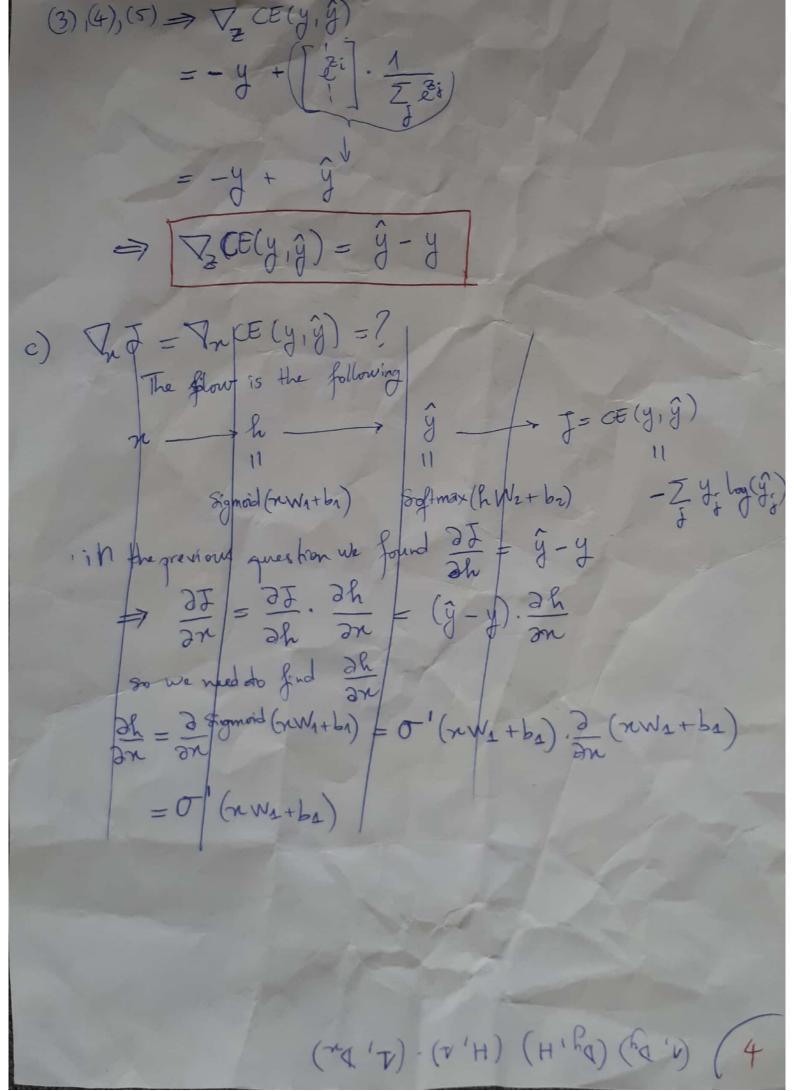
$$= \frac{e^{xx} + (1 - a)}{(1 + e^{xx})(1 + e^{xx})}$$

$$= O(x) - O(x)$$

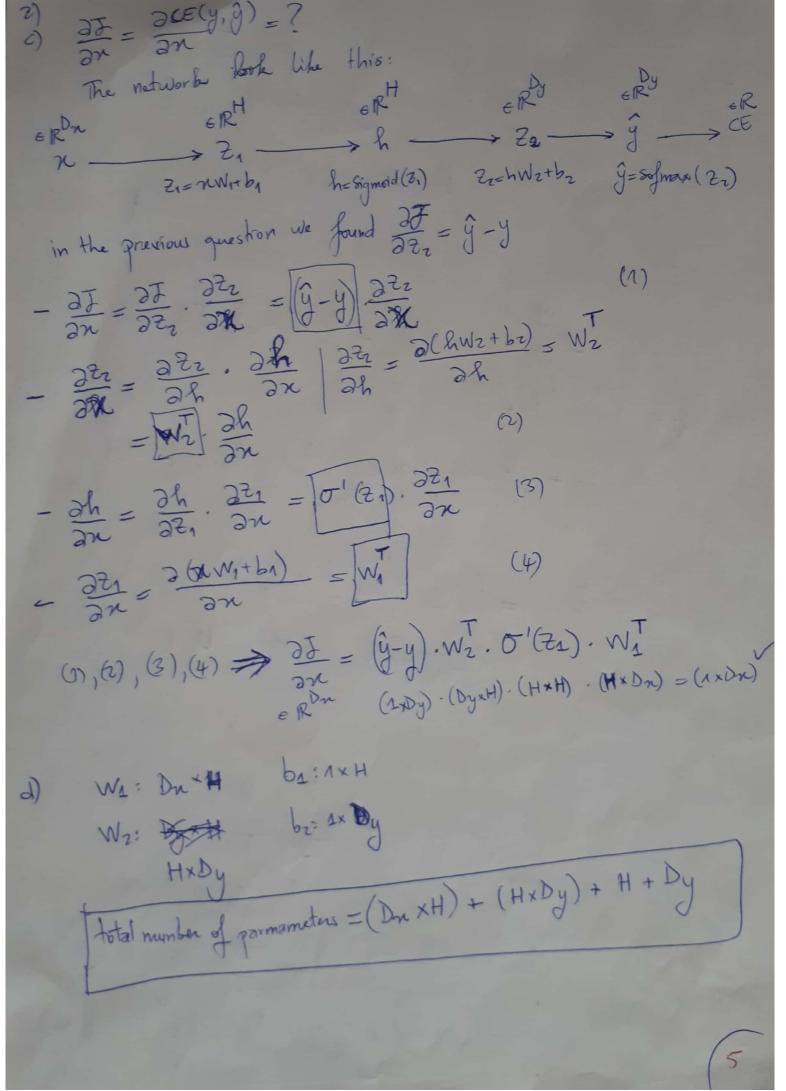
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b)
$$CE(y, \hat{y}) = \overline{Z}_y \text{ top}(\hat{y})$$
 $\hat{y}_{\hat{y}} = 800 \text{ timax}(2)_{\hat{y}}$
 $\nabla_z CE(y, \hat{y}) = \nabla_z (-\overline{Z}_y \log(\hat{y}))$
 $= \nabla_z \log(\hat{y}_{\hat{y}}) + \overline{Z}_z \log(\hat{y}_{\hat{y}})$
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3) Word 2 Vec

8) Sheip-gram model
$$\hat{g} = P(0|0) = \frac{\exp(U_0 V_0)}{\sum_{w} \exp(U_w V_0)}$$

$$J = J_{w} \lim_{w \to \infty} ce(0, N_c, U) = ce(y, \hat{y}) \quad | \text{ Where } 0 \text{ is that } idx \text{ of } 1$$

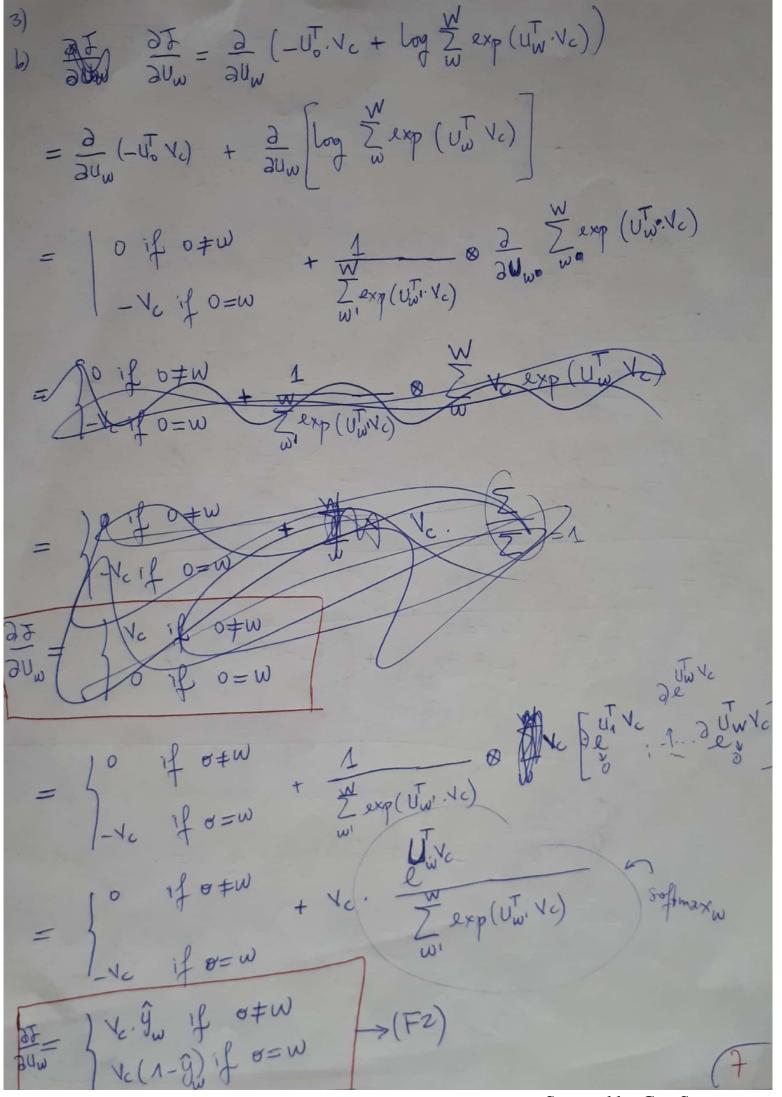
$$Ce(y, \hat{y}) = -\sum_{w} y_w \log(\hat{y}) = -\log(\hat{y}_0) = -U_0 V_0 + \log \sum_{w} v_w V_0$$

$$\Rightarrow \frac{3J}{3V_0} = \frac{3}{4V_0} \left(-U_0 V_0 + \frac{1}{4} \int_{w}^{N} \exp(U_w V_0)\right)$$

$$= -U_0 + \frac{1}{2} \exp(U_w V_0) = \frac{3}{2} \int_{w}^{N} \left(\frac{y}{w} \exp(U_w V_0)\right) \left(\frac{y}{w} \exp(U_w V_0)\right)$$

$$= \frac{3J}{3V_0} = \frac{3}{4} \left(-\frac{1}{4} \int_{w}^{N} \exp(U_w V_0)\right) = \frac{3J}{2} \int_{w}^{N} \left(\frac{y}{w} \exp(U_w V_0)\right) = \frac{1}{2} \int_{w}^{N} \left(\frac{y}{w} \exp(U_w V_0)\right) = \frac{1}{2$$

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$$\int_{\text{reg.inapple}} \left(0, v_0, u\right) = -\log \left(\sigma \left(v_0^T v_0\right)\right) - \sum_{k=1}^{N} \log \left(\sigma \left(-v_k^T v_0\right)\right)$$

$$= -\sigma \left(v_0^T v_0\right) \otimes \frac{\partial}{\partial v_0} \sigma \left(v_0^T v_0\right) - \sum_{k=1}^{N} \frac{1}{\sigma \left(-v_k^T v_0\right)} \otimes \frac{\partial}{\partial v_0} \sigma \left(-v_k^T v_0\right)$$

$$= -\frac{1}{\sigma \left(v_0^T v_0\right)} \otimes \left(\sigma' \left(v_0^T v_0\right) \cdot \partial_0 v_0\right) - \sum_{k=1}^{N} \frac{1}{\sigma \left(-v_k^T v_0\right)} \otimes \left(\sigma' \left(v_k^T v_0\right) \cdot \partial_0 v_0\right)$$

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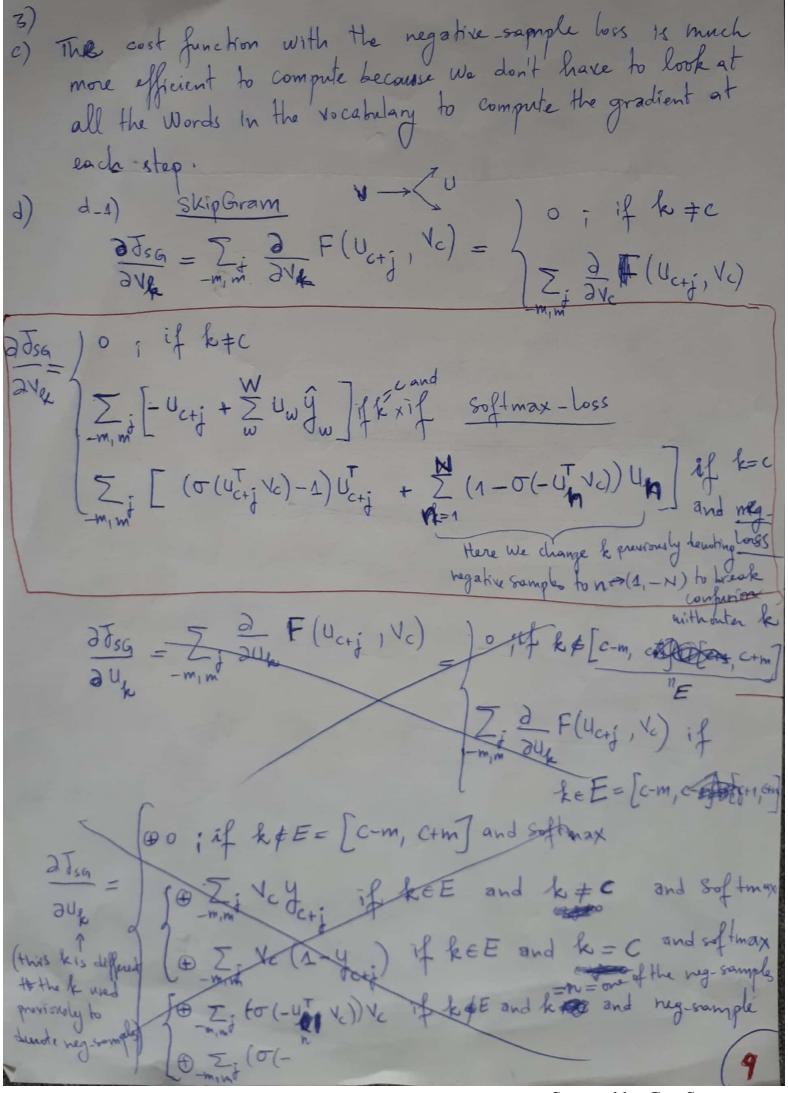
$$= -\frac{1}{\sigma \left(v_0^T v_0\right)} \otimes \left(\sigma' \left(v_0^T v_0\right) \cdot \partial_0 v_0\right) - \sum_{k=1}^{N} \frac{1}{\sigma \left(-v_0^T v_0\right)} \otimes \left(\sigma' \left(v_0^T v_0\right) \cdot \partial_0 v_0\right)$$

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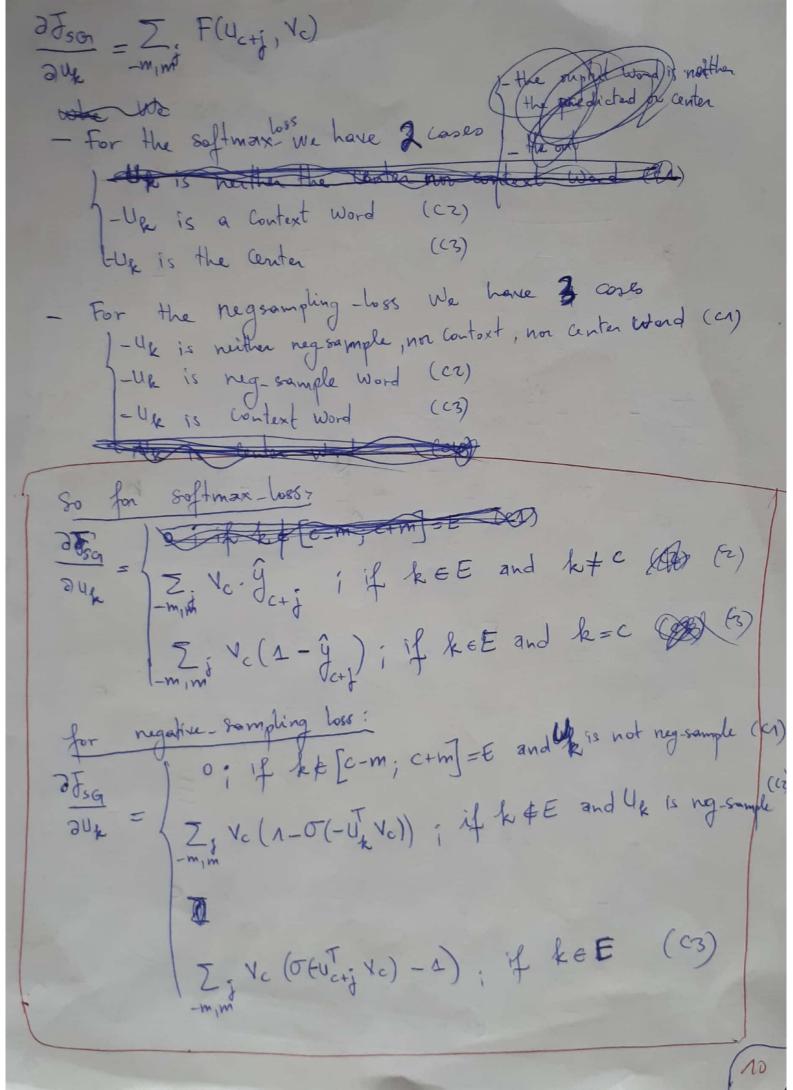
$$= -\frac{1}{\sigma \left(v_0^T v_0\right)} \otimes \left(\sigma' \left(v_0^T v_0\right) \cdot \partial_0 v_0\right) - \sum_{k=1}^{N} \frac{1}{\sigma \left(-v_0^T v_0\right)} \otimes \left(\sigma' \left(v_0^T v_0\right) \cdot \partial_0 v_0\right)$$

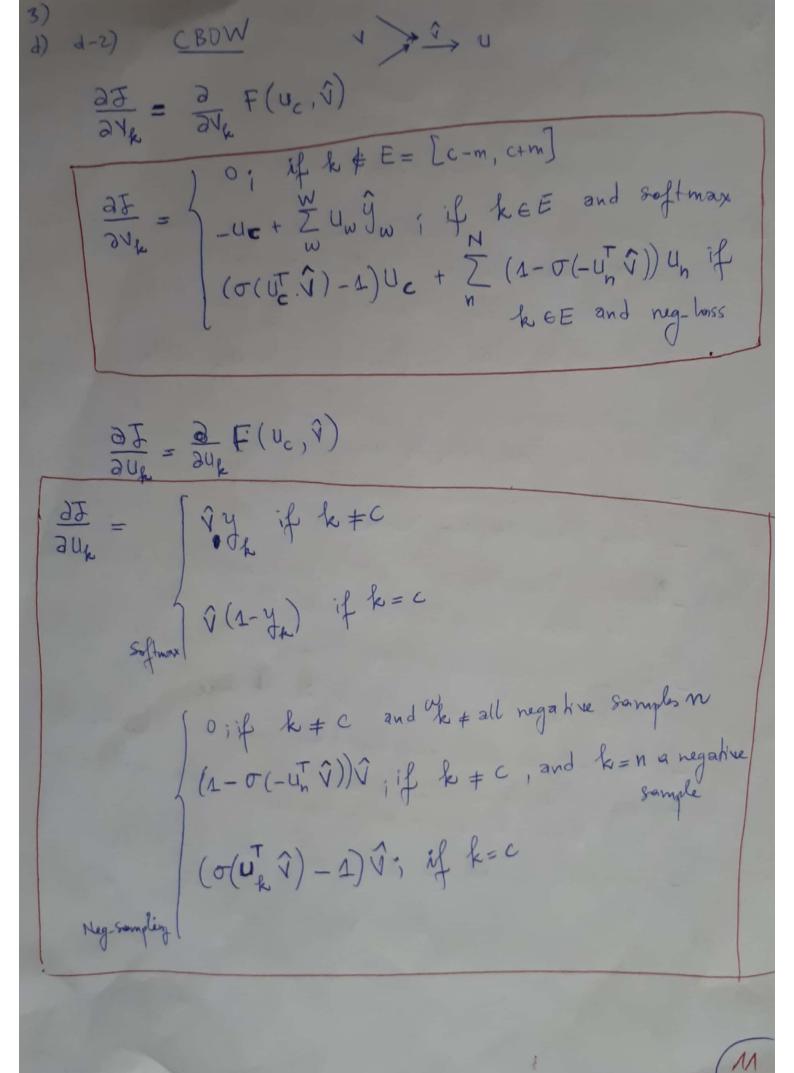
$$= -\frac{1}{\sigma \left(v_0^T v_0\right)} \otimes \left(\sigma' \left(v_0^T v_0\right) \cdot \partial_0 v_0\right) - \sum_{k=1}^{N} \frac{1}{\sigma \left(-v_0^T v_0\right)} \otimes \left(\sigma' \left(v_0$$

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3) g) What i can see of the 73-word-vectors prog : 1) articles (a, the) are more close to each other than they are to other words (boring, waste worth)

E) semantically firmitar words (wonderful, great, amazing) one cluster next to each other => they appear in similar cartest 4) b) We want to add reguralization to our training poro cedure to keep the weights of our model low and hence Fight overfitting; which ultimately will lead to more gene · ralization power When Confronted to Unseen data d) the pretrained works better because:
-trained on more data => more generalization power - hyperparameters were chosed more correfully for pretrained - Maybe Glove To may capture is better for the task. e) - After a threshold (= 10 here) decreasing the regularization factor doesn't increase the accuracy that much - train recurracy is lower than der accurracy once the model has "converged" which is strange - the previous point may suggest we may be under Bing 100 f) - globally the model tend to ovoid very extreme reviews (++, -)
hence shore classes are poorly classified - the model favored (-, +) classes a bit how much