The architecture is a RNN language model. The model is formally defined as:

$$e^{(t)} = x^{(t)}L$$

$$h^{(t)} = \operatorname{sigmoid}\left(h^{(t-1)}H + e^{(t)}I + b_1\right)$$

$$\hat{y}^{(t)} = \operatorname{softmax}\left(h^{(t)}U + b_2\right)$$

$$p\left(x_{t+1} = v_j | x_t, \dots, x_1\right) = \hat{y}_j^{(t)}$$

where L is the embedding matrix, I the input word representation matrix, H the hidden transformation matrix, and U is the output word representation matrix. b1 and b2 are biases. d is the embedding dimension, |V| is the vocabulary size, and Dh is the hidden layer dimension.

2. Compute the gradients for all the model parameters at a single point in time t:

$$\frac{\partial J^{(t)}}{\partial U} \quad \frac{\partial J^{(t)}}{\partial b_2} \quad \frac{\partial J^{(t)}}{\partial L_{x^{(t)}}} \quad \frac{\partial J^{(t)}}{\partial I} \bigg|_{(t)} \quad \frac{\partial J^{(t)}}{\partial H} \bigg|_{(t)} \quad \frac{\partial J^{(t)}}{\partial b_1} \bigg|_{(t)}$$

The solution is provided as:

The partial derivatives:

$$\begin{split} &\frac{\partial J^{(t)}}{\partial U} = \left(\boldsymbol{h}^{(t)}\right)^T (\boldsymbol{y} - \hat{\boldsymbol{y}}) \\ &\frac{\partial J^{(t)}}{\partial \boldsymbol{h}^{(t)}} = (\boldsymbol{y} - \hat{\boldsymbol{y}}) \boldsymbol{U}^T \\ &\frac{\partial J^{(t)}}{\partial \boldsymbol{b}_2} = (\boldsymbol{y} - \hat{\boldsymbol{y}}) \\ &\frac{\partial J^{(t)}}{\partial \boldsymbol{b}_1} \bigg|_{(t)} = \left(\frac{\partial J^{(t)}}{\partial \boldsymbol{h}^{(t)}} \odot \operatorname{sigmoid}' \left(\boldsymbol{h}^{(t-1)} \boldsymbol{H} + e^{(t)} \boldsymbol{I} + \boldsymbol{b}_1\right)\right) \\ &\frac{\partial J^{(t)}}{\partial \boldsymbol{L}_{\boldsymbol{x}^{(t)}}} = \frac{\partial J^{(t)}}{\partial e^{(t)}} = \frac{\partial J^{(t)}}{\partial \boldsymbol{b}_1} \bigg|_{(t)} \boldsymbol{I}^T \\ &\frac{\partial J^{(t)}}{\partial \boldsymbol{I}} \bigg|_{(t)} = \left(e^{(t)}\right)^T \frac{\partial J^{(t)}}{\partial \boldsymbol{b}_1} \bigg|_{(t)} \\ &\frac{\partial J^{(t)}}{\partial \boldsymbol{H}} \bigg|_{(t)} = \left(\boldsymbol{h}^{(t-1)}\right)^T \frac{\partial J^{(t)}}{\partial \boldsymbol{b}_1} \bigg|_{(t)} \\ &\frac{\partial J^{(t)}}{\partial \boldsymbol{h}^{(t-1)}} = \boldsymbol{H}^T \frac{\partial J^{(t)}}{\partial \boldsymbol{b}_1} \bigg|_{(t)} \end{split}$$

TODO: I was wondering (taking the first partial derivative as an example) where the h-transpose comes from in the calculation for the first partial derivative.