1 Question 1

• Confident correct : p = 0.99, logloss = 0.01

• Unsure correct : p = 0.6, logloss = 0.51

• Strongly incorrect : p = 0.01, logloss = 4.6

The log loss strongly penalizes heavy mistakes. The loss will favorize having 5 unsure predictions instead of 4 confident correct and a strongly incorrect one.

2 Question 2

$$v = \begin{pmatrix} 0 \\ 2 \\ 2 \end{pmatrix} \circledast \begin{pmatrix} 0 \\ -1 \\ -1 \end{pmatrix} + \begin{pmatrix} 1 \\ 1 \\ 2 \end{pmatrix} \circledast \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} + 1 = -3$$

3 Question 3

We could also use the binary cross-entropy loss which expects only one unit (instead of two) in the final layer.

4 Question 4

• Embedding matrix : $(V+2) \times d$ parameters

• Convolution : $n_f \times h + n_f$ parameters

• Output layers : $2 \times n_f + 2$ parameters

Total : $(V+2) \times d + n_f \times (h+3) + 2$ parameters

5 Question 5

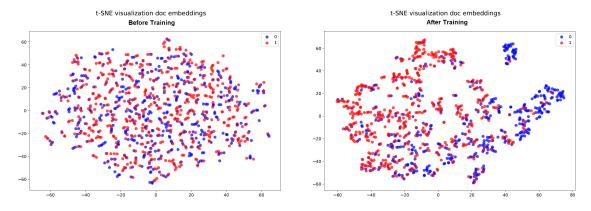


Figure 1: t-SNE visualizaton of doc embeddings before and after training

It appears that the 2D distribution of class 0 and class 1 documents embeddings have been separed during training. Before training, both distributions were roughly the same whereas afterwards distributions have been "shifted" in different directions. This translates that embeddings learnt to represent documents given their class.

6 Question 6

It appears that the saliency map takes high values for the words that are polarized, i.e. for the words that translate how positive / negative the review is. In our case the word worst is the most relevant one.

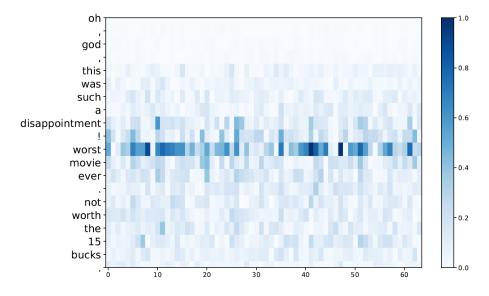


Figure 2: Saliency map

7 Question 7

The main limitation is that it only captures local interactions between words. Moreover, word-based Convolutional Neural Networks perform worse than word-based Recurrent Neural Networks, and are usually slower. However, CNN have proven to be really effective at when used at character level, they appeared to be robust to syntax errors (see [1]).

References

[1] Xiang Zhang, Junbo Jake Zhao, and Yann LeCun. Character-level convolutional networks for text classification. *CoRR*, abs/1509.01626, 2015.