

## Ex. 2 part 3 description file

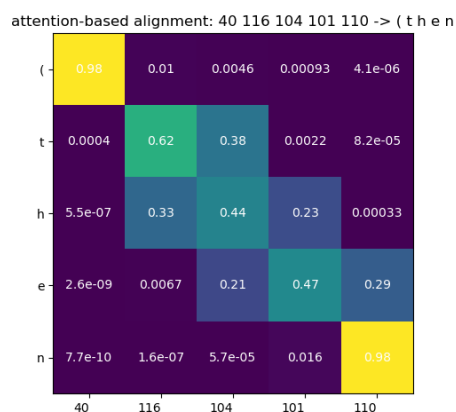
In this part I have generated heatmaps showing the weights applied to each encoder's output in order to compose the context vector concatenated to each encoder input.

The images below show the heatmap in an increasing order according to the epoch number.

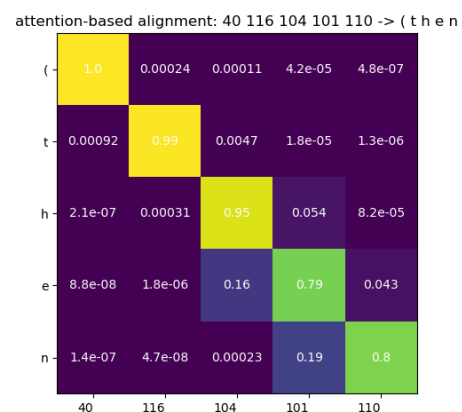
One can easily see that at first the weights are not initialized and therefore different weights are generated for the different encoder outputs. Once the weights matrix converges, we can see that the most influential character in the input on the current output character is the character in the corresponding position i.e. one to one mapping between the characters. In previous architecture, we used the encoded representation of the last character to determine the output. This forced the network to encode information about the whole word into that vector. We know from the problem setup that this architecture is not optimal since there is a clear one-to-one correspondence between the input and output characters.

In the heatmaps, we see this correspondence. High weights were given to the input representation corresponding to the character in the same position in the input.

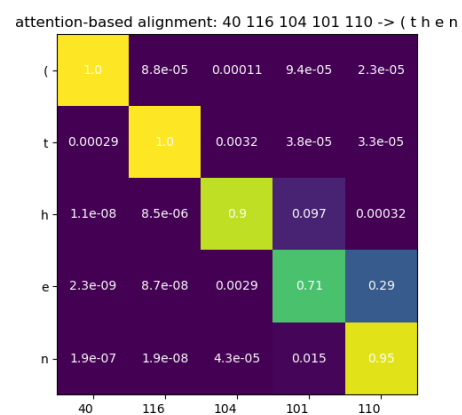
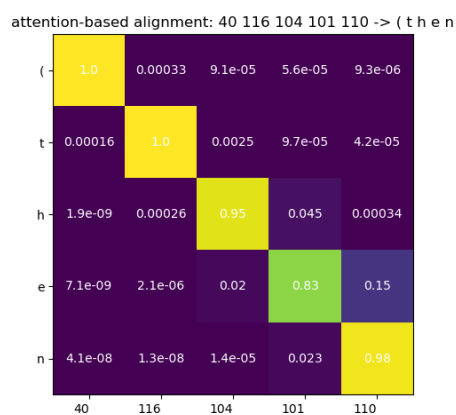
Note that the weights are also saved in '.npy' pickle format in 'attention\_weights' folder.



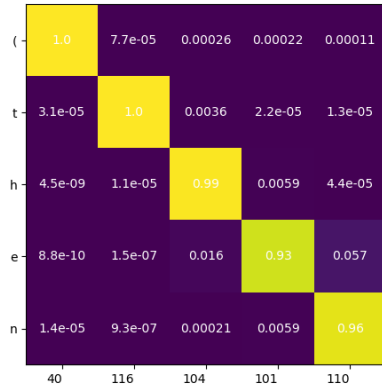
Epoch 1



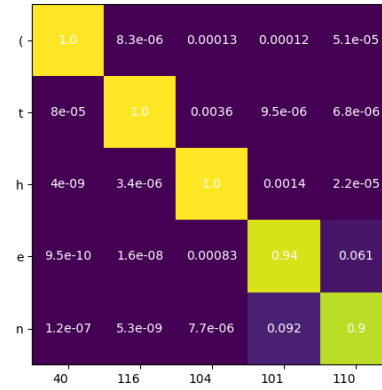
Epoch 2



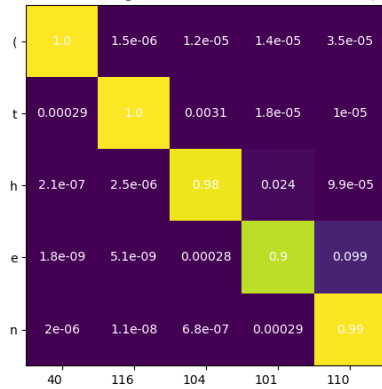
attention-based alignment: 40 116 104 101 110 -&gt; ( t h e n



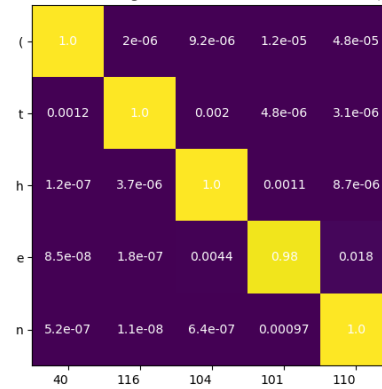
attention-based alignment: 40 116 104 101 110 -&gt; ( t h e n



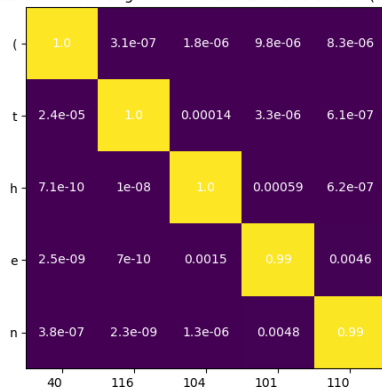
attention-based alignment: 40 116 104 101 110 -&gt; ( t h e n



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