CS7643: Deep Learning
Assignment 4

Instructor: Zsolt Kira

Deadline: 11:59pm ET April 8, 2021

- This assignment is due on the date/time posted on canvas. We will have a 48-hour grace period for this assignment. However, no questions regarding the assignment are answered during the grace period in any form.
- Discussion is encouraged, but each student must write his/her own answers and explicitly mention any collaborators.
- Each student is expected to respect and follow the GT Honor Code. **We will apply anti-cheating software to check for plagiarism**. Anyone who is flagged by the software will automatically receive 0 for the homework and be reported to OSI.
- Please **do not change the filenames and function definitions** in the skeleton code provided, as this will cause the test scripts to fail and you will receive no points in those failed tests. You may also **NOT** change the import modules in each file or import additional modules.
- It is your responsibility to make sure that all code and other deliverables are in the correct format and that your submission compiles and runs. We will not manually check your code (this is not feasible given the class size). Thus, **non-runnable code in our test environment will directly lead to a score of 0**. Also, your entire programming parts will **NOT** be graded and given 0 score if your code prints out anything that is not asked in each question.

In this assignment, we will work with **Python 3**. If you do not have a python distribution installed yet, we recommend installing Anaconda (or miniconda) with Python 3. Given that you should already have your PyTorch installed in your local anaconda environment in assignment 2, we do not

provide environment files for you to setup anaconda environment. You should make sure you have the following packages installed

```
$ pip install torchtext==0.8.1
$ pip install torch
$ pip install spacy
$ pip install tqdm
$ pip install numpy
```

Additionally, you will need the Spacy tokenizers in English and German language, which can be downloaded as such:

```
$python -m spacy download en
$python -m spacy download de
```

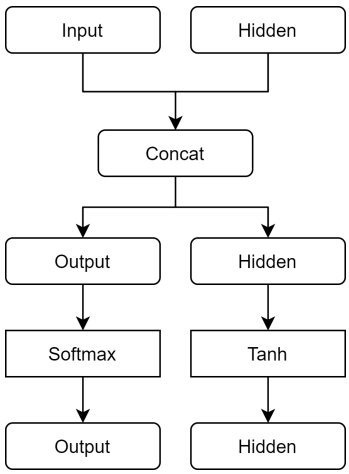
In your assignment you will see the notebook `Machine_Translation.ipynb` which contains test cases and shows the training progress. You can follow that notebook for instructions as well.

1 RNNs and LSTMs

In `models/naive` you will see files necessary to complete this section. In both of these files you will complete the initialization and forward pass.

1.1 RNN Unit

You will be using PyTorch Linear layers and activations to implement a vanilla RNN unit. Please refer to the following structure and complete the code in `RNN.py`:

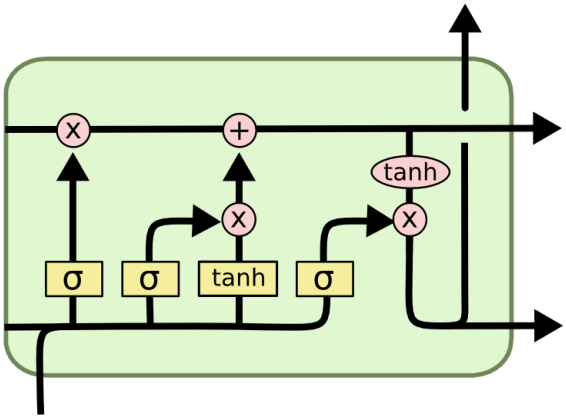


1.2 LSTM

You will be using PyTorch nn.Parameter and activations to implement an LSTM unit. You can simply translate the following equations using nn.Parameter and PyTorch activation functions to build an LSTM from scratch:

$$
\begin{aligned}
i_t &= \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi}) \\
f_t &= \sigma(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf}) \\
g_t &= \tanh(W_{ig}x_t + b_{ig} + W_{hg}h_{t-1} + b_{hg}) \\
o_t &= \sigma(W_{io}x_t + b_{io} + W_{ho}h_{t-1} + b_{ho}) \\
c_t &= f_t \odot c_{t-1} + i_t \odot g_t \\
h_t &= o_t \odot \tanh(c_t)
\end{aligned}
$$

Here's a great visualization of the above equation from Colah's blog to help you understand LSTM unit.



If you want to see nn.Parameter in example, check out this tutorial from PyTorch.

2 Seq2Seq Implementation

In `models/seq2seq` you will see the files needed to complete this section. In these files you will complete the initialization and forward pass in `__init__` and `forward` function. `Encoder.py` `Decoder.py` `Seq2Seq.py`

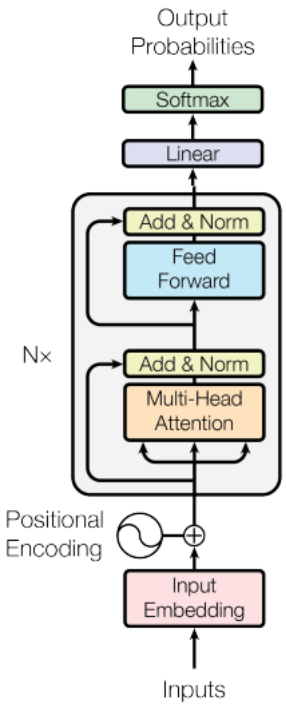
2.1 Training and Hyperparameter Tuning

Train seq2seq on the dataset with the default hyperparameters – you should get a perplexity smaller than 250. Then perform hyperparameter tuning and include the improved results in a report explaining what you have tried. Do NOT just increase the number of epochs as this is too trivial. You should get a perplexity smaller than 100 for full credit.

3 Transformers

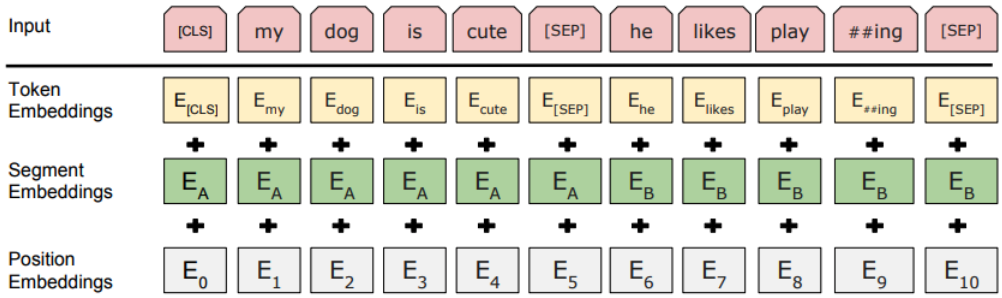
We will be implementing a one-layer Transformer encoder which, similar to an RNN, can encode a sequence of inputs and produce a final output of possibility of tokens in target language. The architecture can be seen below.

You can refer to the original paper. In `models` you will see the file `Transformer.py`. You will implement the functions in the `TransformerTranslator` class.



3.1 Embeddings

We will format our input embeddings similarly to how they are constructed in [BERT (source of figure)](https://arxiv.org/pdf/1810.04805.pdf). Recall from lecture that unlike a RNN, a Transformer does not include any positional information about the order in which the words in the sentence occur. Because of this, we need to append a positional encoding token at each position. (We will ignore the segment embeddings and [SEP] token here, since we are only encoding one sentence at a time). We have already appended the [CLS] token for you in the previous step.



Your first task is to implement the embedding lookup, including the addition of positional encodings. Complete the code section for **Deliverable 1**, which will include part of `__init__` and `embed`.

3.2 Multi-head Self-Attention

Attention can be computed in matrix-form using the following formula:

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

We want to have multiple self-attention operations, computed in parallel. Each of these is called a *head*. We concatenate the heads and multiply them with the matrix *attention_head_projection* to produce the output of this layer.

After every multi-head self-attention and feedforward layer, there is a residual connection + layer normalization. Make sure to implement this, using the following formula:

$$\text{LayerNorm}(x + \text{Sublayer}(x))$$

Implement the function `multi_head_attention` to do this. We have already initialized all of the layers you will need in the constructor.

3.3 Element-Wise Feedforward Layer

Complete code for **Deliverable 3** in `feedforward_layer`: the element-wise feed-forward layer consisting of two linear transformers with a ReLU layer in between.

$$\text{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

3.4 Final Layer

Complete code for **Deliverable 4** in `final_layer`., to produce probability scores for all tokens in target language.

3.5 Forward Pass

Put it all together by completing the method `forward`, where you combine all of the methods you have developed in the right order to perform a full forward pass.

3.6 Training and Hyperparameter Tuning

Train the transformer architecture on the dataset with the default hyperparameters – you should get a perplexity better than that for seq2seq. Then perform hyperparameter tuning and include the improved results in a report explaining what you have tried. Do NOT just increase the number of epochs as this is too trivial. Your best result should have perplexity smaller than 50 for full credit.

4 Deliverables

You will need to submit the notebook as well as your code in the `models` folder. Your report should include the accuracy of the Seq2Seq model and Transformer architecture before and after hyperparameter tuning with explanations of what you did.