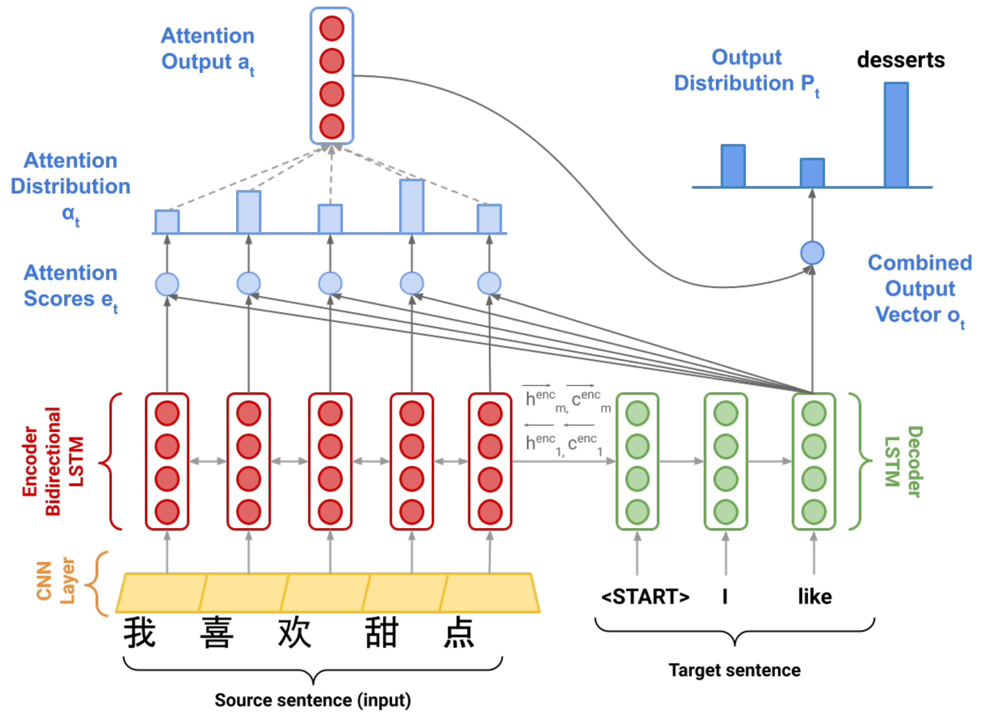
CS 224n: Assignment #4

This assignment is split into two sections: *Neural Machine Translation with RNNs* and *Analyzing NMT Systems*. The first is primarily coding and implementation focused, whereas the second entirely consists of written, analysis questions. If you get stuck on the first section, you can always work on the second as the two sections are independent of each other. Note that the NMT system is more complicated than the neural networks we have previously constructed within this class and takes about **2 hours to train on a GPU**. Thus, we strongly recommend you get started early with this assignment. Finally, the notation and implementation of the NMT system is a bit tricky, so if you ever get stuck along the way, please come to Office Hours so that the TAs can support you.

1. Neural Machine Translation with RNNs (45 points)

In Machine Translation, our goal is to convert a sentence from the *source* language (e.g. Mandarin Chinese) to the *target* language (e.g. English). In this assignment, we will implement a sequence-to-sequence (Seq2Seq) network with attention, to build a Neural Machine Translation (NMT) system. In this section, we describe the **training procedure** for the proposed NMT system, which uses a Bidirectional LSTM Encoder and a Unidirectional LSTM Decoder.



Attention Output a_t
Output Distribution P_t
desserts
Attention Distribution α_t
Attention Scores e_t
Combined Output Vector o_t
Encoder Bidirectional LSTM
$\overrightarrow{h^{enc}_m}, \overrightarrow{c^{enc}_m}$
$\overleftarrow{h^{enc}_1}, \overleftarrow{c^{enc}_1}$
Decoder LSTM
CNN Layer
我 喜 欢 甜 点
Source sentence (input)
<START> I like
Target sentence

Figure 1: Seq2Seq Model with Multiplicative Attention, shown on the third step of the decoder. Hidden states $\mathbf{h}_i^{\text{enc}}$ and cell states $\mathbf{c}_i^{\text{enc}}$ are defined on the next page.

Model description (training procedure)

Given a sentence in the source language, we look up the character or word embeddings from an **embeddings matrix**, yielding $\mathbf{x}_1, \dots, \mathbf{x}_m$ ($\mathbf{x}_i \in \mathbb{R}^{e\times 1}$), where m is the length of the source sentence and e is the embedding size. We then feed the embeddings to a **convolutional layer** [1] while maintaining their shapes. We feed the convolutional layer outputs to the **bidirectional encoder**, yielding hidden states and cell states for both the forwards ($\rightarrow$) and backwards ($\leftarrow$) LSTMs. The forwards and backwards versions are concatenated to give hidden states $\mathbf{h}_i^{\text{enc}}$ and cell states $\mathbf{c}_i^{\text{enc}}$:

$$\mathbf{h}_i^{\text{enc}} = [\overleftarrow{\mathbf{h}_i^{\text{enc}}}; \overrightarrow{\mathbf{h}_i^{\text{enc}}}] \text{ where } \mathbf{h}_i^{\text{enc}} \in \mathbb{R}^{2h\times 1}, \overleftarrow{\mathbf{h}_i^{\text{enc}}}, \overrightarrow{\mathbf{h}_i^{\text{enc}}} \in \mathbb{R}^{h\times 1} \qquad 1 \le i \le m \tag{1}$$

$$\mathbf{c}_i^{\text{enc}} = [\overleftarrow{\mathbf{c}_i^{\text{enc}}}; \overrightarrow{\mathbf{c}_i^{\text{enc}}}] \text{ where } \mathbf{c}_i^{\text{enc}} \in \mathbb{R}^{2h\times 1}, \overleftarrow{\mathbf{c}_i^{\text{enc}}}, \overrightarrow{\mathbf{c}_i^{\text{enc}}} \in \mathbb{R}^{h\times 1} \qquad 1 \le i \le m \tag{2}$$

We then initialize the **decoder**'s first hidden state $\mathbf{h}_0^{\text{dec}}$ and cell state $\mathbf{c}_0^{\text{dec}}$ with a linear projection of the encoder's final hidden state and final cell state.[2]

$$\mathbf{h}_0^{\text{dec}} = \mathbf{W}_h[\overleftarrow{\mathbf{h}_1^{\text{enc}}}; \overrightarrow{\mathbf{h}_m^{\text{enc}}}] \text{ where } \mathbf{h}_0^{\text{dec}} \in \mathbb{R}^{h\times 1}, \mathbf{W}_h \in \mathbb{R}^{h\times 2h} \tag{3}$$

$$\mathbf{c}_0^{\text{dec}} = \mathbf{W}_c[\overleftarrow{\mathbf{c}_1^{\text{enc}}}; \overrightarrow{\mathbf{c}_m^{\text{enc}}}] \text{ where } \mathbf{c}_0^{\text{dec}} \in \mathbb{R}^{h\times 1}, \mathbf{W}_c \in \mathbb{R}^{h\times 2h} \tag{4}$$

With the decoder initialized, we must now feed it a target sentence. On the t^{th} step, we look up the embedding for the t^{th} subword, $\mathbf{y}_t \in \mathbb{R}^{e\times 1}$. We then concatenate $\mathbf{y}_t$ with the *combined-output vector* $\mathbf{o}_{t-1} \in \mathbb{R}^{h\times 1}$ from the previous timestep (we will explain what this is later down this page!) to produce $\overline{\mathbf{y}_t} \in \mathbb{R}^{(e+h)\times 1}$. Note that for the first target subword (i.e. the start token) $\mathbf{o}_0$ is a zero-vector. We then feed $\overline{\mathbf{y}_t}$ as input to the decoder.

$$\mathbf{h}_t^{\text{dec}}, \mathbf{c}_t^{\text{dec}} = \text{Decoder}(\overline{\mathbf{y}_t}, \mathbf{h}_{t-1}^{\text{dec}}, \mathbf{c}_{t-1}^{\text{dec}}) \text{ where } \mathbf{h}_t^{\text{dec}} \in \mathbb{R}^{h\times 1}, \mathbf{c}_t^{\text{dec}} \in \mathbb{R}^{h\times 1} \tag{5}$$

$$\tag{6}$$

We then use $\mathbf{h}_t^{\text{dec}}$ to compute multiplicative attention over $\mathbf{h}_1^{\text{enc}}, \ldots, \mathbf{h}_m^{\text{enc}}$:

$$\mathbf{e}_{t,i} = (\mathbf{h}_t^{\text{dec}})^T \mathbf{W}_{\text{attProj}} \mathbf{h}_i^{\text{enc}} \text{ where } \mathbf{e}_t \in \mathbb{R}^{m\times 1}, \mathbf{W}_{\text{attProj}} \in \mathbb{R}^{h\times 2h} \qquad 1 \le i \le m \tag{7}$$

$$\alpha_t = \text{softmax}(\mathbf{e}_t) \text{ where } \alpha_t \in \mathbb{R}^{m\times 1} \tag{8}$$

$$\mathbf{a}_t = \sum_{i=1}^{m} \alpha_{t,i} \mathbf{h}_i^{\text{enc}} \text{ where } \mathbf{a}_t \in \mathbb{R}^{2h\times 1} \tag{9}$$

$\mathbf{e}_{t,i}$ is a scalar, the ith element of $\mathbf{e}_t \in \mathbb{R}^{m\times 1}$, computed using the hidden state of the decoder at the tth step, $\mathbf{h}_t^{\text{dec}} \in \mathbb{R}^{h\times 1}$, the attention projection $\mathbf{W}_{\text{attProj}} \in \mathbb{R}^{h\times 2h}$, and the hidden state of the encoder at the ith step, $\mathbf{h}_i^{\text{enc}} \in \mathbb{R}^{2h\times 1}$.

We now concatenate the attention output $\mathbf{a}_t$ with the decoder hidden state $\mathbf{h}_t^{\text{dec}}$ and pass this through a linear layer, tanh, and dropout to attain the *combined-output* vector $\mathbf{o}_t$.

$$\mathbf{u}_t = [\mathbf{a}_t; \mathbf{h}_t^{\text{dec}}] \text{ where } \mathbf{u}_t \in \mathbb{R}^{3h\times 1} \tag{10}$$

$$\mathbf{v}_t = \mathbf{W}_u \mathbf{u}_t \text{ where } \mathbf{v}_t \in \mathbb{R}^{h\times 1}, \mathbf{W}_u \in \mathbb{R}^{h\times 3h} \tag{11}$$

$$\mathbf{o}_t = \text{dropout}(\tanh(\mathbf{v}_t)) \text{ where } \mathbf{o}_t \in \mathbb{R}^{h\times 1} \tag{12}$$

[1] Checkout https://cs231n.github.io/convolutional-networks for an in-depth description for convolutional layers if you are not familiar

[2] If it's not obvious, think about why we regard $[\overleftarrow{\mathbf{h}_1^{\text{enc}}}, \overrightarrow{\mathbf{h}_m^{\text{enc}}}]$ as the 'final hidden state' of the Encoder.

Then, we produce a probability distribution $\mathbf{P}_t$ over target subwords at the t^{th} timestep:

$$\mathbf{P}_t = \text{softmax}(\mathbf{W}_{\text{vocab}}\mathbf{o}_t) \text{ where } \mathbf{P}_t \in \mathbb{R}^{V_t \times 1}, \mathbf{W}_{\text{vocab}} \in \mathbb{R}^{V_t \times h} \tag{13}$$

Here, V_t is the size of the target vocabulary. Finally, to train the network we then compute the cross entropy loss between $\mathbf{P}_t$ and $\mathbf{g}_t$, where $\mathbf{g}_t$ is the one-hot vector of the target subword at timestep t:

$$J_t(\theta) = \text{CrossEntropy}(\mathbf{P}_t, \mathbf{g}_t) \tag{14}$$

Here, θ represents all the parameters of the model and $J_t(\theta)$ is the loss on step t of the decoder. Now that we have described the model, let's try implementing it for Mandarin Chinese to English translation!

Setting up your Virtual Machine

Follow the instructions in the CS224n Azure Guide (link also provided on website and Ed) in order to create your VM instance. This should take you approximately 45 minutes. Though you will need the GPU to train your model, we strongly advise that you first develop the code locally and ensure that it runs, before attempting to train it on your VM. GPU time is expensive and limited. It takes approximately **1.5 to 2 hours** to train the NMT system. We don't want you to accidentally use all your GPU time for debugging your model rather than training and evaluating it. Finally, **make sure that your VM is turned off whenever you are not using it.**

If your Azure subscription runs out of money, your VM will be temporarily locked and inaccessible. If that happens, please fill out a request form here.

In order to run the model code on your **local** machine, please run the following command to create the proper virtual environment:

```
conda env create --file local_env.yml
```

Note that this virtual environment **will not** be needed on the VM.

Implementation and written questions

(a) (2 points) (coding) In order to apply tensor operations, we must ensure that the sentences in a given batch are of the same length. Thus, we must identify the longest sentence in a batch and pad others to be the same length. Implement the pad_sents function in utils.py, which shall produce these padded sentences.

(b) (3 points) (coding) Implement the __init__ function in model_embeddings.py to initialize the necessary source and target embeddings.

(c) (4 points) (coding) Implement the __init__ function in nmt_model.py to initialize the necessary model layers (LSTM, CNN, projection, and dropout) for the NMT system.

(d) (8 points) (coding) Implement the encode function in nmt_model.py. This function converts the padded source sentences into the tensor $\mathbf{X}$, generates $\mathbf{h}_1^{\text{enc}}, \ldots, \mathbf{h}_m^{\text{enc}}$, and computes the initial state $\mathbf{h}_0^{\text{dec}}$ and initial cell $\mathbf{c}_0^{\text{dec}}$ for the Decoder. You can run a non-comprehensive sanity check by executing:

```
python sanity_check.py 1d
```

(e) (8 points) (coding) Implement the decode function in nmt_model.py. This function constructs $\bar{\mathbf{y}}$ and runs the step function over every timestep for the input. You can run a non-comprehensive sanity check by executing:

```
python sanity_check.py 1e
```

(f) (10 points) (coding) Implement the step function in nmt_model.py. This function applies the Decoder's LSTM cell for a single timestep, computing the encoding of the target subword $\mathbf{h}_t^{\text{dec}}$, the attention scores $\mathbf{e}_t$, attention distribution α_t, the attention output $\mathbf{a}_t$, and finally the combined output $\mathbf{o}_t$. You can run a non-comprehensive sanity check by executing:

```
python sanity_check.py 1f
```

(g) (3 points) (written) The generate_sent_masks() function in nmt_model.py produces a tensor called enc_masks. It has shape (batch size, max source sentence length) and contains 1s in positions corresponding to 'pad' tokens in the input, and 0s for non-pad tokens. Look at how the masks are used during the attention computation in the step() function (lines 311-312).

First explain (in around three sentences) what effect the masks have on the entire attention computation. Then explain (in one or two sentences) why it is necessary to use the masks in this way.

Solution: The masks will assign $-\infty$ values to the attention scores at positions corresponding to 'pad' tokens in the input. This will give the probability of the 'pad' tokens to be 0 after applying softmax, which means the 'pad' token embeddings will not affect the attention outputs. It is necessary because the 'pad' tokens are just additional elements we use to make the length of sentences equal and they do not appear in actual sentences. Thus we don't want these tokens to affect the output probability distribution.

Another solution:

1. **What effect:** for every batch, those attention scores which have corresponding zero-padded embeddings are set to $-\infty$. This way, during the calculation of *attention distributions* α_t, the probabilities are calculated with corresponding non-padded words whereas the scores with corresponding padded words are negligible. Finally, during the calculation of *attention outputs* A_t, for every batch only the addition of those hidden states matter which are not multiplied by a probability close to 0.
2. **Why necessary:** using masks in this way is an efficient way to determine the true *attention distribution* that only involves the non-padded entries. Involving padded entries would result in false *attention* representation.

Now it's time to get things running! As noted earlier, we recommend that you develop the code on your personal computer. Confirm that you are running in the proper conda environment and then execute the following command to train the model on your local machine:

```
sh run.sh train_local
(Windows) run.bat train_local
```

For a faster way to debug by training on less data, you can run the following instead:

```
sh run.sh train_debug
(Windows) run.bat debug
```

To help with monitoring and debugging, the starter code uses tensorboard to log loss and perplexity during training using TensorBoard[3]. TensorBoard provides tools for logging and visualizing training information from experiments. To open TensorBoard, run the following in your conda environment:

```
tensorboard --logdir=runs
```

You should see a significant decrease in loss during the initial iterations. Once you have ensured that your code does not crash (i.e. let it run till iter 10 or iter 20), power on your VM from the Azure Web Portal. Then read the *Managing Code Deployment to a VM* section of our Practical Guide to VMs (link also given on website and Ed) for instructions on how to upload your code to the VM.

Next, install necessary packages to your VM by running:

```
pip install -r gpu_requirements.txt
```

Finally, turn to the *Managing Processes on a VM* section of the Practical Guide and follow the instructions to create a new tmux session. Concretely, run the following command to create tmux session called nmt.

```
tmux new -s nmt
```

Once your VM is configured and you are in a tmux session, execute:

```
sh run.sh train
(Windows) run.bat train
```

Once you know your code is running properly, you can detach from session and close your ssh connection to the server. To detach from the session, run:

```
tmux detach
```

You can return to your training model by ssh-ing back into the server and attaching to the tmux session by running:

```
tmux a -t nmt
```

(h) (3 points) (written) Once your model is done training (**this should take under 2 hours on the VM**), execute the following command to test the model:

```
sh run.sh test
(Windows) run.bat test
```

Please report the model's corpus BLEU Score. It should be larger than 18.

Solution: Corpus BLEU: 20.349133759154903 (with early stopping after 4 epochs, 18800 iterations)

(i) (4 points) (written) In class, we learned about dot product attention, multiplicative attention, and additive attention. As a reminder, dot product attention is $\mathbf{e}_{t,i} = \mathbf{s}_t^T \mathbf{h}_i$, multiplicative attention is $\mathbf{e}_{t,i} = \mathbf{s}_t^T \mathbf{W} \mathbf{h}_i$, and additive attention is $\mathbf{e}_{t,i} = \mathbf{v}^T \tanh(\mathbf{W}_1 \mathbf{h}_i + \mathbf{W}_2 \mathbf{s}_t)$.

i. (2 points) Explain one advantage and one disadvantage of *dot product attention* compared to multiplicative attention.

ii. (2 points) Explain one advantage and one disadvantage of *additive attention* compared to multiplicative attention.

[3]https://pytorch.org/docs/stable/tensorboard.html

Solution:

i. An advantage of *dot product* attention compared to *multiplicative attention* is that it does not have any learnable parameters and it is a vector dot product, meaning it is fast to compute. A disadvantage, however, is that a simple dot product is not sufficient to capture what parts of $\mathbf{s}_t$ and what part of $\mathbf{h}_t$ to pay attention to because it is a simple piece-wise similarity.

ii. An advantage of *additive attention* compared to *multiplicative attention* is that similarity is computed in a non-linearly transformed space where both $\mathbf{h}_i$ and $\mathbf{s}_t$ have their own learnable weights. This add more flexibility in terms of parameter space. A disadvantage is that the computation is very expensive.

2. Analyzing NMT Systems (25 points)

(a) (3 points) Look at the `src.vocab` file for some examples of phrases and words in the source language vocabulary. When encoding an input Mandarin Chinese sequence into "pieces" in the vocabulary, the tokenizer maps the sequence to a series of vocabulary items, each consisting of one or more characters (thanks to the `sentencepiece` tokenizer, we can perform this segmentation even when the original text has no white space). Given this information, how could adding a 1D Convolutional layer after the embedding layer and before passing the embeddings into the bidirectional encoder help our NMT system? **Hint:** each Mandarin Chinese character is either an entire word or a morpheme in a word. Look up the meanings of 电, 脑, and 电脑 separately for an example. The characters 电 (electricity) and 脑 (brain) when combined into the phrase 电脑 mean computer.

Solution: Adding a 1D Convolutional layer after the embedding layer and before passing the embeddings into the bidirectional encoder could help the NMT system by allowing the model to capture local dependencies and patterns among the character sequences. Since each Mandarin Chinese character is either an entire word or a morpheme in a word, the convolutional layer can identify these patterns and use them to inform the representation of the word or phrase as a whole. For example, in the case of the characters 电, 脑, and 电脑, the convolutional layer could potentially learn to recognize the pattern of the characters 电 (electricity) and 脑 (brain) occurring together to form the word 电脑 (computer). By capturing these patterns, the model may be able to improve its ability to handle rare or unseen words, which is important for NMT systems since they must be able to translate sentences containing previously unseen vocabulary.

(b) (8 points) Here we present a series of errors we found in the outputs of our NMT model (which is the same as the one you just trained). For each example of a reference (i.e., 'gold') English translation, and NMT (i.e., 'model') English translation, please:

1. Identify the error in the NMT translation.
2. Provide possible reason(s) why the model may have made the error (either due to a specific linguistic construct or a specific model limitation).
3. Describe one possible way we might alter the NMT system to fix the observed error. There are more than one possible fixes for an error. For example, it could be tweaking the size of the hidden layers or changing the attention mechanism.

Below are the translations that you should analyze as described above. Only analyze the underlined error in each sentence. Rest assured that you don't need to know Mandarin to answer these questions. You just need to know English! If, however, you would like some additional color on the source sentences, feel free to use a resource like https://www.archchinese.com/chinese_english_dictionary.html to look up words. Feel free to search the training data file to have a better sense of how often certain characters occur.

i. (2 points) **Source Sentence:** 贼人其后被警方拘捕及被判处盗窃罪名成立。
Reference Translation: *<u>the culprits were</u> subsequently arrested and convicted.*
NMT Translation: *<u>the culprit was</u> subsequently arrested and sentenced to theft.*

Solution:

1. The error in the NMT translation is the use of singular form "culprit" instead of its plural form "culprits".
2. The model might have made this error because of a lack of attention to the plural form of the noun "culprits" in the source sentences (Mandarin). Additionally, the model might be trained on a dataset that the frequency of the singular form "culprit" is higher than the plural form.
3. A possible way to address this error is to increase the weight of the attention mechanism on the number of nouns in the source sentence or to increase the occurrence of plural words in our dataset.

ii. (2 points) **Source Sentence**: 几乎已经没有地方容纳这些人, 资源已经用尽。
Reference Translation: *there is almost no space to accommodate these people, and resources have run out.*
NMT Translation: *the resources have been exhausted and <u>resources have been exhausted</u>.*

Solution:

1. The error in the NMT translation is the repetition of the phrase "resources have been exhausted".
2. One possible reason for this error is that the NMT system didn't capture the meaning of the word "space" or "accommodate", leads to the inaccurate weights of attention in the source sentence while trying to translate the first part of the sentence ("there is almost no space to accommodate these people").
3. This error can be solved by adjusting the attention mechanism to better capture the meaning of sentence. Another the way to do so is to increase the amount of training data which helps improve the accuracy of the translation.

iii. (2 points) **Source Sentence**: 当局已经宣布今天是国殇日。
Reference Translation: *authorities have announced <u>a national mourning today.</u>*
NMT Translation: *the administration has announced <u>today's day.</u>*

Solution:

1. The error of the NMT translation is that it misses the meaning of 国殇日 ("national mourning day") and mistranslates it as "today's day".
2. The model may not have learned the specific translation of " 国殇日" as it is a culturally specific term, and may have relied on the literal translation of each individual character.
3. The model may benefit from being trained on a larger corpus of text that includes culturally specific terms and phrases. Additionally, the model could be improved by incorporating additional context and domain-specific knowledge during the training process, such as incorporating knowledge of national holidays and events.

iv. (2 points) **Source Sentence**[4]**:** 俗语有云:"唔做唔错"。

[4]This is a Cantonese sentence! The data used in this assignment comes from GALE Phase 3, which is a compilation of news

Reference Translation: *“ act not, err not ”, so a saying goes.*
NMT Translation: *as the saying goes, “ it’s not wrong. ”*

Solution:

1. The error is that the NMT translation is missing the first half of the reference translation, which is the translation of the Chinese idiom.
2. One possible reason for this error is the shortage of idiom phrases in the training data, which make model to have difficulty understanding idiomatic expressions, as well as the structure of the Chinese language.
3. To help the model better understand idiomatic expressions, we could provide it a larger training set that includes more diverse examples of idioms and their translations. Additionally, we could explore incorporating a pre-trained language model to improve its understanding of the structure of Chinese language.

(c) (14 points) BLEU score is the most commonly used automatic evaluation metric for NMT systems. It is usually calculated across the entire test set, but here we will consider BLEU defined for a single example.[5] Suppose we have a source sentence $\mathbf{s}$, a set of k reference translations $\mathbf{r}_1, \dots, \mathbf{r}_k$, and a candidate translation $\mathbf{c}$. To compute the BLEU score of $\mathbf{c}$, we first compute the *modified n-gram precision* p_n of $\mathbf{c}$, for each of $n = 1, 2, 3, 4$, where n is the n in n-gram:

$$p_n = \frac{\displaystyle\sum_{\text{ngram} \in \mathbf{c}} \min\left(\max_{i=1,\dots,k} \text{Count}_{\mathbf{r}_i}(\text{ngram}),\ \text{Count}_{\mathbf{c}}(\text{ngram}) \right)}{\displaystyle\sum_{\text{ngram} \in \mathbf{c}} \text{Count}_{\mathbf{c}}(\text{ngram})} \tag{15}$$

Here, for each of the n-grams that appear in the candidate translation $\mathbf{c}$, we count the maximum number of times it appears in any one reference translation, capped by the number of times it appears in $\mathbf{c}$ (this is the numerator). We divide this by the number of n-grams in $\mathbf{c}$ (denominator).

Next, we compute the *brevity penalty* BP. Let $len(c)$ be the length of $\mathbf{c}$ and let $len(r)$ be the length of the reference translation that is closest to $len(c)$ (in the case of two equally-close reference translation lengths, choose $len(r)$ as the shorter one).

$$BP = \begin{cases} 1 & \text{if } len(c) \geq len(r) \\ \exp\left(1 - \frac{len(r)}{len(c)}\right) & \text{otherwise} \end{cases} \tag{16}$$

Lastly, the BLEU score for candidate $\mathbf{c}$ with respect to $\mathbf{r}_1, \dots, \mathbf{r}_k$ is:

$$BLEU = BP \times \exp\left(\sum_{n=1}^{4} \lambda_n \log p_n \right) \tag{17}$$

where $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ are weights that sum to 1. The log here is natural log.

i. (5 points) Please consider this example:
Source Sentence $\mathbf{s}$: **需要有充足和可预测的资源。**

written in simplified Chinese from various sources scraped from the internet along with their translations. For more details, see https://catalog.ldc.upenn.edu/LDC2017T02.

[5] This definition of sentence-level BLEU score matches the sentence_bleu() function in the nltk Python package. Note that the NLTK function is sensitive to capitalization. In this question, all text is lowercased, so capitalization is irrelevant. http://www.nltk.org/api/nltk.translate.html#nltk.translate.bleu_score.sentence_bleu

Reference Translation $\mathbf{r}_1$: *resources have to be sufficient and they have to be predictable*
Reference Translation $\mathbf{r}_2$: *adequate and predictable resources are required*
NMT Translation $\mathbf{c}_1$: there is a need for adequate and predictable resources
NMT Translation $\mathbf{c}_2$: resources be sufficient and predictable to
Please compute the BLEU scores for $\mathbf{c}_1$ and $\mathbf{c}_2$. Let $\lambda_i = 0.5$ for $i \in \{1, 2\}$ and $\lambda_i = 0$ for $i \in \{3, 4\}$ (**this means we ignore 3-grams and 4-grams**, i.e., don't compute p_3 or p_4). When computing BLEU scores, show your work (i.e., show your computed values for p_1, p_2, $len(c)$, $len(r)$ and BP). Note that the BLEU scores can be expressed between 0 and 1 or between 0 and 100. The code is using the 0 to 100 scale while in this question we are using the **0 to 1** scale. Please round your responses to 3 decimal places.

Which of the two NMT translations is considered the better translation according to the BLEU Score? Do you agree that it is the better translation?

Solution:

1. BLEU score for $\mathbf{c}_1$
   We will first compute the *modified n-gram precision p_1 and p_2* of $\mathbf{c}_1$:
   $$p_1 = \frac{0+0+0+0+0+1+1+1+1}{9} = \frac{4}{9}$$
   $$p_2 = \frac{0+0+0+0+0+1+1+1}{8} = \frac{3}{8}$$
   We then compute the length of candidate translation $len(c)$ and the length of the reference translation $len(r)$ that is closest to $len(c)$ ($len(r)$ in this case is the first Reference Translation $\mathbf{r}_1$):
   $$len(c_1) = 9$$
   $$len(r_1) = 11$$
   Next, we compute the *brevity penalty* BP:
   $$BP = \exp\left(1 - \frac{len(r)}{len(c)}\right) = \exp\left(1 - \frac{11}{9}\right) = e^{-\frac{2}{9}}$$
   Finally, the BLEU score for candidate $\mathbf{c}_1$ with respect $\mathbf{r}_1, \mathbf{r}_2$ is:
   $$BLEU = BP \times \exp\left(\sum_{n=1}^{2} \lambda_n \log p_n\right) = \exp\left(-\frac{2}{9} + 0.5 \times (\log\frac{4}{9} + \log\frac{3}{8})\right) \approx 0.327$$
2. We will compute the BLEU score for $\mathbf{c}_2$ similar to $\mathbf{c}_1$:
   $$p_1 = \frac{1+1+1+1+1+1}{6} = 1$$
   $$p_2 = \frac{0+1+1+1+0}{5} = \frac{3}{5}$$
   $$len(c_2) = 6$$
   $$len(r_2) = 6$$
   $$BP = 1 \text{ (because } len(c) = len(r))$$
   $$BLEU = BP \times \exp\left(\sum_{n=1}^{2} \lambda_n \log p_n\right) = \exp\left(0.5 \times (\log 1 + \log\frac{3}{5})\right) \approx 0.775$$

According to the BLEU score for $\mathbf{c}_1$ and $\mathbf{c}_2$, the second NMT translation $\mathbf{c}_2$ is considered the better translation. However, I would not agree that $\mathbf{c}_2$ is translated well compared to $\mathbf{c}_1$.

ii. (5 points) Our hard drive was corrupted and we lost Reference Translation $\mathbf{r}_1$. Please recompute BLEU scores for $\mathbf{c}_1$ and $\mathbf{c}_2$, this time with respect to $\mathbf{r}_2$ only. Which of the two NMT translations now receives the higher BLEU score? Do you agree that it is the better translation?

Solution:

1. BLEU score for $\mathbf{c}_1$ with respect to $\mathbf{r}_2$:

$$p_1 = \frac{0+0+0+0+0+1+1+1+1}{9} = \frac{4}{9}$$

$$p_2 = \frac{0+0+0+0+0+1+1+1}{8} = \frac{3}{8}$$

$$len(c_1) = 9$$
$$len(r_2) = 6$$

$$BP = 1 \text{ (because } len(c) > len(r))$$

$$BLEU = BP \times \exp\left(\sum_{n=1}^{2} \lambda_n \log p_n\right) = \exp\left(0.5 \times (\log\frac{4}{9} + \log\frac{3}{8})\right) \approx 0.408$$

2. BLEU score for $\mathbf{c}_2$ with respect to $\mathbf{r}_2$:

$$p_1 = \frac{1+0+0+1+1+0}{6} = \frac{1}{2}$$

$$p_2 = \frac{0+0+0+1+0}{5} = \frac{1}{5}$$

$$len(c_1) = 6$$
$$len(r_2) = 6$$

$$BP = 1 \text{ (because } len(c) = len(r))$$

$$BLEU = BP \times \exp\left(\sum_{n=1}^{2} \lambda_n \log p_n\right) = \exp\left(0.5 \times (\log\frac{1}{2} + \log\frac{1}{5})\right) \approx 0.316$$

The first translation $\mathbf{c}_1$ now has a higher BLEU score, which is reasonable as $\mathbf{c}_1$ seems to be the better translation.

iii. (2 points) Due to data availability, NMT systems are often evaluated with respect to only a single reference translation. Please explain (in a few sentences) why this may be problematic. In your explanation, discuss how the BLEU score metric assesses the quality of NMT translations when there are multiple reference translations versus a single reference translation.

Solution: Translations from a source language can vary a lot due to the flexibility of the target language, e.g. using synonyms, antonyms... NMT systems being evaluated with respect to only a single reference translation can ignore the variations, resulting in it being given low BLEU score even though it is a high quality translation. With multiple reference translations, the BLEU score metric can be more reliable and accurate as it can cover different variations of the translated sentences. On the contrary, the BLEU score can vary widely and does not give an accurate score when assessing the quality of the NMT translations with respect to a single reference translation. However, in the original BLEU paper, they stated that we may use a big test corpus with a single reference translation, provided that the translations are not all from the same translator.

iv. (2 points) List two advantages and two disadvantages of BLEU, compared to human evaluation, as an evaluation metric for Machine Translation.

Solution:
Advantages:

1. BLEU is an automatic evaluation metric that is quicker and inexpensive compared to human evaluation, which can take weeks or months to finish and involve human labor that can not be reused.
2. BLEU score is language-independent, i.e. reliable with different source - target translation and shows a significantly high correlation with human judgements.

Disadvantages:

1. BLEU metric neither consider the meanings of the word nor understands the significance of the words in the context. For example, the propositions usually have the lowest level of importance. However, BLEU sees them as important as nouns and verb keywords.
2. BLEU doesn't understand the variants of the words and can't take the word order into account.

Submission Instructions

You shall submit this assignment on GradeScope as two submissions – one for "Assignment 4 [coding]" and another for 'Assignment 4 [written]":

1. Run the collect_submission.sh script on Azure to produce your assignment4.zip file. You can use scp to transfer files between Azure and your local computer.
2. Upload your assignment4.zip file to GradeScope to "Assignment 4 [coding]".
3. Upload your written solutions to GradeScope to "Assignment 4 [written]". When you submit your assignment, make sure to tag all the pages for each problem according to Gradescope's submission directions. Points will be deducted if the submission is not correctly tagged.