Lab 3: Conditional Sequence-to-sequence VAE

● Lab objective

In this lab, you need to implement a conditional seq2seq VAE for English tense conversion and generation.

● Important Date

1. Deadline: 8/13 (Tue.) 11:59
2. Demo date: 8/13 (Tue)

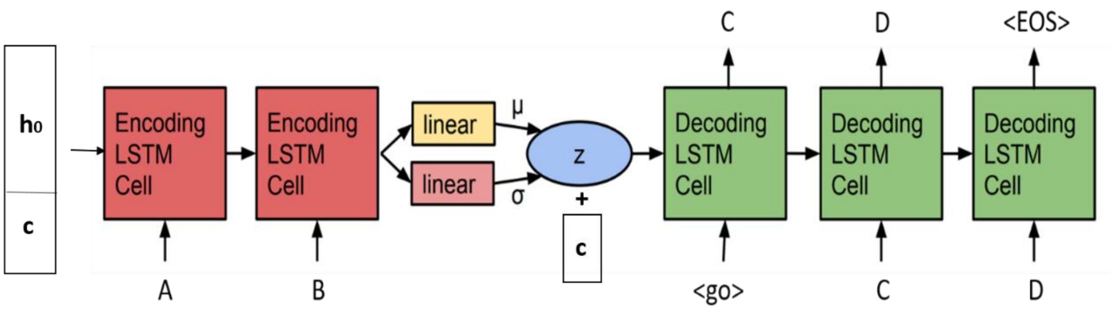
● Turn in

1. Experimental Report (.pdf) and Source code

Notice: zip all files in one file and name it like DLP_LAB3_your studentID_name.zip. e.g. DLP_LAB3_0756051_李仕柏.zip

● Lab Description

When we feed the input word 'access' with the tense (the condition) 'simple present' to the encoder, it will generate a latent vector z. Then, we feed z with the tense 'present progressive' to the decoder and we expect that the output word should be 'accessing'. In addition, we can also manually generate a Gaussian noise vector and feed it with different tenses to the decoder and generate a word those tenses. The figure blow is the overall conditional seq2seq VAE model architecture modified from [Samuel R. Bowman et al. 2016].

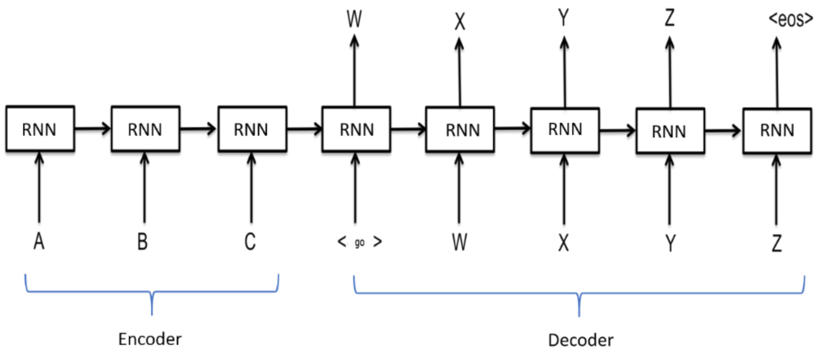


● Requirements

1. Implement a conditional seq2seq VAE.
   A. Modify encoder, decoder, and training functions
   B. Implement evaluation function, dataloader, and reparameterization trick.
2. Plot the CrossEntropy loss, KL loss and BLEU-4 score of testing data curves during training with different settings of your model
   A. Teacher forcing ratio
   B. KL annealing schedules (two methods)
3. Output the conversion results between tenses (from tense A to tense B)
4. Output the results generated by a Gaussian noise with 4 tenses.

- ## Implementation details

1. Seq2seq architecture



Each character in a word can be regarded as a vector. One simple approach to convert a character to a vector is encoding a character to a number and adopting Embedding Layer (see more information in [1]). In the decoder part, you will first feed the hidden output from the encoder and a <go> or <start of string> token to the decoder and stop generation process until you receive a <end of string> token or reach the last token of the target word (the token should also be <end of string>).

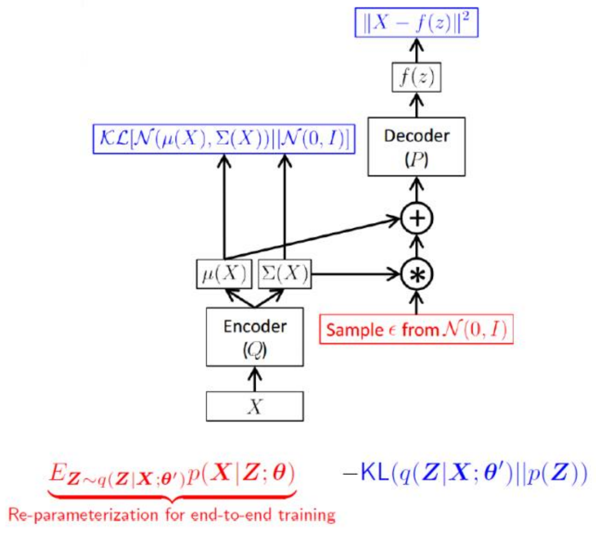
2. VAE
   A. Recall that the loss function of VAE:

$$\mathcal{L}(\mathrm{X}, \mathrm{q}, \theta) = E_{Z \sim q(Z|X;\,\phi)} \log p(X|Z;\theta) - KL(q(Z|X;\phi)||p(Z))$$

   where $q(Z|X;\phi)$ is considered as encoder and $p(X|Z;\theta)$ as decoder.

   B. Reparameterization trick:

   Train the encoder and decoder jointly.


$\|X - f(z)\|^2$
$f(z)$
$KL[\mathcal{N}(\mu(X), \Sigma(X))||\mathcal{N}(0, I)]$
Decoder (P)
$\mu(X)$
$\Sigma(X)$
Encoder (Q)
X
Sample ϵ from $\mathcal{N}(0, I)$
$E_{Z \sim q(Z|X;\theta')} p(X|Z;\theta)$
$-\mathrm{KL}(q(Z|X;\theta')||p(Z))$
Re-parameterization for end-to-end training

   C. Log variance:

   The output of reparameterization trick should be log variance instead of variance directly. (see more information in [Diederik P. Kingma et al. 2014])

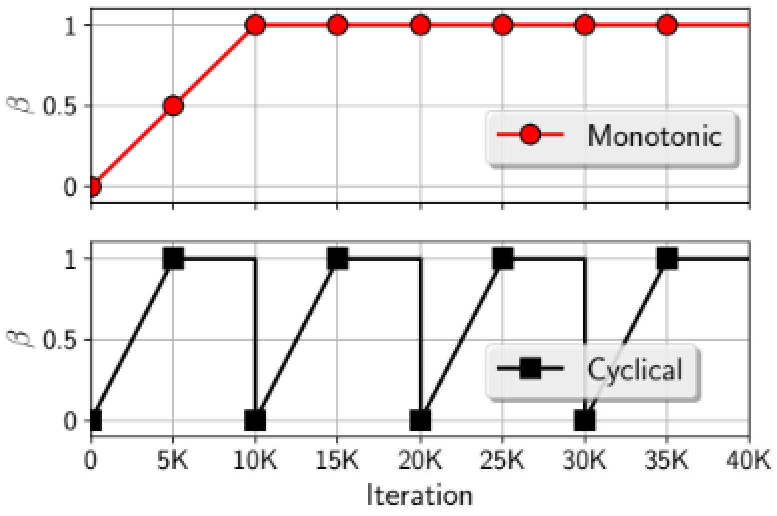
D. Conditional VAE:

$$E_{\boldsymbol{Z}\sim q(\boldsymbol{Z}|\boldsymbol{X},c;\boldsymbol{\theta}')} \log p(\boldsymbol{X}|\boldsymbol{Z},c;\boldsymbol{\theta}) - \mathrm{KL}(q(\boldsymbol{Z}|\boldsymbol{X},c;\boldsymbol{\theta}')||p(\boldsymbol{Z}|c))$$

Both the encoder $q(Z|X,c;\phi)$ and the decoder $p(X|Z,c;\theta)$ need to take c as part of their input. There several ways to add the conditional part to your VAE model. In the figure of model architecture, we concatenate the condition part with the initial hidden part as input of encoder. Similarly, we concatenate the condition part with the latent vector z as input of decoder. Before the concatenation, we construct condition embeddings via projection. You can adopt nn.Embedding and decide the size of your condition embeddings. You can also try to convert your condition into one-hot vector.

KL cost annealing:

This is a simple approach adopted by [Samuel R. Bowman et al. 2016]. We add a variable weight to the KL term in the loss function. We initially set the weight to 0. The maximum value is 1 (at most). There are two ways to implement the annealing schedule: **Monotonic method** and **Cyclical method.** You should adopt these two methods and compare their results.



3. Teacher forcing

In the course, we have talked about teacher forcing technique (L10, slide 25-26), which feeds the correct target $y^{(t-1)}$ into $h^{(t)}$ during training. Thus, in this part, you will need to implement teacher forcing technique. Furthermore, according to [Samuel R. Bowman et al. 2016], we can do the word dropout to weaken the decoder by randomly replacing the input character tokens with the unknown token (defined by yourself). This forces the model only relying on the latent vector z to make predictions.

4. Other implementation details
    - The encoder and decoder are implemented by LSTM.
    - The loss function is nn.CrossEntropyLoss().
    - The optimizer is SGD
    - Adopt BLEU-4 score function in NLTK [4] and **Gaussian_score**() to help you compute your generation score. Both sample codes will be provided.
5. Hyper-parameters and model setting
    - LSTM hidden size: 256 or 512
    - Latent size: 32
    - Condition embedding size: 8
    - Teacher forcing ratio: 0~1
    - Learning rate: 0.05
    - KL weight: 0~1

Dataset Descriptions

You can download the .zip file from new e3. There are three files in the .zip: readme.txt, train.txt, and test.txt. All the details of the dataset are in the readme.txt.

● **Scoring Criteria**

1. Report (50%)

◆ Introduction (5%)

◆ Implementation details (15%)

A. Describe how you implement your model (encoder, decoder, reparameterization trick, dataloader, etc.). Notice: You must prove that your text generation is produced by Gaussian noise (paste/screenshot your code)

B. Specify the hyperparameters (KL weight, learning rate, teacher forcing ratio, epochs, etc.)

◆ Results and discussion (30%)

A. Show your results of tense conversion and generation (5%)

B. Plot the Crossentropy loss, KL loss and BLEU-4 score curves during training and discuss the results according to your setting of teacher forcing ratio, KL weight, and learning rate. Notice: This part mainly focuses on your discussion, if you simply just paste your results, you will get a low score.

2. Demo (50%)

A. Capability of tense conversion on testing data. (10%)

score = **BLUE-4 score (**Average your score with 10 testing data)

■	score >= 0.7	----	100%
■	0.7 > score >= 0.6	----	90%
■	0.6 > score >= 0.4	----	80%
■	score < 0.4	----	0%

B. Capability of word generation. (Gaussian noise + tense) (20%)

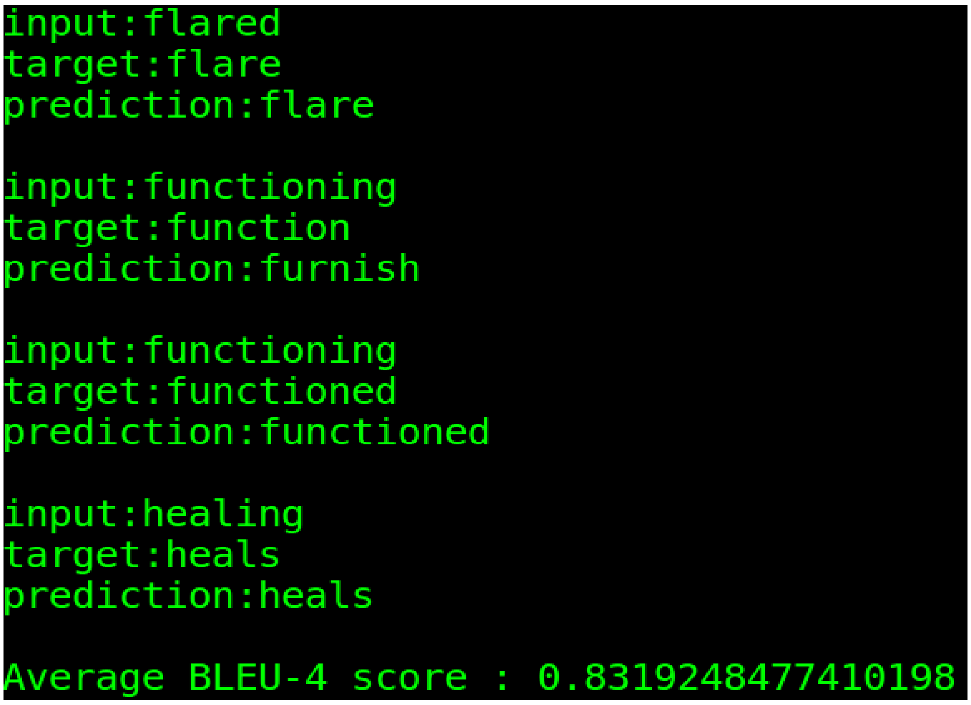
score = **Gaussian_score**(100 words with 4 tenses). In Gaussian_score function, 'yourpath' should be your train.txt; that is, the generation results will compare to the words in train.txt

■	score >= 0.3	----	100%
■	0.3 > score >= 0.2	----	90%
■	0.2 > score >= 0.05	----	80%
■	Score < 0.05	----	0%

C. Questions (20%)

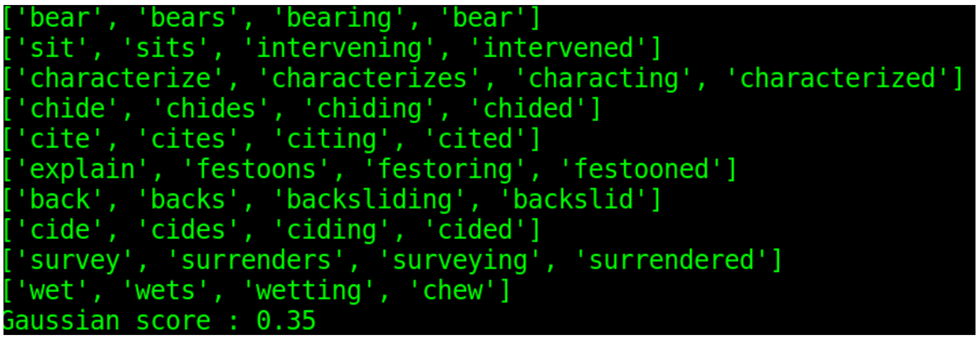
● **Output examples**

1. English tense conversion with BLEU-4 score(test.txt)



```
input:flared
target:flare
prediction:flare

input:functioning
target:function
prediction:furnish

input:functioning
target:functioned
prediction:functioned

input:healing
target:heals
prediction:heals

Average BLEU-4 score : 0.8319248477410198
```

2. Gaussian noise with 4 tenses with Gaussian score



```
['bear', 'bears', 'bearing', 'bear']
['sit', 'sits', 'intervening', 'intervened']
['characterize', 'characterizes', 'characting', 'characterized']
['chide', 'chides', 'chiding', 'chided']
['cite', 'cites', 'citing', 'cited']
['explain', 'festoons', 'festoring', 'festooned']
['back', 'backs', 'backsliding', 'backslid']
['cide', 'cides', 'ciding', 'cided']
['survey', 'surrenders', 'surveying', 'surrendered']
['wet', 'wets', 'wetting', 'chew']
Gaussian score : 0.35
```

● **Very Useful Hints**

1. While training, your input and output words should have the same tense. For example, if your input is 'accessing'+'progress', then your output should also be 'accessing'+'progress'.
2. Sequence-to-sequence model is very sensitive to the previous hidden input and hence, I **strongly** suggest you save your model weights after each epoch so that you can decide which weight you want to use.
3. The teacher forcing ratio and KL weight are very important for training this model and **significantly influence** the performance.
4. You should carefully check the mechanisms of nn.LSTM() and nn.CrossEntropyLoss(), there are some tricks that can help you to train your model.
5. You should know how traditional VAE works before you start to build the model.

● Reference

1. VAE reference code: https://github.com/pytorch/examples/tree/master/vae
2. Seq2seq reference code:
   https://pytorch.org/tutorials/intermediate/seq2seq_translation_tutorial.html
   https://github.com/pytorch/tutorials/blob/master/intermediate_source/seq2seq_translation_tutorial.py
3. Generating Sentences from a Continuous Space [Samuel R. Bowman et al. 2016]
4. Auto-Encoding Variational Bayes [Diederik P. Kingma et al. 2014]
5. Natural Language Toolkit: https://www.nltk.org/