ADL Homework 1 Report

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Q1: Data processing (1%)

1. How do you tokenize the data.
   - Lower all the word
   - replace character which is not 「a-z」 「A-Z」 「!」 「?」 「'」 「,」 「.」 with " "
   - Use nltk package to tokenize.
2. Number of negative samples used to train your model.

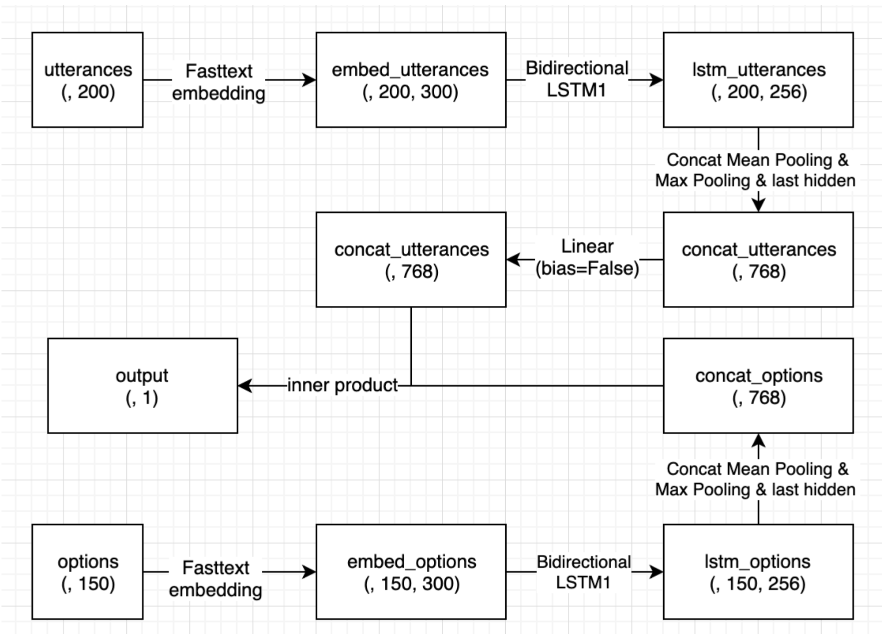
   4 for each data.
3. Truncation length of the utterances and the options.

   utterances: 200, options: 150
4. The pre-trained embedding you used.

   Fasttext: crawl-300d-2M.vec

Q2: Describe your RNN w/o attention model. (1%)

Model Structure:



After word embedding, I use a two layers bidirectional lstm on embed_utterence and embed_options. Then do the max pooling and mean pooling on each lstm output. For each, concat last output, max pooling output and mean pooling output, get two vector a and b. Finally, calculate the score with a^TWb, which W is a trainable weight.

Performance:

- recall@10 (on validation set): 0.6504
- public leaderboard: 9.56666
- private leaderboard: 9.64571

Loss Function:

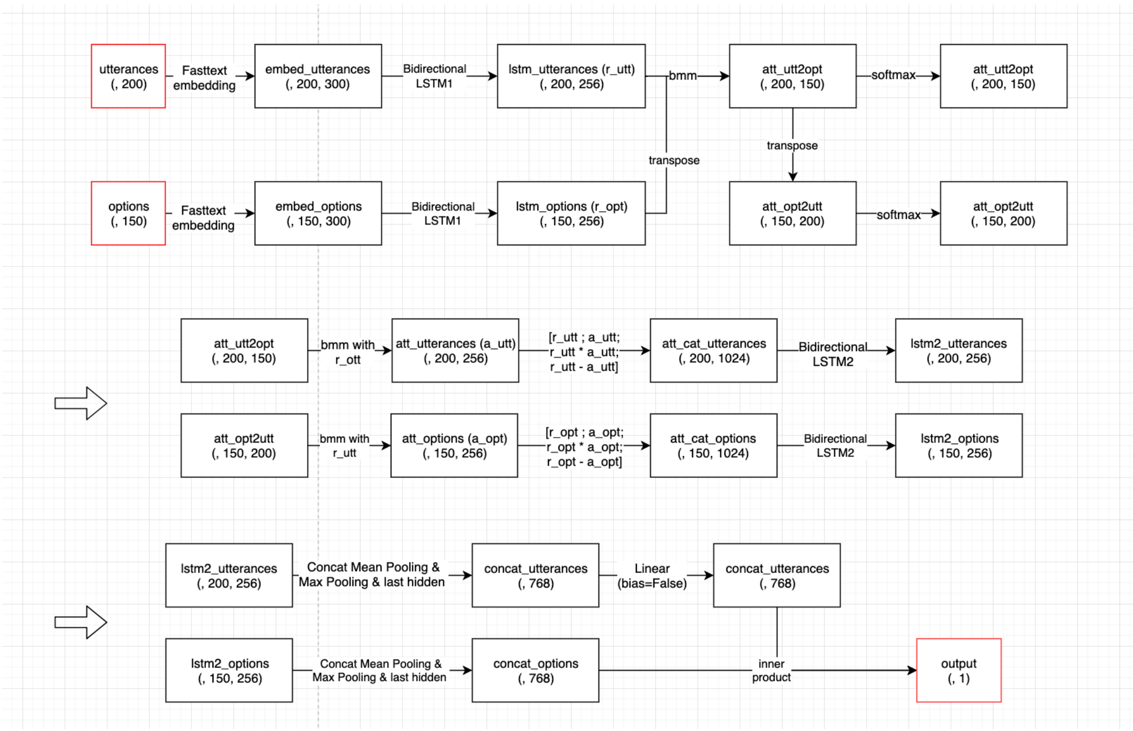
- BCEWithLogitsLoss

Optimization:

- Adam
- learning rate: 1e-3
- batch size: 100

Q3: Describe your RNN w/ attention model. (1%)

Model Structure -- Cross attention:



After word embedding, I use a one layer bidirectional lstm1 on embed_utterence and embed_options and get the output **r_utt** and **r_opt**. and I get the attention map by $r_{utt} r_{opt}^T$ and names as att_utt2opt, adding a softmax on its dimension 2. Using this attension on r_opt and get the **a_utt** (attention of utterences).

Meanwhile, transpose the att_utt2opt and get att_opt2utt, adding a softmax on its dimension 2.Using this attension on r_utt and get the **a_opt** (attention of options). This can be a kind of **cross attention**.

I concatenate two matrix (r and a) of utterences and options by **[r; a; r*a; r-a]** and get the att_cat_utterences and att_cat_options. And I used another one layer bidirectional lstm2 on them, getting 2 lstm2 output.

Then do the max pooling and mean pooling on each lstm2 output. For each, concat last output, max pooling output and mean pooling output, get two vector a and b. Finally, calculate the score with $a^T Wb$, which W is a trainable weight.

Performance:

- recall@10 (on validation set): unknown
- public leaderboard: 9.33333
- private leaderboard: 9.39714

Loss Function:

- BCEWithLogitsLoss

Optimization:

- Adam
- learning rate: 1e-3
- batch size: 100

Q4: Describe your best model. (2%)

1. Describe (1%)

   I ensemble 11attention models above. The ensemble method is voting by 11 models and each model has 10 tickets. and output the top10 result.

   Performance:

   - recall@10 (on validation set): 0.7698
   - public leaderboard: 9.32666
   - private leaderboard: 9.35428

   Loss Function and Optimization:

   - as same as the attention model above

1. Describe the reason you think why your best model is better than your RNN w/ and w/o attention model. (1%)
   1. The advantage of ensemble

      Due to the instability of the only one attention model. I have trained two results, and one get the 9.34666 on publice board and another get 9.40.

So the easiest way is using their output to vote and thier is a large improvent in private score.

2. Cross attention vs Self attention

   I have trained a poor attention rnn model, which the different is that its attention weight is $r_{utt}r_{utt}^T$ and $r_{opt}r_{opt}^T$ and attent on itself.

   But the better way is $r_{utt}r_{opt}^T$, which attent on the other one and it will **get the more imformation**. Utterence can access more imformation of options, and so do options.

3. w/ attention vs w/o attention

   I find that self attention's result is little better than the rnn w/o attention's. I think that the reason is self attention model can not get more imformation and **just increase the model's complexity**.

   Compared with self attention, corss attention get more imformation as I mentioned above. So it can have a great improvement from rnn w/o attention.

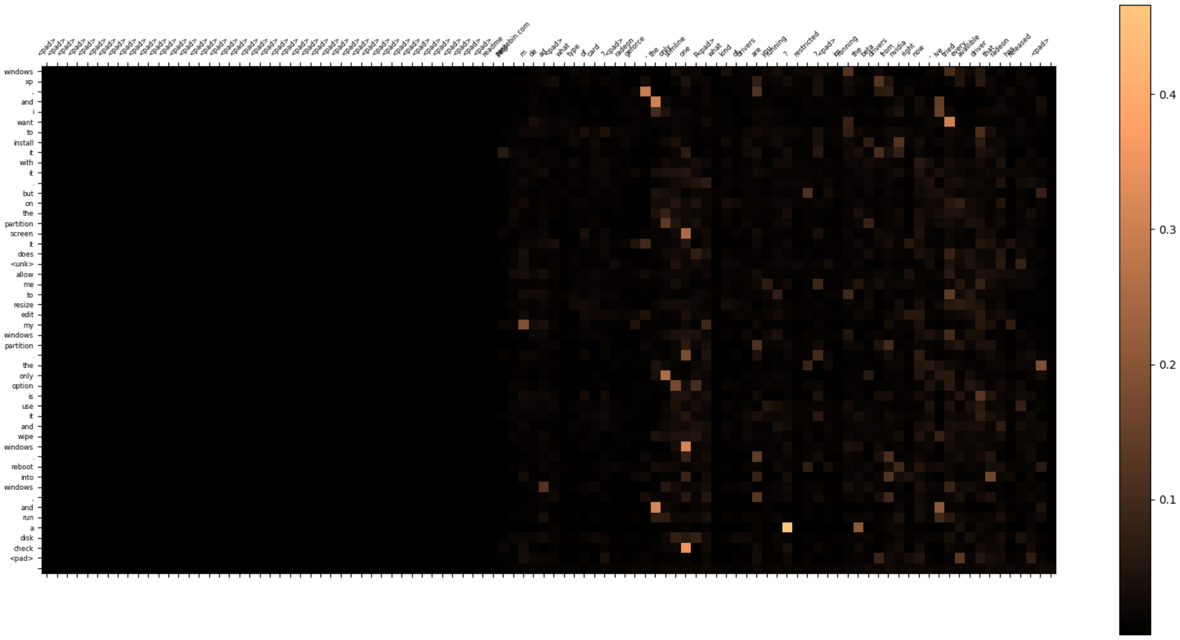
Q5: Compare GRU and LSTM (1%)

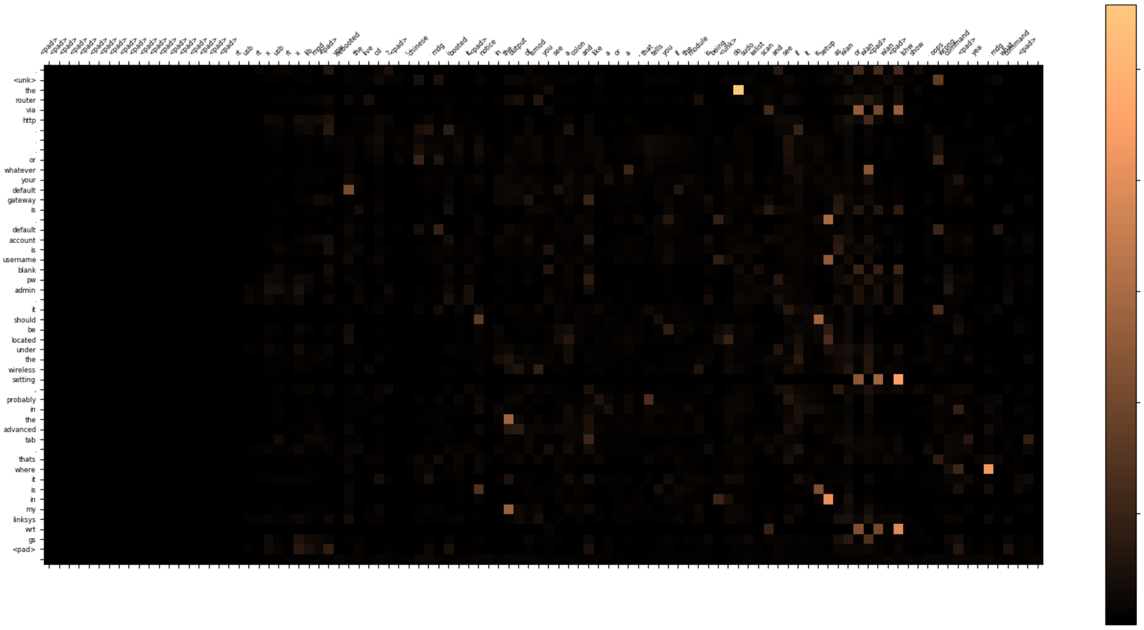
	LSTM	GRU
recall@10 (on validation set)	**0.7698**	0.7544
public leaderboard / recall@10	**9.33333**	9.39333
private leaderboard / recall@10	**9.39714**	9.40857
required GPU memory	about 2.6G	about **2G**
training speed (sec per epoch)	about 780s	about **720s**
testing speed	47s	**45s**

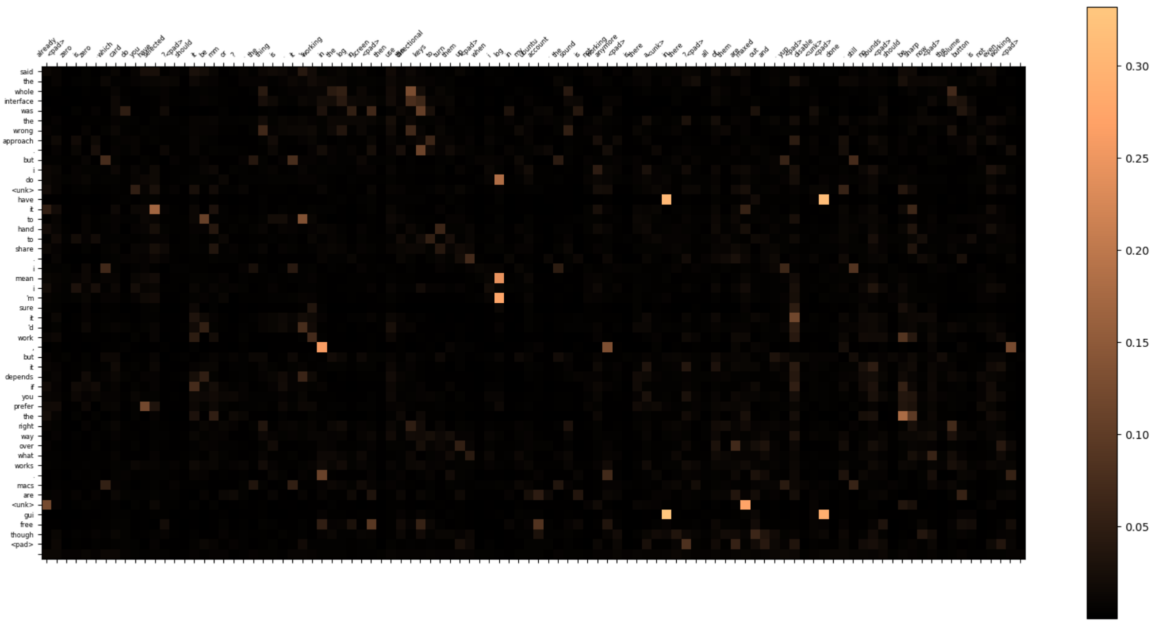
Q6: Visualize the attention weights (2%).

1. Take one example in the validation set and visualize the attention weights (after softmax)

   --> *Notice that each row's sum is 1*


windows xp , and i want to install it with it . but on the partition screen it does <unk> allow me to resize edit my windows partition . the only option is use it and wipe windows . reboot into windows , and run a disk check <pad>
0.1
0.2
0.3
0.4


. <unk> the router via http . . . or whatever your default gateway is . default account is username blank pw admin . it should be located under the wireless setting , probably in the advanced tab . thats where it is in my linksys wrt gs <pad>
0.1
0.2
0.3
0.4
0.5


said the whole interface was the wrong approach . but i do <unk> have it to hand to share . i mean i 'm sure it 'd work , but it depends if you prefer the right way over what works . macs are <unk> gui free though <pad>
0.05
0.10
0.15
0.20
0.25
0.30

2. Describe your findings. (1%)

   I found that my attention not have some obviously feature. It might catch some similar vectors to mix a new states. Maybe it generate something meanful sequence and this really works!

   The another interesting dicoveries is that this attention could help handling the padding sequence, giving the `<pad>` word lower attention. Let the attented sequence has more useful imformation.

Q7: Compare different settings. (1% + bonus)

- Compare training with different settings:
  - different reasonable loss functions (1%).

	BCEwithLogit	**BCE**	**MSE**
recall@10 (on validation set)	**0.7698**	0.767	0.7674
public leaderboard / recall@10	**9.33333**	9.37333	9.40000
private leaderboard / recall@10	**9.39714**	**9.39714**	9.40857

  - different number of negative samples (1%).

	3	**4**	**9**
recall@10 (on validation set)	0.7686	**0.7698**	0.7596
public leaderboard / recall@10	9.37333	**9.33333**	9.38666
private leaderboard / recall@10	**9.37428**	9.39714	9.40571

  - different number of utterances in a dialog (1%).

	100	**200**	**300**	**400**
recall@10 (on validation set)	0.7684	0.7698	0.7698	**0.7738**
public leaderboard / recall@10	9.37333	**9.33333**	9.38666	9.40000
private leaderboard / recall@10	9.40000	9.39714	**9.37428**	9.39428

- different pre-trained word embeddings (1%).

	fasttext	**gensim**
Known Words Num	57294	33951
recall@10 (on validation set)	**0.7698**	0.6908
public leaderboard / recall@10	**9.38666**	9.60000
private leaderboard / recall@10	**9.37428**	9.60571