Applied Deep Learning - Homework 2

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> *(1) This document is edited with Typora. In case some markdown extensions (e.g. math mode) are not supported by native markdown editor, you can read [report.pdf]() for better reading experience.*
>
> *(2) Due to my improper time arrangement, I started to work on the homework late. After I finished the coding part, I was not able to tune / improve my model to pass the simple baseline.*

Q1: Data Preprocessing

(a) Tokenizer

The tokenizer for `bert-base-chinese` (and almost every chinese BERT model) is character-based. That is, a chinese character is considered as a token. However, some non-chinese character are still tokenized at a vocabulary-level, (e.g. some numbers, english words). For example, `你好啊！` will be tokenized into `['你', '好', '啊', '！']`, while `314159 tokenization` will be tokenized into `['314', '##15', '##9', 'to', '##ken', '##i', '##za', '##tion']`.

(b) Answer Span

To answer the questions, I'm going to explain my preprocessing procedure first.

1. Tokenize the question: Use the tokenizer to tokenize the question text into Q.
2. Tokenize the paragraph: Since the paragraph may be too long for the BERT model, I splitted the original paragraph into fragments by chinese dot `。`, and merge the fragments such that any fragment cannot be longer. Therefore, the number of fragments is minimized. For each fragment, we derive its tokens F in the following two ways.

    1. If the fragment does not contain answer span, we directly tokenize the fragment.
       Note: this kind of fragment will not be used in the question answering task
    2. Otherwise, we specially handle this case. The fragment can be splitted into `(before, answer span, after)`, and we tokenize each sub-fragment and concatenate them together. By doing this, we can explicitly know the start/end position of the answer span from the token level.
3. Construct a data sample: Finally, we can have a data sample
    - input token: `[CLS] + Q + [SEP] + F + [SEP]`
    - `has_answer`: determines whether the fragment has answer as in step 2
    - start/end position (for those whose `has_answer` is True): can be derived in step 2-2

Thus,

1. The start/end position can be derived by calculating the offsets before the answer span, as explained in step 2-2.
2. Since the tokens are passed into the model as well, we can directly take the tokens and reconstruct the answer text.

Q2: Modeling with BERT and their variants

Following the guides on the homework slides, I split the task into two subtasks, (1) context selection and (2) question answering. The two models are trained seperately.

(a) Describe your model

1. Model
    - The backbone model is set to `bert-base-chinese` as suggested on the homework slide.
    - For context selection model, we apply an additional Linear layer to take the BERT's pooler output $\text{BERT}_{\text{pooler\_output}}$ as input and predicts a single score s_{context} as output, representing how likely the question is relevant to the given fragment. Technically speacking,

- For question answering model, we apply an additional Linear layer to take the each of BERT's last hidden output $\text{BERT}_{\text{last\_hidden}}$ as input and predicts two scores s_{start}, s_{end} as output, representing how likely the token is the start/end index for answer span.

2. Performance
    - Context selection (validation set)
        - Accuracy (binary classification): 0.94359
    - Question answering (validation set)
        - EM: 0.64979
        - F1: 0.84613
    - Overall (public set)
        - EM: 0.62762
        - F1: 0.69477
3. Loss function
    1. For context selection, I regard the task as a binary classification -- predicting whether a *fragment* has answer span in it. Thus, the loss function I use is a standard binary cross entropy loss.
    2. For question answering, I regard the task as a span selection -- predicting two 512-class indices representing the start/end index. Therefore, the loss function I use is a standard cross entropy loss.
4. Optimizer: Adam with learning rate 1e-5, weight decay 5e-6 and *effective* batch size 32. The *effective* batch size is the real batch size (4, limited by the GPU) times gradient accumulation steps (8). The model is trained for 10 epochs, the checkpoint with the highest validation accuracy will be used.

(b) Another type of pretrained model

Besides `bert-base-chinese`, I also tried another pretrained model, MacBert. It's publicly available on transformers's model page.

1. Model

    Only the backbone bert model is changed to `hfl/chinese-macbert-base`. Other parts are the same.

2. Performance

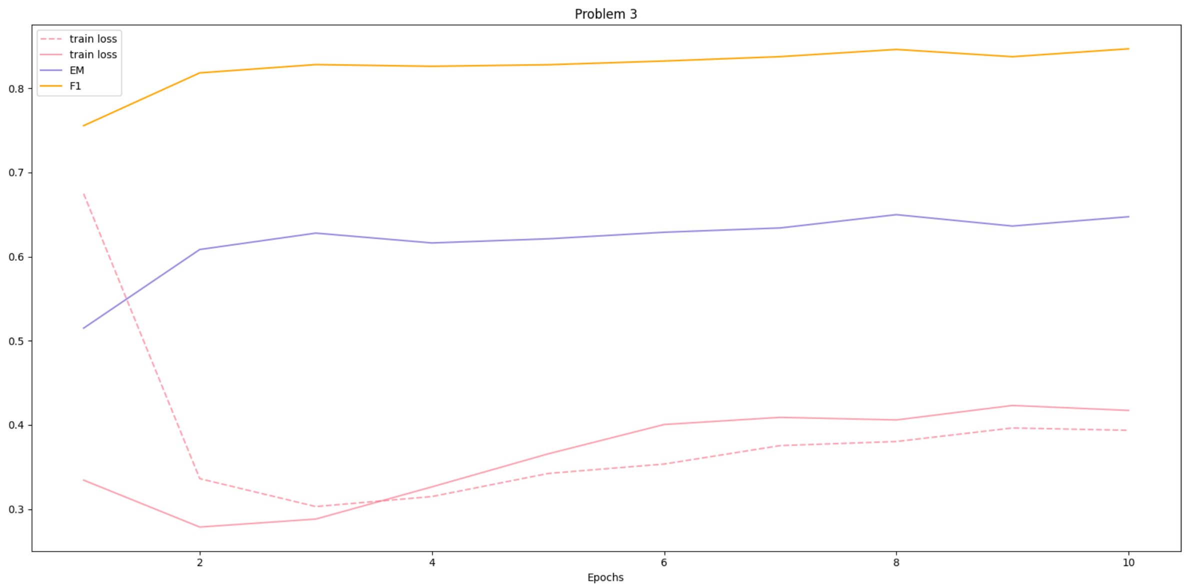
- Context selection (validation set)
    - Accuracy (binary classification): 0.96472
- Question answering (validation set)
    - EM: 0.71127
    - F1: 0.88021
- Overall (public set)
    - EM: 0.66222
    - F1: 0.73890

3. Difference between the pretrained model

   The MacBert is actually an improved BERT. In constract to the original MLM pretraining task, MacBERT is trained with a novel MLM as correct pretraining task. The authors proposed to use similar words for the masking purpose. Reference: [MacBert's GitHub].

Q3: Curves

> *(1) Based on the discussion on the forum, I only consider the question answering task. The data used is the validation set.*
>
> *(2) I plot the two curves in the same graph.*



Q4: Pretrained v.s. Not Pretrained

> *I didn't train a non-pretrained version.*

Q5: Bonus - HW1 with BERTs

I also tried to apply BERT in my homework 1. Generally speaking, the model is exactly the same as the one I implement in HW1, except I changed the RNN module to BERT.

(a) Model Architecture

1. The bert model I use is `bert-base-uncased`. And the tokenizer, of course, is inherited from `bert-base-uncased`.
2. Two customized fully-connected heads are used for each task. The input dimension is the hidden dimension of the bert model, which is 768 for `bert-base-uncased`. The output dimension is related to the output domain, 150 for intent classification and 9 for slot tagging.
3. The model flow is the same as it in Hoemwork 1.

(b) Performance

- Intent classification

Model	Validation Acc.	Public Score	Private Score
RNN	0.9037	0.90000	0.89733
BERT	0.964	0.95600	0.96177

- Slot tagging

Model	Validation Token Acc.	Validation Joint Acc.	Public Score	Private Score
RNN	0.96369	0.77990	0.78498	0.79635
BERT	0.968	0.806	0.80697	0.79421

(c) Loss Function

Same as Homework 1, I use the standard cross entropy loss as the loss function in both tasks.

(d) Optimizer

I use the same optimizer settings in the two tasks for training the BERT model.

- Optimizer: Adam with learning rate=2e-5 and weight_decay=1e-5
- Batch size: 64
- Trained for 50 epochs, the checkpoints at the 15 epoch are selected by their validation loss.