Q1: Data processing

1. tokenizer:主要對詞做切割,讓分詞器能取得有意義的文字,但因為會出現一些沒看過的詞,不像英文一樣以單字作為單位,所以採選擇最大機率的詞。並會在 先前定義每個單字的大小去做選擇,在我們建立LM時可以選擇最大機率的詞。

2. Answer Span:

- a. 使用huggingface的範例程式碼「run_qa_no_trainer.py」,透過offsets可以 得到每個token的start、end的位置,然後找出與span start、span end相同 的位置,即為start postions、end postions。
- b. 對每種start_postions、end_postions做機率統計,選出最大機率的詞,最 後再用offset對應回去,即為最後選擇的結果。

```
# Start/end character index of the answer in the text.
start_char = answers["start"]
end_char = start_char + len(answers["text"])
# Start token index of the current span in the text.
token_start_index = 0
while sequence ids[token start index] != (1 if pad on right else 0):
    token_start_index += 1
# End token index of the current span in the text.
token\_end\_index = len(input\_ids) - 1
while sequence_ids[token_end_index] != (1 if pad_on_right else 0):
   token_end_index -= 1
# Detect if the answer is out of the span (in which case this feature is labeled with the CLS index).
if not (offsets[token_start_index][0] <= start_char and offsets[token_end_index][1] >= end_char):
   tokenized_example["start_positions"].append(cls_index)
   tokenized_example["end_positions"].append(cls_index)
else:
    # Otherwise move the token_start_index and token_end_index to the two ends of the answer.
   # Note: we could go after the last offset if the answer is the last word (edge case).
   while token_start_index < len(offsets) and offsets[token_start_index][0] <= start_char:</pre>
       token_start_index += 1
    tokenized_example["start_positions"].append(token_start_index - 1)
    while offsets[token_end_index][1] >= end_char:
        token_end_index -= 1
   tokenized_example["end_positions"].append(token_end_index + 1)
```

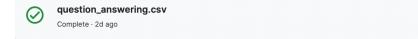
0.76513

0.75316

Q2: Modeling with BERTs and their variants

1.

a. model: bert-base-chineseb. performance: 0.75316



- c. loss function: torch.nn.CrossEntropyLoss()
- d. optimization algorithm: torch.optim.AdamW()

learning rate: 3e-5, batch size: 1

epoch: mutiple choice=1 qustion answering=2

2.

a. model: hfl/chinese-roberta-wwm-ext-large

b. performance: 0.79385



0.80307

0.79385

c. loss function: torch.nn.CrossEntropyLoss()

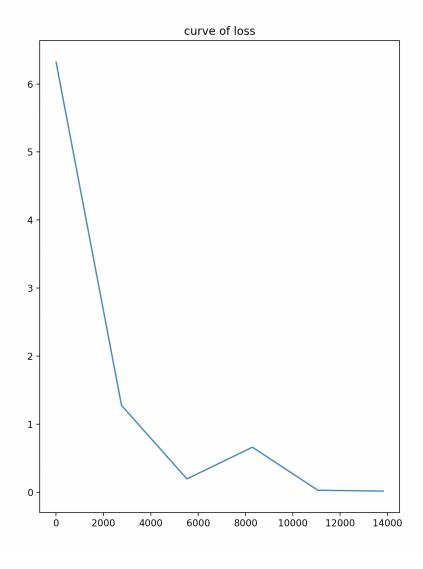
d. optimization algorithm: torch.optim.AdamW()

learning rate: 3e-5, batch size: 1

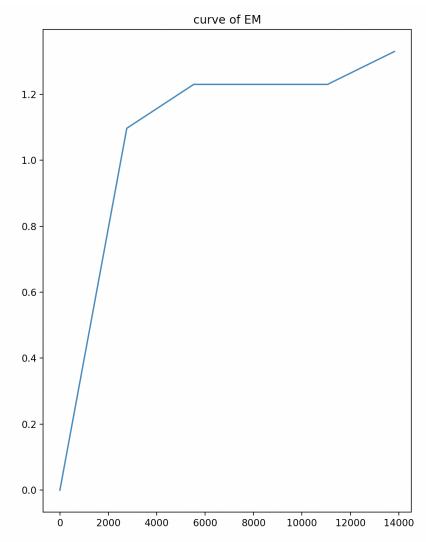
epoch: mutiple_choice=1, qustion_answering=2

Q3: Curves

a. Learning curve of loss (epoch: 1)



b. Learning curve of EM (epoch: 1)



Q4: Pretrained vs Not Pretrained

- a. describe:變更question的訓練方式,基本上就是將其預訓練的權重去除掉,所以在僅僅訓練少少epoch時,沒辦法達到跟已經預訓練過的模型一樣,他的performance會極低。有可能訓練很多個epoch或是給予較多資料訓練,就會有比較好的performance。
- b. model: bert-base-chinese
- c. performance: 0.0018



d. loss function: torch.nn.CrossEntropyLoss()e. optimization algorithm: torch.optim.AdamW()

learning rate: 3e-5, batch size: 1 epoch: qustion answering=2