NTU ADL 2024 Fall
HW1 Report

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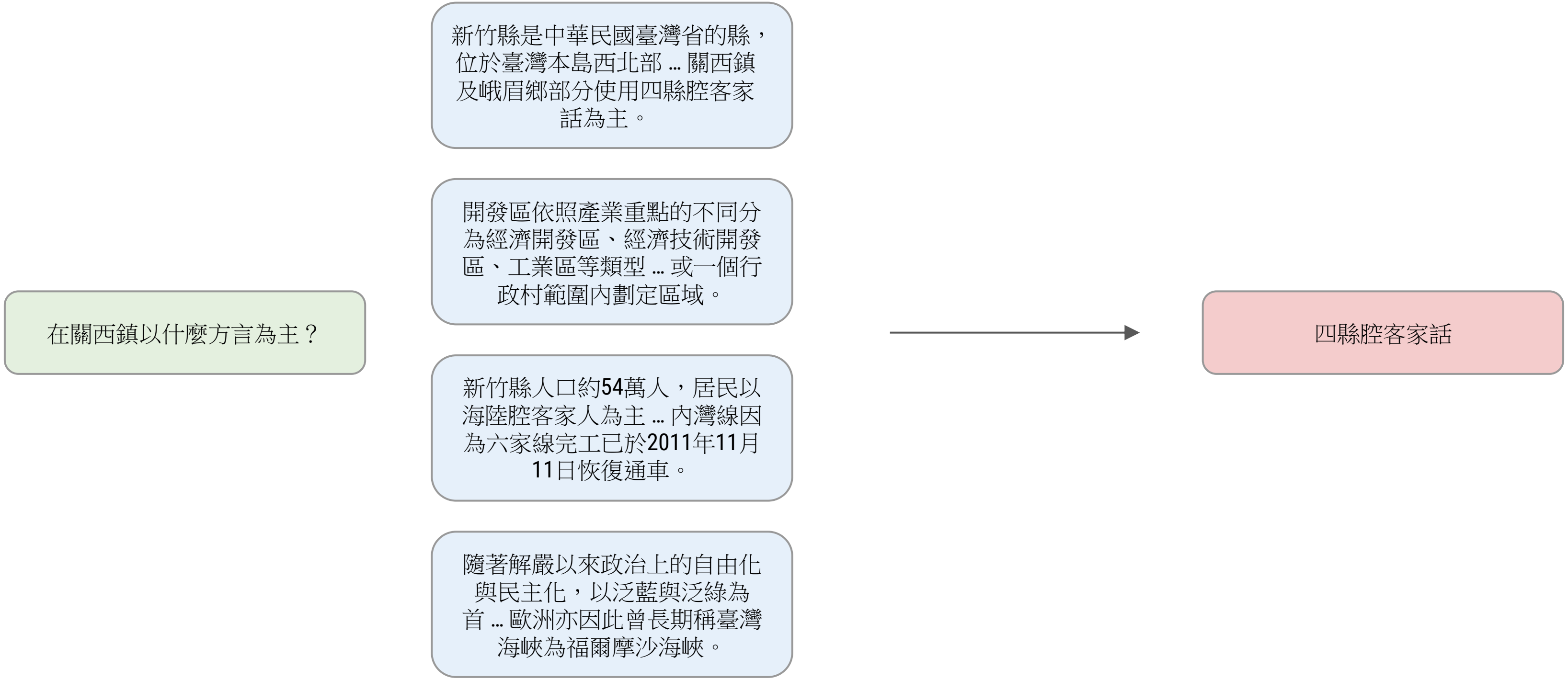
Task Description - Chinese Extractive Question Answering (QA)



在關西鎮以什麼方言為主？

新竹縣是中華民國臺灣省的縣，位於臺灣本島西北部 … 關西鎮及峨眉鄉部分使用四縣腔客家話為主。

開發區依照產業重點的不同分為經濟開發區、經濟技術開發區、工業區等類型 … 或一個行政村範圍內劃定區域。

新竹縣人口約54萬人，居民以海陸腔客家人為主 … 內灣線因為六家線完工已於2011年11月11日恢復通車。

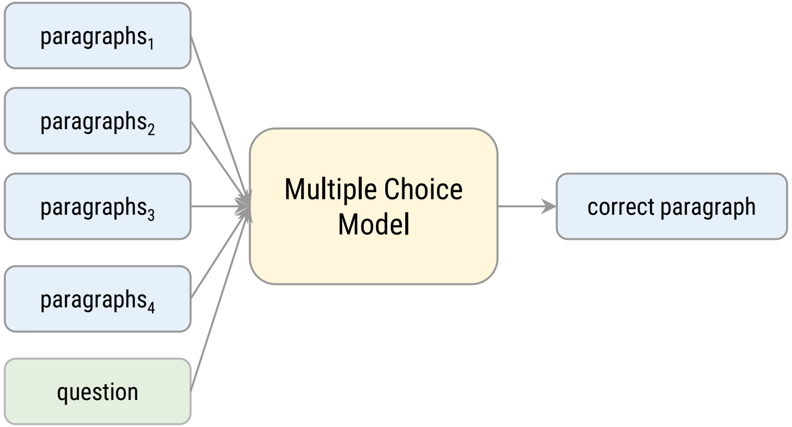
隨著解嚴以來政治上的自由化與民主化，以泛藍與泛綠為首 … 歐洲亦因此曾長期稱臺灣海峽為福爾摩沙海峽。

四縣腔客家話

Task Description - Chinese Extractive Question Answering (QA)

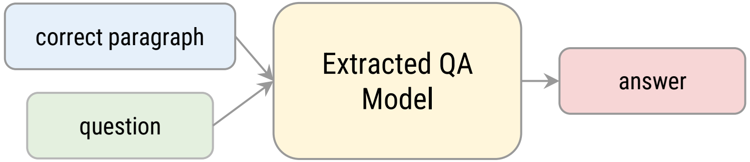
Paragraph Selection:

Determine which paragraph is relevant.



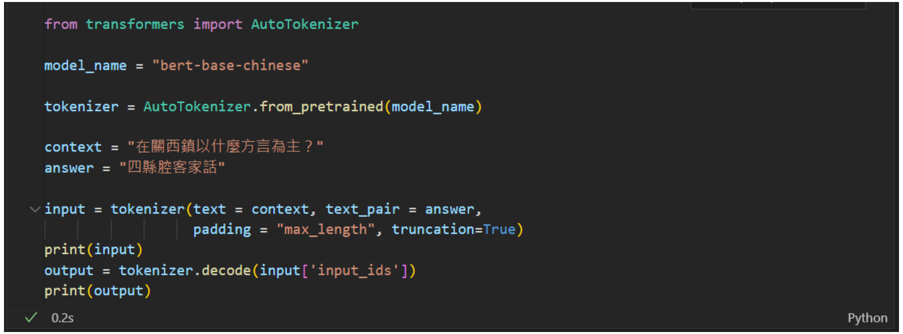
Span selection:

Determine the start and end position of the answer span.



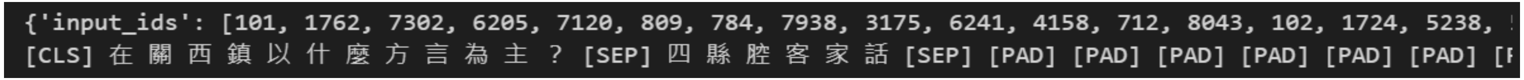
The answer is always a **span in the correct paragraph.*

Report - Q1: Data processing (2%)



```python
from transformers import AutoTokenizer

model_name = "bert-base-chinese"

tokenizer = AutoTokenizer.from_pretrained(model_name)

context = "在關西鎮以什麼方言為主？"
answer = "四縣腔客家話"

input = tokenizer(text = context, text_pair = answer,
                  padding = "max_length", truncation=True)
print(input)
output = tokenizer.decode(input['input_ids'])
print(output)
```

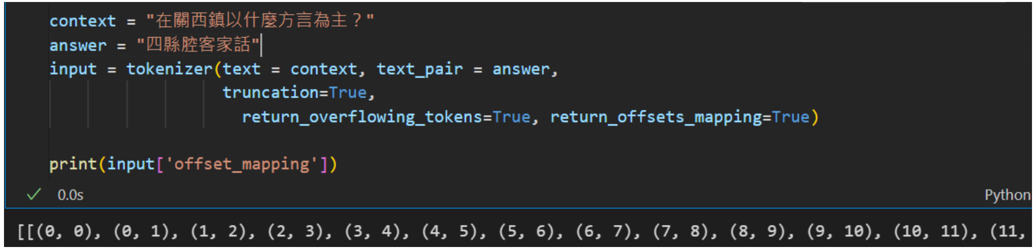
- Tokenizer (1%):
  - Tokenizer processing separates English words into subwords, which are meaningful unit. The advantage is that the model can use the meaning by these tokens to predict unseen words.
  - Chinese word are separates to each individual words, like



```
{'input_ids': [101, 1762, 7302, 6205, 7120, 809, 784, 7938, 3175, 6241, 4158, 712, 8043, 102, 1724, 5238,
[CLS] 在 關 西 鎮 以 什 麼 方 言 為 主 ？ [SEP] 四 縣 腔 客 家 話 [SEP] [PAD] [PAD] [PAD] [PAD] [PAD] [PAD] [P
```

  - There are some special token like
    - [CLS] : for the beginning of the sequence.
    - [SEP] : using it to separate different sentences
    - [PAD] : padding token, in order to pad sequence to same length
    - [UNK] : if input have unseen token, it will be represented this token

Report - Q1: Data processing (2%)



```python
context = "在關西鎮以什麼方言為主？"
answer = "四縣腔客家話"
input = tokenizer(text = context, text_pair = answer,
                  truncation=True,
                    return_overflowing_tokens=True, return_offsets_mapping=True)

print(input['offset_mapping'])
```

```
[[(0, 0), (0, 1), (1, 2), (2, 3), (3, 4), (4, 5), (5, 6), (6, 7), (7, 8), (8, 9), (9, 10), (10, 11), (11,
```

- Answer Span (1%):
  - (a). In question answering task, when doing tokenization, I use the "return_offset_mapping" option to record the start and end position in sequence of each token. By doing this, I can convert the answer span to corresponding position.
  - (b). Since we need to predict start, end positions of the span, so we must to calculate the logits probabilities to identify the best answer. Using above function to find the best answer.

$$i^*, j^* = \mathrm{argmax}_{i,j} \mathrm{P}(s_i)\mathrm{P}(e_j) = \arg\max_{i,j} e^{l(s_i)}\, e^{l(e_j)}$$

$$= \arg\max_{i,j} \log\left(e^{l(s_i)} e^{l(e_j)}\right) = \arg\max_{i,j} \log\left(e^{l(s_i)}\right) + \log\left(e^{l(e_j)}\right)$$

$$= \arg\max_{i,j} l\,(s_i) + l(e_j)$$

Report - Q2: Modeling with BERTs and their variants (4%)

In Multiple choice task

	Bert-base-Chinese	Chinese-lert-base
Performance (acc in validation)	0.96078	0.96975
Loss function	Cross-Entropy Loss	Cross-Entropy Loss
Optimizer	AdamW	AdamW
Learning rate	5e-5	5e-5
Batch size	8(4 * 2 gradient accumulation step)	8(4 * 2 gradient accumulation step)
Max seq length	512	512
Epoch	5	5

Report - Q2: Modeling with BERTs and their variants (4%)

In question answering task, because my best model is Chinese-lert-base in mc task, I use Chinese-lert-base model to infer test dataset.

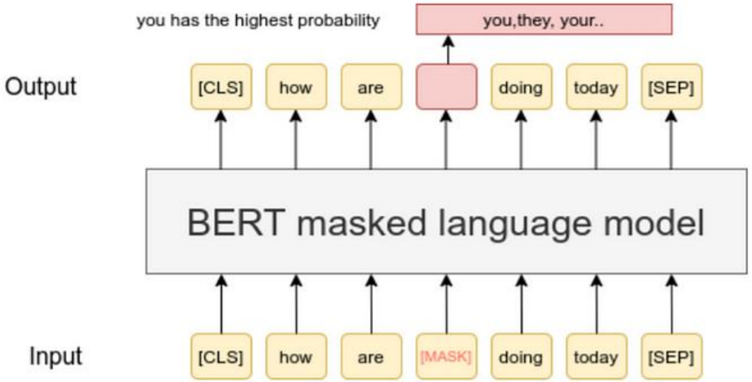
	Chinese-lert-base	**Chinese-lert-large**
Performance (EM in validation / Private score / Public score)	86.075 / 0.80265 / 0.79298	86.274 / 0.81222 / 0.80116
Loss function	Cross-Entropy Loss	Cross-Entropy Loss
Optimizer	AdamW	AdamW
Learning rate	8e-5	2e-5
Batch size	32 (8 * 4 gradient accumulation step)	32 (8 * 4 gradient accumulation step)
Max seq length	512	512
Epoch	25	25

Report - Q2: Modeling with BERTs and their variants (4%)

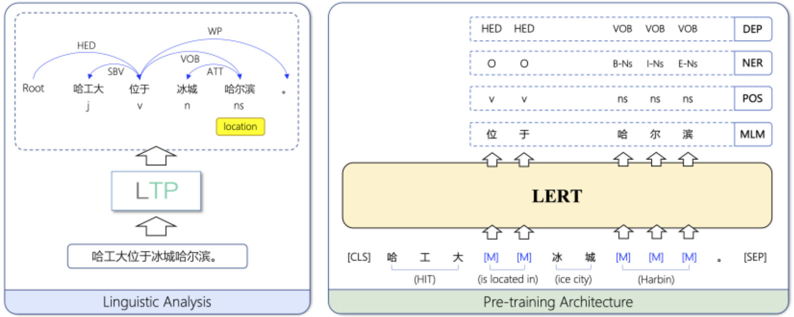
The difference between Bert and Lert

- Bert is a model in NLP that uses MLM (Masked Language Model) and NSP(Next Sentence Prediction) tasks to train. In contrast, Lert not only focuses surface-level textual but also integrates linguistic features like DEP (Dependency Parsing), NER (Named Entity Recognition), POS (Part-of-Speech) task to train model, which provide the model richer language representations.

- In addition, Lert use LIP (Linguistic Information-Enhenced Pre-training) mechanism, which captures and utilizes linguistic information more effectively.

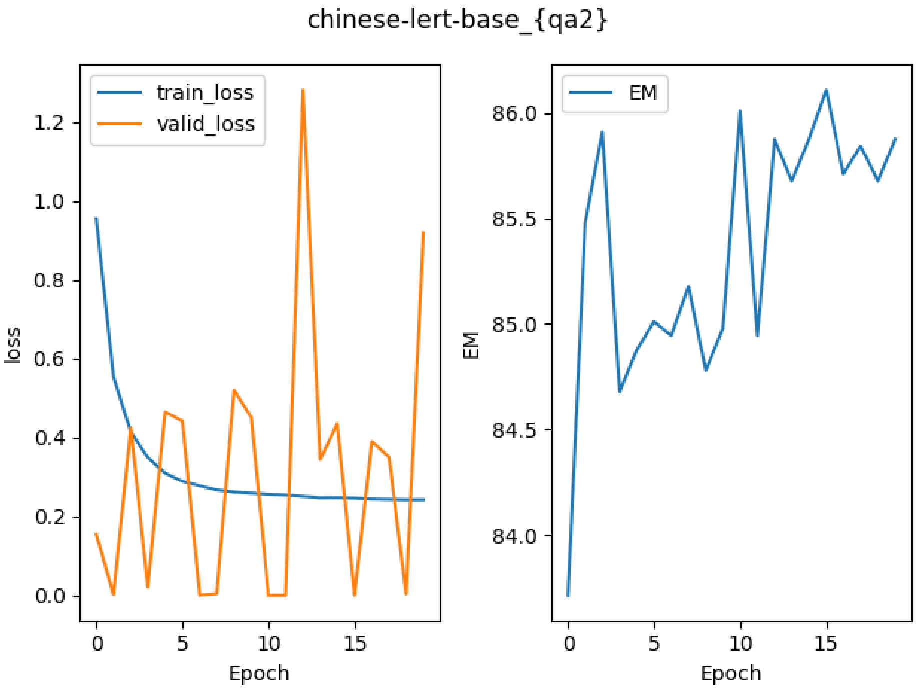


Bert

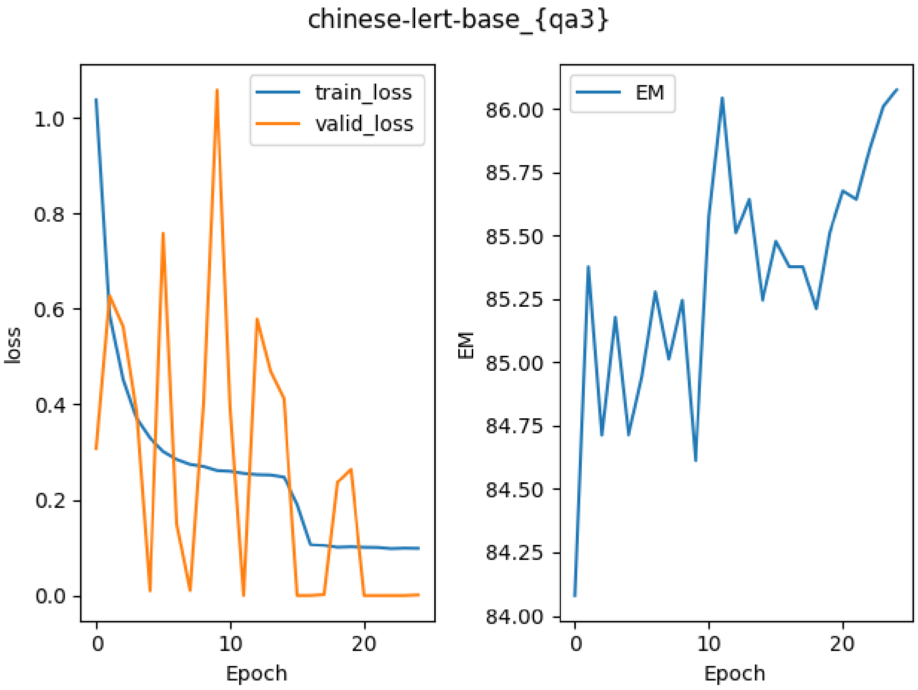


Lert

Report - Q3: Curves (1%)

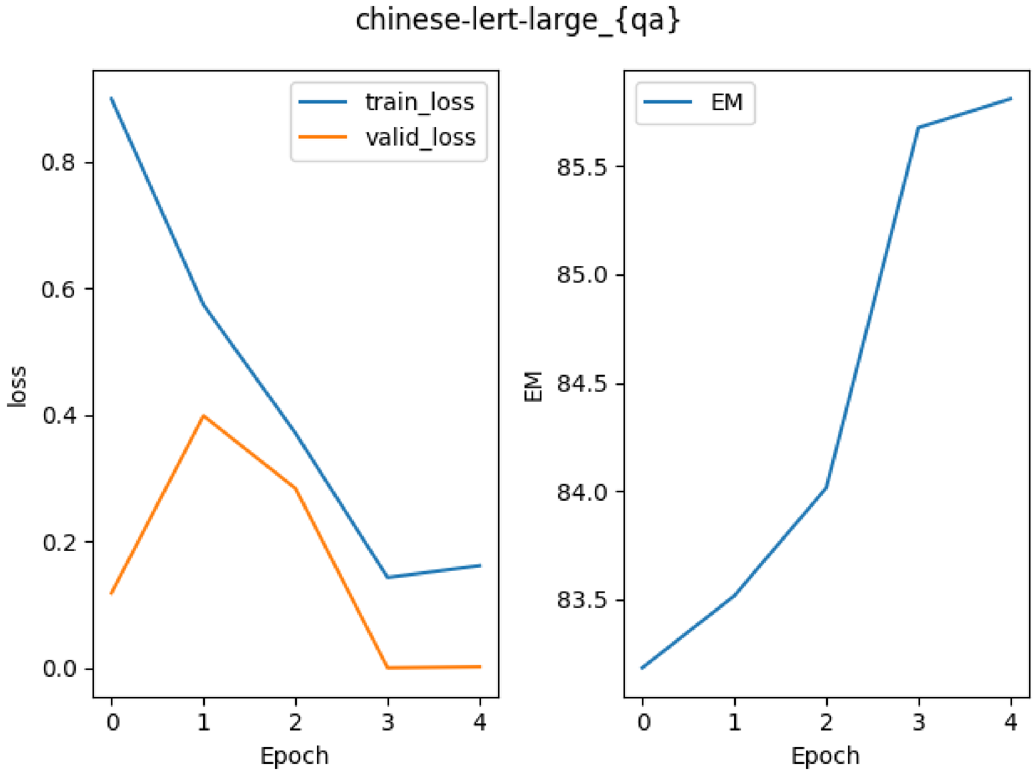


Epoch = 20



Epoch = 25

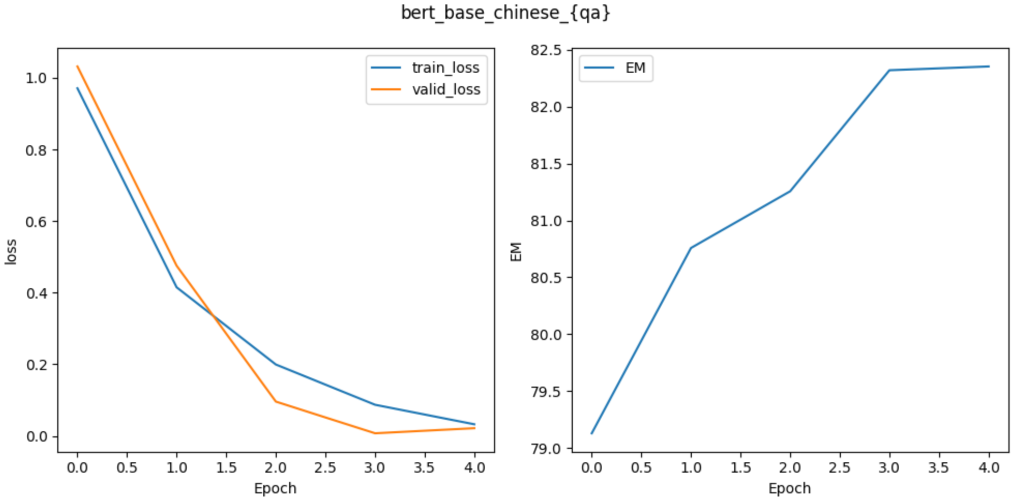
Report - Q3: Curves (1%)



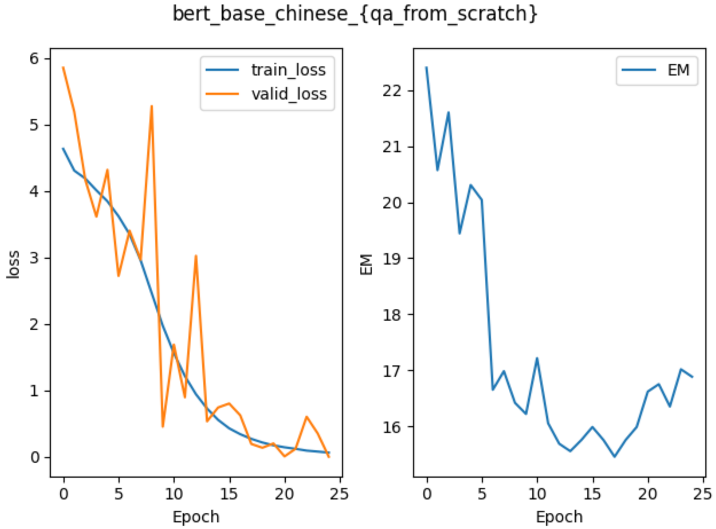
Epoch = 5

Report - Q3: Curves (1%)

Pretrained model vs train from scratch (bert-base-Chinese)


bert_base_chinese_{qa}

Epoch = 5


bert_base_chinese_{qa_from_scratch}

Epoch = 25

“Lottery Ticket Hypothesis”, above plot illustrate initial weight from pretrain model is important and performer is better than random model weight. (EM value of from scratch model even drops XD)

Report - Q4: Pre-trained vs Not Pre-trained (2%)

Pretrained model vs train from scratch for question answering (bert-base-Chinese)

	Pretrained model	**Train from scratch**
Performance (“Best” EM in validation)	82.352	22.399
Loss function	Cross-Entropy Loss	Cross-Entropy Loss
Optimizer	AdamW	AdamW
Learning rate	8e-5	8e-5
Batch size	32 (8 * 4 gradient accumulation step)	32 (8 * 4 gradient accumulation step)
Max seq length	512	512
Epoch	5	25