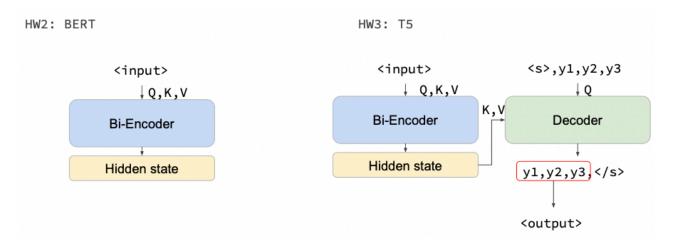
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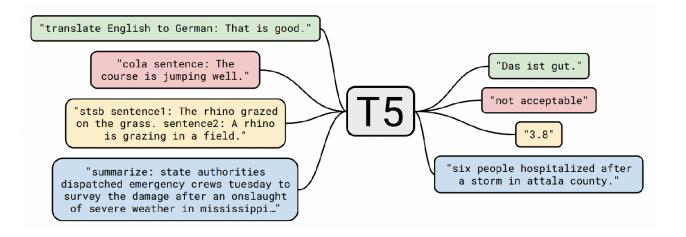
Q1: Model (2%)

Model (1%)

Describe the model architecture and how it works on text summarization.



T5 不同於 BERT 是 encoder-decoder 架構 (如上方右圖),特色是 pre-train 的時候把很多本來不是 seq-to-seq 的 task 也用 seq-to-seq 來做,如下圖範例有數值評分預測、分類問題等等。



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Preprocessing (1%)

Describe your preprocessing (e.g. tokenization, data cleaning and etc.)

```
tokenizer = AutoTokenizer.from_pretrained("google/mt5-small")
def preprocess(articles):
   encode_articles = {}
   maintext = [article["maintext"] for article in articles]
   # Tokenize
   encode_articles = tokenizer(maintext,
                       max_length=max_length,
                       truncation=True,
                       padding=True)
   if 'title' in examples[0].keys():
      titles = [article["title"] for article in articles]
      encode articles['title'] = tokenizer(titles,
                                max_length=56,
                                truncation=False,
                                padding=True)
   return encode_articles
```

我僅使用文章前 384 字、title 的部分則取 56 字(原因是 training data 中最長 title 是 56 字)。

Q2: Training (2%)

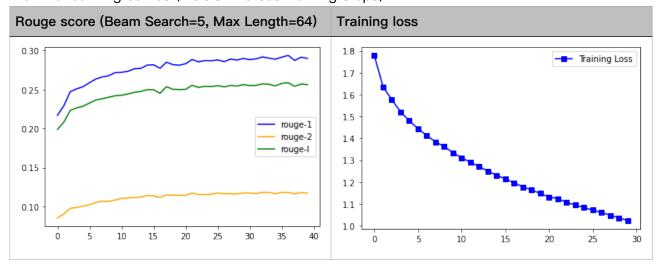
Hyperparameter (1%)

Describe your hyperparameter you use and how you decide it.

Batch size: 32 Optimizer: AdamW Learning rate: 1e-4

Learning Curves (1%)

Plot the learning curves (ROUGE versus training steps)



Q3: Generation Strategies(6%)

Stratgies (2%)

Describe the detail of the following generation strategies:

	Description	
Greedy	Greedy Solution	
Beam Search	每次選機率最大的字,不一定會是最佳路徑。但因為計算所有可能的 word 組合,time complexity 會很高,因此會決定要觀察 k 條 path,取最終機率最大的那條。也就是説當 k=1 時,等同於 Greedy。	
Top-k Sampling	從大到小排序前 k 的字 sample	
Top-p Sampling	從大到小排序機率加起來小於 p 的字 sample	
Temperature	$P(w_t) = rac{e^{S_W/ au}}{\sum_{w \in V} e^{S_{w'}/ au}}$ 字在算 softmax 的時候指數多除上一個參數 temperature hyperparameter $ au$,所以當 $ au$ 大,機率分佈會比較請向於 uniform 分佈,反之則會集中於某幾個字。	

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Hyperparameters (4%)

Try at least 2 settings of each strategies and compare the result. What is your final generation strategy? (you can combine any of them)

	Greedy	Beam Search (K=5)
Rouge-1	0.280191408252007	0.289943029055722
Rouge-2	0.103900554513634	0.117273801546114
Rouge-I	0.245942529959404	0.256366734128703
Elapse (secs.)	178.7218	314.4461

從上面數值可以看到使用 beam search 在各項 rouge score,然而在時間上的確也需約一倍的時間。