

EE-559 Deep learning – Practice 5, Students' questions

A question is denoted by **Q**; the corresponding answer is denoted by **A**. The questions-related exercises are marked by their numbers in Practice_5.pdf and Practice_5.ipynb documents.

Data Processing and Tokenization

Q: Why are all values in `token_type_ids` equal to zero in exercise 5.1?

A: Some models are designed for tasks such as question answering. This requires “two different sequences to be joined in a single `input_ids` entry, which usually is performed with the help of special tokens, such as the classifier (`[CLS]`) and separator (`[SEP]`) tokens (example of paired sequences: `[CLS]` HuggingFace is based in NYC `[SEP]` Where is HuggingFace based? `[SEP]`). This is enough for some models to understand where one sequence ends and where another begins. However, other models, such as BERT, also deploy token type IDs (also called segment IDs). They are represented as a binary mask identifying the two types of sequence in the model.” The above example of paired sequences will be represented with the following `token_type_ids`: `[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1]`. “The first sequence, the context used for the question, has all its tokens represented by a 0, whereas the second sequence, corresponding to the question, has all its tokens represented by a 1.” [source]

In the classification task of exercise 5, there is only one type of sequence as the input sequence is not paired. Thus the `token_type_ids` are all zeros.

Q: How does the `.map()` function in 5.1 work? How to see tokens rather than token IDs?

A: The `imdb` is a Hugging Face `DatasetDict` object. It is similar to a dictionary structure, where the keys could be the “train” and “test”, and the values are the `Dataset` objects [link]. The `map()` function applies the transformation to the specified dataset. This function is available in both `DatasetDict` and `Dataset` objects. The `map` function can (1) change the existing values of the features in the `Dataset`, or (2) append the new ones.

For example, the code below will add a prefix to all strings which are stored in ‘text’, illustrating (1).

```
cache_files_2 = {
    "train": "~/cache/imdb/imdb_train_modified.arrow",
    "test": "~/cache/imdb/imdb_test_modified.arrow"
}
def add_prefix(example):
    example["text"] = "NEW TEXT " + example["text"]
    return example
imdb_modified = imdb.map(add_prefix, cache_file_names=cache_files_2)
print(imdb_modified)
```

Now consider the `tokenize_function()` provided in the Practice 5 notebook.

```
def tokenize_function(examples):
    return tokenizer(examples["text"], padding="max_length",
                      truncation=True)
```

Here, the function returns the output of the `tokenizer` function, which is a dictionary with the following keys: `'input_ids'`, `'token_type_ids'`, `'attention_mask'`. In this case, the features are appended to the `Dataset` object, illustrating (2).

To obtain the tokens, you can use the following code:

```
cache_files_3 = {
    "train": "~/.cache/imdb/imdb_train_tokenized_tokens.arrow",
    "test": "~/.cache/imdb/imdb_test_tokenized_tokens.arrow"
}
def obtain_tokens(example):
    return {"tokens": tokenizer.convert_ids_to_tokens(example['input_ids'])}

tokenized_imdb_tokens = tokenized_imdb.map(obtain_tokens,
                                           cache_file_names=cache_files_3)
print(tokenized_imdb_tokens)
```

You can check the dictionary for the `bert_uncased_L-2_H-128_A-2` used in Practice 5 here.

Model and optimizer

Q: For the learning rate scheduler in exercise 5.2, why do we use `num_warmup_steps=1`?

A: Setting `num_warmup_steps=1` means the learning rate increases from zero to the base value in `num_warmup_steps=1` step before linearly decaying. Since the dataset is small, here we use a small value as an example. You can experiment with higher values of `num_warmup_steps` to evaluate its impact on model performance and convergence.

Additional useful material

- tips and tricks for training transformers can be found in this article
- papers addressing the complexity of transformers:

Linformer <https://arxiv.org/pdf/2006.04768.pdf>

Reformer <https://arxiv.org/pdf/2001.04451.pdf>

- working with long sequences: Longformer <https://arxiv.org/abs/2004.05150>