

Part 4: Large Language Model

```
In [ ]: import time, random, numpy as np, argparse, sys, re, os
        from types import SimpleNamespace

        import torch
        import torch.nn.functional as F
        from torch.utils.data import Dataset, DataLoader
        from sklearn.metrics import classification_report, f1_score, recall_score, accuracy

        # change it with respect to the original model
        from tokenizer import BertTokenizer
        from bert import BertModel
        from tqdm import tqdm
        from classifier import BertSentClassifier
```

```
c:\Users\mi_ke\AppData\Local\Programs\Python\Python38\lib\site-packages\tqdm\auto.p
y:21: TqdmWarning: IProgress not found. Please update jupyter and ipywidgets. See ht
tps://ipywidgets.readthedocs.io/en/stable/user_install.html
    from .autonotebook import tqdm as notebook_tqdm
```

4.1 The fine-tuned minBERT classifier

Instantiate a BertSentClassifier model. Load the state dict from the checkpoint saved from the previous question.

Load the best model checkpoint from the previous question. and instantiate a BertSentClassifier

```
In [ ]: device = torch.device(
        'cpu')
        filepath = 'flexible-10-1e-05.pt'

        saved = torch.load(filepath)
        config = saved['model_config']
        model = BertSentClassifier(config)
        model.load_state_dict(saved['model'])
        print('model loaded')
        print('model config: ', config)
        model = model.to(device)
```

model loaded

model config: namespace(data_dir='.', hidden_dropout_prob=0.3, hidden_size=768, num_labels=2, option='flexible')

Specify the batch of sentences

- Very positive: The movie was a masterpiece with a brilliant storyline and exceptional performances by the entire cast.
- Less positive: The film was enjoyable overall, but some of the dialogues felt a bit clichéd.

- Slightly negative: The plot was somewhat predictable, and it failed to capture my interest throughout the movie.
- Very negative: It was a terrible movie with poor acting, a weak script, and subpar visual effects that made it unbearable to watch.
- Off-the-topic: I had a delicious sandwich for lunch from the new café around the corner.

```
In [ ]: sentences = [
    "The movie was a masterpiece with a brilliant storyline and exceptional perform
    "The film was okay overall, but the pacing was a bit slow in some parts. It cou
    "The plot was somewhat predictable, and it failed to capture my interest throug
    "It was a terrible movie with poor acting, a weak script, and subpar visual eff
    "I had a delicious sandwich for lunch from the new café around the corner."
]
```

```
In [ ]: def pad_data(data):
    sents = [x[0] for x in data]
    tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
    encoding = tokenizer(sents, return_tensors='pt', padding=True, truncation=True)
    token_ids = torch.LongTensor(encoding['input_ids'])
    attention_mask = torch.LongTensor(encoding['attention_mask'])
    token_type_ids = torch.LongTensor(encoding['token_type_ids'])

    return token_ids, token_type_ids, attention_mask, sents

# create the data which is a list of (sentence, label, token for the labels)
def create_data(sentences):
    # specify the tokenizer
    tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
    data = []

    for line in sentences:
        sent = line.lower().strip()
        tokens = tokenizer.tokenize("[CLS] " + sent + " [SEP]")
        data.append((sent, tokens))

    return data
```

```
In [ ]: data = create_data(sentences=sentences)

token_ids, type_ids, mask, sents = pad_data(data)

model_output = model(token_ids, mask)
model_output = model_output.detach().cpu().numpy()
```

```
In [ ]: for index, logits in enumerate(model_output):
    # Exponentiate the logits to get the probabilities
    prob = np.exp(logits) / np.sum(np.exp(logits))
    positive_prob = prob[1]
    negative_prob = prob[0]
    label = None
    if positive_prob >= negative_prob:
```

```

        label = 'Positive'
    else:
        label = 'Negative'

    print(sentences[index] + ' --- ' + 'Class Label: ' + label )
    print('Positive Probability: ' + str(positive_prob))
    print('Negative Probability: ' + str(negative_prob))
    print('-----')

```

The movie was a masterpiece with a brilliant storyline and exceptional performances by the entire cast. --- Class Label: Positive

Positive Probability: 0.9933058

Negative Probability: 0.006694194

The film was okay overall, but the pacing was a bit slow in some parts. It could have been better if it was a bit shorter. --- Class Label: Positive

Positive Probability: 0.92735577

Negative Probability: 0.07264426

The plot was somewhat predictable, and it failed to capture my interest throughout the movie, but the characters have some interesting personalities. --- Class Label: Negative

Positive Probability: 0.004681286

Negative Probability: 0.9953188

It was a terrible movie with poor acting, a weak script, and subpar visual effects that made it unbearable to watch. --- Class Label: Negative

Positive Probability: 0.00055427477

Negative Probability: 0.9994457

I had a delicious sandwich for lunch from the new café around the corner. --- Class Label: Positive

Positive Probability: 0.7240719

Negative Probability: 0.2759281

Comments:

The model performs relatively well on the task of capturing the polarity of the sentences. It correctly classifies the sentence "The movie was a masterpiece with a brilliant storyline and exceptional performances by the entire cast" with strong positive probability of 0.993, while the sentence "It was a terrible movie with poor acting, a weak script, and subpar visual effects that made it unbearable to watch" was correctly given a negative probability of 0.999.

As for the fine-grained polarity, the model's prediction mostly aligns with the sentiment of the sentences. For the slightly positive and negative sentences, the model struggles to assign the proper probabilities because of the mixed sentiment nature. The slightly positive sentence has a positive probability of 0.927, which is slightly lower than the very positive sentence mostly because it contains words such as "a bit slow", "could have been better". The slightly negative sentence is only slightly less negative with probability of 0.995, could be because the model giving more weight to the negative aspects mentioned in the

sentence (e.g., "predictable" and "failed to capture my interest). They do both align with the fine-grained polarity expected values.

The off-topic sentence was classified as positive with probability of 0.724 which is reasonable considering the sentiment of the sentence e.g.(delicious)even though it's unrelated to the movie domain.

4.2 A general-purpose multi-task learner

Use huggingface's Transformers library to load a AutoModelForCausalLM (previously this was also called AutoModelWithLMHead) model. To allow comparison against the previous question, let's load the bert-base-uncased model.

```
In [ ]: from transformers import AutoModelForCausalLM, AutoTokenizer

model = AutoModelForCausalLM.from_pretrained("bert-base-uncased")
tokenizer = AutoTokenizer.from_pretrained("bert-base-uncased")
```

```
Downloading (...)lve/main/config.json: 100%|██████████| 570/570 [00:00<00:00, 190kB/s]
c:\Users\mi_ke\AppData\Local\Programs\Python\Python38\lib\site-packages\huggingface_
hub\file_download.py:133: UserWarning: `huggingface_hub` cache-system uses symlinks
by default to efficiently store duplicated files but your machine does not support t
hem in C:\Users\mi_ke\.cache\huggingface\hub. Caching files will still work but in a
degraded version that might require more space on your disk. This warning can be dis
abled by setting the `HF_HUB_DISABLE_SYMLINKS_WARNING` environment variable. For mor
e details, see https://huggingface.co/docs/huggingface_hub/how-to-cache#limitations.
To support symlinks on Windows, you either need to activate Developer Mode or to run
Python as an administrator. In order to see activate developer mode, see this articl
e: https://docs.microsoft.com/en-us/windows/apps/get-started/enable-your-device-for-
development
  warnings.warn(message)
Downloading pytorch_model.bin: 100%|██████████| 440M/440M [00:11<00:00, 39.4MB/s]
If you want to use `BertLMHeadModel` as a standalone, add `is_decoder=True.`
Some weights of the model checkpoint at bert-base-uncased were not used when initial
izing BertLMHeadModel: ['cls.seq_relationship.bias', 'cls.seq_relationship.weight']
- This IS expected if you are initializing BertLMHeadModel from the checkpoint of a
model trained on another task or with another architecture (e.g. initializing a Bert
ForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing BertLMHeadModel from the checkpoint o
f a model that you expect to be exactly identical (initializing a BertForSequenceCla
ssification model from a BertForSequenceClassification model).
Downloading (...)okenizer_config.json: 100%|██████████| 28.0/28.0 [00:00<00:00, 9.36k
B/s]
Downloading (...)solve/main/vocab.txt: 100%|██████████| 232k/232k [00:00<00:00, 12.2M
B/s]
Downloading (...)main/tokenizer.json: 100%|██████████| 466k/466k [00:00<00:00, 27.5M
B/s]
```

Prepare the sentences to be inputted to the CasualLM model

```
In [ ]: sentences = [
    "The movie was a masterpiece with a brilliant storyline and exceptional perform
    "The film was okay overall, but the pacing was a bit slow it some parts. It cou
```

```

    "The plot was somewhat predictable, and it failed to capture my interest through
    "It was a terrible movie with poor acting, a weak script, and subpar visual effects."
    "I had a delicious sandwich for lunch from the new café around the corner."
]
CausalLM_sentences = []
for sentence in sentences:
    CausalLM_sentences.append(sentence + " This movie review is")

CausalLM_sentences.append(sentences[-1] + " This sentence is")

```

```

In [ ]: for sentence in CausalLM_sentences:
    input_ids = tokenizer.encode(sentence, return_tensors='pt')
    outputs = model(input_ids, labels=input_ids)

    probs = outputs.logits.softmax(dim=-1)
    pos_prob = probs[0, -1, tokenizer.convert_tokens_to_ids("positive")].item()
    neg_prob = probs[0, -1, tokenizer.convert_tokens_to_ids("negative")].item()
    if pos_prob >= neg_prob:
        label = 'positive'
    else:
        label = 'negative'
    print('Sentence: ' + sentence + ' ' + label)
    print('Probability of the next word being "positive": ', str(pos_prob))
    print('Probability of the next word being "negative": ', str(neg_prob))

    print('-----')

```

Sentence: The movie was a masterpiece with a brilliant storyline and exceptional performances by the entire cast. This movie review is negative

Probability of the next word being "positive": 1.8164472148640698e-09

Probability of the next word being "negative": 6.8217440585272016e-09

Sentence: The film was okay overall, but the pacing was a bit slow in some parts. It could have been better if it was a bit shorter. This movie review is negative

Probability of the next word being "positive": 3.055683635011519e-07

Probability of the next word being "negative": 3.890874609169259e-07

Sentence: The plot was somewhat predictable, and it failed to capture my interest throughout the movie, but the characters have some interesting personalities. This movie review is negative

Probability of the next word being "positive": 4.4362411522058665e-09

Probability of the next word being "negative": 2.7725267415235066e-08

Sentence: It was a terrible movie with poor acting, a weak script, and subpar visual effects that made it unbearable to watch. This movie review is negative

Probability of the next word being "positive": 1.0296430374978627e-08

Probability of the next word being "negative": 5.131980174155615e-08

Sentence: I had a delicious sandwich for lunch from the new café around the corner. This movie review is positive

Probability of the next word being "positive": 3.78358500860512e-09

Probability of the next word being "negative": 9.271172163316521e-10

Sentence: I had a delicious sandwich for lunch from the new café around the corner. This sentence is positive

Probability of the next word being "positive": 1.7360509696473514e-09

Probability of the next word being "negative": 2.389891340381922e-10

Mask [SEP] token to improve model performance

```
In [ ]: for sentence in CausalLM_sentences:

    input_ids = tokenizer.encode(sentence, return_tensors='pt')

    input_ids_list = input_ids.tolist()[0]
    # Create the attention mask with 0s for [SEP] tokens and 1s for all other tokens
    attention_mask_list = [0 if token_id == tokenizer.sep_token_id else 1 for token_id in input_ids_list]

    # Convert the attention_mask list to a tensor
    attention_mask = torch.tensor([attention_mask_list], dtype=torch.long)

    outputs = model(input_ids, attention_mask=attention_mask, labels=input_ids)

    probs = outputs.logits.softmax(dim=-1)
    pos_prob = probs[0, -1, tokenizer.convert_tokens_to_ids("positive")].item()
    neg_prob = probs[0, -1, tokenizer.convert_tokens_to_ids("negative")].item()
    if pos_prob >= neg_prob:
        label = 'positive'
    else:
        label = 'negative'
    print('Sentence: ' + sentence + ' ' + label)
    print('Probability of the next word being "positive": ', str(pos_prob))
```

```
print('Probability of the next word being "negative": ', str(neg_prob))

print('-----')
```

Sentence: The movie was a masterpiece with a brilliant storyline and exceptional performances by the entire cast. This movie review is positive

Probability of the next word being "positive": 3.7384117604233325e-05

Probability of the next word being "negative": 1.3341978956304956e-05

Sentence: The film was okay overall, but the pacing was a bit slow in some parts. It could have been better if it was a bit shorter. This movie review is positive

Probability of the next word being "positive": 1.2243726814631373e-06

Probability of the next word being "negative": 1.480306650591956e-07

Sentence: The plot was somewhat predictable, and it failed to capture my interest throughout the movie, but the characters have some interesting personalities. This movie review is positive

Probability of the next word being "positive": 2.0652452803915367e-05

Probability of the next word being "negative": 1.5916912161628716e-06

Sentence: It was a terrible movie with poor acting, a weak script, and subpar visual effects that made it unbearable to watch. This movie review is negative

Probability of the next word being "positive": 8.030186222640623e-07

Probability of the next word being "negative": 7.834878488210961e-06

Sentence: I had a delicious sandwich for lunch from the new café around the corner. This movie review is positive

Probability of the next word being "positive": 1.66432982950937e-06

Probability of the next word being "negative": 6.550917532877065e-07

Sentence: I had a delicious sandwich for lunch from the new café around the corner. This sentence is positive

Probability of the next word being "positive": 2.3779614366503665e-07

Probability of the next word being "negative": 1.4282123572684213e-07

Sentence: I had a delicious sandwich for lunch from the new café around the corner. This sentence is positive

Probability of the next word being "positive": 2.3779614366503665e-07

Probability of the next word being "negative": 1.4282123572684213e-07

Comments:

Before masking the [SEP] token, the AutoModelForCausalLM's performance is quite poor, since it is only querying the probability at the last token which [SEP]. After masking the [SEP] token, the model is still not as good as the pretrained BERT model but does capture the polarity to some extent. Since it is not trained to perform sentiment analysis nor trained on any movie review dataset, it is expected to have a poor performance when querying the probability of the positive or negative tokens, which indicates the polarity of the sentence.

In all sentences, the LM predicts probabilities of positive and negative with very low values which indicates the model's low confidence in the prediction, however it does give a slightly higher positive probability for very positive and slightly positive sentences and a slightly

negative probability for very negative sentence, which shows some abilities to recognize the polarities of the sentences.

The changing the appendix to e.g., "This sentence is" does not improve the out-of-domain generalization ability as shown above with the similar positive probabilities.

4.3 A large-scale multi-task learner

choose an LLM and use it in the generation mode (i.e., let it continue writing given a prompt). Design a form of your choice (e.g., S+"This movie review is", or other forms) that allows the LLM to output its prediction of whether the 5 sentences you wrote are positive or not.

For 4.3, I chose to use GPT-3 via its playground. Screenshots are provided below which shows the prediction of the 5 sentences.

Prompt used: Sentence + "This movie review is (positive/negative)?"

Generation hyperparameters:

Temperature: 0.5 -> This controls the randomness and creativity of the response. I chose 0.5 because too much creativity could make the classification not accurate but too deterministic would limit model's performance

Max-Token: 50 -> The prompt above formulates a one word response so I chose to limit the number of words generated to improve performance.

Top-p : 0.8 -> This controls the diversity, I chose 0.8 to keep the word choice relatively diverse.


Show-Probability: Full-Spectrum -> So I can see the probability of each token, to compare fine-grained polarity.

Very Positive Sentence:

Playground

Load a preset...

Save

The movie was a masterpiece with a brilliant storyline and exceptional performances by the entire cast. 
This movie review is (positive/negative)?

Positive.

Pos = 98.68%

positive = 1.31%


POS = 0.01%

Positive = 0.00%

positive = 0.00%

Total: -0.01 logprob on 1 tokens
(100.00% probability covered in top 5 logits)

Slightly Positive Sentence:

The film was okay overall, but the pacing was a bit slow in some parts. It could have been better if it was a bit shorter. This movie review is (positive/negative)? 

Negative.

Neg = 67.53%

Pos = 32.13%


positive = 0.33%

negative = 0.01%

Ne = 0.00%

Total: -0.39 logprob on 1 tokens
(100.00% probability covered in top 5 logits)

Slightly Negative Sentence:

The plot was somewhat predictable, and it failed to capture my interest throughout the movie, but the characters have some interesting personalities. This movie review is (positive/negative)? 

Negative.

Neg = 72.68%

\n = 23.03%

negative = 2.70%

Negative = 1.09%

negative = 0.41%

Total: -0.32 logprob on 1 tokens
(99.91% probability covered in top 5 logits)

Very Negative Sentence:

Playground

Load a preset...

Save

It was a terrible movie with poor acting, a weak script, and subpar visual effects that made it unbearable to watch. This movie review is (positive/negative)?



Negative

Neg = 99.46%

negative = 0.47%

Negative = 0.05%

negative = 0.01%

\n = 0.00%

Total: -0.01 logprob on 1 tokens
(100.00% probability covered in top 5 logits)

Off Topic Sentence:

Playground

Load a preset...

Save

I had a delicious sandwich for lunch from the new café around the corner. This sentence is (positive/negative)?



Positive

Pos = 97.08%

positive = 2.92%

Positive = 0.00%

positive = 0.00%

This = 0.00%

Total: -0.03 logprob on 1 tokens
(100.00% probability covered in top 5 logits)

Comments:

GPT-3 shows much better capabilities than the AutoModelForCausalLM model and performs almost the same with the pre-trained BERT model in section 4.1. However it does misclassify the less positive sentence, showing negative probability of 67.5% and positive probability of 32.5%, which may be because the model weights negative sentiment more. In general LLM like GPT3 would have better performance than smaller models due to its ability to capture and understand more complex linguistic structures and nuances on unseen tasks. However, smaller models that are pretrained on specific task like the one in section 4.1 could definitely outperform LLM on that specific task.