CSE 256: Statistical NLP UCSD Assignment 3

Text Decoding From GPT-2 using Beam Search (40 points)

Due: Friday, June 02, 2023 at 10pm

IMPORTANT: After copying this notebook to your Google Drive, paste a link to it below. To get a publicly-accessible link, click the *Share* button at the top right, then click "Get shareable link" and copy the link.

Link: paste your link here:

https://colab.research.google.com/drive/1BVYZHS1ZG24-Ir0EQsh1Gus6ZAWrtM1V

Notes:

Make sure to save the notebook as you go along.

Submission instructions are located at the bottom of the notebook.

Part 0: Setup

Adding a hardware accelerator

Go to the menu and add a GPU as follows:

`Edit > Notebook Settings > Hardware accelerator > (GPU)`

Run the following cell to confirm that the GPU is detected.

```
import torch

# Confirm that the GPU is detected
assert torch.cuda.is_available()

# Get the GPU device name.
device_name = torch.cuda.get_device_name()
n_gpu = torch.cuda.device_count()
print(f"Found device: {device_name}, n_gpu: {n_gpu}")
```

```
---------------------------------------------------------------------------
AssertionError                            Traceback (most recent call last)
<ipython-input-1-376e9c6ea54a> in <cell line: 4>()
      2 
      3 # Confirm that the GPU is detected
----> 4 assert torch.cuda.is_available()
      5 
      6 # Get the GPU device name.

AssertionError: 
```

SEARCH STACK OVERFLOW

Installing Hugging Face's Transformers and Additional Libraries

We will use Hugging Face's Transformers (https://github.com/huggingface/transformers).

Run the following cell to install Hugging Face's Transformers library and some other useful tools. This cell will also download data used later in the assignment.

```
!pip install -q transformers==4.17.0  rich[jupyter]
```

```
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  Preparing metadata (setup.py) ... done
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  Building wheel for sacremoses (setup.py) ... done
```

Part 1. Beam Search

We are going to explore decoding from a pretrained GPT-2 model using beam search. Run the below cell to set up some beam search utilities.

```
from transformers import GPT2LMHeadModel, GPT2Tokenizer

tokenizer = GPT2Tokenizer.from_pretrained("gpt2")
model = GPT2LMHeadModel.from_pretrained("gpt2", pad_token_id=tokenizer.eos_token_id)

# Beam Search

def init_beam_search(model, input_ids, num_beams):
    assert len(input_ids.shape) == 2
    beam_scores = torch.zeros(num_beams, dtype=torch.float32, device=model.device)
    beam_scores[1:] = -1e9 # Break ties in first round.
    new_input_ids = input_ids.repeat_interleave(num_beams, dim=0).to(model.device)
    return new_input_ids, beam_scores


def run_beam_search_(model, tokenizer, input_text, num_beams=5, num_decode_steps=10, score_processors=[], to_cpu=True):

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

    input_ids, beam_scores = init_beam_search(model, input_ids, num_beams)

    token_scores = beam_scores.clone().view(num_beams, 1)

    model_kwargs = {}
    for i in range(num_decode_steps):
        model_inputs = model.prepare_inputs_for_generation(input_ids, **model_kwargs)
        outputs = model(**model_inputs, return_dict=True)
        next_token_logits = outputs.logits[:, -1, :]
        vocab_size = next_token_logits.shape[-1]
        this_token_scores = torch.log_softmax(next_token_logits, -1)

        # Process token scores.
        processed_token_scores = this_token_scores
        for processor in score_processors:
            processed_token_scores = processor(input_ids, processed_token_scores)

        # Update beam scores.
        next_token_scores = processed_token_scores + beam_scores.unsqueeze(-1)

        # Reshape for beam-search.
        next_token_scores = next_token_scores.view(num_beams * vocab_size)

        # Find top-scoring beams.
        next_token_scores, next_tokens = torch.topk(
            next_token_scores, num_beams, dim=0, largest=True, sorted=True
        )

        # Transform tokens since we reshaped earlier.
        next_indices = torch.div(next_tokens, vocab_size, rounding_mode="floor") # This is equivalent to `next_tokens // vocab_siz
        next_tokens = next_tokens % vocab_size

        # Update tokens.
        input_ids = torch.cat([input_ids[next_indices, :], next_tokens.unsqueeze(-1)], dim=-1)

        # Update beam scores.
        beam_scores = next_token_scores

        # Update token scores.

        # UNCOMMENT: To use original scores instead.
        # token_scores = torch.cat([token_scores[next_indices, :], this_token_scores[next_indices, next_tokens].unsqueeze(-1)], di
        token_scores = torch.cat([token_scores[next_indices, :], processed_token_scores[next_indices, next_tokens].unsqueeze(-1)],

        # Update hidden state.
        model_kwargs = model._update_model_kwargs_for_generation(outputs, model_kwargs, is_encoder_decoder=False)
        model_kwargs["past"] = model._reorder_cache(model_kwargs["past"], next_indices)

    def transfer(x):
      return x.cpu() if to_cpu else x
```

```
    return {
        "output_ids": transfer(input_ids),
        "beam_scores": transfer(beam_scores),
        "token_scores": transfer(token_scores)
    }


def run_beam_search(*args, **kwargs):
    with torch.inference_mode():
        return run_beam_search_(*args, **kwargs)


# Add support for colored printing and plotting.

from rich import print as rich_print

import numpy as np

import matplotlib
from matplotlib import pyplot as plt
from matplotlib import cm

RICH_x = np.linspace(0.0, 1.0, 50)
RICH_rgb = (matplotlib.colormaps.get_cmap(plt.get_cmap('RdYlBu'))(RICH_x)[:, :3] * 255).astype(np.int32)[range(5, 45, 5)]


def print_with_probs(words, probs, prefix=None):
  def fmt(x, p, is_first=False):
    ix = int(p * RICH_rgb.shape[0])
    r, g, b = RICH_rgb[ix]
    if is_first:
      return f'[bold rgb(0,0,0) on rgb({r},{g},{b})]{x}'
    else:
      return f'[bold rgb(0,0,0) on rgb({r},{g},{b})] {x}'
  output = []
  if prefix is not None:
    output.append(prefix)
  for i, (x, p) in enumerate(zip(words, probs)):
    output.append(fmt(x, p, is_first=i == 0))
  rich_print(''.join(output))

# DEMO

# Show range of colors.

for i in range(RICH_rgb.shape[0]):
  r, g, b = RICH_rgb[i]
  rich_print(f'[bold rgb(0,0,0) on rgb({r},{g},{b})]hello world rgb({r},{g},{b})')

# Example with words and probabilities.

words = ['the', 'brown', 'fox']
probs = [0.14, 0.83, 0.5]
print_with_probs(words, probs)
```

```
Downloading: 100%    0.99M/0.99M [00:00<00:00, 3.12MB/s]
Downloading: 100%    446k/446k [00:00<00:00, 6.05MB/s]
Downloading: 100%    665/665 [00:00<00:00, 17.1kB/s]
Downloading: 100%    523M/523M [00:09<00:00, 90.7MB/s]
hello world rgb(215,49,39)
hello world rgb(244,111,68)
hello world rgb(253,176,99)
hello world rgb(254,226,147)
hello world rgb(251,253,196)
hello world rgb(217,239,246)
hello world rgb(163,210,229)
hello world rgb(108,164,204)
the brown fox
```

Question 1.1 (5 points)

Run the cell below. It produces a sequence of tokens using beam search and the provided prefix.

```
num_beams = 5
num_decode_steps = 10
input_text = 'The brown fox jumps'

beam_output = run_beam_search(model, tokenizer, input_text, num_beams=num_beams, num_decode_steps=num_decode_steps)
for i, tokens in enumerate(beam_output['output_ids']):
    score = beam_output['beam_scores'][i]
    print(i, round(score.item() / tokens.shape[-1], 3), tokenizer.decode(tokens, skip_special_tokens=True))
```

```
0 -1.106 The brown fox jumps out of the fox's mouth, and the fox
1 -1.168 The brown fox jumps out of the fox's cage, and the fox
2 -1.182 The brown fox jumps out of the fox's mouth and starts to run
3 -1.192 The brown fox jumps out of the fox's mouth and begins to lick
4 -1.199 The brown fox jumps out of the fox's mouth and begins to bite
```

Double-click (or enter) to edit

To get you more acquainted with the code, let's do a simple exercise first. Write your own code in the cell below to generate 3 tokens with a beam size of 4, and then print out the **third most probable** output sequence found during the search. Use the same prefix as above.

```
input_text = 'The brown fox jumps'

num_beams = 4
num_decode_steps = 3

beam_output = run_beam_search(model, tokenizer, input_text, num_beams=num_beams, num_decode_steps=num_decode_steps)
the_third_ind = 2
tokens = beam_output['output_ids'][the_third_ind]
print(tokenizer.decode(tokens, skip_special_tokens=True))
```

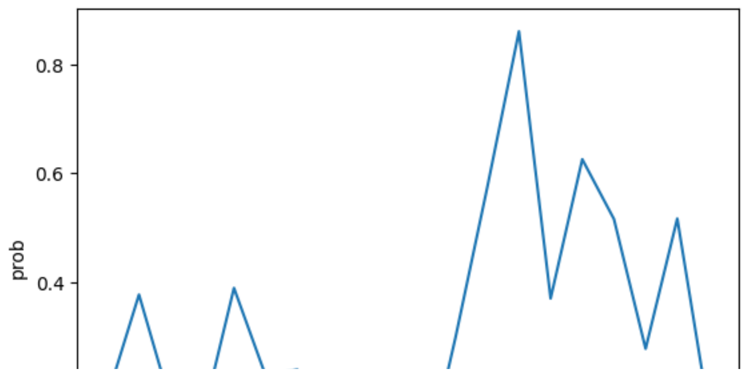
```
The brown fox jumps up and down
```

Question 1.2 (5 points)

Run the cell below to visualize the probabilities the model assigns for each generated word when using beam search with beam size 1 (i.e., greedy decoding).

```
input_text = 'The brown fox jumps'
beam_output = run_beam_search(model, tokenizer, input_text, num_beams=1, num_decode_steps=20)
probs = beam_output['token_scores'][0, 1:].exp()
output_subwords = [tokenizer.decode(tok, skip_special_tokens=True) for tok in beam_output['output_ids'][0]]

print('Visualizeation with plot:')

fig, ax = plt.subplots()
plt.plot(range(len(probs)), probs)
ax.set_xticks(range(len(probs)))
ax.set_xticklabels(output_subwords[-len(probs):], rotation = 45)
plt.xlabel('word')
plt.ylabel('prob')
plt.show()

print('Visualization with colored text (red for lower probability, and blue for higher):')

print_with_probs(output_subwords[-len(probs):], probs, ' '.join(output_subwords[:-len(probs)]))
```

```
Visualizeation with plot:
```



Why does the model assign higher probability to tokens generated later than to tokens generated earlier?

Double-click (or enter) to edit

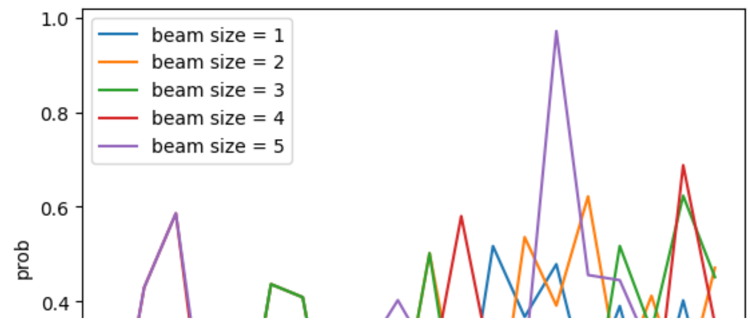
Write your answer here

Because if each token on our list has a uniform probablility, then longer hypothesis will have a lower possibility based on the beam search model's property, and then the model will more likely to converge early on and missed other possible alternate solution. By assigning higher probabilities to tokens generated later, it encourages the exploration of alternative solution.

Run the cell below to visualize the word probabilities when using different beam sizes.

```
input_text = 'Once upon a time, in a barn near a farm house,'
num_decode_steps = 20
model.cuda()

beam_size_list = [1, 2, 3, 4, 5]
output_list = []
probs_list = []
for bm in beam_size_list:
  beam_output = run_beam_search(model, tokenizer, input_text, num_beams=bm, num_decode_steps=num_decode_steps)
  output_list.append(beam_output)
  probs = beam_output['token_scores'][0, 1:].exp()
  probs_list.append((bm, probs))

print('Visualization with plot:')
fig, ax = plt.subplots()
for bm, probs in probs_list:
  plt.plot(range(len(probs)), probs, label=f'beam size = {bm}')
plt.xlabel('decode step')
plt.ylabel('prob')
plt.legend(loc='best')
plt.show()

print('Model predictions:')
for bm, beam_output in zip(beam_size_list, output_list):
  tokens = beam_output['output_ids'][0]
  print(bm, beam_output['beam_scores'][0].item() / tokens.shape[-1], tokenizer.decode(tokens, skip_special_tokens=True))
```

```
Visualization with plot:
```



Question 1.3 (10 points)

Beam search often results in repetition in the predicted tokens. In the following cell we pass a score processor called `WordBlock` to `run_beam_search`. At each time step, it reduces the probability for any previously seen word so that it is not generated again.

Run the cell to see how the output of beam search changes with and without using `WordBlock`.

```
import collections

class WordBlock:
    def __call__(self, input_ids, scores):
        for batch_idx in range(input_ids.shape[0]):
            for x in (input_ids[batch_idx].tolist()):
                scores[batch_idx, x] = -1e9
        return scores

input_text = 'Once upon a time, in a barn near a farm house,'
num_beams = 1

print('Beam Search')
beam_output = run_beam_search(model, tokenizer, input_text, num_beams=num_beams, num_decode_steps=40, score_processors=[])
print(tokenizer.decode(beam_output['output_ids'][0], skip_special_tokens=True))

print('Beam Search w/ Word Block')
beam_output = run_beam_search(model, tokenizer, input_text, num_beams=num_beams, num_decode_steps=40, score_processors=[WordBlock(
print(tokenizer.decode(beam_output['output_ids'][0], skip_special_tokens=True))
```

```
ch
 a time, in a barn near a farm house, a young boy was playing with a stick. He was playing with a stick, and the boy was play
ch w/ Word Block
 a time, in a barn near a farm house, the young girl was playing with her father's dog. She had been told that she would be g
```

Is `WordBlock` a practical way to prevent repetition in beam search? What (if anything) could go wrong when using `WordBlock`?

Write your answer here

Yes it is practical to prevent repetition to a extent. The problem is that because it add panelty to the previous seen word, so it will evantually bias the model towards generating shorter outputs. If the goal is to generate text for story telling, in longer sequence, it could eventually "run out of word" to make sense. In the above example, the commonly highly repeated word like 'was' 'had been' 'would' can run out and then the tense can be confused later. So for a intend longer sequence, the deminishing probability for word block needs to be carefully handled.

Question 1.4 (20 points)

Use the previous `WordBlock` example to write a new score processor called `BeamBlock`. Instead of uni-grams, your implementation should prevent tri-grams from appearing more than once in the sequence.

Note: This technique is called "beam blocking" and is described [here](#) (section 2.5). Also, for this assignment you do not need to re-normalize your output distribution after masking values, although typically re-normalization is done.

Write your code in the indicated section in the below cell.

```
import collections

class BeamBlock:
    def __call__(self, input_ids, scores):
```

```
        trigram_mem = collections.defaultdict(list)
        for batch_idx in range(input_ids.shape[0]):
            lst = input_ids[batch_idx].tolist()
            for i in range(3, len(lst)+1):
                trigram = tuple(lst[i-3:i])

                trigram_mem[trigram[:2]].append(trigram[-1])

            last_two_bigram = tuple(lst[-2:])
            if last_two_bigram in trigram_mem:
              for x in trigram_mem[last_two_bigram]:
                scores[batch_idx, x] = -1e9

        return scores


input_text = 'Once upon a time, in a barn near a farm house,'
num_beams = 1

print('Beam Search')
beam_output = run_beam_search(model, tokenizer, input_text, num_beams=num_beams, num_decode_steps=40, score_processors=[])
print(tokenizer.decode(beam_output['output_ids'][0], skip_special_tokens=True))

print('Beam Search w/ Beam Block')
beam_output = run_beam_search(model, tokenizer, input_text, num_beams=num_beams, num_decode_steps=40, score_processors=[BeamBlock(
print(tokenizer.decode(beam_output['output_ids'][0], skip_special_tokens=True))
```

```
Beam Search
Once upon a time, in a barn near a farm house, a young boy was playing with a stick. He was playing with a stick, and the boy
Beam Search w/ Beam Block
Once upon a time, in a barn near a farm house, a young boy was playing with a stick. He was playing on the stick, and the boy
```

Submission Instructions

1. Click the Save button at the top of the Jupyter Notebook.
2. Select Edit -> Clear All Outputs. This will clear all the outputs from all cells (but will keep the content of all cells).
3. Select Runtime -> Run All. This will run all the cells in order, and will take several minutes.
4. Once you've rerun everything, select File -> Download as -> PDF via LaTeX (If you have trouble using "PDF via LaTex", you can also save the webpage as pdf. Make sure all your solutions especially the coding parts are displayed in the pdf, it's okay if the provided codes get cut off because lines are not wrapped in code cells).
5. Look at the PDF file and make sure all your solutions are there, displayed correctly. The PDF is the only thing your graders will see!
6. Submit your PDF on Gradescope.

Acknowledgements

This assignment is based on an assignment developed by Mohit Iyyer