PA3_CS256_SP24_Ke_Xu

May 20, 2024

1 CSE 256: NLP UCSD, Programming Assignment 3

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

1.1.1 Due: Wednesday, May 29, 2024 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://drive.google.com/file/d/1rw26-v7BJ6M_KZJeqVYQqVqawF4J2L2K/view?usp=sharing

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Notes:

Make sure to save the notebook as you go along.

Submission instructions are located at the bottom of the notebook.

2 Part 0: Setup

2.1 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.

[1]:
```
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}")
```

```
Found device: Tesla T4, n_gpu: 1
```

2.2 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.

[2]:
```
!pip install -q transformers==4.17.0  rich[jupyter]
```

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```

3 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.

[3]:
```
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_size`
        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)], dim=-1)
        token_scores = torch.cat([token_scores[next_indices, :],␣
↪processed_token_scores[next_indices, next_tokens].unsqueeze(-1)], dim=-1)
```

```python
        # 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:   0%|          | 0.00/0.99M [00:00<?, ?B/s]

Downloading:   0%|          | 0.00/446k [00:00<?, ?B/s]

Downloading:   0%|          | 0.00/26.0 [00:00<?, ?B/s]

Downloading:   0%|          | 0.00/665 [00:00<?, ?B/s]

Downloading:   0%|          | 0.00/523M [00:00<?, ?B/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
```

3.1 Question 1.1 (5 points)

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

[4]:
```
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
```

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.

[5]:
```
input_text = 'The brown fox jumps'

# Set the parameters for beam search
num_beams = 4
num_decode_steps = 3
input_text = 'The brown fox jumps'

# Run beam search
beam_output = run_beam_search(model, tokenizer, input_text,␣
 ↪num_beams=num_beams, num_decode_steps=num_decode_steps)

# Extract and print the third most probable output sequence
third_most_probable_index = 2  # Since indexing starts at 0
tokens = beam_output['output_ids'][third_most_probable_index]
score = beam_output['beam_scores'][third_most_probable_index]

print(f"Third most probable output sequence:")
print(f"Score: {round(score.item() / tokens.shape[-1], 3)}")
print(f"Sequence: {tokenizer.decode(tokens, skip_special_tokens=True)}")
```

```
Third most probable output sequence:
```

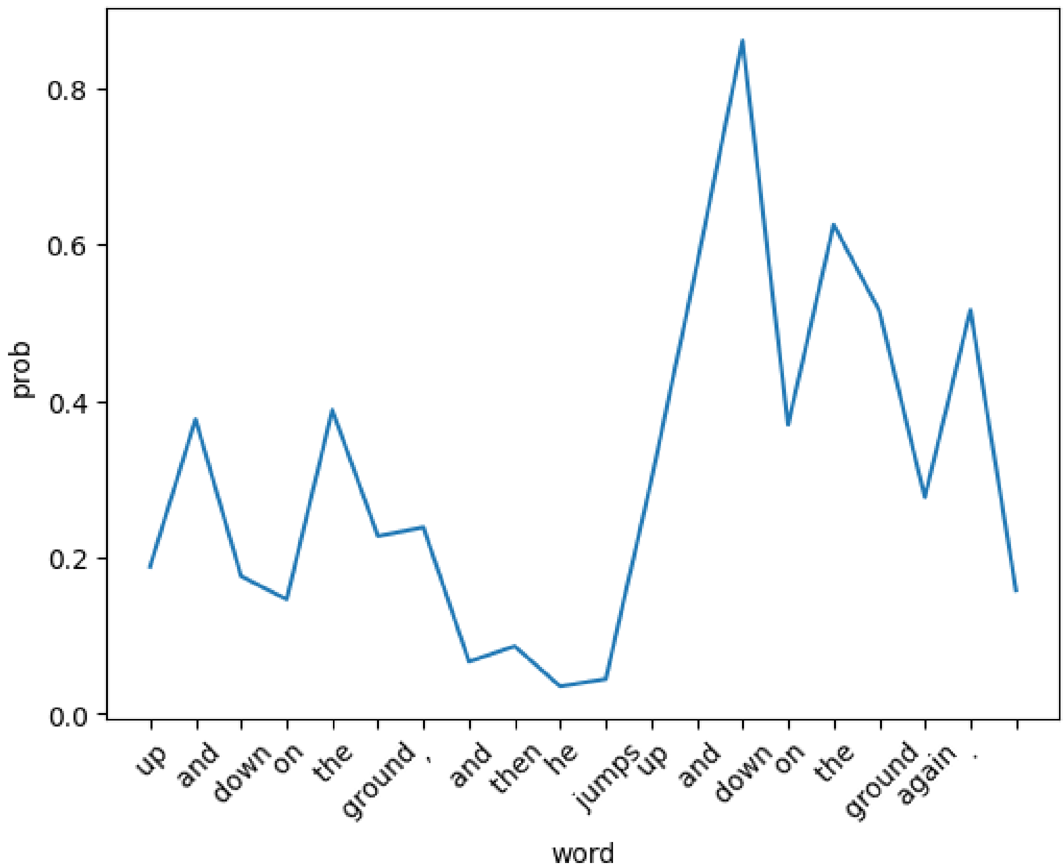
```
Score: -0.627
Sequence: The brown fox jumps up and down
```

3.2 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).

[6]:
```
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:
```




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

The brown fox ␣
↪jumps up and down on the ground , and then he jumps up and down on the ground
again .
```

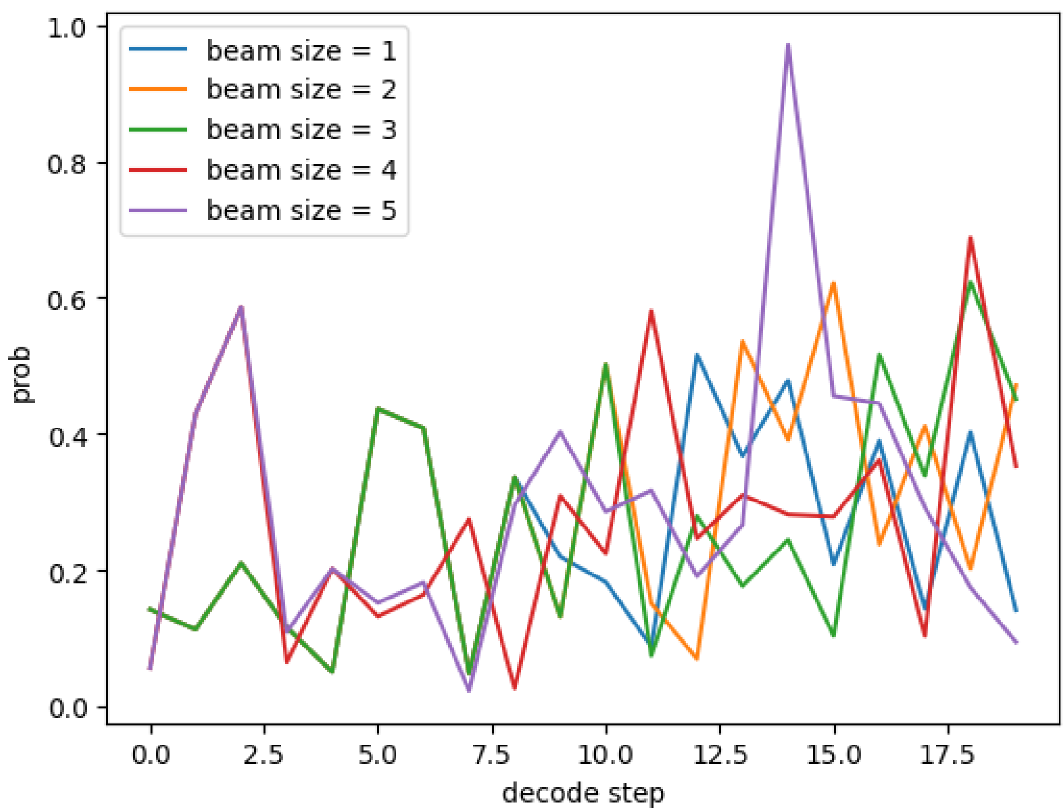
Why does the model assign higher probability to tokens generated later than to tokens generated earlier?

Write your answer here: The model assigns higher probabilities to tokens generated later due to the accumulation of context, which allows for more informed and confident predictions. As more tokens are generated, the model leverages the richer context to refine its outputs, leading to higher probabilities for subsequent tokens. Additionally, the softmax function used to normalize probabilities often results in more peaked distributions as the context grows, further contributing to higher probabilities for tokens generated later in the sequence. Run the cell below to visualize the word probabilities when using different beam sizes.

[7]:

```python
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:
```




```
Model predictions:
1 -0.9706197796445905 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 was
2 -0.9286185177889738 Once upon a time, in a barn near a farm house, a young boy
was playing with a stick. The boy was playing with a stick, and the boy
3 -0.9597567933978457 Once upon a time, in a barn near a farm house, a young boy
was playing with a stick. The boy, who had been playing with a stick,
4 -0.9205130952777285 Once upon a time, in a barn near a farm house, there was a
young girl who had been brought up by her mother. She had been brought up by
5 -0.9058780092181582 Once upon a time, in a barn near a farm house, there was a
man who had been living in the house for a long time. He was a man
```

3.3 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`.

[8]:
```
import collections
```

```python
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))
```

```
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 was playing with a stick. The
boy was playing with a stick, and the boy was playing with a
Beam Search w/ Word Block
Once upon 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 given to him by his wife
and he could take care of it for herself if needed; but when they
```

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, WordBlock can be an effective method to prevent repetition in beam search by reducing the probability of previously seen words, encouraging more diverse and coherent output. However, it may inadvertently block legitimate repetitions that are contextually appropriate, such as common phrases or necessary repetitions for clarity. This can lead to unnatural or less fluent sentences, as important context-specific repetitions might be unfairly penalized. Therefore, while WordBlock helps mitigate redundancy, it must be applied judiciously to balance between reducing repetition and maintaining natural language flow.

3.4 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.

[10]:
```
import collections

class BeamBlock:
    def __call__(self, input_ids, scores):
        for batch_idx in range(input_ids.shape[0]):
            # WRITE YOUR CODE HERE!

            # Collect all trigrams in the current sequence
            trigrams = collections.Counter()
            for i in range(2, input_ids.shape[1]):
                trigram = tuple(input_ids[batch_idx, i-2:i+1].tolist())
                trigrams[trigram] += 1

            # Reduce scores for any tokens that would result in a repeated␣
↪trigram
            for i in range(2, input_ids.shape[1]):
                trigram_prefix = tuple(input_ids[batch_idx, i-2:i].tolist())
                for token in range(scores.shape[1]):
                    candidate_trigram = trigram_prefix + (token,)
                    if trigrams[candidate_trigram] > 0:
                        scores[batch_idx, token] = -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 was playing with a stick. The
boy was playing with a stick, and the boy was playing with a
Beam Search w/ Beam Block
Once upon 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 given to him by his wife
```

```
and he could take care of it for herself if needed; but when they
```

4 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, save a PDF version of your notebook. 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