toybnzok2

December 2, 2024

1 CSE 256: NLP UCSD, Programming Assignment 4

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

1.1.1 Due: Dec 2, 2024

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/1QUXCoz3zqe3Ykhlhk_3rsslP

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.

[2]:
```
pip install -q sentence-transformers==2.2.2 transformers==4.17.0
```

```
                           86.0/86.0 kB
7.2 MB/s eta 0:00:00
  Preparing metadata (setup.py) … done
                           67.9/67.9 kB
5.6 MB/s eta 0:00:00
                         3.8/3.8 MB
97.6 MB/s eta 0:00:00
                         897.5/897.5 kB
55.5 MB/s eta 0:00:00
  Building wheel for sentence-transformers (setup.py) … done
```

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)

        # 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]

/usr/local/lib/python3.10/dist-packages/transformers/modeling_utils.py:1439:
FutureWarning: You are using `torch.load` with `weights_only=False` (the current
default value), which uses the default pickle module implicitly. It is possible
to construct malicious pickle data which will execute arbitrary code during
unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for
more details). In a future release, the default value for `weights_only` will be
flipped to `True`. This limits the functions that could be executed during
unpickling. Arbitrary objects will no longer be allowed to be loaded via this
mode unless they are explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control of the
loaded file. Please open an issue on GitHub for any issues related to this
experimental feature.
  state_dict = torch.load(resolved_archive_file, map_location="cpu")
```

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'
# WRITE YOUR CODE HERE!
import heapq
```

```
beam_op = run_beam_search(model,tokenizer,input_text,4,3)
heap = [(-s.item(),t) for s,t in␣
 ↪zip(beam_op['beam_scores'],beam_op['output_ids'])]
top_op = heapq.nsmallest(3,heap)[-1]
sc,t = top_op
# taking -sc since i have taken negative of score for sorting heap.
print(2, round(-sc/ t.shape[-1], 3), tokenizer.decode(t,␣
 ↪skip_special_tokens=True))
```

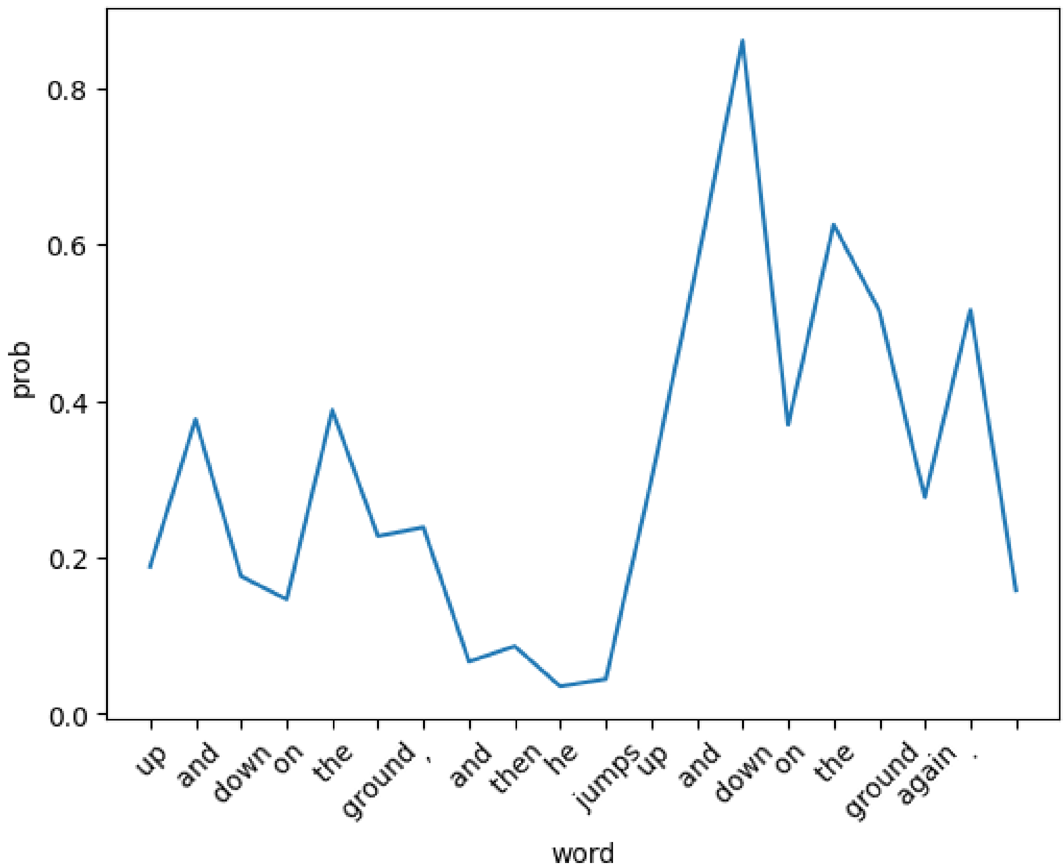
```
2 -0.627 The brown fox jumps up and down
```

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?

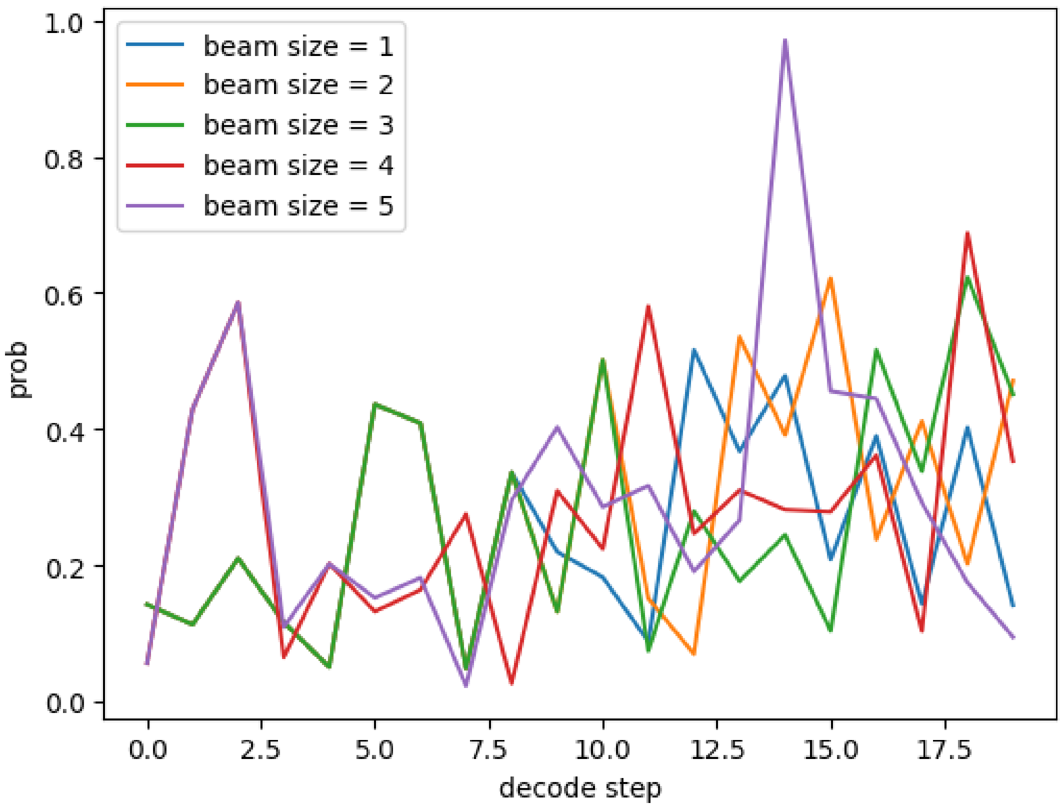
Write your answer here Observations: * Graph: The graph has 3 peaks at jumps (p=0.85), down(p=0.62),ground(p=0.5). The initial probabilities are in range 0.2 to 0.4 and has spike at jumps. The susbsequent probabilities are in range 0.4 to 0.6. This shows the model uses sequential information and has increased confidence due to accumulated context for subsequent word predictions * Visualization with coloured sequences: The connecting words: and, on,the hare in red => low probability. The probability increases as it learns context as shown in the colors.

Explanation: * For later tokens the model accumulates context hence more confidence in predicitons * There are peaks whennn the words are in a pattern e.g. "jumps up and down". The model is confident in predicting similar motion related words. * Beam search keeps the most likely appearing sequences. Since the model learns earlier decisions this guides selections for future tokens with lesser uncertainity.

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

[7]:
```
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:
```



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

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))
```

```
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 -0.9597569667931759 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 -0.9205132108746152 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 -0.9058780670166016 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
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 Word block is not a practical way to prevent repetition in beam search. The pros of word block : * prevents exact repetition of words * easy to implement * improves fluency and good for short term repetition. * more diversity of words are used in a sentence.

The cons of word block: * Loss of grammer as words like "is" , "a" , "the", "or" etc. are lost but humans repeat such words frequently in a sentence. * It blocks words initally itself hence in future sentences uses less optimal words. * It creates bad sentences by using unnatural words to form a sentence. * It reduces available vocabulary for building a sentence hence worse performance for larger data.

So the word block is an ineffecient way to prevent repetition in beam search. The other ways or possible extensions to try are: * using N-gram blocking as used in next question * reduce repetitions for certain words like nouns/verbs and not words like "a","is","the" * use a threshold for words and not repeat if it exceeds a certain threshold * Instead of theshold we can use a score and increase or decrease it based on if we repeat or not. This is useful when u want to repeat after some words and not immediately. * Use time or have a count of words after which we reset or can repeat the particular word.

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.

[9]:
```
from ast import And
import collections

class BeamBlock:
    def __call__(self, input_ids, scores):
        for batch_idx in range(input_ids.shape[0]):
            # WRITE YOUR CODE HERE!
            t = input_ids[batch_idx].tolist()
            sz = scores.shape[1]
            tri_gram = [[t[i],t[i+1],t[i+2]] for i in range(len(t)-2)]
            for x in t:
                tri_new = [t[-2],t[-1],x] if len(t)>=2 else [x]
                if tri_new in tri_gram:
                    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 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, a young boy was playing with a
stick. He was playing on the stick, and the boy was trying to get a ball. The
boy was holding the stick in his hand, and he was trying
```

3.5 # Submission Instructions

1. Click the Save button at the top of the Jupyter Notebook.
2. Select Cell -> All Output -> Clear. This will clear all the outputs from all cells (but will keep the content of all cells).
3. Select Cell -> Run All. This will run all the cells in order, and will take several minutes.
4. Once you've rerun everything, convert the notebook to PDF, you can use tools such as nbconvert, which requires first downloading the ipynb to your local machine, and then running "nbconvert" . (If you have trouble using nbconvert, you can also save the webpage as pdf. Make sure all your solutions 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