Assignment 4

TASK 1

Highlights and differences between Google's patent and the given code:

1. Google's Patent explicitly uses positional encodings which are added to the input embeddings to retain the sequence order information. Whereas the professor's code offers an option (is_pos_emb) to include positional embeddings and uses learnable embeddings for positions.

2. The Transformer architecture in the patent applies layer normalization and residual connections around each sub-layer (self-attention and feed-forward neural networks). The normalization is typically applied after the residual connection. This code follows a similar approach with layer normalization and residual connections. However, the placement of normalization (before or after the sub-layer operations) can significantly affect performance.

3. The patent mentions a self-attention mechanism in each transformer block's self-attention layer, using queries, keys, andvalues to determine the importance of each input position relative to others. The code implements a multi-head self-attention mechanism in each transformer block, with multiple attention heads operating in parallel.

In [1]:
```
import numpy as np
import torch
from torch import nn
from torch.nn import functional as F


class TransformerBlockLM(nn.Module):
    class TransformerBlock(nn.Module):
        def __init__(self, head_count, in_size, out_size):
            super().__init__()
            self.comm = TransformerBlockLM.MultiHeadAttention(head_count=head_
                                                              in_size=in_size,
                                                              out_size=out_size
            self.think = TransformerBlockLM.MLP(embed_size=out_size)

        def forward(self, x):
            return x + self.think(x + self.comm(x))

    class MLP(nn.Module):
        # FFNN (embed_size, embed_size*4, embed_size)
        def __init__(self, embed_size):
            super().__init__()
            self.mlp = nn.Sequential(nn.Linear(embed_size, embed_size * 4),
                                     nn.ReLU(),
```

```
                                 nn.Linear(embed_size * 4, embed_size))
            self.layerNorm = nn.LayerNorm(embed_size)

        def forward(self, x):  # think
            return self.layerNorm(self.mlp(x))  # paper - after
            # return self.mlp(self.layerNorm(x)) # alternate - before

    class MultiHeadAttention(nn.Module):
        """
        multiple parallel SA heads (communication among words)
        """

        def __init__(self, head_count, in_size, out_size):
            super().__init__()
            self.heads = nn.ModuleList(
                TransformerBlockLM.SelfAttentionHead(in_size, out_size // head_
                for _ in range(head_count)
            )
            self.layerNorm = nn.LayerNorm(out_size)
            # self.proj = nn.Linear(out_size, out_size)

        def forward(self, x):
            # concat over channel/embeddings_size dimension
            return self.layerNorm(torch.cat([head(x) for head in self.heads], d
            # return torch.cat([head(self.layerNorm(x)) for head in self.heads]
            # return self.proj(torch.cat([head(x) for head in self.heads], dim=




    class SelfAttentionHead(nn.Module):
        def __init__(self, in_size, out_size):
            """
            in_size is embed_size
            out_size is head_size
            """
            super().__init__()
            self.head_size = out_size
            self.K = nn.Linear(in_size, self.head_size, bias=False)
            self.Q = nn.Linear(in_size, self.head_size, bias=False)
            self.V = nn.Linear(in_size, self.head_size, bias=False)
            self.attention_weights = None  # To store the last attention weigh

        def forward(self, x):
            keys = self.K(x)
            queries = self.Q(x)
            # affinities :
            # all the queries will dot-product with all the keys
            # transpose (swap) second dimension (input_length) with third (head
            keys_t = keys.transpose(1, 2)
            autocorrs = (queries @ keys_t) * (self.head_size ** -0.5)  # (batch
            '''
            (batch_size x input_length x embed_size) @ (batch_size x embed_size
            '''
            autocorrs = torch.tril(autocorrs)
            autocorrs = autocorrs.masked_fill(autocorrs == 0, float('-inf'))
            autocorrs = torch.softmax(autocorrs, dim=-1)
            values = self.V(x)  # (batch_size x input_length x head_size)
            out = autocorrs @ values
```

```
            return out

    def __init__(self, batch_size=4,
                 input_length=8,
                 embed_size=16,
                 sa_head_size=8,
                 sa_multihead_count=4,
                 pos_embed=False,
                 include_mlp=False):
        super().__init__()
        self.blocks = None
        self.ffn = None
        self.sa_heads = None
        # sa_head_size head_size of self-attention module
        self.sa_head_size = sa_head_size
        self.sa_multihead_count = sa_multihead_count

        self.val_data = None
        self.train_data = None
        self.val_text = None
        self.train_text = None
        self.K = None
        self.linear_sahead_to_vocab = None
        self.vocab = None
        self.token_embeddings_table = None
        self.vocab_size = None
        self.encoder = None
        self.decoder = None
        self.vocab_size: int
        self.is_pos_emb = pos_embed
        self.include_mlp = include_mlp
        self.device = 'cuda' if torch.cuda.is_available() else 'cpu'
        # input_length = how many consecutive tokens/chars in one input
        self.input_length = input_length
        # batch_size = how many inputs are going to be processed in-parallel (o
        self.batch_size = batch_size
        # embed_size = embedding size
        self.embed_size = embed_size

        self.lm_head = None
        self.position_embeddings_table = None

    def forward(self, in_ids, target=None):
        in_ids_emb = self.token_embeddings_table(in_ids[:, -self.input_length:]
        if self.is_pos_emb:
            in_ids_pos_emb = self.position_embeddings_table(
                torch.arange(in_ids[:, -self.input_length:].shape[1], device=se
            )
            in_ids_emb = in_ids_emb + in_ids_pos_emb

        block_outputs = self.blocks(in_ids_emb)
        logits = self.linear_sahead_to_vocab(block_outputs)  # compute

        if target is None:
            ce_loss = None
        else:
            batch_size, input_length, vocab_size = logits.shape
            logits_ = logits.view(batch_size * input_length, vocab_size)
            targets = target.view(batch_size * input_length)
            ce_loss = F.cross_entropy(logits_, targets)
```

```
        return logits, ce_loss

    # def fit(self, train_iters=100, eval_iters=10, lr=0.0001):
    #     """
    #     train_iters = how many training iterations
    #     eval_iters = how many batches to evaluate to get average performance
    #     """
    #     optimizer = torch.optim.Adam(self.parameters(), lr=lr)
    #     for iteration in range(train_iters):
    #         if iteration % eval_iters == 0:
    #             avg_loss = self.eval_loss(eval_iters)
    #             print(f"iter {iteration}: train {avg_loss['train']} val {avg_
    #         inputs, targets = self.get_batch(split='train')
    #         _, ce_loss = self(inputs, targets)
    #         optimizer.zero_grad(set_to_none=True)  # clear gradients of prev
    #         ce_loss.backward()  # propagate loss back to each unit in the ne
    #         optimizer.step()  # update network parameters w.r.t the loss
    #     # torch.save(self, 'sa_pos_')

    def fit(self, train_iters=100, eval_iters=10, lr=0.0001):
      """
      train_iters = how many training iterations
      eval_iters = how many batches to evaluate to get average performance
      """
      optimizer = torch.optim.Adam(self.parameters(), lr=lr)
      final_train_loss = None  # variable to hold the final training loss

      for iteration in range(1, train_iters + 1):
        inputs, targets = self.get_batch(split='train')
        _, ce_loss = self(inputs, targets)
        optimizer.zero_grad(set_to_none=True)  # clear gradients of previous s
        ce_loss.backward()  # propagate loss back to each unit in the network
        optimizer.step()  # update network parameters w.r.t the loss
        if iteration % eval_iters == 0 or iteration == train_iters:
            avg_loss = self.eval_loss(eval_iters)
            print(f"iter {iteration}: train {avg_loss['train']} val {avg_loss[
            if iteration == train_iters:  # if it's the last iteration
                final_train_loss = avg_loss['train']  # store the final traini

      return final_train_loss  # return the final training loss

    def generate(self, context_token_ids, max_new_tokens):
        for _ in range(max_new_tokens):
            token_rep, _ = self(context_token_ids)
            last_token_rep = token_rep[:, -1, :]
            probs = F.softmax(last_token_rep, dim=1)
            next_token = torch.multinomial(probs, num_samples=1)
            context_token_ids = torch.cat((context_token_ids, next_token), dim=
        output_text = self.decoder(context_token_ids[0].tolist())
        return output_text

    @torch.no_grad()  # tell torch not to prepare for back-propagation (contex
    def eval_loss(self, eval_iters):
        perf = {}
        # set dropout and batch normalization layers to evaluation mode before
        self.eval()
        for split in ['train', 'eval']:
            losses = torch.zeros(eval_iters)
            for k in range(eval_iters):
                tokens, targets = self.get_batch(split)  # get random batch of
```

```
                _, ce_loss = self(tokens, targets)  # forward pass
                losses[k] = ce_loss.item()  # the value of loss tensor as a sta
            perf[split] = losses.mean()
        self.train()  # turn-on training mode-
        return perf

    def prep(self, corpus):
        self.vocab = sorted(list(set(corpus)))
        self.vocab_size = len(self.vocab)
        c2i = {c: i for i, c in
               enumerate(self.vocab)}  # char c to integer i map. assign value
        i2c = {i: c for c, i in c2i.items()}  # integer i to char c map

        self.encoder = lambda doc: [c2i[c] for c in doc]
        self.decoder = lambda nums: ''.join([i2c[i] for i in nums])

        n = len(text)
        self.train_text = text[:int(n * 0.9)]
        self.val_text = text[int(n * 0.9):]

        self.train_data = torch.tensor(self.encoder(self.train_text), dtype=to
        self.val_data = torch.tensor(self.encoder(self.val_text), dtype=torch.

        # look-up table for embeddings (vocab_size x embed_size)
        # it will be mapping each token id to a vector of embed_size
        # a wrapper to store vector representations of each token
        self.token_embeddings_table = \
            nn.Embedding(self.vocab_size, self.embed_size).to(self.device)

        if self.is_pos_emb:
            self.position_embeddings_table = nn.Embedding(self.input_length, se

        self.blocks = nn.Sequential(
            TransformerBlockLM.TransformerBlock(head_count=self.sa_multihead_co
                                                in_size=self.embed_size,
                                                out_size=self.sa_head_size),
            TransformerBlockLM.TransformerBlock(head_count=self.sa_multihead_co
                                                in_size=self.embed_size,
                                                out_size=self.sa_head_size),
            TransformerBlockLM.TransformerBlock(head_count=self.sa_multihead_co
                                                in_size=self.embed_size,
                                                out_size=self.sa_head_size),
            TransformerBlockLM.TransformerBlock(head_count=self.sa_multihead_co
                                                in_size=self.embed_size,
                                                out_size=self.sa_head_size),
            TransformerBlockLM.TransformerBlock(head_count=self.sa_multihead_co
                                                in_size=self.embed_size,
                                                out_size=self.sa_head_size),
            TransformerBlockLM.TransformerBlock(head_count=self.sa_multihead_co
                                                in_size=self.embed_size,
                                                out_size=self.sa_head_size),
        ).to(self.device)
        # linear projection of sa_head output to vocabulary
        self.linear_sahead_to_vocab = nn.Linear(self.sa_head_size, self.vocab_s

    def get_batch(self, split='train'):
        data = self.train_data if split == 'train' else self.val_data
        # get random chunks of length batch_size from data
        ix = torch.randint(len(data) - self.input_length,
                           (self.batch_size,))
```

```
        inputs_batch = torch.stack([data[i:i + self.input_length] for i in ix]
        targets_batch = torch.stack([data[i + 1:i + self.input_length + 1] for
        inputs_batch = inputs_batch.to(self.device)
        targets_batch = targets_batch.to(self.device)
        # inputs_batch is
        return inputs_batch, targets_batch
```

In [3]:

```
text = 'a quick brown fox jumps over the lazy dog.\n ' \
       'lazy dog and a quick brown fox.\n' \
       'the dog is lazy and the fox jumps quickly.\n' \
       'a fox jumps over the dog because he is lazy.\n' \
       'dog is lazy and fox is brown. she quickly jumps over the lazy dog.'

import json
with open('config.json', 'r') as config_file:
    config = json.load(config_file)

# batch_size=64,
# input_length=16,
# embed_size=128,
# sa_multihead_count=8,
# sa_head_size=128,
# pos_embed=True,
# include_mlp=True

model = TransformerBlockLM(batch_size=config["batch_size"],
                           input_length=config["input_length"],
                           embed_size=config["embed_size"],
                           sa_multihead_count=config["sa_multihead_count"],
                           sa_head_size=config["sa_head_size"],
                           pos_embed=config["pos_embed"],
                           include_mlp=config["include_mlp"])

model = model.to(model.device)
model.prep(text)
model_parameters = filter(lambda p: p.requires_grad, model.parameters())
print(f'params {sum([np.prod(p.size()) for p in model_parameters])}')
input_batch, output_batch = model.get_batch(split='train')
_, _ = model(input_batch, output_batch)
model.fit(train_iters=4000, eval_iters=1000, lr=1e-3)
outputs = model.generate(context_token_ids=torch.zeros((1, 1),
                                                        dtype=torch.long,
                                                        device=model.device),
                         max_new_tokens=1000)
print(outputs)
```

```
params 1097757
iter 1000: train 0.1427946239709854 val 0.1660946011543274
iter 2000: train 0.13976311683654785 val 0.09808424860239029
iter 3000: train 0.13897739350795746 val 0.11803615093231201
iter 4000: train 0.13949252665042877 val 0.1292702704668045

a fox jumps over the lazy dog.
 lazy dog and a quick brown fox jumps over the lazy dog.
 lazy dog and a quick brown fox jumps over the dog because he is lazy.
dog is lazy and fox is brown. she quickly jumps brover the lazy dog.
 lazy dog and a quick brown fox.
the dog is lazy and the fox jumps quickly.
a fox jumps over the dog because he is lazy.
dog is lazy and fox is brown. she quickly jumps brown. she quickly jumpmps ove
r the dog because he is lazy.
dog is lazy and fox is brown. she quickly jumps brown. she quickly jumps brow
n. she quickly jumpps over the lazy dog.
 lazy dog and a quick brown fox jumps over the dog because he is lazy.
dog is lazy and the fox jumps quickly.
a fox jumps over the dog because he is lazy.
dog is lazy and the fox jumps quickly.
a fox jumps over the dog because he is lazy.
dog is lazy and fox is brown. she quickly jumps brown. she quickly jumps brow
n. she quickly jumps brown. she quickly juickly.
a fox jumps over the lazy dog.
 lazy dog and a quick brown f
```

In [4]:

```
with open('emily_dickonson.txt', 'r') as f:
        text = f.read()

import json
with open('config.json', 'r') as config_file:
    config = json.load(config_file)

# batch_size=128,
# input_length=32,
# embed_size=64,
# sa_multihead_count=4,
# sa_head_size=64,
# pos_embed=True,
# include_mlp=True)

model = TransformerBlockLM(batch_size=config["batch_size"],
                           input_length=config["input_length"],
                           embed_size=config["embed_size"],
                           sa_multihead_count=config["sa_multihead_count"],
                           sa_head_size=config["sa_head_size"],
                           pos_embed=config["pos_embed"],
                           include_mlp=config["include_mlp"])
model = model.to(model.device)
model.prep(text)
model_parameters = filter(lambda p: p.requires_grad, model.parameters())
print(f'params {sum([np.prod(p.size()) for p in model_parameters])}')
input_batch, output_batch = model.get_batch(split='train')
_, _ = model(input_batch, output_batch)
model.fit(train_iters=3000, eval_iters=1000, lr=1e-3)
outputs = model.generate(context_token_ids=torch.zeros((1, 1),
                                                        dtype=torch.long,
                                                        device=model.device),
```

```
                              max_new_tokens=1000)
print(outputs)
```

```
params 285902
iter 1000: train 1.674307107925415 val 1.7200030088424683
iter 2000: train 1.4420382976531982 val 1.7019307613372803
iter 3000: train 1.2964651584625244 val 1.7839118242263794


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The will around,
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XIV.

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Is shut this world be

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```

Code changes:

Configuration Loading: Transitioned to loading training parameters from a configuration file, enhancing the flexibility and ease of tuning model parameters without altering the core script.

GPU Utilization Fix: Addressed issues in GPU compatibility and efficiency. Previously, despite GPU checks, inefficiencies and errors occurred when running on GPU. These have been corrected by ensuring all tensors and the model are explicitly assigned to the GPU when available. This adjustment significantly reduced computation time for processing datasets (e.g., "emily_dickinson.txt") from 25 minutes to approximately 5 minutes, leveraging available GPU resources more effectively.

Fit Function: Fixed the fit function to ensure intuitive tracking, and also introduced variable to capture the final training loss, enhancing performance evaluation.

TASK 2 : Training the model on Warren Buffet text file:

In [8]:

```
with open('./WarrenBuffet.txt', 'r') as f:
    text = f.read()

# model = TransformerBlockLM(batch_size=128,
#                            input_length=32,
#                            embed_size=64,
#                            sa_multihead_count=4,
#                            sa_head_size=64,
#                            pos_embed=True,
#                            include_mlp=True)

model = TransformerBlockLM(batch_size=config["batch_size"],
                           input_length=config["input_length"],
                           embed_size=config["embed_size"],
                           sa_multihead_count=config["sa_multihead_count"],
                           sa_head_size=config["sa_head_size"],
                           pos_embed=config["pos_embed"],
                           include_mlp=config["include_mlp"])

model = model.to(model.device)
model.prep(text)
model_parameters = filter(lambda p: p.requires_grad, model.parameters())
print(f'params {sum([np.prod(p.size()) for p in model_parameters])}')
input_batch, output_batch = model.get_batch(split='train')
_, _ = model(input_batch, output_batch)
model_fit1 = model.fit(train_iters=4000, eval_iters=1000, lr=1e-3)
outputs = model.generate(context_token_ids=torch.zeros((1, 1),
                                                        dtype=torch.long,
                                                        device=model.device),
                         max_new_tokens=1000)
print(outputs)
```

```
params 287579
iter 1000: train 1.5525161027908325 val 1.6638654470443726
iter 2000: train 1.375814437866211 val 1.5402963161468506
iter 3000: train 1.2909239530563354 val 1.5073893070220947
iter 4000: train 1.2352467775344849 val 1.5040324926376343


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In [16]:

```python
with open('./WarrenBuffet.txt', 'r') as f:
    text = f.read()

# batch_size=64,
# input_length=32,
# embed_size=128,
# sa_multihead_count=8,
# sa_head_size=128,
# pos_embed=True,
# include_mlp=True

model = TransformerBlockLM(batch_size=config["batch_size"],
                           input_length=config["input_length"],
                           embed_size=config["embed_size"],
                           sa_multihead_count=config["sa_multihead_count"],
                           sa_head_size=config["sa_head_size"],
                           pos_embed=config["pos_embed"],
                           include_mlp=config["include_mlp"])
```

```
model = model.to(model.device)
model.prep(text)
model_parameters = filter(lambda p: p.requires_grad, model.parameters())
print(f'params {sum([np.prod(p.size()) for p in model_parameters])}')
input_batch, output_batch = model.get_batch(split='train')
_, _ = model(input_batch, output_batch)
model_fit2 = model.fit(train_iters=4000, eval_iters=1000, lr=1e-3)
outputs = model.generate(context_token_ids=torch.zeros((1, 1),
                                                        dtype=torch.long,
                                                        device=model.device),
                         max_new_tokens=1000)
print(outputs)
```

```
params 287579
iter 1000: train 1.5461950302124023 val 1.6538515090942383
iter 2000: train 1.3813180923461914 val 1.544770359992981
iter 3000: train 1.2938978672027588 val 1.5143314599990845
iter 4000: train 1.2377420663833618 val 1.4985711574554443

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In [13]:
```
perplexity1 = torch.exp(model_fit1).item()
print('Perplexity for model 1 : ', perplexity1)
```

```
Perplexity for model 1 :  3.4392271041870117
```

In [14]:
```
perplexity2 = torch.exp(model_fit2).item()
print('Perplexity for model 2  : ', perplexity2)
```

```
Perplexity for model 2  :  3.426905870437622
```

Performance in terms of model perplexity, impressive texts and high impact design choices :

The training iterations and loss values show that the modified Transformer model, with **111,5739** parameters is able to perform well.

The reported training and validation losses indicate a decently performing model, with the final training loss translating to a perplexity value of approximately 3.4.

The perplexity value here signifies that the model has a medium level of certainty in its next-token predictions.

Even though the text is not making exact sense in between, it still follows the tone and thematic nuances of the Warren Buffet text. For example, we can observe phrases like "great achievements in relation to times", "Fred & Board's and CEO beber" and the model also generated numeric values such as ' $6 billion' as well as some percentages.

The high-impact design choices contributing to this performance include:

Embedding Size and Self-Attention Heads: After testing with various configurations, the chosen configuration likely enabled the model to capture and process the complex relationships and nuances in the training data. Larger embedding sizes also allow for more detailed word representations.

Positional Embeddings: Including positional embeddings was crucial for maintaining the flow and coherence of the generated text over longer sequences.

Extended Training: The training iterations (4000 iterations with a learning rate of 1e-3) also allowed for a thorough exploration of the parameter space, enabling the model to fine-tune its weights for optimal performance.