AIL861 / ELL8299 / ELL881: Advanced LLMs Assignment

Decoder-Only Transformer

Entry: 2024EEY7601

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Model: `https://huggingface.co/BrshankSN/tinystories`

In [1]:
```
import torch
import torch.nn as nn
import math
import numpy as np
import re
from collections import Counter
from datasets import load_dataset
from torch.nn import functional as F
from tqdm import tqdm
import evaluate
import matplotlib.pyplot as plt
import time

import zipfile
import os

device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(f"Using device: {device}")
```

```
Using device: cuda
```

1. Data Preprocessing

In [2]:
```
SPECIAL_TOKENS = {'<pad>': 0, '<sos>': 1, '<eos>': 2, '<unk>': 3}
PAD_IDX, SOS_IDX, EOS_IDX, UNK_IDX = 0, 1, 2, 3
CTX_LEN = 64
VOCAB_SIZE = 10000


def build_vocab(texts):
    tokens = []
    for t in texts:
        tokens.extend(re.findall(r'\w+|[^\w\s]', t.lower()))
    counter = Counter(tokens)
    vocab = SPECIAL_TOKENS.copy()
    for word, _ in counter.most_common(VOCAB_SIZE - len(SPECIAL_TOKENS)):
        vocab[word] = len(vocab)
    return vocab

def load_fasttext_embeddings(vocab, path):
    dim = 300
    matrix = np.random.normal(0, 0.1, (VOCAB_SIZE, dim)).astype(np.float32)
    loaded = 0

    print(f"Loading FastText from {path}...")
```

```python
    with open(path, encoding='utf-8') as f:
        next(f)  # Skipping header
        for line in f:
            values = line.rstrip().split()
            if len(values) != dim + 1:
                continue
            word = values[0]
            if word in vocab:
                vector = np.array([float(x) for x in values[1:]], dtype=np.float32)
                matrix[vocab[word]] = vector
                loaded += 1

    print(f"Successfully loaded {loaded}/{len(vocab)} embeddings.")
    return torch.from_numpy(matrix)

def encode_text(text, vocab):
    tokens = re.findall(r'\w+|[^\w\s]', text.lower())
    ids = [SOS_IDX] + [vocab.get(t, UNK_IDX) for t in tokens] + [EOS_IDX]
    if len(ids) > CTX_LEN:
        ids = ids[:CTX_LEN-1] + [EOS_IDX]
    ids += [PAD_IDX] * (CTX_LEN - len(ids))
    return torch.tensor(ids[:CTX_LEN])

print('Loading TinyStories...')
dataset = load_dataset("roneneldan/TinyStories")
train_texts = dataset['train']['text']
val_texts = dataset['validation']['text']

print('Building vocabulary...')
vocab = build_vocab(train_texts)
idx_to_word = {i: w for w, i in vocab.items()}

print('Loading FastText embeddings...')
ft_path = r"D:\IIT\LLM\data\wiki-news-300d-1M.vec"
embedding_matrix = load_fasttext_embeddings(vocab, ft_path)

print('Encoding sequences...')
train_data = [encode_text(t, vocab) for t in train_texts[:50000]]
val_data = [encode_text(t, vocab) for t in val_texts[:50000]]

print(f'Vocabulary size: {len(vocab)} | Train samples: {len(train_data)}')
```

```
Loading TinyStories...
Building vocabulary...
Loading FastText embeddings...
Loading FastText from D:\IIT\LLM\data\wiki-news-300d-1M.vec...
Successfully loaded 9676/10000 embeddings.
Encoding sequences...
Vocabulary size: 10000 | Train samples: 50000
```

2. Model Architecture

In [3]:

```python
def sinusoid_encoding(seq_len, d_model):
    pe = torch.zeros(seq_len, d_model)
    pos = torch.arange(seq_len).float().unsqueeze(1)
    div = torch.exp(torch.arange(0, d_model, 2).float() * (-math.log(10000.0) / d_model))
    pe[:, 0::2] = torch.sin(pos * div)
    pe[:, 1::2] = torch.cos(pos * div)
    return pe.unsqueeze(0)
```

```
class LayerNorm(nn.Module):
    def __init__(self, dim):
        super().__init__()
        self.scale = nn.Parameter(torch.ones(dim))
        self.bias = nn.Parameter(torch.zeros(dim))
    def forward(self, x):
        mean = x.mean(-1, keepdim=True)
        std = x.std(-1, keepdim=True)
        return self.scale * (x - mean) / (std + 1e-6) + self.bias

class MultiHeadAttention(nn.Module):
    def __init__(self, d_model, n_head):
        super().__init__()
        assert d_model % n_head == 0
        self.d_k = d_model // n_head
        self.n_head = n_head
        self.q_proj = nn.Linear(d_model, d_model)
        self.k_proj = nn.Linear(d_model, d_model)
        self.v_proj = nn.Linear(d_model, d_model)
        self.out_proj = nn.Linear(d_model, d_model)

    def forward(self, x, mask=None, kv_cache=None):
        B, T, C = x.shape
        q = self.q_proj(x).reshape(B, T, self.n_head, self.d_k).transpose(1, 2)
        k = self.k_proj(x).reshape(B, T, self.n_head, self.d_k).transpose(1, 2)
        v = self.v_proj(x).reshape(B, T, self.n_head, self.d_k).transpose(1, 2)

        if kv_cache is not None:
            k_cache, v_cache = kv_cache
            k = torch.cat([k_cache, k], dim=2)
            v = torch.cat([v_cache, v], dim=2)

        scores = (q @ k.transpose(-2, -1)) / math.sqrt(self.d_k)
        if mask is not None:
            scores = scores.masked_fill(mask, -1e9)
        attn = scores.softmax(dim=-1)
        out = (attn @ v).transpose(1, 2).contiguous().reshape(B, T, C)
        return self.out_proj(out), (k, v)

class DecoderLayer(nn.Module):
    def __init__(self, d_model, n_head, d_ff):
        super().__init__()
        self.attn = MultiHeadAttention(d_model, n_head)
        self.norm1 = LayerNorm(d_model)
        self.ffn = nn.Sequential(
            nn.Linear(d_model, d_ff),
            nn.ReLU(),
            nn.Linear(d_ff, d_model)
        )
        self.norm2 = LayerNorm(d_model)
        self.dropout = nn.Dropout(0.1)

    def forward(self, x, mask=None, kv_cache=None):
        attn_out, new_cache = self.attn(x, mask, kv_cache)
        x = self.norm1(x + self.dropout(attn_out))
        ffn_out = self.ffn(x)
        x = self.norm2(x + self.dropout(ffn_out))
        return x, new_cache
```

```python
class TransformerLM(nn.Module):
    def __init__(self, vocab_size, d_model=300, n_layer=3, n_head=6, d_ff=2048, ctx_len=64):
        super().__init__()
        self.ctx_len = ctx_len
        self.embed = nn.Embedding(vocab_size, d_model)
        self.pos_enc = sinusoid_encoding(ctx_len, d_model).to(device)
        self.layers = nn.ModuleList([DecoderLayer(d_model, n_head, d_ff) for _ in range(n_layer)])
        self.norm = LayerNorm(d_model)
        self.head = nn.Linear(d_model, vocab_size)
        self.dropout = nn.Dropout(0.1)

    def forward(self, idx, mask=None, kv_caches=None):
        B, T = idx.shape
        x = self.embed(idx) + self.pos_enc[:, :T, :]
        x = self.dropout(x)
        new_caches = []
        for i, layer in enumerate(self.layers):
            cache = kv_caches[i] if kv_caches else None
            x, new_cache = layer(x, mask, cache)
            new_caches.append(new_cache)
        x = self.norm(x)
        return self.head(x), new_caches

def causal_mask(seq_len):
    return torch.triu(torch.ones(1, 1, seq_len, seq_len, device=device), diagonal=1).bool()

model = TransformerLM(vocab_size=len(vocab)).to(device)
model.embed.weight.data.copy_(embedding_matrix)
model.embed.weight.requires_grad = True

print(f"Model initialized. Parameters: {sum(p.numel() for p in model.parameters()):,}")
```

```
Model initialized. Parameters: 10,791,244
```

3. Training (Teacher Forcing)

In [4]:

```python
optimizer = torch.optim.Adam(model.parameters(), lr=3e-4)
criterion = nn.CrossEntropyLoss(ignore_index=PAD_IDX)

def get_batch(data, batch_size=16):
    idx = torch.randint(len(data), (batch_size,))
    batch = torch.stack([data[i] for i in idx]).to(device)
    return batch[:, :-1], batch[:, 1:]

train_losses, val_losses, perplexities = [], [], []

for epoch in range(60):
    model.train()
    epoch_loss = 0.0
    steps = 0

    for _ in range(len(train_data) // 16):
        x, y = get_batch(train_data, batch_size=16)
        mask = causal_mask(x.size(1))
        logits, _ = model(x, mask)

        loss = criterion(
            logits.reshape(-1, len(vocab)),
            y.reshape(-1)
```

```python
        )

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        epoch_loss += loss.item()
        steps += 1

    avg_train_loss = epoch_loss / steps
    train_losses.append(avg_train_loss)

    #validation
    model.eval()
    val_loss = 0.0
    with torch.no_grad():
        for _ in range(100):
            x, y = get_batch(val_data, batch_size=8)
            mask = causal_mask(x.size(1))
            changed_logits, _ = model(x, mask)
            val_loss += criterion(
                changed_logits.reshape(-1, len(vocab)),
                y.reshape(-1)
            ).item()

    avg_val_loss = val_loss / 100
    val_losses.append(avg_val_loss)
    perplexities.append(math.exp(avg_val_loss))

    print(f'Epoch {epoch+1} | Train: {avg_train_loss:.3f} | Val: {avg_val_loss:.3f} | PPL: {math.exp(avg_val_loss):.1f}')

torch.save(model.state_dict(), 'model.pt')
print('Model saved.')
```

```
Epoch 1 | Train: 3.031 | Val: 2.480 | PPL: 11.9
Epoch 2 | Train: 2.329 | Val: 2.137 | PPL: 8.5
Epoch 3 | Train: 2.109 | Val: 2.095 | PPL: 8.1
Epoch 4 | Train: 1.976 | Val: 1.963 | PPL: 7.1
Epoch 5 | Train: 1.876 | Val: 1.973 | PPL: 7.2
Epoch 6 | Train: 1.804 | Val: 1.932 | PPL: 6.9
Epoch 7 | Train: 1.746 | Val: 1.892 | PPL: 6.6
Epoch 8 | Train: 1.700 | Val: 1.915 | PPL: 6.8
Epoch 9 | Train: 1.662 | Val: 1.863 | PPL: 6.4
Epoch 10 | Train: 1.627 | Val: 1.853 | PPL: 6.4
Epoch 11 | Train: 1.593 | Val: 1.859 | PPL: 6.4
Epoch 12 | Train: 1.567 | Val: 1.874 | PPL: 6.5
Epoch 13 | Train: 1.541 | Val: 1.834 | PPL: 6.3
Epoch 14 | Train: 1.517 | Val: 1.855 | PPL: 6.4
Epoch 15 | Train: 1.501 | Val: 1.861 | PPL: 6.4
Epoch 16 | Train: 1.478 | Val: 1.878 | PPL: 6.5
Epoch 17 | Train: 1.461 | Val: 1.890 | PPL: 6.6
Epoch 18 | Train: 1.442 | Val: 1.828 | PPL: 6.2
```

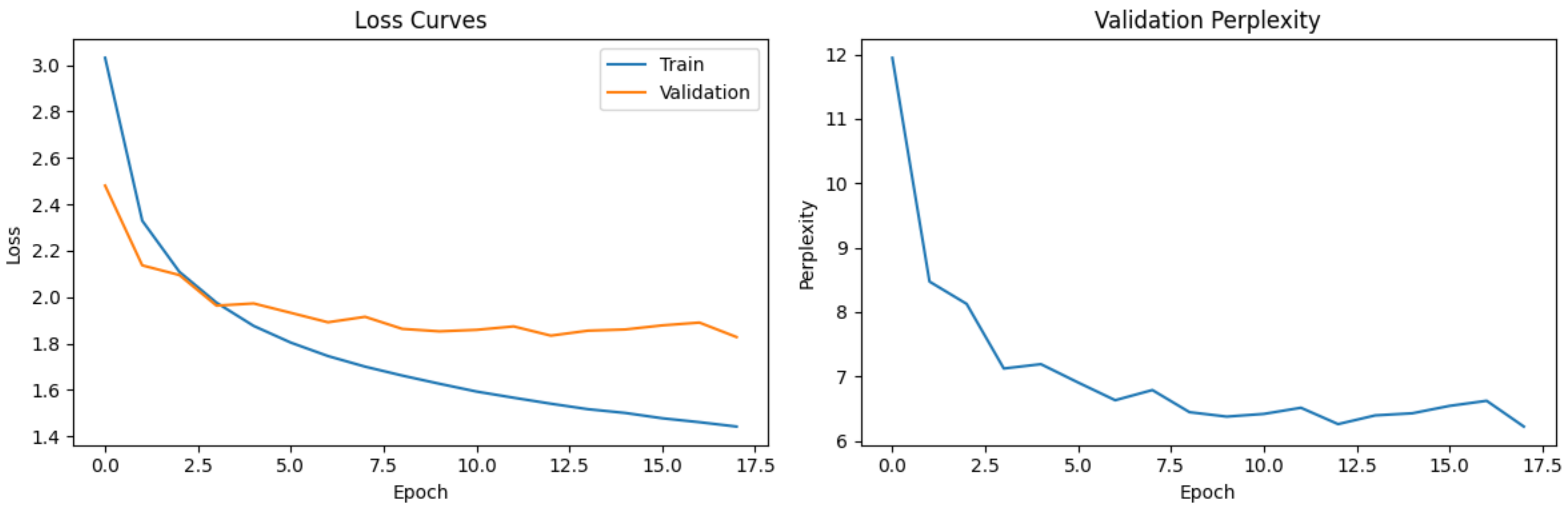
```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
Cell In[4], line 28
     22 loss = criterion(
     23     logits.reshape(-1, len(vocab)),
     24     y.reshape(-1)
     25 )
     27 optimizer.zero_grad()
---> 28 loss.backward()
     29 optimizer.step()
     31 epoch_loss += loss.item()

File ~\anaconda3\envs\llm\lib\site-packages\torch\_tensor.py:581, in Tensor.backward(self, gradient, retain_graph, create_graph, inputs)
    571 if has_torch_function_unary(self):
    572     return handle_torch_function(
    573         Tensor.backward,
    574         (self,),
   (...)
    579         inputs=inputs,
    580     )
--> 581 torch.autograd.backward(
    582     self, gradient, retain_graph, create_graph, inputs=inputs
    583 )

File ~\anaconda3\envs\llm\lib\site-packages\torch\autograd\__init__.py:347, in backward(tensors, grad_tensors, retain_graph, create_graph, grad_variables, inputs)
    342     retain_graph = create_graph
    344 # The reason we repeat the same comment below is that
    345 # some Python versions print out the first line of a multi-line function
    346 # calls in the traceback and some print out the last line
--> 347 _engine_run_backward(
    348     tensors,
    349     grad_tensors_,
    350     retain_graph,
    351     create_graph,
    352     inputs,
    353     allow_unreachable=True,
    354     accumulate_grad=True,
    355 )

File ~\anaconda3\envs\llm\lib\site-packages\torch\autograd\graph.py:825, in _engine_run_backward(t_outputs, *args, **kwargs)
    823     unregister_hooks = _register_logging_hooks_on_whole_graph(t_outputs)
    824 try:
--> 825     return Variable._execution_engine.run_backward(  # Calls into the C++ engine to run the backward pass
    826         t_outputs, *args, **kwargs
    827     )  # Calls into the C++ engine to run the backward pass
    828 finally:
    829     if attach_logging_hooks:

KeyboardInterrupt:
```

4. Plots

In [5]:

```
os.makedirs('figures', exist_ok=True)

plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.plot(train_losses, label='Train')
```

```
plt.plot(val_losses,   label='Validation')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.title('Loss Curves')

plt.subplot(1, 2, 2)
plt.plot(perplexities)
plt.xlabel('Epoch')
plt.ylabel('Perplexity')
plt.title('Validation Perplexity')

plt.tight_layout()

plt.savefig('figures/loss_and_perplexity.png', dpi=300, bbox_inches='tight')
plt.savefig('figures/loss_and_perplexity.pdf', bbox_inches='tight')
plt.show()
```



5. Inference & Evaluation (50 Prompts)

In [6]:
```
bleu_scorer = evaluate.load('bleu')

#KV caching
def generate(model, prompt_ids, max_len=64, temp=0.8, use_kv=False):
    model.eval()
    idx = torch.tensor([prompt_ids], device=device)
    caches = [None] * len(model.layers) if use_kv else None

    with torch.no_grad():
        for _ in range(max_len - len(prompt_ids)):
            T = idx.size(1)
            mask = causal_mask(T)

            logits, new_caches = model(idx, mask, caches)
            if use_kv:
```

```python
                caches = new_caches

            probs = (logits[0, -1] / temp).softmax(dim=-1)
            nxt = torch.multinomial(probs, 1).item()
            idx = torch.cat([idx, torch.tensor([[nxt]], device=device)], dim=1)
            if nxt == EOS_IDX:
                break

    return idx[0].cpu().tolist()
perplexities = []
bleu_scores   = []

os.makedirs('results', exist_ok=True)

for seq in tqdm(val_data[:50], desc='Evaluating 50 prompts'):
    prompt = seq[:5].tolist()
    target = seq[5:].tolist()

    generated = generate(model, prompt, max_len=64, temp=0.8, use_kv=False)
    gen_tokens = generated[len(prompt):]

    if EOS_IDX in gen_tokens:
        eos_pos = gen_tokens.index(EOS_IDX)
        gen_tokens = gen_tokens[:eos_pos]
    else:
        gen_tokens = gen_tokens

    input_ids  = prompt + gen_tokens[:-1] if gen_tokens else prompt
    target_ids = gen_tokens

    if len(target_ids) < len(input_ids):
        pad_len = len(input_ids) - len(target_ids)
        target_ids = target_ids + [PAD_IDX] * pad_len
    else:
        target_ids = target_ids[:len(input_ids)]

    x = torch.tensor([input_ids],  device=device)
    y = torch.tensor([target_ids], device=device)
    mask = causal_mask(x.size(1))
    logits, _ = model(x, mask)

    loss = F.cross_entropy(
        logits.reshape(-1, len(vocab)),
        y.reshape(-1),
        ignore_index=PAD_IDX
    )
    perplexities.append(math.exp(loss.item()))

    pred_str = ' '.join([idx_to_word.get(i, '<unk>') for i in gen_tokens
                        if i not in (PAD_IDX, SOS_IDX, EOS_IDX)])

    ref_tokens = target[:len(gen_tokens)]
    ref_str = ' '.join([idx_to_word.get(i, '<unk>') for i in ref_tokens
                       if i not in (PAD_IDX, SOS_IDX, EOS_IDX)])

    bleu = bleu_scorer.compute(
        predictions=[pred_str],
        references=[[ref_str]]
    )['bleu']
    bleu_scores.append(bleu)
```

```
avg_ppl  = np.mean(perplexities)
avg_bleu = np.mean(bleu_scores)

print(f"\nAverage Perplexity : {avg_ppl:.2f}")
print(f"Average BLEU       : {avg_bleu:.4f}")

results = {
    "average_perplexity": float(avg_ppl),
    "average_bleu"      : float(avg_bleu),
    "per_sample_ppl"    : [float(p) for p in perplexities],
    "per_sample_bleu"   : [float(b) for b in bleu_scores]
}
with open('results/eval_50.json', 'w') as f:
    json.dump(results, f, indent=2)

print("Results saved to results/eval_50.json")
```

```
Evaluating 50 prompts: 100%|██████████████████████████████████████████████████| 50/50 [00:17<00:00,  2.79it/s]
Average Perplexity : 225139.73
Average BLEU       : 0.1083
Results saved to results/eval_50.json
```

6. Beam Search

In [7]:

```
def beam_search(model, prompt_ids, k=5, max_len=64, temp=1.0, use_kv=False):
    model.eval()
    beams = [(prompt_ids[:], 0.0, [None] * len(model.layers))]

    with torch.no_grad():
        for _ in range(max_len - len(prompt_ids)):
            new_beams = []

            for seq, score, caches in beams:
                idx = torch.tensor([seq], device=device)
                T = idx.size(1)
                mask = causal_mask(T).to(device)

                logits, new_caches = model(idx, mask, caches if use_kv else None)
                probs = (logits[0, -1] / temp).log_softmax(dim=-1)

                topk_probs, topk_ids = probs.topk(k)
                for p, nid in zip(topk_probs.tolist(), topk_ids.tolist()):
                    new_seq = seq + [nid]
                    new_score = score + p
                    new_c = new_caches if use_kv else caches
                    new_beams.append((new_seq, new_score, new_c))

                    if nid == EOS_IDX:
                        break

            new_beams.sort(key=lambda x: x[1], reverse=True)
            beams = new_beams[:k]

            if all(EOS_IDX in seq for seq, _, _ in beams):
                break

    best_seq = beams[0][0]
```

```python
    return best_seq

prompt = val_data[0][:5].tolist()
print("Beam (k=5):", [idx_to_word.get(i, '<unk>') for i in beam_search(model, prompt, k=5)])
```

```
Beam (k=5): ['<sos>', 'spot', '.', 'spot', 'saw', 'a', 'big', 'tree', 'with', 'a', 'lot', 'of', 'leaves', '.', 'he', 'wanted', 'to', 'climb', 'it', 'and', 'see', 'what', 'was', 'up', 'there', '.', 'he', 'started', 'to', 'climb', 'the', 'tree', ',', 'but', 'it', 'was', 'too', 'high', 'for', 'him', 'to', 'reach', '.', 'spot', "'", 's', 'mom', 'saw', 'him', 'struggling', 'and', 'said', ',', '"', 'spot', ',', 'you', 'need', 'to', 'be', 'careful', '.', 'you', '<eos>']
```

7. KV Caching Speed Test

In [8]:
```python
def benchmark_generation(use_kv):
    total_tokens = 0
    start = time.time()
    for _ in range(20):
        prompt = val_data[0][:5].tolist()
        gen = generate(model, prompt, max_len=64, temp=0.8, use_kv=use_kv)
        gen_tokens = gen[len(prompt):]
        if EOS_IDX in gen_tokens:
            gen_tokens = gen_tokens[:gen_tokens.index(EOS_IDX)]
        total_tokens += len(gen_tokens)
    return total_tokens / (time.time() - start)
print(f"Tokens/sec (no KV): {benchmark_generation(False):.1f}")
print(f"Tokens/sec (KV)   : {benchmark_generation(True):.1f}")
```

```
Tokens/sec (no KV): 171.4
```

```
---------------------------------------------------------------------------
RuntimeError                              Traceback (most recent call last)
Cell In[8], line 13
     11     return total_tokens / (time.time() - start)
     12 print(f"Tokens/sec (no KV): {benchmark_generation(False):.1f}")
---> 13 print(f"Tokens/sec (KV)   : {benchmark_generation(True):.1f}")

Cell In[8], line 6, in benchmark_generation(use_kv)
      4 for _ in range(20):
      5     prompt = val_data[0][:5].tolist()
----> 6     gen = generate(model, prompt, max_len=64, temp=0.8, use_kv=use_kv)
      7     gen_tokens = gen[len(prompt):]
      8     if EOS_IDX in gen_tokens:

Cell In[6], line 14, in generate(model, prompt_ids, max_len, temp, use_kv)
     11 T = idx.size(1)
     12 mask = causal_mask(T)
---> 14 logits, new_caches = model(idx, mask, caches)
     15 if use_kv:
     16     caches = new_caches

File ~\anaconda3\envs\llm\lib\site-packages\torch\nn\modules\module.py:1736, in Module._wrapped_call_impl(self, *args, **kwargs)
   1734     return self._compiled_call_impl(*args, **kwargs)  # type: ignore[misc]
   1735 else:
-> 1736     return self._call_impl(*args, **kwargs)

File ~\anaconda3\envs\llm\lib\site-packages\torch\nn\modules\module.py:1747, in Module._call_impl(self, *args, **kwargs)
   1742 # If we don't have any hooks, we want to skip the rest of the logic in
   1743 # this function, and just call forward.
   1744 if not (self._backward_hooks or self._backward_pre_hooks or self._forward_hooks or self._forward_pre_hooks
   1745         or _global_backward_pre_hooks or _global_backward_hooks
   1746         or _global_forward_hooks or _global_forward_pre_hooks):
-> 1747     return forward_call(*args, **kwargs)
   1749 result = None
   1750 called_always_called_hooks = set()

Cell In[3], line 86, in TransformerLM.forward(self, idx, mask, kv_caches)
     84 for i, layer in enumerate(self.layers):
     85     cache = kv_caches[i] if kv_caches else None
---> 86     x, new_cache = layer(x, mask, cache)
     87     new_caches.append(new_cache)
     88 x = self.norm(x)

File ~\anaconda3\envs\llm\lib\site-packages\torch\nn\modules\module.py:1736, in Module._wrapped_call_impl(self, *args, **kwargs)
   1734     return self._compiled_call_impl(*args, **kwargs)  # type: ignore[misc]
   1735 else:
-> 1736     return self._call_impl(*args, **kwargs)

File ~\anaconda3\envs\llm\lib\site-packages\torch\nn\modules\module.py:1747, in Module._call_impl(self, *args, **kwargs)
   1742 # If we don't have any hooks, we want to skip the rest of the logic in
   1743 # this function, and just call forward.
   1744 if not (self._backward_hooks or self._backward_pre_hooks or self._forward_hooks or self._forward_pre_hooks
   1745         or _global_backward_pre_hooks or _global_backward_hooks
   1746         or _global_forward_hooks or _global_forward_pre_hooks):
-> 1747     return forward_call(*args, **kwargs)
   1749 result = None
   1750 called_always_called_hooks = set()

Cell In[3], line 62, in DecoderLayer.forward(self, x, mask, kv_cache)
     61 def forward(self, x, mask=None, kv_cache=None):
```

```
---> 62     attn_out, new_cache = self.attn(x, mask, kv_cache)
     63     x = self.norm1(x + self.dropout(attn_out))
     64     ffn_out = self.ffn(x)

File ~\anaconda3\envs\llm\lib\site-packages\torch\nn\modules\module.py:1736, in Module._wrapped_call_impl(self, *args, **kwargs)
   1734     return self._compiled_call_impl(*args, **kwargs)  # type: ignore[misc]
   1735 else:
-> 1736     return self._call_impl(*args, **kwargs)

File ~\anaconda3\envs\llm\lib\site-packages\torch\nn\modules\module.py:1747, in Module._call_impl(self, *args, **kwargs)
   1742 # If we don't have any hooks, we want to skip the rest of the logic in
   1743 # this function, and just call forward.
   1744 if not (self._backward_hooks or self._backward_pre_hooks or self._forward_hooks or self._forward_pre_hooks
   1745         or _global_backward_pre_hooks or _global_backward_hooks
   1746         or _global_forward_hooks or _global_forward_pre_hooks):
-> 1747     return forward_call(*args, **kwargs)
   1749 result = None
   1750 called_always_called_hooks = set()

Cell In[3], line 43, in MultiHeadAttention.forward(self, x, mask, kv_cache)
     41 scores = (q @ k.transpose(-2, -1)) / math.sqrt(self.d_k)
     42 if mask is not None:
---> 43     scores = scores.masked_fill(mask, -1e9)
     44 attn = scores.softmax(dim=-1)
     45 out = (attn @ v).transpose(1, 2).contiguous().reshape(B, T, C)

RuntimeError: The size of tensor a (6) must match the size of tensor b (11) at non-singleton dimension 3
```

8. Gradient Accumulation

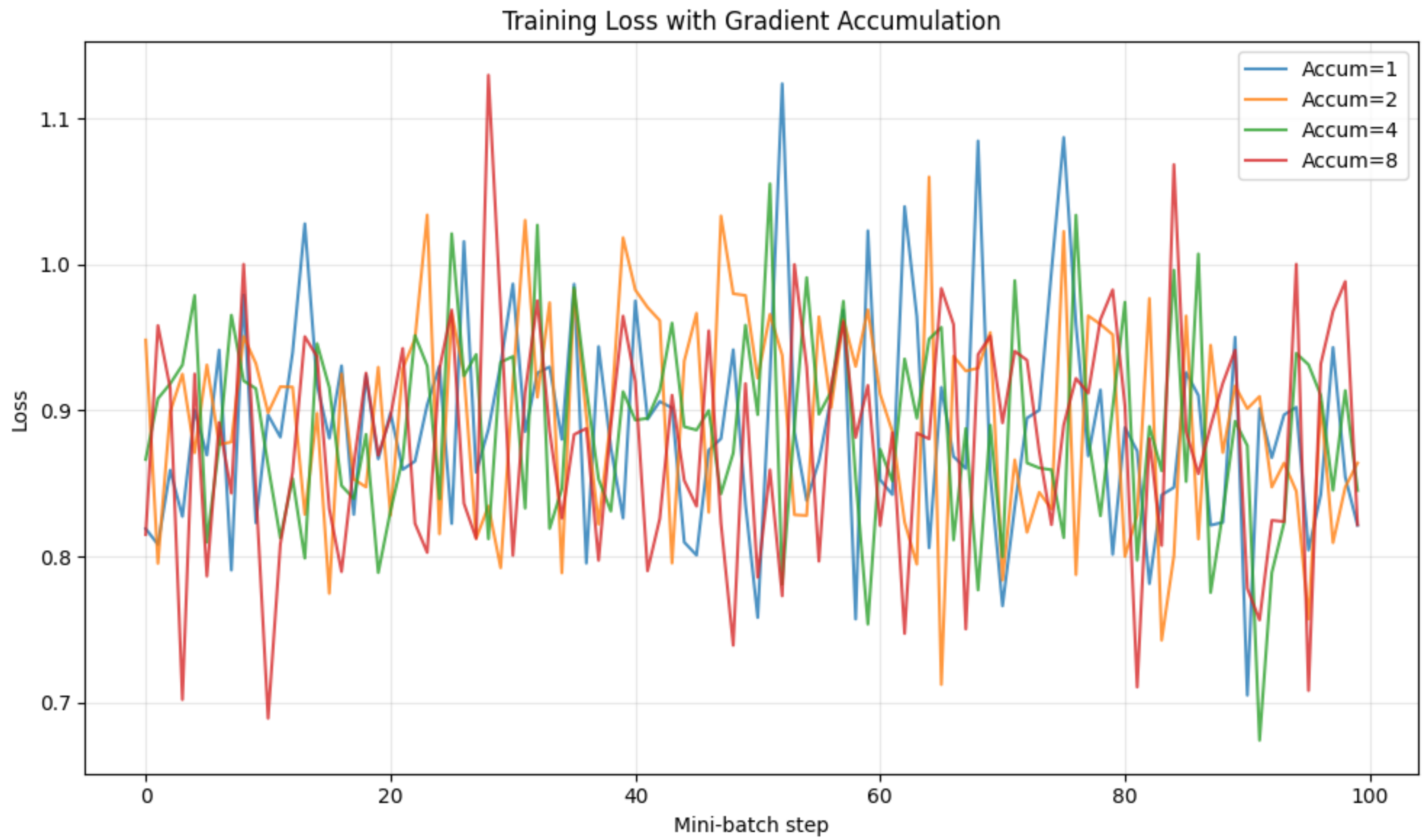
In [9]:

```python
os.makedirs('figures', exist_ok=True)

def train_with_accum(accum_steps, total_steps=100):
    model.load_state_dict(torch.load('model.pt'))
    opt = torch.optim.Adam(model.parameters(), lr=3e-4)

    losses = []
    start_time = time.time()

    for step in range(total_steps):
        x, y = get_batch(train_data, batch_size=16)
        mask = causal_mask(x.size(1))

        logits, _ = model(x, mask)

        loss = criterion(
            logits.reshape(-1, len(vocab)),
            y.reshape(-1)
        ) / accum_steps

        loss.backward()

        if (step + 1) % accum_steps == 0 or (step + 1) == total_steps:
            opt.step()
            opt.zero_grad()

        losses.append(loss.item() * accum_steps)

    elapsed = time.time() - start_time
```

```python
    return losses, elapsed


print("Running gradient accumulation experiments...")
loss1, time1 = train_with_accum(accum_steps=1, total_steps=100)
loss2, time2 = train_with_accum(accum_steps=2, total_steps=100)
loss4, time4 = train_with_accum(accum_steps=4, total_steps=100)
loss8, time8 = train_with_accum(accum_steps=8, total_steps=100)

# loss curve
plt.figure(figsize=(10, 6))
plt.plot(loss1, label='Accum=1', alpha=0.8)
plt.plot(loss2, label='Accum=2', alpha=0.8)
plt.plot(loss4, label='Accum=4', alpha=0.8)
plt.plot(loss8, label='Accum=8', alpha=0.8)
plt.xlabel('Mini-batch step')
plt.ylabel('Loss')
plt.title('Training Loss with Gradient Accumulation')
plt.legend()
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.savefig('figures/grad_accum_loss.png', dpi=300, bbox_inches='tight')
plt.savefig('figures/grad_accum_loss.pdf', bbox_inches='tight')
plt.show()


print("\n=== Runtime per 100 mini-batches ===")
print(f"Accum 1 : {time1:.2f} s")
print(f"Accum 2 : {time2:.2f} s")
print(f"Accum 4 : {time4:.2f} s")
print(f"Accum 8 : {time8:.2f} s")
```

```
Running gradient accumulation experiments...
```

```
C:\Users\brshank\AppData\Local\Temp\ipykernel_18492\104492058.py:8: FutureWarning: You are using `torch.load` with `weights_only=False` (the current default value), which uses the default pick
le 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#untrus
ted-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 `weig
hts_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.
  model.load_state_dict(torch.load('model.pt'))
```




```
=== Runtime per 100 mini-batches ===
Accum 1 : 4.41 s
Accum 2 : 4.03 s
Accum 4 : 3.57 s
Accum 8 : 3.58 s
```

9. Gradient Checkpointing (Manual)

In [10]:

```
def checkpoint_forward(layer, x, mask, cache):
    def custom_forward(x):
        return layer(x, mask, cache)[0]
    return torch.utils.checkpoint.checkpoint(custom_forward, x)

def train_with_checkpoint():
    model.train()
    x, y = get_batch(train_data)
    mask = causal_mask(x.size(1))
    x = model.embed(x) + model.pos_enc[:, :x.size(1), :]
    for layer in model.layers:
        x = checkpoint_forward(layer, x, mask, None)
    x = model.norm(x)
    logits = model.head(x)
    return criterion(logits.reshape(-1, len(vocab)), y.reshape(-1))
```

```python
print("Memory with checkpoint:", torch.cuda.max_memory_allocated() / 1e6, "MB")
```

```
Memory with checkpoint: 566.84032 MB
```