StandardMinimal

October 23, 2024

[20]:
```
import torch
import torch.nn as nn
from torch.nn import functional as F
from torch.utils.data import Dataset, DataLoader
import numpy as np
from tqdm import tqdm
import time
import matplotlib.pyplot as plt
```

[21]:
```
# Hyperparameters - significantly reduced for minimal CPU training
#BATCH_SIZE = 16
#BLOCK_SIZE = 64  # Reduced context window
#MAX_ITERS = 1000
#LEARNING_RATE = 1e-3
#DEVICE = 'cpu'  # Fixed to CPU
#EMB_SIZE = 64   # Reduced embedding dimensions
#HEAD_SIZE = 64  # Reduced head size
#NUM_HEADS = 2   # Reduced number of heads
#NUM_LAYERS = 2  # Reduced number of layers
#DROPOUT = 0.1   # Reduced dropout

# Modified hyperparameters
BATCH_SIZE = 16
BLOCK_SIZE = 64
MAX_ITERS = 1000
LEARNING_RATE = 1e-3
DEVICE = 'cpu' # Fixed to CPU
EMB_SIZE = 64  # Changed from 128 to 64 to match the embedding size
HEAD_SIZE = 32  # Changed from 64 to 32 to match the head output size
NUM_HEADS = 2  # Changed from 8 to 2 to match the number of heads
NUM_LAYERS = 2 # Changed from 8 to 2 to match the number of layers
DROPOUT = 0.1 # Reduced dropout
```

[22]:
```
# Load and preprocess text
with open('input.txt', 'r', encoding='utf-8') as f:
    text = f.read()

# Create vocabulary
```

```python
chars = sorted(list(set(text)))
VOCAB_SIZE = len(chars)

print(chars)
```

```
['\n', ' ', '!', '$', '&', "'", ',', '-', '.', '3', ':', ';', '?', 'A', 'B',
'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J', 'K', 'L', 'M', 'N', 'O', 'P', 'Q', 'R',
'S', 'T', 'U', 'V', 'W', 'X', 'Y', 'Z', 'a', 'b', 'c', 'd', 'e', 'f', 'g', 'h',
'i', 'j', 'k', 'l', 'm', 'n', 'o', 'p', 'q', 'r', 's', 't', 'u', 'v', 'w', 'x',
'y', 'z']
```

[23]:
```python
# Create encoding/decoding maps
stoi = {ch: i for i, ch in enumerate(chars)}
itos = {i: ch for i, ch in enumerate(chars)}
encode = lambda s: [stoi[c] for c in s]
decode = lambda l: ''.join([itos[i] for i in l])
```

[24]:
```python
# Create train/val split
data = torch.tensor(encode(text), dtype=torch.long)
n = int(0.9 * len(data))
train_data = data[:n]
val_data = data[n:]

class TextDataset(Dataset):
    def __init__(self, data, block_size):
        self.data = data
        self.block_size = block_size

    def __len__(self):
        return len(self.data) - self.block_size

    def __getitem__(self, idx):
        chunk = self.data[idx:idx + self.block_size + 1]
        x = chunk[:-1]
        y = chunk[1:]
        return x, y

dataset = TextDataset(train_data, BLOCK_SIZE)

# Print some example data
x, y = dataset[0]
print("Input tensor (x):", x)
print("Target tensor (y):", y)
print("\nDecoded input text:")
print(decode(x.tolist()))  # Convert tensor to list before decoding

# We can also see the relationship between input and target:
print("\nFirst few tokens as (input, target) pairs:")
```

```
for i in range(5):
    print(f"Position {i}: ({decode([x[i].item()])}, {decode([y[i].item()])})")
```

```
Input tensor (x): tensor([18, 47, 56, 57, 58,  1, 15, 47, 58, 47, 64, 43, 52,
10,  0, 14, 43, 44,
        53, 56, 43,  1, 61, 43,  1, 54, 56, 53, 41, 43, 43, 42,  1, 39, 52, 63,
         1, 44, 59, 56, 58, 46, 43, 56,  6,  1, 46, 43, 39, 56,  1, 51, 43,  1,
        57, 54, 43, 39, 49,  8,  0,  0, 13, 50])
Target tensor (y): tensor([47, 56, 57, 58,  1, 15, 47, 58, 47, 64, 43, 52, 10,
0, 14, 43, 44, 53,
        56, 43,  1, 61, 43,  1, 54, 56, 53, 41, 43, 43, 42,  1, 39, 52, 63,  1,
        44, 59, 56, 58, 46, 43, 56,  6,  1, 46, 43, 39, 56,  1, 51, 43,  1, 57,
        54, 43, 39, 49,  8,  0,  0, 13, 50, 50])

Decoded input text:
First Citizen:
Before we proceed any further, hear me speak.

Al

First few tokens as (input, target) pairs:
Position 0: (F, i)
Position 1: (i, r)
Position 2: (r, s)
Position 3: (s, t)
Position 4: (t,  )
```

[25]:

```
# Attention Mechanism
class Head(nn.Module):
    def __init__(self, head_size):
        super().__init__()
        self.key = nn.Linear(EMB_SIZE, head_size, bias=False)
        self.query = nn.Linear(EMB_SIZE, head_size, bias=False)
        self.value = nn.Linear(EMB_SIZE, head_size, bias=False)

    def forward(self, x):
        B, T, C = x.shape
        k = self.key(x)
        q = self.query(x)
        v = self.value(x)

        # Compute attention scores
        wei = q @ k.transpose(-2, -1) * C**-0.5
        wei = F.softmax(wei, dim=-1)

        # Weighted aggregation
        out = wei @ v
```

```
        return out

class MultiHeadAttention(nn.Module):
    def __init__(self, head_size):
        super().__init__()
        self.heads = nn.ModuleList([Head(head_size) for _ in range(NUM_HEADS)])
        self.proj = nn.Linear(head_size * NUM_HEADS, EMB_SIZE)
        self.dropout = nn.Dropout(DROPOUT)

    def forward(self, x):
        out = torch.cat([h(x) for h in self.heads], dim=-1)
        out = self.dropout(self.proj(out))
        return out
```

[26]:
```
# Feed Forward Block
class FeedForward(nn.Module):
    def __init__(self):
        super().__init__()
        self.net = nn.Sequential(
            nn.Linear(EMB_SIZE, 2 * EMB_SIZE),
            nn.ReLU(),
            nn.Linear(2 * EMB_SIZE, EMB_SIZE),
        )

    def forward(self, x):
        return self.net(x)
```

[27]:
```
# Transformer Block, composed of Multi-Head Attention and Feed Forward blocks
class TransformerBlock(nn.Module):
    def __init__(self):
        super().__init__()
        self.attention = MultiHeadAttention(HEAD_SIZE)
        self.ffwd = FeedForward()
        self.ln1 = nn.LayerNorm(EMB_SIZE)
        self.ln2 = nn.LayerNorm(EMB_SIZE)

    def forward(self, x):
        x = x + self.attention(self.ln1(x))
        x = x + self.ffwd(self.ln2(x))
        return x
```

[28]:
```
class ShakespeareTransformer(nn.Module):
    def __init__(self):
        super().__init__()
        self.token_embedding = nn.Embedding(VOCAB_SIZE, EMB_SIZE)
        self.position_embedding = nn.Embedding(BLOCK_SIZE, EMB_SIZE)
```

```python
        self.blocks = nn.Sequential(*[TransformerBlock() for _ in range(NUM_LAYERS)])
        self.ln_f = nn.LayerNorm(EMB_SIZE)
        self.lm_head = nn.Linear(EMB_SIZE, VOCAB_SIZE)

    def forward(self, idx):
        B, T = idx.shape

        # Get token and position embeddings
        tok_emb = self.token_embedding(idx)
        pos = torch.arange(T, device=idx.device)
        pos_emb = self.position_embedding(pos)

        x = tok_emb + pos_emb
        x = self.blocks(x)
        x = self.ln_f(x)
        logits = self.lm_head(x)

        return logits

    def generate(self, idx, max_new_tokens, temperature=0.7):
        """Generate text with optional temperature control."""
        self.eval()  # Ensure model is in evaluation mode
        with torch.no_grad():
            for _ in range(max_new_tokens):
                # Get last block_size tokens or pad if needed
                if idx.size(1) < BLOCK_SIZE:
                    padding = torch.zeros((1, BLOCK_SIZE - idx.size(1)), dtype=torch.long, device=idx.device)
                    idx_cond = torch.cat([padding, idx], dim=1)
                else:
                    idx_cond = idx[:, -BLOCK_SIZE:]

                # Get predictions
                logits = self(idx_cond)
                logits = logits[:, -1, :] / temperature

                # Apply softmax with temperature
                probs = F.softmax(logits, dim=-1)

                # Sample from top-k tokens to avoid generating rare/garbage tokens
                top_k = 40
                top_k_probs, top_k_indices = torch.topk(probs, top_k)
                probs = torch.zeros_like(probs).scatter_(-1, top_k_indices, top_k_probs)
                probs = probs / probs.sum(dim=-1, keepdim=True)
```

```
            # Sample next token
            idx_next = torch.multinomial(probs, num_samples=1)

            # Append to sequence
            idx = torch.cat((idx, idx_next), dim=1)

        return idx
```

[29]:
```
train_dataset = TextDataset(train_data, BLOCK_SIZE)
train_loader = DataLoader(train_dataset, batch_size=BATCH_SIZE, shuffle=True)
print(f"Total batches in one epoch: {len(train_loader)}")
```

```
Total batches in one epoch: 62737
```

[30]:
```
'''
def train_model():
    model = ShakespeareTransformer()
    print(f"Number of parameters: {sum(p.numel() for p in model.parameters())}")

    optimizer = torch.optim.AdamW(model.parameters(), lr=LEARNING_RATE)
    train_dataset = TextDataset(train_data, BLOCK_SIZE)
    train_loader = DataLoader(train_dataset, batch_size=BATCH_SIZE,␣
 ↪shuffle=True)

    best_loss = float('inf')
    start_time = time.time()

    # Training loop with progress tracking
    train_iter = iter(train_loader)
    for iteration in tqdm(range(MAX_ITERS), desc="Training Progress"):
        try:
            # Get batch
            try:
                xb, yb = next(train_iter)
            except StopIteration:
                train_iter = iter(train_loader)
                xb, yb = next(train_iter)

            # Forward pass
            logits = model(xb)
            loss = F.cross_entropy(logits.view(-1, VOCAB_SIZE), yb.view(-1))

            # Backward pass and optimize
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
```

```
            # Print progress every 100 iterations
            if iteration % 100 == 0:
                print(f"\nIteration {iteration}: loss {loss.item():.4f}")

        except Exception as e:
            print(f"\nError in iteration {iteration}")
            print("Error details:", str(e))
            raise e

    total_time = time.time() - start_time
    print(f"\nTraining completed in {total_time:.2f} seconds")

    return model
'''
'''
def train_model():
    model = ShakespeareTransformer()
    print(f"Number of parameters: {sum(p.numel() for p in model.parameters())}")

    optimizer = torch.optim.AdamW(model.parameters(), lr=LEARNING_RATE)
    train_dataset = TextDataset(train_data, BLOCK_SIZE)
    train_loader = DataLoader(train_dataset, batch_size=BATCH_SIZE,␣
 ↪shuffle=True)

    best_loss = float('inf')
    start_time = time.time()
    num_epochs = 3  # Increased number of epochs

    # Training loop with progress tracking
    for epoch in range(num_epochs):
        print(f"\nEpoch {epoch+1}/{num_epochs}")
        train_iter = iter(train_loader)
        running_loss = 0.0

        # Progress bar for each epoch
        num_batches = len(train_loader)
        progress_bar = tqdm(range(num_batches), desc=f"Epoch {epoch+1}")

        for batch_idx in progress_bar:
            try:
                # Get batch
                try:
                    xb, yb = next(train_iter)
                except StopIteration:
                    train_iter = iter(train_loader)
                    xb, yb = next(train_iter)
```

```
            # Forward pass
            logits = model(xb)
            loss = F.cross_entropy(logits.view(-1, VOCAB_SIZE), yb.view(-1))

            # Backward pass and optimize
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

            # Update running loss
            running_loss += loss.item()

            # Update progress bar
            progress_bar.set_postfix({
                'loss': f"{loss.item():.4f}",
                'avg_loss': f"{running_loss/(batch_idx+1):.4f}"
            })

            # Generate sample text every 500 batches
            if batch_idx % 500 == 0:
                model.eval()
                with torch.no_grad():
                    context = torch.zeros((1, 1), dtype=torch.long)
                    sample = model.generate(context, max_new_tokens=50,␣
↪temperature=0.7)[0]
                    #print(f"\nSample text at batch {batch_idx}:")
                    #print(decode(sample.tolist()))
                    print("-" * 50)
                model.train()

        except Exception as e:
            print(f"\nError in epoch {epoch+1}, batch {batch_idx}")
            print("Error details:", str(e))
            raise e

    # End of epoch stats
    avg_loss = running_loss / num_batches
    print(f"\nEpoch {epoch+1} completed. Average loss: {avg_loss:.4f}")

    # Save if best model
    if avg_loss < best_loss:
        best_loss = avg_loss
        torch.save({
            'epoch': epoch,
            'model_state_dict': model.state_dict(),
            'optimizer_state_dict': optimizer.state_dict(),
```

```
                'loss': best_loss,
            }, 'best_shakespeare_model.pth')
            print(f"New best model saved! Loss: {best_loss:.4f}")

    total_time = time.time() - start_time
    print(f"\nTraining completed in {total_time:.2f} seconds")
    print(f"Best loss achieved: {best_loss:.4f}")

    return model
'''

def train_model():
    """
    Training Loop Hyperparameters:

    num_epochs: Number of times to iterate through training data
        - Higher = More thorough training, longer time
        - Lower = Faster training, less thorough

    max_iters_per_epoch: How much of each epoch to process (percentage of total␣
 ↪dataset)
        - max_iters_per_epoch = len(train_loader) processes 100% of data per␣
 ↪epoch
        - max_iters_per_epoch = len(train_loader)//2 processes 50% of data per␣
 ↪epoch
        - max_iters_per_epoch = 1000 processes fixed 1000 batches per epoch

    log_every: How often to print loss statistics
        - Higher = Less frequent updates
        - Lower = More frequent updates

    generate_every: How often to generate sample text
        - Set to None to disable generation
        - Higher = Less frequent generation
        - Lower = More frequent generation

    save_best: Whether to save best model based on loss
        - True = Save best model (more disk usage)
        - False = Don't save models
    """

    model = ShakespeareTransformer()
    print(f"Number of parameters: {sum(p.numel() for p in model.parameters())}")

    optimizer = torch.optim.AdamW(model.parameters(), lr=LEARNING_RATE)
    train_dataset = TextDataset(train_data, BLOCK_SIZE)
    train_loader = DataLoader(train_dataset, batch_size=BATCH_SIZE, shuffle=True)
```

```python
# Training Configuration
num_epochs = 3
max_iters_per_epoch = 1000  # Adjust this to control how much of each epoch
↪to process max: 62737
log_every = 100
generate_every = 500  # Set to None to disable generation
save_best = True

best_loss = float('inf')
start_time = time.time()

# Training loop with progress tracking
for epoch in range(num_epochs):
    print(f"\nEpoch {epoch+1}/{num_epochs}")
    train_iter = iter(train_loader)
    running_loss = 0.0

    # Progress bar for specified iterations per epoch
    progress_bar = tqdm(range(max_iters_per_epoch), desc=f"Epoch {epoch+1}")

    for batch_idx in progress_bar:
        try:
            # Get batch
            try:
                xb, yb = next(train_iter)
            except StopIteration:
                train_iter = iter(train_loader)
                xb, yb = next(train_iter)

            # Forward pass
            logits = model(xb)
            loss = F.cross_entropy(logits.view(-1, VOCAB_SIZE), yb.view(-1))

            # Backward pass and optimize
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

            # Update running loss and progress bar
            running_loss += loss.item()
            if batch_idx % log_every == 0:
                progress_bar.set_postfix({
                    'loss': f"{loss.item():.4f}",
                    'avg_loss': f"{running_loss/(batch_idx+1):.4f}"
                })
```

```
                # Generate sample text if enabled
                if generate_every and batch_idx % generate_every == 0:
                    model.eval()
                    with torch.no_grad():
                        context = torch.zeros((1, 1), dtype=torch.long)
                        sample = model.generate(context, max_new_tokens=50,␣
↪temperature=0.7)[0]
                        print("-" * 50)
                    model.train()

            except Exception as e:
                print(f"\nError in epoch {epoch+1}, batch {batch_idx}")
                print("Error details:", str(e))
                raise e

        # End of epoch stats
        avg_loss = running_loss / max_iters_per_epoch
        print(f"\nEpoch {epoch+1} completed. Average loss: {avg_loss:.4f}")

        # Save if best model and enabled
        if save_best and avg_loss < best_loss:
            best_loss = avg_loss
            torch.save({
                'epoch': epoch,
                'model_state_dict': model.state_dict(),
                'optimizer_state_dict': optimizer.state_dict(),
                'loss': best_loss,
            }, 'best_shakespeare_model.pth')
            print(f"New best model saved! Loss: {best_loss:.4f}")

    total_time = time.time() - start_time
    print(f"\nTraining completed in {total_time:.2f} seconds")
    print(f"Best loss achieved: {best_loss:.4f}")

    return model

def train_model_with_embedding_tracking():
    """
    Training Loop Hyperparameters:

    num_epochs: Number of times to iterate through training data
    max_iters_per_epoch: Number of batches to process per epoch
        - Set to len(train_loader) for full dataset
        - Set to len(train_loader)//2 for half dataset
        - Set to fixed number (e.g., 1000) for partial processing
    log_every: How often to save embedding snapshots
    chars_to_track: Which characters to track in embedding space
```

```python
    """
    model = ShakespeareTransformer()
    optimizer = torch.optim.AdamW(model.parameters(), lr=LEARNING_RATE)

    # Training Configuration
    num_epochs = 3
    log_every = 100  # Save embeddings every 100 batches
    chars_to_track = ['a', 'e', 'i', 'o', 'u', '.', ',', ' ']
    char_indices = [stoi[c] for c in chars_to_track]

    # Setup data
    train_dataset = TextDataset(train_data, BLOCK_SIZE)
    train_loader = DataLoader(train_dataset, batch_size=BATCH_SIZE,␣
↪shuffle=True)
    max_iters_per_epoch = len(train_loader) // 3  # Process 25% of dataset per␣
↪epoch

    # Storage for histories
    embedding_history = []
    loss_history = []
    global_steps = []

    # Track total steps across all epochs
    total_steps = 0

    for epoch in range(num_epochs):
        print(f"\nEpoch {epoch+1}/{num_epochs}")
        train_iter = iter(train_loader)

        progress_bar = tqdm(range(max_iters_per_epoch),
                          desc=f"Epoch {epoch+1}/{num_epochs}")

        for batch_idx in progress_bar:
            try:
                # Get batch
                try:
                    xb, yb = next(train_iter)
                except StopIteration:
                    train_iter = iter(train_loader)
                    xb, yb = next(train_iter)

                # Forward pass
                logits = model(xb)
                loss = F.cross_entropy(logits.view(-1, VOCAB_SIZE), yb.view(-1))

                # Backward pass and optimize
                optimizer.zero_grad()
```

```
                loss.backward()
                optimizer.step()

                # Update progress bar
                progress_bar.set_postfix({'loss': f"{loss.item():.4f}"})

                # Save embeddings and loss periodically
                if batch_idx % log_every == 0:
                    current_embeddings = model.token_embedding.weight[char_indices].detach().numpy()
                    embedding_history.append(current_embeddings)
                    loss_history.append(loss.item())
                    global_steps.append(total_steps)

                total_steps += 1

            except Exception as e:
                print(f"\nError in epoch {epoch+1}, batch {batch_idx}")
                print("Error details:", str(e))
                raise e

    # Convert histories to numpy arrays
    embedding_history = np.array(embedding_history)
    loss_history = np.array(loss_history)
    global_steps = np.array(global_steps)

    # Plot results
    plt.figure(figsize=(15, 5))

    # Plot loss
    plt.subplot(121)
    plt.plot(global_steps, loss_history)
    plt.title('Training Loss')
    plt.xlabel('Steps')
    plt.ylabel('Loss')

    # Plot embedding trajectories
    plt.subplot(122)
    for i, char in enumerate(chars_to_track):
        plt.plot(embedding_history[:, i, 0],
                embedding_history[:, i, 1],
                'o-', label=char, alpha=0.5,
                markersize=2)
        # Mark start and end
        plt.plot(embedding_history[0, i, 0],
                embedding_history[0, i, 1],
                'o', color='red', markersize=5)
```

```python
        plt.plot(embedding_history[-1, i, 0],
                embedding_history[-1, i, 1],
                'o', color='green', markersize=5)

    plt.title('Embedding Evolution')
    plt.xlabel('Dimension 1')
    plt.ylabel('Dimension 2')
    plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
    plt.tight_layout()
    plt.show()

    return model, embedding_history, loss_history, global_steps, chars_to_track

'''
# Visualize the evolution of embeddings
plt.figure(figsize=(15, 5))

# Plot loss
plt.subplot(121)
plt.plot(loss_history)
plt.title('Training Loss')
plt.xlabel('Steps (x100)')
plt.ylabel('Loss')

# Plot embedding changes for first two dimensions
plt.subplot(122)
embedding_history = np.array(embedding_history)
for i, char in enumerate(chars_to_track):
    # Plot trajectory of each character
    plt.plot(embedding_history[:, i, 0], embedding_history[:, i, 1], 'o-',␣
 ↪label=char, alpha=0.5)
    # Mark start and end points
    plt.plot(embedding_history[0, i, 0], embedding_history[0, i, 1], 'o',␣
 ↪color='red')  # start
    plt.plot(embedding_history[-1, i, 0], embedding_history[-1, i, 1], 'o',␣
 ↪color='green')  # end

plt.title('Embedding Evolution (First 2 Dimensions)')
plt.xlabel('Dimension 1')
plt.ylabel('Dimension 2')
plt.legend()
plt.tight_layout()
plt.show()

# You could also create an animation
from matplotlib.animation import FuncAnimation
```

```
def animate_embeddings():
    fig, ax = plt.subplots(figsize=(8, 8))

    def update(frame):
        ax.clear()
        # Plot each character at this frame
        for i, char in enumerate(chars_to_track):
            ax.scatter(embedding_history[frame, i, 0],
                       embedding_history[frame, i, 1],
                       label=char)
            ax.annotate(char, (embedding_history[frame, i, 0],
                              embedding_history[frame, i, 1]))

        ax.set_title(f'Frame {frame}, Loss: {loss_history[frame]:.3f}')
        ax.legend()
        ax.set_xlim([embedding_history[:,:,0].min(), embedding_history[:,:,0].
↪max()])
        ax.set_ylim([embedding_history[:,:,1].min(), embedding_history[:,:,1].
↪max()])

    anim = FuncAnimation(fig, update, frames=len(embedding_history),
                        interval=100, repeat=False)
    plt.show()

# Create animation
animate_embeddings()
'''
```

[30]:
```
"\n# Visualize the evolution of embeddings\nplt.figure(figsize=(15, 5))\n\n#
Plot loss\nplt.subplot(121)\nplt.plot(loss_history)\nplt.title('Training
Loss')\nplt.xlabel('Steps (x100)')\nplt.ylabel('Loss')\n\n# Plot embedding
changes for first two dimensions\nplt.subplot(122)\nembedding_history =
np.array(embedding_history)\nfor i, char in enumerate(chars_to_track):\n    #
Plot trajectory of each character\n    plt.plot(embedding_history[:, i, 0],
embedding_history[:, i, 1], 'o-', label=char, alpha=0.5)\n    # Mark start and
end points\n    plt.plot(embedding_history[0, i, 0], embedding_history[0, i, 1],
'o', color='red')  # start\n    plt.plot(embedding_history[-1, i, 0],
embedding_history[-1, i, 1], 'o', color='green')  # end\n\nplt.title('Embedding
Evolution (First 2 Dimensions)')\nplt.xlabel('Dimension
1')\nplt.ylabel('Dimension
2')\nplt.legend()\nplt.tight_layout()\nplt.show()\n\n# You could also create an
animation\nfrom matplotlib.animation import FuncAnimation\n\ndef
animate_embeddings():\n    fig, ax = plt.subplots(figsize=(8, 8))\n    \n    def
update(frame):\n        ax.clear()\n        # Plot each character at this
frame\n        for i, char in enumerate(chars_to_track):\n
ax.scatter(embedding_history[frame, i, 0], \n
embedding_history[frame, i, 1],\n                      label=char)\n
```

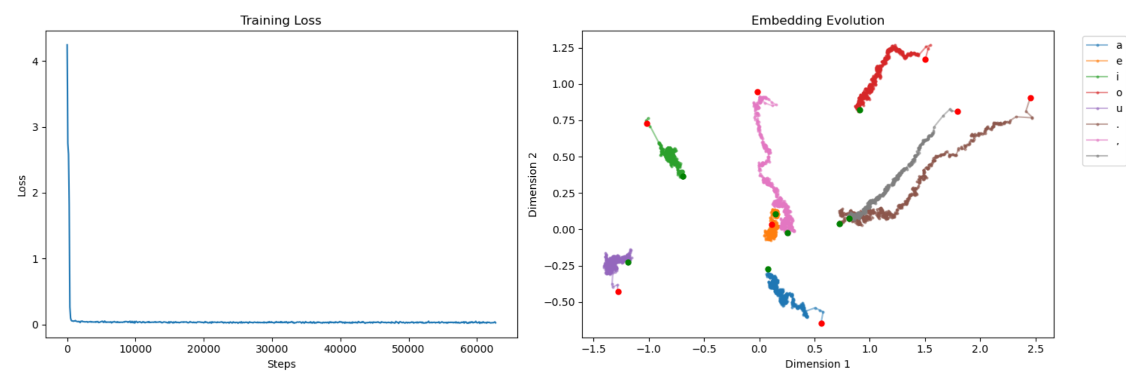
```
ax.annotate(char, (embedding_history[frame, i, 0], \n
embedding_history[frame, i, 1]))\n        \n        ax.set_title(f'Frame
{frame}, Loss: {loss_history[frame]:.3f}')\n        ax.legend()\n
ax.set_xlim([embedding_history[:,:,0].min(), embedding_history[:,:,0].max()])\n
ax.set_ylim([embedding_history[:,:,1].min(), embedding_history[:,:,1].max()])\n
\n    anim = FuncAnimation(fig, update, frames=len(embedding_history), \n
interval=100, repeat=False)\n    plt.show()\n\n# Create
animation\nanimate_embeddings()\n"
```

[31]:

```
# After training, save the model
def save_model(model, filename='shakespeare_model.pth'):
    # Save the model state dict
    torch.save({
        'model_state_dict': model.state_dict(),
        'vocab_mappings': {
            'stoi': stoi,
            'itos': itos
        },
        'model_config': {
            'EMB_SIZE': EMB_SIZE,
            'HEAD_SIZE': HEAD_SIZE,
            'NUM_HEADS': NUM_HEADS,
            'NUM_LAYERS': NUM_LAYERS,
            'BLOCK_SIZE': BLOCK_SIZE,
            'VOCAB_SIZE': VOCAB_SIZE
        }
    }, filename)
    print(f"Model saved to {filename}")

# Function to load the model
def load_model(filename='shakespeare_model.pth'):
    # Load the saved state
    checkpoint = torch.load(filename)

    # Create a new model instance with the saved configuration
    model = ShakespeareTransformer()

    # Load the state dict
    model.load_state_dict(checkpoint['model_state_dict'])

    # Load the vocabulary mappings
    global stoi, itos  # Update the global vocabulary mappings
    stoi = checkpoint['vocab_mappings']['stoi']
    itos = checkpoint['vocab_mappings']['itos']

    return model
```

[32]:
```python
# Usage:
# Train the model
#model = train_model()

# Train model and track embeddings
model, embedding_history, loss_history, global_steps, chars_to_track = train_model_with_embedding_tracking()

# Save the model
save_model(model)
```

```
Epoch 1/3

Epoch 1/3: 100%|      | 20912/20912 [08:13<00:00, 42.35it/s, loss=0.0231]


Epoch 2/3

Epoch 2/3: 100%|      | 20912/20912 [08:20<00:00, 41.76it/s, loss=0.0279]


Epoch 3/3

Epoch 3/3: 100%|      | 20912/20912 [13:58<00:00, 24.95it/s, loss=0.0372]
```




```
Model saved to shakespeare_model.pth
```

1 Embedding Evolution Analysis

1.1 Overall Pattern

The plot shows how different characters' embeddings evolved in 2D space during training, with each character's trajectory shown in a different color. Red dots mark starting positions and green dots mark ending positions.

1.2 Color-Coded Characters

- Blue trajectory: 'a' - Shows movement in the lower right quadrant
- Orange trajectory: 'e' - Positioned near the middle of the plot
- Green trajectory: 'i' - Located in the upper portion
- Red trajectory: 'o' - Shows movement in the middle region
- Purple trajectory: 'u' - Located in the uppermost portion of the plot
- Brown/Gray trajectories: '.' and ',' (punctuation) - Found in the lower portion
- Pink/Light trajectory: Space character (' ') - Distinct from both vowels and punctuation

1.3 Character Clustering

- Vowels ('a', 'e', 'i', 'o', 'u') have formed distinct clusters in different regions
- Related vowels ended up closer to each other (e.g., 'o' and 'i' show some proximity)
- Punctuation marks (',' and '.') and space character (' ') are clearly separated from vowels, suggesting the model learned fundamental differences between character types

1.4 Movement Patterns

- Each colored trajectory shows smooth movement from red dot (start) to green dot (end)
- Trajectories don't cross much, suggesting stable learning of relative relationships
- Characters maintain consistent distances once settled, visible in the parallel nature of some trajectories
- Space and punctuation embeddings (lighter colors) are distinctly clustered away from vowels (darker colors)

1.5 Training Implications

- Loss plot (left) shows rapid early reduction then stabilization
- Embedding trajectories mirror this: large initial movements followed by fine-tuning
- Final positions show clear separation between character types, indicating learned linguistic distinctions

[33]:
```python
# Load the model
loaded_model = load_model()

# Get embeddings from loaded model
embeddings = loaded_model.token_embedding.weight.data
print("\nEmbedding shape:", embeddings.shape)

# Simple similarity analysis
def find_similar_chars(char, top_k=3):
    char_idx = stoi[char]
    char_embedding = embeddings[char_idx]
    similarities = F.cosine_similarity(char_embedding.unsqueeze(0), embeddings)
    values, indices = torch.topk(similarities, top_k)
    return [(itos[idx.item()], sim.item()) for idx, sim in zip(indices, values)]

# Print similarities for example characters
```

```
for char in ['a', 'e', 't']:
    print(f"\nSimilar characters to '{char}':")
    print(find_similar_chars(char))

# Optional: Print some basic statistics about the embeddings
print("\nEmbedding Statistics:")
print(f"Mean embedding magnitude: {torch.norm(embeddings, dim=1).mean():.3f}")
print(f"Std of embedding magnitudes: {torch.norm(embeddings, dim=1).std():.3f}")

# Compare a specific pair of characters
char1, char2 = 'a', 'e'
emb1 = embeddings[stoi[char1]]
emb2 = embeddings[stoi[char2]]
similarity = F.cosine_similarity(emb1.unsqueeze(0), emb2.unsqueeze(0))
print(f"\nSimilarity between '{char1}' and '{char2}': {similarity.item():.3f}")
```

```
Embedding shape: torch.Size([65, 64])

Similar characters to 'a':
[('a', 0.9999999403953552), ('A', 0.3074165880680084), ('&',
0.19649668037891388)]

Similar characters to 'e':
[('e', 0.9999999403953552), ('u', 0.2676204741001129), ('3',
0.18413430452346802)]

Similar characters to 't':
[('t', 1.0000001192092896), ('T', 0.3213370144367218), ('p',
0.16861285269260406)]

Embedding Statistics:
Mean embedding magnitude: 4.591
Std of embedding magnitudes: 0.293

Similarity between 'a' and 'e': 0.175
```

[34]:
```
# Test the generation with different prompts
test_prompts = [
    #"GREMIO: Good morrow, neighbour Baptista.",
    #"ROMEO: O, she doth teach the torches to burn bright!",
    "HAMLET: To be, or not to be,"
]

for prompt in test_prompts:
    print("\nPrompt:", prompt)
    print("-" * 50)
```

```
    # Encode prompt
    context = torch.tensor([encode(prompt)], dtype=torch.long)

    # Generate completion
    with torch.no_grad():
        generated = loaded_model.generate(context, max_new_tokens=50,␣
↪temperature=0.7)[0]

    # Print result
    generated_text = decode(generated.tolist())
    prompt_len = len(prompt)
    print("Completion:")
    print(generated_text[prompt_len:])
    print("-" * 50)
```

```
Prompt: HAMLET: To be, or not to be,
--------------------------------------------------
Completion:

Bour the stair thou to dairs: thee word,
Thou to
--------------------------------------------------
```

[52]:
```
import os
import matplotlib.pyplot as plt
from matplotlib.animation import FuncAnimation

def save_embedding_animation():
    # Print current working directory
    current_dir = os.getcwd()
    print(f"Current working directory: {current_dir}")

    # Create full path for the gif
    gif_path = os.path.join(current_dir, 'embedding_evolution.gif')
    print(f"Will save animation to: {gif_path}")

    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 6))

    def update(frame):
        ax1.clear()
        ax2.clear()

        # Plot paths up to current frame
        for i, char in enumerate(chars_to_track):
            # Plot the full path with low alpha
```

```
            ax1.plot(embedding_history[:frame+1, i, 0],
                    embedding_history[:frame+1, i, 1],
                    'o-', alpha=0.3, markersize=2,
                    color=f'C{i}')

            # Plot current point with full opacity
            ax1.scatter(embedding_history[frame, i, 0],
                       embedding_history[frame, i, 1],
                       label=char,
                       color=f'C{i}')

            # Add character label
            ax1.annotate(char,
                        (embedding_history[frame, i, 0],
                         embedding_history[frame, i, 1]))

            # Mark start point with red
            if frame > 0:
                ax1.plot(embedding_history[0, i, 0],
                        embedding_history[0, i, 1],
                        'o', color='red', markersize=5)

        # Plot loss history up to current frame
        ax2.plot(loss_history[:frame+1])

        # Titles and labels
        ax1.set_title(f'Embedding Space (Frame {frame})')
        ax2.set_title(f'Loss History (Current: {loss_history[frame]:.3f})')
        ax1.legend()
        ax1.set_xlabel('Dimension 1')
        ax1.set_ylabel('Dimension 2')
        ax2.set_xlabel('Iteration')
        ax2.set_ylabel('Loss')

        # Set consistent axis limits
        ax1.set_xlim([embedding_history[:,:,0].min(), embedding_history[:,:,0].
↪max()])
        ax1.set_ylim([embedding_history[:,:,1].min(), embedding_history[:,:,1].
↪max()])
        ax2.set_ylim([min(loss_history), max(loss_history)])

    anim = FuncAnimation(fig, update,
                        frames=len(embedding_history),
                        interval=100,
                        repeat=False)

    # Save animation
```

```
    anim.save(gif_path, writer='pillow')
    plt.close()

    # Verify file was created
    if os.path.exists(gif_path):
        print(f"\nAnimation saved successfully to: {gif_path}")
        print(f"File size: {os.path.getsize(gif_path) / 1024:.2f} KB")
    else:
        print("\nError: File was not created!")

# Save animation
save_embedding_animation()
```

```
Current working directory:
/Users/pranavdhinakar/Documents/LLM/Experiments/Shakespeare
Will save animation to: /Users/pranavdhinakar/Documents/LLM/Experiments/Shakespe
are/embedding_evolution.gif

Animation saved successfully to: /Users/pranavdhinakar/Documents/LLM/Experiments
/Shakespeare/embedding_evolution.gif
File size: 5800.58 KB
```

[54]:
```
import os
import matplotlib.pyplot as plt
from matplotlib.animation import FuncAnimation
from mpl_toolkits.mplot3d import Axes3D

def save_embedding_animation_3d(max_frames=None, frame_interval=100,␣
 ↪frame_stride=1,
                              rotation_speed=0.5,  # Reduced from 2 to 0.5␣
 ↪degrees per frame
                              initial_elevation=20,
                              initial_azimuth=45):
    """
    Create and save a 3D animation of embedding evolution.

    Parameters:
    max_frames (int, optional): Maximum number of frames to show. If None,␣
 ↪shows all frames
    frame_interval (int): Milliseconds between frames (controls animation speed)
    frame_stride (int): Show every nth frame (e.g., 2 means show every second␣
 ↪frame)
    rotation_speed (float): Degrees to rotate per frame (smaller = slower␣
 ↪rotation)
    initial_elevation (float): Initial camera elevation angle in degrees
    initial_azimuth (float): Initial camera azimuth angle in degrees
    """
```

```python
current_dir = os.getcwd()
print(f"Current working directory: {current_dir}")

gif_path = os.path.join(current_dir, 'embedding_evolution_3d.gif')
print(f"Will save animation to: {gif_path}")

# Calculate total frames to show
total_frames = len(embedding_history)
if max_frames is not None:
    total_frames = min(max_frames, total_frames)

# Create frame indices with stride
frame_indices = range(0, total_frames, frame_stride)

fig = plt.figure(figsize=(15, 6))
ax1 = fig.add_subplot(121, projection='3d')
ax2 = fig.add_subplot(122)

def update(frame_idx):
    ax1.clear()
    ax2.clear()

    # Get actual frame number based on stride
    frame = frame_indices[frame_idx]

    # Update view angle for rotation effect
    current_azimuth = initial_azimuth + frame * rotation_speed
    ax1.view_init(elev=initial_elevation, azim=current_azimuth)

    # Plot paths up to current frame in 3D
    for i, char in enumerate(chars_to_track):
        # Plot the full path with low alpha
        ax1.plot3D(embedding_history[:frame+1, i, 0],
                   embedding_history[:frame+1, i, 1],
                   embedding_history[:frame+1, i, 2],
                   'o-', alpha=0.3, markersize=2,
                   color=f'C{i}')

        # Plot current point with full opacity
        ax1.scatter(embedding_history[frame, i, 0],
                    embedding_history[frame, i, 1],
                    embedding_history[frame, i, 2],
                    label=char,
                    color=f'C{i}',
                    s=100)

        # Add character label
```

```
            ax1.text(embedding_history[frame, i, 0] + 0.02,
                    embedding_history[frame, i, 1] + 0.02,
                    embedding_history[frame, i, 2] + 0.02,
                    char,
                    color=f'C{i}')

            # Mark start point with red
            if frame > 0:
                ax1.scatter(embedding_history[0, i, 0],
                          embedding_history[0, i, 1],
                          embedding_history[0, i, 2],
                          color='red',
                          s=100)

        # Plot loss history
        ax2.plot(loss_history[:frame+1])

        # Titles and labels
        ax1.set_title(f'3D Embedding Space (Frame {frame}/{total_frames-1})')
        ax2.set_title(f'Loss History (Current: {loss_history[frame]:.3f})')
        ax1.set_xlabel('Dimension 1')
        ax1.set_ylabel('Dimension 2')
        ax1.set_zlabel('Dimension 3')
        ax2.set_xlabel('Iteration')
        ax2.set_ylabel('Loss')

        # Set consistent axis limits
        ax1.set_xlim([embedding_history[:,:,0].min(), embedding_history[:,:,0].
↪max()])
        ax1.set_ylim([embedding_history[:,:,1].min(), embedding_history[:,:,1].
↪max()])
        ax1.set_zlim([embedding_history[:,:,2].min(), embedding_history[:,:,2].
↪max()])
        ax2.set_ylim([min(loss_history), max(loss_history)])

        # Add legend
        ax1.legend()

    anim = FuncAnimation(fig, update,
                        frames=len(frame_indices),
                        interval=frame_interval,
                        repeat=False)

    # Save animation
    anim.save(gif_path, writer='pillow')
    plt.close()
```

```
    if os.path.exists(gif_path):
        print(f"\nAnimation saved successfully to: {gif_path}")
        print(f"File size: {os.path.getsize(gif_path) / 1024:.2f} KB")
    else:
        print("\nError: File was not created!")

# Example usage with different rotation speeds:
# Very slow rotation
save_embedding_animation_3d(rotation_speed=0.2, max_frames=50)

# Medium rotation
# save_embedding_animation_3d(rotation_speed=0.5)

# Faster rotation
# save_embedding_animation_3d(rotation_speed=1.0)

# You can also combine with other parameters:
# save_embedding_animation_3d(
#     max_frames=100,
#     rotation_speed=0.3,
#     initial_elevation=30,
#     initial_azimuth=0
# )
```

```
Current working directory:
/Users/pranavdhinakar/Documents/LLM/Experiments/Shakespeare
Will save animation to: /Users/pranavdhinakar/Documents/LLM/Experiments/Shakespe
are/embedding_evolution_3d.gif

Animation saved successfully to: /Users/pranavdhinakar/Documents/LLM/Experiments
/Shakespeare/embedding_evolution_3d.gif
File size: 1187.28 KB
```

[56]:

```
import os
import matplotlib.pyplot as plt
from matplotlib.animation import FuncAnimation
from mpl_toolkits.mplot3d import Axes3D

def save_embedding_animation_3d(max_frames=None, frame_interval=100,␣
 ↪frame_stride=1,
                              rotation_speed=0.5,
                              initial_elevation=20,
                              initial_azimuth=45):
    """
    Create and save a 3D animation of embedding evolution.

    Parameters:
```

```
    max_frames (int, optional): Maximum number of frames to show. If None,␣
↪shows all frames
    frame_interval (int): Milliseconds between frames (controls animation speed)
    frame_stride (int): Show every nth frame (e.g., 2 means show every second␣
↪frame)
    rotation_speed (float): Degrees to rotate per frame (smaller = slower␣
↪rotation)
    initial_elevation (float): Initial camera elevation angle in degrees
    initial_azimuth (float): Initial camera azimuth angle in degrees
    """
    current_dir = os.getcwd()
    print(f"Current working directory: {current_dir}")

    gif_path = os.path.join(current_dir, 'embedding_evolution_3d.gif')
    print(f"Will save animation to: {gif_path}")

    # Calculate total frames to show
    total_frames = len(embedding_history)
    if max_frames is not None:
        total_frames = min(max_frames, total_frames)

    # Create frame indices with stride
    frame_indices = range(0, total_frames, frame_stride)

    fig = plt.figure(figsize=(15, 6))
    ax1 = fig.add_subplot(121, projection='3d')
    ax2 = fig.add_subplot(122)

    def update(frame_idx):
        ax1.clear()
        ax2.clear()

        # Get actual frame number based on stride
        frame = frame_indices[frame_idx]

        # Update view angle for rotation effect
        current_azimuth = initial_azimuth + frame * rotation_speed
        ax1.view_init(elev=initial_elevation, azim=current_azimuth)

        # Plot paths up to current frame in 3D
        for i, char in enumerate(chars_to_track):
            # Plot the historical path with very low alpha
            ax1.plot3D(embedding_history[:frame+1, i, 0],
                      embedding_history[:frame+1, i, 1],
                      embedding_history[:frame+1, i, 2],
                      '-', alpha=0.15, linewidth=1,  # Reduced alpha and␣
↪removed dots from path
```

```
                    color=f'C{i}')

          # Plot current point with full opacity and larger size
          ax1.scatter(embedding_history[frame, i, 0],
                     embedding_history[frame, i, 1],
                     embedding_history[frame, i, 2],
                     label=char,
                     color=f'C{i}',
                     s=150)  # Increased size for better visibility

          # Add character label with slight offset
          ax1.text(embedding_history[frame, i, 0] + 0.02,
                  embedding_history[frame, i, 1] + 0.02,
                  embedding_history[frame, i, 2] + 0.02,
                  char,
                  color=f'C{i}',
                  fontsize=10,
                  fontweight='bold')  # Made text bold for better visibility

      # Plot loss history
      ax2.plot(loss_history[:frame+1])

      # Titles and labels
      ax1.set_title(f'3D Embedding Space (Frame {frame}/{total_frames-1})')
      ax2.set_title(f'Loss History (Current: {loss_history[frame]:.3f})')
      ax1.set_xlabel('Dimension 1')
      ax1.set_ylabel('Dimension 2')
      ax1.set_zlabel('Dimension 3')
      ax2.set_xlabel('Iteration')
      ax2.set_ylabel('Loss')

      # Set consistent axis limits
      ax1.set_xlim([embedding_history[:,:,0].min(), embedding_history[:,:,0].
↪max()])
      ax1.set_ylim([embedding_history[:,:,1].min(), embedding_history[:,:,1].
↪max()])
      ax1.set_zlim([embedding_history[:,:,2].min(), embedding_history[:,:,2].
↪max()])
      ax2.set_ylim([min(loss_history), max(loss_history)])

      # Add legend
      ax1.legend(bbox_to_anchor=(1.05, 1), loc='upper left')

  anim = FuncAnimation(fig, update,
                      frames=len(frame_indices),
                      interval=frame_interval,
                      repeat=False)
```

```
    # Save animation
    anim.save(gif_path, writer='pillow')
    plt.close()

    if os.path.exists(gif_path):
        print(f"\nAnimation saved successfully to: {gif_path}")
        print(f"File size: {os.path.getsize(gif_path) / 1024:.2f} KB")
    else:
        print("\nError: File was not created!")

# Example usage with different rotation speeds:
# Very slow rotation
save_embedding_animation_3d(rotation_speed=0.2, max_frames=500)

# Medium rotation
# save_embedding_animation_3d(rotation_speed=0.5)

# Faster rotation
# save_embedding_animation_3d(rotation_speed=1.0)

# You can also combine with other parameters:
# save_embedding_animation_3d(
#     max_frames=100,
#     rotation_speed=0.3,
#     initial_elevation=30,
#     initial_azimuth=0
# )
```

```
Current working directory:
/Users/pranavdhinakar/Documents/LLM/Experiments/Shakespeare
Will save animation to: /Users/pranavdhinakar/Documents/LLM/Experiments/Shakespe
are/embedding_evolution_3d.gif

Animation saved successfully to: /Users/pranavdhinakar/Documents/LLM/Experiments
/Shakespeare/embedding_evolution_3d.gif
File size: 11614.72 KB
```

[ ]:

```

```