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# SoME Transformer V4.3 - Production-Optimized & All Bugs Fixed
# Implements:
#   1. All previous optimizations.
#   2. Definitive fix for DataLoader TypeError.
#   3. Definitive fix for index_add_ RuntimeError.
#   4. Using your specified "shrunk" A100-Safe configuration.
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# Part 1: Setup and Dependencies
# ================================
!pip install torch datasets transformers huggingface_hub tokenizers matplotlib -q

import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader, Dataset
from transformers import PreTrainedTokenizerFast
from tokenizers import Tokenizer
from tokenizers.models import BPE
from tokenizers.trainers import BpeTrainer
from tokenizers.pre_tokenizers import Whitespace
from datasets import load_dataset
import copy
from tqdm import tqdm
import math
import os
import numpy as np
import matplotlib.pyplot as plt

# Verify that a GPU is available and set the device
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")

# Enable TF32 for A100 GPUs for a free performance boost
if torch.cuda.is_available() and torch.cuda.get_device_capability(0)[0] >= 8:
   print("A100 GPU detected. Enabling TF32.")
   torch.set_float32_matmul_precision('high')

torch.backends.cudnn.benchmark = True
```

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# Part 2: Data Preparation (Fixed)
# ==========================================
SEQ_LEN = 512
BATCH_SIZE = 64
VOCAB_SIZE = 8192

print("--- Loading/Training Custom Tokenizer ---")
tokenizer_path = "tinystories-tokenizer-v2.json"
if not os.path.exists(tokenizer_path):
    dataset = load_dataset("roneneldan/TinyStories", split="train")
    def get_training_corpus():
        for i in range(0, len(dataset), 1000):
            yield dataset[i : i + 1000]["text"]
    tokenizer = Tokenizer(BPE(unk_token="[UNK]"))
    tokenizer.pre_tokenizer = Whitespace()
    trainer = BpeTrainer(special_tokens=["[UNK]", "[PAD]", "[EOS]"], vocab_size=VOCAB_SIZE)
    tokenizer.train_from_iterator(get_training_corpus(), trainer=trainer)
    tokenizer.save(tokenizer_path)
else:
    print("Tokenizer already exists. Loading from file.")

tokenizer = PreTrainedTokenizerFast(tokenizer_file=tokenizer_path)
tokenizer.add_special_tokens({'pad_token': '[PAD]', 'eos_token': '[EOS]'})
print(f"Custom tokenizer loaded with vocab size: {tokenizer.vocab_size}")

print("\n--- Tokenizing Dataset ---")
full_dataset = load_dataset("roneneldan/TinyStories")

train_subset_size = 40000
val_subset_size = 10000
train_subset = full_dataset['train'].select(range(train_subset_size))
val_subset = full_dataset['validation'].select(range(val_subset_size))

def tokenize_function(examples):
    return tokenizer(
        examples["text"], truncation=True, padding="max_length",
        max_length=SEQ_LEN
    )

tokenized_train = train_subset.map(tokenize_function, batched=True, remove_columns=["text"],
num_proc=os.cpu_count())
```
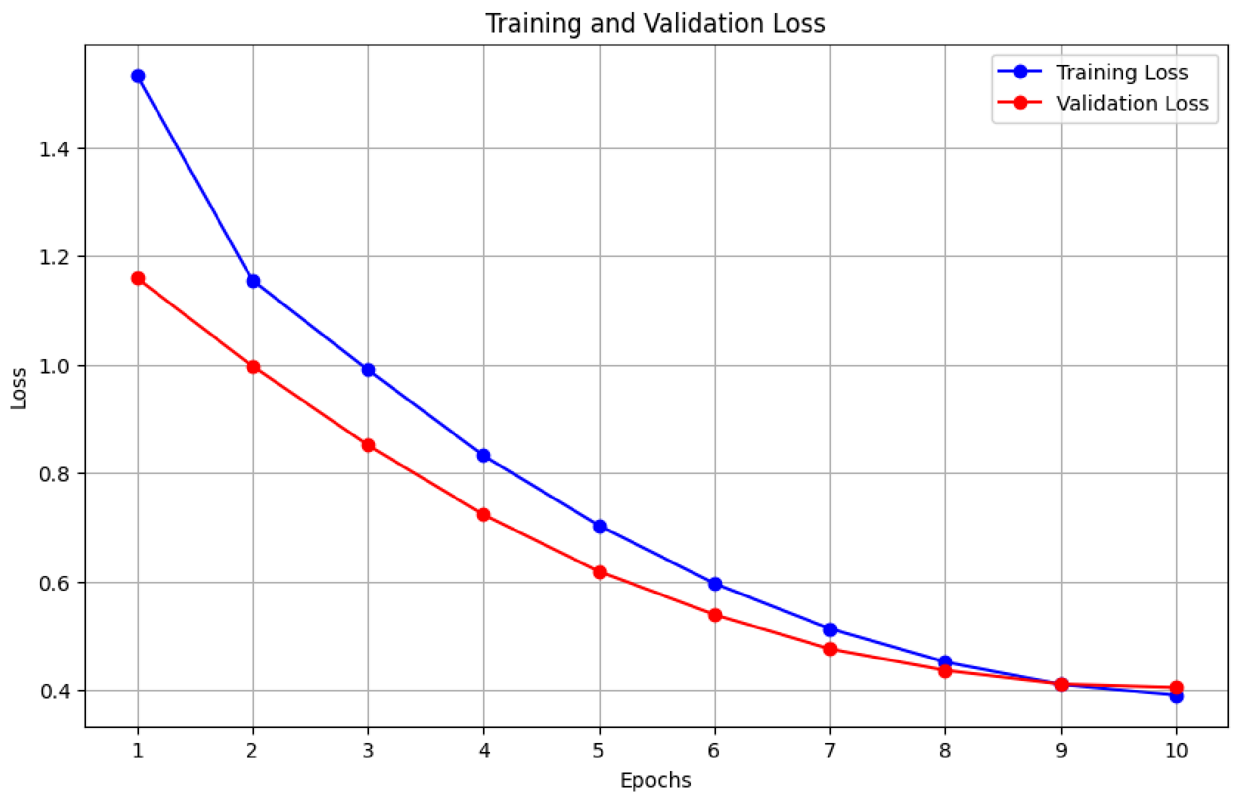

```
tokenized_val = val_subset.map(tokenize_function, batched=True, remove_columns=["text"],
num_proc=os.cpu_count())


class LanguageModelDataset(Dataset):
    def __init__(self, tokenized_data):
        self.data = tokenized_data

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

    def __getitem__(self, idx):
        item = self.data[idx]
        inputs = torch.tensor(item['input_ids'])
        targets = torch.roll(inputs, shifts=-1, dims=0)
        targets[-1] = -100
        return inputs, targets

train_dataset = LanguageModelDataset(tokenized_train)
validation_dataset = LanguageModelDataset(tokenized_val)

CPU_COUNT = os.cpu_count()
NUM_WORKERS = max(2, CPU_COUNT // 2 if CPU_COUNT else 2)
train_loader = DataLoader(train_dataset, batch_size=BATCH_SIZE, shuffle=True,
drop_last=True, num_workers=NUM_WORKERS, pin_memory=True)
validation_loader = DataLoader(validation_dataset, batch_size=BATCH_SIZE, drop_last=True,
num_workers=NUM_WORKERS, pin_memory=True)

print(f"Train dataset size (subset): {len(train_dataset)}")
print(f"Using {NUM_WORKERS} workers for DataLoader.")


# Part 3: Model Definition (Optimized & Fixed)
# ==============================================
class Expert(nn.Module):
    def __init__(self, d_model, d_ffn):
        super().__init__()
        self.w_down = nn.Linear(d_model, d_ffn)
        self.activation = nn.GELU()
        self.w_up = nn.Linear(d_ffn, d_model)
    def forward(self, x):
        return self.w_up(self.activation(self.w_down(x)))

class SOMELayer(nn.Module):
    def __init__(self, d_model, num_experts, d_ffn, top_k, alpha=0.01, beta=0.001, delta=0.001,
theta_percentile=0.05, warmup_steps=1000):
        super().__init__()
        self.d_model, self.num_experts, self.d_ffn, self.top_k = d_model, num_experts, d_ffn, top_k
        self.alpha, self.beta, self.delta = alpha, beta, delta
        self.theta_percentile = theta_percentile
        self.warmup_steps = warmup_steps
        self.query_network = nn.Linear(d_model, d_model)
        keys = torch.randn(num_experts, d_model)
        self.register_buffer("key_store", F.normalize(keys, p=2, dim=-1))
        self.register_buffer("usage_count", torch.zeros(num_experts))
        self.register_buffer("steps", torch.tensor([0], dtype=torch.long))
        self.experts = nn.ModuleList([Expert(d_model, d_ffn) for _ in range(num_experts)])
        for expert in self.experts:
            for param in expert.parameters():
                param.requires_grad = False
        if self.top_k > 1:
            self.register_buffer("peer_pull_indices", torch.combinations(torch.arange(self.top_k),
r=2))

    def forward(self, x):
        batch_size, seq_len, _ = x.shape
        x_flat = x.view(-1, self.d_model)
        queries = self.query_network(x_flat)
        scores = torch.matmul(queries, self.key_store.t())
        top_k_scores, top_k_indices = torch.topk(scores, self.top_k, dim=-1)
        gating_weights = F.softmax(top_k_scores, dim=-1)

        flat_top_k_indices = top_k_indices.view(-1)

        sorted_indices, permutation_map = torch.sort(flat_top_k_indices)
        unique_expert_ids, counts = torch.unique_consecutive(sorted_indices,
return_counts=True)

        flat_inputs = x_flat.repeat_interleave(self.top_k, dim=0)
        permuted_inputs = flat_inputs[permutation_map]

        split_inputs = torch.split(permuted_inputs, counts.tolist(), dim=0)

        output_chunks = []
        for i, expert_id in enumerate(unique_expert_ids):
            output_chunks.append(self.experts[expert_id](split_inputs[i]))

        concatenated_outputs = torch.cat(output_chunks, dim=0)
        inverse_permutation_map = torch.argsort(permutation_map)
        expert_outputs = concatenated_outputs[inverse_permutation_map]

        weighted_outputs = (expert_outputs.view(-1, self.top_k, self.d_model) *
gating_weights.unsqueeze(-1)).sum(dim=1)
        final_output = weighted_outputs.view(batch_size, seq_len, self.d_model)

        return x + final_output, queries, top_k_indices

    @torch.no_grad()
    def update_keys(self, queries, top_k_indices):
        self.steps += 1

        unique_indices, counts = torch.unique(top_k_indices, return_counts=True)

        # DEFINITIVE FIX for RuntimeError: Cast `counts` to float before adding.
        self.usage_count.index_add_(0, unique_indices, counts.float())

        for i in range(self.top_k):
            indices = top_k_indices[:, i]
            inertia = 1.0 + self.usage_count[indices]
            alpha_effective = self.alpha / inertia.unsqueeze(-1)
            update_vec = queries - self.key_store[indices]
            self.key_store.index_add_(0, indices, alpha_effective * update_vec)

        if self.top_k > 1:
            indices_i = top_k_indices[:, self.peer_pull_indices[:, 0]].reshape(-1)
            indices_j = top_k_indices[:, self.peer_pull_indices[:, 1]].reshape(-1)
            keys_i = self.key_store[indices_i]
            keys_j = self.key_store[indices_j]
            inertia_i = (1.0 + self.usage_count[indices_i]).unsqueeze(-1)
            inertia_j = (1.0 + self.usage_count[indices_j]).unsqueeze(-1)
            beta_effective = self.beta / torch.min(inertia_i, inertia_j)
            update_vec_i = beta_effective * (keys_j - keys_i)
            update_vec_j = beta_effective * (keys_i - keys_j)
            self.key_store.index_add_(0, indices_i, update_vec_i)
            self.key_store.index_add_(0, indices_j, update_vec_j)

        self.key_store.data = F.normalize(self.key_store.data, p=2, dim=-1)

        if self.steps > self.warmup_steps:
            active_usage_counts = self.usage_count[self.usage_count > 0]
            if active_usage_counts.numel() > 0:
                dynamic_theta = torch.quantile(active_usage_counts.float(), self.theta_percentile)
            low_usage_mask = self.usage_count < dynamic_theta
            self.key_store[low_usage_mask] *= (1.0 - self.delta)

class SOMETransformerBlock(nn.Module):
    def __init__(self, d_model, num_heads, some_layer):
        super().__init__()
        self.attention = nn.MultiheadAttention(d_model, num_heads, batch_first=True)
        self.norm1 = nn.LayerNorm(d_model)
        self.norm2 = nn.LayerNorm(d_model)
        self.some_layer = some_layer
    def forward(self, x):
        attn_output, _ = self.attention(x, x, x)
        x = self.norm1(x + attn_output)
        some_output, queries, top_k_indices = self.some_layer(x)
        x = self.norm2(some_output)
        return x, queries, top_k_indices

class PositionalEncoding(nn.Module):
    def __init__(self, d_model, max_len=5000):
        super().__init__()
        pe = torch.zeros(max_len, d_model)
        position = torch.arange(0, max_len, dtype=torch.float).unsqueeze(1)
        div_term = torch.exp(torch.arange(0, d_model, 2).float() * (-math.log(10000.0) / d_model))
        pe[:, 0::2] = torch.sin(position * div_term)
        pe[:, 1::2] = torch.cos(position * div_term)
        pe = pe.unsqueeze(0)
        self.register_buffer('pe', pe)
    def forward(self, x):
        return x + self.pe[:, :x.size(1)]

class SOMETransformer(nn.Module):
    def __init__(self, vocab_size, d_model, num_heads, num_layers, some_config):
        super().__init__()
        self.embedding = nn.Embedding(vocab_size, d_model)
        self.pos_encoder = PositionalEncoding(d_model, max_len=SEQ_LEN)
        self.layers = nn.ModuleList([
            SOMETransformerBlock(d_model, num_heads, SOMELayer(d_model=d_model,
**some_config))
            for _ in range(num_layers)
        ])
        self.fc_out = nn.Linear(d_model, vocab_size)

    def forward(self, x):
        x = self.embedding(x) * math.sqrt(self.embedding.embedding_dim)
        x = self.pos_encoder(x)
        all_queries, all_indices = [], []
        for layer in self.layers:
            x, queries, top_k_indices = layer(x)
            all_queries.append(queries)
            all_indices.append(top_k_indices)
        return self.fc_out(x), all_queries, all_indices

    @torch.no_grad()
    def update_all_keys(self, all_queries, all_indices):
        for i, layer_block in enumerate(self.layers):
            queries = all_queries[i].view(-1, layer_block.some_layer.d_model)
            indices = all_indices[i].view(-1, layer_block.some_layer.top_k)
            layer_block.some_layer.update_keys(queries, indices)

# Part 4: Training, Evaluation, and Metrics
# ===========================================================
scaler = torch.amp.GradScaler("cuda")

def calculate_gini(usage_counts):
    counts = usage_counts.cpu().to(torch.float32).numpy()
    if np.sum(counts) == 0: return 0.0
    counts = np.sort(counts)
    n = len(counts)
    index = np.arange(1, n + 1)
    return (np.sum((2 * index - n - 1) * counts)) / (n * np.sum(counts))

def calculate_entropy(usage_counts):
    total_usage = usage_counts.sum()
    if total_usage == 0: return 0.0
    probs = usage_counts / total_usage
    probs = probs[probs > 0]
    return -torch.sum(probs * torch.log2(probs)).item()

def train_epoch(model, dataloader, optimizer, criterion, scheduler):
    model.train()
    total_loss = 0
    progress_bar = tqdm(dataloader, desc="Training", leave=False)
    for inputs, targets in progress_bar:
        inputs, targets = inputs.to(device, non_blocking=True), targets.to(device,
non_blocking=True)
        with torch.amp.autocast("cuda"):
            logits, queries, indices = model(inputs)
            loss = criterion(logits.view(-1, tokenizer.vocab_size), targets.view(-1))
        optimizer.zero_grad(set_to_none=True)
        scaler.scale(loss).backward()
        scaler.unscale_(optimizer)
        torch.nn.utils.clip_grad_norm_(model.parameters(), 1.0)
        scaler.step(optimizer)
        scaler.update()
        scheduler.step()

        model.update_all_keys(queries, indices)

        total_loss += loss.item()
        progress_bar.set_postfix({'loss': f'{loss.item():.4f}', 'lr': f'{scheduler.get_last_lr()[0]:.1e}'})
    return total_loss / len(dataloader)

def evaluate_epoch(model, dataloader, criterion):
    model.eval()
    total_loss = 0
    progress_bar = tqdm(dataloader, desc="Evaluating", leave=False)
    with torch.no_grad():
        for inputs, targets in progress_bar:
            inputs, targets = inputs.to(device, non_blocking=True), targets.to(device,
non_blocking=True)
            with torch.amp.autocast("cuda"):
                logits, _, _ = model(inputs)
                loss = criterion(logits.view(-1, tokenizer.vocab_size), targets.view(-1))
            total_loss += loss.item()
            progress_bar.set_postfix({'loss': f'{loss.item():.4f}'})
    return total_loss / len(dataloader)

def plot_losses(train_losses, val_losses, epochs):
    plt.figure(figsize=(10, 6))
    plt.plot(range(1, epochs + 1), train_losses, 'b-o', label='Training Loss')
    plt.plot(range(1, epochs + 1), val_losses, 'r-o', label='Validation Loss')
    plt.title('Training and Validation Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()
    plt.grid(True)
    plt.xticks(range(1, epochs + 1))
    plt.savefig('loss_curve_a100_safe.png')
    print("\nLoss curve plot saved to loss_curve_a100_safe.png")

# Part 5: Main Execution Block (Your "Shrunk" A100-Safe Config)
# ======================================================
# This is the shrunk configuration you were running that caused the OOM.
D_MODEL = 512
NUM_HEADS = 8
NUM_LAYERS = 8
some_config = {
    "num_experts": 256,
    "d_ffn": 1536,
    "top_k": 8,
    "alpha": 0.01,
    "beta": 0.001,
    "delta": 0.001,
    "theta_percentile": 0.05,
    "warmup_steps": 2000
}

NUM_EPOCHS = 10
LEARNING_RATE = 6e-4

# --- Initialization ---
model = SOMETransformer(
    vocab_size=tokenizer.vocab_size, d_model=D_MODEL, num_heads=NUM_HEADS,
    num_layers=NUM_LAYERS, some_config=some_config
).to(device)

if hasattr(torch, 'compile'):
    print("\nCompiling the model for faster training...")
    model = torch.compile(model)

optimizer = torch.optim.AdamW([p for p in model.parameters() if p.requires_grad],
lr=LEARNING_RATE, betas=(0.9, 0.95), weight_decay=0.1)
criterion = nn.CrossEntropyLoss(ignore_index=-100)
total_steps = len(train_loader) * NUM_EPOCHS
scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=total_steps)

print(f"\nTotal parameters: {sum(p.numel() for p in model.parameters())/1e6:.2f}M")
print(f"Trainable parameters: {sum(p.numel() for p in model.parameters() if
p.requires_grad)/1e6:.2f}M")
print(f"Total training steps: {total_steps}")


# --- Run Training and Metric Tracking ---
train_losses, val_losses = [], []
best_val_loss = float('inf')
```

```
for epoch in range(NUM_EPOCHS):
    print(f"\n--- Epoch {epoch+1}/{NUM_EPOCHS} ---")
    train_loss = train_epoch(model, train_loader, optimizer, criterion, scheduler)
    val_loss = evaluate_epoch(model, validation_loader, criterion)
    perplexity = math.exp(val_loss)

    train_losses.append(train_loss)
    val_losses.append(val_loss)

    model_to_inspect = model._orig_mod if hasattr(model, '_orig_mod') else model
    usage_counts = model_to_inspect.layers[NUM_LAYERS // 2].some_layer.usage_count
    gini_coeff = calculate_gini(usage_counts)
    entropy_val = calculate_entropy(usage_counts)

    print(f"Epoch {epoch+1}: Train Loss = {train_loss:.4f}, Val Loss = {val_loss:.4f}, Val Perplexity
= {perplexity:.2f}")
    print(f"  └─ Middle Layer Expert Metrics: Gini = {gini_coeff:.3f}, Entropy = {entropy_val:.3f}")

    if val_loss < best_val_loss:
        best_val_loss = val_loss
        torch.save(model_to_inspect.state_dict(), "best_some_transformer_a100_safe.pth")
        print("Model saved as best_some_transformer_a100_safe.pth")

print("\n--- A100-Safe Training Complete ---")
plot_losses(train_losses, val_losses, NUM_EPOCHS)
```

```
 Using device: cuda
A100 GPU detected. Enabling TF32.
--- Loading/Training Custom Tokenizer ---
README.md:    1.06k/?  [00:00<00:00,  106kB/s]data/train-00000-of-00004-2d5a1467fff108(…):
  100%  249M/249M  [00:01<00:00,  260MB/s]data/train-00001-of-00004-5852b56a2bd28f(…):
100%  248M/248M  [00:01<00:00,  209MB/s]data/train-00002-of-00004-a26307300439e9(…):
100%  246M/246M  [00:01<00:00,  235MB/s]data/train-00003-of-00004-d243063613e5a0(…):
100%  248M/248M  [00:01<00:00,  230MB/s]data/validation-00000-of-00001-869c898b5(…):  1
00%  9.99M/9.99M  [00:00<00:00,  23.1MB/s]Generating  train  split:  100%  2119719/2119719
[00:06<00:00,  355343.88  examples/s]Generating  validation  split:  100%  21990/21990  [00:00
<00:00,  290010.90  examples/s]Custom tokenizer loaded with vocab size: 8192

--- Tokenizing Dataset ---
```

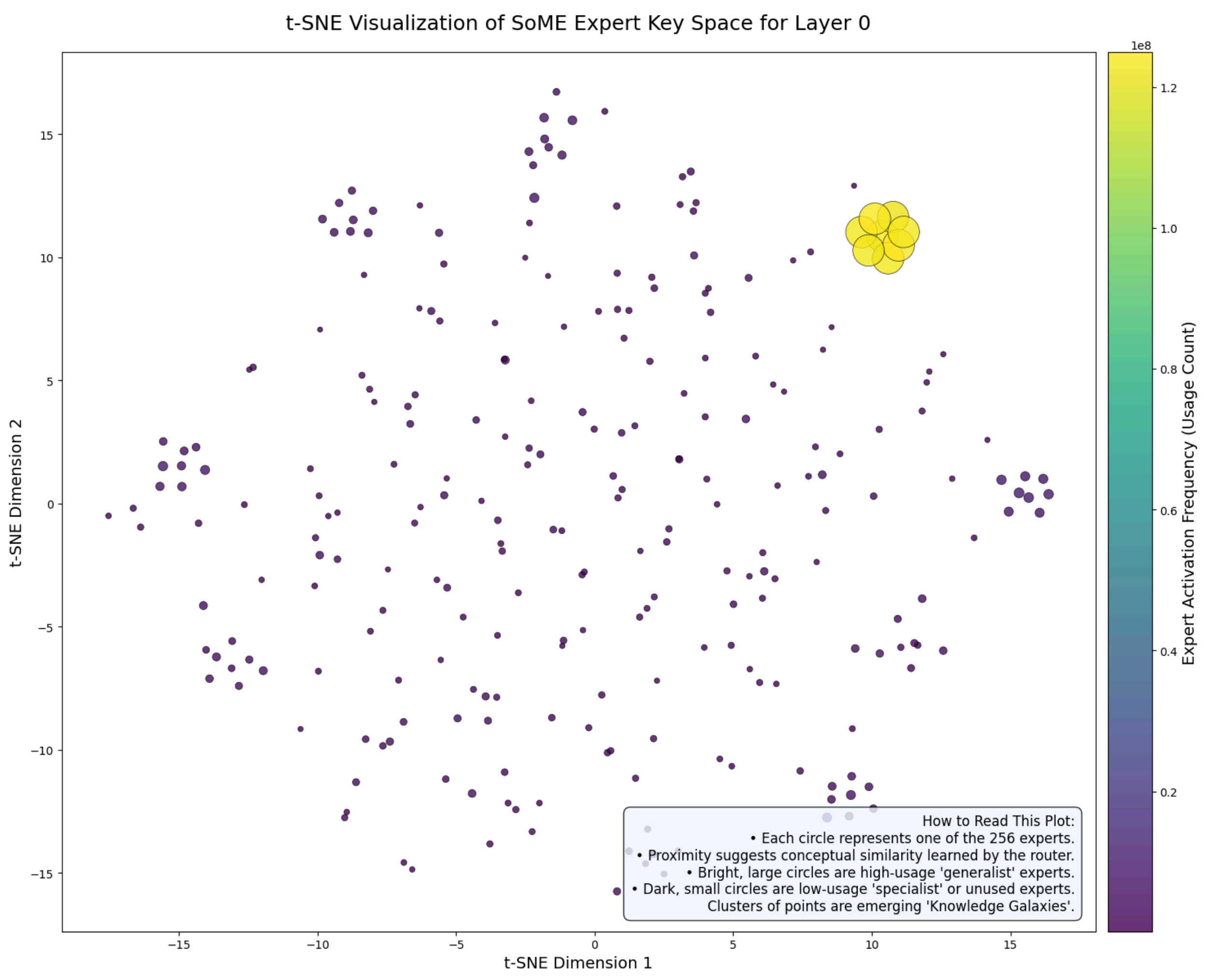
```
Map (num_proc=12): 100% 40000/40000 [00:04<00:00, 14113.17 examples/s]Map (num_pr
oc=12): 100% 10000/10000 [00:01<00:00, 825.39 examples/s]Train dataset size (subset):
40000
Using 6 workers for DataLoader.

Compiling the model for faster training...

Total parameters: 3244.34M
Trainable parameters: 18.92M
Total training steps: 6250

--- Epoch 1/10 ---
Training:   0%|          | 0/625 [00:00<?,
?it/s]/usr/local/lib/python3.12/dist-packages/torch/optim/lr_scheduler.py:192: UserWarning:
Detected call of `lr_scheduler.step()` before `optimizer.step()`. In PyTorch 1.1.0 and later, you
should call them in the opposite order: `optimizer.step()` before `lr_scheduler.step()`.  Failure to
do this will result in PyTorch skipping the first value of the learning rate schedule. See more
details at https://pytorch.org/docs/stable/optim.html#how-to-adjust-learning-rate
  warnings.warn(
Epoch 1: Train Loss = 1.5334, Val Loss = 1.1589, Val Perplexity = 3.19
  └─ Middle Layer Expert Metrics: Gini = 0.878, Entropy = 5.178
Model saved as best_some_transformer_a100_safe.pth

--- Epoch 2/10 ---
Epoch 2: Train Loss = 1.1551, Val Loss = 0.9970, Val Perplexity = 2.71
  └─ Middle Layer Expert Metrics: Gini = 0.874, Entropy = 5.221
Model saved as best_some_transformer_a100_safe.pth

--- Epoch 3/10 ---
Epoch 3: Train Loss = 0.9901, Val Loss = 0.8513, Val Perplexity = 2.34
  └─ Middle Layer Expert Metrics: Gini = 0.871, Entropy = 5.245
Model saved as best_some_transformer_a100_safe.pth

--- Epoch 4/10 ---
Epoch 4: Train Loss = 0.8322, Val Loss = 0.7234, Val Perplexity = 2.06
  └─ Middle Layer Expert Metrics: Gini = 0.869, Entropy = 5.262
Model saved as best_some_transformer_a100_safe.pth

--- Epoch 5/10 ---
Epoch 5: Train Loss = 0.7033, Val Loss = 0.6187, Val Perplexity = 1.86
  └─ Middle Layer Expert Metrics: Gini = 0.867, Entropy = 5.274
Model saved as best_some_transformer_a100_safe.pth

--- Epoch 6/10 ---
```

```
Epoch 6: Train Loss = 0.5965, Val Loss = 0.5393, Val Perplexity = 1.71
  └─ Middle Layer Expert Metrics: Gini = 0.866, Entropy = 5.281
Model saved as best_some_transformer_a100_safe.pth

--- Epoch 7/10 ---
Epoch 7: Train Loss = 0.5132, Val Loss = 0.4757, Val Perplexity = 1.61
  └─ Middle Layer Expert Metrics: Gini = 0.865, Entropy = 5.286
Model saved as best_some_transformer_a100_safe.pth

--- Epoch 8/10 ---
Epoch 8: Train Loss = 0.4517, Val Loss = 0.4365, Val Perplexity = 1.55
  └─ Middle Layer Expert Metrics: Gini = 0.865, Entropy = 5.290
Model saved as best_some_transformer_a100_safe.pth

--- Epoch 9/10 ---
Epoch 9: Train Loss = 0.4108, Val Loss = 0.4113, Val Perplexity = 1.51
  └─ Middle Layer Expert Metrics: Gini = 0.864, Entropy = 5.293
Model saved as best_some_transformer_a100_safe.pth

--- Epoch 10/10 ---
Epoch 10: Train Loss = 0.3904, Val Loss = 0.4049, Val Perplexity = 1.50
  └─ Middle Layer Expert Metrics: Gini = 0.864, Entropy = 5.296
Model saved as best_some_transformer_a100_safe.pth

--- A100-Safe Training Complete ---

Loss curve plot saved to loss_curve_a100_safe.png
```

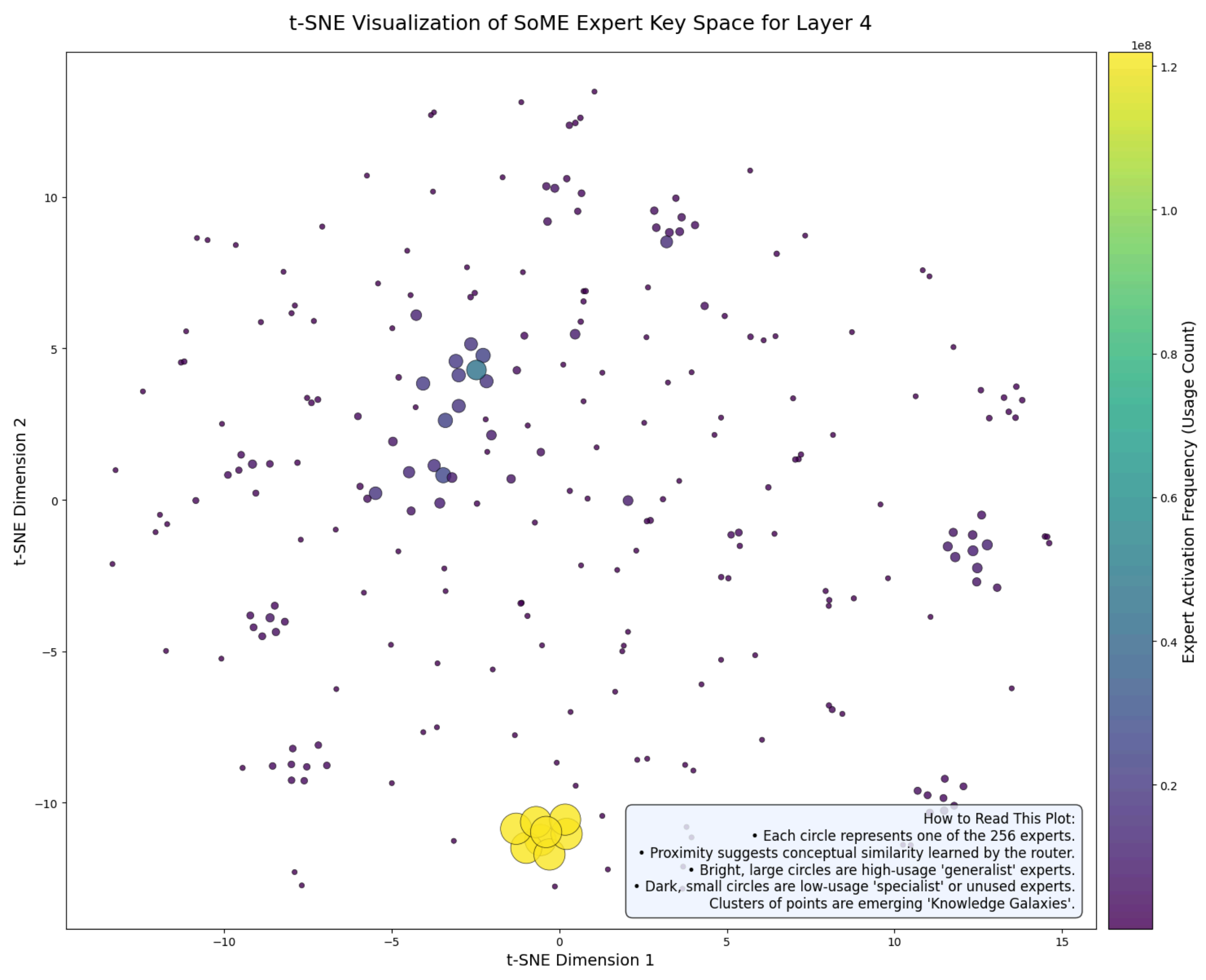


```
# ==========================================================================================
# Cell 2: Advanced Visualization of Expert "Knowledge Galaxies"
# ==========================================================================================

from sklearn.manifold import TSNE
import matplotlib.pyplot as plt
import numpy as np

# Ensure the model class definitions from the previous cell are available
# (SOMETransformer, SOMETransformerBlock, SOMELayer, Expert, PositionalEncoding)

# --- Step 1: Re-instantiate the model with the exact trained architecture ---
# This uses the configuration variables from the previous cell to prevent errors.
print("--- Re-instantiating model for visualization ---")
model_viz = SOMETransformer(
    vocab_size=tokenizer.vocab_size,
    d_model=D_MODEL,
    num_heads=NUM_HEADS,
    num_layers=NUM_LAYERS,
    some_config=some_config
)

# --- Step 2: Load the saved weights ---
model_path = "best_some_transformer_a100_safe.pth"
print(f"--- Loading weights from {model_path} ---")
try:
    # We load onto the CPU for analysis to free up GPU VRAM
    model_viz.load_state_dict(torch.load(model_path, map_location="cpu"))
    print("Successfully loaded trained model weights.")
except Exception as e:
    print(f"Error loading model weights: {e}")
    print("Please ensure the model file exists and the architecture matches the saved weights.")

model_viz.eval()

# --- Step 3: Define a reusable plotting function ---
def plot_galaxy(layer_index, perplexity=30, n_iter=1000):
    """
    Extracts keys and usage from a specific layer, runs t-SNE, and plots the result.
    """
    print(f"\n--- Visualizing Layer {layer_index} ---")

    # Extract data from the specified layer
    try:
        layer_to_inspect = model_viz.layers[layer_index].some_layer
        keys = layer_to_inspect.key_store.detach().cpu().numpy()
        usage = layer_to_inspect.usage_count.detach().cpu().numpy()
    except IndexError:
        print(f"Error: Layer index {layer_index} is out of bounds for a model with {NUM_LAYERS}
layers.")
        return

    print(f"Extracted {keys.shape[0]} keys. Total usage: {int(usage.sum())}")

    # Handle the case where a layer might have zero usage if training was very short
    if usage.sum() == 0:
        print(f"Warning: Layer {layer_index} has zero expert usage. Cannot normalize size or color.
Plotting uniformly.")
        usage_normalized = np.zeros_like(usage)
    else:
        usage_normalized = usage / usage.sum()
    # Perform t-SNE dimensionality reduction
    print(f"Running t-SNE with perplexity={perplexity}... (this may take a moment)")
    tsne = TSNE(n_components=2, perplexity=perplexity, random_state=42, n_iter=n_iter,
init='pca', learning_rate='auto')
    keys_2d = tsne.fit_transform(keys)
    print("t-SNE complete.")

    # Create the plot
    fig, ax = plt.subplots(figsize=(16, 12))
    scatter = ax.scatter(
        keys_2d[:, 0],
        keys_2d[:, 1],
        c=usage,
        s=20 + usage_normalized * 10000, # Increased multiplier for better size variation
        cmap='viridis',
        alpha=0.8,
        edgecolor='k',
        linewidth=0.5
    )

    cbar = fig.colorbar(scatter, ax=ax, pad=0.01)
    cbar.set_label('Expert Activation Frequency (Usage Count)', fontsize=14)

    ax.set_title(f't-SNE Visualization of SoME Expert Key Space for Layer {layer_index}',
fontsize=18, pad=20)
    ax.set_xlabel('t-SNE Dimension 1', fontsize=14)
    ax.set_ylabel('t-SNE Dimension 2', fontsize=14)

    info_text = (
        "How to Read This Plot:\n"
        "• Each circle represents one of the {num_experts} experts.\n"
        "• Proximity suggests conceptual similarity learned by the router.\n"
        "• Bright, large circles are high-usage 'generalist' experts.\n"
        "• Dark, small circles are low-usage 'specialist' or unused experts.\n"
        "Clusters of points are emerging 'Knowledge Galaxies'."
    ).format(num_experts=keys.shape[0])

    ax.text(0.98, 0.02, info_text, transform=ax.transAxes, fontsize=12,
            verticalalignment='bottom', horizontalalignment='right',
            bbox=dict(boxstyle='round,pad=0.5', fc='aliceblue', alpha=0.8))

    plt.tight_layout()
    plt.savefig(f"expert_galaxy_layer_{layer_index}.png", dpi=300)
    print(f"Visualization for layer {layer_index} saved as 'expert_galaxy_layer_{layer_index}.png'")
    plt.show()

# --- Step 4: Generate plots for key layers ---
# We visualize the first, middle, and last layers to see how organization evolves.
layers_to_plot = [0, NUM_LAYERS // 2, NUM_LAYERS - 1]
for layer_idx in layers_to_plot:
    plot_galaxy(layer_index=layer_idx)
```

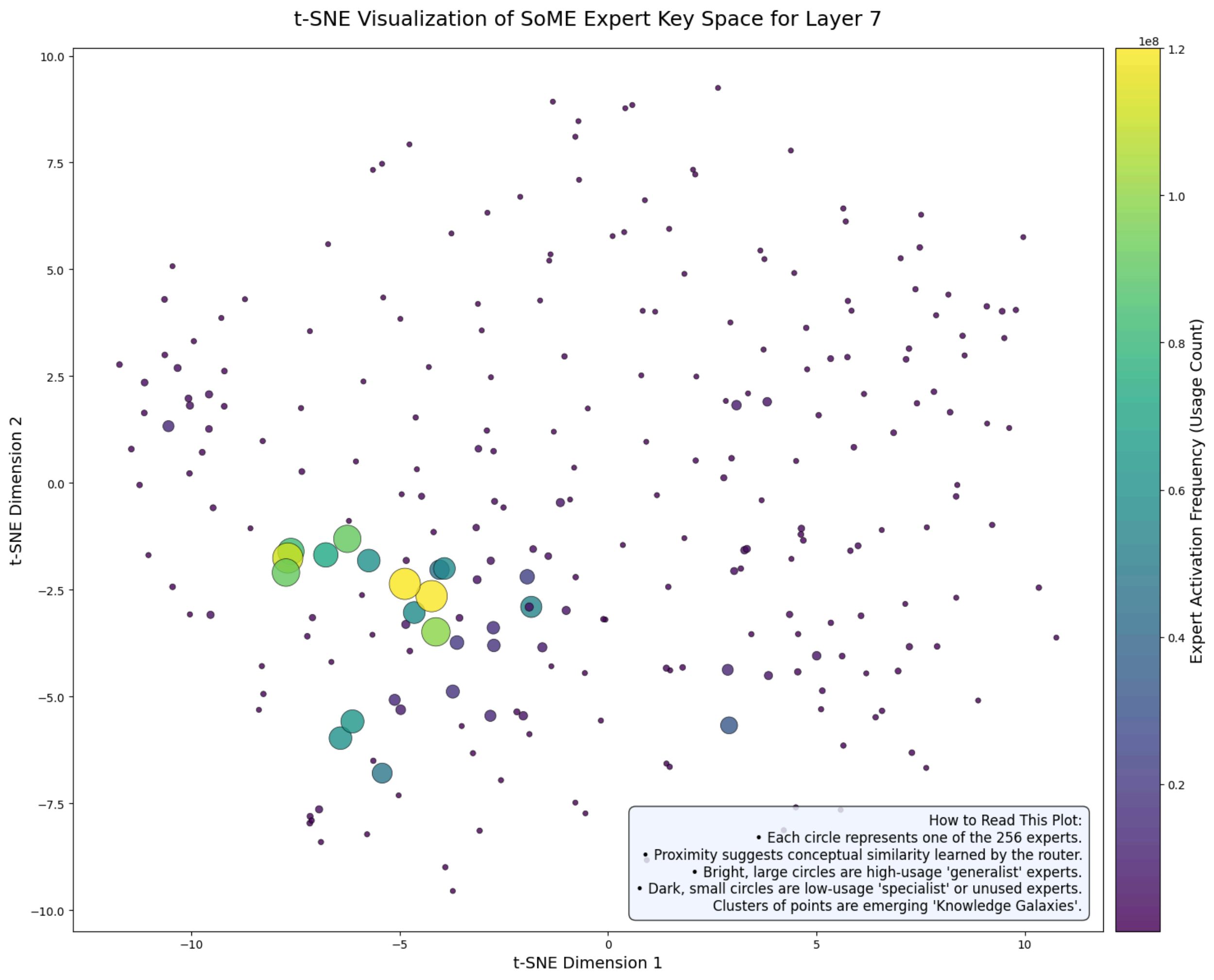
```
--- Re-instantiating model for visualization ---
--- Loading weights from best_some_transformer_a100_safe.pth ---
Successfully loaded trained model weights.

--- Visualizing Layer 0 ---
Extracted 256 keys. Total usage: 1638400128
Running t-SNE with perplexity=30... (this may take a moment)

/usr/local/lib/python3.12/dist-packages/sklearn/manifold/_t_sne.py:1164: FutureWarning: 'n_iter'
was renamed to 'max_iter' in version 1.5 and will be removed in 1.7.
  warnings.warn(

t-SNE complete.
Visualization for layer 0 saved as 'expert_galaxy_layer_0.png'
```



```
--- Visualizing Layer 4 ---
Extracted 256 keys. Total usage: 1638399488
Running t-SNE with perplexity=30... (this may take a moment)

/usr/local/lib/python3.12/dist-packages/sklearn/manifold/_t_sne.py:1164: FutureWarning: 'n_iter'
was renamed to 'max_iter' in version 1.5 and will be removed in 1.7.
  warnings.warn(

t-SNE complete.
Visualization for layer 4 saved as 'expert_galaxy_layer_4.png'
```



```
--- Visualizing Layer 7 ---
Extracted 256 keys. Total usage: 1638399488
Running t-SNE with perplexity=30... (this may take a moment)

/usr/local/lib/python3.12/dist-packages/sklearn/manifold/_t_sne.py:1164: FutureWarning: 'n_iter'
was renamed to 'max_iter' in version 1.5 and will be removed in 1.7.
  warnings.warn(

t-SNE complete.
Visualization for layer 7 saved as 'expert_galaxy_layer_7.png'
```


t-SNE Visualization of SoME Expert Key Space for Layer 7
t-SNE Dimension 1
t-SNE Dimension 2
Expert Activation Frequency (Usage Count)
1e8
How to Read This Plot:
• Each circle represents one of the 256 experts.
• Proximity suggests conceptual similarity learned by the router.
• Bright, large circles are high-usage 'generalist' experts.
• Dark, small circles are low-usage 'specialist' or unused experts.
Clusters of points are emerging 'Knowledge Galaxies'.