SoME v4.5 Residual Grounding Code & Results

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# SoME v4: Router Grounding Edition
# Authors: Focus Labs & Norm
# Environment: Google Colab (A100 Single GPU Optimized)
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# --- Part 1: Dependencies & Setup ---
import subprocess
import sys

def install_dependencies():
    packages = ["torch", "datasets", "transformers", "huggingface_hub", "tokenizers", "matplotlib",
"scikit-learn"]
    subprocess.check_call([sys.executable, "-m", "pip", "install"] + packages + ["-q"])

try:
    import torch
except ImportError:
    install_dependencies()
    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
from sklearn.manifold import TSNE
import copy
from tqdm import tqdm
import math
import os
import numpy as np
import matplotlib.pyplot as plt
import time
```

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# --- Hardware Optimization ---
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")

# A100 Optimization: Enable TF32
if torch.cuda.is_available() and torch.cuda.get_device_capability(0)[0] >= 8:
    print("A100/H100 GPU detected. Enabling TF32.")
    torch.set_float32_matmul_precision('high')

torch.backends.cudnn.benchmark = True

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# --- Part 2: The SoME v4 Architecture (Grounded Router) ---
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class Expert(nn.Module):
    """
    An independent, specialized sub-network.
    In SoME, these are initialized randomly and frozen (reservoir computing).
    """
    def __init__(self, d_model, d_ffn, init_method='default'):
        super().__init__()
        self.w_down = nn.Linear(d_model, d_ffn)
        self.activation = nn.GELU()
        self.w_up = nn.Linear(d_ffn, d_model)

        # Scientific Rigor: Explicit Initialization Control
        if init_method == 'orthogonal':
            nn.init.orthogonal_(self.w_down.weight)
            nn.init.orthogonal_(self.w_up.weight)
        elif init_method == 'sparse':
            nn.init.sparse_(self.w_down.weight, sparsity=0.5)
            nn.init.sparse_(self.w_up.weight, sparsity=0.5)
        elif init_method == 'default':
            pass # Use PyTorch Kaiming/Xavier defaults
        else:
            raise ValueError(f"Unknown initialization method: {init_method}")

        # Bias initialization for stability
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        nn.init.zeros_(self.w_down.bias)
        nn.init.zeros_(self.w_up.bias)

    def forward(self, x):
        return self.w_up(self.activation(self.w_down(x)))

class SOMELayer(nn.Module):
    """
    Self-Organizing Mixture of Experts Layer (v4 Grounded).
    Implements 'Knowledge Gravity' updates with decoupled Routing/Compute manifolds.
    """
    def __init__(self, d_model, some_config):
        super().__init__()
        self.d_model = d_model
        self.num_experts = some_config['num_experts']
        self.d_ffn = some_config['d_ffn']
        self.top_k = some_config['top_k']

        # Grounding Hyperparameters (The v4 Intervention)
        self.grounding_coeff = some_config.get('grounding_coeff', 0.0)

        # Heuristic Update Parameters
        self.alpha = some_config['alpha']
        self.beta = some_config['beta']
        self.delta = some_config['delta']

        # Dynamics Parameters
        self.theta_percentile = some_config['theta_percentile']
        self.warmup_steps = some_config['warmup_steps']
        self.ema_decay = some_config['ema_decay']
        self.ablation_flags = some_config.get('ablation_flags',
                                    {'use_alpha': True, 'use_beta': True, 'use_delta': True})

        # --- The MLP Router (v3 Architecture) ---
        # Maps from Input Space -> Query Space
        hidden_dim = d_model * 2
        self.query_network = nn.Sequential(
            nn.Linear(d_model, hidden_dim),
            nn.GELU(),
            nn.Linear(hidden_dim, d_model)
        )

        # --- The Dynamic Key Store ---
        keys = torch.randn(self.num_experts, d_model)
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        self.register_buffer("key_store", F.normalize(keys, p=2, dim=-1))

        # State Tracking
        self.register_buffer("usage_count", torch.zeros(self.num_experts))
        self.register_buffer("steps", torch.tensor([0], dtype=torch.long))

        # --- The Frozen Expert Pool ---
        self.experts = nn.ModuleList([
            Expert(d_model, self.d_ffn, init_method=some_config['init_method'])
            for _ in range(self.num_experts)
        ])

        # Enforce Frozen State (Reservoir Computing Principle)
        for expert in self.experts:
            for param in expert.parameters():
                param.requires_grad = False

        # Pre-compute indices for Peer Pull (Beta force) to avoid runtime overhead
        if self.top_k > 1:
            self.register_buffer("peer_pull_indices", torch.combinations(torch.arange(self.top_k),
r=2))

    def forward(self, x, temperature=1.0, grounding_input=None):
        batch_size, seq_len, _ = x.shape
        x_flat = x.view(-1, self.d_model)

        # --- v4 Intervention: Router Grounding ---
        # The router sees a mix of the abstract state (x) and the stable anchor (grounding_input)
        if grounding_input is not None and self.grounding_coeff > 0:
            grounding_flat = grounding_input.view(-1, self.d_model)
            # Mix the signal. Note: This creates the "Search Space"
            router_input = x_flat + (self.grounding_coeff * grounding_flat)
        else:
            router_input = x_flat

        # Generate Queries from the (possibly grounded) input
        queries_raw = self.query_network(router_input)
        queries = F.normalize(queries_raw, p=2, dim=-1)

        # Cosine Similarity Search
        # Scores represent how close the query is to the expert's key
        scores = torch.matmul(queries, self.key_store.t())

        # Top-K Selection
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        top_k_scores, top_k_indices = torch.topk(scores, self.top_k, dim=-1)

        # Softmax Gating
        gating_weights = F.softmax(top_k_scores / temperature, dim=-1)

        # --- Efficient Dispatch & Combiner ---
        # We use a permutation-based approach to batch expert computation
        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)

        # Prepare inputs for experts (Note: Experts see 'x_flat', NOT 'router_input')
        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)

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

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

        # Weighted Sum
        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):
        """
        The 'Knowledge Gravity' Update Mechanism.
        Executed in a no_grad context after the forward pass.
        """
        self.steps += 1

        # 1. Update Usage Statistics (EMA for Stability)
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unique_indices, counts = torch.unique(top_k_indices, return_counts=True)
self.usage_count.mul_(self.ema_decay)
self.usage_count.index_add_(0, unique_indices, (1.0 - self.ema_decay) * counts.float())

# 2. Force Alpha: Attraction (Query Pull)
if self.ablation_flags.get('use_alpha', True):
    for i in range(self.top_k):
        indices = top_k_indices[:, i]
        # Inertia: Higher usage = Higher mass = Lower learning rate
        inertia = 1.0 + self.usage_count[indices]
        alpha_effective = self.alpha / inertia.unsqueeze(-1)

        # The Pull: Key moves toward Query
        update_vec = queries - self.key_store[indices]
        self.key_store.index_add_(0, indices, alpha_effective * update_vec)

# 3. Force Beta: Clustering (Peer Pull)
if self.top_k > 1 and self.ablation_flags.get('use_beta', True):
    # Extract pairs of co-activated experts
    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)

    # Shared gravity based on the heavier expert
    beta_effective = self.beta / torch.min(inertia_i, inertia_j)

    # Mutual attraction
    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)

# Re-normalize keys to stay on the hypersphere
self.key_store.data = F.normalize(self.key_store.data, p=2, dim=-1)

# 4. Force Delta: Decay (Use it or Lose it)
if self.steps > self.warmup_steps and self.ablation_flags.get('use_delta', True):
    active_usage_counts = self.usage_count[self.usage_count > 0]
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            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
                # Decay towards origin (magnitude reduction)
                self.key_store[low_usage_mask] *= (1.0 - self.delta)

class SOMETransformerBlock(nn.Module):
    def __init__(self, d_model, num_heads, some_config):
        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 = SOMELayer(d_model, some_config)

    def forward(self, x, temperature=1.0, causal_mask=None, grounding_input=None):
        # Attention Sublayer
        attn_output, _ = self.attention(x, x, x, attn_mask=causal_mask, is_causal=True)
        x = self.norm1(x + attn_output)

        # SoME Sublayer (with optional grounding)
        some_output, queries, top_k_indices = self.some_layer(
            x, temperature=temperature, grounding_input=grounding_input
        )
        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__()
        position = torch.arange(max_len).unsqueeze(1)
        div_term = torch.exp(torch.arange(0, d_model, 2) * (-math.log(10000.0) / d_model))
        pe = torch.zeros(1, max_len, d_model)
        pe[0, :, 0::2] = torch.sin(position * div_term)
        pe[0, :, 1::2] = torch.cos(position * div_term)
        self.register_buffer('pe', pe)

    def forward(self, x):
        return x + self.pe[:, :x.size(1)]

class SOMETransformer(nn.Module):
    def __init__(self, model_config, some_config):
        super().__init__()
        self.model_config = model_config
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        self.d_model = model_config['d_model']

        self.embedding = nn.Embedding(model_config['vocab_size'], self.d_model)
        self.pos_encoder = PositionalEncoding(self.d_model, model_config['seq_len'])

        self.layers = nn.ModuleList([
            SOMETransformerBlock(self.d_model, model_config['num_heads'], some_config)
            for _ in range(model_config['num_layers'])
        ])

        self.fc_out = nn.Linear(self.d_model, model_config['vocab_size'])

        # Register Causal Mask Buffer
        mask = torch.triu(torch.ones(model_config['seq_len'], model_config['seq_len']) * float('-inf'),
diagonal=1)
        self.register_buffer('causal_mask', mask)

        # Grounding Configuration
        self.grounding_start_layer = some_config.get('grounding_start_layer', 0)

    def forward(self, x, temperature=1.0):
        # 1. Embedding & Position
        x = self.embedding(x) * math.sqrt(self.d_model)
        x = self.pos_encoder(x)

        # Capture the Grounding Signal (The stable representation)
        grounding_signal = x.clone()

        all_queries, all_indices = [], []

        # 2. Layer Processing
        for i, layer in enumerate(self.layers):
            # Apply grounding only if we are past the start layer
            current_grounding = grounding_signal if i >= self.grounding_start_layer else None

            x, queries, top_k_indices = layer(
                x,
                temperature=temperature,
                causal_mask=self.causal_mask[:x.size(1), :x.size(1)],
                grounding_input=current_grounding
            )
            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):
        """Batch update for all layers"""
        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)

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# --- Part 3: Data & Utilities ---
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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 = item['input_ids'].clone().detach()
        targets = inputs.clone()
        targets[:-1] = inputs[1:]
        targets[-1] = -100
        return inputs, targets

def prepare_data(config):
    print("\n--- Data Preparation ---")
    tokenizer_path = "tinystories-tokenizer-v4.json"

    # 1. Tokenizer
    if not os.path.exists(tokenizer_path):
        print("Training custom tokenizer...")
        dataset = load_dataset("roneneldan/TinyStories", split="train", streaming=False)
        # Fast iterator
        def batch_iterator(batch_size=1000):
            for i in range(0, len(dataset), batch_size):
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            yield dataset[i : i + batch_size]["text"]

        tokenizer = Tokenizer(BPE(unk_token="[UNK]"))
        tokenizer.pre_tokenizer = Whitespace()
        trainer = BpeTrainer(special_tokens=["[UNK]", "[PAD]", "[EOS]"],
vocab_size=config['model']['vocab_size'])
        tokenizer.train_from_iterator(batch_iterator(), trainer=trainer)
        tokenizer.save(tokenizer_path)
    else:
        print("Loading existing tokenizer.")
        tokenizer = PreTrainedTokenizerFast(tokenizer_file=tokenizer_path)
        tokenizer.add_special_tokens({'pad_token': '[PAD]', 'eos_token': '[EOS]'})

    # 2. Dataset Loading
    full_dataset = load_dataset("roneneldan/TinyStories", streaming=False)
    train_subset = full_dataset['train'].select(range(config['data']['train_subset_size']))
    val_subset = full_dataset['validation'].select(range(config['data']['val_subset_size']))

    def tokenize_function(examples):
        text_with_eos = [s + tokenizer.eos_token for s in examples["text"]]
        return tokenizer(text_with_eos, truncation=True, padding="max_length",
                         max_length=config['model']['seq_len'], return_tensors="pt")

    print(f"Tokenizing {len(train_subset)} training examples...")
    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())

    tokenized_train.set_format(type='torch', columns=['input_ids'])
    tokenized_val.set_format(type='torch', columns=['input_ids'])

    # 3. Dataloaders
    train_loader = DataLoader(LanguageModelDataset(tokenized_train),
                              batch_size=config['data']['batch_size'], shuffle=True,
                              drop_last=True, num_workers=2, pin_memory=True)
    val_loader = DataLoader(LanguageModelDataset(tokenized_val),
                            batch_size=config['data']['batch_size'], drop_last=True,
                            num_workers=2, pin_memory=True)

    return train_loader, val_loader, tokenizer
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# --- Part 4: Training Engine ---
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def calculate_metrics(usage_counts):
    counts = usage_counts.cpu().to(torch.float32).numpy()
    if np.sum(counts) == 0: return 0.0, 0.0

    # Gini
    sorted_counts = np.sort(counts)
    n = len(counts)
    index = np.arange(1, n + 1)
    gini = (np.sum((2 * index - n - 1) * sorted_counts)) / (n * np.sum(sorted_counts))

    # Entropy
    probs = counts / np.sum(counts)
    probs = probs[probs > 0]
    entropy = -np.sum(probs * np.log2(probs))

    return gini, entropy

def train_epoch(model, dataloader, optimizer, criterion, scheduler, current_temp, vocab_size):
    model.train()
    total_loss = 0
    scaler = torch.amp.GradScaler("cuda")

    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, temperature=current_temp)
            loss = criterion(logits.view(-1, 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)
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        scaler.update()
        scheduler.step()

        # Knowledge Gravity Update (Gradient Free)
        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, vocab_size):
    model.eval()
    total_loss = 0
    with torch.no_grad():
        for inputs, targets in dataloader:
            inputs, targets = inputs.to(device, non_blocking=True), targets.to(device,
non_blocking=True)
            with torch.amp.autocast("cuda"):
                logits, _, _ = model(inputs, temperature=0.5) # Sharpen temp for eval
                loss = criterion(logits.view(-1, vocab_size), targets.view(-1))
            total_loss += loss.item()
    return total_loss / len(dataloader)

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# --- Part 5: Visualization & Analysis ---
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def visualize_galaxy(model, layer_idx, run_name):
    """Generates t-SNE plot for a specific layer's expert keys."""
    try:
        layer = model.layers[layer_idx].some_layer
        keys = layer.key_store.detach().cpu().numpy()
        usage = layer.usage_count.detach().cpu().numpy()
    except IndexError:
        print(f"Layer {layer_idx} out of bounds.")
        return

    print(f"Visualizing Layer {layer_idx} Galaxy...")
```

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    # t-SNE
    tsne = TSNE(n_components=2, perplexity=30, init='pca', learning_rate='auto',
random_state=42)
    keys_2d = tsne.fit_transform(keys)

    # Normalize usage for marker size
    if usage.sum() > 0:
        norm_usage = usage / usage.sum()
    else:
        norm_usage = np.zeros_like(usage)

    plt.figure(figsize=(12, 10))
    sc = plt.scatter(keys_2d[:, 0], keys_2d[:, 1], c=usage,
                     s=30 + norm_usage * 5000, cmap='viridis', alpha=0.8, edgecolors='k')
    plt.colorbar(sc, label='Expert Usage (EMA)')
    plt.title(f"Knowledge Galaxy: Layer {layer_idx} (Grounded)\n{run_name}")
    plt.xlabel("t-SNE Dim 1")
    plt.ylabel("t-SNE Dim 2")

    plt.savefig(f"galaxy_layer_{layer_idx}_{run_name}.png", dpi=300)
    plt.close()
    print(f"Saved galaxy_layer_{layer_idx}_{run_name}.png")

def plot_training_curves(train_losses, val_losses, run_name):
    plt.figure(figsize=(10, 6))
    epochs = range(1, len(train_losses) + 1)
    plt.plot(epochs, train_losses, 'b-o', label='Training Loss')
    plt.plot(epochs, val_losses, 'r-o', label='Validation Loss')
    plt.title(f"Training Dynamics: {run_name}")
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend()
    plt.grid(True)
    plt.savefig(f"loss_curve_{run_name}.png")
    plt.close()

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# --- Part 6: Main Execution Block ---
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def main():
    # --- Experiment Configuration ---
    config = {
        "run_name": "v4_Router_Grounding_Experiment",
        "data": {
            "train_subset_size": 20000, # Increased for better signal
            "val_subset_size": 2000,
            "batch_size": 32
        },
        "model": {
            "vocab_size": 8192,
            "d_model": 512,
            "num_heads": 8,
            "num_layers": 12, # Deep model to test stability (A6 scenario)
            "seq_len": 768
        },
        "some_layer": {
            "num_experts": 64,
            "d_ffn": 1024,
            "top_k": 4,
            "init_method": "default",

            # Update Dynamics
            "alpha": 0.01,
            "beta": 0.005,
            "delta": 0.001,
            "theta_percentile": 0.05,
            "warmup_steps": 400,
            "ema_decay": 0.99,

            # --- v4 INTERVENTION: ROUTER GROUNDING ---
            "grounding_coeff": 0.1,      # Mix 10% embedding signal into router
            "grounding_start_layer": 6,  # Apply only to deeper layers (6-11)
        },
        "training": {
            "num_epochs": 5,
            "learning_rate": 6e-4,
            "training_temp": 0.8
        }
    }

    print(f"Starting Experiment: {config['run_name']}")

    # 1. Prepare Data
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    train_loader, val_loader, tokenizer = prepare_data(config)

    # 2. Initialize Model
    model = SOMETransformer(config['model'], config['some_layer']).to(device)

    # Compile if available (PyTorch 2.0+)
    if hasattr(torch, 'compile'):
        print("Compiling model...")
        model = torch.compile(model)

    # 3. Optimizer & Scheduler
    optimizer = torch.optim.AdamW([p for p in model.parameters() if p.requires_grad],
                                  lr=config['training']['learning_rate'],
                                  weight_decay=0.1)
    total_steps = len(train_loader) * config['training']['num_epochs']
    scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=total_steps)
    criterion = nn.CrossEntropyLoss(ignore_index=-100)

    # 4. Training Loop
    train_losses, val_losses = [], []
    best_val_loss = float('inf')

    print(f"\n--- Training for {config['training']['num_epochs']} Epochs ---")
    for epoch in range(config['training']['num_epochs']):
        print(f"\nEpoch {epoch+1}")

        # Train
        t_loss = train_epoch(model, train_loader, optimizer, criterion, scheduler,
                             config['training']['training_temp'], tokenizer.vocab_size)

        # Eval
        v_loss = evaluate_epoch(model, val_loader, criterion, tokenizer.vocab_size)

        train_losses.append(t_loss)
        val_losses.append(v_loss)

        # Metrics Inspection (Deepest Layer)
        orig_model = model._orig_mod if hasattr(model, '_orig_mod') else model
        deep_layer_idx = config['model']['num_layers'] - 2
        gini, entropy =
calculate_metrics(orig_model.layers[deep_layer_idx].some_layer.usage_count)

        print(f"  Train Loss: {t_loss:.4f} | Val Loss: {v_loss:.4f} | Val PPL: {math.exp(v_loss):.2f}")
        print(f"  Layer {deep_layer_idx} Metrics -> Gini: {gini:.3f} | Entropy: {entropy:.3f}")
```

```
        # Save Checkpoint
        if v_loss < best_val_loss:
            best_val_loss = v_loss
            torch.save(orig_model.state_dict(), f"best_{config['run_name']}.pth")

    # 5. Analysis
    plot_training_curves(train_losses, val_losses, config['run_name'])

    # Visualizing early, middle, and deep layers to check for collapse vs. structure
    viz_layers = [0, config['model']['num_layers']//2, config['model']['num_layers']-1]
    for idx in viz_layers:
        visualize_galaxy(orig_model, idx, config['run_name'])

if __name__ == "__main__":
    main()
```

```
 Using device: cuda
A100/H100 GPU detected. Enabling TF32.
Starting Experiment: v4_Router_Grounding_Experiment

--- Data Preparation ---
Loading existing tokenizer.
Tokenizing 20000 training examples...
Map (num_proc=12): 100% 20000/20000 [00:03<00:00, 7420.94 examples/s]Map (num_pr
oc=12): 100% 2000/2000 [00:00<00:00, 3750.89 examples/s]Compiling model...

--- Training for 5 Epochs ---

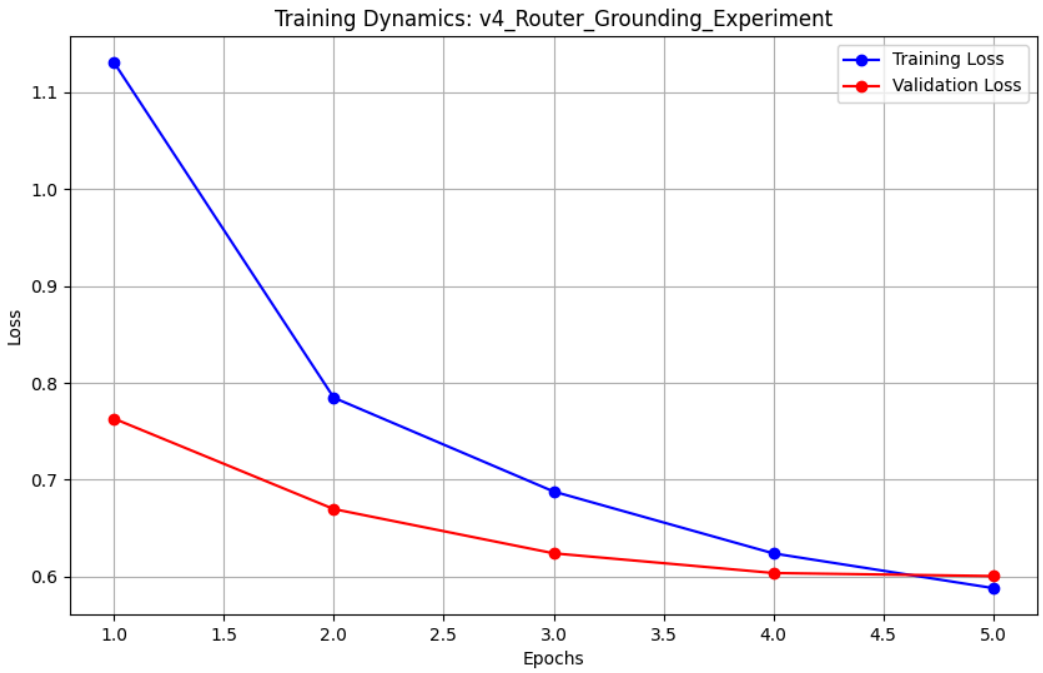
Epoch 1
Training:   0%|          | 0/625 [00:00<?,
?it/s]/usr/local/lib/python3.12/dist-packages/torch/optim/lr_scheduler.py:192: UserWarning:
Detected call of `lr_scheduler.step()` before `optimizer.step()`. In PyTorch 1.1.0 and later, you
should call them in the opposite order: `optimizer.step()` before `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(
  Train Loss: 1.1307 | Val Loss: 0.7632 | Val PPL: 2.15
  Layer 10 Metrics -> Gini: 0.887 | Entropy: 3.169

Epoch 2
  Train Loss: 0.7847 | Val Loss: 0.6698 | Val PPL: 1.95
  Layer 10 Metrics -> Gini: 0.888 | Entropy: 3.168
```

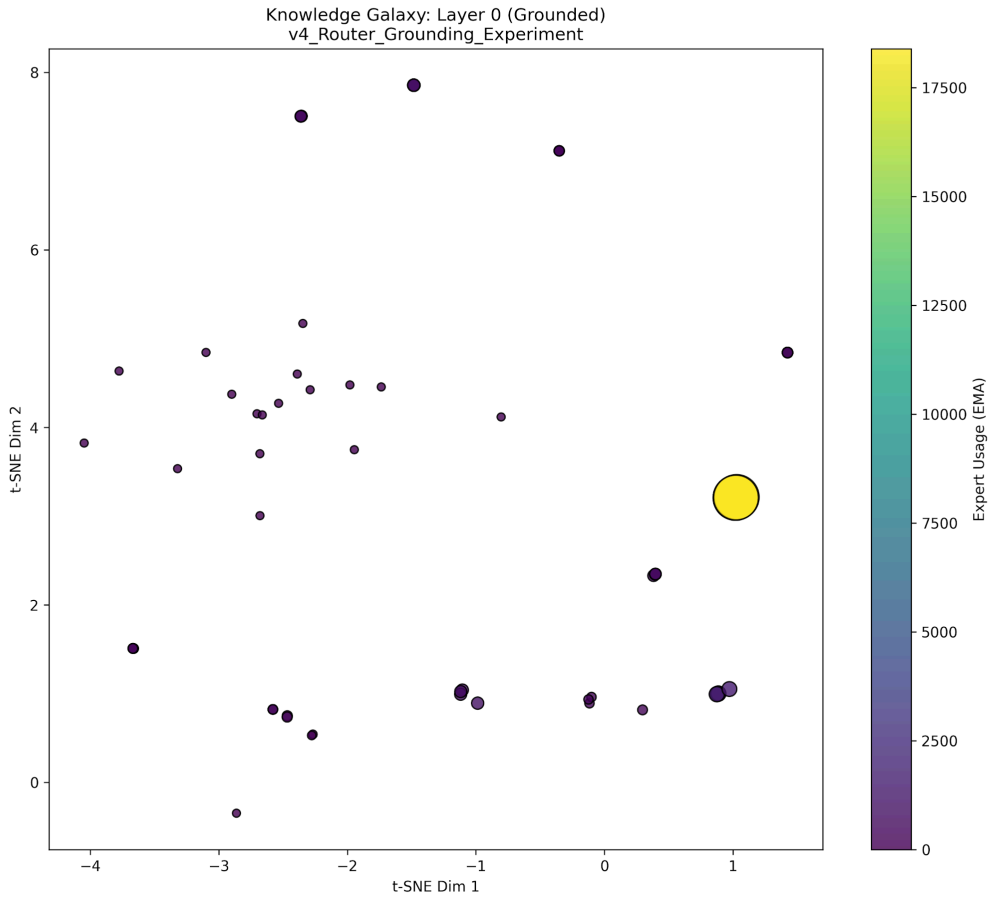
Epoch 3
  Train Loss: 0.6879 | Val Loss: 0.6242 | Val PPL: 1.87
  Layer 10 Metrics -> Gini: 0.886 | Entropy: 3.177

Epoch 4
  Train Loss: 0.6241 | Val Loss: 0.6038 | Val PPL: 1.83
  Layer 10 Metrics -> Gini: 0.886 | Entropy: 3.178

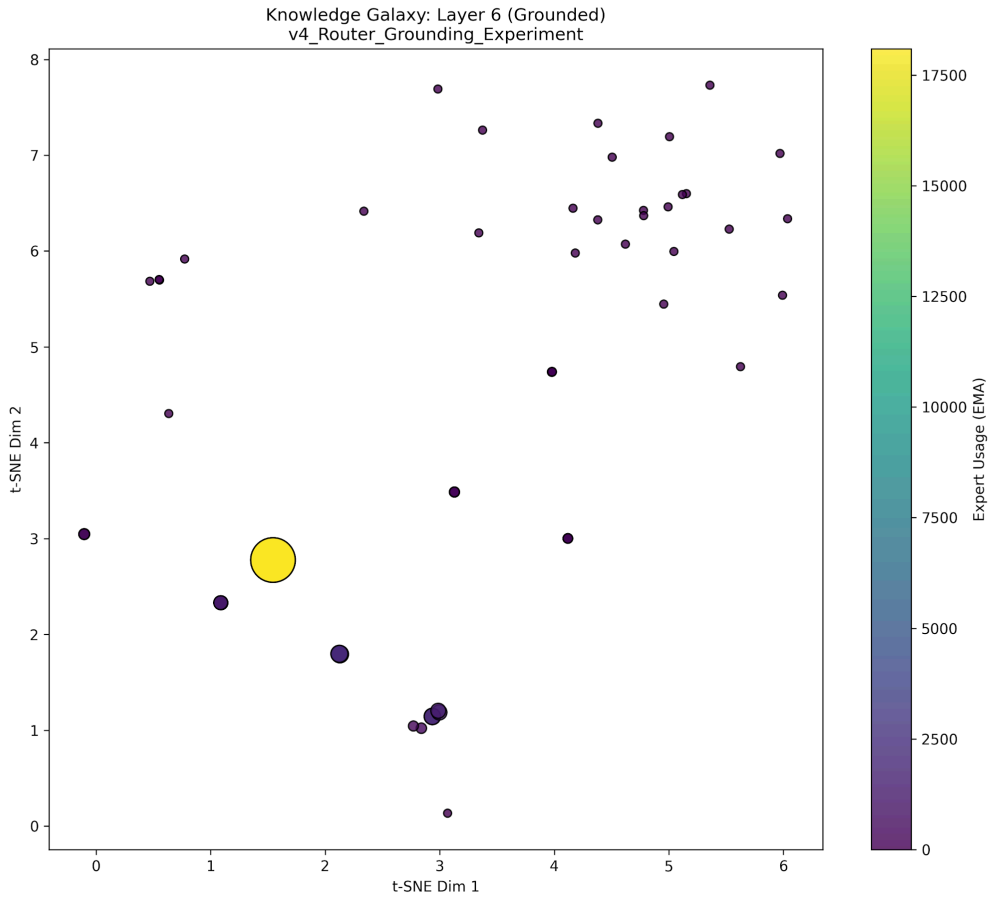
Epoch 5
  Train Loss: 0.5883 | Val Loss: 0.6007 | Val PPL: 1.82
  Layer 10 Metrics -> Gini: 0.886 | Entropy: 3.178



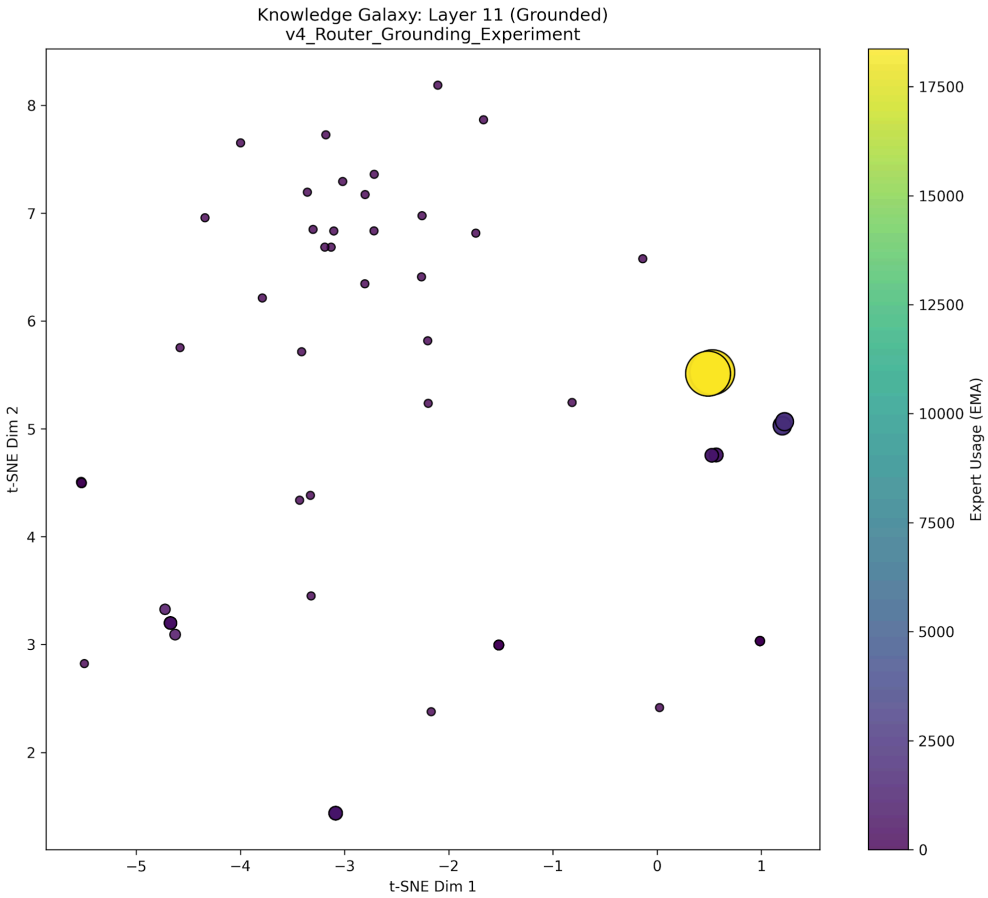
Visualizing Layer 0 Galaxy...
Saved galaxy_layer_0_v4_Router_Grounding_Experiment.png



Visualizing Layer 6 Galaxy...
Saved galaxy_layer_6_v4_Router_Grounding_Experiment.png



Visualizing Layer 11 Galaxy...
Saved galaxy_layer_11_v4_Router_Grounding_Experiment.png


Knowledge Galaxy: Layer 11 (Grounded)
v4_Router_Grounding_Experiment
t-SNE Dim 1
t-SNE Dim 2
Expert Usage (EMA)
8
7
6
5
4
3
2
−5
−4
−3
−2
−1
0
1
17500
15000
12500
10000
7500
5000
2500
0