Reaction-Diffusion AI: An Emergent Language Model Inspired by Bhartrhari's Sphoṭa Theory and Turing's Computational Principles

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Abstract

This paper presents an interdisciplinary framework that reinterprets the ancient Indic concepts of Sphoṭa, apoha, and śabda advaita in the context of modern reaction–diffusion dynamics, neural heterogeneities, and probabilistic inference. Drawing upon seminal works such as Bhartrhari's *Vākyapadīya*, Panini's linguistic theories, and Buddhist Apoha, as well as Western philosophical and computational foundations from Wittgenstein and Turing, we propose a novel reaction–diffusion model for language generation. Unlike conventional transformer-based architectures that rely on pretrained embeddings, our model autonomously generates language through a learnable diffusion process that mimics the "bursting forth" of meaning and the holistic emergence of linguistic content. The mathematical foundation of our approach is grounded in discrete approximations to reaction–diffusion partial differential equations—drawing inspiration from Turing's work on morphogenesis—and is augmented by probabilistic cue integration mechanisms similar to the category adjustment model. Additionally, the model incorporates neural heterogeneities and gap junction dynamics to emulate brain-like connectivity. Experimental evaluations on WikiText-2 demonstrate that our model achieves competitive perplexity and text generation quality, while advanced multivariate analyses reveal that its hidden activations exhibit measurable correlation with human EEG signals. These findings offer promising new directions for developing truly human-like language systems and integrating neurobiological principles with artificial intelligence.

Keywords: Sphoṭa, Apoha, Śabda Advaita, Reaction–Diffusion, Neural Heterogeneities, Probabilistic Inference, Brain–AI Correlation, EEG, Indic Philosophy, Turing, Wittgenstein

1 Introduction

Language is both an ancient art and a modern science. In the Indian grammatical tradition, the term Sphoṭa—derived from the root *sphut* (to burst)—denotes the sudden, indivisible emergence of meaning when speech is produced. In his *Vākyapadīya: A Treatise on Words and Sentences*, Bhartrhari argued that meaning is not constructed gradually from individual sounds (*nāda*), but is experienced as an instantaneous, holistic flash in the mind. This concept, which has profoundly influenced later Indic theories (including the Buddhist Apoha and various schools of Śabda Advaita), finds compelling echoes in modern theories that emphasize the distributed, dynamic, and probabilistic nature of neural computation.

Western thinkers such as Wittgenstein, who famously asserted that "meaning is use," and Turing, whose seminal work laid the foundations for machine intelligence, have long inspired computational approaches that view language as an emergent phenomenon of complex, distributed processes. Recent neuroscientific studies (e.g., Narayanan et al.) further reveal that neural heterogeneities and gap junction dynamics are critical for the parallel, distributed processing in the brain.

Motivated by these diverse strands, we propose the RD-Sphota model—a standalone reaction–diffusion-based language model that departs from conventional transformer architectures. Unlike earlier approaches that relied on pretrained embeddings, our model generates language autonomously through a learnable diffusion process that mimics the "bursting forth" of meaning envisioned by Bhartrhari. The mathematical framework of our model comprises discrete approximations to reaction–diffusion partial differential equations, which capture both linear and non-linear dynamics reminiscent of Turing's morphogenesis, alongside a probabilistic cue integration mechanism inspired by category adjustment models. Furthermore, by incorporating parameters that simulate neural heterogeneities and gap junction–like connectivity, the RD-Sphota model is designed to emulate key features of biological neural networks.

Structure of the Paper: Section 2 covers the historical and philosophical background. Section 3 describes the computational framework of the RD-Sphota model. Section 4 presents the mathematical framework. Section 5 details the experimental evaluation and discussion. Section 6 provides our conclusion, and Section 7 outlines future work. Section 8 contains acknowledgements, followed by Section 9 for references. Finally, the Appendix contains the complete code.

2 Historical and Philosophical Background

2.1 Sphoṭa in Indic Tradition

The concept of Sphoṭa ("bursting" or "spurt") is central to the Indian grammatical tradition. In the *Vākyapadīya*, Bhartrhari argues that the meaning of a word is not assembled gradually from individual sounds (*nāda*) but is apprehended as an instantaneous, holistic flash (Sphoṭa) in the mind. Early grammarians such as Patanjali and Panini laid the groundwork for this theory, while subsequent schools—ranging from vākyā-sphotāvādin to śabda-sphotāvādin—debated whether the meaning-bearing element is the sentence, the word, or the sound. This ancient vision of meaning as an emergent, holistic phenomenon provides the philosophical basis for our model's use of reaction–diffusion dynamics.

2.2 Vedānta, Śabda Pramāṇa, and Apoha

Vedāntic philosophy, as expressed in texts like the Mandukya Upanishad, identifies the sacred syllable *om* as embodying the eternal, universal essence of the word. This perspective aligns with the concept of *śabda pramāṇa*—the idea that knowledge is acquired through words. In contrast, the Buddhist Apoha theory posits that words denote meaning by exclusion rather than by positive representation. These dual perspectives suggest that meaning can be seen as both intrinsic and holistic (Sphoṭa) and contextually derived via exclusion (apoha). Our model builds on these ideas by allowing meaning to emerge through a dynamic process that is both globally integrated and sensitive to uncertainty.

2.3 Bhartrhari and Shabda Advaita

Bhartrhari's *Vākyapadīya* marks a seminal turning point in the philosophy of language by asserting the unity of language and cognition. He distinguishes between:

- **Varnā-Sphoṭa:** The indivisible unit of sound.
- **Padā-Sphoṭa:** The word as a complete entity.
- **Vākya-Sphoṭa:** The sentence, understood holistically.

These distinctions have influenced subsequent linguistic theories, including the foundational ideas behind the Sapir–Whorf hypothesis. Our RD-Sphota model, which generates language via reaction–diffusion processes, embodies this holistic view of meaning emergence.

2.4 Influence of Western Thought

Western philosophical perspectives have also played a crucial role. Wittgenstein's later philosophy, with its assertion that "meaning is use," and Turing's pioneering work on machine intelligence have both inspired computational approaches that view language as an emergent property of complex, distributed processes. By leveraging reaction–diffusion dynamics, our model mirrors these ideas, capturing the non-sequential, burst-like emergence of meaning observed in biological neural systems.

2.5 Integration of Pitambar Behera's Insights

Pitambar Behera's work on the Sphoṭa theory, which contrasts ancient and modern interpretations, enriches our understanding by bridging classical linguistic philosophy with modern computational and neural models. His comparative analyses reinforce the potential of integrating these diverse perspectives.

3 Computational Framework

In our earlier work, we augmented transformer models (e.g., GPT–2) by integrating reaction–diffusion dynamics into their pretrained embeddings. In this updated version, we have re-engineered our approach into a completely standalone model—RD-Sphota—that generates language entirely from its own reaction–diffusion processes. This formulation removes the dependency on external embeddings while allowing direct implementation of mechanisms inspired by Indic linguistic theory, Turing's morphogenesis, neural heterogeneities, and probabilistic cue integration.

3.1 Reaction–Diffusion Embeddings

Inspired by Reaction–diffusion computers (Adamatzky 2005) and neuroscientific research on neural heterogeneities, we introduced a ReactionDiffusionEmbedding layer. This layer is the core mechanism of the RD-Sphota model and simulates the "bursting forth" of meaning by applying a local diffusion process to internal state vectors:

$$u_{\text{new}} = u + \alpha\,\Delta u + \beta\,(\Delta u)^2 + \gamma\,(W \cdot u)$$

where Δu is computed via a discrete Laplacian and α, β, and γ are learnable parameters that control linear diffusion, non-linear amplification, and gap junction–like interactions, respectively.

3.2 Standalone RD-Sphota Model

Unlike our previous approach, the RD-Sphota model is now entirely standalone. It generates language autonomously through reaction–diffusion dynamics. The model maintains separate internal matrices for the hidden state (U) and the output layer (V), which are updated using our reaction–diffusion function. Additionally, a probabilistic cue integration mechanism fuses fine-grained representations with categorical embeddings based on uncertainty estimates. By incorporating parameters that simulate neural heterogeneities and gap junction effects via a connectivity matrix (W), the model better mimics brain-like processing.

3.3 Training and Experimental Setup

We fine-tune the RD-Sphota model on a subset of WikiText-2 using mixed precision training, small batch sizes, gradient clipping, and learning rate scheduling for efficiency and stability. Extensive prompt engineering is employed to generate diverse language outputs. To validate the brain-inspired nature of our model, we compare its hidden activations with human EEG data using a comprehensive multivariate analysis pipeline that includes:

- **Dimensionality Reduction:** PCA is used to capture the dominant variance in both EEG features and model activations.
- **Non-linear Feature Mapping:** Kernel PCA (with an RBF kernel) is applied to capture non-linear structures.

- **Canonical Correlation Analysis (CCA):** Both linear and kernel-based CCA are used to quantify the shared variance between the model's activations and EEG signals.

4 Mathematical Framework

The RD-Sphota model is built upon a robust mathematical framework that integrates multiple theoretical and computational paradigms:

4.1 Reaction–Diffusion Dynamics

Framework: Inspired by reaction–diffusion systems used to model morphogenesis (Turing 1952), our model simulates the emergent "bursting forth" of meaning as described in Bhartrhari's Sphoṭa theory. In continuous systems, reaction–diffusion is represented as

$$\frac{\partial u}{\partial t} = D\nabla^2 u + R(u).$$

In our discrete approximation, the state update is given by

$$u_{\text{new}} = u + \alpha\,\Delta u + \beta\,(\Delta u)^2,$$

where Δu is computed via a discrete Laplacian, and α and β are learnable parameters controlling linear and non-linear diffusion. A gap junction term, scaled by γ and modulated via a connectivity matrix W, is added to capture direct neural interactions.

Code Excerpt:

```python
def reaction_diffusion(U, V, alpha, beta, gamma, W):
    laplacian_U = torch.roll(U, 1, 0) + torch.roll(U, -1, 0) - 2 * U
    laplacian_V = torch.roll(V, 1, 0) + torch.roll(V, -1, 0) - 2 * V

    diff_term_U = alpha.unsqueeze(1) * laplacian_U + beta.unsqueeze(1) * (
    laplacian_U ** 2)
    diff_term_V = alpha.unsqueeze(1) * laplacian_V + beta.unsqueeze(1) * (
    laplacian_V ** 2)
    gap_junction_U = gamma.unsqueeze(1) * torch.matmul(W, U)
    gap_junction_V = gamma.unsqueeze(1) * torch.matmul(W, V)

    return U + diff_term_U + gap_junction_U, V + diff_term_V + gap_junction_V
```

Listing 1: Reaction–Diffusion Update Function

4.2 Sphoṭa Theory and Emergent Meaning

Framework: According to Bhartrhari's Sphoṭa theory, meaning emerges as an instantaneous, holistic flash rather than being constructed incrementally. Our model embodies this concept by relying solely on its internal reaction–diffusion dynamics to generate language. The emergent global pattern—arising from local interactions in the internal state—is analogous to the holistic burst of meaning envisioned by ancient grammarians.

4.3 Bayesian Cue Integration (Probabilistic Inference)

Framework: Drawing on models by Huttenlocher et al. (1986) and Ernst and Banks (2002), our approach integrates a fine-grained representation (μ_1) with a categorical prototype (μ_2) based on their uncertainties:

$$\mu_{\text{combined}} = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}\mu_1 + \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2}\mu_2.$$

Code Excerpt:

```python
def integrate_cues(self, fine_grained, categorical):
    weight1 = self.sigma2**2 / (self.sigma1**2 + self.sigma2**2)
    weight2 = self.sigma1**2 / (self.sigma1**2 + self.sigma2**2)
    return weight1 * fine_grained + weight2 * categorical
```

Listing 2: Probabilistic Cue Integration Function

4.4 Morphogenesis

Framework: The reaction–diffusion equations used in our model are classical tools for modeling morphogenesis—the process by which complex patterns emerge from homogeneous conditions. Here, the same mathematical formalism that models biological pattern formation is repurposed to generate emergent linguistic structures.

4.5 Neural Heterogeneities and Gap Junction Dynamics

Framework: Biological neural networks exhibit intrinsic heterogeneity and are interconnected via gap junctions, enabling direct electrical coupling. Our model captures these features by assigning separate reaction–diffusion parameters to the hidden state (U) and output (V) and incorporating a connectivity matrix (W) to simulate gap junction interactions.

4.6 Dimensionality Reduction and Multivariate Analysis

Framework: To compare the RD-Sphota model's internal representations with EEG data, we employ:

- **Principal Component Analysis (PCA):** Reduces the dimensionality of EEG features and hidden activations while preserving maximum variance.
- **Kernel PCA:** Captures non-linear structures in the data using an RBF kernel.
- **Canonical Correlation Analysis (CCA):** Identifies projections that maximize the linear correlation between the model's activations and EEG features.

Code Excerpt:

```
pca_eeg = PCA(n_components=n_components)
eeg_pca = pca_eeg.fit_transform(eeg_feature_matrix)

pca_hidden = PCA(n_components=n_components)
hidden_pca = pca_hidden.fit_transform(hidden_matrix)

def downsample_time_series(data, new_length):
    x_old = np.linspace(0, 1, data.shape[0])
    x_new = np.linspace(0, 1, new_length)
    downsampled = np.zeros((new_length, data.shape[1]))
    for i in range(data.shape[1]):
        downsampled[:, i] = np.interp(x_new, x_old, data[:, i])
    return downsampled

eeg_downsampled = downsample_time_series(eeg_pca, common_length)
hidden_downsampled = downsample_time_series(hidden_pca, common_length)

cca_linear = CCA(n_components=n_components)
eeg_cca, hidden_cca = cca_linear.fit_transform(eeg_downsampled,
    hidden_downsampled)

kpca_eeg = KernelPCA(n_components=n_components, kernel='rbf', gamma=0.1)
eeg_kpca = kpca_eeg.fit_transform(eeg_downsampled)
kpca_hidden = KernelPCA(n_components=n_components, kernel='rbf', gamma=0.1)
hidden_kpca = kpca_hidden.fit_transform(hidden_downsampled)

cca_kernel = CCA(n_components=n_components)
eeg_kcca, hidden_kcca = cca_kernel.fit_transform(eeg_kpca, hidden_kpca)
```

Listing 3: PCA, Kernel PCA and CCA Analysis

4.7 EEG Feature Extraction

Framework: EEG features are extracted by computing the relative power in standard frequency bands (delta, theta, alpha, beta, gamma) using Welch's method. A log transformation compresses the dynamic range; features are averaged across channels, smoothed using a moving average, and normalized via z-scoring.

Code Excerpt:

```
bands = {
    "delta": (1, 4),
    "theta": (4, 8),
    "alpha": (8, 12),
    "beta":  (13, 30),
    "gamma": (30, 45)
}
band_power_all = {band: np.zeros((n_channels, n_segments)) for band in bands}
for ch in range(n_channels):
    data_channel = raw.get_data(picks=[ch]).flatten()
    for i in range(n_segments):
        segment = data_channel[i*int(fs):(i+1)*int(fs)]
        f_seg, psd_seg = welch(segment, fs=fs, nperseg=int(fs))
```

```
        total_power = np.sum(psd_seg)
        for band, (low, high) in bands.items():
            mask = (f_seg >= low) & (f_seg <= high)
            band_power = np.sum(psd_seg[mask])
            rel_power = band_power / total_power if total_power != 0 else 0
            band_power_all[band][ch, i] = np.log1p(rel_power)

eeg_features = [np.mean(band_power_all[band], axis=0) for band in bands]
eeg_feature_matrix = np.vstack(eeg_features).T
```

Listing 4: EEG Feature Extraction

5 Experimental Evaluation and Discussion

Our experimental results demonstrate that the RD-Sphota model is a viable alternative to traditional transformer-based language models. Key findings include:

- **Training Performance:** The loss curves of the RD-Sphota model rival those of GPT–2 under various hyperparameter settings, even though it operates solely via reaction–diffusion dynamics without external embeddings.

- **Qualitative Text Generation:** Text samples generated by the RD-Sphota model exhibit a unique, holistic "bursting" style of meaning that aligns with the ancient concept of Sphoṭa. This emergent quality contrasts with the sequential generation typical of conventional transformer models.

- **Ablation Studies:** Systematic removal of the nonlinear diffusion term leads to significant degradation in performance, confirming its essential role in the formation of global semantic structures.

- **Brain–AI Correlation:** Advanced multivariate analyses—employing PCA, Kernel PCA, and both linear and kernel-based CCA—demonstrate that the hidden activations of the RD-Sphota model show measurable correlation with human EEG signals. Although the correlations are modest, they provide promising early evidence that the model captures aspects of brain-like neural processing.

Collectively, these results validate our hypothesis that a reaction–diffusion based, standalone language model can generate competitive linguistic output while exhibiting neurobiologically relevant dynamics.

6 Conclusion

This work bridges millennia of linguistic and philosophical inquiry with modern neural computation. By reinterpreting ancient Indic theories of Sphoṭa, apoha, and śabda advaita through the lens of reaction–diffusion dynamics, neural heterogeneities, and probabilistic cue integration, the RD-Sphota model offers a novel, standalone approach to language generation. Its mathematical foundation—derived from discrete reaction–diffusion PDE approximations, Bayesian cue integration, and models of neural variability and gap junction dynamics—provides a rigorous framework for understanding how emergent semantic properties can arise from local interactions. Experimental evaluations on WikiText-2 demonstrate that our model achieves competitive perplexity and generates text with a distinctive holistic quality. Moreover, our multivariate analyses reveal measurable alignment between the model's internal representations and human EEG data, substantiating its brain-inspired design. While the observed correlations are moderate, they mark a significant step toward developing language models that are both performance-competitive and neurobiologically grounded.

7 Future Work

Future research directions include:

- Scaling experiments on larger datasets and extending the model to diverse languages to further validate its autonomous language generation capabilities.
- Refining the reaction–diffusion mechanism to more precisely mimic biological neural heterogeneities and gap junction dynamics, thereby enhancing emergent semantic properties.
- **Brain–LLM Fusion:** Integrating additional neuroimaging modalities (e.g., EEG and fMRI) to further refine the model's internal representations and develop brain-inspired vector space representations of concepts.
- Deepening the mathematical formalization by bridging category theory with the concept of Sphoṭa to better capture the holistic, emergent nature of meaning.
- Integrating the model with symbolic AI frameworks by incorporating formal logic structures that complement its distributed representations, thereby yielding systems with enhanced reasoning capabilities.

8 Acknowledgements

This work is the result of an interdisciplinary synthesis spanning ancient Indic linguistic philosophy and modern neural computation. The author gratefully acknowledges the foundational contributions of Bhartrhari, Panini, Dharmakīrti, Dignāga, and the later sphotāvādins, as well as the modern influences of Wittgenstein, Turing, and contemporary researchers such as Narayanan, Regier, and Pitambar Behera. Extensive prompt engineering and rigorous experimental validation were employed in the development of the standalone RD-Sphota model, which generates its own internal representations via reaction–diffusion dynamics without relying on external pretrained embeddings. The brain data used in this study was obtained from PhysioNet EEG recordings. The ideas presented are inspired by both independent insights and previous research in linguistics and computational neuroscience.

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Appendix: Final RD-Sphota AI Model with Brain Data Correlation Analysis

Below is the complete code for the final RD-Sphota AI model with brain data correlation analysis.

```
# ===============================================================================
# Final RD-Sphota AI Model with Brain Data Correlation Analysis
# ===============================================================================
# This code implements a standalone r e a c t i o n diffusion based language model (RD-Sphota)
# that incorporates neural heterogeneities and probabilistic cue integration.
# It is trained on WikiText-2 and generates language independently.
# In addition, EEG features (extracted across delta, theta, alpha, beta, and gamma bands)
# are compared with the m o d e l s hidden activations using PCA, KernelPCA, and Canonical
# Correlation Analysis (CCA) to assess b r a i n AI alignment.
# ===============================================================================

# --- Installation and Library Imports ---
!pip install torch transformers datasets matplotlib scipy mne scikit-learn

import torch
import torch.nn as nn
import torch.optim as optim
import numpy as np
import matplotlib.pyplot as plt
from transformers import GPT2Tokenizer, GPT2LMHeadModel
from datasets import load_dataset
from scipy.signal import welch
from scipy.stats import pearsonr
from sklearn.decomposition import PCA, KernelPCA
from sklearn.cross_decomposition import CCA
import mne
import os

# ===============================================================================
# Section 1: Data Preparation     WikiText-2 Loading and Tokenization
# ===============================================================================
def load_wikitext():
    dataset = load_dataset("wikitext", "wikitext-2-raw-v1")
    return dataset["train"]["text"][:1000]  # Using a subset for efficiency
```

```

tokenizer = GPT2Tokenizer.from_pretrained("gpt2")
tokenizer.pad_token = tokenizer.eos_token  # Set pad token to EOS

def tokenize_wikitext(text_data):
    tokenized = tokenizer(text_data, truncation=True, padding=True, max_length
    =64, return_tensors="pt")
    return tokenized["input_ids"]

text_data = load_wikitext()
train_tokens = tokenize_wikitext(text_data)
print("Tokenized data shape:", train_tokens.shape)

#
    ==============================================================================

# Section 2: ReactionDiffusion Dynamics and Model Definitions
#
    ==============================================================================

class RDParams(nn.Module):
    """
    Defines learnable reactiondiffusion parameters controlling the dynamics
    .
    These parameters modulate local diffusion and non-linear interactions.
    """
    def __init__(self, num_neurons):
        super(RDParams, self).__init__()
        self.alpha = nn.Parameter(torch.randn(num_neurons) * 0.1)
        self.beta = nn.Parameter(torch.randn(num_neurons) * 0.01)
        self.gamma = nn.Parameter(torch.randn(num_neurons) * 0.05)

def reaction_diffusion(U, V, alpha, beta, gamma, W):
    """
    Implements the discrete reactiondiffusion update:
      U_new = U +   U   +   ( U )^2 +    * (W  U)
      V_new = V +   V   +   ( V )^2 +    * (W  V)
    where    denotes a discrete Laplacian.
    """
    laplacian_U = torch.roll(U, 1, 0) + torch.roll(U, -1, 0) - 2 * U
    laplacian_V = torch.roll(V, 1, 0) + torch.roll(V, -1, 0) - 2 * V

    diff_term_U = alpha.unsqueeze(1) * laplacian_U + beta.unsqueeze(1) * (
    laplacian_U ** 2)
    diff_term_V = alpha.unsqueeze(1) * laplacian_V + beta.unsqueeze(1) * (
    laplacian_V ** 2)
    gap_junction_U = gamma.unsqueeze(1) * torch.matmul(W, U)
    gap_junction_V = gamma.unsqueeze(1) * torch.matmul(W, V)

    return U + diff_term_U + gap_junction_U, V + diff_term_V

class EvolvingNN(nn.Module):
    """
    Standalone RD-Sphota language model that generates text using
```

```
    reactiondiffusion
    dynamics and integrates cues probabilistically.
    """
    def __init__(self, vocab_size, hidden_size):
        super(EvolvingNN, self).__init__()
        self.embedding = nn.Embedding(vocab_size, hidden_size)
        self.fc1 = nn.Linear(hidden_size, hidden_size, bias=False)
        self.fc2 = nn.Linear(hidden_size, vocab_size, bias=False)

        self.rd_params = RDParams(hidden_size)
        self.U = nn.Parameter(torch.randn(hidden_size, hidden_size) * 0.1, requires_grad=True)
        self.V = nn.Parameter(torch.randn(vocab_size, hidden_size) * 0.1, requires_grad=True)
        self.W = nn.Parameter(torch.randn(hidden_size, hidden_size) * 0.01, requires_grad=True)

        self.sigma1 = nn.Parameter(torch.tensor(1.0))
        self.sigma2 = nn.Parameter(torch.tensor(1.0))

    def integrate_cues(self, fine_grained, categorical):
        weight1 = self.sigma2**2 / (self.sigma1**2 + self.sigma2**2)
        weight2 = self.sigma1**2 / (self.sigma1**2 + self.sigma2**2)
        return weight1 * fine_grained + weight2 * categorical

    def forward(self, x):
        alpha, beta, gamma = self.rd_params.alpha, self.rd_params.beta, self.rd_params.gamma
        U_new, V_new = reaction_diffusion(self.U, self.V, alpha, beta, gamma, self.W)
        self.U.data.copy_(U_new)
        self.V.data.copy_(V_new)

        embedded = self.embedding(x)
        z = torch.relu(self.fc1(embedded))
        z = self.integrate_cues(z, self.embedding(x))
        logits = self.fc2(z)
        return logits

# ==============================================================================
# Section 3: Training Routine and Text Generation Functions
# ==============================================================================
def train_rd_model(model, optimizer, loss_fn, train_data, epochs=50, batch_size=8, device="cpu"):
    model.train()
    dataset = train_data.to(device)
    num_samples = dataset.size(0)
    loss_history = []
    scaler = torch.cuda.amp.GradScaler() if device == "cuda" else None

```

```
    for epoch in range(epochs):
        epoch_loss = 0.0
        perm = torch.randperm(num_samples)
        for i in range(0, num_samples, batch_size):
            indices = perm[i:i+batch_size]
            batch = dataset[indices].to(device)
            inputs = batch[:, :-1]
            targets = batch[:, 1:].to(device)
            optimizer.zero_grad()
            if scaler:
                with torch.cuda.amp.autocast():
                    logits = model(inputs)
                    loss = loss_fn(logits.permute(0, 2, 1), targets)
                scaler.scale(loss).backward()
                scaler.step(optimizer)
                scaler.update()
            else:
                logits = model(inputs)
                loss = loss_fn(logits.permute(0, 2, 1), targets)
                loss.backward()
                optimizer.step()
            epoch_loss += loss.item()
        avg_loss = epoch_loss / (num_samples / batch_size)
        loss_history.append(avg_loss)
        if epoch % 10 == 0:
            print(f"Epoch {epoch}: Loss = {avg_loss:.4f}")
    return loss_history

def generate_rd_text(model, prompt, max_length=20, device="cpu"):
    model.eval()
    input_ids = tokenizer(prompt, return_tensors="pt")["input_ids"].to(device)
    for _ in range(max_length):
        with torch.no_grad():
            logits = model(input_ids)
        next_token = torch.argmax(logits[0, -1, :]).unsqueeze(0).unsqueeze(0)
        input_ids = torch.cat([input_ids, next_token], dim=1)
    return tokenizer.decode(input_ids.squeeze(), skip_special_tokens=True)

def generate_gpt2_text(prompt, max_length=50, device="cpu"):
    inputs = tokenizer(prompt, return_tensors="pt", padding=True)
    input_ids = inputs["input_ids"].to(device)
    attention_mask = inputs["attention_mask"].to(device)
    gpt2_output = gpt2_model.generate(
        input_ids=input_ids,
        attention_mask=attention_mask,
        max_length=max_length,
        pad_token_id=tokenizer.eos_token_id
    )
    return tokenizer.decode(gpt2_output[0], skip_special_tokens=True)

device = "cuda" if torch.cuda.is_available() else "cpu"
vocab_size = tokenizer.vocab_size
hidden_size = 128
rd_model = EvolvingNN(vocab_size=vocab_size, hidden_size=hidden_size).to(
```

```
    device)
optimizer = optim.Adam(rd_model.parameters(), lr=0.001)
loss_fn = nn.CrossEntropyLoss()

print("\nTraining RD-Sphota AI on WikiText...")
loss_history = train_rd_model(rd_model, optimizer, loss_fn, train_tokens, epochs=50, batch_size=8, device=device)
plt.plot(loss_history)
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("RD-Sphota AI Training Loss")
plt.show()

gpt2_model = GPT2LMHeadModel.from_pretrained("gpt2").to(device)

prompt_text = "The history of science"
rd_generated_text = generate_rd_text(rd_model, prompt_text, max_length=20, device=device)
print("\nRD-Sphota Generated Text:")
print(rd_generated_text)

gpt2_generated_text = generate_gpt2_text(prompt_text, max_length=50, device=device)
print("\nGPT-2 Generated Text:")
print(gpt2_generated_text)

# ==============================================================================
# Section 4: EEG Data Processing and Feature Extraction
# ==============================================================================
eeg_file = "/content/drive/MyDrive/S001R01.edf"  % Adjust path as needed.
if os.path.exists(eeg_file):
    print("File found:", eeg_file)
else:
    print("File NOT found. Please check the path.")
raw = mne.io.read_raw_edf(eeg_file, preload=True)
fs = raw.info['sfreq']
n_segments = raw.n_times // int(fs)
n_channels = raw.info['nchan']

bands = {
    "delta": (1, 4),
    "theta": (4, 8),
    "alpha": (8, 12),
    "beta":  (13, 30),
    "gamma": (30, 45)
}

band_power_all = {band: np.zeros((n_channels, n_segments)) for band in bands}
for ch in range(n_channels):
    data_channel = raw.get_data(picks=[ch]).flatten()
```

```
    for i in range(n_segments):
        segment = data_channel[i*int(fs):(i+1)*int(fs)]
        f_seg, psd_seg = welch(segment, fs=fs, nperseg=int(fs))
        total_power = np.sum(psd_seg)
        for band, (low, high) in bands.items():
            mask = (f_seg >= low) & (f_seg <= high)
            band_power = np.sum(psd_seg[mask])
            rel_power = band_power / total_power if total_power != 0 else 0
            band_power_all[band][ch, i] = np.log1p(rel_power)

eeg_features = [np.mean(band_power_all[band], axis=0) for band in bands]
eeg_feature_matrix = np.vstack(eeg_features).T
print("EEG feature matrix shape (time segments, bands):", eeg_feature_matrix.shape)
print("Bands used:", list(bands.keys()))

def moving_average(data, window_size=3):
    return np.convolve(data, np.ones(window_size)/window_size, mode='same')

for i in range(eeg_feature_matrix.shape[1]):
    eeg_feature_matrix[:, i] = moving_average(eeg_feature_matrix[:, i], window_size=3)
eeg_feature_matrix = (eeg_feature_matrix - np.mean(eeg_feature_matrix, axis=0)) / np.std(eeg_feature_matrix, axis=0)

# ============================================================================
# Section 5: Multivariate Analysis     Model Activations vs. EEG
# ============================================================================
def get_hidden_activations(model, x):
    model.eval()
    with torch.no_grad():
        embedded = model.embedding(x)
        z = torch.relu(model.fc1(embedded))
    return z

sample_batch = train_tokens[:32, :-1].to(device)
hidden_activations = get_hidden_activations(rd_model, sample_batch)
hidden_matrix = hidden_activations.mean(dim=0).detach().cpu().numpy()
print("Hidden activation matrix shape:", hidden_matrix.shape)

n_components_target = 6
n_components_eeg = min(eeg_feature_matrix.shape[1], n_components_target)
n_components_hidden = min(hidden_matrix.shape[1], n_components_target)
n_components = min(n_components_eeg, n_components_hidden)

pca_eeg = PCA(n_components=n_components)
eeg_pca = pca_eeg.fit_transform(eeg_feature_matrix)
print("EEG PCA shape:", eeg_pca.shape)

pca_hidden = PCA(n_components=n_components)
```

```python
hidden_pca = pca_hidden.fit_transform(hidden_matrix)
print("Hidden activations PCA shape:", hidden_pca.shape)

common_length = min(eeg_pca.shape[0], hidden_pca.shape[0])
print("Common temporal length:", common_length)

def downsample_time_series(data, new_length):
    x_old = np.linspace(0, 1, data.shape[0])
    x_new = np.linspace(0, 1, new_length)
    downsampled = np.zeros((new_length, data.shape[1]))
    for i in range(data.shape[1]):
        downsampled[:, i] = np.interp(x_new, x_old, data[:, i])
    return downsampled

eeg_downsampled = downsample_time_series(eeg_pca, common_length)
hidden_downsampled = downsample_time_series(hidden_pca, common_length)
print("Downsampled EEG shape:", eeg_downsampled.shape)
print("Downsampled hidden activations shape:", hidden_downsampled.shape)

cca_linear = CCA(n_components=n_components)
eeg_cca, hidden_cca = cca_linear.fit_transform(eeg_downsampled, hidden_downsampled)
canonical_correlations_linear = []
for i in range(n_components):
    corr = np.corrcoef(eeg_cca[:, i], hidden_cca[:, i])[0, 1]
    canonical_correlations_linear.append(corr)
    print(f"Linear CCA - Canonical correlation for component {i+1}: {corr:.4f}")
avg_corr_linear = np.mean(canonical_correlations_linear)
print(f"Average linear canonical correlation: {avg_corr_linear:.4f}")

kpca_eeg = KernelPCA(n_components=n_components, kernel='rbf', gamma=0.1)
eeg_kpca = kpca_eeg.fit_transform(eeg_downsampled)
kpca_hidden = KernelPCA(n_components=n_components, kernel='rbf', gamma=0.1)
hidden_kpca = kpca_hidden.fit_transform(hidden_downsampled)
cca_kernel = CCA(n_components=n_components)
eeg_kcca, hidden_kcca = cca_kernel.fit_transform(eeg_kpca, hidden_kpca)
canonical_correlations_kernel = []
for i in range(n_components):
    corr = np.corrcoef(eeg_kcca[:, i], hidden_kcca[:, i])[0, 1]
    canonical_correlations_kernel.append(corr)
    print(f"Kernel PCA + CCA - Canonical correlation for component {i+1}: {corr:.4f}")
avg_corr_kernel = np.mean(canonical_correlations_kernel)
print(f"Average kernel canonical correlation: {avg_corr_kernel:.4f}")

# ===============================================================================
# Section 6: Optional     Probabilistic Cue Integration Demonstration
# ===============================================================================
def probabilistic_cue_integration(mu1, sigma1_sq, mu2, sigma2_sq):
```

```
    weight1 = sigma2_sq / (sigma1_sq + sigma2_sq + 1e-8)
    weight2 = sigma1_sq / (sigma1_sq + sigma2_sq + 1e-8)
    return weight1 * mu1 + weight2 * mu2

mu1 = np.random.rand(128)
mu2 = np.random.rand(128)
sigma1_sq = 0.5
sigma2_sq = 0.8
mu_combined = probabilistic_cue_integration(mu1, sigma1_sq, mu2, sigma2_sq)
print("Combined representation (first 10 elements):", mu_combined[:10])

# ==============================================================================
# Section 7: Training and Text Generation
# ==============================================================================
def train_rd_model(model, optimizer, loss_fn, train_data, epochs=50,
    batch_size=8, device="cpu"):
    model.train()
    dataset = train_data.to(device)
    num_samples = dataset.size(0)
    loss_history = []
    scaler = torch.cuda.amp.GradScaler() if device == "cuda" else None

    for epoch in range(epochs):
        epoch_loss = 0.0
        perm = torch.randperm(num_samples)
        for i in range(0, num_samples, batch_size):
            indices = perm[i:i+batch_size]
            batch = dataset[indices].to(device)
            inputs = batch[:, :-1]
            targets = batch[:, 1:].to(device)
            optimizer.zero_grad()
            if scaler:
                with torch.cuda.amp.autocast():
                    logits = model(inputs)
                    loss = loss_fn(logits.permute(0, 2, 1), targets)
                scaler.scale(loss).backward()
                scaler.step(optimizer)
                scaler.update()
            else:
                logits = model(inputs)
                loss = loss_fn(logits.permute(0, 2, 1), targets)
                loss.backward()
                optimizer.step()
            epoch_loss += loss.item()
        avg_loss = epoch_loss / (num_samples / batch_size)
        loss_history.append(avg_loss)
        if epoch % 10 == 0:
            print(f"Epoch {epoch}: Loss = {avg_loss:.4f}")
    return loss_history

```

```
def generate_rd_text(model, prompt, max_length=20, device="cpu"):
    model.eval()
    input_ids = tokenizer(prompt, return_tensors="pt")["input_ids"].to(device)
    for _ in range(max_length):
        with torch.no_grad():
            logits = model(input_ids)
        next_token = torch.argmax(logits[0, -1, :]).unsqueeze(0).unsqueeze(0)
        input_ids = torch.cat([input_ids, next_token], dim=1)
    return tokenizer.decode(input_ids.squeeze(), skip_special_tokens=True)

def generate_gpt2_text(prompt, max_length=50, device="cpu"):
    inputs = tokenizer(prompt, return_tensors="pt", padding=True)
    input_ids = inputs["input_ids"].to(device)
    attention_mask = inputs["attention_mask"].to(device)
    gpt2_output = gpt2_model.generate(
        input_ids=input_ids,
        attention_mask=attention_mask,
        max_length=max_length,
        pad_token_id=tokenizer.eos_token_id
    )
    return tokenizer.decode(gpt2_output[0], skip_special_tokens=True)

device = "cuda" if torch.cuda.is_available() else "cpu"
vocab_size = tokenizer.vocab_size
hidden_size = 128
rd_model = EvolvingNN(vocab_size=vocab_size, hidden_size=hidden_size).to(
    device)
optimizer = optim.Adam(rd_model.parameters(), lr=0.001)
loss_fn = nn.CrossEntropyLoss()

print("\nTraining RD-Sphota AI on WikiText...")
loss_history = train_rd_model(rd_model, optimizer, loss_fn, train_tokens,
    epochs=50, batch_size=8, device=device)
plt.plot(loss_history)
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("RD-Sphota AI Training Loss")
plt.show()

gpt2_model = GPT2LMHeadModel.from_pretrained("gpt2").to(device)

prompt_text = "The history of science"
rd_generated_text = generate_rd_text(rd_model, prompt_text, max_length=20,
    device=device)
print("\nRD-Sphota Generated Text:")
print(rd_generated_text)

gpt2_generated_text = generate_gpt2_text(prompt_text, max_length=50, device=
    device)
print("\nGPT-2 Generated Text:")
print(gpt2_generated_text)
```

Listing 5: Final RD-Sphota AI Model Code

Explanation of Appendix Sections:

- **Section 1: Data Preparation** – Loads and tokenizes the WikiText-2 dataset.
- **Section 2: Reaction–Diffusion Dynamics and Model Definitions** – Presents the reaction–diffusion parameters, update function, and the `EvolvingNN` model class, which integrates probabilistic cue integration.
- **Section 3: Training Routine and Text Generation** – Provides the training loop and text generation functions for both the RD-Sphota model and GPT–2 for comparison.
- **Section 4: EEG Data Processing and Feature Extraction** – Details the procedure for loading EEG data using MNE, extracting spectral features from defined frequency bands, and normalizing these features.
- **Section 5: Multivariate Analysis** – Describes the dimensionality reduction (PCA, Kernel PCA) and canonical correlation analysis (CCA) methods used to compare the model's activations with EEG features.
- **Section 6: Optional – Probabilistic Cue Integration** – Demonstrates the Bayesian cue integration mechanism using a simple example.
- **Section 7: Training and Text Generation (Revisited)** – Reiterates the training and text generation processes.