

# **Chapter 19: Cognitive Neuroscience and Deep Learning**

# Chapter Goals

After completing this chapter, you will be able to:

- Understand the bidirectional relationship between cognitive neuroscience and deep learning
- Identify key cognitive neuroscience principles that have inspired deep learning architectures
- Apply cognitive constraints to improve deep learning model performance and interpretability
- Analyze deep learning models as computational models of cognition
- Explain how deep learning has contributed to our understanding of brain function
- Implement methods for comparing neural and artificial network representations
- Design experiments that bridge cognitive neuroscience and deep learning

## 19.1 Introduction: The Convergence of Minds and Machines

Cognitive neuroscience and deep learning represent two powerful approaches to understanding intelligence—one through the study of biological brains, and the other through the development of artificial neural systems. While these fields developed largely independently, they have begun to converge in recent years, creating a rich interdisciplinary area that promises to advance both our understanding of natural intelligence and our ability to create artificial intelligence.

This chapter explores this bidirectional relationship: how cognitive neuroscience inspires deep learning architectures and strategies, and how deep learning models serve as computational models of cognition that generate testable predictions about brain function.

```
# Conceptual overview of the relationship between cognitive neuroscience and deep learning
import matplotlib.pyplot as plt
import numpy as np
from matplotlib_venn import venn2

def visualize_field_relationship():
    """
    Visualize the bidirectional relationship between cognitive neuroscience and deep learning
    """
    fig, ax = plt.subplots(figsize=(10, 6))

    # Create a Venn diagram showing the overlap
    v = venn2(subsets=(0.4, 0.4, 0.2), set_labels=('Cognitive Neuroscience', 'Deep Learning'))

    # Change colors and alpha
    v.get_patch_by_id('10').set_color('lightblue')
    v.get_patch_by_id('01').set_color('lightgreen')
    v.get_patch_by_id('11').set_color('orange')

    v.get_patch_by_id('10').set_alpha(0.7)
    v.get_patch_by_id('01').set_alpha(0.7)
    v.get_patch_by_id('11').set_alpha(0.7)

    # Add bidirectional arrow to show mutual influence
    plt.annotate('', xy=(0.3, 0.6), xytext=(0.7, 0.6),
                 arrowprops=dict(arrowstyle='<->', color='black', lw=2))

    # Add examples of cross-disciplinary concepts in the overlap
    ax.text(0.5, 0.55, "Shared Concepts:", ha='center', fontweight='bold')
    ax.text(0.5, 0.5, "• Hierarchical processing", ha='center')
    ax.text(0.5, 0.45, "• Distributed representations", ha='center')
    ax.text(0.5, 0.4, "• Attention mechanisms", ha='center')
    ax.text(0.5, 0.35, "• Predictive coding", ha='center')

    # Add examples specific to each field
    ax.text(0.2, 0.7, "• Neural circuits", ha='center')
    ax.text(0.2, 0.65, "• Cognitive processes", ha='center')
    ax.text(0.2, 0.6, "• Brain imaging", ha='center')

    ax.text(0.8, 0.7, "• Backpropagation", ha='center')
    ax.text(0.8, 0.65, "• Gradient descent", ha='center')
    ax.text(0.8, 0.6, "• Layer architectures", ha='center')

    # Set title
    ax.set_title('The Bidirectional Relationship Between Cognitive Neuroscience and Deep Learning',
                 fontsize=14, pad=20)

    plt.show()
```

# 19.2 Cognitive Science Principles in Deep Learning

## 19.2.1 Attention and Working Memory

The human attention system allows us to selectively focus on relevant information while filtering out distractions. In deep learning, attention mechanisms have revolutionized performance across domains:

- **Visual attention:** Mechanisms that weight the importance of different regions in an image
- **Self-attention:** Found in transformers, allows models to weigh the importance of different elements in a sequence
- **Cross-attention:** Allows models to relate elements from different modalities or sequences

Working memory—our ability to temporarily maintain and manipulate information—has also influenced deep learning through:

- **Memory networks:** Architectures with explicit memory components
- **Gating mechanisms:** Control the flow of information through the network
- **Meta-learning:** Learning to rapidly adapt to new tasks by maintaining task-relevant information

## 19.2.2 Hierarchical Processing and Compositionality

The brain processes information through hierarchical structures, from simple features to complex concepts. This principle has inspired deep learning architectures:

- **Convolutional neural networks:** Hierarchical visual processing from edges to objects
- **Hierarchical reinforcement learning:** Breaking complex tasks into manageable sub-goals
- **Compositional generalization:** Combining learned components in novel ways

```

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Conv2D, MaxPooling2D, Flatten

def create_hierarchical_cnn():
    """
    Create a CNN with hierarchical processing inspired by the visual cortex

    Returns:
    -----
    model : tf.keras.Model
        A CNN with hierarchical processing
    """
    model = Sequential([
        # Input layer (specify for clarity)
        tf.keras.layers.Input(shape=(224, 224, 3)),

        # Stage 1: Low-level feature extraction (analogous to V1)
        # Detect edges and simple contours
        Conv2D(32, (3, 3), activation='relu', padding='same', name='low_level_fea'),
        Conv2D(32, (3, 3), activation='relu', padding='same'),
        MaxPooling2D((2, 2)),

        # Stage 2: Mid-level feature extraction (analogous to V2/V4)
        # Detect shapes and textures
        Conv2D(64, (3, 3), activation='relu', padding='same', name='mid_level_fea'),
        Conv2D(64, (3, 3), activation='relu', padding='same'),
        MaxPooling2D((2, 2)),

        # Stage 3: Higher-level feature extraction (analogous to posterior IT)
        # Detect parts of objects
        Conv2D(128, (3, 3), activation='relu', padding='same', name='high_level_f'),
        Conv2D(128, (3, 3), activation='relu', padding='same'),
        MaxPooling2D((2, 2)),

        # Stage 4: Object-level representation (analogous to anterior IT)
        # Detect whole objects
        Conv2D(256, (3, 3), activation='relu', padding='same', name='object_level'),
        Conv2D(256, (3, 3), activation='relu', padding='same'),
        MaxPooling2D((2, 2)),

        # Flatten and dense layers (analogous to prefrontal cortex)
        # Abstract categorization and decision making
        Flatten(),
        Dense(512, activation='relu', name='abstract_features'),
        Dense(100, activation='softmax', name='classification')
    ])

    return model

def visualize_activations(model, example_image):
    """
    Visualize activations at different stages of the hierarchical network

```

Parameters:

-----

```
model : tf.keras.Model
    The hierarchical CNN model
example_image : numpy.ndarray
    An example image to visualize activations for
"""
# This would extract activations from different layers of the network
# In a real implementation, you would use a model to extract these
# Here we'll just sketch the concept

layer_names = [
    'low_level_features',
    'mid_level_features',
    'high_level_features',
    'object_level_features'
]

fig, axes = plt.subplots(1, len(layer_names), figsize=(15, 3))

for i, layer_name in enumerate(layer_names):
    # In real code, this would extract actual activations
    # feature_map = get_layer_activation(model, layer_name, example_image)

    # For demonstration, we'll create mock activations
    if i == 0: # Low-level (edges)
        feature_map = np.random.rand(56, 56) # Simplified for visualization
    elif i == 1: # Mid-level (textures)
        feature_map = np.random.rand(28, 28)
    elif i == 2: # High-level (parts)
        feature_map = np.random.rand(14, 14)
    else: # Object level
        feature_map = np.random.rand(7, 7)

    axes[i].imshow(feature_map, cmap='viridis')
    axes[i].set_title(f"{layer_name.replace('_', ' ').title()}")
    axes[i].axis('off')

plt.tight_layout()
plt.show()
```

## 19.2.3 Predictive Coding and Generative Models

A fundamental principle in cognitive neuroscience is that the brain continuously predicts future inputs, with perception arising from the integration of these predictions with sensory data. This has influenced deep learning through:

- **Generative models:** Systems that learn to generate likely inputs

- **Self-supervised learning:** Learning from prediction tasks without explicit labels
- **Contrastive predictive coding:** Learning representations by predicting future states
- **Variational autoencoders:** Learning latent representations that capture data distribution

## 19.2.4 Embodied Cognition and Active Learning

Cognitive science increasingly emphasizes that intelligence is embodied—developed through physical interaction with the environment. This has influenced AI through:

- **Reinforcement learning:** Agents learn from interactions with environments
- **Active learning:** Systems actively select what data to learn from
- **Curriculum learning:** Gradually increasing task difficulty during training
- **Curiosity-driven learning:** Using prediction errors to drive exploration

## 19.3 Cognitive Constraints in Deep Learning

### 19.3.1 Inductive Biases from Cognitive Science

Human cognition demonstrates numerous inductive biases—prior assumptions that guide learning. Incorporating these biases into deep learning models can improve performance:

- **Object-centric representations:** Humans naturally parse scenes into discrete objects
- **Causal reasoning:** Humans infer and reason about cause-and-effect relationships
- **Compositional structure:** Humans represent concepts as combinations of simpler parts
- **Few-shot learning:** Humans can learn from very few examples

```

import numpy as np
import torch
import torch.nn as nn
import torch.nn.functional as F

class ObjectCentricNetwork(nn.Module):
    """
    A network that incorporates an object-centric inductive bias
    inspired by human visual cognition
    """

    def __init__(self, n_slots=5, slot_dim=64, hidden_dim=64):
        """
        Initialize the object-centric network

        Parameters:
        -----
        n_slots : int
            Number of object slots
        slot_dim : int
            Dimension of each object slot
        hidden_dim : int
            Dimension of hidden layers
        """
        super().__init__()

        self.n_slots = n_slots
        self.slot_dim = slot_dim

        # Slot attention mechanism
        self.slot_attention = SlotAttention(
            dim=hidden_dim,
            n_slots=n_slots,
            slot_dim=slot_dim
        )

        # CNN encoder to extract features from images
        self.encoder = nn.Sequential(
            nn.Conv2d(3, 32, 5, stride=1, padding=2),
            nn.ReLU(),
            nn.MaxPool2d(2),
            nn.Conv2d(32, 32, 5, stride=1, padding=2),
            nn.ReLU(),
            nn.MaxPool2d(2),
            nn.Conv2d(32, 64, 5, stride=1, padding=2),
            nn.ReLU(),
            nn.Flatten(),
            nn.Linear(64 * 8 * 8, hidden_dim)
        )

        # Object-wise MLP for classification
        self.object_classifier = nn.Sequential(
            nn.Linear(slot_dim, hidden_dim),

```



```

        nn.ReLU(),
        nn.Linear(hidden_dim, hidden_dim),
        nn.ReLU(),
        nn.Linear(hidden_dim, 10) # 10 object classes
    )

def forward(self, x):
    """
    Forward pass through the network

    Parameters:
    -----
    x : torch.Tensor
        Input images of shape (batch_size, channels, height, width)

    Returns:
    -----
    object_preds : torch.Tensor
        Object class predictions
    attention_maps : torch.Tensor
        Attention maps for each object slot
    """
    batch_size = x.shape[0]

    # Extract image features
    features = self.encoder(x)

    # Apply slot attention to segment into objects
    slots, attention_maps = self.slot_attention(features, x.shape)

    # Classify each object
    object_preds = self.object_classifier(slots.view(batch_size * self.n_slot))
    object_preds = object_preds.view(batch_size, self.n_slots, -1)

    return object_preds, attention_maps


class SlotAttention(nn.Module):
    """
    Simplified version of Slot Attention mechanism
    """

    def __init__(self, dim, n_slots, slot_dim):
        super().__init__()
        self.dim = dim
        self.n_slots = n_slots
        self.slot_dim = slot_dim

        # Initialize slot parameters
        self.slots = nn.Parameter(torch.randn(1, n_slots, slot_dim))

        # Projection layers
        self.to_q = nn.Linear(slot_dim, dim)
        self.to_k = nn.Linear(dim, dim)

```

```

self.to_v = nn.Linear(dim, dim)

self.gru = nn.GRUCell(dim, slot_dim)

# MLP for slot update
self.mlp = nn.Sequential(
    nn.Linear(slot_dim, slot_dim),
    nn.ReLU(),
    nn.Linear(slot_dim, slot_dim)
)

# Layer norm
self.norm_slots = nn.LayerNorm(slot_dim)
self.norm_inputs = nn.LayerNorm(dim)

def forward(self, inputs, image_shape, num_iterations=3):
    """
    Apply slot attention mechanism

    Parameters:
    -----
    inputs : torch.Tensor
        Input features of shape (batch_size, dim)
    image_shape : tuple
        Shape of the input images (batch_size, channels, height, width)
    num_iterations : int
        Number of attention iterations

    Returns:
    -----
    slots : torch.Tensor
        Updated slot representations
    attention_maps : torch.Tensor
        Attention maps for visualization
    """
    batch_size = inputs.shape[0]

    # Initialize slots
    slots = self.slots.expand(batch_size, -1, -1)

    # Normalizations
    inputs = self.norm_inputs(inputs)

    # Reshape inputs for attention visualization
    h, w = image_shape[2] // 4, image_shape[3] // 4 # Downsampled due to CNN

    # Multiple rounds of attention
    for _ in range(num_iterations):
        slots_prev = slots

        # Normalize slots
        slots = self.norm_slots(slots)

        # Attention

```

```

q = self.to_q(slots)
k = self.to_k(inputs.unsqueeze(1))
v = self.to_v(inputs.unsqueeze(1))

# Compute attention scores
attn_logits = torch.sum(q.unsqueeze(2) * k, dim=-1)
attn = F.softmax(attn_logits, dim=1)

# Weight values by attention
updates = torch.sum(attn.unsqueeze(-1) * v, dim=2)

# Update slots
slots = self.gru(
    updates.reshape(-1, self.dim),
    slots_prev.reshape(-1, self.slot_dim)
)
slots = slots.reshape(batch_size, self.n_slots, self.slot_dim)

# MLP for additional processing
slots = slots + self.mlp(slots)

# Reshape attention for visualization
attention_maps = attn.reshape(batch_size, self.n_slots, h, w)

return slots, attention_maps

```

## 19.3.2 Neural Architecture Constraints

Beyond specific cognitive principles, the broader architecture of the brain can inform deep learning:

- **Computational resource constraints:** Optimizing for energy efficiency
- **Local learning rules:** Alternatives to global backpropagation
- **Modular architectures:** Specialized components with distinct functions
- **Recurrence and feedback connections:** Incorporating temporal dynamics and top-down processing

## 19.3.3 Cognitively-Plausible Learning Mechanisms

Human learning differs from standard deep learning approaches in key ways:

- **Hebbian learning:** Connections strengthen when neurons co-activate
- **Contrastive learning:** Learning from differences between positive and negative examples

- **Curriculum learning:** Gradually increasing task difficulty
- **Few-shot and continual learning:** Learning efficiently from limited data while avoiding catastrophic forgetting

```

import numpy as np

class HebbianNetwork:
    """
    Simple implementation of a Hebbian learning network
    """

    def __init__(self, input_size, output_size, learning_rate=0.01, decay_rate=0.01):
        """
        Initialize the Hebbian network

        Parameters:
        -----
        input_size : int
            Size of input features
        output_size : int
            Size of output features
        learning_rate : float
            Learning rate for weight updates
        decay_rate : float
            Weight decay rate to prevent unbounded growth
        """
        self.weights = np.random.normal(0, 0.1, (output_size, input_size))
        self.learning_rate = learning_rate
        self.decay_rate = decay_rate

    def forward(self, x):
        """
        Forward pass through the network

        Parameters:
        -----
        x : numpy.ndarray
            Input data of shape (batch_size, input_size)

        Returns:
        -----
        y : numpy.ndarray
            Output activations of shape (batch_size, output_size)
        """
        return np.dot(x, self.weights.T)

    def update(self, x, y):
        """
        Update weights using Hebbian learning rule:
        "Neurons that fire together, wire together"

        Parameters:
        -----
        x : numpy.ndarray
            Input data of shape (batch_size, input_size)
        y : numpy.ndarray
            Output activations of shape (batch_size, output_size)

```

```

    """
    # Basic Hebbian update
    delta_w = self.learning_rate * np.dot(y.T, x)

    # Apply weight decay to prevent unbounded growth
    delta_w -= self.decay_rate * self.weights

    # Update weights
    self.weights += delta_w

def train(self, x, num_epochs=1):
    """
    Train the network for a specified number of epochs

    Parameters:
    -----
    x : numpy.ndarray
        Input data of shape (batch_size, input_size)
    num_epochs : int
        Number of training epochs
    """
    for epoch in range(num_epochs):
        # Forward pass
        y = self.forward(x)

        # Update weights
        self.update(x, y)

        # Optional: Apply normalization to stabilize learning
        self.weights = self.weights / np.maximum(np.linalg.norm(self.weights), 1)

        # Print progress
        if epoch % 10 == 0:
            print(f"Epoch {epoch}: Average activation: {np.mean(np.abs(y)):.4f}")

def visualize_weights(self, reshape=None):
    """
    Visualize the learned weights

    Parameters:
    -----
    reshape : tuple or None
        Reshape dimensions for visualizing weights as images
    """
    fig, axes = plt.subplots(1, min(5, self.weights.shape[0]), figsize=(15, 3))

    for i, ax in enumerate(axes):
        if i < self.weights.shape[0]:
            weight = self.weights[i]

            if reshape is not None:
                weight = weight.reshape(reshape)

            ax.imshow(weight, cmap='viridis')

```

```
ax.set_title(f"Neuron {i+1}")  
ax.axis('off')  
  
plt.tight_layout()  
plt.show()
```

## 19.4 Deep Learning Models as Theories of Cognition

### 19.4.1 Using Deep Learning to Test Cognitive Theories

Deep learning models can serve as computational implementations of cognitive theories:

- **Explicit formalizations:** Converting verbal theories into precise computations
- **Parameter exploration:** Testing hypotheses by manipulating model parameters
- **Counterfactual testing:** Exploring alternative mechanisms
- **Developmental trajectories:** Studying how learning unfolds over time

### 19.4.2 Case Studies in Cognitive Modeling

Deep learning has been used to model various cognitive domains:

- **Visual perception:** CNNs as models of object recognition
- **Language processing:** Transformers as models of language comprehension
- **Decision making:** Reinforcement learning as models of value-based choice
- **Memory:** Sequence models as models of episodic and working memory

```

import torch
import torch.nn as nn
import torch.nn.functional as F
import numpy as np
import matplotlib.pyplot as plt

class VisualCognitiveModel(nn.Module):
    """
    CNN-based model of visual object recognition designed to test
    cognitive theories about human visual processing
    """

    def __init__(self, with_recurrence=False, with_feedback=False):
        """
        Initialize the visual cognitive model

        Parameters:
        -----
        with_recurrence : bool
            Whether to include recurrent connections
        with_feedback : bool
            Whether to include feedback connections
        """
        super().__init__()

        self.with_recurrence = with_recurrence
        self.with_feedback = with_feedback

        # Feedforward pathway (V1-like)
        self.conv1 = nn.Conv2d(3, 32, kernel_size=5, padding=2)
        self.pool1 = nn.MaxPool2d(2)

        # Feedforward pathway (V2-like)
        self.conv2 = nn.Conv2d(32, 64, kernel_size=5, padding=2)
        self.pool2 = nn.MaxPool2d(2)

        # Feedforward pathway (V4-like)
        self.conv3 = nn.Conv2d(64, 128, kernel_size=3, padding=1)
        self.pool3 = nn.MaxPool2d(2)

        # Feedforward pathway (IT-like)
        self.conv4 = nn.Conv2d(128, 256, kernel_size=3, padding=1)
        self.pool4 = nn.MaxPool2d(2)

        # Recurrent connections
        if with_recurrence:
            self.recurrent1 = nn.Conv2d(32, 32, kernel_size=3, padding=1)
            self.recurrent2 = nn.Conv2d(64, 64, kernel_size=3, padding=1)
            self.recurrent3 = nn.Conv2d(128, 128, kernel_size=3, padding=1)

        # Feedback connections
        if with_feedback:
            self.feedback3 = nn.ConvTranspose2d(128, 64, kernel_size=4, stride=2,

```



```

        self.feedback2 = nn.ConvTranspose2d(64, 32, kernel_size=4, stride=2,

# Readout layers
self.flatten = nn.Flatten()
self.fc1 = nn.Linear(256 * 4 * 4, 512)
self.fc2 = nn.Linear(512, 10) # 10 object classes

# Save activations for visualization
self.activations = {}

def forward(self, x, timesteps=3):
    """
    Forward pass through the network

    Parameters:
    -----
    x : torch.Tensor
        Input images
    timesteps : int
        Number of timesteps for recurrent processing

    Returns:
    -----
    output : torch.Tensor
        Class predictions
    """
    batch_size = x.shape[0]

    # Initial feedforward pass
    x1 = F.relu(self.conv1(x))
    p1 = self.pool1(x1)

    x2 = F.relu(self.conv2(p1))
    p2 = self.pool2(x2)

    x3 = F.relu(self.conv3(p2))
    p3 = self.pool3(x3)

    x4 = F.relu(self.conv4(p3))
    p4 = self.pool4(x4)

    # Store initial activations
    self.activations['layer1'] = p1.detach().cpu().numpy()
    self.activations['layer2'] = p2.detach().cpu().numpy()
    self.activations['layer3'] = p3.detach().cpu().numpy()
    self.activations['layer4'] = p4.detach().cpu().numpy()

    # Recurrent and feedback processing
    if self.with_recurrence or self.with_feedback:
        for t in range(timesteps - 1):
            # Store activations for this timestep
            self.activations[f'layer1_t{t+1}'] = p1.detach().cpu().numpy()
            self.activations[f'layer2_t{t+1}'] = p2.detach().cpu().numpy()
            self.activations[f'layer3_t{t+1}'] = p3.detach().cpu().numpy()

```

```

        # Apply recurrent connections
        if self.with_recurrence:
            p1 = p1 + F.relu(self.recurrent1(p1))
            p2 = p2 + F.relu(self.recurrent2(p2))
            p3 = p3 + F.relu(self.recurrent3(p3))

        # Apply feedback connections
        if self.with_feedback:
            feedback_3to2 = self.feedback3(p3)
            feedback_2to1 = self.feedback2(p2)

            # Add feedback to earlier representations
            p2 = p2 + 0.2 * feedback_3to2
            p1 = p1 + 0.2 * feedback_2to1

            # Update forward pass with feedback influence
            x2 = F.relu(self.conv2(p1))
            p2 = self.pool2(x2)

            x3 = F.relu(self.conv3(p2))
            p3 = self.pool3(x3)

            x4 = F.relu(self.conv4(p3))
            p4 = self.pool4(x4)

    # Final classification
    flat = self.flatten(p4)
    fc1 = F.relu(self.fc1(flat))
    output = self.fc2(fc1)

    return output

def analyze_temporal_dynamics(self, image, target_class, timesteps=5):
    """
    Analyze how representation evolves over time due to
    recurrent and feedback processing

    Parameters:
    -----
    image : torch.Tensor
        Input image
    target_class : int
        Target class for the image
    timesteps : int
        Number of timesteps to analyze
    """
    # Ensure the model is in evaluation mode
    self.eval()

    # Forward pass with multiple timesteps
    output = self.forward(image, timesteps=timesteps)

    # Get class probabilities

```

```

probs = F.softmax(output, dim=1)
target_prob = probs[0, target_class].item()

# Visualize how representations change over time
fig, axes = plt.subplots(timesteps, 4, figsize=(15, 3*timesteps))

for t in range(timesteps):
    for l in range(4):
        layer_name = f'layer{l+1}_t{t}' if t > 0 else f'layer{l+1}'
        if layer_name in self.activations:
            # Take first image in batch, first channel for visualization
            act = self.activations[layer_name][0, 0]
            axes[t, l].imshow(act, cmap='viridis')
            axes[t, l].set_title(f"Layer {l+1}, Time {t}")
            axes[t, l].axis('off')

plt.tight_layout()
plt.show()

# Plot target class probability over time
plt.figure(figsize=(8, 4))
plt.plot(range(timesteps), [probs[0, target_class].item() for t in range(timesteps)])
plt.xlabel('Processing Timestep')
plt.ylabel(f'Probability of Class {target_class}')
plt.title('Temporal Dynamics of Recognition')
plt.grid(True, alpha=0.3)
plt.show()

return probs

```

## 19.4.3 Comparing Model Behavior to Human Behavior

A key test of cognitive models is their ability to predict human behavior:

- **Psychophysical experiments:** Testing if models show similar perceptual biases
- **Error patterns:** Comparing model and human mistakes
- **Reaction times:** Relating model processing to response latencies
- **Developmental trajectories:** Comparing learning curves

# 19.5 Neural Representation Comparison Methods

## 19.5.1 Representational Similarity Analysis

Representational Similarity Analysis (RSA) is a framework for comparing neural representations across species, methods, and models:

- **Constructing similarity matrices:** Computing pairwise similarities between activity patterns
- **Computing representational similarity:** Correlating similarity matrices across systems
- **Significance testing:** Statistical approaches for assessing similarity
- **Visualization techniques:** Visualizing representational spaces

```

import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import spearmanr, pearsonr
from scipy.spatial.distance import pdist, squareform

class RepresentationalSimilarityAnalysis:
    """
    Implementation of Representational Similarity Analysis (RSA)
    for comparing neural and model representations
    """

    def __init__(self, distance_metric='correlation'):
        """
        Initialize RSA

        Parameters:
        -----
        distance_metric : str
            Distance metric for computing dissimilarity
            Options: 'correlation', 'euclidean', 'cosine'
        """
        self.distance_metric = distance_metric

    def compute_rdm(self, activations):
        """
        Compute Representational Dissimilarity Matrix (RDM)

        Parameters:
        -----
        activations : numpy.ndarray
            Neural/model activations of shape (n_samples, n_features)

        Returns:
        -----
        rdm : numpy.ndarray
            Representational Dissimilarity Matrix of shape (n_samples, n_samples)
        """
        # Compute pairwise distances
        distances = pdist(activations, metric=self.distance_metric)

        # Convert to square form
        rdm = squareform(distances)

        return rdm

    def compare_rdm(self, rdm1, rdm2, method='spearman'):
        """
        Compare two RDMs to quantify representational similarity

        Parameters:
        -----
        rdm1 : numpy.ndarray
            First RDM of shape (n_samples, n_samples)

```

```

rdm2 : numpy.ndarray
    Second RDM of shape (n_samples, n_samples)
method : str
    Correlation method ('spearman' or 'pearson')

Returns:
-----
correlation : float
    Correlation coefficient between the two RDMS
p_value : float
    p-value for the correlation
"""
# Flatten the upper triangular part of the RDMS (excluding diagonal)
triu_indices = np.triu_indices(rdm1.shape[0], k=1)
rdm1_flat = rdm1[triu_indices]
rdm2_flat = rdm2[triu_indices]

# Compute correlation
if method == 'spearman':
    correlation, p_value = spearmanr(rdm1_flat, rdm2_flat)
elif method == 'pearson':
    correlation, p_value = pearsonr(rdm1_flat, rdm2_flat)
else:
    raise ValueError("Method must be 'spearman' or 'pearson'")

return correlation, p_value

def visualize_rdm(self, rdm, labels=None, title='Representational Dissimilarity Matrix')
    """
    Visualize a Representational Dissimilarity Matrix

    Parameters:
    -----
    rdm : numpy.ndarray
        RDM of shape (n_samples, n_samples)
    labels : list or None
        Labels for the samples
    title : str
        Title for the plot
    """
    plt.figure(figsize=(10, 8))
    plt.imshow(rdm, cmap='viridis')
    plt.colorbar(label='Dissimilarity')
    plt.title(title)

    if labels is not None:
        plt.xticks(range(len(labels)), labels, rotation=90)
        plt.yticks(range(len(labels)), labels)

    plt.tight_layout()
    plt.show()

def visualize_comparison(self, rdm1, rdm2, labels1='Model', labels2='Brain',
    """

```

Visualize a comparison between two RDMs

Parameters:

-----

```
rdm1 : numpy.ndarray
    First RDM
rdm2 : numpy.ndarray
    Second RDM
labels1 : str
    Label for the first RDM
labels2 : str
    Label for the second RDM
title : str
    Title for the plot
"""
# Flatten upper triangular part
triu_indices = np.triu_indices(rdm1.shape[0], k=1)
rdm1_flat = rdm1[triu_indices]
rdm2_flat = rdm2[triu_indices]

# Compute correlation
correlation, p_value = self.compare_rdms(rdm1, rdm2)

# Create scatter plot
plt.figure(figsize=(8, 8))
plt.scatter(rdm1_flat, rdm2_flat, alpha=0.5)
plt.xlabel(f'{labels1} Dissimilarity')
plt.ylabel(f'{labels2} Dissimilarity')
plt.title(f'{title}\nCorrelation: {correlation:.3f} (p={p_value:.3g})')

# Add regression line
z = np.polyfit(rdm1_flat, rdm2_flat, 1)
p = np.poly1d(z)
plt.plot(np.linspace(min(rdm1_flat), max(rdm1_flat), 100),
         p(np.linspace(min(rdm1_flat), max(rdm1_flat), 100)),
         'r--', linewidth=2)

plt.tight_layout()
plt.show()

def mds_visualization(self, rdm, labels=None, title='MDS Visualization'):
    """
    Visualize the representational space using Multi-Dimensional Scaling (MDS)

    Parameters:
    -----
    rdm : numpy.ndarray
        RDM of shape (n_samples, n_samples)
    labels : list or None
        Labels for the samples
    title : str
        Title for the plot
    """
    from sklearn.manifold import MDS
```

```

# Create MDS model
mds = MDS(n_components=2, dissimilarity='precomputed', random_state=42)

# Fit MDS model to RDM
points = mds.fit_transform(rdm)

# Plot results
plt.figure(figsize=(10, 8))
plt.scatter(points[:, 0], points[:, 1], s=100)

if labels is not None:
    for i, label in enumerate(labels):
        plt.annotate(label, (points[i, 0], points[i, 1]),
                      fontsize=12, ha='center', va='center')

plt.title(title)
plt.grid(alpha=0.3)
plt.axis('equal')
plt.tight_layout()
plt.show()

return points

```

## 19.5.2 Neural Encoding and Decoding Models

Neural encoding and decoding create direct mappings between brain activity and model representations:

- **Encoding models:** Predicting neural responses from model activations
- **Decoding models:** Predicting stimuli from neural responses
- **Cross-validated prediction:** Assessing generalization of encoding/decoding models
- **Feature importance analysis:** Identifying critical dimensions of the representation

## 19.5.3 Canonical Correlation Analysis

Canonical Correlation Analysis (CCA) finds shared dimensions between neural and model representations:

- **Canonical variates:** Identifying maximally correlated dimensions
- **Shared variance:** Quantifying overlap between representations
- **Dimensionality analysis:** Determining the number of meaningful shared dimensions



- **Stimulus associations:** Relating shared dimensions to stimulus properties

```

import numpy as np
from sklearn.cross_decomposition import CCA
import matplotlib.pyplot as plt

class CanonicalCorrelationAnalyzer:
    """
    Implementation of Canonical Correlation Analysis (CCA)
    for comparing neural and model representations
    """

    def __init__(self, n_components=2):
        """
        Initialize CCA

        Parameters:
        -----
        n_components : int
            Number of canonical components to extract
        """
        self.n_components = n_components
        self.cca = CCA(n_components=n_components)
        self.correlations = None

    def fit(self, X, Y):
        """
        Fit CCA on two sets of features

        Parameters:
        -----
        X : numpy.ndarray
            First feature set (e.g., neural data) of shape (n_samples, n_features)
        Y : numpy.ndarray
            Second feature set (e.g., model data) of shape (n_samples, n_features)
        """
        # Fit CCA
        self.cca.fit(X, Y)

        # Transform data to canonical space
        X_c, Y_c = self.cca.transform(X, Y)

        # Compute correlations between canonical variates
        self.correlations = np.array([np.corrcoef(X_c[:, i], Y_c[:, i])[0, 1]
                                       for i in range(self.n_components)])

        return X_c, Y_c

    def transform(self, X, Y):
        """
        Transform data to canonical space

        Parameters:
        -----
        X : numpy.ndarray

```

```

        First feature set
Y : numpy.ndarray
        Second feature set

Returns:
-----
X_c : numpy.ndarray
        First feature set in canonical space
Y_c : numpy.ndarray
        Second feature set in canonical space
"""
return self.cca.transform(X, Y)

def visualize_correlations(self, labels=None):
    """
    Visualize canonical correlations

    Parameters:
    -----
    labels : list or None
        Labels for the components
    """
    if self.correlations is None:
        raise ValueError("CCA must be fit before visualizing correlations")

    plt.figure(figsize=(10, 6))

    plt.bar(range(1, self.n_components + 1), self.correlations)
    plt.xlabel('Canonical Component')
    plt.ylabel('Correlation')
    plt.title('Canonical Correlations')

    if labels:
        plt.xticks(range(1, self.n_components + 1), labels)

    plt.grid(axis='y', alpha=0.3)
    plt.tight_layout()
    plt.show()

def visualize_canonical_variates(self, X_c, Y_c, sample_labels=None):
    """
    Visualize the first two canonical variates

    Parameters:
    -----
    X_c : numpy.ndarray
        First feature set in canonical space
    Y_c : numpy.ndarray
        Second feature set in canonical space
    sample_labels : list or None
        Labels for the samples
    """
    if X_c.shape[1] < 2 or Y_c.shape[1] < 2:
        raise ValueError("Need at least 2 components for visualization")

```

```

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

# Plot first set of canonical variates
axes[0].scatter(X_c[:, 0], X_c[:, 1], s=80, alpha=0.7)
axes[0].set_xlabel('First Canonical Variate')
axes[0].set_ylabel('Second Canonical Variate')
axes[0].set_title('Neural Representation')
axes[0].grid(alpha=0.3)

# Plot second set of canonical variates
axes[1].scatter(Y_c[:, 0], Y_c[:, 1], s=80, alpha=0.7)
axes[1].set_xlabel('First Canonical Variate')
axes[1].set_ylabel('Second Canonical Variate')
axes[1].set_title('Model Representation')
axes[1].grid(alpha=0.3)

if sample_labels is not None:
    for i, label in enumerate(sample_labels):
        axes[0].annotate(label, (X_c[i, 0], X_c[i, 1]), fontsize=10)
        axes[1].annotate(label, (Y_c[i, 0], Y_c[i, 1]), fontsize=10)

plt.tight_layout()
plt.show()

def correlation_significance(self, X, Y, n_permutations=1000, alpha=0.05):
    """
    Perform permutation test to assess significance of canonical correlations

    Parameters:
    -----
    X : numpy.ndarray
        First feature set
    Y : numpy.ndarray
        Second feature set
    n_permutations : int
        Number of permutations for the test
    alpha : float
        Significance level

    Returns:
    -----
    p_values : numpy.ndarray
        p-values for each canonical correlation
    """
    if self.correlations is None:
        raise ValueError("CCA must be fit before testing significance")

    # Initialize array to store permutation correlations
    perm_correlations = np.zeros((n_permutations, self.n_components))

    # Original sample size
    n_samples = X.shape[0]

```

```

# Perform permutation test
for i in range(n_permutations):
    # Permute samples in Y
    perm_idx = np.random.permutation(n_samples)
    Y_perm = Y[perm_idx]

    # Fit CCA on permuted data
    cca_perm = CCA(n_components=self.n_components)
    cca_perm.fit(X, Y_perm)

    # Transform data to canonical space
    X_c_perm, Y_c_perm = cca_perm.transform(X, Y_perm)

    # Compute correlations
    for j in range(self.n_components):
        perm_correlations[i, j] = np.corrcoef(X_c_perm[:, j], Y_c_perm[:, j])[0, 1]

# Compute p-values (proportion of permutation correlations >= observed)
p_values = np.zeros(self.n_components)
for j in range(self.n_components):
    p_values[j] = np.mean(perm_correlations[:, j] >= self.correlations[j])

# Visualize results
plt.figure(figsize=(12, 6))

for j in range(self.n_components):
    plt.subplot(1, self.n_components, j+1)
    plt.hist(perm_correlations[:, j], bins=30, alpha=0.7, color='gray')
    plt.axvline(self.correlations[j], color='red', linestyle='--', linewidth=2)
    plt.title(f'Component {j+1}: p={p_values[j]:.3f}')
    plt.xlabel('Correlation')
    plt.ylabel('Frequency')

plt.tight_layout()
plt.show()

return p_values

```

## 19.6 The Impact of Deep Learning on Cognitive Neuroscience

### 19.6.1 New Frameworks for Understanding Brain Function

Deep learning has provided cognitive neuroscience with new conceptual tools:

- **Normative theories:** Explaining neural mechanisms as optimizations for specific objectives

- **Learning dynamics:** Understanding neural development through gradient-based learning
- **Distributed representations:** Conceptualizing neural coding as distributed patterns
- **End-to-end optimization:** Viewing brain regions as components in differentiable systems

## 19.6.2 Tools for Neural Data Analysis

Beyond conceptual advances, deep learning has provided practical tools for neuroscience:

- **Neural decoding:** Better extraction of information from brain recordings
- **Dimensionality reduction:** Discovering meaningful latent structures in neural data
- **Generative modeling:** Creating detailed models of neural activity
- **Automated analysis:** Processing and classifying large neural datasets

```

import torch
import torch.nn as nn
import torch.nn.functional as F
import numpy as np
import matplotlib.pyplot as plt

class LatentDynamicsModel(nn.Module):
    """
    Neural latent dynamics model for analyzing neural population activity
    """

    def __init__(self, n_neurons, latent_dim=3, nonlinearity='tanh'):
        """
        Initialize the latent dynamics model

        Parameters:
        -----
        n_neurons : int
            Number of neurons in the population
        latent_dim : int
            Dimensionality of the latent space
        nonlinearity : str
            Nonlinearity to use ('relu', 'tanh', or 'sigmoid')
        """
        super().__init__()

        self.n_neurons = n_neurons
        self.latent_dim = latent_dim

        # Encoder: neural activity -> latent variables
        self.encoder = nn.Sequential(
            nn.Linear(n_neurons, 128),
            nn.ReLU(),
            nn.Linear(128, 64),
            nn.ReLU(),
            nn.Linear(64, latent_dim * 2) # Mean and log-variance
        )

        # Latent dynamics model
        if nonlinearity == 'relu':
            self.dynamics_nonlinearity = nn.ReLU()
        elif nonlinearity == 'tanh':
            self.dynamics_nonlinearity = nn.Tanh()
        elif nonlinearity == 'sigmoid':
            self.dynamics_nonlinearity = nn.Sigmoid()
        else:
            raise ValueError("Nonlinearity must be 'relu', 'tanh', or 'sigmoid'")

        self.dynamics = nn.Sequential(
            nn.Linear(latent_dim, latent_dim),
            self.dynamics_nonlinearity
        )

```

```

# Decoder: latent variables -> neural activity
self.decoder = nn.Sequential(
    nn.Linear(latent_dim, 64),
    nn.ReLU(),
    nn.Linear(64, 128),
    nn.ReLU(),
    nn.Linear(128, n_neurons)
)

def encode(self, x):
    """
    Encode neural activity to latent variables

    Parameters:
    -----
    x : torch.Tensor
        Neural activity of shape (batch_size, n_neurons)

    Returns:
    -----
    mean : torch.Tensor
        Mean of latent distribution
    logvar : torch.Tensor
        Log-variance of latent distribution
    """
    h = self.encoder(x)
    mean, logvar = torch.chunk(h, 2, dim=1)
    return mean, logvar

def reparameterize(self, mean, logvar):
    """
    Reparameterization trick for sampling from latent distribution

    Parameters:
    -----
    mean : torch.Tensor
        Mean of latent distribution
    logvar : torch.Tensor
        Log-variance of latent distribution

    Returns:
    -----
    z : torch.Tensor
        Sampled latent variables
    """
    std = torch.exp(0.5 * logvar)
    eps = torch.randn_like(std)
    return mean + eps * std

def decode(self, z):
    """
    Decode latent variables to neural activity

    Parameters:
    -----

```



```

-----
z : torch.Tensor
    Latent variables of shape (batch_size, latent_dim)

Returns:
-----
x_recon : torch.Tensor
    Reconstructed neural activity
"""
return self.decoder(z)

def forward(self, x):
    """
    Forward pass through the model

    Parameters:
    -----
    x : torch.Tensor
        Neural activity of shape (batch_size, n_neurons)

    Returns:
    -----
    x_recon : torch.Tensor
        Reconstructed neural activity
    mean : torch.Tensor
        Mean of latent distribution
    logvar : torch.Tensor
        Log-variance of latent distribution
    z : torch.Tensor
        Sampled latent variables
    """
    mean, logvar = self.encode(x)
    z = self.reparameterize(mean, logvar)
    x_recon = self.decode(z)
    return x_recon, mean, logvar, z

def predict_next_state(self, x):
    """
    Predict the next state in the latent space

    Parameters:
    -----
    x : torch.Tensor
        Current neural activity

    Returns:
    -----
    x_next : torch.Tensor
        Predicted next neural activity
    """
    mean, _ = self.encode(x)
    z_next = self.dynamics(mean)
    x_next = self.decode(z_next)
    return x_next

```

```

def loss_function(self, x_recon, x, mean, logvar, beta=1.0):
    """
    Compute the VAE loss function

    Parameters:
    -----
    x_recon : torch.Tensor
        Reconstructed neural activity
    x : torch.Tensor
        Original neural activity
    mean : torch.Tensor
        Mean of latent distribution
    logvar : torch.Tensor
        Log-variance of latent distribution
    beta : float
        Weight of the KL divergence term

    Returns:
    -----
    loss : torch.Tensor
        Total loss
    recon_loss : torch.Tensor
        Reconstruction loss
    kl_loss : torch.Tensor
        KL divergence loss
    """
    # Reconstruction loss (mean squared error)
    recon_loss = F.mse_loss(x_recon, x, reduction='sum')

    # KL divergence loss
    kl_loss = -0.5 * torch.sum(1 + logvar - mean.pow(2) - logvar.exp())

    # Total loss
    loss = recon_loss + beta * kl_loss

    return loss, recon_loss, kl_loss

def visualize_latent_space(self, data, labels=None, title='Latent Space Visualiza
    """
    Visualize the latent space

    Parameters:
    -----
    data : torch.Tensor
        Neural activity data
    labels : numpy.ndarray or None
        Labels for color-coding points
    title : str
        Plot title
    """
    # Switch to evaluation mode
    self.eval()

```

```

# Encode data to get latent representations
with torch.no_grad():
    mean, _ = self.encode(data)
    z = mean.cpu().numpy()

# Create scatter plot
fig = plt.figure(figsize=(10, 8))

if z.shape[1] >= 3:
    ax = fig.add_subplot(111, projection='3d')

    if labels is not None:
        for i, label in enumerate(np.unique(labels)):
            idx = np.where(labels == label)[0]
            ax.scatter(z[idx, 0], z[idx, 1], z[idx, 2], label=f'Class {label}')
    else:
        ax.scatter(z[:, 0], z[:, 1], z[:, 2], s=50, alpha=0.7)

    ax.set_xlabel('Latent Dim 1')
    ax.set_ylabel('Latent Dim 2')
    ax.set_zlabel('Latent Dim 3')

else:
    ax = fig.add_subplot(111)

    if labels is not None:
        for i, label in enumerate(np.unique(labels)):
            idx = np.where(labels == label)[0]
            ax.scatter(z[idx, 0], z[idx, 1], label=f'Class {label}', s=50)
    else:
        ax.scatter(z[:, 0], z[:, 1], s=50, alpha=0.7)

    ax.set_xlabel('Latent Dim 1')
    ax.set_ylabel('Latent Dim 2')

ax.set_title(title)

if labels is not None:
    ax.legend()

plt.tight_layout()
plt.show()

return z

def visualize_trajectory(self, data_sequence, title='Neural Trajectory in Lat
"""
Visualize a neural trajectory in the latent space

Parameters:
-----
data_sequence : torch.Tensor
    Sequence of neural activity patterns
title : str

```

```

    Plot title
"""
# Switch to evaluation mode
self.eval()

# Encode sequence to get latent representations
with torch.no_grad():
    latent_sequence = []
    for x in data_sequence:
        mean, _ = self.encode(x.unsqueeze(0))
        latent_sequence.append(mean.squeeze().cpu().numpy())

    latent_sequence = np.array(latent_sequence)

# Create 3D plot for trajectory
fig = plt.figure(figsize=(10, 8))

if latent_sequence.shape[1] >= 3:
    ax = fig.add_subplot(111, projection='3d')

    # Plot trajectory
    ax.plot(latent_sequence[:, 0], latent_sequence[:, 1], latent_sequence[:, 2],
            'o-', linewidth=2, markersize=8)

    # Highlight start and end points
    ax.scatter(latent_sequence[0, 0], latent_sequence[0, 1], latent_sequence[0, 2],
               color='green', s=100, label='Start')
    ax.scatter(latent_sequence[-1, 0], latent_sequence[-1, 1], latent_sequence[-1, 2],
               color='red', s=100, label='End')

    ax.set_xlabel('Latent Dim 1')
    ax.set_ylabel('Latent Dim 2')
    ax.set_zlabel('Latent Dim 3')

else:
    ax = fig.add_subplot(111)

    # Plot trajectory
    ax.plot(latent_sequence[:, 0], latent_sequence[:, 1], 'o-',
            linewidth=2, markersize=8)

    # Highlight start and end points
    ax.scatter(latent_sequence[0, 0], latent_sequence[0, 1],
               color='green', s=100, label='Start')
    ax.scatter(latent_sequence[-1, 0], latent_sequence[-1, 1],
               color='red', s=100, label='End')

    ax.set_xlabel('Latent Dim 1')
    ax.set_ylabel('Latent Dim 2')

ax.set_title(title)
ax.legend()
plt.tight_layout()
plt.show()

```

```
return latent_sequence
```

## 19.6.3 Generating New Hypotheses

Deep learning models can suggest novel hypotheses about brain function:

- **Optimization principles:** What objectives drive neural organization?
- **Architectural principles:** What network structures enable robust computation?
- **Learning mechanisms:** How does the brain learn efficiently from experience?
- **Feature representations:** What information is encoded in neural activity?

## 19.7 Practical Exercise: Comparing Deep Networks and Brain Representations

In this exercise, we'll demonstrate how to compare representations between a deep neural network and fMRI brain activity patterns in response to the same visual stimuli.

```

import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from scipy.stats import spearmanr

def simulate_fmri_data(n_stimuli=50, n_voxels=1000, n_roi=4, noise_level=0.1):
    """
    Simulate fMRI data for a visual experiment

    Parameters:
    -----
    n_stimuli : int
        Number of stimuli (images)
    n_voxels : int
        Total number of voxels
    n_roi : int
        Number of brain regions (ROIs)
    noise_level : float
        Level of noise to add

    Returns:
    -----
    fmri_data : numpy.ndarray
        fMRI response patterns of shape (n_stimuli, n_voxels)
    roi_masks : list
        Binary masks for each ROI
    """
    # Create random fMRI patterns
    fmri_data = np.zeros((n_stimuli, n_voxels))

    # Create ROI masks (which voxels belong to which brain region)
    voxels_per_roi = n_voxels // n_roi
    roi_masks = []

    for r in range(n_roi):
        # Create binary mask for this ROI
        mask = np.zeros(n_voxels, dtype=bool)
        start_idx = r * voxels_per_roi
        end_idx = (r + 1) * voxels_per_roi if r < n_roi - 1 else n_voxels
        mask[start_idx:end_idx] = True
        roi_masks.append(mask)

    # Generate patterns for this ROI
    # We'll make each ROI sensitive to different stimulus features
    for i in range(n_stimuli):
        # Create a pattern that depends on stimulus index in different ways f
        if r == 0: # Early visual (e.g., V1) - sensitive to low-level features
            pattern = np.sin(i / 5.0) + np.cos(i / 3.0)
        elif r == 1: # Mid-level visual (e.g., V4) - sensitive to shapes
            pattern = np.sin(i / 8.0) * np.cos(i / 2.0)
        elif r == 2: # Higher visual (e.g., LOC) - sensitive to objects
            pattern = np.tanh(i / 10.0 - 2.5)

```

```

        else: # Object category (e.g., IT) - sensitive to categories
            pattern = (i % 5) / 5.0 # 5 categories

    fmri_data[i, mask] = pattern

# Add noise
fmri_data += noise_level * np.random.randn(*fmri_data.shape)

return fmri_data, roi_masks

def simulate_cnn_activations(n_stimuli=50, n_layers=4, units_per_layer=250, noise_level=0.1):
    """
    Simulate CNN activations for the same stimuli

    Parameters:
    -----
    n_stimuli : int
        Number of stimuli (images)
    n_layers : int
        Number of CNN layers
    units_per_layer : int
        Number of units per layer
    noise_level : float
        Level of noise to add

    Returns:
    -----
    cnn_activations : dict
        Dictionary mapping layer names to activation patterns
    """
    cnn_activations = {}

    for l in range(n_layers):
        # Create activations for this layer
        layer_name = f"layer{l+1}"
        activations = np.zeros((n_stimuli, units_per_layer))

        for i in range(n_stimuli):
            # Create activations that depend on stimulus index in different ways
            if l == 0: # Conv1 - sensitive to edges
                pattern = np.sin(i / 5.0) + np.cos(i / 3.0)
            elif l == 1: # Conv2 - sensitive to textures
                pattern = np.sin(i / 7.0) * np.cos(i / 2.0)
            elif l == 2: # Conv3 - sensitive to parts
                pattern = np.sin(i / 10.0) * np.tanh(i / 4.0 - 2)
            else: # Conv4 - sensitive to objects
                pattern = (i % 5) / 5.0 # 5 categories

            activations[i] = pattern + noise_level * np.random.randn(units_per_layer)

        cnn_activations[layer_name] = activations

    return cnn_activations

```

```

def compute_rdms(data_dict):
    """
    Compute Representational Dissimilarity Matrices (RDMs) for different regions/

    Parameters:
    -----
    data_dict : dict
        Dictionary mapping region/layer names to activation patterns

    Returns:
    -----
    rdms : dict
        Dictionary mapping region/layer names to RDMs
    """
    rdms = {}

    for name, data in data_dict.items():
        # Compute pairwise correlation distances
        n_stimuli = data.shape[0]
        rdm = np.zeros((n_stimuli, n_stimuli))

        for i in range(n_stimuli):
            for j in range(i+1, n_stimuli):
                # 1 - correlation as a distance metric
                corr = np.corrcoef(data[i], data[j])[0, 1]
                dist = 1 - corr
                rdm[i, j] = dist
                rdm[j, i] = dist

        rdms[name] = rdm

    return rdms

def compare_representations(brain_rdms, model_rdms, roi_names=None, layer_names=None):
    """
    Compare brain and model representations

    Parameters:
    -----
    brain_rdms : dict
        Dictionary mapping ROI names to brain RDMs
    model_rdms : dict
        Dictionary mapping layer names to model RDMs
    roi_names : list or None
        Names of brain ROIs
    layer_names : list or None
        Names of model layers

    Returns:
    -----
    similarity_matrix : numpy.ndarray
        Matrix of correlations between brain ROIs and model layers
    """
    if roi_names is None:

```



```

        roi_names = list(brain_rdms.keys())
    if layer_names is None:
        layer_names = list(model_rdms.keys())

    n_rois = len(roi_names)
    n_layers = len(layer_names)

    similarity_matrix = np.zeros((n_rois, n_layers))

    for i, roi in enumerate(roi_names):
        brain_rdm = brain_rdms[roi]

        # Extract upper triangular part (excluding diagonal)
        triu_indices = np.triu_indices_from(brain_rdm, k=1)
        brain_rdm_triu = brain_rdm[triu_indices]

        for j, layer in enumerate(layer_names):
            model_rdm = model_rdms[layer]
            model_rdm_triu = model_rdm[triu_indices]

            # Compute Spearman correlation between RDMS
            corr, _ = spearmanr(brain_rdm_triu, model_rdm_triu)
            similarity_matrix[i, j] = corr

    return similarity_matrix

def main():
    """
    Main function to run the analysis
    """
    # 1. Simulate brain fMRI data
    n_stimuli = 50
    print("Simulating fMRI data...")
    fmri_data, roi_masks = simulate_fmri_data(n_stimuli=n_stimuli)

    # 2. Create brain ROI data dictionary
    brain_data = {}
    roi_names = ["V1", "V4", "LOC", "IT"]

    for i, (name, mask) in enumerate(zip(roi_names, roi_masks)):
        brain_data[name] = fmri_data[:, mask]

    # 3. Simulate CNN activations
    print("Simulating CNN activations...")
    cnn_activations = simulate_cnn_activations(n_stimuli=n_stimuli)

    # 4. Compute RDMS for brain ROIs and CNN layers
    print("Computing RDMS...")
    brain_rdms = compute_rdms(brain_data)
    model_rdms = compute_rdms(cnn_activations)

    # 5. Compare representations
    print("Comparing representations...")
    similarity_matrix = compare_representations(brain_rdms, model_rdms, roi_names

```

```

# 6. Visualize results
layer_names = list(cnn_activations.keys())

plt.figure(figsize=(10, 8))
plt.imshow(similarity_matrix, cmap='viridis')
plt.colorbar(label='Representational Similarity (Spearman  $\rho$ )')
plt.xlabel('CNN Layers')
plt.ylabel('Brain ROIs')
plt.title('Brain-CNN Representational Similarity')
plt.xticks(range(len(layer_names)), layer_names)
plt.yticks(range(len(roi_names)), roi_names)

# Add text annotations
for i in range(len(roi_names)):
    for j in range(len(layer_names)):
        plt.text(j, i, f"{similarity_matrix[i, j]:.2f}",
                  ha="center", va="center", color="white" if similarity_matrix[i, j] > 0.5 else "black")

plt.tight_layout()
plt.show()

# 7. Visualize RDMs
plt.figure(figsize=(15, 10))

# Plot brain RDMs
for i, name in enumerate(roi_names):
    plt.subplot(2, 4, i+1)
    plt.imshow(brain_rdm[name], cmap='viridis')
    plt.title(f"Brain: {name}")
    plt.colorbar(label='Dissimilarity')

# Plot model RDMs
for i, name in enumerate(layer_names):
    plt.subplot(2, 4, i+5)
    plt.imshow(model_rdm[name], cmap='viridis')
    plt.title(f"CNN: {name}")
    plt.colorbar(label='Dissimilarity')

plt.tight_layout()
plt.show()

# 8. Find the best matching layer for each ROI
best_layers = []
for i, roi in enumerate(roi_names):
    best_layer_idx = np.argmax(similarity_matrix[i])
    best_layer = layer_names[best_layer_idx]
    best_corr = similarity_matrix[i, best_layer_idx]
    best_layers.append((roi, best_layer, best_corr))

print("\nBest matching CNN layer for each brain ROI:")
for roi, layer, corr in best_layers:
    print(f"{roi}: {layer} ( $\rho$  = {corr:.3f})")

```

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

## 19.8 Chapter Take-aways

- Cognitive neuroscience and deep learning have a bidirectional relationship, with each field informing the other
- Key cognitive principles like attention, hierarchical processing, and predictive coding have inspired advances in deep learning architectures
- Incorporating cognitive constraints and inductive biases can improve deep learning model performance and generalization
- Deep learning models serve as computational theories of cognition, generating testable predictions about brain function
- Methods like RSA, encoding models, and CCA enable direct comparisons between neural and artificial representations
- Deep learning has provided new frameworks and tools for understanding and analyzing brain function
- The convergence of these fields promises advances in both artificial intelligence and our understanding of human cognition

## 19.9 Further Reading

- Kriegeskorte, N., & Douglas, P. K. (2018). Cognitive computational neuroscience. *Nature Neuroscience*, 21(9), 1148-1160.
- Richards, B. A., et al. (2019). A deep learning framework for neuroscience. *Nature Neuroscience*, 22(11), 1761-1770.
- Yamins, D. L., & DiCarlo, J. J. (2016). Using goal-driven deep learning models to understand sensory cortex. *Nature Neuroscience*, 19(3), 356-365.
- Saxe, A., Nelli, S., & Summerfield, C. (2021). If deep learning is the answer, what is the question? *Nature Reviews Neuroscience*, 22(1), 55-67.
- Kietzmann, T. C., McClure, P., & Kriegeskorte, N. (2019). Deep neural networks in computational neuroscience. *Oxford Research Encyclopedia of Neuroscience*.

- Naselaris, T., et al. (2021). Cognitive computational neuroscience: A normative theory of brain function. *Nature Neuroscience*, 24(2), 291-306.