Chapter 13: Multimodal & Diffusion Models

Learning Objectives

By the end of this chapter, you will be able to:

- **Understand** multimodal learning architectures and their parallels to multisensory integration in the brain
- **Master** diffusion model principles and their mathematical foundations
- **Connect** multimodal integration in AI to multisensory processing in biological systems
- **Analyze** cross-modal representations and fusion techniques
- **Explain** generative modeling approaches for different data modalities
- **Implement** basic generative models with controlled generation capabilities

13.1 Multimodal Learning Foundations

Multimodal learning involves training models to process and integrate information from multiple modalities (e.g., vision, language, audio). These models demonstrate remarkable capabilities in cross-modal understanding and generation that mirror the brain's multisensory integration mechanisms.

13.1.1 Cross-modal Representations

Cross-modal representations allow information to be encoded in a way that captures relationships between different modalities. Consider how a visual concept like "apple" relates to textual descriptions ("round red fruit"), tactile sensations (smooth, firm), and taste (sweet-tart).

```
import torch
import torch.nn as nn

class MultimodalEncoder(nn.Module):
    def __init__(self, visual_dim=2048, text_dim=768, joint_dim=512):
        super().__init__()
        # Visual encoder projection
        self.visual_encoder = nn.Sequential(
            nn.Linear(visual_dim, joint_dim*2),
            nn.ReLU(),
            nn.Linear(joint_dim*2, joint_dim)
        )

        # Text encoder projection
        self.text_encoder = nn.Sequential(
            nn.Linear(text_dim, joint_dim*2),
            nn.ReLU(),
            nn.Linear(joint_dim*2, joint_dim)
        )

    def forward(self, visual_features, text_features):
        # Project both modalities to same dimension
        visual_emb = self.visual_encoder(visual_features)
        text_emb = self.text_encoder(text_features)

        # Normalize embeddings for cosine similarity
        visual_emb = visual_emb / visual_emb.norm(dim=-1, keepdim=True)
        text_emb = text_emb / text_emb.norm(dim=-1, keepdim=True)

        return visual_emb, text_emb
```

This architecture resembles how the brain's association areas integrate information from primary sensory regions, creating higher-order representations that combine features across modalities.

13.1.2 Contrastive Learning (CLIP)

Contrastive Language-Image Pretraining (CLIP) represents a breakthrough in multimodal learning. By training on image-text pairs from the internet, CLIP learns to align visual and linguistic representations.

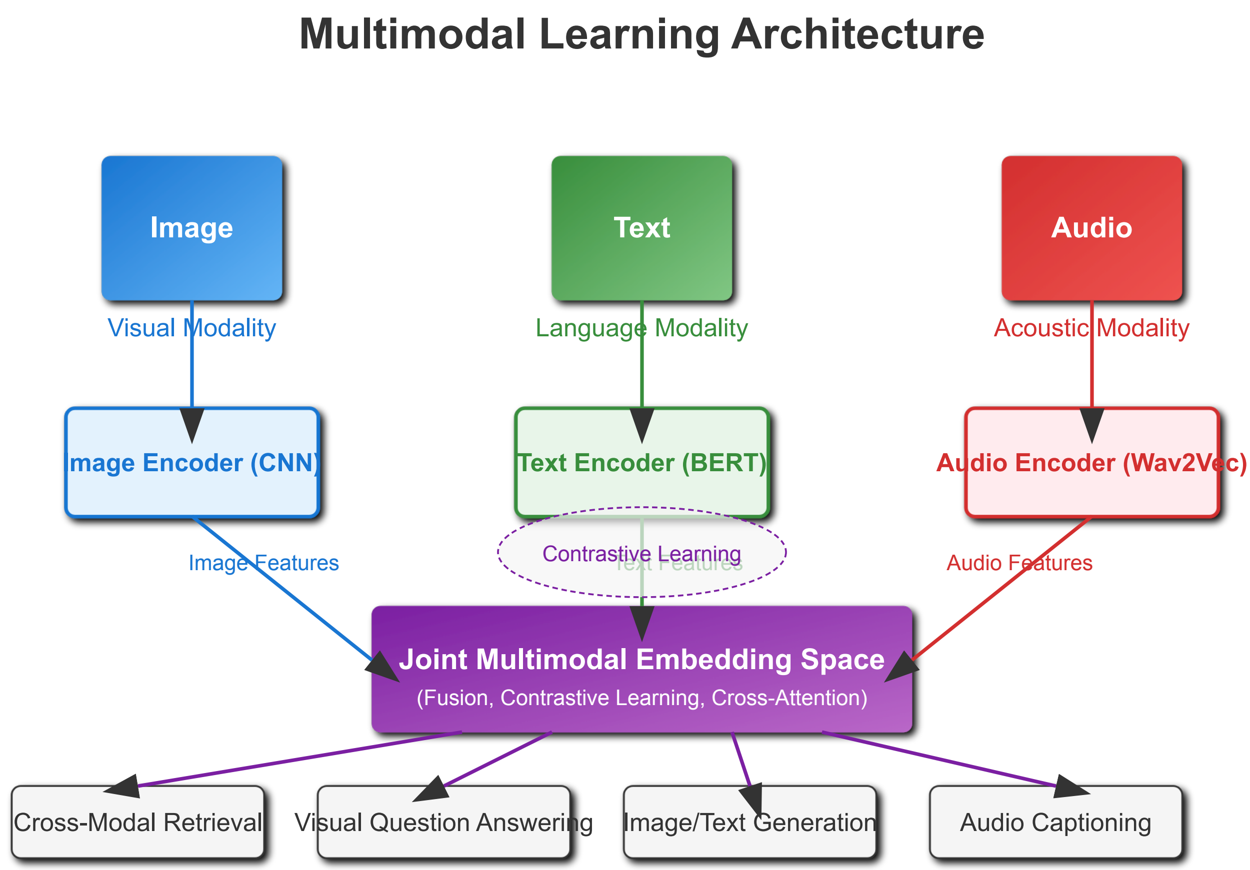
The contrastive objective maximizes similarity between matching image-text pairs while minimizing similarity between non-matching pairs:

```
def contrastive_loss(visual_emb, text_emb, temperature=0.07):
    """
    Compute contrastive loss between visual and text embeddings
    """
    # Compute similarities between all possible image-text pairs
    logits = torch.matmul(visual_emb, text_emb.t()) / temperature

    # Labels: diagonal elements are the matching pairs (= True pairs)
    labels = torch.arange(len(visual_emb), device=visual_emb.device)

    # Compute cross entropy loss in both directions
    loss_i = nn.CrossEntropyLoss()(logits, labels)
    loss_t = nn.CrossEntropyLoss()(logits.t(), labels)

    # Average both directions
    return (loss_i + loss_t) / 2.0
```

This resembles how the brain learns cross-modal associations through temporal coincidence - stimuli that frequently co-occur become associated in neural representations.

13.1.3 Joint Embedding Spaces

Joint embedding spaces map inputs from different modalities into a common representation space where semantic relationships are preserved. In this space, related concepts across modalities (e.g., an image of a dog and the word "dog") are closer together than unrelated concepts.



This resembles how the brain's multisensory neurons in regions like the superior temporal sulcus respond to both visual and auditory stimuli related to the same concept.

13.1.4 Alignment and Grounding

Alignment ensures that representations from different modalities properly correspond to each other, while grounding connects these representations to real-world concepts. Recent models like CLIP demonstrate remarkable zero-shot capabilities by leveraging these principles.

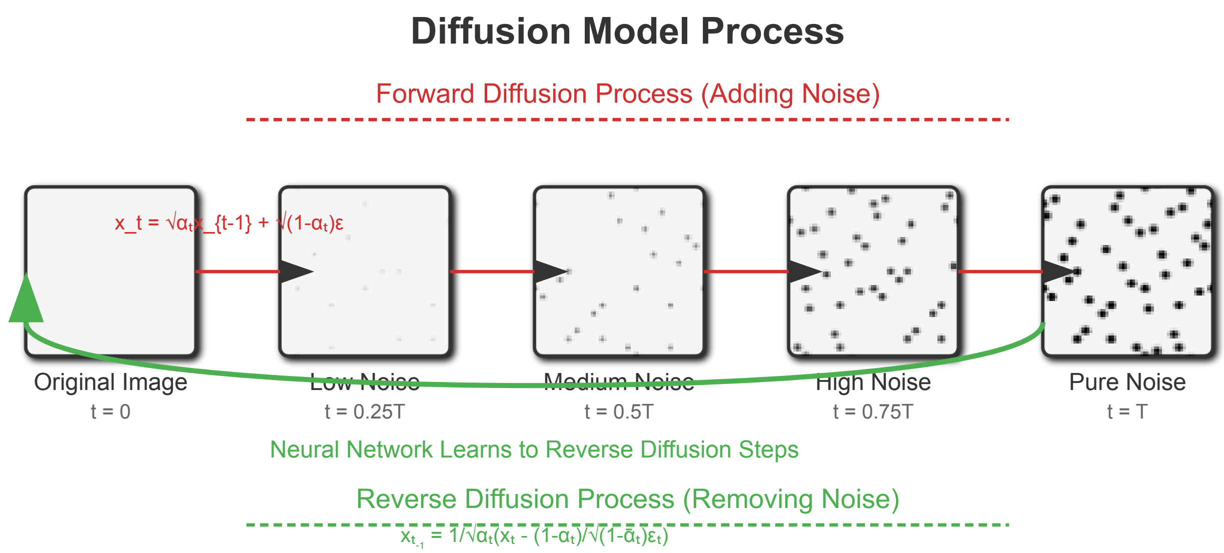
13.2 Diffusion Models

Diffusion models have revolutionized generative AI by enabling high-quality image synthesis through a process inspired by thermodynamics.

13.2.1 Forward and Reverse Diffusion Processes

The diffusion process consists of two phases:

1. **Forward diffusion**: Gradually adds Gaussian noise to an image until it becomes pure noise
2. **Reverse diffusion**: Learns to gradually remove noise to recover the original image



The forward process is defined by:

```python
def forward_diffusion(x_0, t, noise_scheduler):
    """
    Apply t steps of forward diffusion to an image x_0

    Parameters:
    - x_0: Original image
    - t: Timestep (amount of noise to add)
    - noise_scheduler: Controls noise schedule

    Returns:
    - Noised image x_t
    - Noise added
    """
    # Get noise scaling for timestep t
    alpha_t = noise_scheduler.alphas[t]
    sqrt_alpha_t = torch.sqrt(alpha_t)
    sqrt_one_minus_alpha_t = torch.sqrt(1 - alpha_t)

    # Sample noise
    epsilon = torch.randn_like(x_0)

    # Apply noise according to diffusion equation
    x_t = sqrt_alpha_t * x_0 + sqrt_one_minus_alpha_t * epsilon

    return x_t, epsilon
```

13.2.2 Denoising Score Matching

Diffusion models are trained to predict the noise added at each step, enabling the reversal of the diffusion process:

```python
def diffusion_training_loss(model, x_0, noise_scheduler):
    """
    Compute loss for training a diffusion model
    """
    batch_size = x_0.shape[0]

    # Sample random timesteps
    t = torch.randint(0, noise_scheduler.num_timesteps, (batch_size,), device=x_0

    # Apply forward diffusion to get noisy images
    x_t, noise_added = forward_diffusion(x_0, t, noise_scheduler)

    # Predict the noise
    noise_pred = model(x_t, t)

    # Simple MSE loss between actual and predicted noise
    return nn.MSELoss()(noise_pred, noise_added)
```

13.2.3 Sampling Techniques

To generate new images, we start with random noise and iteratively denoise:

```python
def sample(model, noise_scheduler, shape, device):
    """
    Generate a new image by sampling from the diffusion model
    """
    # Start from random noise
    x_T = torch.randn(shape, device=device)
    x_t = x_T

    # Iteratively denoise
    for t in reversed(range(noise_scheduler.num_timesteps)):
        t_tensor = torch.full((shape[0],), t, device=device, dtype=torch.long)

        # Predict noise
        with torch.no_grad():
            predicted_noise = model(x_t, t_tensor)

        # Get alpha values for current timestep
        alpha_t = noise_scheduler.alphas[t]
        alpha_t_prev = noise_scheduler.alphas[t-1] if t > 0 else torch.tensor(1.0

        # Apply formula for reverse process step
        # (Simplified version of the full algorithm)
        coef1 = torch.sqrt(1 / alpha_t)
        coef2 = (1 - alpha_t) / torch.sqrt(1 - alpha_t)

        x_t = coef1 * (x_t - coef2 * predicted_noise)

        # Add noise for t > 0
        if t > 0:
            sigma_t = torch.sqrt(
                (1 - alpha_t_prev) / (1 - alpha_t) * (1 - alpha_t / alpha_t_prev)
            )
            x_t += sigma_t * torch.randn_like(x_t)

    return x_t
```

13.2.4 Model Architectures (U-Nets)

Diffusion models typically use U-Net architectures with time conditioning:

```python
class SimpleUNet(nn.Module):
    def __init__(self, channels=3, time_emb_dim=256):
        super().__init__()
        # Time embedding
        self.time_embed = nn.Sequential(
            nn.Linear(1, time_emb_dim),
            nn.SiLU(),
            nn.Linear(time_emb_dim, time_emb_dim),
        )

        # Simplified U-Net structure
        self.down1 = nn.Conv2d(channels, 64, 3, padding=1)
        self.down2 = nn.Conv2d(64, 128, 3, padding=1, stride=2)
        self.down3 = nn.Conv2d(128, 256, 3, padding=1, stride=2)

        # Middle blocks with time conditioning
        self.mid_conv1 = nn.Conv2d(256, 256, 3, padding=1)
        self.mid_time = nn.Linear(time_emb_dim, 256)
        self.mid_conv2 = nn.Conv2d(256, 256, 3, padding=1)

        # Upsampling path
        self.up1 = nn.ConvTranspose2d(256, 128, 4, stride=2, padding=1)
        self.up2 = nn.ConvTranspose2d(128, 64, 4, stride=2, padding=1)
        self.up3 = nn.Conv2d(64, channels, 3, padding=1)

    def forward(self, x, t):
        # Embed time
        t_emb = self.time_embed(t.unsqueeze(-1).float())

        # Downsample
        x1 = nn.functional.silu(self.down1(x))
        x2 = nn.functional.silu(self.down2(x1))
        x3 = nn.functional.silu(self.down3(x2))

        # Middle with time conditioning
        h = nn.functional.silu(self.mid_conv1(x3))
        h = h + self.mid_time(t_emb)[:, :, None, None]
        h = nn.functional.silu(self.mid_conv2(h))

        # Upsample
        h = nn.functional.silu(self.up1(h))
        h = nn.functional.silu(self.up2(h))
        h = self.up3(h)

        return h
```

13.3 Text-to-Image Models

Text-to-image models combine diffusion models with text conditioning to generate images from text descriptions.

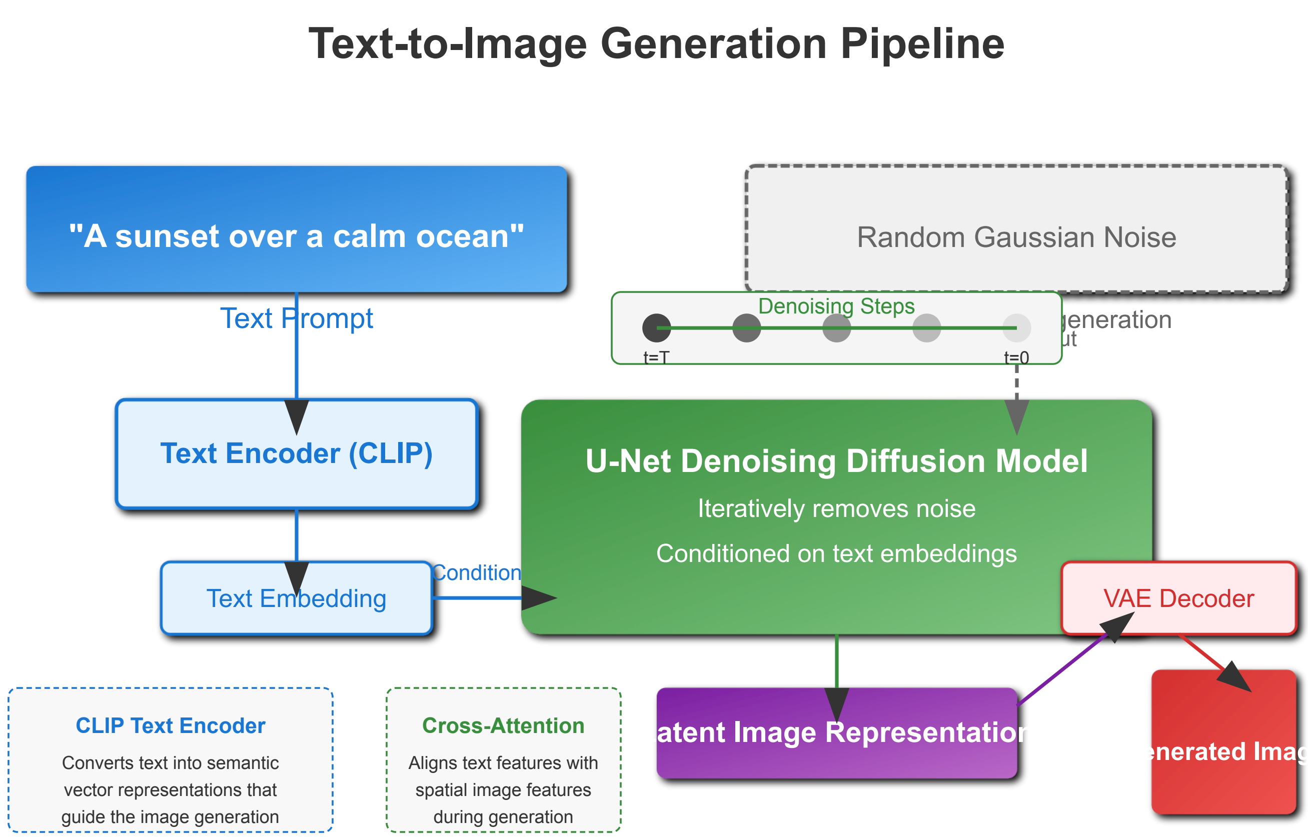
13.3.1 Leading Models: DALL-E, Stable Diffusion, Midjourney

Several breakthrough models have demonstrated impressive text-to-image capabilities:

- **DALL-E 2/3**: OpenAI's models use diffusion and CLIP-like conditioning
- **Stable Diffusion**: Latent diffusion model that operates in a compressed latent space
- **Midjourney**: Proprietary architecture with remarkable aesthetic quality

13.3.2 Conditioning Mechanisms

Text-to-image models incorporate text information through conditioning mechanisms:



```python
def classifier_free_guidance(model, x_t, t, text_emb, guidance_scale=7.5):
    """
    Apply classifier-free guidance for controlled generation
    """
    # Get unconditional prediction (empty text embedding)
    null_text_emb = torch.zeros_like(text_emb)
    noise_pred_uncond = model(x_t, t, null_text_emb)

    # Get conditional prediction (with text embedding)
    noise_pred_text = model(x_t, t, text_emb)

    # Apply guidance
    noise_pred = noise_pred_uncond + guidance_scale * (noise_pred_text - noise_pr

    return noise_pred
```

13.3.3 Latent Spaces

Stable Diffusion operates in a compressed latent space rather than pixel space, reducing computational requirements while maintaining generation quality:

```python
class LatentDiffusionModel:
    def __init__(self):
        self.vae_encoder = VAEEncoder()
        self.vae_decoder = VAEDecoder()
        self.diffusion_model = UNetWithTextCondition()
        self.text_encoder = TextEncoder()

    def encode_image(self, image):
        return self.vae_encoder(image)

    def decode_latents(self, latents):
        return self.vae_decoder(latents)

    def encode_text(self, text):
        return self.text_encoder(text)

    def generate(self, text, steps=50):
        # Encode text prompt
        text_embedding = self.encode_text(text)

        # Start from random latent
        latent = torch.randn(1, 4, 64, 64)

        # Reverse diffusion process
        for t in reversed(range(steps)):
            # Denoise one step with text conditioning
            latent = self.diffusion_step(latent, t, text_embedding)

        # Decode latent to image
        image = self.decode_latents(latent)
        return image
```

13.3.4 Text Encoders and Cross-Attention

Text-to-image models use transformers to encode text and cross-attention to incorporate text information into the diffusion process:

```python
class CrossAttentionBlock(nn.Module):
    def __init__(self, channels, text_dim=768):
        super().__init__()
        self.norm = nn.GroupNorm(32, channels)
        self.q = nn.Linear(channels, channels)
        self.k = nn.Linear(text_dim, channels)
        self.v = nn.Linear(text_dim, channels)
        self.proj_out = nn.Linear(channels, channels)
        self.scale = channels ** -0.5

    def forward(self, x, text_features):
        """
        x: [B, C, H, W] - image features
        text_features: [B, L, D] - text features
        """
        batch, c, h, w = x.shape
        residual = x

        # Normalize input
        x = self.norm(x)

        # Reshape for attention
        x = x.reshape(batch, c, -1).transpose(1, 2)  # [B, H*W, C]

        # Compute attention
        q = self.q(x) * self.scale
        k = self.k(text_features)
        v = self.v(text_features)

        # Attention weights
        attn = torch.bmm(q, k.transpose(1, 2))  # [B, H*W, L]
        attn = torch.softmax(attn, dim=-1)

        # Apply attention
        out = torch.bmm(attn, v)  # [B, H*W, C]
        out = self.proj_out(out)

        # Reshape back and add residual
        out = out.transpose(1, 2).reshape(batch, c, h, w)
        return out + residual
```

13.4 Video and Audio Generation

Diffusion models have been extended to generate video and audio by handling temporal dimensions.

13.4.1 Temporal Extensions of Diffusion Models

Video diffusion models add time as an additional dimension:

```
class VideoUNet(nn.Module):
    def __init__(self, channels=3, frames=16):
        super().__init__()
        # Spatio-temporal convolutions
        self.conv3d_1 = nn.Conv3d(channels, 64, kernel_size=(3, 3, 3), padding=(1
        self.conv3d_2 = nn.Conv3d(64, 128, kernel_size=(3, 3, 3), padding=(1, 1,
        # Additional layers...

    def forward(self, x, t, text_emb):
        # x: [B, C, F, H, W] - batch, channels, frames, height, width
        # Process video with temporal context
        # ...
```

13.4.2 Audio Generation Approaches

Audio generation models leverage similar principles but with adaptations for 1D sequences:

```
class AudioDiffusion(nn.Module):
    def __init__(self, channels=1, sample_rate=16000):
        super().__init__()
        # 1D convolutions for audio
        self.conv1d_1 = nn.Conv1d(channels, 64, kernel_size=3, padding=1)
        self.conv1d_2 = nn.Conv1d(64, 128, kernel_size=3, padding=1)
        # Additional layers...
```

13.4.3 Consistency Techniques

Generating coherent video requires consistency across frames, often addressed through specialized architectures and loss functions:

```python
def consistency_loss(frames_pred, frames_gt):
    """
    Compute both per-frame loss and temporal consistency loss
    """
    # Per-frame reconstruction loss
    frame_loss = nn.MSELoss()(frames_pred, frames_gt)

    # Temporal consistency: compare frame differences
    frame_diffs_pred = frames_pred[:, :, 1:] - frames_pred[:, :, :-1]
    frame_diffs_gt = frames_gt[:, :, 1:] - frames_gt[:, :, :-1]

    temporal_loss = nn.MSELoss()(frame_diffs_pred, frame_diffs_gt)

    return frame_loss + 0.5 * temporal_loss
```

13.5 Neural Multimodal Integration

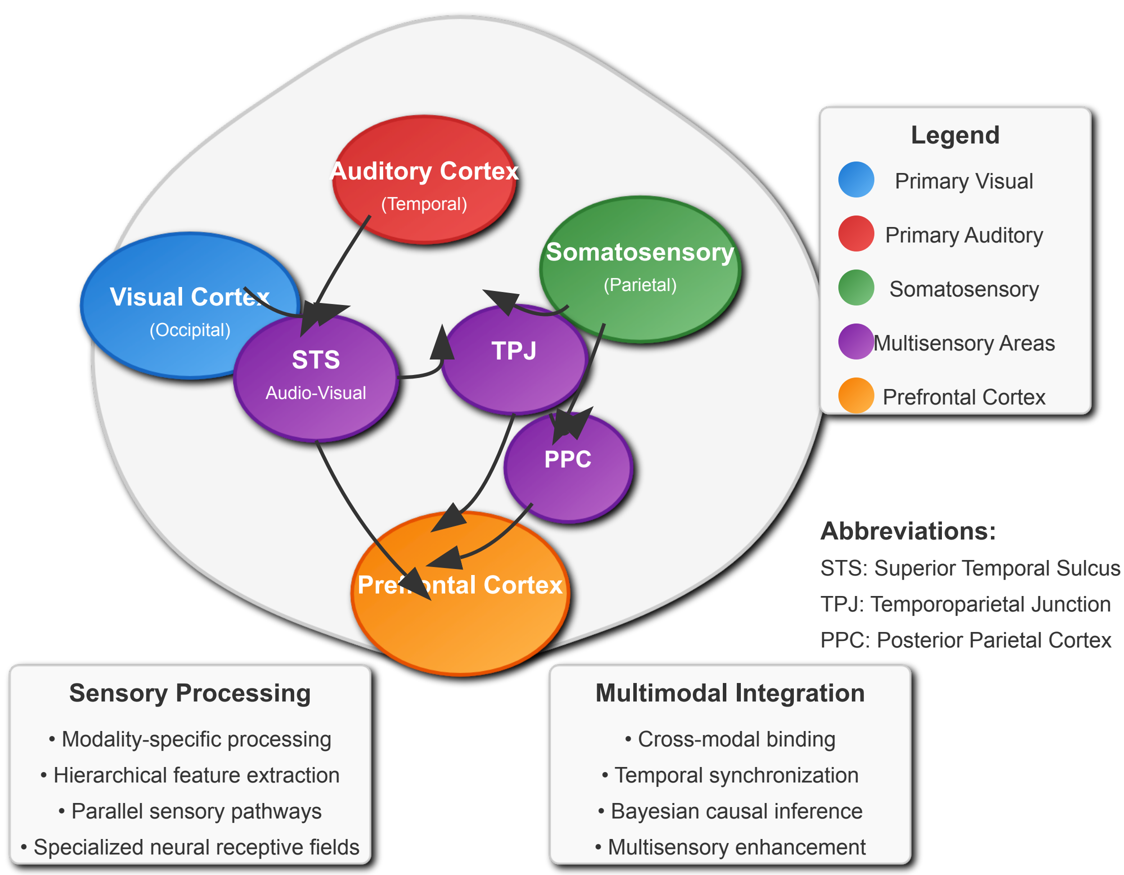
The brain's multisensory integration systems provide inspiration for artificial multimodal models.

13.5.1 Multisensory Areas in the Brain

Several brain regions integrate information across sensory modalities:

- **Superior Temporal Sulcus (STS)**: Integrates visual and auditory information
- **Posterior Parietal Cortex**: Combines visual, proprioceptive, and tactile information
- **Prefrontal Cortex**: Higher-level integration of multiple modalities

Neural Basis of Multimodal Integration



13.5.2 Cross-modal Binding and Attention

The brain uses several mechanisms to bind information across modalities:

```python
def simulate_cross_modal_binding(visual_input, auditory_input, semantic_congruenc
    """
    Simulate cross-modal binding with the McGurk effect

    Parameters:
    - visual_input: Visual speech cue (e.g., lip movements for "ga")
    - auditory_input: Auditory speech cue (e.g., sound "ba")
    - semantic_congruence: How congruent the stimuli are (0-1)

    Returns:
    - Perceived output after cross-modal integration
    """
    # Simple model of superior temporal sulcus integration
    visual_weight = 0.4  # Visual influence
    auditory_weight = 0.6  # Auditory influence

    # Modulate influence by congruence
    if semantic_congruence < 0.5:
        # Less binding when stimuli don't match
        visual_weight *= semantic_congruence
        auditory_weight = 1 - visual_weight

    # Weighted integration (simplified)
    perceived_output = (
        visual_weight * visual_input +
        auditory_weight * auditory_input
    )

    # For McGurk effect, return illusory perception
    if 0.3 < semantic_congruence < 0.7:
        # Create illusory perception (e.g., "da" from visual "ga" + auditory "ba"
        perceived_output = "da"  # Simplified illustration

    return perceived_output
```

13.5.3 Hierarchical Sensory Processing

The brain processes sensory information hierarchically, with increasing complexity and multimodal integration at higher levels:

```python
def hierarchical_sensory_model():
    model = nn.Sequential(
        # Primary visual cortex (V1) - simple features
        nn.Conv2d(3, 64, kernel_size=3, padding=1),
        nn.ReLU(),

        # V2/V4 - more complex features
        nn.Conv2d(64, 128, kernel_size=3, padding=1),
        nn.ReLU(),
        nn.MaxPool2d(2),

        # Inferotemporal cortex - object recognition
        nn.Conv2d(128, 256, kernel_size=3, padding=1),
        nn.ReLU(),
        nn.MaxPool2d(2),

        # Flattening for higher levels
        nn.Flatten(),

        # Higher association areas - multimodal integration
        nn.Linear(256 * 8 * 8, 512),
        nn.ReLU(),

        # Decision outputs
        nn.Linear(512, 10)
    )
    return model
```

13.5.4 Crossmodal Illusions and Phenomena

Studying crossmodal illusions provides insights into how the brain integrates information:

- **McGurk Effect**: Visual lip movements change auditory perception
- **Ventriloquist Effect**: Sound source is perceived as coming from a moving visual target
- **Double Flash Illusion**: A single flash with two beeps is perceived as two flashes

13.6 Code Lab: Simple Diffusion Model

Let’s implement a simplified diffusion model for image generation:

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

class DiffusionScheduler:
    def __init__(self, num_timesteps=1000, beta_start=0.0001, beta_end=0.02):
        """
        Diffusion scheduler that manages the noise schedule
        """
        self.num_timesteps = num_timesteps

        # Linear schedule of variance over time
        self.betas = torch.linspace(beta_start, beta_end, num_timesteps)

        # Calculate alphas for convenience
        self.alphas = 1 - self.betas
        self.alphas_cumprod = torch.cumprod(self.alphas, dim=0)
        self.alphas_cumprod_prev = F.pad(self.alphas_cumprod[:-1], (1, 0), value=

        # Calculate other required values
        self.sqrt_alphas_cumprod = torch.sqrt(self.alphas_cumprod)
        self.sqrt_one_minus_alphas_cumprod = torch.sqrt(1. - self.alphas_cumprod)
        self.sqrt_recip_alphas = torch.sqrt(1.0 / self.alphas)
        self.posterior_variance = self.betas * (1. - self.alphas_cumprod_prev) /

class SimpleUNet(nn.Module):
    def __init__(self, image_channels=1, hidden_channels=64):
        super().__init__()

        # Time embedding
        self.time_mlp = nn.Sequential(
            nn.Linear(1, hidden_channels),
            nn.SiLU(),
            nn.Linear(hidden_channels, hidden_channels),
        )

        # Initial convolution
        self.conv_in = nn.Conv2d(image_channels, hidden_channels, kernel_size=3,

        # Downsampling
        self.down1 = nn.Conv2d(hidden_channels, hidden_channels, kernel_size=3, p
        self.down2 = nn.Conv2d(hidden_channels, hidden_channels*2, kernel_size=3,

        # Middle
        self.middle1 = nn.Conv2d(hidden_channels*2, hidden_channels*2, kernel_siz
        self.middle2 = nn.Conv2d(hidden_channels*2, hidden_channels*2, kernel_siz

        # Upsampling
        self.up1 = nn.ConvTranspose2d(hidden_channels*2, hidden_channels, kernel_
        self.up2 = nn.ConvTranspose2d(hidden_channels*2, hidden_channels, kernel_
```

```python
        # Final layers
        self.conv_out = nn.Conv2d(hidden_channels*2, image_channels, kernel_size=

    def forward(self, x, t):
        """
        x: (B, C, H, W) input image
        t: (B,) diffusion timesteps
        """
        # Encode time
        t_emb = self.time_mlp(t.unsqueeze(-1).float())  # (B, hidden_channels)

        # Initial processing
        h = self.conv_in(x)
        h1 = F.silu(h)

        # Downsample
        h2 = F.silu(self.down1(h1))
        h3 = F.silu(self.down2(h2))

        # Middle with time conditioning
        h3 = h3 + t_emb.unsqueeze(-1).unsqueeze(-1)
        h3 = F.silu(self.middle1(h3))
        h3 = F.silu(self.middle2(h3))

        # Upsample with skip connections
        h = F.silu(self.up1(h3))
        h = torch.cat([h, h2], dim=1)  # Skip connection

        h = F.silu(self.up2(h))
        h = torch.cat([h, h1], dim=1)  # Skip connection

        # Output
        return self.conv_out(h)

def train_diffusion_model(model, dataloader, scheduler, epochs=10, lr=1e-4, devic
    """
    Train a diffusion model
    """
    optimizer = torch.optim.Adam(model.parameters(), lr=lr)

    for epoch in range(epochs):
        total_loss = 0
        for x in tqdm(dataloader):
            x = x.to(device)
            batch_size = x.shape[0]

            # Random timesteps
            t = torch.randint(0, scheduler.num_timesteps, (batch_size,), device=d

            # Add noise according to timesteps
            noise = torch.randn_like(x)
            x_noisy = (
                scheduler.sqrt_alphas_cumprod[t, None, None, None] * x +
```

```python
                scheduler.sqrt_one_minus_alphas_cumprod[t, None, None, None] * no
            )

            # Predict noise
            noise_pred = model(x_noisy, t)

            # Loss (predict the noise that was added)
            loss = F.mse_loss(noise_pred, noise)

            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

            total_loss += loss.item()

        print(f"Epoch {epoch+1}, Loss: {total_loss/len(dataloader):.6f}")

    return model

def sample_from_model(model, scheduler, shape, device="cpu", steps=None):
    """
    Sample a new image from the trained diffusion model
    """
    # Start from pure noise
    img = torch.randn(shape, device=device)
    steps = steps or scheduler.num_timesteps
    step_size = scheduler.num_timesteps // steps

    # Progressively denoise
    for i in tqdm(reversed(range(0, scheduler.num_timesteps, step_size))):
        t = torch.full((shape[0],), i, device=device, dtype=torch.long)

        # Get model prediction (noise)
        with torch.no_grad():
            predicted_noise = model(img, t)

        # Get alpha values for timestep
        alpha = scheduler.alphas[i]
        alpha_hat = scheduler.alphas_cumprod[i]
        beta = scheduler.betas[i]

        # If not the last step, add noise
        if i > 0:
            noise = torch.randn_like(img)
            next_i = max(i - step_size, 0)
            alpha_next = scheduler.alphas_cumprod[next_i]
            variance = scheduler.posterior_variance[i]
            img = (img - beta * predicted_noise / torch.sqrt(1 - alpha_hat)) / to
            img = img + torch.sqrt(variance) * noise
        else:
            # Last step - clean prediction
            img = (img - beta * predicted_noise / torch.sqrt(1 - alpha_hat)) / to

    # Clamp to valid image range
```

```
    img = torch.clamp(img, -1, 1)
    return (img + 1) / 2  # Scale to [0, 1]

# Example usage:
# scheduler = DiffusionScheduler()
# model = SimpleUNet().to(device)
# train_diffusion_model(model, mnist_dataloader, scheduler, device=device)
# sample = sample_from_model(model, scheduler, (1, 1, 28, 28), device=device)
```

13.7 Take-aways

- **Multimodal models capture cross-domain relationships** in ways that mirror the brain's multisensory integration capabilities. Both artificial and biological systems benefit from combining information across modalities.
- **Diffusion models provide high-quality generation** through a principled approach based on gradually adding and removing noise. This approach yields remarkable flexibility in generation tasks.
- **Combining modalities enhances representation quality** by leveraging complementary information across domains, similar to how the brain integrates vision, hearing, and touch to create a unified perception of reality.
- **Cross-modal binding mechanisms** in both artificial and biological systems enable the creation of coherent representations that span multiple sensory domains.

Chapter Summary

In this chapter, we explored:

- **Multimodal learning foundations** that enable models to work across different data types
- **Cross-modal representations** that create shared embedding spaces between modalities
- **Contrastive learning approaches** like CLIP that align visual and textual information
- **Diffusion models** with their forward and reverse processes for high-quality generation
- **Denoising score matching** as the mathematical foundation of diffusion models
- **Sampling techniques** that control the generation process in diffusion models
- **Text-to-image models** like DALL-E, Stable Diffusion, and Midjourney
- **Video and audio generation** through temporal extensions of diffusion approaches
- **Neural multimodal integration** in the brain's multisensory processing areas
- **Implementation details** of a simple diffusion model for image generation

This chapter connects cutting-edge AI generative methods with the brain's multimodal processing systems, highlighting how both artificial and biological intelligence benefit from integrating information across sensory domains.

13.8 Further Reading & Media

- Radford, A., et al. (2021). Learning Transferable Visual Models From Natural Language Supervision. This paper introduces CLIP, a groundbreaking approach to multimodal learning.
- Ho, J., et al. (2020). Denoising Diffusion Probabilistic Models. The seminal paper that introduced the modern formulation of diffusion models.
- Rombach, R., et al. (2022). High-Resolution Image Synthesis with Latent Diffusion Models. Introduces Stable Diffusion and the concept of latent diffusion.
- Nichol, A., et al. (2021). GLIDE: Towards Photorealistic Image Generation and Editing with Text-Guided Diffusion Models. Early work on text-guided diffusion models.
- Ramesh, A., et al. (2022). Hierarchical Text-Conditional Image Generation with CLIP Latents. The DALL-E 2 paper describing a powerful text-to-image system.

- Stein, S., et al. (2023). Phenomenal Multimodal Integration in Superior Temporal Sulcus. A neuroscience perspective on multimodal integration.