04 Vision Transformer new approach to vision processing

1. From CNNs to ViTs

**CNNs

✅ **Local pattern recognition**

- Edges, textures, small objects
- Built-in translation equivariance

✅ **Parameter efficiency**

- Weight sharing across spatial locations
- Small models can work well

✅ **Small dataset performance**

- Strong inductive biases help with limited data
- Work well with < 100K images

❌ **Global context**

- Need many layers to see full image
- Receptive field grows slowly: $O(\sqrt{L})$

❌ **Long-range dependencies**

- Difficult to relate distant pixels
- Information must flow through many layers

❌ **Adaptive computation**

- Same computation everywhere
- Can't focus on important regions

❌ **Scalability**

- Performance saturates with more parameters
- Diminishing returns from depth

The Vision Transformer Motivation

Key Question:

> If Transformers revolutionised NLP by treating text as sequences, can we treat images as sequences too?

The Parallel:

```
NLP:
"The cat sat on the mat" → [The] [cat] [sat] [on] [the] [mat]
                              ↓     ↓     ↓     ↓     ↓     ↓
                           Self-Attention → Understand relationships

Computer Vision:
Image (224×224) → [Patch₁] [Patch₂] ... [Patch₁₉₆]
                     ↓        ↓            ↓
                  Self-Attention → Understand spatial relationships
```

CNN Limitations → ViT Solutions

CNN Limitation	Root Cause	ViT Solution
Slow receptive field growth	Local convolutions	**Global attention from layer 1**
Fixed computation pattern	Sliding window	**Dynamic, content-based routing**
Poor long-range modeling	Information bottleneck	**Direct all-to-all connections**
Architecture complexity	Manual design (ResNet, etc.)	**Minimal architecture**
Texture bias	Local pattern focus	**More shape-aware**

Architectural Comparison

```
CNN Processing:
Input → Conv(3×3) → Conv(3×3) → Conv(3×3) → ... → Global Pool → FC
        ↓           ↓           ↓
      Local       Local       Local
     (receptive field grows slowly)

ViT Processing:
```

```
Input → Patches → Self-Attention → Self-Attention → ... → [CLS] Token → FC
                        ↓                ↓
                     Global           Global
                  (immediate full-image context)
```

The Trade-off: Inductive Bias vs Data

CNNs: Strong Priors, Data Efficient

```python
# CNN priors (built into architecture)
priors = {
    'locality': True,           # Nearby pixels related
    'translation_eq': True,     # Same pattern anywhere
    'hierarchy': True,          # Simple → Complex
    'weight_sharing': True,     # Same filter everywhere
}

result = {
    'data_needed': '10K - 100K images',
    'performance_ceiling': 'Good but limited',
    'flexibility': 'Low (priors may not fit data)'
}
```

ViT: Weak Priors, Data Hungry

```python
# ViT priors (minimal architecture constraints)
priors = {
    'locality': False,          # Learn if needed
    'translation_eq': False,    # Learn if needed
    'hierarchy': False,         # Flat processing
    'weight_sharing': 'Only in attention',
}

result = {
    'data_needed': '1M - 300M images',
    'performance_ceiling': 'State-of-the-art',
    'flexibility': 'High (can learn any pattern)'
}
```

CNNs Win: When Priors Match Reality

✅ **Small datasets** (< 100K images)

- Strong priors compensate for limited data
- Faster convergence

✅ **Truly local tasks**

- Texture classification
- Edge detection
- Small object recognition

✅ **Deployment constraints**

- Mobile devices (100x fewer FLOPs)
- Real-time requirements (lower latency)

ViT Wins: When Flexibility Needed

✅ **Large datasets** (> 1M images)

- Can learn optimal features
- Weak priors don't constrain learning

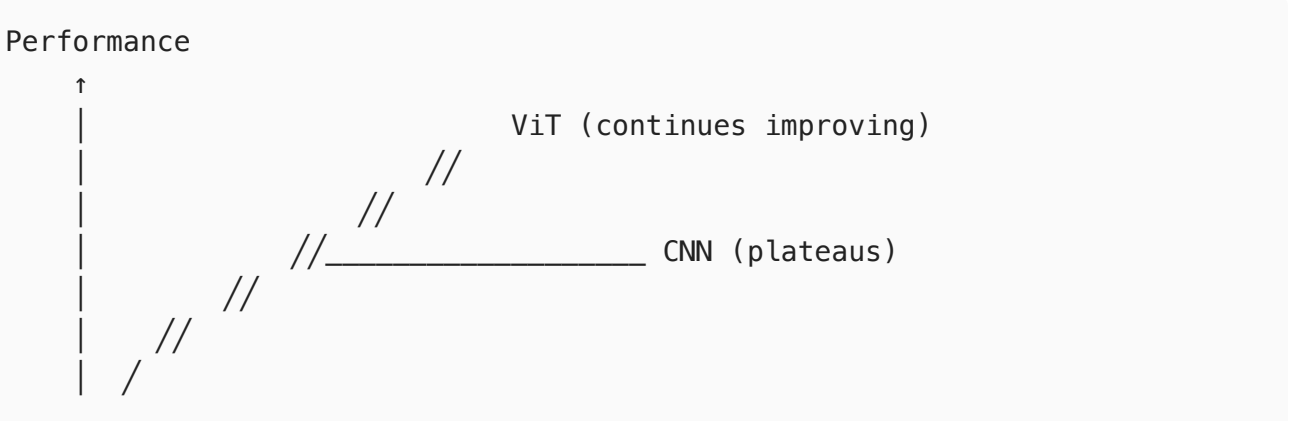
✅ **Global understanding**

- Scene recognition
- Object relationships
- Spatial reasoning

✅ **Out-of-distribution data**

- More robust to domain shift
- Better transfer learning

The Data-Performance Curve



```
    |/
    |
    └──────────────────────────────────────→ Dataset Size
     10K   100K   1M    10M   100M  1B

    Crossover point: ~1M images
    Before: CNNs better
    After:  ViT better
```

Practical Decision Framework

Use CNNs When:

```
if (dataset_size < 100_000 or
    deployment_target == 'mobile' or
    inference_latency_ms < 10 or
    task_requires_fine_details):

    model = 'ResNet-50'  # or EfficientNet, ConvNeXt
```

Use ViT When:

```
if (dataset_size > 1_000_000 or
    transfer_learning_available or
    global_context_crucial or
    robustness_priority):

    model = 'ViT-B/16'  # with pretrained weights
```

Use Hybrid When:

```
if (want_best_of_both):
    model = 'Swin-Transformer'  # or ConvNeXt, CvT
    # CNN-like locality + Transformer flexibility
```

ViT

Architecture Details

1. How to tokenise images (patching)
2. Position encodings (absolute vs relative)

3. Attention mechanism in vision context
4. Multi-head attention for visual features

Training Considerations

1. Why ViT is hard to train from scratch
2. Critical hyperparameters (warmup, weight decay)
3. Data augmentation strategies
4. Transfer learning best practices

Practical Insights

1. When ViT actually helps vs hype
2. Computational costs and optimizations
3. How to debug attention patterns
4. Deployment considerations

The Bigger Picture: Convergence of Architectures

Evolution Timeline

```
2012: AlexNet → CNNs dominate vision

2017: Transformer → Attention dominate NLP

2020: ViT → Can we use Transformers for vision?

2021-2023: Convergence
    ├─ CNNs adopt attention (CBAM, CoordConv)
    ├─ ViT adopt locality (Swin, LocalViT)
    └─ Hybrid models (CvT, ConvNeXt)

2024+: Architecture agnostic
    - Meta-learning optimal structures
    - Task-specific architectures
    - Unified multi-modal models
```

Key Mindset Shift from CNN to Transformer

```
"How can I design layers to extract hierarchical features?"
↓
```

```
Engineer locality → Build hierarchy → Hope for global understanding
```

```
"What relationships matter in this image?"
↓
Let model discover structure → Learn which patterns to attend to
```

The Philosophical Difference:

CNN Philosophy	ViT Philosophy
"Impose structure"	"Discover structure"
"Build hierarchy"	"Learn connections"
"Local first, then global"	"Global always, refine locally"
"Architecture = prior knowledge"	"Architecture = flexible framework"

What Makes ViT Different (Preview)

1. Patch-based Processing

- Image → Non-overlapping patches
- Each patch = token (like word in NLP)
- Position encoding adds spatial info

2. Self-Attention

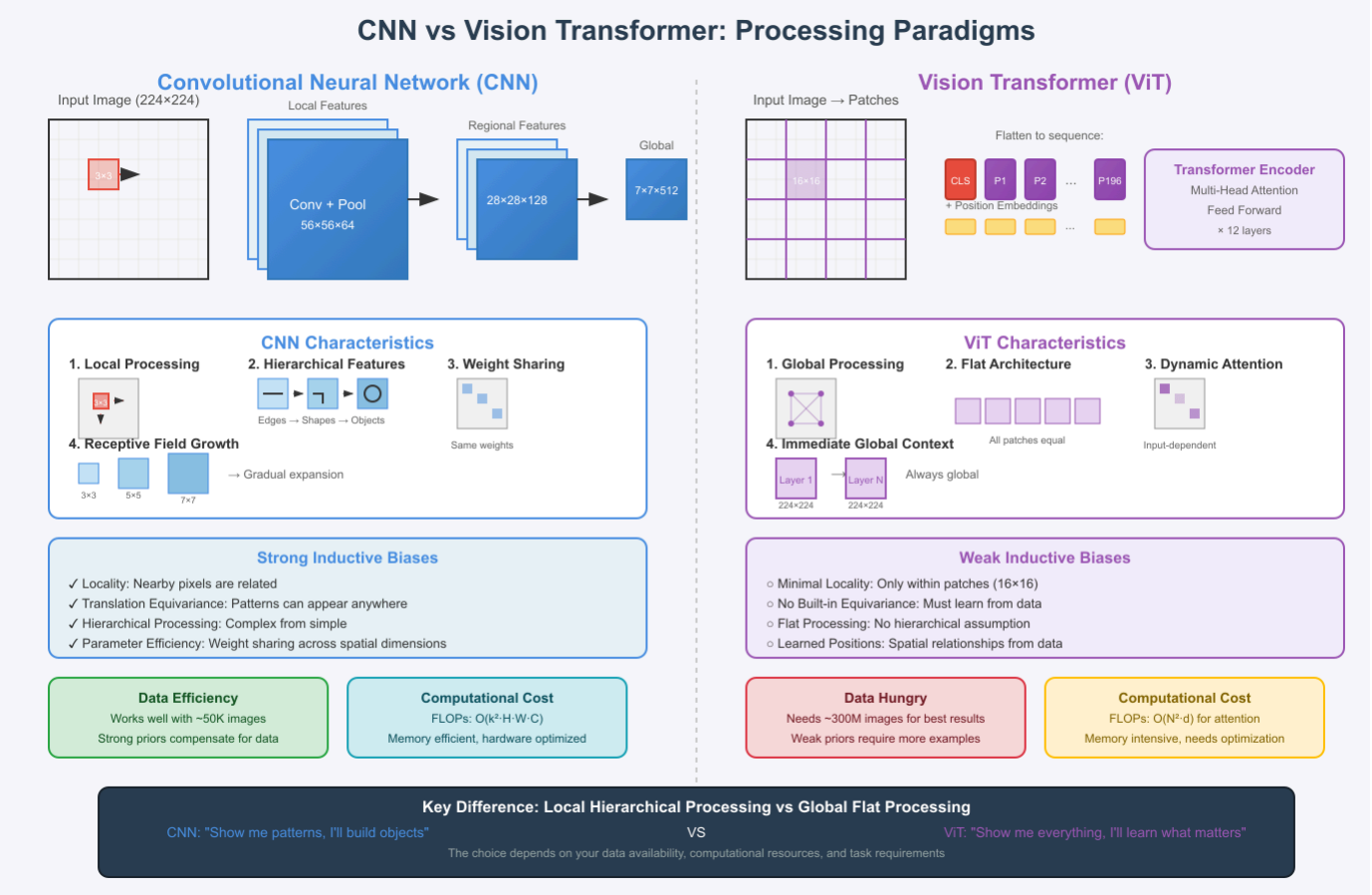
- Every patch attends to every other patch
- Content-based, not position-based
- Dynamic weights, not fixed kernels

3. Global Receptive Field

- Layer 1 sees entire image (!)
- No need for depth to build context
- Different from CNN's gradual expansion

4. Data Requirements

- Needs massive pre-training (300M images)
- Or strong data augmentation
- Transfer learning is crucial



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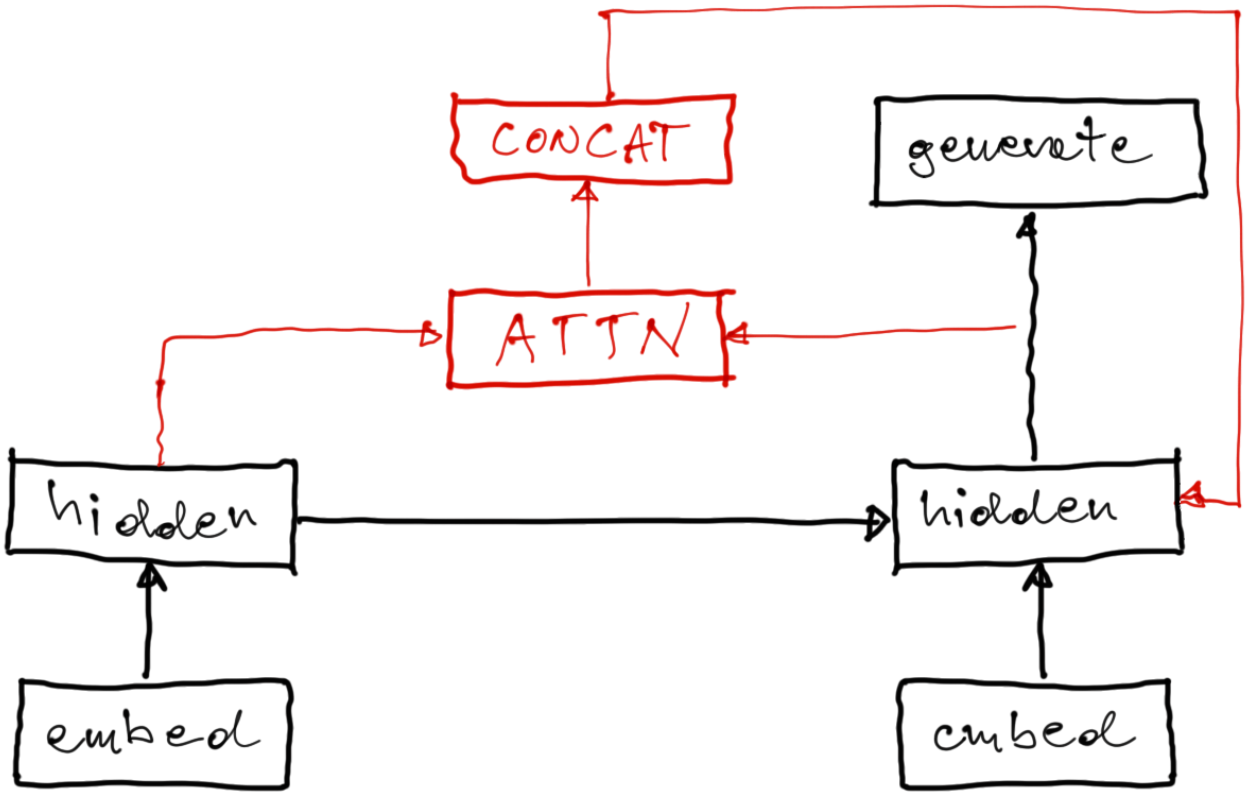
2. The Transformer Revolution

Original idea of attention comes from [Neural machine translation by jointly learning to align and translate, Bahdanau et al., 2014 (ICLR 2015)]



- the hidden states are **recurrent**! (more in-depth, hopefully, in the next lecture)

The idea of Transformer (Attention is all you need,Vaswani et al., 2017)

Originally designed for NLP:

```
"The cat sat on the mat" → [The] [cat] [sat] [on] [the] [mat]
                                ↓     ↓     ↓     ↓     ↓     ↓
                           Tokens → Self-Attention → Output
```

The Vision Transformer Insight (Dosovitskiy et al. An Image is Worth 16x16 Words,)

CNNs have several limitations

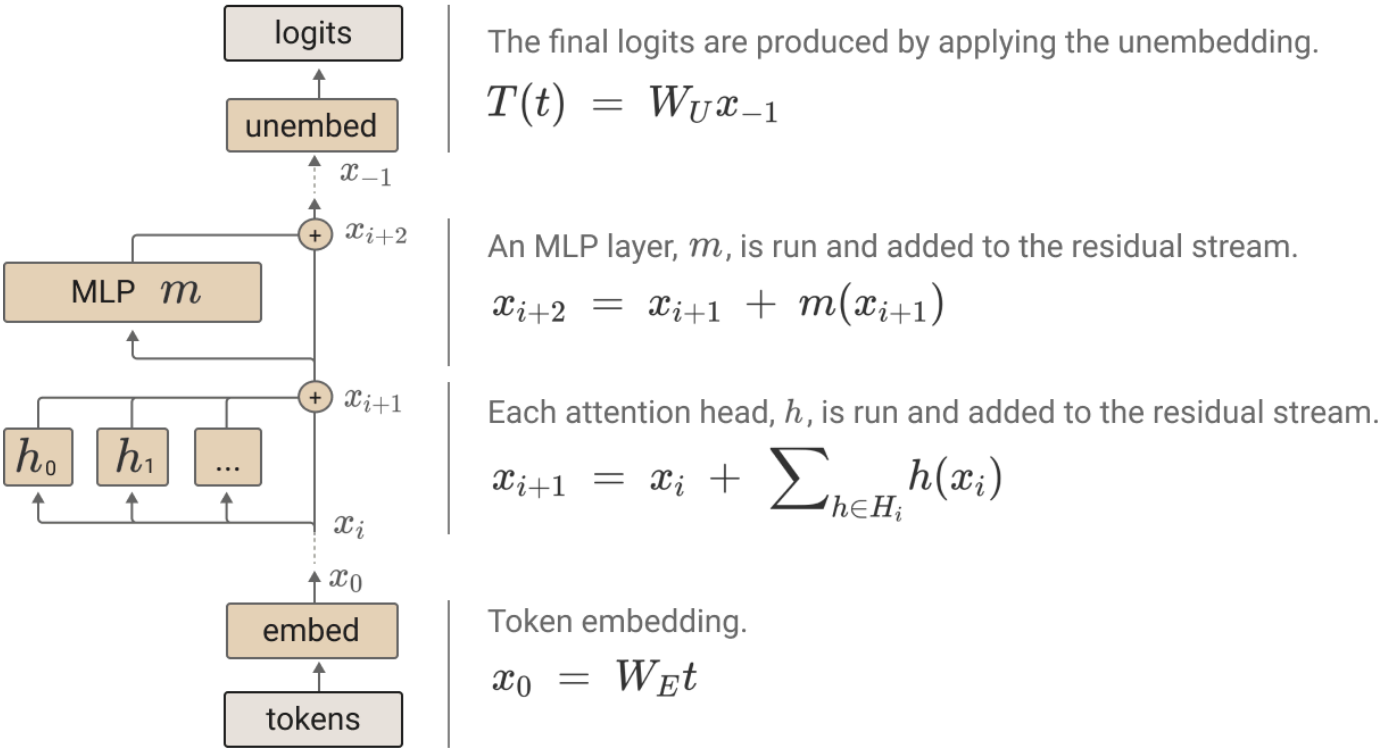
- **Fixed receptive fields**: Need many layers for global context
- **Strong inductive biases**: Sometimes too restrictive
- **Difficulty with long-range dependencies**: Quadratic depth requirement
- **Architecture engineering**: Complex designs (ResNet, DenseNet, NAS)

> "An image is worth 16×16 words"

```
"When trained on sufficient data, ViT attains excellent results,
matching or exceeding state-of-the-art CNNs while being simpler."
```

```
Image (H×W×C) → Patches (N×P²×C) → Tokens → Transformer → Classification
```

- this results in
  - no convolutions
  - no image-specific inductive biases
  - just attention (and ffn), all the way down



(from an Anthropic blog page) a Transformer block

Transformer is *just* a linear combination of nonlinear functions

- an attention,
- and a feed-forward network
- added together to a residual stream (remember the ResNet architecture?)

Key Question: Can we treat images as sequences and leverage Transformers' success?

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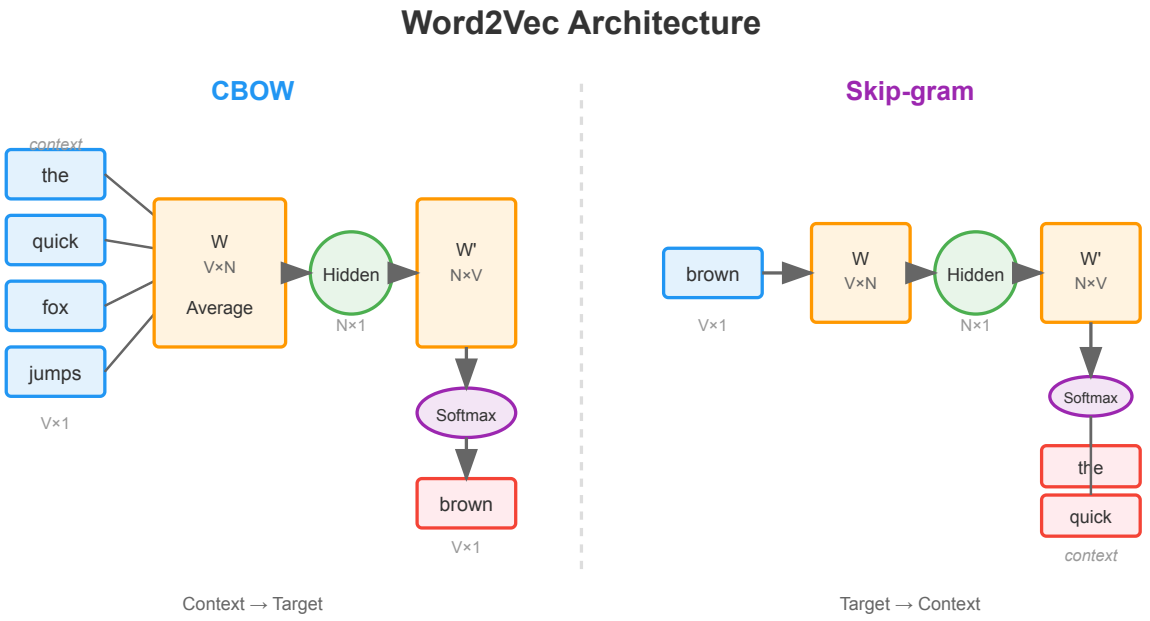
3. Tokenisation: From Pixels to Patches

Tokenisation as such

the Word2Vec architecture (Mikolov)



The Fundamental Problem

1. pixels as tokens

```
# Direct approach (impractical)
Image: 224×224×3 = 150,528 pixels
Attention complexity: O(N²) = O(150,528²) ≈ 22.6 billion operations!
```

```
- computationally prohibitive
- Memory requirements impossible
- Most pixel-to-pixel attention unnecessary
```

```
# ViT solution: Use patches
Patches: (224/16)×(224/16) = 14×14 = 196 patches
Attention complexity: O(196²) = 38,416 operations (manageable!)
```

```
- manageable
```

Patch Embedding Process

```
Step 1: Divide image into non-overlapping patches

┌─────────────────┐
│ ┌─┬─┬─┬─┬─┐   │
│ ├─┼─┼─┼─┼─┤   │  224×224 image
```

```
│ ├──┼──┼──┼──┤ │  → 14×14 grid
│ ├──┼──┼──┼──┤ │  → 196 patches of 16×16
│ └──┴──┴──┴──┘ │
└─────────────────┘

Step 2: Flatten each patch
Each 16×16×3 patch → 768-dimensional vector

Step 3: Linear projection
768 → D (embedding dimension, typically 768 or 1024)
```

Mathematical Formulation

Given image $\mathbf{x} \in \mathbb{R}^{H \times W \times C}$:

1. **Reshape into patches** where

$$N = HW/P^2$$

2. Flatten each patch

$$\text{flatten} : \mathbb{R}^{P \times P \times C} \to \mathbb{R}^{P^2 C}$$

3. **Linear projection** to embedding

$$\mathbf{z}_0 = \mathbf{x}_p \mathbf{E} + \mathbf{x}_{pos}$$

- where $\mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}$ is the patch embedding matrix
- and $\mathbf{x}_{pos} \in \mathbb{R}^{N \times D}$ is the positional embedding

---

[CLS] token (classification token): global representation

```python
# Special learnable token for classification
self.cls_token = nn.Parameter(torch.zeros(1, 1, embed_dim))

# Prepend to patch tokens
cls_tokens = self.cls_token.expand(B, -1, -1)  # (B, 1, embed_dim)
x = torch.cat((cls_tokens, x), dim=1)  # (B, num_patches + 1, embed_dim)
```

- [CLS] is prepended to the input sequence and serves as a global representation
- Aggregates global information through attention
- No positional bias (unlike using first/last patch)

- Used for final classification
- is learnable

---

4. Embeddings & Positional Encoding

What is an Embedding?

An embedding maps discrete objects to continuous vector representations:

```
Discrete Space                  Continuous Space
_____________                   ___________________

Patch (16×16×3)            →    Vector ∈ ℝ^D
Raw pixels                      Semantic representation
High-dimensional                Lower-dimensional
Sparse                          Dense
Patch (16×16×3 raw pixels)  →   Embedding (D-dimensional vector)

Learned representation captures semantic information
```

Are the embeddings learnable?

- embeddings are just linear transformations

```
nn.Embedding(max_length, d_length)
```

```
- embeddings are trained along with all other parameters
- why?
    - same inputs need different embeddings in different contexts, i.e.
are task-specific
    - embeddings work in cooperation with attention
    - learned embeddings can help (optimise) distribution of information
    - can learn token relations
    - allow for flexibility
    - fixed embeddings can be used for very small datasets and for pre-
trained embeddings as initialisations
- embeddings
    - provide model's vocabulary
    - optimise representations in connection with attention
    - develop task-specific coding, adapt to these tasks and datasets
    - can help optimise gradient flow
    - adapt to specific
    - learns optimal representations
    - capture patterns emerging from the data
    - enable true end-to-end learning
```

```
### **Is positional encoding is critical?**
$$\text{Attention}(\pi(\mathbf{X})) = \pi(\text{Attention}(\mathbf{X}))$$
for permutation $\pi$

**Transformers are permutation invariant!**

Without positional information
```

[Patch_1] [Patch_2] [Patch_3] ≡ [Patch_3] [Patch_1] [Patch_2]

```
This would destroy spatial structure!

---
### **Positional Encoding Methods**

#### **1. Learnable Position Embeddings (ViT default)**

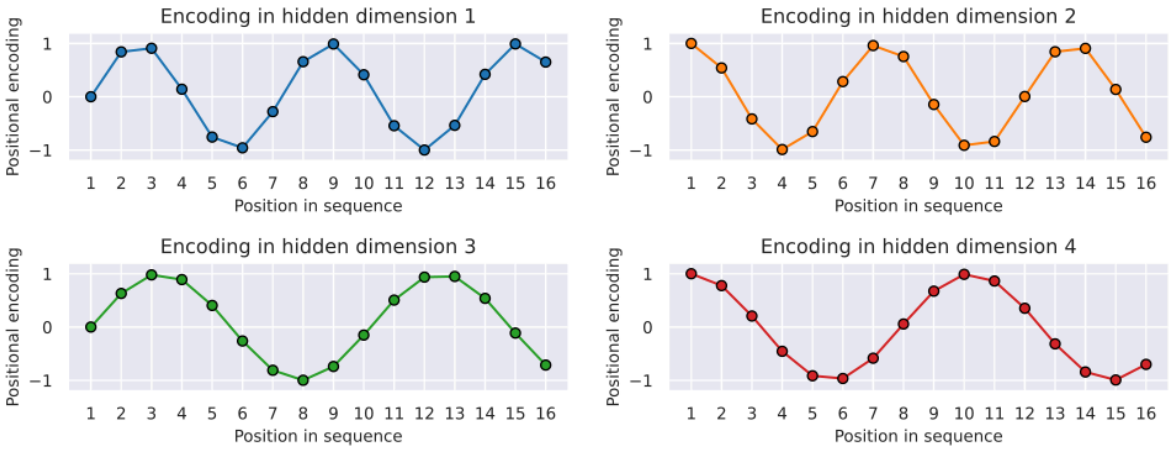
```python
self.pos_embed = nn.Parameter(torch.zeros(1, num_patches + 1, embed_dim))
nn.init.trunc_normal_(self.pos_embed, std=0.02)

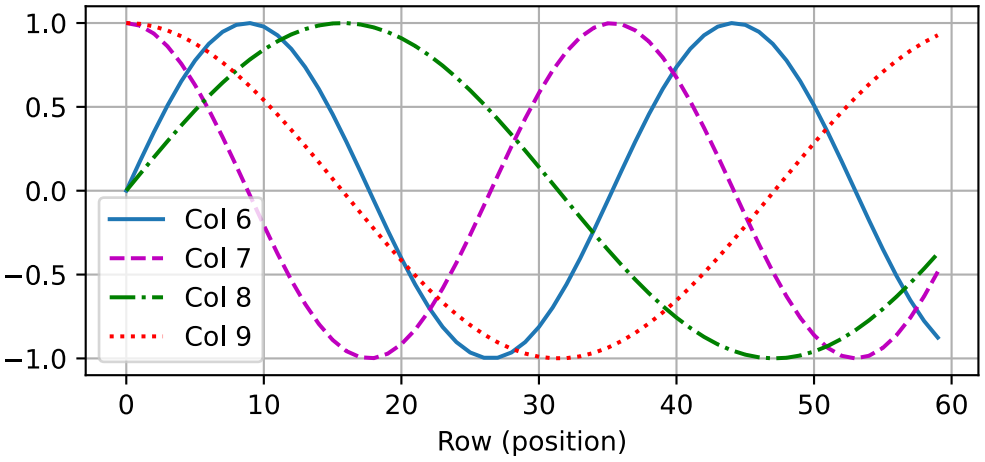
# Add to patch embeddings
x = x + self.pos_embed
```
```

- Should it be **added** or **concatenated**?
  - concatenation extends the dimension but is reversible
  - addition is not reversible
  - but addition carries the position information
    - the same information token in **different** places would convey that info
  - so add or concatenate
    ![[positional-encoding-diagram.svg|800]
  - **Advantages:**
  - Flexible, can learn any pattern
  - Simple to implement
  - Empirically effective
- **Disadvantages:**
  - Fixed resolution at training
  - Doesn't naturally generalise to different image sizes

---

2. Sinusoidal Encoding (from original Transformer)





$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{2i/d}}\right)$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{2i/d}}\right)$$

---

3. 2D Positional Encoding

Encode row and column positions separately:

- encode separately for rows and columns
- add using concatenation

```
pos_embed = pos_embed_row + pos_embed_col
```

---

4. Relative Position Encoding

Instead of absolute positions, encode relative distances:

$$\text{Attention}_{ij} = \text{softmax}\left(\frac{q_i \cdot k_j + r_{ij}}{\sqrt{d}}\right)$$

where r_{ij} encodes the relative position between patches i and j

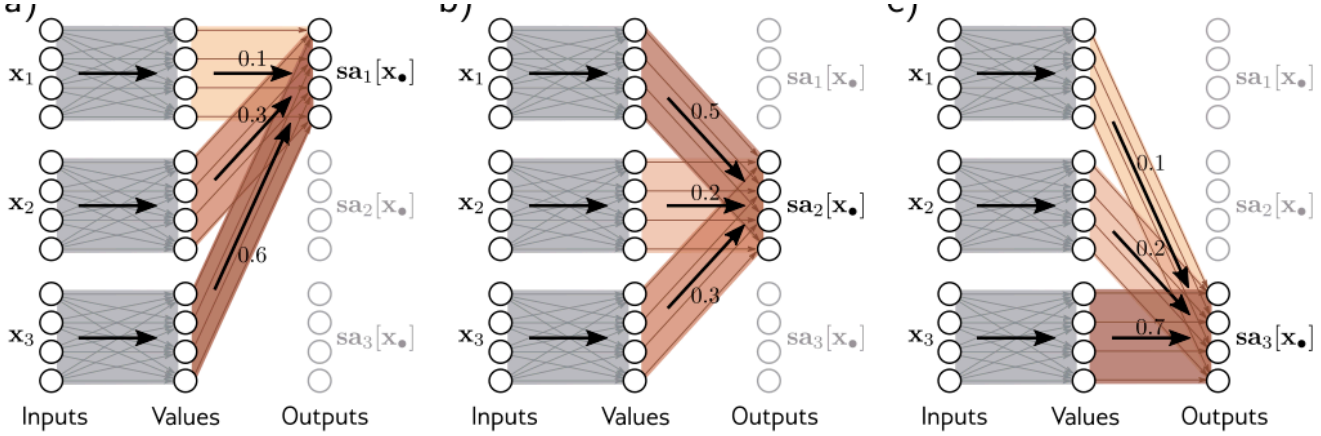
5. Interpolation for different resolutions

- **different** resolutions can be used to use coarse - to fine attention
- the positional tokens may be interpolated, e.g. bilinearly

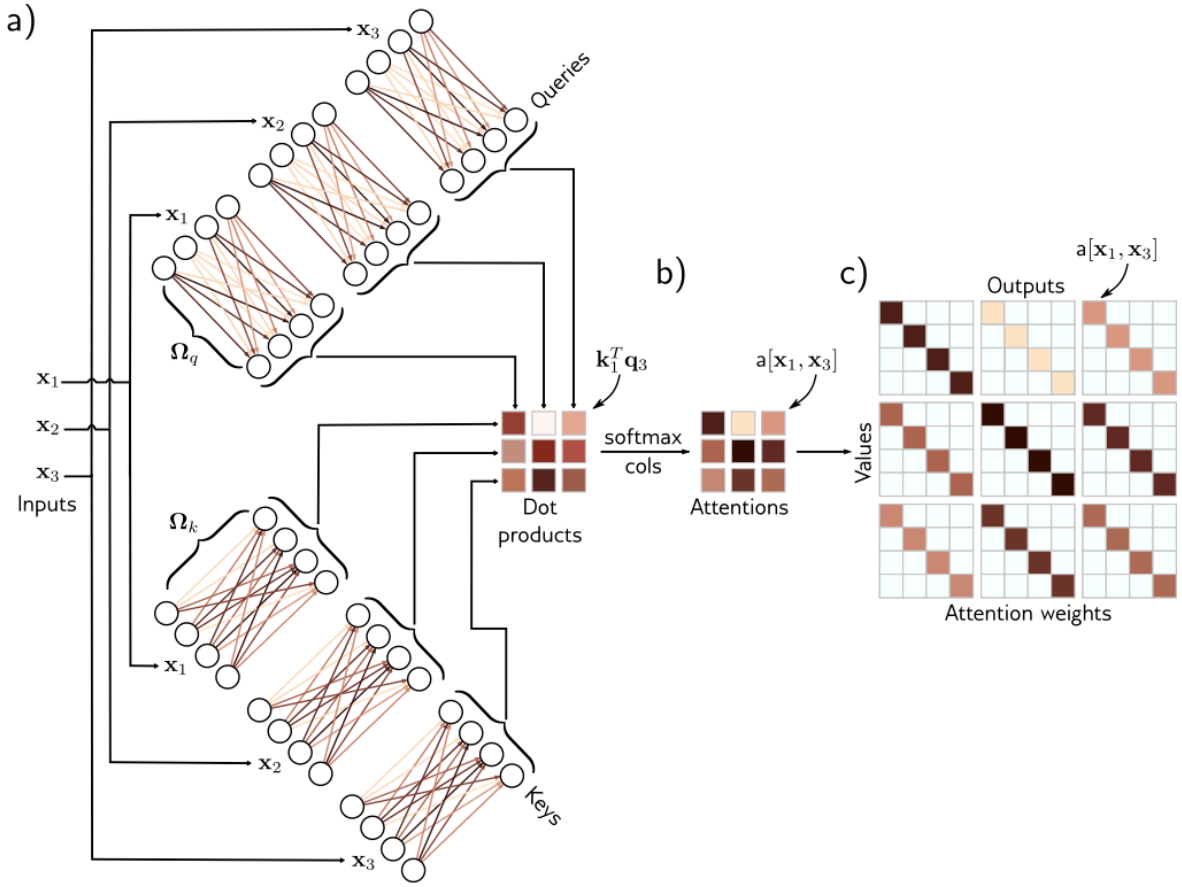
---

5. Attention Mechanism in Vision

Self-Attention: The Core Operation



- a **value** is computed from each token
  - may be done in parallel
  - value v_i is some linear combination of all elements of vector representation of token x_i
- a scalar $a[x_i, x_j]$ is the *attention* that token x_j pays to token x_i
  - attentions $a[\cdot, x_j]$ sum up to 1
- *self attention* $sa_j(x_1, \ldots, x_N) = \sum_{i=1}^{N} a[x_i, x_j] \cdot v_i$
  - each self-attention $sa_i[x.]$ can be thought as a different routing of the original N tokens x_i for the current task
- all can be computed in parallel per token



(from Prince, Understanding deep learning, MIT,2023)

- *query* vectors are computed as $q_n = \beta_q + \Omega_q x_n$
- *key* vectors are computed as $k_n = \beta_k + \Omega_q x_n$
- dot products are passed to a softmax giving attention values

Given input $\mathbf{X} \in \mathbb{R}^{N \times D}$:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Where:

- $Q = XW_Q$ (Queries): "What am I looking for?"
- $K = XW_K$ (Keys): "What information do I have?"
- $V = XW_V$ (Values): "What information to aggregate?"
  where dimensions are
- d model dimension, size of the embedding,
- d_k the key and query dimension: $d_k = d/n_{heads}$ (standard relationship)
- d_v dimension of values in attention: $d_v = d/n_{heads}$ (typically $d_v = d_k$)
  - typically embedding dimension needs to be a multiple of the number of heads
  - if $d_v \neq d_k$, an additional attention may be used where additional trained matrices map both to the same dimension
- $W_Q \in \mathbb{R}^{d \times d_v}$, $W_K \in \mathbb{R}^{d \times d_k}$, $W_V \in \mathbb{R}^{d \times d_v}$

Visual Interpretation

```
For each patch:
1. Query: "I'm a patch containing an eye"
2. Keys: All patches respond with what they contain
3. Attention weights: High for other eye, nose, face patches
4. Values: Aggregate features from attended patches
5. Output: Enriched representation with context
```

Multi-Head Attention

Key Idea

Different heads learn different types of relationships

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O$$

where each head:

$$\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

```
# Instead of single attention:
MultiHead(Q, K, V) = Concat(head_1, ..., head_h)W_O

# Where each head attends to different aspects:
head_i = Attention(QW_Q^i, KW_K^i, VW_V^i)
```

Intuition

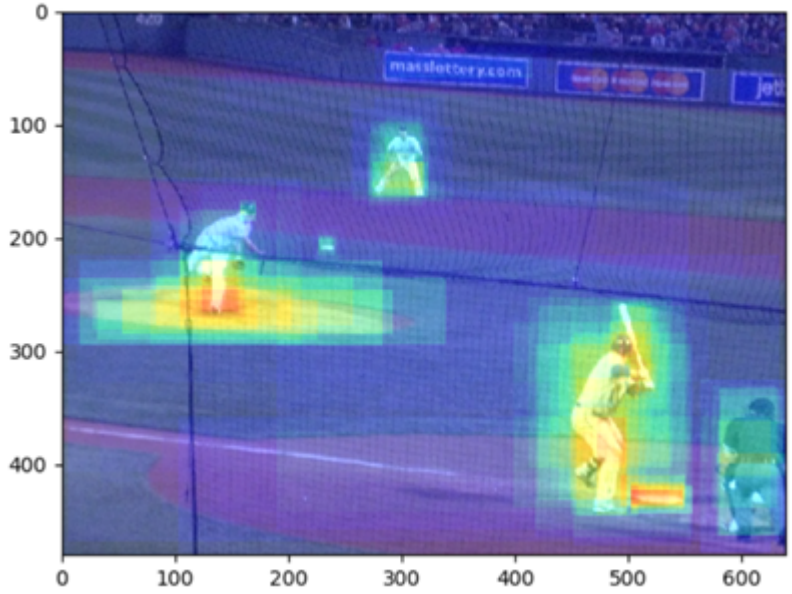
Different heads should capture different relationships

```
# Empirical observations from trained ViTs:

Head 1-3: Local patterns (similar to small convolutions)
Head 4-6: Texture and colour similarity
Head 7-9: Semantic grouping (objects)
Head 10-12: Global context and spatial relationships
```

Visualising Attention

- to show "important" places in a grid




```
def visualize_attention(model, image, patch_size=16, layer_idx=11):
    """Visualize attention from CLS token to patches"""
    # Get attention weights
    _, attention_weights = model.get_attention(image, layer_idx)

    # attention_weights: (batch, num_heads, num_patches+1, num_patches+1)
    # We want CLS token attention (index 0) to all patches
    cls_attention = attention_weights[0, :, 0, 1:]  # (num_heads,
num_patches)

    # Average across heads
    cls_attention = cls_attention.mean(dim=0)

    # Reshape to image grid
    h = w = int(math.sqrt(cls_attention.shape[0]))
    attention_map = cls_attention.reshape(h, w)


    # Interpolate to original image size
    attention_map = F.interpolate(
        attention_map.unsqueeze(0).unsqueeze(0),
        size=image.shape[-2:],
        mode='bilinear'
    ).squeeze()

    return attention_map
```

Computational Complexity of Attention

Standard Self-Attention:

- Complexity: $O(N^2 \cdot d)$ where N is sequence length
- Memory: $O(N^2)$ for attention matrix

For Vision (196 patches):

```
# ViT-B/16 on 224×224 image
num_patches = 196
embed_dim = 768
num_heads = 12

# Per layer:
attention_flops = 2 * num_patches**2 * embed_dim  # ~59M
projection_flops = 4 * num_patches * embed_dim**2  # ~462M
total_flops_per_layer = ~521M

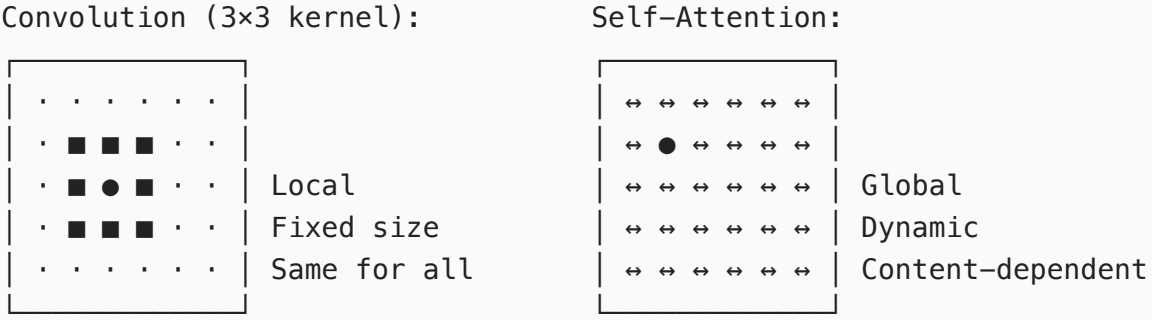
# For 12 layers:
total_flops = ~6.3B
```

---

6. Attention vs Convolution: Fundamental Differences

- **convolutions**
  - **Locality** Only sees k×k neighborhood
  - **Weight sharing** Same kernel everywhere
  - **Translation equivariance** Built-in
  - **No content adaptation** Same operation regardless of input
- **attention**
  - **Global reach** Every patch sees every other patch
  - **Dynamic weights** Attention weights depend on input
  - **No built-in equivariance** Must be learned or added
  - **Content adaptation** Different weights for different inputs

Receptive Field Comparison



Key Differences

Aspect	Convolution	Self-Attention
Receptive Field	Local (kernel size)	Global (all patches)
Weight Sharing	Same kernel everywhere	Dynamic, input-dependent
Computational Pattern	Sliding window	All-to-all comparison
Inductive Bias	Locality, translation equivariance	Minimal (only architecture)
Parameters	O(k²CD)	O(D²)
Compute	O(k²HWCD)	O(HW)²D

Mathematical Comparison

Convolution:

$$y_{ij} = \sum_{m,n} w_{mn} \cdot x_{i+m,j+n}$$

- Static weights w_{mn}
- Local neighborhood

Self-Attention:

$$y_i = \sum_{j=1}^{N} \alpha_{ij} \cdot v_j$$

- Dynamic weights $\alpha_{ij} = \text{softmax}(q_i \cdot k_j / \sqrt{d})$
- Global context

Receptive Field Evolution

```
# CNN: Receptive field grows slowly
Layer 1: 3×3
Layer 2: 5×5
Layer 3: 7×7
...
Layer L: (2L+1)×(2L+1)  # Linear growth

# ViT: Immediate global receptive field
Layer 1: 224×224  # Full image
Layer 2: 224×224  # Full image
```

```
...
Layer L: 224×224  # Always global
```

Inductive Bias Comparison

Property	Convolution	Self-Attention
Locality	Strong (kernel size)	None (learns if needed)
Translation Equivariance	Built-in	Must learn
Weight Sharing	Enforced	Across positions only
Scale Invariance	Partial (via architecture)	None
Permutation Invariance	No	Yes (without pos. encoding)
Long-range Dependencies	Difficult (need depth)	Natural (one layer)

When Each Excels

Convolution Wins:

```
# Small datasets - strong priors help
if dataset_size < 100_000:
    use_cnn()

# Mobile/edge deployment
if deployment == "mobile":
    use_mobilenet()  # 100x fewer FLOPs

# Known local patterns
if task == "edge_detection":
    use_cnn()
```

Attention Wins:

```
# Large datasets - can learn priors
if dataset_size > 10_000_000:
    use_vit()

# Global relationships crucial
if task in ["scene_understanding", "object_relationships"]:
    use_transformer()

# Variable input sizes (with adaptation)
if input_size == "variable":
    use_transformer_with_interpolation()
```

7. Inductive biases: what priors do ViTs encode?

What is an inductive bias?

Inductive bias: Assumptions built into the model architecture that guide learning

```
Strong Bias                          Weak Bias
    ↓                                    ↓
Less flexible                        More flexible
Less data needed                     More data needed
Faster convergence                   Slower convergence
May miss patterns                    Can learn any pattern
```

CNN Priors (Strong)

```
1. Locality: Nearby pixels are related
2. Translation Equivariance: f(shift(x)) = shift(f(x))
3. Hierarchical Processing: Simple → Complex features
4. Weight Sharing: Same pattern detector everywhere
```

1. Locality Bias

$$y_{i,j} = \sum_{m=-k}^{k} \sum_{n=-k}^{k} w_{m,n} \cdot x_{i+m,j+n}$$

implies the need of many layers for global context

2. Translation Equivariance

```
# If pattern appears at position (x, y) or (x+dx, y+dy)
# CNN responds similarly (shifted)
Conv(Shift(image)) ≈ Shift(Conv(image))
```

But NOT rotation/scale equivariant:

```
Conv(Rotate(image)) ≠ Rotate(Conv(image))
Conv(Scale(image)) ≠ Scale(Conv(image))
```

3. Spatial Hierarchy

```
# CNNs build features hierarchically
Layer 1: Edges (3×3 receptive field)
Layer 2: Textures (5×5 receptive field)
Layer 3: Parts (11×11 receptive field)
...
Layer N: Objects (full image)
```

4. Weight Sharing

```
# Same filter applied everywhere
parameters_conv = kernel_size² × in_channels × out_channels
# NOT: image_size² × in_channels × out_channels
```

ViT Priors (Weak)

```
1. Patch Structure: Minimal spatial assumption
2. Position Encoding: Weak spatial prior
3. Architecture: Transformer structure only
```

1. Patch Structure (Minimal Locality)

```
# Only assumes pixels within patch might be related
patch_size = 16  # Weak locality assumption
```

2. Position Encoding (Learned Spatial Prior)

```
# Positions are learned, not hard-coded
self.pos_embed = nn.Parameter(torch.randn(1, num_patches, embed_dim))
```

3. Attention Structure

```
# Only architectural constraint: attention mechanism
# No assumption about what to attend to
attention = softmax(Q @ K.T / sqrt(d)) @ V
```

Measuring Inductive Bias Strength

Data Efficiency Test

ViTs need 10x more data for ImageNet processing to achieve 75% accuracy

Generalisation to Different Domains

```
# Train on natural images, test on:
                    CNN    ViT
Medical images:     65%    71%  # ViT better (less bias)
Sketches:          45%    42%  # CNN better (edge bias helps)
Satellite:         55%    68%  # ViT better (different structure)
```

The Data Efficiency Trade-off

```
# CNNs: Strong priors → Less data needed
CNN_ImageNet_Top1 = 76.2%  # with 1.3M images

# ViT: Weak priors → More data needed
ViT_ImageNet_Top1 = 77.9%  # Needs pre-training on 300M images!
ViT_ImageNet_Top1 = 74.5%  # Without pre-training (worse than CNN)
```

The Bias-Variance Tradeoff in Deep Learning

Classical View:

- High bias → Underfitting
- High variance → Overfitting

Modern Deep Learning View:

CNNs: High bias, lower variance

- Strong assumptions may prevent learning optimal solution
- But more stable with limited data

ViTs: Low bias, higher variance

- Can learn optimal solution given enough data
- But may overfit or fail to converge with limited data

When Each Approach Wins

CNNs Excel When:

- Limited training data
- Strong locality matters
- Need parameter efficiency
- Edge devices/mobile deployment

ViTs Excel When:

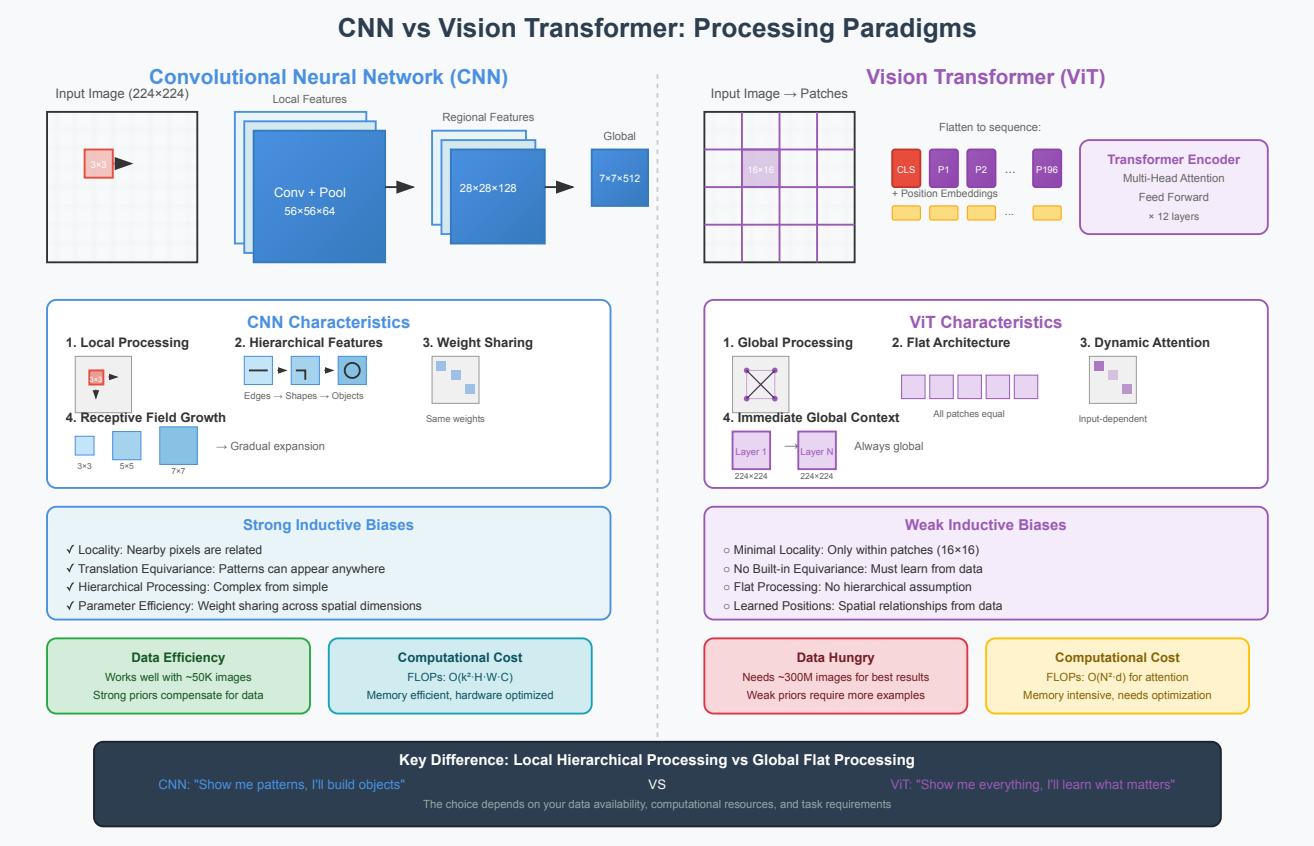
- Massive datasets available

- Global context crucial
- Long-range dependencies
- Transfer learning scenarios

---

8. Comparative Analysis: ViT vs CNN

Performance Comparison



ImageNet Classification Results

```
# Model comparisons (ImageNet validation accuracy)
results = {
    # CNNs
    "ResNet-50": {"params": "25.6M", "FLOPs": "4.1G", "Top-1": 76.2},
    "ResNet-152": {"params": "60.2M", "FLOPs": "11.3G", "Top-1": 77.8},
    "EfficientNet-B0": {"params": "5.3M", "FLOPs": "0.39G", "Top-1":
77.1},
    "EfficientNet-B7": {"params": "66M", "FLOPs": "37G", "Top-1": 84.3},
    "ConvNeXt-B": {"params": "89M", "FLOPs": "15.4G", "Top-1": 85.8},

    # ViTs (without pre-training)
    "ViT-B/16 (scratch)": {"params": "86.6M", "FLOPs": "17.6G", "Top-1":
74.5},
    "ViT-L/16 (scratch)": {"params": "307M", "FLOPs": "63.6G", "Top-1":
76.5},
```

```
    # ViTs (with JFT-300M pre-training)
    "ViT-B/16": {"params": "86.6M", "FLOPs": "17.6G", "Top-1": 84.0},
    "ViT-L/16": {"params": "307M", "FLOPs": "63.6G", "Top-1": 87.5},
    "ViT-H/14": {"params": "632M", "FLOPs": "167G", "Top-1": 88.6},
}
```

Scaling Behavior

Data Scaling

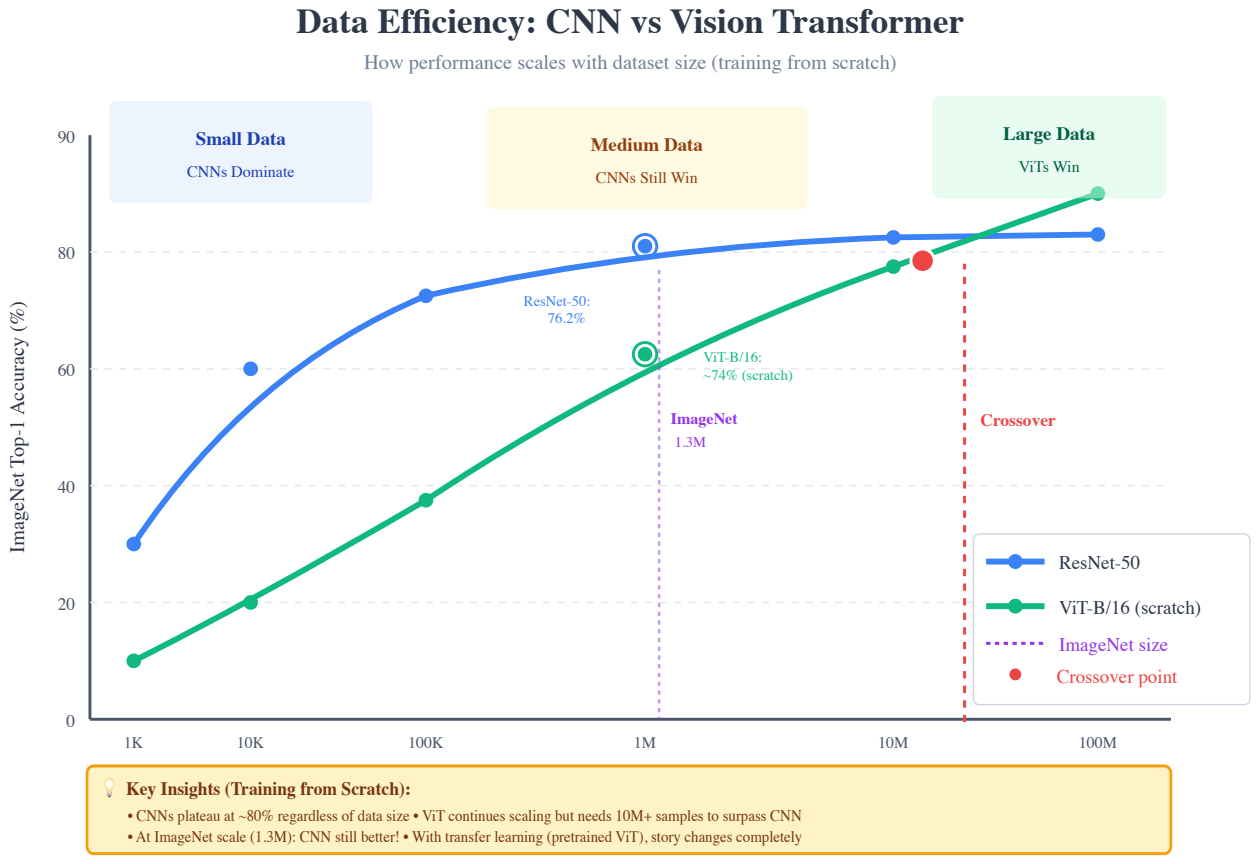
```
def plot_data_scaling():
    """How performance improves with more data"""

    data_points = [1e3, 1e4, 1e5, 1e6, 1e7, 1e8, 1e9  ]

    # CNN saturates quickly
    cnn_perf =    [ 45,  65,  75,  80,  82,  83,  83.5]

    # ViT keeps improving
    vit_perf =    [ 20,  35,  55,  75,  83,  87,  90  ]

    # ViT surpasses CNN at ~1M samples
    crossover_point = 1e7
```



Model Scaling

```
# Parameters vs Performance
                Params    ImageNet   Scaling Efficiency
ViT-S/16:       22M       81.4%      ███████▒
ViT-B/16:       86M       84.0%      ███████▒
ViT-L/16:       307M      87.5%      ████████▒
ViT-H/14:       632M      88.6%      ████████▒

ResNet-50:      25M       76.2%      ██████▒▒
ResNet-152:     60M       77.8%      ███▒▒▒▒▒
ResNet-200:     65M       78.3%      ██▒▒▒▒▒▒ (Saturating!)
```

Computational Complexity Analysis

Theoretical Complexity

Component	CNN	ViT
Convolution/Attention	$O(k^2 \cdot HW \cdot C_{in} \cdot C_{out})$	$O(N^2 \cdot d)$
Projection	-	$O(N \cdot d^2)$
Memory	$O(k^2 \cdot C_{in} \cdot C_{out})$	$O(N^2 + Nd)$
Parameters	$\sum_l k^2 \cdot C_{in}^l \cdot C_{out}^l$	$12 \cdot (3d^2 + d \cdot d_{mlp})$

Practical Measurements

```python
import time
import torch

def benchmark_models(batch_size=32, image_size=224):
    """Compare actual inference time"""

    x = torch.randn(batch_size, 3, image_size, image_size).cuda()

    models = {
        'ResNet-50': torchvision.models.resnet50(),
        'ViT-B/16': timm.create_model('vit_base_patch16_224'),
        'EfficientNet-B0': timm.create_model('efficientnet_b0'),
    }

    results = {}
    for name, model in models.items():
        model = model.cuda().eval()

        # Warmup
        for _ in range(10):
            _ = model(x)
```

```
        # Benchmark
        torch.cuda.synchronize()
        start = time.time()
        for _ in range(100):
            with torch.no_grad():
                _ = model(x)
        torch.cuda.synchronize()
        end = time.time()

        results[name] = (end - start) / 100

    return results

# Typical results (V100 GPU):
# ResNet-50: 8.2ms
# EfficientNet-B0: 5.1ms
# ViT-B/16: 15.3ms
```

Training Dynamics

Convergence Behavior

```
# Training characteristics

# CNNs: Fast initial convergence
epoch      1    5   10   20   50  100
CNN_acc:  45%  68%  74%  78%  80%  81%

# ViTs: Slower start, better final performance
ViT_acc:  20%  45%  62%  75%  83%  86%

# Key differences:
- ViTs need careful warmup (learning rate schedule)
- ViTs benefit more from longer training
- ViTs more sensitive to optimization hyperparameters
```

Optimization Challenges

```
# ViT-specific training techniques

class ViTTrainer:
    def __init__(self):
        # 1. Learning rate warmup (critical!)
        self.warmup_steps = 10000

        # 2. Large batch size (helps stability)
```

```
        self.batch_size = 4096

        # 3. Strong augmentation
        self.augmentation = RandAugment(n=2, m=10)

        # 4. Stochastic depth (drop paths)
        self.drop_path_rate = 0.1

        # 5. Weight decay (but not on all params)
        self.weight_decay = 0.05  # Higher than CNN typical 1e-4

        # 6. AdamW optimizer (not SGD)
        self.optimizer = torch.optim.AdamW

        # 7. Gradient clipping
        self.grad_clip = 1.0
```

Robustness and Generalization

Out-of-Distribution Performance

```
# Robustness benchmarks
                    Natural  Adversarial  Corruption  Sketch
ResNet-50:          76.2%    29.3%         39.2%      24.1%
ViT-B/16:           84.0%    61.2%         52.3%      32.4%
Difference:         +7.8%   +31.9%        +13.1%      +8.3%

# ViTs are significantly more robust!
```

Shape vs Texture Bias

```
def measure_shape_texture_bias(model):
    """Test if model relies on shape or texture"""

    # Create images with conflicting shape/texture
    # e.g., elephant texture on cat shape

    results = {
        "ResNet-50": {"shape": 0.23, "texture": 0.77},    # Texture biased
        "ViT-B/16":  {"shape": 0.45, "texture": 0.55},     # More balanced
        "Human":     {"shape": 0.96, "texture": 0.04}         # Shape
biased
    }

    # ViTs are closer to human vision in efficience!
```

Memory and Storage Requirements

```python
# Model sizes and memory usage

def calculate_memory_usage(model_name, batch_size=32):
    """Calculate GPU memory requirements"""

    memory = {
        # Storage (parameters)
        "ResNet-50": {"params_mb": 98, "gradients_mb": 98},
        "ViT-B/16": {"params_mb": 346, "gradients_mb": 346},


        # Activations (depends on batch size)
        # For batch_size=32, image_size=224
        "ResNet-50": {"activations_mb": 412},
        "ViT-B/16": {"activations_mb": 856},

        # Attention matrices (ViT only)
        "ViT-B/16": {"attention_mb": batch_size * 12 * 196 * 196 * 4 /
1e6}
    }

    # Total for training (params + grads + activations + optimizer state)
    resnet_total = 98 + 98 + 412 + 196  # ~804MB
    vit_total = 346 + 346 + 856 + 692 + 147  # ~2387MB
```

---

9. ViT Architecture: Complete Picture

Standard ViT Architecture

```
Input Image (H×W×C)
        ↓
Patch Embedding (N×D)
        ↓
   + Positional Embedding
        ↓
┌──────────────────┐
│ Transformer      │ × L layers
│ ┌──────────────┐ │
│ │ Layer Norm   │ │
│ │     ↓        │ │
│ │ Multi-Head   │ │
│ │ Attention    │ │
│ │     ↓        │ │
│ │   Residual   │ │
```

Key Components

```
class VisionTransformer(nn.Module):
    def __init__(self, image_size=224, patch_size=16, num_classes=1000,
                 dim=768, depth=12, heads=12, mlp_dim=3072):
        super().__init__()
        num_patches = (image_size // patch_size) ** 2

        self.patch_embed = PatchEmbed(patch_size, dim)
        self.cls_token = nn.Parameter(torch.zeros(1, 1, dim))
        self.pos_embed = nn.Parameter(torch.zeros(1, num_patches + 1,
dim))

        self.transformer = Transformer(dim, depth, heads, mlp_dim)
        self.mlp_head = nn.Linear(dim, num_classes)

    def forward(self, x):
        # Embed patches
        x = self.patch_embed(x)  # (B, N, D)

        # Add [CLS] token
        cls_tokens = self.cls_token.expand(x.shape[0], -1, -1)
        x = torch.cat((cls_tokens, x), dim=1)

        # Add positional embedding
        x = x + self.pos_embed

        # Transformer blocks
        x = self.transformer(x)

        # Classification head
```

```
        x = x[:, 0]  # [CLS] token
        x = self.mlp_head(x)
        return x
```

Fine-tuning Pre-trained ViT

```
def finetune_vit(pretrained_model, num_classes, image_size=384):
    """Fine-tune pre-trained ViT for new task"""

    # Load pre-trained model
    model = timm.create_model(pretrained_model, pretrained=True)

    # Handle different image size
    if image_size != 224:

        # Interpolate position embeddings
        pos_embed = interpolate_pos_encoding(
            model.pos_embed,
            image_size // model.patch_size
        )
        model.pos_embed = nn.Parameter(pos_embed)

    # Replace classification head
    model.head = nn.Linear(model.embed_dim, num_classes)

    # Different learning rates for different parts
    param_groups = [
        {'params': model.patch_embed.parameters(), 'lr': 1e-5},  # Lower
LR
        {'params': model.blocks[:-2].parameters(), 'lr': 1e-5},  # Lower
LR
        {'params': model.blocks[-2:].parameters(), 'lr': 1e-4},  # Medium
LR
        {'params': model.head.parameters(), 'lr': 1e-3},  # Higher LR
    ]

    optimizer = torch.optim.AdamW(param_groups, weight_decay=0.05)

    return model, optimizer
```

Efficient ViT Variants

1. DeiT: Data-Efficient Image Transformers

Original Vision Transformers (ViT) required massive datasets to train effectively:

- ImageNet-21k (14M images) or JFT-300M (300M images)
- Without such data, ViTs underperformed CNNs
- Reason: ViTs lack the **inductive biases** of CNNs (locality, translation equivariance)
  Challenge: How to train ViTs on smaller datasets like ImageNet-1k (1.3M images)?
- **distillation** where a smaller model (student) learns from a larger model (teacher)
- build a **teacher** module
  - teacher is generally a CNN architecture
- **student** learns from hard targets (true labels) assisted with teacher's soft predictions
  - the datasets are different
- needs two specialised tokens
  - [CLS] to learn to predict true labels
  - [DIST] to learn to mimic teacher's prediction
- during training
  - gets output from teacher
  - computes the losses
    - student (transformer) output
    - loss between the teacher output and student output (cross-entropy, KL divergence)
  - total loss as sum and add
- during inference
  - compute both transformer and distillation models
  - average both
- DeiT is data efficient

```
class DeiT(VisionTransformer):
    """ViT with distillation token for knowledge transfer"""

    def __init__(self, *args, **kwargs):
        super().__init__(*args, **kwargs)
        self.dist_token = nn.Parameter(torch.randn(1, 1, self.dim))
        # Update pos_embed for extra token
        self.pos_embed = nn.Parameter(
            torch.randn(1, self.num_patches + 2, self.dim)
        )

    def forward(self, x):
        # Add both cls and distillation tokens
        cls_tokens = self.cls_token.expand(x.shape[0], -1, -1)
        dist_tokens = self.dist_token.expand(x.shape[0], -1, -1)
        x = torch.cat((cls_tokens, dist_tokens, x), dim=1)
        # ... rest of forward pass
```

```
| Model | Params | Top-1 Acc | Training Data |
|-------|--------|-----------|---------------|
| **ViT-B (original)** | 86M | 77.9% | ImageNet-21k (pre-train) +
ImageNet-1k |
| **DeiT-B** | 86M | **81.8%** | ImageNet-1k only! |
| **DeiT-B ⚗ (distilled)** | 86M | **83.4%** | ImageNet-1k + CNN teacher |
```

✅ Trains ViT from scratch on ImageNet-1k (no pre-training on huge datasets!)
✅ Matches or exceeds CNNs trained on same data
✅ 3x faster training than original ViT
✅ Competitive with models pre-trained on 10-20x more data

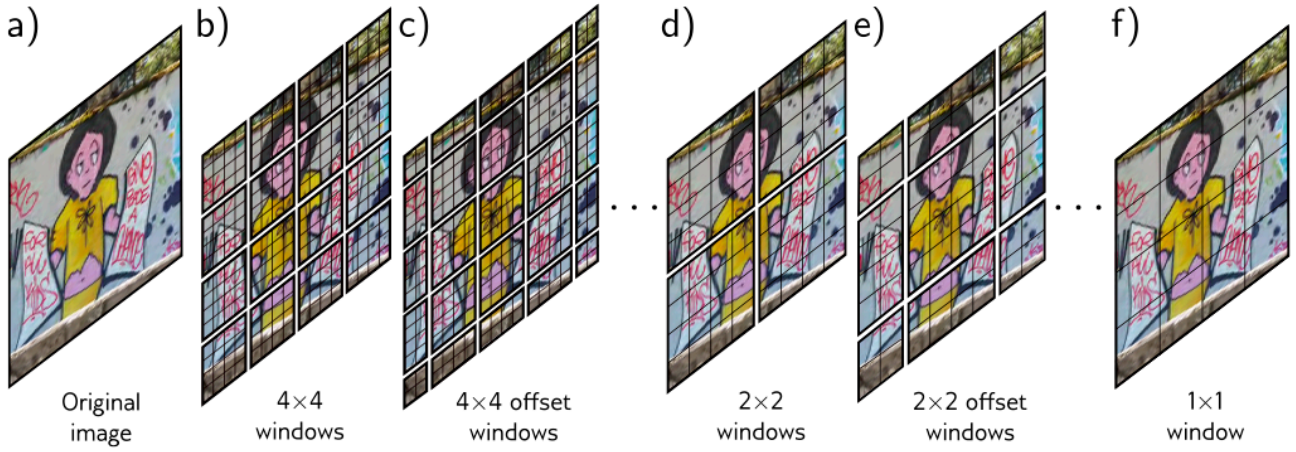
2. Swin Transformer: Hierarchical with Shifted Windows

Standard ViT limitations:

- **Fixed resolution**: Processes image at single scale (e.g., 16×16 patches throughout)
- **Quadratic complexity**: Self-attention across all patches → O(n²), n = number of patches
- **No hierarchical structure**: Unlike CNNs - ViT maintains constant resolution
- **Expensive for dense prediction**: Segmentation, detection need multi-scale features

The Swin (Shifted window) Solution (Liu et al., 2021)

Key Innovation: Replace global attention with **local window attention** + **shifted windows** to enable cross-window connections.



Hierarchical Architecture with Windows

Instead of fixed-size patches throughout,

- breaks the image into a grid of windows
- each of these windowsinto a sub-grid of patches
- transformer applies self-attention to the patches within each window **independently**
- alternate layer shifts windows
    - subsets of interacting patches with one another, change

    - information propagates across whole image
- several layers are built e.g., four for ImageNet's 224x224
- after several layers layers
    - 2x2 blocks of patch representations are concatenated
    - patch and window size grow
- alternate layers use **shifted** windows at new lower resolutions
    - windows communicate with each other
    - may be very effectively implemented
- eventually there is just a single window
    - patches cover the whole image

```
Stage 1: 56×56 feature map  (patch size 4×4,  token dim 96)
   ↓ Window attention + patch merging
Stage 2: 28×28 feature map  (merged 2×2,  token dim 192)
   ↓ Window attention + patch merging
Stage 3: 14×14 feature map  (merged 2×2,  token dim 384)
   ↓ Window attention + patch merging
Stage 4: 7×7 feature map    (merged 2×2,  token dim 768)
```

Like CNNs: Progressively reduce spatial resolution while increasing channels!

- ✅ Transformers can be **hierarchical** (don't need flat structure)
- ✅ **Local attention** sufficient with proper design (don't always need global)
- ✅ ViTs can **match CNNs for dense tasks** (detection, segmentation)
- ✅ **Scalable to high-resolution** images (1024×1024+)

Legacy: Swin became the de facto vision backbone for many applications, proving Transformers could replace CNNs even in domains requiring multi-scale hierarchical features. Inspired many follow-up works combining local and global attention (e.g., Swin V2, CSWin, MaxViT).

```python
class SwinTransformerBlock(nn.Module):
    """Swin Transformer block with shifted window attention"""

    def __init__(self, dim, num_heads, window_size=7, shift_size=0):
        super().__init__()
        self.dim = dim
        self.num_heads = num_heads
        self.window_size = window_size
        self.shift_size = shift_size

        self.norm1 = nn.LayerNorm(dim)
        self.attn = WindowAttention(dim, window_size, num_heads)
        self.norm2 = nn.LayerNorm(dim)
        self.mlp = FeedForward(dim, dim * 4)
```

```
    def forward(self, x, H, W):
        # Save shape
        B, L, C = x.shape

        # Reshape to image
        x = x.view(B, H, W, C)

        # Cyclic shift
        if self.shift_size > 0:
            x = torch.roll(x, shifts=(-self.shift_size, -self.shift_size),
dims=(1, 2))

        # Partition windows
        x_windows = window_partition(x, self.window_size)

        # Window attention
        attn_windows = self.attn(x_windows)

        # Merge windows
        x = window_reverse(attn_windows, self.window_size, H, W)

        # Reverse cyclic shift
        if self.shift_size > 0:
            x = torch.roll(x, shifts=(self.shift_size, self.shift_size),
dims=(1, 2))

        # Reshape back
        x = x.view(B, H * W, C)

        # Residual connections
        x = x + self.norm1(x)
        x = x + self.mlp(self.norm2(x))

        return x
```

10. Computational Complexity Analysis

Complexity Comparison

Operation	CNN	ViT
Per Layer	$O(k^2 \cdot H \cdot W \cdot C_{\text{in}} \cdot C_{\text{out}})$	$O(N^2 \cdot D + N \cdot D^2)$
Memory	$O(k^2 \cdot C_{\text{in}} \cdot C_{\text{out}})$	$O(N^2 + N \cdot D)$
Receptive Field Growth	$O(\sqrt{L})$	$O(1)$ - immediate global

Concrete Example: ImageNet

```
# ResNet-50
Parameters: 25.6M
FLOPs: 4.1G
Memory: ~100MB

# ViT-B/16
Parameters: 86.6M
FLOPs: 17.6G
Memory: ~350MB

# But ViT achieves better accuracy with sufficient pre-training!
```

Scaling Behaviour

```
As image resolution increases:
CNN: O(N) - Linear in pixels
ViT: O(N²) - Quadratic in patches

Solution: Hierarchical ViTs (Swin Transformer)
```

---

11. Performance: The Complete Picture

ImageNet Results

```
                    Top-1 Accuracy
                    ├──────────────────────────┤
ResNet-50:          76.2% ████████████████▒▒▒▒
ResNet-152:         77.8% ████████████████▒▒▒▒
EfficientNet-B7:    84.3% ████████████████▒▒▒▒

ViT-B/16 (no pre):  74.5% ████████████████▒▒▒▒ ← Worse!
ViT-B/16 (JFT-300M):79.7% ████████████████▒▒▒▒
ViT-L/16 (JFT-300M):87.5% ████████████████▒▒▒▒ ← Best!
ViT-H/14 (JFT-3B):  88.6% ████████████████▒▒▒▒
```

Key Observations

1. **Data Requirements**: ViT needs ~100× more data than CNNs
2. **Scaling**: ViTs scale better with data and compute
3. **Transfer Learning**: Pre-trained ViTs transfer exceptionally well
4. **Robustness**: ViTs more robust to occlusions, perturbations

12. Practical Insights & Trade-offs

When to Use What?

```
Error parsing Mermaid diagram!

Cannot read properties of null (reading 'getBoundingClientRect')
```

Hybrid Approaches

1. CNN + Transformer

```
Early layers: CNN (extract local features efficiently)
Later layers: Transformer (model global relationships)
Example: LeViT, CvT
```

2. Hierarchical ViT

```
Swin Transformer: Windowed attention + shifting
- Reduces O(N²) to O(N)
- Maintains global receptive field
- Better for dense tasks
```

3. Convolutional Stem

```
# Replace patch embedding with Conv layers
self.conv_stem = nn.Sequential(
    nn.Conv2d(3, 64, 3, 2, 1),
    nn.Conv2d(64, 128, 3, 2, 1),
    nn.Conv2d(128, dim, 3, 2, 1)
)
# Reduces patches, adds inductive bias
```

---

13. Recent Advances & Future Directions

Efficient Attention Mechanisms

```
# Linear Attention: O(N) instead of O(N²)
attention = (Q @ K.T).softmax(dim=-1) @ V  # Standard O(N²)
attention = Q @ (K.T @ V)                 # Linear O(N)
```

```
# Sparse Attention: Attend to subset
# Local + Global attention patterns
```

Key Innovations

1. **DeiT** (Data-efficient ViT): Knowledge distillation from CNNs
2. **Swin Transformer**: Hierarchical architecture with shifted windows
3. **MLP-Mixer**: Replace attention with MLPs
4. **ConvNeXt**: Modernized CNN inspired by ViT designs

Open Questions

- Can we reduce ViT data requirements?
- Optimal patch size?
- Better positional encodings?
- Unified architecture for all vision tasks?

Efficient Attention Mechanisms

1. Linear Attention (Performer)

```
class LinearAttention(nn.Module):
    """O(N) complexity instead of O(N²)"""

    def __init__(self, dim, heads=8):
        super().__init__()
        self.heads = heads
        self.dim_head = dim // heads
        self.to_qkv = nn.Linear(dim, dim * 3)

    def forward(self, x):
        b, n, _ = x.shape
        qkv = self.to_qkv(x).chunk(3, dim=-1)
        q, k, v = map(lambda t: rearrange(t, 'b n (h d) -> b h n d',
h=self.heads), qkv)

        # Apply random features for linear attention
        q = self.kernel_function(q)
        k = self.kernel_function(k)

        # O(N) attention: (Q @ K.T) @ V becomes Q @ (K.T @ V)
        kv = torch.einsum('bhnd,bhne->bhde', k, v)
        out = torch.einsum('bhnd,bhde->bhne', q, kv)



        # Normalize
```

```
        q_sum = q.sum(dim=-1, keepdim=True)
        out = out / q_sum

        return rearrange(out, 'b h n d -> b n (h d)')
```

2. Flash Attention (Memory Efficient)

```
# Flash Attention: Fused kernel for memory efficiency
# Reduces memory from O(N²) to O(N)
from flash_attn import flash_attn_func

class FlashAttention(nn.Module):
    def __init__(self, dim, heads=8):
        super().__init__()
        self.heads = heads
        self.to_qkv = nn.Linear(dim, dim * 3)

    def forward(self, x):
        b, n, _ = x.shape
        qkv = self.to_qkv(x)
        qkv = rearrange(qkv, 'b n (three h d) -> b n three h d',
                        three=3, h=self.heads)

        # Use flash attention (fused CUDA kernel)
        out = flash_attn_func(qkv[:, :, 0], qkv[:, :, 1], qkv[:, :, 2])
        return rearrange(out, 'b n h d -> b n (h d)')
```

Multi-Scale Vision Transformers

Pyramid Vision Transformer (PVT)

```
class PVT(nn.Module):
    """Multi-scale feature pyramid with transformers"""

    def __init__(self, img_size=224, num_classes=1000):
        super().__init__()

        # 4 stages with decreasing resolution
        self.stages = nn.ModuleList([
            # Stage 1: H/4 × W/4
            PVTStage(dim=64, patches_resolution=56, depth=3, num_heads=1),
            # Stage 2: H/8 × W/8
            PVTStage(dim=128, patches_resolution=28, depth=4,
num_heads=2),
            # Stage 3: H/16 × W/16
            PVTStage(dim=320, patches_resolution=14, depth=6,
num_heads=5),
```

```
            # Stage 4: H/32 × W/32
            PVTStage(dim=512, patches_resolution=7, depth=3, num_heads=8),
        ])

        self.head = nn.Linear(512, num_classes)

    def forward(self, x):
        features = []
        for stage in self.stages:
            x = stage(x)
            features.append(x)

        # Use final stage for classification
        x = x.mean(dim=1)
        return self.head(x), features  # Return multi-scale features
```

Cross-Modal Vision Transformers

CLIP-style Vision-Language Model

```
class CLIPVisionTransformer(nn.Module):
    """Vision transformer for multi-modal learning"""

    def __init__(self, image_size=224, patch_size=16, dim=512):
        super().__init__()
        self.vit = VisionTransformer(
            image_size=image_size,
            patch_size=patch_size,
            dim=dim,
            pool='cls'
        )

        # Project to shared embedding space
        self.projection = nn.Linear(dim, 512)

    def forward(self, images, return_features=False):
        # Get image features
        features = self.vit(images)

        # Project to shared space
        embeddings = self.projection(features)
        embeddings = F.normalize(embeddings, dim=-1)

        if return_features:
            return embeddings, features
        return embeddings

def contrastive_loss(image_embeddings, text_embeddings, temperature=0.07):
```

```
    """CLIP-style contrastive loss"""
    # Normalized embeddings
    image_embeddings = F.normalize(image_embeddings, dim=-1)
    text_embeddings = F.normalize(text_embeddings, dim=-1)

    # Cosine similarity as logits
    logits = torch.matmul(image_embeddings, text_embeddings.T) /
temperature

    # Symmetric loss
    labels = torch.arange(len(logits)).to(logits.device)
    loss_i2t = F.cross_entropy(logits, labels)
    loss_t2i = F.cross_entropy(logits.T, labels)

    return (loss_i2t + loss_t2i) / 2
```

Self-Supervised Learning with ViT

Masked Autoencoder (MAE)

```
class MAE(nn.Module):
    """Masked Autoencoder for self-supervised learning"""

    def __init__(self, encoder, decoder_dim=512, mask_ratio=0.75):
        super().__init__()
        self.encoder = encoder
        self.mask_ratio = mask_ratio

        # Decoder (lighter than encoder)
        self.decoder = nn.TransformerDecoder(
            nn.TransformerDecoderLayer(decoder_dim, 8),
            num_layers=4
        )

        # Prediction head
        self.prediction_head = nn.Linear(decoder_dim, patch_dim)

    def forward(self, x):
        # Get patches
        patches = self.encoder.to_patch_embedding(x)
        B, N, D = patches.shape

        # Random masking
        num_mask = int(N * self.mask_ratio)
        indices = torch.randperm(N)
        mask_indices = indices[:num_mask]
        keep_indices = indices[num_mask:]
```

```
        # Keep only visible patches for encoder
        visible_patches = patches[:, keep_indices]

        # Encode
        encoded = self.encoder.transformer(visible_patches)

        # Decode (with mask tokens)
        mask_tokens = self.mask_token.repeat(B, num_mask, 1)
        full_sequence = torch.cat([encoded, mask_tokens], dim=1)

        # Restore original order
        full_sequence = restore_order(full_sequence, indices)

        # Decode
        decoded = self.decoder(full_sequence)

        # Predict masked patches
        predictions = self.prediction_head(decoded)

        # Compute reconstruction loss (only on masked patches)
        loss = F.mse_loss(predictions[:, mask_indices], patches[:,
mask_indices])

        return loss, predictions
```

Future Directions

1. Unified Architecture for All Vision Tasks

```
class UniversalViT(nn.Module):
    """Single model for classification, detection, segmentation"""

    def __init__(self):
        super().__init__()
        self.backbone = VisionTransformer(...)

        # Task-specific heads
        self.heads = nn.ModuleDict({
            'classification': ClassificationHead(),
            'detection': DetectionHead(),
            'segmentation': SegmentationHead(),
            'depth': DepthHead(),
        })

    def forward(self, x, task='classification'):
        features = self.backbone(x, return_all_patches=True)
        return self.heads[task](features)
```

2. Neural Architecture Search for ViTs

```
# AutoFormer: Automated transformer architecture search
search_space = {
    'depth': [12, 14, 16, 18],
    'embed_dim': [384, 512, 640, 768],
    'num_heads': [6, 8, 10, 12],
    'mlp_ratio': [3.0, 3.5, 4.0],
    'patch_size': [14, 16, 18],
}
```

3. Efficient Deployment

```
# Quantization for edge devices
quantized_vit = torch.quantization.quantize_dynamic(
    model, {nn.Linear}, dtype=torch.qint8
)

# Knowledge distillation to smaller models
tiny_vit = distill_from_teacher(
    teacher=vit_huge,
    student=vit_tiny,
    temperature=3.0
)

# Token pruning during inference
def adaptive_token_pruning(x, keep_ratio=0.5):
    """Keep only important tokens"""
    importance_scores = compute_token_importance(x)
    keep_indices = torch.topk(importance_scores, int(len(x) * keep_ratio))
    return x[keep_indices]
```

---

14. Summary: The Paradigm Shift

From Local to Global

```
CNNs:                              ViTs:
Local → Hierarchical → Global      Global from the start
Strong priors                      Minimal priors
Data efficient                     Compute efficient (at scale)
Hardware optimized                 Emerging optimizations
```

Key Takeaways

1. **ViT treats images as sequences** of patches (tokens)
2. **Attention enables global interactions** from layer 1
3. **Weak inductive bias** requires more data but enables flexibility
4. **Superior scaling** with data and compute
5. **Not always better** - depends on your constraints

The Future is Hybrid

The best models increasingly combine:

- CNN efficiency for local patterns
- Transformer flexibility for global reasoning
- Task-specific architectural biases

Practical Recommendations

For Your Projects

```
# Small dataset (<50K images)
model = torchvision.models.resnet50(pretrained=True)

# Medium dataset with compute
model = timm.create_model('convnext_base', pretrained=True)

# Large dataset or transfer learning
model = timm.create_model('vit_base_patch16_224', pretrained=True)

# Dense prediction tasks
model = timm.create_model('swin_base_patch4_window7_224')

# Mobile/edge deployment
model = timm.create_model('efficientnet_b0')
```

Key Hyperparameters to Tune

1. **Patch size**: Smaller → more patches → more compute but finer details
2. **Embedding dim**: Match model size to data availability
3. **Number of heads**: 12 often optimal
4. **Depth vs width**: Deeper better for complex tasks
5. **Drop path rate**: Critical for training deep ViTs

Extension Points for Advanced Topics

Potential Deep Dives

1. **Mathematical Foundations**
   - Attention as kernel regression
   - Connection to graph neural networks
   - Fourier analysis of positional encodings
2. **Advanced Architectures**
   - Cross-attention for multi-modal (CLIP)
   - Hierarchical vision transformers (Swin, PVT)
   - Efficient attention mechanisms (Performer, Linformer)
3. **Training Dynamics**
   - Why ViTs are hard to optimize
   - Role of LayerNorm placement
   - Attention pattern evolution during training
4. **Interpretability**
   - Attention visualization techniques
   - What do ViTs learn vs CNNs?
   - Probing intermediate representations
5. **Applications Beyond Classification**
   - Object detection (DETR)
   - Segmentation (SegFormer)
   - Video understanding (TimeSformer)

Code Example: Minimal ViT Implementation

```
import torch
import torch.nn as nn

class SimpleViT(nn.Module):
    def __init__(self, image_size=224, patch_size=16, num_classes=10,
                 dim=512, depth=6, heads=8, mlp_ratio=4):
        super().__init__()
        assert image_size % patch_size == 0
        num_patches = (image_size // patch_size) ** 2
        patch_dim = 3 * patch_size ** 2

        self.patch_size = patch_size
        self.pos_embedding = nn.Parameter(torch.randn(1, num_patches + 1,
```

```
dim))
        self.patch_to_embedding = nn.Linear(patch_dim, dim)
        self.cls_token = nn.Parameter(torch.randn(1, 1, dim))

        self.transformer = nn.TransformerEncoder(
            nn.TransformerEncoderLayer(
                d_model=dim,
                nhead=heads,
                dim_feedforward=dim * mlp_ratio,
                batch_first=True
            ),
            num_layers=depth
        )

        self.to_cls_token = nn.Identity()
        self.mlp_head = nn.Sequential(
            nn.LayerNorm(dim),
            nn.Linear(dim, num_classes)
        )

    def forward(self, img):
        B, C, H, W = img.shape
        P = self.patch_size

        # Create patches
        patches = img.unfold(2, P, P).unfold(3, P, P)  # (B, C, H/P, W/P,
P, P)
        patches = patches.contiguous().view(B, C, -1, P*P)  # (B, C,
num_patches, P*P)
        patches = patches.permute(0, 2, 1, 3)  # (B, num_patches, C, P*P)
        patches = patches.flatten(2)  # (B, num_patches, C*P*P)

        # Embed patches
        x = self.patch_to_embedding(patches)

        # Add cls token
        cls_tokens = self.cls_token.expand(B, -1, -1)
        x = torch.cat((cls_tokens, x), dim=1)

        # Add positional embedding
        x += self.pos_embedding

        # Transformer
        x = self.transformer(x)

        # Classification
        return self.mlp_head(x[:, 0])

# Test
model = SimpleViT(image_size=32, patch_size=8, num_classes=10, dim=128,
```

```
depth=4)
x = torch.randn(2, 3, 32, 32)
out = model(x)
print(f"Output shape: {out.shape}")  # [2, 10]
```

References & Further Reading

Essential Papers

- Attention Is All You Need - Original Transformer
- An Image is Worth 16x16 Words - Vision Transformer
- Training data-efficient image transformers - DeiT
- Swin Transformer - Hierarchical Vision Transformer
- **Masked Autoencoders Are Scalable Vision Learners** - MAE
- **A ConvNet for the 2020s** - ConvNeXt

Practical Resources

- timm library - Pre-trained ViTs, best implementations
- **Hugging Face Transformers** - Easy to use
- Annotated ViT - Clear implementation
- ViT Tutorial - Hugging Face guide
