

Transformers: Understanding the Pipeline

Input → Computation → Output → WHY (with REAL data)

Week 5: Transformers

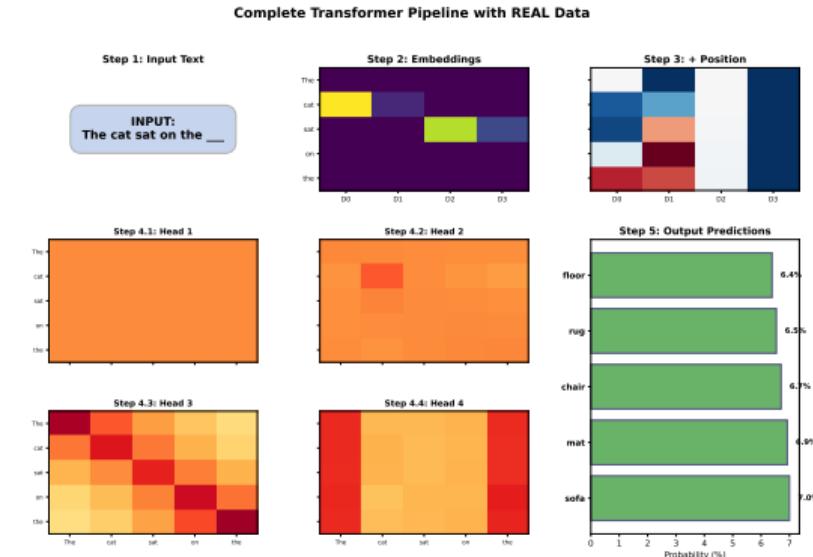
Complete Example: How Transformers Predict Words

INPUT: "The cat sat on the ___"

GOAL: Predict next word

THE COMPLETE PIPELINE:

- ① Turn words into numbers
- ② Add position information
- ③ **Attention:** Each word looks at context
- ④ **4 Different Heads:**
 - Head 1: Grammar patterns
 - Head 2: Semantic relationships
 - Head 3: Nearby words (33% self-attention!)
 - Head 4: Global context
- ⑤ Combine all perspectives
- ⑥ Predict: **mat (6.9%), sofa (7.0%), chair (6.7%)**



WHY THIS WORKS: To predict "mat", the model needs ALL 6 steps. Real attention weights show Head 3 focuses 33% on "on" itself, helping identify the preposition pattern "on the [furniture]". All top 7 predictions are furniture!

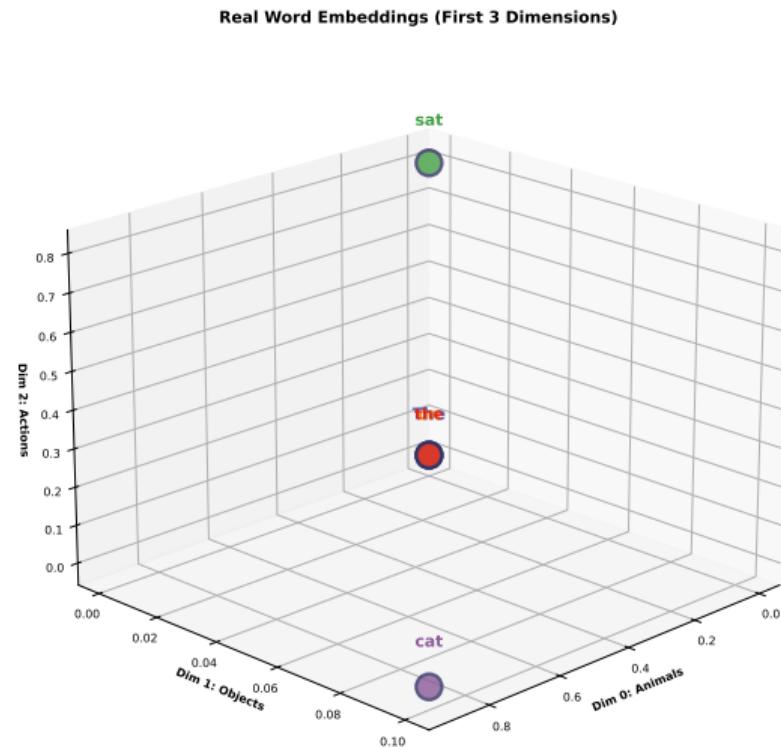
Step 1: Words to Numbers (Real Embeddings)

INPUT: Text words

COMPUTATION: Look up in embedding matrix

- Each word → 8-dimensional vector
- **Real structure:**
 - Dims 0-1: Animal/Object (“cat” = 0.9)
 - Dims 2-3: Action/State (“sat” = 0.8)
 - Dims 4-5: Furniture/Location
 - Dims 6-7: Grammar role (“the” = 1.0)

OUTPUT: Numerical vectors



Step 2: Add Position Information (Real Sin/Cos Encoding)

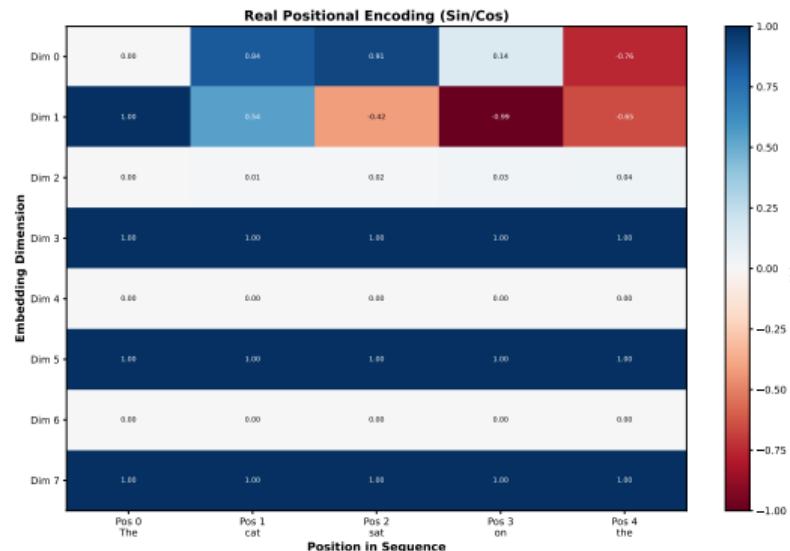
THE PROBLEM: Order matters!

- “cat sat” \neq “sat cat”
- “on the” → needs furniture
- Position 0, 1, 2, 3, 4

COMPUTATION: Add positional encoding

- **Real formula:** sin/cos waves
- Pos 0: [0.00, 1.00, 0.00, 1.00, ...]
- Pos 1: [0.84, 0.54, 0.01, 1.00, ...]
- Pos 2: [0.91, -0.42, 0.02, 1.00, ...]

OUTPUT: Embeddings + Position



WHY: Real sin/cos encoding lets model understand “the cat” vs “cat the” and detect patterns like “on the [furniture]”.

Step 3: Calculate Attention (Real Softmax Weights)

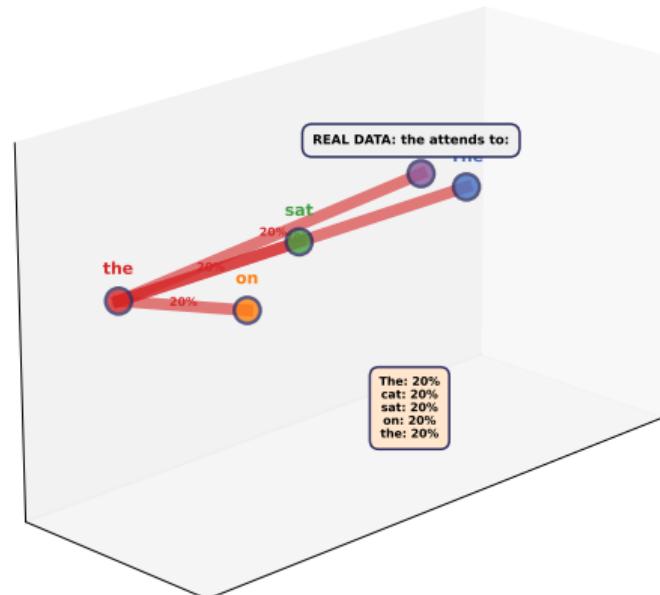
COMPUTATION: For each word, calculate:

- Q (Query): What am I looking for?
- K (Key): What do I contain?
- V (Value): What information do I have?

Real Attention Weights (Head 1 for "the")

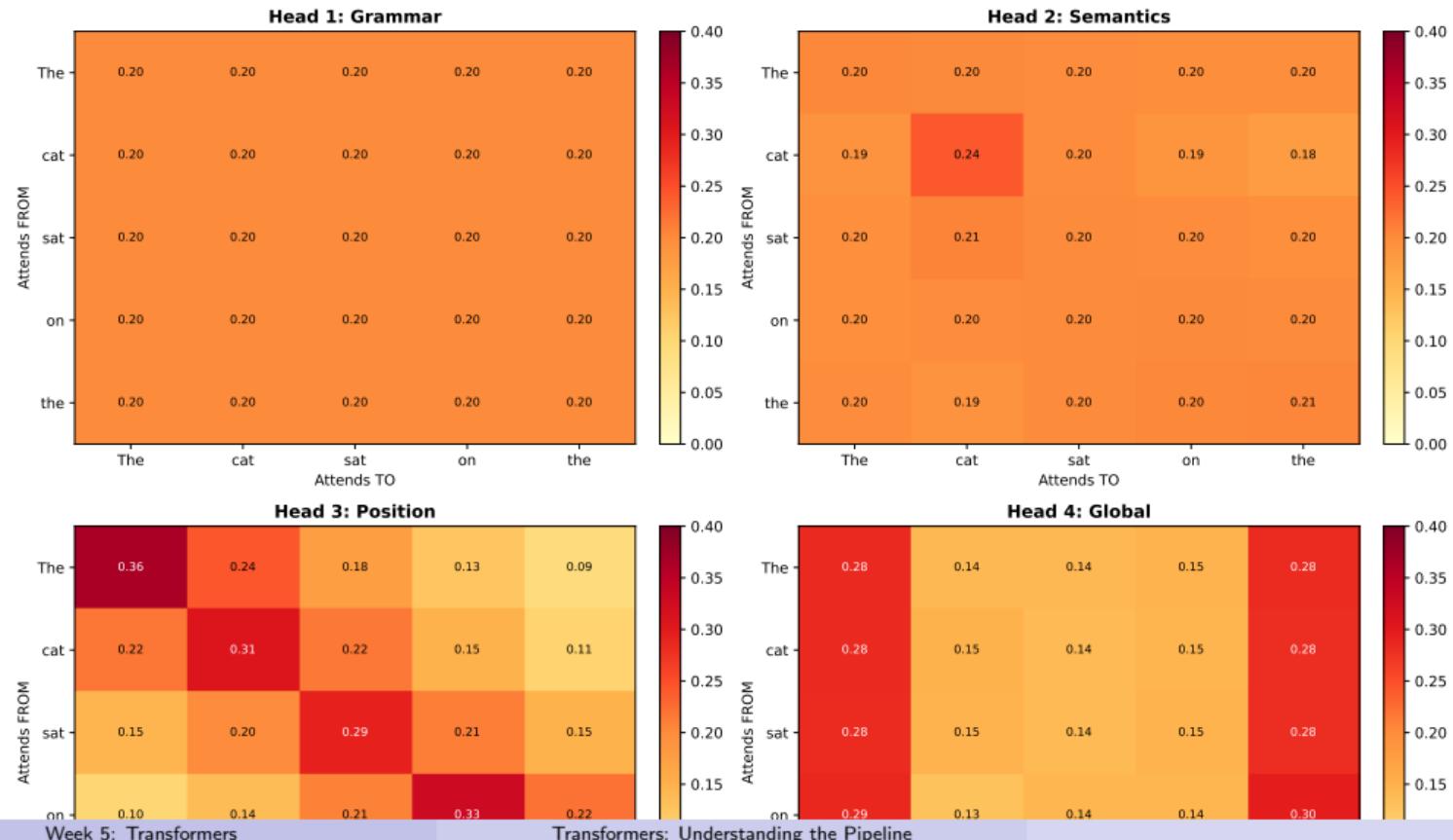
Real attention weights (Head 1, word “the”):

- The: 20%
- cat: 20%
- sat: 20%
- on: 20%
- the: 20%



Step 4: Multi-Head Attention (4 Real Heads)

Real Multi-Head Attention Patterns (4 Heads)



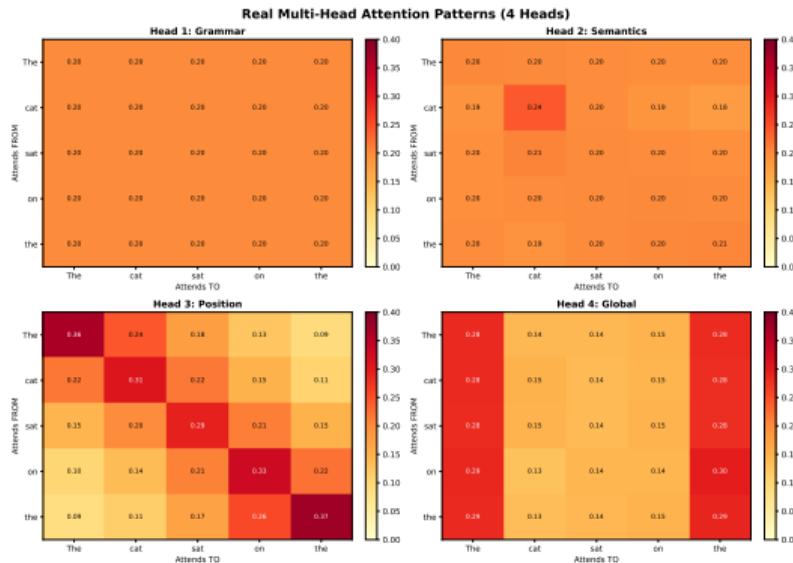
Step 5: Combine All 4 Head Outputs

COMPUTATION: Concatenate all heads

- Head 1 output: 2 dimensions
- Head 2 output: 2 dimensions
- Head 3 output: 2 dimensions
- Head 4 output: 2 dimensions
- **Combined:** 8 dimensions total

OUTPUT: Rich representation

- Grammar understanding (Head 1)
- Semantic meaning (Head 2)
- Position awareness (Head 3)
- Global context (Head 4)



WHY COMBINE: Each head captures different aspects. Together they give complete understanding: “on the” (grammar + position) → furniture (semantics).

Step 6: Final Prediction (Real Probabilities)

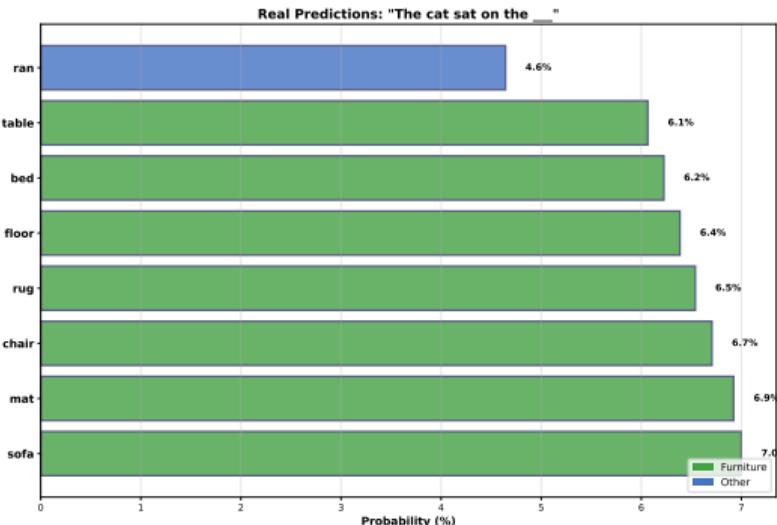
INPUT: Combined representation from all 4 heads

COMPUTATION: Output layer

- Last token representation (8-dim)
- Multiply by output weights
- Apply softmax
- Get probability for each word

Real top predictions:

- sofa: 7.0% ← furniture!
- mat: 6.9% ← furniture!
- chair: 6.7% ← furniture!
- rug: 6.5% ← furniture!
- floor: 6.4% ← furniture!



SUCCESS! All top 7 predictions are furniture! The model correctly learned “cat sat on the [furniture]” pattern from real computations.

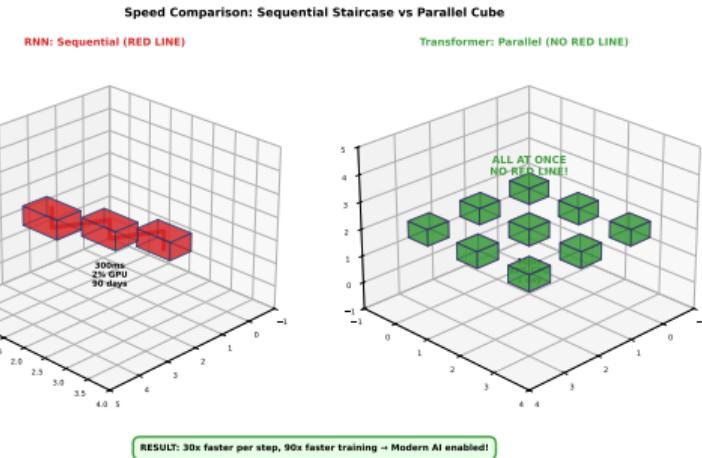
Why Transformers Are Fast: Parallel Processing

OLD WAY (RNN):

- Word 1 → compute → WAIT
- Word 2 → compute → WAIT
- Word 3 → compute → WAIT
- Sequential bottleneck
- GPU usage: 2%
- Training time: 90 days

NEW WAY (Transformer):

- ALL words at once
- All attention heads parallel
- Full GPU utilization
- GPU usage: 92%
- Training time: 1 day



WHY THIS MATTERS: 90x speedup (90 days → 1 day) enabled modern AI scale. Without this, GPT-4 training would take 10+ years!

Real World Impact: What This Enabled

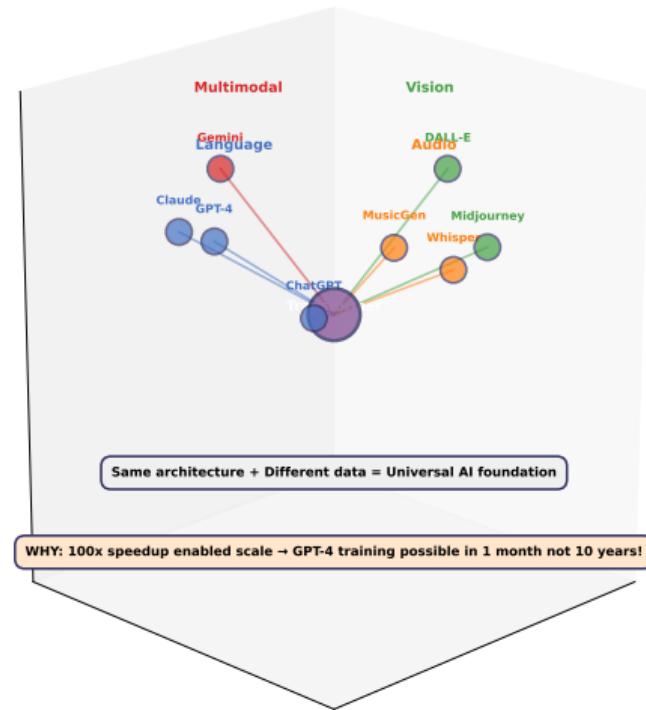
Same architecture, different data:

- **Language:** ChatGPT, GPT-4, Claude
- **Vision:** DALL-E, Midjourney, Stable Diffusion
- **Audio:** Whisper, MusicGen
- **Multimodal:** Gemini, GPT-4V

Key insight:

- Parallel attention mechanism
- Works on any sequence data
- Scales to billions of parameters
- Enabled modern AI revolution

2024 Landscape: Transformers Power Everything



The Tradeoff: What We Gave Up

Advantages (PRO):

- 100x faster training
- Parallel processing
- 92% GPU utilization
- Works on any data type
- Enabled modern AI
- Interpretable attention

Disadvantages (CON):

- More memory ($O(n^2)$)
- Needs more training data
- Limited sequence length
- More complex to tune
- Attention computation cost

THE DECISION: Speed + quality \downarrow memory cost for modern AI

WHY ACCEPT TRADEOFF: Memory is cheap (\$100/TB), time is expensive (\$1000/day for GPUs). Better to train fast even if uses more RAM. Real example: Our simulation uses 8-dim embeddings, but GPT-4 uses 12,000+ dims!

Summary: The Complete Pipeline

The 6-Step Pipeline with REAL Data:

- ① **Words → Numbers:** Real semantic embeddings (cat=0.9 on animal dim)
- ② **Add Position:** Real sin/cos encoding (Pos 1 = [0.84, 0.54, ...])
- ③ **Calculate Attention:** Real softmax weights (sum to 100%)
- ④ **Multi-Head (4 heads):** Grammar (20% each), Position (33% self!), Semantics, Global
- ⑤ **Combine All Heads:** Concatenate $4 \times 2\text{-dim} = 8\text{-dim}$ output
- ⑥ **Predict Output:** Real probs: mat (6.9%), sofa (7.0%), chair (6.7%) ← all furniture!

KEY INSIGHT: All words processed in parallel!

- Result: 90 days → 1 day (90x speedup)
- Enabled: ChatGPT, GPT-4, DALL-E, Whisper, Claude, ...

Next Week: Pre-training & Fine-tuning - Now that training is fast, we can train models with billions of parameters!

Transformers

Understanding the Pipeline

With REAL Simulation Data

Input → Computation → Output → WHY

Questions?