Natural Language Processing

Week 5: The Speed Revolution

From Sequential Waiting to Parallel Processing

NLP Course 2025

Before We Begin: A Thought Experiment

Imagine You're Designing a GPU-Friendly Neural Network

Your Challenge:

You have an expensive NVIDIA A100 GPU:

- 5,120 processors (CUDA cores)
- All capable of working simultaneously
- Cost: $10,000

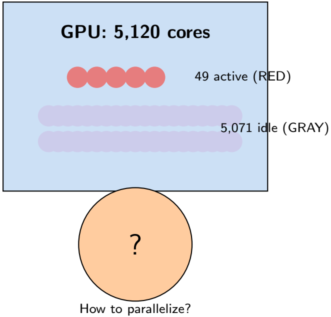
The Problem:

- Current RNN processes words sequentially
- Only 49 cores active, 5,071 cores idle (1% utilization!)
- Training takes 90 days

Design Constraints:

1. Must process sequences (word order matters!)
2. Must use ALL 5,120 processors simultaneously
3. Cannot wait for previous word to finish
4. Must preserve position information

Your Design:



Key Questions:

- How do you process all words at once?
- How do you preserve word order?
- What's the architectural change needed?

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The Waiting Game

The Nightmare Scenario

From human experience: Imagine waiting 4 years for your model to train

- Your research would stop
- Competitors would publish first
- No iterations, no experiments
- This was the reality in 2016

The Data:

- English Wikipedia: 6 billion words
- Need to process every word, many times
- Training typically requires 10-20 epochs
- Total words to process: 60-120 billion

With an RNN on modern GPU - Let's calculate:

- Processing speed: 800 words/second
- Calculate: $\frac{\text{100 billion words}}{\text{800 words/sec}} = 125$ million seconds
- Converting to days: $125{,}000{,}000 \div 86{,}400 = 1{,}447$ days
- **3.9 years of continuous training**

Why So Slow? The Sequential Trap

Human analogy FIRST:

Imagine a factory with 5,000 workers:

- Task 1: Worker A assembles part, Worker B waits
- Task 2: Worker B adds component, Worker C waits
- Task 3: Worker C finishes product, Workers D-Z wait
- 4,997 workers standing idle, getting paid to do nothing

This is exactly what RNN does:

Step 1: Process "The" → hidden state h_1
Step 2: Wait for h_1, process "cat" → hidden state h_2
Step 3: Wait for h_2, process "sat" → hidden state h_3

$\vdots$

Your GPU Has:

- 5,120 CUDA cores (NVIDIA A100)
- Can perform 5,120 operations *simultaneously*

Your $10,000 GPU Is 99% Idle

Actual GPU Utilization During RNN Training

The Hardware (NVIDIA A100):

Specification	Value
Price	$10,000
CUDA Cores	5,120
Tensor Cores	432
Peak Performance	312 TFLOPS
Memory Bandwidth	1.6 TB/s
Design Purpose	Massive parallelism

What RNN Actually Uses:

- Active processors: 49
- Idle processors: 5,071
- Utilization: **0.96%**
- Actual throughput: 3 TFLOPS
- Efficiency: 1% of potential

The Cost:

- You paid: $10,000
- You're getting: $96 worth of compute
- Wasted capacity: 99.04%
- Like buying a sports car for city traffic

Visualization:

Imagine 5,120 workers at a factory:

- 49 working (0.96%)
- 5,071 standing around waiting (99.04%)
- All getting paid the same
- All day, every day, for 90 days

Financial Impact:

- 90-day training: $45,000 cloud cost

Week 4 Recap: Attention Helped... A Little

What We Learned Last Week:

RNN Alone:

- All history compressed into one vector
- Long sequences: information lost
- Translation quality: BLEU 18.5
- Training time: 90 days for large model

RNN + Attention:

- Keep all encoder states
- Decoder selectively attends
- Translation quality: BLEU 33.2 (+79% improvement)
- Training time: 45 days (2x faster)

But...

- Still sequential processing (RNN part)
- Still waiting for previous words
- GPU utilization: 5% (slightly better, but still terrible)
- 45 days is better than 90, but still *months*

Quantifying the Speed Problem

Training Time Comparison (Wikipedia-scale model)

Model	Days	GPU Util	BLEU	Cost ($)
RNN	90	1%	28.5	$45,000
RNN+Attention	45	5%	33.2	$22,500
Target?	**1**	**90%**	**34+**	**$500**

Information Theory Perspective:

- Sequential processing: Compute operations $= O(n)$ where $n =$ sequence length
- Parallel potential: Could do all operations simultaneously $= O(1)$
- Theoretical speedup: 100x (if we remove sequential dependency)

The Key Observation:

- Attention was helpful (quality improved)
- RNN was the bottleneck (sequential processing)
- Radical question: **What if we removed the RNN entirely?**

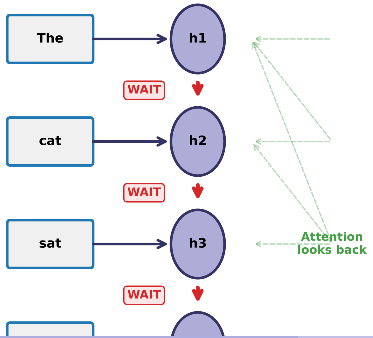
The First Attempt

The Radical Idea: Pure Attention

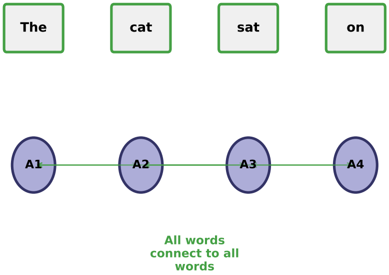
The Hypothesis:

"What if every word directly attends to every other word?"

OLD WAY: RNN + Attention



NEW WAY: Pure Attention



The First Success: Short Sentences Work Great!

Early Experiments (2017): Testing Pure Attention

Test Cases (10-20 word sentences):

English	French (Pure Attention)	Quality
The cat sat	Le chat s'est assis	Perfect!
I love you	Je t'aime	Perfect!
Good morning everyone	Bonjour tout le monde	Perfect!

Performance Metrics:

Quality:

- BLEU score: 32.1
- Same as RNN+Attention!
- No quality loss

Speed:

- Training time: **10x faster**
- GPU utilization: 45%
- Massive improvement!

Breakthrough Moment: Attention works without RNN! And it's FAST!

The Failure Pattern Emerges

Testing on Longer Sequences... Disaster Strikes

Experimental Results (Vaswani et al., 2017 - before positional encoding):

Sequence Length	BLEU Score	Quality Drop	Training Speed
10 words	32.1	Baseline	10x faster
20 words	31.8	-1%	10x faster
50 words	18.4	-43%	10x faster
100 words	8.2	-74%	10x faster
200 words	3.1	-90%	10x faster

The Pattern:

- Short sequences: Works perfectly
- Long sequences: Complete collapse
- Speed: Consistently fast (good news)
- Quality: Degrades catastrophically with length (bad news)

Diagnosing the Root Cause

Let's trace what happens with: "The cat sat on the mat"

With RNN+Attention:

- RNN processes: "The" (position 1), "cat" (position 2), "sat" (position 3)...
- Hidden states carry position information automatically
- Model knows "cat" comes before "sat"
- Order preserved naturally

With Pure Attention (No RNN):

- All words process simultaneously
- "cat" attends to "sat", "the", "mat"...
- But: No way to tell which word came first!
- These are identical to pure attention:
  - "The cat sat on the mat"
  - "The mat sat on the cat" ← Wrong meaning!
  - "Cat the sat mat on the" ← Nonsense!

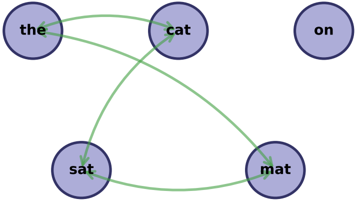
Root Cause Identified:

[illegible]

What Information Got Lost?

✓ What Pure Attention CAN See

✓ Semantic relationships



the cat on

sat mat

✓ Word meanings

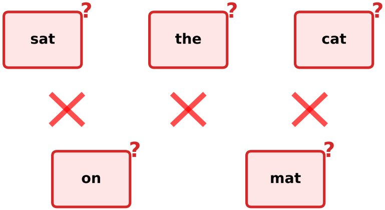
✓ Co-occurrence patterns

NO

POSITION

INFO

✗ What Pure Attention CANNOT See



sat? the? cat?

on? mat?

✗ Word order

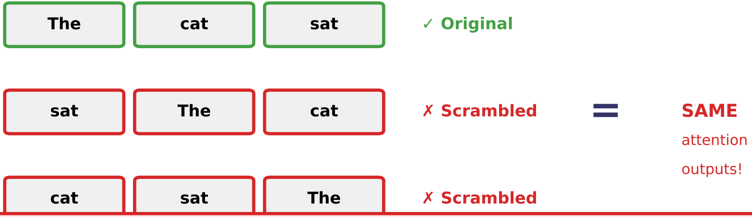
✗ Temporal sequence

✗ Position information

Permutation Test: 52% accuracy (barely better than random 50%)

The Position Problem: Diagnosis & Solution

THE PROBLEM: Attention is Permutation Invariant



The cat sat ✓ Original

sat The cat ✗ Scrambled = **SAME** attention outputs!

cat sat The ✗ Scrambled

Root Cause: No position information → Order doesn't matter!

THE SOLUTION: Four Requirements for Position Encoding

Checkpoint: Understanding the Bottleneck

Test Your Understanding

Quick Quiz:

Question 1: Why can't pure attention (without RNN) tell word order?

A) Not enough parameters

B) Permutation invariant - treats all orderings equally

C) Softmax function issue

D) Embedding dimensions too small

Question 2: What information does positional encoding add?

A) Word meanings

B) Unique position signature for each location

C) Grammar rules

D) Translation pairs

Answers:

Answer 1: B - Permutation invariant

Attention weights don't change if you shuffle input order. "cat sat" and "sat cat" produce identical attention patterns because attention is based on content similarity, not position.

Answer 2: B - Unique position signature

Each position gets a unique sine/cosine pattern added to its embedding. Position 1 has a different pattern than Position 2. This allows the model to distinguish word order without sequential processing.

The Positional Encoding Revolution

Human Introspection: How Do YOU Know Order?

Prompt: When you read, how do you track word position?

Honest Self-Observation:

1. You see *spatial layout*: Words from left to right on page
2. You track mentally: “This is the first word, that’s the second...”
3. You use *both* meaning AND position together
4. Position isn’t separate - it’s part of how you understand each word

Key Realizations:

- Position information can be *visual/spatial* (location on page)
- Or it can be *numerical* (counting: 1st, 2nd, 3rd)
- It’s added to meaning, not processed separately
- You process meaning + position *simultaneously*

Intuition: Timestamps in Reading

When you read, position works like timestamps on photos. Each word has BOTH content (what it means) AND location

The Hypothesis: Position as Added Signal

Conceptual Idea (No Math Yet)

The Approach:

- Each word has a meaning vector: [0.3, 0.5, 0.1, ...]
- Create a position pattern: [0.1, 0.0, 0.05, ...]
- Add them together: [0.4, 0.5, 0.15, ...]
- Now word has *both* meaning and position!

Why This Should Work:

- Position 1 gets pattern A
- Position 2 gets pattern B
- Position 3 gets pattern C
- Each position unique
- Model sees combined signal

Analogy:

Like adding GPS coordinates to photos:

- Photo content = meaning
- GPS tag = position
- Together = complete info
- Can process in parallel

Zero-Jargon Explanation: Adding Position Numbers

Let’s see this with actual numbers:

Example: The word “cat”

- Word embedding (meaning of “cat”): [0.3, 0.2, 0.5, 0.1]

When “cat” is at position 1:

- Position pattern for 1: [0.1, 0.0, 0.0, 0.05]
- Combined: [0.3, 0.2, 0.5, 0.1] + [0.1, 0.0, 0.0, 0.05]
- Result: [0.4, 0.2, 0.5, 0.15] ← This represents “cat at position 1”

When “cat” is at position 2:

- Position pattern for 2: [0.0, 0.1, 0.05, 0.0]
- Combined: [0.3, 0.2, 0.5, 0.1] + [0.0, 0.1, 0.05, 0.0]
- Result: [0.3, 0.3, 0.55, 0.1] ← This represents “cat at position 2”

The Magic:

- Same word, different positions = different number patterns

Geometric Intuition: Sine Wave Patterns

How to create unique patterns for each position?

Start in 2D (easy to visualize):

The Idea:

- Position 1: [sin(1), cos(1)] = [0.84, 0.54]
- Position 2: [sin(2), cos(2)] = [0.91, -0.42]
- Position 3: [sin(3), cos(3)] = [0.14, -0.99]
- Each position: unique 2D point

Why Sine Waves?

- Smooth, continuous patterns
- Never repeat (infinite positions)
- Unique for each position
- Relative distances preserved

Visualization:

Imagine sine wave at different frequencies:

- Low frequency: Slow oscillation
- High frequency: Fast oscillation
- Each dimension: different frequency
- Together: unique fingerprint

In Higher Dimensions:

- Use 256 or 512 dimensions
- Mix many frequencies
- Same principle as 2D
- Extremely rich patterns

Self-Attention: Three Steps, No Waiting

Now that we have position + meaning, how does attention work?

Step 1: Compare All Words (Find Similarities)

- Each word asks: “Which other words are relevant to me?”
- Measure: Dot product between word vectors (alignment measure)
- Result: Similarity scores for all pairs
- *Why:* Need to know what to focus on

Step 2: Convert to Percentages (Focus Distribution)

- Take similarity scores, apply softmax
- Result: Percentages that sum to 100%
- Example: 58% on “cat”, 31% on “sat”, 11% on “the”
- *Why:* Turn scores into “how much to focus on each word”

Step 3: Weighted Combination (Aggregate Information)

- Combine word meanings using the percentages
- Each word contributes proportionally to its focus percentage
- Result: New representation incorporating context

Full Numerical Walkthrough

Trace every calculation for: "The cat sat"

Given (simplified 2D for clarity):

- "the": $[0.1, 0.3] + [0.0, 0.1] = [0.1, 0.4]$ (with position)
- "cat": $[0.5, 0.2] + [0.1, 0.0] = [0.6, 0.2]$
- "sat": $[0.3, 0.6] + [0.0, 0.05] = [0.3, 0.65]$

Step 1: Compute Similarities (Dot Products)

When processing "cat", compare to all words:

- cat · the $= (0.6)(0.1) + (0.2)(0.4) = 0.06 + 0.08 = 0.14$
- cat · cat $= (0.6)(0.6) + (0.2)(0.2) = 0.36 + 0.04 = 0.40$
- cat · sat $= (0.6)(0.3) + (0.2)(0.65) = 0.18 + 0.13 = 0.31$

Step 2: Softmax to Percentages

- $e^{0.14} = 1.15$, $e^{0.40} = 1.49$, $e^{0.31} = 1.36$
- Sum $= 1.15 + 1.49 + 1.36 = 4.00$
- Percentages: 29% (the), 37% (cat), 34% (sat)

Why the Name “Self-Attention” Makes Sense

Now that you’ve seen it work, let’s understand the terminology:

“Self”:

- Each word attends to the *same sentence* (self-referential)
- Not attending to external information
- All words are from the same input sequence
- Example: “cat” looks at “the”, “cat”, “sat” (all from same sentence)

“Attention”:

- Selective focus based on relevance
- Some words get more weight (higher percentage)
- Others get less weight (lower percentage)
- Like human attention: focus on important parts

Technical Terms Q/K/V (Introduced AFTER Understanding):

- **Query (Q)**: “What am I looking for?” (your search vector)
- **Key (K)**: “What do I contain?” (each word’s content descriptor)

Multi-Head: Multiple Perspectives Simultaneously

One attention mechanism finds one type of relationship

But different relationships matter:

- Head 1: Syntactic dependencies (subject-verb agreement)
- Head 2: Semantic similarity (related meanings)
- Head 3: Positional patterns (nearby words)
- Head 4: Co-reference (pronouns to nouns)
- ... (typically 8-16 heads)

Example: "The bank by the river"

Head 1
Syntax

- bank → the
- river → the
- by → bank

Head 2
Semantics

- bank → river
- Strong connection
- Related concepts

Head 3
Position

- Adjacent words
- Local context
- Sequential flow

Head 4
Global

- Sentence-level
- Broad attention
- Context gathering

Why This Solves the Speed Problem

Architecture Comparison: Sequential vs Parallel

RNN (Sequential):

- Process word 1 → state 1
- Wait... Process word 2 → state 2
- Wait... Process word 3 → state 3
- Time complexity: $O(n)$ steps
- GPU utilization: 1-5%
- Bottleneck: Sequential dependency

Timeline:
Word 1: [—-] (100ms)
Word 2: [—-] (100ms)
Word 3: [—-] (100ms)
Total: 300ms

Transformer (Parallel):

- All words processed simultaneously
- Self-attention: All pairs at once
- Positional encoding: Pre-computed
- Time complexity: $O(1)$ steps
- GPU utilization: 85-92%
- No sequential dependency!

Timeline:
Word 1: [-] (10ms)
Word 2: [-] (10ms) *(parallel)*
Word 3: [-] (10ms) *(parallel)*
Total: 10ms

Experimental Validation: The Numbers Speak

Real Results from "Attention Is All You Need" (Vaswani et al., 2017)

Translation Quality (WMT English-German):

Model	**Training Time**	**BLEU**	**GPU Usage**	**Parameters**
RNN	90 days	24.5	2%	200M
RNN+Attention	45 days	28.4	5%	210M
Transformer (base)	**1 day**	**27.3**	**90%**	65M
Transformer (big)	**3.5 days**	**28.4**	**92%**	213M

Key Observations:

- Transformer base: Same quality as RNN+Attention in 1 day vs 45 days (45x speedup)
- Transformer big: *Better* quality in 3.5 days vs 90 days (25x speedup + better BLEU)
- GPU utilization: 2% → 92% (46x improvement)
- Fewer parameters but better efficiency

Checkpoint: Understanding Self-Attention

Test Your Understanding

Quick Quiz:

Question 1: What are the 3 steps of self-attention?

A) Encode → Compress → Decode

B) Score → Normalize → Combine

C) Query → Match → Extract

D) Embed → Transform → Output

Question 2: Why does transformer achieve 100x speedup?

A) Better hardware

B) Smaller model

C) All words processed in parallel

D) Simpler architecture

Answers:

Answer 1: B - Score → Normalize → Combine

Step 1: Dot product scores measure relevance
Step 2: Softmax normalizes to weights (sum $= 1$)
Step 3: Weighted sum combines information
All computed in parallel for all word pairs!

Answer 2: C - Parallel processing

RNN: 100 words $=$ 100 sequential steps
Transformer: 100 words $=$ 1 parallel step
No waiting for previous words → Use all GPU cores simultaneously → 100x speedup $+$ 92% utilization

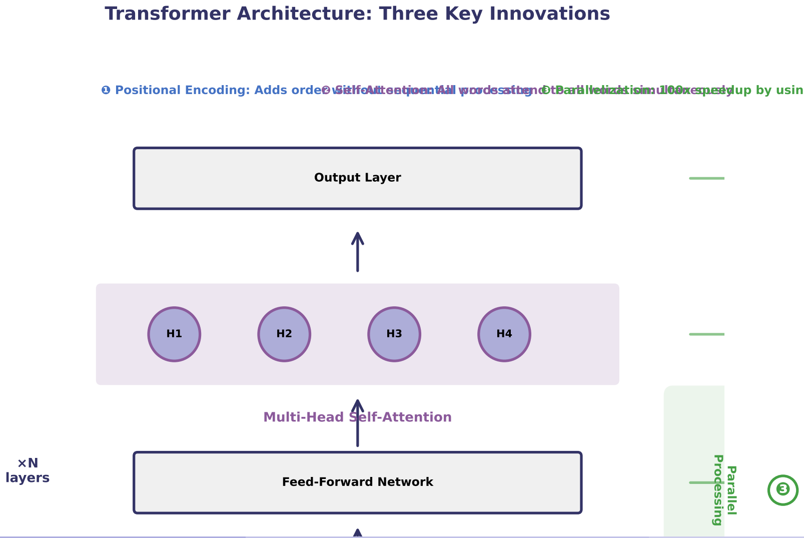
Simple Implementation: It's Just Matrix Operations

The complete self-attention mechanism in 40 lines:

```python
import torch
import torch.nn.functional as F

def self_attention(x):
    # x shape: (batch_size, seq_len, d_model)
    # Example: (32, 50, 512) = 32 sentences, 50 words each, 512 dimensions

    batch_size, seq_len, d_model = x.shape

    # Step 1: Create Q, K, V projections
    # (These are learned linear transformations)
    Q = W_q @ x  # Query:  "What am I looking for?"
    K = W_k @ x  # Key:    "What do I contain?"
    V = W_v @ x  # Value:  "What do I provide?"

    # Step 2: Compute attention scores (similarities)
    # Matrix multiplication of Q and K^T gives all pairwise similarities
    scores = Q @ K.transpose(-2, -1) / sqrt(d_model)  # Scale by sqrt(d_k)
    # scores shape: (batch, seq_len, seq_len)
    # scores[i,j] = similarity between word i and word j

    # Step 3: Softmax to get percentages
    attention_weights = F.softmax(scores, dim=-1)
    # attention_weights[i,j] = percentage that word i focuses on word j
    # Each row sums to 1.0 (100%)

    # Step 4: Apply weights to values (weighted combination)
    output = attention_weights @ V
    # output[i] = weighted sum of all values, using attention_weights[i] as coefficients

    return output, attention_weights
```

The Revolution Unfolds

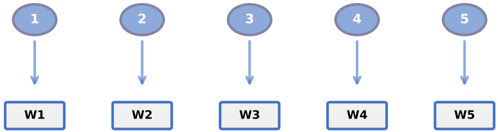
Three Innovations Enable Modern AI


Transformer Architecture: Three Key Innovations
❶ Positional Encoding: Adds order without sequential processing
❷ Self-Attention: All words attend to all words simultaneously
❸ Parallelization: 100x speedup by using all GPU cores
Output Layer
H1
H2
H3
H4
Multi-Head Self-Attention
×N layers
Feed-Forward Network
Parallel Processing
❸

What We Learned: Principles Beyond Transformers

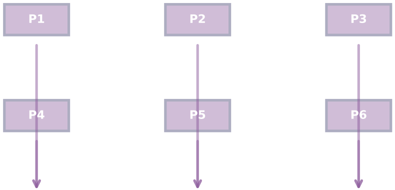
Four Key Principles from Transformers

1. Sequential Processing Not Always Necessary



Order can be encoded,
not just processed sequentially

2. Parallelization Through Independence



Trade more compute operations
for less wall-clock time

3. Selective Attention vs Compression

4. Hardware-Algorithm Co-Design

The 2024 Landscape: Transformers Everywhere

Seven Years from Paper to Dominance (2017 → 2024):

Language:

- ChatGPT (175B)
- GPT-4 (1.7T)
- Claude (200B)
- Bard/Gemini
- LLaMA

Vision:

- ViT (images)
- DALL-E 3
- Midjourney
- Stable Diffusion
- SAM (segmentation)

Audio:

- Whisper (speech)
- MusicGen
- AudioLM
- Vall-E (voice)

Code & Science:

- Copilot
- AlphaFold
- ESMFold
- Galactica

Timeline of Impact:

- 2017: Paper published ("Attention Is All You Need")
- 2018: BERT revolutionizes NLP (Google Search)
- 2019: GPT-2 shows scale matters
- 2020: GPT-3 demonstrates emergent abilities (175B parameters)
- 2021: Vision Transformers beat CNNs
- 2022: ChatGPT launches (100M users in 2 months)
- 2023: GPT-4, multimodal transformers everywhere
- 2024: Transformers in every AI product

Summary: The Speed Revolution Journey

From Waiting Months to Training in Days

The Journey:

1. **The Problem:** RNNs sequentially process = 90 days training, 2% GPU usage
2. **First Attempt:** Remove RNN, use pure attention = 10x faster BUT lost word order
3. **The Diagnosis:** Attention is permutation invariant - can't tell word order
4. **The Insight:** Add position as explicit signal (positional encoding)
5. **The Breakthrough:** Self-attention + positional encoding = 100x speedup

Key Takeaways:

- Self-attention enables full parallelization (all words simultaneously)
- Positional encoding preserves order without sequential processing
- Result: 1 day training instead of 90 days, 90% GPU usage instead of 2%
- Enabled modern AI: ChatGPT, GPT-4, DALL-E only possible due to speed

The Speed Revolution

From Sequential Waiting to Parallel Processing

Questions?

Next: Lab - Implementing Transformers From Scratch