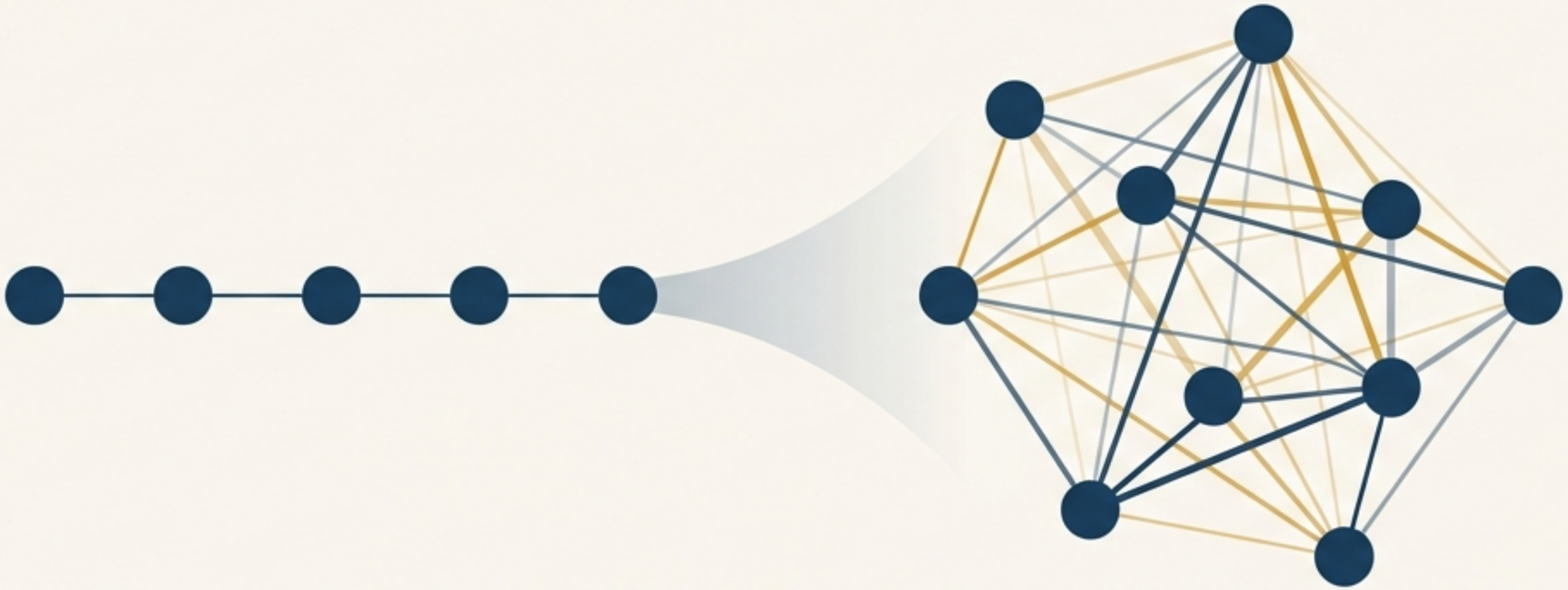
Attention Is All You Need

A New Paradigm for Sequence Transduction Based Solely on Attention



Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones,
Aidan N. Gomez, Łukasz Kaiser, Illia Polosukhin

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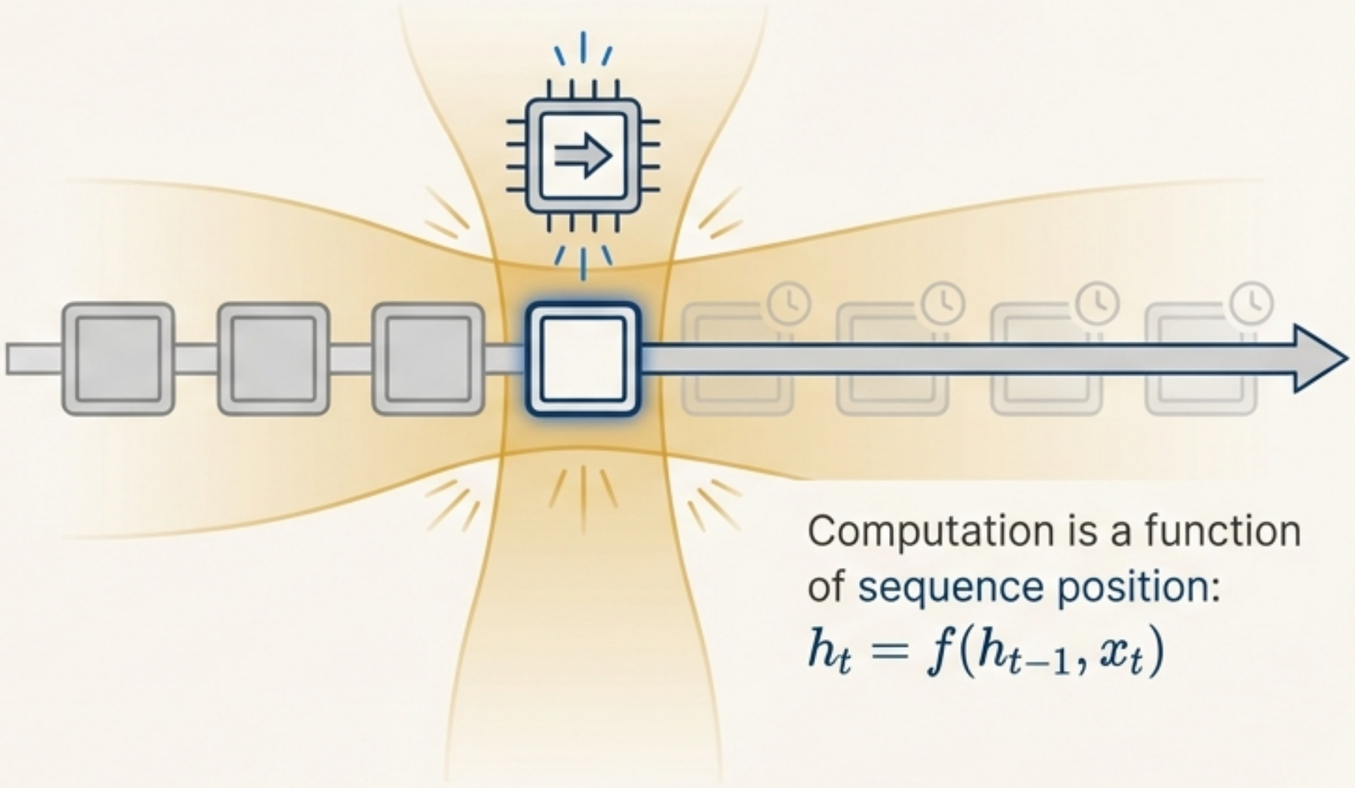
The Sequential Bottleneck of Recurrent Models

- Dominant architectures (RNNs, LSTMs, GRUs) process data sequeriially, token by token.
- This inherent sequential nature **precludes parallelization** within training examples.
- Learning **long-range dependencies** is difficult due to long signal paths.
- The fundamental constraint of sequential computation remains, limiting performance and scalability.

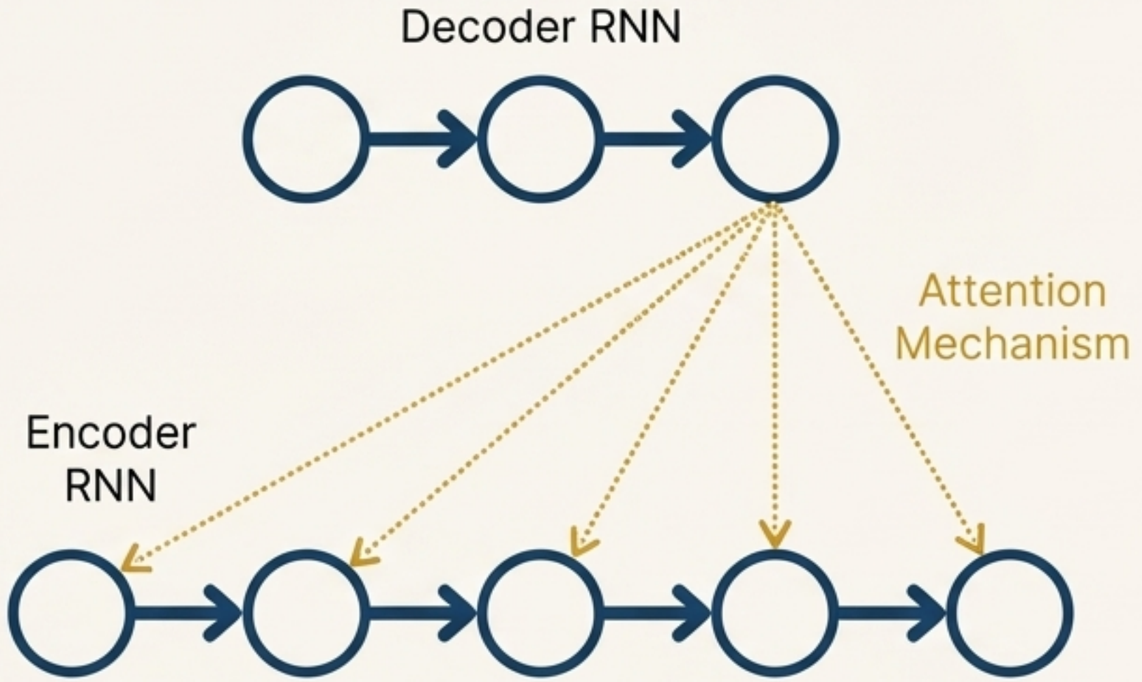


Computation is a function of sequence position:

$$h_t = f(h_{t-1}, x_t)$$

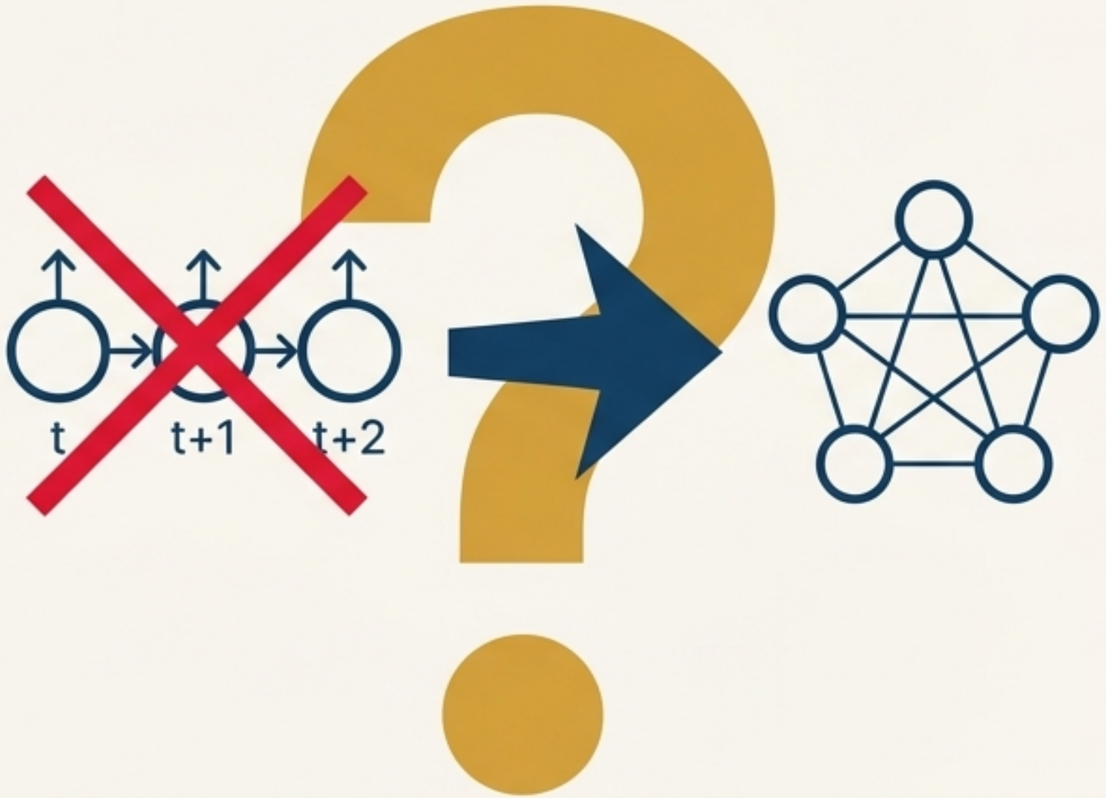
Attention Was an Add-on, Not the Main Engine

- Attention mechanisms were created to help RNNs model dependencies regardless of distance.
- They allowed a model to selectively focus on relevant parts of the input sequence.
- However, attention was almost always used **in conjunction with a recurrent network**.
- The core constraint of sequential computation was never resolved.



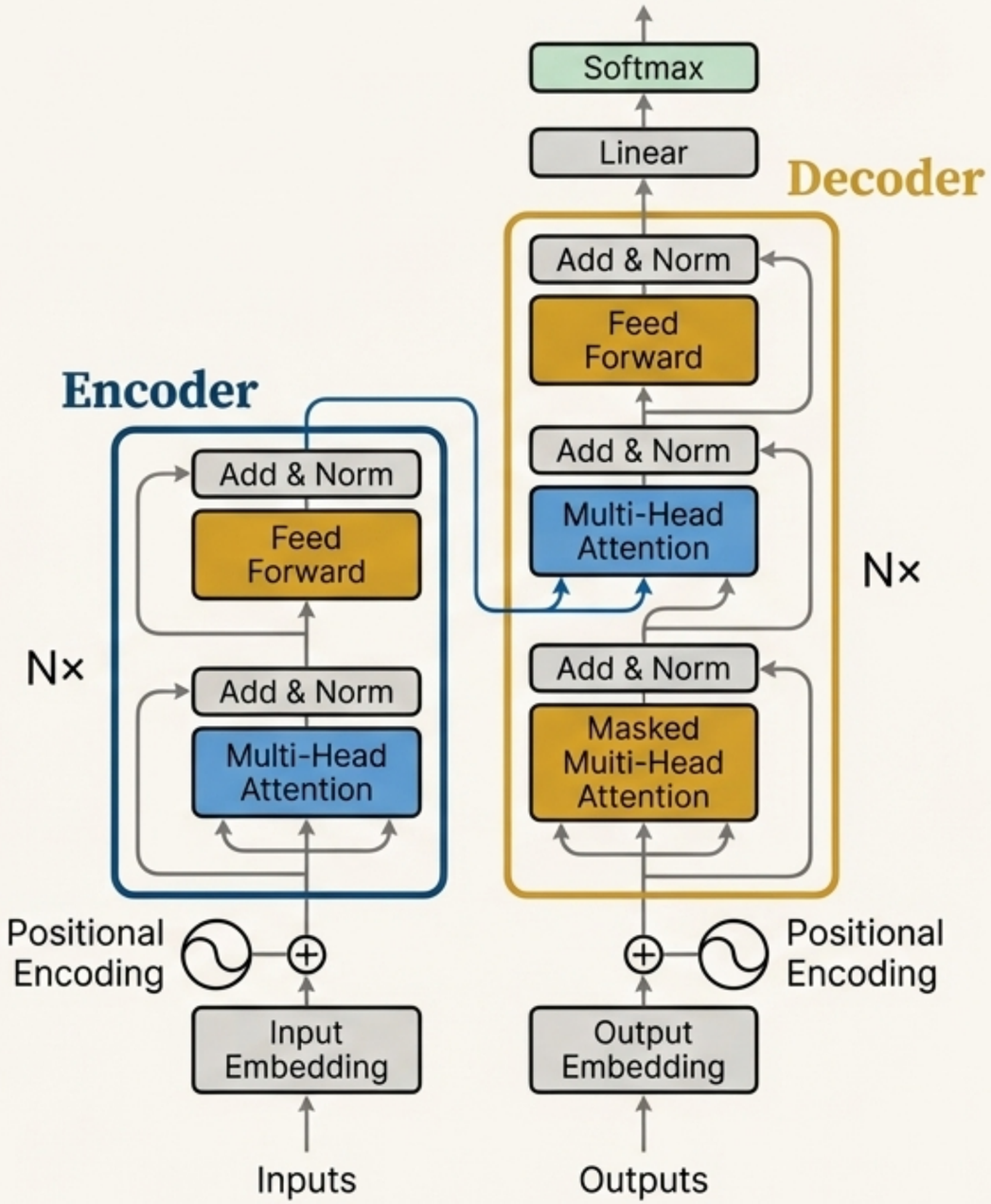
Can We Build a High-Performance Model Using *Only* Attention?

- **Hypothesis:** Recurrence and convolution are not essential for state-of-the-art sequence transduction.
- **Research Question:** Can a model based *solely* on attention mechanisms match or exceed the performance of the best recurrent models?
- **The Goal:** Eliminate the sequential bottleneck to unlock massive parallelization and directly model global dependencies with constant path length.



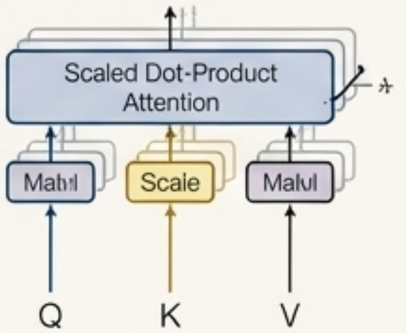
The Transformer: An Architecture Built on Self-Attention

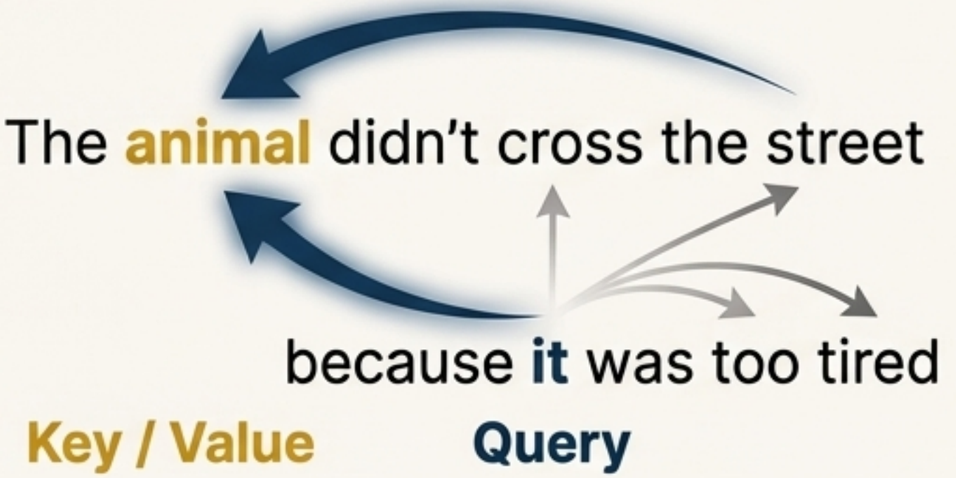
- A standard **Encoder-Decoder** structure for transduction tasks.
- The encoder and decoder are built from stacks of identical layers (N=6 in the base model).
- Each layer contains two primary sub-layers:
  1. **Multi-Head Self-Attention**
  2. **Position-wise Feed-Forward Network**
- Crucially, the model contains **no recurrent or convolutional layers**.



The Core Engine: Calculating Relevance with Queries, Keys, and Values

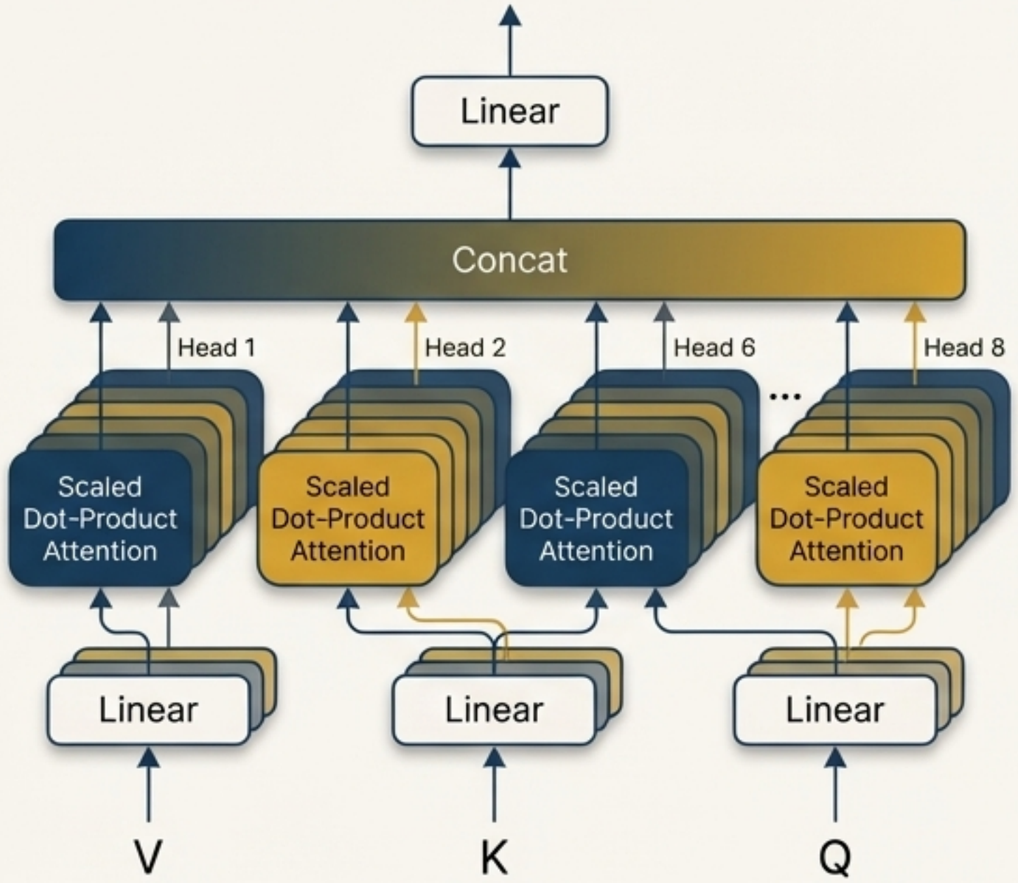
- Self-attention allows the model to weigh the importance of all words in a sequence relative to a single word.
- For each word's input vector, the model creates three new vectors:
  - **Query (Q):** What am I looking for?
  - **Key (K):** What information do I contain?
  - **Value (V):** What information should I provide?
- The model calculates a score between a word's **Query** and every other word's **Key**. These scores become the weights for the **Values**.





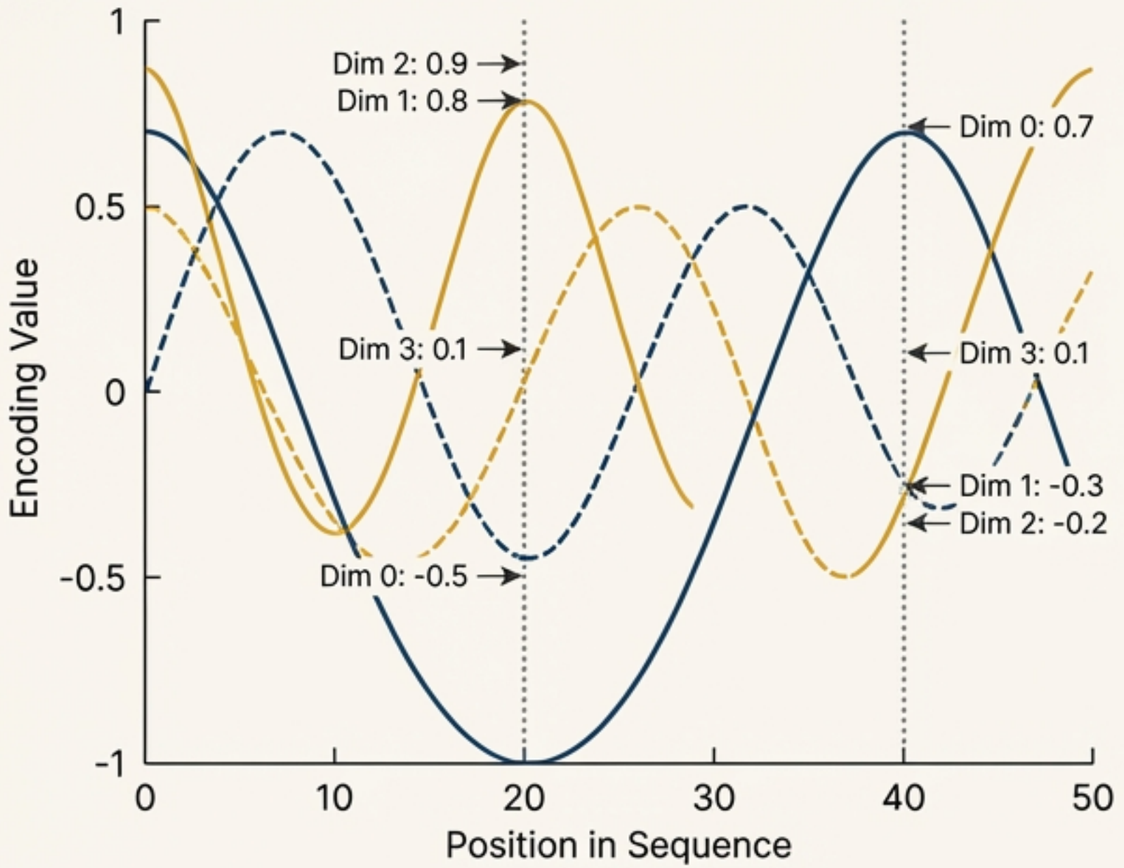
Multi-Head Attention: Analyzing from Multiple Perspectives

- Instead of one attention calculation, Multi-Head Attention runs the process in parallel multiple times (h=8 heads in the paper).
- Each 'head' is a separate projection of the Queries, Keys, and Values.
- This allows the model to jointly attend to information from different representation subspaces at different positions.
- For example, one head might learn syntactic links while another learns semantic relationships.



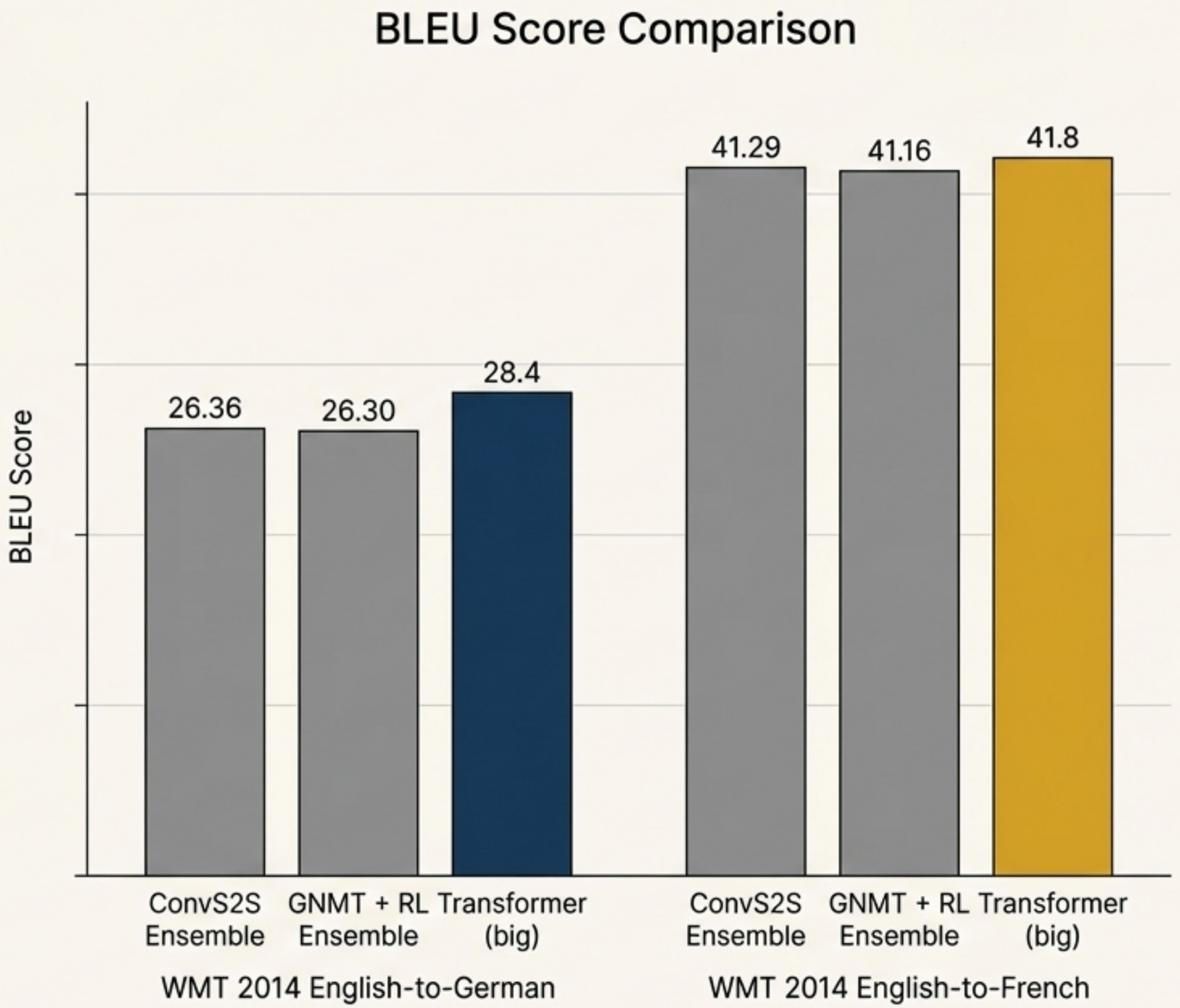
Injecting Word Order with Positional Encodings

- A pure self-attention model is a “bag of words”—it has no inherent sense of word order.
- **Solution**: A “positional encoding” vector is added to each input embedding.
- The paper uses sine and cosine functions of different frequencies to create a unique positional signature for each token.
- This allows the model to learn relative and absolute positions from the input signal itself.



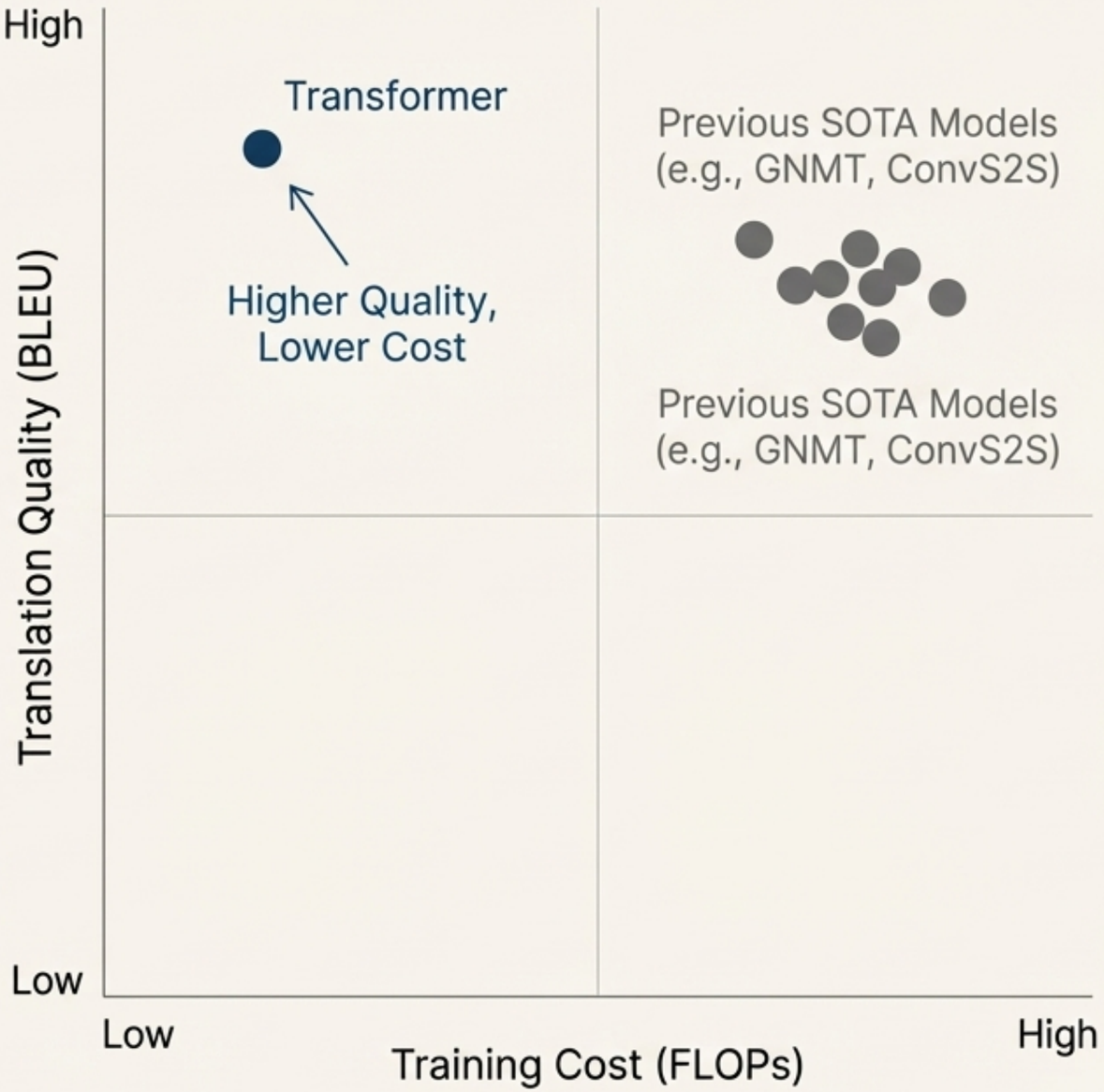
A New State of the Art in Machine Translation

- The Transformer outperformed all previous models on the WMT 2014 English-to-German task.
- Achieved a **28.4 BLEU** score, an improvement of over 2.0 BLEU against the previous best results, including ensembles.
- Established a new single-model record on the English-to-French task with a **41.8 BLEU** score.
- Even the base model surpassed all previous models and ensembles.



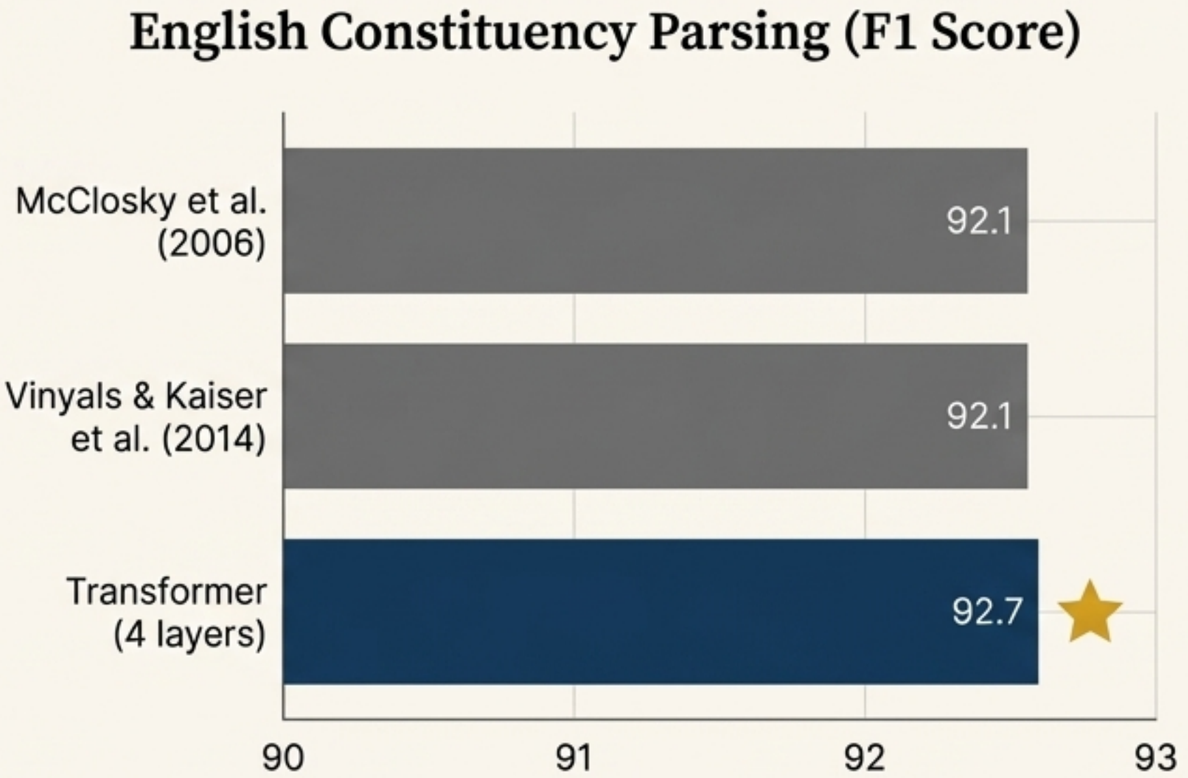
SOTA Performance at a Fraction of the Training Cost

- The parallel architecture is highly efficient on modern hardware (GPUs/TPUs).
- The large model was trained in **just 3.5 days on 8 P100 GPUs**.
- This was a “small fraction of the training costs of the best models from the literature.”
- The training cost (FLOPs) was an order of magnitude lower than top competing models like GNMT.



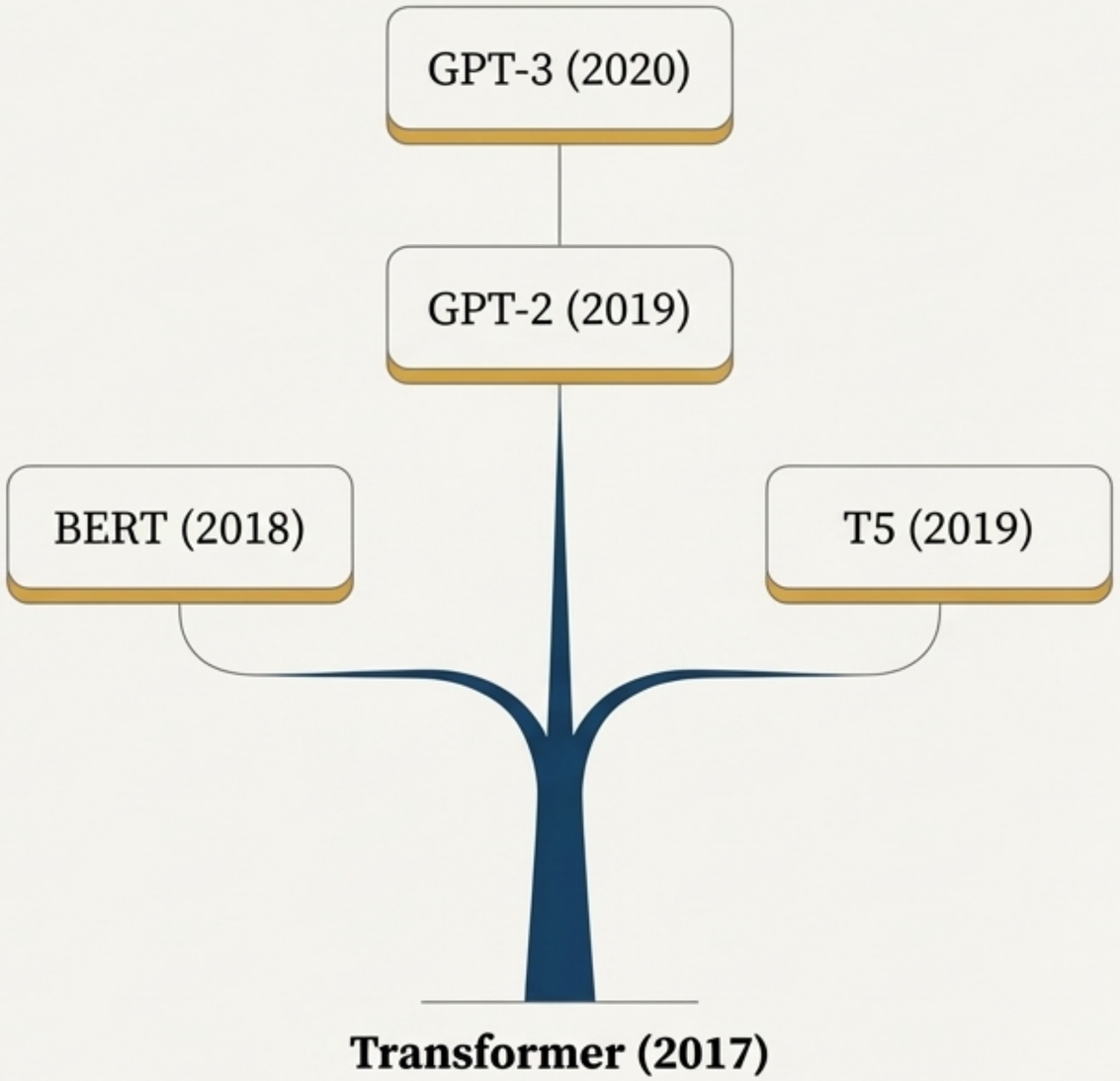
The Architecture Generalizes to Other Complex Tasks

- The model was tested on **English constituency parsing**, a structurally difficult task.
- Despite minimal task-specific tuning, the Transformer performed surprisingly well.
- Achieved an F1 score of **92.7** in a semi-supervised setting, outperforming previous models like the BerkeleyParser.
- It proved its effectiveness even when trained on a small dataset of only 40K sentences.



The Foundation for Modern Large Language Models

- **A Break from Recurrence:** Proved that recurrence is not necessary for top-tier sequence modeling.
- **Unlocking Scale:** The parallelizable architecture enabled the training of massive models that were previously infeasible.
- **The Blueprint for Modern AI:** The Transformer is the foundational building block for nearly all modern LLMs, including BERT, GPT, T5, and beyond.



The Future is Attention-Based

- The paper concluded by proposing several avenues for future research:
  - Applying Transformers to new modalities like **images**, **audio**, and **video**.
  - Developing **restricted attention mechanisms** to handle very long sequences more efficiently.
  - Making the generation process (decoding) **less sequential**.
- **Conclusion**: By replacing recurrence with self-attention, the Transformer provided a more powerful, parallelizable, and scalable foundation for sequence modeling, setting the agenda for years of AI research to come.

Images & Video

Audio

Efficient Attention for Long Sequences