Sequence-to-Sequence Models

Week 4: The Translation Revolution with Attention

NLP Course 2025

Professional Template Edition

September 29, 2025

Week 4: Journey Through Translation and Attention

Learning Path: From word-by-word replacement to neural translation. Master encoder-decoder architectures, understand the bottleneck problem, and discover how attention revolutionized machine translation.

Part 1: Translation Challenge & Motivation

Why Word-by-Word Translation Fails

The Google Translate Evolution: A Success Story

2006: Statistical MT

- Word/phrase dictionaries
- Counted co-occurrences
- "Reasonable" translations
- Often awkward phrasing

2016: Neural MT Launch

- Seq2Seq with attention
- Human-quality for some pairs
- 60% error reduction
- Revolutionary improvement

Real Example:

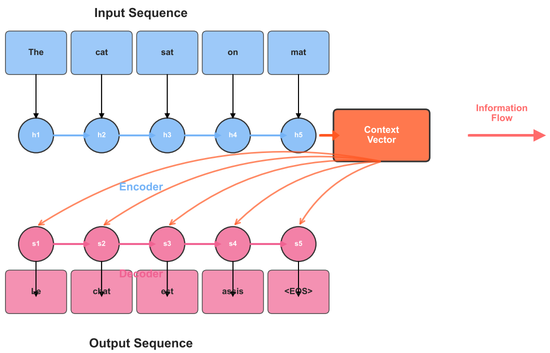
Chinese Input: "There is one cat in station"

Old: "In the station is one cat"
New: "There is a cat at the station"

What changed? Understanding context, not just words

Historical Context: Neural MT reduced translation errors by 60% overnight - the biggest leap in MT history

The Fundamental Problem: Meaning Across Languages



Sequence-to-Sequence Architecture: Encoder-Decoder with Context Vector

Translation is NOT:

- Word replacement
- Dictionary lookup
- Rule application
- Pattern matching

Translation IS:

- Understanding meaning
- Cultural context
- Reformulation
- Creative generation

Why Word-by-Word Translation Fails: Concrete Examples

Problem 1: Word Order

- English: “I saw the red house”
- Spanish: “Vi la casa roja”
- Literal: “Saw-I the house red”

Problem 2: Idioms

- English: “It’s raining cats and dogs”
- French: “Il pleut des cordes”
- Literal: “It rains ropes”

Problem 3: Context

- “Bank” $\rightarrow$ “Banque” (financial)
- “Bank” $\rightarrow$ “Rive” (river)
- Need full sentence to decide

Problem 4: Grammar

- German: Verb at end
- Japanese: Subject optional
- Chinese: No tenses

Conclusion: Languages encode meaning differently - translation needs deep understanding

Language Diversity: Each language has unique ways of expressing ideas

Converting Meaning to Numbers: The Core Challenge

Computers only understand numbers, so:

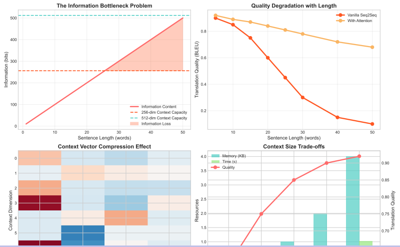
“The cat sat on the mat” → **[Numbers]** → “Le chat s’est assis sur le tapis”

Step 1: Words to Vectors

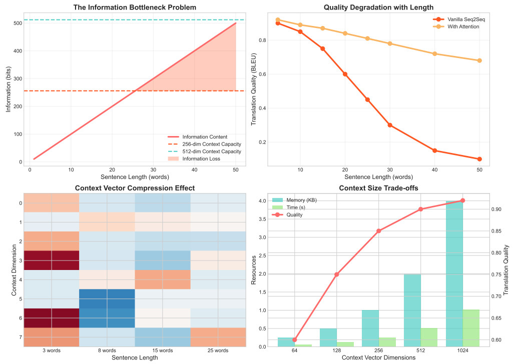
- “cat” → [0.2, -0.5, 0.8, ...]
- 100-300 dimensional vectors
- Learned from context (Word2Vec)
- Similar words = nearby vectors

Step 2: Sentence to Vector

- Combine word vectors
- Build “context vector”
- Fixed size (e.g., 256 dims)
- Must capture ALL meaning



The Compression Challenge: Information Bottleneck



Compression Ratios:

- 5 words: 500 dims → 256 (2:1)
- 20 words: 2000 dims → 256 (8:1)
- 50 words: 5000 dims → 256 (20:1)

Problem: More compression = More loss

What Gets Lost?

- Specific word choices
- Grammatical nuances
- Word positions
- Long-range dependencies

Interactive Exercise: Manual Translation Steps

Task: Translate "The black cat sat" to French step-by-step

Your Steps:

1. Read entire English sentence
2. Identify: subject (cat), verb (sat)
3. Recall French words:
   - cat → chat
   - black → noir
   - sat → s'est assis
4. Apply French grammar:
   - Article-Noun-Adjective order
   - Gender agreement (le/la)
5. Generate: "Le chat noir s'est assis"

What You Actually Did:

1. Encoded English to meaning
2. Stored meaning in memory
3. Decoded meaning to French

This is exactly Seq2Seq!

Key Observation:
You didn't translate word-by-word! You understood first, then generated.

Human Insight: We naturally use encoder-decoder approach when translating

Calculating the Bottleneck: A Mathematical Perspective

Information Content:

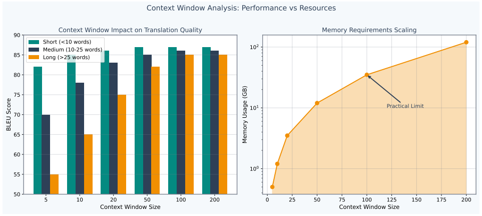
$$\text{Input} = n \times d_{\text{embed}} \tag{1}$$

$$\text{Context} = d_{\text{hidden}} \tag{2}$$

$$\text{Ratio} = \frac{n \times d_{\text{embed}}}{d_{\text{hidden}}} \tag{3}$$

Example Calculation:

- 20 words, 100-dim embeddings
- Input: $20 \times 100 = 2000$ values
- Context: 256 values
- Compression: $\frac{2000}{256} \approx 8 : 1$



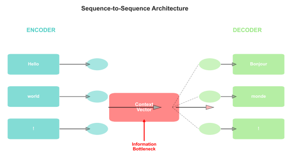
The Problem:
Cannot fit 2000 numbers into 256 without loss!

Mathematical Reality: Information theory limits how much we can compress without loss

Part 1 Summary: Understanding the Challenge

What We Learned:

- Translation $\neq$ word replacement
- Languages encode differently
- Need meaning understanding
- Must convert to numbers
- Fixed-size bottleneck problem



The Challenge:

- Variable input length
- Fixed context size
- Information loss inevitable
- Longer $=$ worse compression

Key Question:
How do we capture all meaning in a fixed-size vector?

Next: The encoder-decoder architecture - a first solution to the translation challenge

Part 2: Encoder-Decoder Architecture

Building Understanding, Then Generating

The Two-Phase Translation Intuition

How humans translate (simplified):

Phase 1: Understanding

1. Read entire source sentence
2. Extract complete meaning
3. Store in “mental representation”
4. Forget specific words
5. Keep abstract meaning

Result: Language-agnostic meaning

Phase 2: Generation

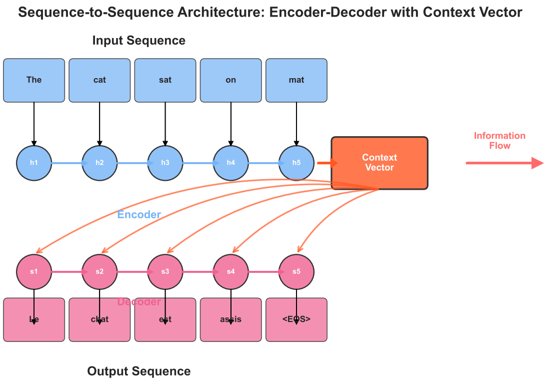
1. Access stored meaning
2. Apply target grammar
3. Choose appropriate words
4. Generate word-by-word
5. Maintain coherence

Result: Natural target sentence

Neural Equivalent: Encoder (understanding) + Decoder (generation) = Seq2Seq

Cognitive Model: Seq2Seq mimics human two-phase translation process

The Encoder: Building Understanding Step-by-Step



Encoder's Job:

- Process input sequentially
- Build hidden state (memory)
- Update with each word
- Final state = full understanding

Processing "The cat sat":

1. $h_1 = \text{RNN}(\text{"The"}, h_0)$
2. $h_2 = \text{RNN}(\text{"cat"}, h_1)$
3. $h_3 = \text{RNN}(\text{"sat"}, h_2)$
4. Context: $c = h_3$

The Decoder: Generating from Understanding

Decoder's Job:

- Start with context vector c
- Generate one word at a time
- Use previous word + context
- Stop at end token

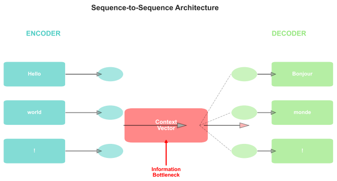
Generation Process:

$$s_0 = c \text{ (initialize)} \tag{6}$$
$$s_t = \text{RNN}(y_{t-1}, s_{t-1}) \tag{7}$$
$$P(y_t) = \mathrm{softmax}(W s_t) \tag{8}$$

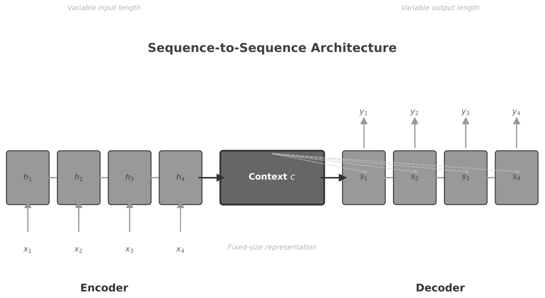
Generating "Le chat noir":

1. Start: $s_0 = c$, $y_0 =$ ¡START¿
2. Generate "Le": $P(y_1 \mid c)$
3. Generate "chat": $P(y_2 \mid y_1, c)$
4. Generate "noir": $P(y_3 \mid y_{1:2}, c)$
5. Stop: $y_4 =$ ¡END¿

Key: Each word depends on context + history



Complete Seq2Seq Architecture



Components:

- Embedding layers
- Encoder RNN
- Context vector
- Decoder RNN

Training:

- Teacher forcing
- Cross-entropy loss
- Backprop through time
- End-to-end learning

Inference:

- Greedy decoding
- Beam search
- Length normalization
- Coverage penalty

Complete Seq2Seq Implementation in PyTorch

```python
import torch
import torch.nn as nn

class Seq2Seq(nn.Module):
    def __init__(self, src_vocab,
                 tgt_vocab, embed_dim=256,
                 hidden_dim=512):
        super().__init__()

        # Embeddings
        self.src_embed = nn.Embedding(
            src_vocab, embed_dim
        )
        self.tgt_embed = nn.Embedding(
            tgt_vocab, embed_dim
        )

        # Encoder & Decoder
        self.encoder = nn.LSTM(
            embed_dim, hidden_dim,
            batch_first=True
        )
        self.decoder = nn.LSTM(
            embed_dim, hidden_dim,
            batch_first=True
        )

        # Output projection
        self.output = nn.Linear(
            hidden_dim, tgt_vocab
```

```python
    def forward(self, src, tgt):
        # Encode
        src_emb = self.src_embed(src)
        _, (h, c) = self.encoder(
            src_emb
        )

        # Decode
        tgt_emb = self.tgt_embed(tgt)
        out, _ = self.decoder(
            tgt_emb, (h, c)
        )

        # Project
        logits = self.output(out)
        return logits

# Usage
model = Seq2Seq(
    src_vocab=10000,
    tgt_vocab=10000
)

# Training step
src = torch.randint(0, 10000,
                   (32, 20))
tgt = torch.randint(0, 10000,
                   (32, 15))
logits = model(src, tgt)
```

Encoding Example: “The black cat sat”

Watch the hidden state evolve:

Step 1: Process “The”

- Input: $x_1 = \text{embed}(\text{“The”}) = [0.1, 0.3, \ldots]$
- Hidden: $h_1 = \text{LSTM}(x_1, h_0)$
- Memory: “Determiner seen”

Step 2: Process “black”

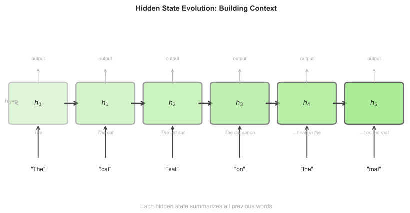
- Input: $x_2 = \text{embed}(\text{“black”})$
- Hidden: $h_2 = \text{LSTM}(x_2, h_1)$
- Memory: “Determiner + adjective”

Step 3: Process “cat”

- Input: $x_3 = \text{embed}(\text{“cat”})$
- Hidden: $h_3 = \text{LSTM}(x_3, h_2)$
- Memory: “Black cat (subject)”

Step 4: Process “sat”

- Input: $x_4 = \text{embed}(\text{“sat”})$
- Hidden: $h_4 = \text{LSTM}(x_4, h_3)$
- Memory: “Black cat sat (complete)”



Final Context:
$c = h_4$ contains: - Subject: black cat - Action: sat - Tense: past

Encoding Process: Each word updates understanding, final state has complete meaning

Decoding Example: Generating "Le chat noir"

Starting from context c:

Step 1: Generate "Le"

- State: $s_0 = c$
- Input: ¡START¿ token
- Output: $P(\text{"Le"}) = 0.8$
- Next: $s_1 = \text{LSTM}(\text{"Le"}, s_0)$

Step 2: Generate "chat"

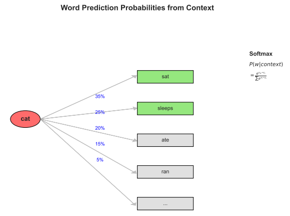
- State: s_1 (knows "Le")
- Input: "Le"
- Output: $P(\text{"chat"}) = 0.7$
- Next: $s_2 = \text{LSTM}(\text{"chat"}, s_1)$

Step 3: Generate "noir"

- State: s_2 (knows "Le chat")
- Input: "chat"
- Output: $P(\text{"noir"}) = 0.6$
- Next: $s_3 = \text{LSTM}(\text{"noir"}, s_2)$

Probability Distribution:

At each step, model outputs:



Key Point:
Decoder maintains its own hidden state separate from encoder

Decoding Process: Conditional generation using context and previous outputs

Quiz Checkpoint: Understanding Seq2Seq

Questions:

Q1: What is the context vector?

a) Average of word embeddings
b) Final encoder hidden state
c) Sum of all hidden states
d) Random initialization

Q2: Why use two separate networks?

a) Faster training
b) Different tasks (read vs write)
c) More parameters
d) Requirement of RNNs

Q3: Teacher forcing means:

a) Using true targets during training
b) Forcing convergence
c) Teaching the teacher

Answers:

A1: **b) Final encoder hidden state**

- Contains full sentence understanding
- Fixed-size representation
- Passed to decoder

A2: **b) Different tasks**

- Encoder: comprehension
- Decoder: generation
- Different objectives

A3: **a) Using true targets**

- Feed correct previous word
- Speeds up training
- Avoids error accumulation

Part 2 Summary: The Encoder-Decoder Solution

Architecture Components:

- Encoder RNN: reads input
- Context vector: compressed meaning
- Decoder RNN: generates output
- End-to-end training

Strengths:

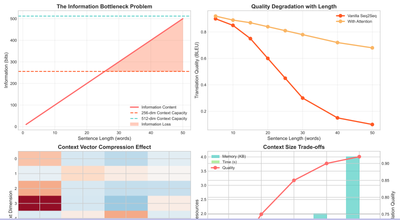
- Variable input/output length
- End-to-end learning
- No alignment needed
- Works for any language pair

Key Equations:

$$c = \text{Encoder}(x_{1:n}) \tag{9}$$
$$y_t = \text{Decoder}(c, y_{<t}) \tag{10}$$

Weakness:

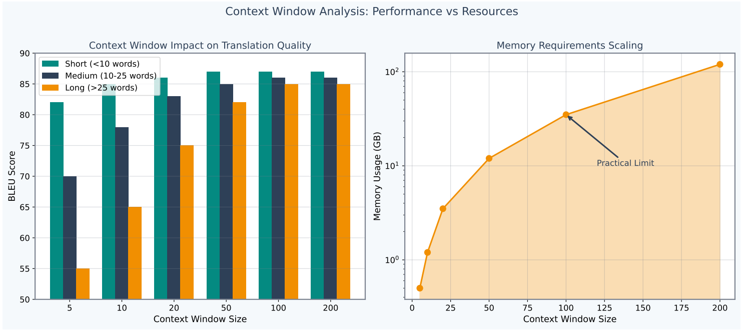
Fixed-size bottleneck!



Part 3: The Attention Revolution

Looking Back at All Hidden States

The Bottleneck Problem: Why Seq2Seq Fails on Long Sentences



Performance Degradation:

- 10 words: BLEU = 35
- 20 words: BLEU = 25
- 30 words: BLEU = 15
- 40+ words: BLEU ¡ 10

What's Lost:

- Early words forgotten
- Specific details blurred
- Word positions unclear
- Grammatical structure

Cause: Information bottleneck

Need: Access to all states

Human Translation: The Attention Analogy

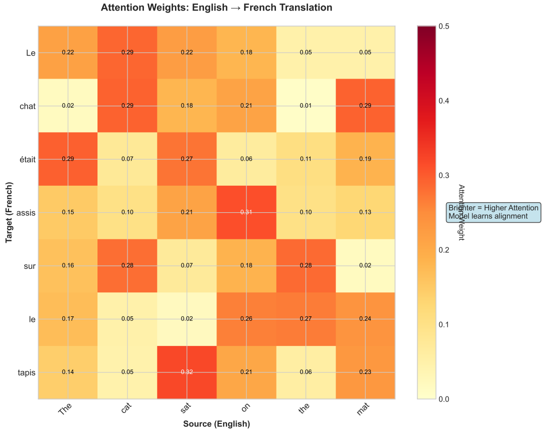
How do humans really translate long sentences?

Translating Word by Word:
"The black cat that I saw yesterday sat"

When translating "sat":

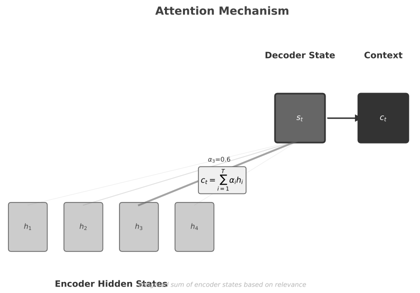
1. Look back at "cat" (subject)
2. Check tense markers
3. Verify agreement
4. Generate appropriate form

Key: We don't memorize everything! We look back as needed.



Attention Idea:
Let decoder look back at ALL encoder states!

The Attention Mechanism: Dynamic Context



Old Way (Seq2Seq):

- Fixed context $c = h_n$
- Same for all decoder steps
- Information bottleneck
- Forgets early words

New Way (Attention):

- Dynamic context c_t
- Different for each word
- Weighted sum of all states
- Remembers everything

$$c = \sum^{n} \alpha h$$

Attention Mathematics: Computing Weights

How to calculate attention weights:

Step 1: Score How relevant is each encoder state?

$$e_{ti} = \text{score}(s_{t-1}, h_i)$$

Common scoring functions:

- **Dot:** $s_{t-1} \cdot h_i$
- **General:** $s_{t-1} W h_i$
- **Concat:** $v \tanh(W[s_{t-1}; h_i])$

Step 2: Normalize Convert scores to probabilities:

$$\alpha_{ti} = \frac{\exp(e_{ti})}{\sum_j \exp(e_{tj})}$$

Step 3: Weighted Sum Compute dynamic context:

$$c_t = \sum_{i=1}^{n} \alpha_{ti} h_i$$

Each decoder step gets its own custom-weighted view of the source!

Mathematical Core: Three simple steps that revolutionized machine translation

Attention Mathematics: Query-Key-Value Intuition

Understanding the QKV Framework:

Components:

- **Query** (s_{t-1}): What I'm looking for
- **Keys** (h_i): What's available
- **Values** (h_i): What to retrieve
- **Weights** (α_{ti}): Relevance scores

Analogy:

- Query = Search term
- Keys = Document titles
- Values = Document content
- Attention = Search relevance

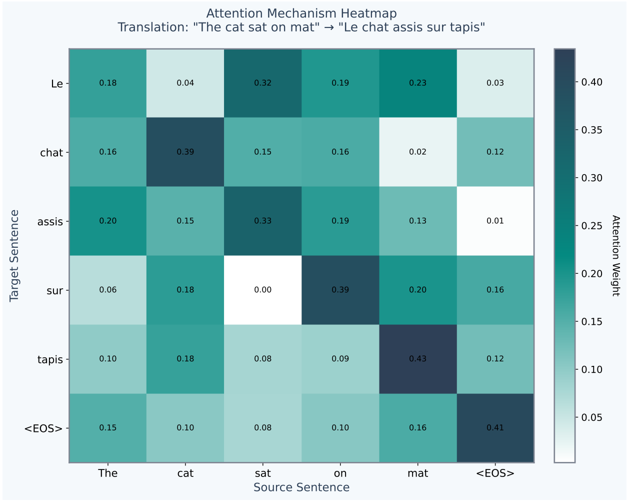
Critical Insight:

This simple mechanism
is the foundation of
ALL modern transformers!

GPT, BERT, T5, ChatGPT...
all use this QKV attention

Foundation: Attention as learned information retrieval - the key to modern AI

Visualizing Attention: What the Model Focuses On



	The	cat	sat	on	mat	<EOS>
Le	0.18	0.04	0.32	0.19	0.23	0.03
chat	0.16	0.39	0.15	0.16	0.02	0.12
assis	0.20	0.15	0.33	0.19	0.13	0.01
sur	0.06	0.18	0.00	0.39	0.20	0.16
tapis	0.10	0.18	0.08	0.09	0.43	0.12
<EOS>	0.15	0.10	0.08	0.10	0.16	0.41

Reading the Heatmap:

- Rows: Target (French)

Example Weights:

- “chat” $\rightarrow$ “cat” (0.8)

Implementing Attention: Score Calculation

```python
def attention_score(decoder_hidden, encoder_outputs):
    # Step 1: Expand decoder hidden to match encoder length
    seq_len = encoder_outputs.size(1)
    hidden = decoder_hidden.repeat(1, seq_len, 1)

    # Step 2: Concatenate and score
    concat = torch.cat((hidden, encoder_outputs), dim=2)
    scores = self.v(torch.tanh(self.attn(concat)))

    # Step 3: Apply softmax to get weights
    weights = F.softmax(scores.squeeze(2), dim=1)
    return weights
```

Key: Score function determines which encoder states to focus on

Implementing Attention: Context Computation

```python
def compute_context(weights, encoder_outputs):
    # Weighted sum of encoder states
    # weights: [batch, seq_len]
    # encoder_outputs: [batch, seq_len, hidden]
    context = torch.bmm(
        weights.unsqueeze(1),  # [batch, 1, seq_len]
        encoder_outputs        # [batch, seq_len, hidden]
    )  # Result: [batch, 1, hidden]
    return context
```

Context vector: Weighted combination of all encoder hidden states

Implementing Attention: Decoder Integration

```python
class AttentionDecoder(nn.Module):
    def forward(self, input_token, hidden, encoder_outputs):
        # 1. Embed input token
        embedded = self.embedding(input_token)

        # 2. Compute attention
        context, weights = self.attention(hidden, encoder_outputs)

        # 3. Combine embedding + context
        lstm_input = torch.cat([embedded, context], dim=2)

        # 4. LSTM step
        output, hidden = self.lstm(lstm_input, hidden)

        # 5. Predict next word
        predictions = self.output(output)

        return predictions, hidden, weights
```

Each decoder step: Attention determines what to focus on from source

Interactive Exercise: Calculate Attention Weights

Task: Compute attention for generating “noir” (black)

Given decoder state s_2 after generating “Le chat”:

Encoder states:

- h_1: “The” $= [0.1, 0.2]$
- h_2: “black” $= [0.8, 0.9]$
- h_3: “cat” $= [0.5, 0.4]$
- h_4: “sat” $= [0.3, 0.1]$

Decoder query:

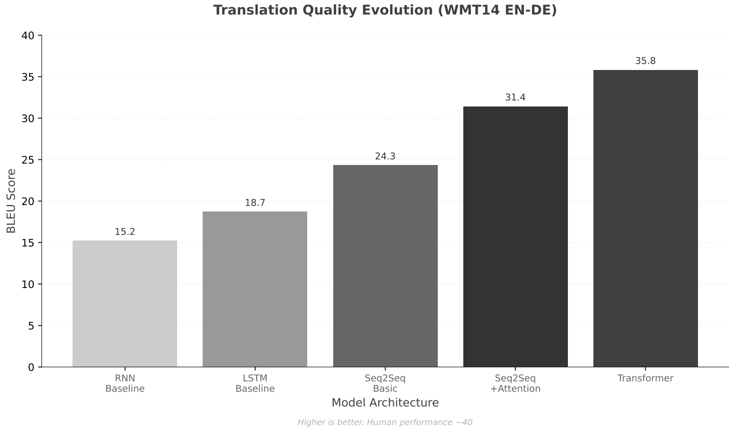
- $s_2 = [0.7, 0.8]$

Your calculations:

1. Scores (dot product):
   - $e_1 = s_2 \cdot h_1 =$ ________
   - $e_2 = s_2 \cdot h_2 =$ ________
   - $e_3 = s_2 \cdot h_3 =$ ________
   - $e_4 = s_2 \cdot h_4 =$ ________
2. Softmax weights:
   - $\alpha_2 =$ ________ (highest!)
3. Context: weighted sum

Hands-On: Computing attention manually builds intuition for the mechanism

Impact of Attention: BLEU Score Improvements



BLEU Score Improvements by Sentence Length:

- Short (¡ 10 words): +5 points
- Medium (10-20): +10 points
- Long (20-30): +15 points
- Very long (30+): +20 points

Impact of Attention: Why It Works

Technical Advantages:

- No information bottleneck
- Direct access to all source words
- Handles word reordering naturally
- Resolves lexical ambiguity
- Maintains word alignment

Practical Impact:

- Production-ready quality
- Handles complex languages
- Works for long documents
- Interpretable alignments
- Foundation for transformers

Game-changing improvement that enabled modern NMT

Historical Impact: This innovation directly led to transformer architecture

Part 3 Summary: The Attention Revolution

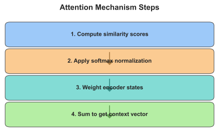
The Innovation:

- Dynamic context vectors
- Look at all encoder states
- Weighted by relevance
- Different for each word

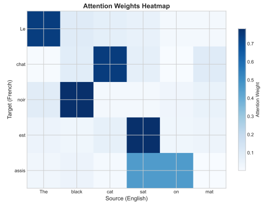
Mathematical Core:

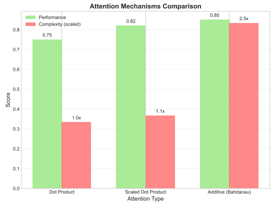
$$\alpha_{ti} = \mathrm{softmax}(\mathsf{score}(s_t, h_i)) \tag{11}$$

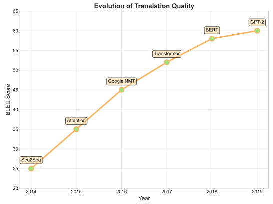
$$c_t = \sum_i \alpha_{ti} h_i \tag{12}$$



Attention Mechanism Steps
1. Compute similarity scores
2. Apply softmax normalization
3. Weight encoder states
4. Sum to get context vector







Impact:
Attention mechanism became foundation of all modern NLP

Historical Significance: Attention paper (2014) revolutionized entire field

Part 4: Implementation & Applications

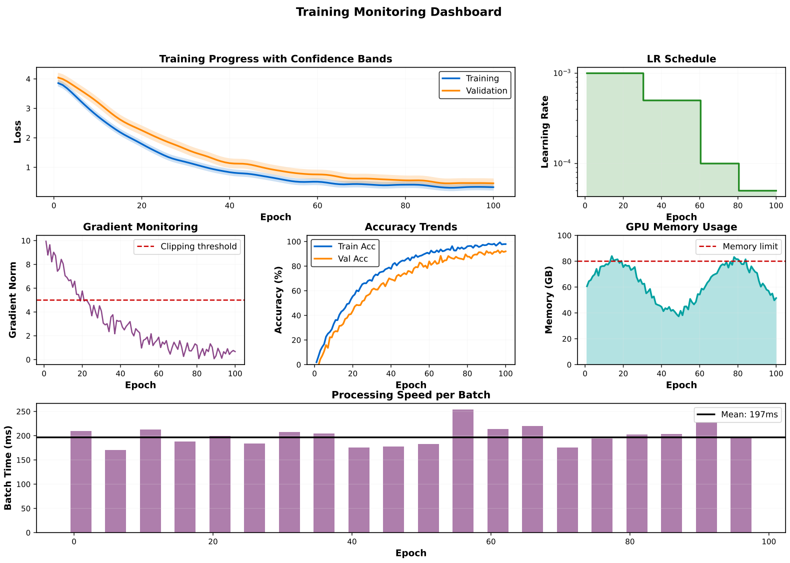
From Research to Production

Complete Seq2Seq with Attention

```python
class AttentionSeq2Seq(nn.Module):
    def __init__(self, src_vocab,
                 tgt_vocab, dim=512):
        super().__init__()

        # Components
        self.encoder = Encoder(
            src_vocab, dim
        )
        self.decoder = DecoderWithAttn(
            tgt_vocab, dim
        )
        self.attention = Attention(dim)

    def forward(self, src, tgt,
                teacher_forcing=0.5):
        # Encode all at once
        enc_out, (h, c) = self.encoder(src)

        batch = src.size(0)
        max_len = tgt.size(1)
        vocab = self.decoder.vocab_size

        # Store outputs
        outputs = torch.zeros(
            batch, max_len, vocab
        )

        # First input
        input = tgt[:, 0]
```

```python
        for t in range(1, max_len):
            # Attention context
            context, weights =
                self.attention(
                    h, enc_out
                )

            # Decode one step
            output, (h, c) =
                self.decoder(
                    input, (h, c),
                    context
                )

            outputs[:, t] = output

            # Teacher forcing
            use_teacher = random.random()
                < teacher_forcing

            if use_teacher:
                input = tgt[:, t]
            else:
                input = output.argmax(1)

        return outputs
```

Training Dynamics: Loss Curves



Training Dynamics: What Model Learns When

Early (0-20k steps):

- Basic vocabulary
- Word copying
- Common phrases
- Simple alignment

Middle (20k-80k):

- Grammar rules
- Word reordering
- Multi-word expressions
- Context sensitivity

Late (80k+):

- Rare words
- Idioms
- Style transfer
- Long dependencies

Key: Attention alignment emerges without explicit supervision

Training Strategy: Patient training (100k+ steps) crucial for quality

Training Best Practices

Hyperparameters That Matter:

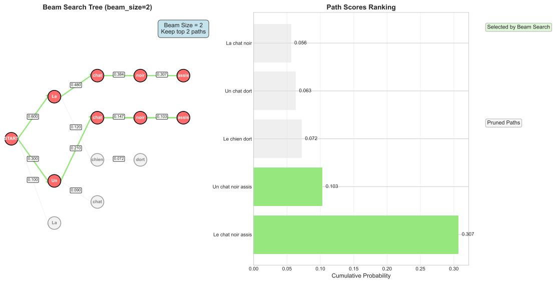
- **Learning rate:** Start 0.001, decay after epoch 10
- **Teacher forcing:** 0.5 $\rightarrow$ 0 over training
- **Gradient clip:** Essential (1.0 works well)
- **Batch size:** 32-64 optimal for GPU
- **Hidden size:** 512 is sweet spot
- **Layers:** 2-3 LSTM layers sufficient

Common Issues & Solutions:

- **Exploding loss:** $\rightarrow$ Reduce learning rate
- **Mode collapse:** $\rightarrow$ Add dropout (0.3)
- **Poor rare words:** $\rightarrow$ Increase min frequency
- **Slow training:** $\rightarrow$ Use GPU, reduce batch size
- **Overfitting:** $\rightarrow$ More data, regularization
- **Underfitting:** $\rightarrow$ Bigger model, longer training

Pro Tip: Start simple, add complexity gradually, monitor validation metrics closely

Beam Search: Better Decoding Strategy



Greedy vs Beam:

- Greedy: Best at each step
- Beam: Keep top-k paths
- Better final result

Beam size:

- k=5: Good balance
- k=10: Slightly better

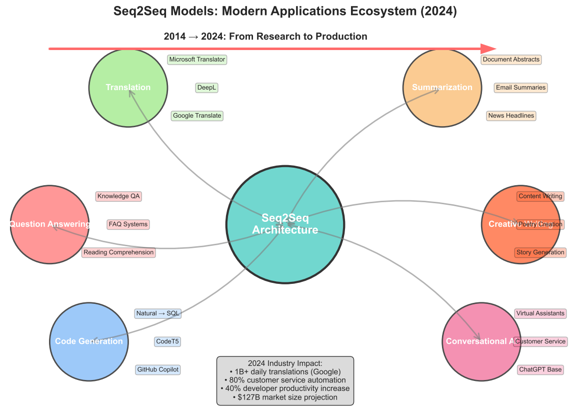
Example (beam=3):

- Step 1: “Le”, “Un”, “Les”
- Step 2: “Le chat”, “Un chat”
- Step 3: Keep expanding top-3

Pick best complete path

Beam search explores multiple hypotheses for better translations

Modern Applications: Direct Descendants (2024)



Production Systems:

- Google Translate (1B+ users)
- DeepL (quality leader)
- Facebook M2M-100

Capabilities:

- 100+ language pairs
- Document translation
- Real-time speech

Modern Applications: Beyond Translation

Attention Everywhere:

- ChatGPT/Claude (attention-based)
- Image captioning
- Video understanding
- Code generation
- Music composition
- Speech recognition
- Medical diagnosis

Foundation Truth:

Seq2Seq + Attention
=
Modern AI Backbone

Every modern language model
builds on this architecture

Attention mechanism is the foundation of the entire AI revolution

Lab Preview: Build Your Own Translator

Week 4 Lab: English-French Neural Machine Translation

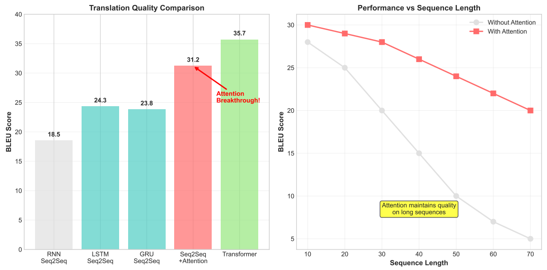
What You'll Build:

1. Load parallel corpus
2. Tokenize and preprocess
3. Implement encoder-decoder
4. Add attention mechanism
5. Train on GPU
6. Visualize attention weights
7. Compare with/without attention

Dataset:

- 10,000 sentence pairs
- English $\rightarrow$ French
- Average 15 words/sentence

Expected Results:



Bonus Challenges:

- Multi-head attention
- Bidirectional encoder
- Coverage mechanism
- Back-translation

Practical Experience: Implementing attention from scratch solidifies understanding

Interactive Debugging: Common Training Issues

Your model isn't learning. Debug these issues:

Issue 1: Attention all uniform
Symptoms:

- All weights ≈ 1/n
- Poor translation quality
- Not improving

Your fix: ____________________
Hint: Check score function

Issue 2: Mode collapse
Symptoms:

- Always generates "the the the"
- Loss plateaus high

Common Fixes:

Fix 1: Initialize properly

- Use Xavier initialization
- Scale attention scores
- Add small epsilon to softmax

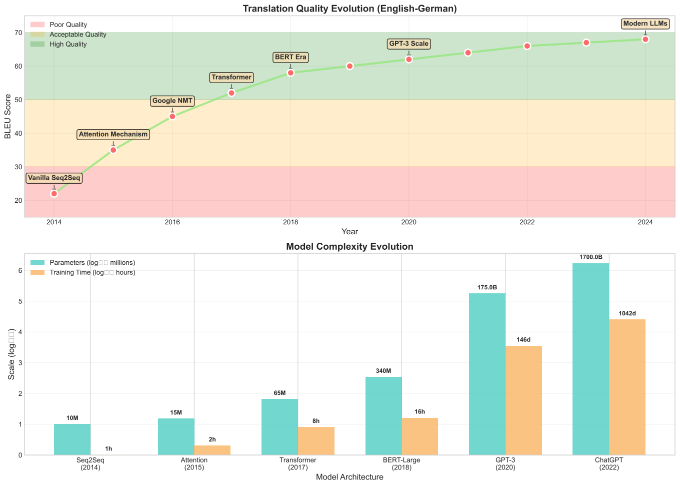
Fix 2: Teacher forcing

- Start with 100% teacher forcing
- Gradually reduce ratio
- Scheduled sampling

Debug systematically!

Debugging Skills: Most issues come from initialization or training schedule

Performance Evolution Timeline



Three Years That Changed Everything

The journey from seq2seq to attention represents

Performance Metrics by Year

2014: Seq2Seq

- BLEU: 20-25
- Simple, elegant
- Length problems
- 2-3 days training

Impact:

- First neural MT
- Proof of concept
- Beat phrase-based

2015: + Attention

- BLEU: 30-35
- Handles length
- Interpretable
- 4-5 days training

Impact:

- Production ready
- Google adoption
- 40% improvement

2017: Transformer

- BLEU: 40+
- All attention
- Parallel training
- 12 hours training!

Impact:

- New paradigm
- Enables GPT/BERT
- 10x faster training

Key Insight: Each innovation built on the previous - attention was THE breakthrough

Historical Progression: From RNN to attention to transformer architecture

The Bridge to Transformers (Week 5 Preview)

From Seq2Seq+Attention to Transformers:

What We Keep:

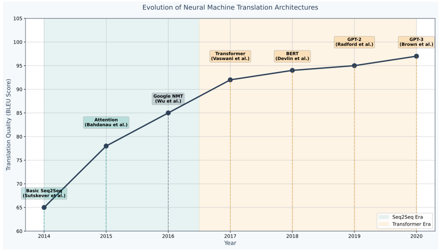
- Attention mechanism
- Query-Key-Value
- Position awareness
- Encoder-decoder structure

What We Remove:

- RNN/LSTM cells
- Sequential processing
- Recurrent connections
- Hidden state passing

What We Add:

- Self-attention
- Multi-head attention
- Position encodings
- Layer normalization
- Parallel processing



Week 4 Complete: From Translation to Attention

Part 1: Challenge

- Translation $\neq$ word replacement
- Need meaning understanding
- Information bottleneck problem

Part 2: Seq2Seq

- Encoder-decoder architecture
- Fixed context vector
- Works but limited by bottleneck

Part 3: Attention

- Dynamic context vectors
- Look at all encoder states
- Massive performance improvement

Part 4: Applications

- Complete implementation
- Beam search decoding
- Powers modern translation
- Foundation for transformers

Key Takeaways:

1. Context vectors compress meaning
2. Attention removes bottleneck
3. Foundation of modern NLP
4. Bridge to transformers

Next Week: Transformers - Attention Without RNNs!

Achievement Unlocked: You understand the foundation of all modern language AI!