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:

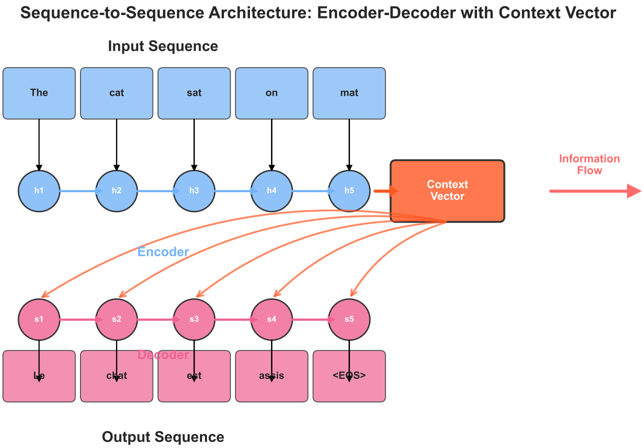
Chinese Input: "There is one cat in station"

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



Translation is NOT:

- Word replacement

Translation IS:

- Understanding meaning

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

Computers only understand numbers, so:

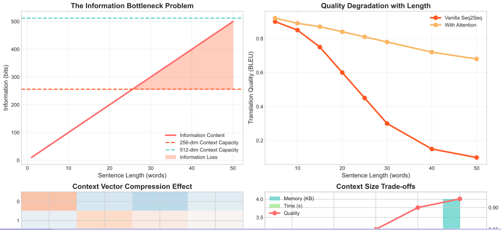
"The cat sat on the mat" → **[Numbers]** → "Le chat s'est assis sur le tapis"

Step 1: Words to Vectors

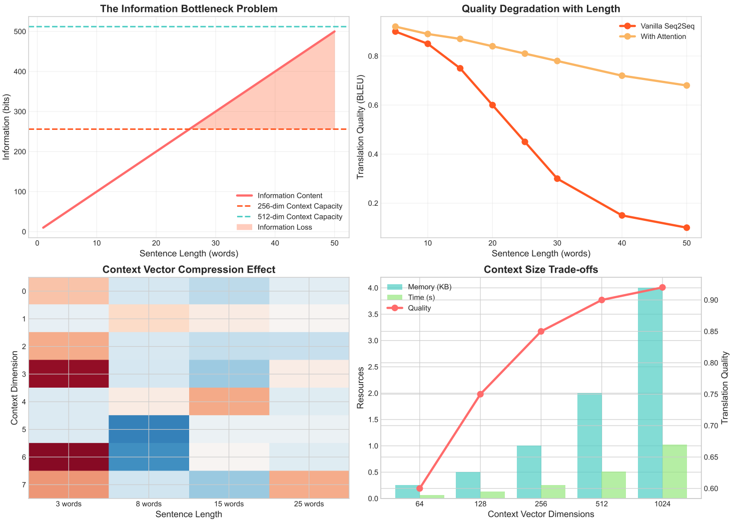
- "cat" → [0.2, -0.5, 0.8, ...]
- 100-300 dimensional vectors
- Learned from context (Word2Vec)
- Similar words = nearby vectors

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:

What Gets Lost?

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 $\rightarrow$ chat
   - black $\rightarrow$ noir
   - sat $\rightarrow$ 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

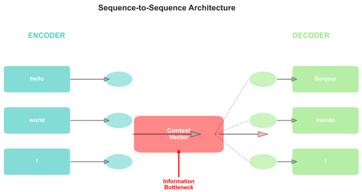
Part 1 Summary: Understanding the Challenge

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

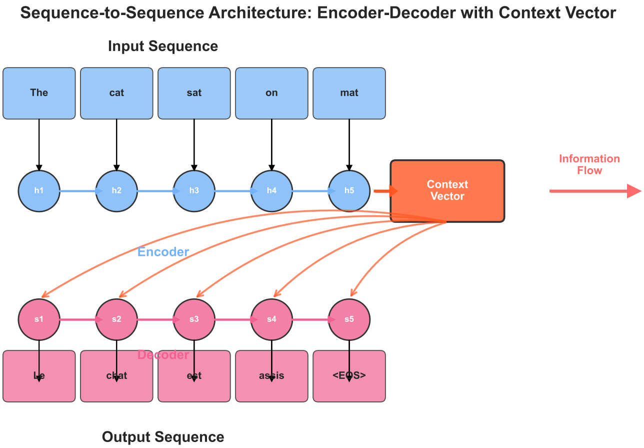
1. Access stored meaning
2. Apply target grammar
3. Choose appropriate words
4. Generate word-by-word
5. Maintain coherence

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)

Processing "The cat sat":

1. $h_1 = \text{RNN}(\text{"The"}, h_0)$
2. $h_2 = \text{RNN}(\text{"cat"}, h_1)$

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:

$$s_0 = c \text{ (initialize)} \tag{6}$$

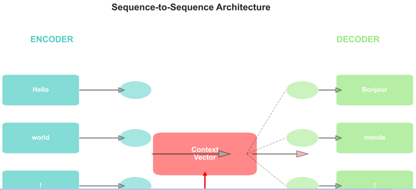
$$s_t = \mathrm{RNN}(y_{t-1}, s_{t-1}) \tag{7}$$

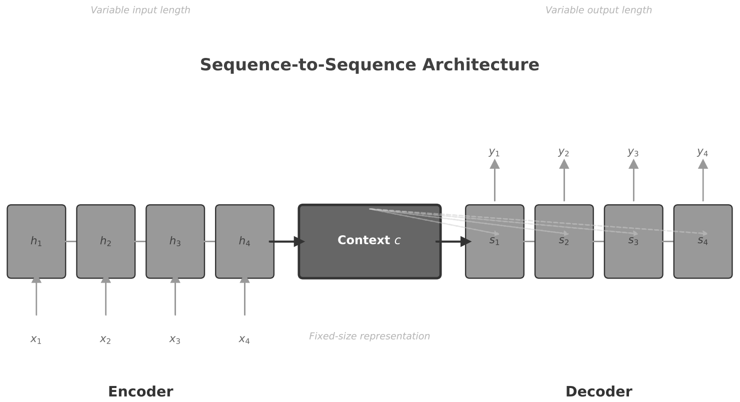
$$P(y_t) = \mathrm{softmax}(W s_t) \tag{8}$$

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





Components:

Training:

Inference:

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)
```

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”

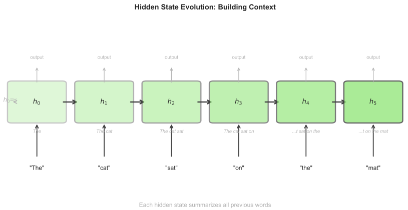
- Input: $x_2 = \text{embed}(\text{“black”})$
- Hidden: $h_2 = \text{LSTM}(x_2, h_1)$
- Memory: “Determiner + adjective”

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"

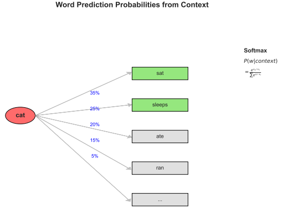
- State: s_1 (knows "Le")
- Input: "Le"
- Output: $P(\text{"chat"}) = 0.7$
- Next: $s_2 = \text{LSTM}(\text{"chat"}, s_1)$

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

Key Equations:

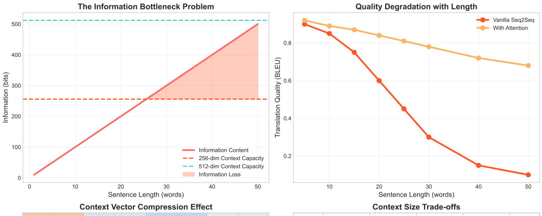
$$c = \text{Encoder}(x_{1:n}) \tag{9}$$
$$y_t = \text{Decoder}(c, y_{<t}) \tag{10}$$

Strengths:

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

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

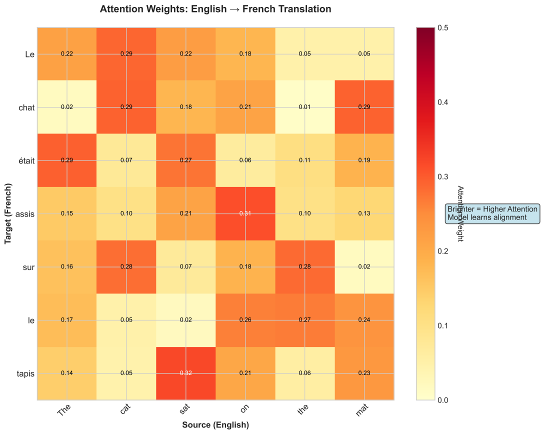
How do humans really translate long sentences?

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

When translating "sat":

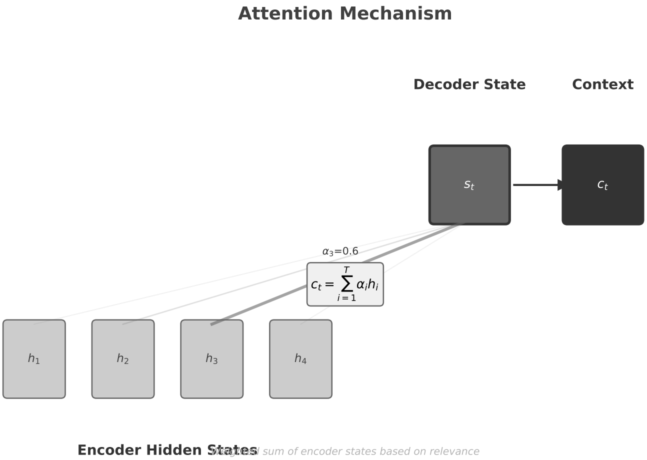
1. Look back at "cat" (subject)
2. Check tense markers
3. Verify agreement
4. Generate appropriate form

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



Attention Idea:

The Attention Mechanism: Dynamic Context



Attention Mathematics: Query, Key, Value

Computing 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:

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

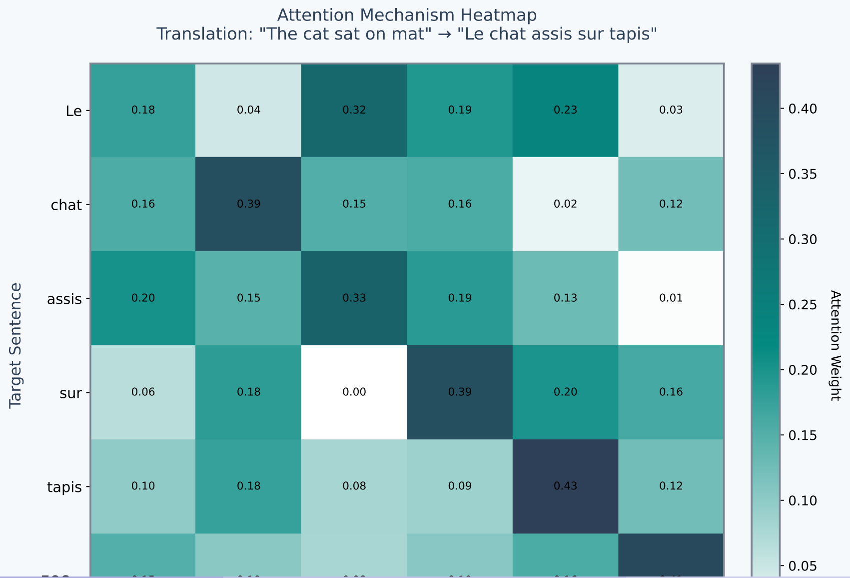
Intuition:

- s_{t-1} = Query (what I need)
- h_i = Key (what's available)
- h_i = Value (what to use)
- α_{ti} = Relevance weight

This is the foundation of all modern transformers!

Mathematical Foundation: Attention as weighted information retrieval

Visualizing Attention: What the Model Focuses On



Implementing Attention in PyTorch

```python
class Attention(nn.Module):
    def __init__(self, hidden_dim):
        super().__init__()
        self.attn = nn.Linear(
            hidden_dim * 2, hidden_dim
        )
        self.v = nn.Linear(
            hidden_dim, 1, bias=False
        )

    def forward(self, hidden,
                encoder_outputs):
        # hidden: [1, batch, hidden]
        # encoder_outputs:
        #   [batch, seq_len, hidden]

        batch = encoder_outputs.size(0)
        seq_len = encoder_outputs.size(1)

        # Repeat decoder hidden
        hidden = hidden.squeeze(0)
        hidden = hidden.unsqueeze(1)
        hidden = hidden.repeat(
            1, seq_len, 1
        )

        # Concatenate and score
        energy = torch.tanh(self.attn(
            torch.cat((hidden,
                       encoder_outputs), 2)
```

```python
        # Compute attention weights
        attention = self.v(energy)
        attention = attention.squeeze(2)

        # Softmax over seq_len
        weights = F.softmax(
            attention, dim=1
        )

        # Weighted sum
        context = torch.bmm(
            weights.unsqueeze(1),
            encoder_outputs
        )

        return context, weights

# Usage in decoder
attn = Attention(hidden_dim=512)

# Each decoding step
context, weights = attn(
    decoder_hidden,
    encoder_outputs
)

# Combine context with input
decoder_input = torch.cat(
    (embedded, context), dim=2
)
```

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:

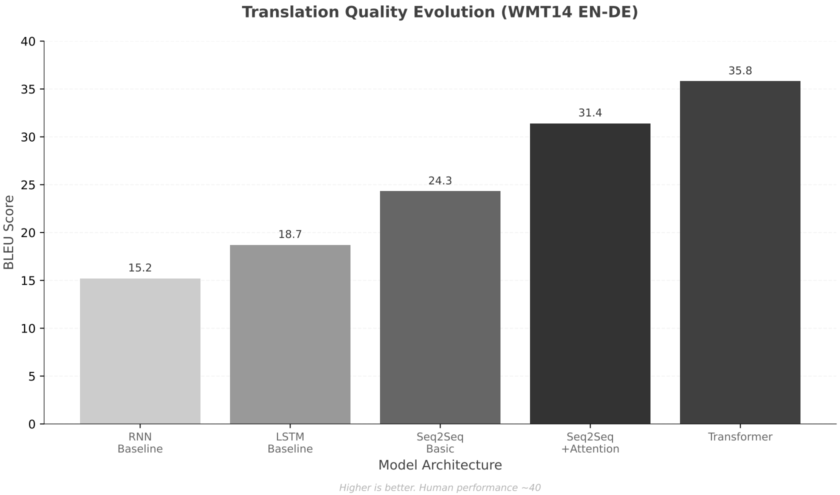
- $s_2 = [0.7, 0.8]$

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: Dramatic Improvements



BLEU Score Improvements:

Why It Works:

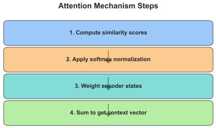
The Innovation:

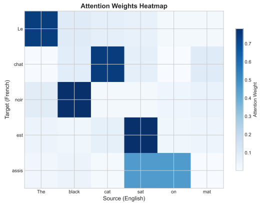
- Dynamic context vectors
- Look at all encoder states
- Weighted by relevance
- Different for each word

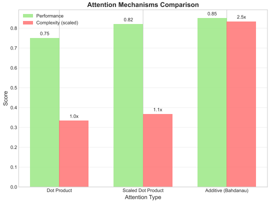
Mathematical Core:

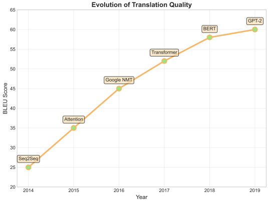
$$\alpha_{ti} = \mathrm{softmax}(\mathsf{score}(s_t, h_i)) \quad (11)$$

$$c_t = \sum_i \alpha_{ti} h_i \quad (12)$$









Impact:
Attention mechanism became foundation of all modern NLP

Historical Significance: Attention paper (2014) revolutionized entire field

Part 4: Implementation & Applications

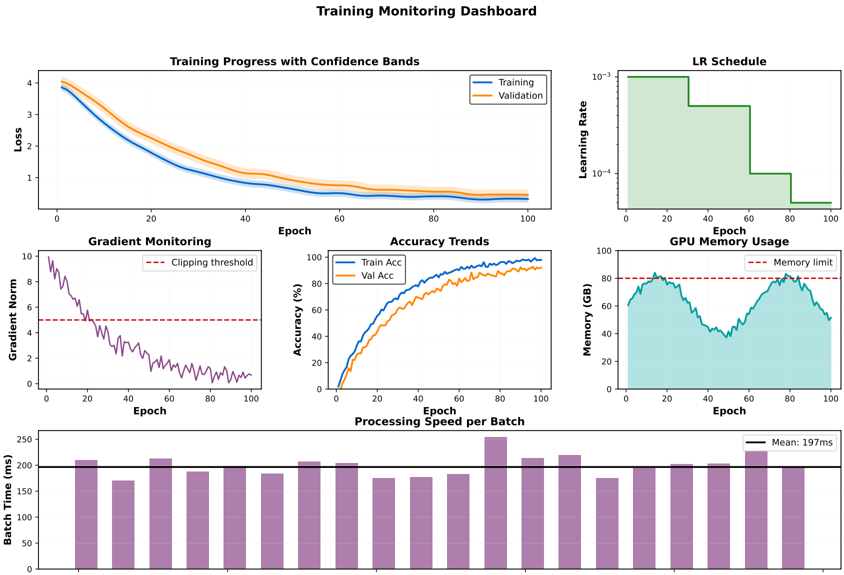
From Research to Production

Complete Seq2Seq with Attention

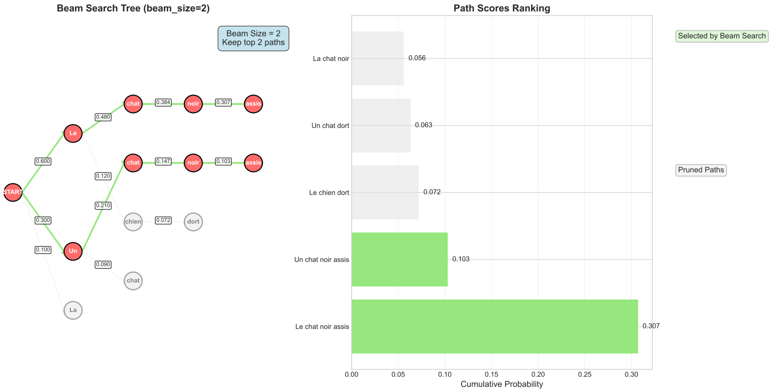
```python
class AttentionSeq2Seq(nn.Module):
    def __init__(self, src_vocab,
                 tgt_vocab, dim=512):
        super().__init__()

        # 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: Learning to Translate



Beam Search: Better Decoding Strategy



Greedy vs Beam Search:

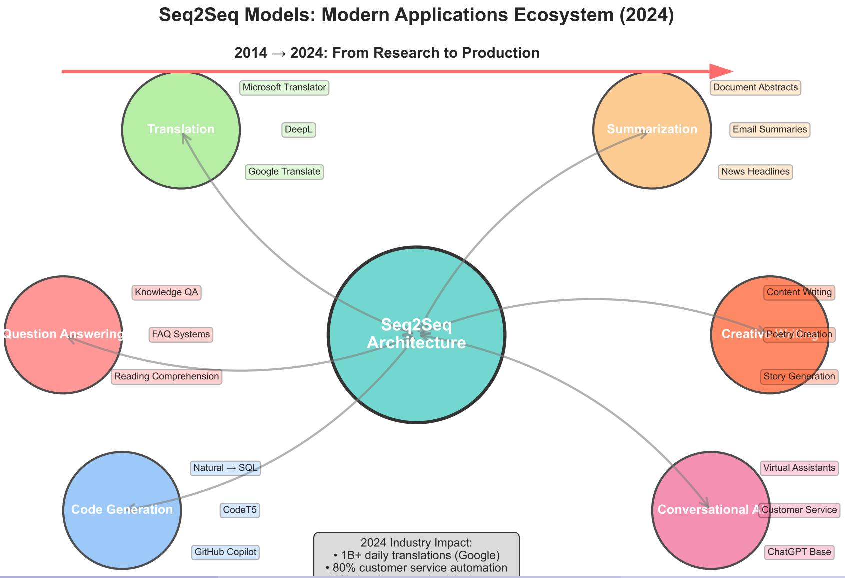
- Greedy: Pick best at each step
- Beam: Keep top-k hypotheses
- Explore multiple paths
- Better final translations

Example with beam=3:

Step 1: "Le", "Un", "Les"
Step 2:

- "Le chat", "Le chien"
- "Un chat", "Les chats"

Step 3: Keep expanding top-3


Seq2Seq Models: Modern Applications Ecosystem (2024)
2014 → 2024: From Research to Production
Translation
Microsoft Translator
DeepL
Google Translate
Summarization
Document Abstracts
Email Summaries
News Headlines
Question Answering
Knowledge QA
FAQ Systems
Reading Comprehension
Seq2Seq Architecture
Content Writing
Poetry Creation
Story Generation
Code Generation
Natural → SQL
CodeT5
GitHub Copilot
Virtual Assistants
Customer Service
ChatGPT Base
2024 Industry Impact:
• 1B+ daily translations (Google)
• 80% customer service automation

Lab Preview: Build Your Own Translator

Week 4 Lab: English-French Neural Machine Translation

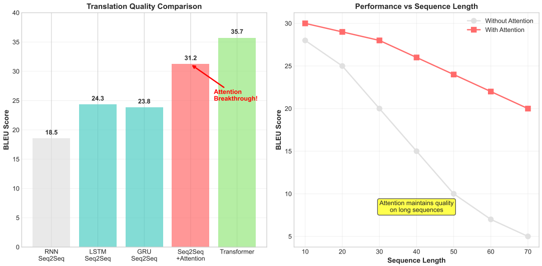
What You'll Build:

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 $\approx 1/n$
- 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

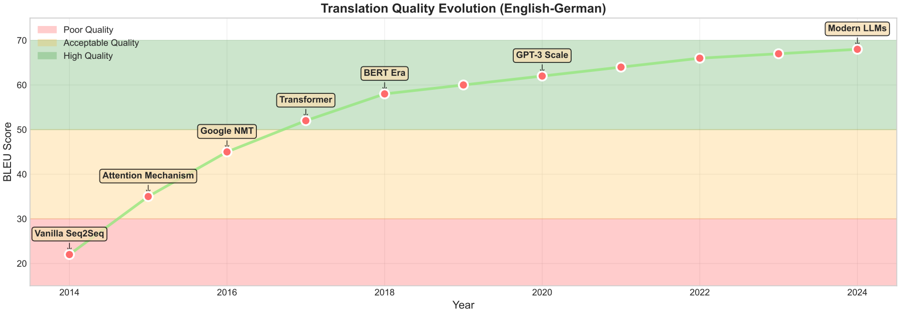
Fix 2: Teacher forcing

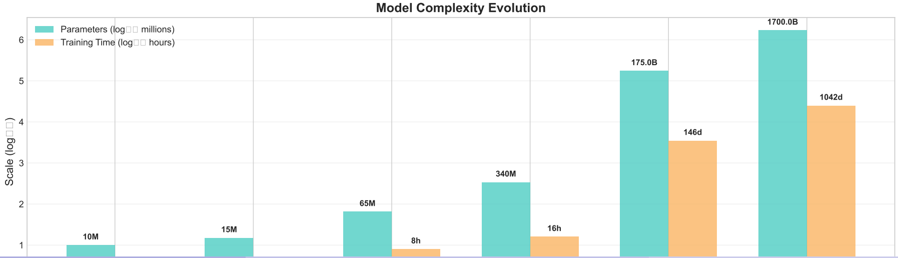
- Start with 100% teacher forcing
- Gradually reduce ratio
- Scheduled sampling

Debug systematically!

Debugging Skills: Most issues come from initialization or training schedule

Performance Comparison: Evolution of Translation





From Seq2Seq+Attention to Transformers:

What We Keep:

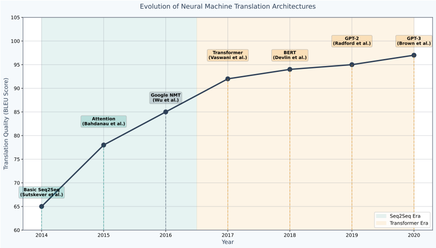
- Attention mechanism
- Query-Key-Value
- Position awareness
- Encoder-decoder structure

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!