

# Week 3: Teaching Networks to Remember

Discovering RNNs, LSTMs, and the Memory Problem  
Pre-Lab Exercise (No Programming Required)

NLP Course 2025 - Student Version

**Time:** 40 minutes

**Objective:** Discover why networks need memory and how gates solve the vanishing gradient problem.

## Part 1: The Context Problem (10 minutes)

### Why Order Matters

#### Task 1: Same words, different meanings

Rearrange these words to create two sentences with opposite meanings:

{dog, bites, man}

Sentence 1: \_\_\_\_\_

Sentence 2: \_\_\_\_\_

#### Task 2: Context tracking

Read this sentence word by word and track what you remember:

"The student who studied hard..."

1. After "The": I expect \_\_\_\_\_
2. After "student": I remember \_\_\_\_\_
3. After "who": I expect \_\_\_\_\_
4. After "studied hard": I'm waiting for \_\_\_\_\_

#### Task 3: What information are you maintaining?

List three things your brain tracks while reading:

- \_\_\_\_\_
- \_\_\_\_\_
- \_\_\_\_\_

### Think About It

Word embeddings (Week 2) treat "dog bites man" and "man bites dog" as identical - they have the same word vectors. How can we teach networks that order matters?

## Part 2: Building Memory - Discovering Hidden States (10 minutes)

### Designing Memory for Networks

**Scenario:** You're teaching a computer to read "The cat sat on the mat" word by word.

#### Task 1: Design your memory system

The computer can only see one word at a time. How would you help it remember previous words?

Your design:

#### Task 2: Memory updates

Fill in how memory should update at each step:

Current Word	Previous Memory	New Memory Should Contain
"The"	(empty)	_____
"cat"	"The"	_____
"sat"	"The cat"	_____

#### Task 3: Mathematical pattern

The pattern you discovered can be written as:

New Memory = Function(Current Word, Previous Memory)

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

What are the inputs to this function?

- Input 1: \_\_\_\_\_
- Input 2: \_\_\_\_\_

What is the output? \_\_\_\_\_

### Discovery Moment

Congratulations! You've just invented the core idea of RNNs - using hidden states ( $h_t$ ) to maintain memory of previous inputs!

## Part 3: When Memory Fails - The Vanishing Gradient Problem (10 minutes)

### Long-Distance Dependencies

#### Task 1: The forgetting problem

Try to complete this sentence: "The keys that I left on the table in the kitchen yesterday before going to work \_\_\_\_\_ missing."

What word did you need to remember? \_\_\_\_\_

How many words back was it? \_\_\_\_\_

#### Task 2: Memory decay simulation

Imagine your memory fades by 10% at each word. Starting with strength 1.0:

Step	Calculation	Memory Strength
Start	1.0	1.0
After 1 word	$1.0 \times 0.9$	0.9
After 2 words	$0.9 \times 0.9$	_____
After 5 words	$0.9^5$	_____
After 10 words	$0.9^{10}$	_____
After 20 words	$0.9^{20}$	_____

#### Task 3: The problem

At what point does memory become effectively zero ( $\leq 0.01$ )? \_\_\_\_\_

This is why RNNs can't handle long sequences - the gradient (learning signal) vanishes!

### Think About It

If memory decays exponentially, how can we preserve important information for longer?

## Part 4: The Gate Solution - Selective Memory (10 minutes)

### Designing Gates

**Scenario:** You're managing your email inbox. You have three actions:

- Delete (forget) spam
- Save (input) important emails
- Reply to (output) urgent emails

#### Task 1: Gate design

For the sentence "The cat that was black sat on the mat", decide what to do with each word:

Word	Forget? (0=forget all, 1=keep all)	Save? (0=ignore, 1=save)	Use Now? (0=hide, 1=use)
"The"	0.5	0.3	0.2
"cat"	_____	_____	_____
"that"	_____	_____	_____
"was"	_____	_____	_____
"black"	_____	_____	_____
"sat"	_____	_____	_____

#### Task 2: Gate benefits

How do gates help with the vanishing gradient problem?

If forget gate = 1.0, then memory decay =  $1.0^{20} =$  \_\_\_\_\_

This creates a "highway" for gradients!

#### Task 3: Memory update with gates

New formula with gates:

$$\text{New Memory} = (\text{Forget Gate} \times \text{Old Memory}) + (\text{Input Gate} \times \text{New Info})$$

Write this mathematically using your notation:

\_\_\_\_\_

### Discovery Moment

You've just invented LSTM! The three gates you designed (Forget, Input/Save, Output/Use) are exactly how LSTMs work!

## Part 5: Comparing Memory Systems (10 minutes)

### RNN vs LSTM vs GRU

#### Task 1: Complete the comparison

Based on your discoveries, fill in this table:

Aspect	Simple RNN (No gates)	LSTM (3 gates)	GRU (2 gates)
How it handles memory	Overwrites completely		Selective update
Maximum sequence length	10-20 words		100 words
Gradient flow	Exponential decay		Good preservation
Best for		Long documents	Quick training

#### Task 2: Application matching

Which architecture would you choose for:

1. Predicting the next character in a name: \_\_\_\_\_
2. Summarizing a 10-page document: \_\_\_\_\_
3. Real-time speech recognition on phone: \_\_\_\_\_
4. Analyzing sentiment in tweets: \_\_\_\_\_

#### Task 3: Design your own architecture

If you could add a fourth gate to LSTM, what would it do?

Gate name: \_\_\_\_\_

Function: \_\_\_\_\_

When would it activate (0 or 1)? \_\_\_\_\_

## Synthesis Questions

1. Why can't we just make the memory infinitely large?
2. The forget gate seems counterintuitive - why would we want to forget?
3. How is an LSTM like a computer's RAM?

4. Could we have more than 3 gates? What would be the trade-off?

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**Key Discoveries:**

- Order matters in language  $\rightarrow$  need memory
  - Hidden states maintain context  $\rightarrow$  RNN
- Gradients vanish over time  $\rightarrow$  long sequences fail
- Gates control information flow  $\rightarrow$  LSTM solves vanishing gradients