

# Recurrent Neural Networks (RNNs)

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Recurrent Neural Networks (RNNs), which were the brains behind early AI systems for language, speech, and time-series prediction before Transformers came along.

Let's make this one clean, structured, and professional — perfect for your technical writing portfolio.

## Overview

A **Recurrent Neural Network (RNN)** is a type of neural network designed to handle **sequential data** — data where order matters.

Unlike traditional networks, RNNs remember previous inputs through internal memory, allowing them to make predictions based on **context over time**.

They were the foundation for early **natural language processing (NLP)** systems, **speech recognition**, and **time-series forecasting**.

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## Key Concepts

### 1. Sequence and Memory

RNNs process data **one element at a time**, maintaining a **hidden state** that carries information from earlier steps in the sequence.

For example, in a sentence:

"Leslie loves writing technical documentation."

An RNN reads one word at a time and uses memory from previous words to predict what comes next — maintaining *context*.

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### 2. Hidden State

The hidden state acts like the network's "memory."

At each step, it's updated based on:

New hidden state =  $f(\text{previous hidden state, current input})$

This allows RNNs to make decisions not just from the current input, but from everything seen before.

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### 3. Long Short-Term Memory (LSTM)

A special RNN architecture designed to overcome the **vanishing gradient problem** (where early information is forgotten).

LSTMs can remember information over **longer sequences** — e.g., whole paragraphs, not just sentences.

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## 4. Gated Recurrent Unit (GRU)

A simplified version of LSTM that performs similarly but with fewer parameters, making it faster to train.

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### Visual Summary

Input ( $x_1$ ) → Hidden ( $h_1$ ) → Output ( $y_1$ ) ↓ Input ( $x_2$ ) → Hidden ( $h_2$ ) → Output ( $y_2$ ) ↓ Input ( $x_3$ ) → Hidden ( $h_3$ ) → Output ( $y_3$ )

The hidden state “flows” through the sequence, carrying past context forward.

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### Real-World Applications

-  **Language Modelling:** Predicting the next word in a sentence.
  -  **Speech Recognition:** Understanding spoken commands or dictation.
  -  **Text Generation:** Writing captions, lyrics, or stories.
  -  **Stock Market Forecasting:** Predicting trends over time.
  -  **Healthcare:** Analysing patient time-series data for diagnosis.
  -  **Sensor Data Analysis:** Predictive maintenance in IoT systems.
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### Example

Suppose you want to predict the next temperature reading from a weather station.

An RNN receives:

Inputs: [22°C, 24°C, 23°C, 25°C] → predicts: 26°C

It learns the pattern of how temperatures evolve over time.

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### Why It Matters

RNNs introduced the ability for AI to “remember” — a key leap from static models.

They paved the way for voice assistants, translation systems, and chatbots.

While largely replaced by **Transformers**, RNNs remain useful for smaller, real-time applications.

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### Famous RNN Architectures

- **Elman Network (1990):** The original simple RNN.
  - **LSTM (1997):** Solved long-term memory loss.
  - **GRU (2014):** A lighter, faster alternative to LSTM.
  - **Seq2Seq (2014):** Used in machine translation before Transformers.
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### Real-World Systems Using RNNs

- **Google Translate (early versions)**

- **Apple Siri (before Transformer updates)**
- **Predictive text keyboards**
- **Financial time-series forecasting systems**