



ALMA MATER STUDIORUM  
UNIVERSITÀ DI BOLOGNA  
CAMPUS DI FORLÌ

# 91258 / B0385

## Natural Language Processing

### Lesson 17. Recurrent Neural Networks

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### Previously

- CNNs for text

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2025 2 / 17

### Table of Contents

1. Introduction
2. Keeping the past in mind
3. RNNs in Keras

Chapter 8 of Lane et al. (2019)

### Introduction

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3 / 17

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## Introduction

### CNNs

- Adequate for processing *full* texts ( $\sim$ sentences)
- Words tending to appear close to each other are spotted and play a joint role
- Longer relationships —farther than [3, 4] words are ignored

### What is missing?

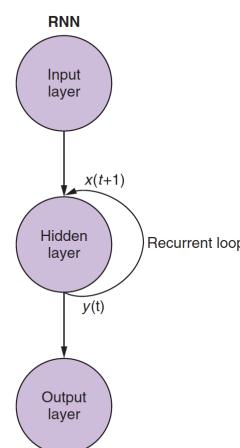
- Keeping track of what happened long ago
- Memory
- Language is **not an image** —no snapshots
- Language is a **sequence**; both text and speech

Keeping the past *in mind*

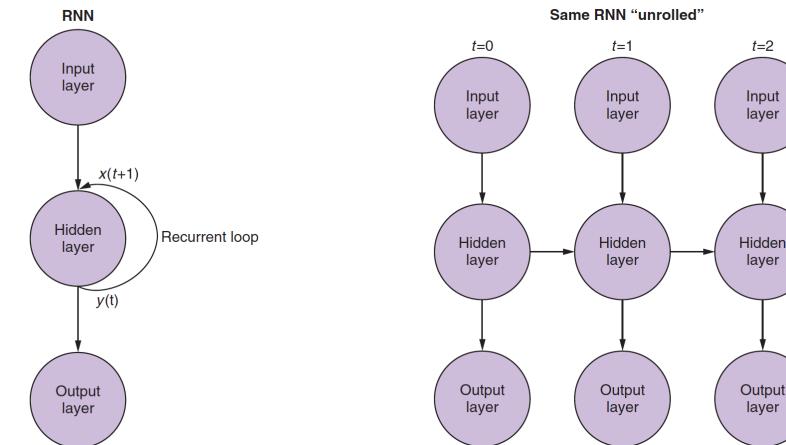
## Remembering the Past

$w_0 w_1 w_2 w_3 \dots w_{t-1} w_t w_{t+1}$

- To understand a text at time  $t$ , we need to consider what happened at time  $t - 1, t - 2, \dots, t - k$
- Recurrent neural nets (RNN) come into play
- RNNs combine what is happening **now** with what happened **earlier**

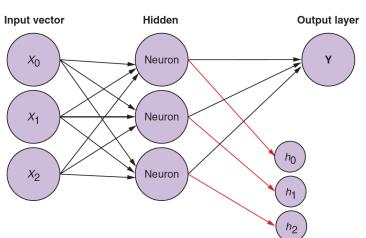


## Full feed-forward networks that consider their own output



\* All three columns represent the **same network** (at different times)

## Zooming into the *unrolled RNN*: $t$ and $t + 1$



$t = 0$

- The red arrows are just *standard* connections, with weights
- Now we can feed the text, **one word at a time**

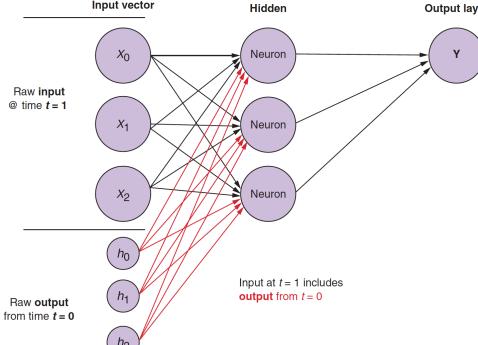
(Lane et al., 2019, p. 252–253)

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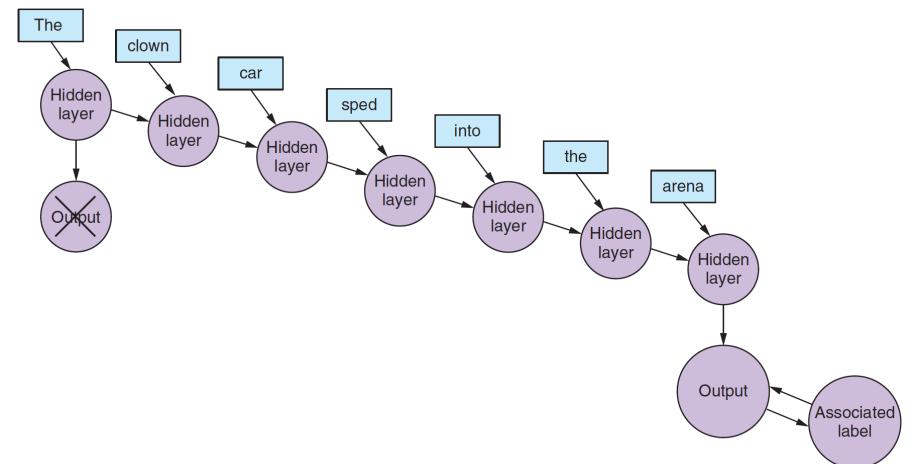
2025

9 / 17



$t = 1$

## “Multiple inputs, one output”



- A network for variable input lengths (lengthy inputs be troublesome)
- Rather than *mutually-independent* snapshots,<sup>1</sup> there is a sense of time

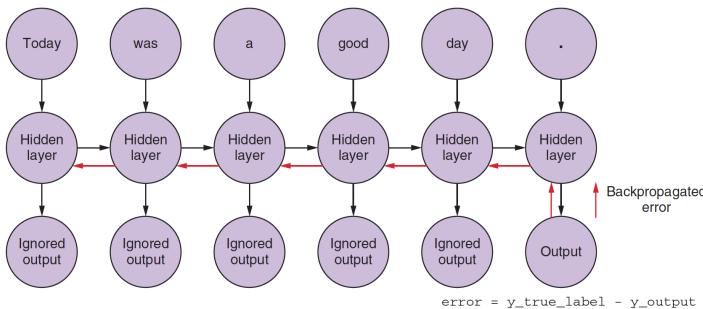
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2025 10 / 17

(Lane et al., 2019, p. 254)

## Backpropagation through Time: the “Vanilla” Way



- All intermediate outputs are ignored; the loss is computed at the end
- The same chain rule is applied to do backpropagation; but this time it heads to “the past”
- The weight corrections are calculated for each  $t$
- The combined updates are applied **only** until reaching  $t = 0$

(Lane et al., 2019, p. 256)

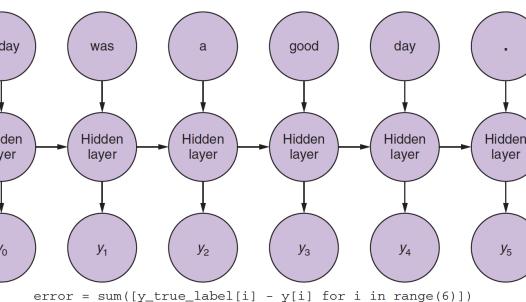
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2025

11 / 17

## Backpropagation through Time: the Better Way



- We compute the loss combining all intermediate outputs
- The weight corrections are still additive: the update is applied until
  - computing all errors and
  - reaching back to the weight adjustments in  $t = 0$



Let us see

(Lane et al., 2019, p. 258)

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2025 12 / 17

## RNNs in Keras

## RNN in Keras: further details

- A Dense layer expects a *flat* vector

```
model.add(Flatten())
      5 x 3
      1 x 15
Flatten( [ ] ) → [ ]
```

- In our case:  $400 \times 50 \rightarrow 1 \times 20,000$

Let us see

Example derived from

<https://stackoverflow.com/questions/43237124/role-of-flatten-in-keras>

## RNN in Keras: what we have so far

We have setup a simple recurrent neural network

- The input sequences have fixed length: 400 tokens (each 300D)
- Our recurrent layer contains 50 units
- The output will be  $400 \times 50$ :
  - 400 elements
  - one 50D vector each

`return_sequences=True`

`True` return the network value at each  $t$ : 400 50D vectors

`False` return a single 50D vector (default)

`True` → this is why we are padding

Let us see

## Some parameters are “free”

`embedding_dims` comes from the embedding space; hard to change, but possible: other embeddings, 1-hot

`num_neurons` kind of arbitrary; can be changed

`maxlen` kind of arbitrary; can be changed (or neglected)

`batch_size` bigger→faster (higher local minimum risk)

`epochs` trivial to increase (avoid starting from scratch each time)

Let us see

**Important:** unless you have access to HPC, don't go *bananas* when exploring parameters (and perhaps even in that case)

Try some sensitive configurations and keep track of all the settings and outputs<sup>2</sup>

<sup>2</sup>See, for instance, Fericola et al. (2020) ↗.

## References

- Fernicola, F., S. Zhang, F. Garcea, P. Bonora, and A. Barrón-Cedeño  
2020. Ariemozione: Identifying emotions in opera verses. In *Italian Conference on Computational Linguistics*.
- Lane, H., C. Howard, and H. Hapkem  
2019. *Natural Language Processing in Action*. Shelter Island, NY: Manning Publication Co.