ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA
CAMPUS DI FORLÌ

91258 / B0385
Natural Language Processing

Lesson 16. Recurrent Neural Networks

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Previously

- CNNs for text

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Chapter 8 of Lane et al. (2019)

Introduction

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CNNs

- Good for analysing *full* texts ($\sim$sentences)
- Words tending to appear close to each other are spotted and play a joint role

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- Language is not an image —no snapshots
- Language is a sequence; both text and speech

Keeping the past *in mind*

Remembering the Past

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

(Lane et al., 2019, p. 250)

Remembering the Past

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- To understand a text at time t, we need to consider what happened at time $t - k$

(Lane et al., 2019, p. 250)

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- Recurrent neural nets (RRN) come into play

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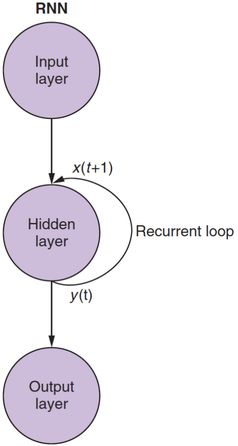

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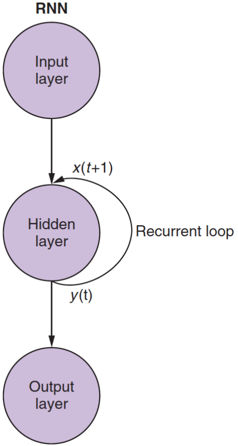
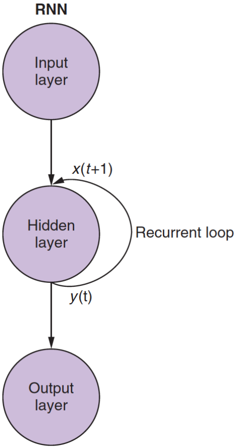
- RNNs combine what happened before with what is happening now



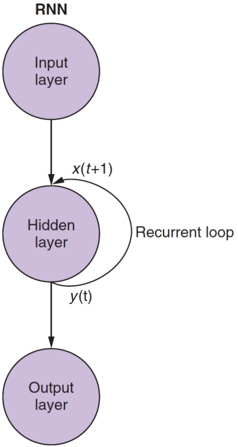
(Lane et al., 2019, p. 250)

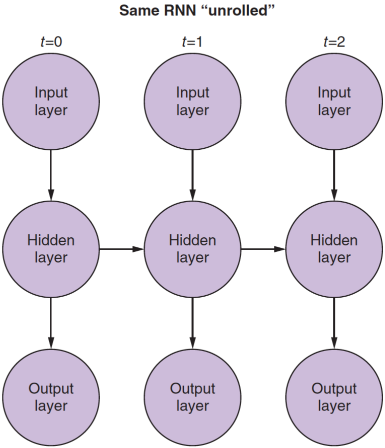
Full feed-forward networks that consider their own output



(Lane et al., 2019, p. 252)

Full feed-forward networks that consider their own output

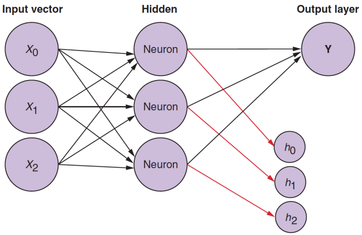




(all three columns are the same)

(Lane et al., 2019, p. 252)

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



$$t = 0$$

(Lane et al., 2019, p. 252–253)

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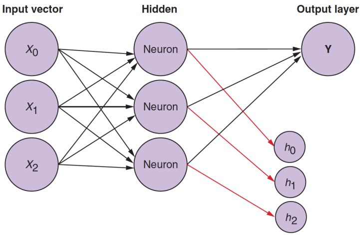

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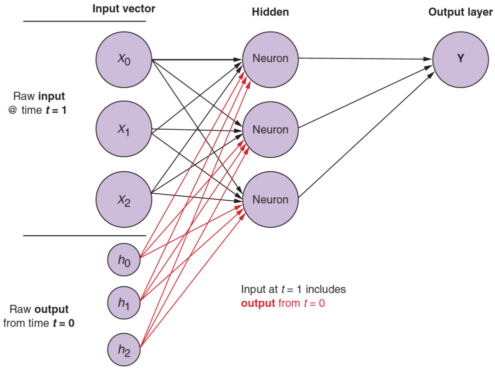
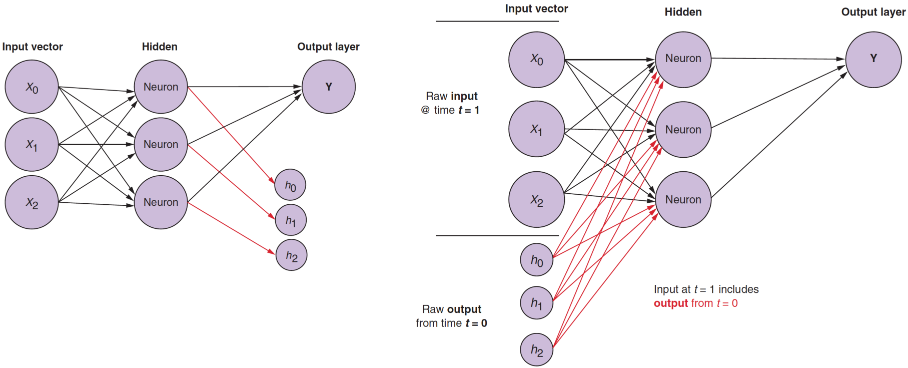


$t = 1$

(Lane et al., 2019, p. 252–253)

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



$t = 0$ $\qquad$ $t = 1$

- The red arrows are just *standard* connections, with weights

(Lane et al., 2019, p. 252–253)

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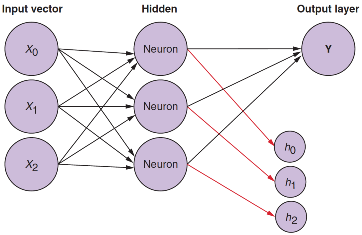

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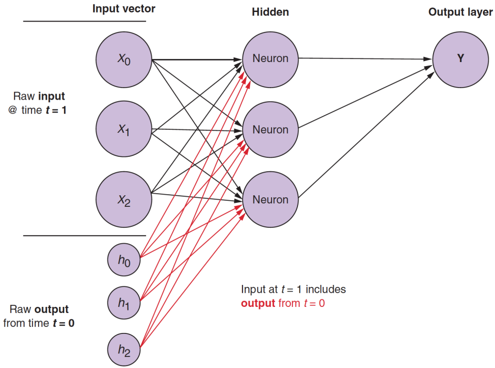
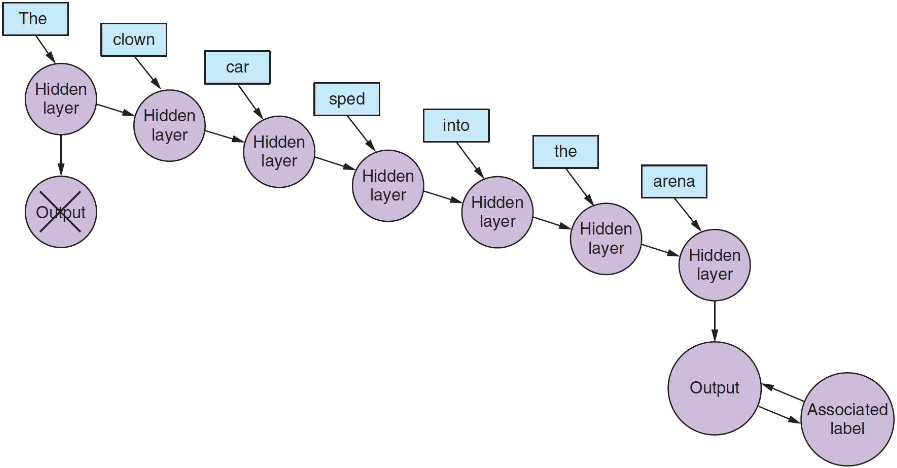


$t = 1$

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

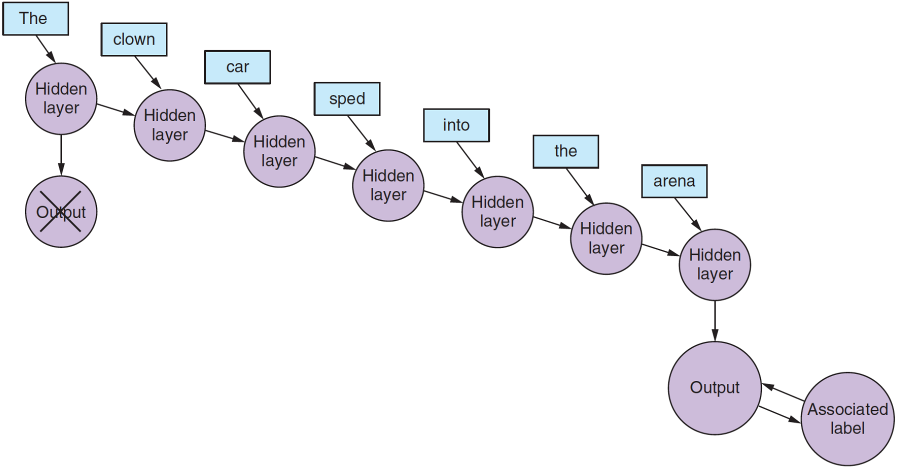
(Lane et al., 2019, p. 252–253)

"Multiple inputs, one output"



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

“Multiple inputs, one output”



- No more length constraints (although we have to be reasonable)

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

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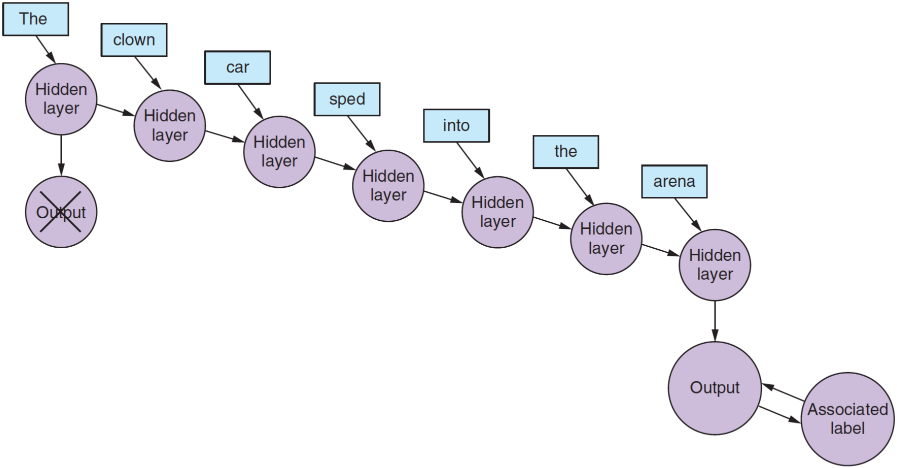
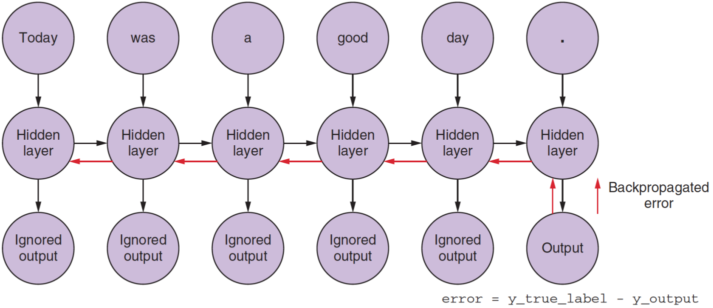


- No more length constraints (although we have to be reasonable)
- No more a bunch of snapshots; there is a sense of time

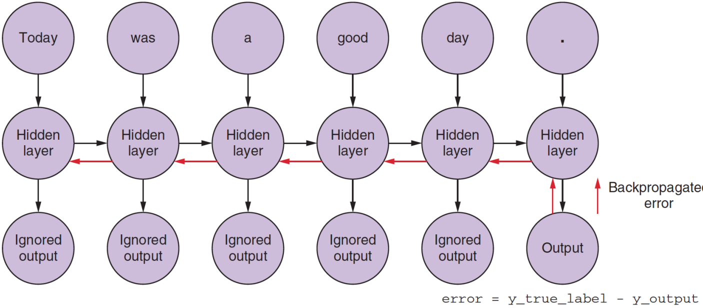
(Lane et al., 2019, p. 254)

Backpropagation through Time: the "Vanilla" Way



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

Backpropagation through Time: the "Vanilla" Way



- All intermediate outputs are ignored; the loss is computed at the end

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

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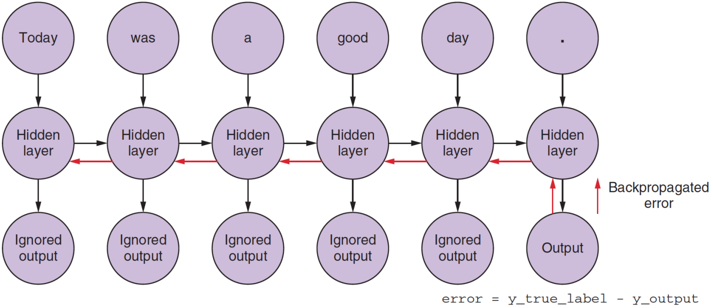

- All intermediate outputs are ignored; the loss is computed at the end
- The same chain rule is applied to do backpropagation; but this time it heads to “the past”

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

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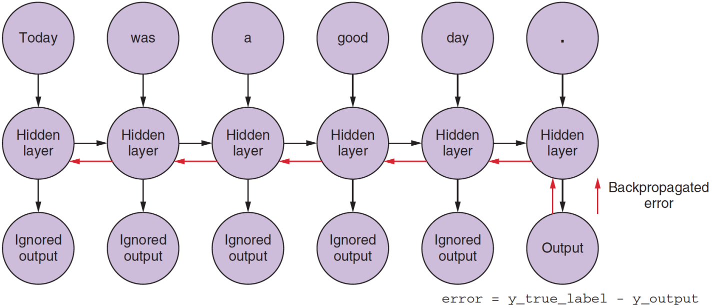

- All intermediate outputs are ignored; the loss is computed at the end
- The same chain rule is applied to do backpropagation; but this time it heads to "the past"
- The weight corrections are calculated for each t

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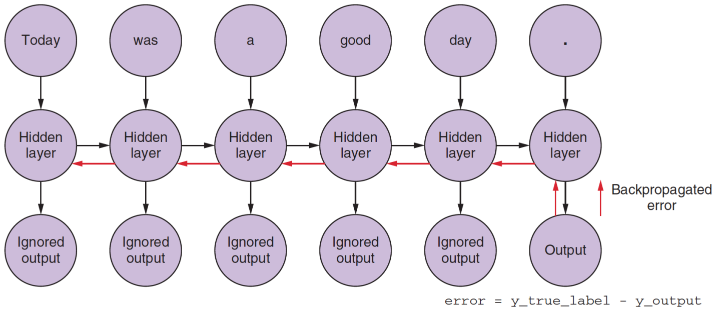
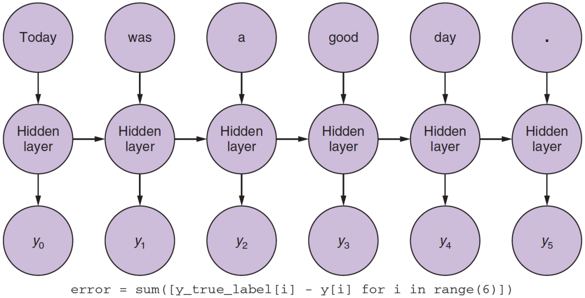


- All intermediate outputs are ignored; the loss is computed at the end
- The same chain rule is applied to do backpropagation; but this time it heads to "the past"
- The weight corrections are calculated for each t
- The combined updates are applied only until reaching $t = 0$

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

Backpropagation through Time: the Better Way



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

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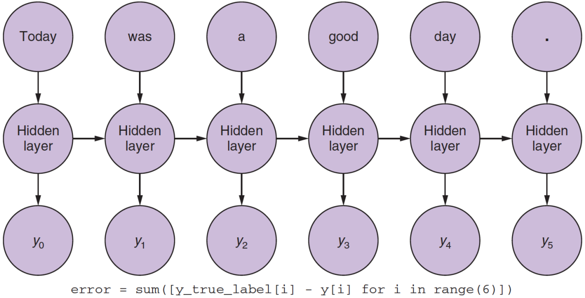
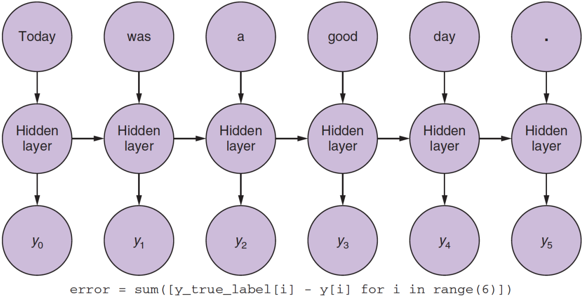


- We compute the loss combining all intermediate outputs

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

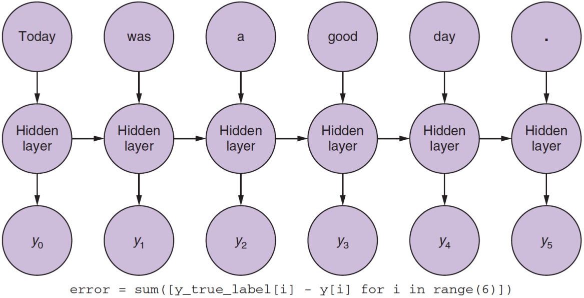
Backpropagation through Time: the Better Way



- We compute the loss combining all intermediate outputs
- The weight corrections are still additive: the update is applied until
    1. computing all errors and

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

Backpropagation through Time: the Better Way



- We compute the loss combining all intermediate outputs
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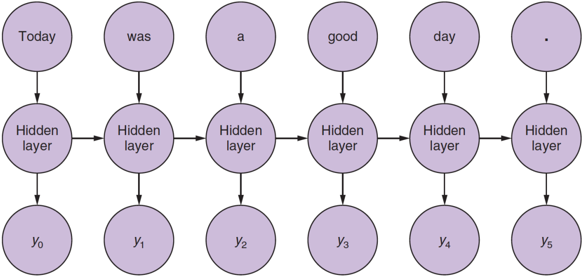


```
error = sum([y_true_label[i] - y[i] for i in range(6)])
```

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Let us see

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

RNNs in Keras

RNN in Keras: what we have so far

We have setup a simple recurrent neural network

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RNN in Keras: further details

- A `Dense` layer expects a *flat* vector

Example derived from https://stackoverflow.com/questions/43237124/role-of-flatten-in-keras

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model.add(Flatten())
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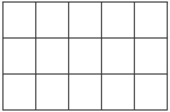
5×3



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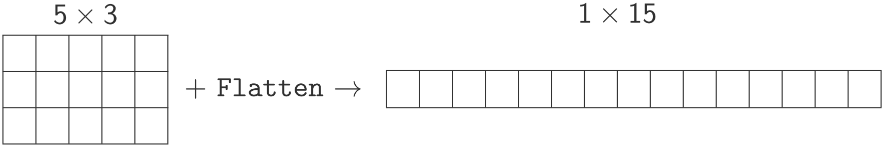

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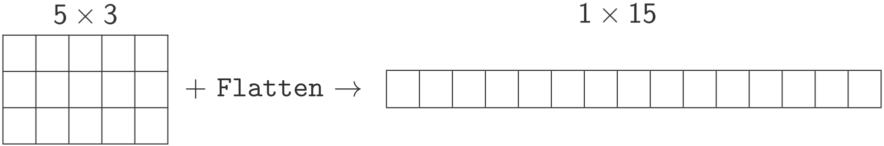

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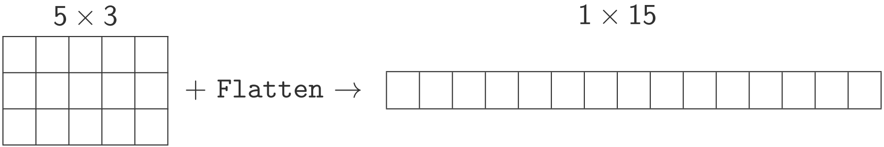

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embedding_dims comes from the embedding space; hard to change, but possible: other embeddings, 1-hot

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Try some sensitive configurations and keep track of all the settings and outputs[1]

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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
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