92586 Computational Linguistics

16. Recurrent Neural Networks

Alberto Barrón-Cedeño

Alma Mater Studiorum-Università di Bologna
a.barron@unibo.it @_albarron_

7/05/2020

Previously

- CNNs for text

Table of Contents

Chapter 8 of Lane et al. (2019)

Introduction

Introduction

CNNs

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

What is missing?

- Keeping track of what happened long ago
- Memory

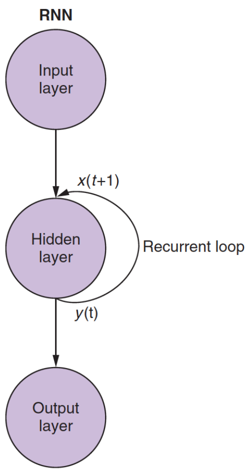
- Language is **not an image** —no snapshots
- Language is a **sequence**; both text and speech

Keeping the past in mind

Remembering the Past

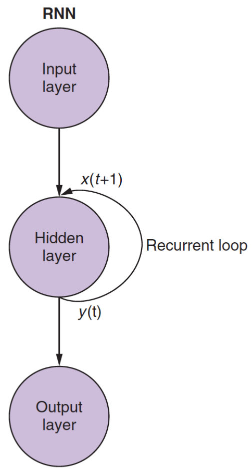
$$w_0\ w_1\ w_2\ w_3\ \ldots\ w_{t-1}\ w_t\ w_{t+1}$$

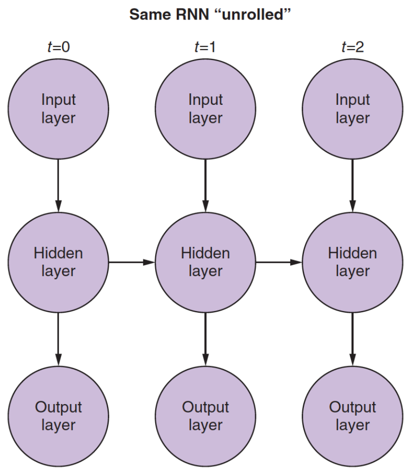
- To understand a text at time t, we need to keep in mind what happened at time $t-k$
- Recurrent neural nets come into play
- **RNNs** combine what happened before with what happens now



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

Full feed-forward networks that consider their own output

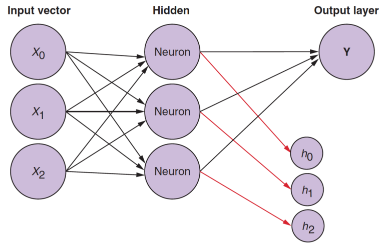




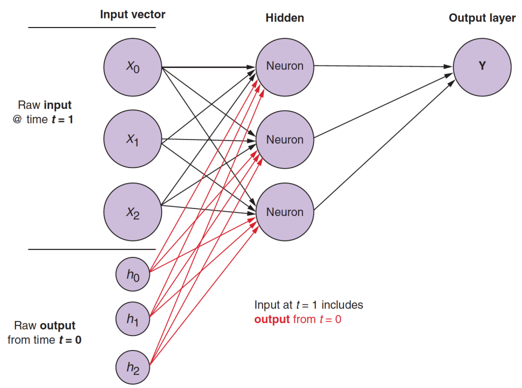
(all three columns are the same)

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

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



$t = 0$

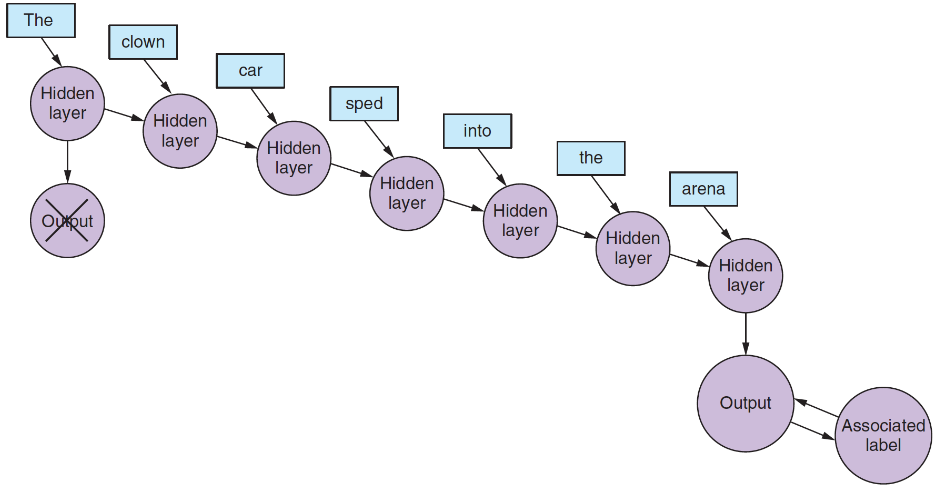


$t = 1$

- 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)

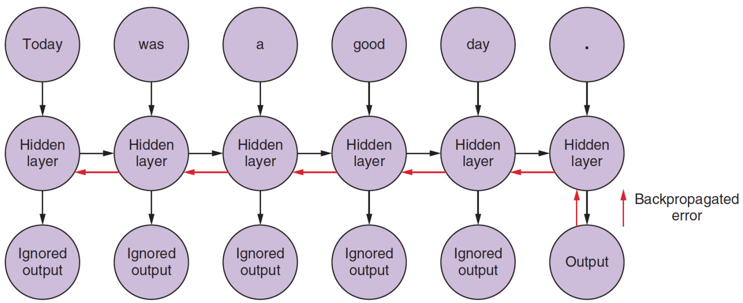
"Multiple inputs, one output"



- 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

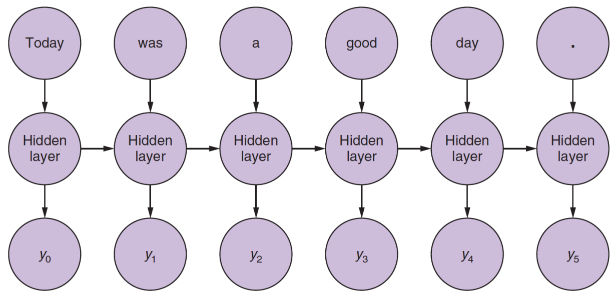



```
error = y_true_label - y_output
```

- 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




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

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

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

- The input sequences have fixed length: 400 tokens (each 300D)
- Our recurrent layer contains 50 neurons
- The output will be 400×50:
  - 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)

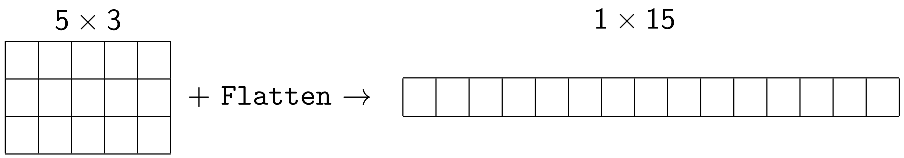
True → this is why we are padding

Let us see

RNN in Keras: further details

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

```
model.add(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

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 (don't start 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

What is next?

- Consider the output of a previous instances (not only within one)
- Go bidirectional

```
from keras.models import Sequential
from keras.layers import SimpleRNN
from keras.layers.wrappers import Bidirectional
num_neurons = 10
maxlen = 100 embedding_dims = 300 model = Sequential()
model.add(Bidirectional(SimpleRNN(num_neurons,
return_sequences=True),
input_shape=(maxlen, embedding_dims)))
```

- Long Short-Term Memories (LSTM) (Lane et al., 2019, Chapter 9)

Recap

Recap: The path

1. Baby steps into computing
2. What is NLP? From rule-based to statistical
3. Pre-processing text: tokens, stemming, stopwording...
4. From words to vectors: the vector space model
5. A few supervised models
6. Training and evaluating in machine learning
7. From words to meaning: topic modeling
8. Using one neuron: perceptrons
9. Fully-connected neural networks
10. From words to semantics: word embeddings
11. Taking snapshots of texts: CNNs
12. Texts as sequences: RNNs

Recap: The future path

1. Deeper and better memory: LSTM
2. Producing sequences: sequence-to-sequence models & attention

That's 8 out of 10 chapters of Natural Language Processing in Action!

You are ready to go on your own now

Celebrate the end of the course

worry about your project from Monday!

Still here??

- **No more lessons**
- Feedback, comments? Please, **drop an email**
- I'm available during the lesson times for 1-to-1 discussion on your project **upon request!**
- It would be nice to have the poster session, in September **(COVID will)**
- **Meanwhile, take care!**

References

Lane, H., C. Howard, and H. Hapkem
2019. *Natural Language Processing in Action*. Shelter Island, NY: Manning Publication Co.