Part-of-Speech Tagging: Neural Methods

Katharina Kann — CSCI/LING5832

Word Classes: Parts of Speech

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  - Lots of names for this notion: Part of speech, lexical category, word class, morphological class, lexical tag...
  - Lots of debate within linguistics about the number, nature, and universality of these categories

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- Sources of evidence
  - Morphological evidence
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  - Distributional evidence
    - The crash, A crash, Two crashes, The big crash…
    - probably a noun

Penn Treebank POS Tagset

Tag	Description	Example	Tag	Description	Example
CC	coordin. conjunction	*and, but, or*	SYM	symbol	+,%, &
CD	cardinal number	*one, two, three*	TO	“to”	*to*
DT	determiner	*a, the*	UH	interjection	*ah, oops*
EX	existential ‘there’	*there*	VB	verb, base form	*eat*
FW	foreign word	*mea culpa*	VBD	verb, past tense	*ate*
IN	preposition/sub-conj	*of, in, by*	VBG	verb, gerund	*eating*
JJ	adjective	*yellow*	VBN	verb, past participle	*eaten*
JJR	adj., comparative	*bigger*	VBP	verb, non-3sg pres	*eat*
JJS	adj., superlative	*wildest*	VBZ	verb, 3sg pres	*eats*
LS	list item marker	*1, 2, One*	WDT	wh-determiner	*which, that*
MD	modal	*can, should*	WP	wh-pronoun	*what, who*
NN	noun, sing. or mass	*llama*	WP$	possessive wh-	*whose*
NNS	noun, plural	*llamas*	WRB	wh-adverb	*how, where*
NNP	proper noun, singular	*IBM*	$	dollar sign	$
NNPS	proper noun, plural	*Carolinas*	#	pound sign	#
PDT	predeterminer	*all, both*	“	left quote	‘ or “
POS	possessive ending	*’s*	”	right quote	’ or ”
PRP	personal pronoun	*I, you, he*	(	left parenthesis	[, (, {, <
PRP$	possessive pronoun	*your, one’s*	)	right parenthesis	],), }, >
RB	adverb	*quickly, never*	,	comma	,
RBR	adverb, comparative	*faster*	.	sentence-final punc	. ! ?
RBS	adverb, superlative	*fastest*	:	mid-sentence punc	: ; ... – -
RP	particle	*up, off*			

POS Tagging

- The process of assigning a part of speech or lexical class marker to each word in a text.
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- Often a useful first step in an NLP pipeline.
- Fast and accurate taggers are widely available for many languages.
  - (Now we will learn how to make one!)

POS Tagging

- The process of assigning a part of speech or lexical class marker to each word in a text.
- The is our first example of a **sequence labeling** task:
  - Assigning a category label to each element of a sequence.

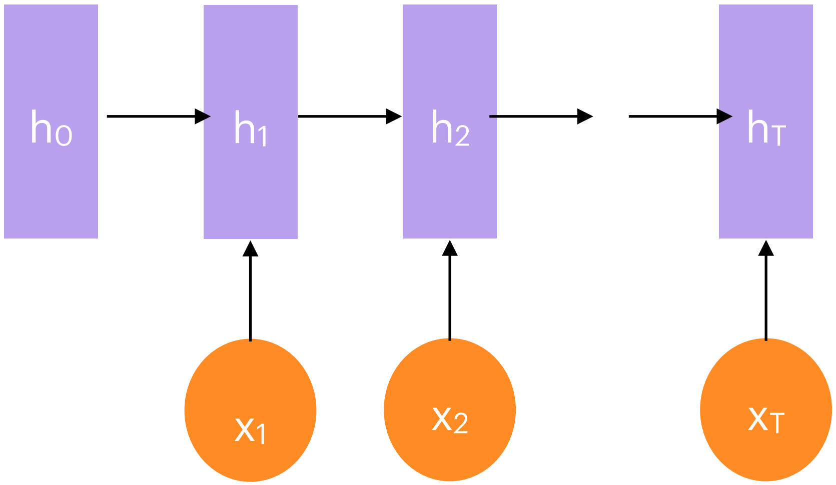
Recap from Lecture 07: More on RNNs

Recurrent Neural Networks

Input: $x_1, x_2, \ldots, x_T$

$h_i = \text{sigmoid}(W_h h_{i-1} + W_x x_i)$

$y = argmax(\text{softmax}(W_y h_T))$



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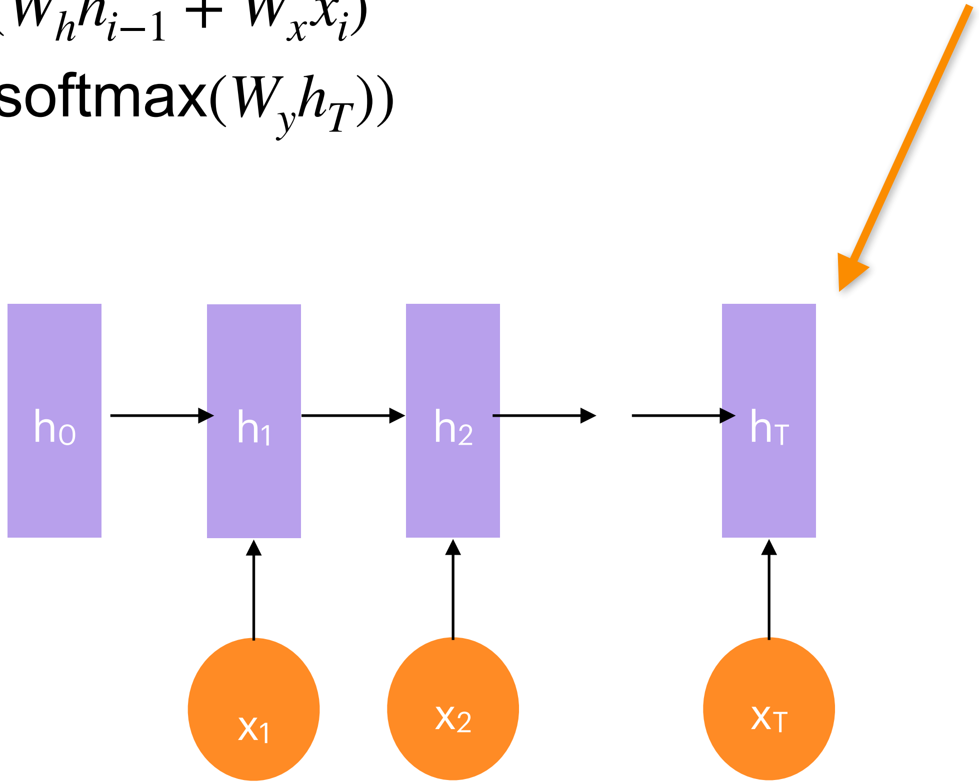

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- History gets forgotten over time.

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The flights the airline was cancelling were full.

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Solutions

- **Gradient Clipping**: Normalize the gradient of a parameter vector when its L2 norm reaches a certain value.

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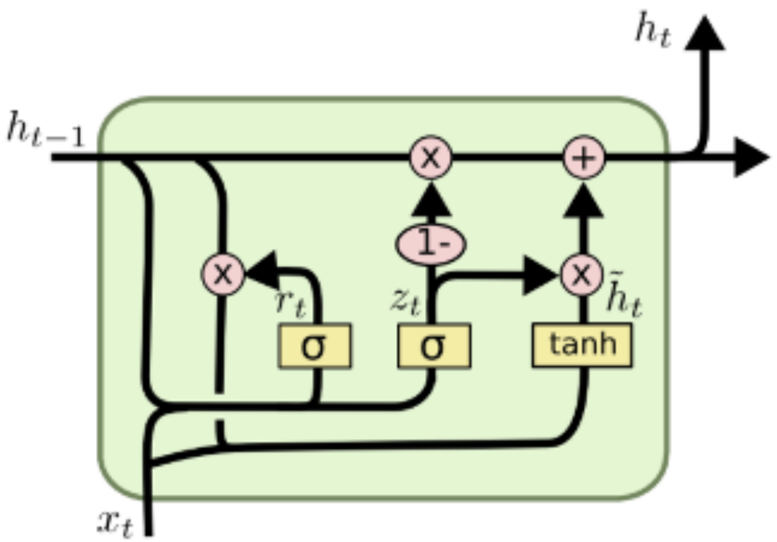
- Explicit **memory cell** with which a model can keep important long-term information.

Gated Recurrent Units (GRUs)



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Visual Obtained from: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

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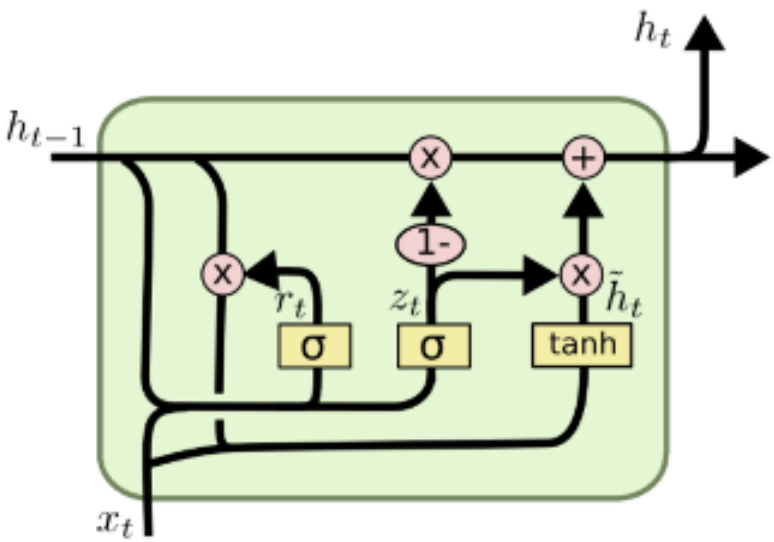

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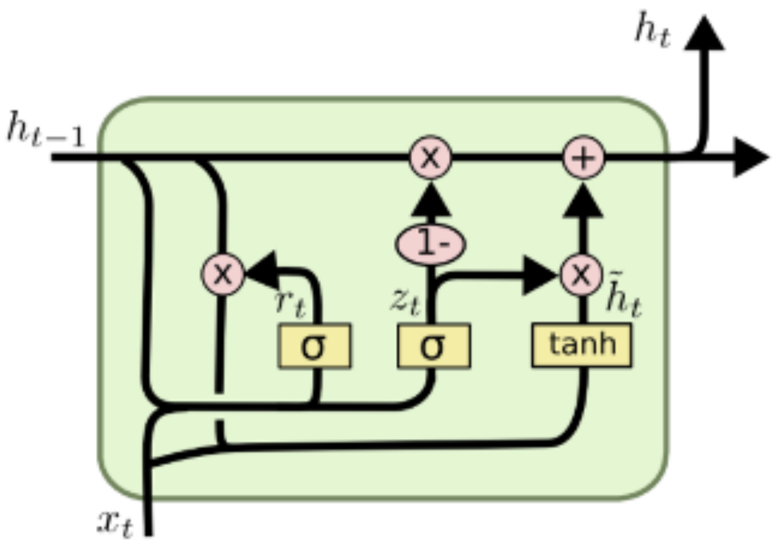

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Reset gate: controls how much of the previous hidden state to keep

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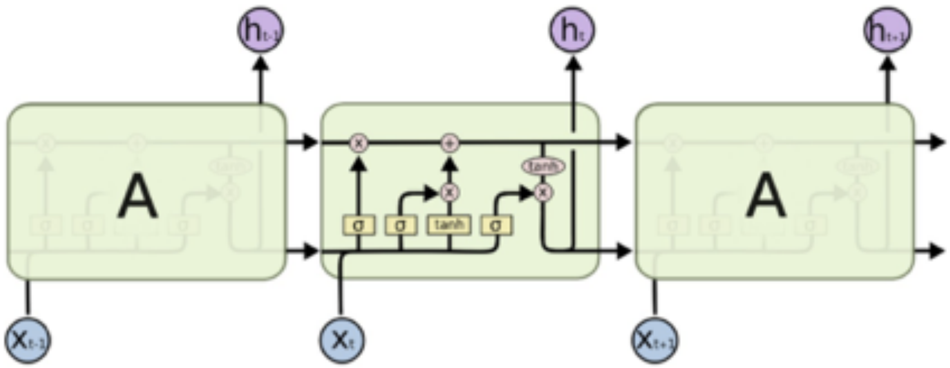
Long Short-Term Memory Networks (LSTMs)

- First proposed by Hochreiter and Schmidhuber (1997).
- Similar to the GRU, but some more parameters.
- Performance is usually extremely similar.

Long Short-Term Memory Networks (LSTMs)



The repeating module in an LSTM contains four interacting layers.

$$
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g_t &= tanh(U_g h_{t-1} + W_g x_t) \\
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o_t &= \sigma(U_o h_{t-1} + W_o x_t) \\
c_t &= f_t \odot c_{t-1} + i_t \odot g_t \\
h_t &= o_t \odot tanh(c_t)
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Visual Obtained from: http://colah.github.io/posts/2015-08-Understanding-LSTMs/, J&M, Ch.9

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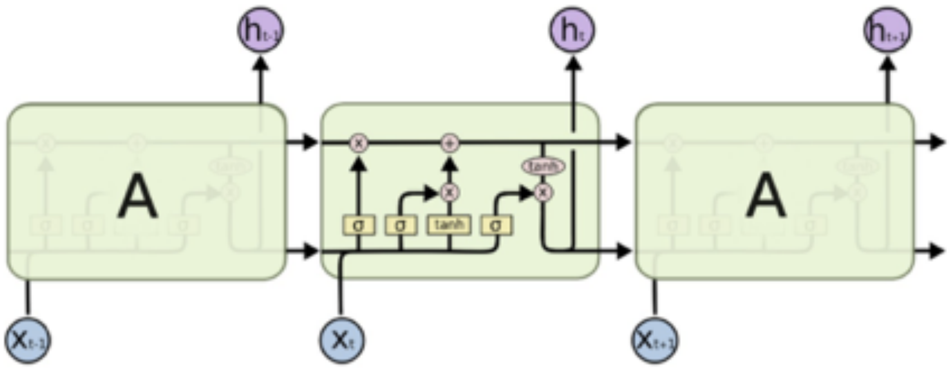

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Add gate

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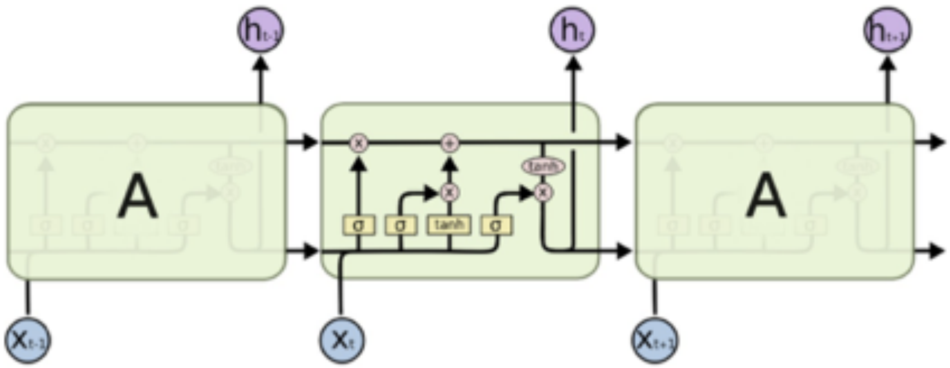

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Forget gate

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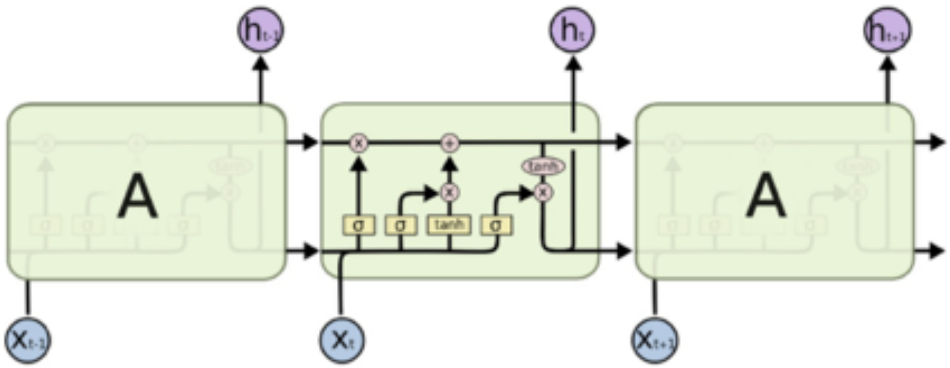

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Output gate

Visual Obtained from: http://colah.github.io/posts/2015-08-Understanding-LSTMs/, [J&M, Ch.9]()

How Do We Get a Sentence Representation?

- Apply the RNN to all words in a sequence.
- Use the last hidden vector as the representation of your sentence.
- The sentence representation is often called *h*.

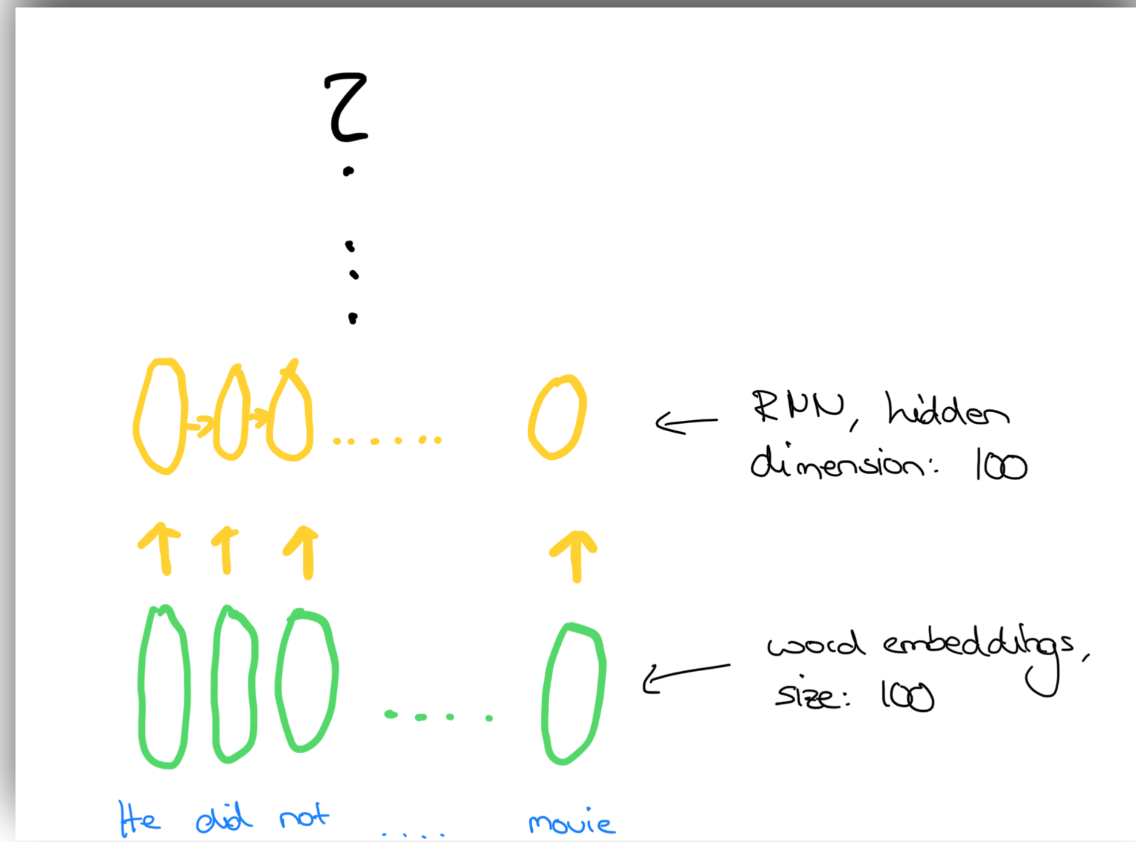
Bidirectional Recurrent Neural Networks

- Most prominent one: BiLSTM
- Idea: Read the input from both sides.
  - Beginning isn’t forgotten!
- For the final representation:
  - Concatenate the last hidden vectors of the two individual RNNs.
  - (What is the size of the final sentence representation computed by a bidirectional RNN?)

In-Class Exercise (Exercise 3 in Lecture 07)

- Assume that we want to classify the sentiment of tweets into *positive*, *neutral*, and *negative*.
- Design a neural network that can learn this task, given a large-enough training set.
- Which preprocessing steps do we need?
- Write down all dimensions explicitly. What is your output dimension?
- (Keep your architecture safe for later!)

In-Class Exercise (Exercise 3 in Lecture 07)



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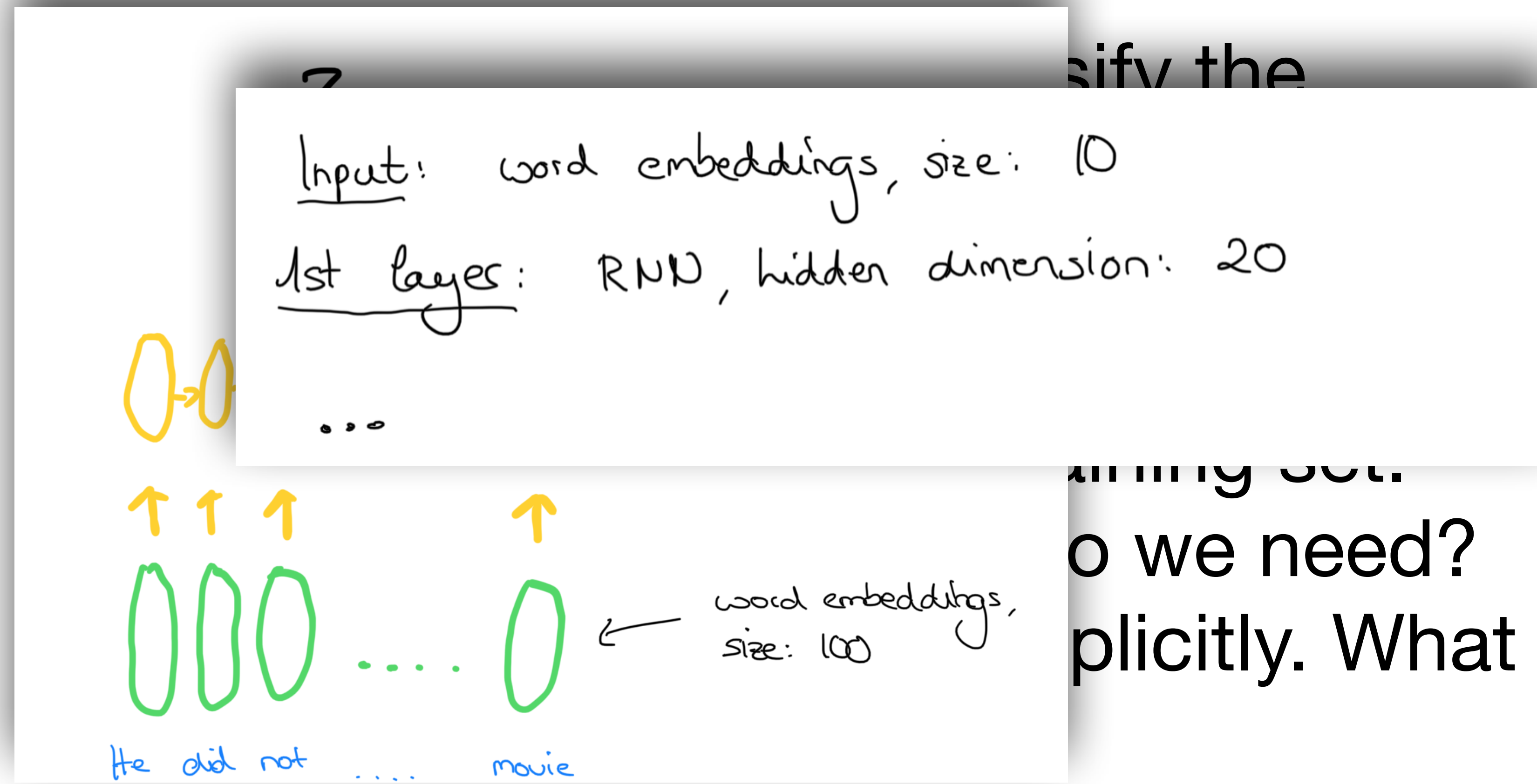

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RNNs for Sequence Labeling

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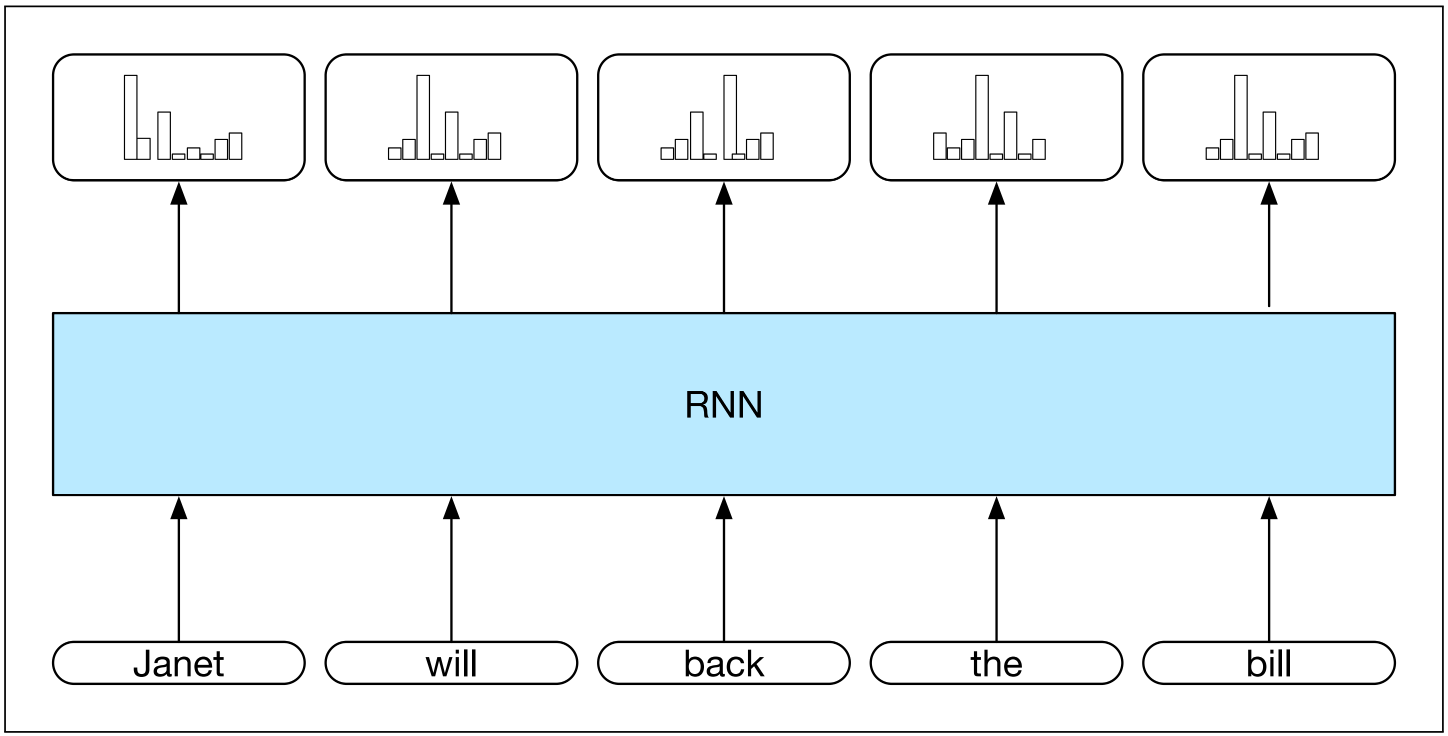
- For sequence labeling, we don’t exclusively use the last hidden state of the RNN
    - (Why?)

Sequence Labeling with RNNs

- For sequence labeling, we don't exclusively use the last hidden state of the RNN
  - (Why?)
- Instead, we assign a class to each hidden state
  - Use a feedforward layer and a sigmoid/softmax function

Sequence Labeling with RNNs



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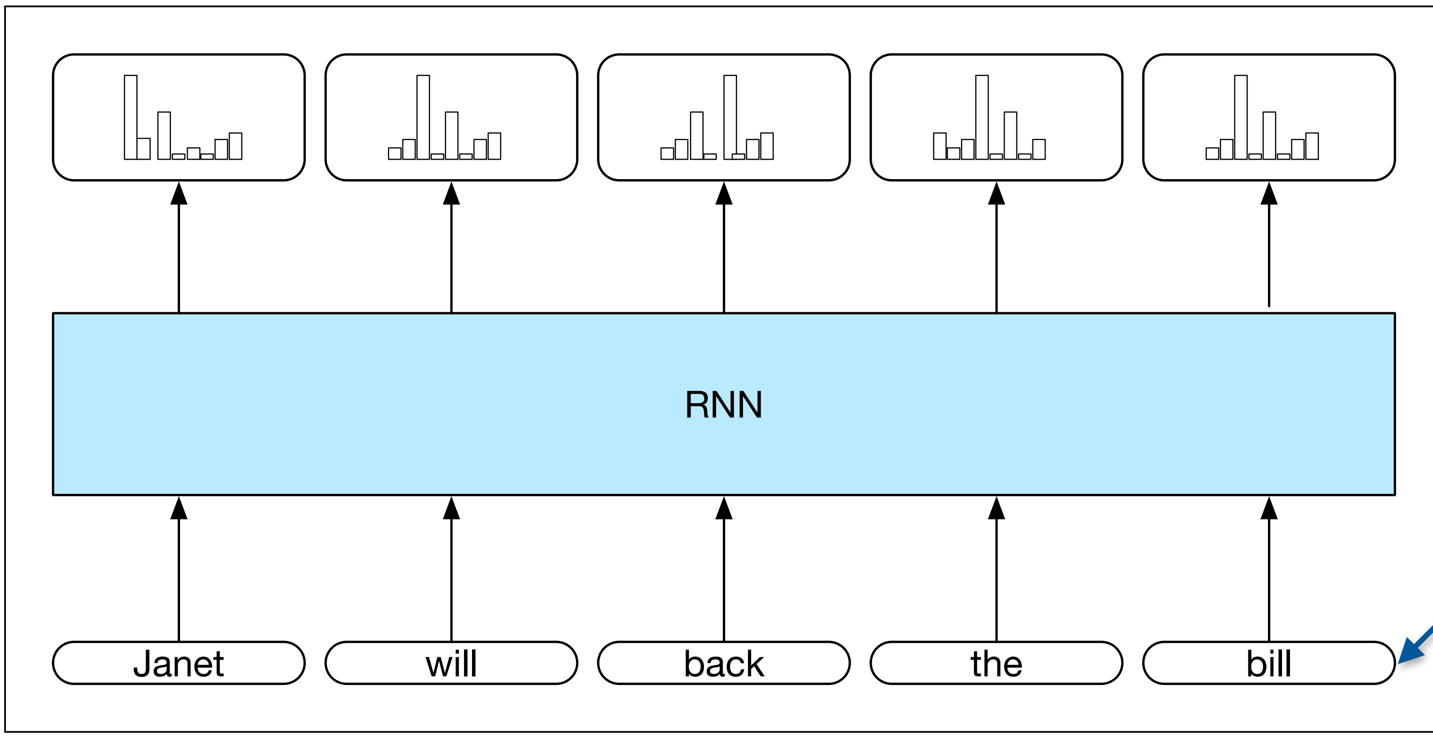

Input: word embeddings

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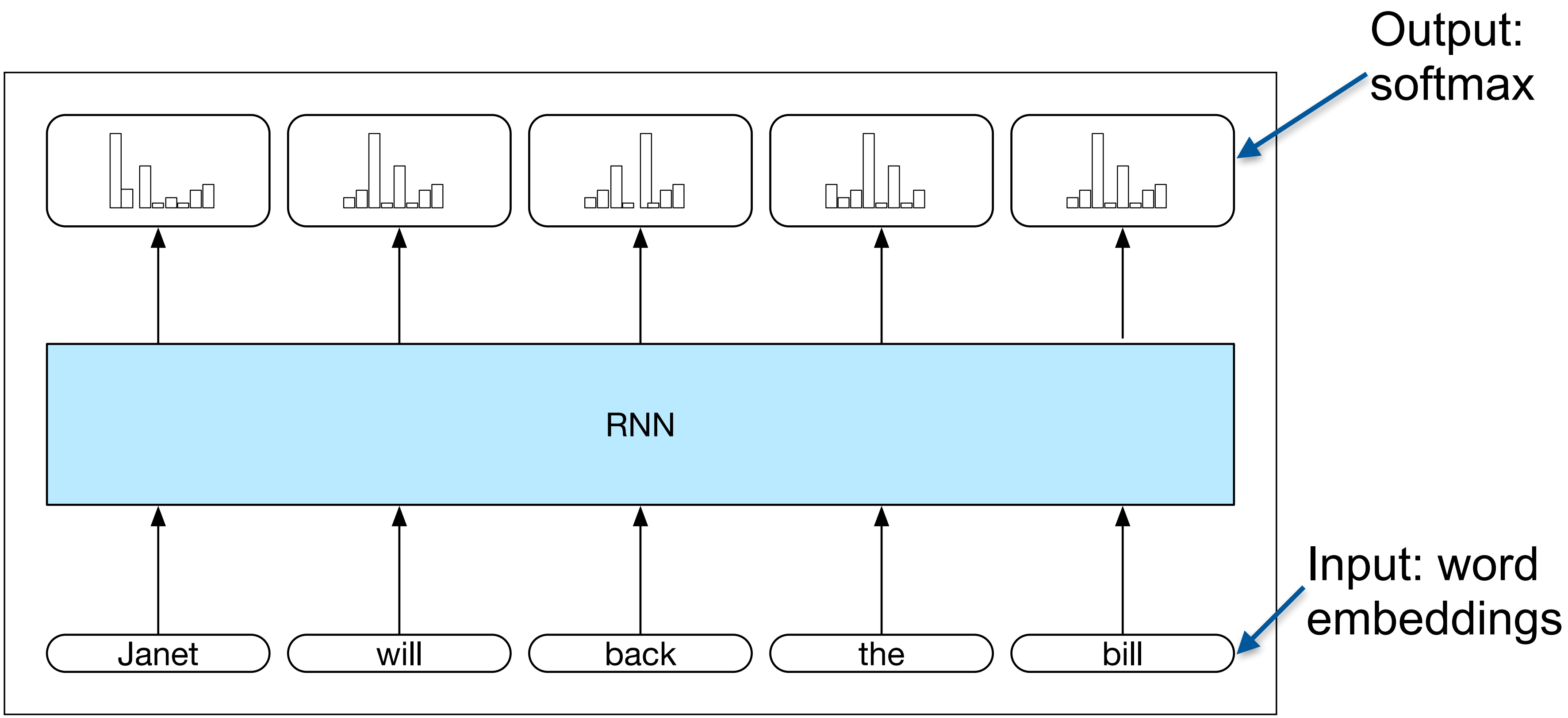
Sequence Labeling with RNNs



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Example: Sequence Labeling with RNNs

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- (What would be the formula to predict the label for sequence labeling?)

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- **we like books**

- we = [1, 2], like = [0.5, 0.1], books = [0.2, 1]
- W_h = [[0.4]], W_x = [[0.1, 0.14]], W_y = [[0.3], [0.2], [0.01]], h_0 = [0]
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In-Class Exercise 2

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- Compute the classes of “like” and “books”!

Hierarchical LSTMs

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  - help**ful**, joy**ful**, cheer**ful**, …

Characters and POS Tagging

- We want to use this information for POS tagging
- How can we do that?

Characters and POS Tagging

- We want to use this information for POS tagging
- How can we do that?
  - RNN over characters

Characters and POS Tagging

- We want to use this information for POS tagging
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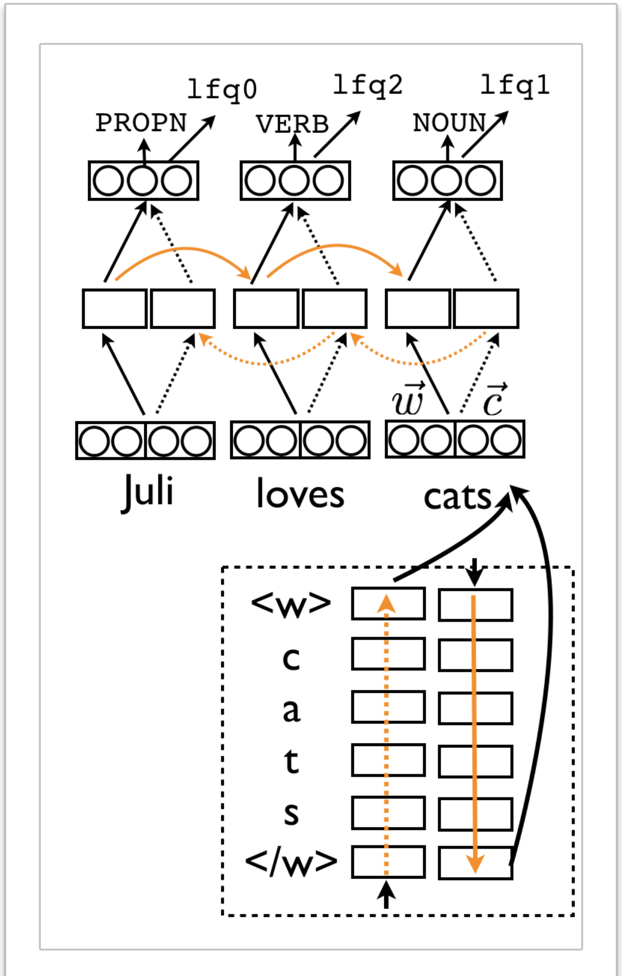
  - CNN over characters

Characters and POS Tagging

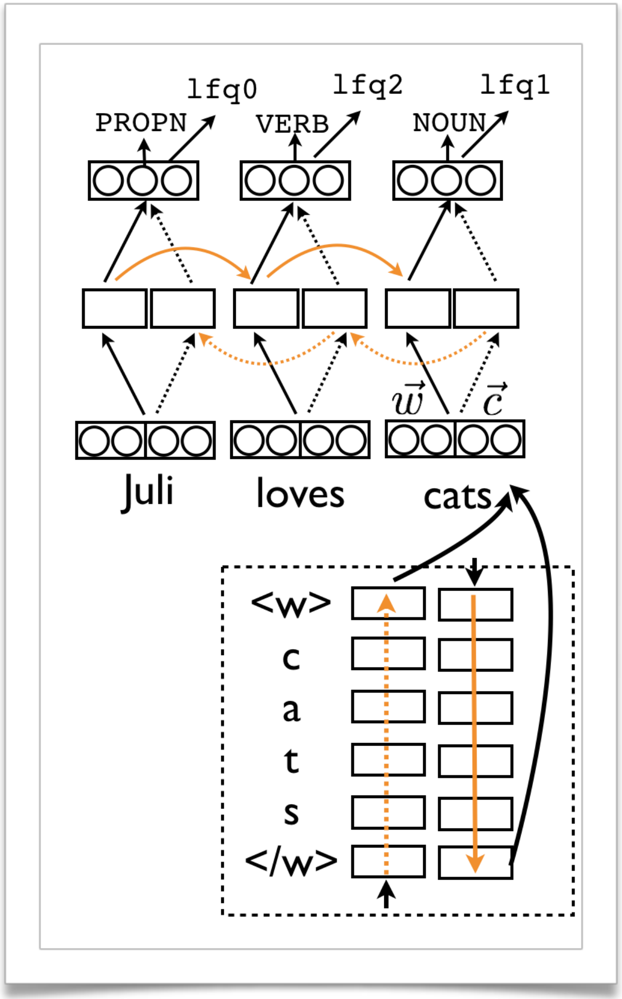
- We want to use this information for POS tagging
- How can we do that?
  - RNN over characters
  - CNN over characters
  - Two RNNs: one over characters and one over words!

Hierarchical RNN for POS Tagging



From [Plank et al., 2016]()

Hierarchical RNN for POS Tagging



From [Plank et al., 2016]

- Concatenate last hidden states of the character-level RNN with the word embeddings!

Other Sequence Labeling Tasks in NLP

Named Entity Recognition

- Named entities are spans in a text that correspond to names of people, places or organizations:
  - Barack Obama
  - CNN
  - Donald Trump Jr.
- Task: Find named entities in a given text
  - This required finding **spans** which correspond to named entities

IOB Encoding

- Label token with
  - B: beginning of span of interest
  - I: inside of span of interest
  - O: “outside”, not part of the span of interest

Named Entity Recognition

(9.13) *United cancelled the flight from Denver to San Francisco.*

B O O O O B O B I

J&M, Ch.9

Named Entity Recognition

(9.13)	*United*	*cancelled*	*the*	*flight*	*from*	*Denver*	*to*	*San*	*Francisco.*
	B	O	O	O	O	B	O	B	I

J&M, Ch.9

(9.14)	*United*	*cancelled*	*the*	*flight*	*from*	*Denver*	*to*	*San*	*Francisco.*
	B-ORG	O	O	O	O	B-LOC	O	B-LOC	I-LOC

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- We can encode more detail!

More Sequence Labeling Tasks

- Morphological tagging
- Language identification for code-switched text
- Constituency parsing
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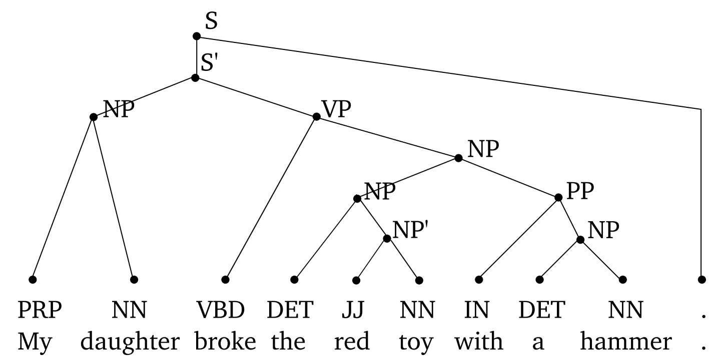

Linearized tree (absolute scale):

3NP 2S' 3VP 5NP 6NP' 4NP 5PP 6NP 1S

Linearized tree (relative scale):

3NP -1S' 1VP 2NP 1NP' -2NP 1PP 1NP -5S

Linearized tree (simplified relative scale):

3NP -S' 1VP 2NP 1NP' -NP 1PP 1NP -S

Figure 2: An example of a binarized constituency tree, linearized both applying absolute and relative scales.

From [Gomez-Rodrıguez and Vilares (2018)](#)

Wrapping up

- Discussed today:
  - Recap: RNNs
  - RNNs for sequence labeling tasks
  - Hierarchical RNNs

- On Wednesday: Training neural networks