Recurrent Neural Networks

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August 10, 2018

Motivation

Introduction

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- In natural language processing we often deal with sequences:
  - Characters
  - Tokens
  - Part-of-Speech tags
- If x^n is the n-th element of a sequence, we also want to take into account:
  - Preceding elements: $\mathbf{x}^1 \ldots \mathbf{x}^{n-2}, \mathbf{x}^{n-1}$
  - Preceding labeling choices: $y^1 \ldots y^{n-2}, y^{n-1}$

Example 1: part-of-speech tagging

(1) Hij hoorde/*vfin* de blikken vallen/*vinf* .
He heard the cans fall .

(Example from Prins, 2005)

- Dutch uses the same form for the infinitive and the third person plural of the verb *vallen* (*to fall*).

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- To assign a proper tag for the verb *vallen*, the tagger needs to memorize whether the finite verb for this clause has already occured.
- A trigram tagger will often mistag such infinitives.

Example 1: part-of-speech tagging

The tagger should **not** use this information in a relative clause:

(2) Hij hoorde/*vfin* de blikken die van de tafel
He heard the cans that off the table
vallen/*vfin* .
fall .

He heard the cans that fall of the table

Example 1: part-of-speech tagging

However, starting a relative clause should not drop the information either:

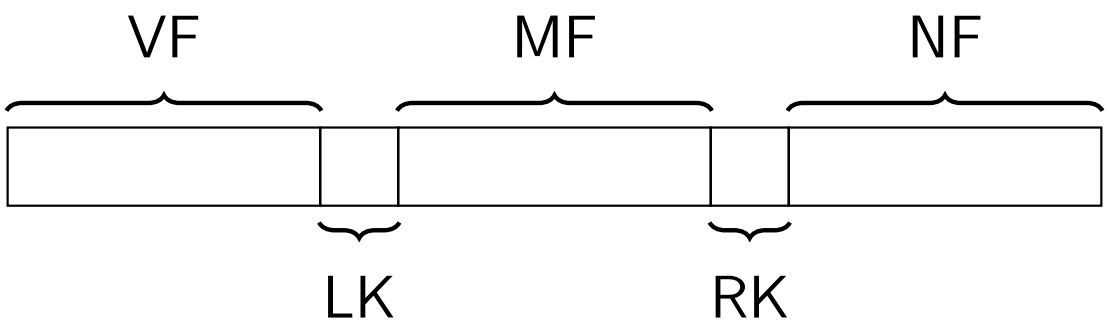
(3)

Hij	hoorde/*vfin*	de	blikken	,	die	Jan	aanstootte/*vfin*	,
He	heard	the	cans	,	that	Jan	nudged	,
vallen/*vinf*	.							
fall	.							

Example 2: topological fields

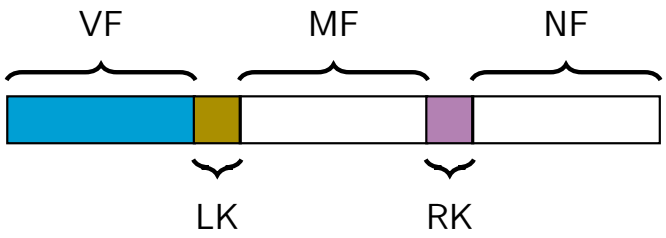
The **topological field model** has been used to account for regularities in word order across different clause types in many germanic languages (ie. German and Dutch).

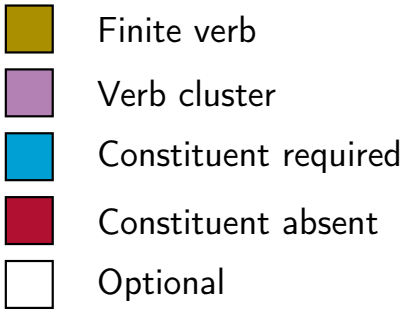
Example 2: topological fields



Example 2: topological fields

Declarative clause with auxiliary/modal verb:





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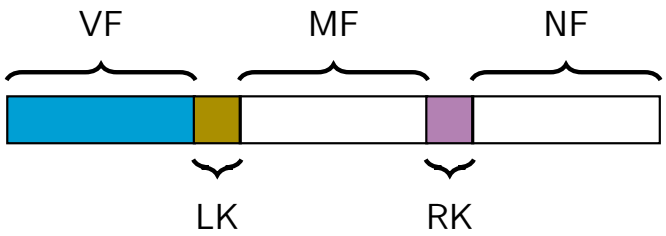

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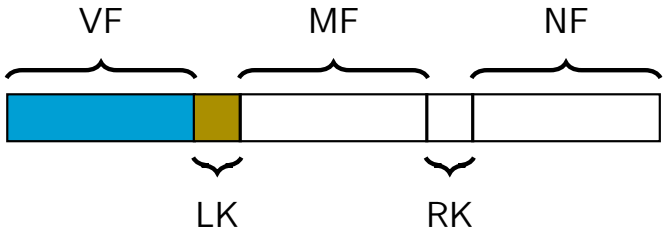

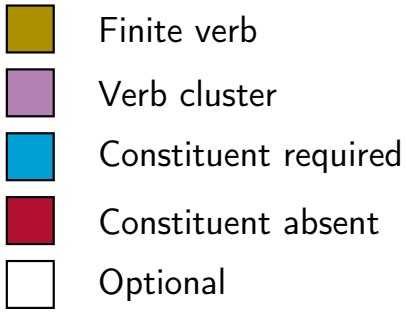

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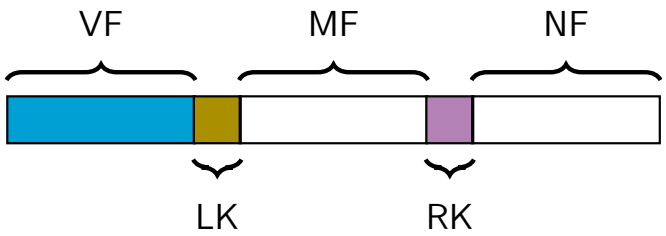

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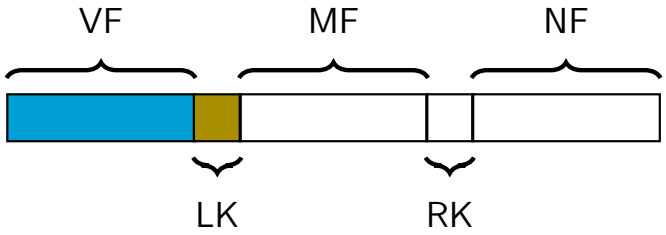
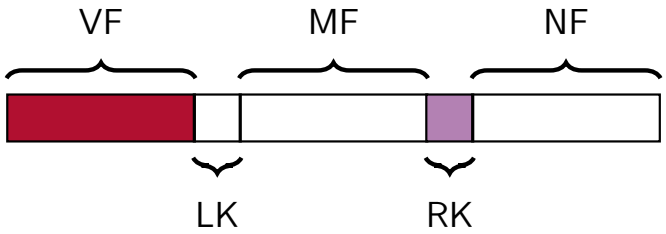
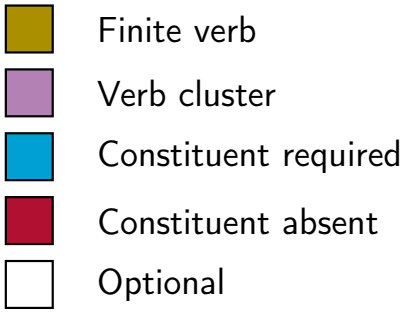


Verb-final subordinate clause:





Example 2: topological fields

	VF	LK	MF	RK	NF
MC:	Gestern	hat	er häufiger	angerufen	als heute
	Yesterday	has	he more-often	called	than today
MC:	Er	ruft	häufig	an	
	He	calls	frequently	up	
SC:		der	noch häufiger	anruft	als er
		who	more often	calls	than him

Example 2: topological fields

Topological field analysis can be seen as a sequence labeling task:

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Gestern	hat	er	häufiger	angerufen	als	heute
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- Preceding tokens are relevant: similarly to Dutch, V2 word order requires us to keep track of tokens that were seen earlier, such as verbs, separable verb particles, etc.
- Preceding classification choices are also relevant: e.g. the *MF* cannot precede the *VF*.

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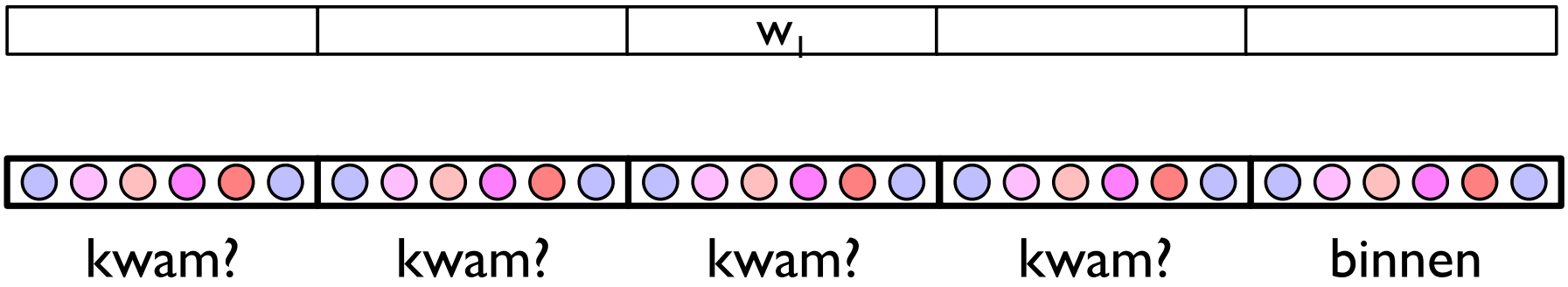
- Problems:
  - Sequences are variable-length, while feed-forward networks have a fixed-width input.
  - Dependencies between tokens may have large distances.
  - Does not generalize well, since the network would have to learn separate weights for some interesting phenomenon occuring in every position.

Long-distance dependencies

(5) Het kwam/*vfin* allemaal bij stukjes en brokjes bij de
It came all with bits and pieces at the
familie Balemans binnen/*part* .
family Balemans within .
It arrived at family Balemans in bits and pieces.

Lack of generalization



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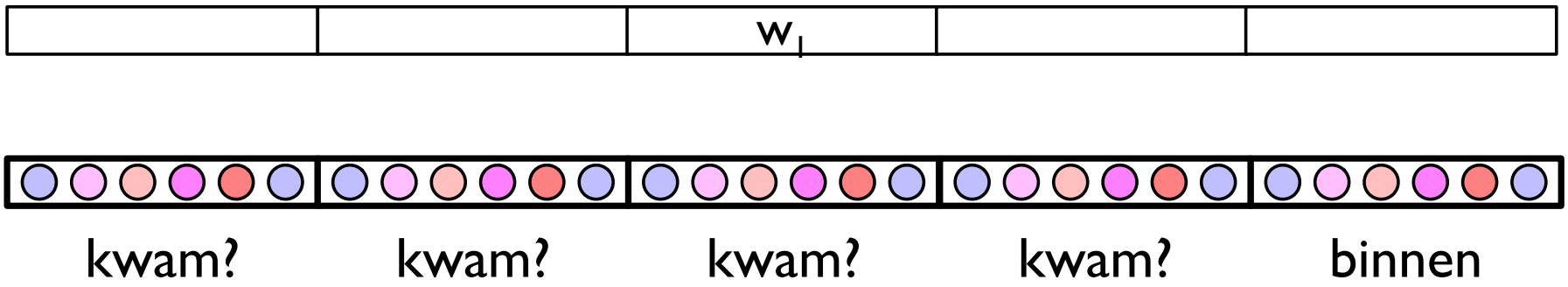

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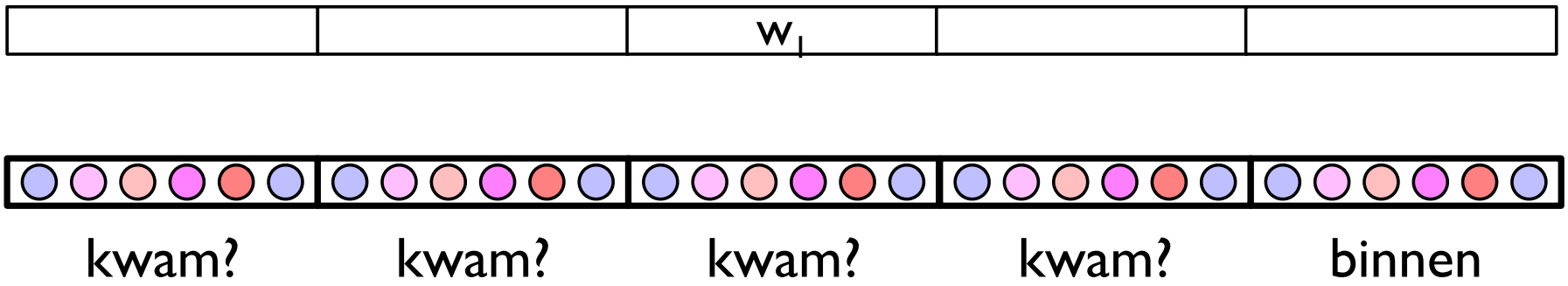

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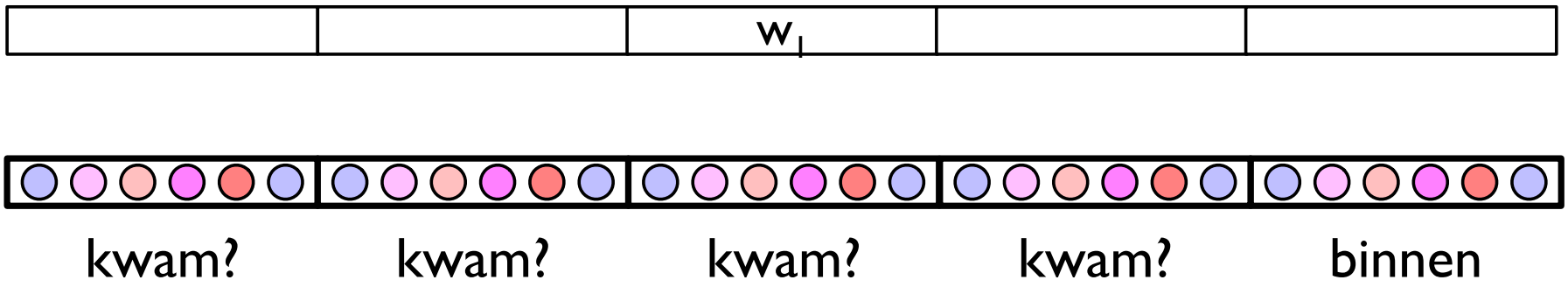

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- Problem: data sparseness.

Basic principles of RNNs

Goal

- Our goal is to process sequences of linguistic units (characters, words, etc.).

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  - The current element;
  - previous elements.

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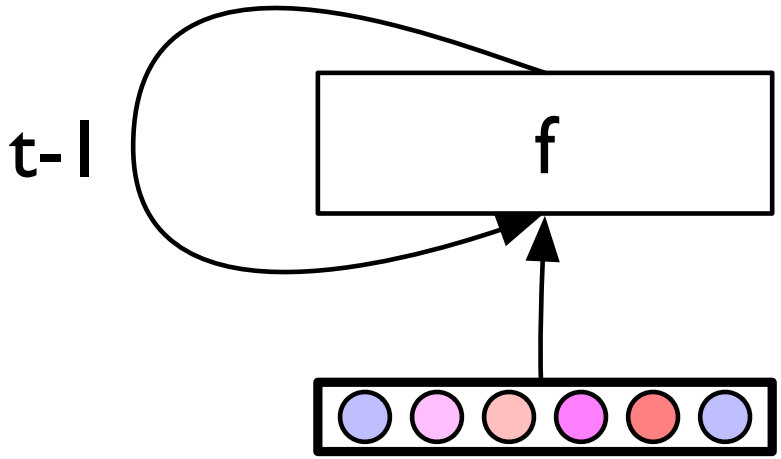
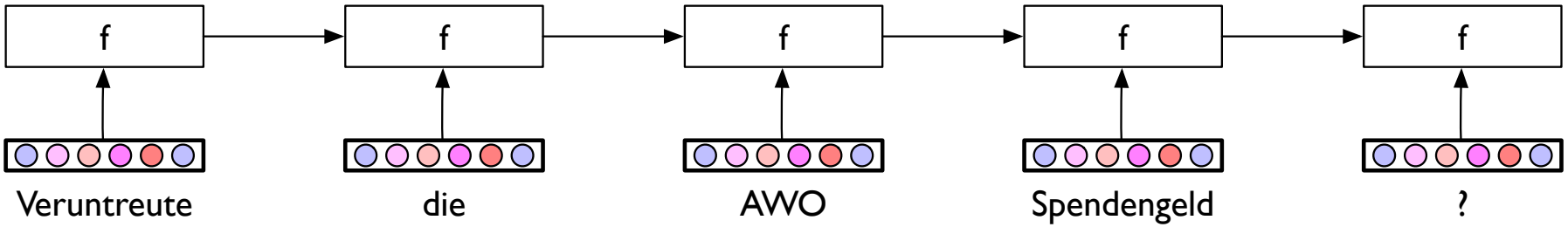
- $\boldsymbol{h}^{<i>}$ is a hidden layer at time step i.
- We will use $\boldsymbol{h}^{<i>}$ as a representation of time step i and all preceding time steps.
- We use a f to compute the hidden state.

$$\boldsymbol{h}^{<t>} = f(\boldsymbol{h}^{<t-1>}, \boldsymbol{x}^{<t>})$$

Graphically



Graphically (unrolled)



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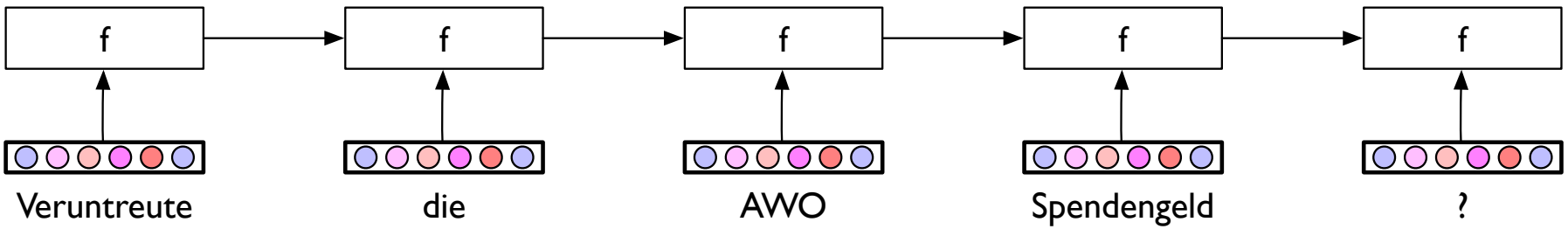

- Every timestep normally uses the same function/parameters.
- During training and prediction, the RNN is typically **unrolled**:
  - A different 'unit' is used for every time step.
  - Parameters are shared between units.

Sequence classification

- $\boldsymbol{h}^{<i>}$ can be used as a regular hidden layer:
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$$p(y|\boldsymbol{x}^{<1>\cdots<n>}) = \frac{e^{\boldsymbol{W}_y \boldsymbol{h}^{<n>}}}{\sum_{i=1}^{k} e^{\boldsymbol{W}_k \boldsymbol{h}^{<n>}}}$$

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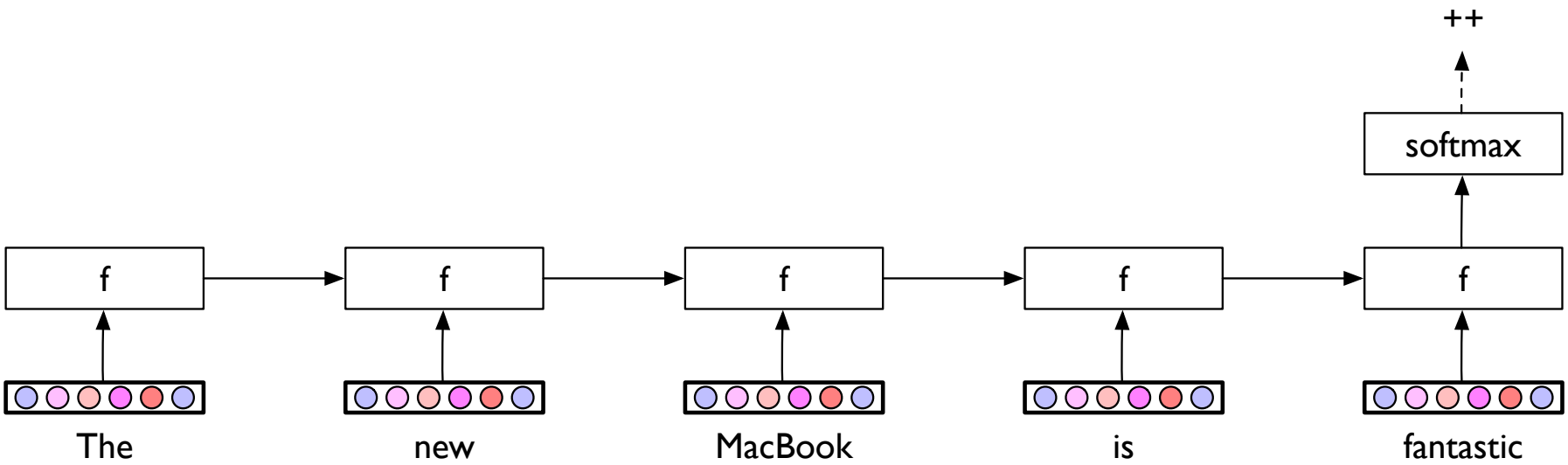
Examples:

- Sentiment analysis
- Question type classification
- Subjectivity detection

Sequence classification



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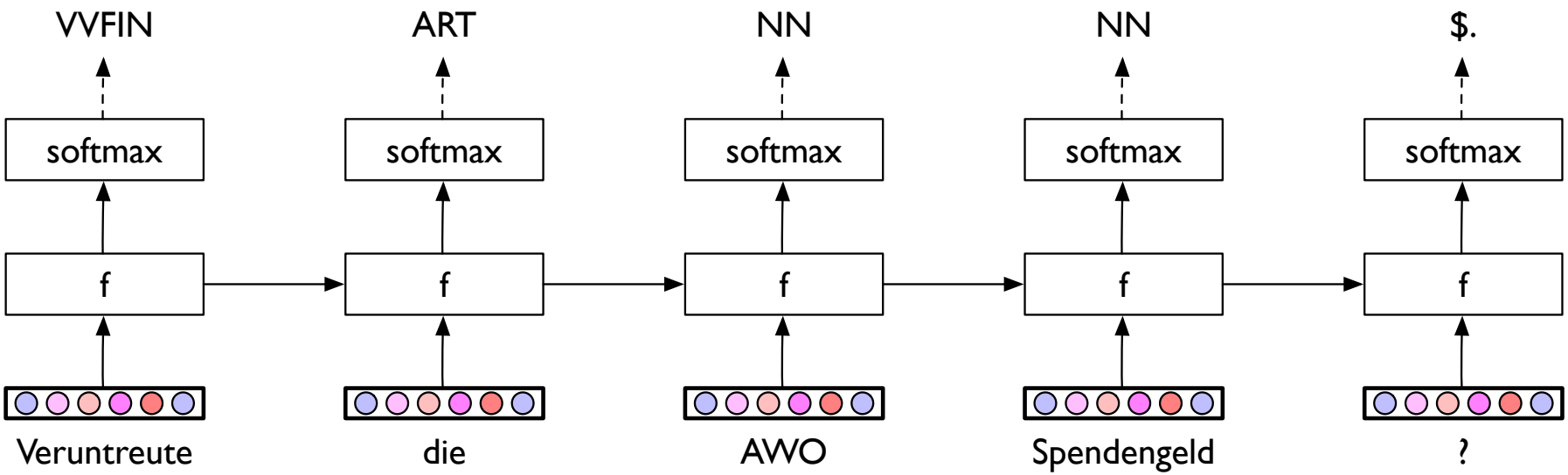
Examples:

- Tokenization
- Part-of-speech tagging
- **Topological field labeling**

Sequence labeling



Limits of left-context

(6) [die Siegerin]$_{\text{VF}}$ wurde disqualifiziert .
[the winner/*fem*] was disqualified .

(7) [die Siegerin]$_{\text{MF}}$ zu disqualifizieren .
[the winner/*fem*] to disqualify .

(De Kok & Hinrichs, 2016)

Forwards/backwards RNNs

- First we rename our existing hidden layer $\boldsymbol{h}^{<t>}$ to $\overrightarrow{\boldsymbol{h}}^{<t>}$

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  This is a **forward RNN**.
- Then we define a **backward RNN** $\overleftarrow{\boldsymbol{h}}^{t}$ that uses the hidden layer of a future timestep:

$$\overleftarrow{\boldsymbol{h}}^{<t>} = f(\overleftarrow{\boldsymbol{h}}^{<t+1>}, \boldsymbol{x}^{<t>})$$

Bidirectional RNN

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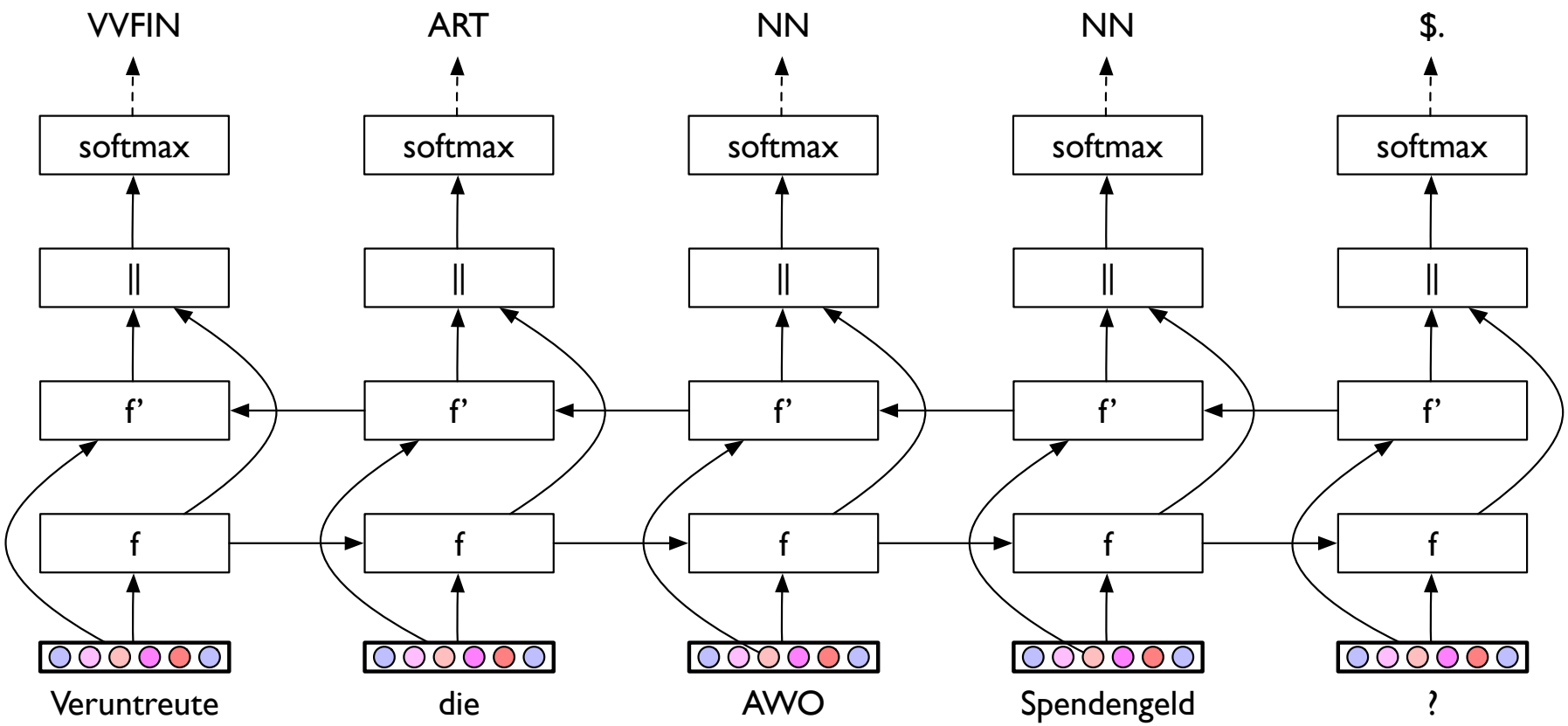
  - A forward RNN hidden layer; and
  - a backward RNN hidden layer.
- If $\|$ is the vector concatenation operator, such that $(\boldsymbol{u} \in \mathbb{R}^n \| \boldsymbol{v} \in \mathbb{R}^m) \in \mathbb{R}^{n+m}$, then:

$$\overleftrightarrow{\boldsymbol{h}}^{<t>} = \overrightarrow{\boldsymbol{h}}^{<t>} \| \overleftarrow{\boldsymbol{h}}^{<t>}$$

Bidirectional RNN for sequence labeling



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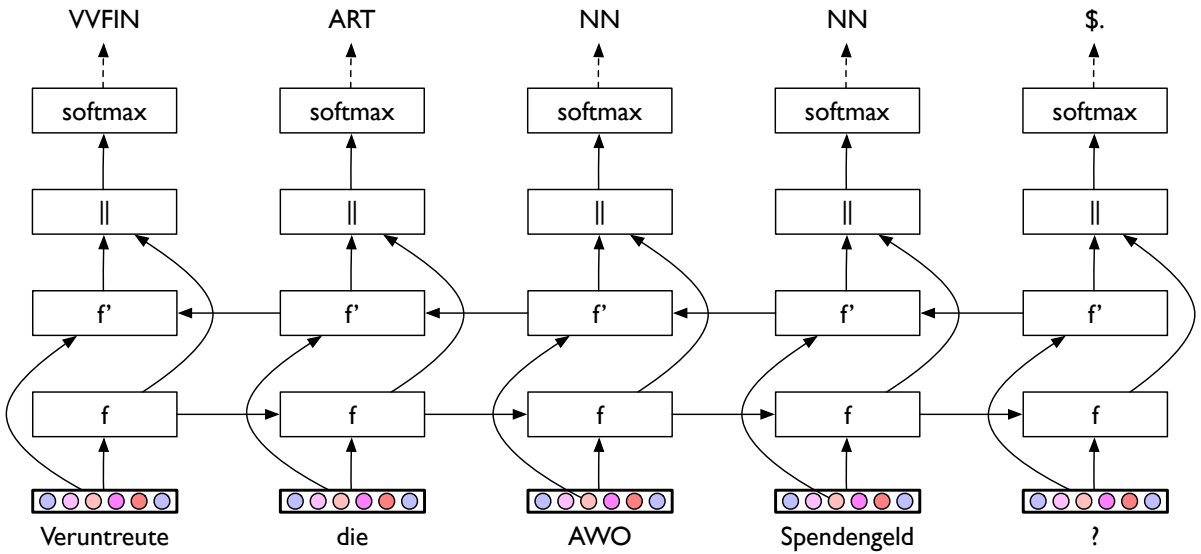

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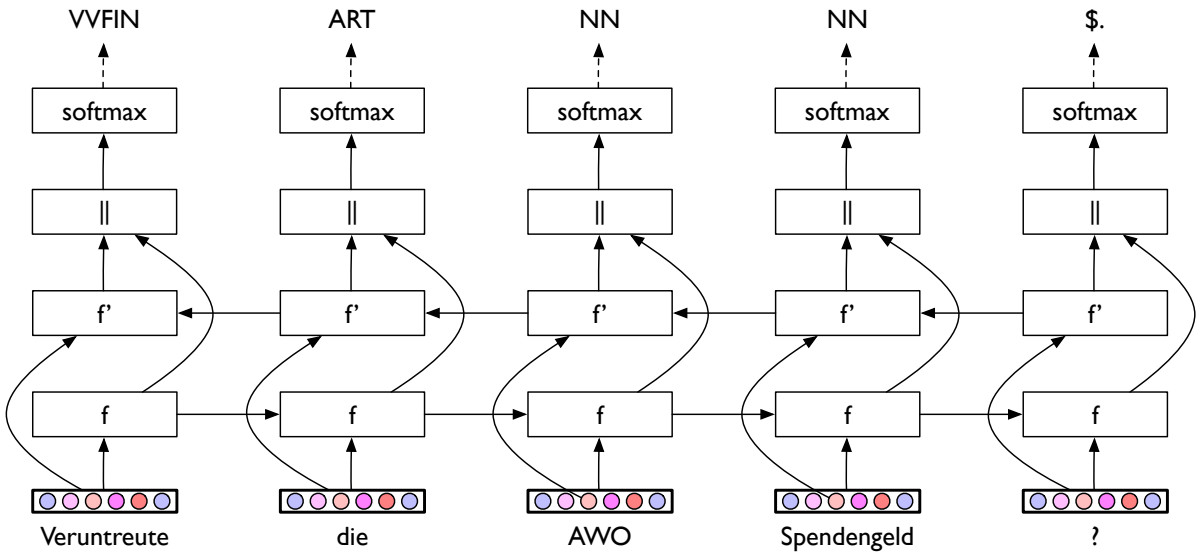
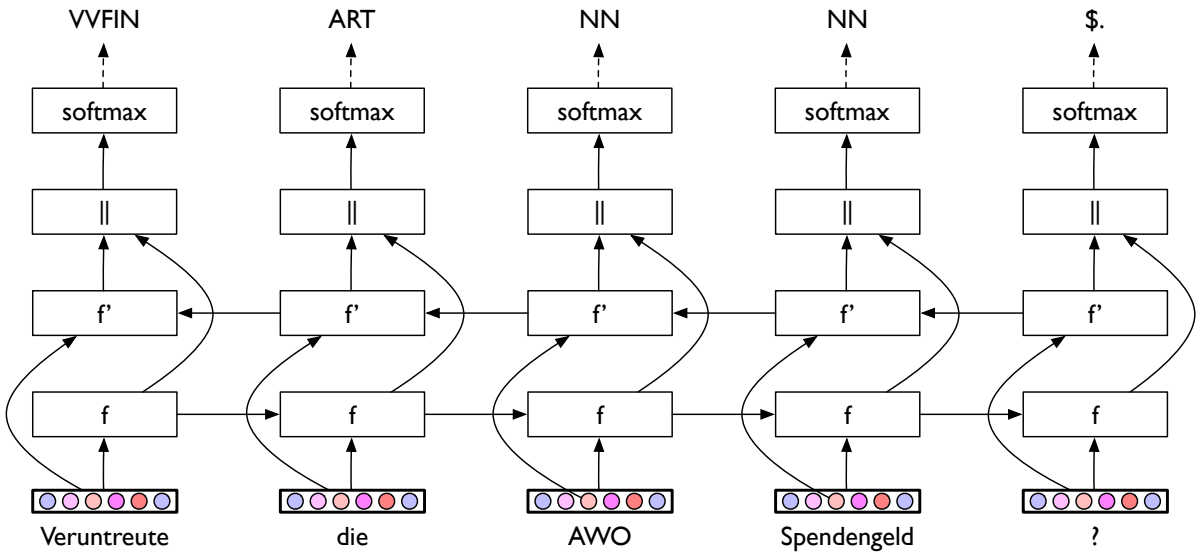


Note:

- This network can be made even more powerful by applying another non-linear transformation to $\overleftrightarrow{\boldsymbol{h}}^{<t>}$.

Bidirectional RNN for sequence labeling



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- When this non-linear transformation is also an RNN, this a **stacked RNN**.

RNN functions

Introduction

- We have looked at how RNNs can be used for sequence labeling and classification tasks.
- Open question: what is a good function f for our hidden units?

$$\boldsymbol{h}^{<t>} = f(\boldsymbol{h}^{<t-1>}, \boldsymbol{x}^{<t>})$$

Elman networks (Elman, 1990)

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$$f(\boldsymbol{h}^{<t-1>}, \boldsymbol{x}^{<t>}) = \quad \boldsymbol{U}\boldsymbol{h}^{<t-1>} \quad \boldsymbol{W}\boldsymbol{x}^{<t>}$$

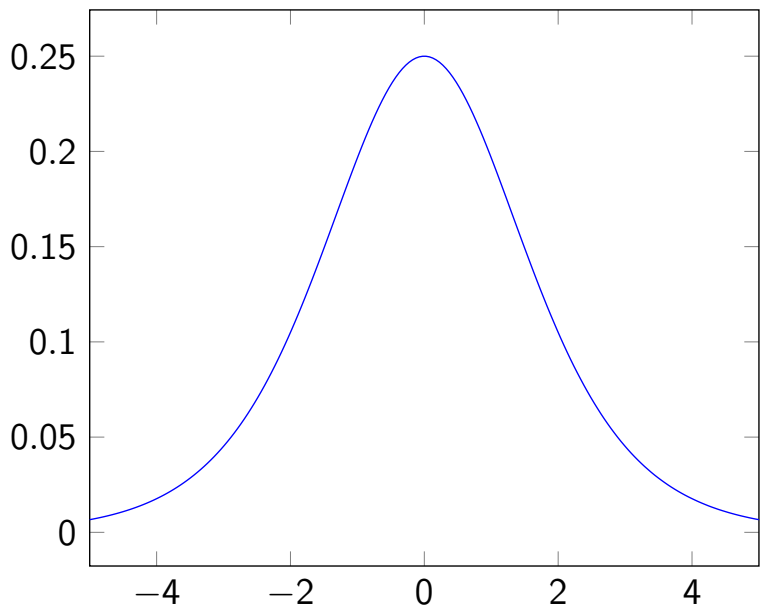
Elman networks (Elman, 1990)

$$f(\boldsymbol{h}^{<t-1>}, \boldsymbol{x}^{<t>}) = \quad \boldsymbol{U}\boldsymbol{h}^{<t-1>} + \boldsymbol{W}\boldsymbol{x}^{<t>}$$

Elman networks (Elman, 1990)

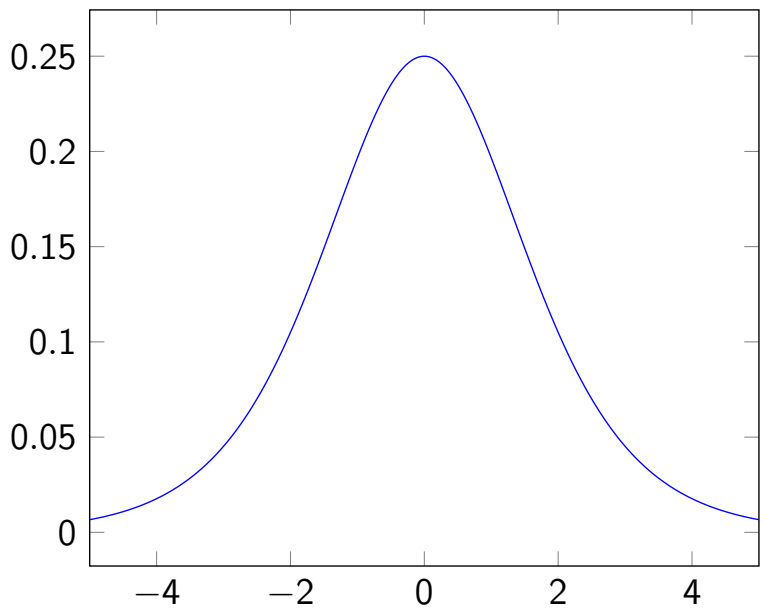
$$f(\boldsymbol{h}^{<t-1>}, \boldsymbol{x}^{<t>}) = \sigma(\boldsymbol{U}\boldsymbol{h}^{<t-1>} + \boldsymbol{W}\boldsymbol{x}^{<t>})$$

Gradient



- In backpropagation, each parameter is updated with a fraction of the partical derivative of the loss with regards to that parameter.
- The derivative of the logistic function is: $\sigma(x)(1 - \sigma(x)$.

Gradient



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- The gradient is in the range $(0, \frac{1}{4}]$.
- We apply the chain rule for computing the derivatives when backpropagating in time.

Gated Recurrent Unit

$$\boldsymbol{h}^{<t>} = \boldsymbol{z}^{<t>} \odot \boldsymbol{h}^{<t-1>} + (1 - \boldsymbol{z}^{<t>}) \odot \tilde{\boldsymbol{h}}^{<t>}$$

Gated Recurrent Unit

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$$\tilde{\boldsymbol{h}}^{<t>} = \tanh(\boldsymbol{W}^{h}\boldsymbol{x}^{<t>} + \boldsymbol{U}^{h}(\boldsymbol{r}^{<t>} \odot \boldsymbol{h}^{<t-1>}) + \mathbf{b}^{h})$$

Gated Recurrent Unit

$$
\begin{aligned}
\boldsymbol{h}^{<t>} &= \boldsymbol{z}^{<t>} \odot \boldsymbol{h}^{<t-1>} + (1 - \boldsymbol{z}^{<t>}) \odot \tilde{\boldsymbol{h}}^{<t>} \\
\boldsymbol{z}^{<t>} &= \sigma(\boldsymbol{W}^{z}\boldsymbol{x}^{<t>} + \boldsymbol{U}^{z}\boldsymbol{h}^{<t-1>} + \boldsymbol{b}^{z}) \\
\tilde{\boldsymbol{h}}^{<t>} &= \tanh(\boldsymbol{W}^{h}\boldsymbol{x}^{<t>} + \boldsymbol{U}^{h}(\boldsymbol{r}^{<t>} \odot \boldsymbol{h}^{<t-1>}) + \mathbf{b}^{h}) \\
\boldsymbol{r}^{<t>} &= \sigma(\boldsymbol{W}^{r}\boldsymbol{x}^{<t>} + \boldsymbol{U}^{r}\boldsymbol{h}^{<t-1>} + \mathbf{b}^{r})
\end{aligned}
$$

RNNs in parsing

Topological field labeling (De Kok & Hinrichs, 2016)

Labeler	Accuracy (%)
LSTM + LSTM	93.33
Bidirectional LSTM + LSTM	97.24

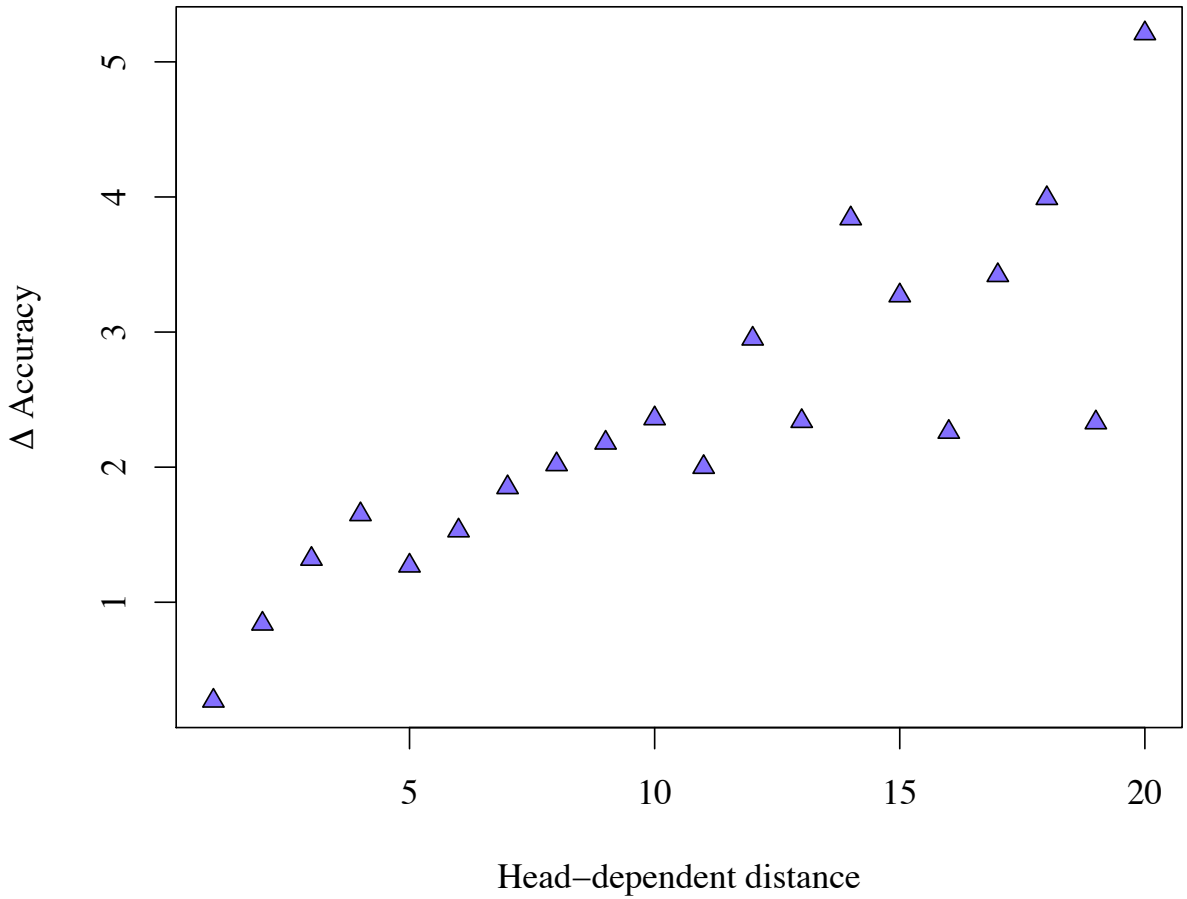
Parsing improvement

Parser	LAS	UAS
De Kok (2015)	89.49	91.88
Neural net + TFs	90.00	92.36
Neural net + gold TFs	90.42	92.76

Analysis of improvements

Dependency label	**LAS Δ**
Coordinating conjunction (clausal)	11.48
Parenthesis	8.31
Dependent clause	3.49
Conjunct	3.38
Sentence root	2.92
Expletive *es*	2.71
Sentence	2.64
Comparative	1.87
Separated verb prefix	1.64
Direct object	1.59

Analysis of improvements (2)



Most frequent parsing errors

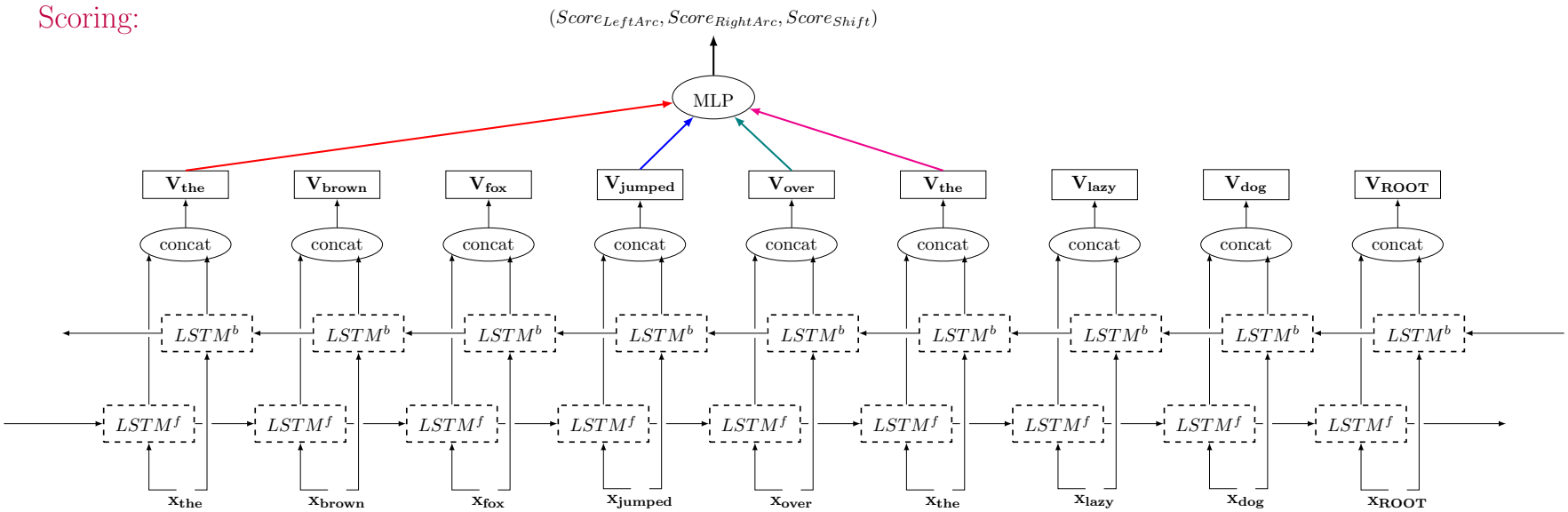
Relation	% of errors
PP	17.48
ADV	11.82
KON	8.70
SUBJ	6.21
OBJA	5.79
ROOT	5.52
OBJP	5.14
PRED	3.66
APP	3.29
REL	3.12

LSTM feature representations (Kiperwasser & Goldberg, 2016)

- Key idea:
  - Take Chen & Manning-like neural dependency parser.
  - Replace word representations by RNN hidden states.
- A token w_i is now represented as: $\boldsymbol{v}^i = \overleftrightarrow{\boldsymbol{h}}^{<i>}$
- v_i is a representation of a token in its sentential context.
- $\mathcal{O}(n)$ time when $\boldsymbol{v}^0 \ldots \boldsymbol{v}^n$ is computed once, not per parser state.

LSTM feature representations (Kiperwasser & Goldberg, 2016)

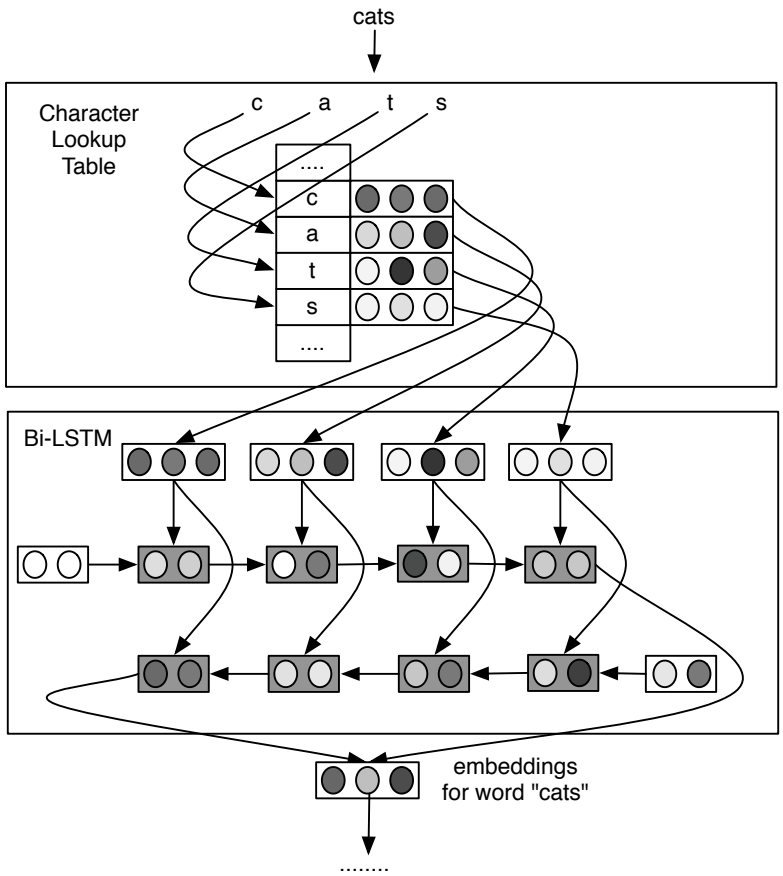
Scoring:



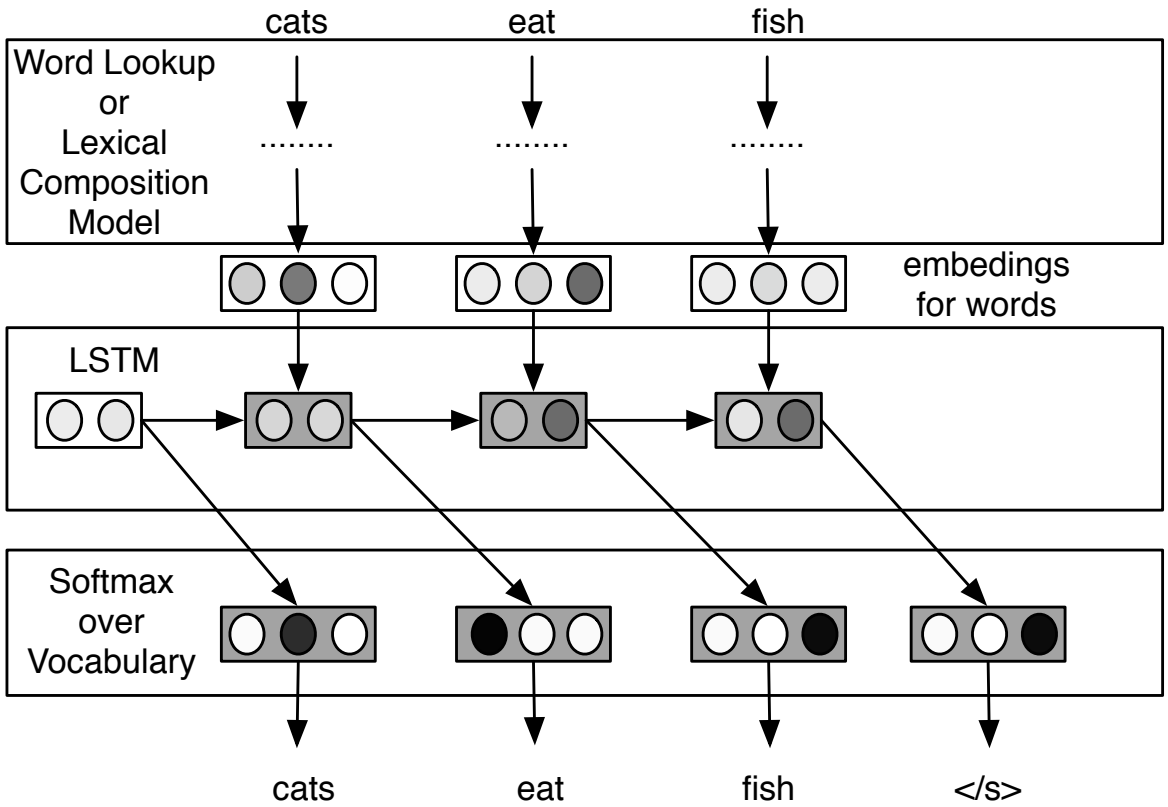
LSTM feature representations (Kiperwasser & Goldberg, 2016)

System	Method	Representation	Emb	PTB-YM	PTB-SD		CTB	
				UAS	UAS	LAS	UAS	LAS
This work	graph, 1st order	2 BiLSTM vectors	–	–	93.1	91.0	**86.6**	**85.1**
This work	transition (greedy, dyn-oracle)	4 BiLSTM vectors	–	–	93.1	91.0	86.2	85.0
This work	transition (greedy, dyn-oracle)	11 BiLSTM vectors	–	–	**93.2**	**91.2**	86.5	84.9
ZhangNivre11	transition (beam)	large feature set (sparse)	–	92.9	–	–	86.0	84.4
Martins13 (TurboParser)	graph, 3rd order+	large feature set (sparse)	–	92.8	93.1	–	–	–
Pei15	graph, 2nd order	large feature set (dense)	–	93.0	–	–	–	–
Dyer15	transition (greedy)	Stack-LSTM + composition	–	–	92.4	90.0	85.7	84.1
Ballesteros16	transition (greedy, dyn-oracle)	Stack-LSTM + composition	–	–	92.7	90.6	86.1	84.5
This work	graph, 1st order	2 BiLSTM vectors	YES	–	93.0	90.9	86.5	84.9
This work	transition (greedy, dyn-oracle)	4 BiLSTM vectors	YES	–	93.6	91.5	87.4	85.9
This work	transition (greedy, dyn-oracle)	11 BiLSTM vectors	YES	–	93.9	91.9	**87.6**	86.1
Weiss15	transition (greedy)	large feature set (dense)	YES	–	93.2	91.2	–	–
Weiss15	transition (beam)	large feature set (dense)	YES	–	**94.0**	**92.0**	–	–
Pei15	graph, 2nd order	large feature set (dense)	YES	93.3	–	–	–	–
Dyer15	transition (greedy)	Stack-LSTM + composition	YES	–	93.1	90.9	87.1	85.5
Ballesteros16	transition (greedy, dyn-oracle)	Stack-LSTM + composition	YES	–	93.6	91.4	**87.6**	**86.2**
LeZuidema14	reranking /blend	inside-outside recursive net	YES	93.1	93.8	91.5	–	–
Zhu15	reranking /blend	recursive conv-net	YES	93.8	–	–	85.7	–

C2W model (Ling, et al. 2015)



C2W model (Ling, et al. 2015)



C2W model (Ling, et al. 2015)

System	Fusional			Agglutinative	
	EN	PT	CA	DE	TR
Word	96.97	95.67	98.09	97.51	83.43
C2W	**97.36**	97.47	**98.92**	**98.08**	**91.59**
Stanford	97.32	**97.54**	98.76	97.92	87.31

A sobering note

- Erik Schill, 2018, out-of-domain tagging:
  - Training on TüBa-D/Z.
  - Evaluation on German NoSta-D corpus of German non-standard varieties.

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A sobering note

- Erik Schill, 2018, out-of-domain tagging:
  - Training on TüBa-D/Z.
  - Evaluation on German NoSta-D corpus of German non-standard varieties.
- Network architecture:
  - RNN (GRU) over words
  - CRF layer
- Various word representations:
  - Word embedding
  - RNN over characters + word embedding
  - Prefix + suffix character, fed through a feed-forward layer (similar to De Kok, 2015) + word embedding
  - FastText embedding
- For word embedding, the context-sensitive skip-gram model was used.

Results

Tagger	Accuracy
Trigram HMM	85.97
RNN + prefix/suffix feed-forward	**89.63**
RNN + char RNN	88.79
RNN + fastText	87.52