Neural language modeling

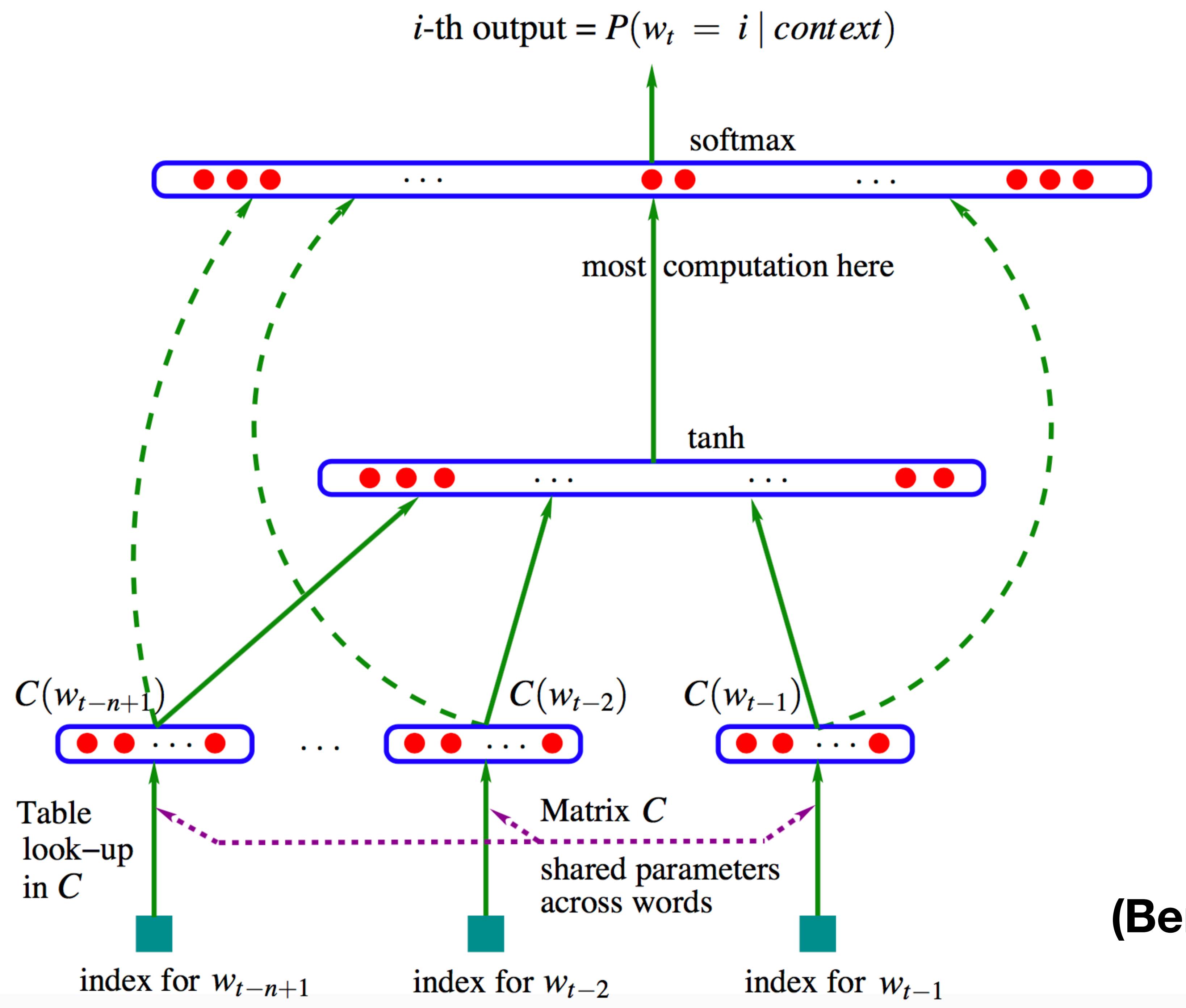
The boys went outside to _____

$$\hat{P}(w_t = w^k \mid w_1, \ldots, w_{t-1})$$

Objective: minimize the surprisal of the word that in fact occurred in the corpus:

$$-log\hat{P}(w)$$

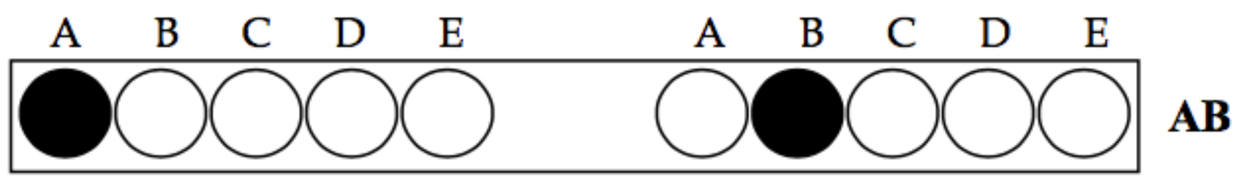
Neural language model



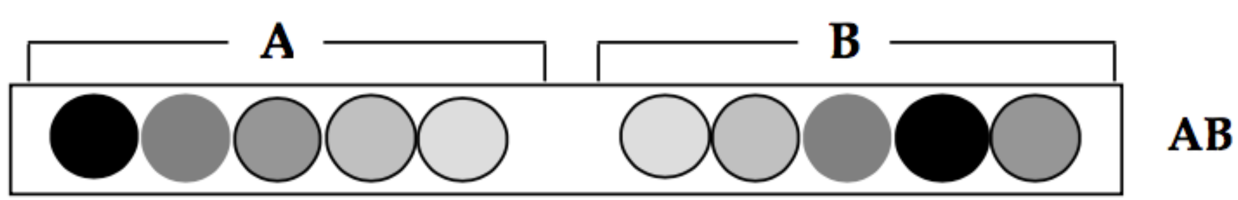
(Bengio et al., 2003)

How do we represent discrete inputs and outputs in a network?

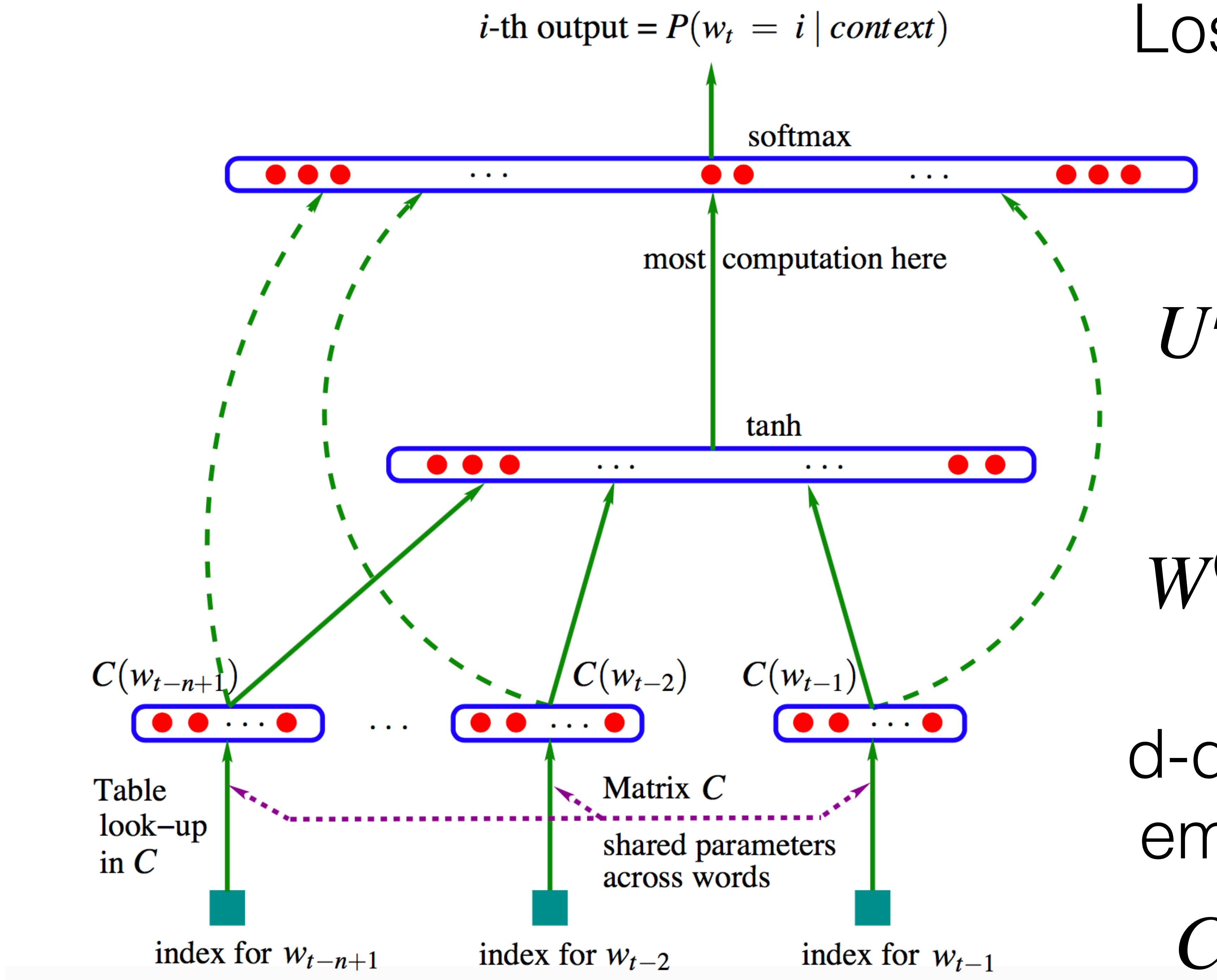
Localist ("one hot") representation: each input unit represents an item (e.g., a word)



Distributed representation: each item is represented by multiple units, and each unit participates in representing multiple items



Neural language model



Loss: $-log\hat{P}(w)$

$U^{h\times|V|}$

$W^{(n-1)d\times h}$

d-dimensional embeddings: $C_1, \ldots, C_{|V|}$

The chain rule

$$(f(g(x)))' = f'(g(x))g'(x)$$

$$f(y) = y^2 \qquad g(x) = \sin x$$

$$f'(y) = 2y \qquad g'(x) = \cos x$$

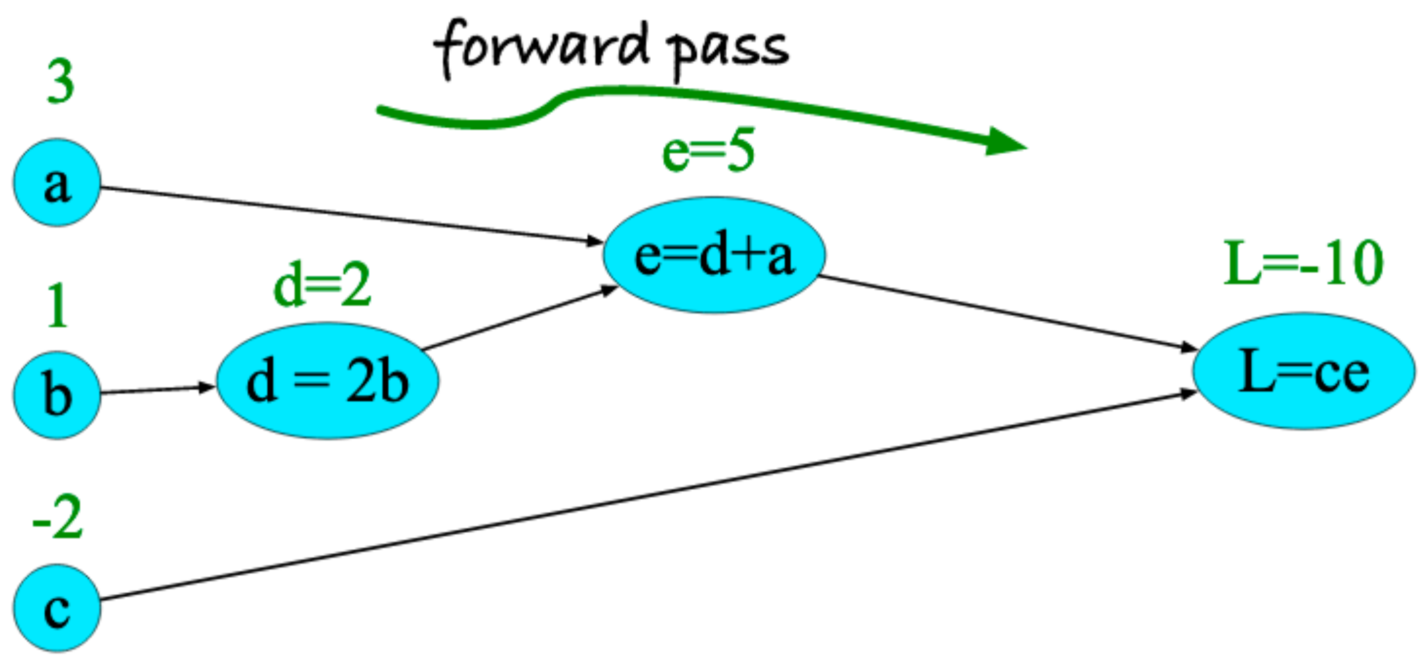
$$h(x) = f(g(x)) = (\sin x)^2$$

$$h'(x) = f'(g(x))g'(x) = 2\sin x \cos x$$

Substituting sin(x) for y in f'(y) = 2y

Computation graphs

$$L(a, b, c) = c(a + 2b)$$

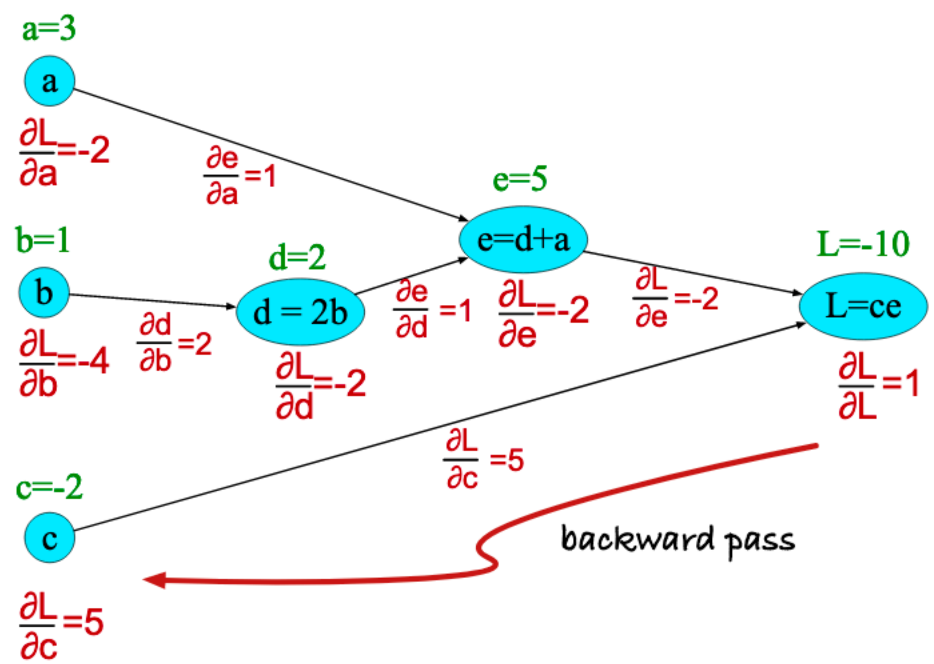


$$(f(g(x)))' = f'(g(x))g'(x)$$

Backpropagation

$$L(a,b,c) = c(a+2b)$$

$$d = 2b \qquad e = a + d$$



$$L = ce \qquad \frac{\partial L}{\partial c} = e$$

$$\frac{\partial L}{\partial a} = \frac{\partial L}{\partial e}\frac{\partial e}{\partial a} \qquad \left.\frac{\partial L}{\partial a}\right|_a = \left.\frac{\partial L}{\partial e}\right|_{e(a)} \left.\frac{\partial e}{\partial a}\right|_a$$

$$\frac{\partial L}{\partial e} = c \qquad \frac{\partial e}{\partial a} = 1$$

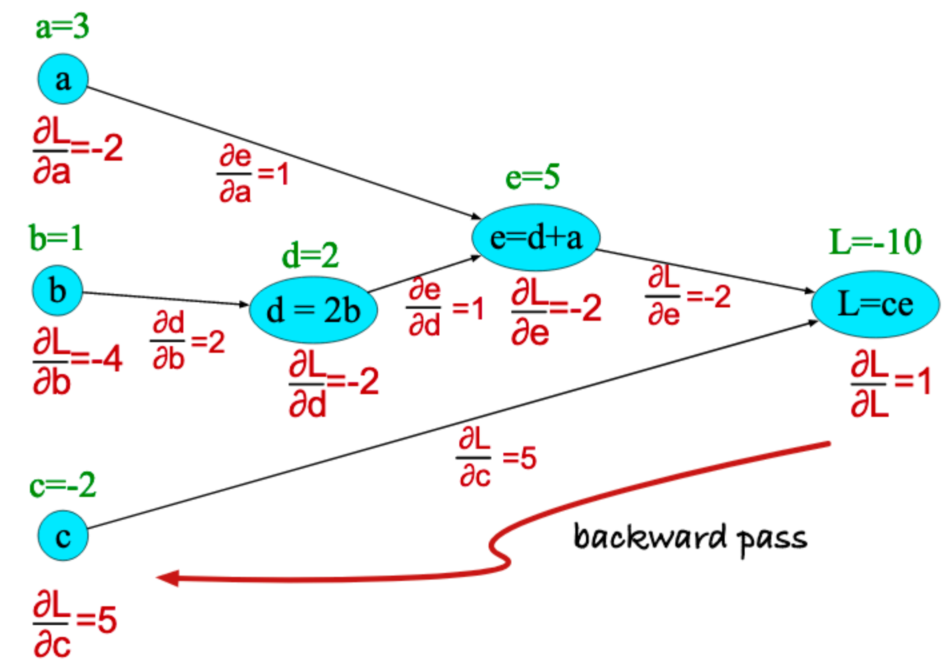
Backpropagation

$$L(a, b, c) = c(a + 2b)$$

$$L = ce \qquad e = a + d \qquad d = 2b$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial e}\frac{\partial e}{\partial d}\frac{\partial d}{\partial b}$$

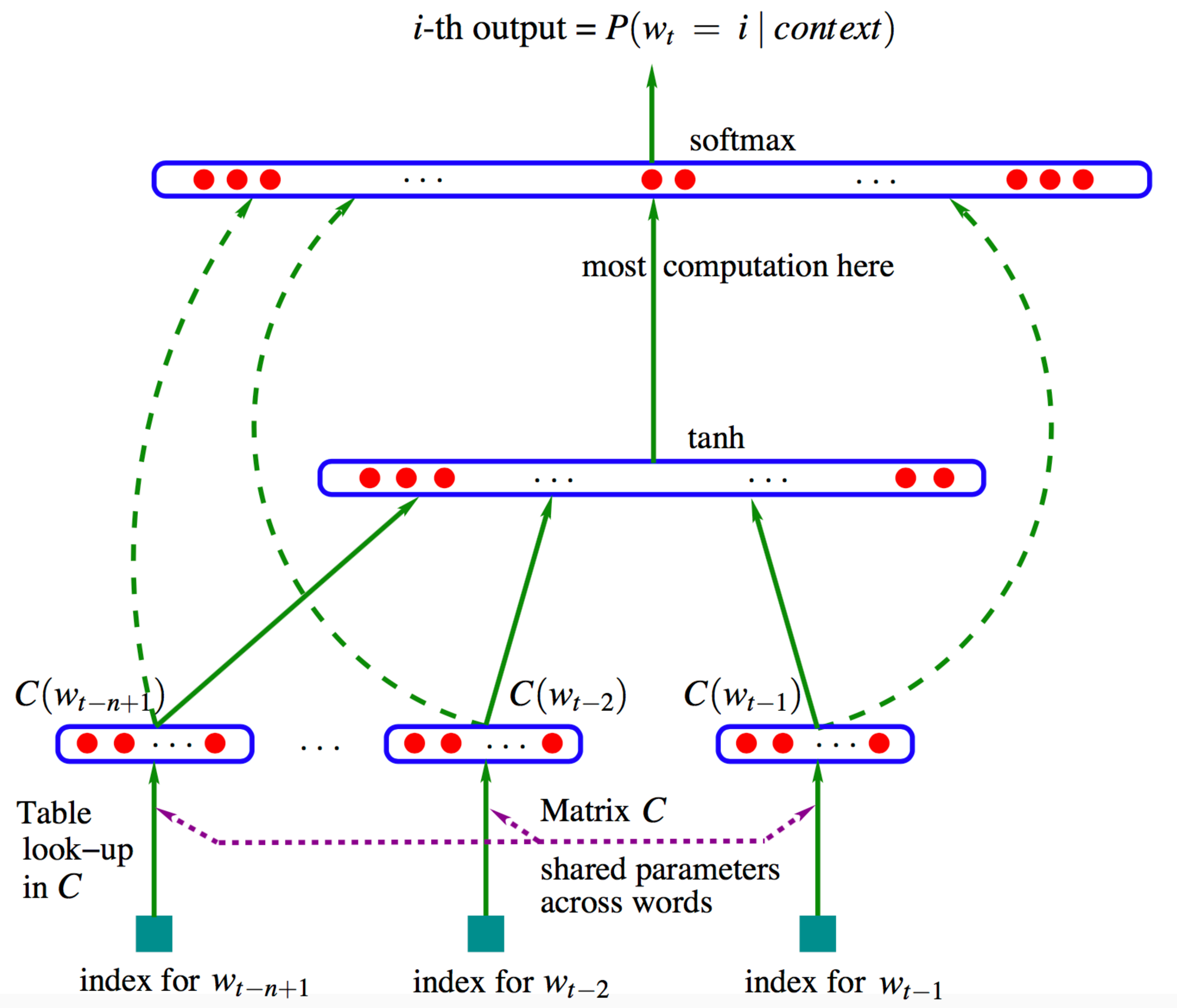
$$\frac{\partial L}{\partial e} = c \qquad \frac{\partial e}{\partial d} = 1 \qquad \frac{\partial d}{\partial b} = 2$$



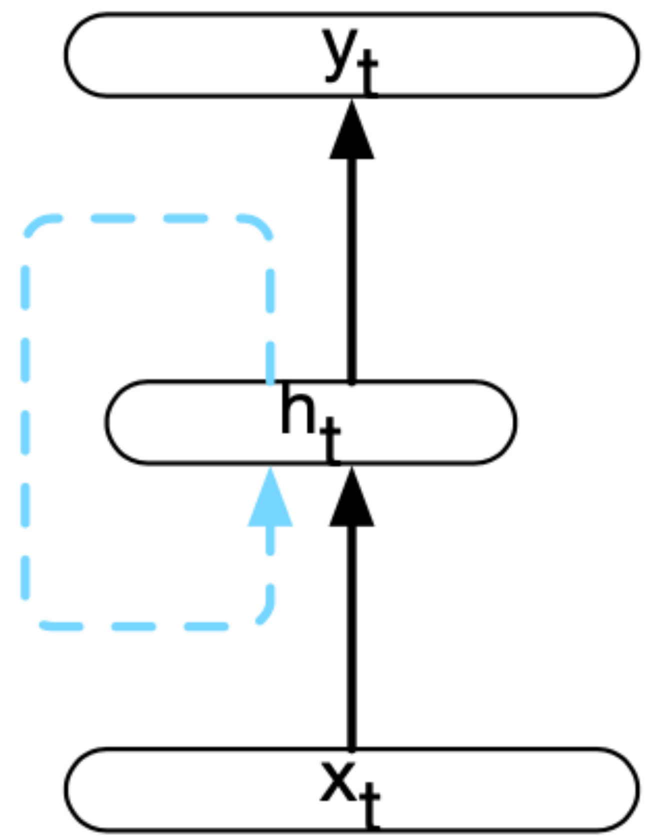
Long-distance dependencies

- A neural feedforward language model can generalize across n-grams (*easy money* → *easy cash*)
- But it still makes the Markov assumption, which ignores long-distance dependencies:
    - The **people** you saw at the grocery store last night **are** my friends.
    - I went to **Paris** but I didn't get a chance to see the rest of **France**.

Lack of temporal invariance



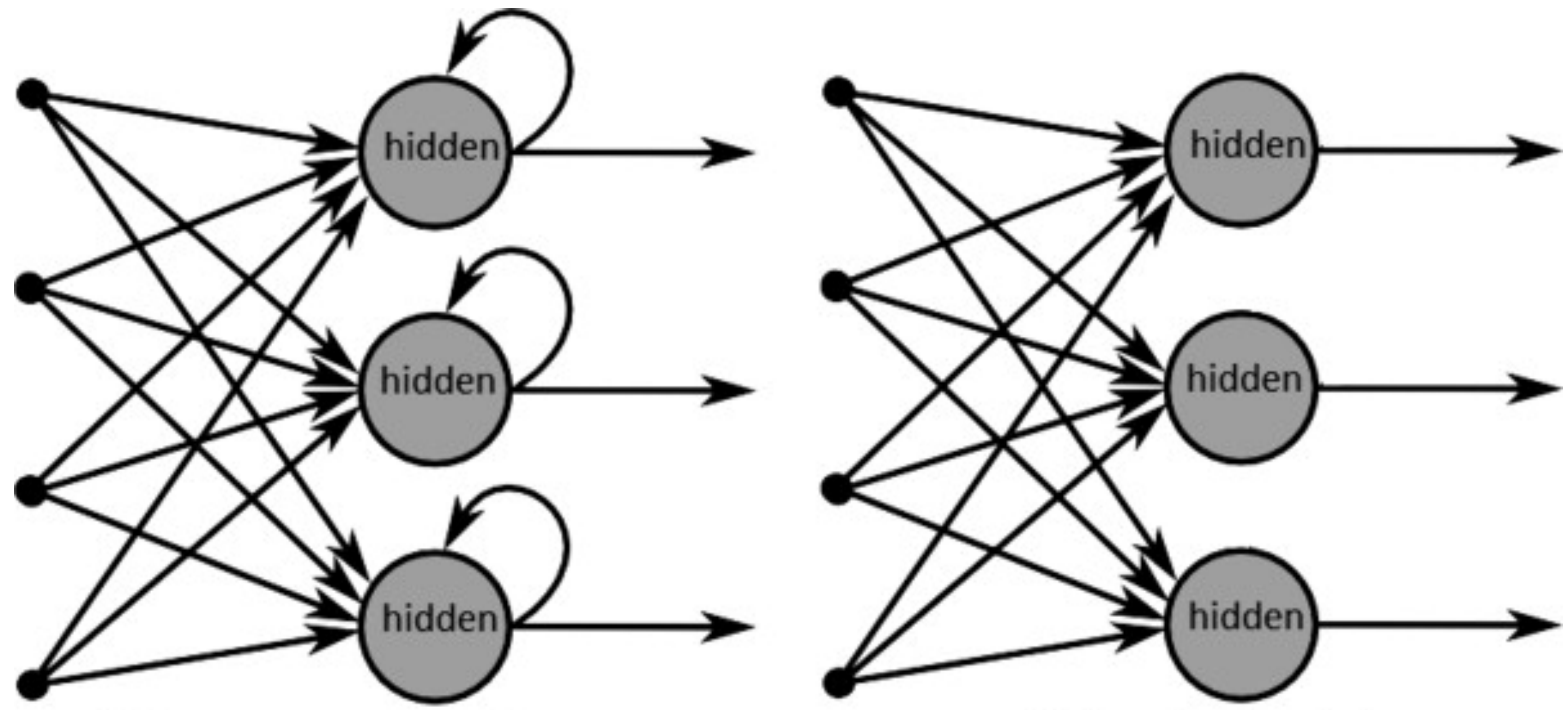
Recurrent neural network



(Elman, 1990)

Simple recurrent network

$$\overrightarrow{h}_t = U\vec{i}_t + W\overrightarrow{h}_{t-1} \qquad \overrightarrow{h}_t = U\vec{i}_t$$

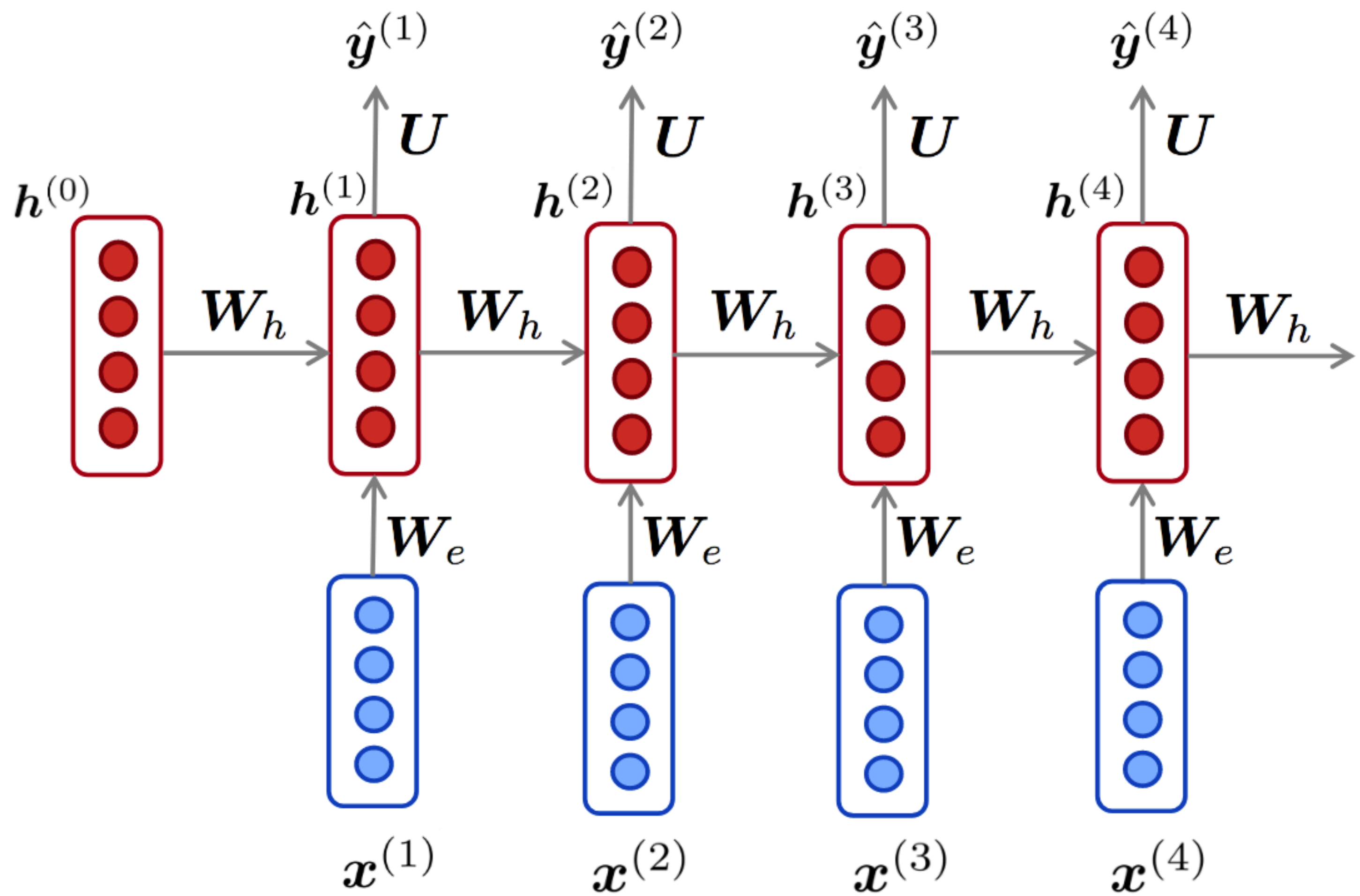


(a) Recurrent neural network

(b) Forward neural network

(figure from Mulder et al., 2015)

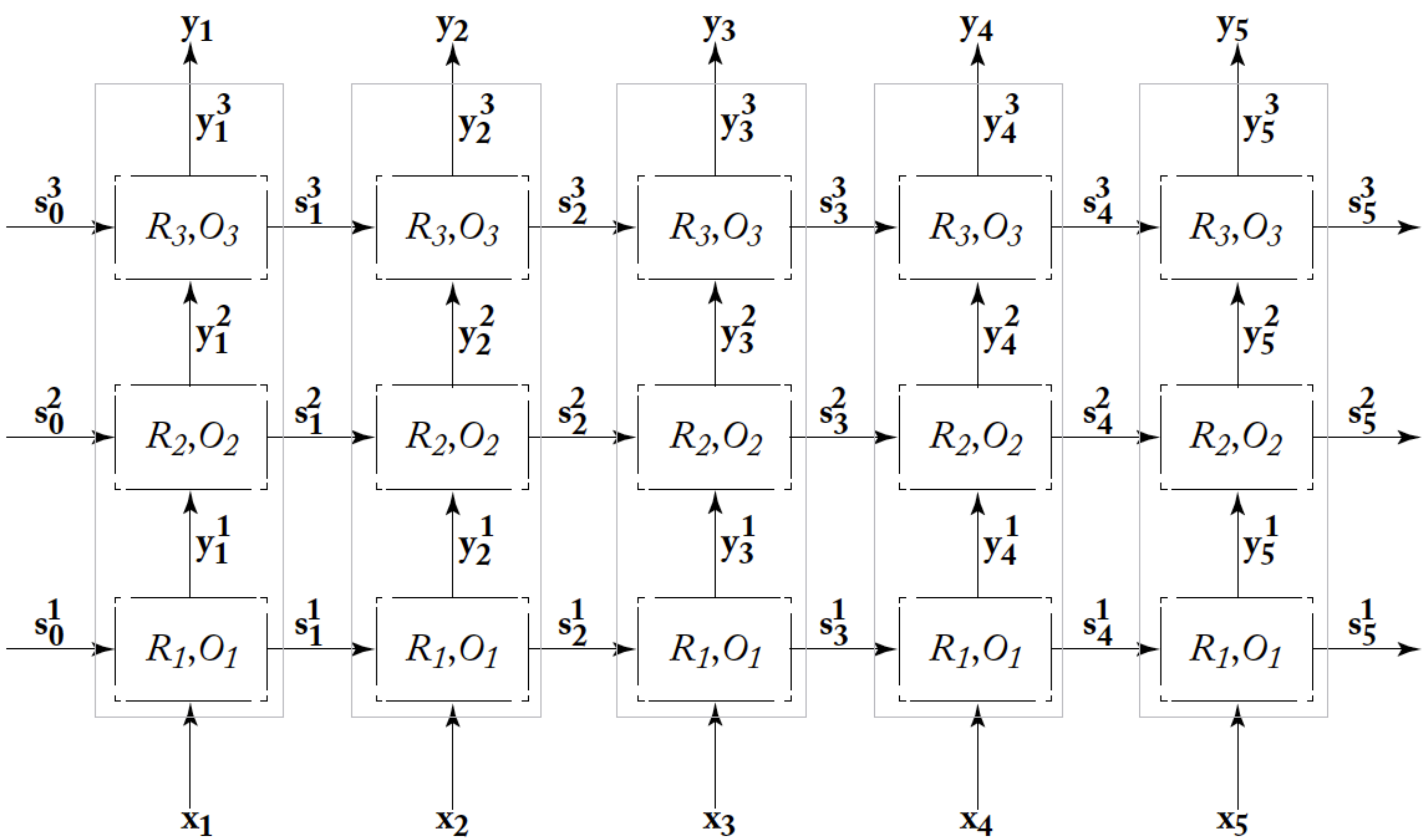
Unrolling an RNN



$$\frac{\partial L}{\partial W_h} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial W_h}$$

(Figure credit: Richard Socher)

Stacked RNNs



(From Goldberg 2017)

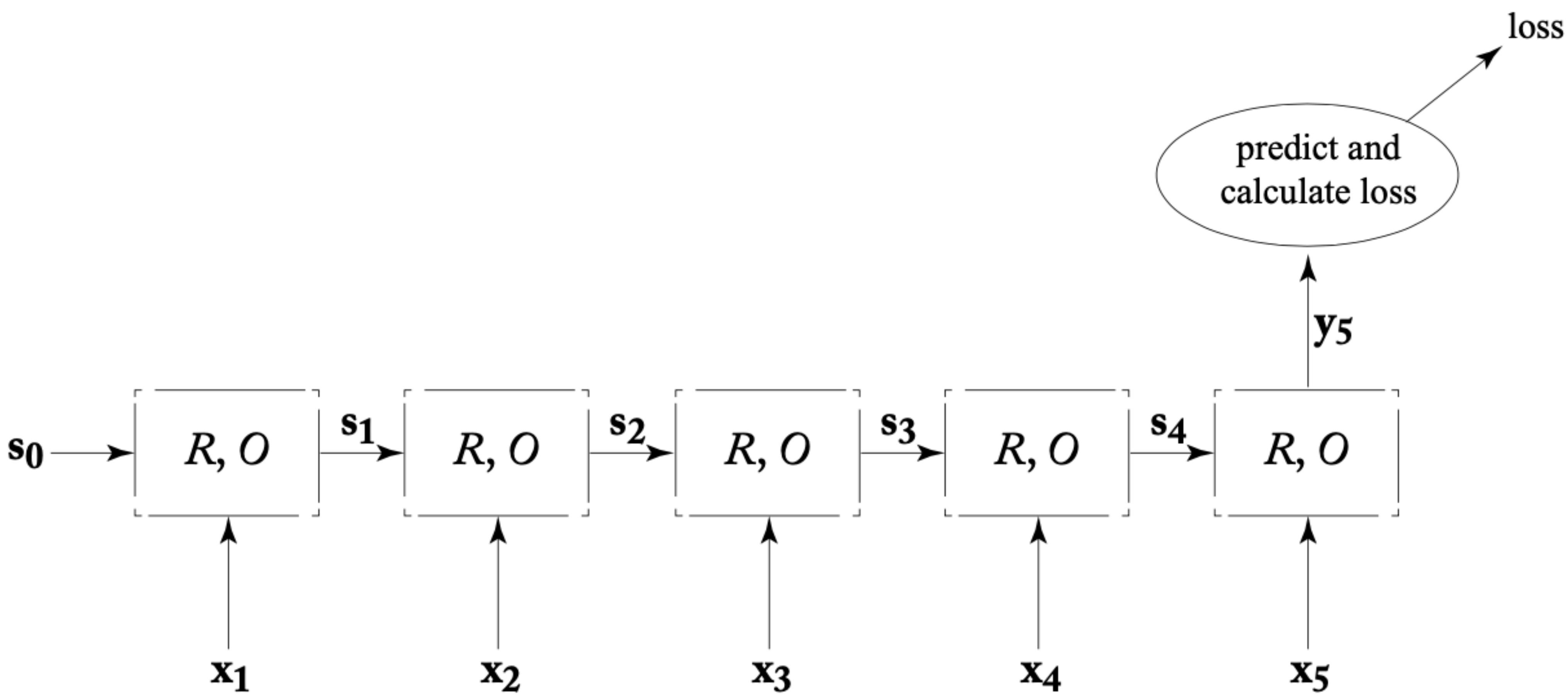
RNN as a language model

	PPL		WER	
Model	RNN	RNN+KN	RNN	RNN+KN
KN5 - baseline	-	221	-	13.5
RNN 60/20	229	186	13.2	12.6
RNN 90/10	202	173	12.8	12.2
RNN 250/5	173	155	12.3	11.7
RNN 250/2	176	156	12.0	11.9
RNN 400/10	171	152	12.5	12.1
3xRNN static	151	143	11.6	11.3
3xRNN dynamic	128	121	11.3	11.1

(Mikolov et al., 2010)

Sequence classification

Sentiment analysis, language classification, authorship identification, genre classification…

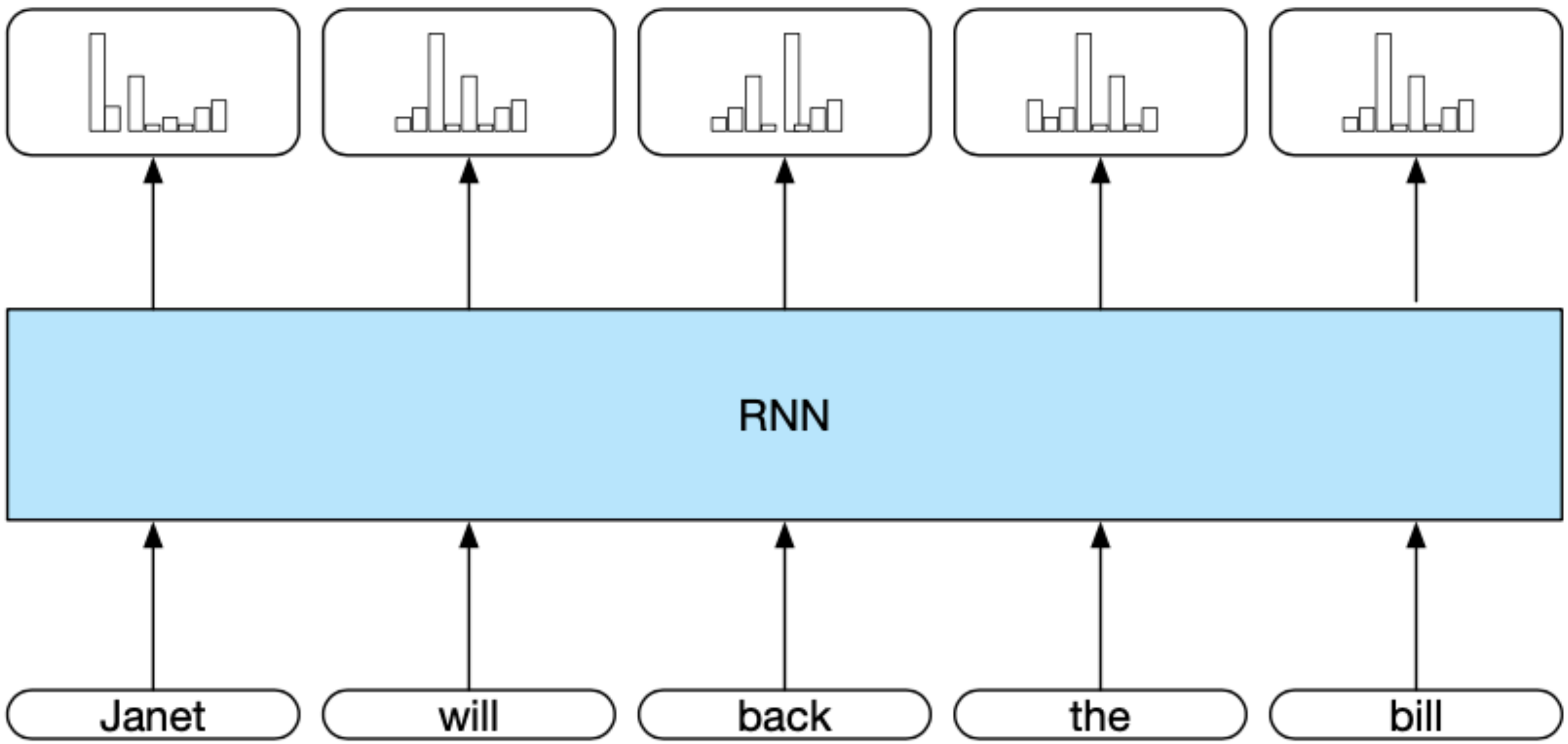


(Figure from Goldberg, 2017)

Sequence tagging

- Part-of-speech tagging:
  - The cat is about to **fall** from the tree.
  - Last **fall** I traveled to Europe.
- Named entity recognition:
  - Seattle is in **Washington**.
  - **Washington** was the first president of the United States.

Sequence tagging



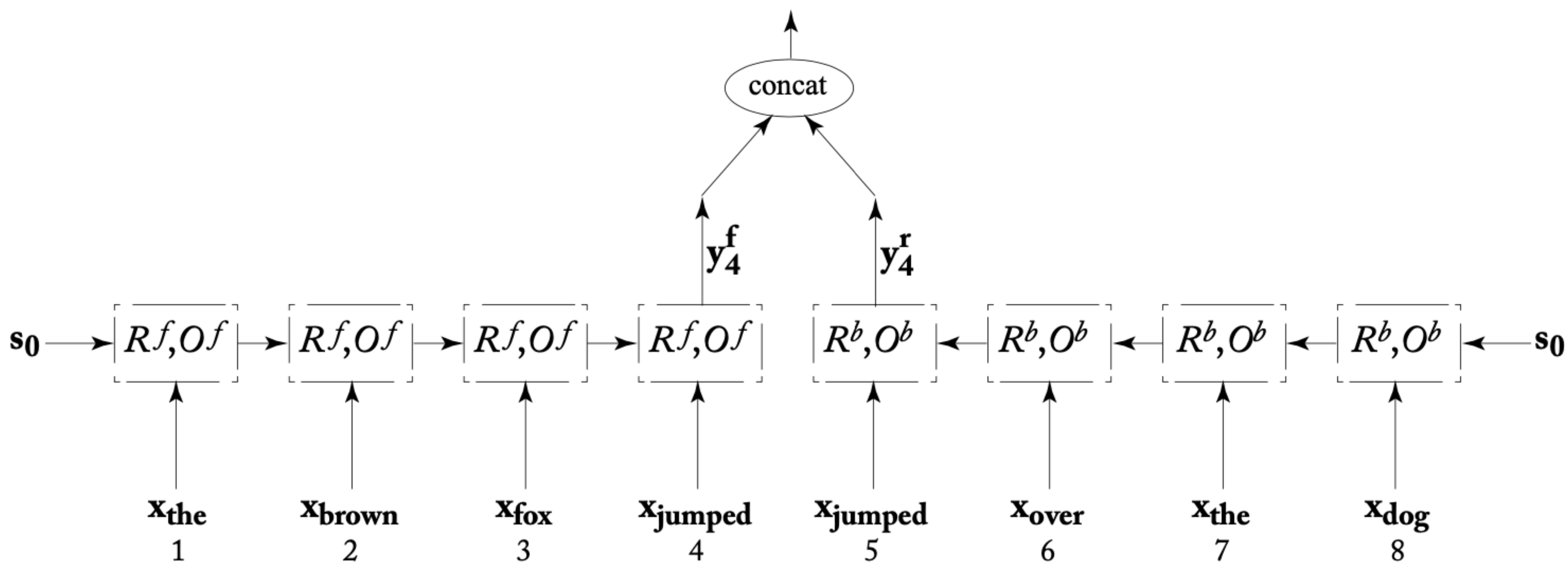
Bidirectional context can help

- **Will** gets his revenge by masquerading as Sue's hairdresser and forcibly shaving her head bald.

- **Will** putting a patch over my eye help to get the object out of it?

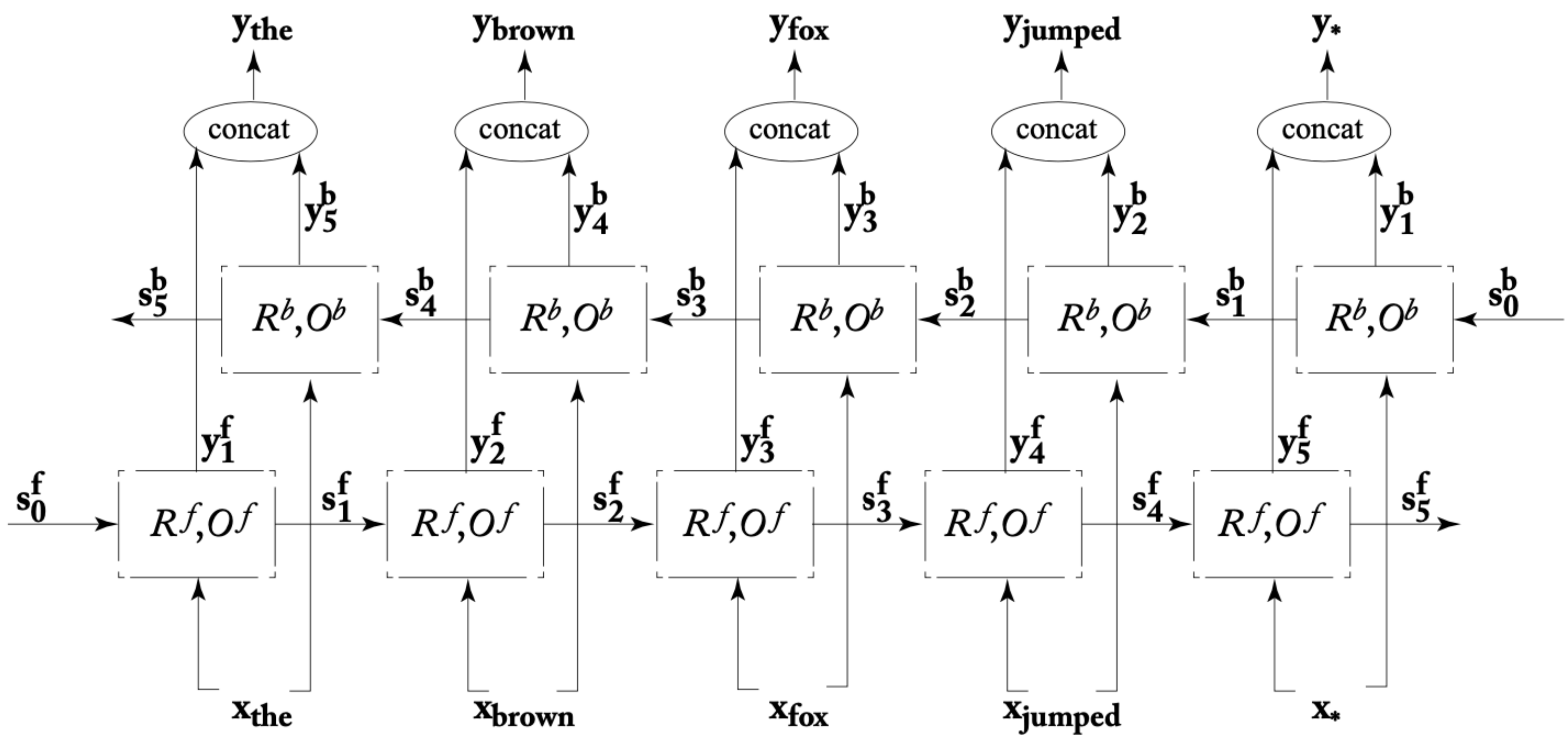
(Elkahky et al. 2018)

Bidirectional RNN



(From Goldberg 2017)

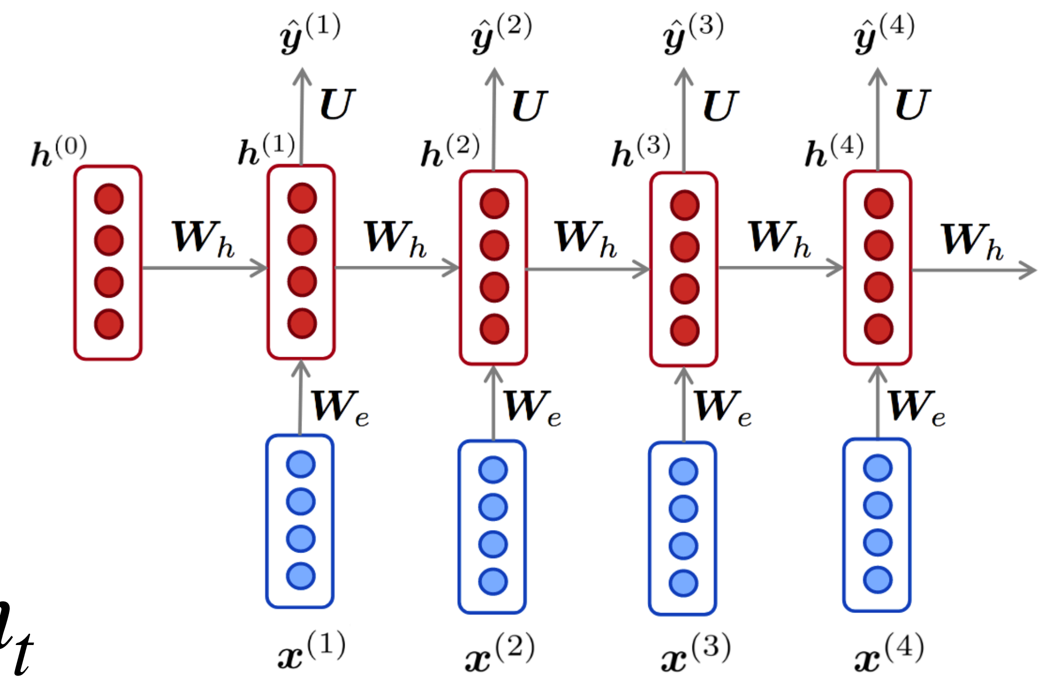
Bidirectional RNN



(From Goldberg 2017)

Vanishing gradients

$$\frac{\partial L_t}{\partial W_h} = \sum_{k=1}^{t} \frac{\partial L_t}{\partial y_t} \frac{\partial y_t}{\partial h_t} \boxed{\frac{\partial h_t}{\partial h_k}} \frac{\partial h_k}{\partial W_h}$$



$$\frac{\partial h_t}{\partial h_k} = \prod_{j=k+1}^{t} \frac{\partial h_j}{\partial h_{j-1}} = \frac{\partial h_{k+1}}{\partial h_k} \cdots \frac{\partial h_t}{\partial h_{t-1}}$$

$$\frac{\partial h_j}{\partial h_{j-1}} = W_h \, \mathbf{diag}(\sigma'(h_{j-1}))$$

(Pascanu et al., 2013)

Vanishing gradients

$$\frac{\partial h_j}{\partial h_{j-1}} = W_h \, \textbf{diag}(\sigma'(h_{j-1}))$$

$$\left\| \frac{\partial h_j}{\partial h_{j-1}} \right\| \leq \| W_h \| \| \textbf{diag}(\sigma'(h_{j-1})) \| \leq \| W_h \| \gamma$$

Fixed

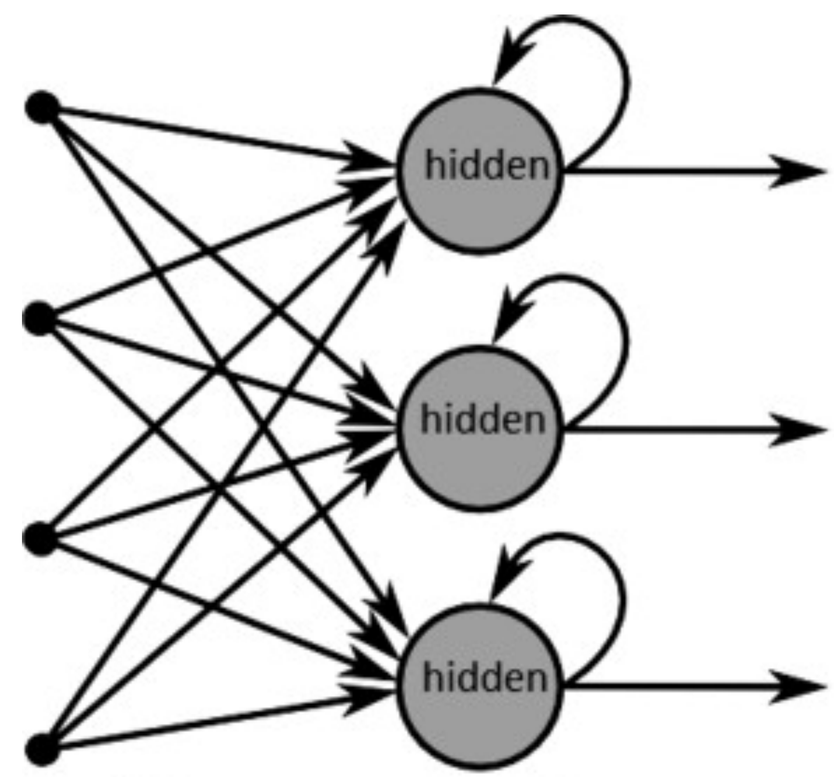
Bounded

$$\left\| \frac{\partial h_t}{\partial h_k} \right\| \leq (\| W_h \| \gamma)^{t-k}$$

(Pascanu et al., 2013)

Simple recurrent network

$$\overrightarrow{h}_t = U\vec{i}_t + W\overrightarrow{h}_{t-1}$$



(a) Recurrent neural network

LSTM ("long short-term memory")

$$c_t = f_t c_{t-1} + i_t g_t$$

$$z_t = \textbf{concat}(D_{t-1}, x_t)$$

$$i_t = \sigma(W_i z_t + b_i)$$

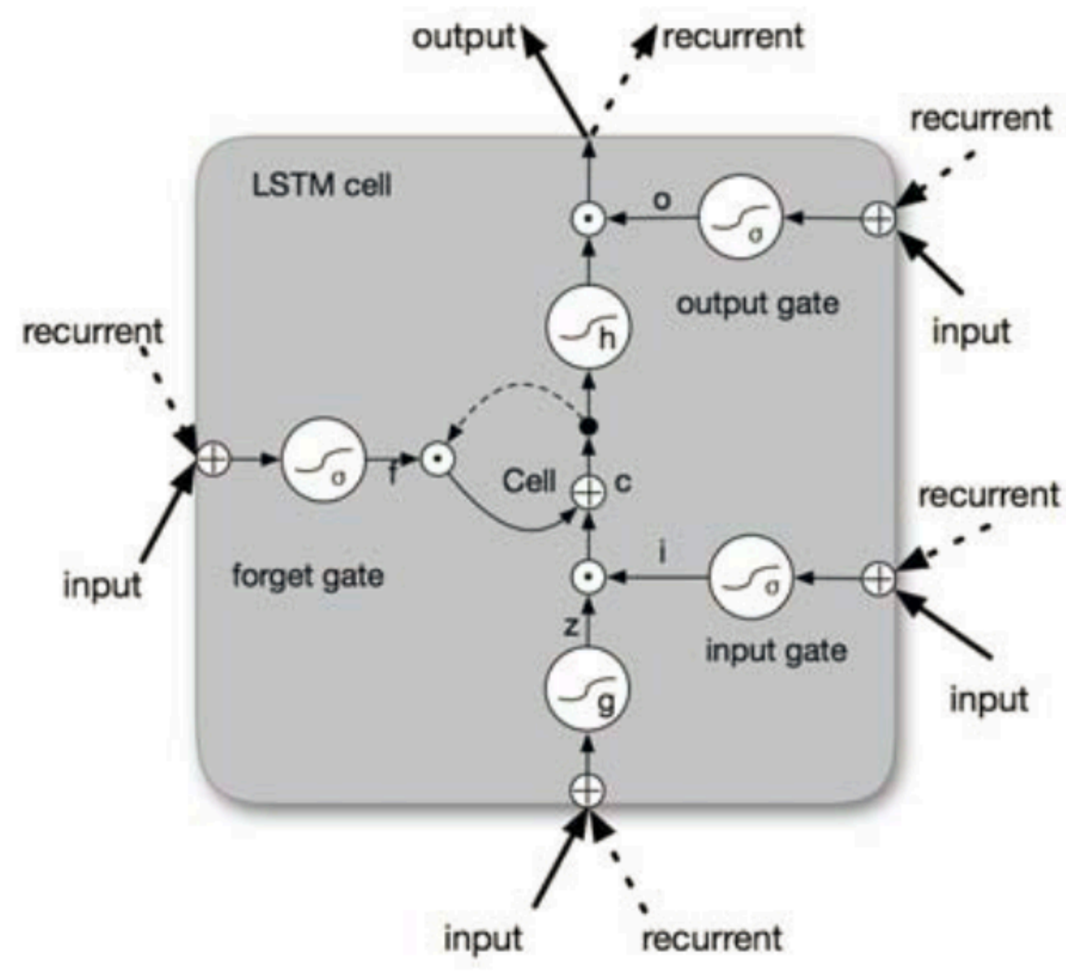
$$f_t = \sigma(W_f z_t + b_f)$$

$$g_t = \tanh(W_g z_t + b_g)$$

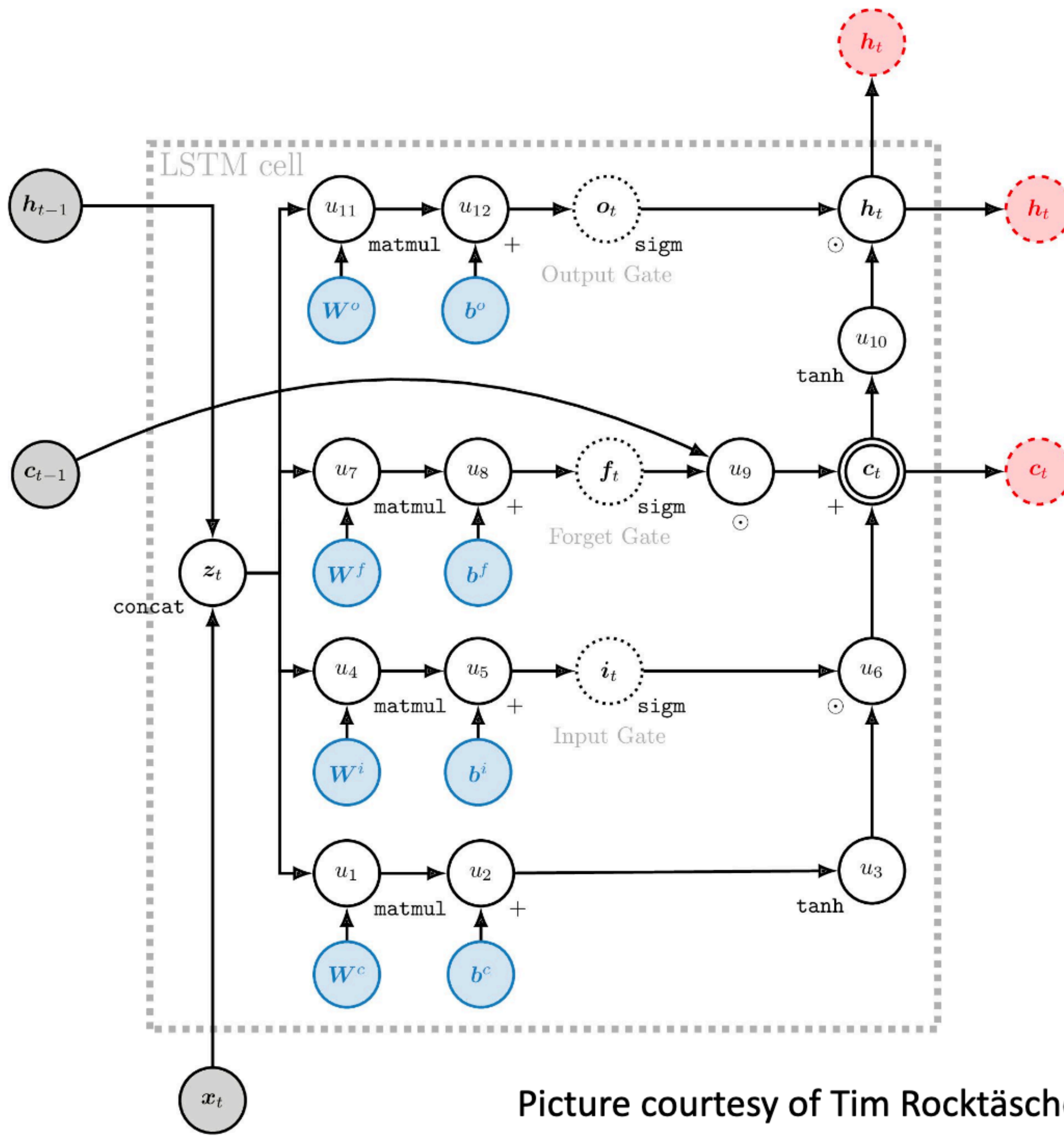
$$D_t = o_t \tanh(c_t)$$

$$o_t = \sigma(W_o z_t + b_o)$$

(Hochreiter & Schmidhuber 1997; figure from Ma & Hovy 2016)



LSTM computation graph



Picture courtesy of Tim Rocktäschel

LSTM language models

MODEL	TEST PERPLEXITY	NUMBER OF PARAMS [BILLIONS]
SIGMOID-RNN-2048 (JI ET AL., 2015A)	68.3	4.1
INTERPOLATED KN 5-GRAM, 1.1B N-GRAMS (CHELBA ET AL., 2013)	67.6	1.76
SPARSE NON-NEGATIVE MATRIX LM (SHAZEER ET AL., 2015)	52.9	33
RNN-1024 + MAXENT 9-GRAM FEATURES (CHELBA ET AL., 2013)	51.3	20
LSTM-512-512	54.1	0.82
LSTM-1024-512	48.2	0.82
LSTM-2048-512	43.7	0.83
LSTM-8192-2048 (NO DROPOUT)	37.9	3.3
LSTM-8192-2048 (50% DROPOUT)	32.2	3.3
2-LAYER LSTM-8192-1024 (BIG LSTM)	30.6	1.8
BIG LSTM+CNN INPUTS	**30.0**	**1.04**

(Jozefowicz et al., 2016)

Gated Recurrent Units

Reset gate: $r_t = \sigma(U_r h_{t-1} + W_r x_t)$

Update gate: $z_t = \sigma(U_z h_{t-1} + W_z x_t)$

$$\tilde{h}_t = \tanh(U(r_t h_{t-1}) + W x_t)$$

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

(Cho et al. 2014)

Part-of-speech tagging

Penn TreeBank tag set:

Your query

Tal loves making slides for the lecture.

Tagging

```
Tal/NNP  loves/VBZ  making/VBG  slides/NNS  for/IN  the/DT  lecture/NN  ./.
```

Present verb, third person singular

Singular noun

http://nlp.stanford.edu:8080/parser/index.jsp

Part-of-speech tagging

A simpler tag set:

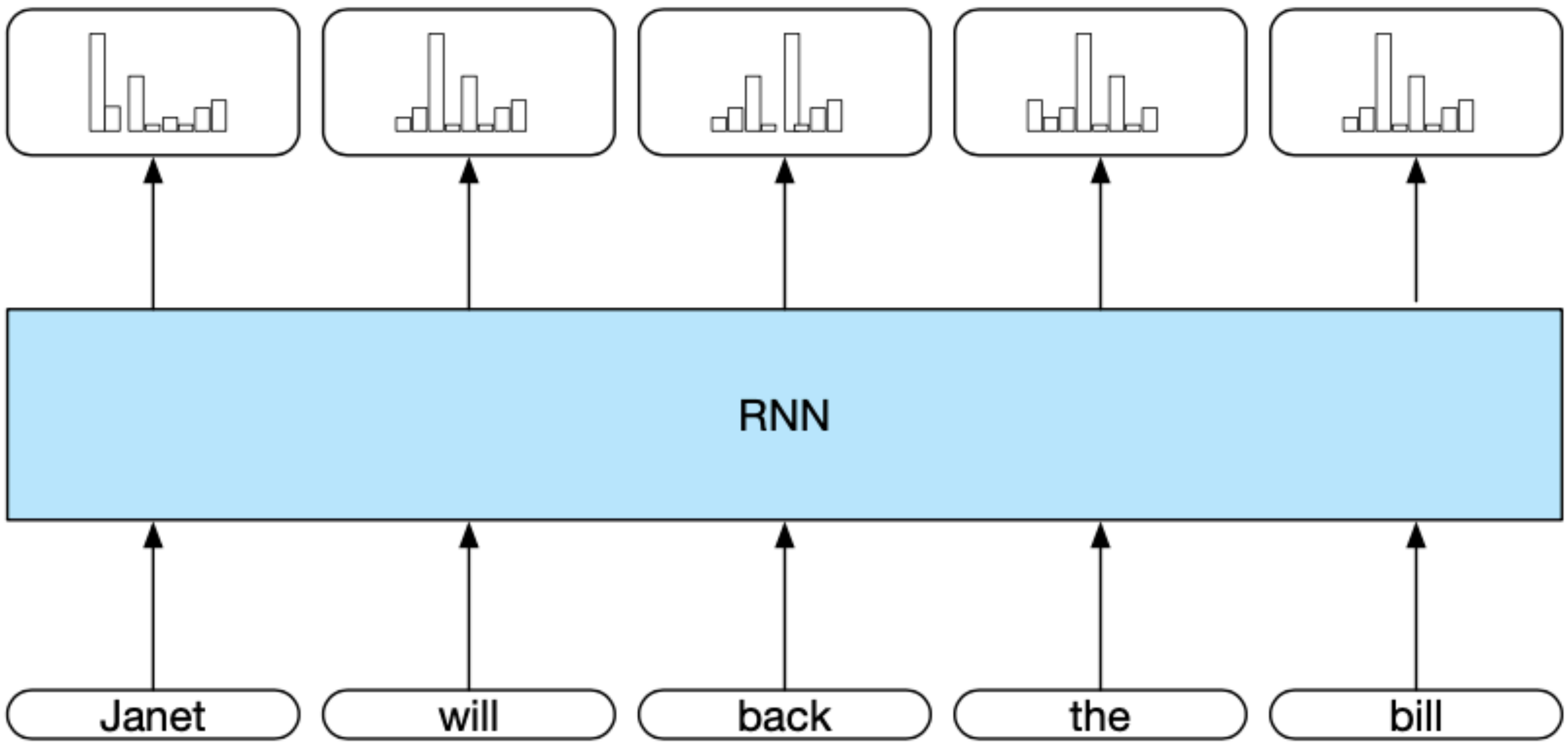
Tal	loves	making	slides	.
PROPN	VERB	VERB	NOUN	PUNCT

There's no one correct annotation scheme!

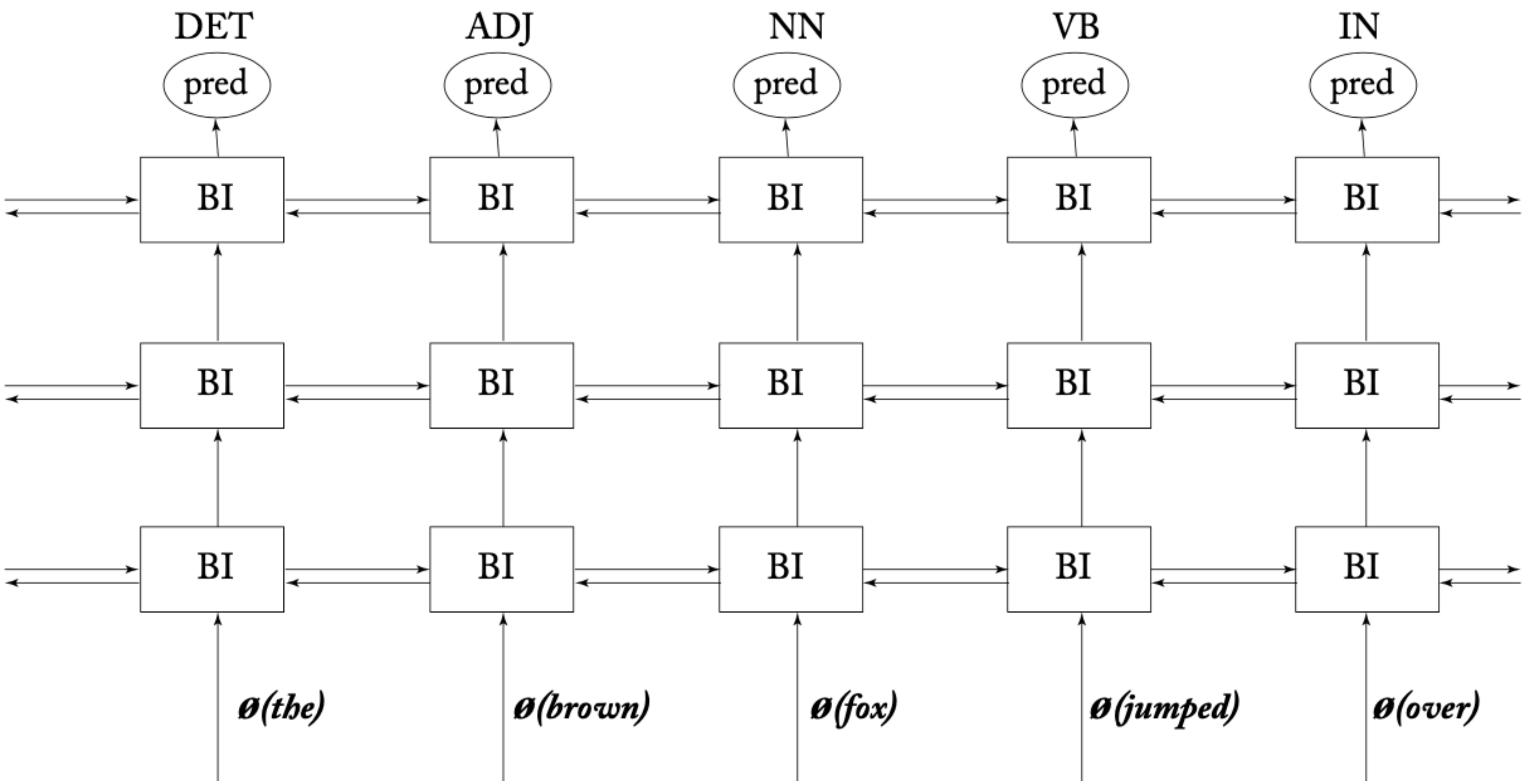
https://explosion.ai/demos/displacy

Part-of-speech tagging: ambiguity and baselines

RNN for sequence labeling: POS tagging



RNN for sequence labeling: POS tagging

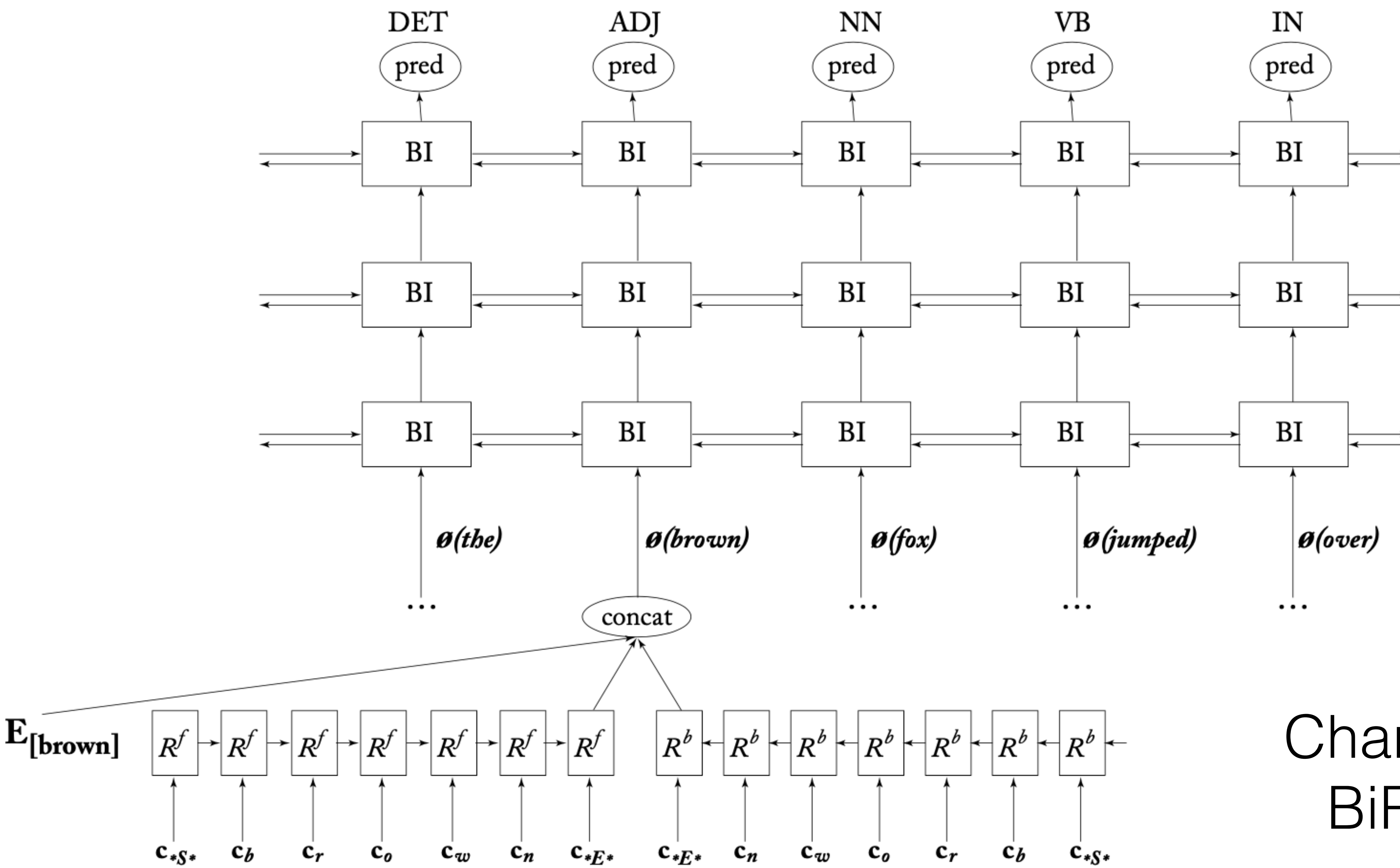


(From Goldberg 2017)

RNN for sequence labeling: POS tagging

- What's the part of speech of the following words?
  - Vectorize
  - LSTMification
  - Goldbergian
- With atomic word embeddings - or a symbolic model without morphological decomposition - we will have to treat those words as UNKs!

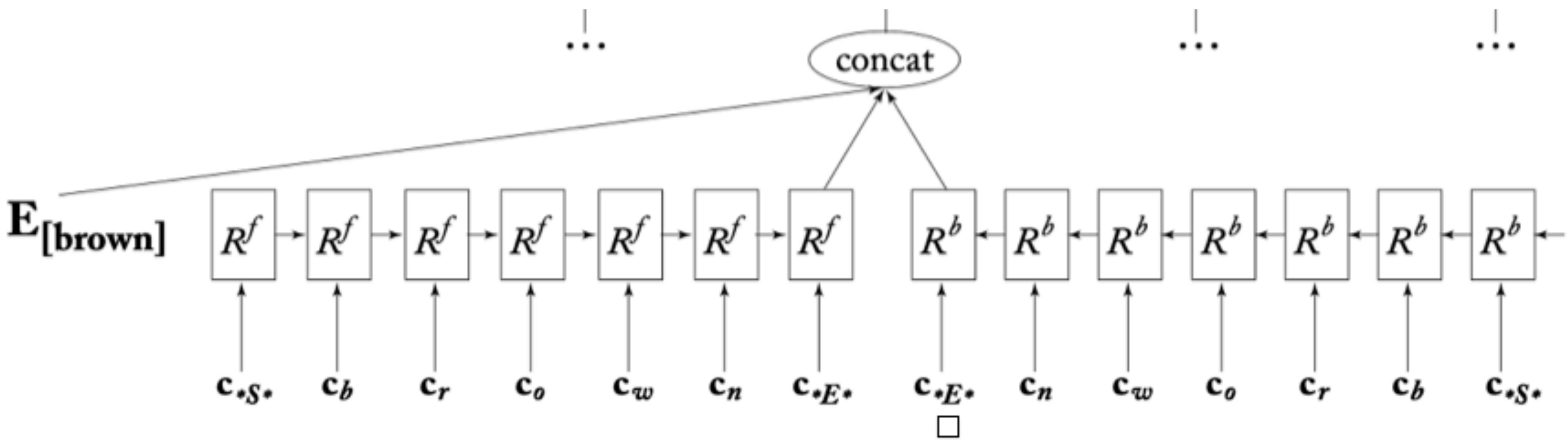
Character-based word embeddings



Character BiRNN

Character-based word embeddings

The embedding for each word is generated dynamically



We still train a full word embedding (useful for frequent words)

Character embeddings

RNN for sequence labeling: Named entity recognition

Goal: extract proper names from a document and classify them into categories

Italy GPE 's business world was rocked by the announcement last Thursday DATE that Mr. Verdi PERSON would leave his job as vice president of Music Masters of Milan, Inc. ORG to become operations director of Arthur Andersen ORG .

(GPE = Geopolitical entity)

https://explosion.ai/demos/displacy-ent

Isn’t NER really easy?

> Italy's business world was rocked by the announcement last Thursday that Mr. Verdi would leave his job as vice president of Music Masters of Milan, Inc. to become operations director of Arthur Andersen.

- Italy is in the beginning of the sentence: capitalization does help
- Milan is part an organization, not a location, as usual
- Arthur Andersen is an organization, not a person…
- Context matters!

(Borthwick, 1999)

Span labeling using IOB

- NER is a span labeling problem; how can we reduce it to token labeling?

- IOB = **I**nside, **B**eginning, **O**utside

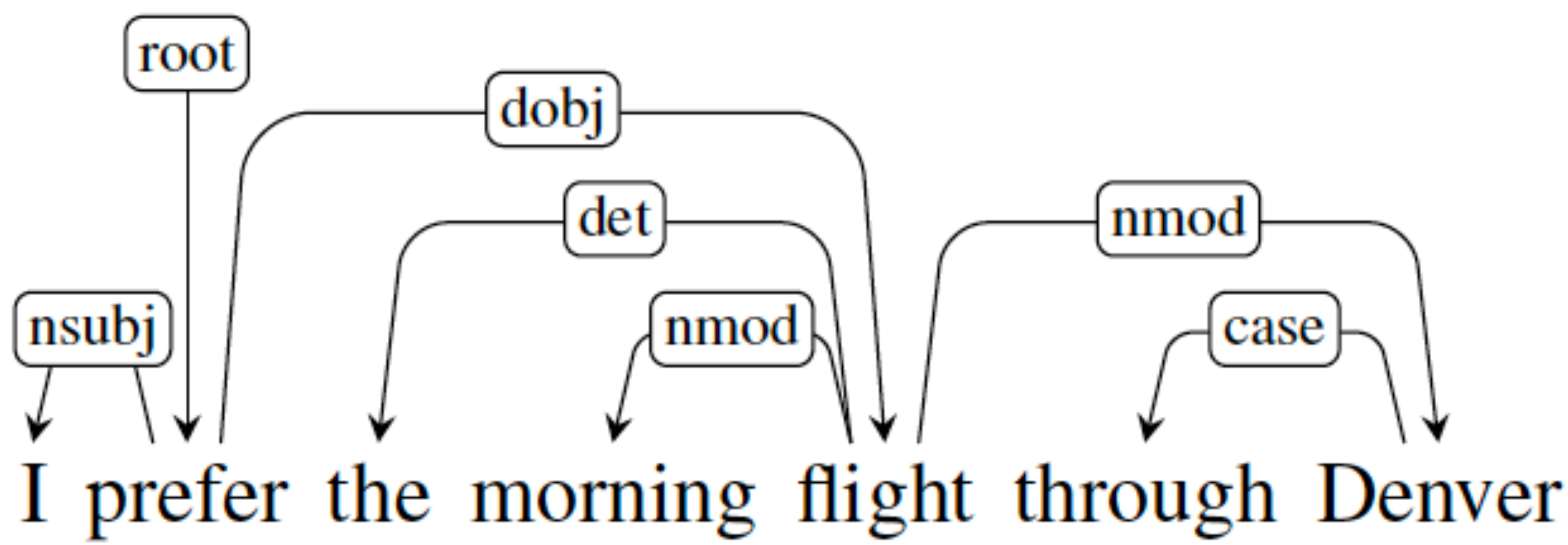
United	*cancelled*	*the*	*flight*	*from*	*Denver*	*to*	*San*	*Francisco.*
B	O	O	O	O	B	O	B	I

- With entity types:

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

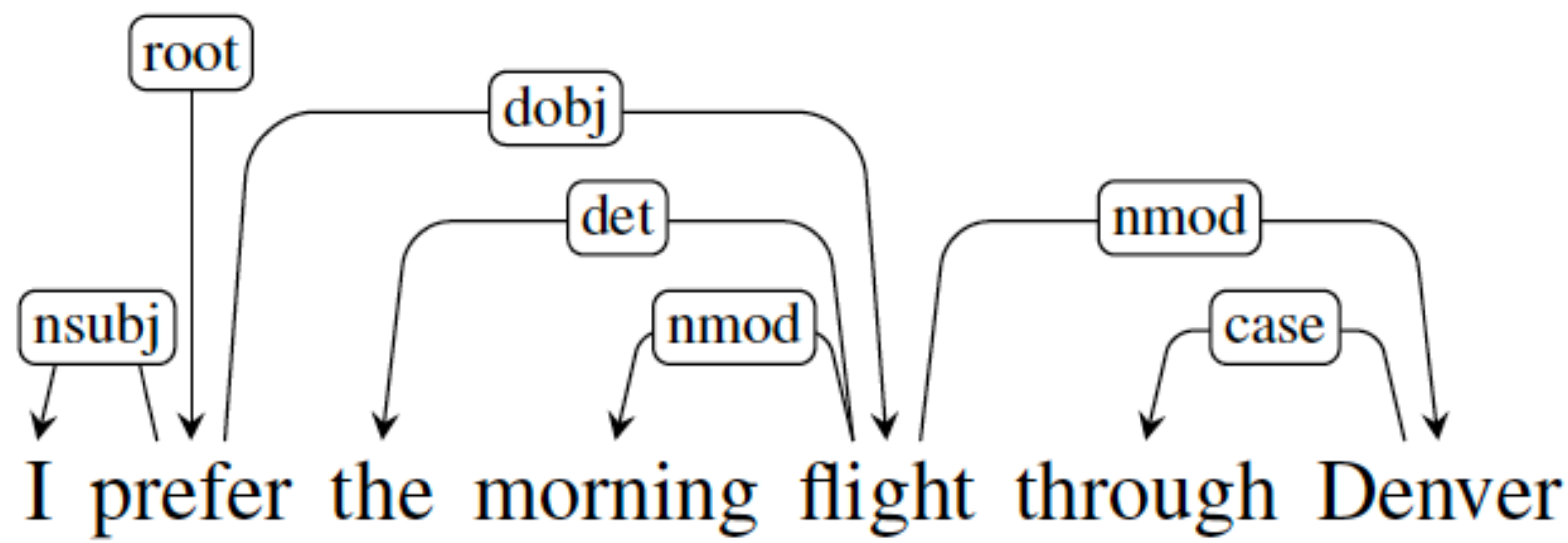
Dependency parse

No explicit constituents: all syntactic information expressed as relations between words



Dependency parse

- Easier to work with in languages with flexible word order
- More direct relationship with semantic roles: head can be read off automatically



VP -> V NP
VP -> NP V

NP -> PP N PP
NP -> N PP PP
NP -> N PP

…

Universal dependencies treebank

Standardized labels for dozens of languages!

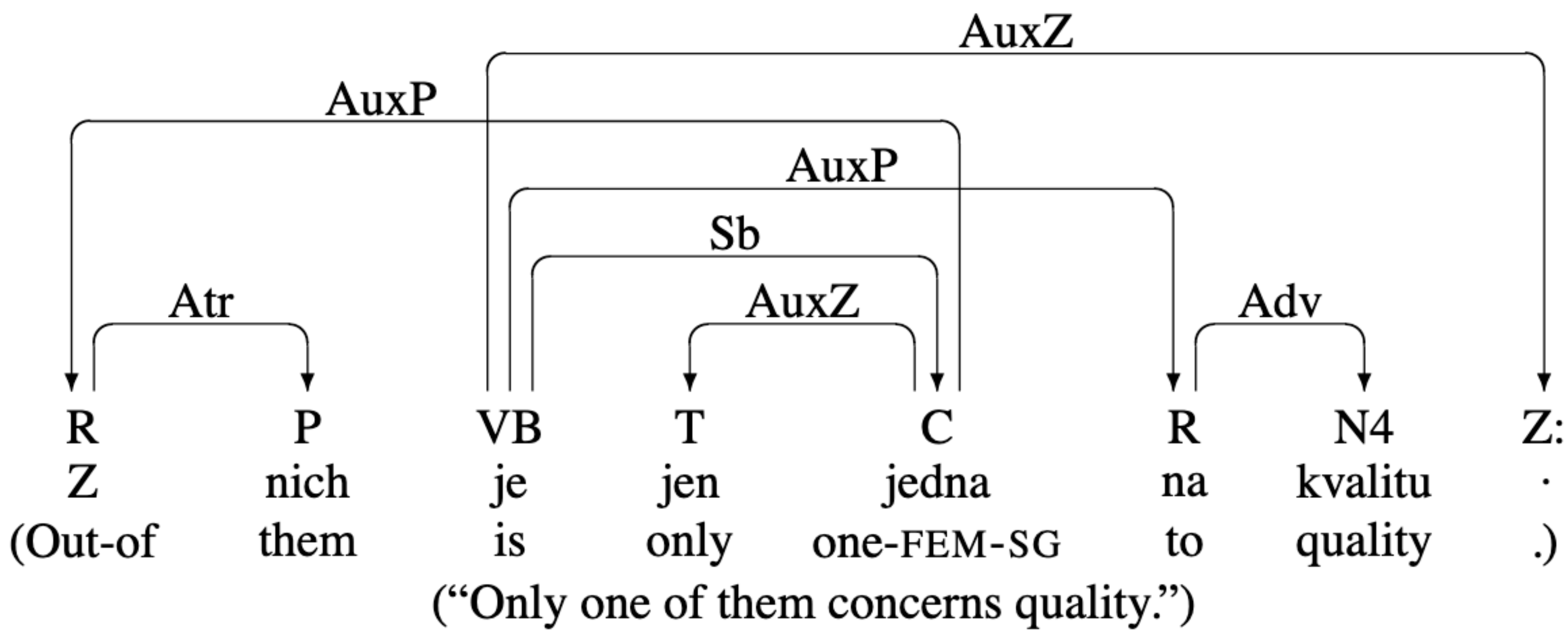
Relation	Examples with *head* and **dependent**
NSUBJ	**United** *canceled* the flight.
DOBJ	United *diverted* the **flight** to Reno.
	We *booked* her the first **flight** to Miami.
IOBJ	We *booked* **her** the flight to Miami.
NMOD	We took the **morning** *flight*.
AMOD	Book the **cheapest** *flight*.
NUMMOD	Before the storm JetBlue canceled **1000** *flights*.
APPOS	*United*, a **unit** of UAL, matched the fares.
DET	**The** *flight* was canceled.
	Which *flight* was delayed?
CONJ	We *flew* to Denver and **drove** to Steamboat.
CC	We flew to Denver **and** *drove* to Steamboat.
CASE	Book the flight **through** *Houston*.

Figure 15.3 Examples of core Universal Dependency relations.

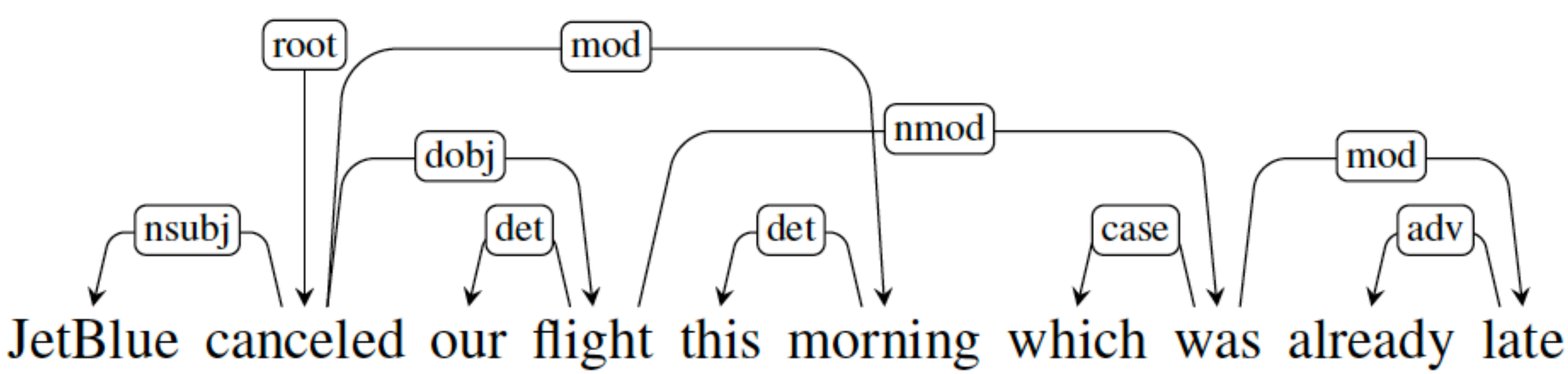
https://universaldependencies.org/

Projectivity

Czech:



(Nivre & Nilsson, 2005)



Shift-reduce for constituency parsing

Step	Stack	Input buffer	Move
0		the aged bottle flies fast	
1	the	aged bottle flies fast	shift "the"
2	Det	aged bottle flies fast	reduce (Det $\rightarrow$ the)
3	Det aged	bottle flies fast	shift "aged"
4	Det Adj	bottle flies fast	reduce (Adj $\rightarrow$ aged)
5	Det Adj bottle	flies fast	shift "bottle"
6	Det Adj N	flies fast	reduce (N $\rightarrow$ bottle)
7	NP	flies fast	reduce (NP $\rightarrow$ Det Adj N)
8	NP flies	fast	shift "flies"
9	NP V	fast	reduce (V $\rightarrow$ flies)
10	NP V fast		shift "fast"
11	NP V Adv		reduce (Adv $\rightarrow$ fast)
12	NP VP		reduce (VP $\rightarrow$ V Adv)
13	S		reduce (S $\rightarrow$ NP VP)

S $\rightarrow$ NP VP, VP $\rightarrow$ V Adv,
NP $\rightarrow$ Det Adj N, Det $\rightarrow$ the,
Adj $\rightarrow$ aged, N $\rightarrow$ bottle,
V $\rightarrow$ flies, Adv $\rightarrow$ fast

(Roark and Sproat, 2007)

If anything can be reduced on the top of the stack, do so; otherwise shift.