Recurrent Neural Networks

Yoav Goldberg

Dealing with Sequences

- For an input sequence **x1**,...,**xn**, we can:
  - If *n* is **fixed**: *concatenate* and feed into an MLP.
  - *sum* the vectors (*CBOW*) and feed into an MLP.
  - Break the sequence into *windows.* Find n-gram embedding, sum into an MLP.
  - Find good ngrams using ConvNet, using *pooling* (either sum/avg or max) to combine to a single vector.

Dealing with Sequences

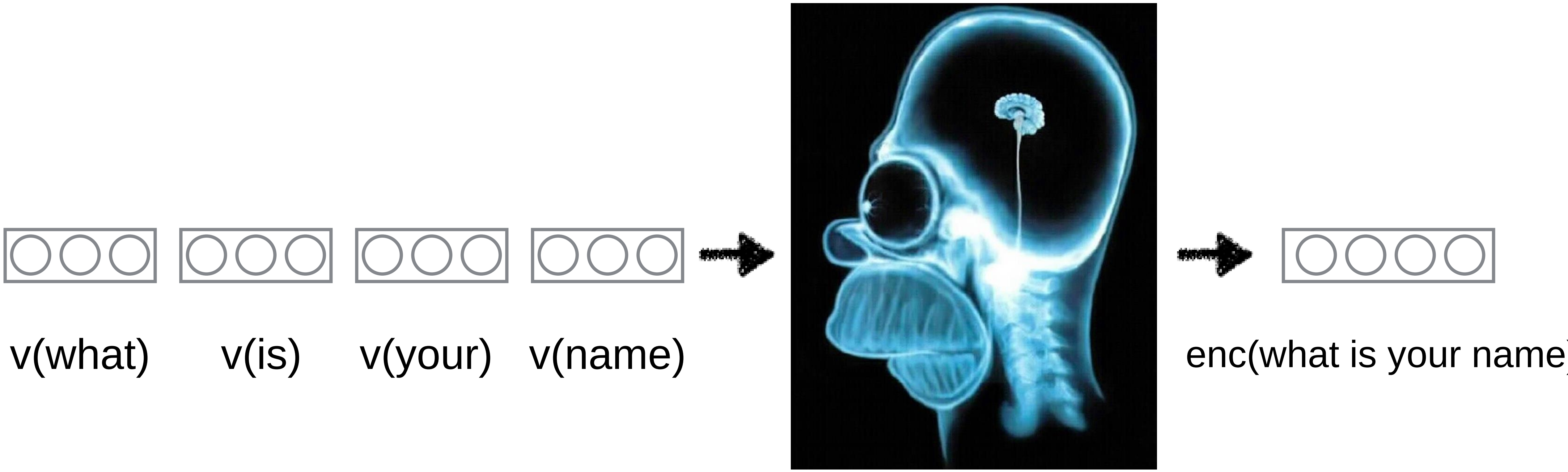
- For an input sequence **x1**,...,**xn**, we can:

Some of these approaches consider **local** word order (which ones?).

How can we consider **global** word order?

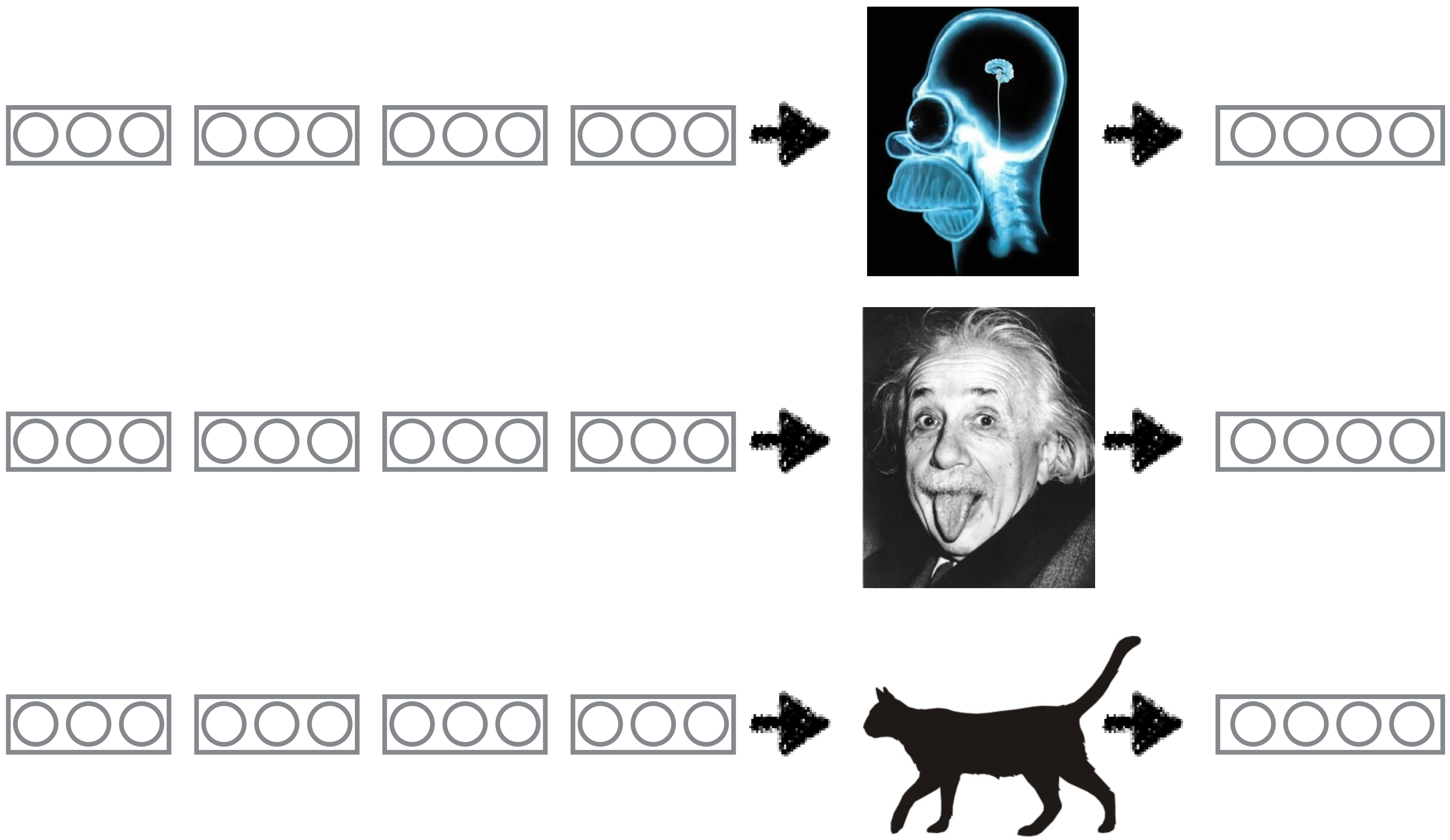
  - Find good ngrams using ConvNet, using *pooling* (either sum/avg or max) to combine to a single vector.

Recurrent Neural Networks



- Very strong models of sequential data.
- **Trainable** function from *n* vectors to a single vector.

Recurrent Neural Networks



- There are different variants (implementations).
- So far, we focused on the interface level.

Recurrent Neural Networks

$$RNN(\mathbf{s_0}, \mathbf{x_{1:n}}) = \mathbf{s_n}, \mathbf{y_n}$$

$$\mathbf{x_i} \in \mathbb{R}^{d_{in}},\ \mathbf{y_i} \in \mathbb{R}^{d_{out}},\ \mathbf{s_i} \in \mathbb{R}^{f(d_{out})}$$

- Very strong models of sequential data.
- **Trainable** function from *n* vectors to a single* vector.

Recurrent Neural Networks

$$RNN(\mathbf{s_0}, \mathbf{x_{1:n}}) = \mathbf{s_n}, \mathbf{y_n}$$

*this one is internal. we only care about the **y**

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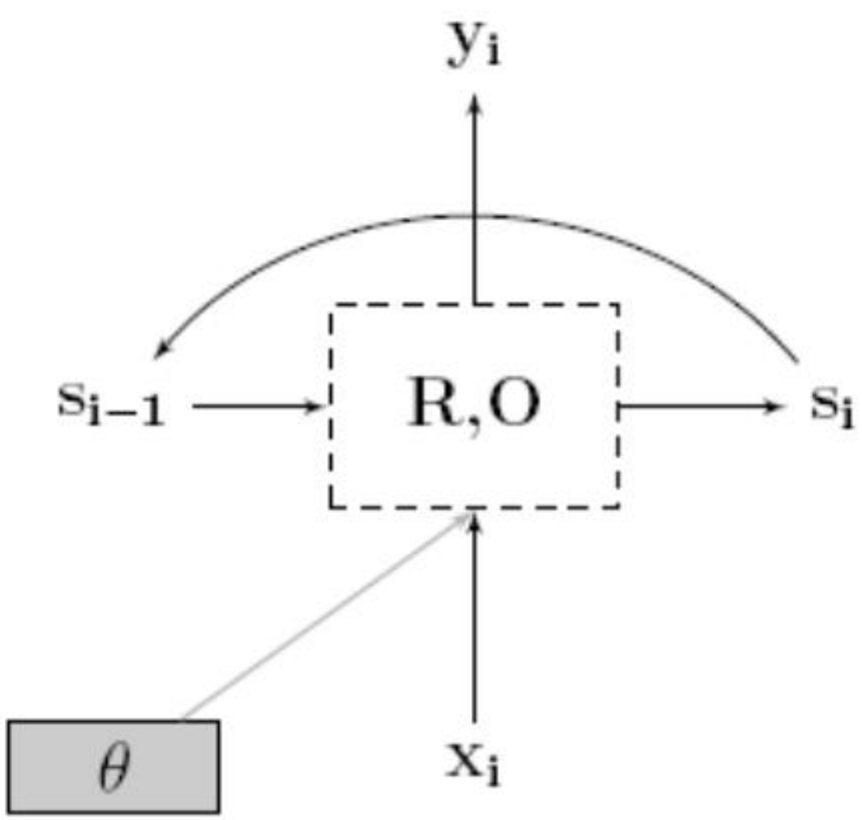
- **Recursively defined.**
- There's a vector $\mathbf{y_i}$ for every prefix $\mathbf{x_{1:i}}$

Recurrent Neural Networks



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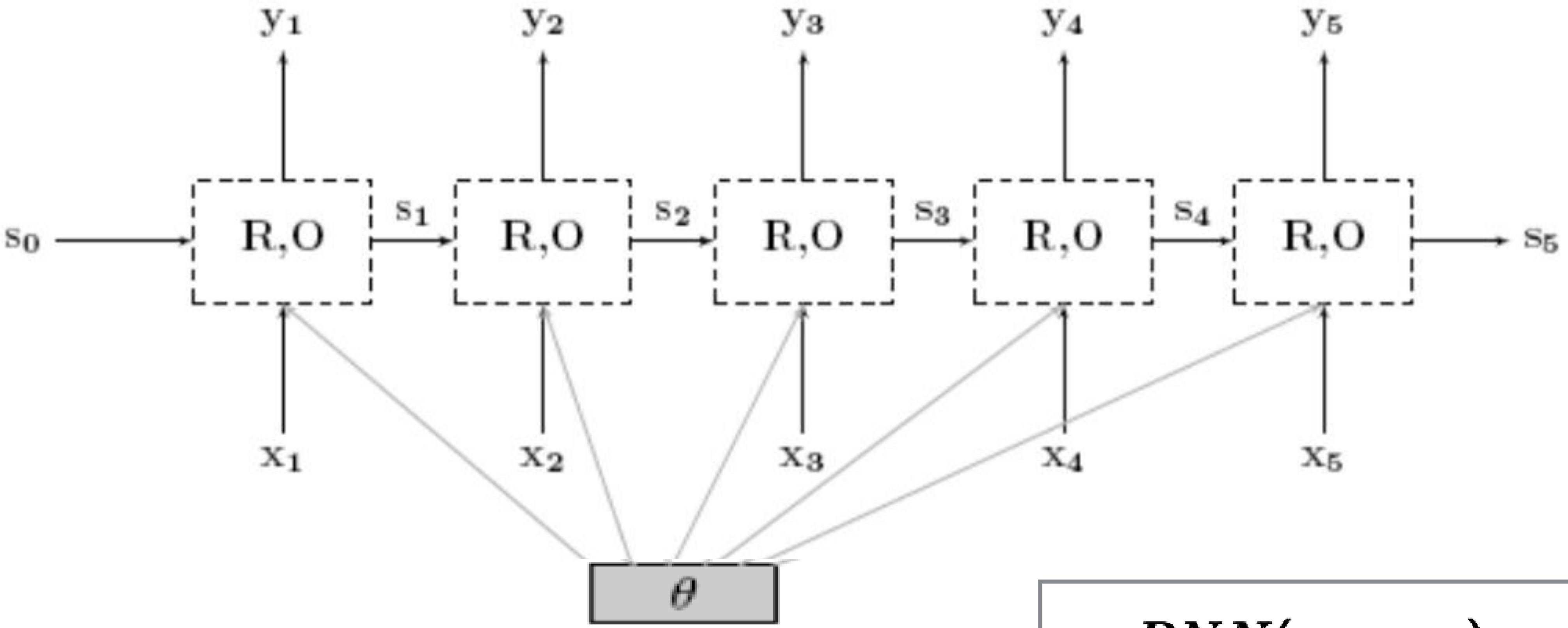

for every finite input sequence,
can unroll the recursion.

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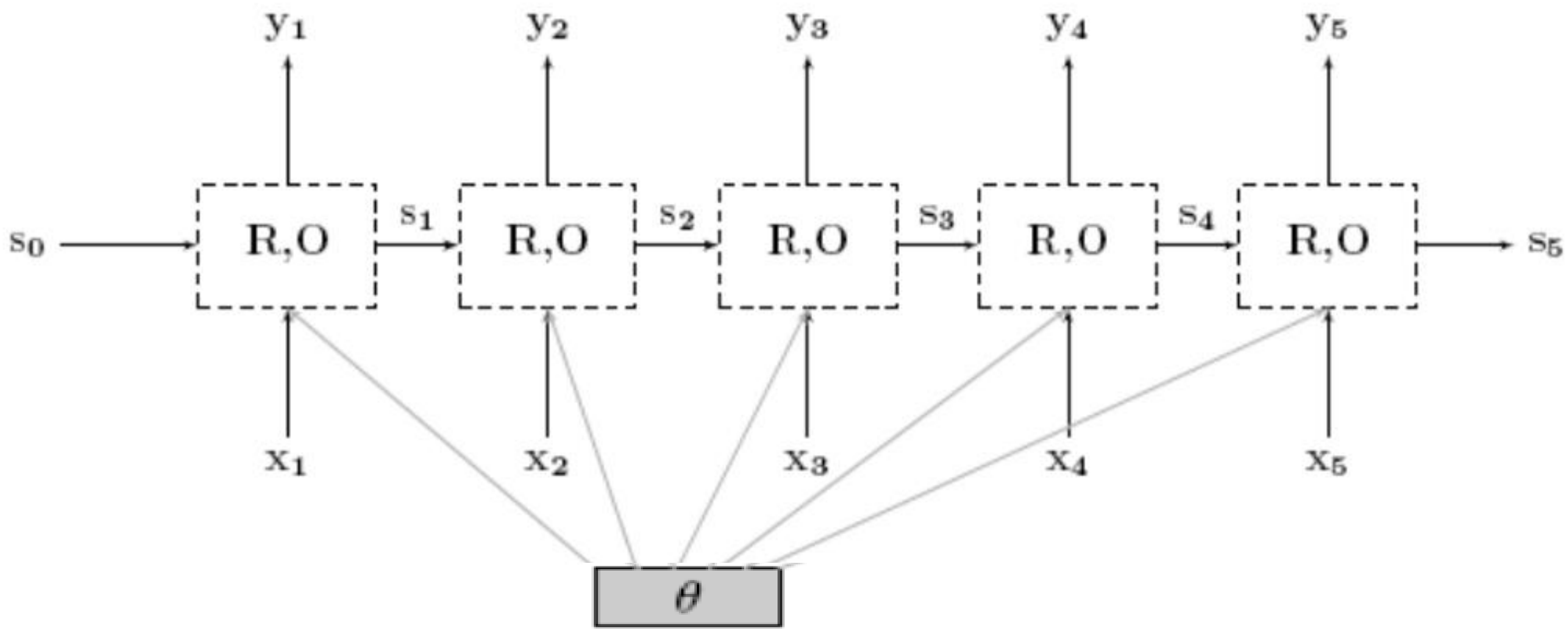
Recurrent Neural Networks



for every finite input sequence,
can unroll the recursion.

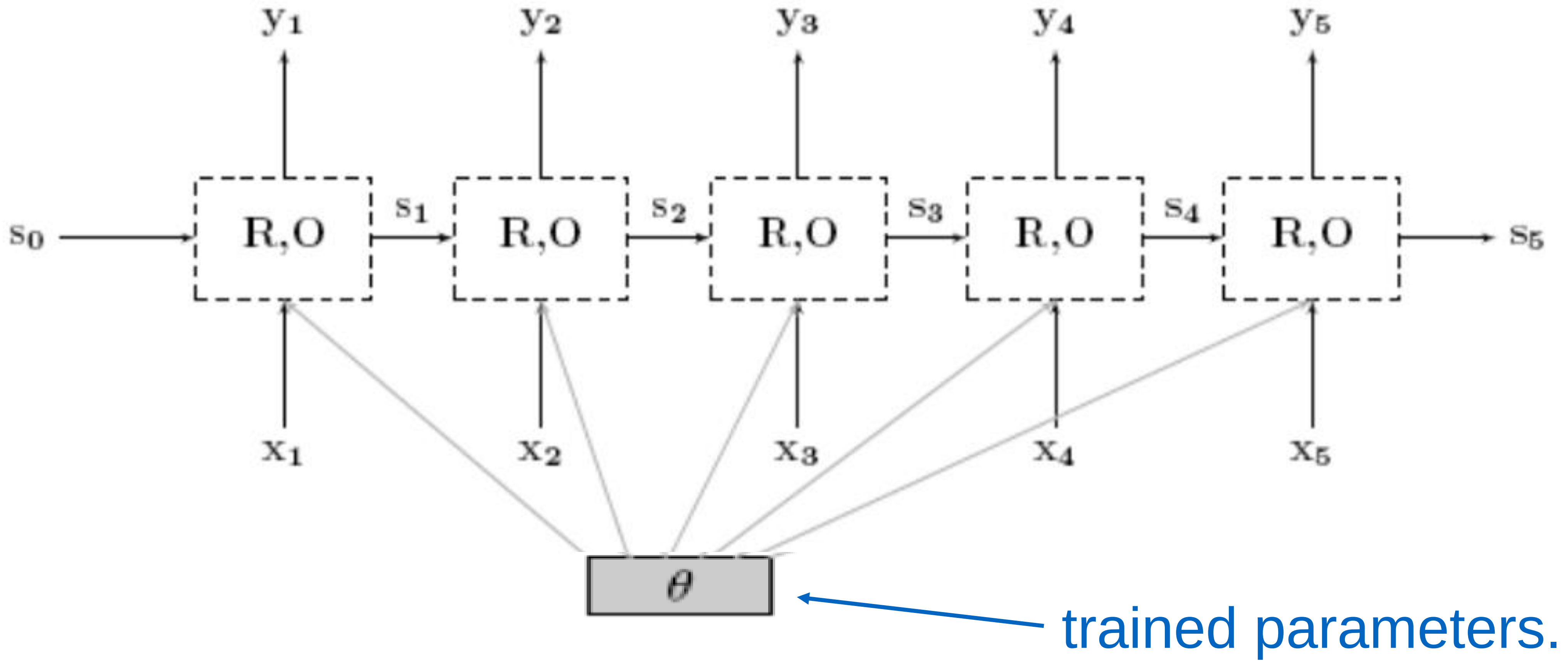
An unrolled RNN is just a very deep Feed Forward Network with shared parameters across the layers, and a new input at each layer.

Recurrent Neural Networks

$$
\begin{aligned}
\mathbf{y_4} &= O(\mathbf{s_4}) \\
\mathbf{s_4} &= R(\mathbf{s_3}, \mathbf{x_4}) \\
&= R(\overbrace{R(\mathbf{s_2}, \mathbf{x_3})}^{\mathbf{s_3}}, \mathbf{x_4}) \\
&= R(R(\overbrace{R(\mathbf{s_1}, \mathbf{x_2})}^{\mathbf{s_2}}, \mathbf{x_3}), \mathbf{x_4}) \\
&= R(R(R(\overbrace{R(\mathbf{s_0}, \mathbf{x_1})}^{\mathbf{s_1}}, \mathbf{x_2}), \mathbf{x_3}), \mathbf{x_4})
\end{aligned}
$$

- The output vector $\mathbf{y_i}$ depends on **all** inputs $\mathbf{x_{1:i}}$

Recurrent Neural Networks



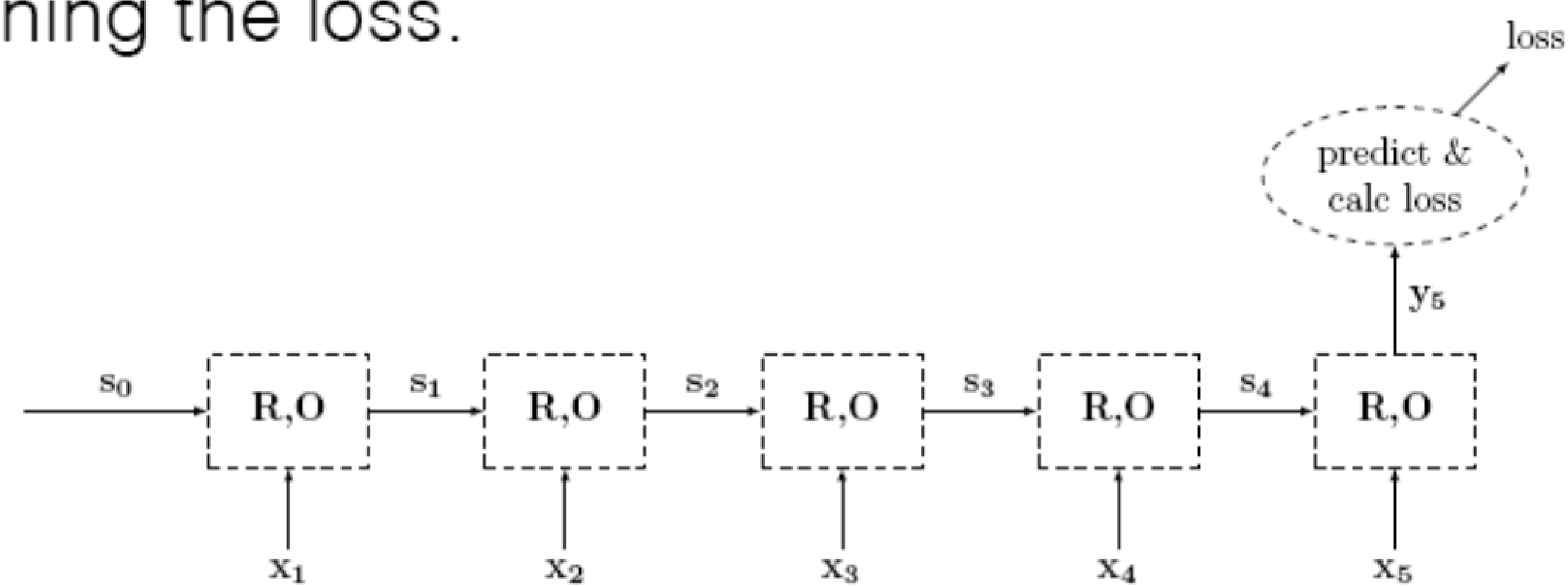
- **But we can train them.**

define function form

define loss

Recurrent Neural Networks for Text Classification

Defining the loss.



Acceptor: predict something from end state.
Backprop the error all the way back.
Train the network to capture meaningful information

CBOW as an RNN

$$R_{CBOW}(\mathbf{s_{i-1}}, \mathbf{x_i}) = \mathbf{s_{i-1}} + \mathbf{x_i}$$

(what are the parameters?)

CBOW as an RNN

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(what are the parameters?)

$$R_{CBOW}(\mathbf{s_{i-1}}, x_i) = \mathbf{s_{i-1}} + \mathbf{E}_{[x_i]}$$

CBOW as an RNN

Is this a good parameterization?

$$R_{CBOW}(\mathbf{s_{i-1}}, x_i) = \mathbf{s_{i-1}} + \mathbf{E}_{[x_i]}$$

CBOW as an RNN

how about this modification?

$$R_{CBOW}(\mathbf{s_{i-1}}, x_i) = \tanh(\mathbf{s_{i-1}} + \mathbf{E}_{[x_i]})$$

Simple RNN (Elman RNN)

$$R_{SRNN}(\mathbf{s_{i-1}}, \mathbf{x_i}) = tanh(\mathbf{W^s} \cdot \mathbf{s_{i-1}} + \mathbf{W^x} \cdot \mathbf{x_i})$$

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- Looks very simple.
- Theoretically very powerful.
- In practice not so much (hard to train).
- Why? Vanishing gradients.

Simple RNN (Elman RNN)

$$R_{SRNN}(\mathbf{s_{i-1}}, \mathbf{x_i}) = tanh(\mathbf{W^s} \cdot \mathbf{s_{i-1}} + \mathbf{W^x} \cdot \mathbf{x_i})$$

Another view on behavior:

- RNN as a "computer":
  input **xi** arrives, memory **s** is updated.

- In the Elman RNN, **entire memory is written** at each time-step.

LSTM RNN

better controlled memory access

continuous gates

Differentiable "Gates"

- The main idea behind the LSTM is that you want to somehow control the "memory access".

- In a SimpleRNN:

$$R_{SRNN}(\mathbf{s_{i-1}}, \mathbf{x_i}) = tanh(\mathbf{W^s} \cdot \mathbf{s_{i-1}} + \mathbf{W^x} \cdot \mathbf{x_i})$$

read previous state memory

write new input

- All the memory gets overwritten

Vector "Gates"

- We'd like to:
  * Selectively read from some memory "cells".
  * Selectively write to some memory "cells".

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  * Selectively read from some memory "cells".
  * Selectively write to some memory "cells".
- A gate function:

$$\underset{\mathbf{g}}{\begin{bmatrix}0\\1\\0\\0\\0\\1\end{bmatrix}} \odot \underset{\mathbf{x}}{\begin{bmatrix}10\\11\\12\\13\\14\\15\end{bmatrix}}$$

(element-wise multiplication)

gate controls access

vector of values

Vector "Gates"

- We'd like to:
  * Selectively read from some memory "cells".
  * Selectively write to some memory "cells".

- A gate function: $\mathbf{s_{i-1}} \odot \mathbf{g}$ $\quad\quad \mathbf{g} \in \{0, 1\}^d$

vector of values

gate controls access

Vector "Gates"

- Using the gate function to control access:

$$\mathbf{s_i} \leftarrow \mathbf{s_{i-1}} \odot \mathbf{g^r} + \mathbf{x_i} \odot \mathbf{g^w} \qquad \mathbf{g} \in \{0,1\}^d$$

which cells to read

which cells to write

Vector "Gates"

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which cells to read

which cells to write

- (can also tie them: $\mathbf{g^r} = 1 - \mathbf{g^w}$)

Vector "Gates"

$$\begin{bmatrix}8\\11\\3\\7\\5\\15\end{bmatrix} \leftarrow \begin{bmatrix}0\\1\\0\\0\\0\\1\end{bmatrix} \odot \begin{bmatrix}10\\11\\12\\13\\14\\15\end{bmatrix} + \begin{bmatrix}1\\0\\1\\1\\1\\0\end{bmatrix} \odot \begin{bmatrix}8\\9\\3\\7\\5\\8\end{bmatrix}$$

$$\mathbf{s}' \qquad \mathbf{g} \qquad \mathbf{x} \qquad (\mathbf{1}-\mathbf{g}) \qquad \mathbf{s}$$

Differentiable "Gates"

- **Problem with the gates**:
  * they are fixed.
  * they don't depend on the input or the output.

Differentiable "Gates"

- **Problem with the gates**:
  * they are fixed.
  * they don't depend on the input or the output.

- Solution: make them smooth, input dependent, and trainable.

$$\mathbf{g^r} = \sigma(\mathbf{W} \cdot \mathbf{x_i} + \mathbf{U} \cdot \mathbf{s_{i-1}})$$

"almost 0"
or
"almost 1"

function of input and state

LSTM

(Long short-term Memory)

- The LSTM is a specific combination of gates.

$$R_{LSTM}(\mathbf{s_{j-1}}, \mathbf{x_j}) = [\mathbf{c_j}; \mathbf{h_j}]$$

$$\mathbf{c_j} = \mathbf{c_{j-1}} \odot \mathbf{f} + \mathbf{g} \odot \mathbf{i}$$

$$\mathbf{i} = \sigma(\mathbf{W^{xi}} \cdot \mathbf{x_j} + \mathbf{W^{hi}} \cdot \mathbf{h_{j-1}})$$

$$\mathbf{f} = \sigma(\mathbf{W^{xf}} \cdot \mathbf{x_j} + \mathbf{W^{hf}} \cdot \mathbf{h_{j-1}})$$

$$\mathbf{g} = \tanh(\mathbf{W^{xg}} \cdot \mathbf{x_j} + \mathbf{W^{hg}} \cdot \mathbf{h_{j-1}})$$

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GRU
(Gated Recurrent Unit)

- The GRU is a different combination of gates.

$$\mathbf{s_j} = R_{\mathrm{GRU}}(\mathbf{s_{j-1}}, \mathbf{x_j}) = (1 - \mathbf{z}) \odot \mathbf{s_{j-1}} + \mathbf{z} \odot \tilde{\mathbf{s_j}}$$

$$\mathbf{z} = \sigma(\mathbf{x_j} \mathbf{W^{xz}} + \mathbf{s_{j-1}} \mathbf{W^{sz}})$$

$$\mathbf{r} = \sigma(\mathbf{x_j} \mathbf{W^{xr}} + \mathbf{s_{j-1}} \mathbf{W^{sr}})$$

$$\tilde{\mathbf{s_j}} = \tanh(\mathbf{x_j} \mathbf{W^{xs}} + (\mathbf{r} \odot \mathbf{s_{j-1}}) \mathbf{W^{sg}})$$

GRU vs LSTM

- The GRU and the LSTM are very similar ideas.
- Invented independently of the LSTM, almost two decades later.

GRU
(Gated Recurrent Unit)

- The GRU formulation:

$$\mathbf{s_j} = R_{\mathrm{GRU}}(\mathbf{s_{j-1}}, \mathbf{x_j}) =$$

Proposal state: $\tilde{\mathbf{s}}_{\mathbf{j}} = \tanh(\mathbf{x_j}\mathbf{W^{xs}} + (\mathbf{r} \odot \mathbf{s_{j-1}})\mathbf{W^{sg}})$

GRU
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- The GRU formulation:

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gate controlling effect of prev on proposal:

$$\mathbf{r} = \sigma(\mathbf{x_j W^{xr}} + \mathbf{s_{j-1} W^{sr}})$$

$$\tilde{\mathbf{s_j}} = \tanh(\mathbf{x_j W^{xs}} + (\mathbf{r} \odot \mathbf{s_{j-1}})\mathbf{W^{sg}})$$

GRU
(Gated Recurrent Unit)

blend of old state and proposal state

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gate for controlling the blend

$$\mathbf{z} = \sigma(\mathrm{x_j}\mathbf{W}^{\mathbf{xz}} + \mathrm{s_{j-1}}\mathbf{W}^{\mathbf{sz}})$$

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Other Variants

- Many other variants exist.
- Mostly perform similarly to each other.
  - Different tasks may work better with different variants.
- **The important idea is the differentiable gates.**

LSTM
(Long short-term Memory)

- The LSTM is formulation:

$$
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R_{LSTM}(\mathbf{s_{j-1}}, \mathbf{x_j}) &= [\mathbf{c_j}; \mathbf{h_j}] \\
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\mathbf{g} = \cancel{\tanh}(\mathbf{W^{xg}} \cdot \mathbf{x_j} \cancel{+ \mathbf{W^{hg}} \cdot \mathbf{h_{j-1}}})
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Recurrent Additive Networks

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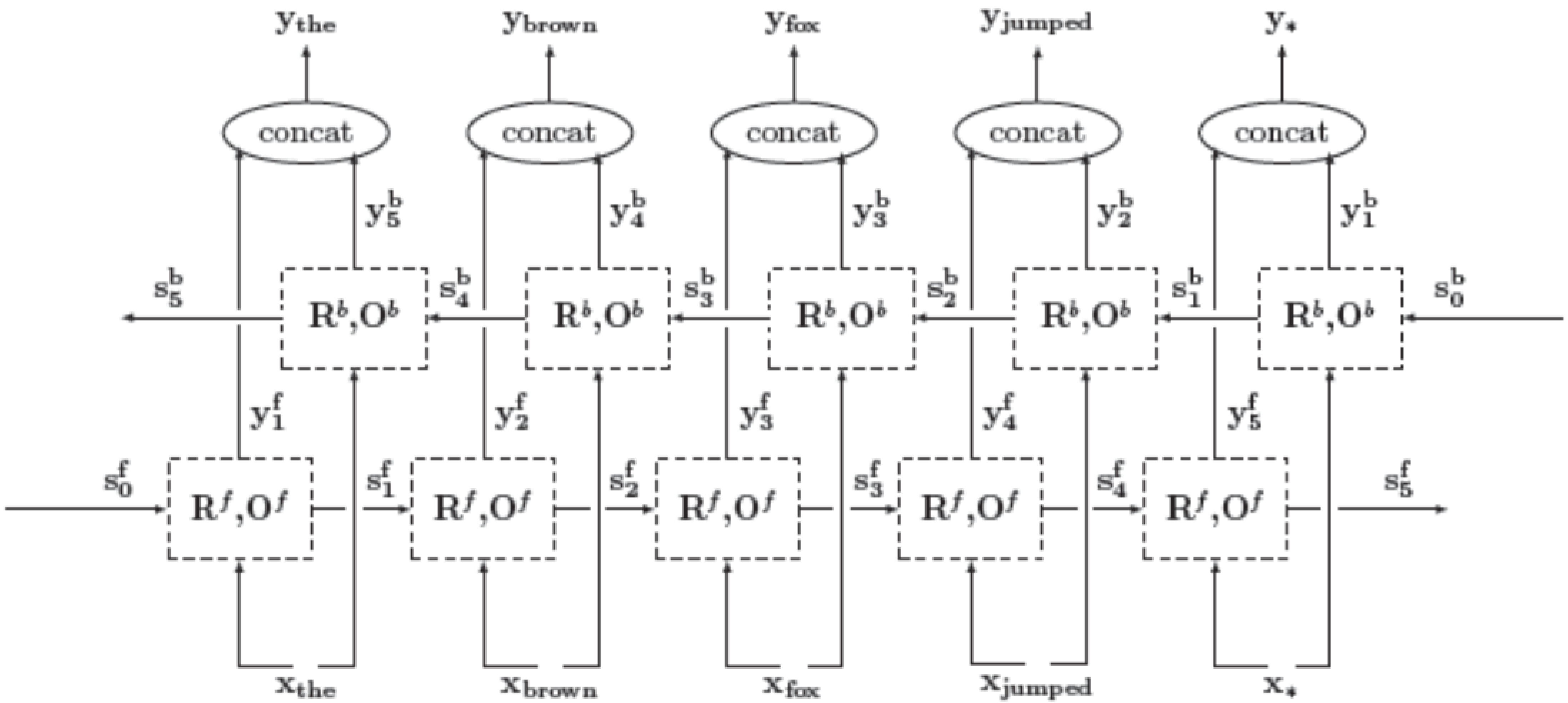
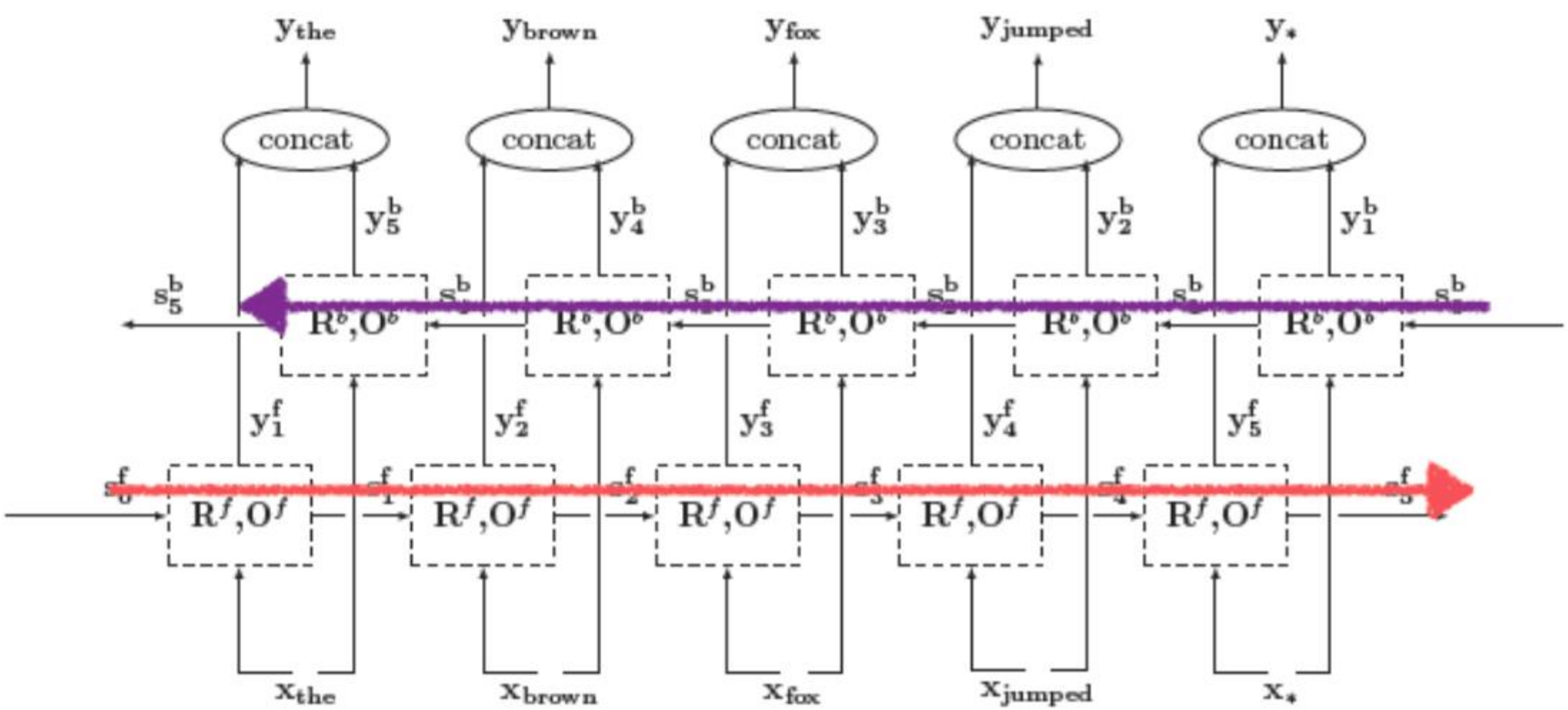
\mathbf{g} &= \mathbf{W^{xg}} \cdot \mathbf{x_j}
\end{aligned}
$$

Bidirectional LSTMs



One RNN runs left to right.
Another runs right to left.
Encode **both future and history** of a word.



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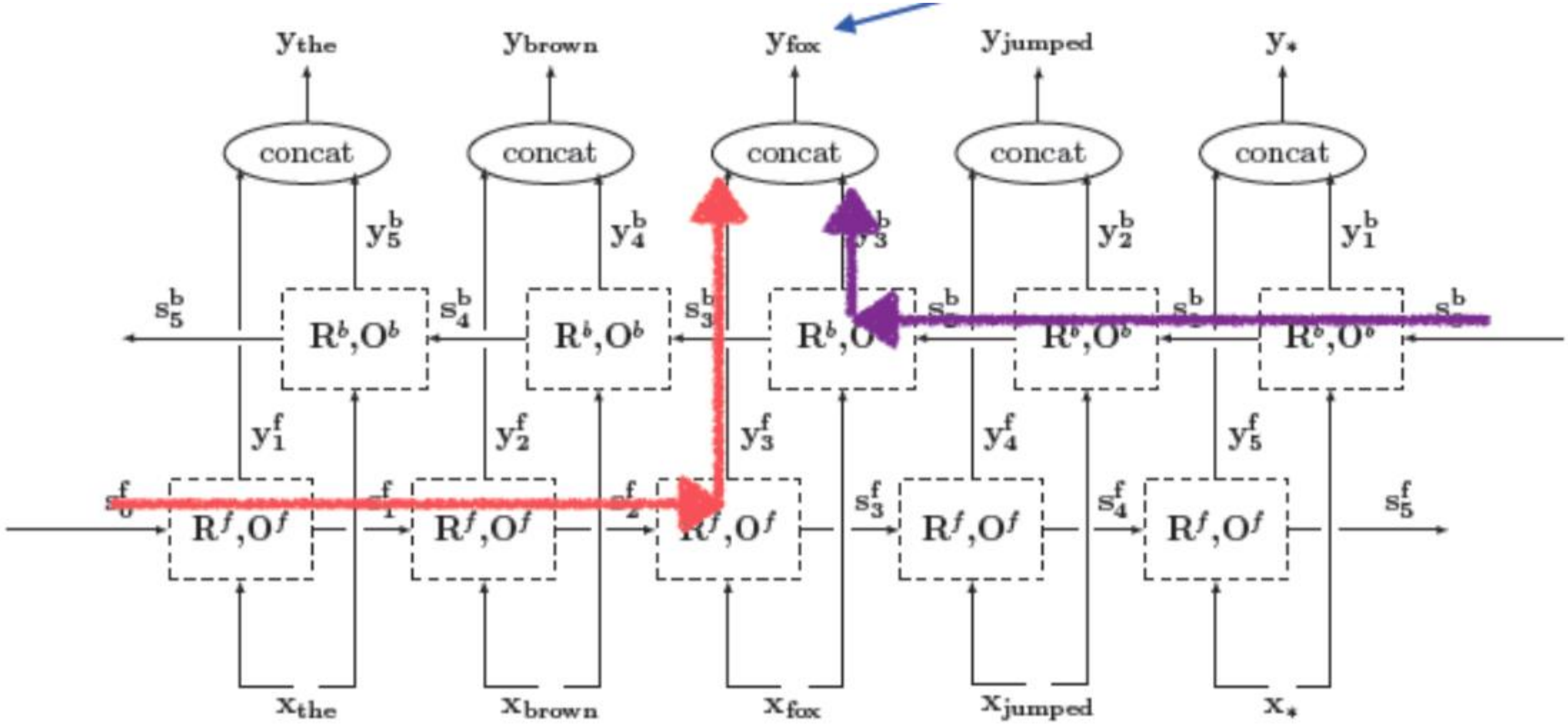
Infinite window around the word



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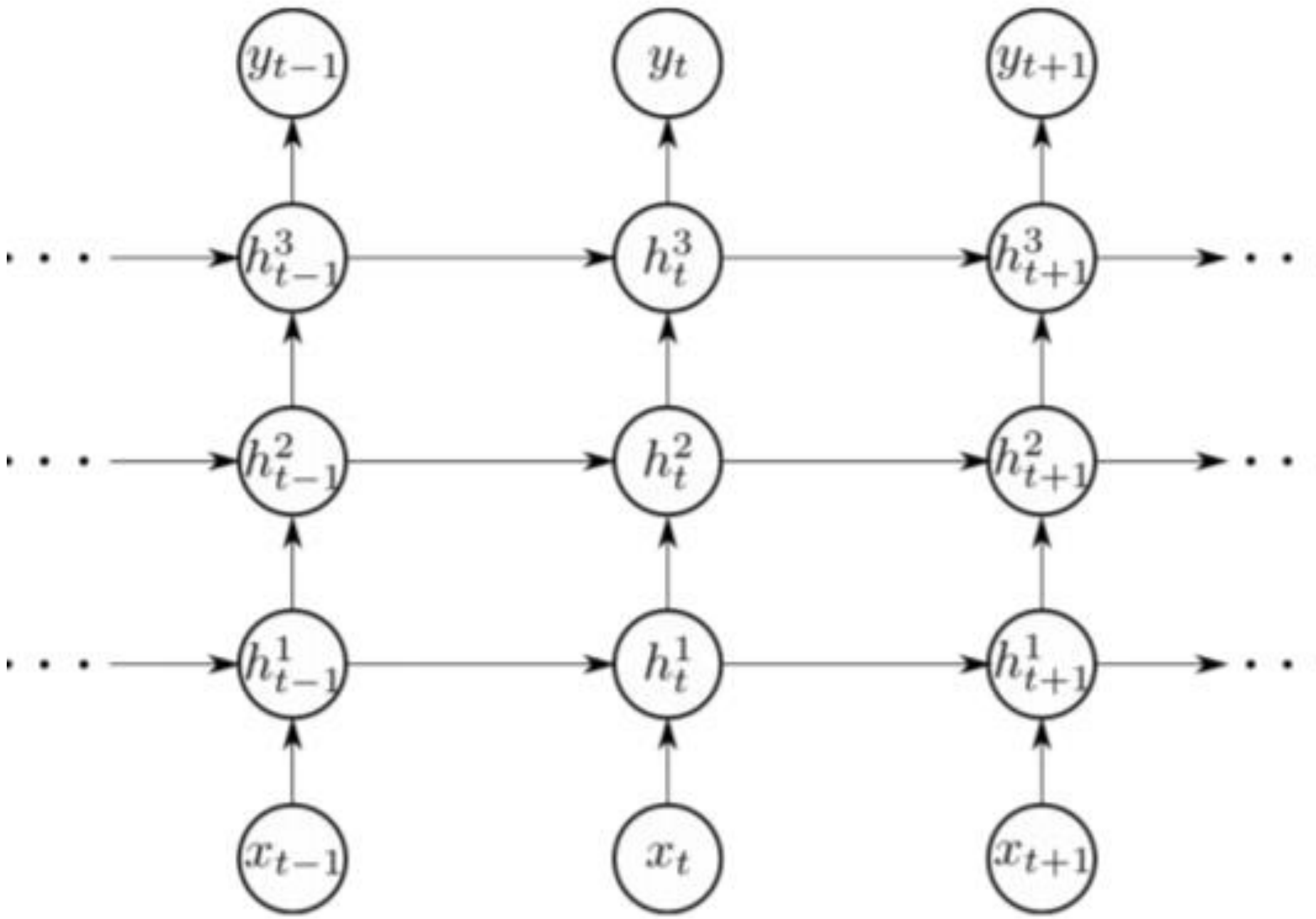
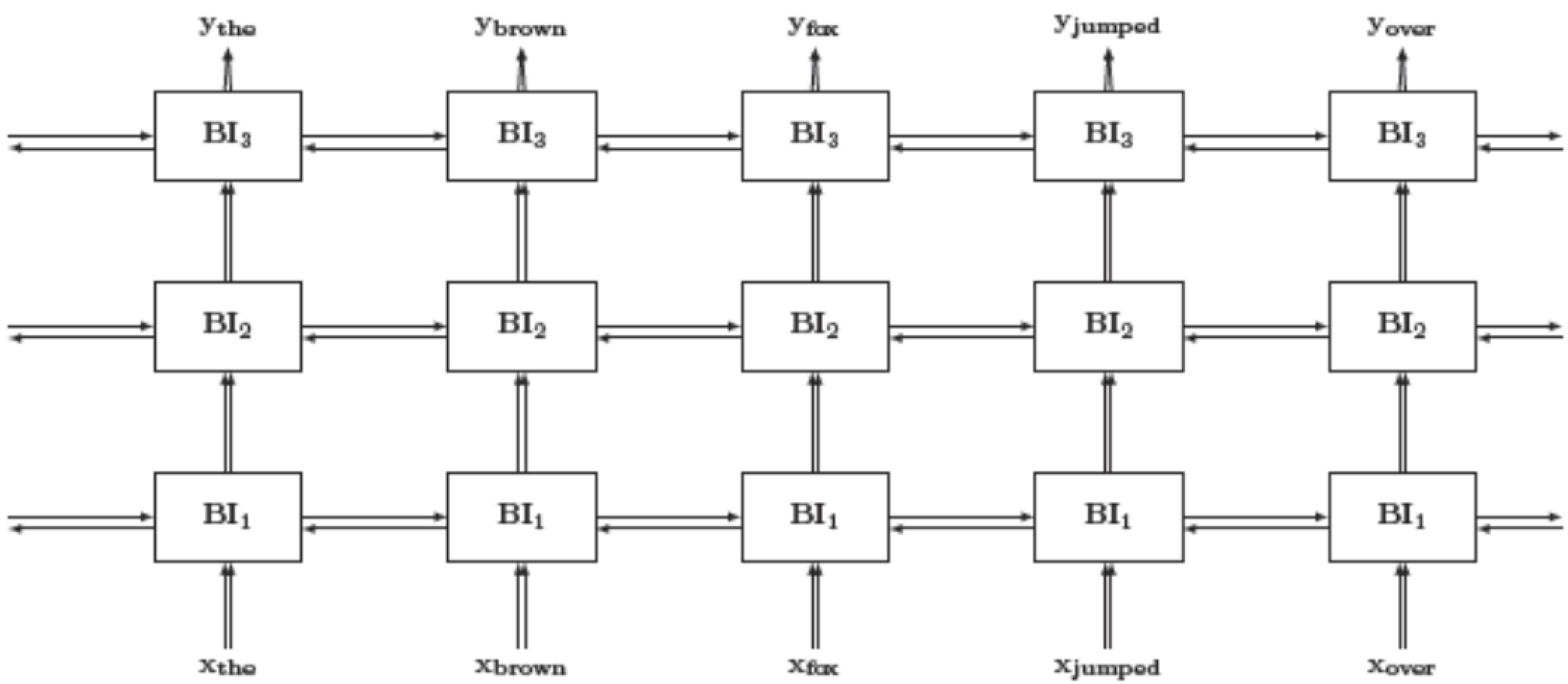
Deep LSTMs



(a) Conventional stacked RNN

Deep Bi-LSTMs



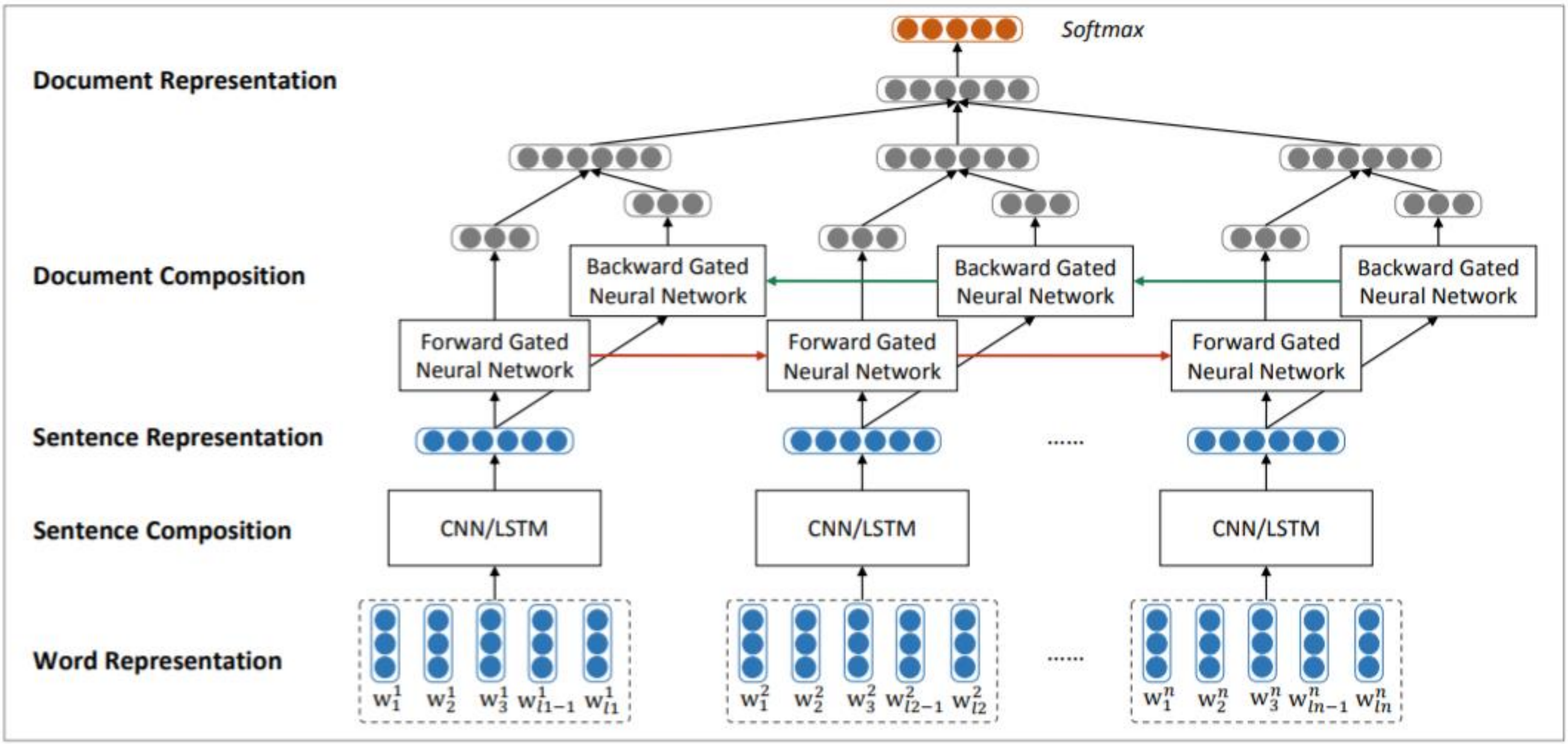
Read More

- The gated architecture also helps the vanishing gradients problems.

- For a good explanation, see Kyunghyun Cho's notes: http://arxiv.org/abs/1511.07916 sections 4.2, 4.3

- Chris Olah's blog post

Hierarchical RNN for Doc Classification



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