(1) a. I convinced her children are noisy.
b. The old man the boats.
c. The florist sent the flowers was pleased.

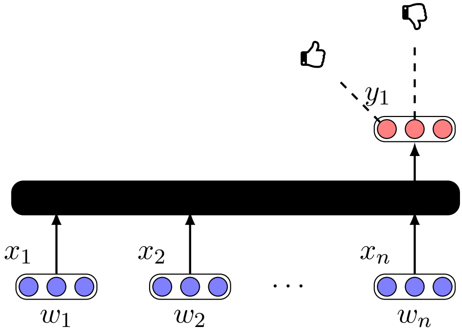
Language is an inherently temporal phenomenon

Lecture 8: Recurrent Neural Networks

1. Modeling sequences
2. Recurrent Neural Networks
3. Neural Language Models

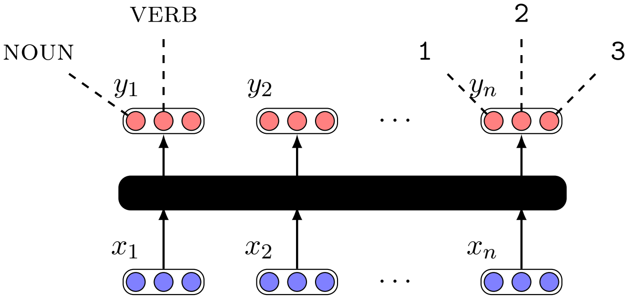
Modeling Sequences

Many input tokens; one output token



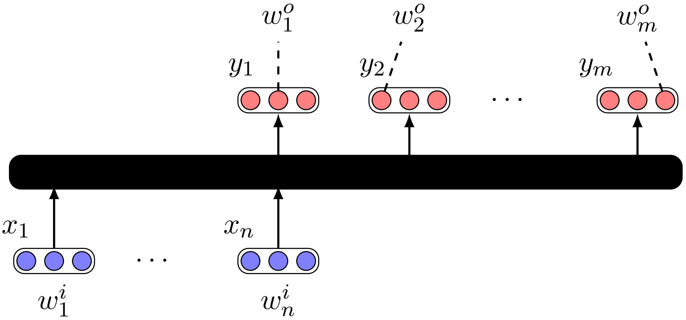
- Sentiment classification
- Document classification
- Automatic essay scoring
- ...

Many input tokens; many output token



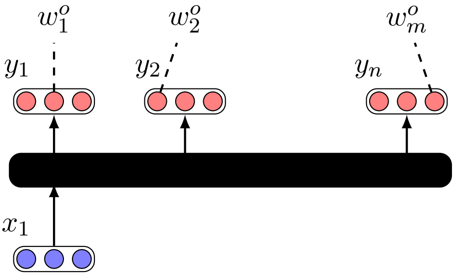
- POS tagging
- Segmentation and chunking
- Information extraction
- Dependency parsing
- ...

Many input tokens; many output token



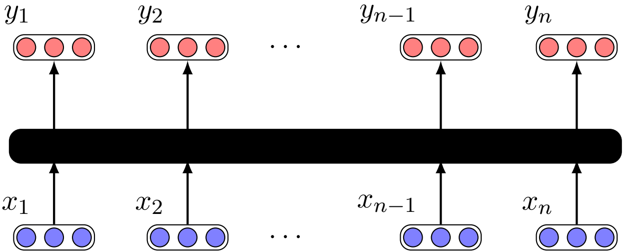
- Machine translation
- Text summarization
- ChatBot?
- ...

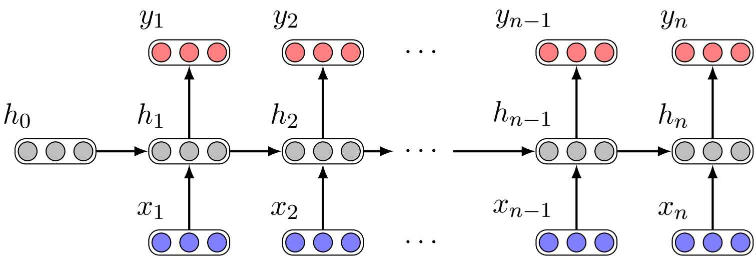
One input token; many output tokens

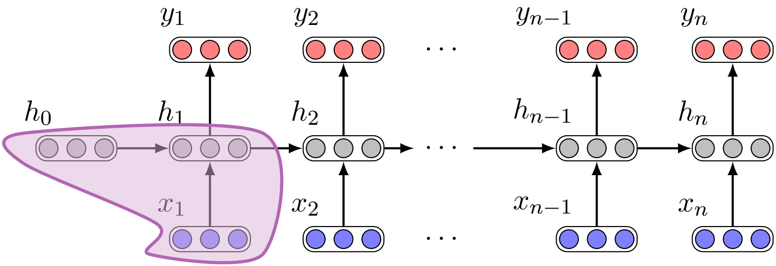


- Image captioning
- ...

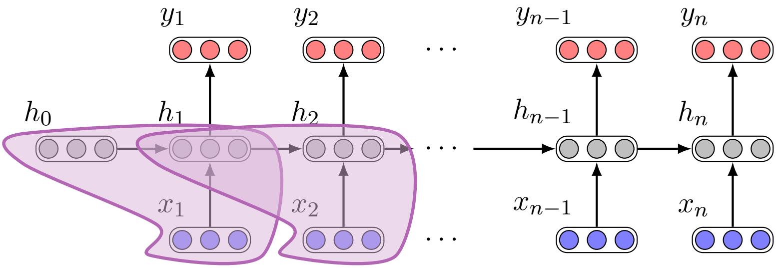
Recurrent Neural Networks


y_1
y_2
$\cdots$
y_{n-1}
y_n
x_1
x_2
$\cdots$
x_{n-1}
x_n

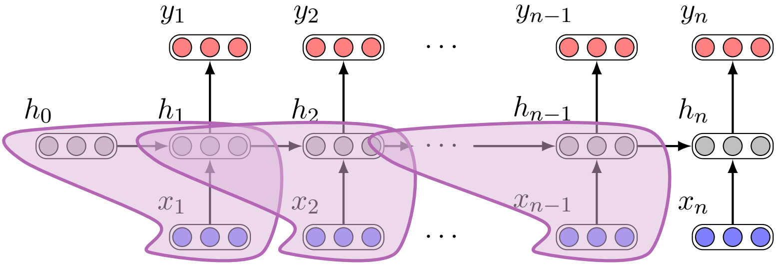

y_1
y_2
$\cdots$
y_{n-1}
y_n
h_0
h_1
h_2
h_{n-1}
h_n
x_1
x_2
x_{n-1}
x_n



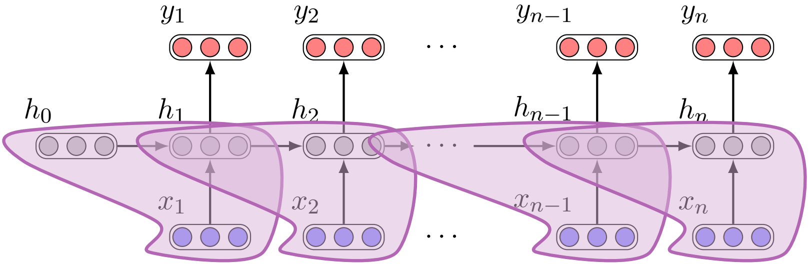
y_1
y_2
y_{n-1}
y_n
h_0
h_1
h_2
h_{n-1}
h_n
x_1
x_2
x_{n-1}
x_n



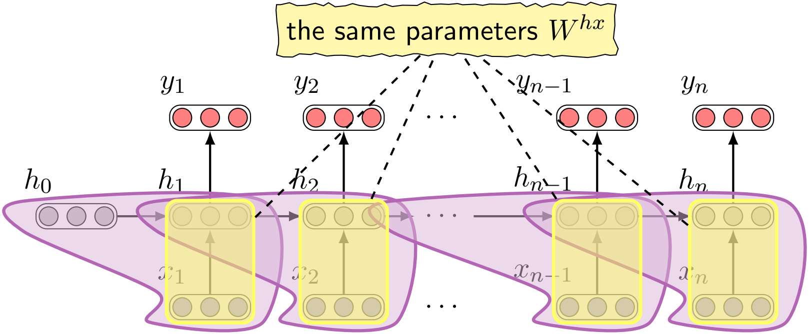
y_1
y_2
y_{n-1}
y_n
h_0
h_1
h_2
h_{n-1}
h_n
x_1
x_2
x_{n-1}
x_n
$\cdots$



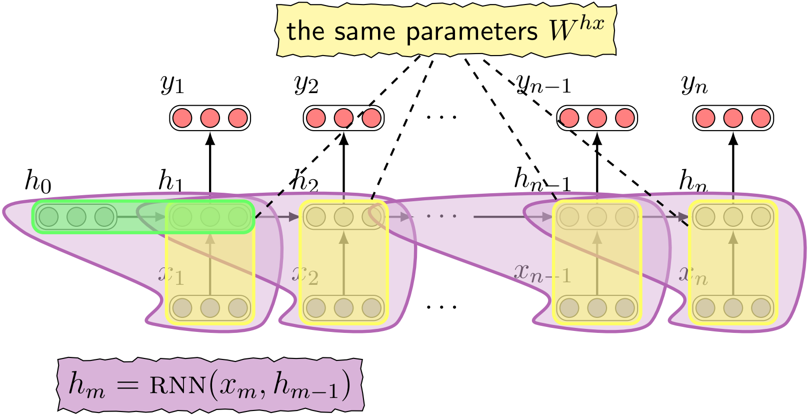
y_1
y_2
$\cdots$
y_{n-1}
y_n
h_0
h_1
h_2
$\cdots$
h_{n-1}
h_n
x_1
x_2
$\cdots$
x_{n-1}
x_n

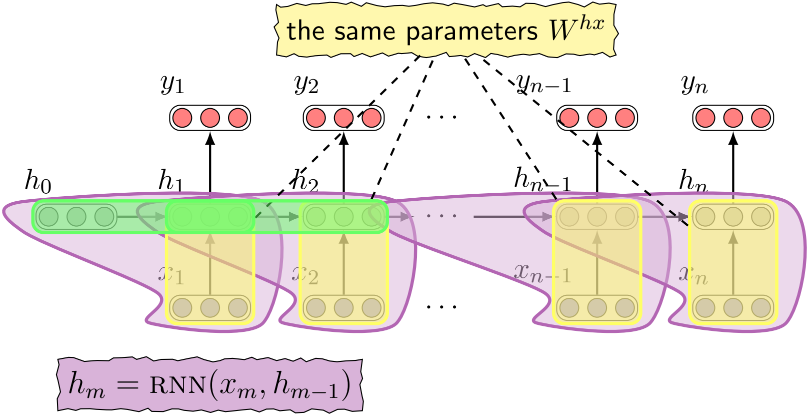


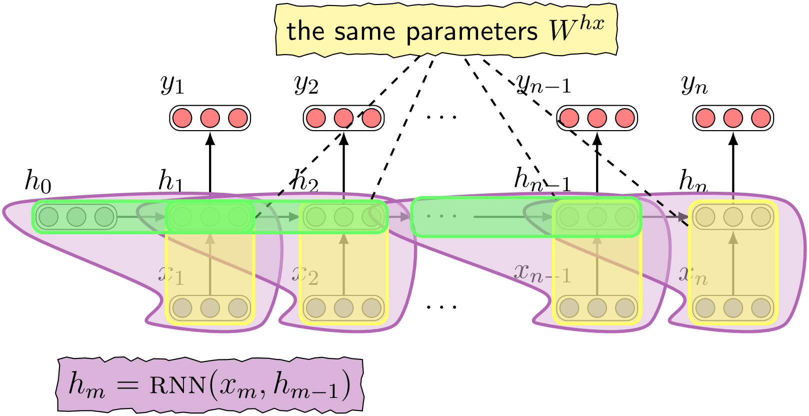
$$h_m = \text{RNN}(x_m, h_{m-1})$$

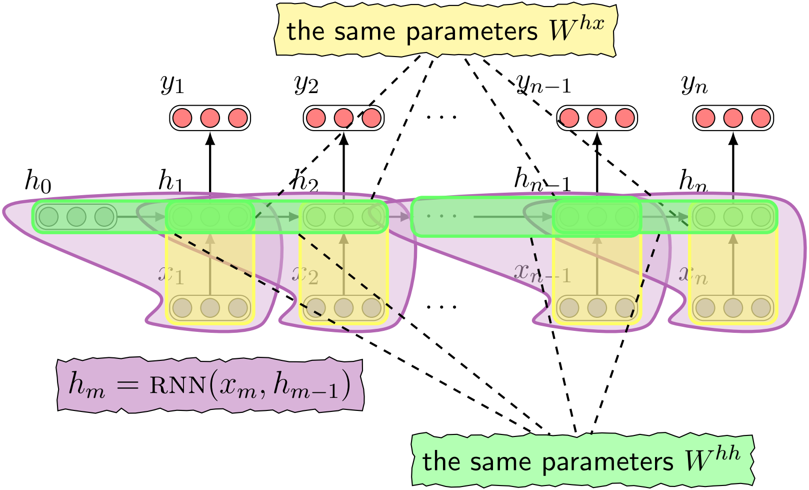


$$h_m = \text{RNN}(x_m, h_{m-1})$$

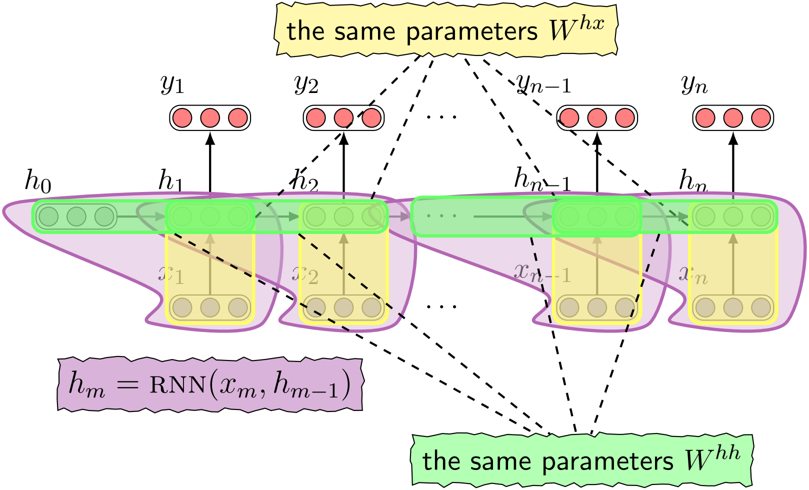

the same parameters W^{hx}
y_1
y_2
y_{n-1}
y_n
h_0
h_1
h_2
h_{n-1}
h_n
x_1
x_2
x_{n-1}
x_n
$h_m = \mathrm{RNN}(x_m, h_{m-1})$


the same parameters W^{hx}
y_1
y_2
y_{n-1}
y_n
h_0
h_1
h_2
h_{n-1}
h_n
x_1
x_2
x_{n-1}
x_n
$h_m = \text{RNN}(x_m, h_{m-1})$


the same parameters W^{hx}
y_1
y_2
y_{n-1}
y_n
h_0
h_1
h_2
h_{n-1}
h_n
x_1
x_2
x_{n-1}
x_n
$h_m = \mathrm{RNN}(x_m, h_{m-1})$

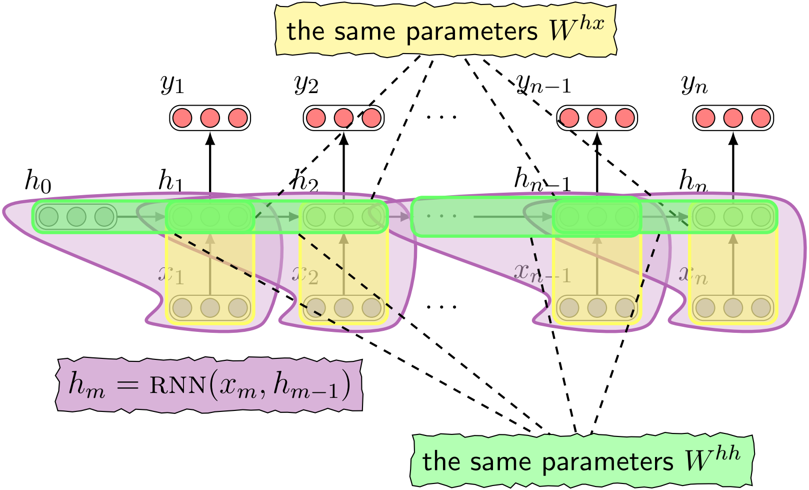


the same parameters W^{hx}
y_1
y_2
y_{n-1}
y_n
h_0
h_1
h_2
h_{n-1}
h_n
x_1
x_2
x_{n-1}
x_n
$h_m = \text{RNN}(x_m, h_{m-1})$
the same parameters W^{hh}



The context at token m is summarized by a recurrently-updated vector:

$$h_m = g(W^{hx} x_m + W^{hh} h_{m-1} + b^h)$$

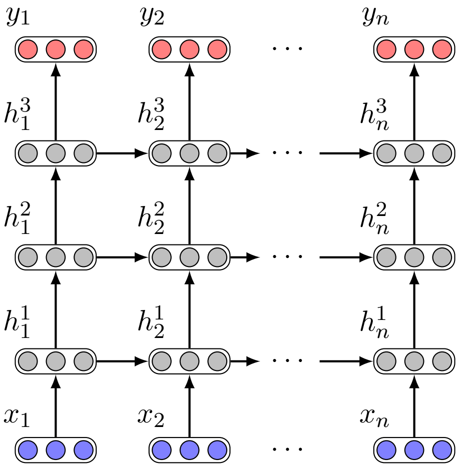


The context at token m is summarized by a recurrently-updated vector:

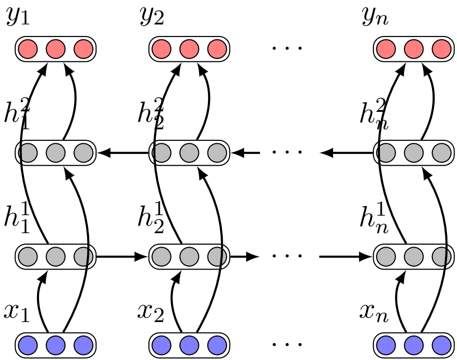
$$h_m = g(W^{hx}x_m + W^{hh}h_{m-1} + b^h)$$

A straightforward application to sequence labeling is to score each tag y_m with a log-linear function: $\texttt{softmax}(W^{yh}h_i)$

Multiple hidden layers



Bidirectional RNN



- $h_i^f = \text{RNN}_{\textsf{forward}}(x, i)$
- $h_i^b = \text{RNN}_{\textsf{backward}}(x, i)$
- $h_i = h_i^f \oplus h_i^b$

Difficulties

- Despite having access to the entire preceding sequence, the information encoded in hidden states tends to be fairly local, more relevant to the most recent parts of the input sequence and recent decisions.
- It is often the case, however, that distant information is critical to many language applications.

(2) The flights the airline was cancelling were full.

- A second difficulty with training SRNs arises from the need to backpropagate the error signal back through time.
- A frequent result of this process is that the gradients are eventually driven to zero — the so-called vanishing gradients problem.

How do the two problems solved with syntax?

Long Short-Term Memory (1)

Long short-term memory (LSTM) networks

- remove information no longer needed from the context
- add information likely to be needed for later decision making

Long Short-Term Memory (1)

Long short-term memory (LSTM) networks

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- add information likely to be needed for later decision making

The *key* is to learn how to manage the context rather than hard-coding a strategy: *adding gates* to control the flow of information into and out of the units.

Long Short-Term Memory (2)

basic computation

$$g_i = \tanh(W^{hh} h_{i-1} + W^{hx} x_i)$$

context vector

$$c_i = j_i + k_i$$

add gate: select the information to add to the current context.

$$\begin{aligned} i_i &= \sigma(W^{i,h} h_{i-1} + W^{i,x} x_i) \\ j_i &= g_i \odot i_i \end{aligned}$$

forget gate: delete information from the context ▷cf LEFT-ARC

$$\begin{aligned} f_i &= \sigma(W^{f,h} h_{i-1} + W^{f,x} x_i) \\ k_i &= c_{i-1} \odot f_i \end{aligned}$$

output gate: decide the information for the current hidden state.

$$\begin{aligned} o_i &= \sigma(W^{o,h} h_{i-1} + W^{o,x} x_i) \\ h_i &= o_i \odot \tanh(c_i) \end{aligned}$$

Neural Language Models

Language Model

Assign a probability to a sentence:

$$p(w_1, w_2, \ldots, w_n)$$

Typically p is decomposed into $p(w_i|\text{context})$ (aka word prediction)

Why

- unsupervised training for various models (esp. neural networks, e.g. `word2vec`).
- word prediction for communication aids:
  e.g., to help enter text that's input to a synthesiser
  search engine (dynamically maintain a list of upcoming words/phrases),
- natural langauge generation: machine translation, text summarization, etc.
- spelling correction, speech recognition

N-gram models

$$p(w_1, w_2, \ldots, w_n) = \prod_{k=1}^{n} p(w_i | w_1, w_2, \ldots, w_{i-1})$$

Too many possible sentences! No enough data for paramter estimation

N-gram models assume some independence ▷ Markov assumption

$$p(w_i | \text{local left context}) = p(w_i | w_{i-l}, w_{i-l+1}, \ldots, w_{i-1})$$

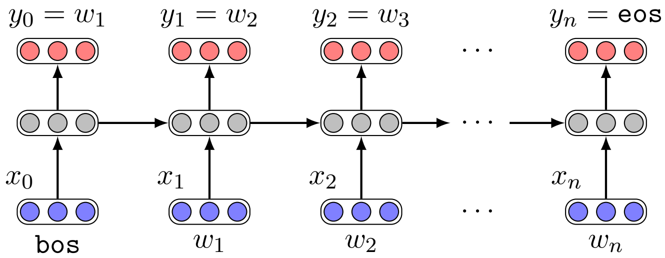
Bigram: a probability is assigned to a word based on the previous word

$$p(w_1, w_2, \ldots, w_n) = \prod_{k=1}^{n} p(w_i | w_{i-1})$$

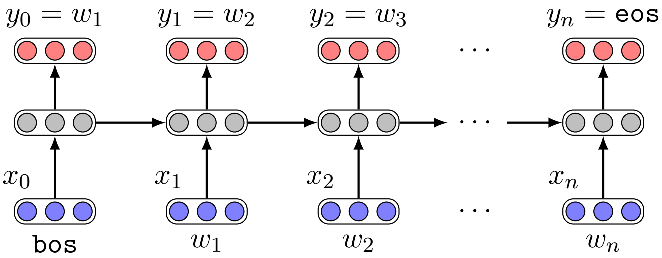
Probability can be estimated from counts in a training corpus:

$$\frac{\textsc{count}(w_{i-1} w_i)}{\textsc{count}(w_i)}$$

Neural language models



Neural language models



Many variants

ELMo: Deep Contextualized Word Representations

TASK	PREVIOUS SOTA		OUR BASELINE	ELMO + BASELINE	INCREASE (ABSOLUTE/ RELATIVE)
SQuAD	Liu et al. (2017)	84.4	81.1	85.8	4.7 / 24.9%
SNLI	Chen et al. (2017)	88.6	88.0	88.7 ± 0.17	0.7 / 5.8%
SRL	He et al. (2017)	81.7	81.4	84.6	3.2 / 17.2%
Coref	Lee et al. (2017)	67.2	67.2	70.4	3.2 / 9.8%
NER	Peters et al. (2017)	91.93 ± 0.19	90.15	92.22 ± 0.10	2.06 / 21%
SST-5	McCann et al. (2017)	53.7	51.4	54.7 ± 0.5	3.3 / 6.8%

- Peters et al. (2018)
- Bidirectional LSTM language models
- embeddings from LMs: intermediate layer representations
- characters $\rightarrow$ token representations
- ...

Reading

- D Jurafsky and J Martin. *Speech and Language Processing* Chapter 9. Sequence Processing with Recurrent Networks. `web.stanford.edu/~jurafsky/slp3/9.pdf`