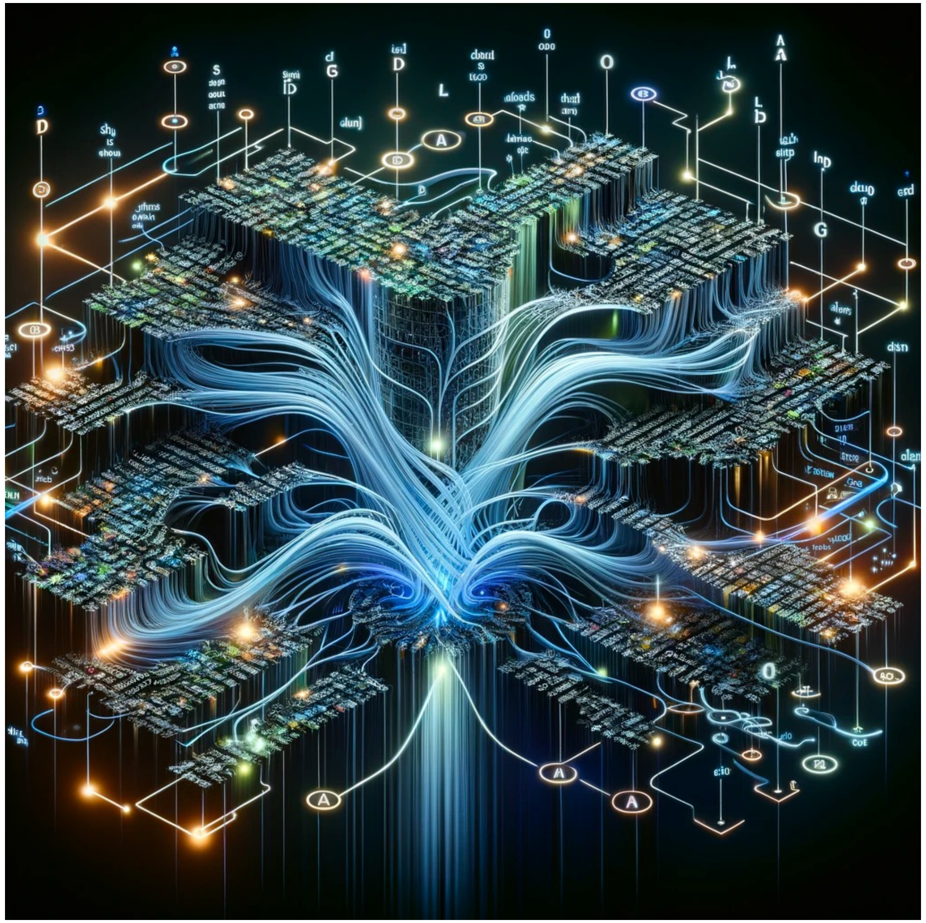
BOSTON UNIVERSITY

Recurrent Neural Networks



Dall-E: *create an image of a recurrent neural network processing text strings*

DL4DS – Spring 2024

Topics

- Plain (vanilla) Recurrent Neural Network
- Problem of vanish gradients
- Long Short-Term Memory
- Gradient Recurrent Unit
- Example applications

Topics

- Plain (vanilla) Recurrent Neural Network
- Problem of vanish gradients
- Long Short-Term Memory
- Gradient Recurrent Unit
- Example applications

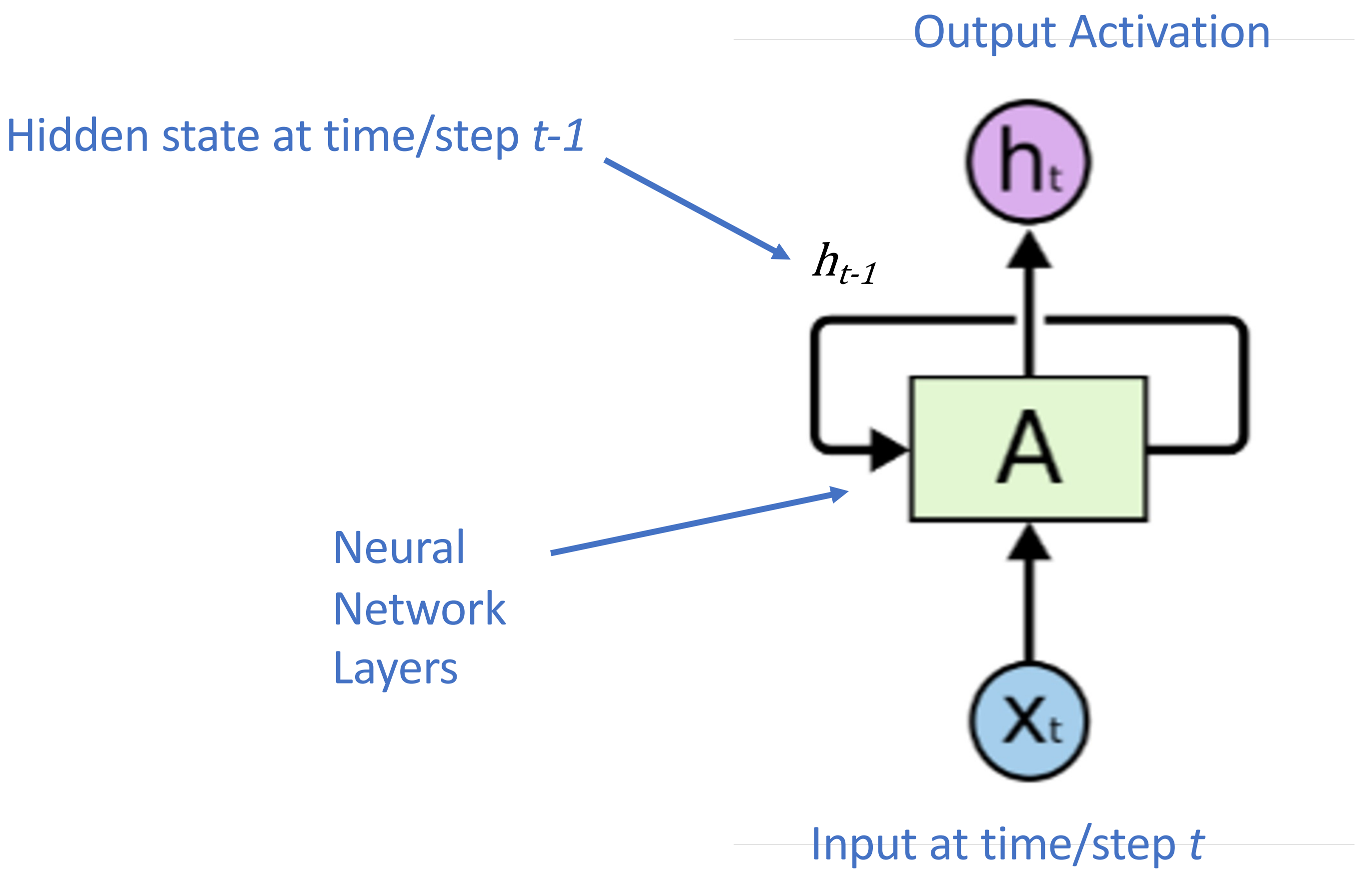
Motivation

- We want to process a sequence of data like text, digitized speech, video frames, etc.
- Want past samples to influence output from current sample

References

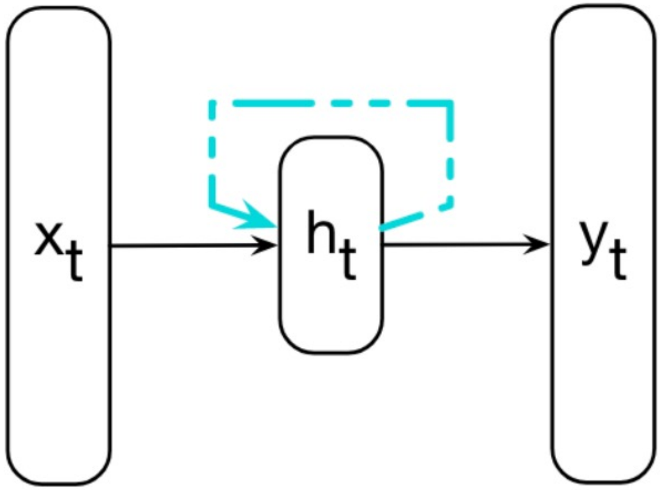
1. Understanding LSTMs, Colah's blog, 2015, https://colah.github.io/posts/2015-08-Understanding-LSTMs/
2. Speech and Language Processing. Daniel Jurafsky & James H. Martin. Draft of January 5, 2024. – Chapter 9, RNNs and LSTMs, https://web.stanford.edu/~jurafsky/slpdraft/9.pdf
3. The Unreasonable Effectiveness of LSTMs, Andrej Karpathy, 2015, https://karpathy.github.io/2015/05/21/rnn-effectiveness/

Recurrent Neural Network



Understanding LSTM Networks, C. Colah Blog Post

Recurrent Neural Network – Weight Matrices



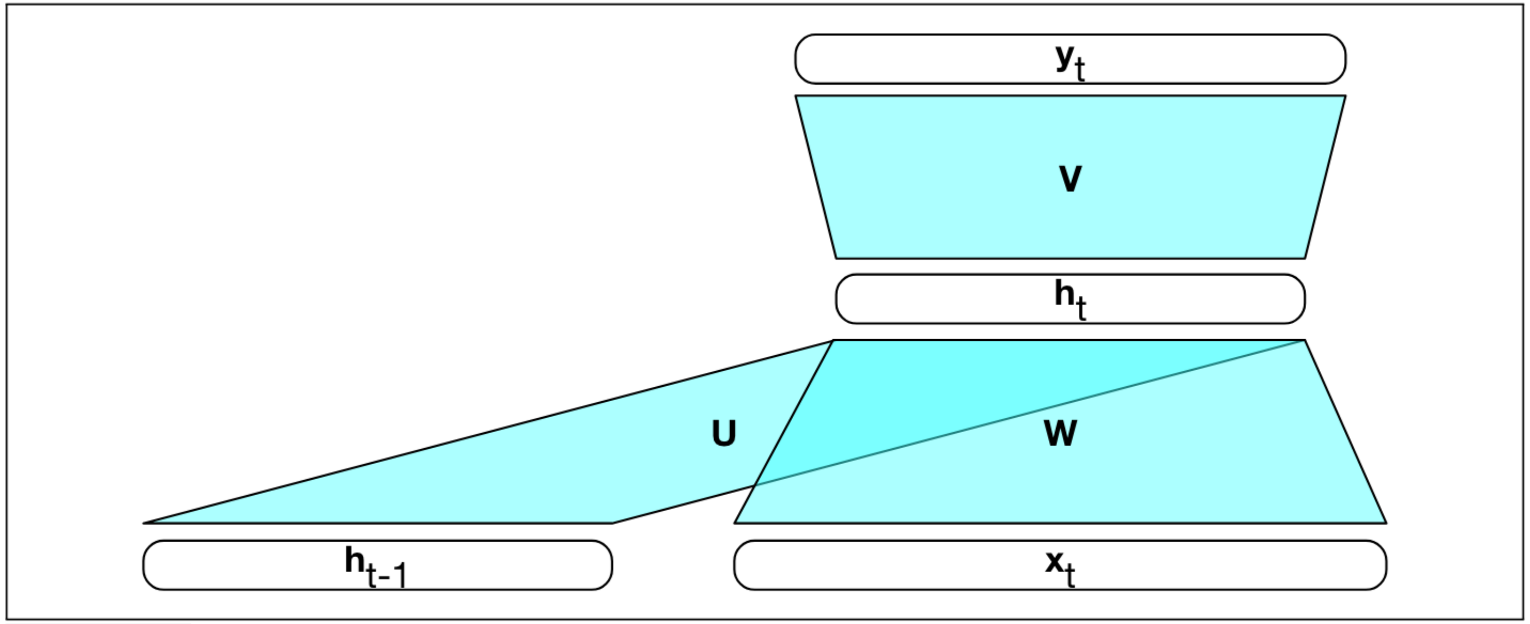
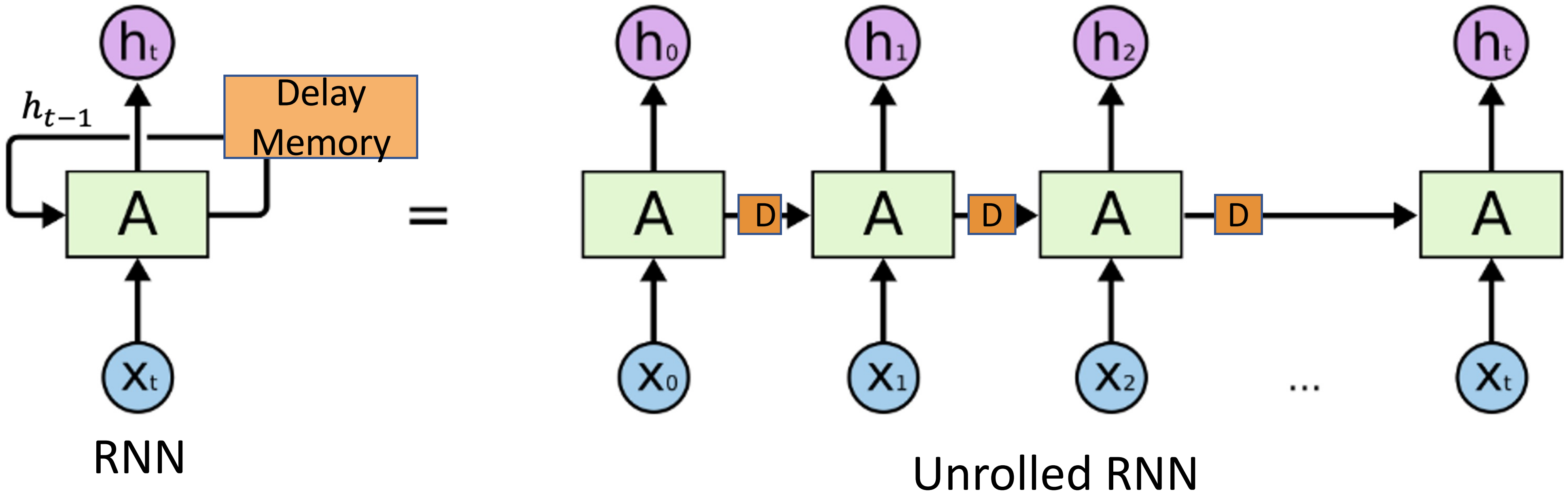


Figure 9.2 Simple recurrent neural network illustrated as a feedforward network.

$$
\begin{aligned}
\mathbf{h}_t &= g(\mathbf{U}\mathbf{h}_{t-1} + \mathbf{W}\mathbf{x}_t) \\
\mathbf{y}_t &= f(\mathbf{V}\mathbf{h}_t)
\end{aligned}
$$

S&LP, Jurafsky & Martin

Unrolled view over time



In this case you are emitting an output for every input token

Unrolled network is fed sequentially (not all at once)

[Understanding LSTM Networks, C. Colah Blog Post]

Unrolled Network

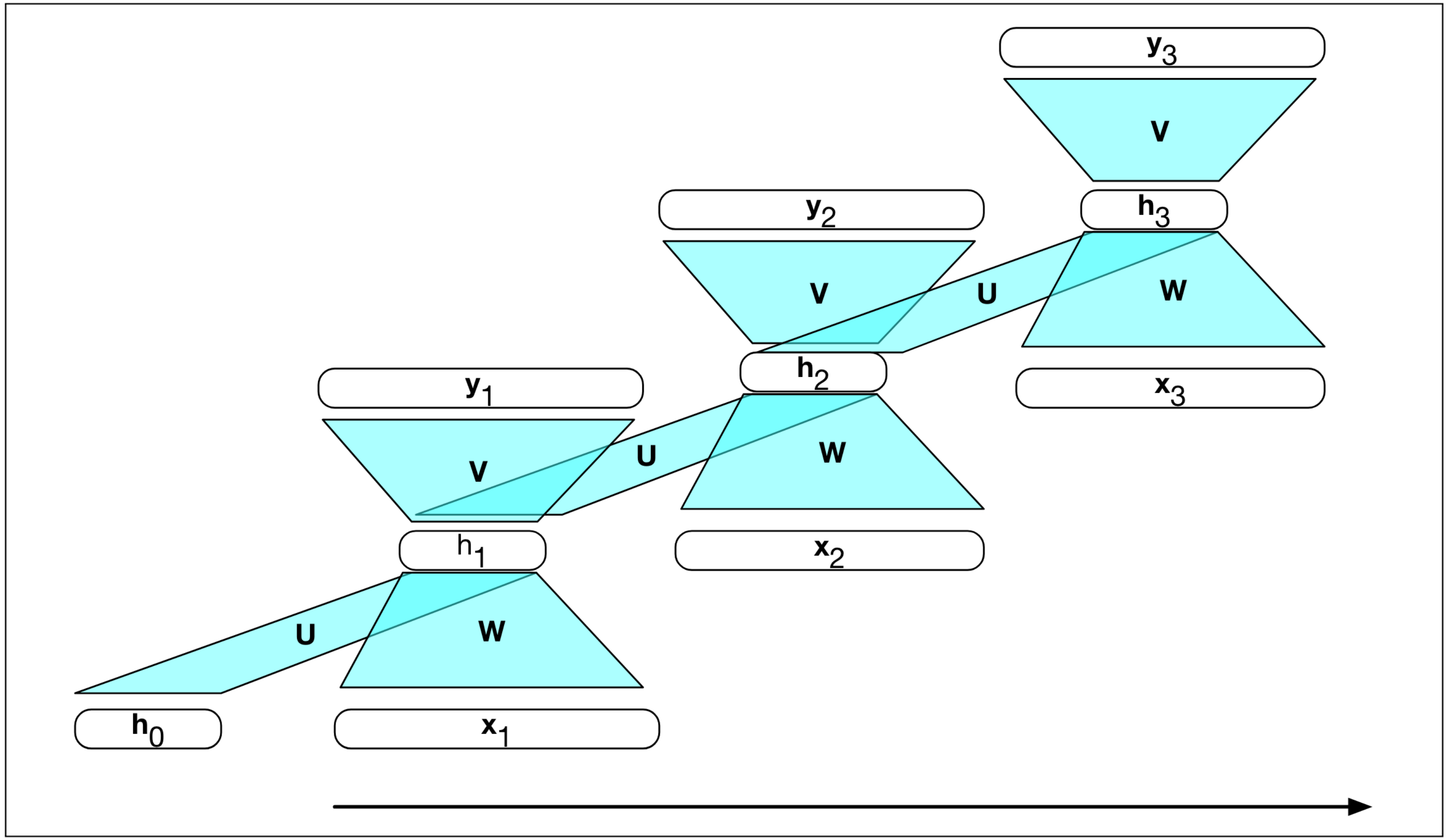
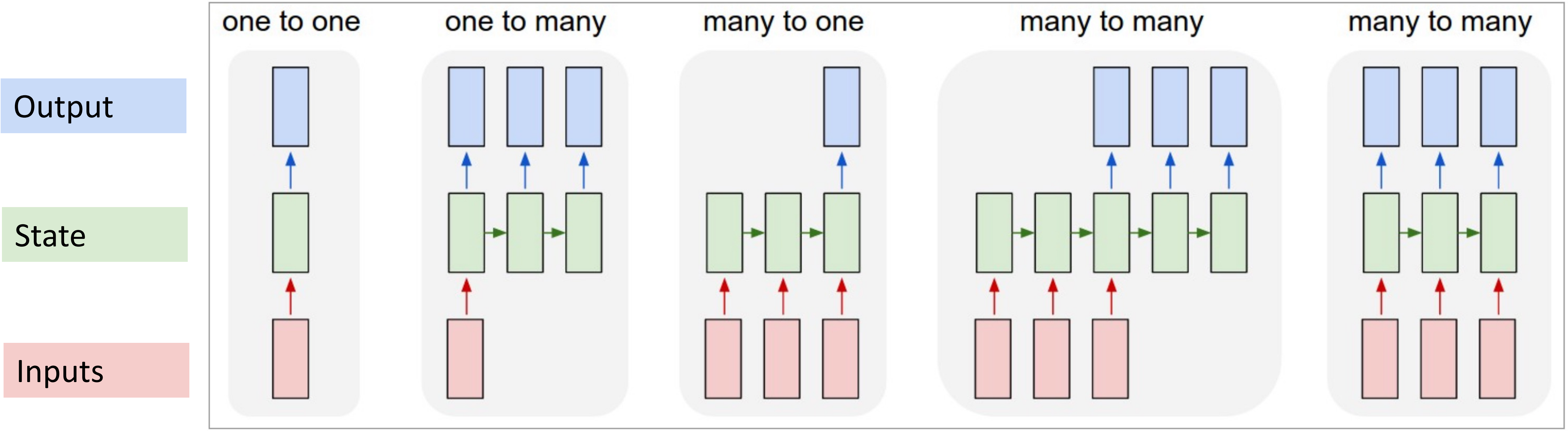


Figure 9.4 A simple recurrent neural network shown unrolled in time. Network layers are recalculated for each time step, while the weights **U**, **V** and **W** are shared across all time steps.

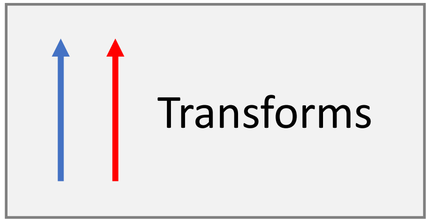
The weights, U, W and V, are the same at each time step. Only the inputs (x_t, h_{t-1}) change.

S&LP, Jurafsky & Martin

Different RNN configurations

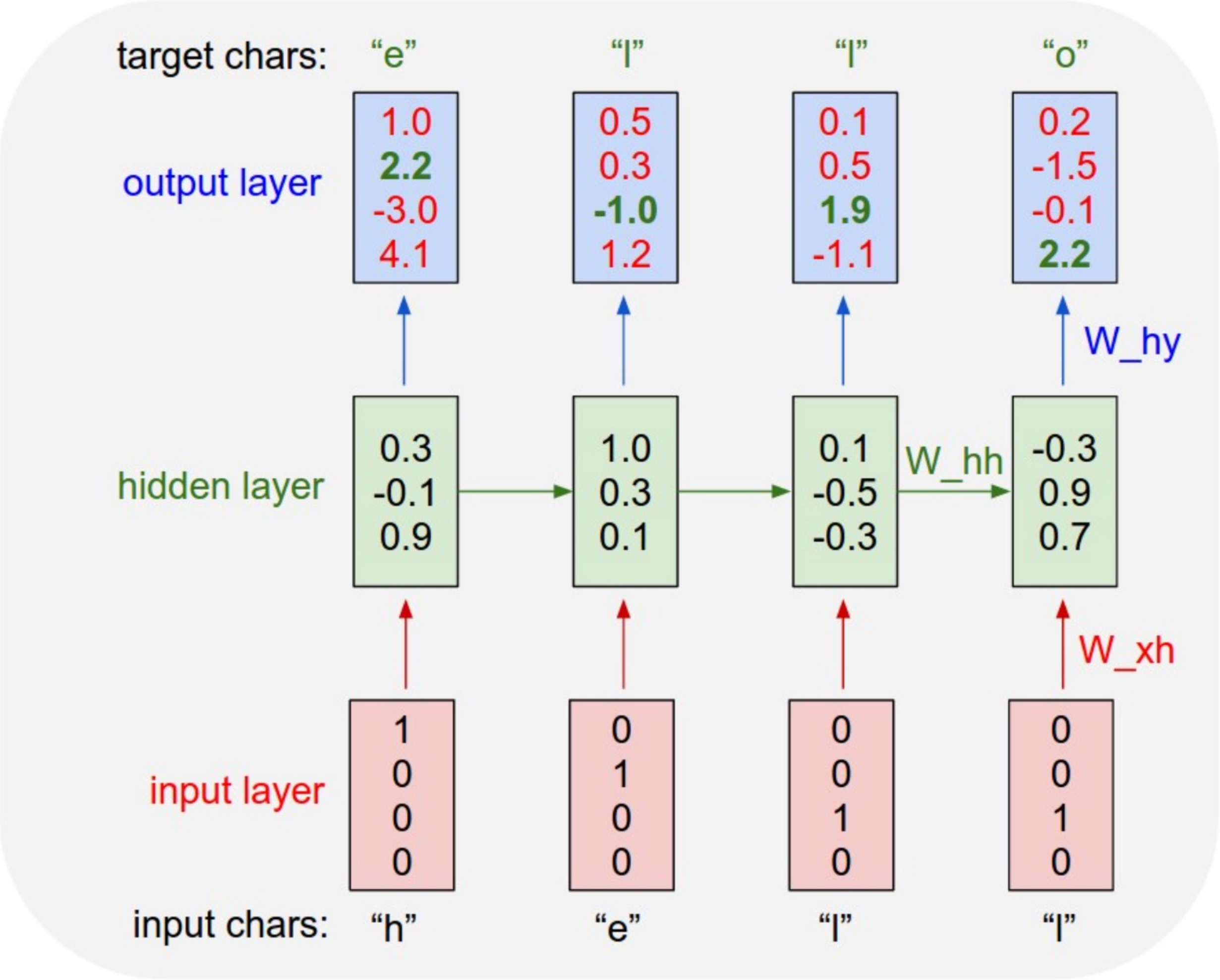


(a) (b) (c) (d) (e)



(a) Regular Feed Forward Network
(b) E.g. image captioning – input 1 image, outputs sequence of words
(c) E.g. sentiment analysis from string of words or characters
(d) E.g. machine translation such as English to French
(e) Synced sequence input and output, e.g. video frame-by-frame action classification or text generation

RNN next letter prediction example



Output is probability or likelihood over the vocabulary

Hidden layer encodes history, here e.g. length 3.

One-hot encoded input of vocabulary length, e.g. (‘h’, ‘e’, ‘l’, ‘o’)

Training an RNN

```python
import torch.nn as nn

class RNN(nn.Module):
    def __init__(self, input_size, hidden_size, output_size):
        super().__init__()

        self.hidden_size = hidden_size

        self.i2h = nn.Linear(input_size + hidden_size, hidden_size)
        self.h2o = nn.Linear(hidden_size, output_size)
        self.softmax = nn.LogSoftmax(dim=1)

    def forward(self, input, hidden):
        combined = torch.cat((input, hidden), 1)
        hidden = self.i2h(combined)
        output = self.h2o(hidden)
        output = self.softmax(output)
        return output, hidden

    def initHidden(self):
        return torch.zeros(1, self.hidden_size)
```

Simple feed forward network.

History and recurrence managed outside the model

https://pytorch.org/tutorials/intermediate/char_rnn_classification_tutorial.html

Training an RNN – Same Backprop as FFN

```
# If you set this too high, it might explode. If too low, it might not learn
learning_rate = 0.005

def train(category_tensor, line_tensor):
    hidden = rnn.initHidden()

    rnn.zero_grad()

    for i in range(line_tensor.size()[0]):
        output, hidden = rnn(line_tensor[i], hidden)

    loss = criterion(output, category_tensor)
    loss.backward()

    # Add parameters' gradients to their values, multiplied by learning rate
    for p in rnn.parameters():
        p.data.add_(p.grad.data, alpha=-learning_rate) # in-place addition

    return output, loss.item()
```

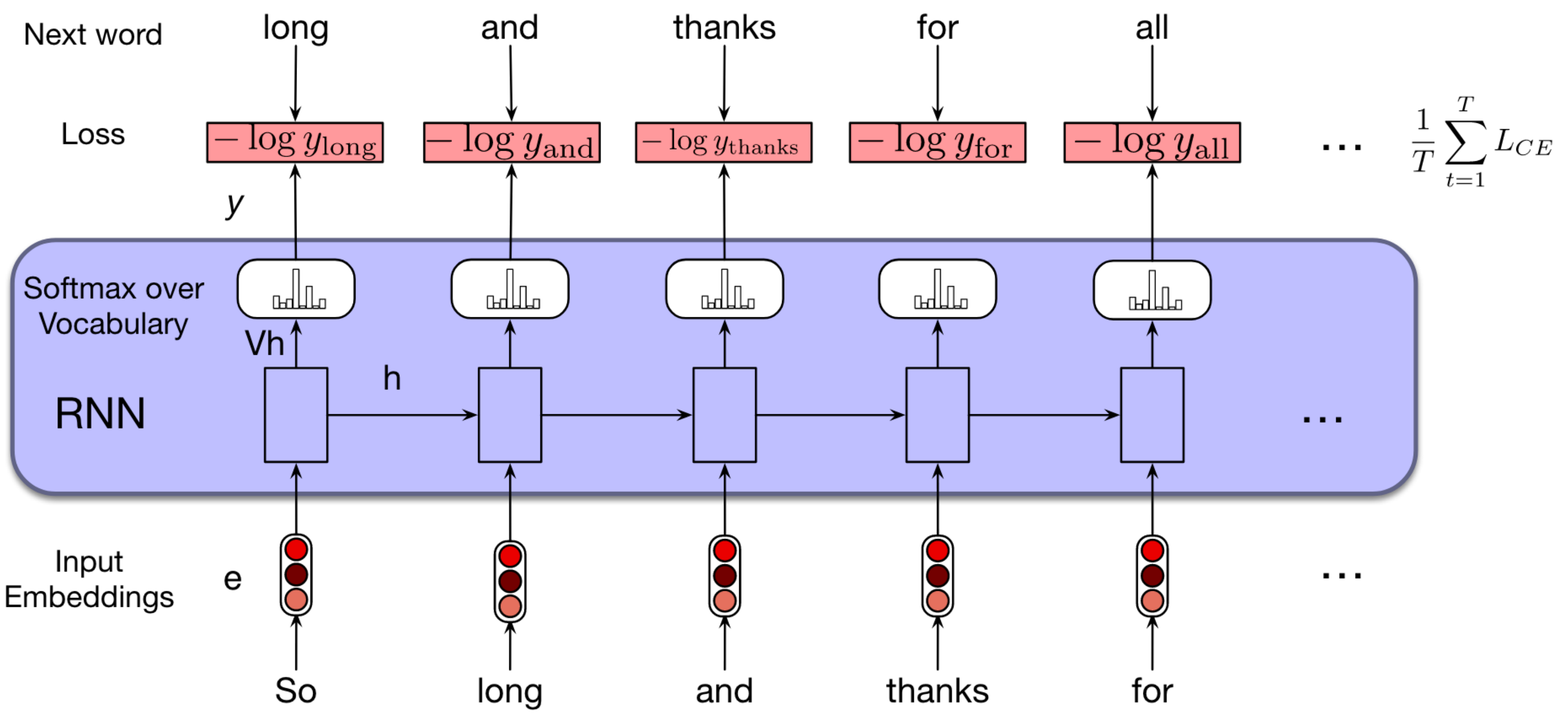
Managing recurrence.

Single output for classification in this case.

"Back propagation Through Time", e.g. BPTT

https://pytorch.org/tutorials/intermediate/char_rnn_classification_tutorial.html

Loss Calculation for Sequence



$$L_{CE} = -\sum_{w \in V} \mathbf{y}_t[w] \log \hat{\mathbf{y}}_t[w]$$

$$L_{CE}(\hat{\mathbf{y}}_t, \mathbf{y}_t) = -\log \hat{\mathbf{y}}_t[w_{t+1}]$$

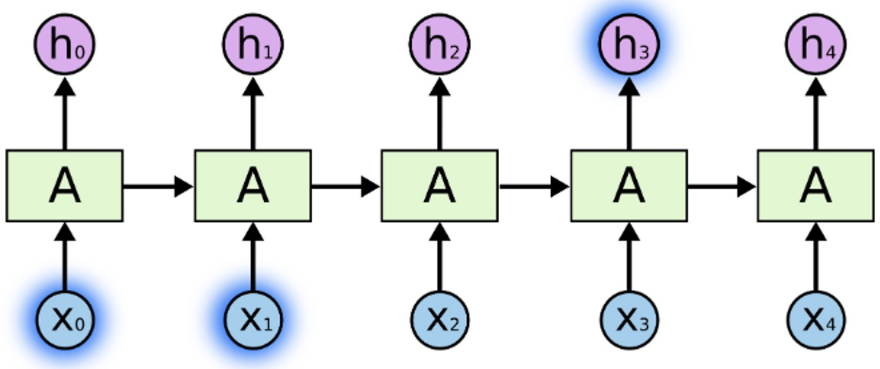
The probability that the model assigns to the next word in the training sequence.

S&LP, Jurafsky & Martin

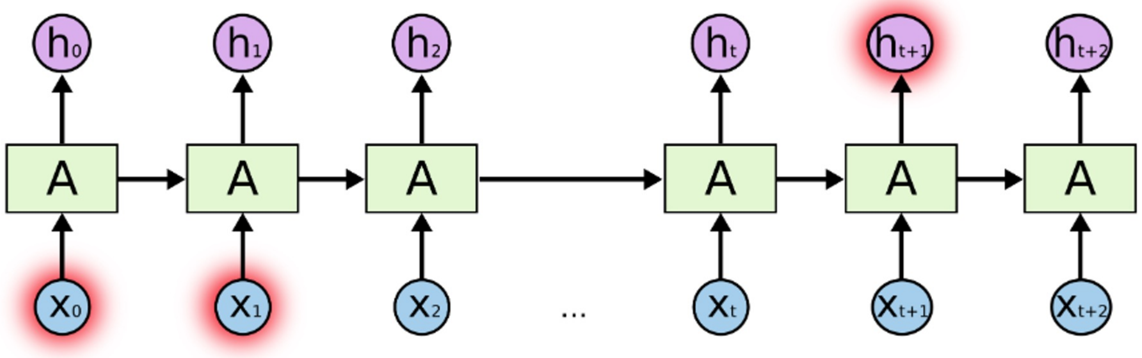
Topics

- Plain (vanilla) Recurrent Neural Network
- Problem of vanish gradients
- Long Short-Term Memory
- Gradient Recurrent Unit
- Example applications

Problem of vanishing gradients



Tokens from earlier in the sequence can influence the current output



But for plain RNNs, the influence can reduce rapidly the further the sequence difference

Understanding LSTM Networks, C. Colah Blog Post

Topics

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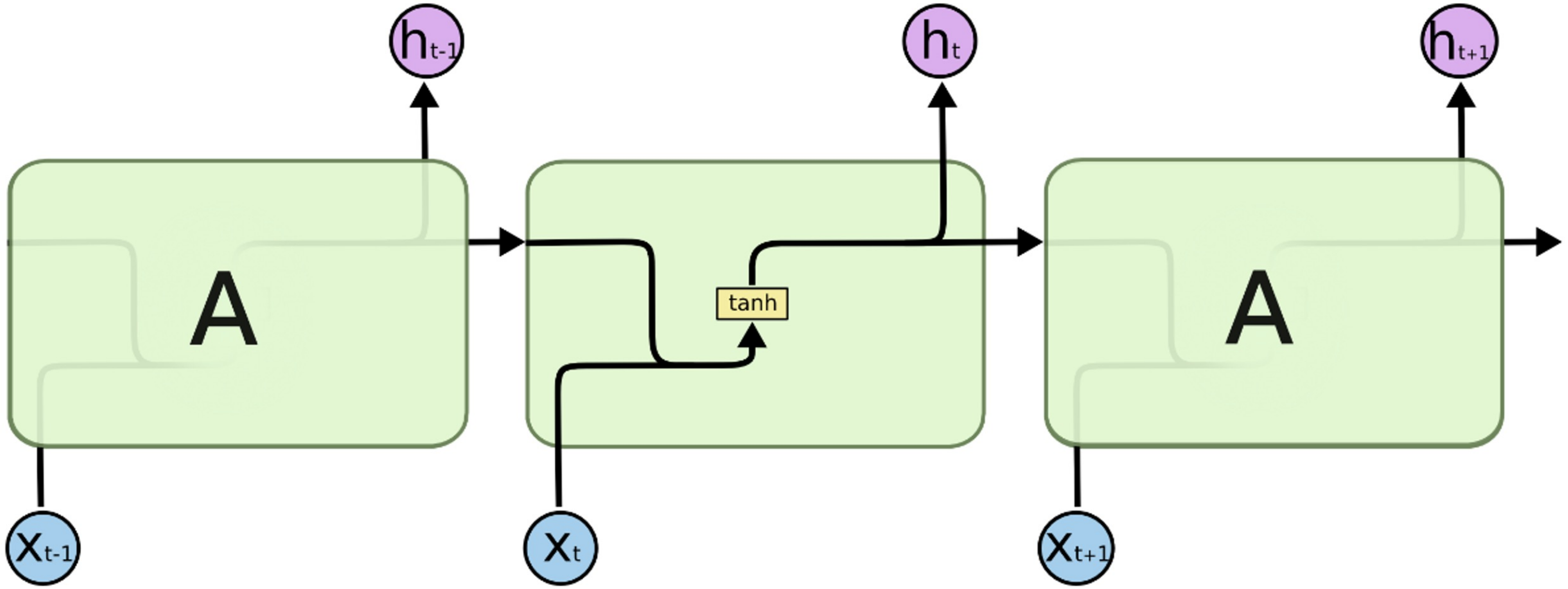
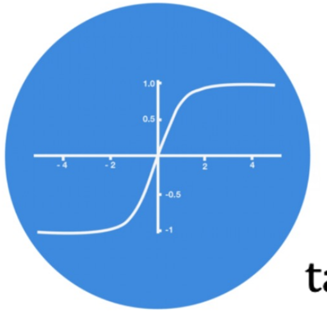
Redrawing RNN

Redraw the RNN in slightly more detail





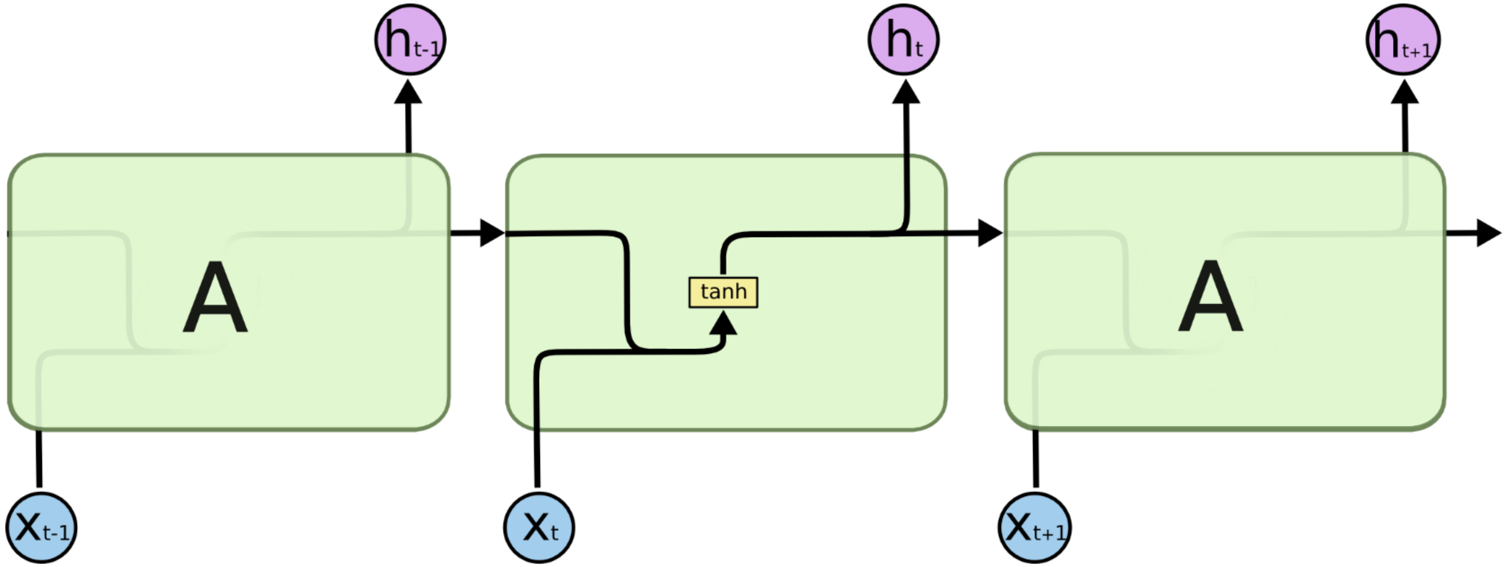
Neural Network Layer:

$$h_t = tanh(W \cdot [h_{t-1}, x_t] + b)$$

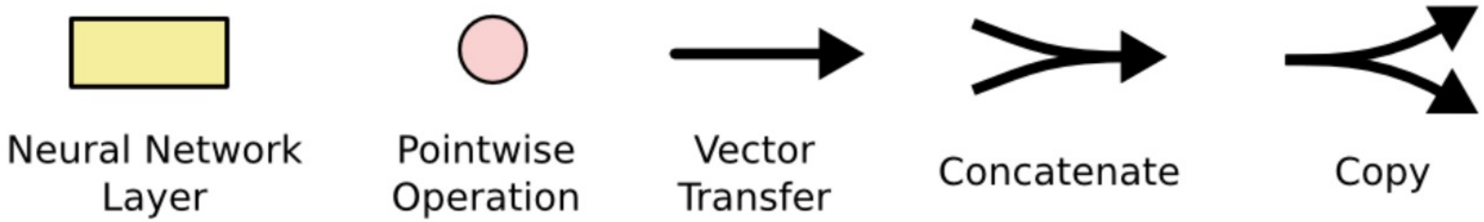
$\tanh(), \ \mathbb{R} \rightarrow [-1,1]$

Understanding LSTM Networks, C. Colah Blog Post

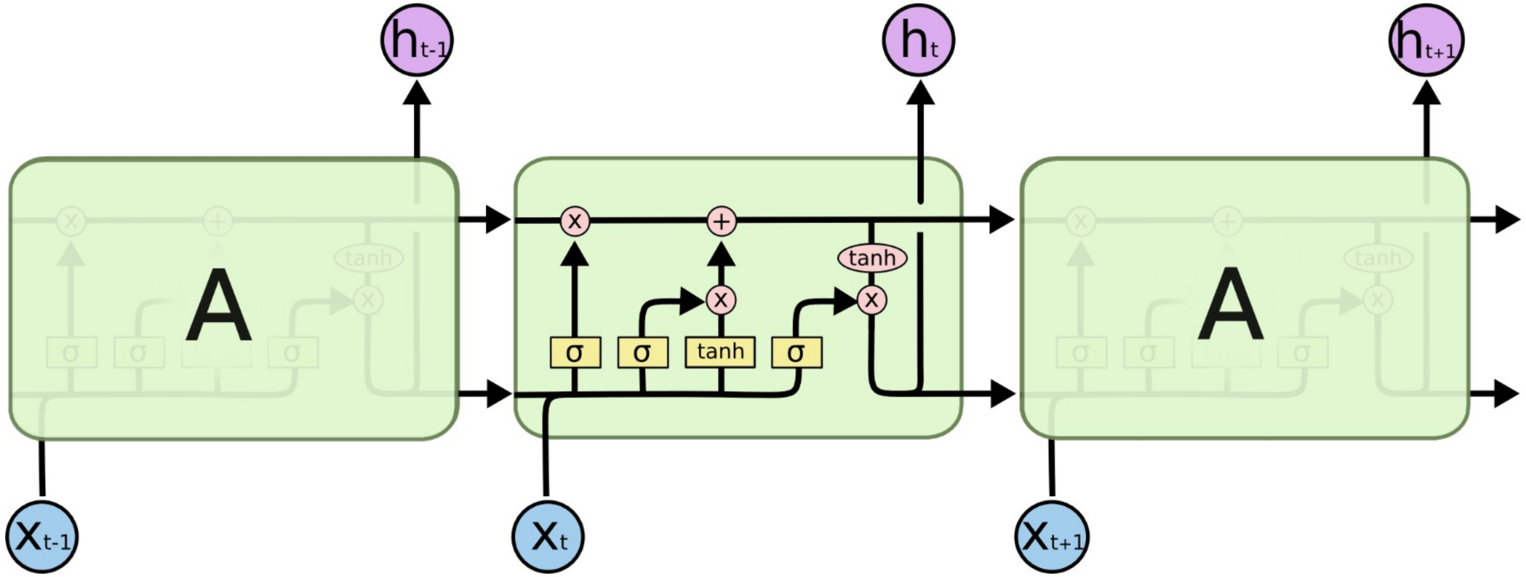
First redraw RNN



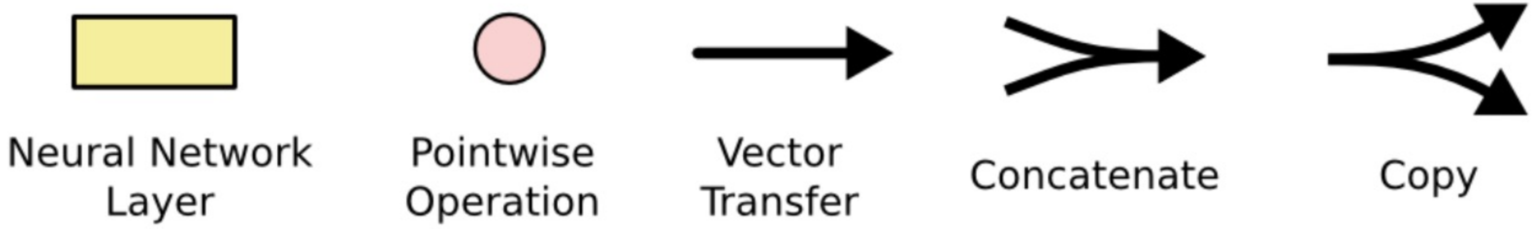
The repeating module in a standard RNN contains a single layer.



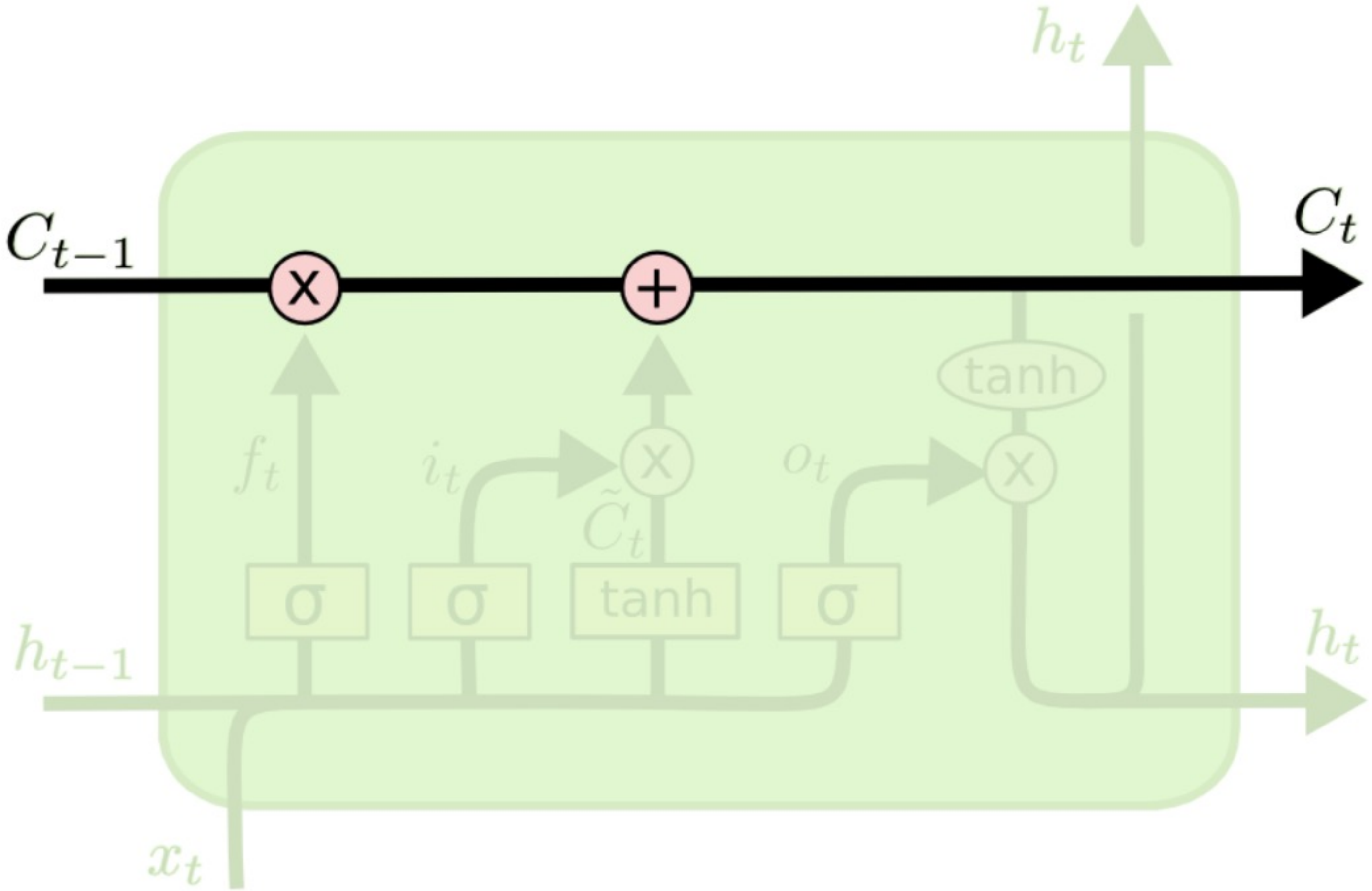
Long Short Term Memory (LSTM)

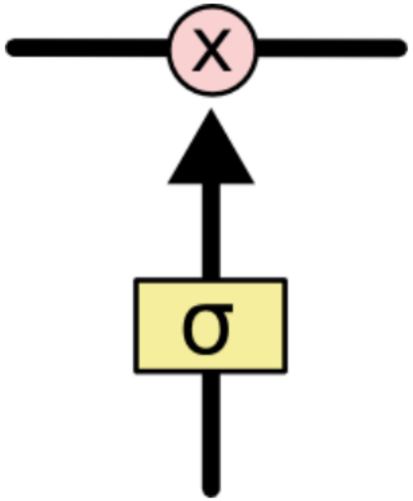


The repeating module in an LSTM contains four interacting layers.

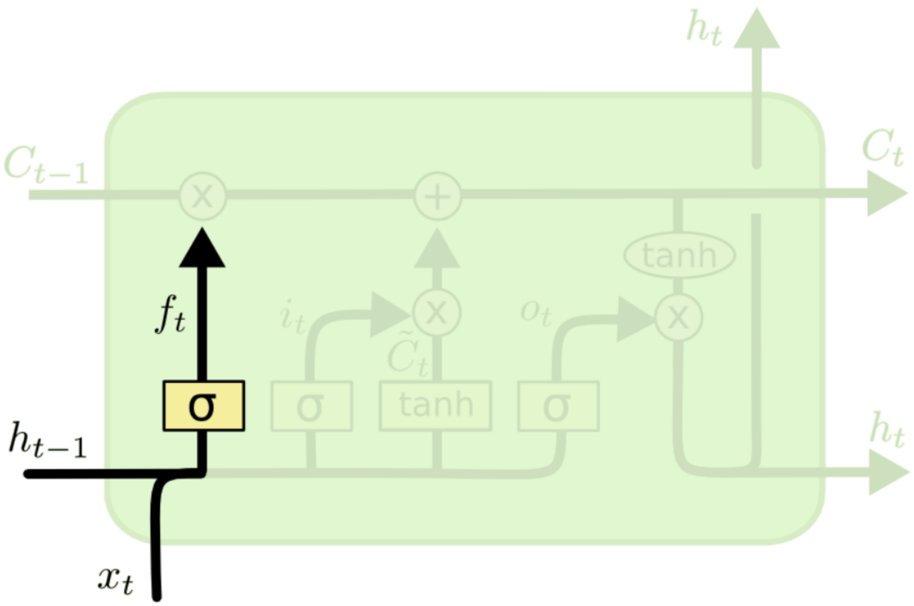


LSTM – Cell State





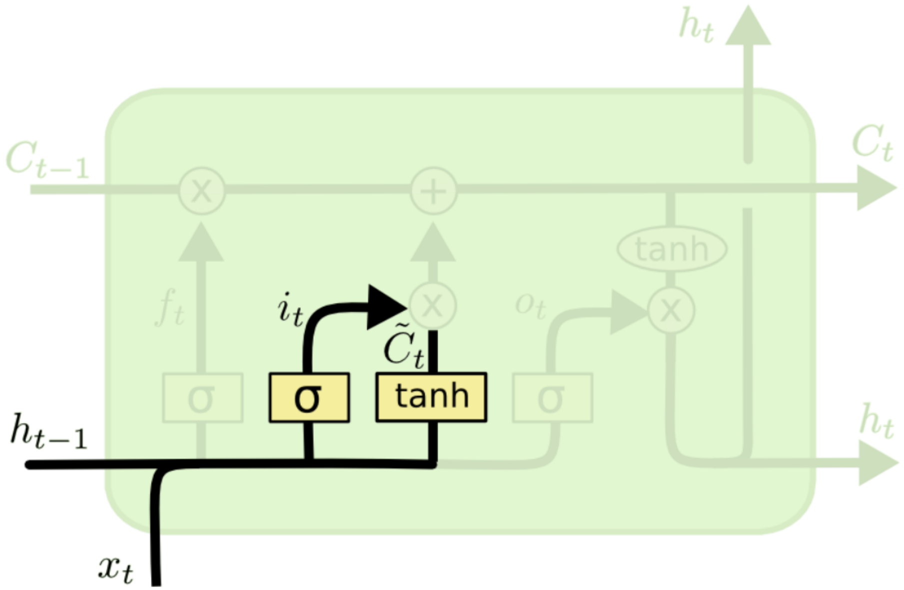
LSTM -- Forgetting Gate



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

Decides what part of cell state to suppress

LSTM – Cell state update



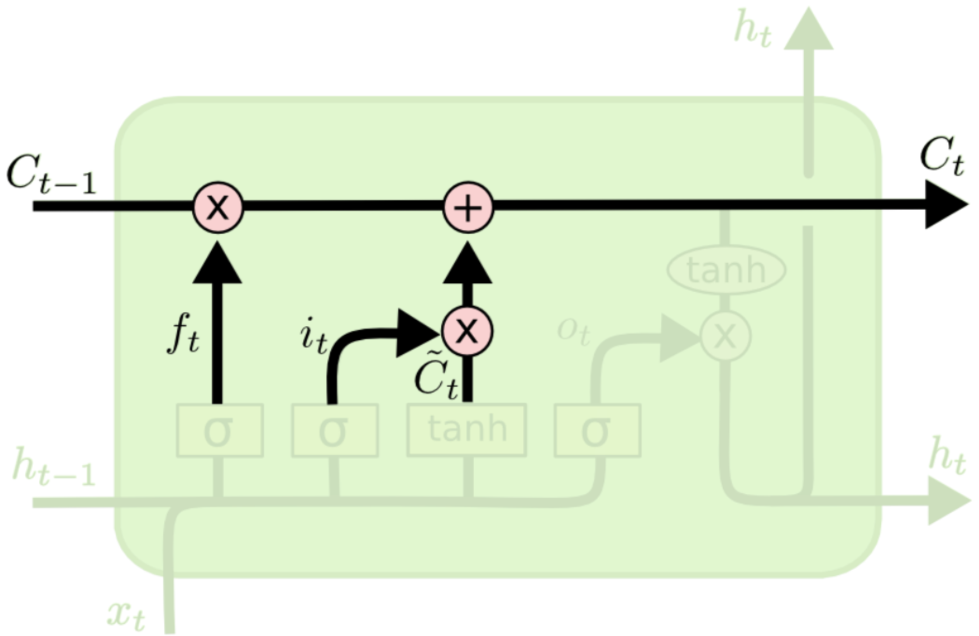
Input Gate Layer

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

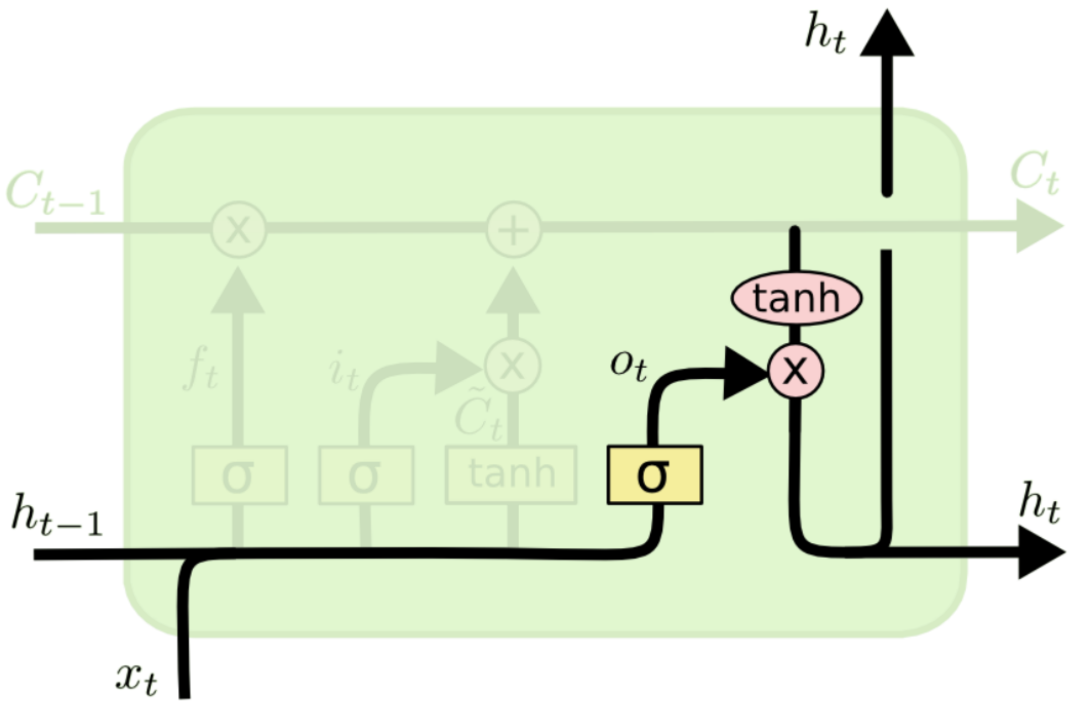
Candidate Cell State

LSTM – Apply changes to cell state



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

LSTM – Output and Hidden State Update



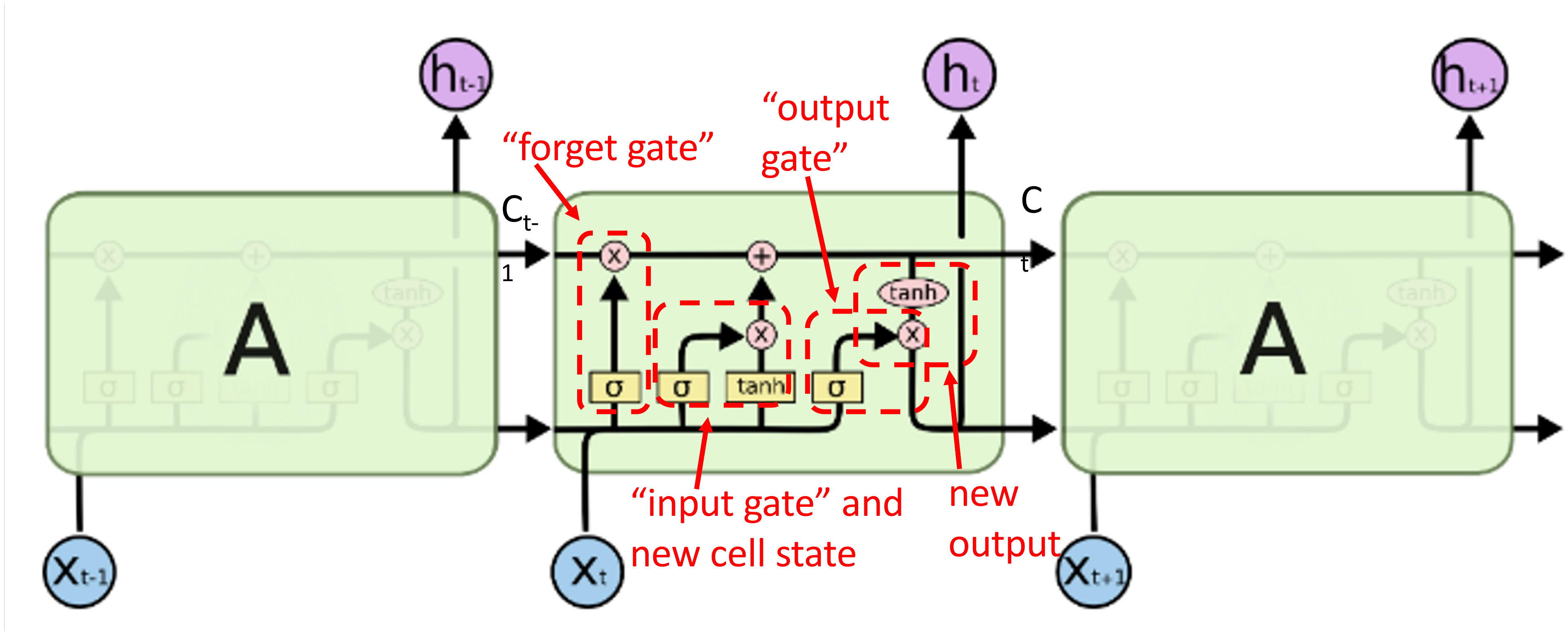
Output Gate

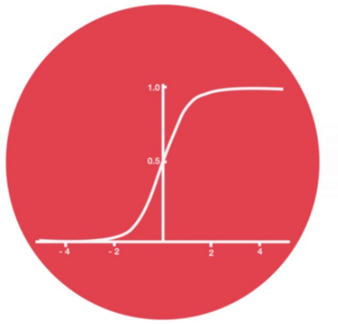
$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

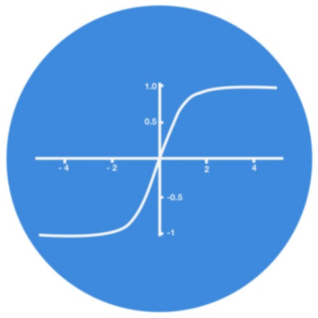
Next hidden state and output

Long Short Term Memory (LSTM)

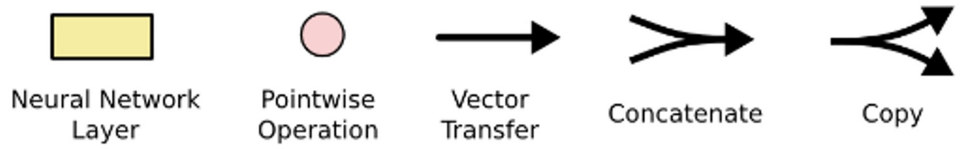




σ – Sigmoid, $\mathbb{R} \rightarrow [0,1]$



$\tanh()$, $\mathbb{R} \rightarrow [-1,1]$



<u>Neural Network Layer</u>:

$$out_t = activation(W \cdot [h_{t-1}, x_t] + b)$$

Understanding LSTM Networks, C. Colah Blog Post
Illustrated Guide to LSTM's and GRU's, M. Phi Blog Post

Topics

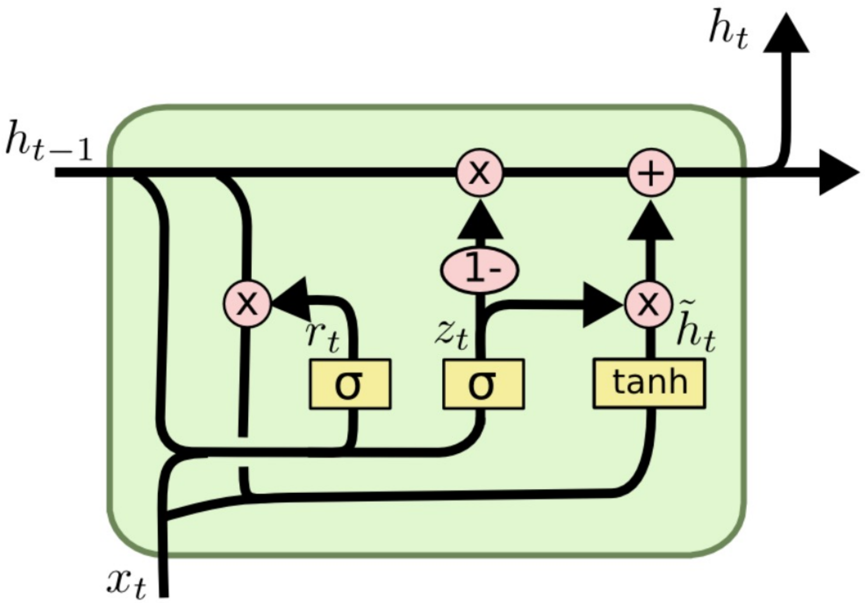
- Plain (vanilla) Recurrent Neural Network
- Problem of vanish gradients
- Long Short-Term Memory
- Gradient Recurrent Unit
- Example applications

Gradient Recurrent Unit

- Combines the forget and input gates into a single “update gate.”
- Merges the cell state and hidden state

The resulting model is simpler than standard LSTM models.

Results are mixed.



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

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

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

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

K. Cho *et al.*, “Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation.” arXiv, Sep. 02, 2014. doi: [10.48550/arXiv.1406.1078](https://doi.org/10.48550/arXiv.1406.1078).

Topics

- Plain (vanilla) Recurrent Neural Network
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Andrej Karpathy blog   About

The Unreasonable Effectiveness of Recurrent Neural Networks

May 21, 2015

Trained on complete works of Shakespeare

3-layer RNN with 512 hidden nodes on each layer.

Trained for a few hours on a GPU

```
PANDARUS:
Alas, I think he shall be come approached and the day
When little srain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:
They are away this miseries, produced upon my soul,
Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCENTIO:
Well, your wit is in the care of side and that.

Second Lord:
They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.

Clown:
Come, sir, I will make did behold your worship.

VIOLA:
I'll drink it.
```

Andrej Karpathy blog

About

The Unreasonable Effectiveness of Recurrent Neural Networks

May 21, 2015

Trained and Generated Wikipedia Content

```
Naturalism and decision for the majority of Arab countries' capitalide was grounded
by the Irish language by [[John Clair]], [[An Imperial Japanese Revolt]], associated
with Guangzham's sovereignty. His generals were the powerful ruler of the Portugal
in the [[Protestant Immineners]], which could be said to be directly in Cantonese
Communication, which followed a ceremony and set inspired prison, training. The
emperor travelled back to [[Antioch, Perth, October 25|21]] to note, the Kingdom
of Costa Rica, unsuccessful fashioned the [[Thrales]], [[Cynth's Dajoard]], known
in western [[Scotland]], near Italy to the conquest of India with the conflict.
Copyright was the succession of independence in the slop of Syrian influence that
was a famous German movement based on a more popular servicious, non-doctrinal
and sexual power post. Many governments recognize the military housing of the
[[Civil Liberalization and Infantry Resolution 265 National Party in Hungary]],
that is sympathetic to be to the [[Punjab Resolution]]
(PJS)[http://www.humah.yahoo.com/guardian.
cfm/7754800786d17551963s89.htm Official economics Adjoi
was swear to advance to the resources for those Sociali
was starting to signing a major tripad of aid exile.]]
```

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{ { cite journal | id=Cerling Nonforest Department|format=Newlymeslated|none } }
''www.e-complete''.

'''See also''': [[List of ethical consent processing]]

== See also ==
*[[Iender dome of the ED]]
*[[Anti-autism]]

===[[Religion|Religion]]===
*[[French Writings]]
*[[Maria]]
*[[Revelation]]
*[[Mount Agamul]]

== External links==
* [http://www.biblegateway.nih.gov/entrepre/ Website of the World Festival. The labour

stitution of the Netherlands and Hispanic Competition
```

Structured Markdown

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      <id>23</id>
    </contributor>
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  </revision>
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Valid XML

Deep Visual-Semantic Alignments for Generating Image Descriptions

Multimodal Recurrent Neural Network

Our Multimodal Recurrent Neural Architecture generates sentence descriptions from images. Below are a few examples of generated sentences:

"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

"boy is doing backflip on wakeboard."

"girl in pink dress is jumping in air."

"black and white dog jumps over bar."

"young girl in pink shirt is swinging on swing."

"man in blue wetsuit is surfing on wave."

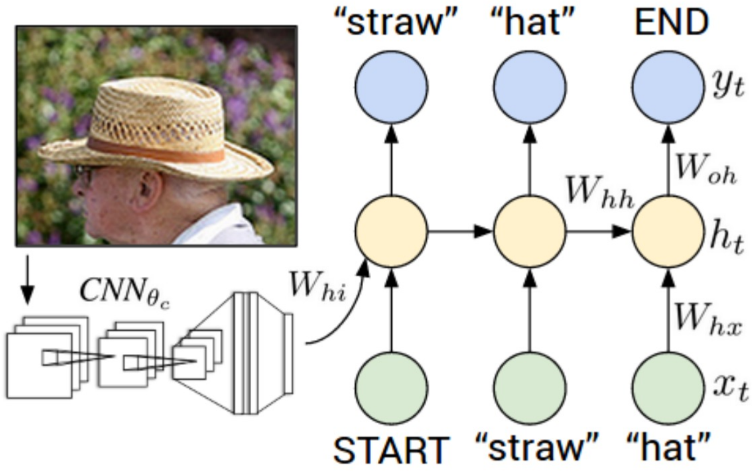


Figure 4. Diagram of our multimodal Recurrent Neural Network generative model. The RNN takes a word, the context from previous time steps and defines a distribution over the next word in the sentence. The RNN is conditioned on the image information at the first time step. START and END are special tokens.

Andrej Karpathy blog About

The Unreasonable Effectiveness of Recurrent Neural Networks

May 21, 2015

...

Inductive Reasoning, Memories and Attention.

...

The first convincing example of moving towards these directions was developed in DeepMind's Neural Turing Machines paper. This paper sketched a path towards models that can perform read/write operations between large, external memory arrays and a smaller set of memory registers (think of these as our working memory) where the computation happens. Crucially, the NTM paper also featured very interesting memory addressing mechanisms that were implemented with a (soft, and fully-differentiable) attention model. The concept of **soft attention** has turned out to be a powerful modeling feature and was also featured in Neural Machine Translation by Jointly Learning to Align and Translate for Machine Translation and Memory Networks for (toy) Question Answering. In fact, I'd go as far as to say that

> *The concept of **attention** is the most interesting recent architectural innovation in neural networks.*

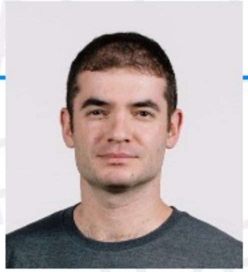
A Brief History of Transformers

2000

Yoshua Bengio*

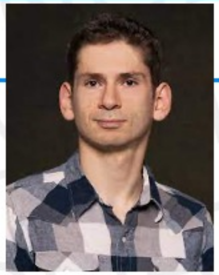
2014

Ilya Sutskever*



2014

Dzmitry Bahdanau*



2017

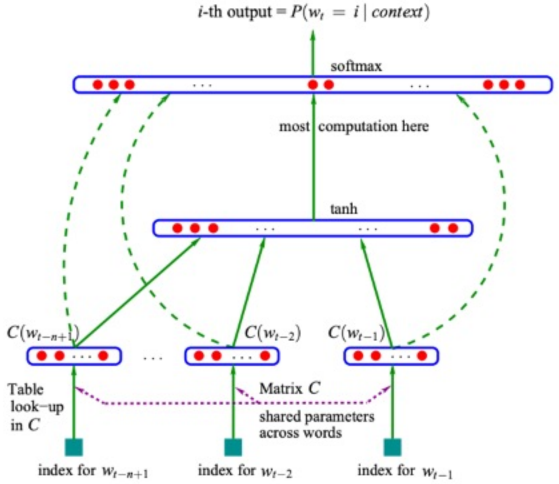
A Team at Google

Use LSTMs

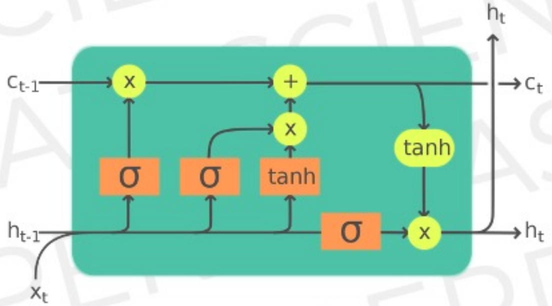
Add Attention

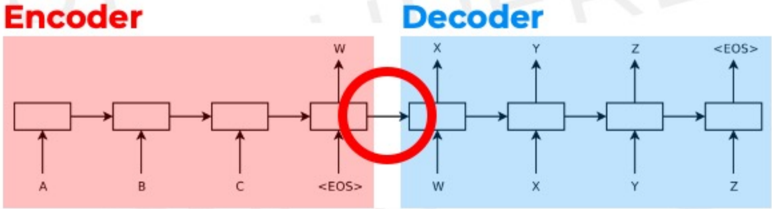
Remove LSTMs

A Neural Probabilistic Language Model

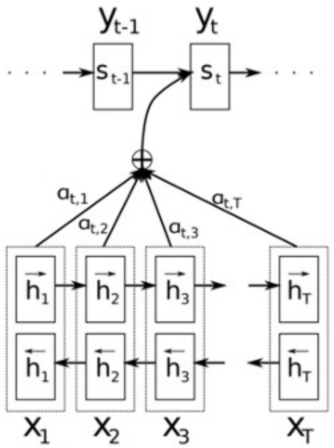


Seq-to-Seq Learning with Neural Networks

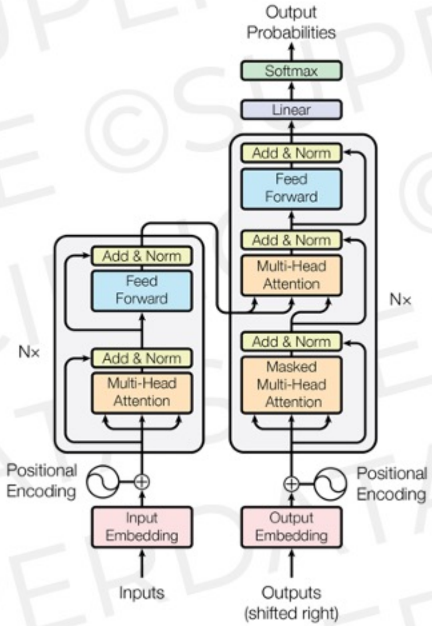




Neural Machine Translation by Jointly Learning to Align and Translate



Attention is all you need



*And others; Chronological analysis inspired by Andrej Karpathy's lecture, youtube.com/watch?v=XfpMkf4rD6E

Next Up

- Transformers!
- LLMs, embeddings, multi-modal, foundation models

Feedback?

Link