CPSC 540: Machine Learning

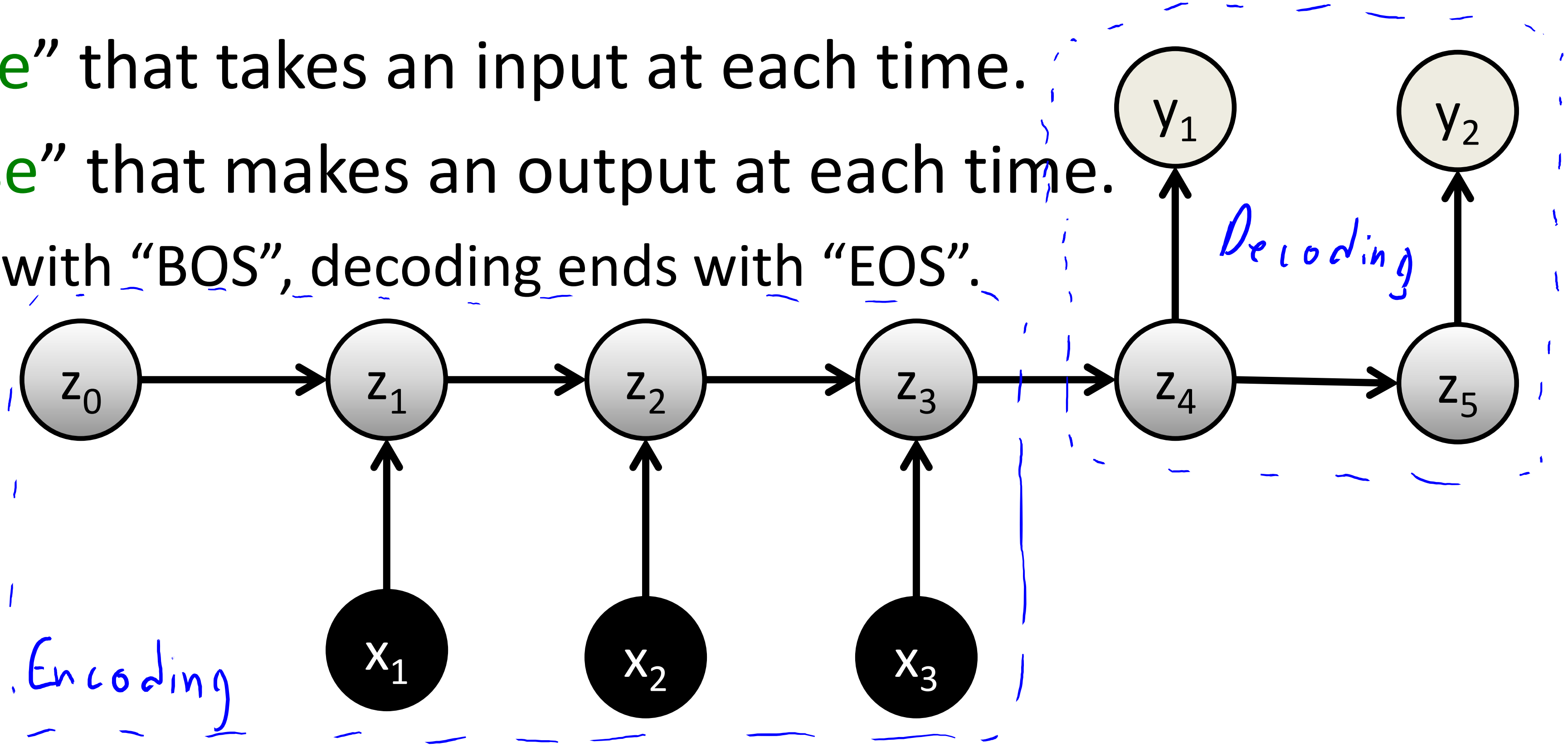
Long Short Term Memory

Winter 2019

Last Time: Sequence-to-Sequence

- Sequence-to-sequence:
  - Recurrent neural network for sequences of different lengths.

- "Encoding phase" that takes an input at each time.
- "Decoding phase" that makes an output at each time.
  - Encoding ends with "BOS", decoding ends with "EOS".



Variations on Recurrent Neural Networks

- Bi-directional RNNs: feedforward from past and future.
- Recursive neural networks: consider sequences through non-chain data.
- Graphical models to explicitly encourage output dependencies:
  - https://arxiv.org/abs/1711.04956

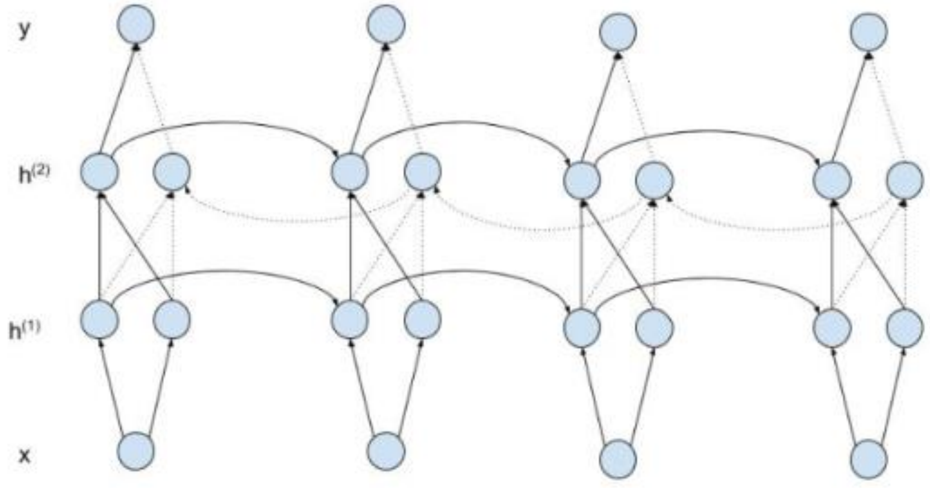
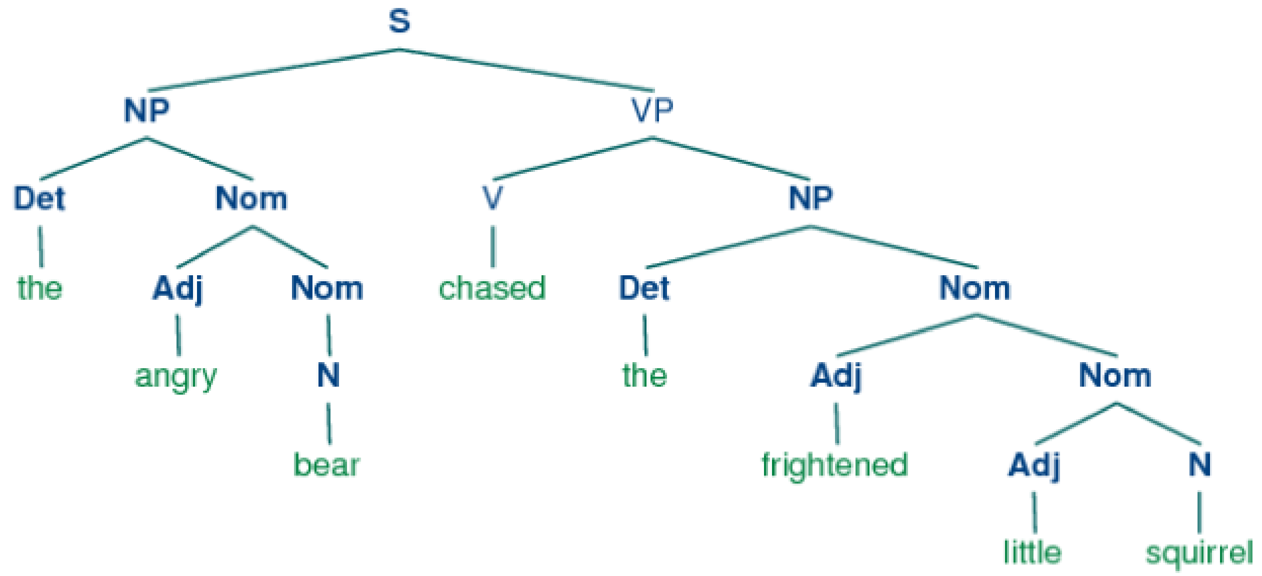


Figure 2: A deep bi-directional RNN with 2 stakced layers



Long Short Term Memory (LSTM)

- Long short term memory (LSTM) models are special case of RNNs:
  - Designed so that model can “remember things for a long time”.
- LSTMs have been the analogy of convolutions for RNNs:
  - “The trick that makes them work in applications.”
- LSTMs are getting impressive performance in various settings:
  - Cursive handwriting recognition.
    - https://www.youtube.com/watch?v=mLxsbWAYIpw
  - Speech recognition.
  - Machine translation.
  - Image and video captioning.

LSTMs for Image Captioning

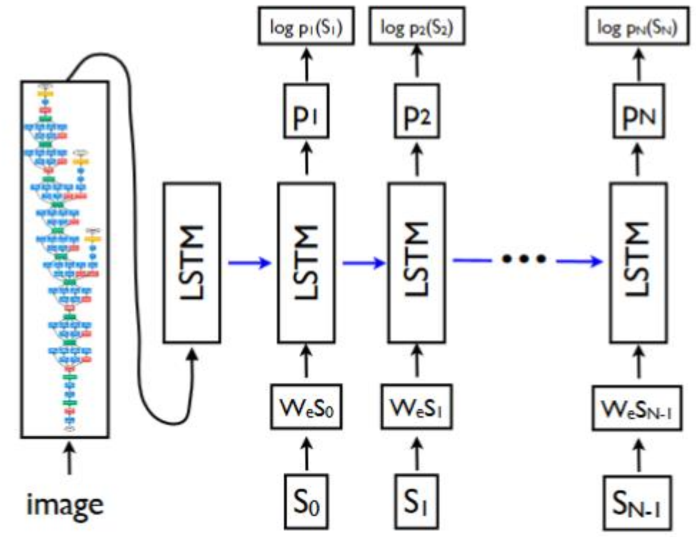
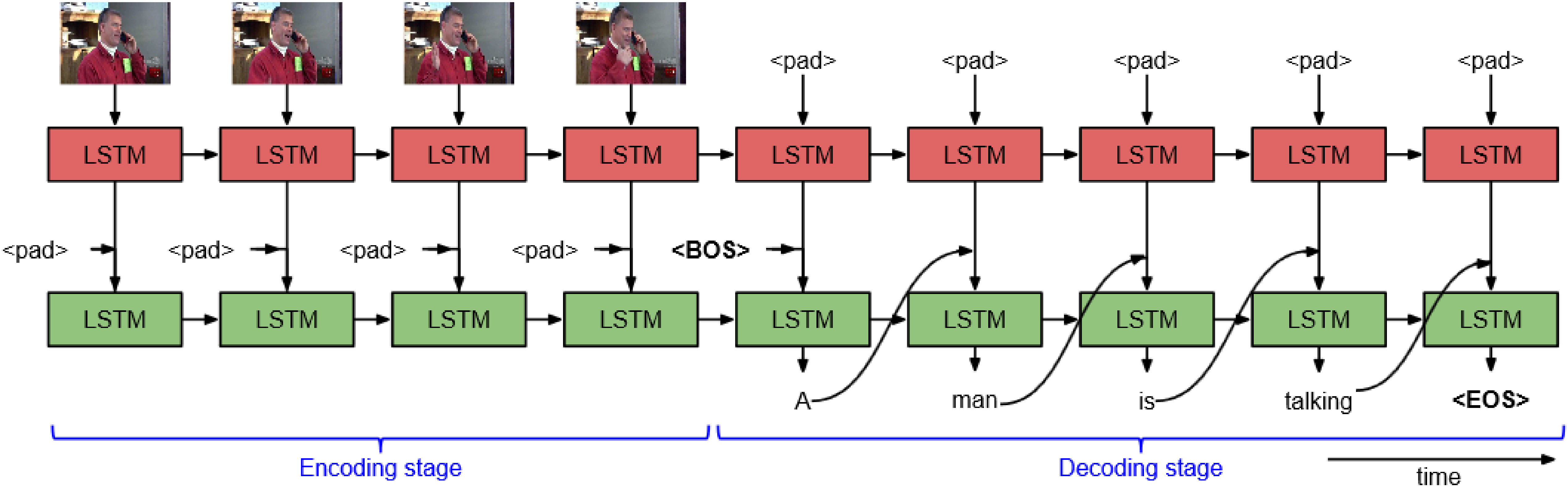


Figure 3. LSTM model combined with a CNN image embedder (as defined in [12]) and word embeddings. The unrolled connections between the LSTM memories are in blue and they correspond to the recurrent connections in Figure 2. All LSTMs share the same parameters.

Figure 5. A selection of evaluation results, grouped by human rating.

https://arxiv.org/pdf/1411.4555.pdf

LSTMs for Video Captioning



http://www.cv-foundation.org/openaccess/content_iccv_2015/papers/Venugopalan_Sequence_to_Sequence_ICCV_2015_paper.pdf

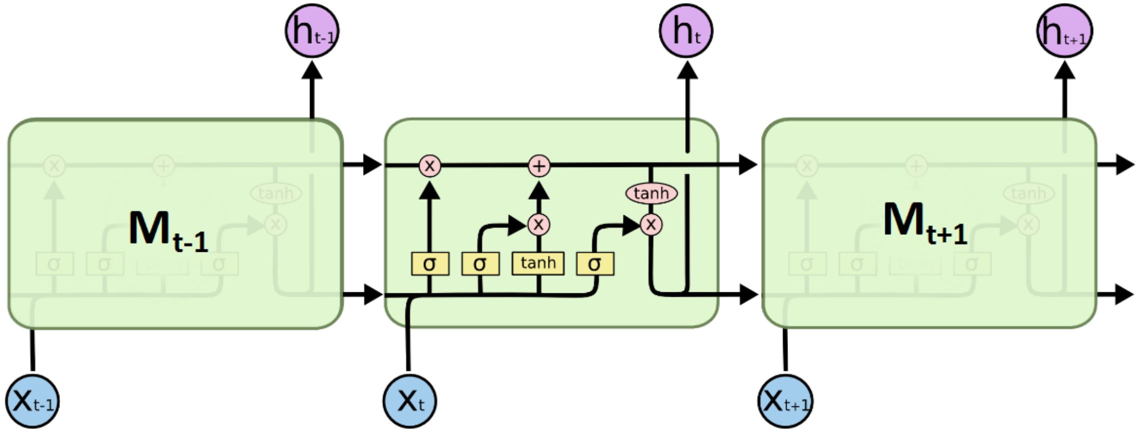
LSTMs for Video Captioning

Figure 3. Qualitative results on MSVD YouTube dataset from our S2VT model (RGB on VGG net). (a) Correct descriptions involving different objects and actions for several videos. (b) Relevant but incorrect descriptions. (c) Descriptions that are irrelevant to the event in the video.

http://www.cv-foundation.org/openaccess/content_iccv_2015/papers/Venugopalan_Sequence_to_Sequence_ICCV_2015_paper.pdf

Long Short Term Memory

- In addition to usual hidden values ‘z’, LSTMs have memory cells ‘c’:
  - Purpose of memory cells is to remember things for a long time.

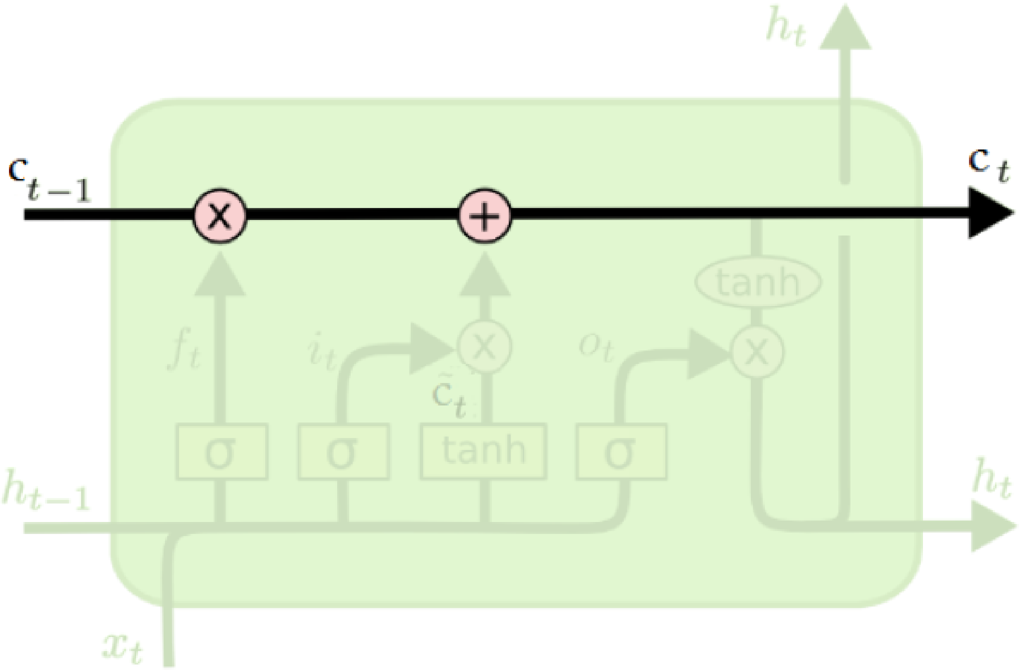


- “Read/write/forget”:
  - Information gets into the cell when its input gate is on.
  - Information is read from the cell when the output gate is on.
  - Information is thrown away when the forget gate is off.
- “Gate functions”: approximate binary operations (like “write or not”).
  - Replace operation by a sigmoid functions to make it continuous/differentiable.

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

The Core Idea Behind LSTMs: Cell State (Memory Cell)

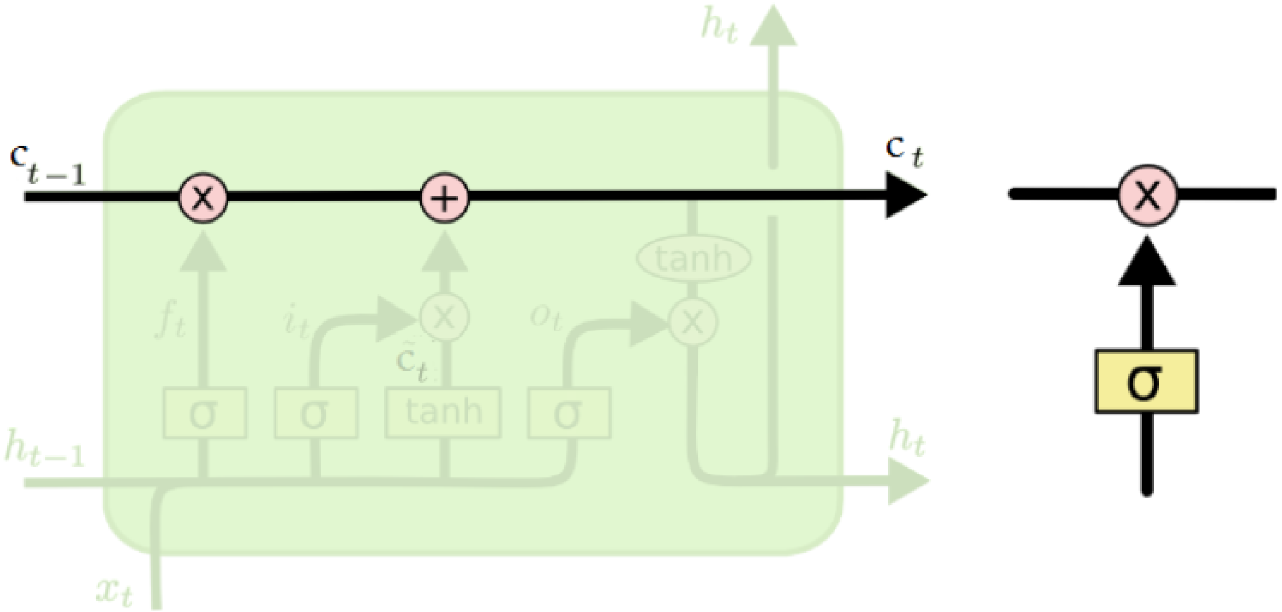
- Information can flow along the **memory cell unchanged**.
- Information can be **removed** or **written** to the **memory cell**, regulated by gates.



Adapted from: *C. Olah*

Gates

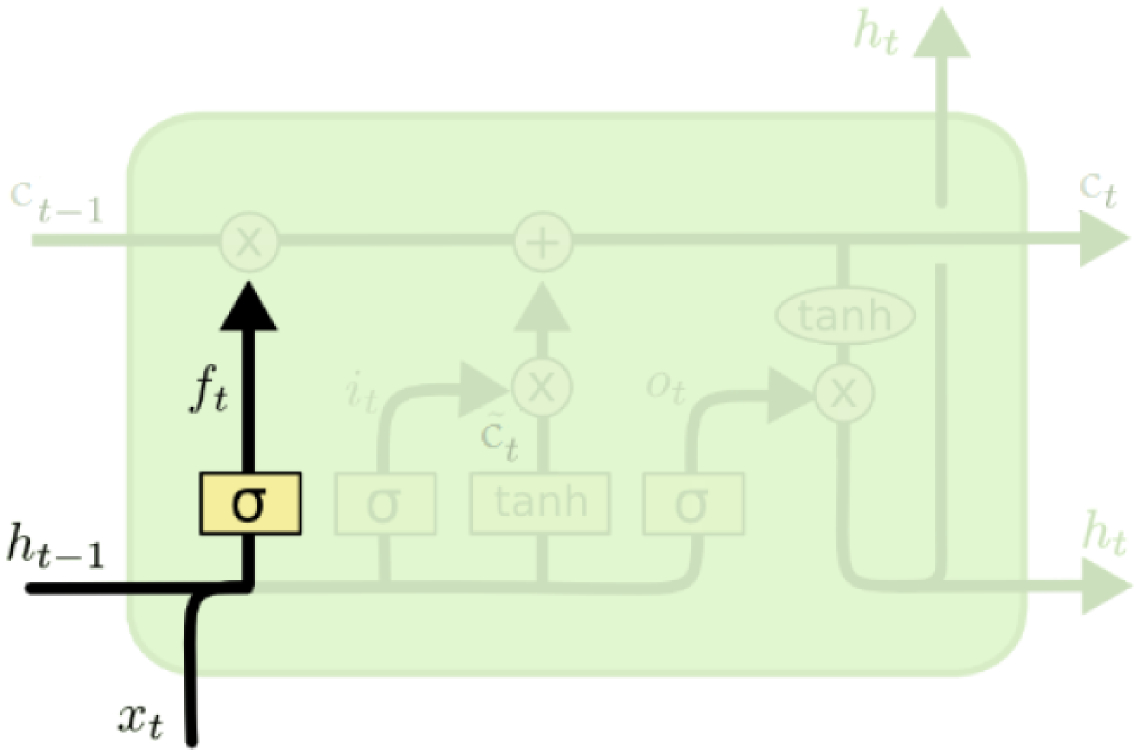
- **Gates** are a way to optionally let information through.
  - A **sigmoid layer** outputs number between 0 and 1, **deciding** how much of each component should be let through.
  - A pointwise multiplication operation applies the decision.



Adapted from: *C. Olah*

Forget Gate

- A **sigmoid** layer, **forget gate**, **decides** which values of the **memory cell** to **reset**.



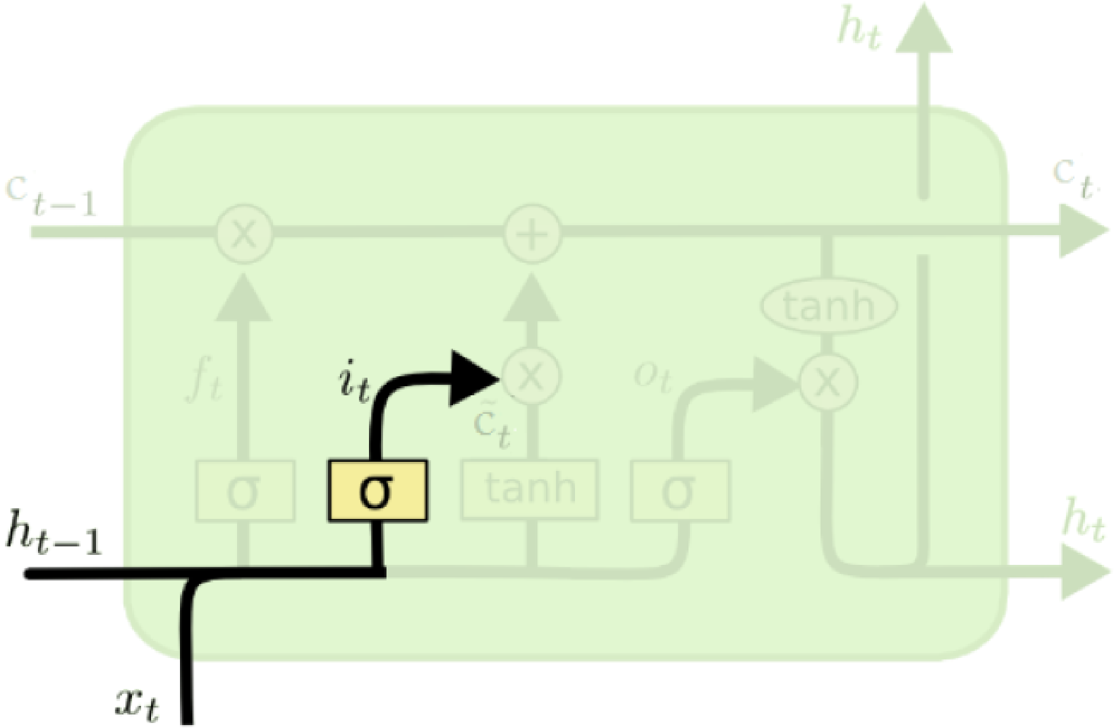
$$\mathbf{f}_t = \sigma(W_f.[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_f)$$

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Adapted from: *C. Olah*

Input Gate

- A **sigmoid** layer, **input gate**, **decides** which values of the **memory cell** to **write** to.

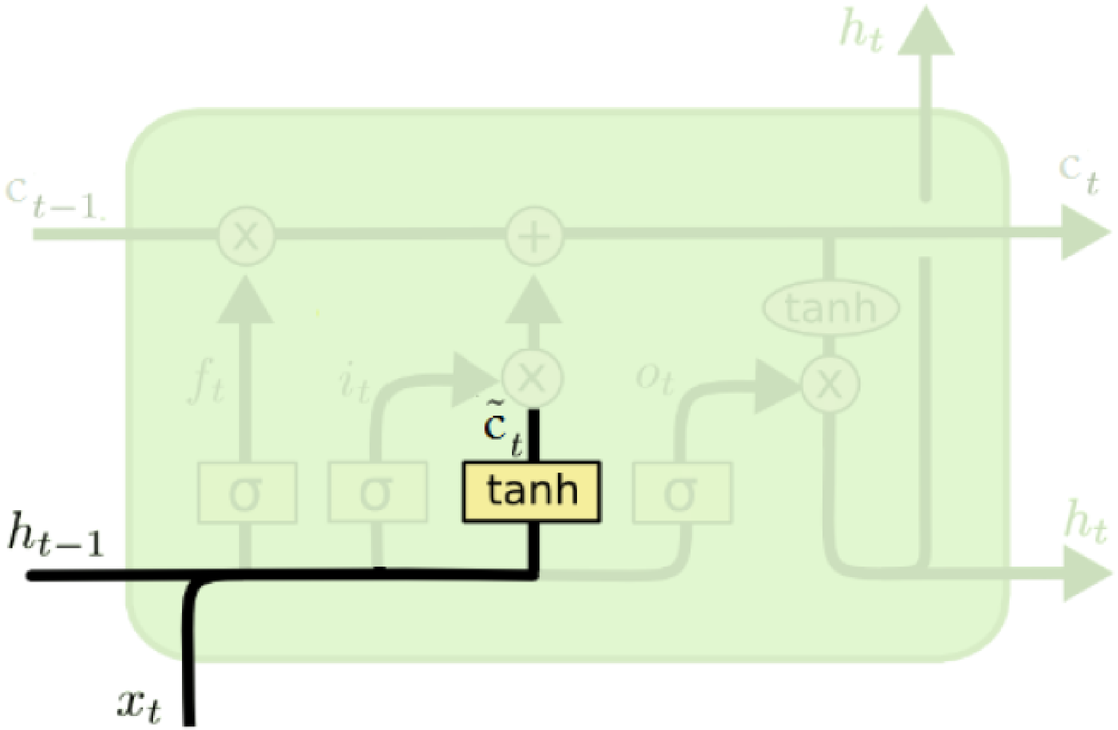


$$\mathbf{i}_t = \sigma(W_i.[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_i)$$

Adapted from: *C. Olah*

Vector of New Candidate Values

- A **Tanh** layer creates a **vector of new candidate values** $\tilde{c}_t$ to **write** to the **memory cell**.



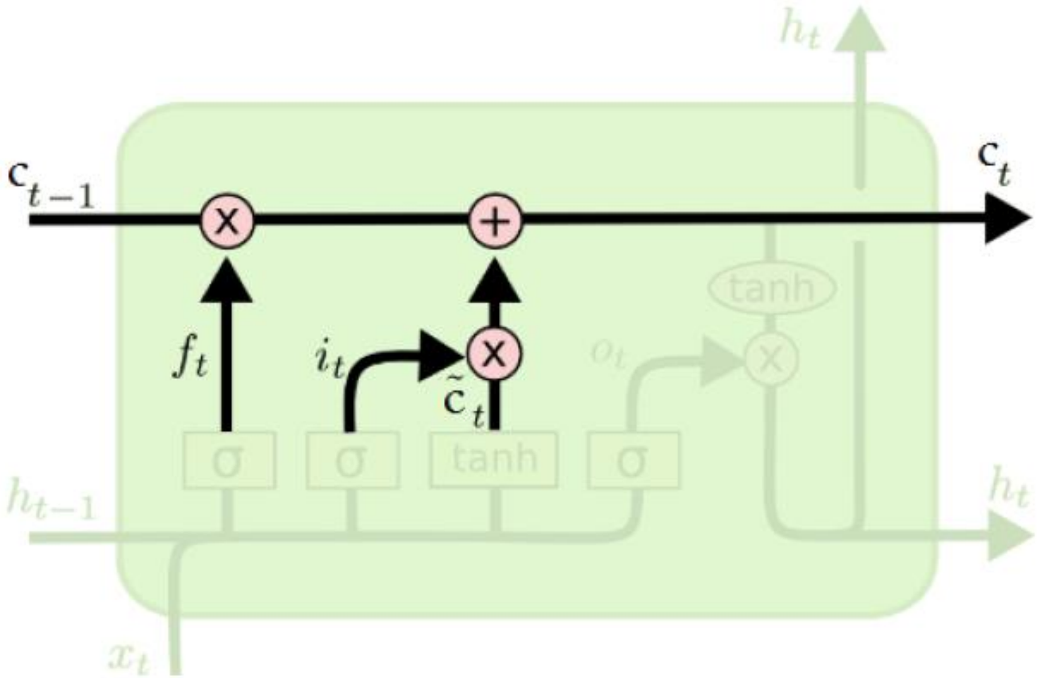
$$\tilde{\mathbf{c}}_t = \text{Tanh}(W_c.[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_c)$$

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Adapted from: *C. Olah*

Memory Cell Update

- The previous steps decided which values of the **memory cell** to **reset** and **overwrite**.
- Now the LSTM **applies the decisions** to the **memory cell**.



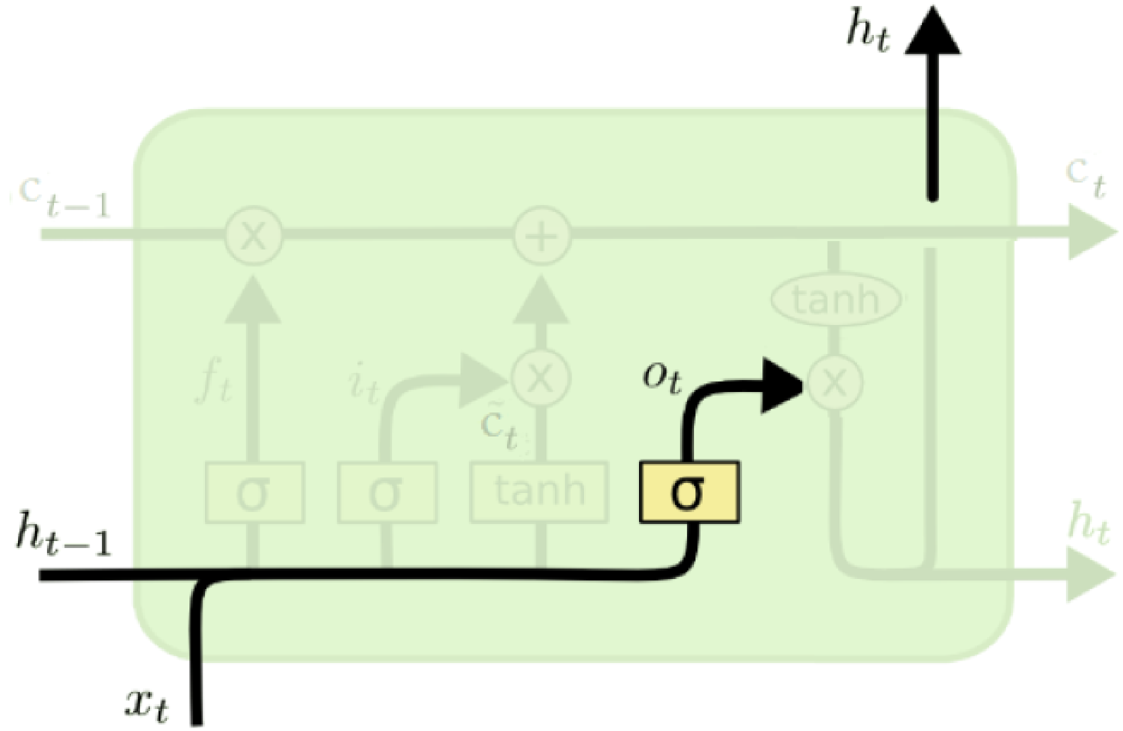
$$\mathbf{c}_t = \mathbf{f}_t * \mathbf{c}_{t-1} + \mathbf{i}_t * \widetilde{\mathbf{c}_t}$$

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Adapted from: *C. Olah*

Output Gate

- A **sigmoid** layer, **output gate**, **decides** which values of the **memory cell** to **output**.



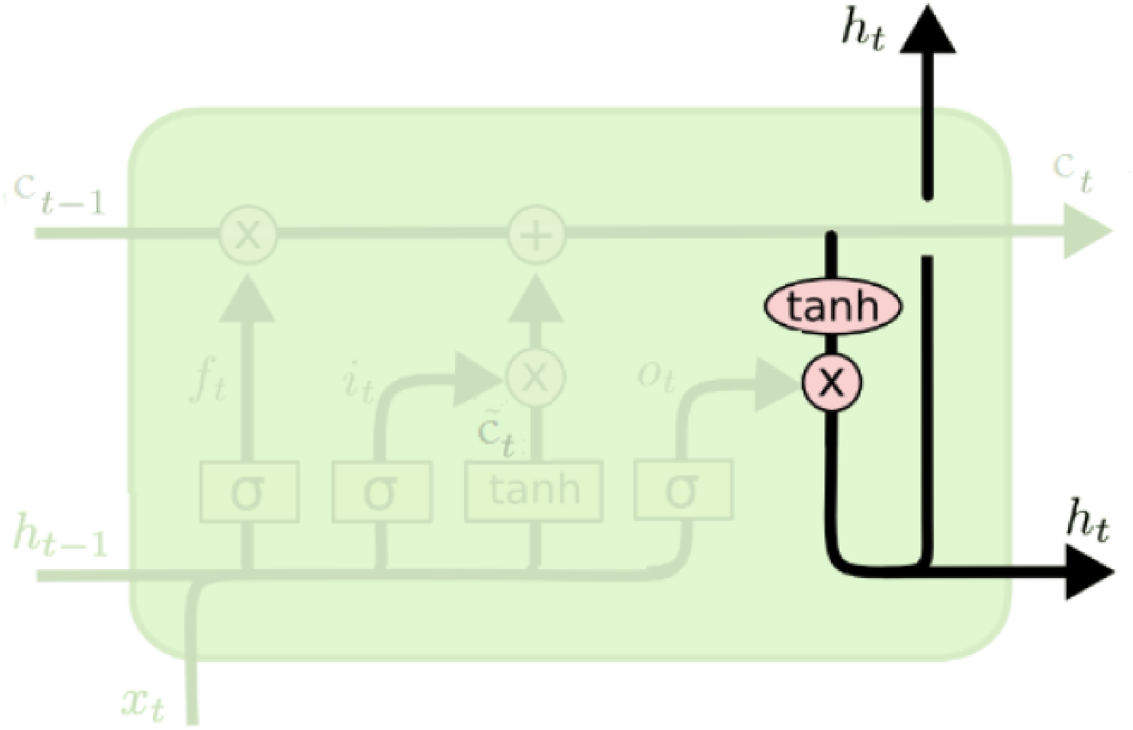
$$\mathbf{o}_t = \sigma(W_o.[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_o)$$

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Adapted from: *C. Olah*

Output Update

- The **memory cell** goes through **Tanh** and is multiplied by the **output gate**.



$$\mathbf{h}_t = \mathbf{o}_t * \text{Tanh}(\mathbf{c}_t)$$

LSTM Structure

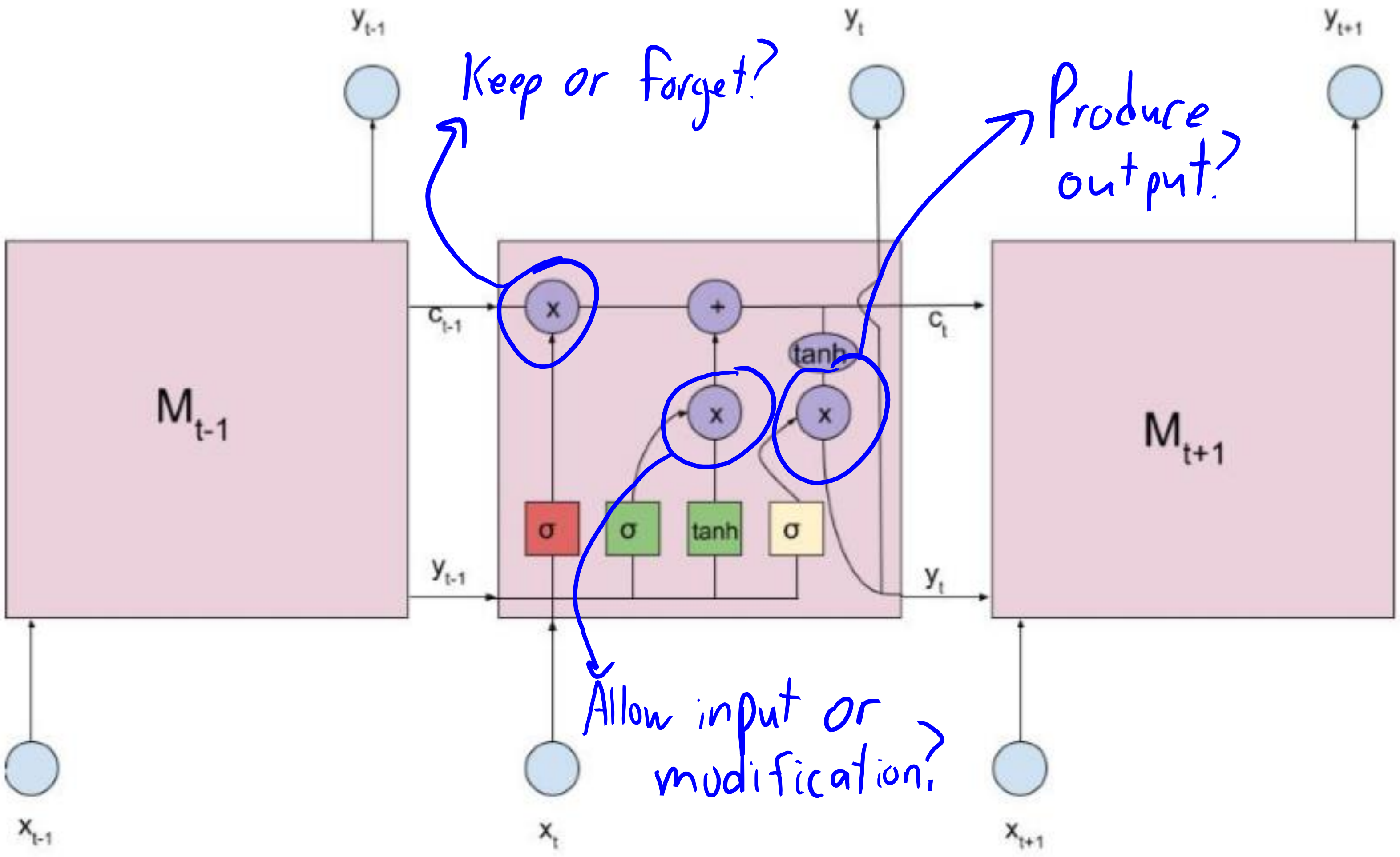


Figure 6: A close look at LSTM structure

Vanilla RNN vs. LSTM

Vanilla Recurrent Neural Network (RNN) has a recurrence of the form

$$h_t^l = \tanh W^l \begin{pmatrix} h_t^{l-1} \\ h_{t-1}^l \end{pmatrix}$$

Previous layer, same time.
Same layer, previous time.

memory vector c_t^l. At each time step the LSTM can choose to read from, write to, or reset the cell using explicit gating mechanisms. The precise form of the update is as follows:

Forget times old memory.

Input
Forget
Output
Candidate

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \text{sigm} \\ \text{sigm} \\ \text{sigm} \\ \tanh \end{pmatrix} W^l \begin{pmatrix} h_t^{l-1} \\ h_{t-1}^l \end{pmatrix}$$

Cell $\rightarrow$ $c_t^l = f \odot c_{t-1}^l + i \odot g$ $\rightarrow$ Input times candidate

Output $\rightarrow$ $h_t^l = o \odot \tanh(c_t^l)$ $\rightarrow$ Output times current memory

Here, the sigmoid function sigm and tanh are applied element-wise, and W^l is a $[4n \times 2n]$ matrix.

- Notice that if "f=1" and "i=0", then memory is unchanged.
  - Memory might only change for specific inputs.
- More recent: gated recurrent unit (GRU):
  - Similar performance but a bit simpler.

http://arxiv.org/pdf/1506.02078v2.pdf

Variants on LSTM

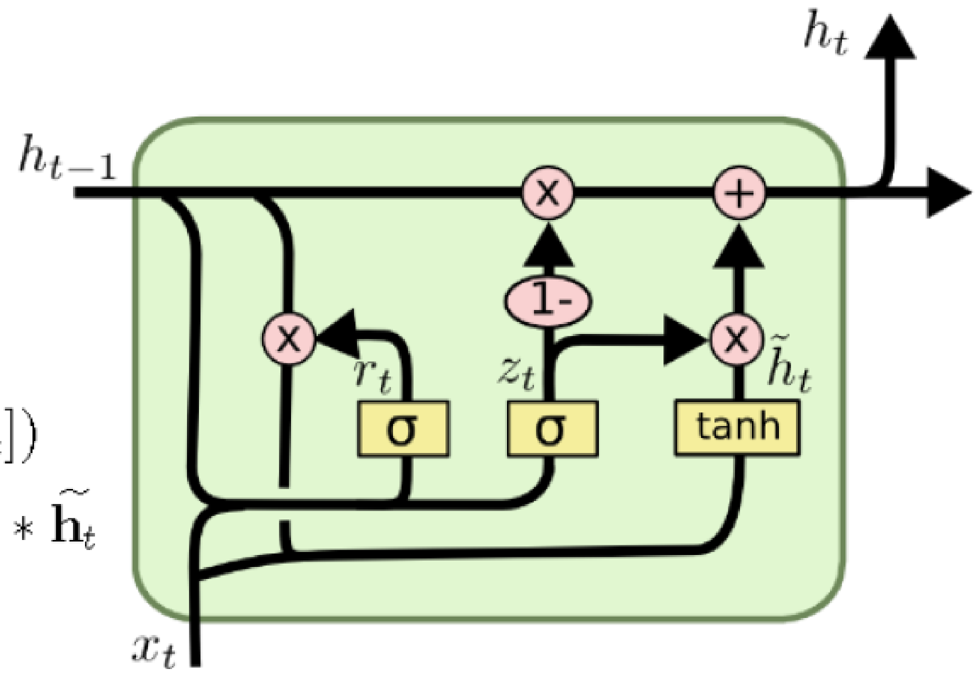
- Gated Recurrent Unit (GRU) [Cho et al., 2014]:
  - Combine the **forget** and **input** gates into a single **update** gate.
  - **Merge the memory cell and the hidden state**.
  - ...

$$z_t = \sigma(W_z.[\mathbf{h}_{t-1}, \mathbf{x}_t])$$

$$r_t = \sigma(W_r.[\mathbf{h}_{t-1}, \mathbf{x}_t])$$

$$\widetilde{\mathbf{h}}_t = \text{Tanh}(W.[r_t * \mathbf{h}_{t-1}, \mathbf{x}_t])$$

$$\mathbf{h}_t = (1 - z_t) * \mathbf{h}_{t-1} + (z_t) * \widetilde{\mathbf{h}}_t$$



Adapted from: *C. Olah*

Residual Connections

- As in ResNets, modern RNNs are including residual connections:

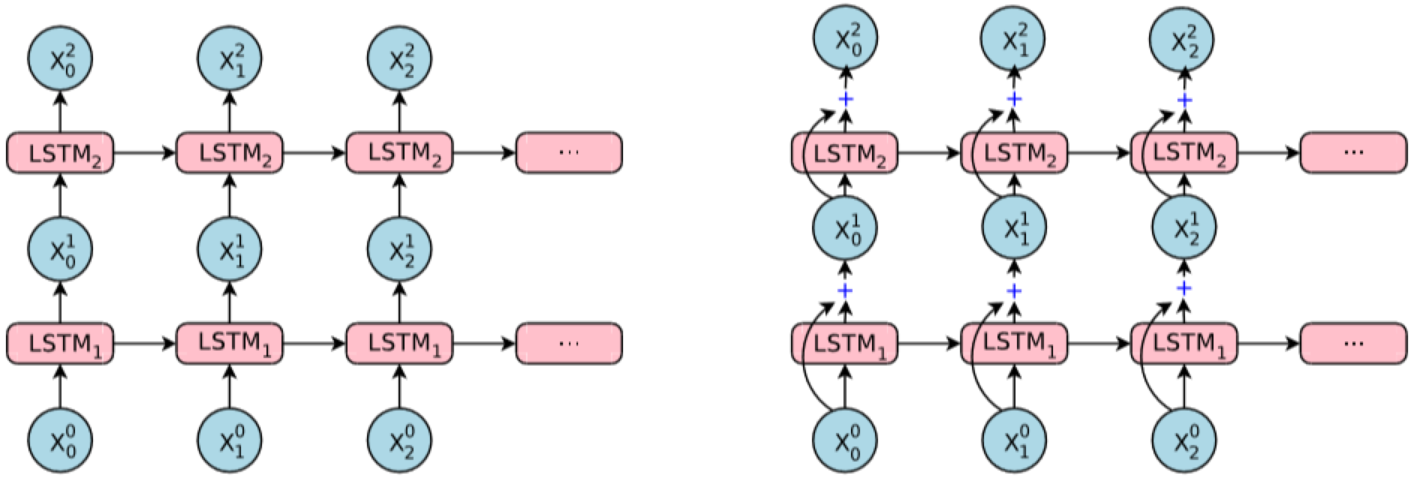


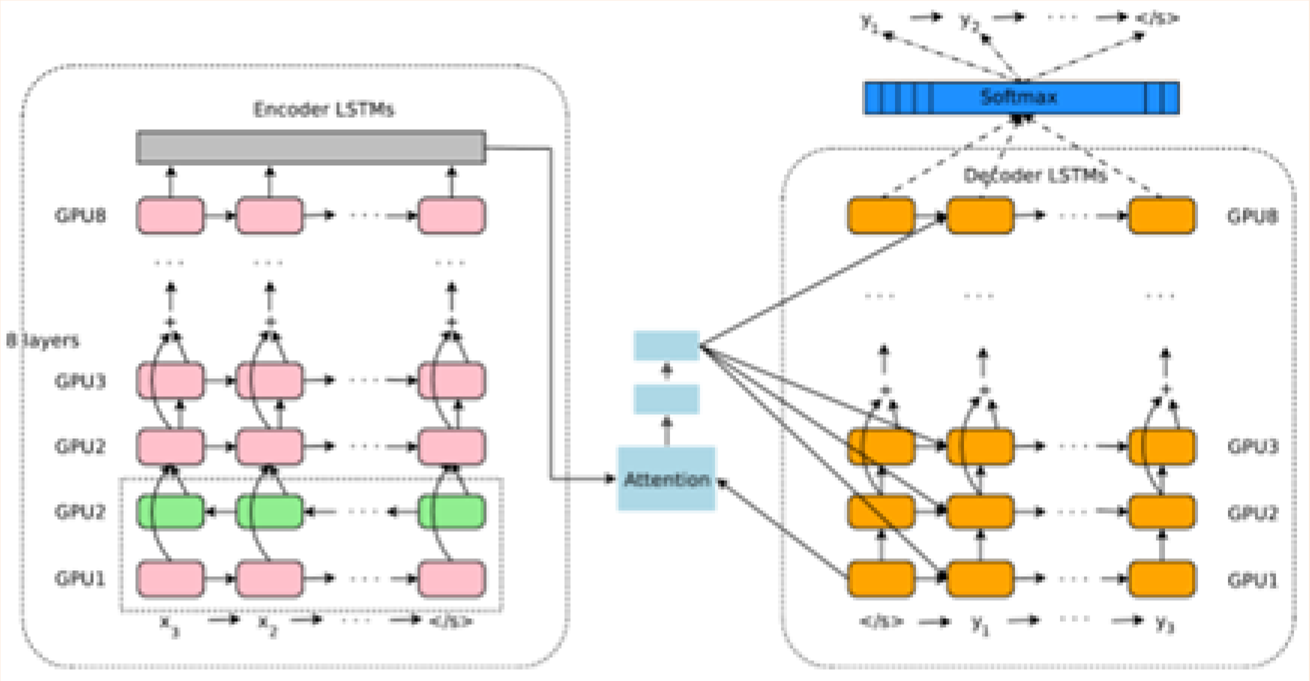
Figure 2: The difference between normal stacked LSTM and our stacked LSTM with residual connections. On the left: simple stacked LSTM layers [41]. On the right: our implementation of stacked LSTM layers with residual connections. With residual connections, input to the bottom LSTM layer ($\mathbf{x_i^0}$'s to $\mathrm{LSTM_1}$) is element-wise added to the output from the bottom layer ($\mathbf{x_i^1}$'s). This sum is then fed to the top LSTM layer ($\mathrm{LSTM_2}$) as the new input.

- You can also add residual connections across time.
  - Many variations on "skip connections"

https://arxiv.org/pdf/1609.08144.pdf

Attention

- Many recent systems incorporate attention.
  - Including “neural machine translation” system of Google Translate.

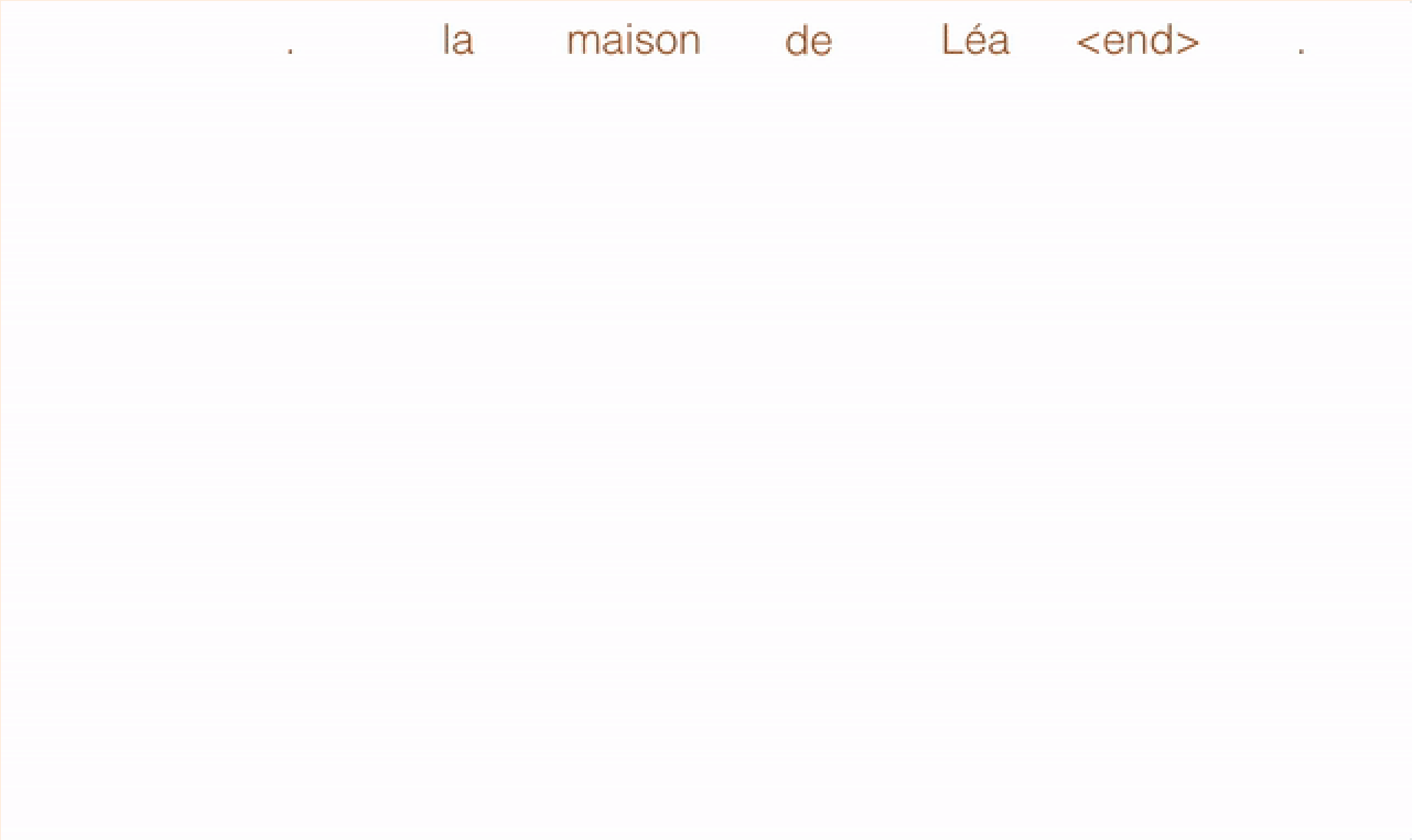


- Learn to re-weight during decoding to emphasize important parts

https://arxiv.org/pdf/1609.08144.pdf

Attention

- Attention for language translation:

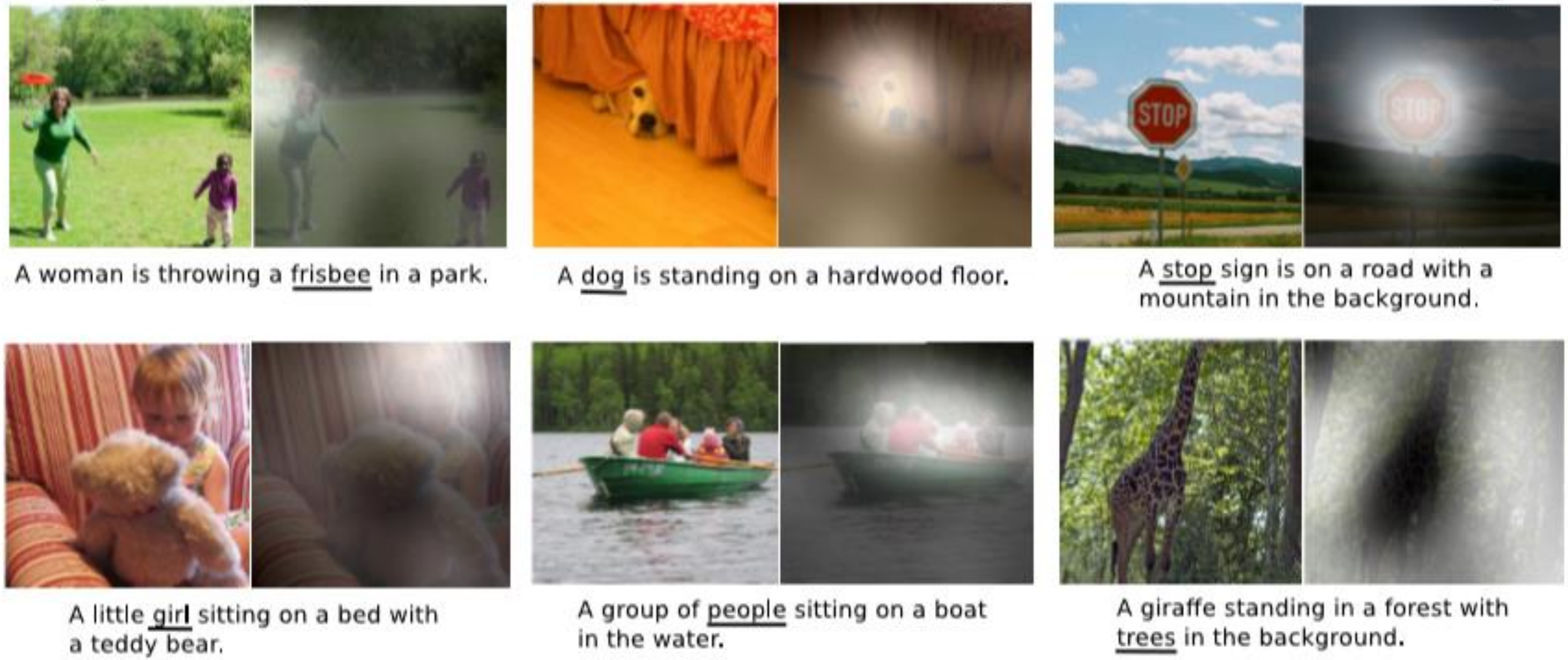


https://code.facebook.com/posts/1978007565818999/a-novel-approach-to-neural-machine-translation/

Attention

- Attention for image captioning:

Figure 3. Examples of attending to the correct object (*white* indicates the attended regions, *underlines* indicated the corresponding word)

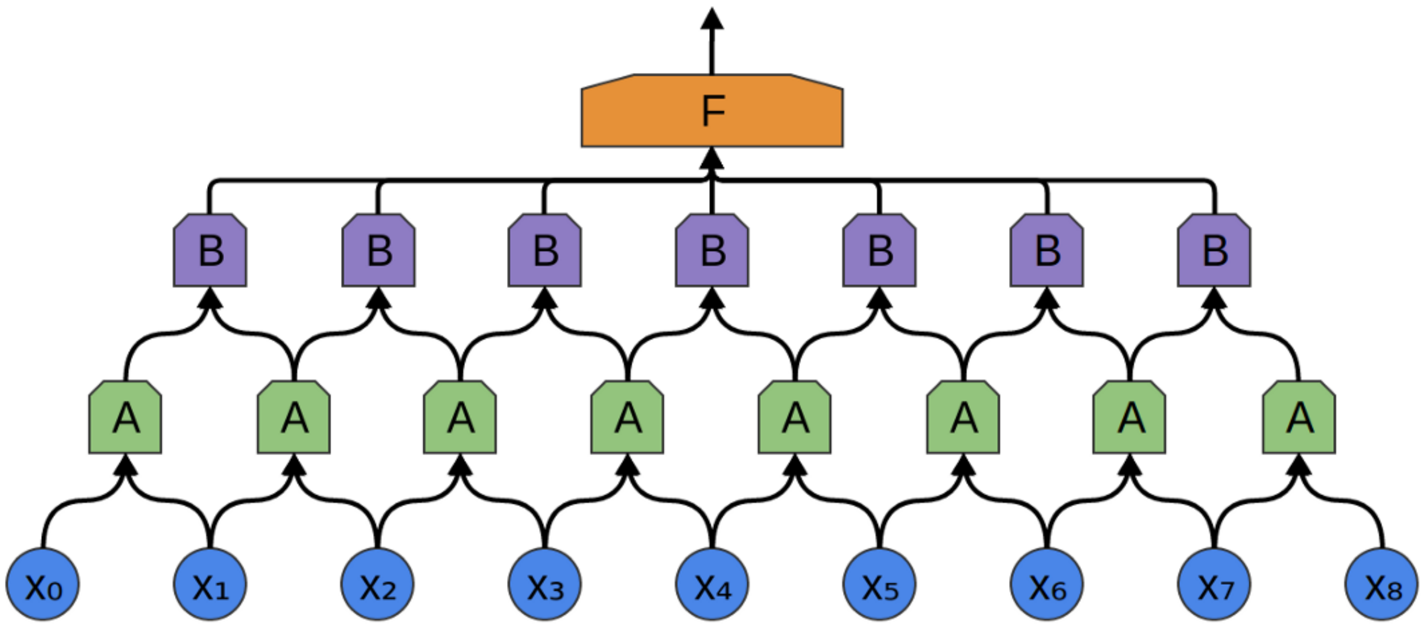


https://arxiv.org/pdf/1502.03044.pdf

Convolutions for Sequences?

- Should we really be going through a sequence sequentially?
  - What if stuff in the middle is really important, and changes meaning?

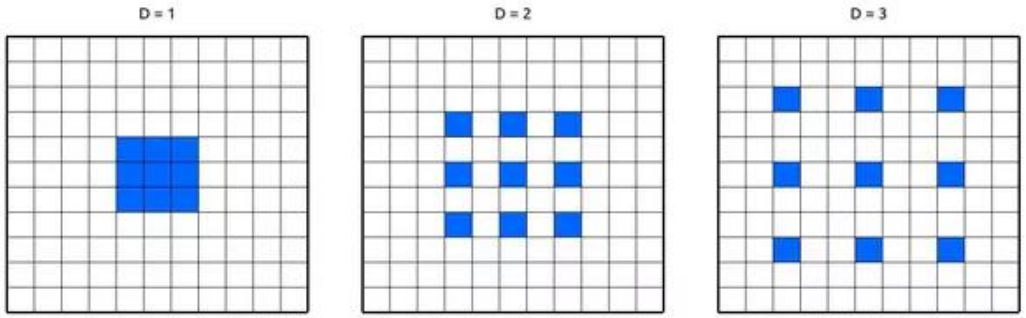
- Recent works have started using convolutions for sequences.

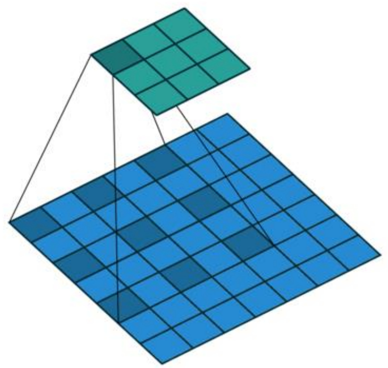


https://medium.com/@TalPerry/convolutional-methods-for-text-d5260fd5675f

Digression: Dilated Convolutions ("a trous")

- Best CNN systems have gradually reduced convolutions sizes.
  - Many modern architectures use 3x3 convolutions, far fewer parameters!
- Sequences of convolutions take into account larger neighbourhood.
  - 3x3 convolution followed by another gives a 5x5 neighbourhood.
  - But need many layers to cover a large area.
- Alternative recent strategy is dilated convolutions ("a trous").



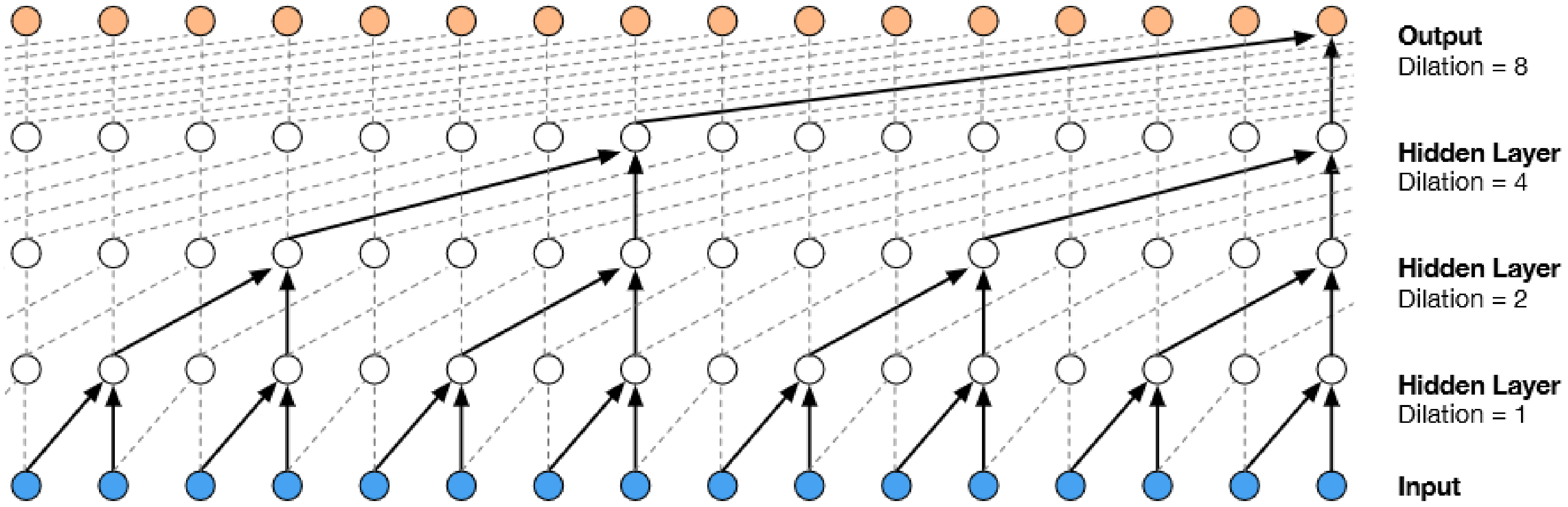


- Not the same as "stride" in a CNN:
  - Doing a 3x3 convolution at all locations, but using pixels that are not adjacent.
  - During upsampling, you can use interpolation to fill the holes.

https://medium.com/@TalPerry/convolutional-methods-for-text-d5260fd5675f
https://github.com/vdumoulin/conv_arithmetic

Dilated Convolutions ("a trous")

- Modeling music and language and with dilated convolutions:



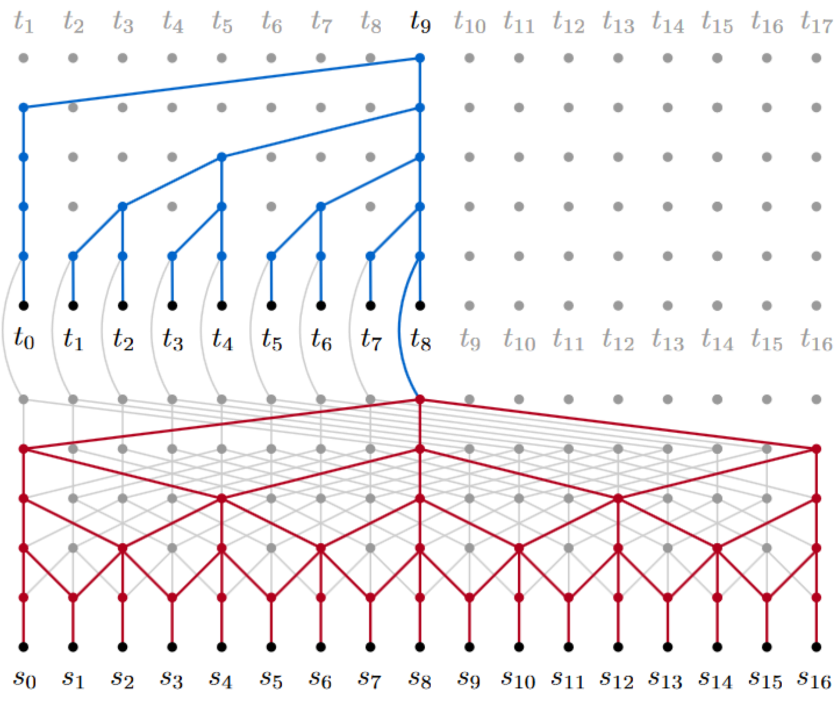


Figure 1. The architecture of the ByteNet. The target decoder (blue) is stacked on top of the source encoder (red). The decoder generates the variable-length target sequence using dynamic unfolding.

https://arxiv.org/pdf/1610.10099.pdf
https://arxiv.org/pdf/1609.03499.pdf

More RNN/CNN Applications

- Generating text:
  - https://pjreddie.com/darknet/rnns-in-darknet
- Fake positive/negative Amazon reviews:
  - https://blog.openai.com/unsupervised-sentiment-neuron
- PDF to LaTeX:

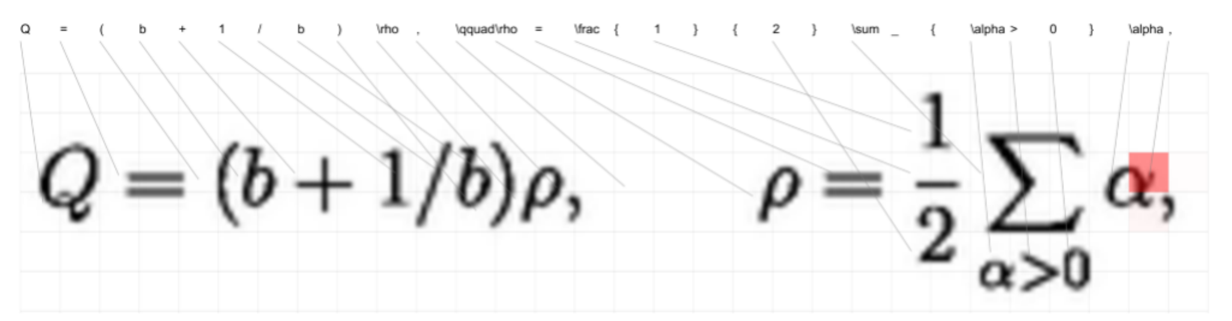


Figure 1: Example of the model generating mathematical markup. The model generates one LaTeX symbol y at a time based on the input image $\mathbf{x}$. The gray lines highlight $H' \times V'$ grid features after the CNN $\mathbf{V}$ and RNN Encoder $\tilde{\mathbf{V}}$. The dotted lines indicate the center of mass of α for each word (only non-structural words are shown). Red cells indicate the relative attention for the last token. See http://lstm.seas.harvard.edu/latex/ for a complete interactive version of this visualization over the test set.

- Lip reading:
  - https://www.youtube.com/watch?v=5aogzAUPilE

https://arxiv.org/pdf/1609.04938v1.pdf

RNNs/CNNs for Poetry

- Generating poetry:

And still I saw the Brooklyn stairs
With the shit, the ground, the golden haze
Of the frozen woods where the boat stood.
When I thought of shame and silence,
I was a broken skull;
I was the word which I called it,
And I saw the black sea still,
So long and dreary and true;
The way a square shook out my ground,
And the black things were worth a power,
To find the world in a world of reason,
And I saw how the mind saw me.

- Image-to-poetry:

A man is sitting on the edge of the waters.
I should see him begin to stand at the throat of the graveyard
and my love is like a stairway in his left arm and a piece of the stairs,
and there is a girl in the doorway and she and I am a good time.
I want to see her the best thing with the footprints in the woods
and the candle shifts back to the shrine and the last late sun
the sky and the candle and the noise of the snow.

Dropout 0.25, Loss 1.1465, 1:16:1, Railroad

A train traveling over a bridge over a river to the end of the street and the sea is a strange street with a cold sun on the street where the sun stands and the sun is still and the sun is still and the sun is gone. The sun is all around me. I am the same as the sun on the street with a strange contract.

A train traveling over a bridge over a river to the graveyard and the barn was a strange street of straw halls and the sun was always sinking in the sun.

I was the one who was still in the street when he was standing in the sun and the sun was still alive.

He was a big smile and I was a child who was a stranger.

- Movie script:
  - https://www.youtube.c

https://medium.com/artists-and-machine-intelligence/adventures-in-narrated-reality-6516ff395ba3

RNNs/CNNs for Music and Dance

- Music generation:
  – https://www.youtube.com/watch?v=RaO4HpM07hE

- Text to speech and music waveform generation:
  – https://deepmind.com/blog/wavenet-generative-model-raw-audio

- Dance choreography:
  – http://theluluartgroup.com/work/generative-choreography-using-deep-learning

- Music composition:
  – https://www.facebook.com/yann.lecun/videos/10154941390687143

Neural Turing/Programmers

- Many interesting recent variations on memory/attention.
  - A good place to start is here: https://distill.pub/2016/augmented-rnns

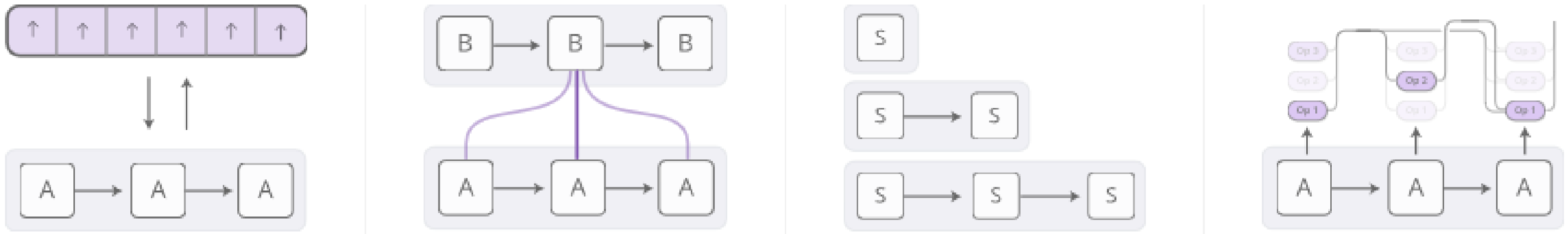
Here is an example of what the system can do. After having been trained, it was fed the following short story containing key events in JRR Tolkien's Lord of the Rings:

Bilbo travelled to the cave.
Gollum dropped the ring there.
Bilbo took the ring.
Bilbo went back to the Shire.
Bilbo left the ring there.
Frodo got the ring.
Frodo journeyed to Mount-Doom.
Frodo dropped the ring there.
Sauron died.
Frodo went back to the Shire.
Bilbo travelled to the Grey-havens.
The End.

After seeing this text, the system was asked a few questions, to which it provided the following answers:

Q: Where is the ring?
A: Mount-Doom
Q: Where is Bilbo now?
A: Grey-havens
Q: Where is Frodo now?
A: Shire

It's probably one of the few technical papers that cite "Lord of the Rings".



Neural Turing Machines have external memory that they can read and write to.

Attentional Interfaces allow RNNs to focus on parts of their input.

Adaptive Computation Time allows for varying amounts of computation per step.

Neural Programmers can call functions, building programs as they run.

https://www.facebook.com/FBAIResearch/posts/362517620591864

Summary

- Long short term memory:
  - Gating functions which update "memory cells" for long-range interactions.

- Dilated convolutions:
  - Convolutions with holes to model long-term dependencies.