Recurrent Neural Networks

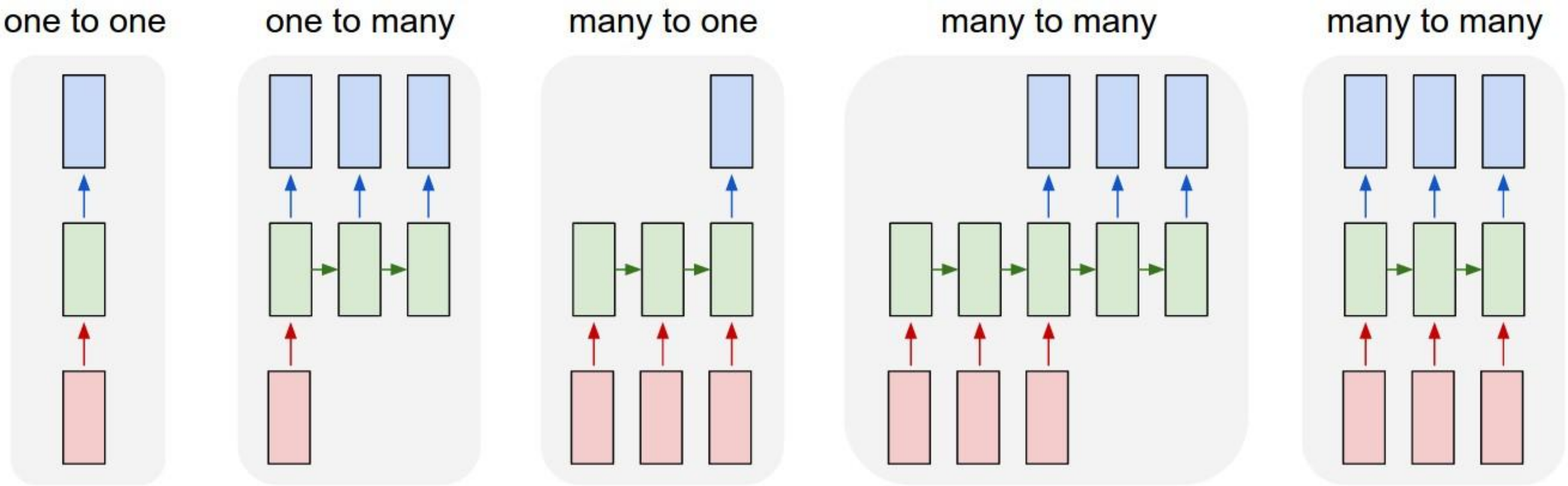
Processing Sequences

Summary

- Variable size input/output
- Recurrent neural networks
- Sequence to sequence learning
- LSTM
- GRU
- Attention
- Dynamic memory networks for question answering

Variable size input/output

Different options for input/output cardinality



Andrej Karpathy: The Unreasonable Effectiveness of Recurrent Neural Networks

Examples

- One to many
    - Image captioning
- Many to one
    - Sentiment analysis
    - Question answering (single word)
- Many to many
    - Translation
    - Question answering
    - (synced) Video frames classification

Image captioning

Image source: Show and Tell

Sentiment analysis

I would rather watch my avocado grow for 90 minutes than watching that match. (me)

Probably: negative

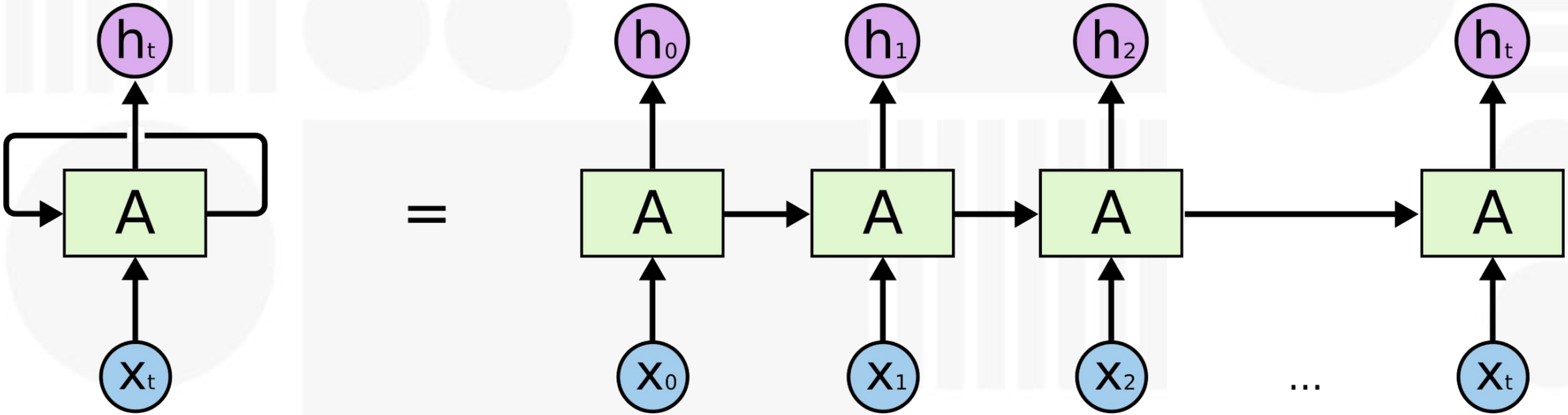
Translation

I don't know what I am talking about (English) =

Ich weiß nicht, wovon ich rede(German)

Recurrent Neural Networks

RNNs - the idea



- The one on the right is rolled out version of the network on the left
- All **A**-s on the right are the SAME network - they have the same weights

But how do we train such a thing?

- Typical approach would be back propagation
- Steps may be many, even ∞(we’ll see later)
- The solution:
  - Unroll for fixed number of steps
  - Backpropagate the error
  - You have to combine all the gradients!

Notes

- With many steps the gradient for the first few either:
  - Vanishes (most of the time)
  - Explodes (less frequently)
  - A solution - gradient clipping (or later slides)
- We typically use tanh for activation function
- Take extra care with batches
- Deep RNNs
- Bi-directional RNNs

Gradient clipping

$$g = \frac{df}{dg}$$

$$\text{if } g > \alpha$$

$$\boxed{\hat{g} = \frac{\alpha}{||g||} g}$$

Deep RNNs

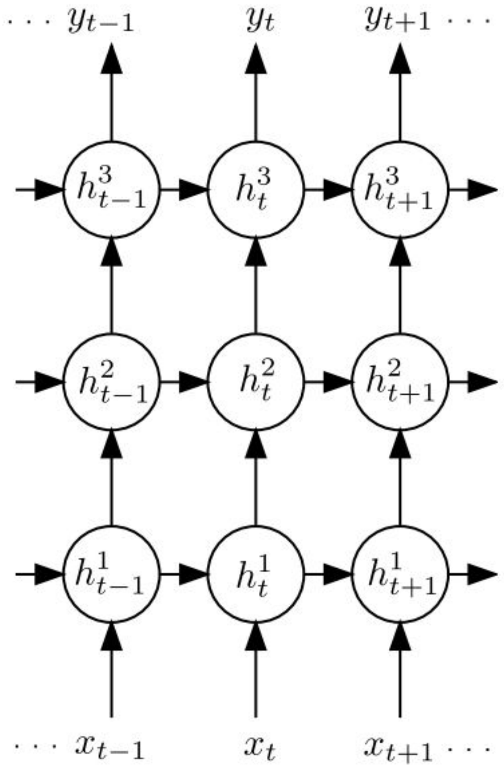


Image source: Hybrid speech recognition with deep bidirectional LSTM

Bidirectional RNN

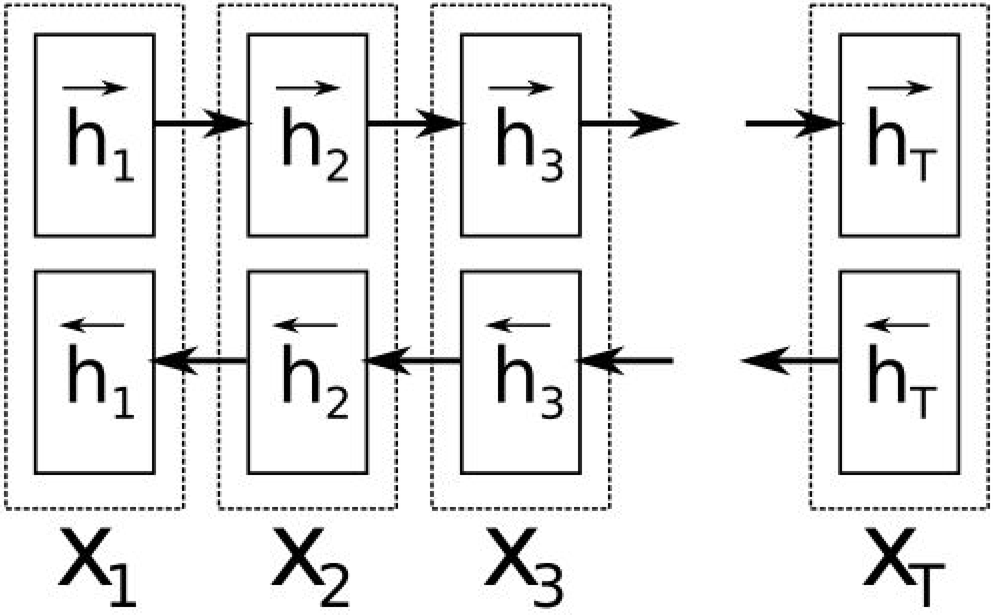


Image source: Neural Machine Translation by Jointly Learning to Align and Translate

Sequence to Sequence learning

The task

- We are given a sequence
- Our target is another sequence
- The two sequences may be of different size and order

Example

I don't know what I am talking about (English) =

Ich weiß nicht, wovon ich rede(German)

Note that:

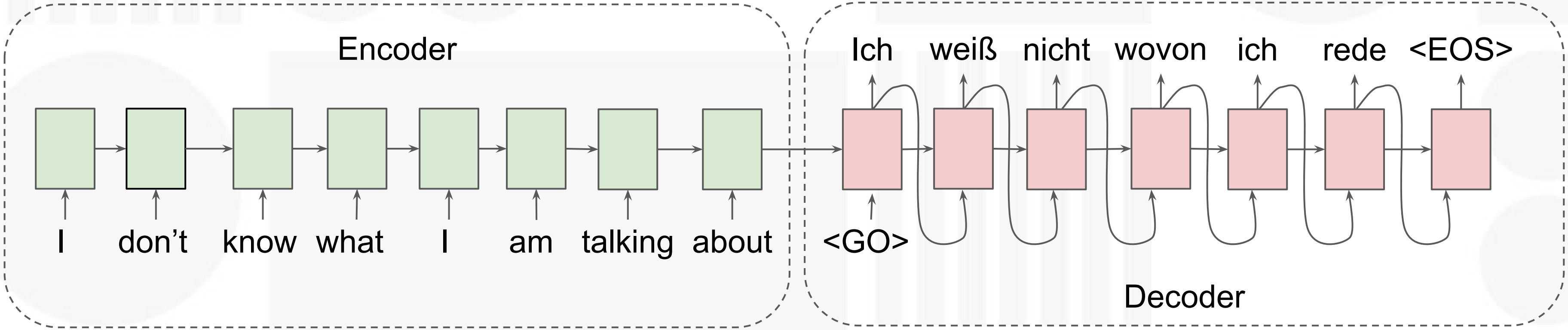
- The length is different
- The order is different

How do we do it

Two networks:

- Encoder that converts the input to machine-readable
- Decoder that produces the desired output

Encoder / Decoder



NOTE: in fact we are using embeddings not the words

Notes

- Experiments proved better results if we reverse input
- Same problems as with RNNs
  - Solved using LSTM/GRU
- We have problems with long sentences
  - Solved using attention

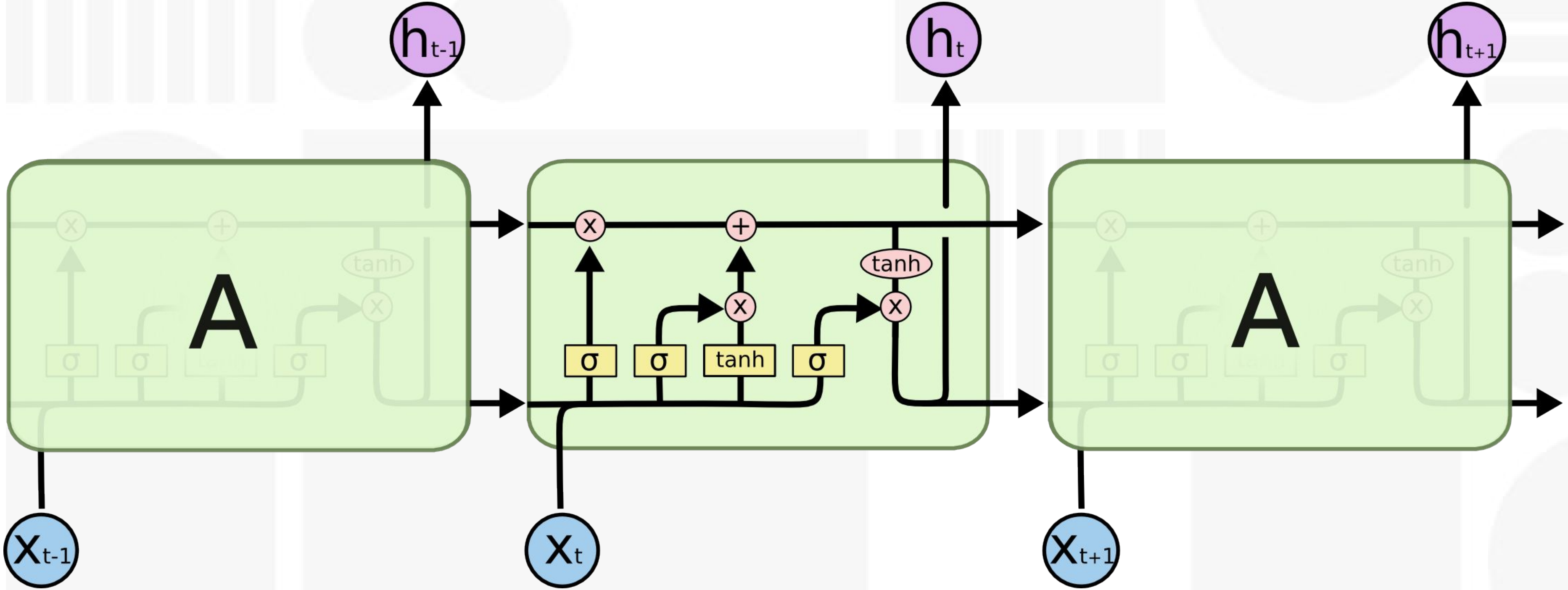
LSTM

What is it?

- Stands for “long short term memory”
- Special type of RNN cell
- Able to decide what to forget/remember
- Alleviates the vanishing/exploding gradient problem

source: Cris Olah's blog

Picture or it did not happen!

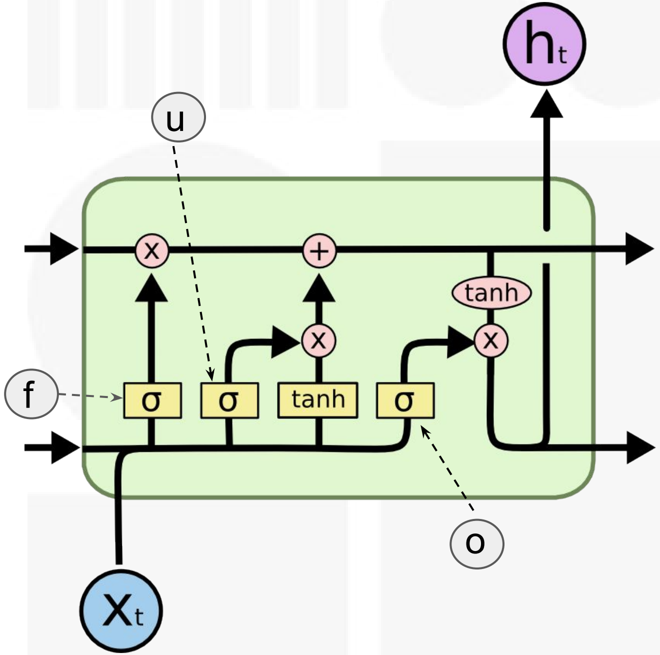


Doesn't help much, does it?

Components

- We have two states - hidden state and cell state
  - Hidden state equivalent to the typical RNN state
  - Cell state ‘flows freely’ and propagates gradients
- Three gates:
  - Forget gate
  - Update gate
  - Output gate

Step by step



Input: $X = \text{concat}(X_t , H_{t-1})$ (size: p + n)

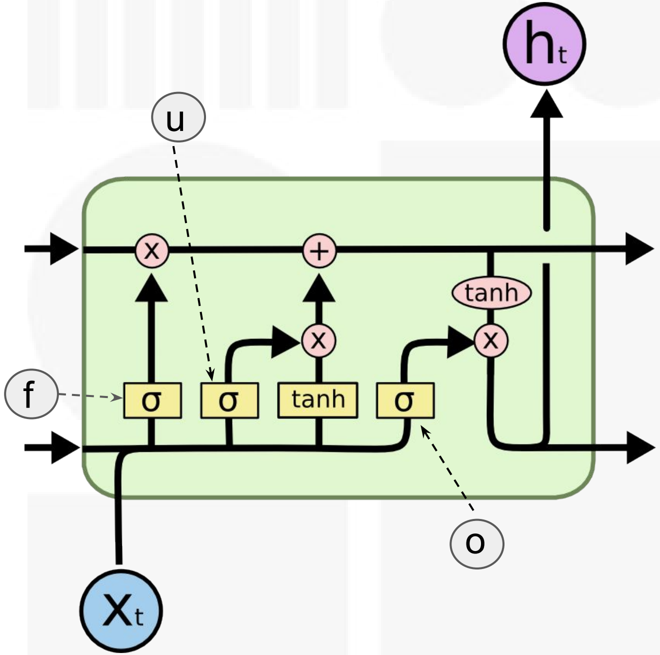
Forget gate: $f = \boldsymbol{\sigma}(X * W_f + b_f)$ (size n)
Update gate: $u = \boldsymbol{\sigma}(X * W_u + b_u)$ (size n)
Output gate: $o = \boldsymbol{\sigma}(X * W_o + b_o)$ (size n)

Input: $X' = \tanh(X * W_C + b_C)$ (size n)
New C: $C_t = f * C_{t-1} + u * X'$ (size n)
New H: $H_t = o * \tanh(C_t)$ (size n)

Output (if exists):
$Y_t = \text{softmax}(H_t * W + b)$ (size m)

Image Source: Chris Olah's blog (labels added)

How does it help?



- There is a direct path for the gradient - no activation applied on C
- The cell ‘learns’ what to remember for longer period

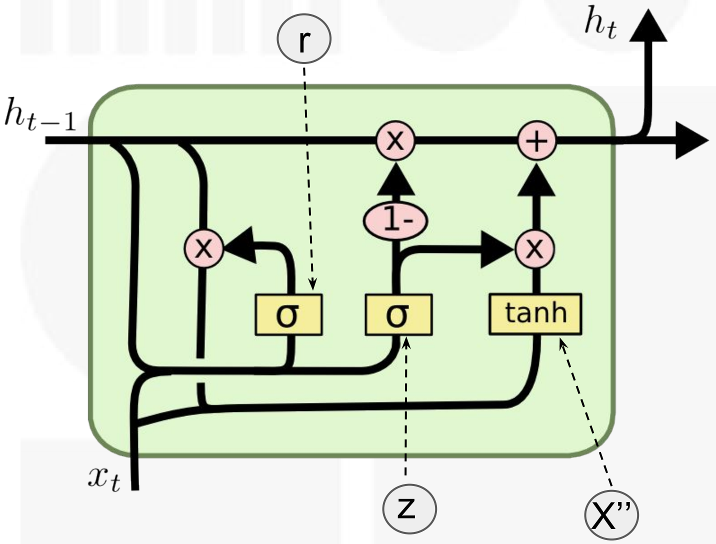
Image Source: Chris Olah’s blog (labels added)

GRU

What is it?

- Stands for “gated recurrent unit”
- Similar to LSTM
- Has only two gates instead of 3
- Exposes its whole state to the outside

GRU - how does it work?



Input: X = concat(X_t , h_{t-1}) (size: p + n)

Update gate: z = **σ**(X * W_z + b_z) (size n)
Reset gate: r = **σ**(X * W_r + b_r) (size n)

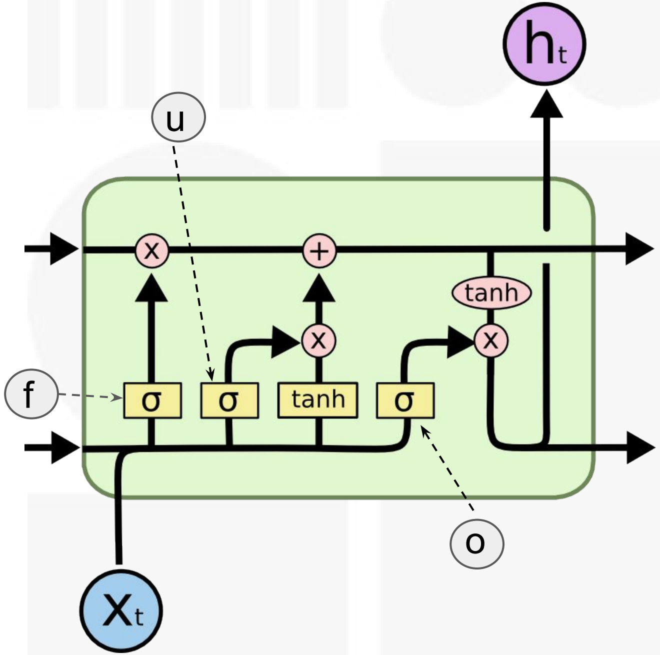
Input:
X' = concat(X_t, (r * h_{t-1})) (size p + n)
X'' = tanh(X' * W_C + b_C) (size n)

New h: h_t = (1 - z) * h_{t-1} + z * X'' (size n)

Output (if exists):
Y_t = softmax(h_t * W + b) (size m)

Image Source: Chris Olah's blog (labels added)

LSTM vs GRU (1 / 2)



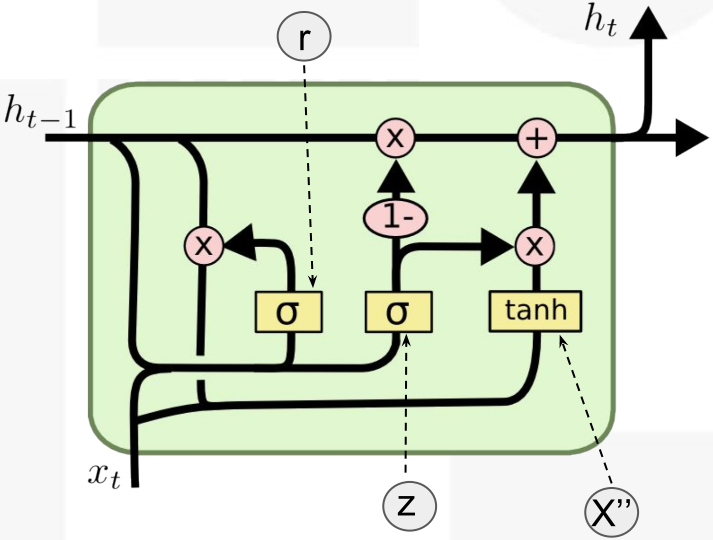


Image Source: Chris Olah's blog (labels added)

LSTM vs GRU (2 / 2)

Input: $X = \text{concat}(X_t\ , H_{t-1})$

Forget gate: $f = \boldsymbol{\sigma}(X * W_f + b_f)$
Update gate: $u = \boldsymbol{\sigma}(X * W_u + b_u)$
Output gate: $o = \boldsymbol{\sigma}(X * W_o + b_o)$

Input: $X' = \tanh(X * W_C + b_C)$
New C: $C_t = f * C_{t-1} + u * X'$
New H: $H_t = o * \tanh(C_t)$

Output (if exists):

$Y_t = \text{softmax}(H_t * W + b)$

Input: $X = \text{concat}(X_t\ , H_{t-1})$

Update gate: $z = \boldsymbol{\sigma}(X * W_z + b_z)$
Reset gate: $r = \boldsymbol{\sigma}(X * W_r + b_r)$
Just two gates!

Input:

$X' = \text{concat}(X_t, (r * H_{t-1}))$
$X'' = \tanh(X' * W_C + b_C)$

No C!

New H: $H_t = (1 - z) * H_{t-1} + z * X''$

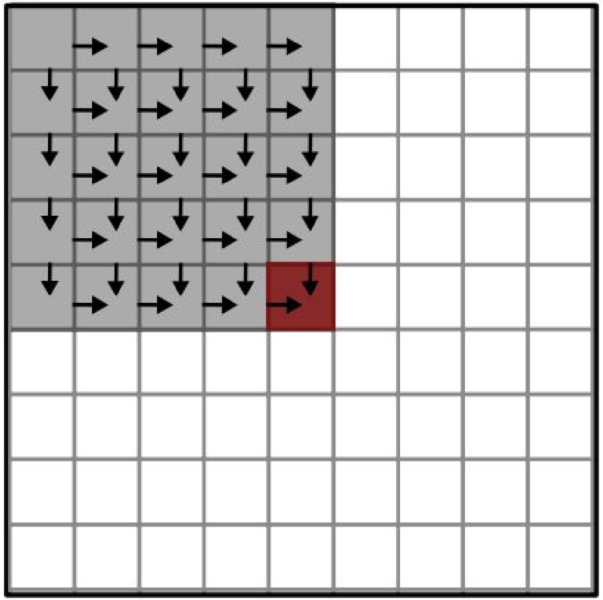
Output (if exists):

$Y_t = \text{softmax}(H_t * W + b)$

Notes on GRU and LSTM

- GRU has fewer parameters
  - faster to compute
  - faster to train
- Empirically GRU performs on par with LSTM
- GRU is getting more popular recently
- Other architectures for recurrent units exist

MDLSTM



(a) Standard MD-LSTM

Image Source: Parallel Multi-Dimensional LSTM, With Application to Fast Biomedical Volumetric Image Segmentation (cropped)


ATTENTION

What is attention

- Trainable function
- We enable the decoder to look at encoder outputs
- No longer rely on single encoder hidden state to encode all information
- We can visualize the information used for a prediction

What is attention

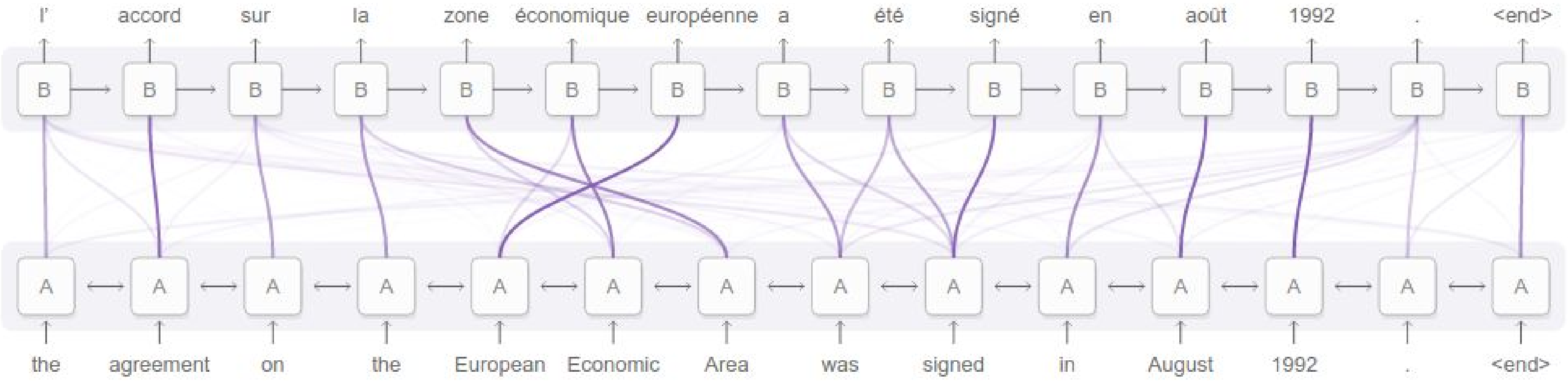


Image Source: Attention and Augmented Recurrent Neural Networks (colah's blog)

Hard Attention

- Binary value - either 1 or 0 for each feature
- Fast and easy to compute during forward pass
- Non-differentiable -needs different mechanism to train
  - reinforcement learning
  - variance reduction

Soft attention

- Real value between 0 and 1 for each feature
- Each feature is included to some extent
- Differentiable
    - can use backpropagation as usual
- More common

An example

Soft attention Hard attention

Image Source: Show attend and tell (hard attention version added separately)

Bahdanau attention

$$c_i = \sum_{j=1}^{T_x} a_{ij} h_j$$

$$a_{ij} = \frac{exp(e_{ij})}{\sum_{k=1}^{T} exp(e_{ik})}$$

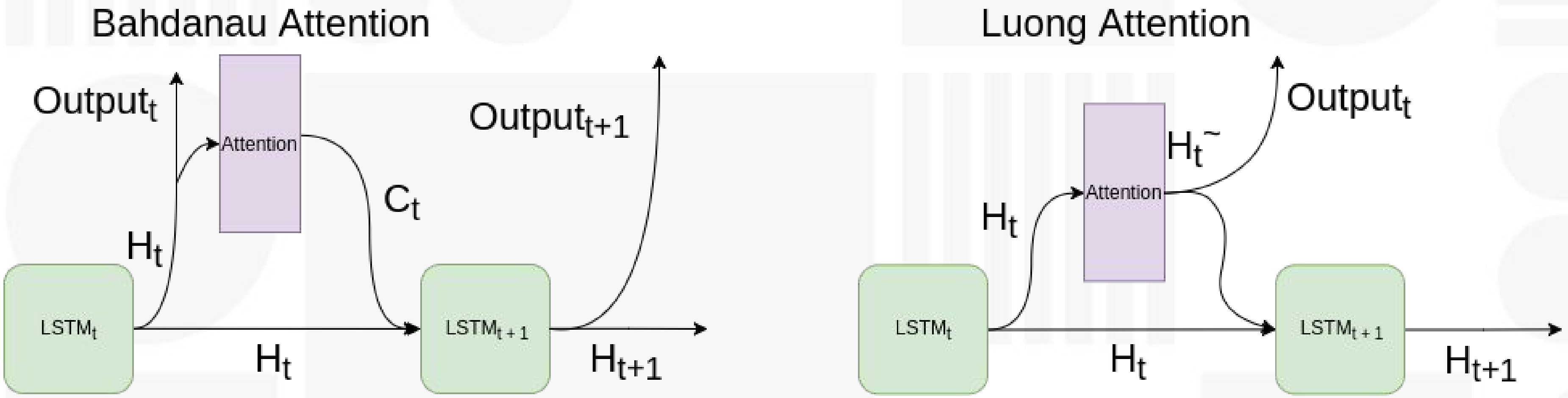
$$e_{ij} = a(s_{i-1}, h_j)$$

- New input component c_i called “context”
- h_j- encoder output at step j
- a_{ij} - weight of the j-th annotation(encoder output)
- e_{ij} - attention energy for the j-th annotation
- a - an attention function(a fully connected layer)
- s_{i-1} - decoder hidden state after step i - 1
- NOTE: for each step we iterate over **all** encoder outputs

Luong attention

- Proposes more attention functions
- Attention layer comes **after** the RNN cell
- Proposes “global” and “local” versions
  - global is more similar to Bahdanau
  - local: p_i for each decoder step, consider $[p_i - D, p_i + D]$
    - monotonic version $p_i = i$
    - predictive - p_i is computed by a trained function
    - still differentiable

Bahdanau vs Luong



Different attentions

- Neural turing machines - using external memory
- Adaptive computation time - dynamically deciding how many cells we need
- Neural Programmer - dynamically decide **what** cells to run

Dynamic Memory Networks for Question Answering

Question answering - the problem

- We are given a set of “facts”
- We are given a single question
- We need to produce an answer to that question

Question answering - example

Two supporting fact example(from the bAbI dataset):

1 Mary got the milk there.
2 John moved to the bedroom.
3 Sandra went back to the kitchen.
4 Mary travelled to the hallway.
5 Where is the milk? hallway 1 4

Dynamic Memory Networks for question answering

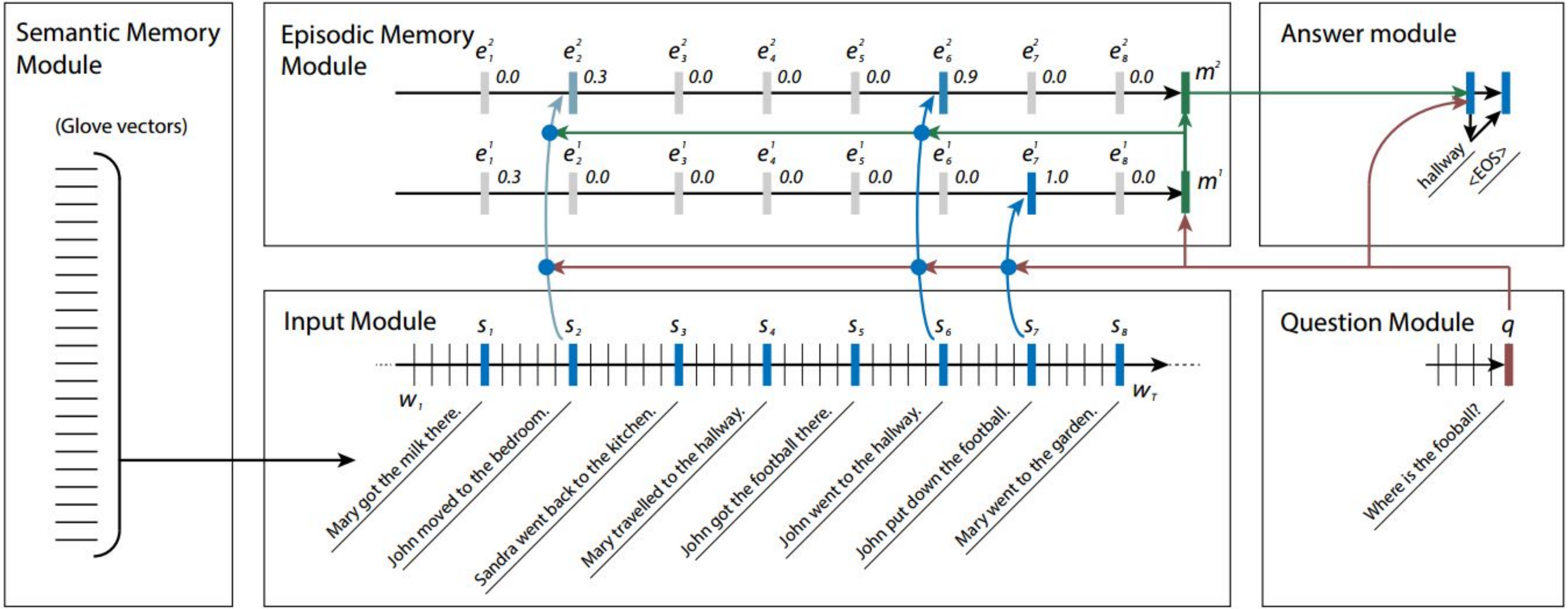
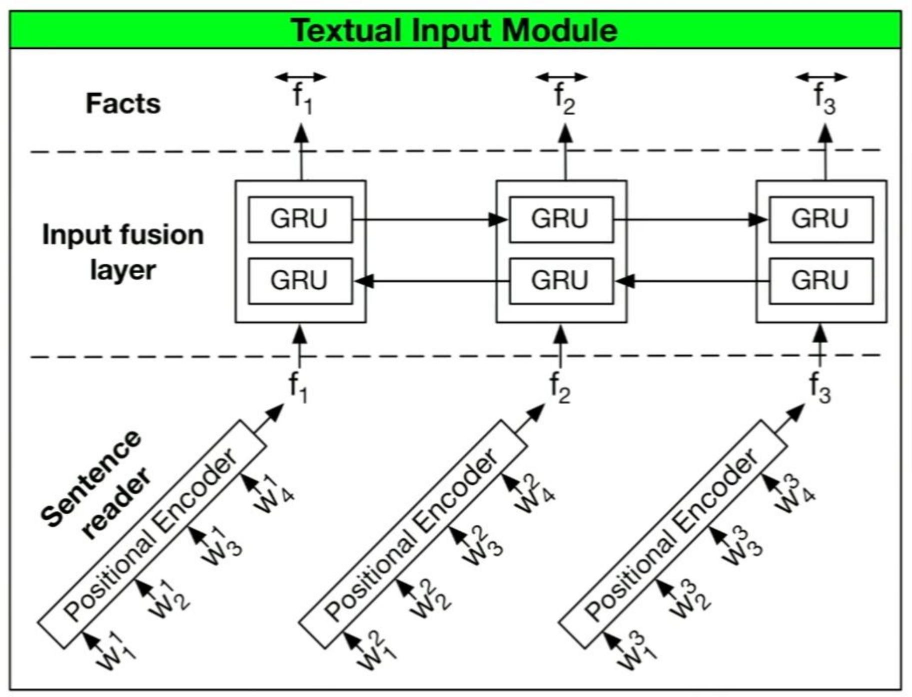


Image Source: Dynamic Memory Networks for Question Answering (Chris Manning & Richard Socher)

Dynamic Memory Networks for question answering



Concatenate the encodings in the two directions

Image Source: Dynamic Memory Networks for Visual and Textual Question Answering (Xiong et al)

DMNs - The question

- Standard GRU RNN

$$q_t = GRU(v_t, q_{t-1})$$

DMNs - Episodic Memory

$$z_i^t = [s_i \circ q; s_i \circ m^{t-1}; |s_i - q|; |s_i - m^{t-1}|]$$

$$Z_i^t = W^{(2)} * tanh(W^{(1)} * z_i^t + b^{(1)}) + b^{(2)}$$

$$g_i^t = \frac{exp(Z_i^t)}{\sum_{k=1}^{M_i} exp(Z_k^t)}$$

$$h_i^t = g_i^t * GRU(c_t, h_{t-1}^i) + (1 - g_i^t) * h_{t-1}^i$$

Episodic Memory - notes

- When g_i^t is close to zero, we entirely ignore the GRU, when it is close to 1, we entirely ignore the hidden state
- We measure cosine similarity between vectors
- On the first layer m^{t-1} is the question itself
- We could replace the softmax with sigmoids at each point
- Another GRU over the memory states

DMNs - The answer

- For the bAbI dataset the answer is a single word, so we use softmax
- For variable length answers we use a decoder much like in the translation case

Dynamic Memory Networks - the example

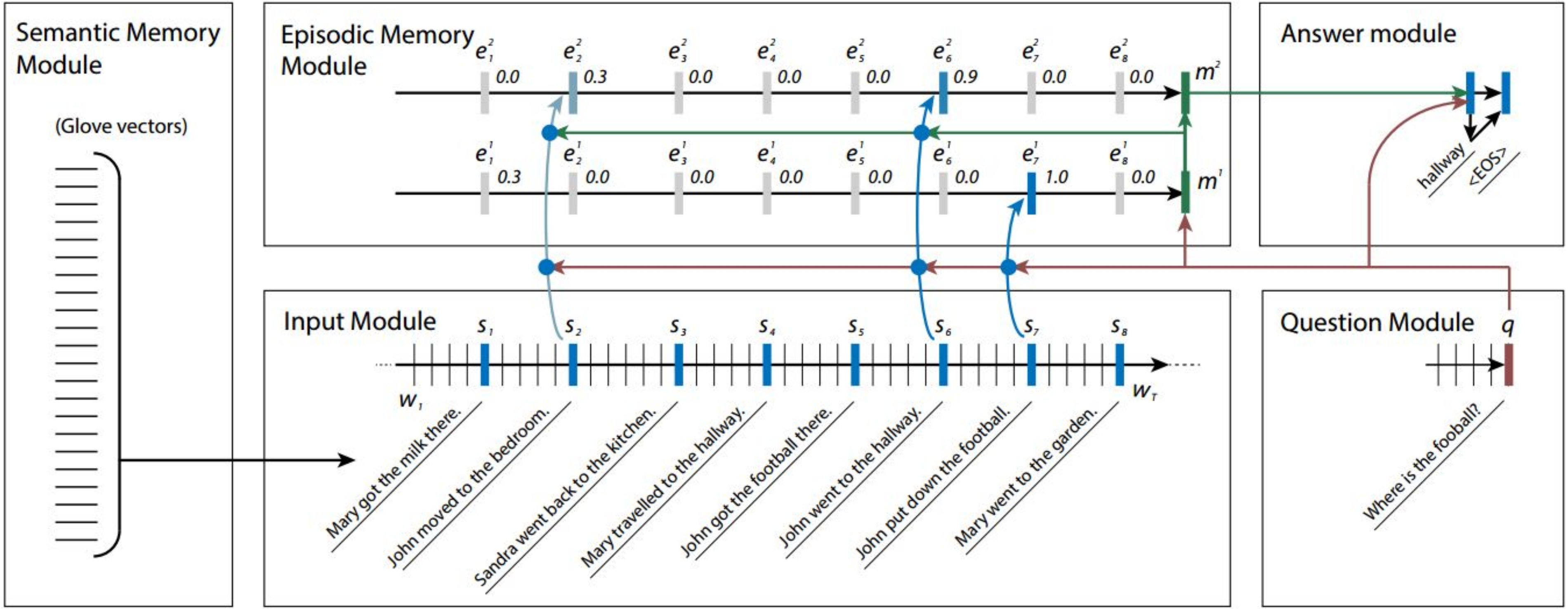


Image Source: Dynamic Memory Networks for Question Answering (Chris Manning & Richard Socher)

DMNs for visual question and answering (VQA)

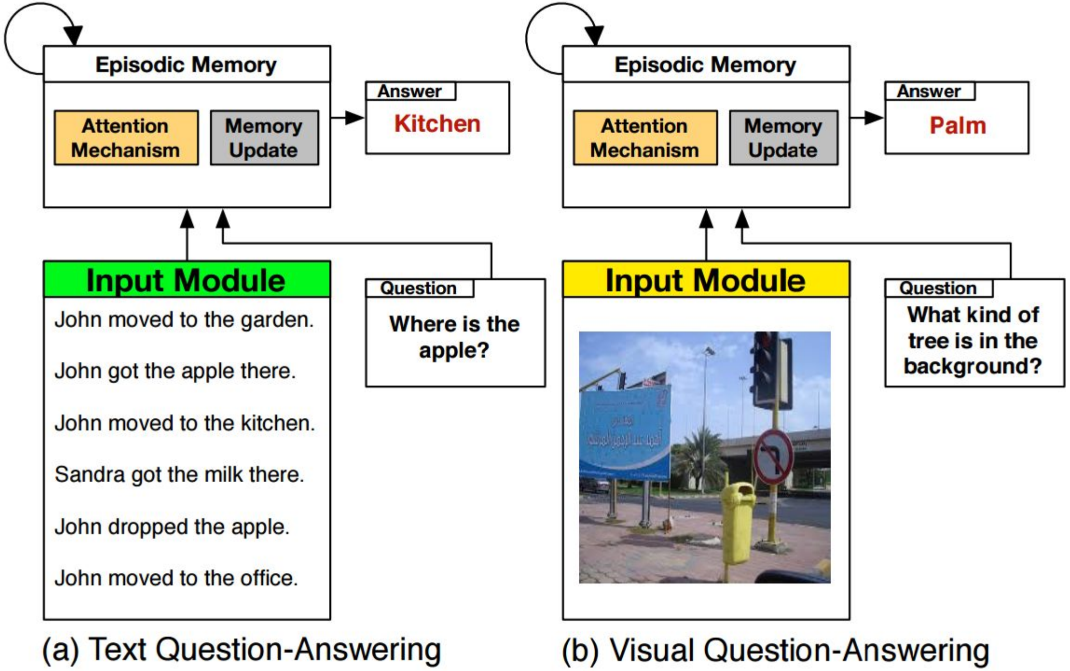


Image Source: Dynamic Memory Networks for Visual and Textual Question Answering (Xiong et al)

VQA input module for DMNs

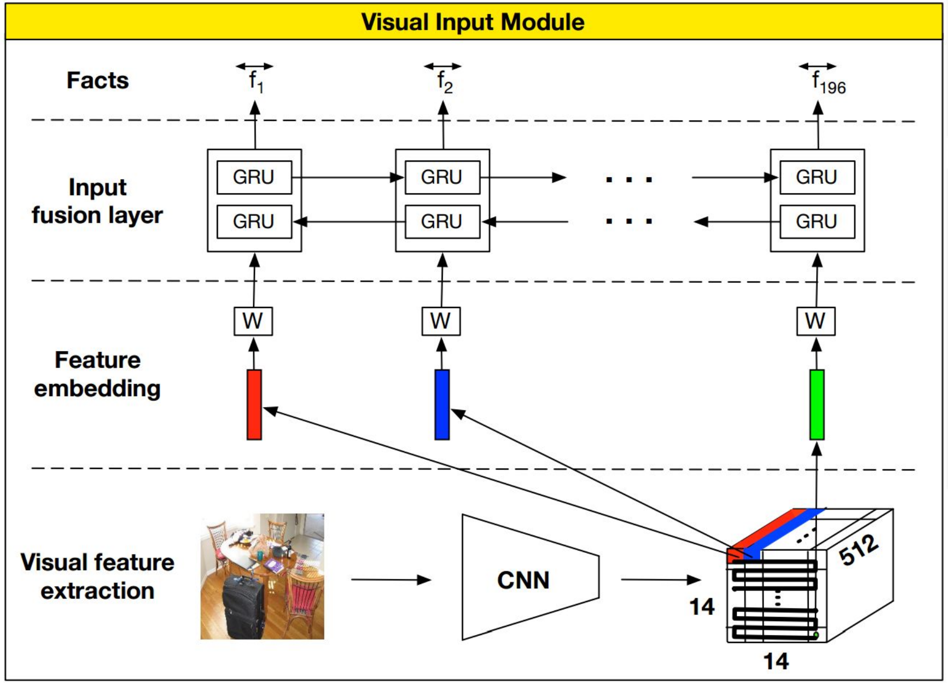


Image Source: Dynamic Memory Networks for Visual and Textual Question Answering (Xiong et al)

VQA - visualizing the attention

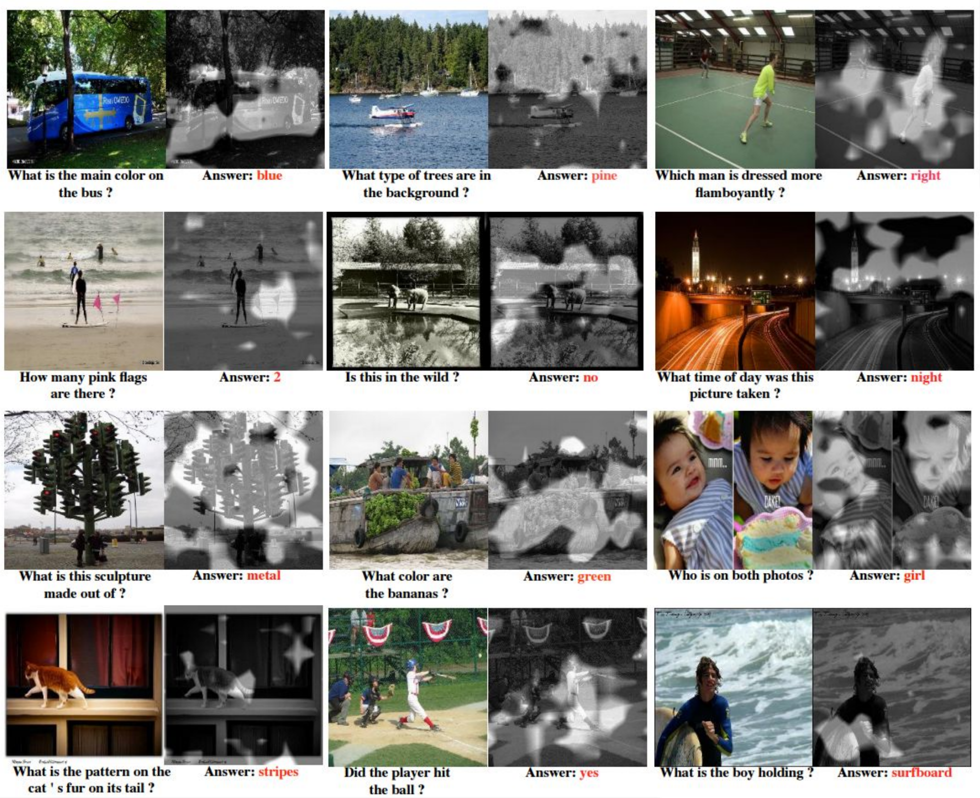


Image Source: Dynamic Memory Networks for Visual and Textual Question Answering (Xiong et al)

Visual Question answering with DMNs - notes

- Instead of word embeddings we use the feature vectors
- The network is the same but for the input module
- We introduce a “snake-like” order to the feature vectors
- Attention is actually meaningful

questions any have you do

References (1/2)

- Tensorflow and deep learning - without a PhD by Martin Görner(RNNs): https://www.youtube.com/watch?v=vq2nnJ4g6N0&t=107m25s
- Chris Olah's blog - RNNs and LSTM http://colah.github.io/posts/2015-08-Understanding-LSTMs/
- Andrej Karpathy- The Unreasonable Effectiveness of Recurrent Neural Networks: http://karpathy.github.io/2015/05/21/rnn-effectiveness/
- Cs231n - Recurrent Neural Networks: https://youtu.be/yCC09vCHzF8
- Sequence to Sequence Learning https://arxiv.org/pdf/1409.3215.pdf
- Comparison of LSTM and GRU https://arxiv.org/pdf/1412.3555v1.pdf
- Chris Olah - Attention and Augmented Recurrent Neural Networks https://distill.pub/2016/augmented-rnns/

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- Neural Machine Translation by Jointly Learning to Align and Translate (Bahdanau et al.)- https://arxiv.org/abs/1409.0473
- Effective Approaches to Attention-based Neural Machine Translation (Luong et al.) - https://arxiv.org/pdf/1508.04025.pdf
- Show attend and tell (Xu et al.) - https://arxiv.org/pdf/1502.03044.pdf
- Parallel Multi-Dimensional LSTM, With Application to Fast Biomedical Volumetric Image Segmentation - https://arxiv.org/pdf/1506.07452.pdf
- Dynamic Neural Networks for Question Answering (Stanford University lecture): https://youtu.be/T3octNTE7Is
- Dynamic Memory Networks for Question Answering (Raguvanshi & Chase): https://cs224d.stanford.edu/reports/RaghuvanshiChase.pdf
- The bAbI dataset: https://research.fb.com/downloads/babi/
- Dynamic Memory Networks for Visual and Textual Question Answering: https://arxiv.org/pdf/1603.01417.pdf