Recurrent neural networks

Materials for this section:

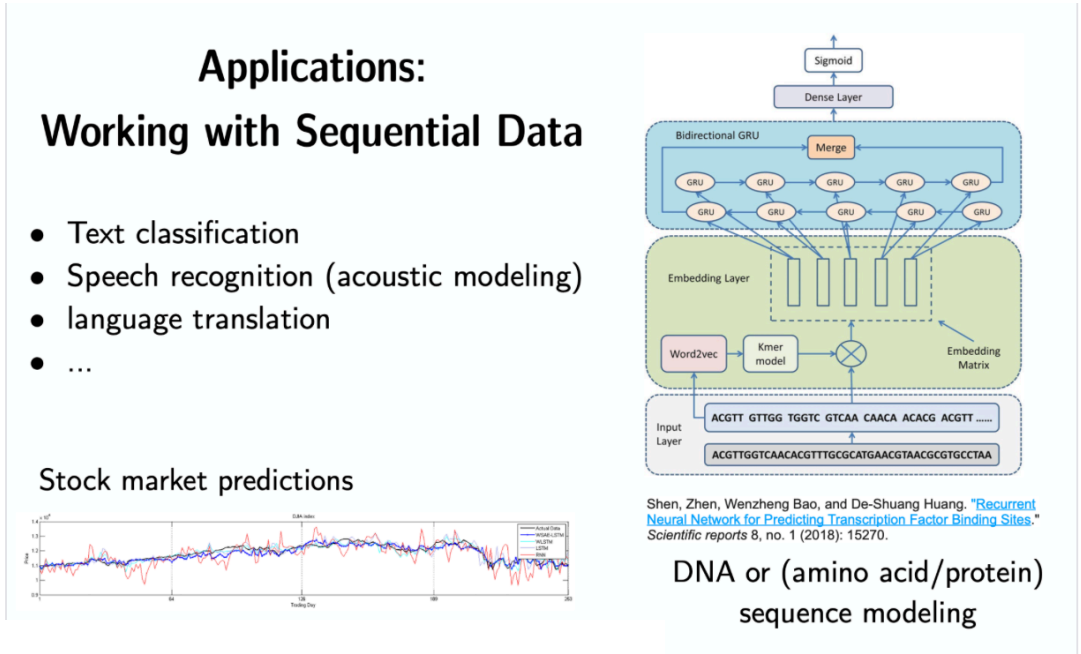
- https://atcold.github.io/pytorch-Deep-Learning/en/week06/06-3/
- https://stanford.edu/~shervine/teaching/cs-230/cheatsheet-recurrent-neural-networks
- http://colah.github.io/posts/2015-08-Understanding-LSTMs/
- https://blog.floydhub.com/attention-mechanism/

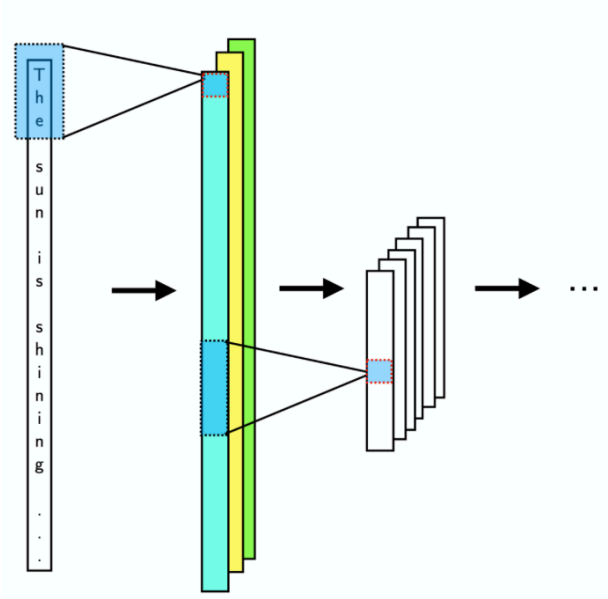
Recurrent neural networks

Recurrent neural networks (RNNs) are a family of networks specialized for processing sequential data:

$$x(0), \ldots, x(T)$$

- RNNs can scale to long sequences, and even process sequences of variable length





We can apply CNNs but there is a problem: sequences are not i.i.d

- they typically have long-range correlations, for example dependence between words in sentence

Parameters sharing:

- in convolutional nets we share the same kernel across „**space**”,
- recurrent neural network shares the same weights across several **time** steps, not limited to kernel size as in CNNs.

Recurrent neural networks

How to capture these correlations?

- by introducing *loops* into networks

https://github.com/rasbt/stat479-deep-learning-ss19/blob/master/L14_intro-rnn/L14_intro-rnn-part1_slides.pdf

Networks we used previously: also called feedforward neural networks

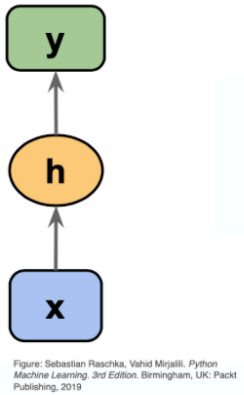
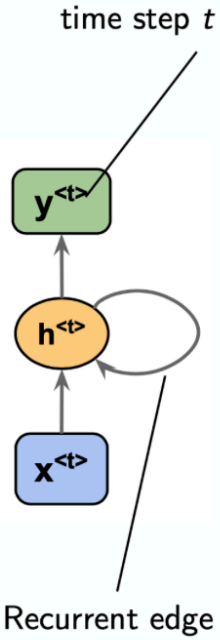
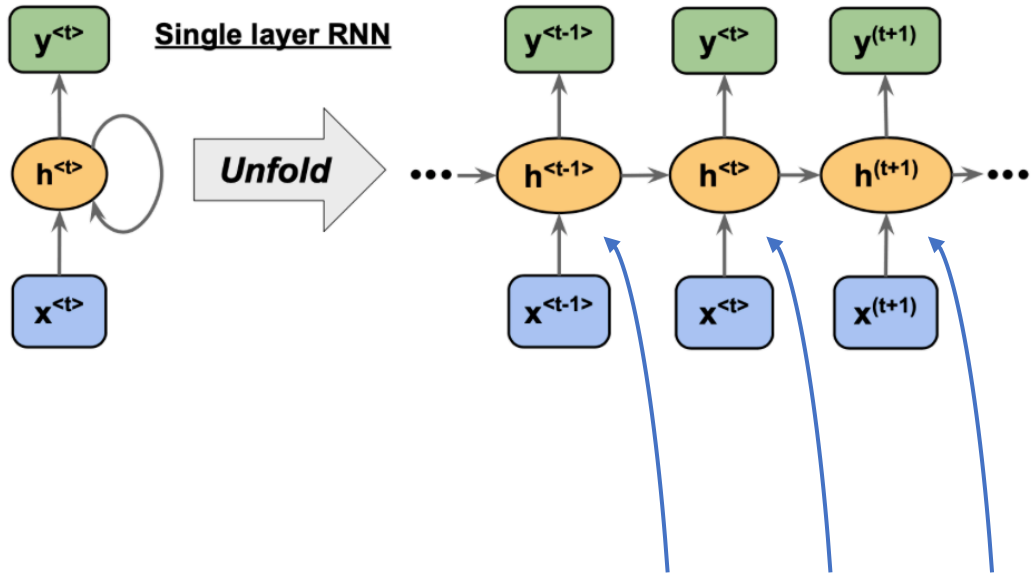


Figure: Sebastian Raschka, Vahid Mirjalili. *Python Machine Learning, 3rd Edition*. Birmingham, UK: Packt Publishing, 2019

Recurrent Neural Network (RNN)



Unroll the loop

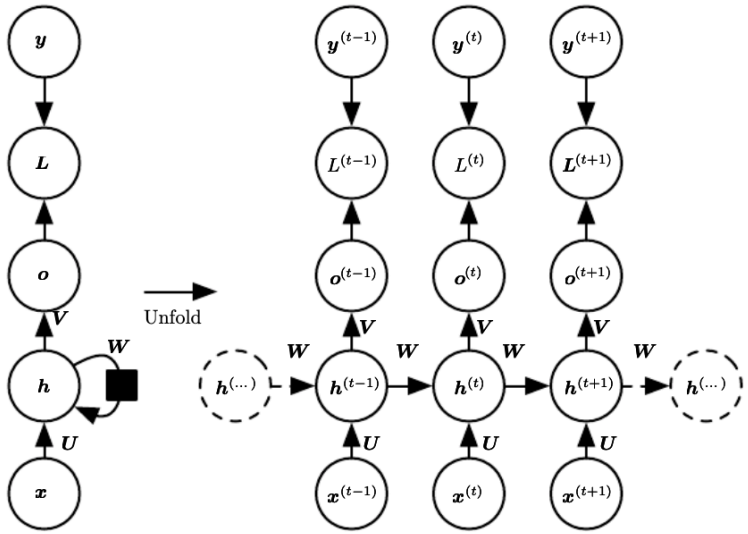


- we process sequence *step-by step*
- hidden state is a depends not only on input at given step, but also on **previous** hidden states

$$\boldsymbol{h}^{(t)} = f(\boldsymbol{h}^{(t-1)}, \boldsymbol{x}^{(t)}; \boldsymbol{\theta}),$$

parameters (weights) are **shared**

Recurrent neural networks

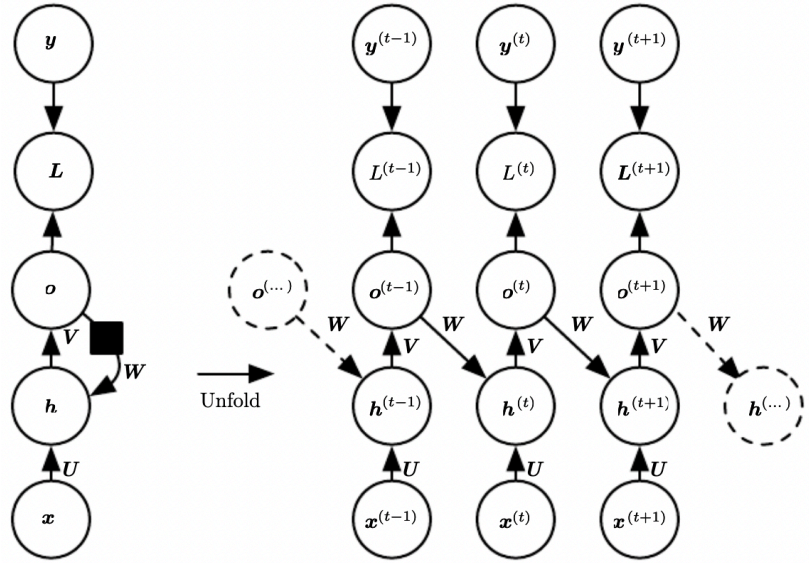


$$
\begin{aligned}
\boldsymbol{a}^{(t)} &= \boldsymbol{b} + \boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)}, \\
\boldsymbol{h}^{(t)} &= \tanh(\boldsymbol{a}^{(t)}), \\
\boldsymbol{o}^{(t)} &= \boldsymbol{c} + \boldsymbol{V}\boldsymbol{h}^{(t)}, \\
\hat{\boldsymbol{y}}^{(t)} &= \operatorname{softmax}(\boldsymbol{o}^{(t)}),
\end{aligned}
$$

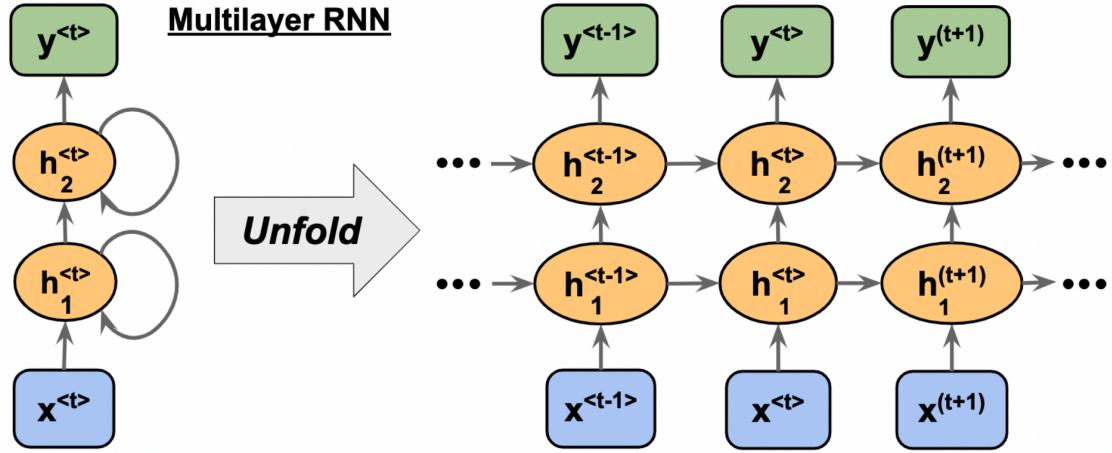
Forward propagation starts with $\boldsymbol{h}^{(0)}$ initialized *randomly*

https://www.deeplearningbook.org/contents/rnn.html

- different loop connections

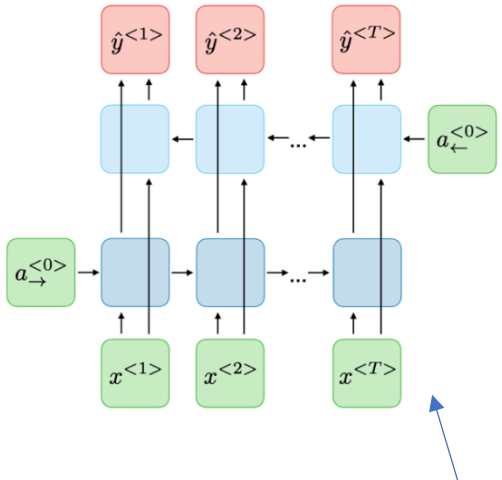
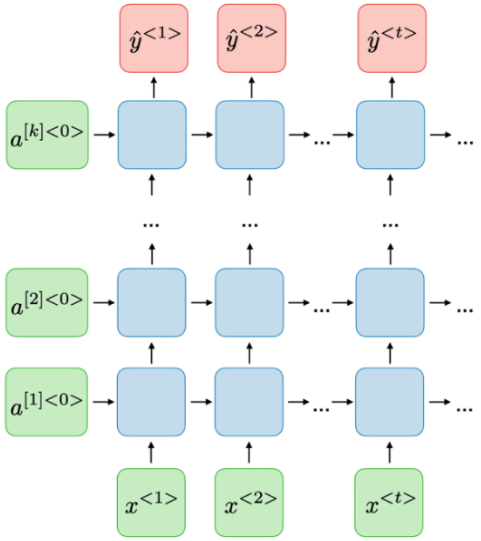


- multiple hidden layers



Recurrent neural networks

□ **Variants of RNNs** — The table below sums up the other commonly used RNN architectures:

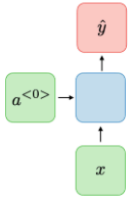
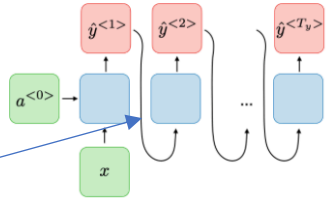
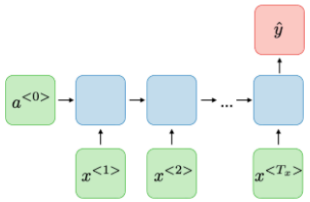
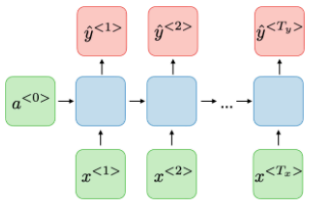
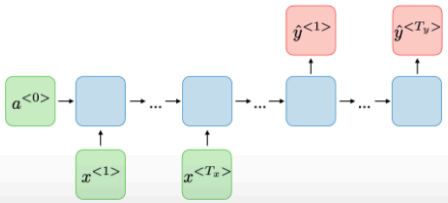
Bidirectional (BRNN)	**Deep** (DRNN)
	

two separate passes

outputs may also affects hidden states (*autoregressive* network)

like before

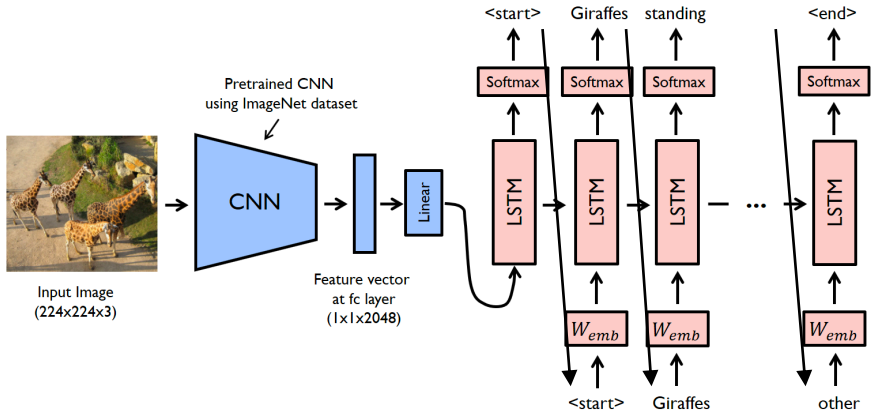
□ **Applications of RNNs** — RNN models are mostly used in the fields of natural language processing and speech recognition. The different applications are summed up in the table below:

Type of RNN	Illustration	Example
One-to-one $T_x = T_y = 1$		Traditional neural network
One-to-many $T_x = 1, T_y > 1$		Music generation
Many-to-one $T_x > 1, T_y = 1$		Sentiment classification
Many-to-many $T_x = T_y$		Name entity recognition
Many-to-many $T_x \neq T_y$		Machine translation

stanford.edu/~shervine/teaching/cs-230/cheatsheet-recurrent-neural-networks

Recurrent neural networks: applications

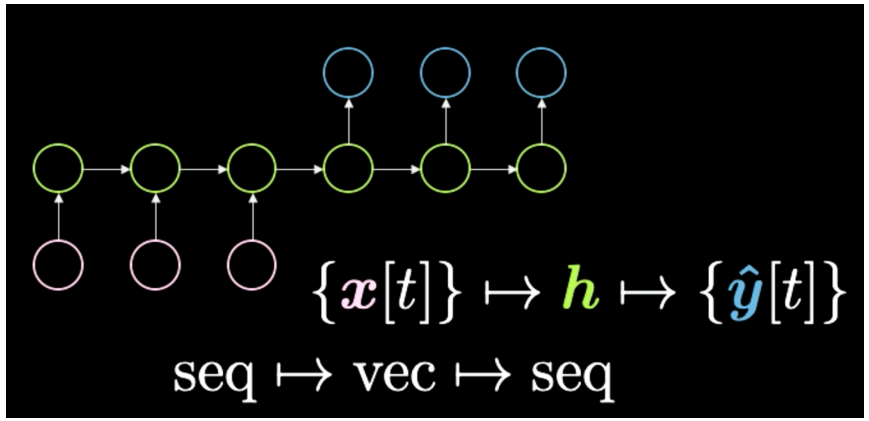
Example: image captioning system



github.com/anunay999/image_captioning_vgg16

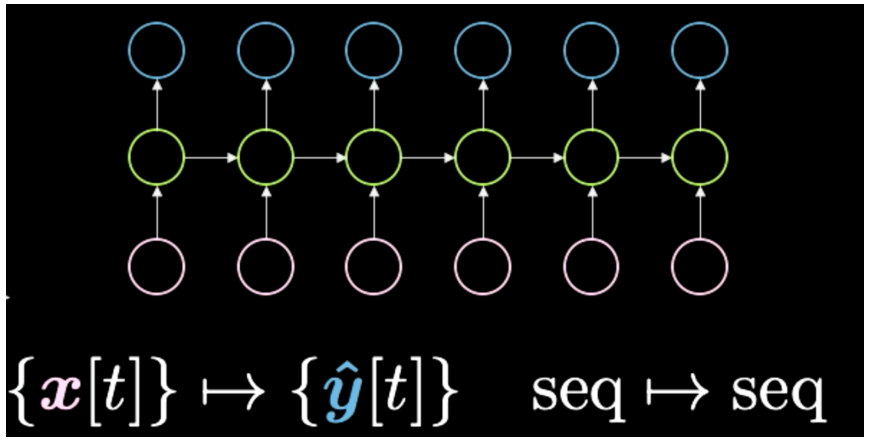
https://cv-tricks.com/artificial-intelligence/show-attend-tell-image-captioning-explained/

Recurrent neural networks: applications



State-of-the-art in machine translation about three years ago (2018), until *Transformers* era

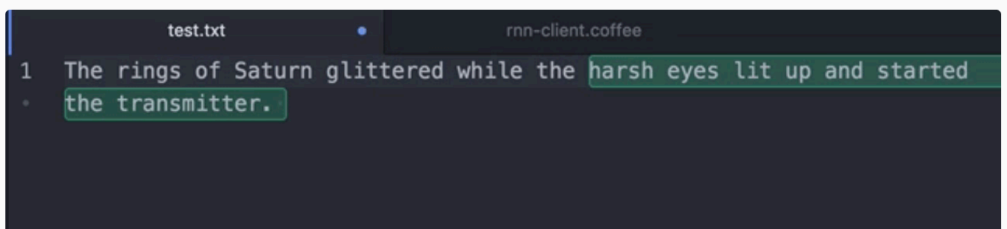
https://atcold.github.io/pytorch-Deep-Learning/en/week06/06-3/



Examples:

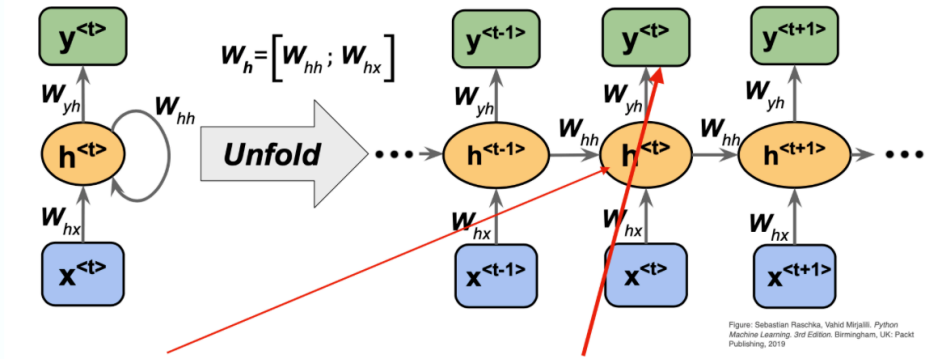
- word autocompletion algorithm,
- live streams captioning,
- RNN-writer trained on a corpus of old sci-fi stories:

https://www.robinsloan.com/notes/writing-with-the-machine/



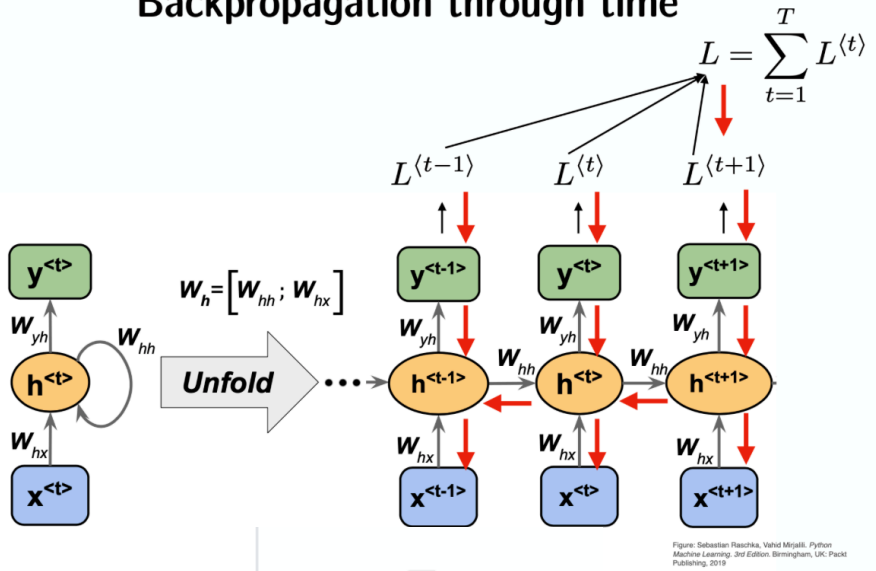
Recurrent neural networks: training

Weight matrices in a single-hidden layer RNN



Sebastian Raschka STAT 453:

Backpropagation through time



The loss is calculated as sum over all time steps:

$$L = \sum_{t=1}^{T} L^{(t)}$$

Training: vanishing/exploding gradients problem
-> the bigger the longer timeseries is!

$$L = \sum_{t=1}^{T} L^{(t)} \qquad \frac{\partial L^{(t)}}{\partial \mathbf{W}_{hh}} = \frac{\partial L^{(t)}}{\partial y^{(t)}} \cdot \frac{\partial y^{(t)}}{\partial \mathbf{h}^{(t)}} \cdot \left(\sum_{k=1}^{t} \frac{\partial \mathbf{h}^{(t)}}{\partial \mathbf{h}^{(k)}} \cdot \frac{\partial \mathbf{h}^{(k)}}{\partial \mathbf{W}_{hh}} \right)$$

computed as a multiplication of adjacent time steps:

https://github.com/rasbt/stat479-deep-learning-ss19/blob/master/L14_intro-rnn/L14_intro-rnn-part1_slides.pdf

Recurrent neural networks: long-range dependencies

Recurrent networks involve the composition of the same function multiple times, once per time step:

$$\boldsymbol{h}^{(t)} = \boldsymbol{W}^{\top} \boldsymbol{h}^{(t-1)}$$

and lacking inputs $\boldsymbol{x}$. As described in section 8.2.5, this recurrence relation essentially describes the power method. It may be simplified to

$$\boldsymbol{h}^{(t)} = \left(\boldsymbol{W}^{t}\right)^{\top} \boldsymbol{h}^{(0)}, \tag{10.37}$$

and if $\boldsymbol{W}$ admits an eigendecomposition of the form

$$\boldsymbol{W} = \boldsymbol{Q}\boldsymbol{\Lambda}\boldsymbol{Q}^{\top}, \tag{10.38}$$

with orthogonal $\boldsymbol{Q}$, the recurrence may be simplified further to

$$\boldsymbol{h}^{(t)} = \boldsymbol{Q}^{\top}\boldsymbol{\Lambda}^{t}\boldsymbol{Q}\boldsymbol{h}^{(0)}. \tag{10.39}$$

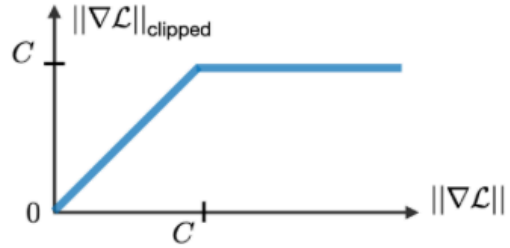
The eigenvalues are raised to the power of t, causing eigenvalues with magnitude less than one to decay to zero and eigenvalues with magnitude greater than one to explode. Any component of $\boldsymbol{h}^{(0)}$ that is not aligned with the largest eigenvector

Problem with learning **long-range** dependencies:

- signal about these dependencies will be hidden by the smallest fluctuations arising from **short-term** dependencies

Exploding gradients are easier to overcome:

□ **Gradient clipping** — It is a technique used to cope with the exploding gradient problem sometimes encountered when performing backpropagation. By capping the maximum value for the gradient, this phenomenon is controlled in practice.



Gated RNNs:

- Long short-term memory (LSTM) -- uses a memory cell for modeling long-range dependencies and avoid vanishing gradient problems

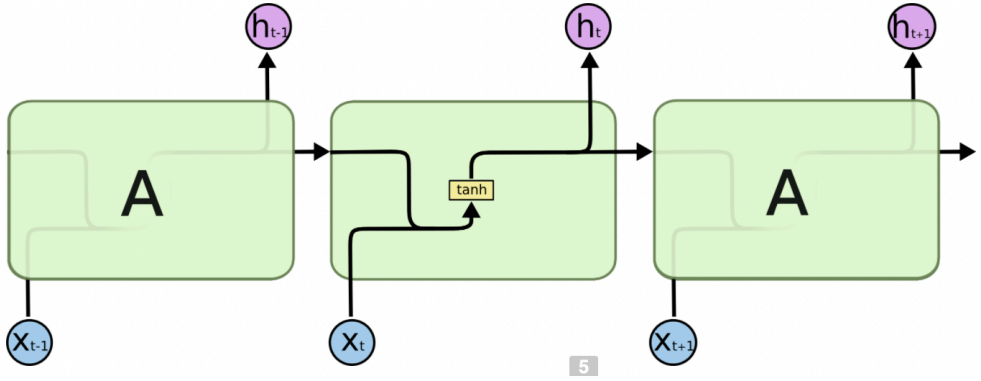
Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." *Neural computation* 9, no. 8 (1997): 1735-1780.

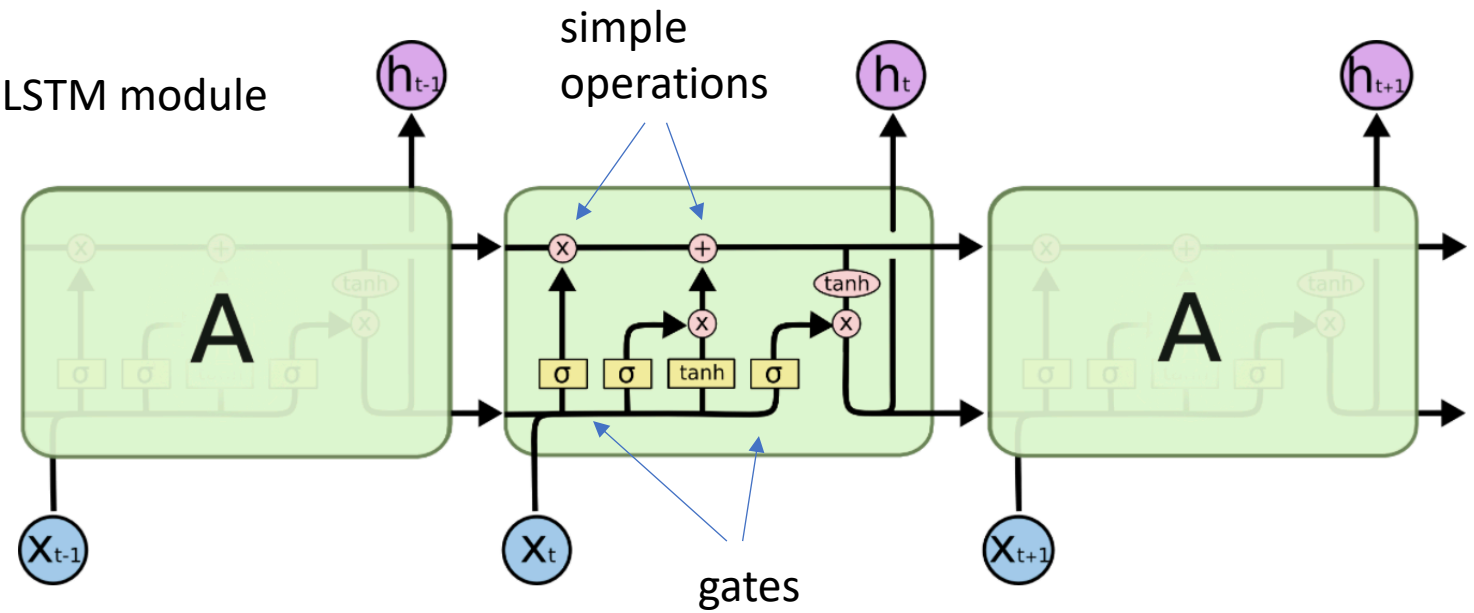
- Gated recurrent unit (GRU)

https://www.deeplearningbook.org/contents/rnn.html

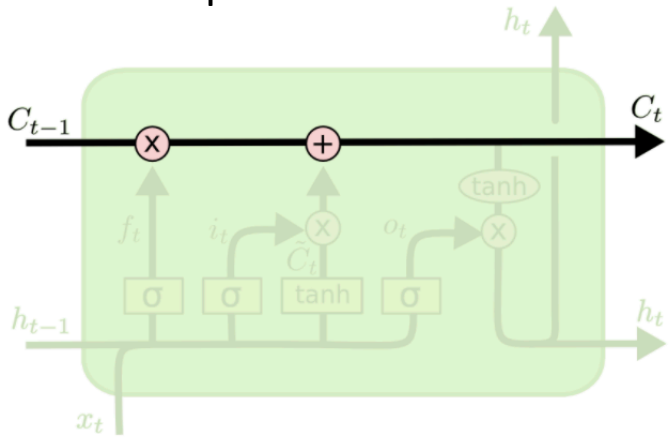
Recurrent neural networks: LSTM nets

ordinary RNN vs. LSTM module





The crucial part in LSTMs is the cell state



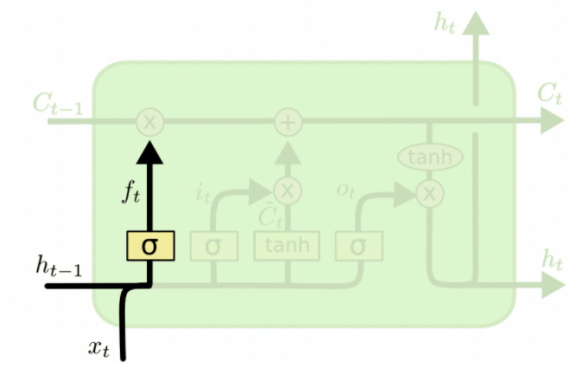
- gates regulate what amount of information is preserved or removed from the cell state

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

Recurrent neural networks: LSTM nets

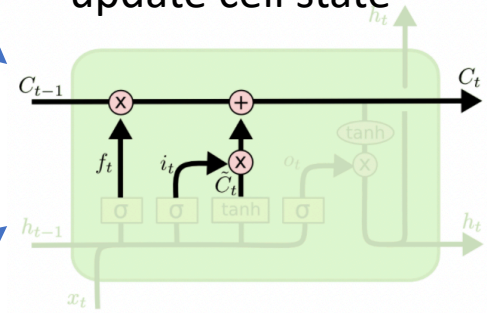
colah.github.io/posts/2015-08-Understanding-LSTMs/

forget gate



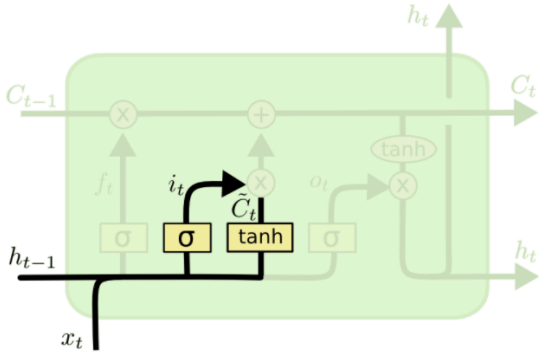
$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

update cell state



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

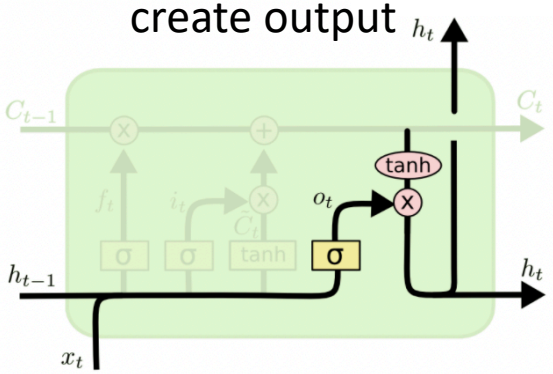
input gate



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

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

create output



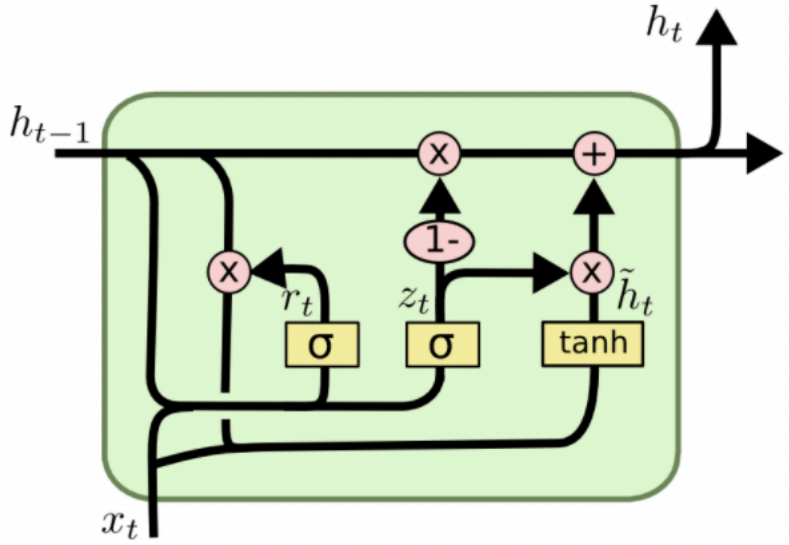
$$o_t = \sigma\left(W_o \; [h_{t-1}, x_t] \; + \; b_o\right)$$

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

Recurrent neural networks: LSTM nets

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

- LSTM simplification: GRU



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

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

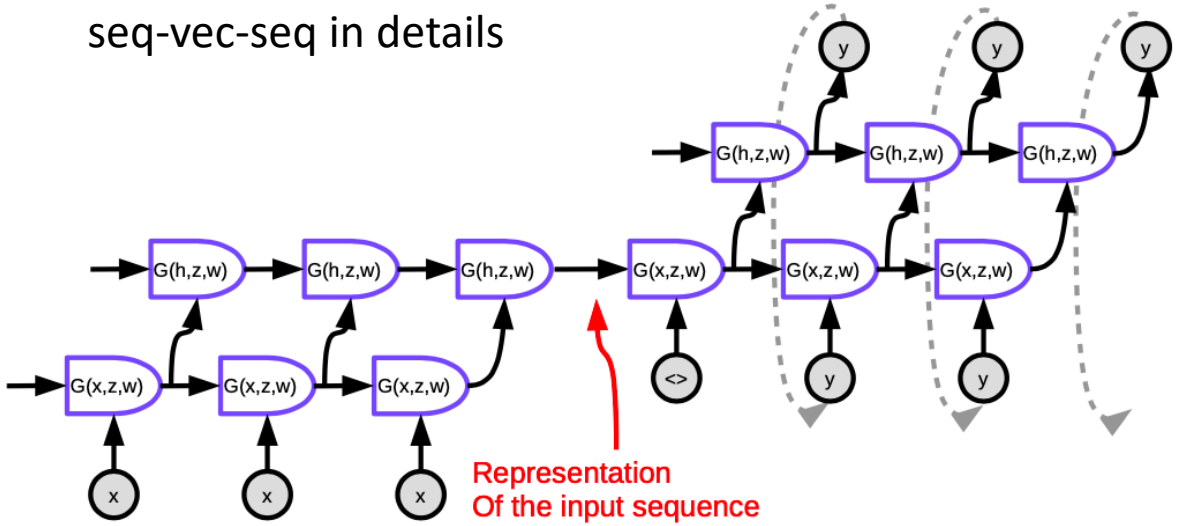
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

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

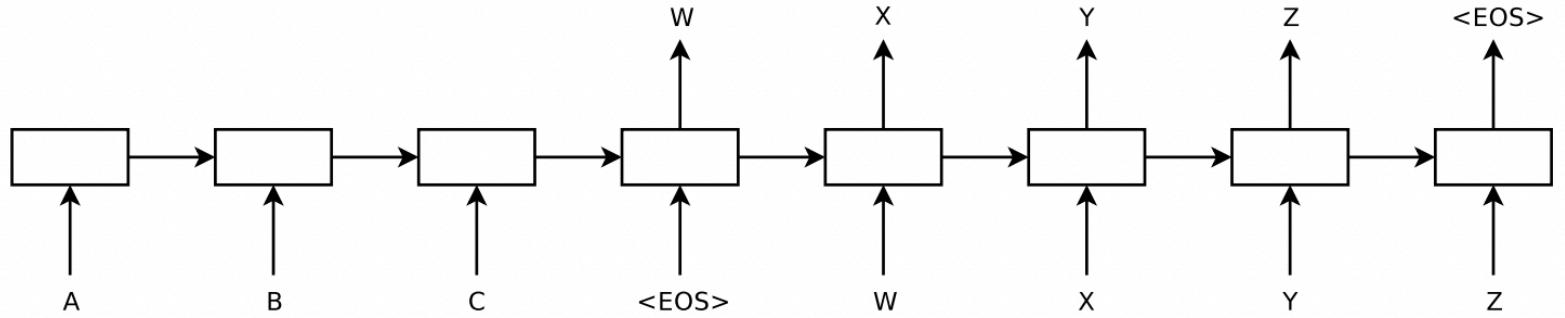
- GRU sometimes performs better than LSTM sometimes not
- LSTMs/GRUs are still widely used (e.g. in NLP), their popularity is decreasing

Attention in neural nets

seq-vec-seq in details



The approach proposed by Sutskever in 2014 is the first neural machine translation system to have comparable performance to classic approaches. It uses an *encoder-decoder* architecture where both the encoder and decoder are multi-layered LSTMs.

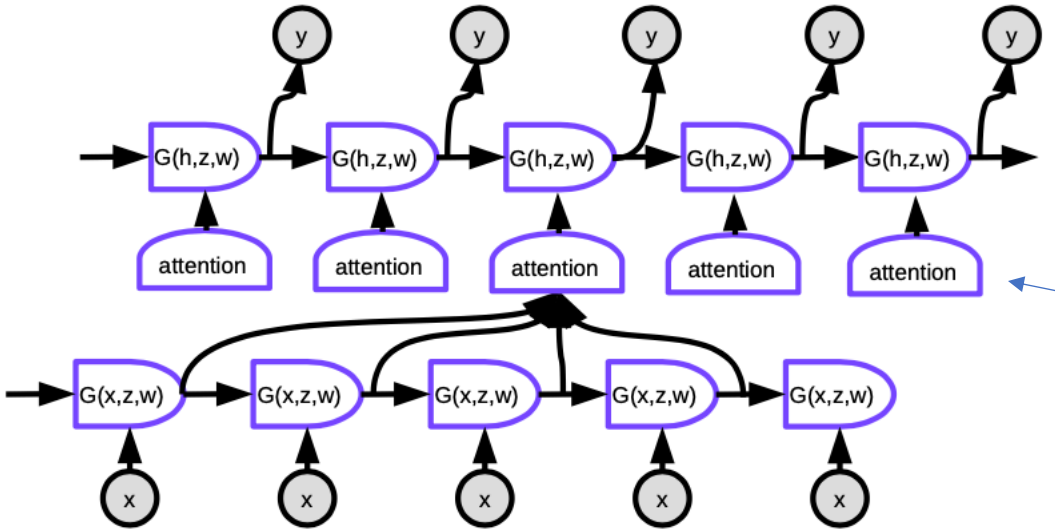


Unfortunately, even using LSTMs, such model does not preserve information for more than 20 words

papers.nips.cc/paper/2014/file/a14ac55a4f27472c5d894ec1c3c743d2-Paper.pdf

Attention in neural nets

Attention mechanism



separate attention scores at each time step

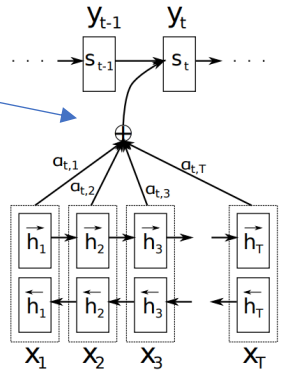
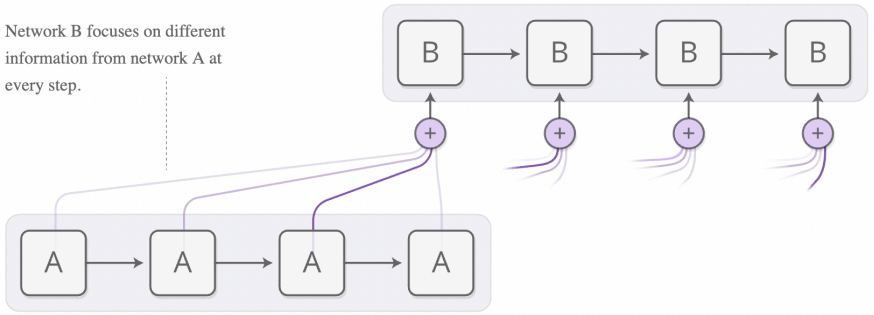


Figure 1: The graphical illustration of the proposed model trying to generate the t-th target word y_t given a source sentence $(x_1, x_2, \ldots, x_T)$.

Neural networks can achieve the same behavior using *attention*, focusing on part of a subset of the information they're given.

- For example, an RNN can attend over the output of another RNN. At every time step, it focuses on different positions in the other RNN



The context vector c_i is, then, computed as a weighted sum of these annotations h_i:

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j. \quad (5)$$

The weight α_{ij} of each annotation h_j is computed by

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})}, \quad (6)$$

where

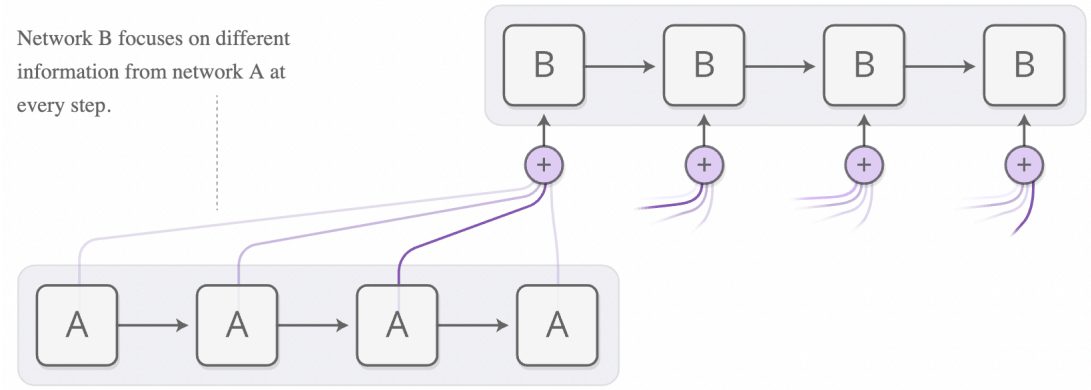
$$e_{ij} = a(s_{i-1}, h_j)$$

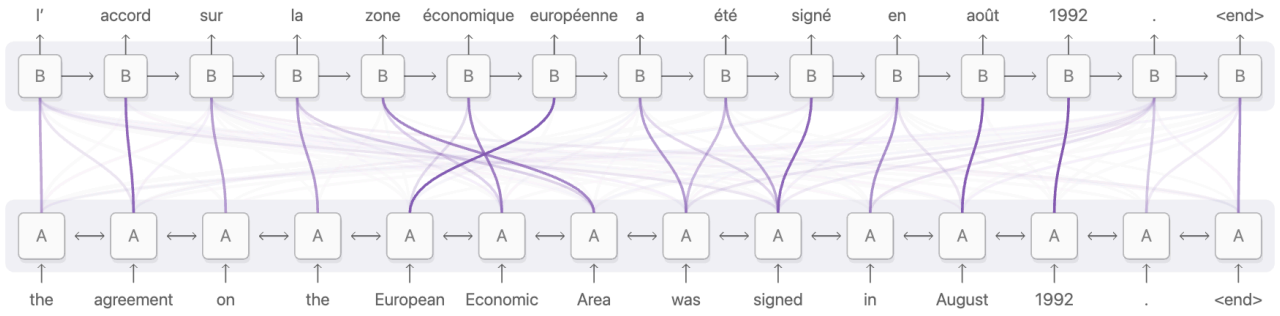
is an *alignment model* which scores how well the inputs around position j and the output at position i match. The score is based on the RNN hidden state s_{i-1} (just before emitting y_i, Eq. (4)) and the j-th annotation h_j of the input sentence.

https://arxiv.org/pdf/1409.0473.pdf

Attention in neural nets

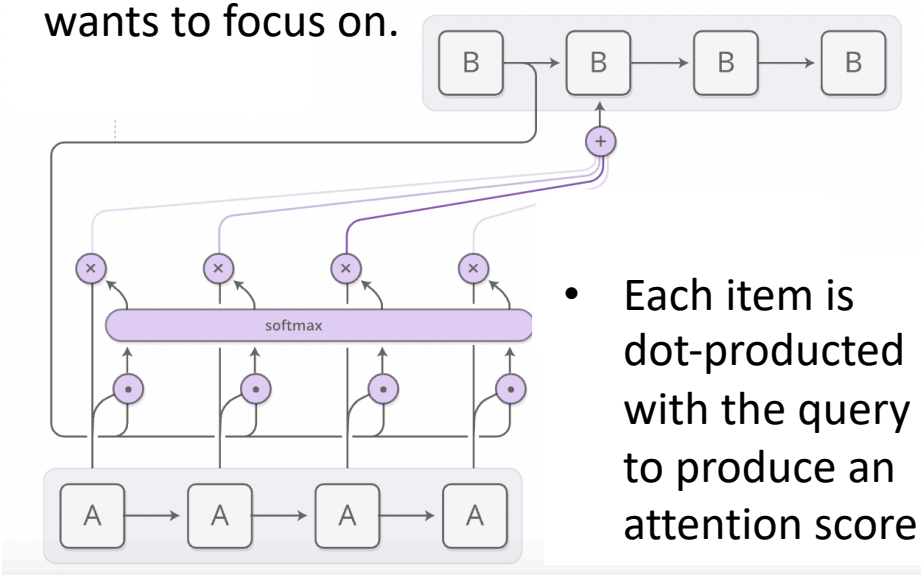
How to generate attention distribution?
-- content-based attention





- When generating the output we focus on words as they become relevant

- The attending RNN generates a query describing what it wants to focus on.



- Each item is dot-producted with the query to produce an attention score

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

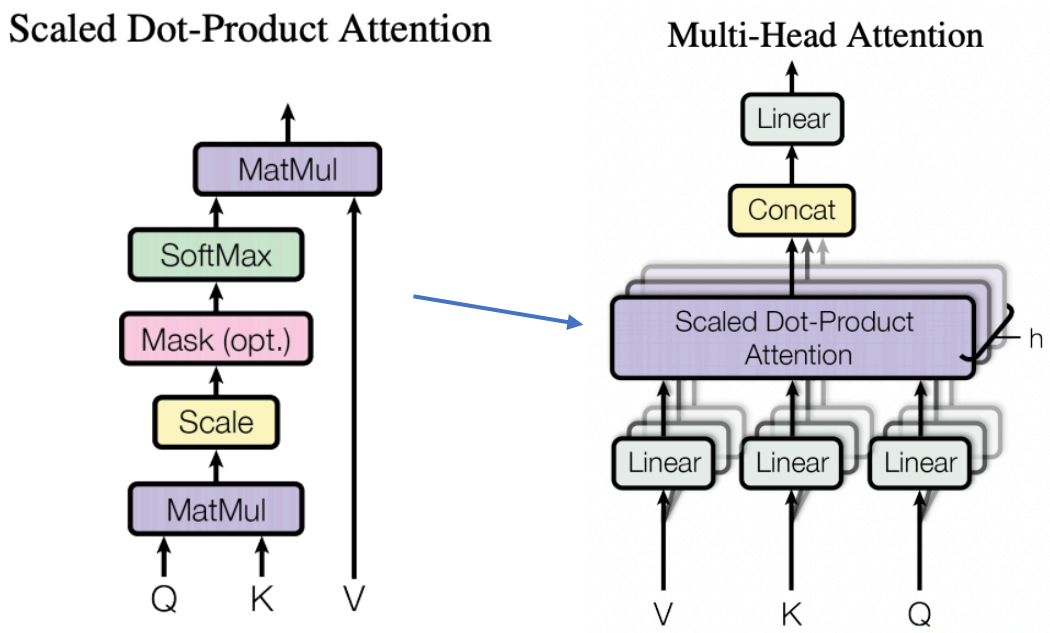
A stop sign is on a road with a

https://distill.pub/2016/augmented-rnns/

Attention in neural nets

Transformer architecture

- utilize *self-attention*
- just feed-forward connections, without recurrence



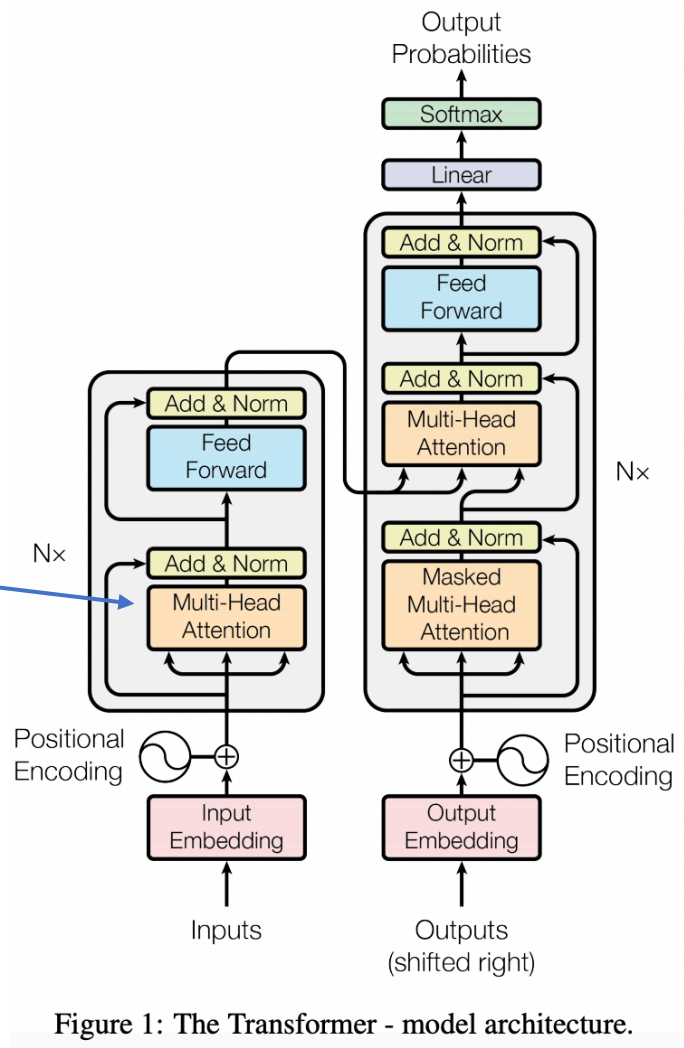


Figure 1: The Transformer - model architecture.

Notable transformers:

- **BERT** (2018): SOTA in machine translations
- **DETR** (2020): object detection with transformers

https://arxiv.org/pdf/1706.03762.pdf