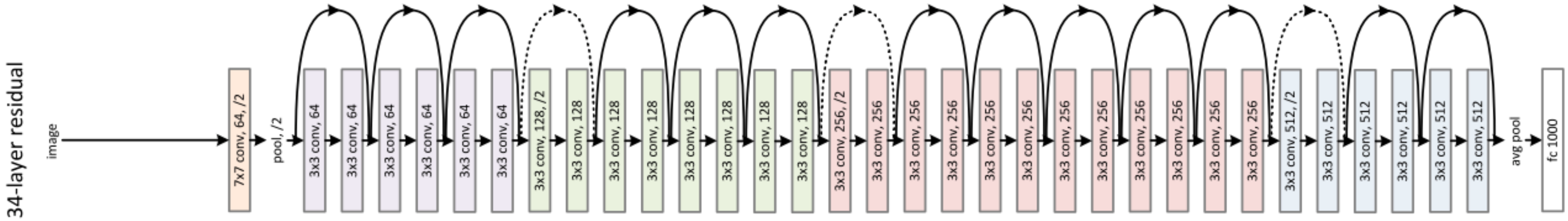
RNNs and Transformers

Transfer Learning

ResNet



ResNet-152:
60M parameters

[He et al. CVPR'16] ResNet

Transfer Learning

- Training your own model can be difficult with limited data and other resources

e.g.,

- It is a laborious task to manually annotate your own training dataset
- Why not reuse already pre-trained models?

Transfer Learning

Distribution

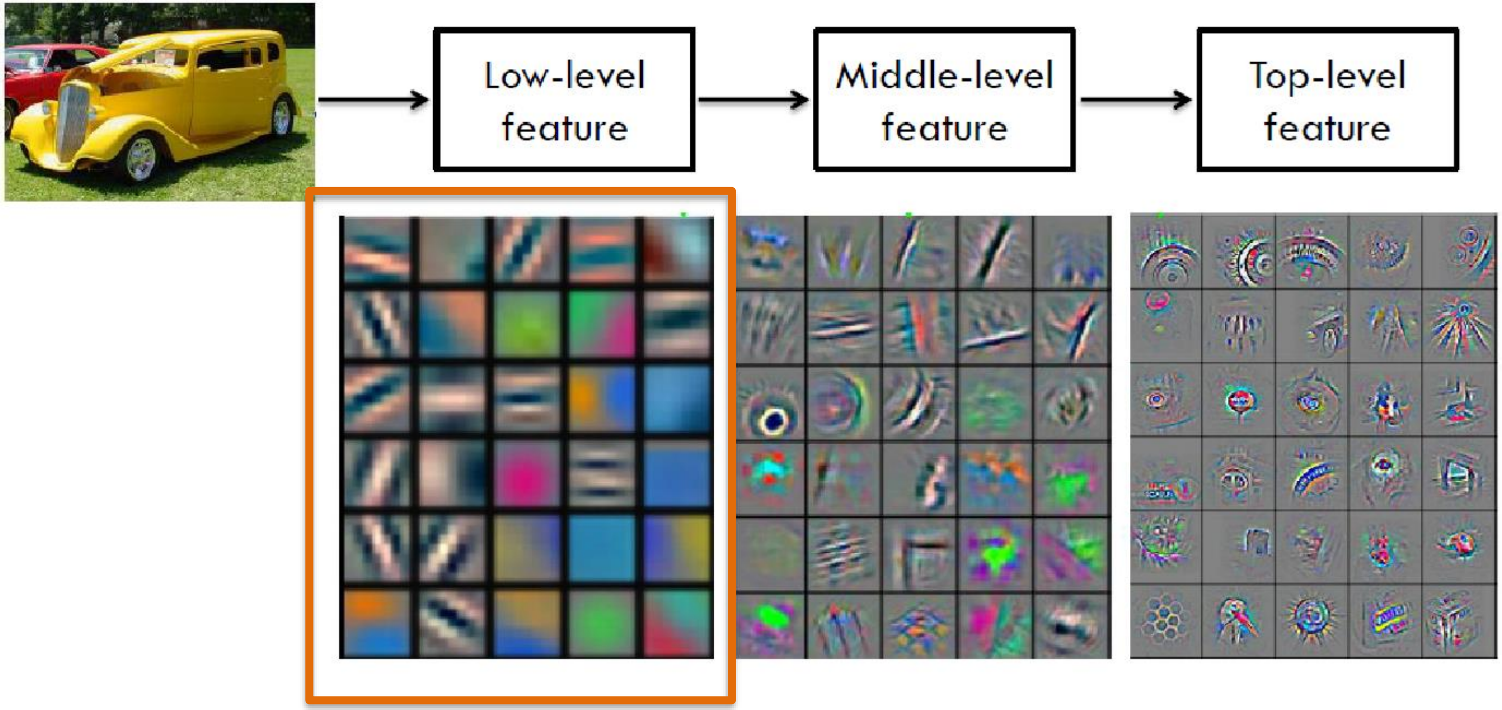
Large dataset

Distribution

Small dataset

Use what has been learned for another setting

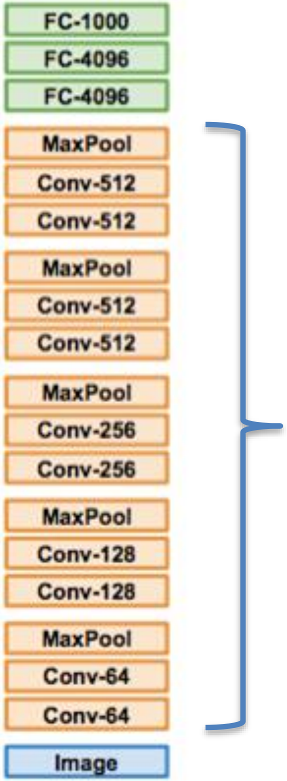
Transfer Learning for Images



[Zeiler al., ECCV'14] Visualizing and Understanding Convolutional Networks

Transfer Learning

Trained on ImageNet



Feature extraction

[Donahue et al., ICML'14] DeCAF,
[Razavian et al., CVPRW'14] CNN Features off-the-shelf

Transfer Learning

Trained on ImageNet

Decision layers

Parts of an object (wheel, window)

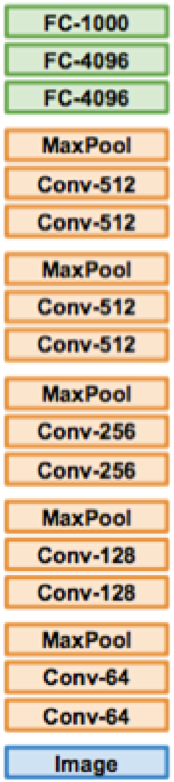
Simple geometrical shapes (circles, etc)

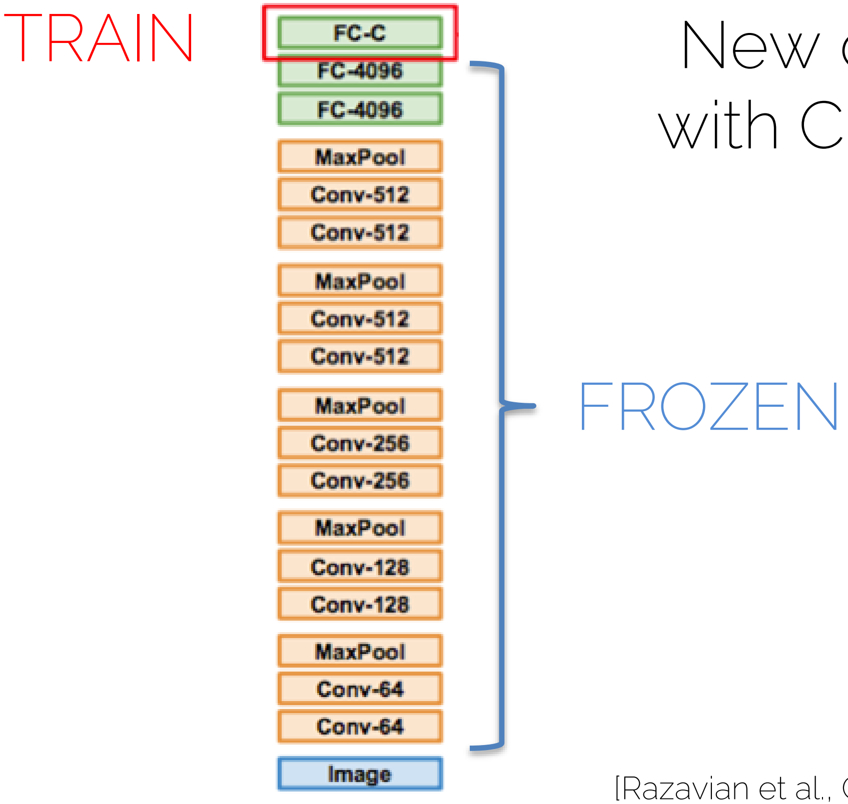
Edges

[Donahue et al., ICML'14] DeCAF,
[Razavian et al., CVPRW'14] CNN Features off-the-shelf

Transfer Learning

Trained on ImageNet



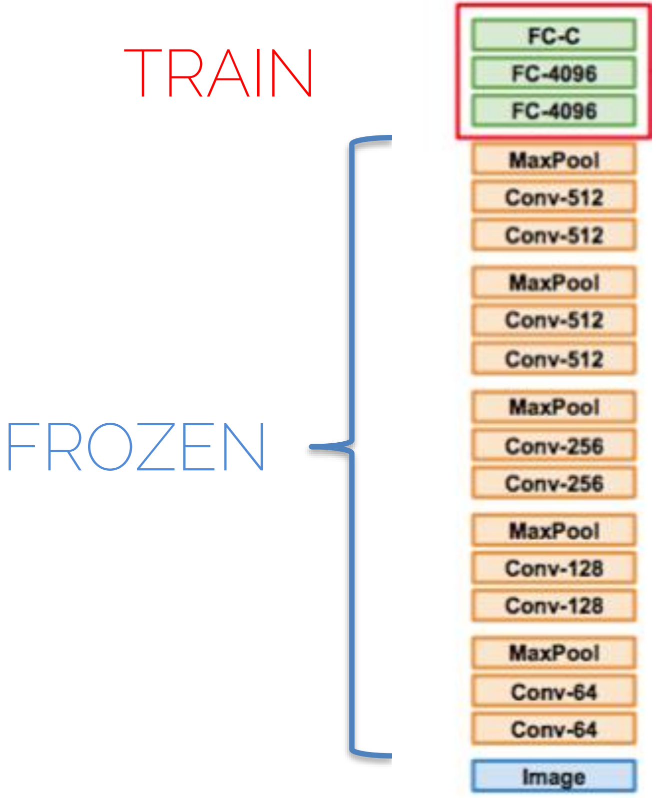


New dataset with C classes

[Donahue et al., ICML'14] DeCAF,
[Razavian et al., CVPRW'14] CNN Features off-the-shelf

Transfer Learning

If the dataset is big enough train more layers with a low learning rate



When Transfer Learning Makes Sense

- When task T1 and T2 have the same input (e.g. an RGB image)

- When you have more data for task T1 than for task T2

- When the low-level features for T1 could be useful to learn T2

Representation Learning

Learning Good Features

- Good features are essential for successful machine learning

- (Supervised) deep learning depends on training data used: input/target labels

- Change in inputs (noise, irregularities, etc.) can result in drastically different results

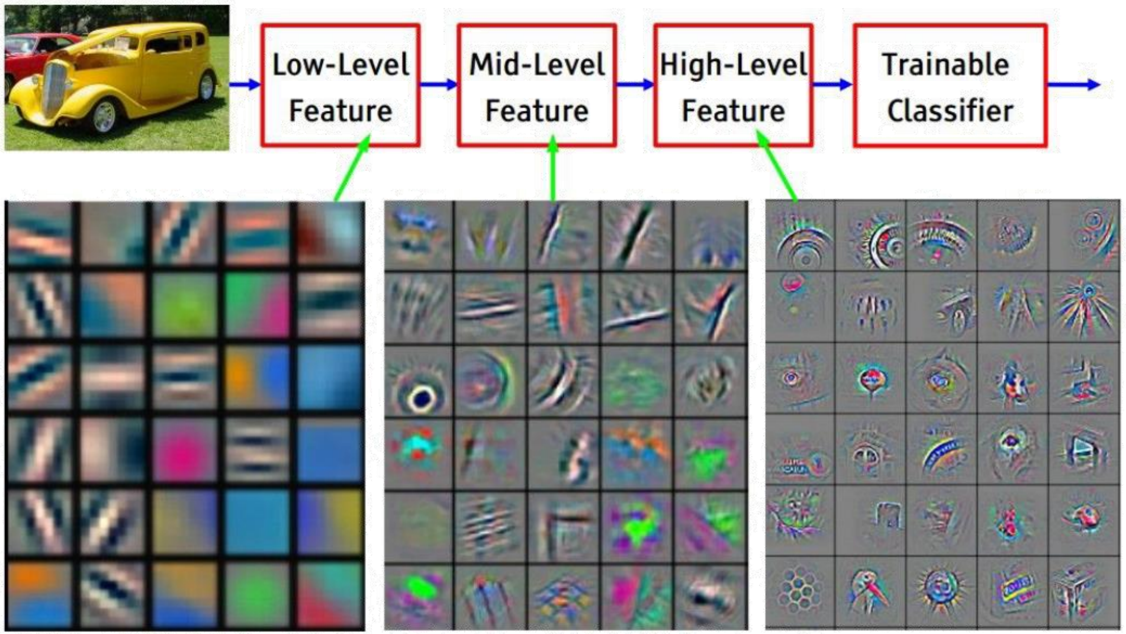
Representation Learning

- Allows for discovery of representations required for various tasks

- Deep representation learning: model maps input $\boldsymbol{X}$ to output $\boldsymbol{Y}$

Deep Representation Learning

- Intuitively, deep networks learn multiple levels of abstraction

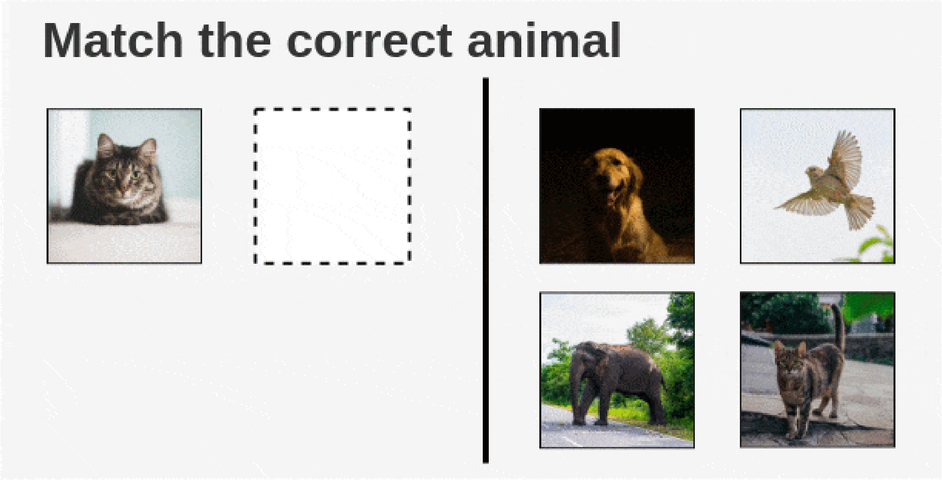


Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

How to Learn Good Features?

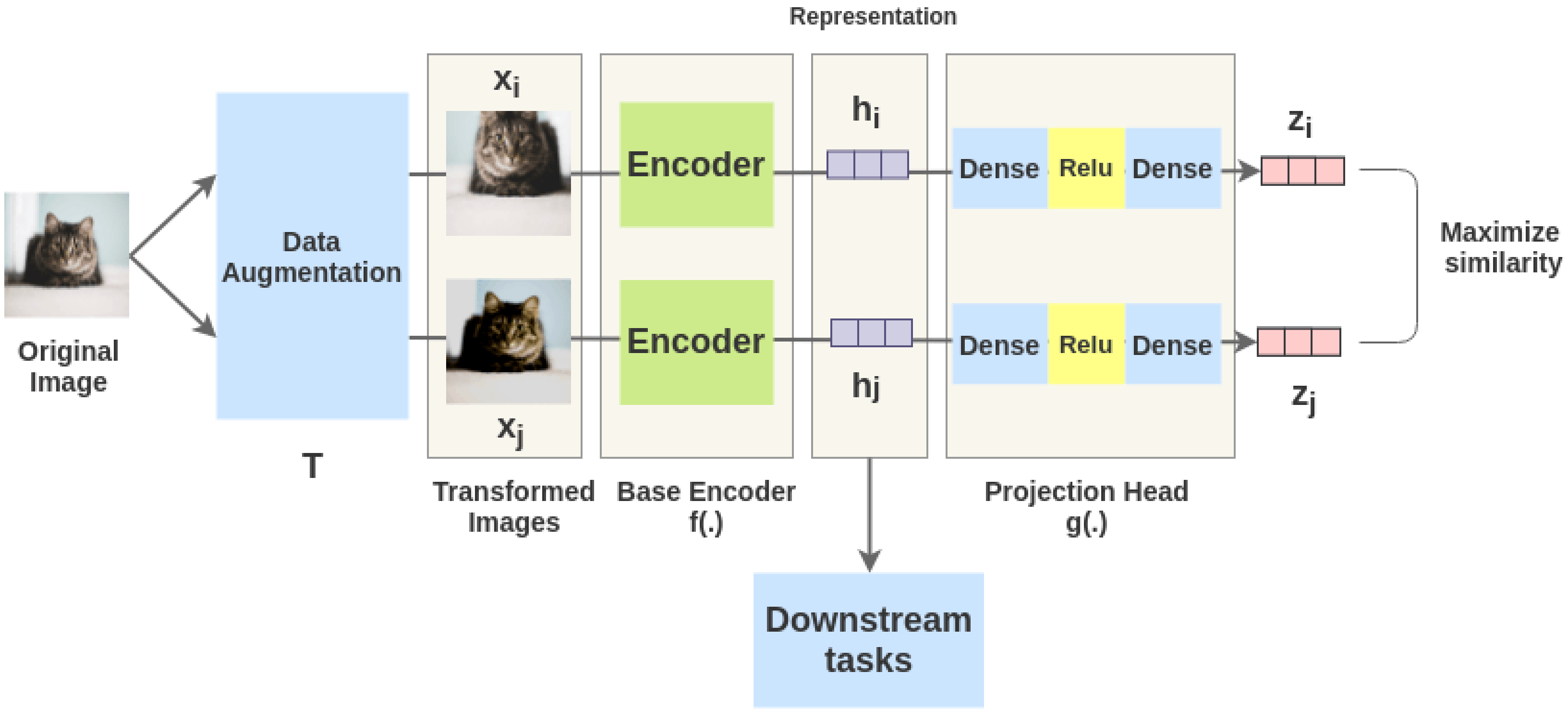
- Determine desired feature invariances

- Teach machines to distinguish between similar and dissimilar things



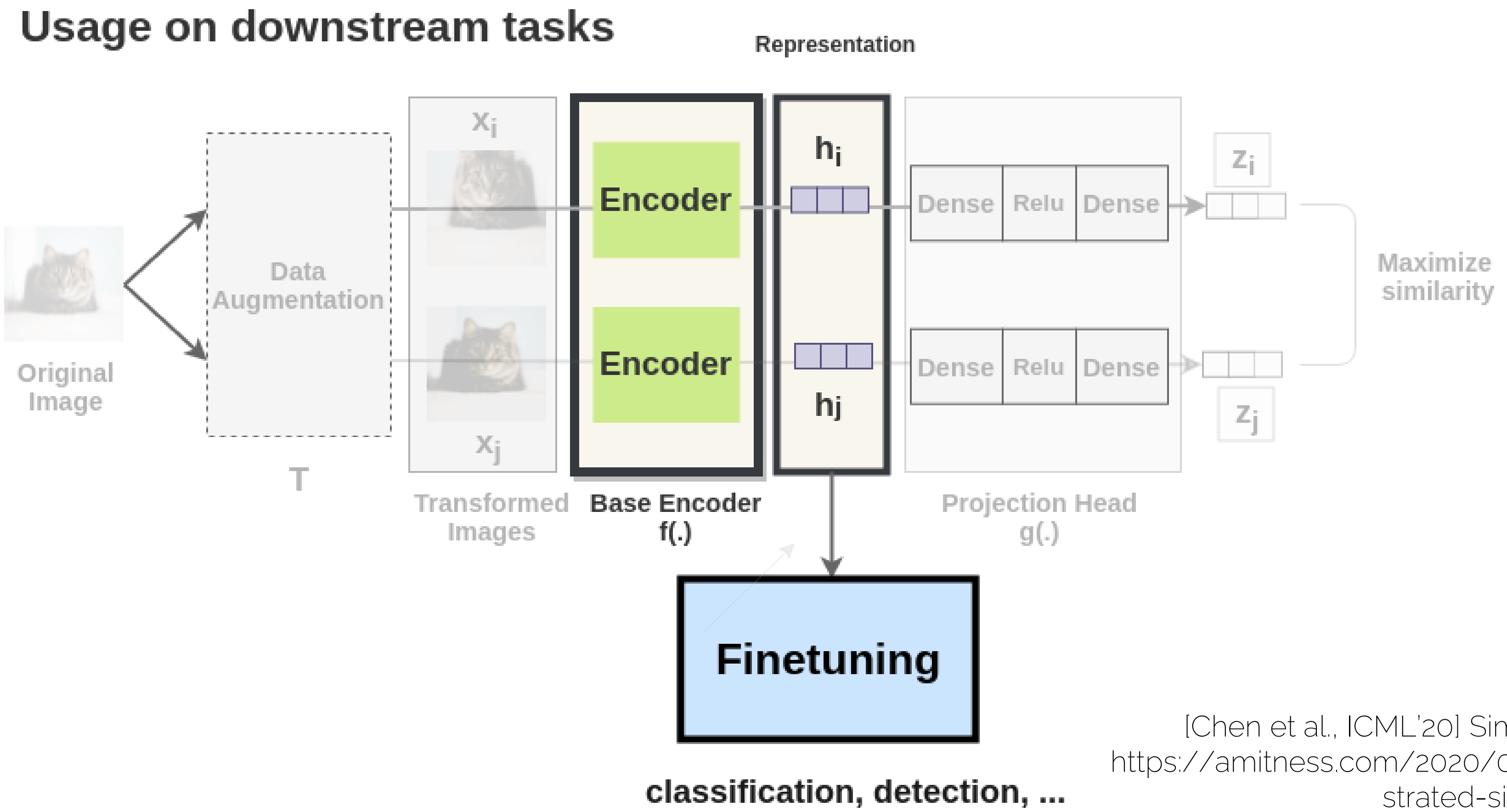
https://amitness.com/2020/03/illustrated-simclr/

How to Learn Good Features?



[Chen et al., ICML'20] SimCLR,
https://amitness.com/2020/03/illustrated-simclr/

Apply to Downstream Tasks



[Chen et al., ICML'20] SimCLR, https://amitness.com/2020/03/illustrated-simclr/

Transfer & Representation Learning

- Transfer learning can be done via representation learning

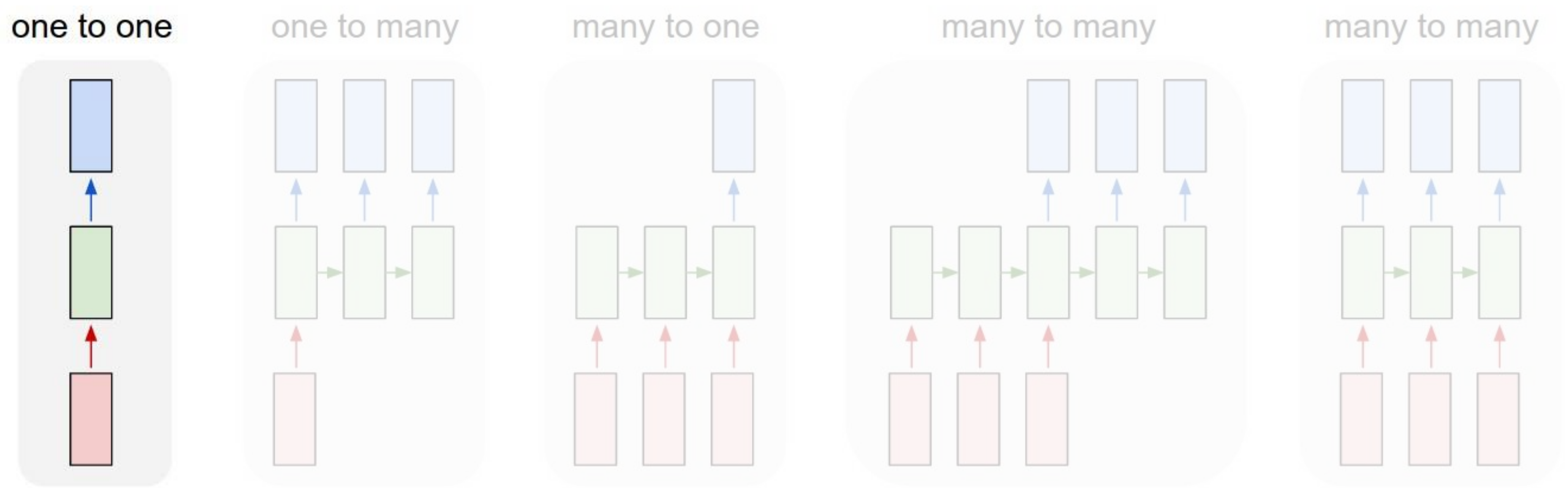
- Effectiveness of representation learning often demonstrated by transfer learning performance (but also other factors, e.g., smoothness of the manifold)

Recurrent Neural Networks

Processing Sequences

- Recurrent neural networks process sequence data
- Input/output can be sequences

RNNs are Flexible



Classical neural networks for image classification

Source: http://karpathy.github.io/2015/05/21/rnn-effectiveness/

RNNs are Flexible

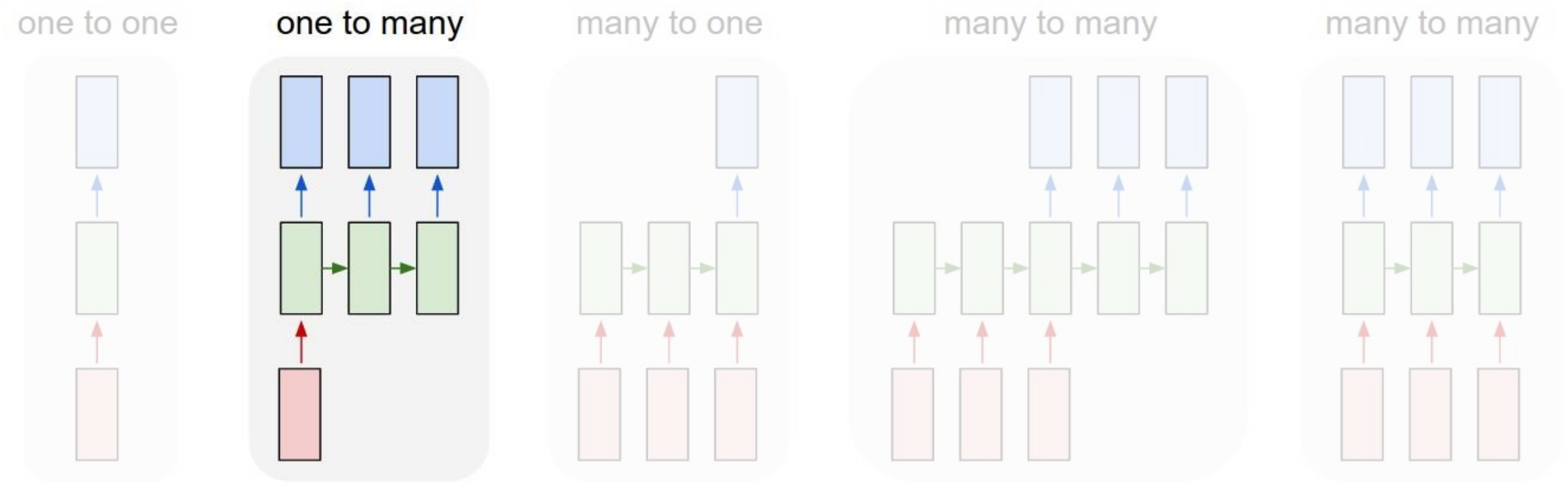
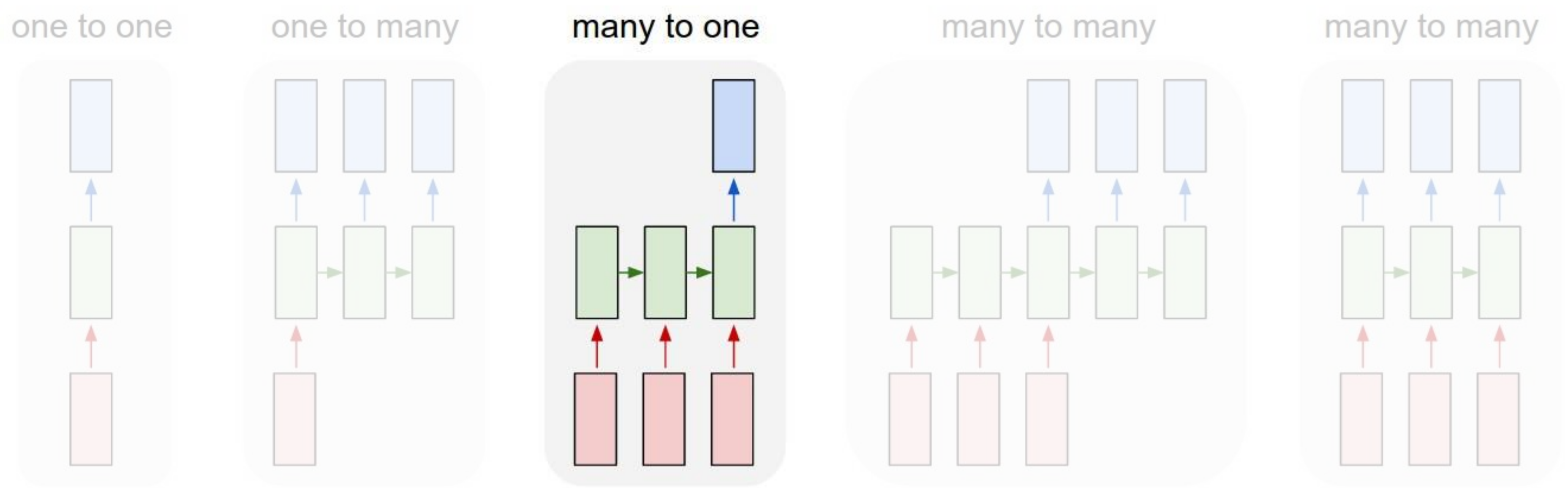


Image captioning

Source: http://karpathy.github.io/2015/05/21/rnn-effectiveness/

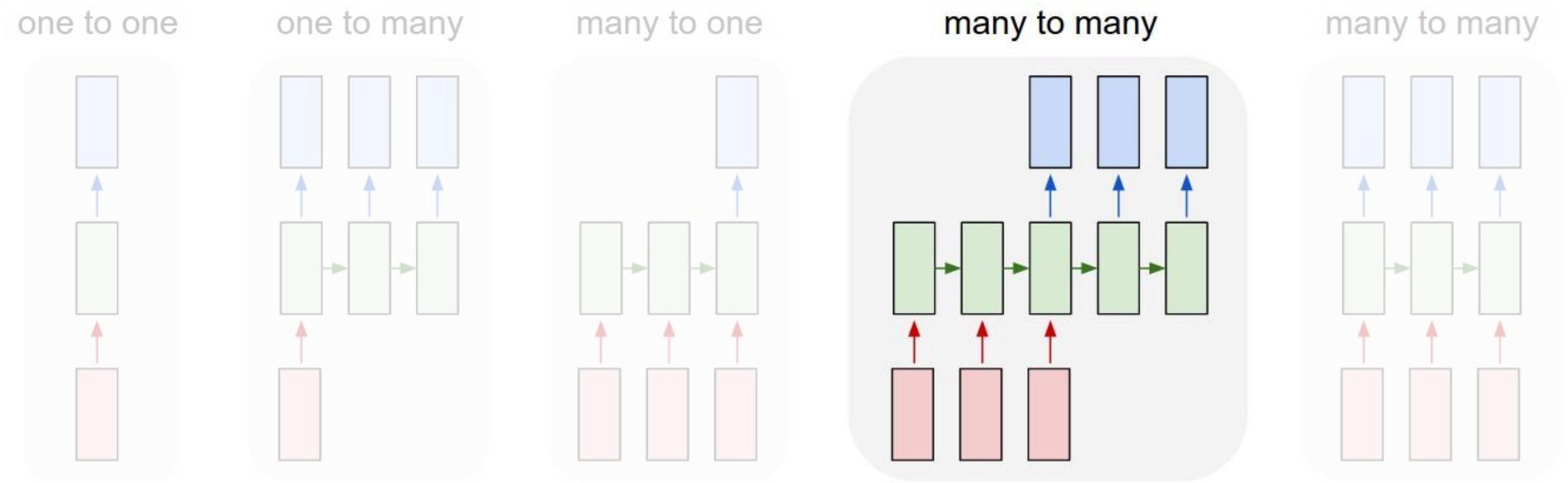
RNNs are Flexible



Language recognition

Source: http://karpathy.github.io/2015/05/21/rnn-effectiveness/

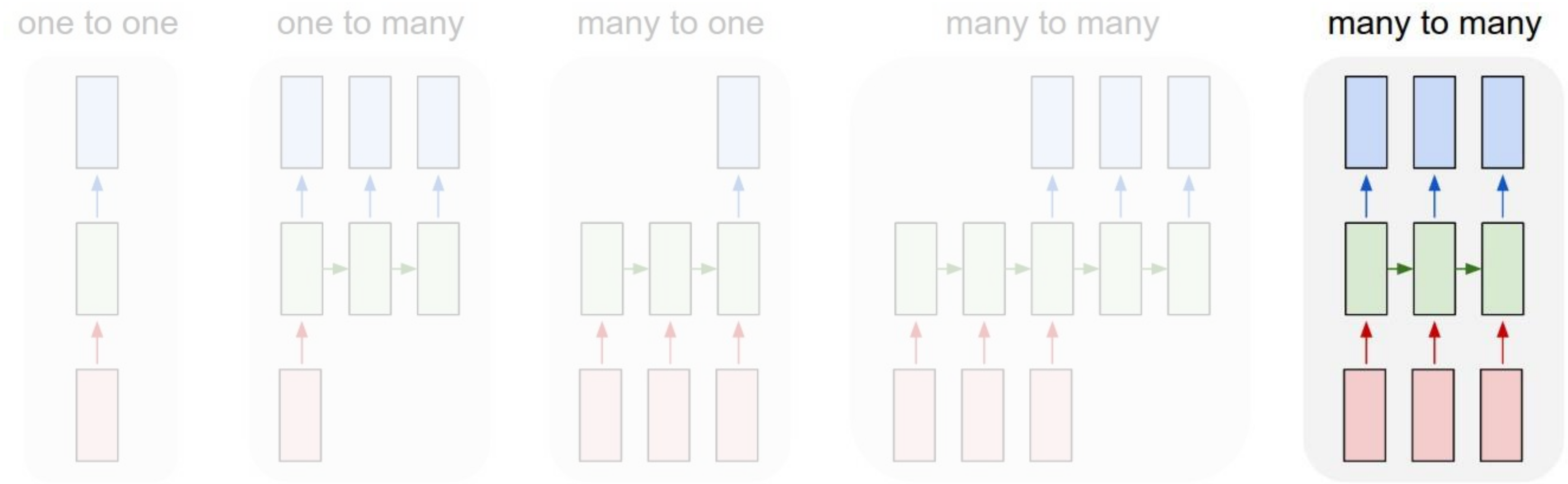
RNNs are Flexible



Machine translation

Source: http://karpathy.github.io/2015/05/21/rnn-effectiveness/

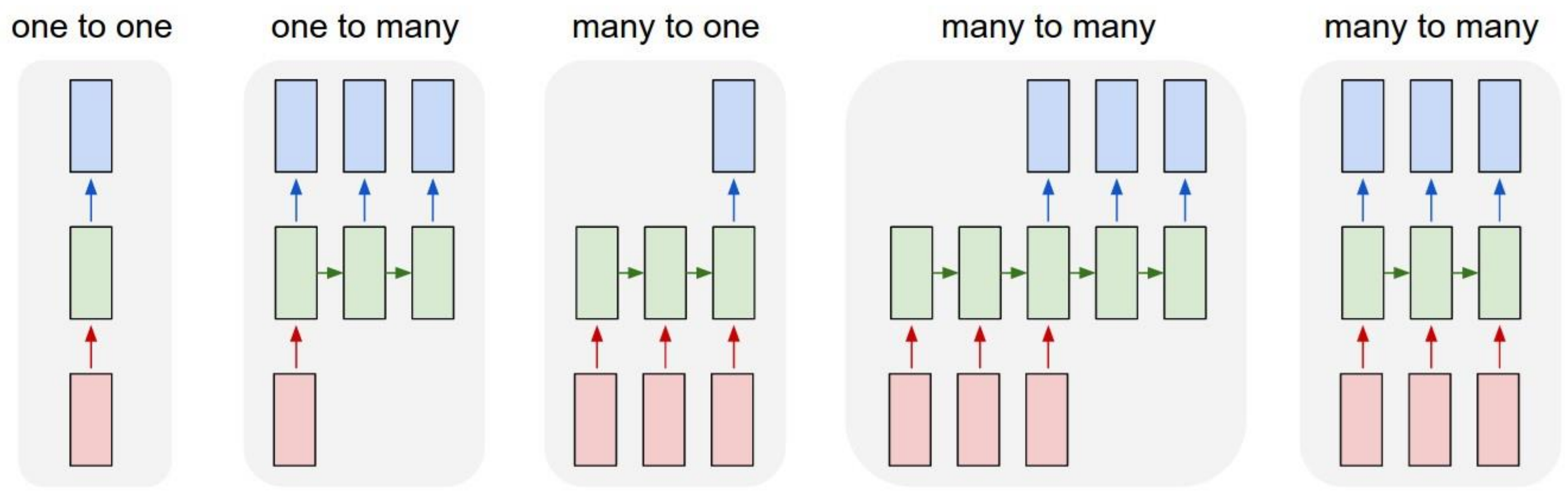
RNNs are Flexible



Event classification

Source: http://karpathy.github.io/2015/05/21/rnn-effectiveness/

RNNs are Flexible

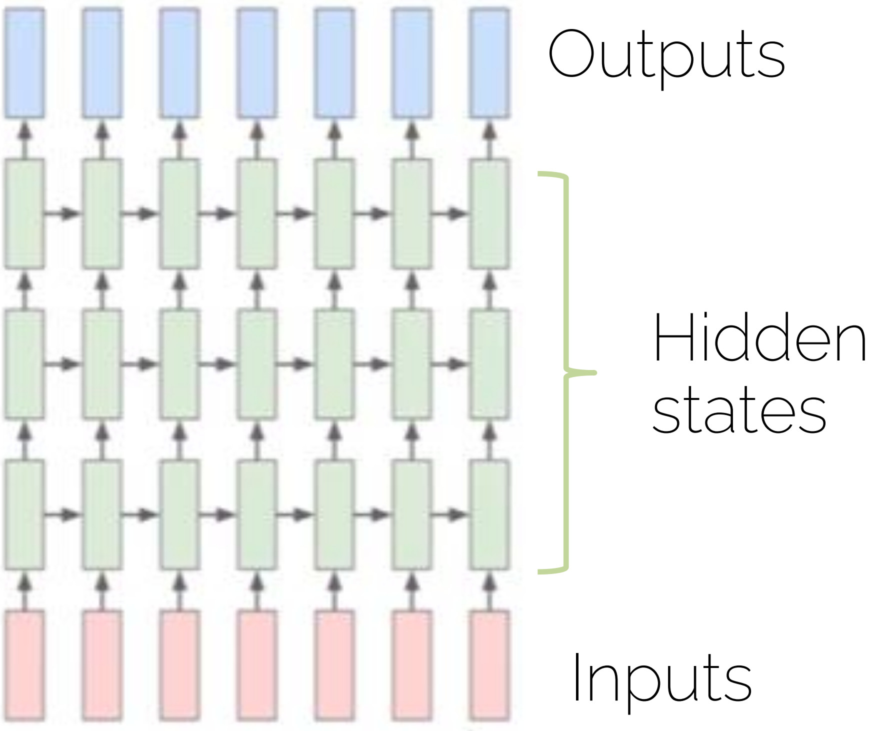


Event classification

Source: http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Basic Structure of an RNN

- Multi-layer RNN



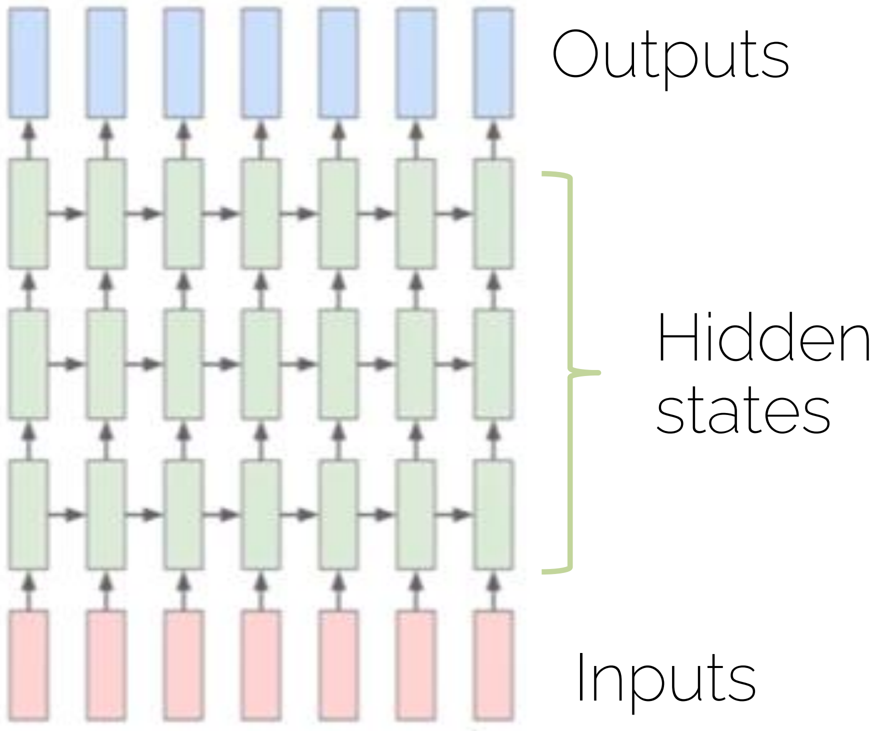
Basic Structure of an RNN

- Multi-layer RNN

The hidden state will have its own internal dynamics

↓

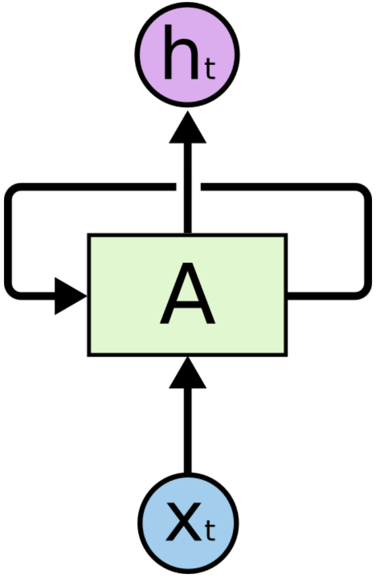
More expressive model!



Basic Structure of an RNN

- We want to have notion of "time" or "sequence"

Hidden state



$$\boldsymbol{A}_t = \boldsymbol{\theta}_c \boldsymbol{A}_{t-1} + \boldsymbol{\theta}_x \boldsymbol{x}_t$$

Previous hidden state

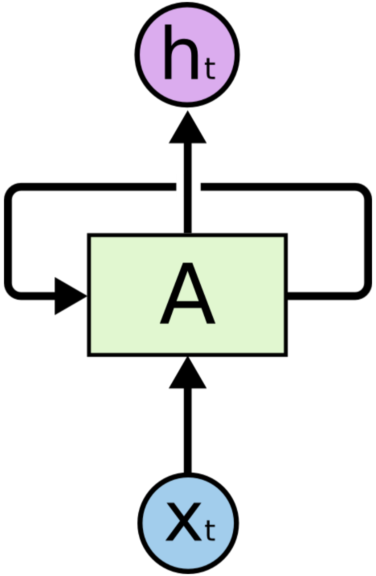
input

[Olah, https://colah.github.io '15] Understanding LSTMs

Basic Structure of an RNN

- We want to have notion of "time" or "sequence"

Hidden state



$$A_t = \theta_c A_{t-1} + \theta_x x_t$$

Parameters to be learned

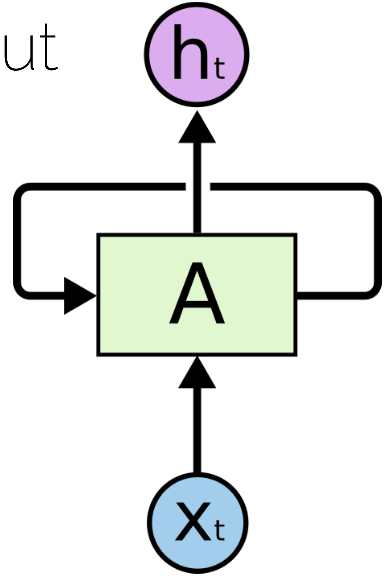
[Olah, https://colah.github.io '15] Understanding LSTMs

Basic Structure of an RNN

- We want to have notion of "time" or "sequence"

Output

Hidden state



$$\boldsymbol{A}_t = \boldsymbol{\theta}_c \boldsymbol{A}_{t-1} + \boldsymbol{\theta}_x \boldsymbol{x}_t$$

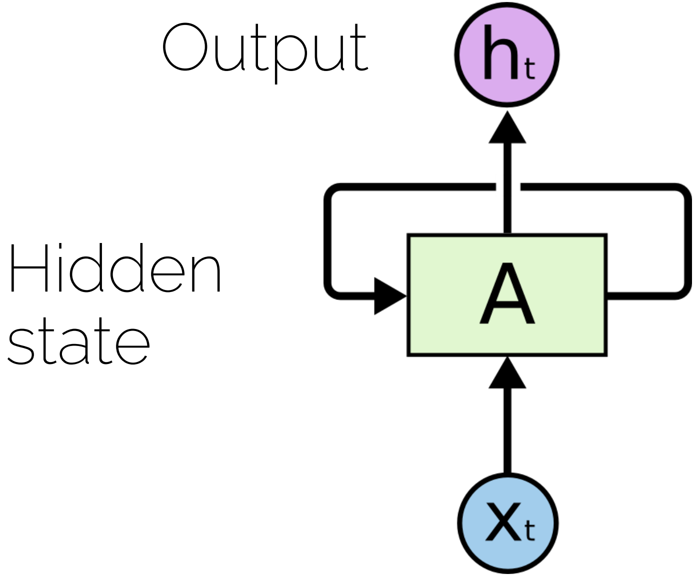
$$\boldsymbol{h}_t = \boldsymbol{\theta}_h \boldsymbol{A}_t$$

Note: non-linearities ignored for now

[Olah, https://colah.github.io '15] Understanding LSTMs

Basic Structure of an RNN

- We want to have notion of "time" or "sequence"



$$\boldsymbol{A}_t = \boldsymbol{\theta}_c \boldsymbol{A}_{t-1} + \boldsymbol{\theta}_x \boldsymbol{x}_t$$

$$\boldsymbol{h}_t = \boldsymbol{\theta}_h \boldsymbol{A}_t$$

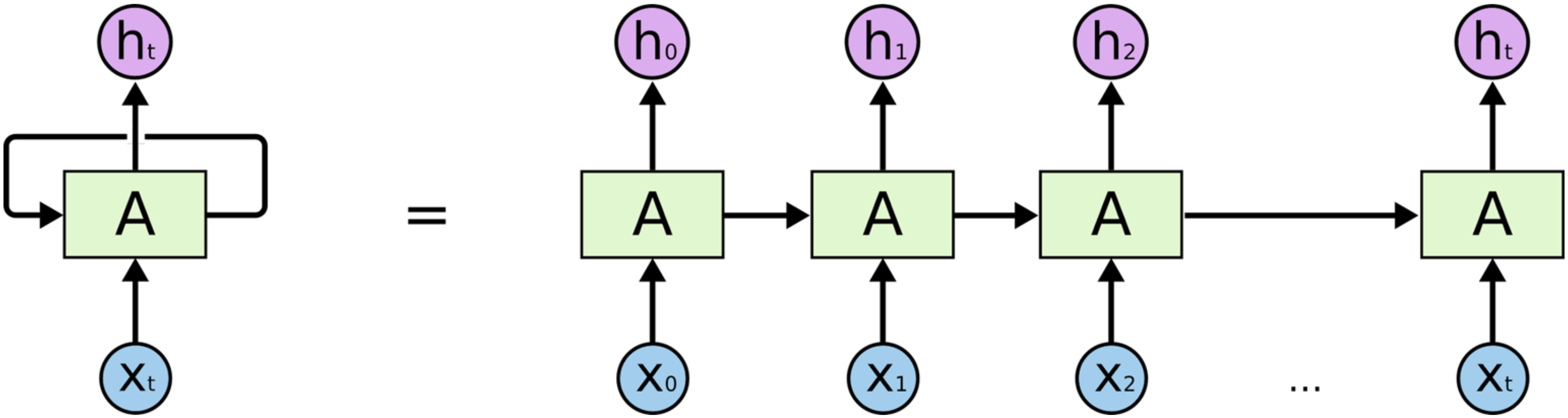
Same parameters for each time step = generalization!

[Olah, https://colah.github.io '15] Understanding LSTMs

Basic Structure of an RNN

- Unrolling RNNs

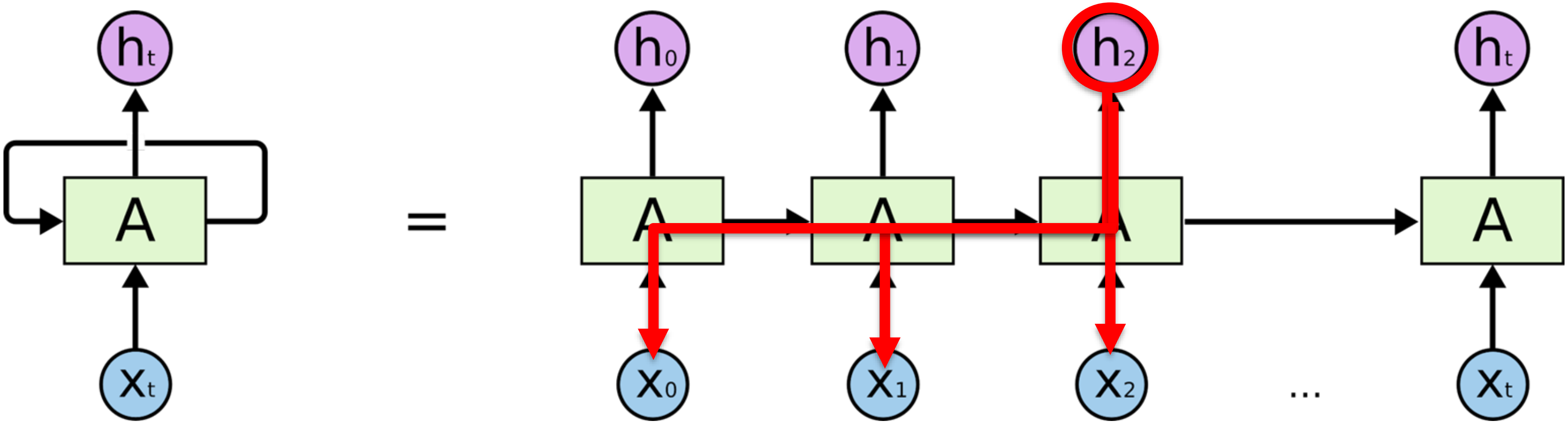
Same function for the hidden layers



[Olah, https://colah.github.io '15] Understanding LSTMs

Basic Structure of an RNN

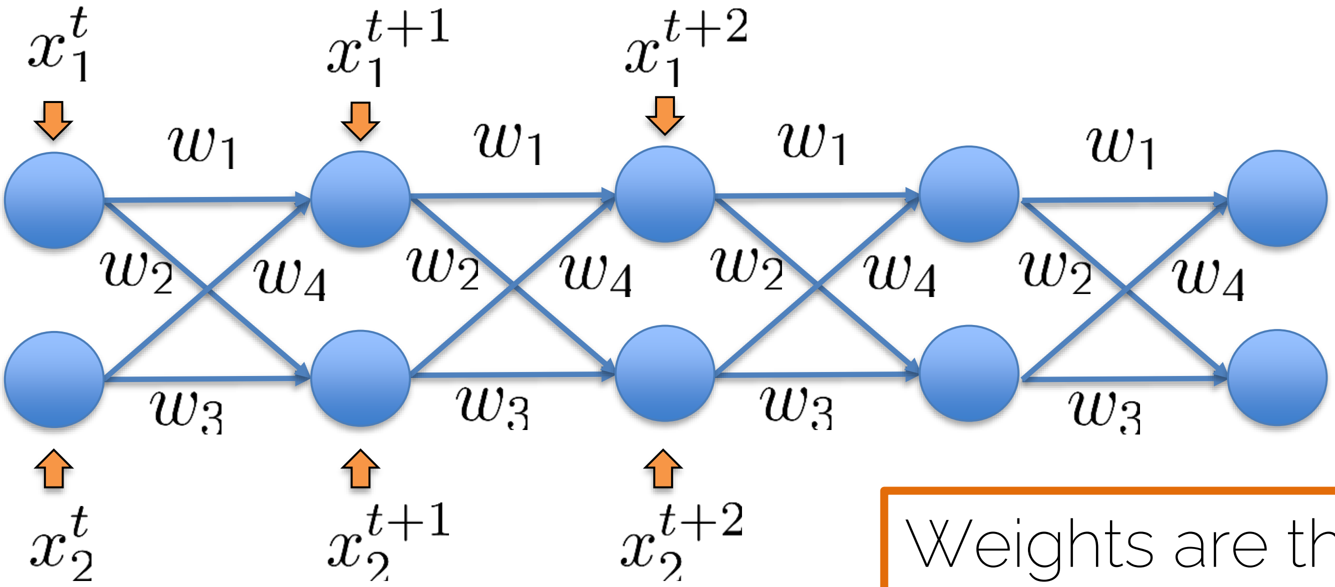
- Unrolling RNNs



[Olah, https://colah.github.io '15] Understanding LSTMs

Basic Structure of an RNN

- Unrolling RNNs as feedforward nets

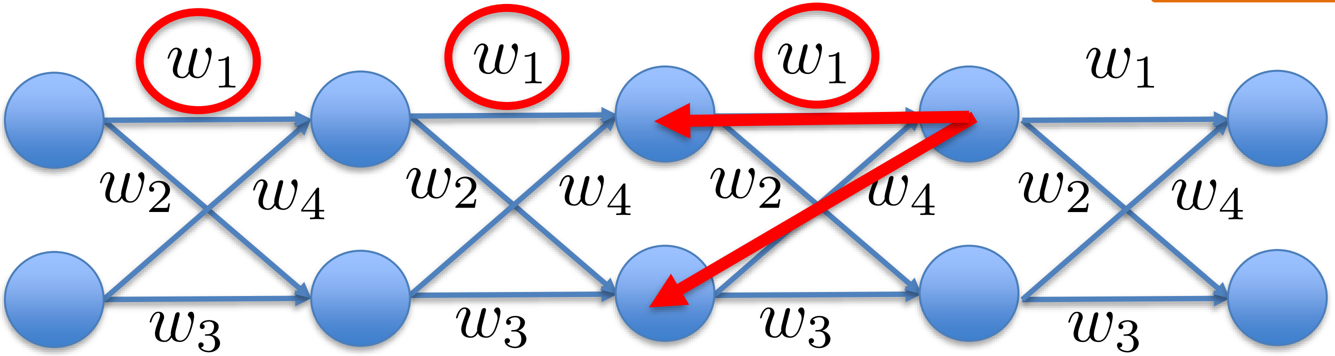


Weights are the same!

Backprop through an RNN

- Unrolling RNNs as feedforward nets

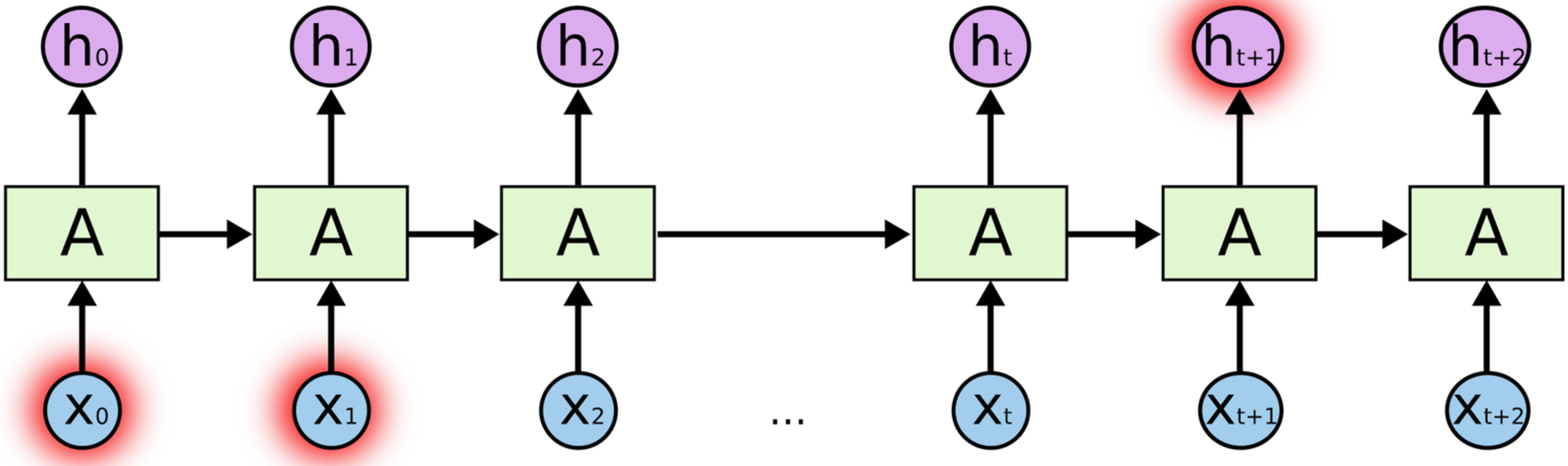
Chain rule



All the way to $t = 0$

Add the derivatives at different times for each weight

Long-term Dependencies



I moved to Germany … so I speak German fluently.

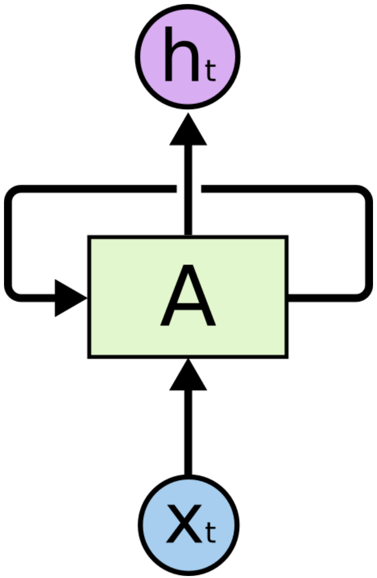
[Olah, https://colah.github.io '15] Understanding LSTMs

Long-term Dependencies

- Simple recurrence $\boldsymbol{A}_t = \boldsymbol{\theta}_c \boldsymbol{A}_{t-1} + \boldsymbol{\theta}_x \boldsymbol{x}_t$

- Let us forget the input $\boldsymbol{A}_t = \boldsymbol{\theta}_c{}^t \boldsymbol{A}_0$

Same weights are multiplied over and over again



Long-term Dependencies

- Simple recurrence $\boldsymbol{A_t = \theta_c}^t \boldsymbol{A_0}$

What happens to small weights?

Vanishing gradient

What happens to large weights?

Exploding gradient

Long-term Dependencies

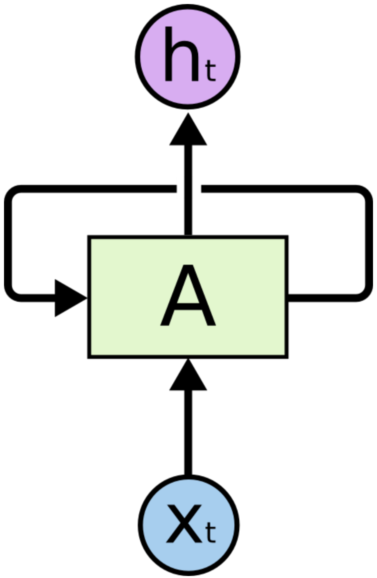
- Simple recurrence $\boldsymbol{A_t = \theta_c}^{t}\boldsymbol{A_0}$

- If $\boldsymbol{\theta}$ admits eigendecomposition

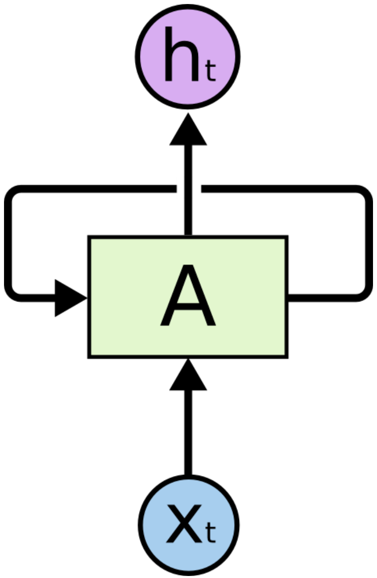
$$\boldsymbol{\theta = Q\Lambda Q^T}$$

Matrix of eigenvectors

Diagonal of this matrix are the eigenvalues



Long-term Dependencies



- Simple recurrence $\boldsymbol{A}_t = \boldsymbol{\theta}^t \boldsymbol{A}_0$

- If $\boldsymbol{\theta}$ admits eigendecomposition

$$\boldsymbol{\theta} = \boldsymbol{Q}\boldsymbol{\Lambda}\boldsymbol{Q}^T$$

- Orthogonal $\boldsymbol{\theta}$ allows us to simplify the recurrence

$$\boldsymbol{A}_t = \boldsymbol{Q}\boldsymbol{\Lambda}^t\boldsymbol{Q}^T\boldsymbol{A}_0$$

Long-term Dependencies

- Simple recurrence $\boldsymbol{A}_t = \boldsymbol{Q}\boldsymbol{\Lambda}^{\mathrm{t}}\boldsymbol{Q}^T\boldsymbol{A}_0$

What happens to eigenvalues with magnitude less than one?

Vanishing gradient

What happens to eigenvalues with magnitude larger than one?

Exploding gradient

Gradient clipping

Long-term Dependencies

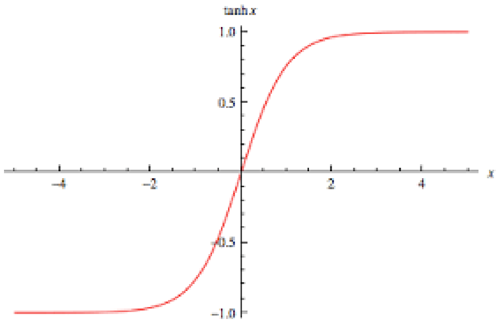
- Simple recurrence $\boldsymbol{A_t = \theta_c{}^t A_0}$

Let us just make a matrix with eigenvalues = 1

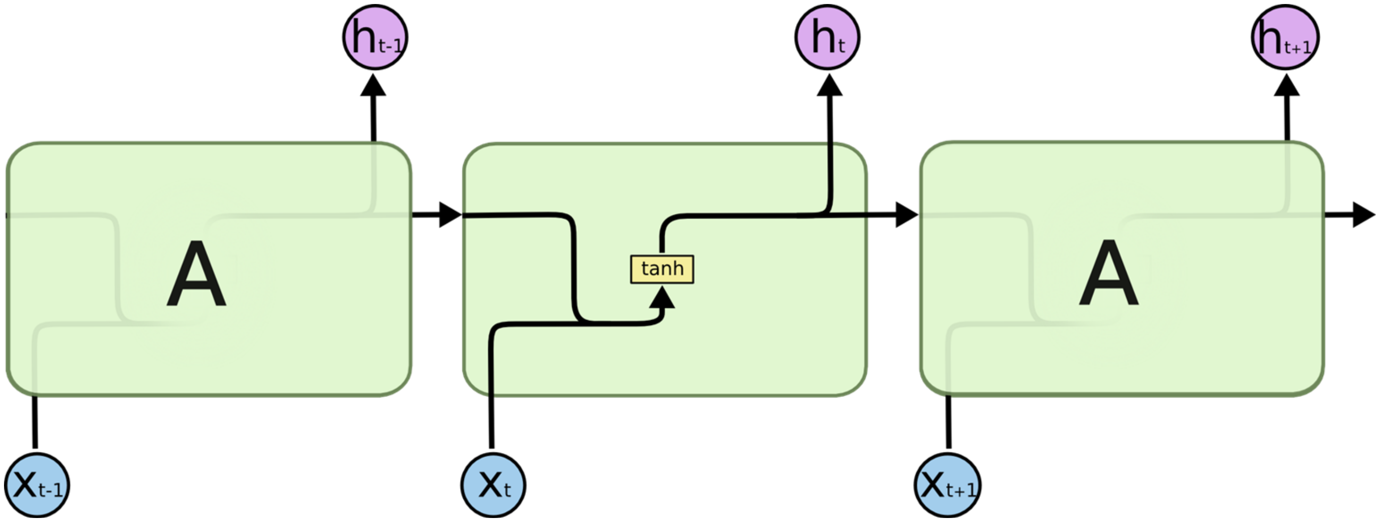
Allow the **cell** to maintain its "*state*"

Vanishing Gradient

- 1. From the weights $\boldsymbol{A_t = \theta_c{}^t A_0}$



- 2. From the activation functions ($\boldsymbol{tanh}$)



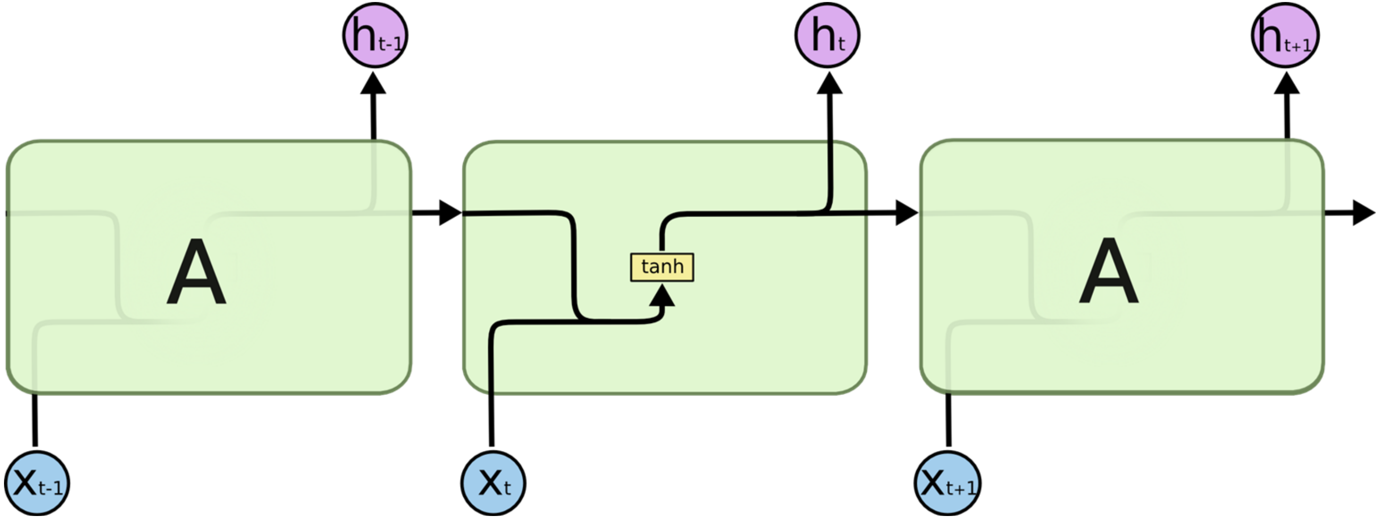
[Olah, https://colah.github.io '15] Understanding LSTMs

Vanishing Gradient

- 1. From the weights $\quad \boldsymbol{A}_t = \cancel{\boldsymbol{\theta}}^t \boldsymbol{A}_0$

1

- 2. From the activation functions ($\boldsymbol{tanh}$) ?



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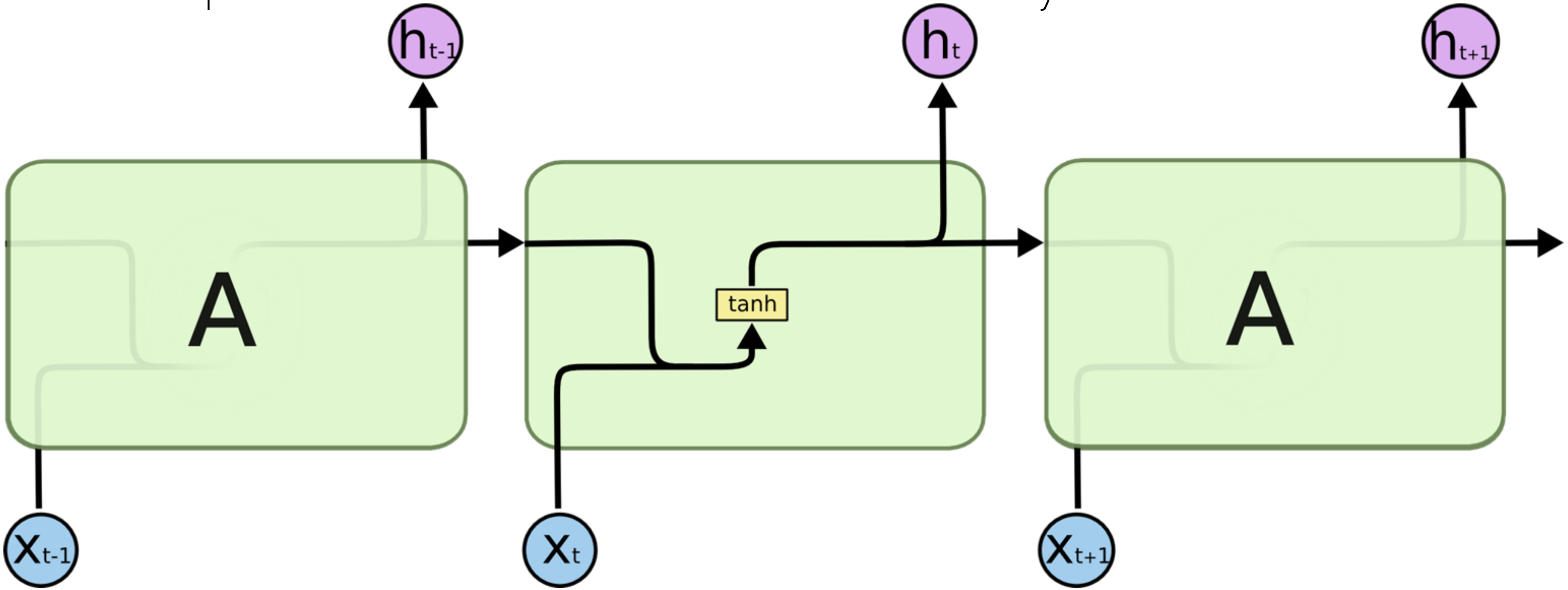
Long Short Term Memory

[Hochreiter et al., Neural Computation'97] Long Short-Term Memory

Long-Short Term Memory Units

- Simple RNN has **tanh** as non-linearity



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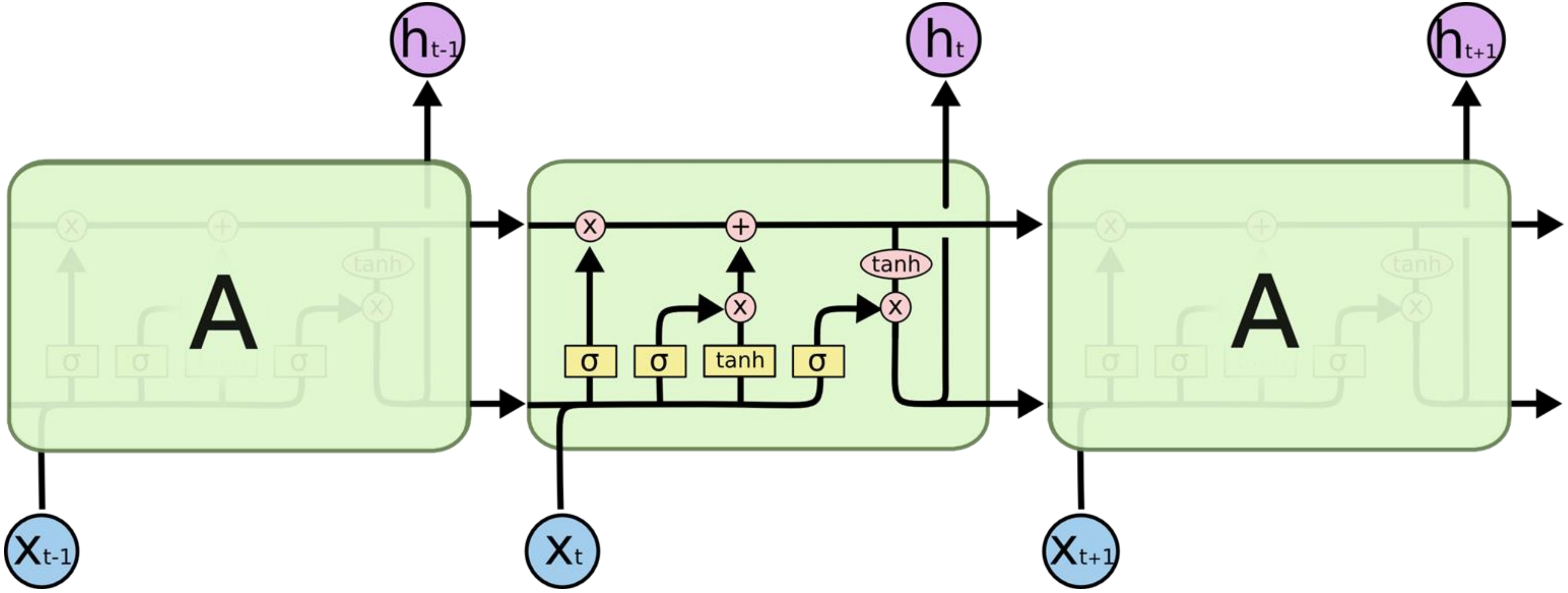
Long-Short Term Memory Units

LSTM



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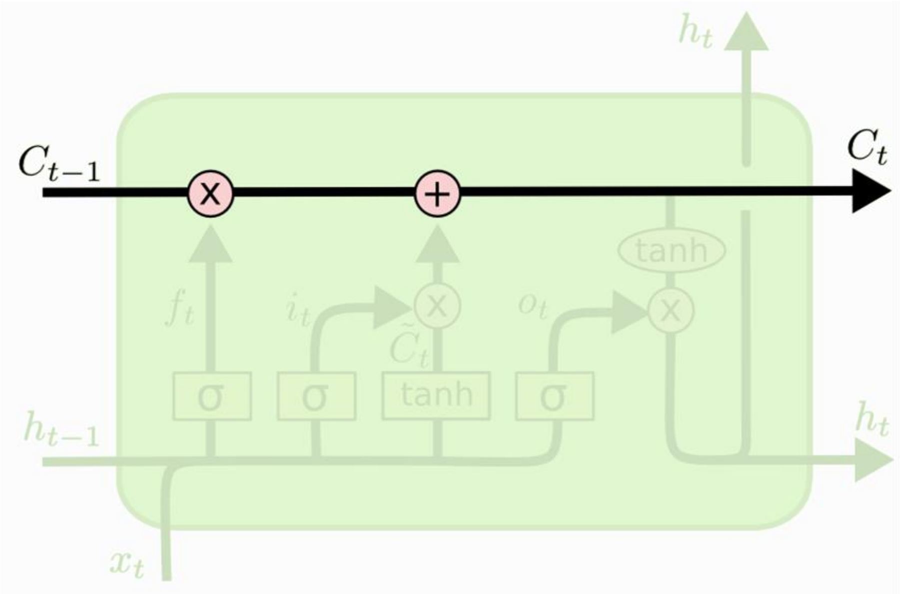
Long-Short Term Memory Units

- Key ingredients
- Cell = transports the information through the unit



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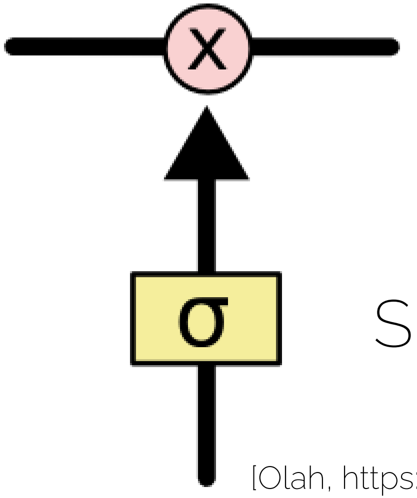
Long-Short Term Memory Units

- Key ingredients
- Cell = transports the information through the unit
- Gate = remove or add information to the cell state



Sigmoid

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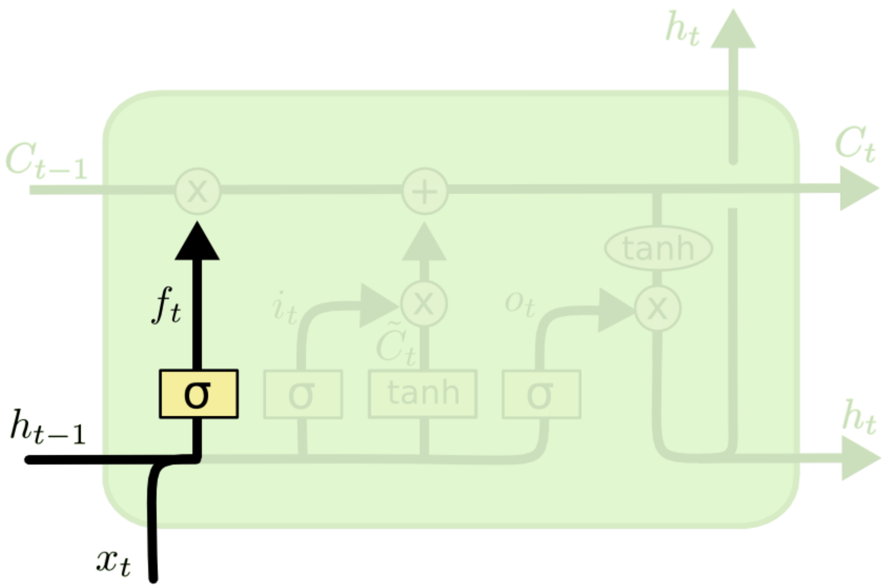
LSTM: Step by Step

- Forget gate $\boldsymbol{f}_t = sigm(\boldsymbol{\theta}_{xf}\boldsymbol{x}_t + \boldsymbol{\theta}_{hf}\boldsymbol{h}_{t-1} + \boldsymbol{b}_f)$



Decides when to erase the cell state

Sigmoid = output between **0** (forget) and **1** (keep)

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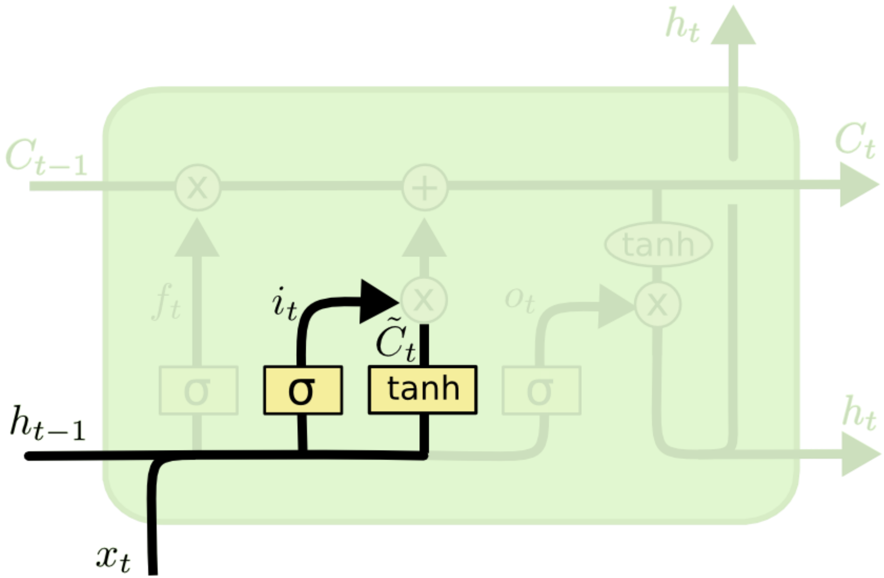
LSTM: Step by Step

- Input gate $\quad \boldsymbol{i}_t = sigm(\boldsymbol{\theta}_{xi}\boldsymbol{x}_t + \boldsymbol{\theta}_{hi}\boldsymbol{h}_{t-1} + \boldsymbol{b}_i)$



Decides which values will be updated

New cell state, output from a $\tanh\ (-1,1)$

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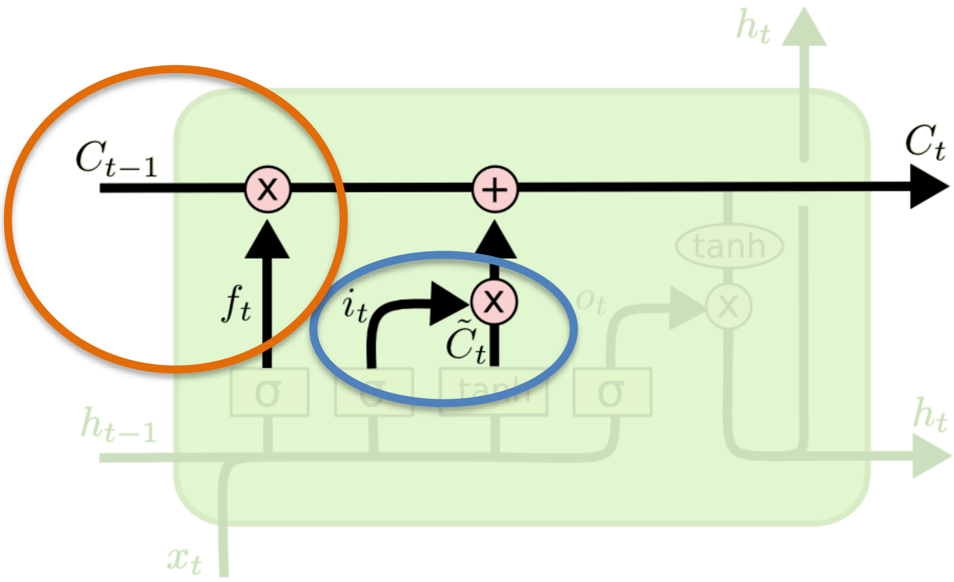
LSTM: Step by Step

- Element-wise operations



$$\boldsymbol{c}_t = \boldsymbol{f}_t \odot \boldsymbol{c}_{t-1} + \boldsymbol{i}_t \odot \boldsymbol{g}_t$$

Previous states

Current state

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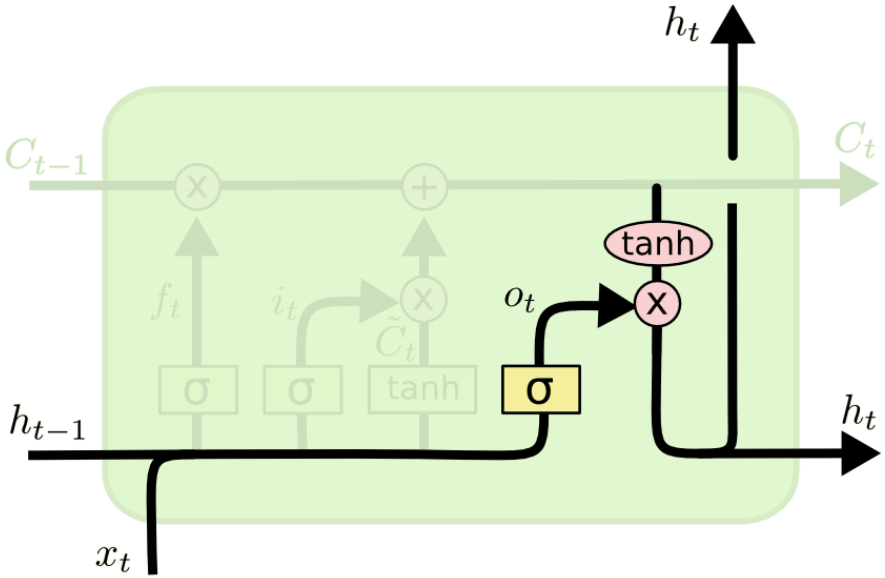
LSTM: Step by Step

- Output gate $\boldsymbol{h}_t = \boldsymbol{o}_t \odot \tanh(\boldsymbol{C}_t)$



Decides which values will be outputted

Output from a **tanh** $(-1, 1)$

[Olah, https://colah.github.io '15] Understanding LSTMs

LSTM: Step by Step

- Forget gate $\boldsymbol{f}_t = sigm(\boldsymbol{\theta}_{xf}\boldsymbol{x}_t + \boldsymbol{\theta}_{hf}\boldsymbol{h}_{t-1} + \boldsymbol{b}_f)$
- Input gate $\boldsymbol{i}_t = sigm(\boldsymbol{\theta}_{xi}\boldsymbol{x}_t + \boldsymbol{\theta}_{hi}\boldsymbol{h}_{t-1} + \boldsymbol{b}_i)$
- Output gate $\boldsymbol{o}_t = sigm(\boldsymbol{\theta}_{xo}\boldsymbol{x}_t + \boldsymbol{\theta}_{ho}\boldsymbol{h}_{t-1} + \boldsymbol{b}_o)$
- Cell update $\boldsymbol{g}_t = tanh(\boldsymbol{\theta}_{xg}\boldsymbol{x}_t + \boldsymbol{\theta}_{hg}\boldsymbol{h}_{t-1} + \boldsymbol{b}_g)$
- Cell $\boldsymbol{C}_t = \boldsymbol{f}_t \odot \boldsymbol{C}_{t-1} + \boldsymbol{i}_t \odot \boldsymbol{g}_t$
- Output $\boldsymbol{h}_t = \boldsymbol{o}_t \odot \tanh(\boldsymbol{C}_t)$

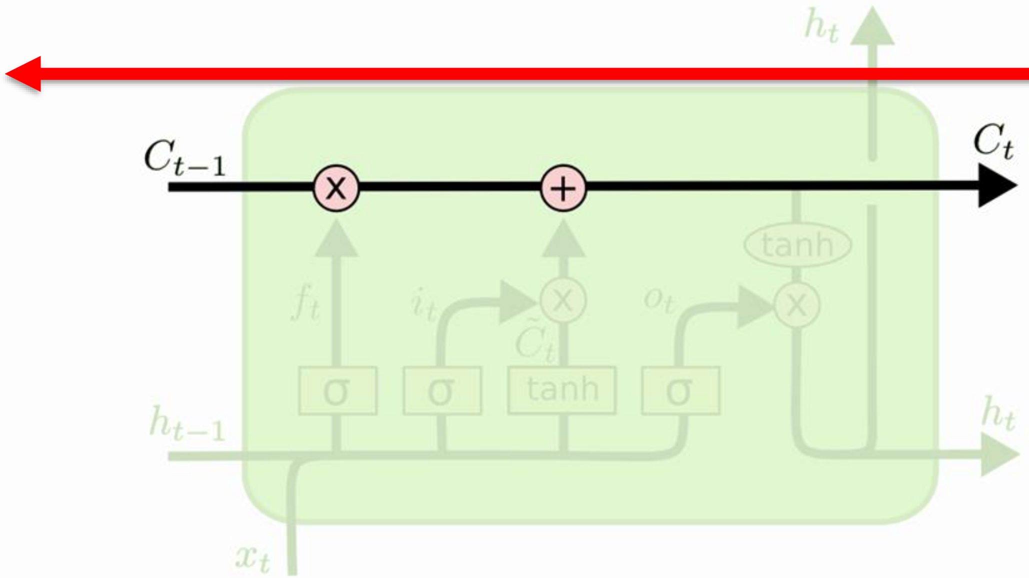
LSTM: Step by Step

- Forget gate $\boldsymbol{f}_t = sigm(\boldsymbol{\theta}_{xf}\boldsymbol{x}_t + \boldsymbol{\theta}_{hf}\boldsymbol{h}_{t-1} + \boldsymbol{b}_f)$
- Input gate $\boldsymbol{i}_t = sigm(\boldsymbol{\theta}_{xi}\boldsymbol{x}_t + \boldsymbol{\theta}_{hi}\boldsymbol{h}_{t-1} + \boldsymbol{b}_i)$
- Output gate $\boldsymbol{o}_t = sigm(\boldsymbol{\theta}_{xo}\boldsymbol{x}_t + \boldsymbol{\theta}_{ho}\boldsymbol{h}_{t-1} + \boldsymbol{b}_o)$
- Cell update $\boldsymbol{g}_t = tanh(\boldsymbol{\theta}_{xg}\boldsymbol{x}_t + \boldsymbol{\theta}_{hg}\boldsymbol{h}_{t-1} + \boldsymbol{b}_g)$
- Cell $\boldsymbol{C}_t = \boldsymbol{f}_t \odot \boldsymbol{C}_{t-1} + \boldsymbol{i}_t \odot \boldsymbol{g}_t$
- Output $\boldsymbol{h}_t = \boldsymbol{o}_t \odot \tanh(\boldsymbol{C}_t)$

Learned through backpropagation

LSTM

- Highway for the gradient to flow



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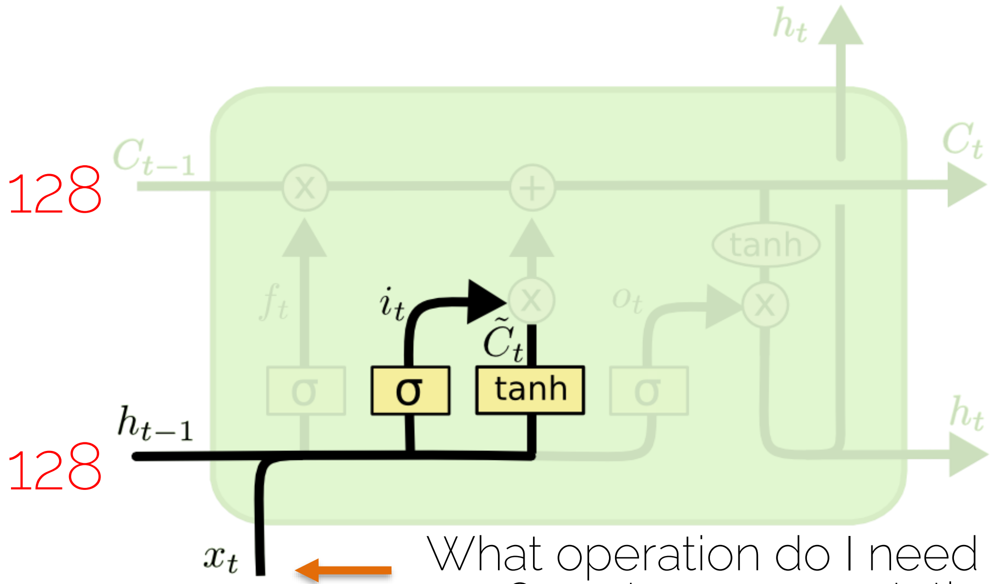
LSTM: Dimensions

- Cell update $\boldsymbol{g}_t \overset{128}{=} tanh(\boldsymbol{\theta}_{xg}\boldsymbol{x}_t \overset{128}{+} \boldsymbol{\theta}_{hg}\boldsymbol{h}_{t-1} \overset{128}{+} \boldsymbol{b}_g)$



When coding an LSTM, we have to define the size of the hidden state

Dimensions need to match

What operation do I need to do to my input to get a 128 vector representation?

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LSTM in code

```python
def lstm_step_forward(x, prev_h, prev_c, Wx, Wh, b):
    """
    Forward pass for a single timestep of an LSTM.

    The input data has dimension D, the hidden state has dimension H, and we use
    a minibatch size of N.

    Inputs:
    - x: Input data, of shape (N, D)
    - prev_h: Previous hidden state, of shape (N, H)
    - prev_c: previous cell state, of shape (N, H)
    - Wx: Input-to-hidden weights, of shape (D, 4H)
    - Wh: Hidden-to-hidden weights, of shape (H, 4H)
    - b: Biases, of shape (4H,)

    Returns a tuple of:
    - next_h: Next hidden state, of shape (N, H)
    - next_c: Next cell state, of shape (N, H)
    - cache: Tuple of values needed for backward pass.
    """
    next_h, next_c, cache = None, None, None

    N, H = prev_h.shape
    # 1
    a = np.dot(x, Wx) + np.dot(prev_h, Wh) + b

    # 2
    ai = a[:, :H]
    af = a[:, H:2*H]
    ao = a[:, 2*H:3*H]
    ag = a[:, 3*H:]

    # 3
    i = sigmoid(ai)
    f = sigmoid(af)
    o = sigmoid(ao)
    g = np.tanh(ag)

    # 4
    next_c = f * prev_c + i * g

    # 5
    next_h = o * np.tanh(next_c)

    cache = i, f, o, g, a, ai, af, ao, ag, Wx, Wh, b, prev_h, prev_c, x, next_c, next_h

    return next_h, next_c, cache
```

```python
def lstm_step_backward(dnext_h, dnext_c, cache):
    """
    Backward pass for a single timestep of an LSTM.

    Inputs:
    - dnext_h: Gradients of next hidden state, of shape (N, H)
    - dnext_c: Gradients of next cell state, of shape (N, H)
    - cache: Values from the forward pass

    Returns a tuple of:
    - dx: Gradient of input data, of shape (N, D)
    - dprev_h: Gradient of previous hidden state, of shape (N, H)
    - dprev_c: Gradient of previous cell state, of shape (N, H)
    - dWx: Gradient of input-to-hidden weights, of shape (D, 4H)
    - dWh: Gradient of hidden-to-hidden weights, of shape (H, 4H)
    - db: Gradient of biases, of shape (4H,)
    """
    dx, dh, dc, dWx, dWh, db = None, None, None, None, None, None

    i, f, o, g, a, ai, af, ao, ag, Wx, Wh, b, prev_h, prev_c, x, next_c, next_h = cache

    # backprop into step 5
    do = np.tanh(next_c) * dnext_h
    dnext_c += o * (1 - np.tanh(next_c) ** 2) * dnext_h

    # backprop into 4
    df = prev_c * dnext_c
    dprev_c = f * dnext_c
    di = g * dnext_c
    dg = i * dnext_c

    # backprop into 3
    dai = sigmoid(ai) * (1 - sigmoid(ai)) * di
    daf = sigmoid(af) * (1 - sigmoid(af)) * df
    dao = sigmoid(ao) * (1 - sigmoid(ao)) * do
    dag = (1 - np.tanh(ag) ** 2) * dg

    # backprop into 2
    da = np.hstack((dai, daf, dao, dag))

    # backprop into 1
    db = np.sum(da, axis = 0)
    dprev_h = np.dot(Wh, da.T).T
    dWh = np.dot(prev_h.T, da)
    dx = np.dot(da, Wx.T)
    dWx = np.dot(x.T, da)

    return dx, dprev_h, dprev_c, dWx, dWh, db
```

Attention

Attention is all you need

Attention Is All You Need

Ashish Vaswani[*]
Google Brain
avaswani@google.com

Noam Shazeer[*]
Google Brain
noam@google.com

Niki Parmar[*]
Google Research
nikip@google.com

Jakob Uszkoreit[*]
Google Research
usz@google.com

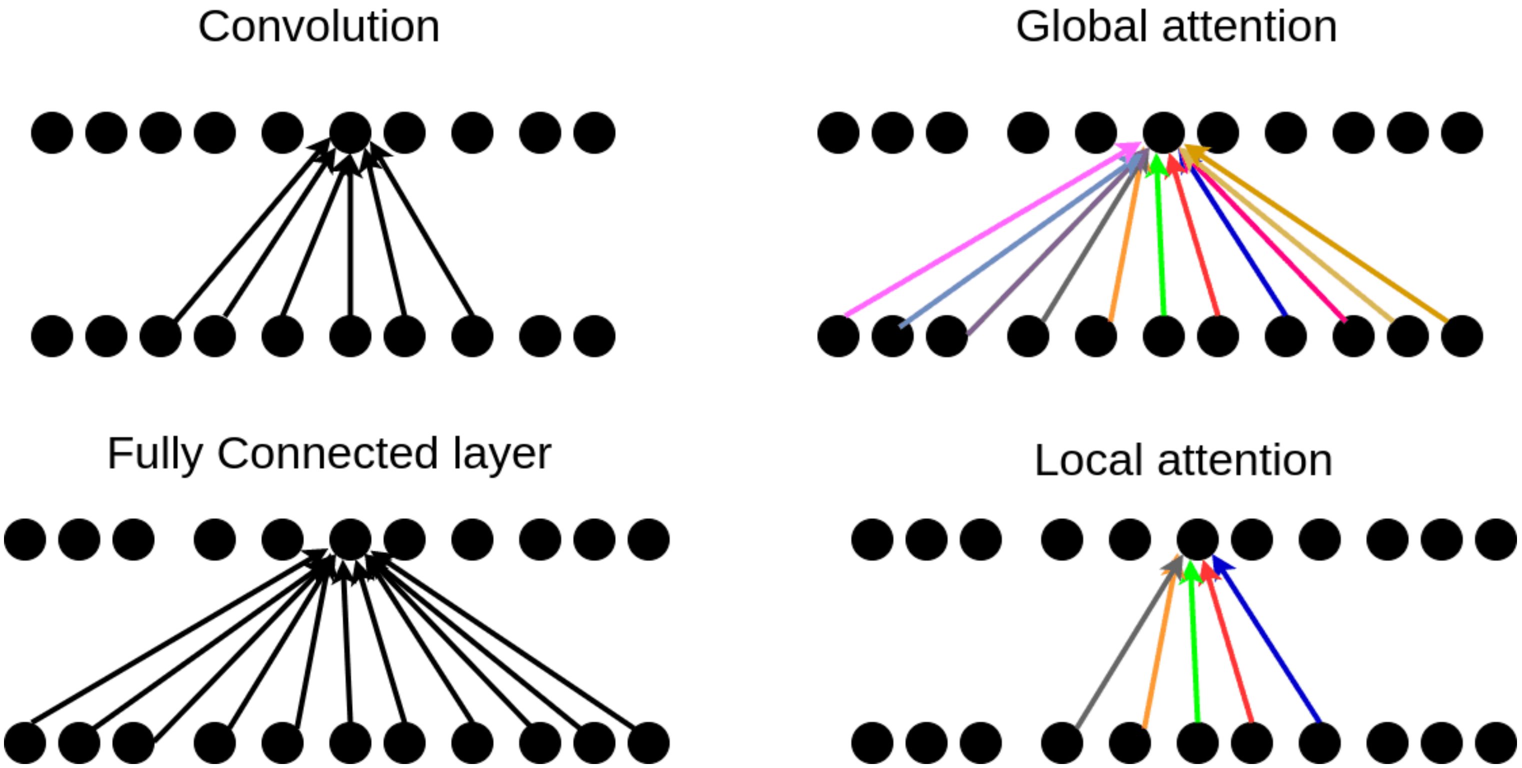
Llion Jones[*]
Google Research
llion@google.com

Aidan N. Gomez[*, †]
University of Toronto
aidan@cs.toronto.edu

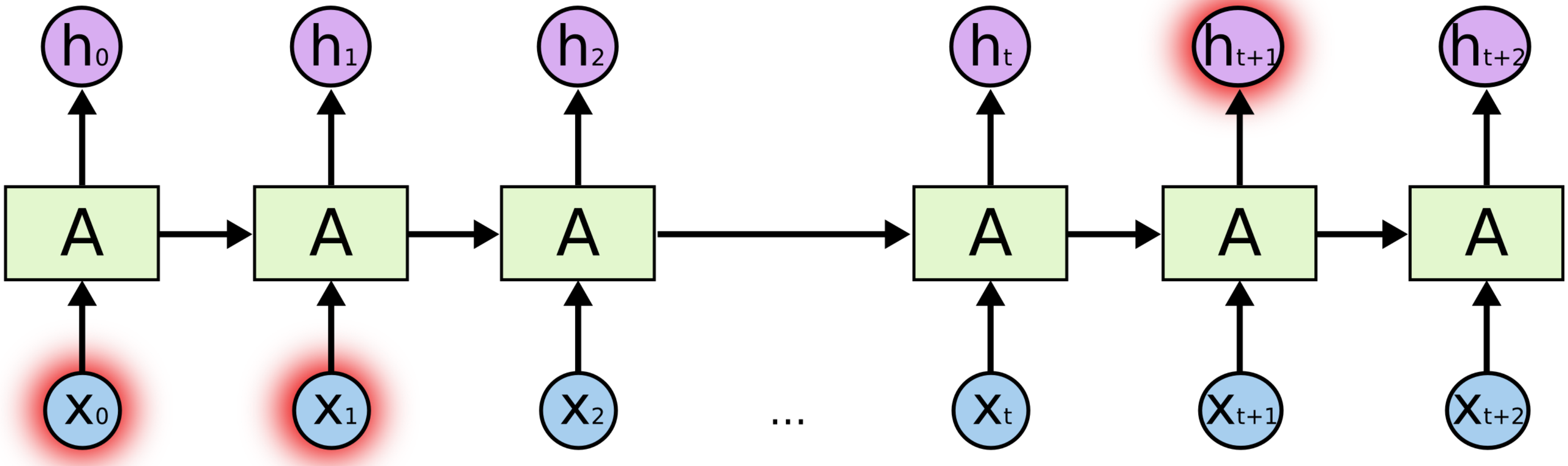
Łukasz Kaiser[*]
Google Brain
lukaszkaiser@google.com

Illia Polosukhin[*, ‡]
illia.polosukhin@gmail.com

Attention vs convolution



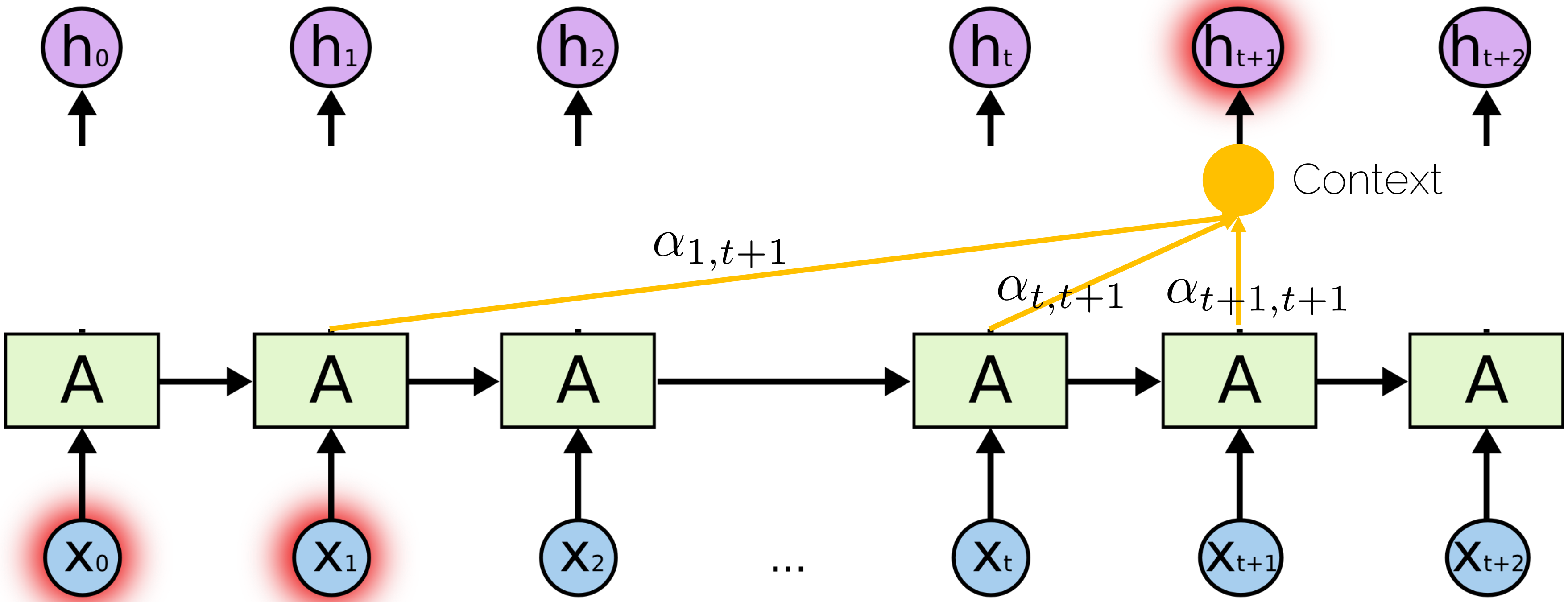
Long-Term Dependencies



I moved to Germany … so I speak German fluently.

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

Attention: Intuition



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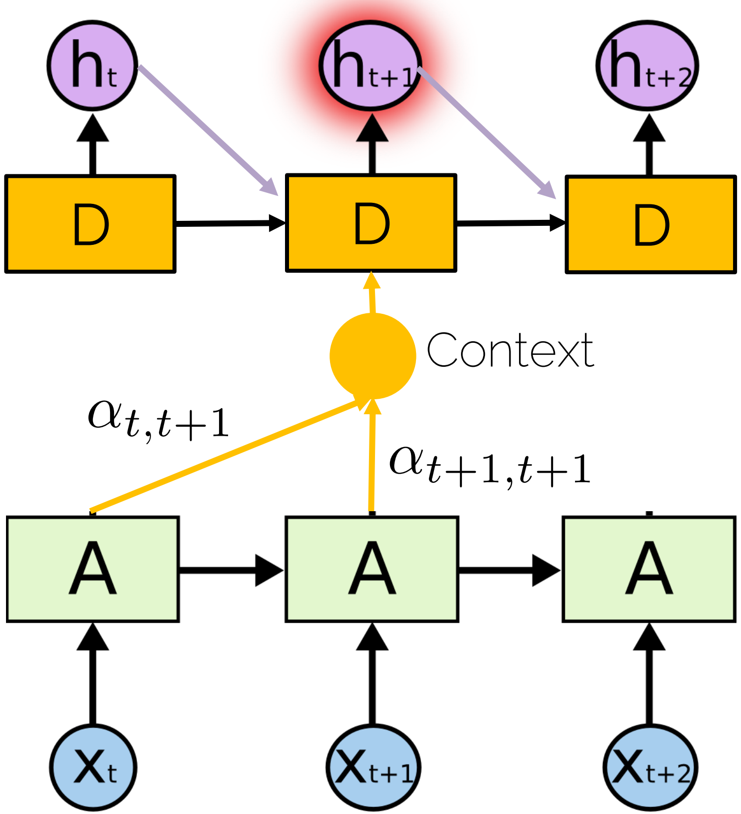
Attention: Architecture

- A decoder processes the information

- Decoders take as input:
  - Previous decoder hidden state
  - Previous output
  - Attention



Transformers

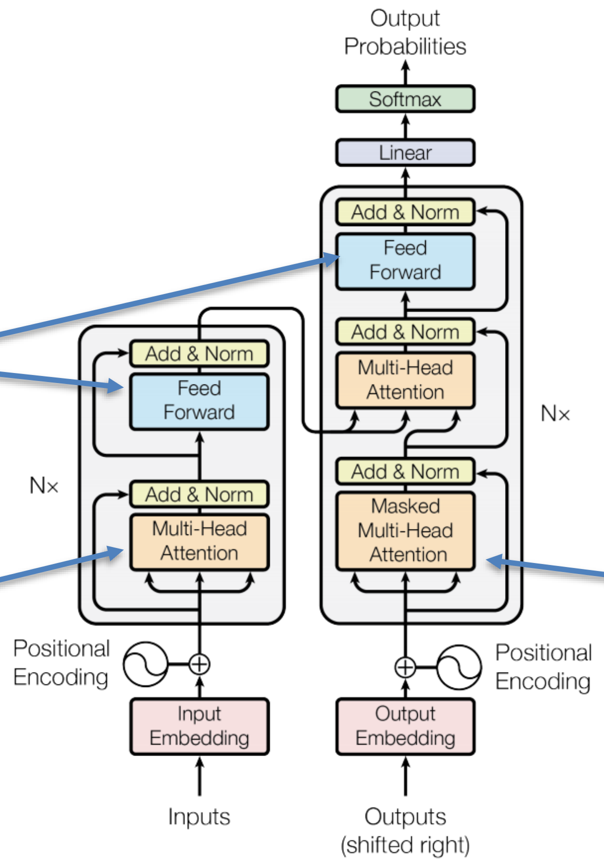
Deep Learning Revolution

	Deep Learning	Deep Learning 2.0
Main idea	Convolution	Attention
Field invented	Computer vision	NLP
Started	NeurIPS 2012	NeurIPS 2017
Paper	AlexNet	Transformers
Conquered vision	Around 2014-2015	Around 2020-2021
~~Replaced~~ (Augmented)	Traditional ML/CV	CNNs, RNNs

Transformers

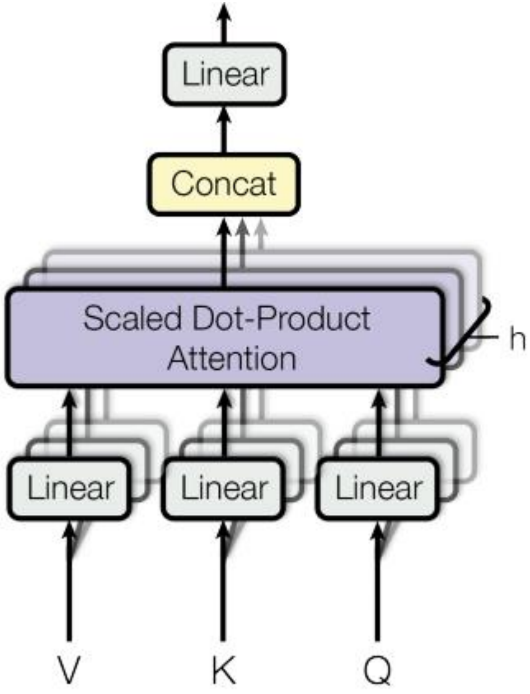
Fully connected layer

Multi-Head Attention on the "encoder"



Masked Multi-Head Attention on the "decoder"

Multi-Head Attention



Intuition: Take the query Q, find the most similar key K, and then find the value V that corresponds to the key.

In other words, learn V, K, Q where:
V – here is a bunch of interesting things.
K – here is how we can index some things.
Q – I would like to know this interesting thing.

Loosely connected to Neural Turing Machines (Graves et al.).

Multi-Head Attention

Index the values via a differentiable operator.

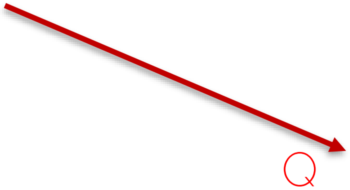
Multiply queries with keys

Get the values

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

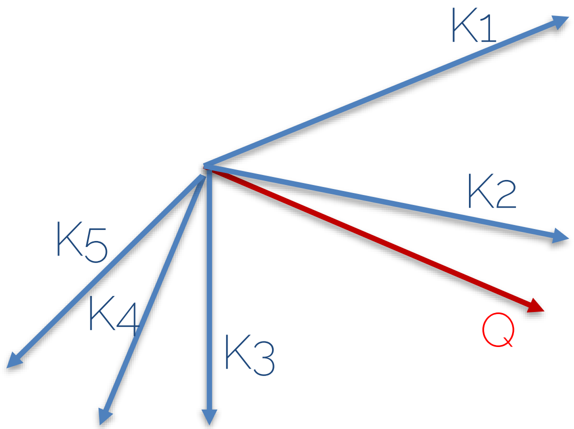
To train them well, divide by $\sqrt{d_k}$, "probably" because for large values of the key's dimension, the dot product grows large in magnitude, pushing the softmax function into regions where it has extremely small gradients.

Multi-Head Attention

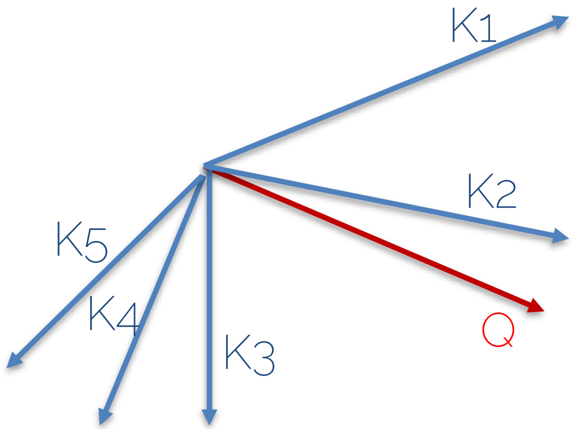


Adapted from Y. Kilcher

Multi-Head Attention

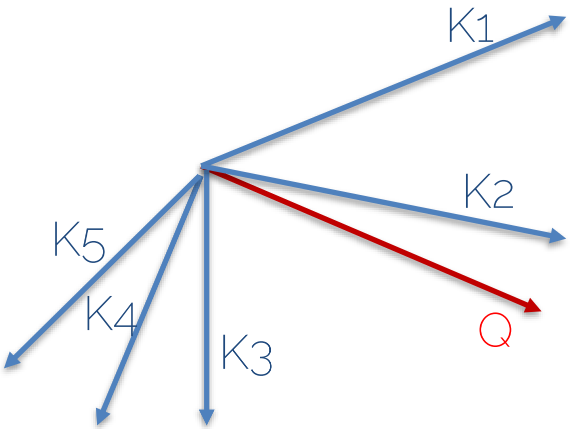


Multi-Head Attention



Values
V1
V2
V3
V4
V5

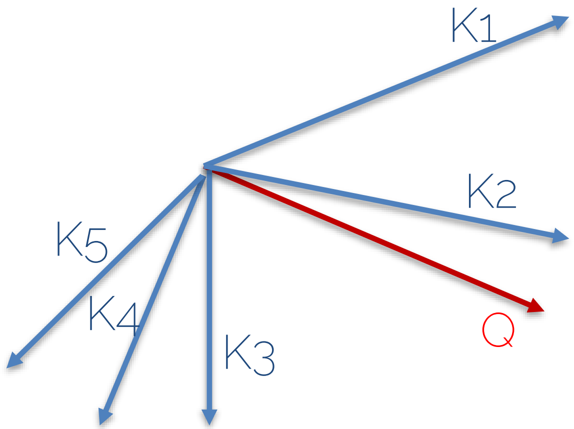
Multi-Head Attention



Values
V1
V2
V3
V4
V5

QK^T Essentially, dot product between (<Q,K1>), (<Q,K2>), (<Q,K3>), (<Q,K4>), (<Q,K5>).

Multi-Head Attention

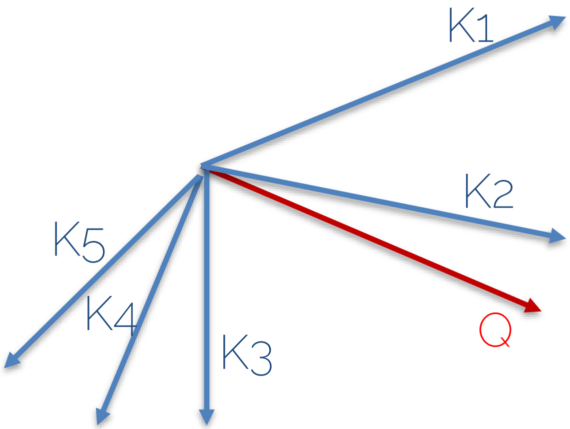


Values
V1
V2
V3
V4
V5

$$\mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)$$

Is simply inducing a distribution over the values.
The larger a value is, the higher is its softmax value.
Can be interpreted as a differentiable soft indexing.

Multi-Head Attention



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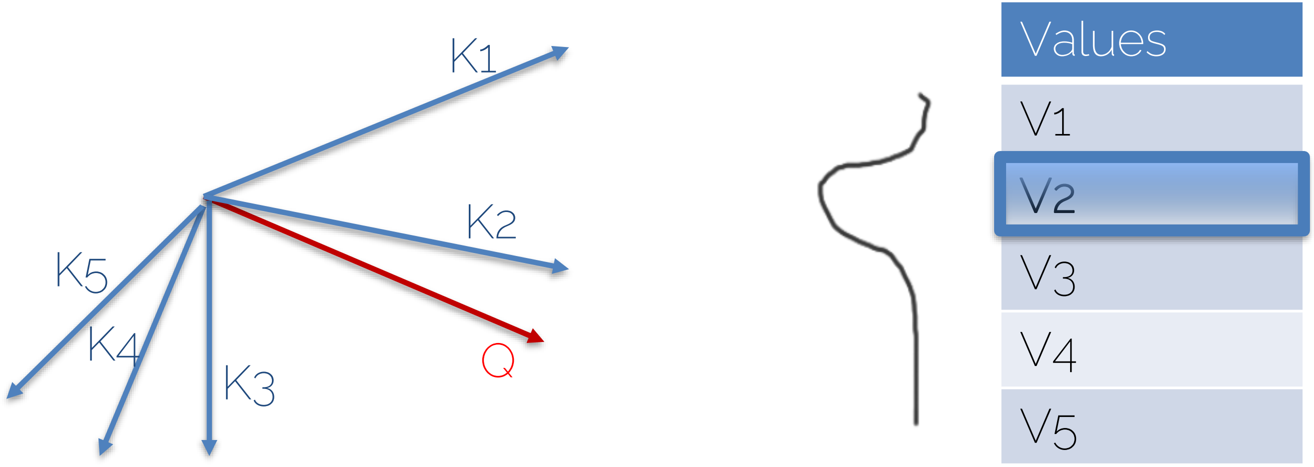
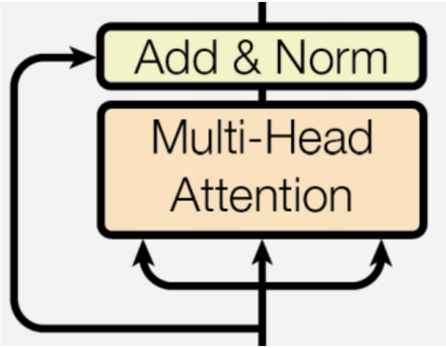


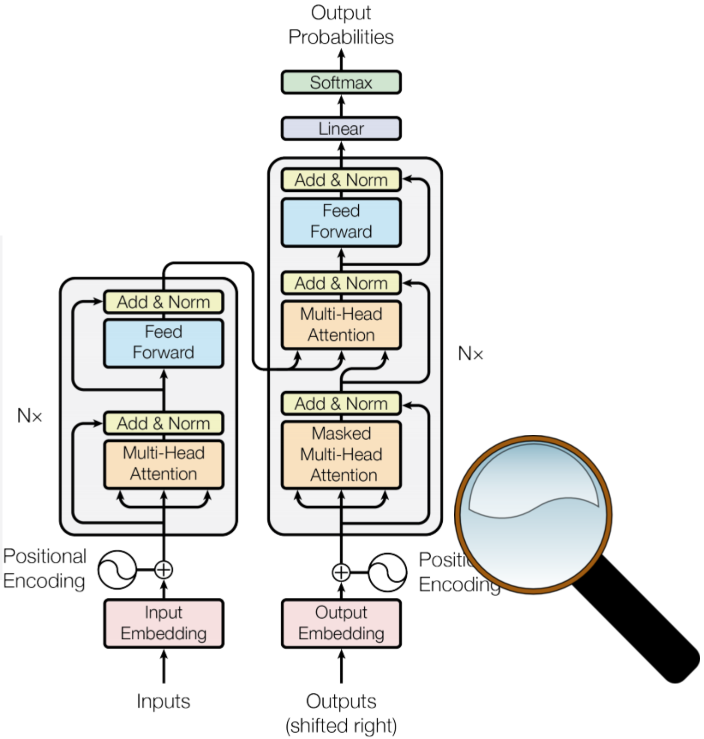
$$\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)$$

Selecting the value V where the network needs to attend..

Transformers – a closer look

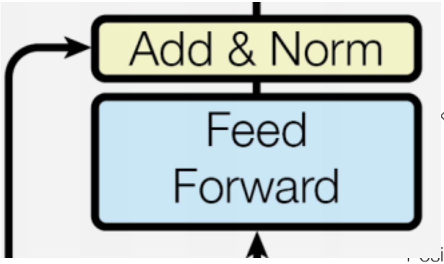
K parallel attention heads.

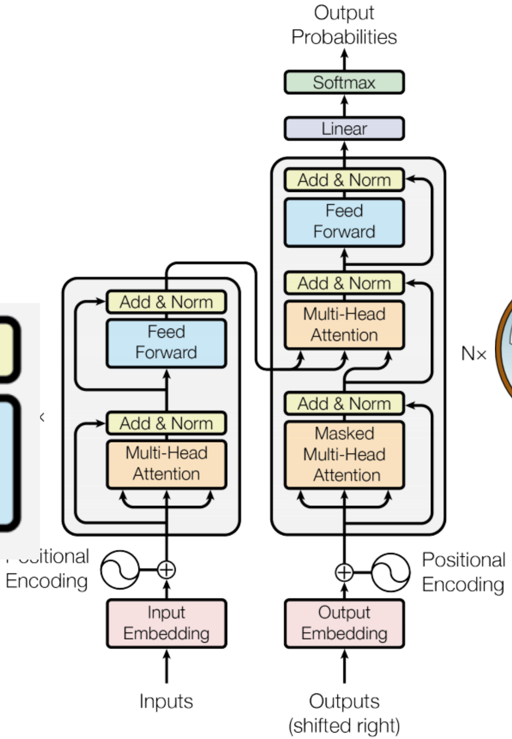




Transformers – a closer look

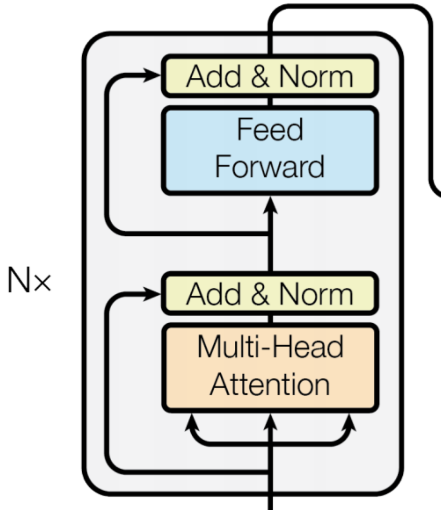
Good old fully-connected layers.

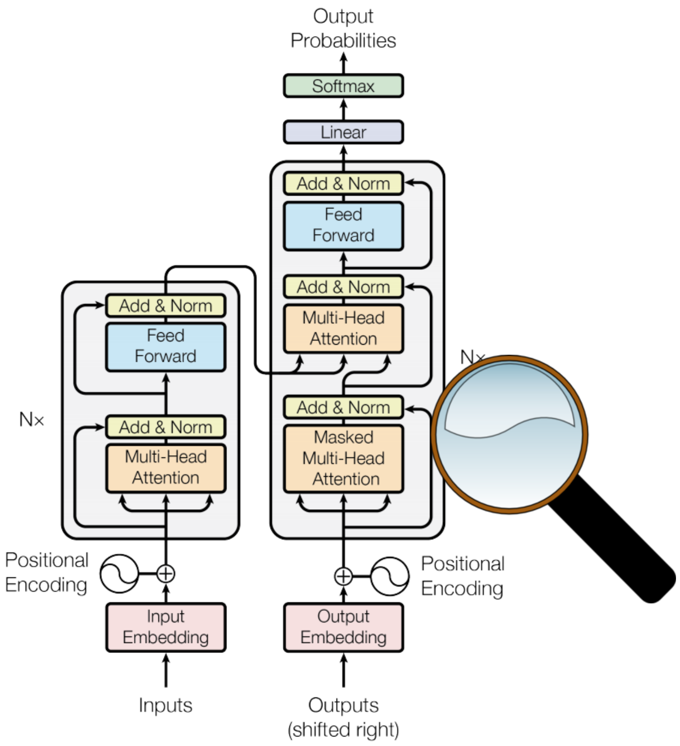




Transformers – a closer look

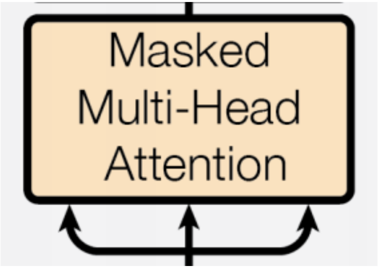
N layers of attention followed by FC

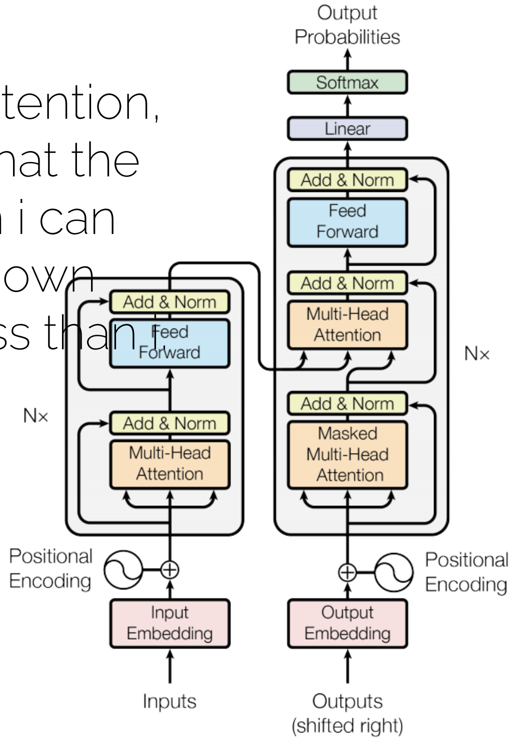




Transformers – a closer look

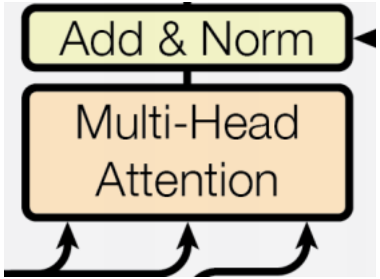
Same as multi-head attention, but masked. Ensures that the predictions for position i can depend only on the known outputs at positions less than i.

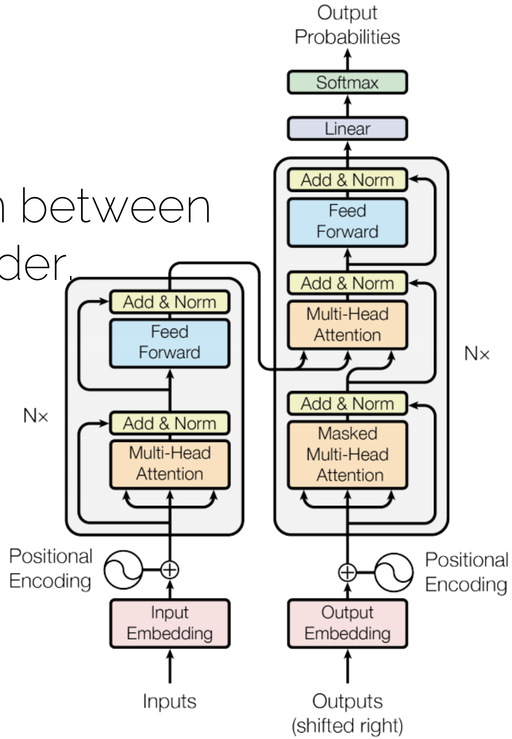




Transformers – a closer look

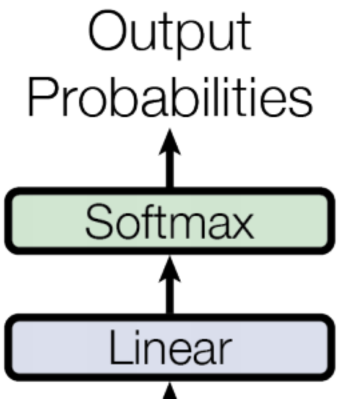
Multi-headed attention between encoder and the decoder.

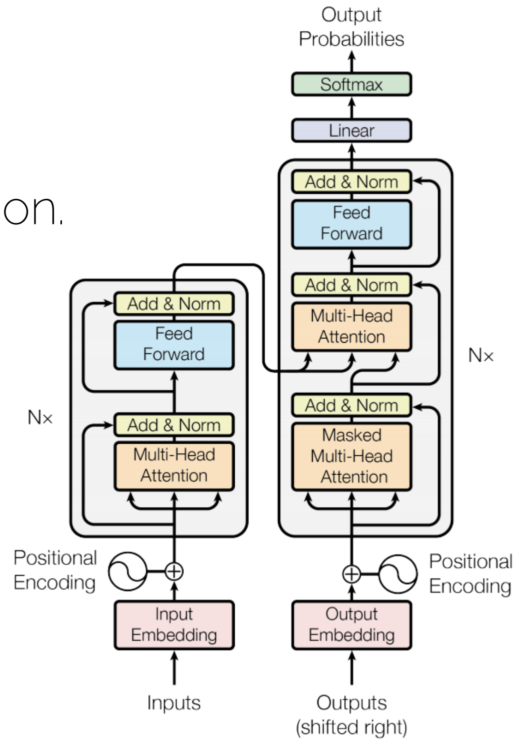




Transformers – a closer look

Projection and prediction.





What is missing from self-attention?

- Convolution: a different linear transformation for each relative position. Allows you to distinguish what information came from where.
- Self-attention: a weighted average.

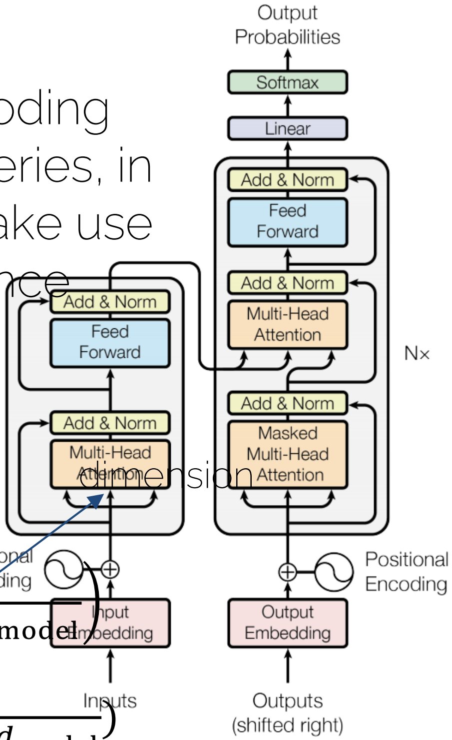
Transformers – a closer look

Uses fixed positional encoding based on trigonometric series, in order for the model to make use of the order of the sequence

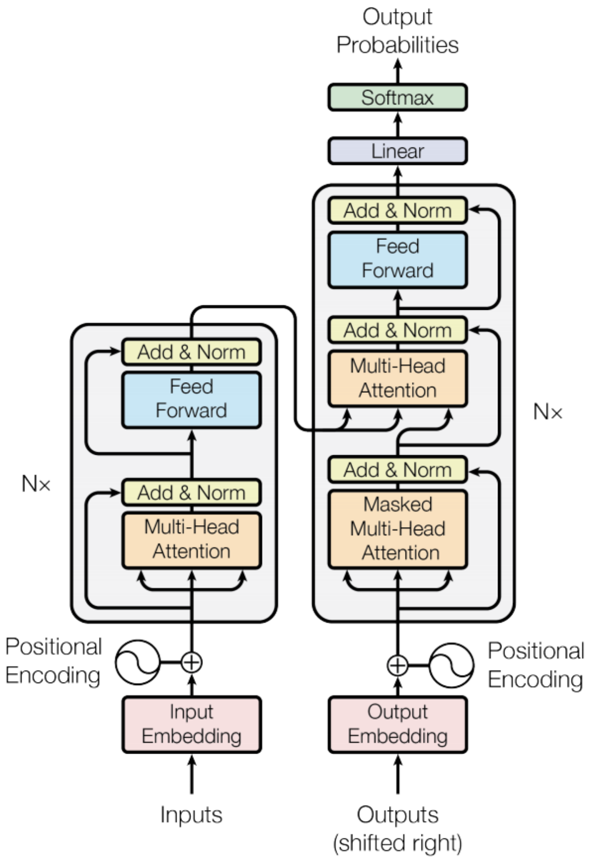
$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{2i/d_{\text{model}}}}\right)$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{2i/d_{\text{model}}}}\right)$$

dimension



Transformers – a final look



Self-attention: complexity

Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(log_k(n))$
Self-Attention (restricted)	$O(r \cdot n \cdot d)$	$O(1)$	$O(n/r)$

where n is the sequence length, d is the representation dimension,
k is the convolutional kernel size, and r is the size of the neighborhood.

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where n is the sequence length, d is the representation dimension,
k is the convolutional kernel size, and r is the size of the neighborhood.

Considering that most sentences have a smaller dimension than the representation dimension (in the paper, it is 512), self-attention is very efficient.

Transformers – training tricks

- ADAM optimizer with proportional learning rate:

$$lrate = d_{\text{model}}^{-0.5} \cdot \min(step\_num^{-0.5}, step\_num \cdot warmup\_steps^{-1.5})$$

- Residual dropout
- Label smoothing
- Checkpoint averaging

Transformers - results

Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [15]	23.75			
Deep-Att + PosUnk [32]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [31]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [8]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [26]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [32]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [31]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [8]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	$\mathbf{3.3 \cdot 10^{18}}$	
Transformer (big)	**28.4**	**41.0**	$2.3 \cdot 10^{19}$	

Transformers - summary

- Significantly improved SOTA in machine translation
- Launched a new deep-learning revolution in MLP
- Building block of NLP models like BERT (Google) or GPT/ChatGPT (OpenAI)
- BERT has been heavily used in Google Search

- And eventually made its way to computer vision (and other related fields)*

*Dosovitskiy et al. "An image is worth 16x16 words: Transformers for image recognition at scale", ICLR 2020.

See you next time!