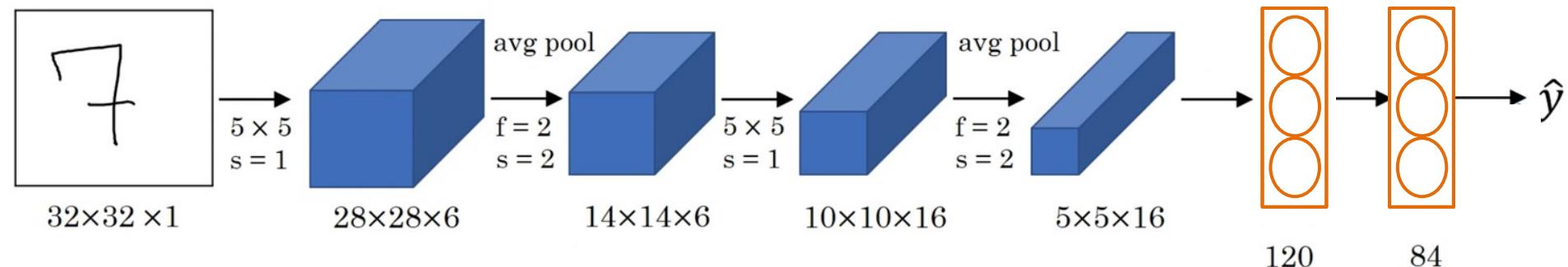


Lecture 10 Recap

LeNet

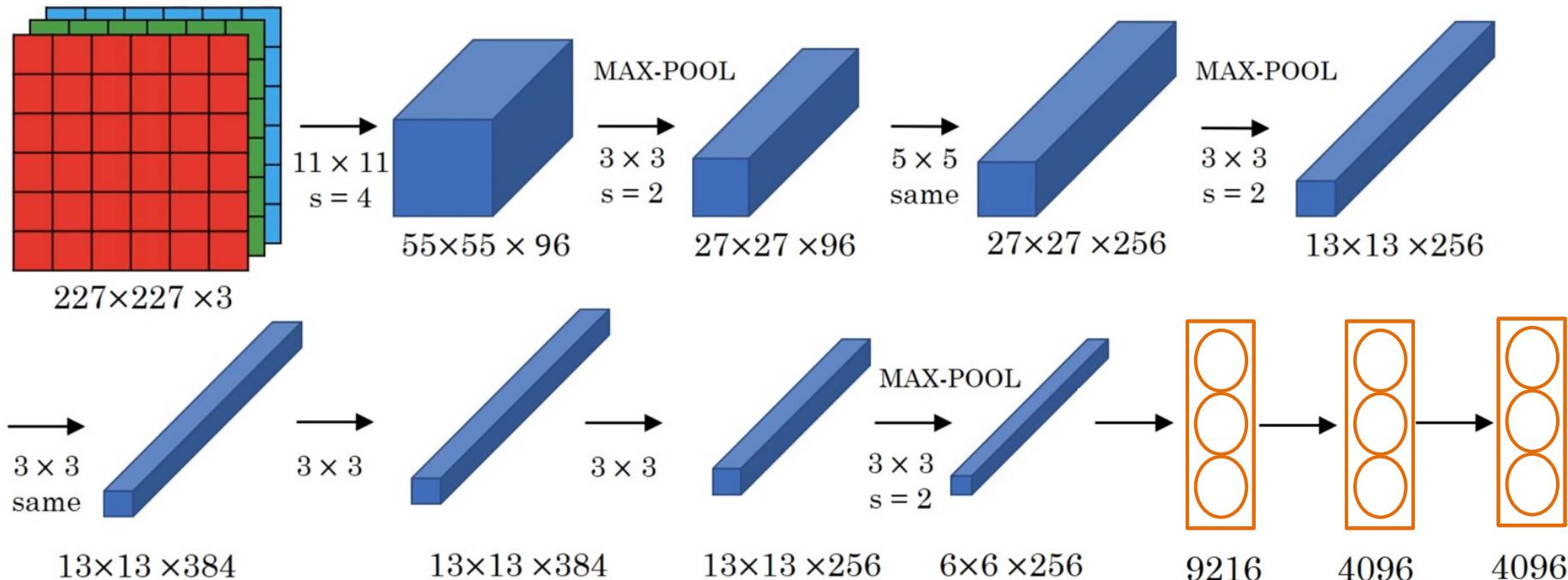
- Digit recognition: 10 classes

60k parameters



- Conv -> Pool -> Conv -> Pool -> Conv -> FC
- As we go deeper: Width, Height \downarrow Number of Filters \uparrow

AlexNet



- Softmax for 1000 classes

[Krizhevsky et al., ANIPS'12] AlexNet

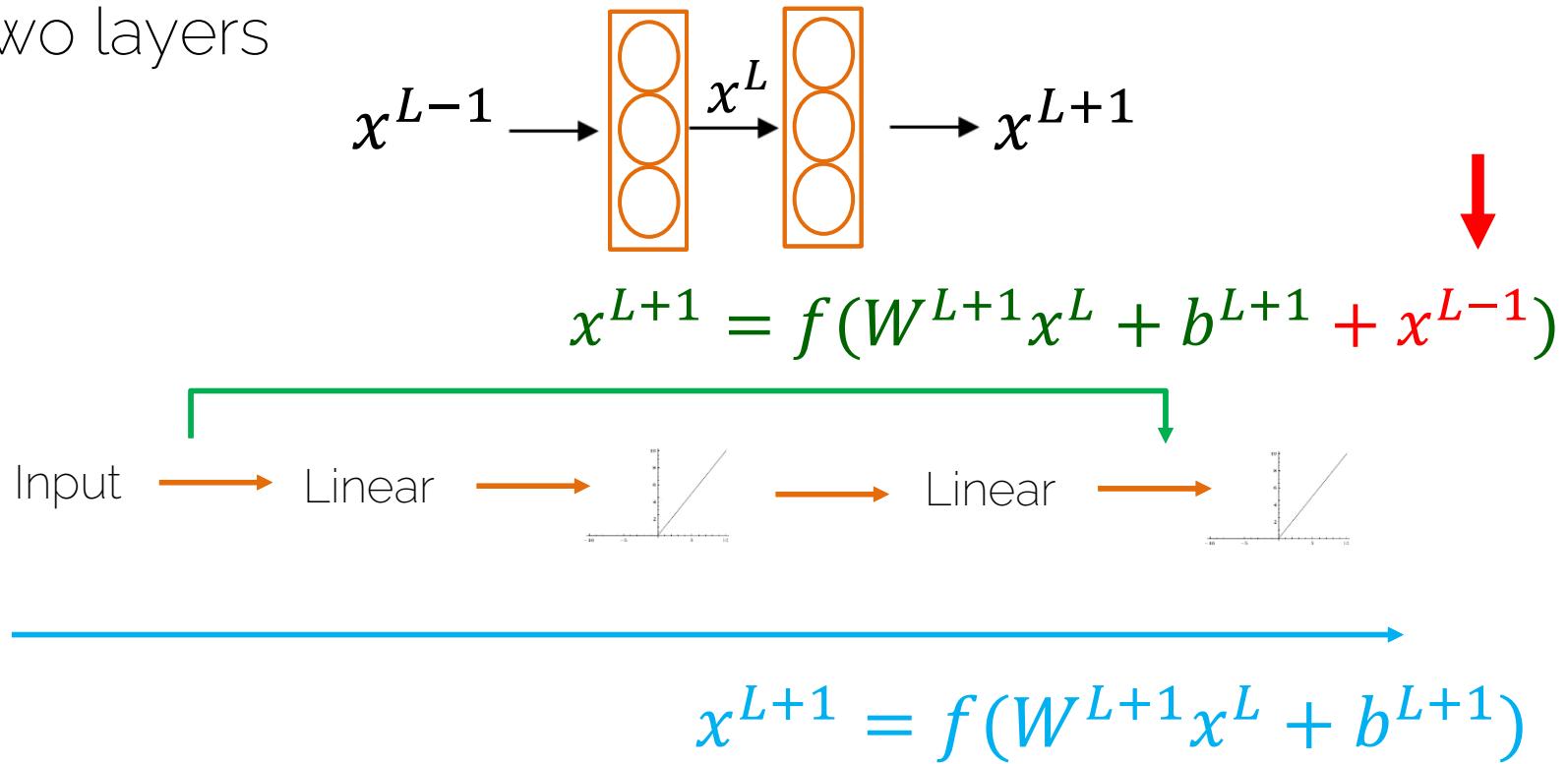
VGGNet

- Striving for simplicity
 - Conv -> Pool -> Conv -> Pool -> Conv -> FC
 - Conv=3x3, s=1, same; Maxpool=2x2, s=2
- As we go deeper: Width, Height  Number of Filters 
- Called VGG-16: 16 layers that have weights
 - 138M parameters
- Large but simplicity makes it appealing

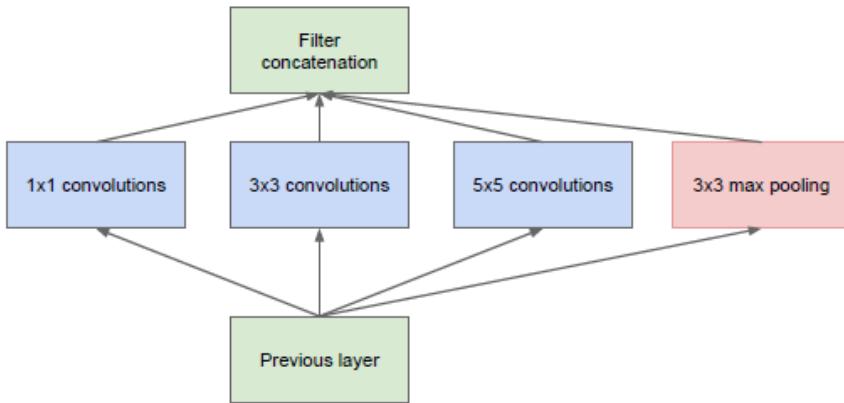
[Simonyan et al., ICLR'15] VGGNet

Residual Block

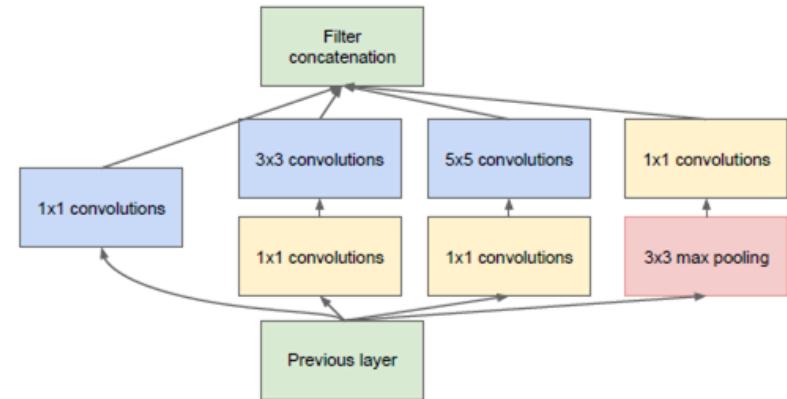
- Two layers



Inception Layer



(a) Inception module, naïve version



(b) Inception module with dimensionality reduction

[Szegedy et al., CVPR'15] GoogleNet

Lecture 11

Transfer Learning

Transfer Learning

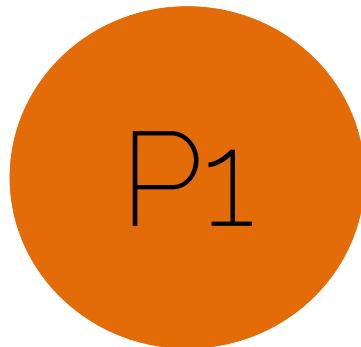
- Training your own model can be difficult with limited data and other resources

e.g.,

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

Transfer Learning

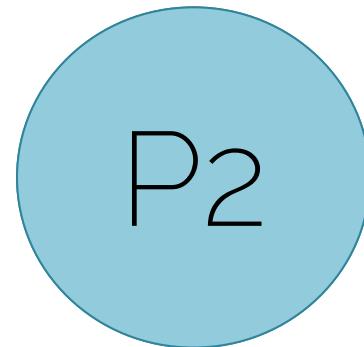
Distribution



Large dataset



Distribution

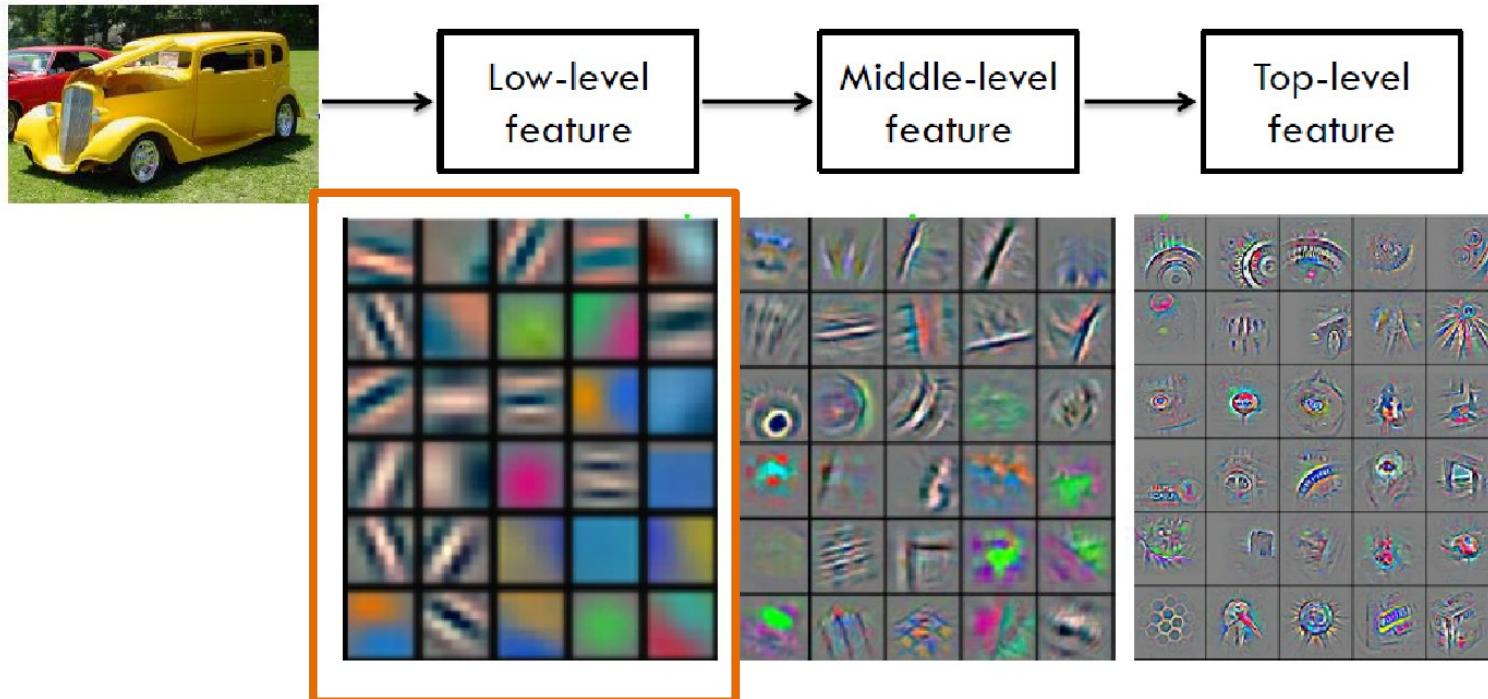


Small dataset



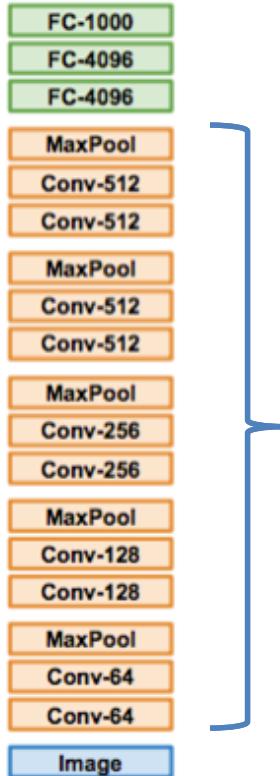
Use what has been
learned for another
setting

Transfer Learning for Images



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

Trained on
ImageNet

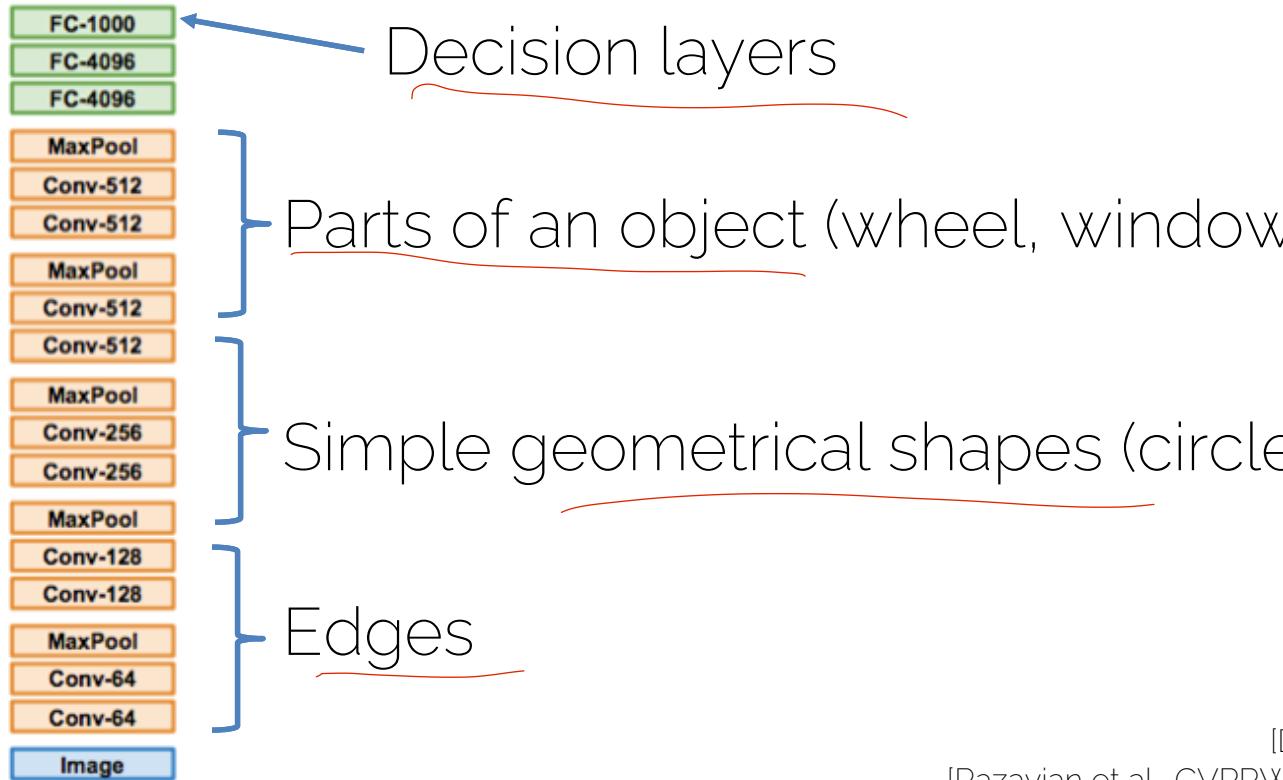


|| Feature
extraction

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

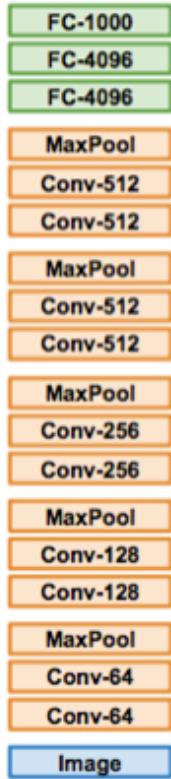
Trained on
ImageNet

Transfer Learning

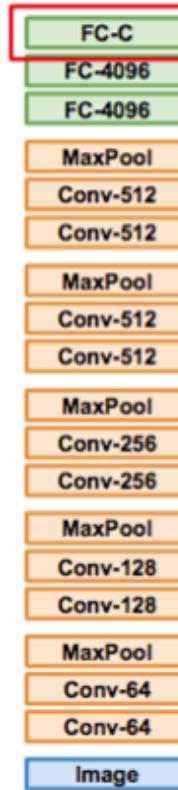


[Donahue et al., ICML'14] DeCAF,
[Razavian et al., CVPRW'14] CNN Features off-the-shelf

Trained on
ImageNet



Transfer Learning



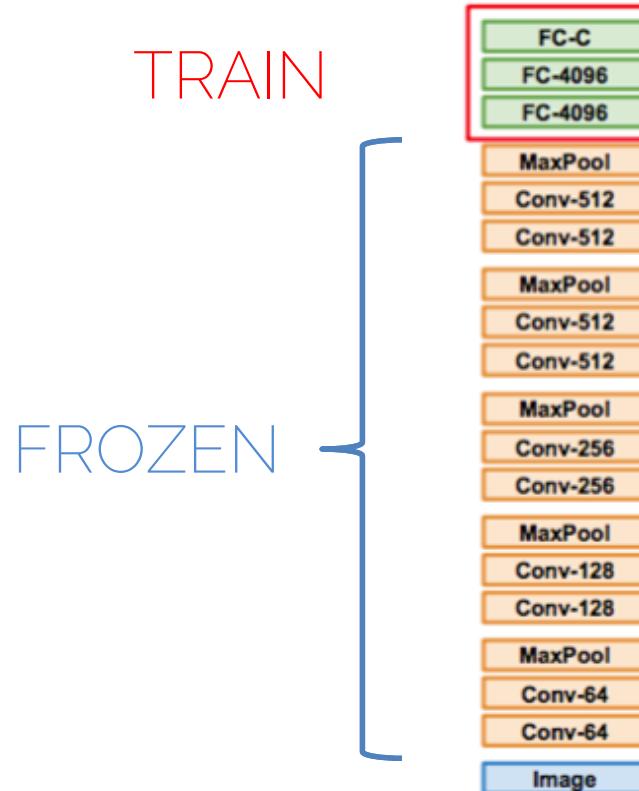
New dataset
with C classes

FROZEN

[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

Now you are:

- Ready to perform image classification on any dataset
- Ready to design your own architecture
- Ready to deal with other problems such as semantic segmentation (Fully Convolutional Network)

Representation Learning

Learning Good Features

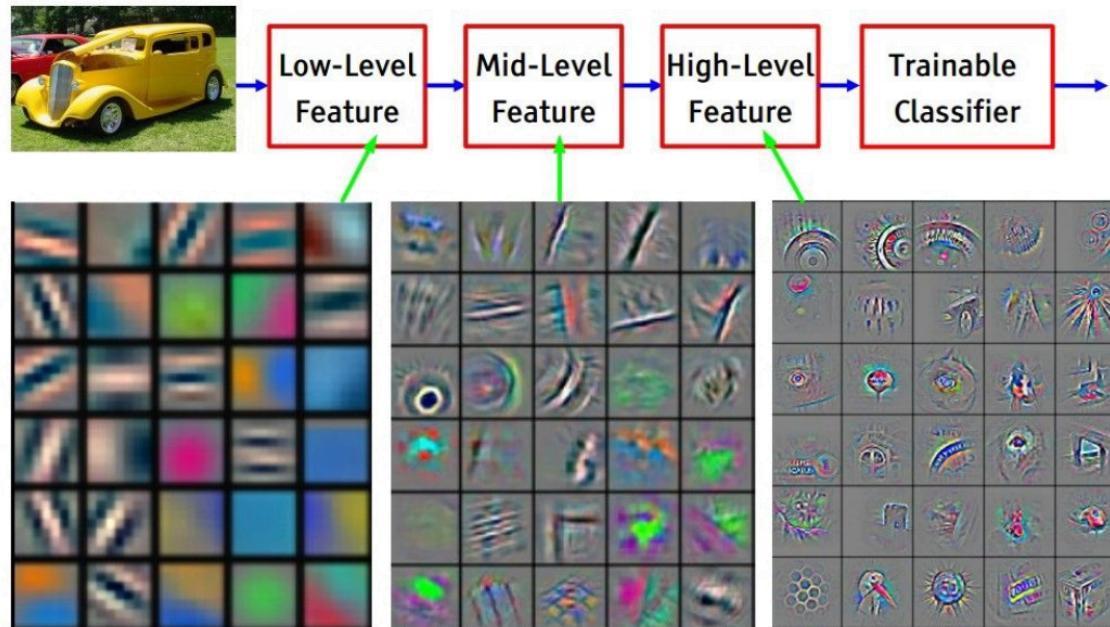
- Good features are essential for successful machine learning
- (Supervised) deep learning depends on training data used: input/target labels
- Change in inputs (noise, irregularities, etc) can result in drastically different results

Representation Learning

- Allows for discovery of representations required for various tasks
- Deep representation learning: model maps input \mathbf{X} to output \mathbf{Y}

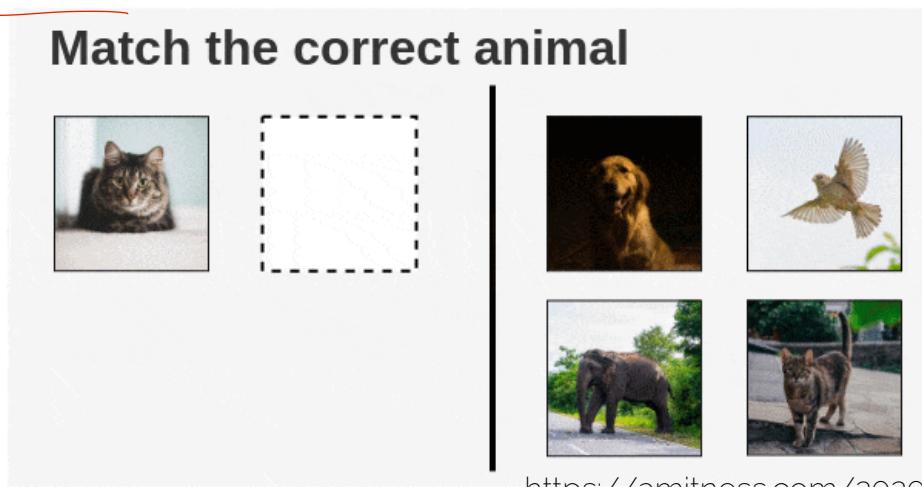
Deep Representation Learning

- Intuitively, deep networks learn multiple levels of abstraction

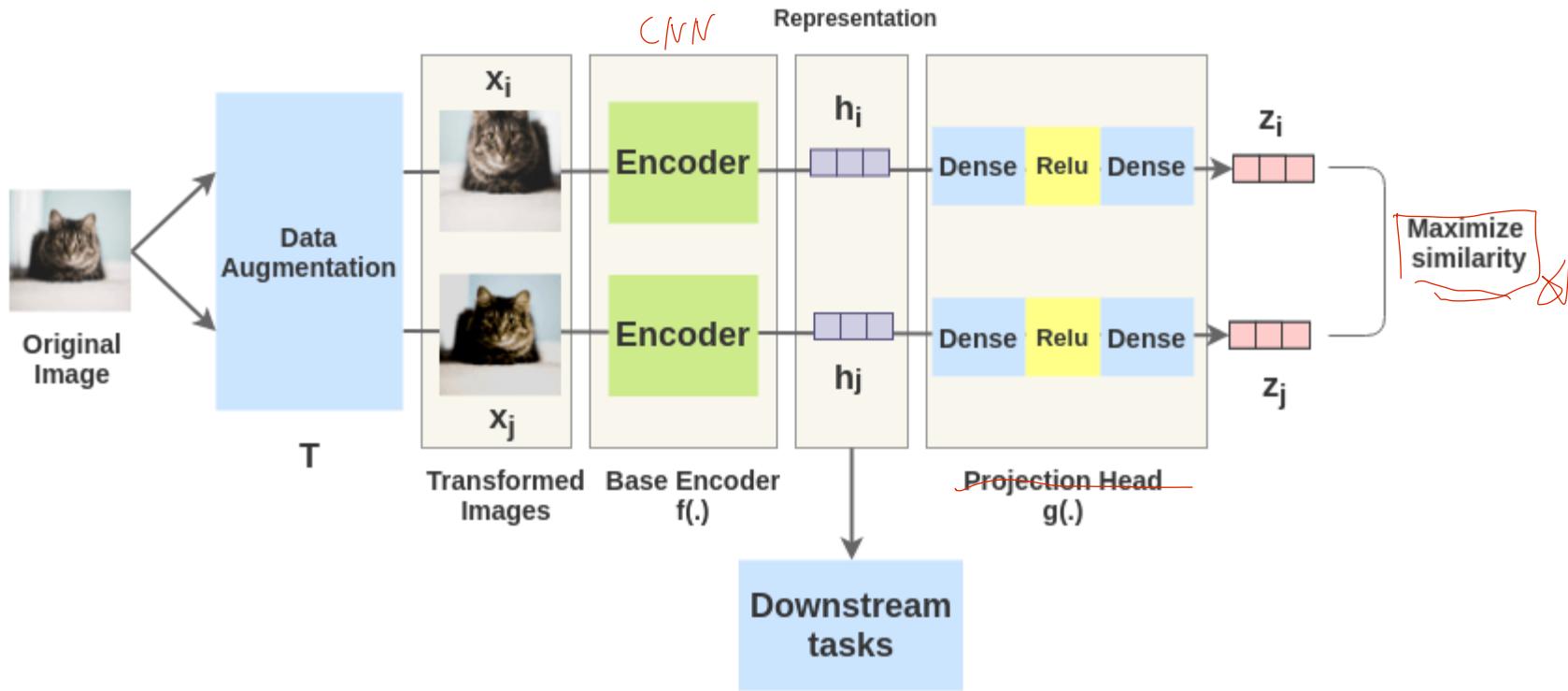


How to Learn Good Features?

- Determine desired feature invariances
- Teach machines to distinguish between similar and dissimilar things

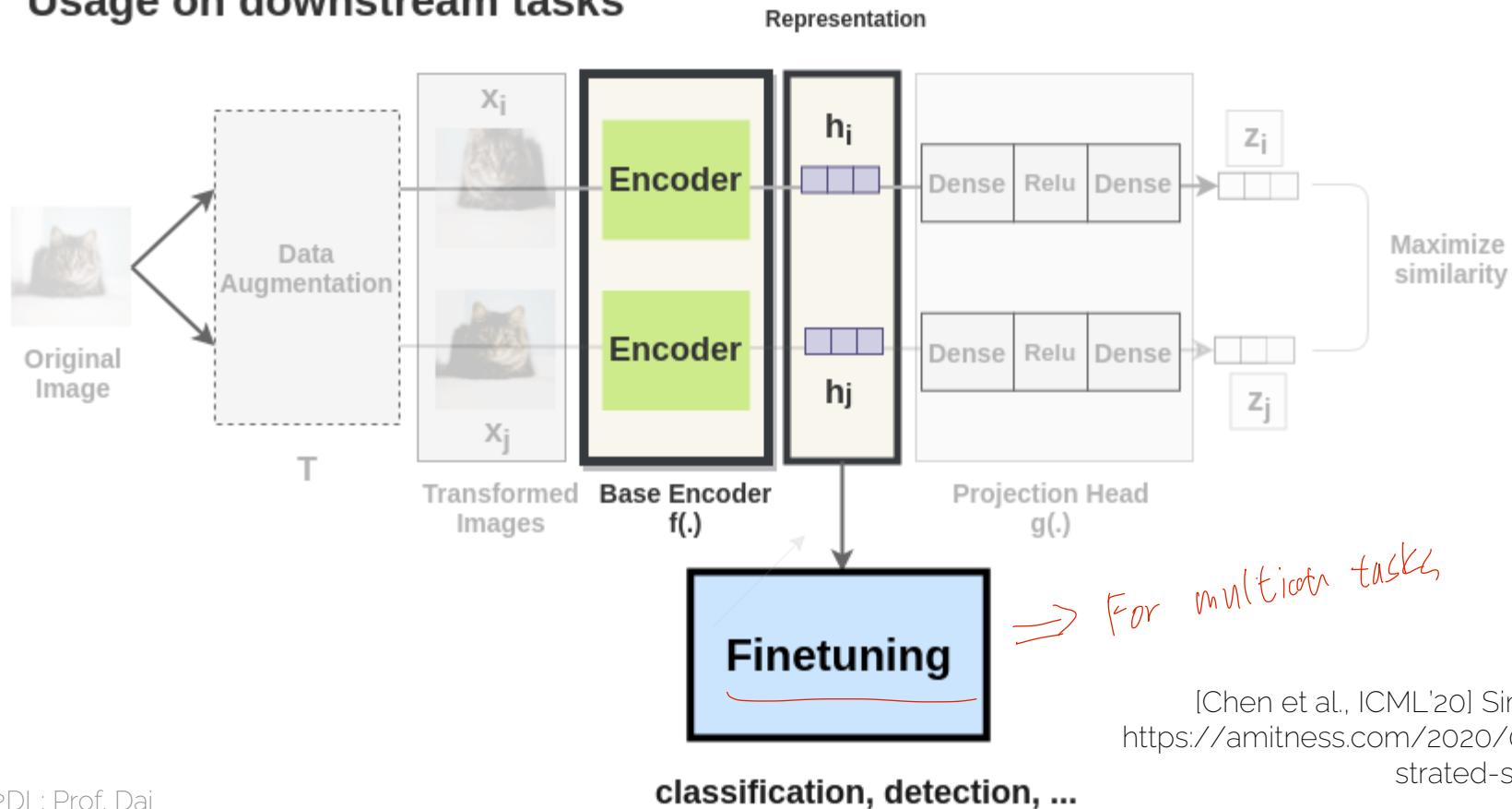


How to Learn Good Features?



Apply to Downstream Tasks

Usage on 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)

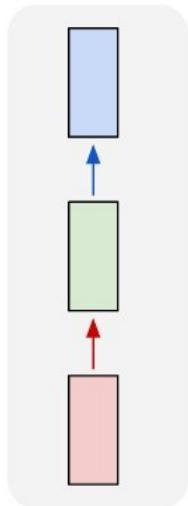
Recurrent Neural Networks

Processing Sequences

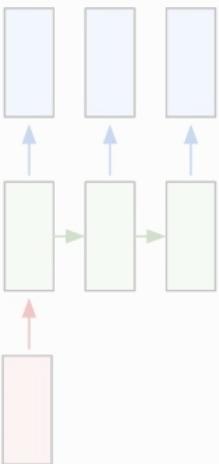
- Recurrent neural networks process sequence data
- Input/output can be sequences

RNNs are Flexible

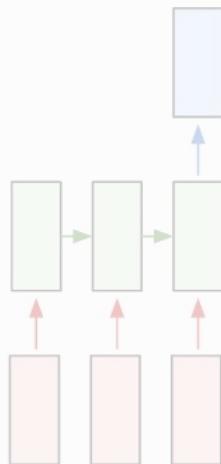
one to one



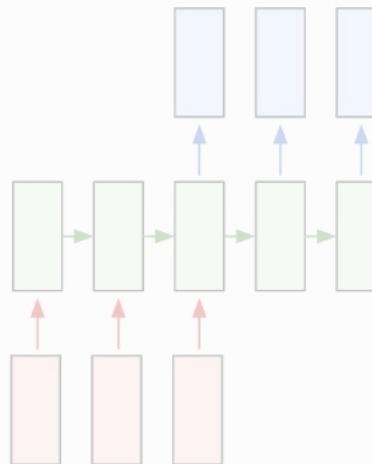
one to many



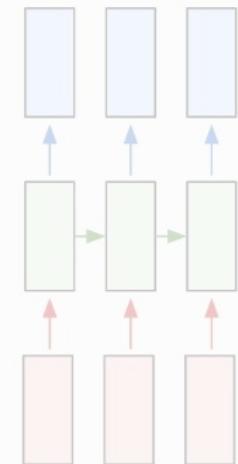
many to one



many to many



many to many



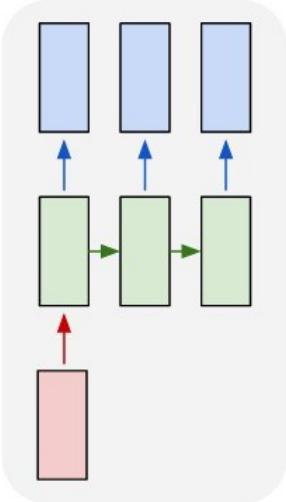
Classical neural networks for image classification

RNNs are Flexible

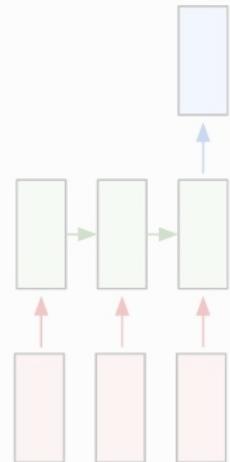
one to one



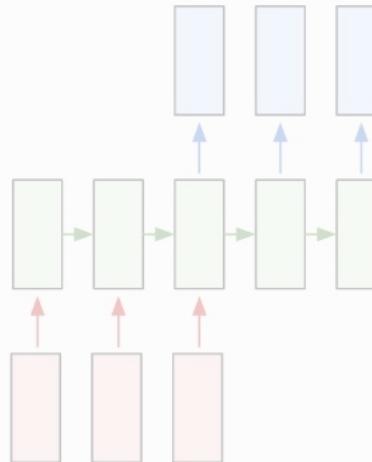
one to many



many to one



many to many



many to many

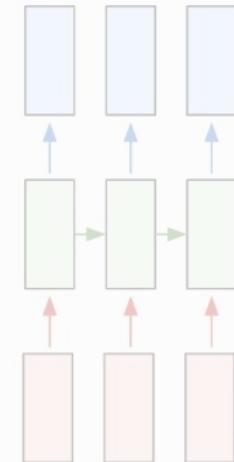


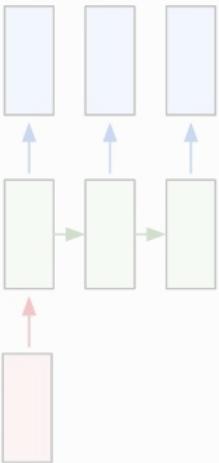
Image captioning

RNNs are Flexible

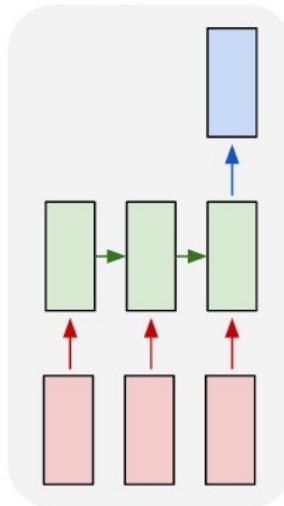
one to one



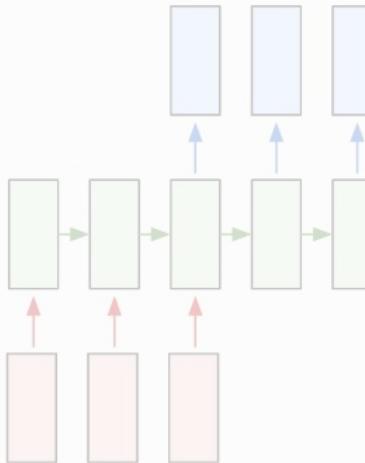
one to many



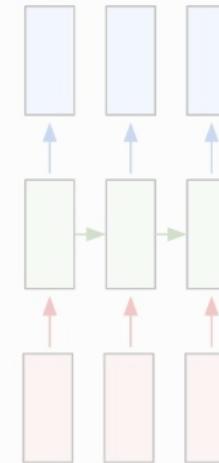
many to one



many to many



many to many



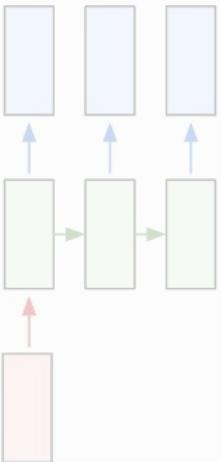
Language recognition

RNNs are Flexible

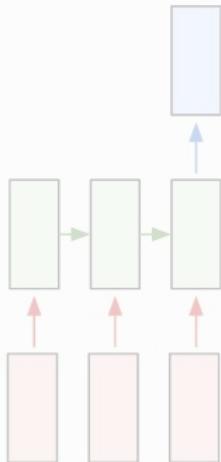
one to one



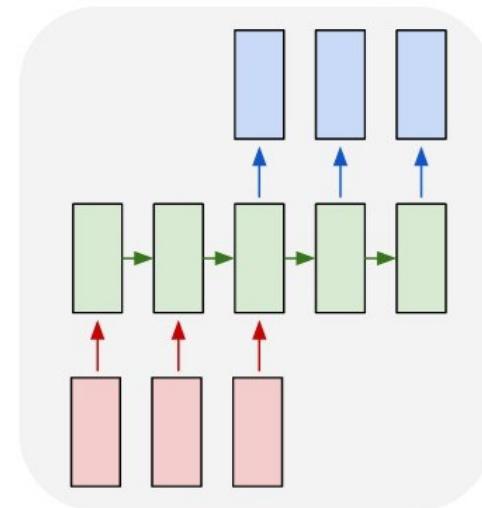
one to many



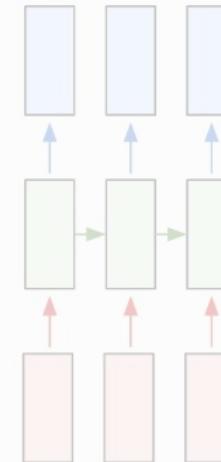
many to one



many to many



many to many



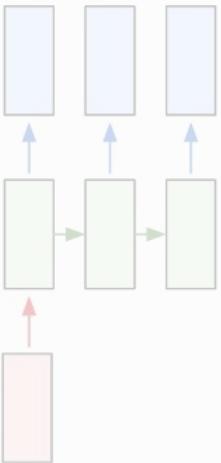
Machine translation

RNNs are Flexible

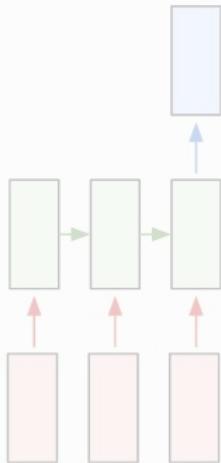
one to one



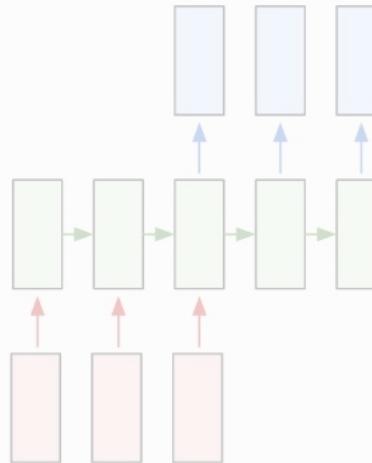
one to many



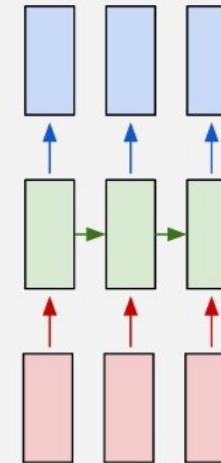
many to one



many to many



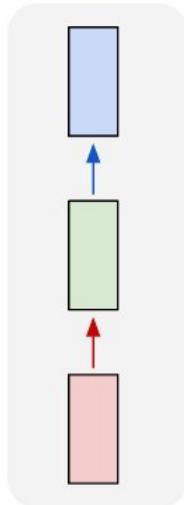
many to many



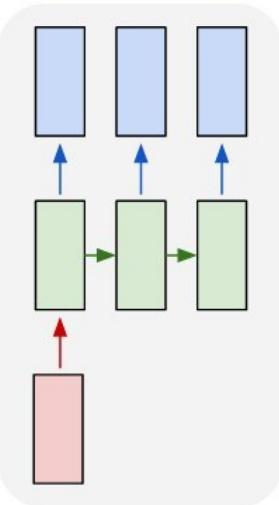
Event classification

RNNs are Flexible

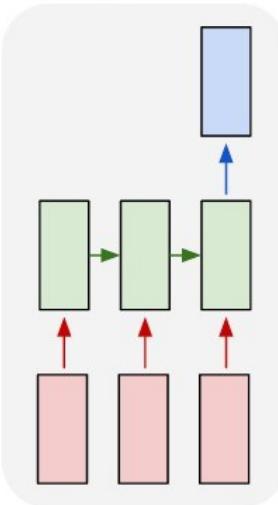
one to one



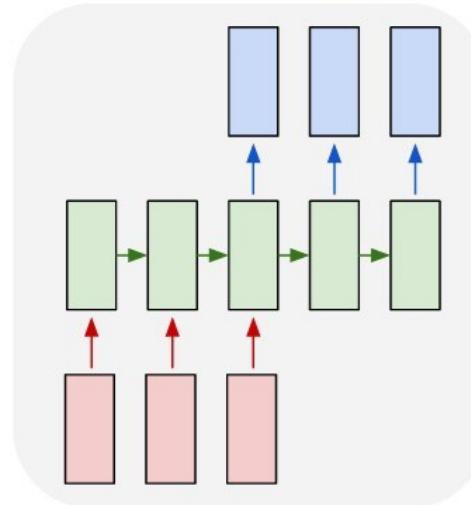
one to many



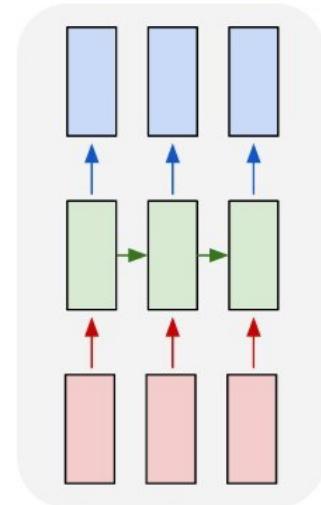
many to one



many to many



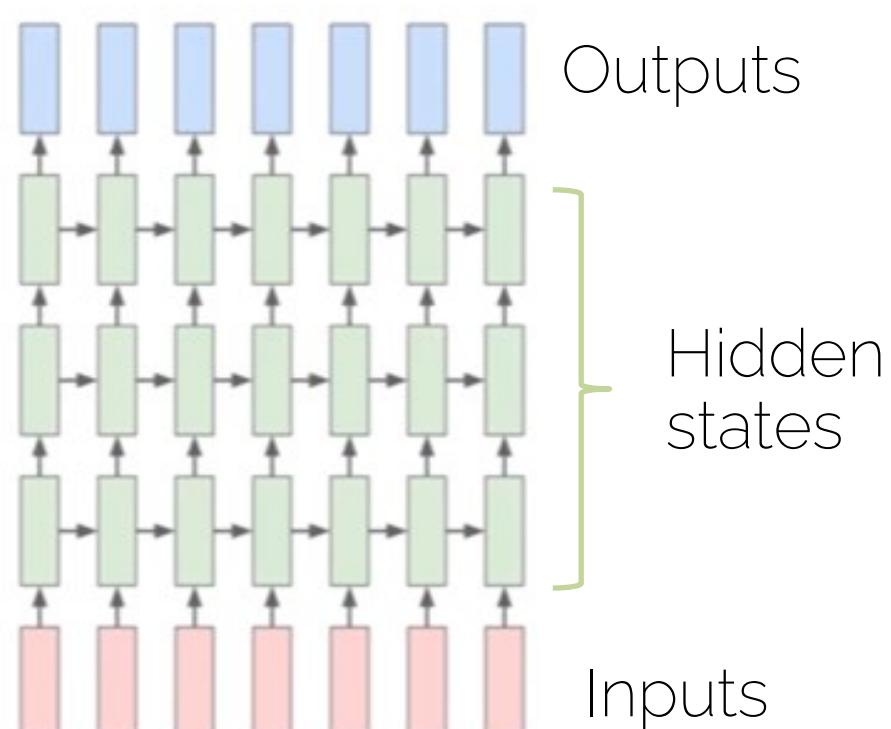
many to many



Event classification

Basic Structure of an RNN

- Multi-layer RNN

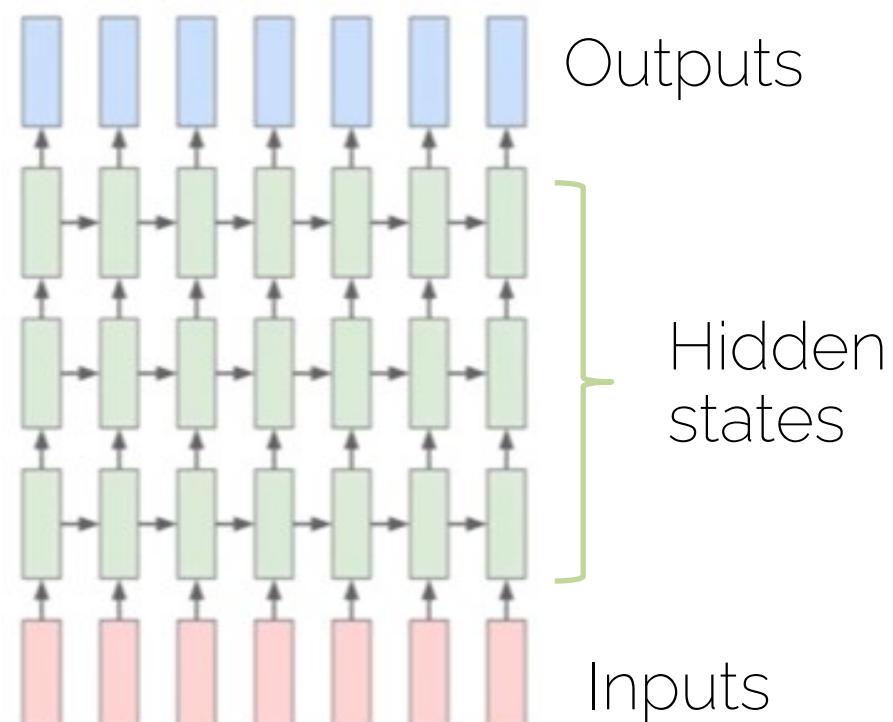


Basic Structure of an RNN

- Multi-layer RNN

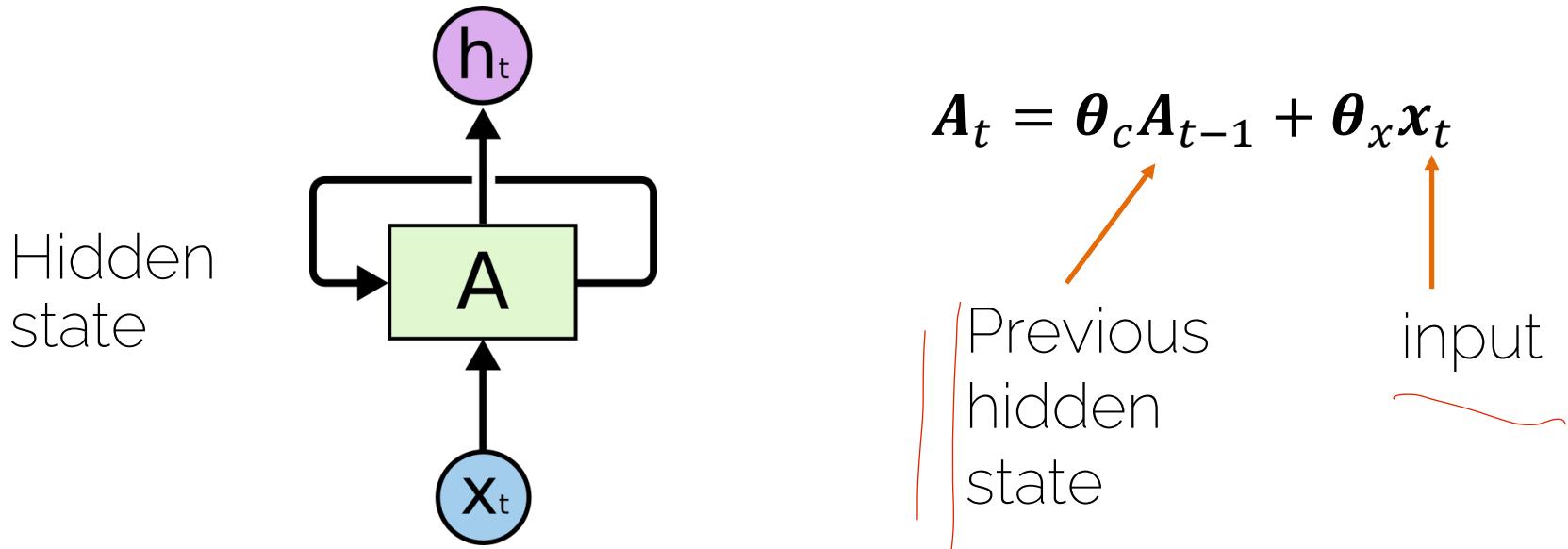
The hidden state
will have its own
internal dynamics

More expressive
model!



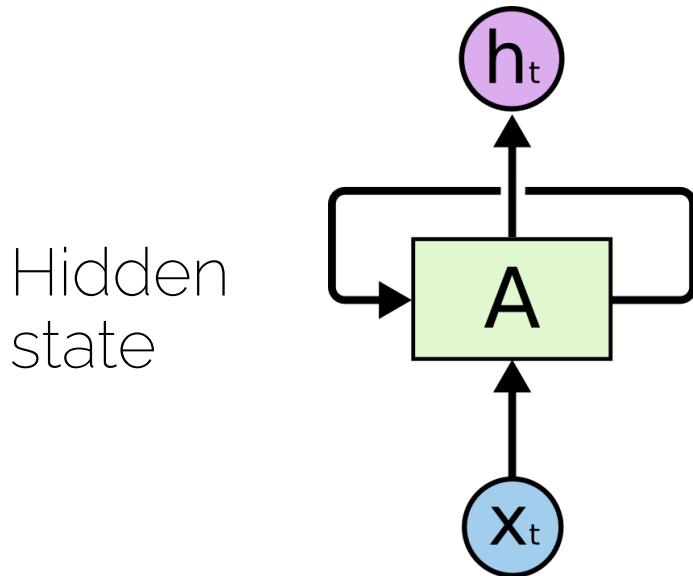
Basic Structure of an RNN

- We want to have notion of “time” or “sequence”



Basic Structure of an RNN

- We want to have notion of “time” or “sequence”

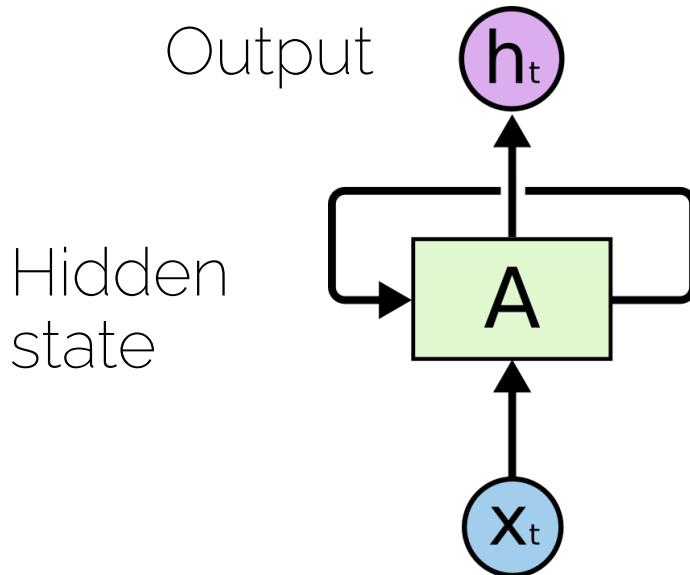


$$A_t = \theta_c A_{t-1} + \theta_x x_t$$

Parameters to be learned

Basic Structure of an RNN

- We want to have notion of “time” or “sequence”

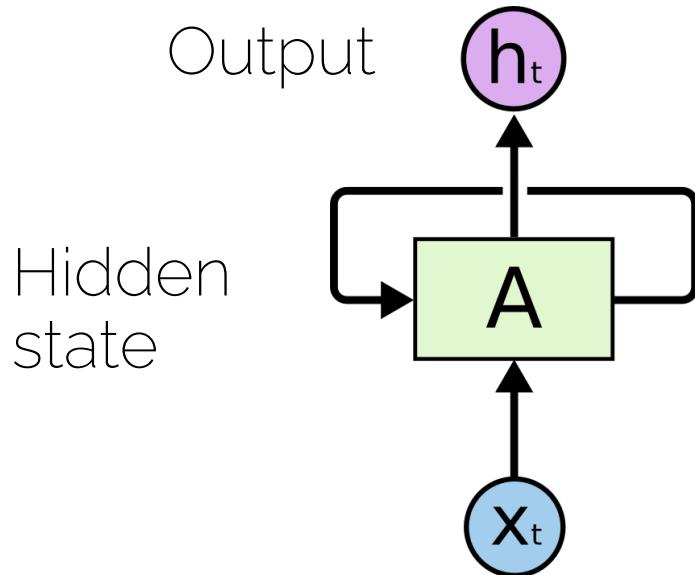


$$\begin{aligned} A_t &= \theta_c A_{t-1} + \theta_x x_t \\ h_t &= \theta_h A_t \end{aligned}$$

Note: non-linearities
ignored for now

Basic Structure of an RNN

- We want to have notion of “time” or “sequence”



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

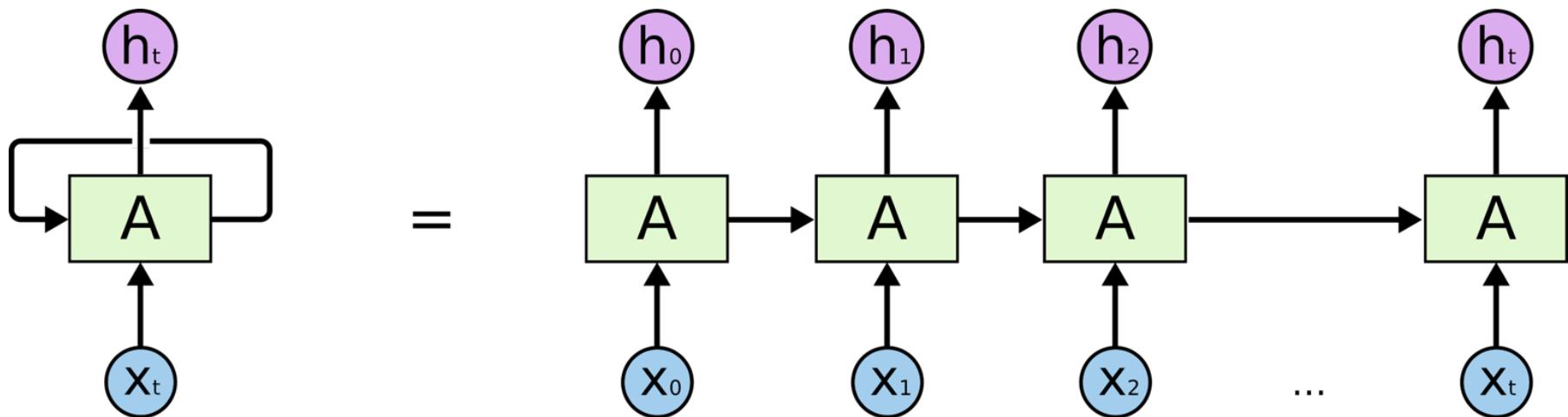
$$h_t = \theta_h A_t$$

Same parameters for each
time step = generalization!

Basic Structure of an RNN

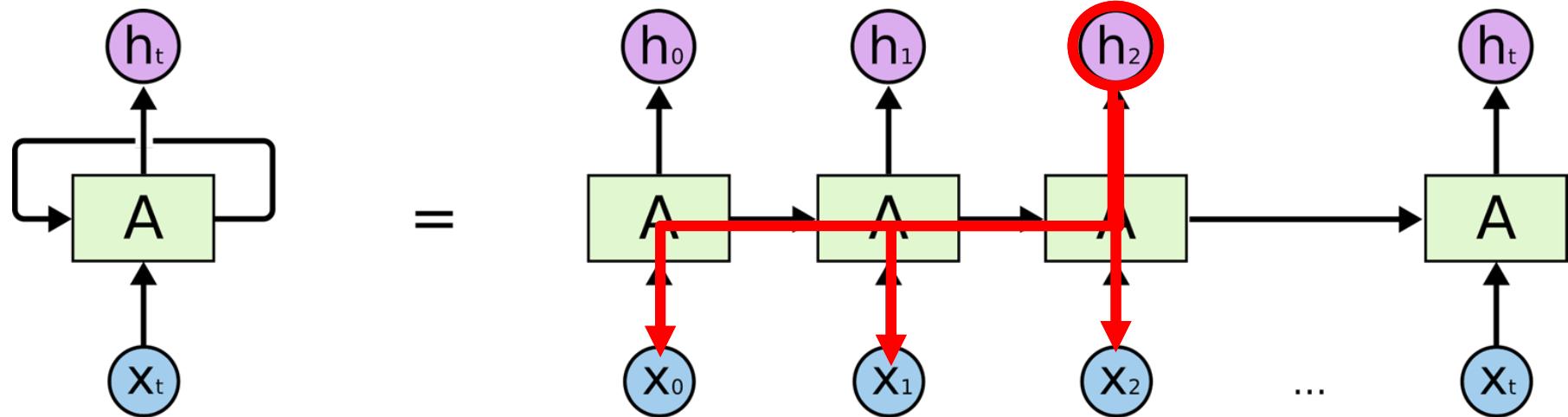
- Unrolling RNNs

Same function for the hidden layers



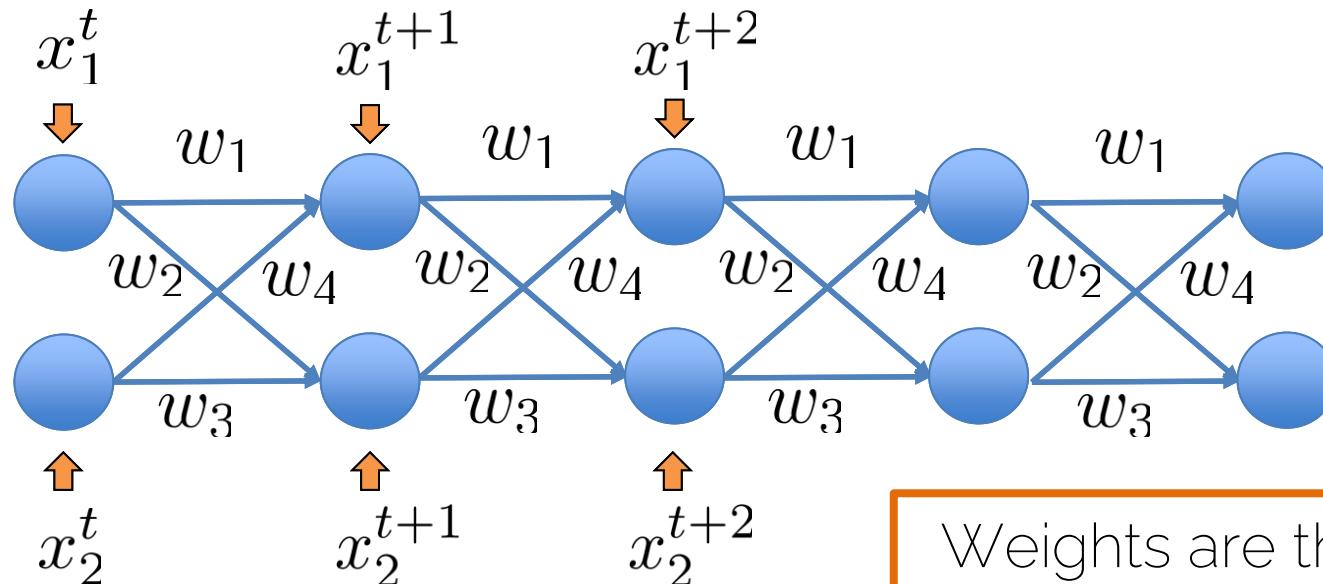
Basic Structure of an RNN

- Unrolling RNNs



Basic Structure of an RNN

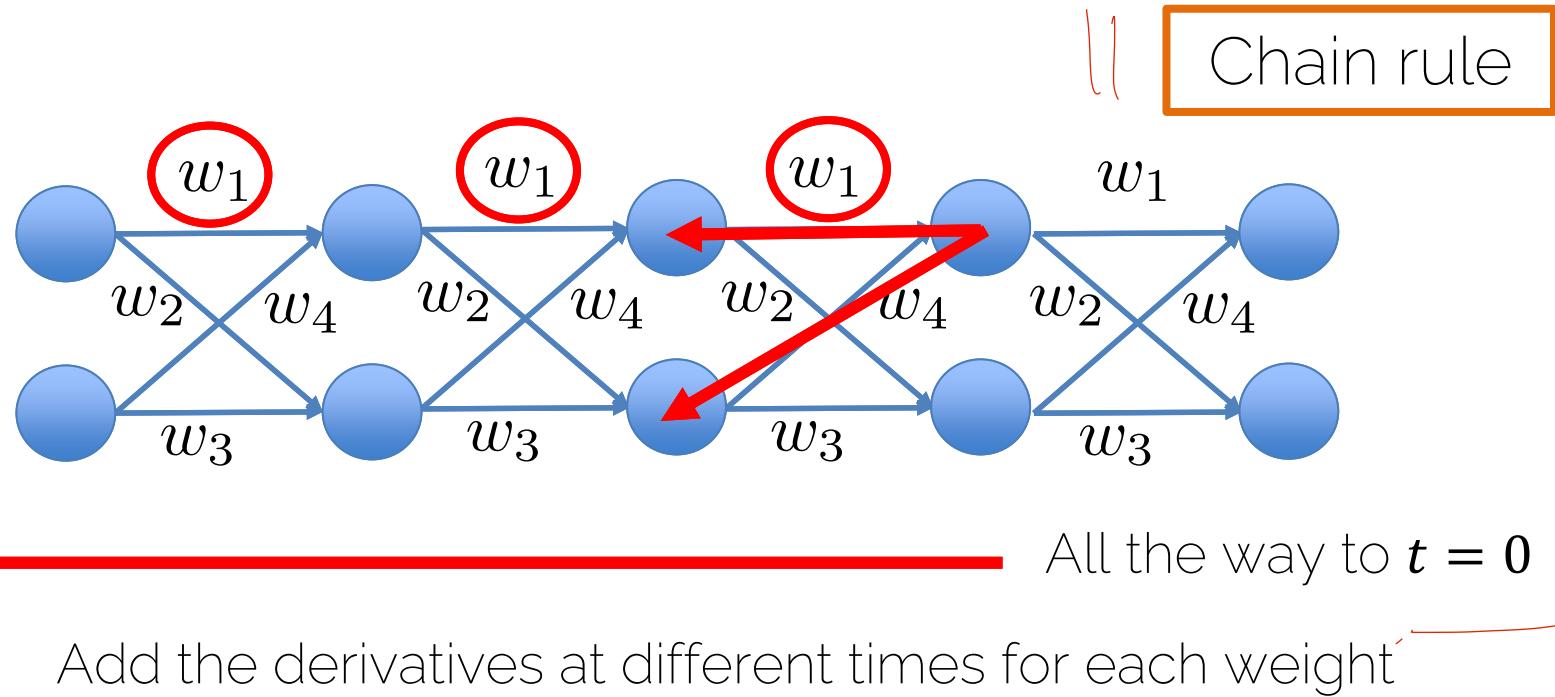
- Unrolling RNNs as feedforward nets



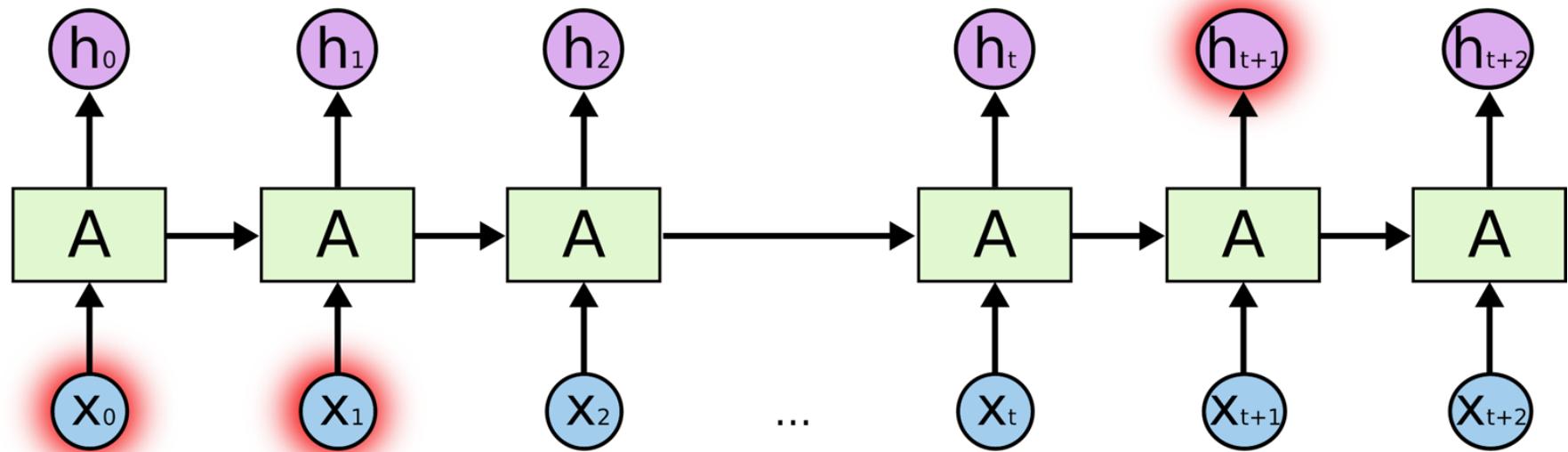
Weights are the same!

Backprop through an RNN

- Unrolling RNNs as feedforward nets



Long-term Dependencies



I moved to Germany ...

so I speak German fluently.

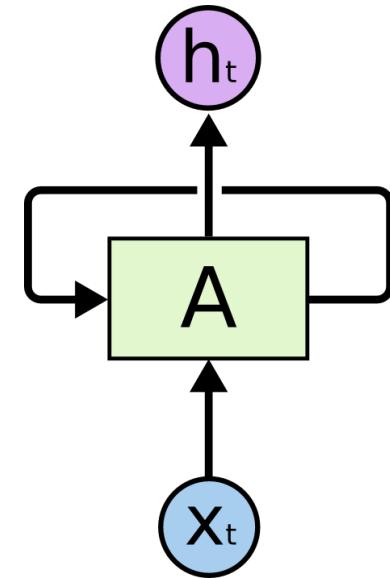
Long-term Dependencies

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

- Let us forget the input

$$A_t = \theta_c^t A_0$$

|| Same weights are
multiplied over and over
again



Long-term Dependencies

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

What happens to small weights?

Vanishing gradient

What happens to large weights?

Exploding gradient

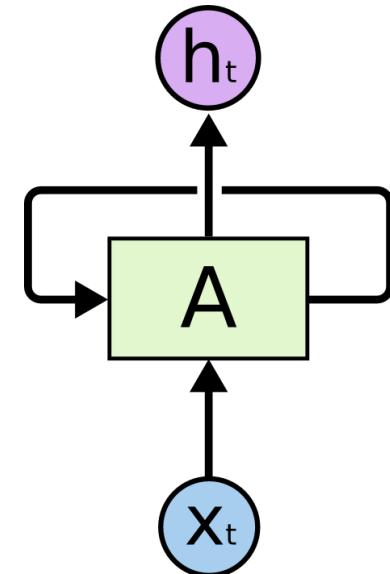
Long-term Dependencies

- Simple recurrence $\mathbf{A}_t = \boldsymbol{\theta}_c^t \mathbf{A}_0$
- If $\boldsymbol{\theta}$ admits eigendecomposition

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

Matrix of
eigenvectors

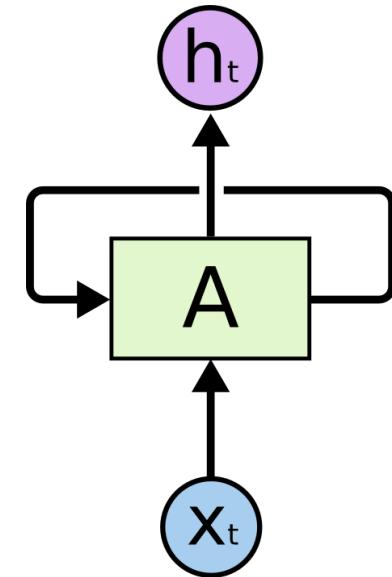
Diagonal of this
matrix are the
eigenvalues



Long-term Dependencies

- Simple recurrence $\mathbf{A}_t = \boldsymbol{\theta}^t \mathbf{A}_0$
- If $\boldsymbol{\theta}$ admits eigendecomposition

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



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

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

Long-term Dependencies

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

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

$$\mathbf{A}_t = \theta_c^t \mathbf{A}_0$$

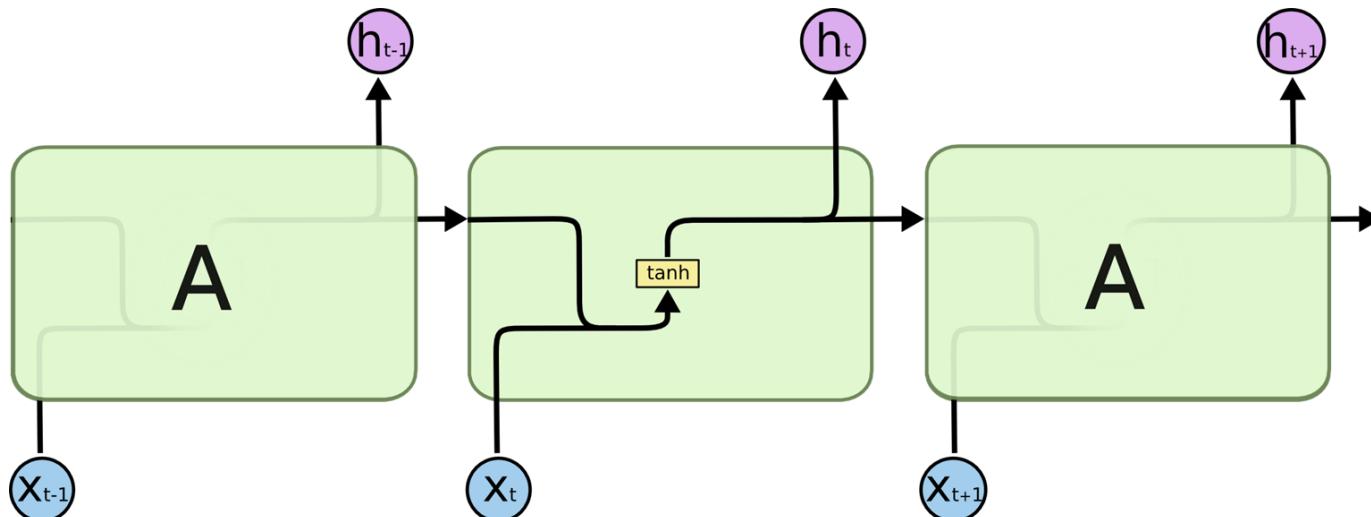
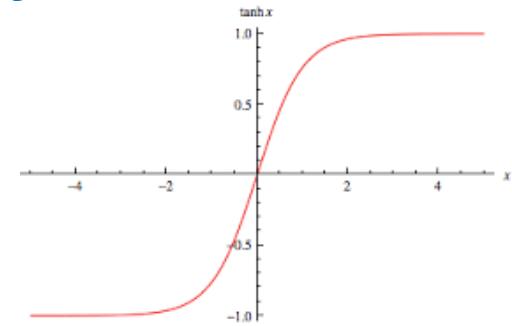


Let us just make a matrix with eigenvalues = 1

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

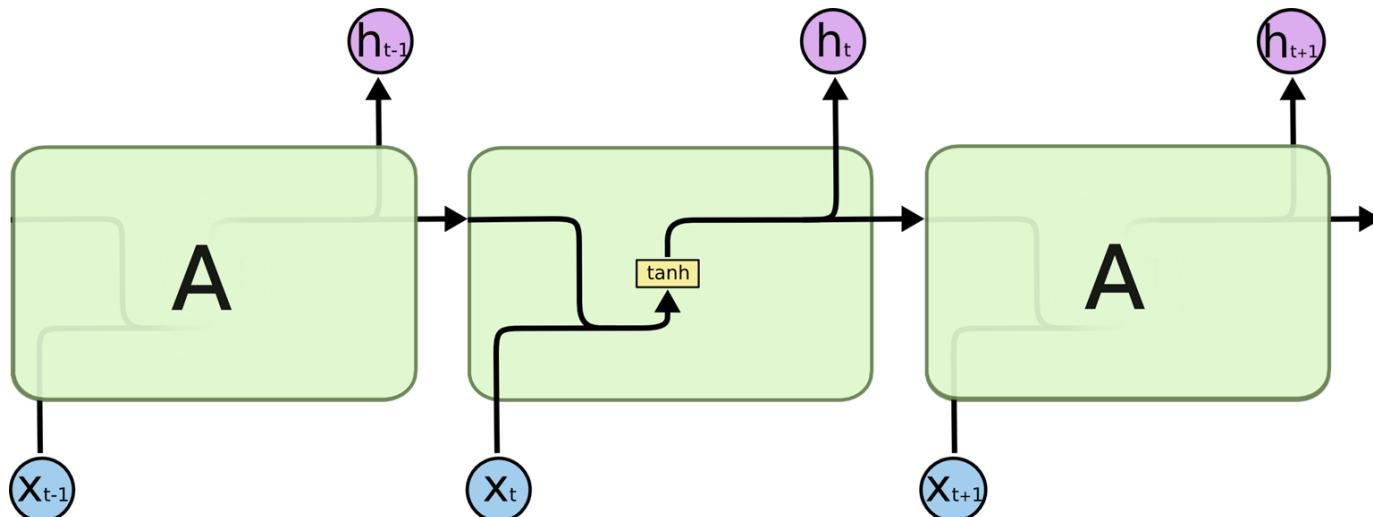
Vanishing Gradient

- 1. From the weights $\mathbf{A}_t = \boldsymbol{\theta}_c^t \mathbf{A}_0$
- 2. From the activation functions (*tanh*)



Vanishing Gradient

- 1. From the weights $A_t = \cancel{\theta^t} A_0$
1
- 2. From the activation functions (\tanh) ?

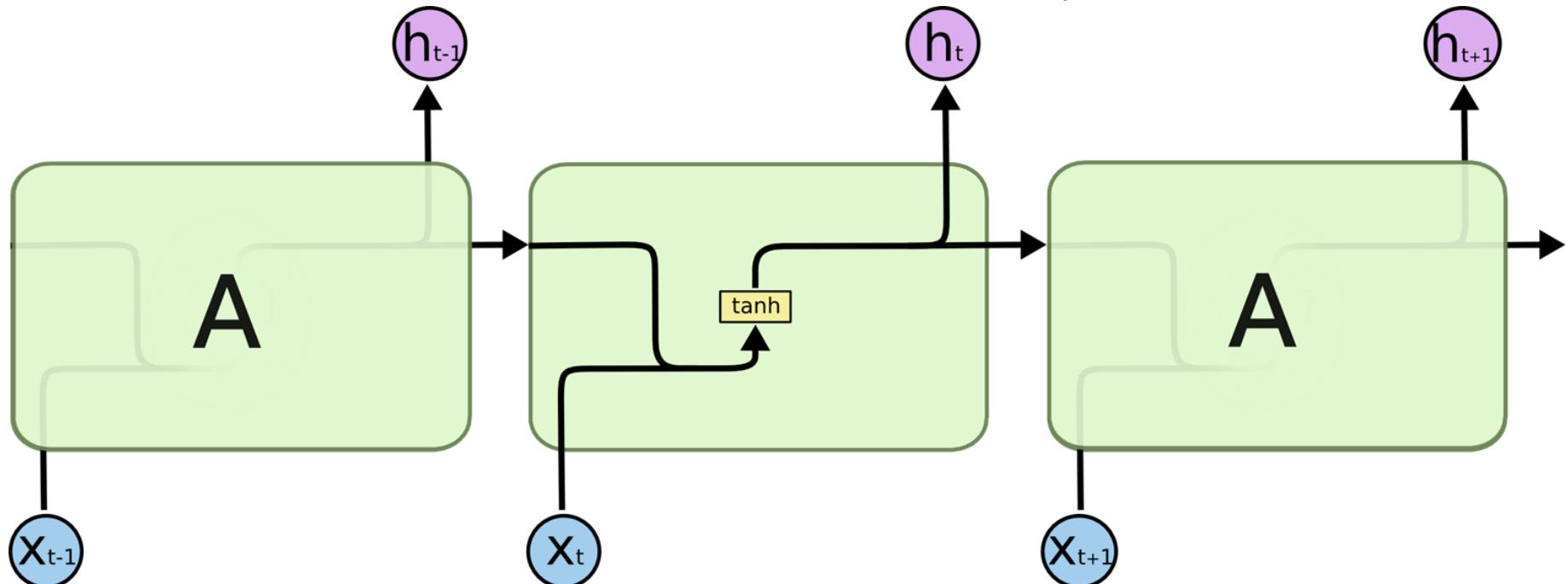


Long Short Term Memory

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

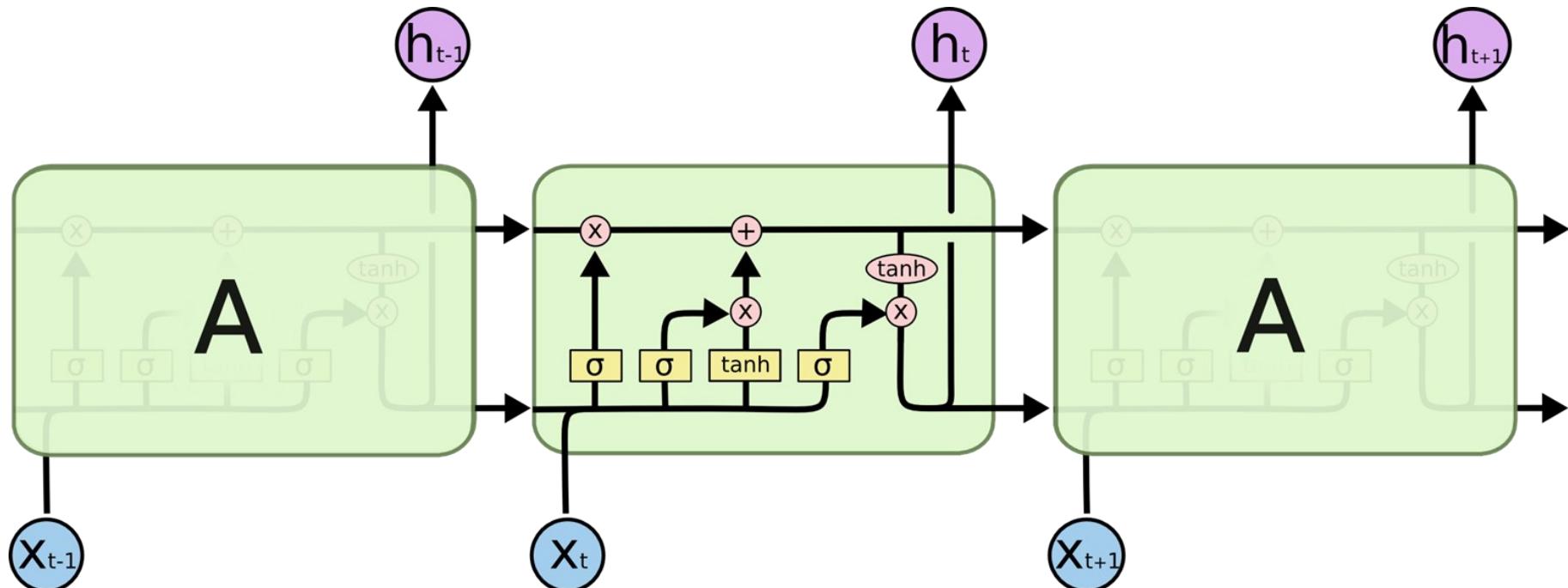
Long-Short Term Memory Units

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



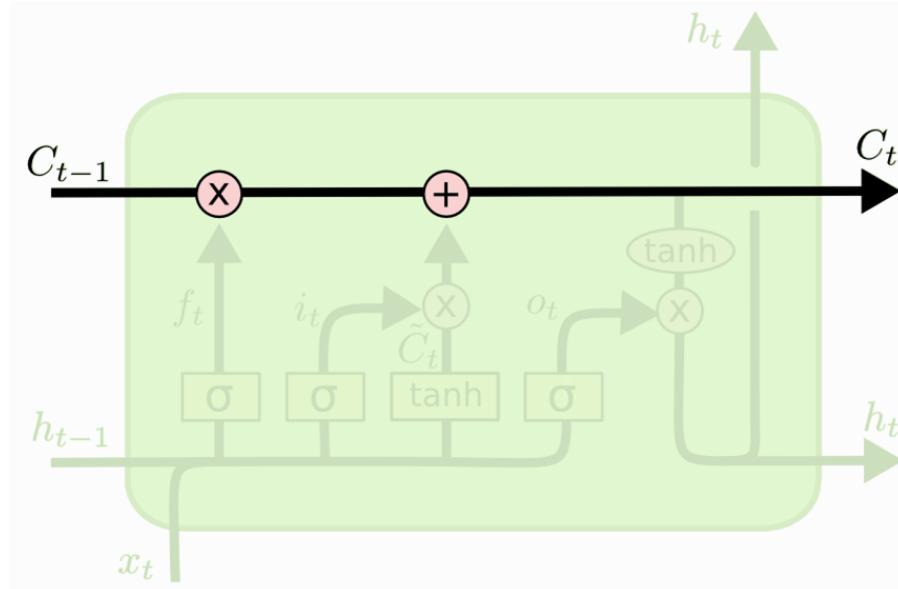
Long-Short Term Memory Units

LSTM



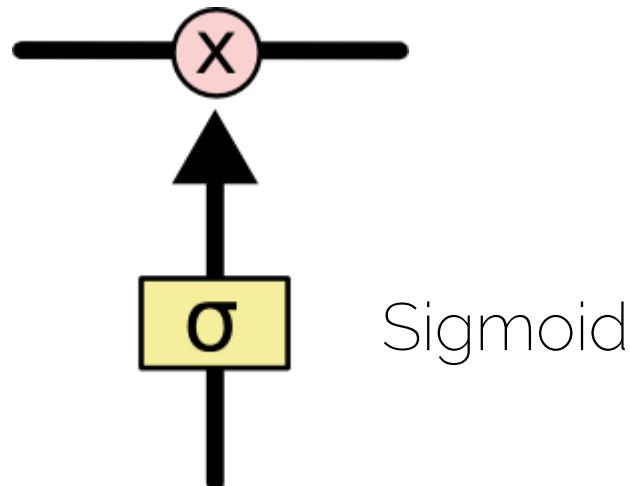
Long-Short Term Memory Units

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



Long-Short Term Memory Units

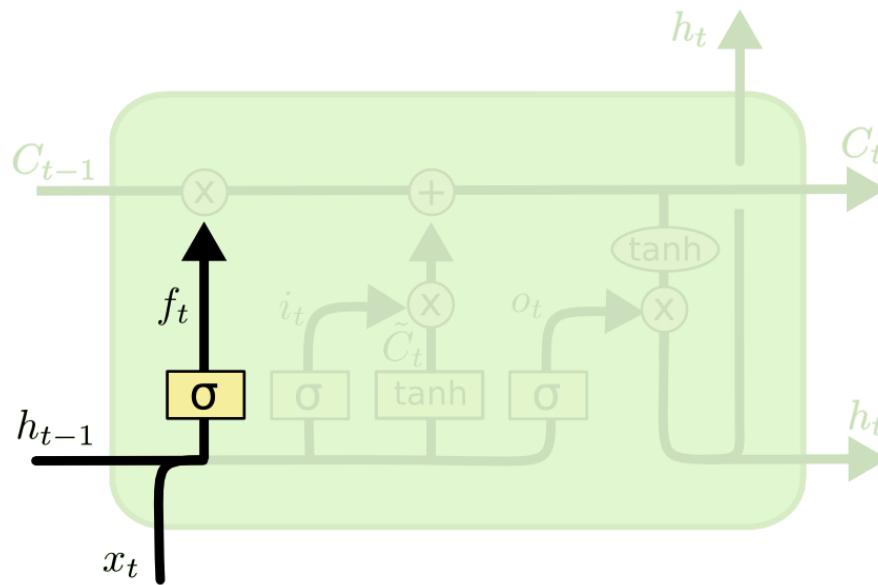
- Key ingredients
- Cell = transports the information through the unit
- Gate = remove or add information to the cell state



LSTM: Step by Step

- Forget gate

$$f_t = \text{sigm}(\theta_{xf} x_t + \theta_{hf} h_{t-1} + b_f)$$

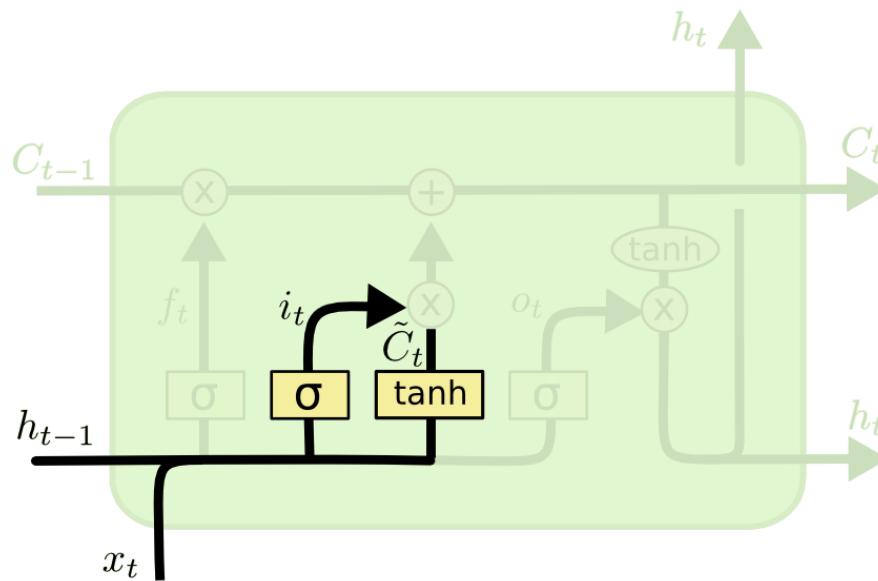


Decides when
erases the cell state

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

LSTM: Step by Step

- Input gate $i_t = \text{sigm}(\theta_{xi}x_t + \theta_{hi}h_{t-1} + b_i)$

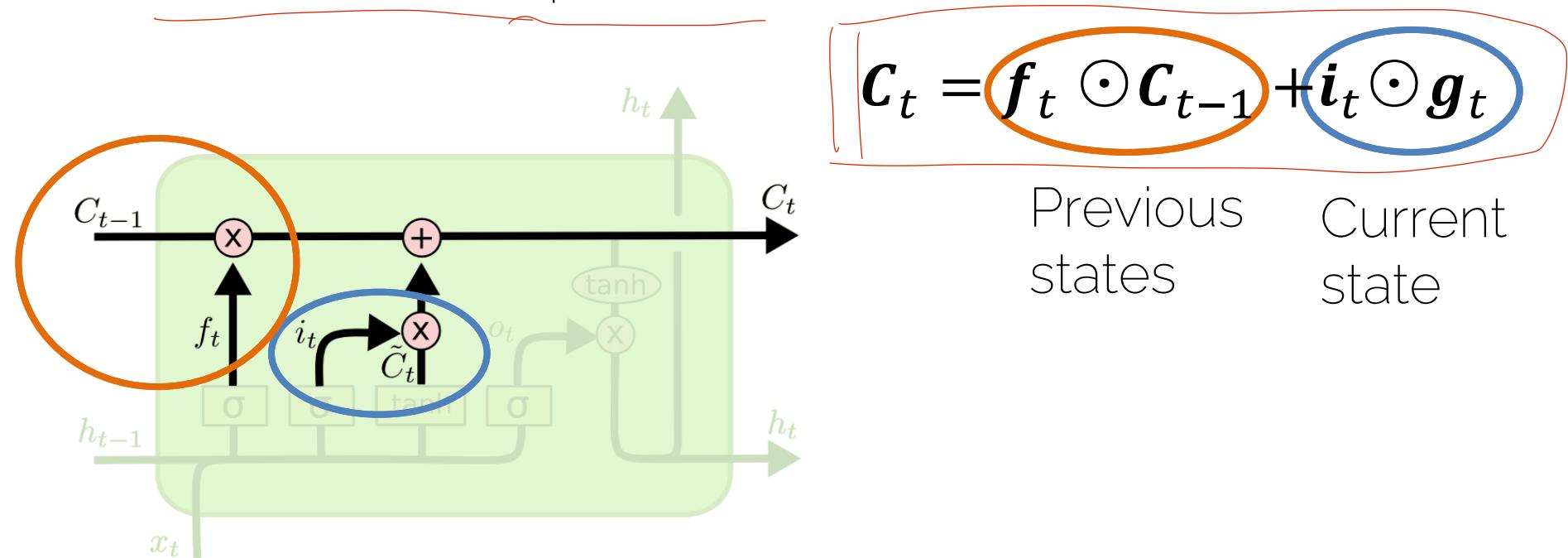


Decides which values will be updated

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

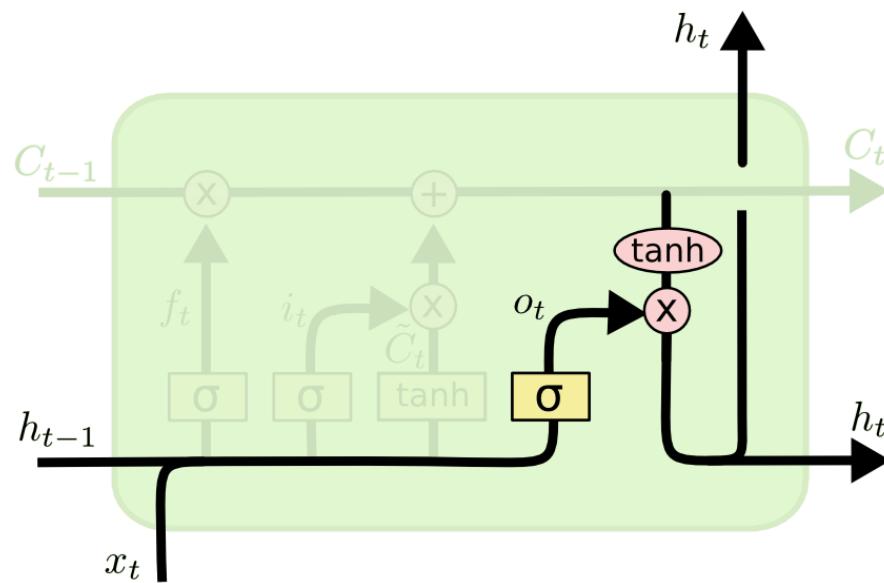
LSTM: Step by Step

- Element-wise operations



LSTM: Step by Step

- Output gate $\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$



Decides which values will be outputted

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

LSTM: Step by Step

- Forget gate $f_t = \text{sigm}(\theta_{xf}x_t + \theta_{hf}h_{t-1} + b_f)$
- Input gate $i_t = \text{sigm}(\theta_{xi}x_t + \theta_{hi}h_{t-1} + b_i)$
- Output gate $o_t = \text{sigm}(\theta_{xo}x_t + \theta_{ho}h_{t-1} + b_o)$
- Cell update $g_t = \tanh(\theta_{xg}x_t + \theta_{hg}h_{t-1} + b_g)$
- Cell $C_t = f_t \odot C_{t-1} + i_t \odot g_t$
- Output $h_t = o_t \odot \tanh(C_t)$

LSTM: Step by Step

- Forget gate
- Input gate
- Output gate
- Cell update
- Cell
- Output

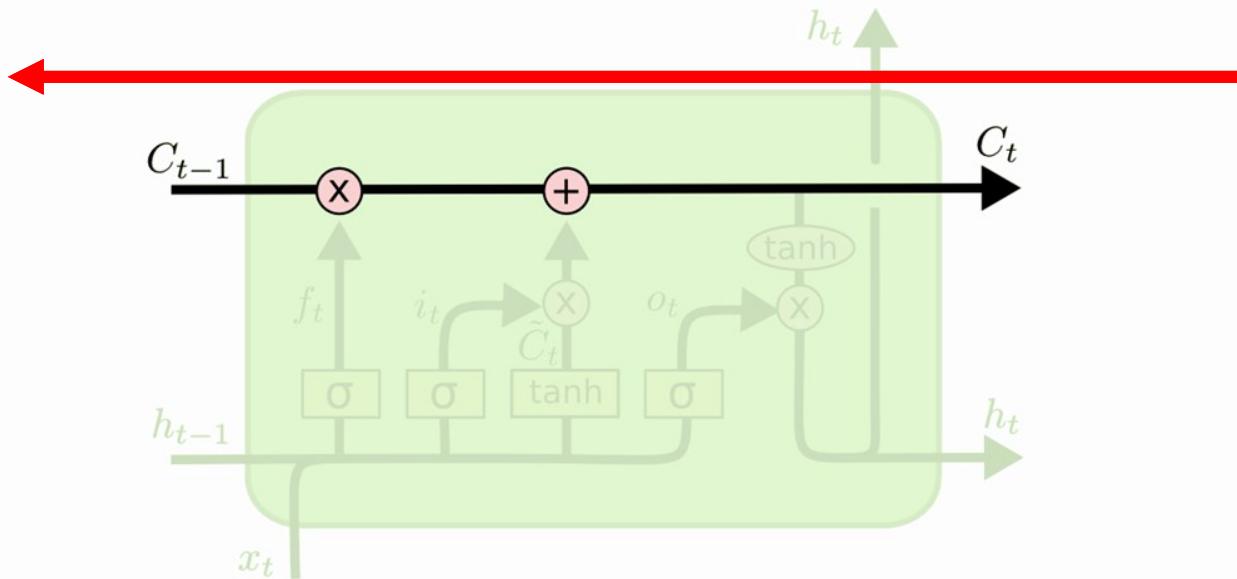
$$\begin{aligned} f_t &= \text{sigm}(\theta_{xf}x_t + \theta_{hf}h_{t-1} + b_f) \\ i_t &= \text{sigm}(\theta_{xi}x_t + \theta_{hi}h_{t-1} + b_i) \\ o_t &= \text{sigm}(\theta_{xo}x_t + \theta_{ho}h_{t-1} + b_o) \\ g_t &= \tanh(\theta_{xg}x_t + \theta_{hg}h_{t-1} + b_g) \\ C_t &= f_t \odot C_{t-1} + i_t \odot g_t \end{aligned}$$

$$h_t = o_t \odot \tanh(C_t)$$

Learned through
backpropagation

LSTM

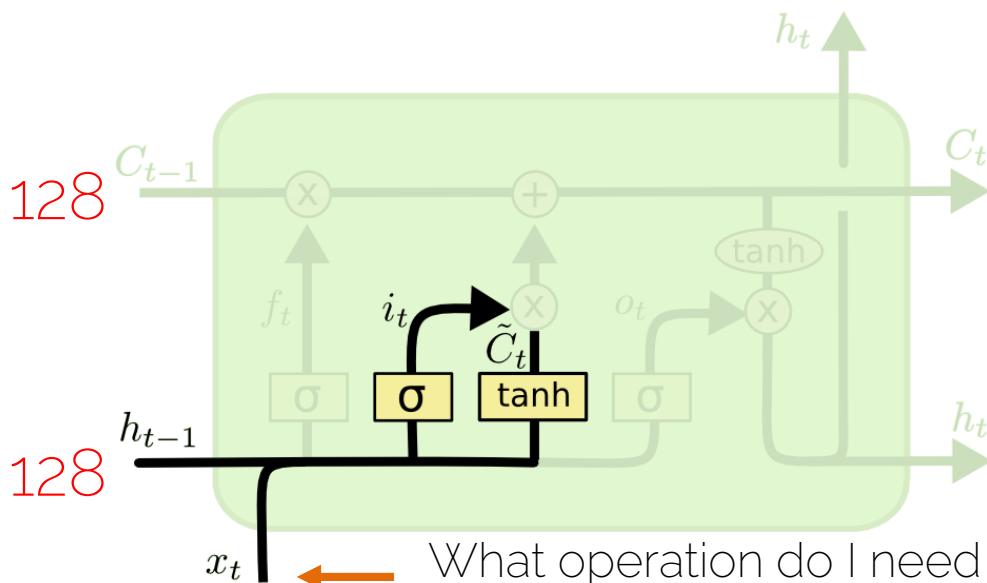
- Highway for the gradient to flow



LSTM: Dimensions

- Cell update

$$128 \quad 128 \quad 128 \\ \mathbf{g}_t = \tanh(\theta_{xg} \mathbf{x}_t + \theta_{hg} \mathbf{h}_{t-1} + \mathbf{b}_g)$$



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?

LSTM in code

```
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|
```

```
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

Lukasz Kaiser*

Google Brain

lukaszkaiser@google.com

Illia Polosukhin* ‡

illia.polosukhin@gmail.com

Attention is all you need

Attention Is All You Need

~62,000 citations in
5 years!

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

Lukasz Kaiser*

Google Brain

lukaszkaiser@google.com

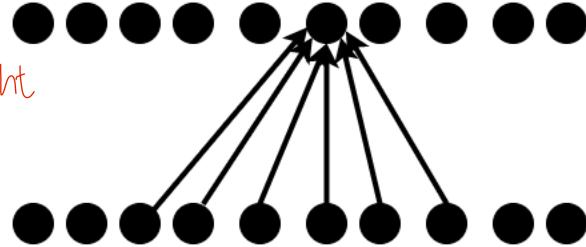
Illia Polosukhin* ‡

illia.polosukhin@gmail.com

Attention vs convolution

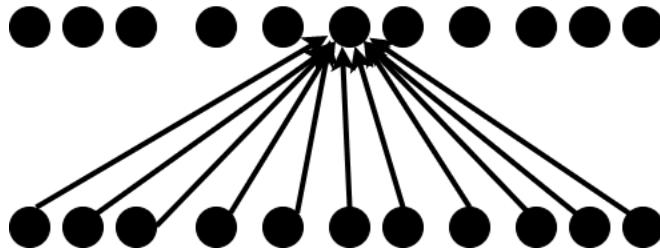
Convolution

Share Weight

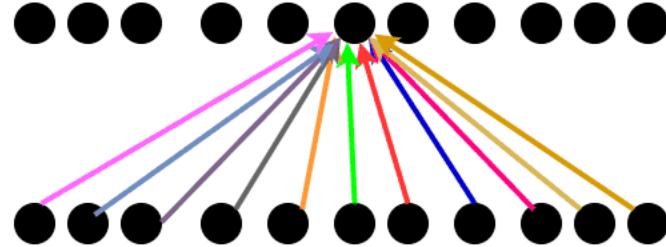


Fully Connected layer

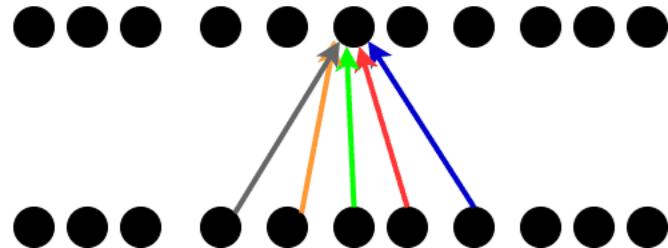
connect all



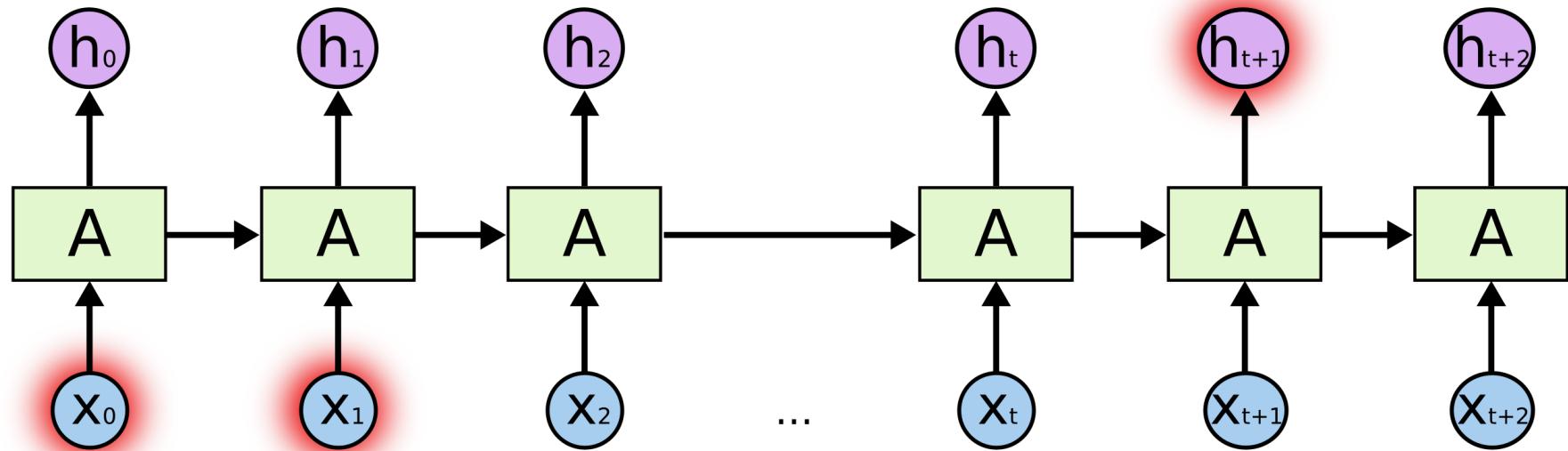
Global attention



Local attention



Long-Term Dependencies



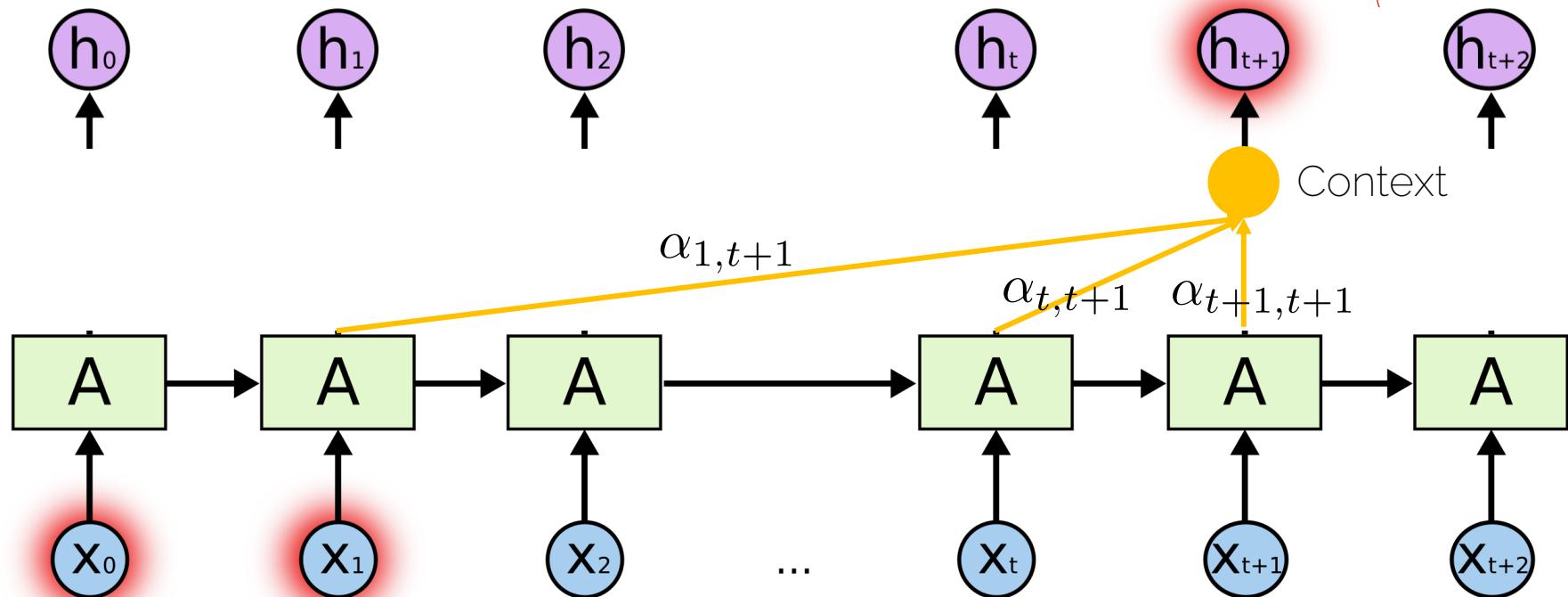
I moved to Germany ...

so I speak German fluently.

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

Attention: Intuition

Find which is the
most important context



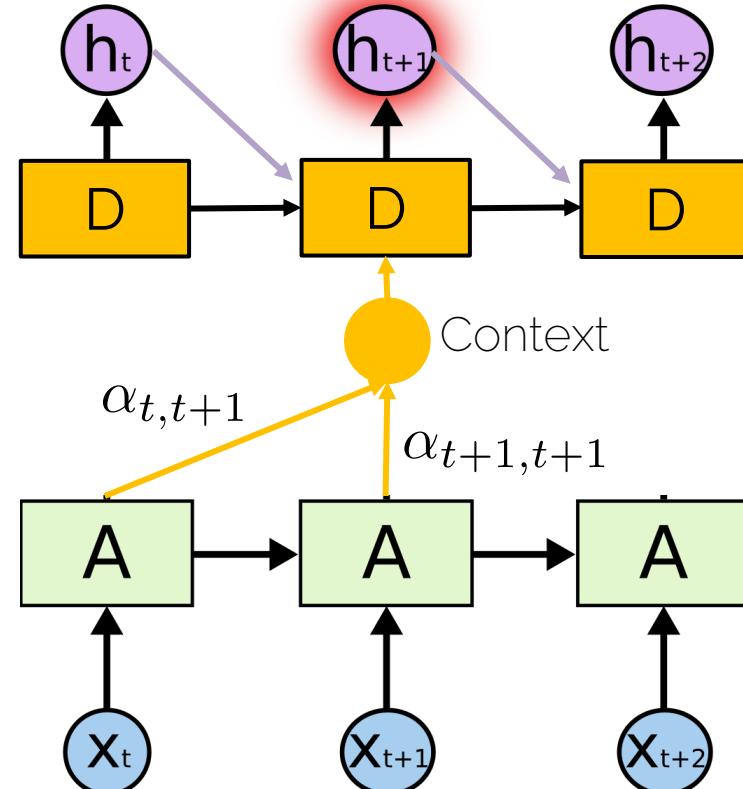
I moved to Germany ...

so I speak German fluently

Attention: Architecture

- A decoder processes the information

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



Transformers

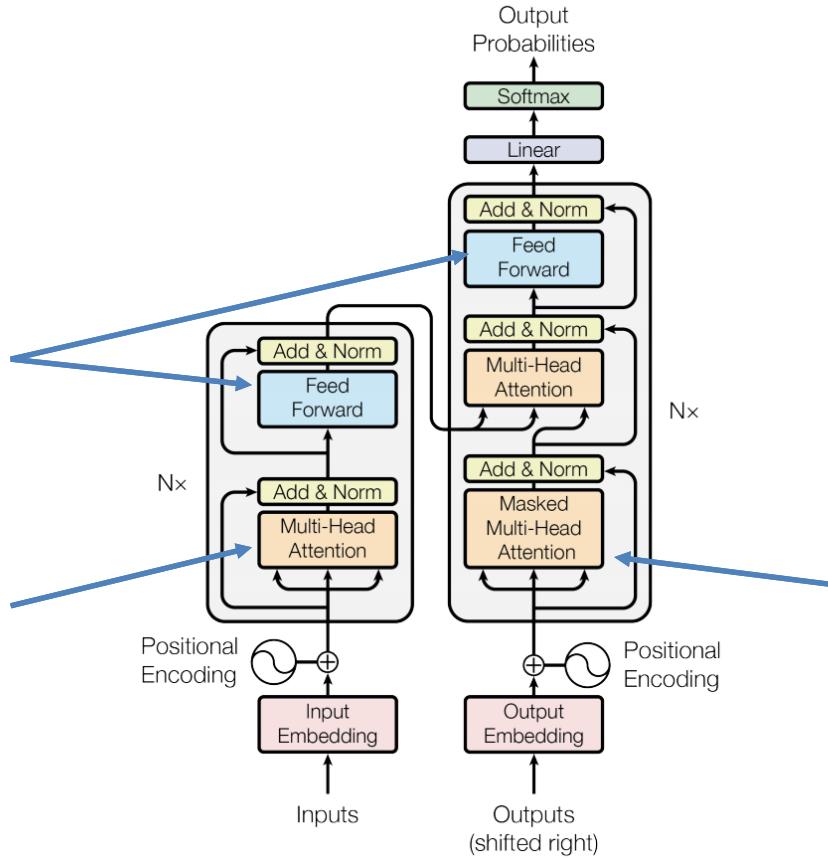
Deep Learning Revolution

	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

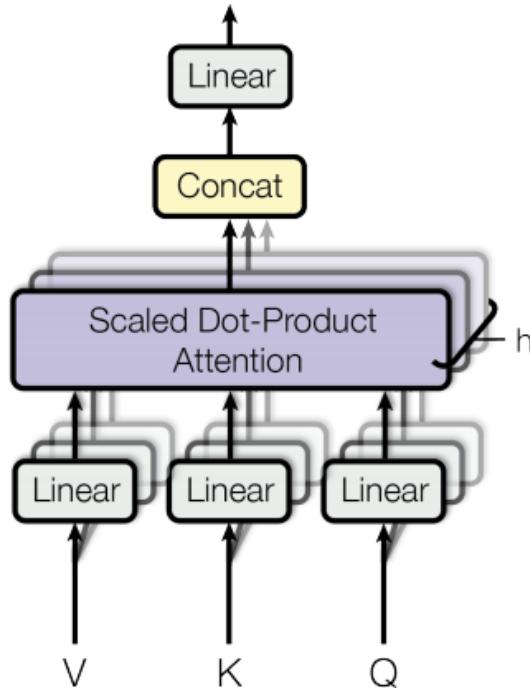
Fully connected layer

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.

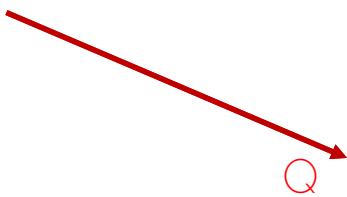
Multiply queries with keys

Get the values

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

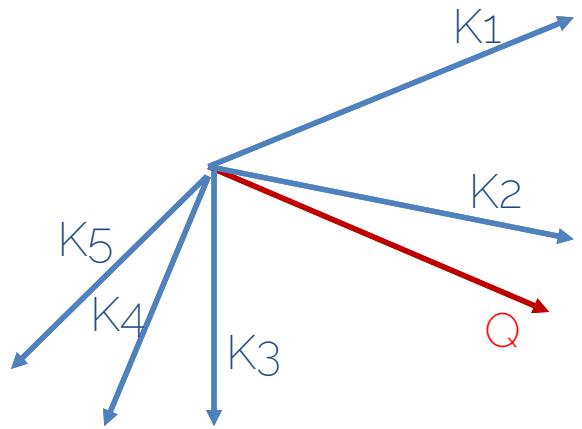
To train them well, divide by $\sqrt{d_k}$, "probably" because for large values of the key's dimension, the dot product grows large in magnitude, pushing the softmax function into regions where it has extremely small gradients.

Multi-Head Attention

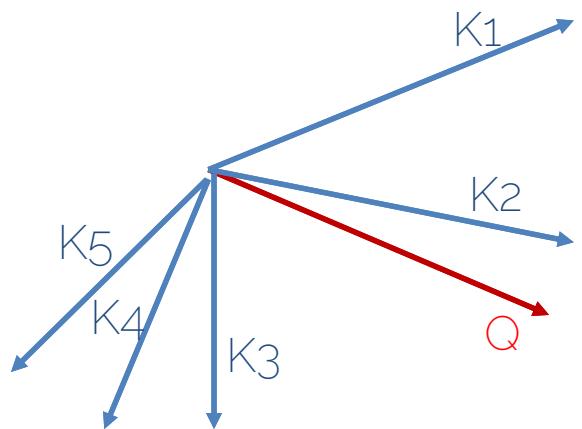


Adapted from Y. Kilcher

Multi-Head Attention

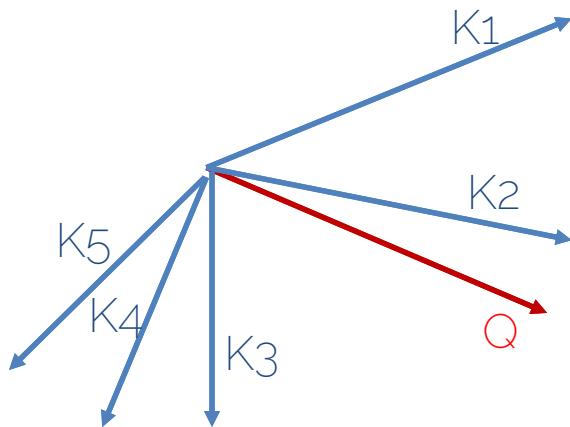


Multi-Head Attention



Values
V1
V2
V3
V4
V5

Multi-Head Attention

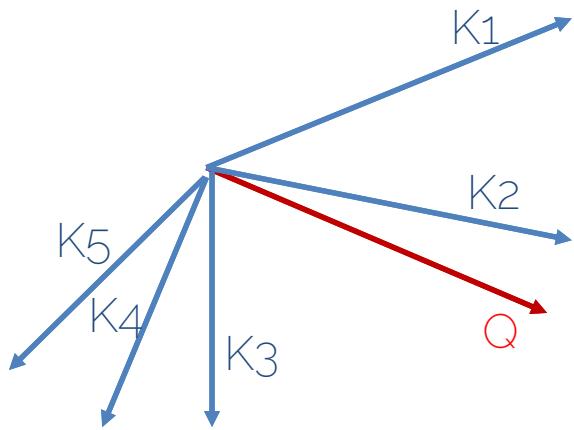


Values
V1
V2
V3
V4
V5

$$QK^T$$

Essentially, dot product between ($\langle Q, K_1 \rangle$), ($\langle Q, K_2 \rangle$), ($\langle Q, K_3 \rangle$), ($\langle Q, K_4 \rangle$), ($\langle Q, K_5 \rangle$).

Multi-Head Attention

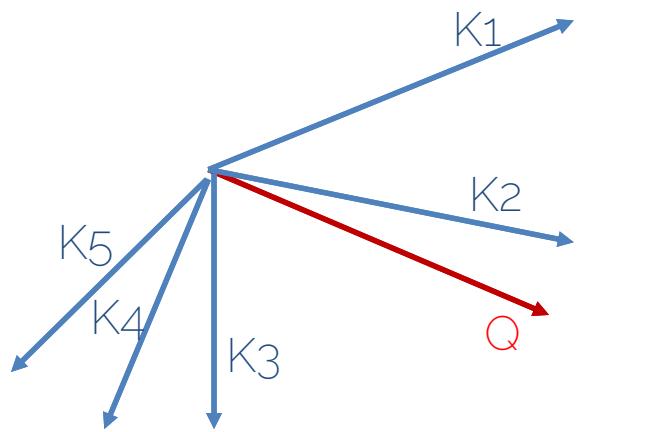


Values
V1
V2
V3
V4
V5

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

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

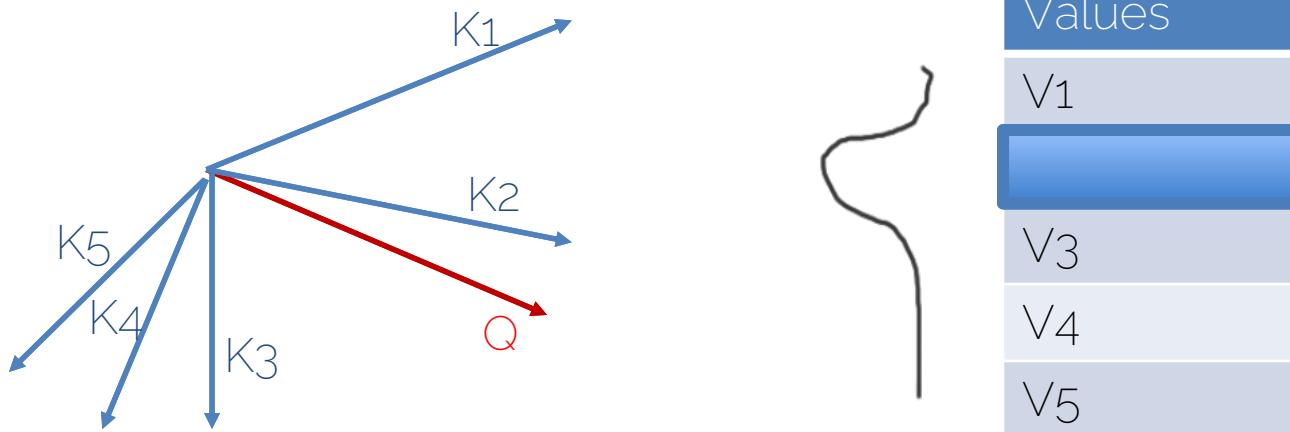


Values
V ₁
V ₂
V ₃
V ₄
V ₅

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

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

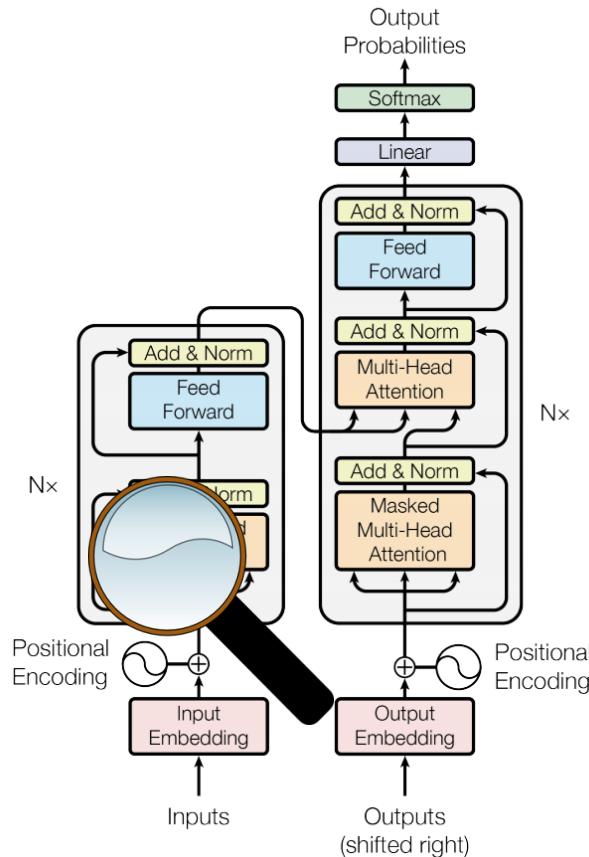
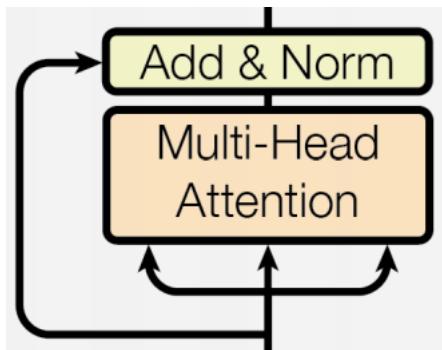


$$\text{softmax} \left(\frac{QK^T}{\sqrt{d_k}} \right)$$

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

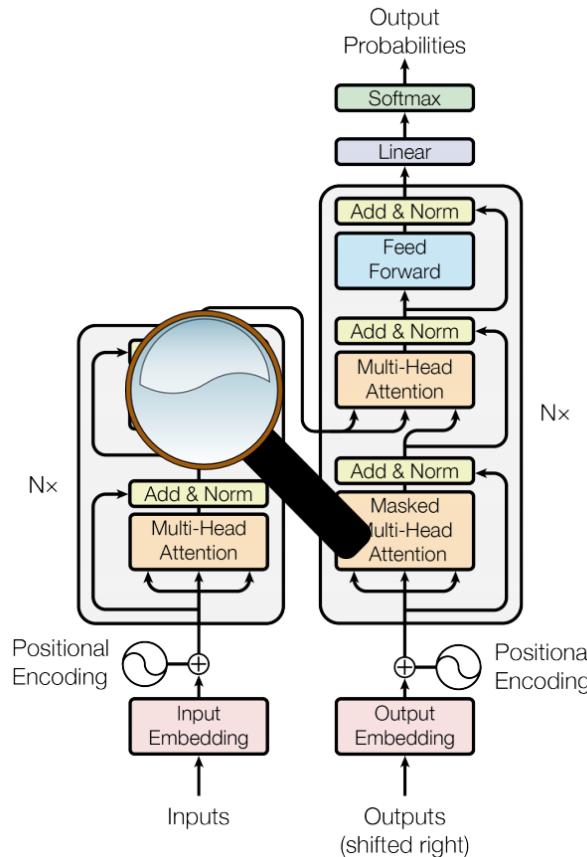
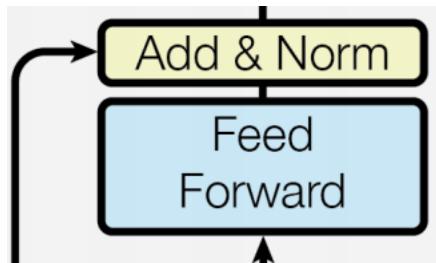
Transformers – a closer look

K parallel
attention heads.



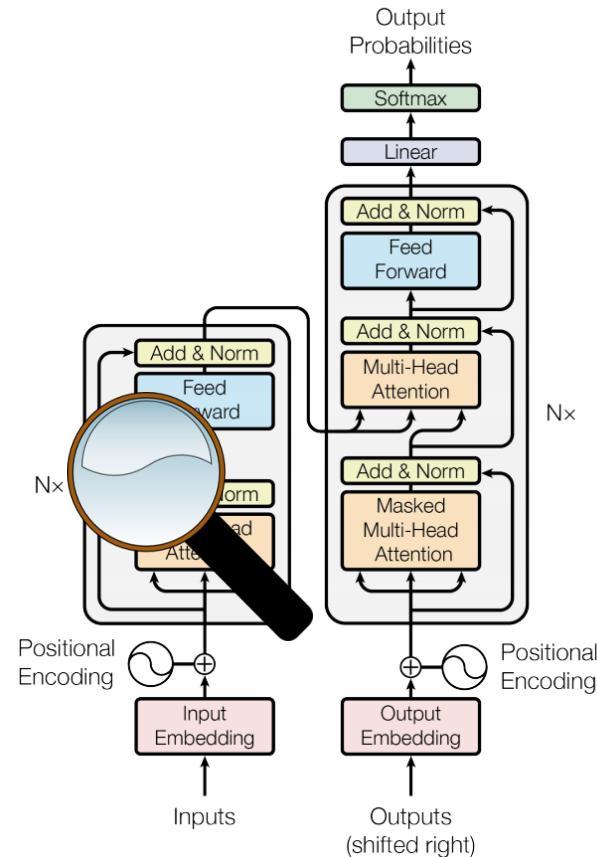
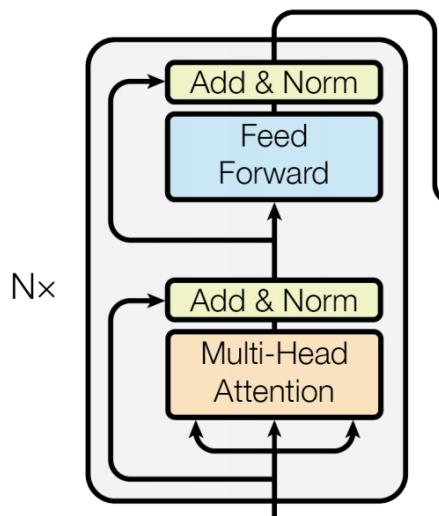
Transformers – a closer look

Good old fully-connected layers.



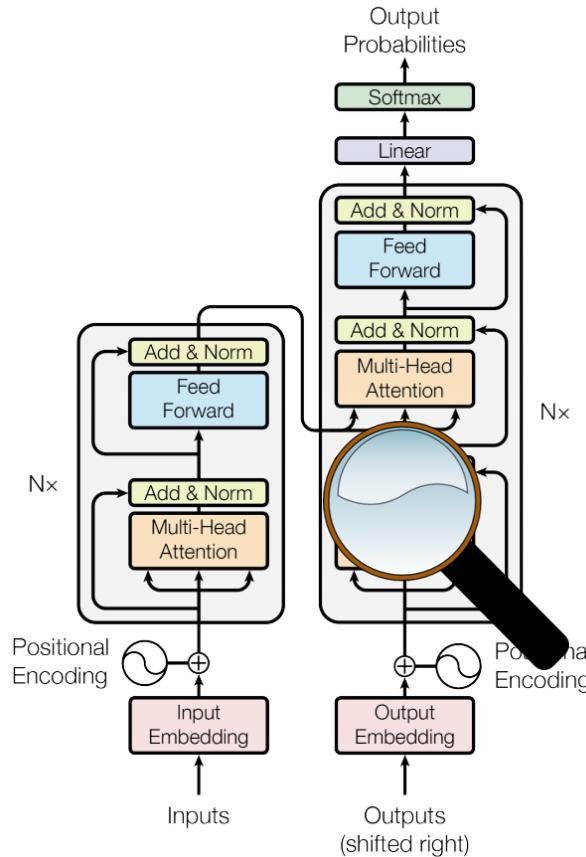
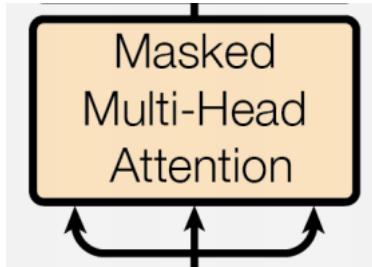
Transformers – a closer look

N layers of
attention
followed by FC



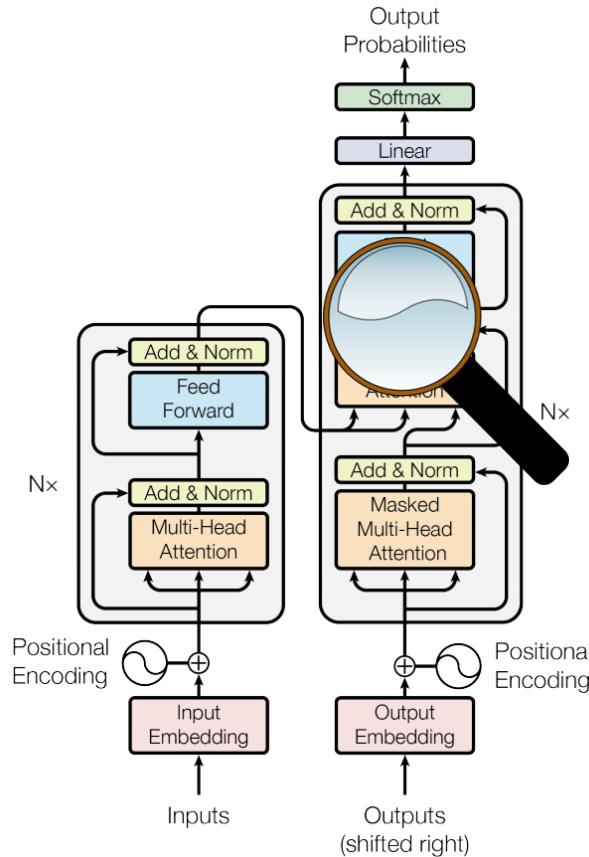
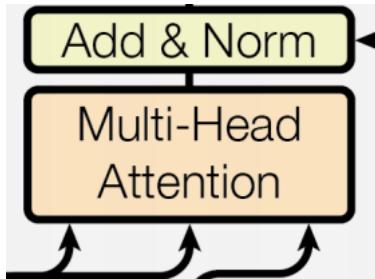
Transformers – a closer look

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 .



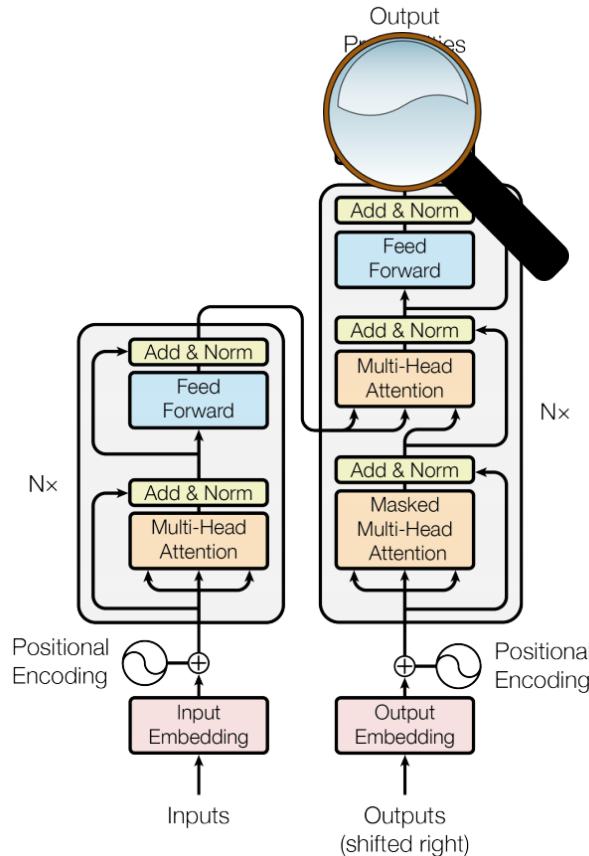
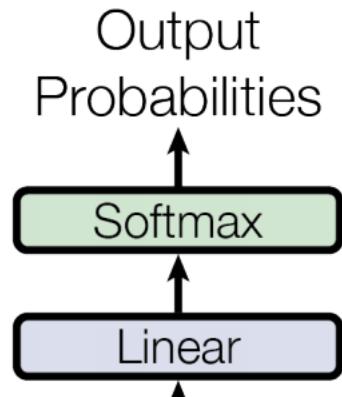
Transformers – a closer look

Multi-headed attention between encoder and the decoder.



Transformers – a closer look

Projection and prediction.



What is missing from self-attention?

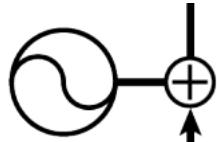
- Convolution: a different linear transformation for each relative position. Allows you to distinguish what information came from where.
- Self-attention: a weighted average.



Transformers – a closer look

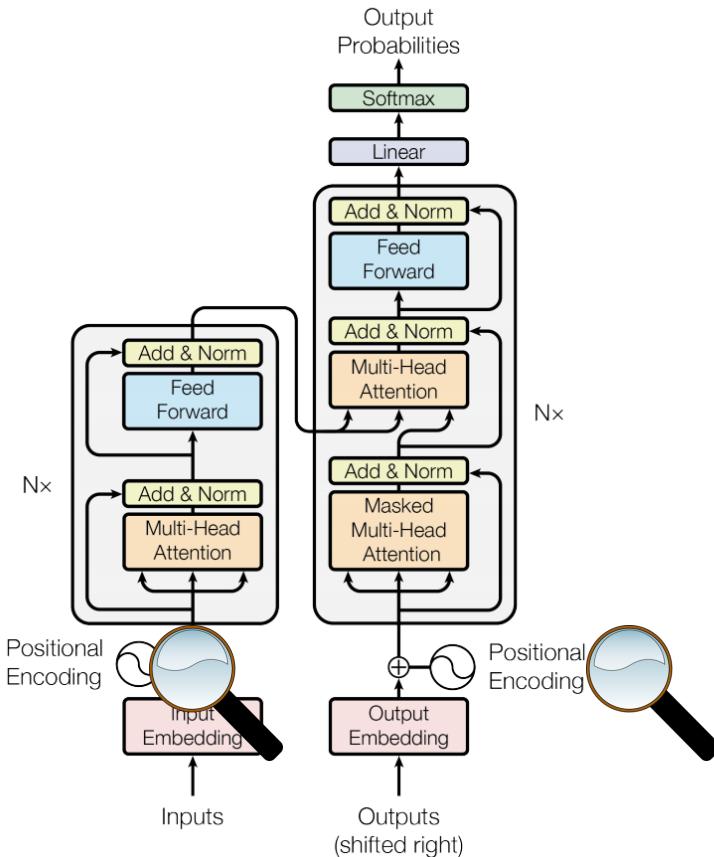
Uses fixed positional encoding based on trigonometric series, in order for the model to make use of the order of the sequence

Positional Encoding

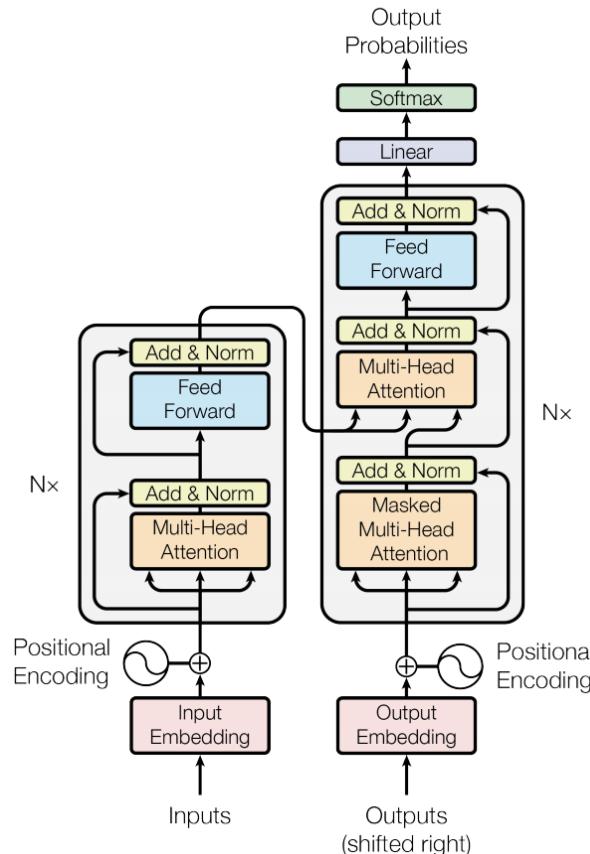


$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{2i/d_{\text{model}}}}\right)$$

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



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.

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.

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		$3.3 \cdot 10^{18}$
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)

See you next time!