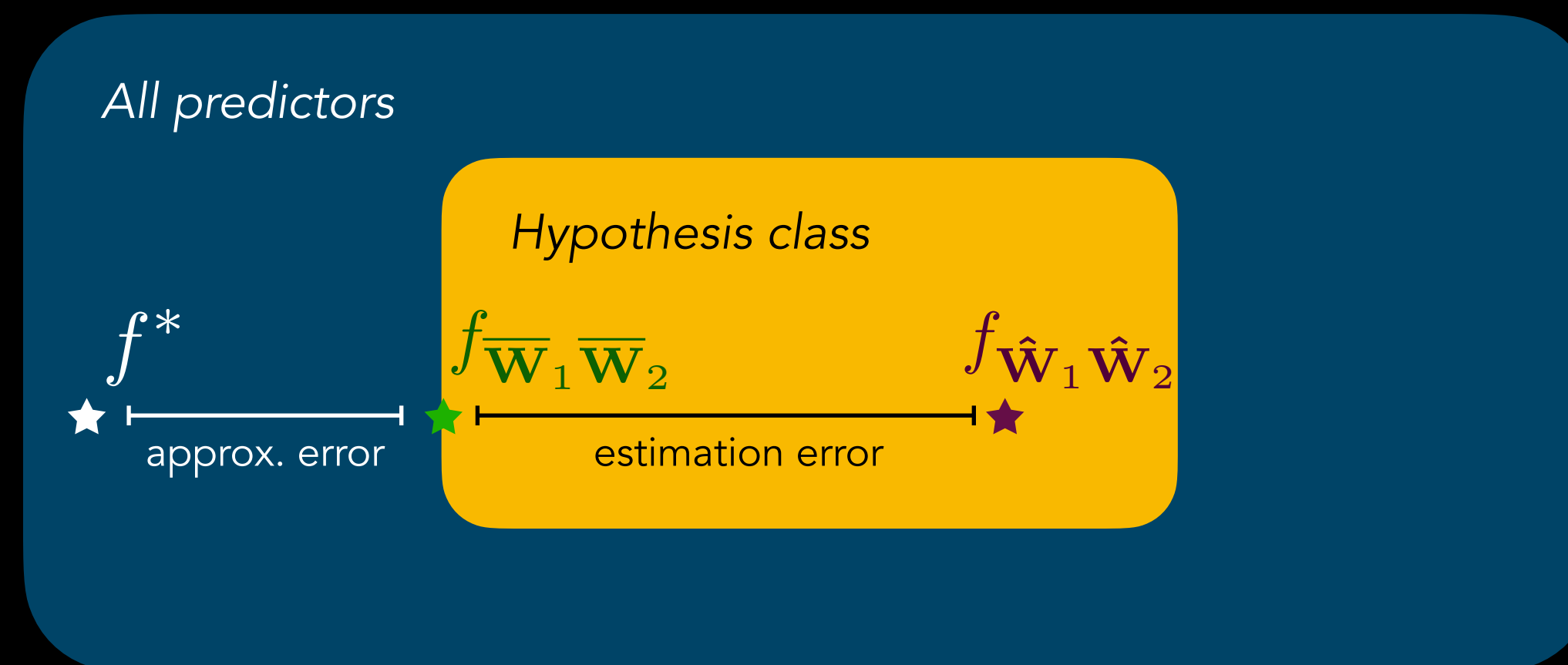


Advanced Deep Learning

Hypothesis Class

$$f_{\mathbf{W}_1 \mathbf{W}_2}(\mathbf{x}) = \sigma(\mathbf{W}_2 \sigma(\mathbf{W}_1 \mathbf{x}))$$

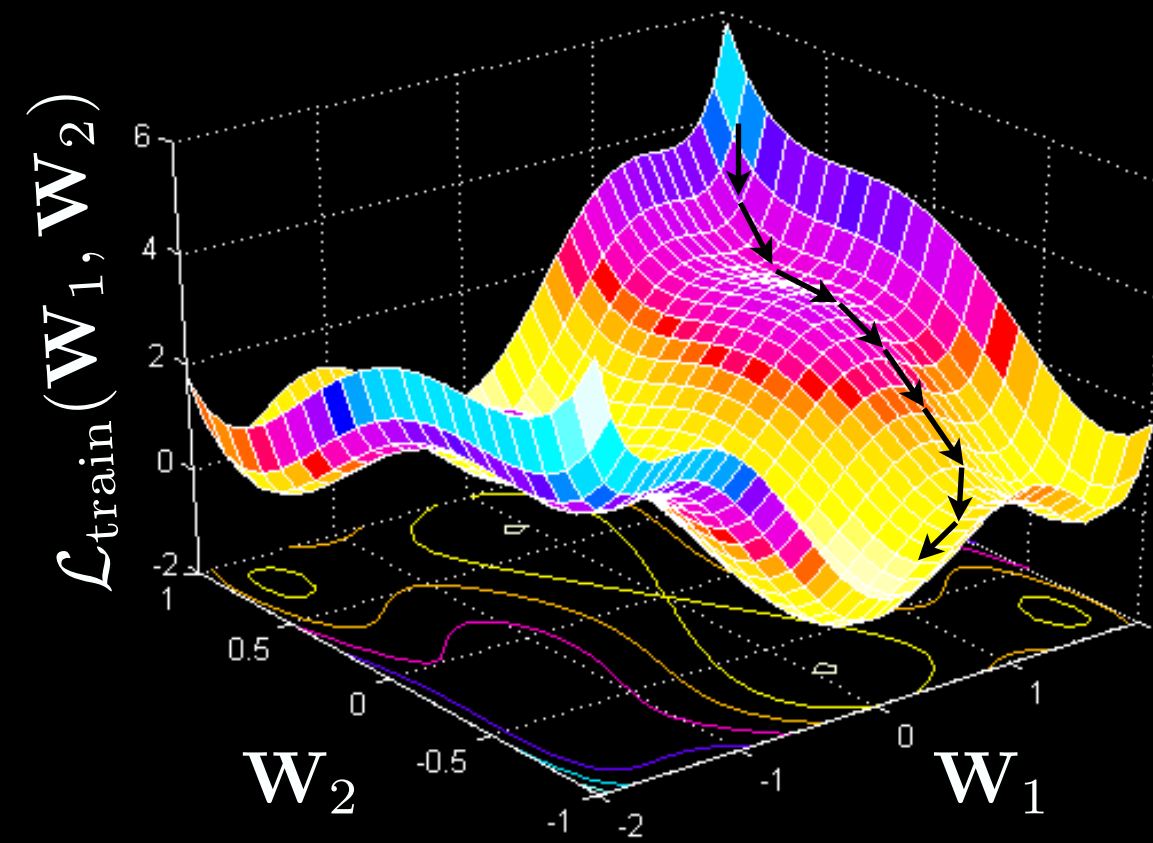
$$\mathcal{F} = \{f_{\mathbf{W}_1 \mathbf{W}_2}(\mathbf{x}) \mid \mathbf{W}_1 \in \mathbb{R}^{k \times n}, \mathbf{W}_2 \in \mathbb{R}^{m \times k}\}$$



Hyperparameters

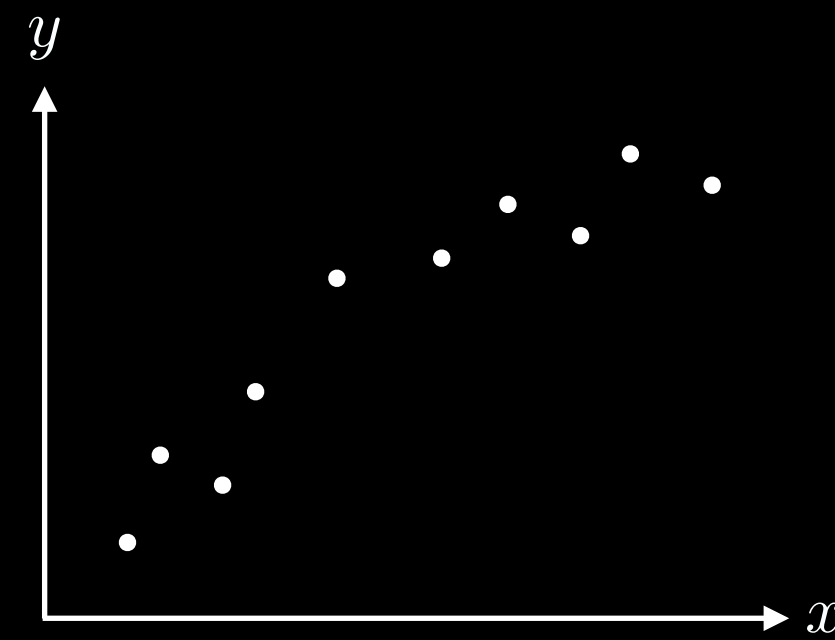
How do you train a deep network?

- Use many hidden layers for abstraction
- Use adaptive time steps
- Use hyper-parameter optimization



The ML workflow

Training Set Validation Set Test Set



- Data cleaning
- Dimensionality reduction
- Unsupervised metrics



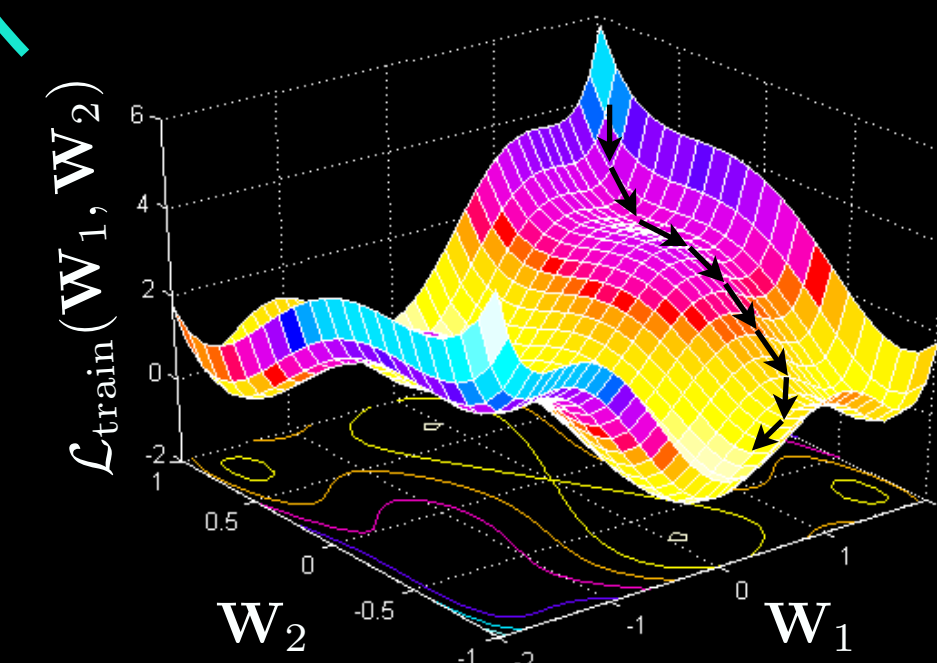
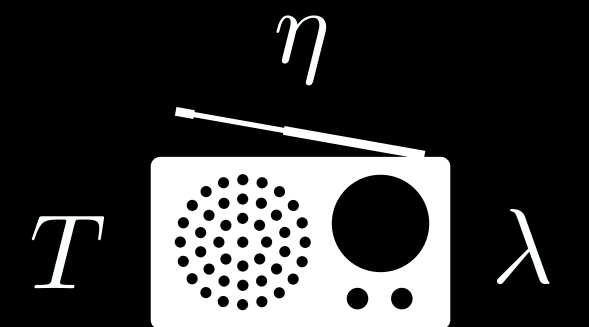
$$\phi(\mathbf{x})$$

not satisfied

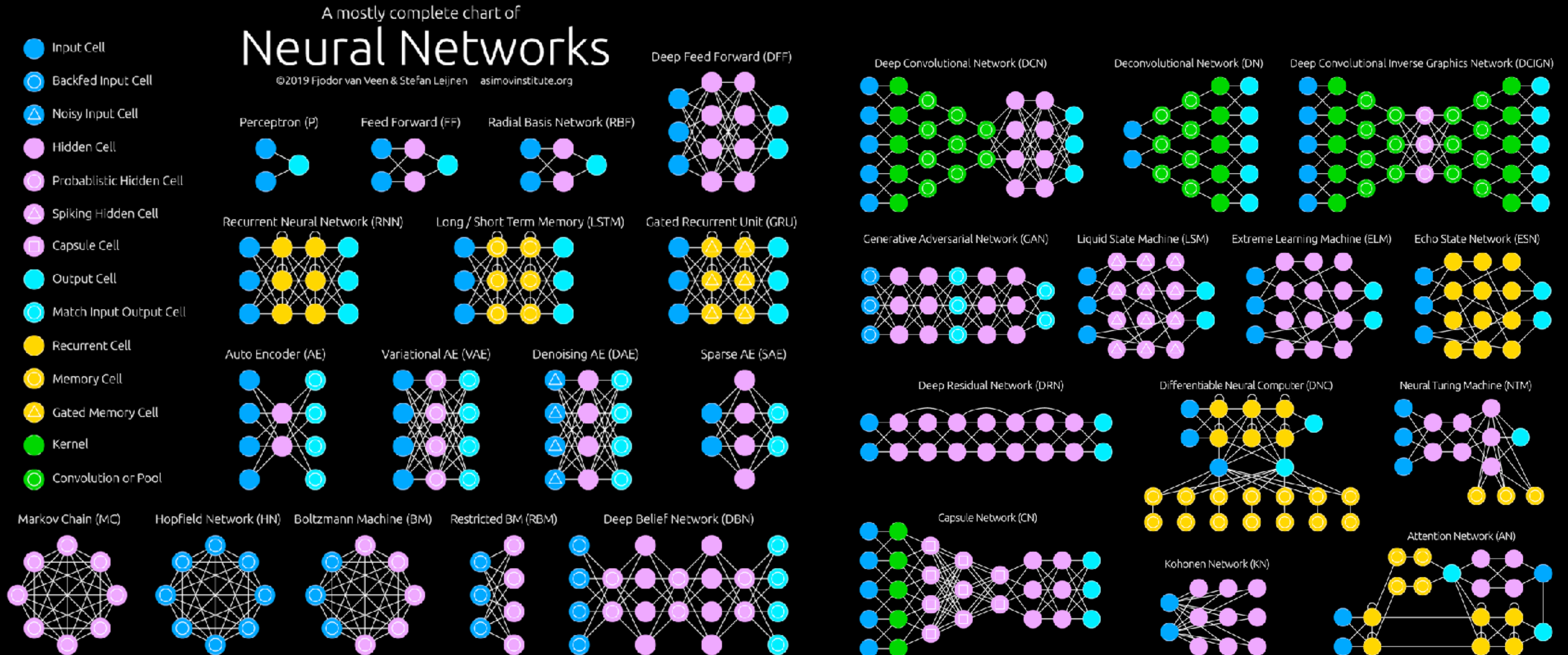
$\mathcal{L}_{\text{test}}$

satisfied

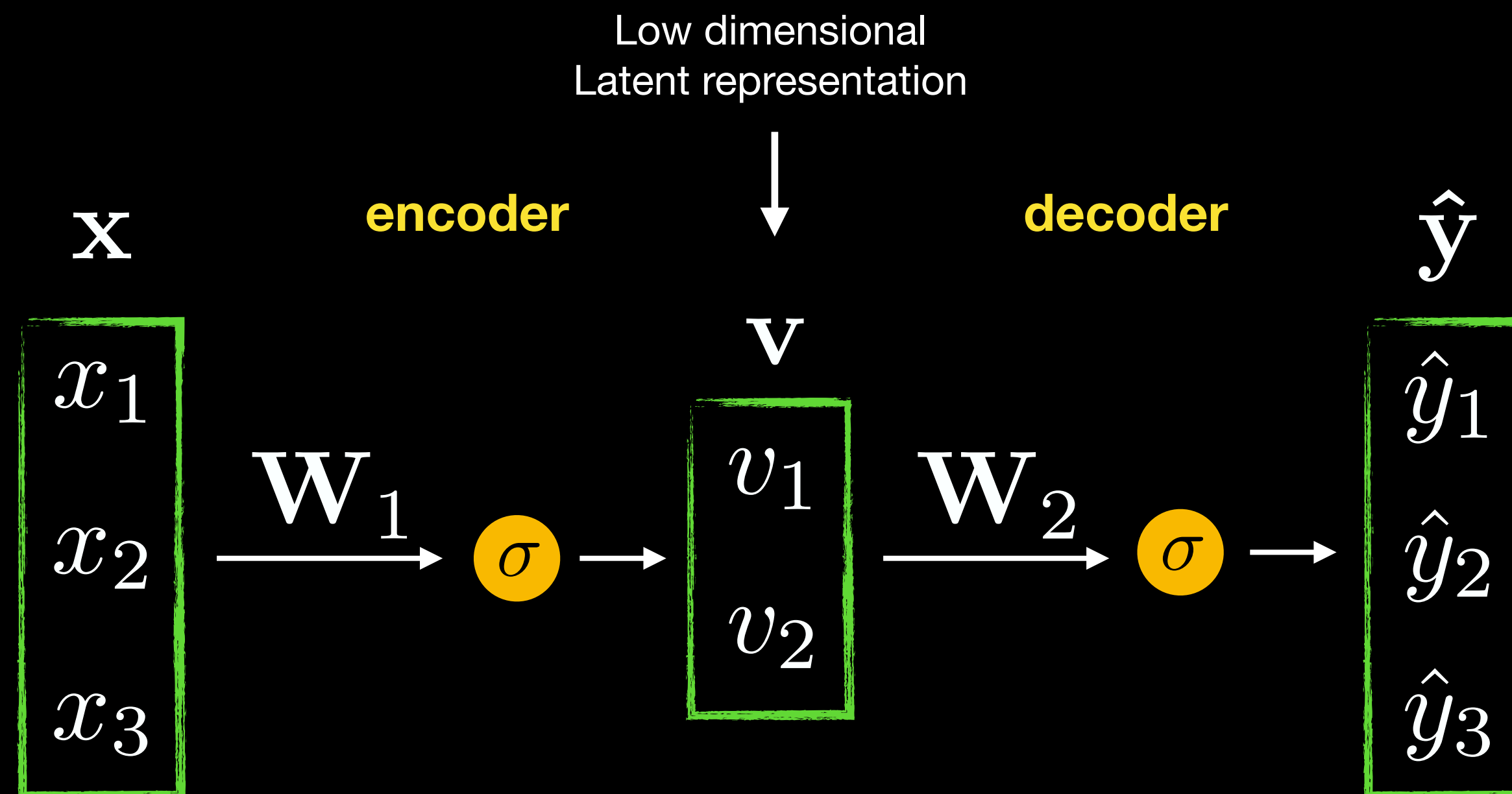
$\mathcal{L}_{\text{val}}$



Neural network zoo



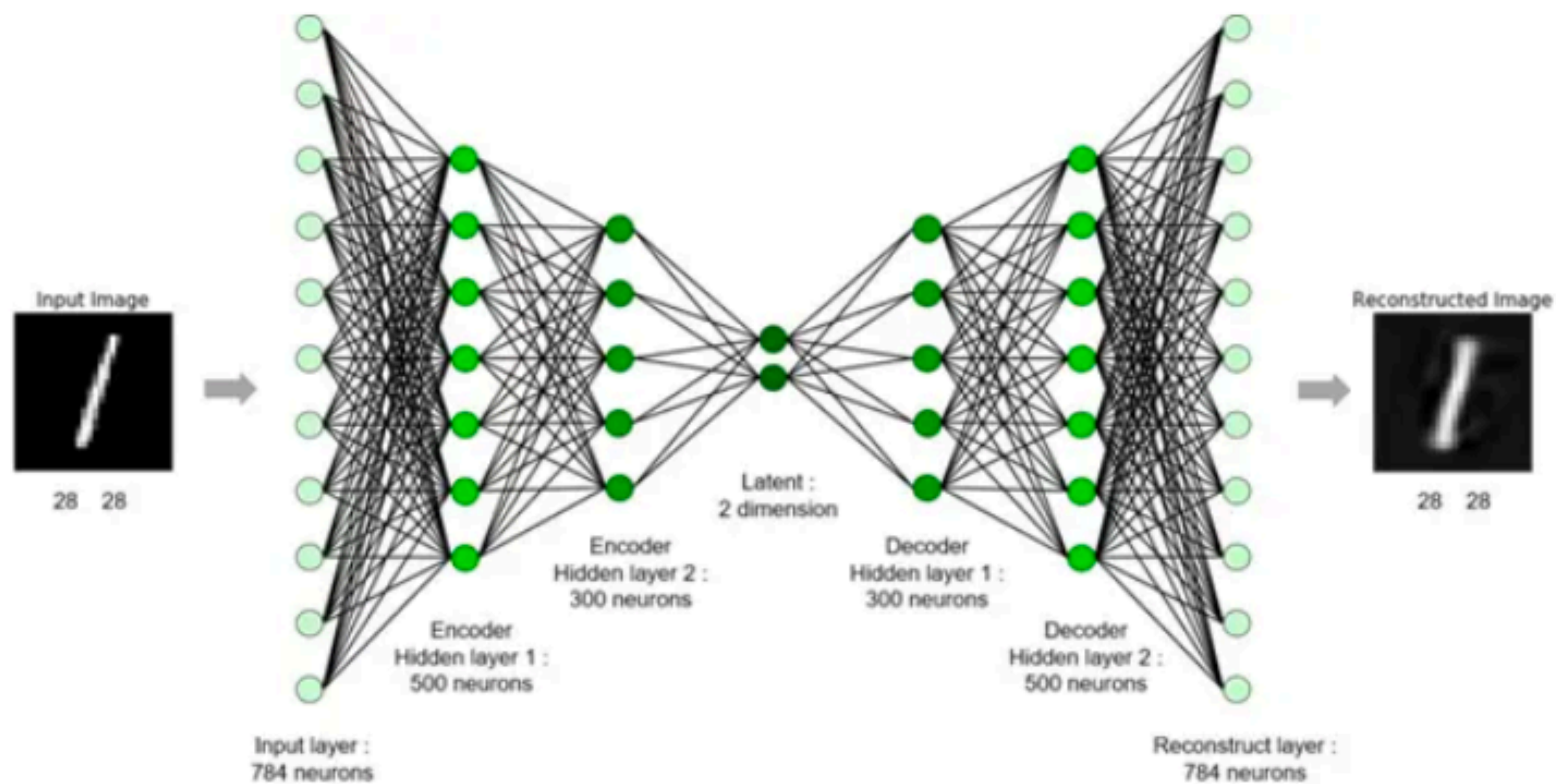
Auto-encoders



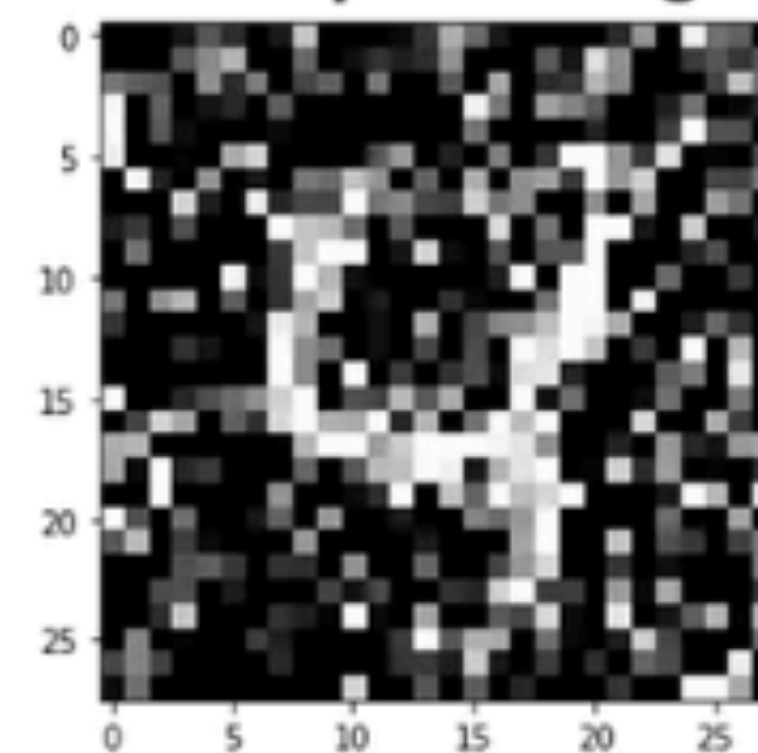
$$\mathcal{L} = \|f_{\mathbf{W}_1 \mathbf{W}_2}(\mathbf{x}) - \mathbf{x}\|^2$$

if $\sigma = I$, network performs SVD decomposition

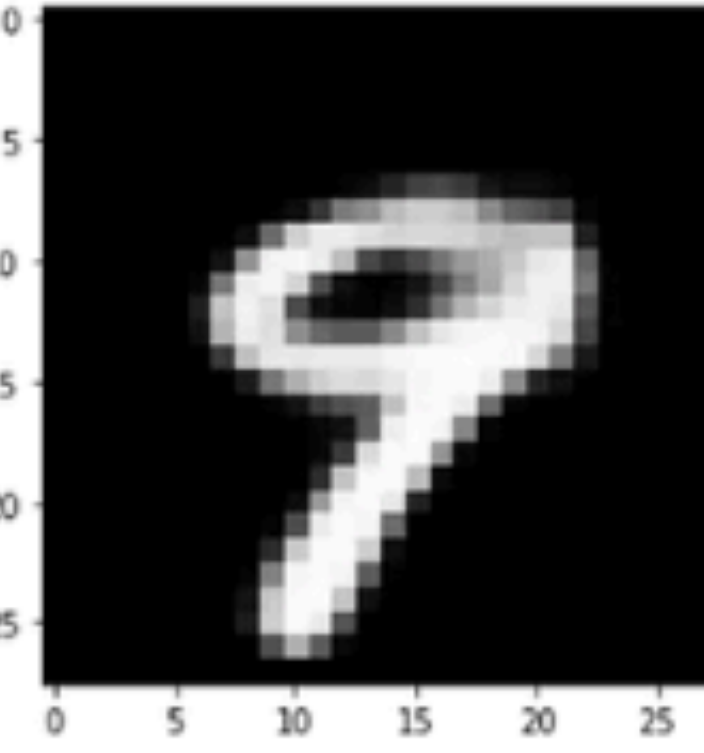
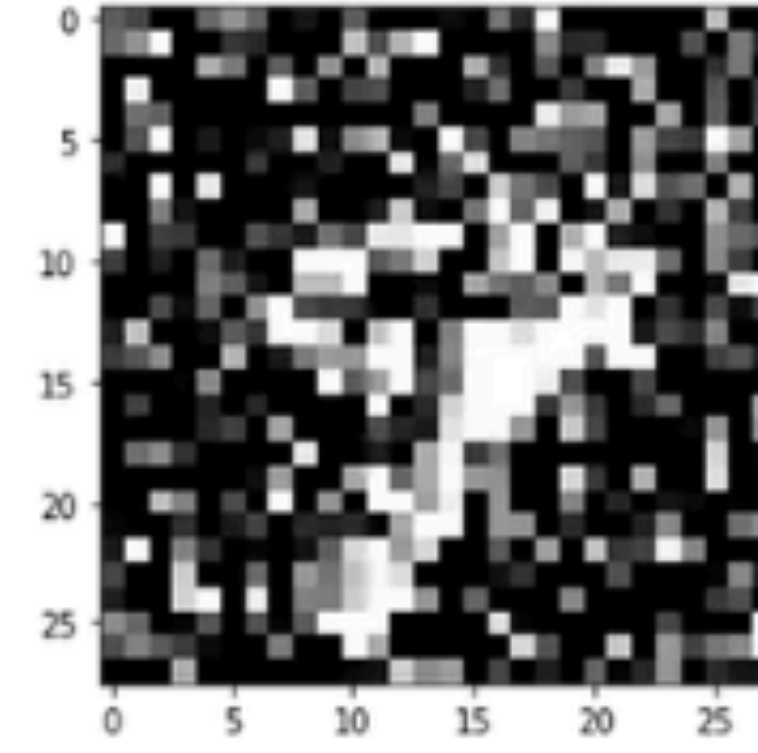
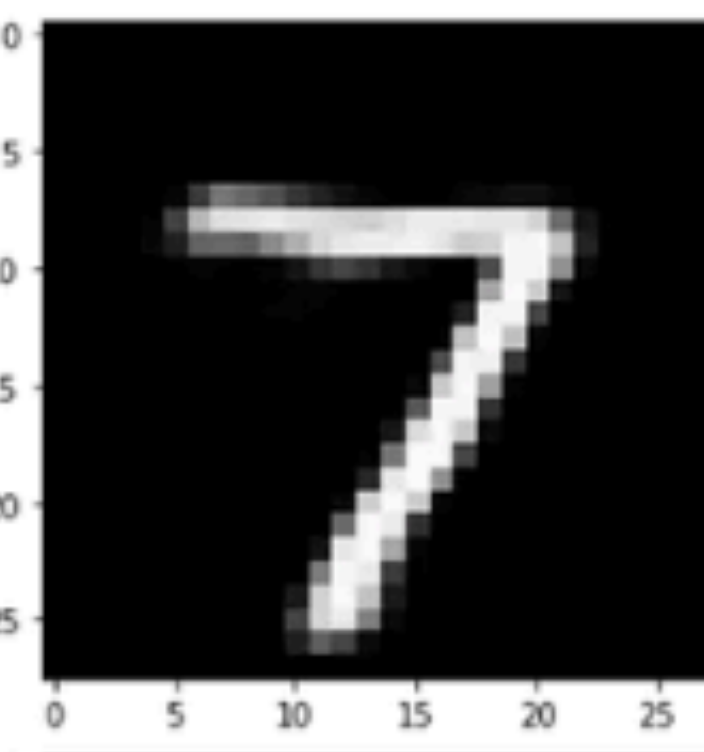
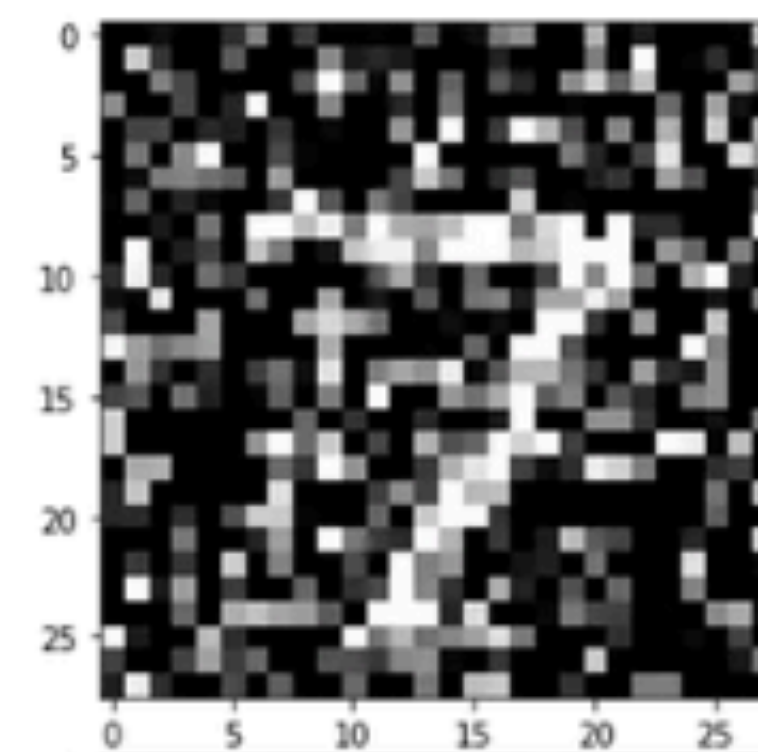
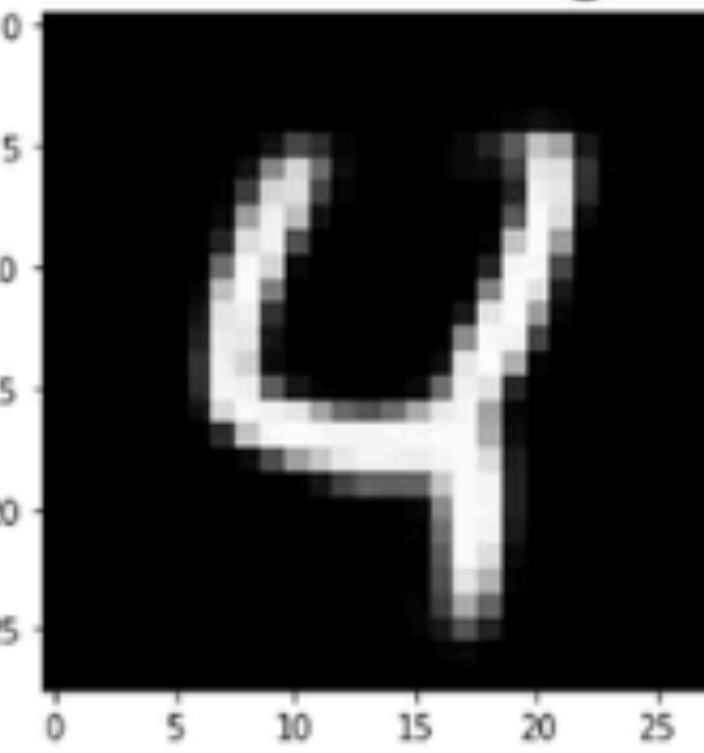
$$\mathbf{X} = \mathbf{U}\Sigma\mathbf{V}^*$$



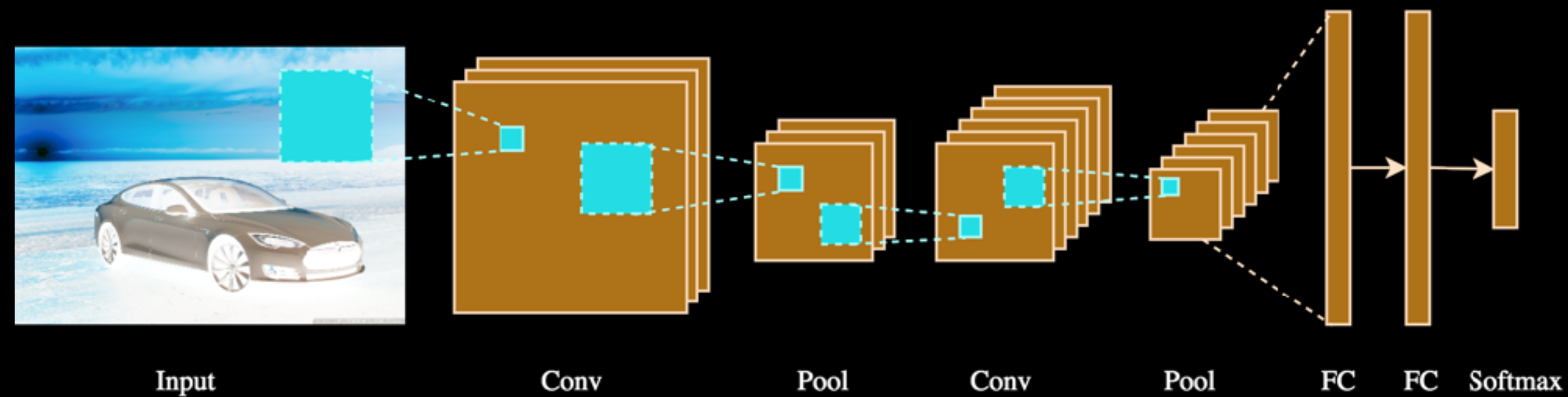
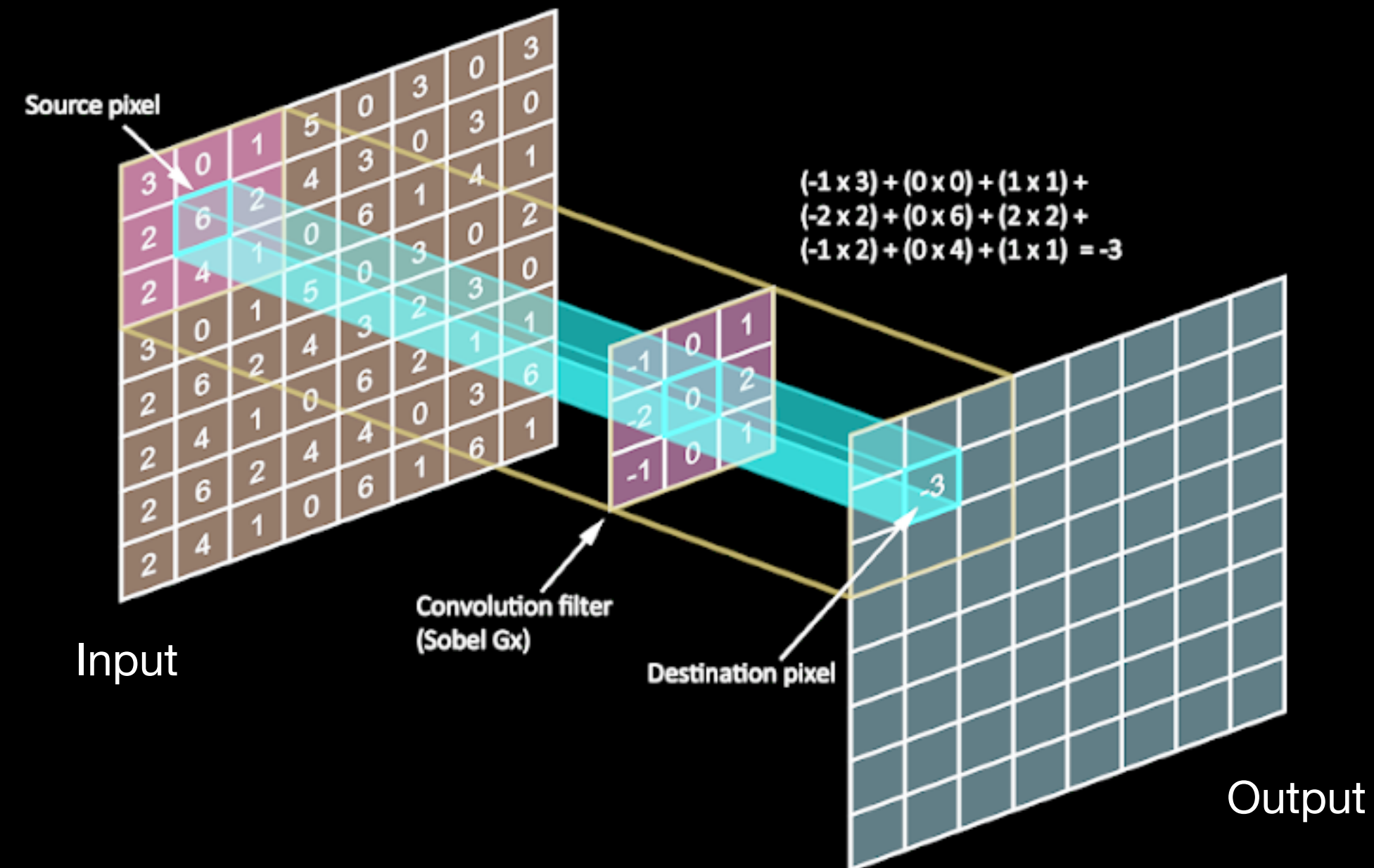
Corrupted image



Predicted image

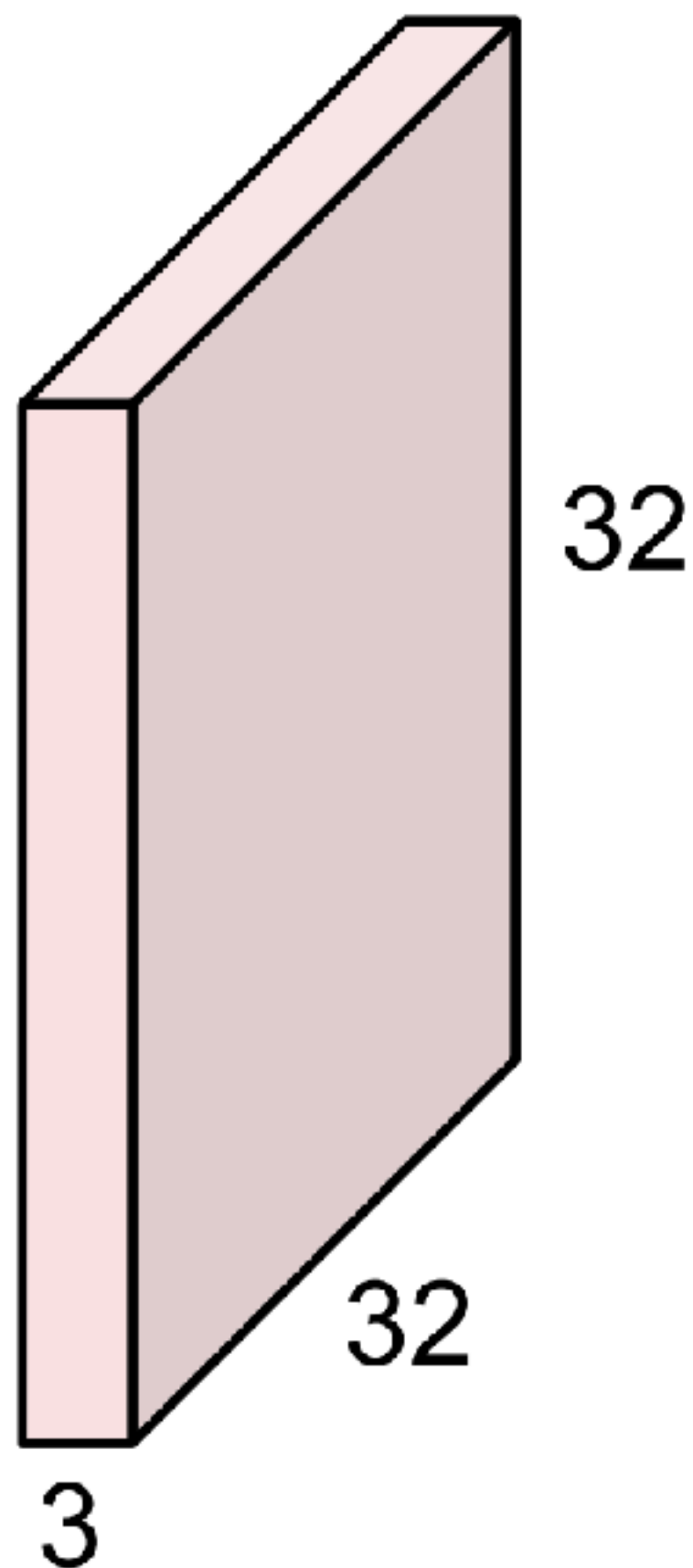


Convolutional neural networks



Convolution Layer

32x32x3 image



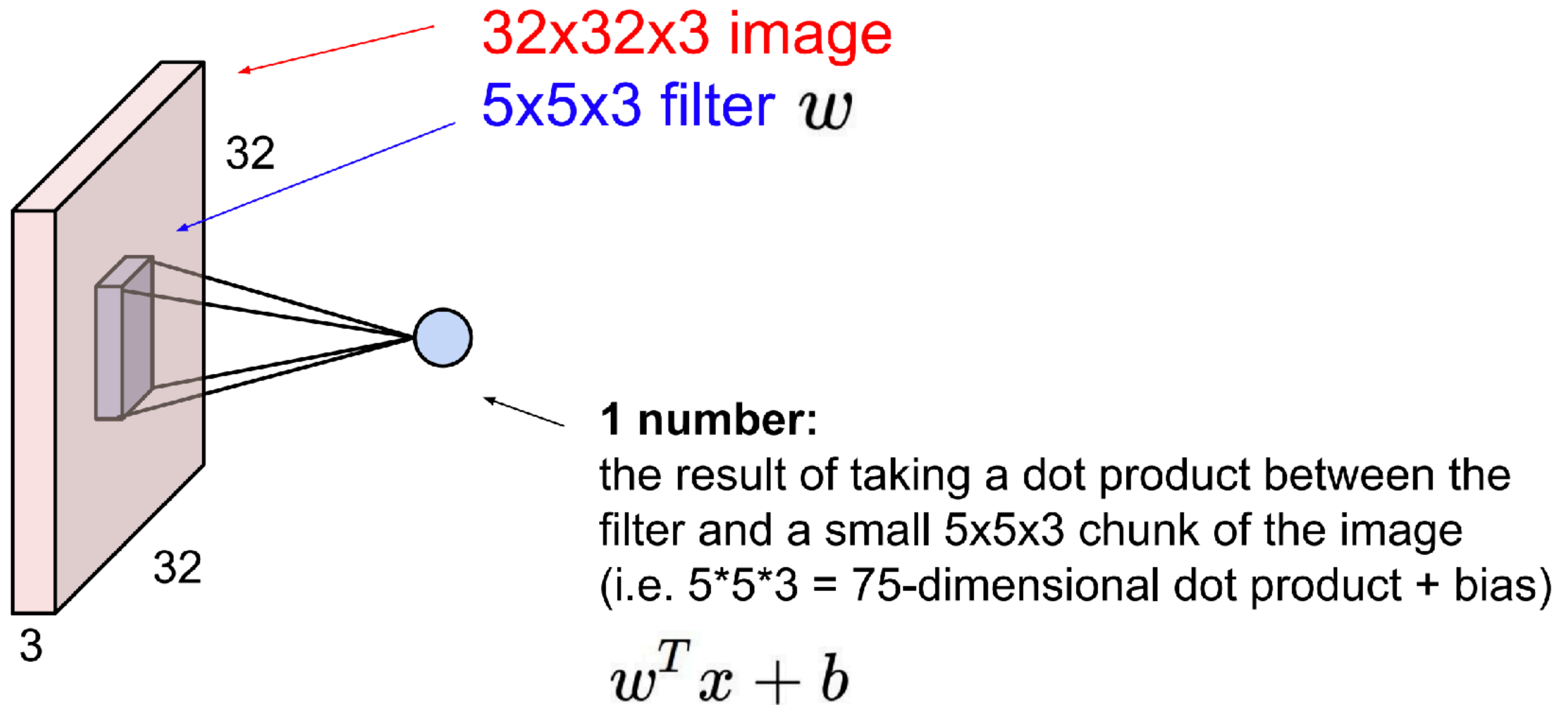
Filters always extend the full depth of the input volume

5x5x3 filter



Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

Convolution Layer



Convolution Layer

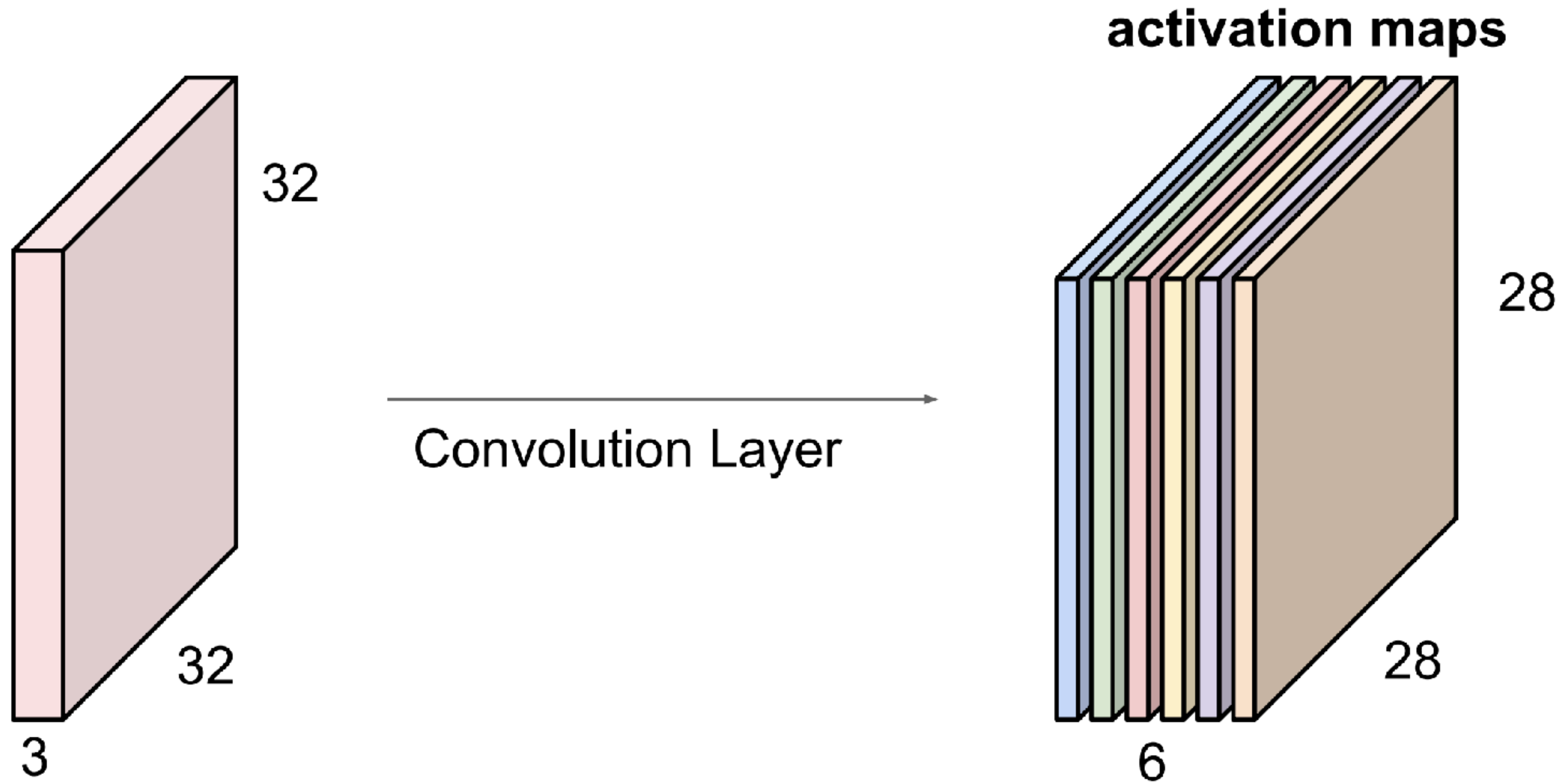


Convolution Layer

consider a second, **green** filter

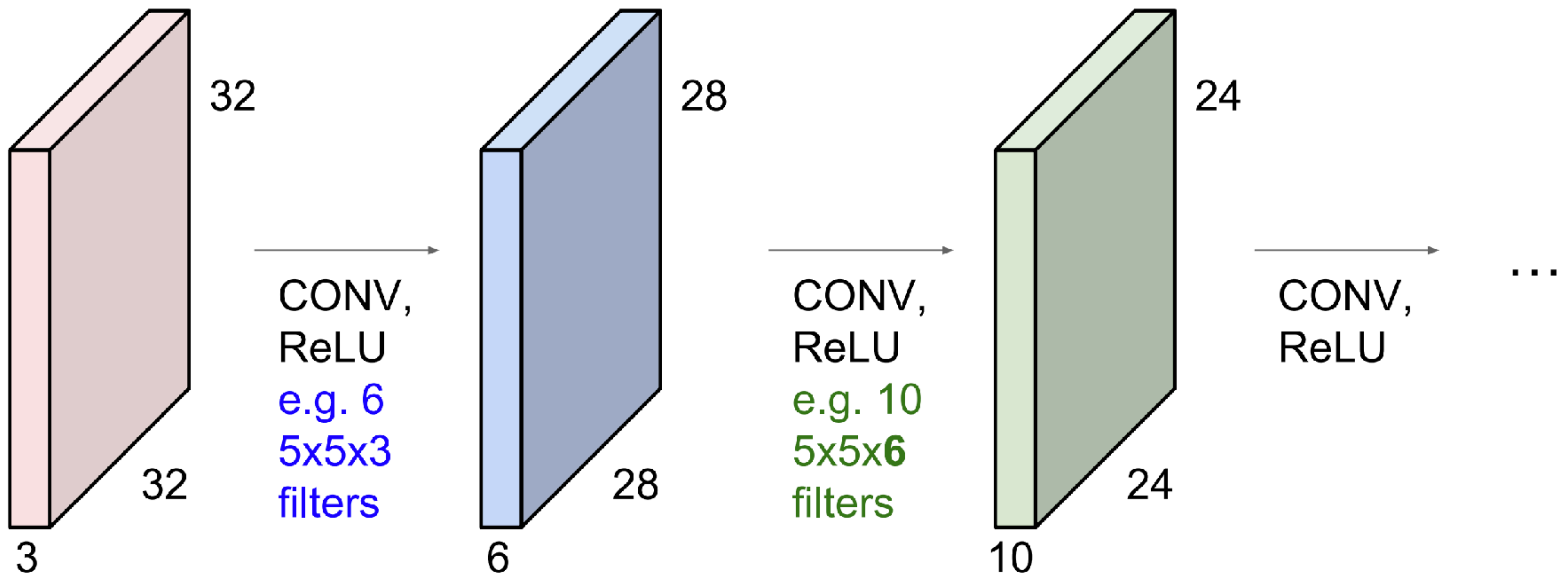


For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



We stack these up to get a “new image” of size 28x28x6!

Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions



For more details + an animated demo see:
<https://cs231n.github.io/convolutional-networks/>

MAX POOLING

Single depth slice

1	1	2	4
5	6	7	8
3	2	1	0
1	2	3	4

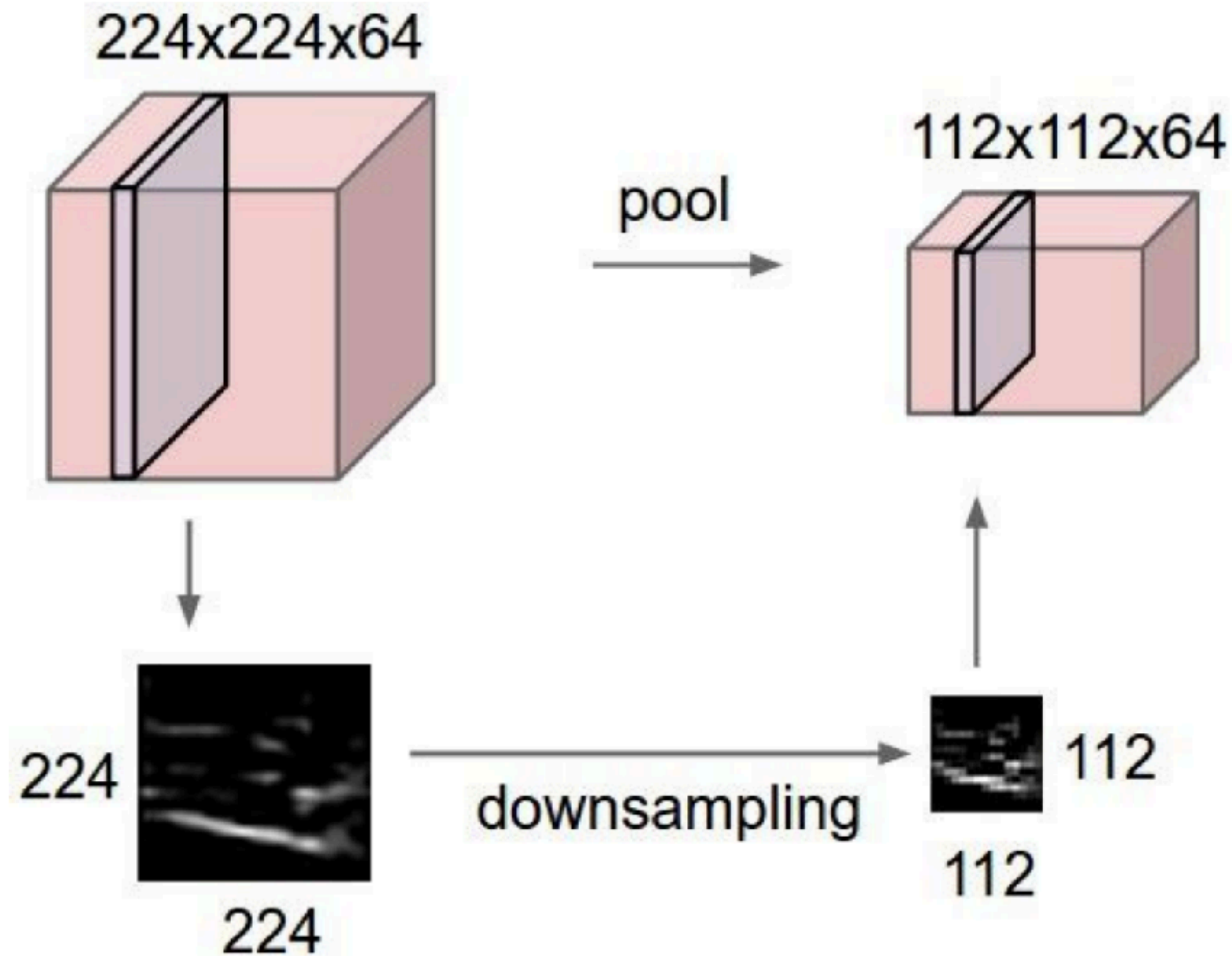
max pool with 2x2 filters
and stride 2

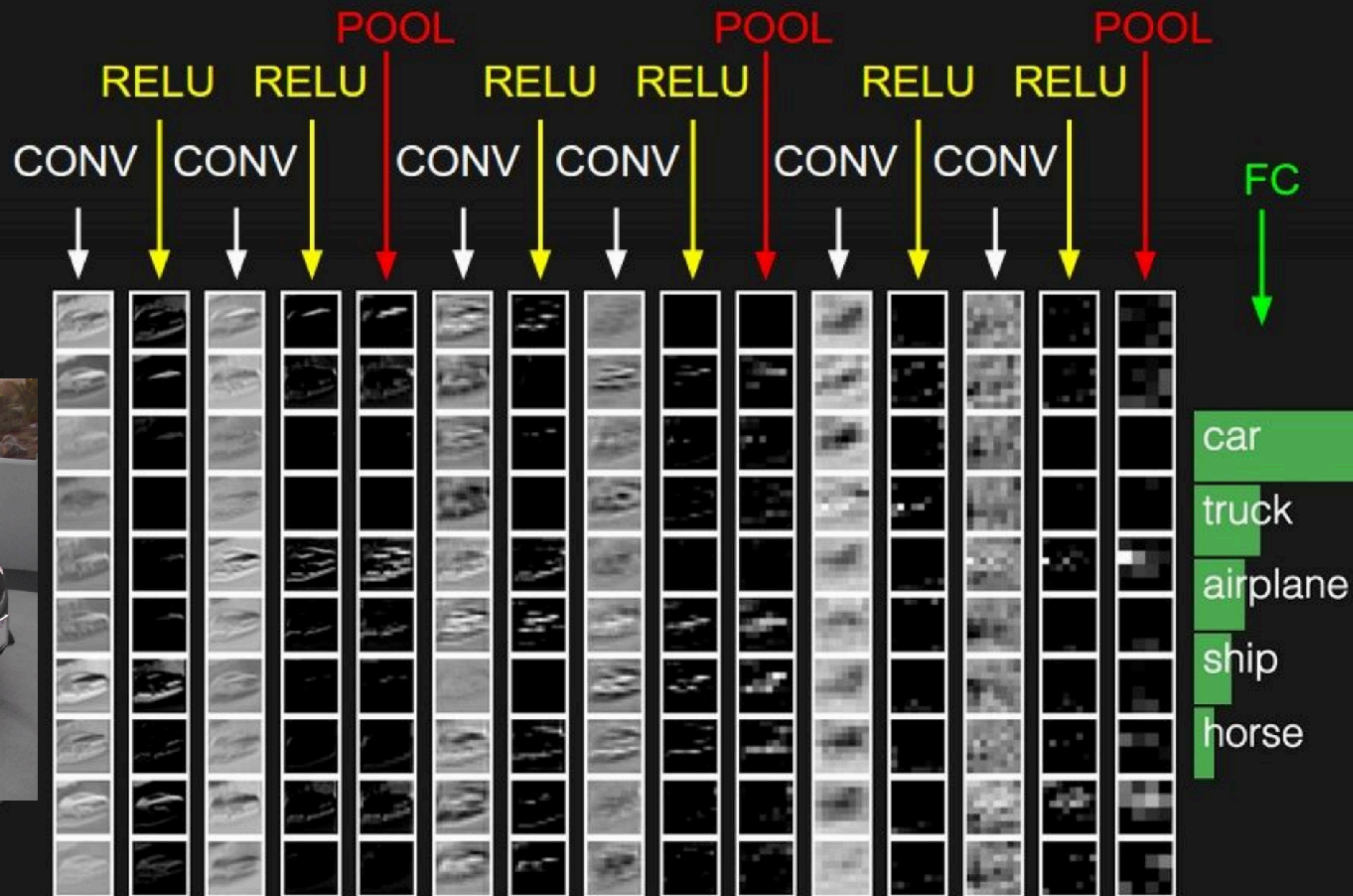


6	8
3	4

Pooling layer

- makes the representations smaller and more manageable
- operates over each activation map independently:






```
import torch.nn as nn
import torch.nn.functional as F
```

```
class Net(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(3, 6, 5)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = torch.flatten(x, 1) # flatten all dimensions except batch
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

```
net = Net()
```

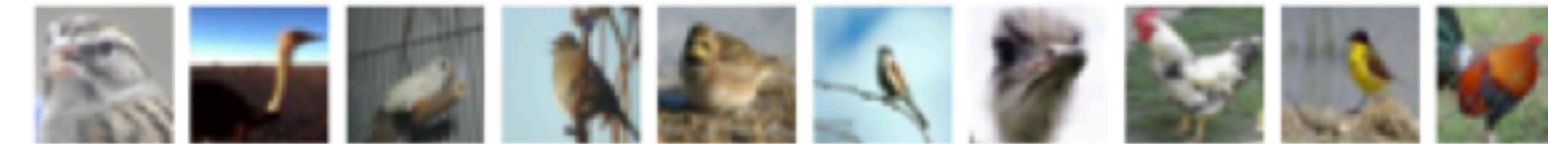
airplane



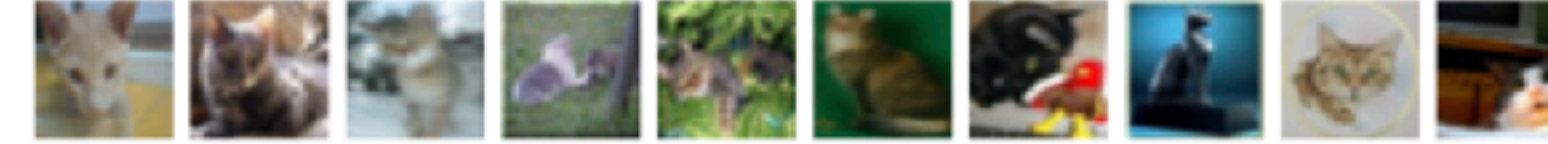
automobile



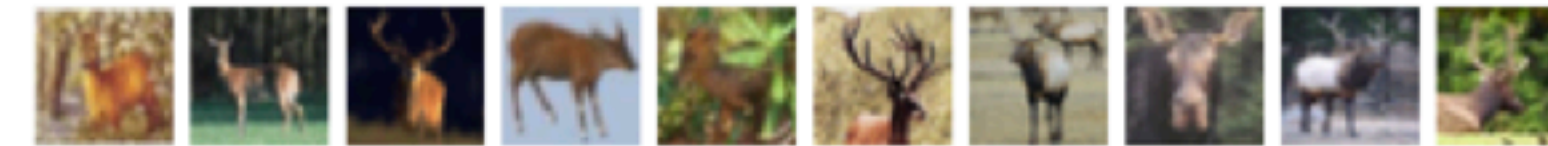
bird



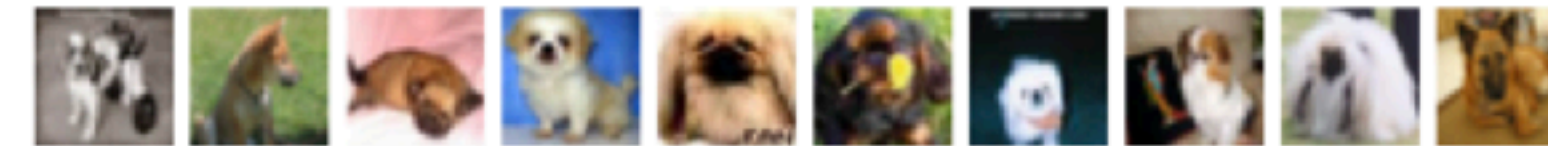
cat



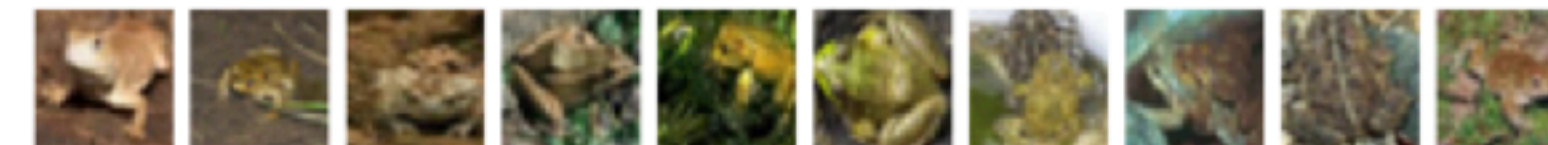
deer



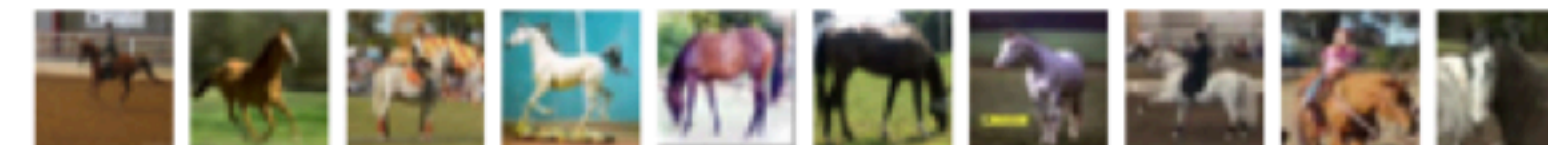
dog



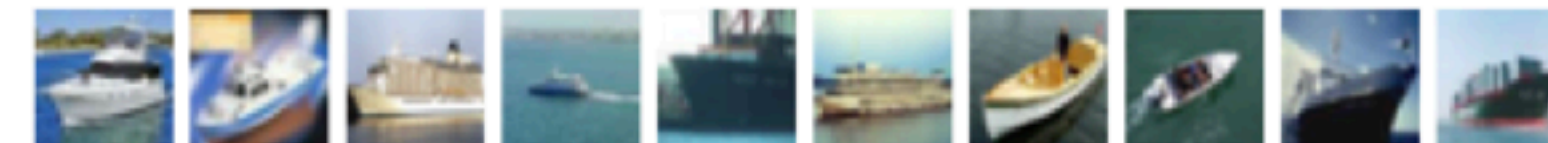
frog



horse



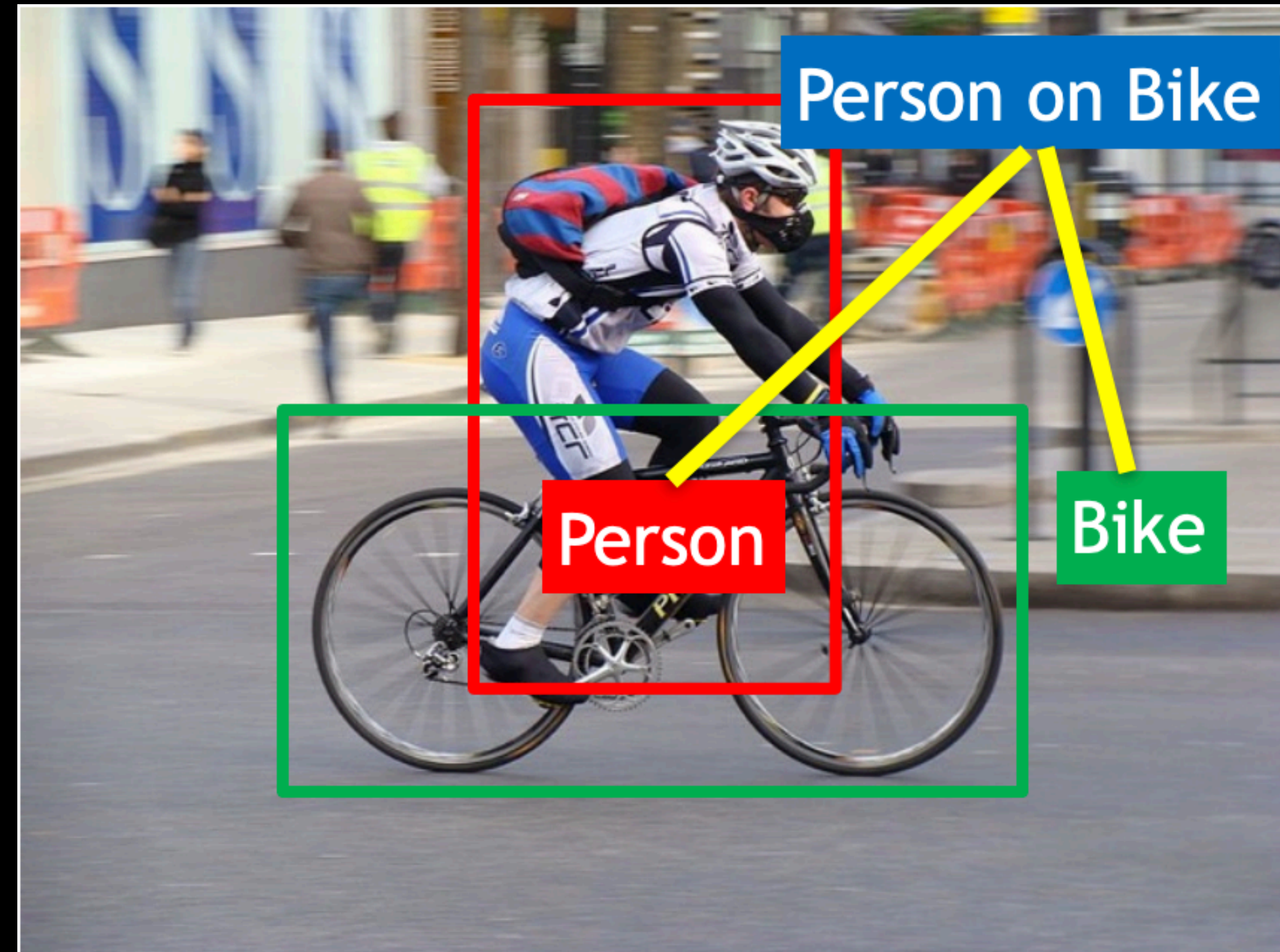
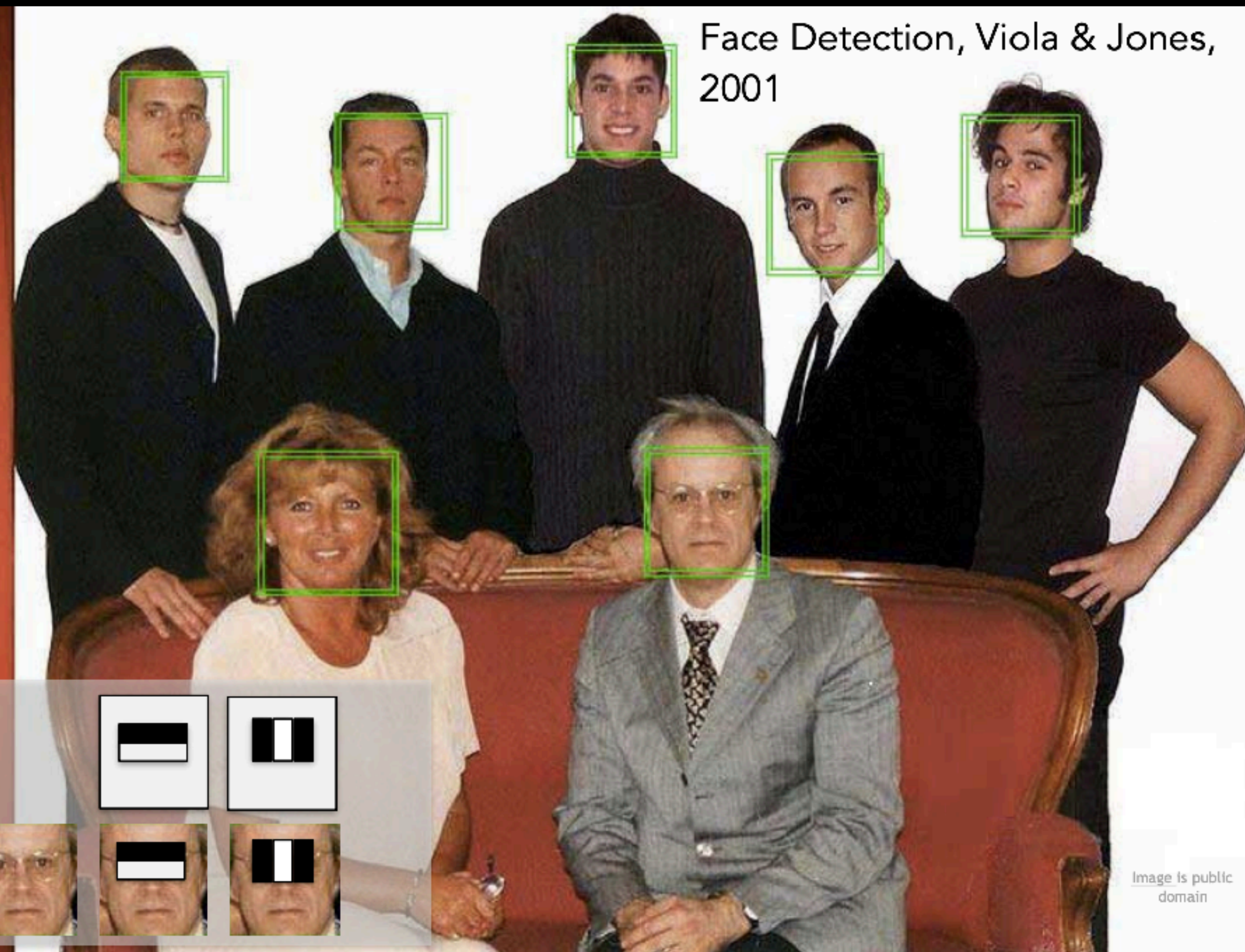
ship



truck

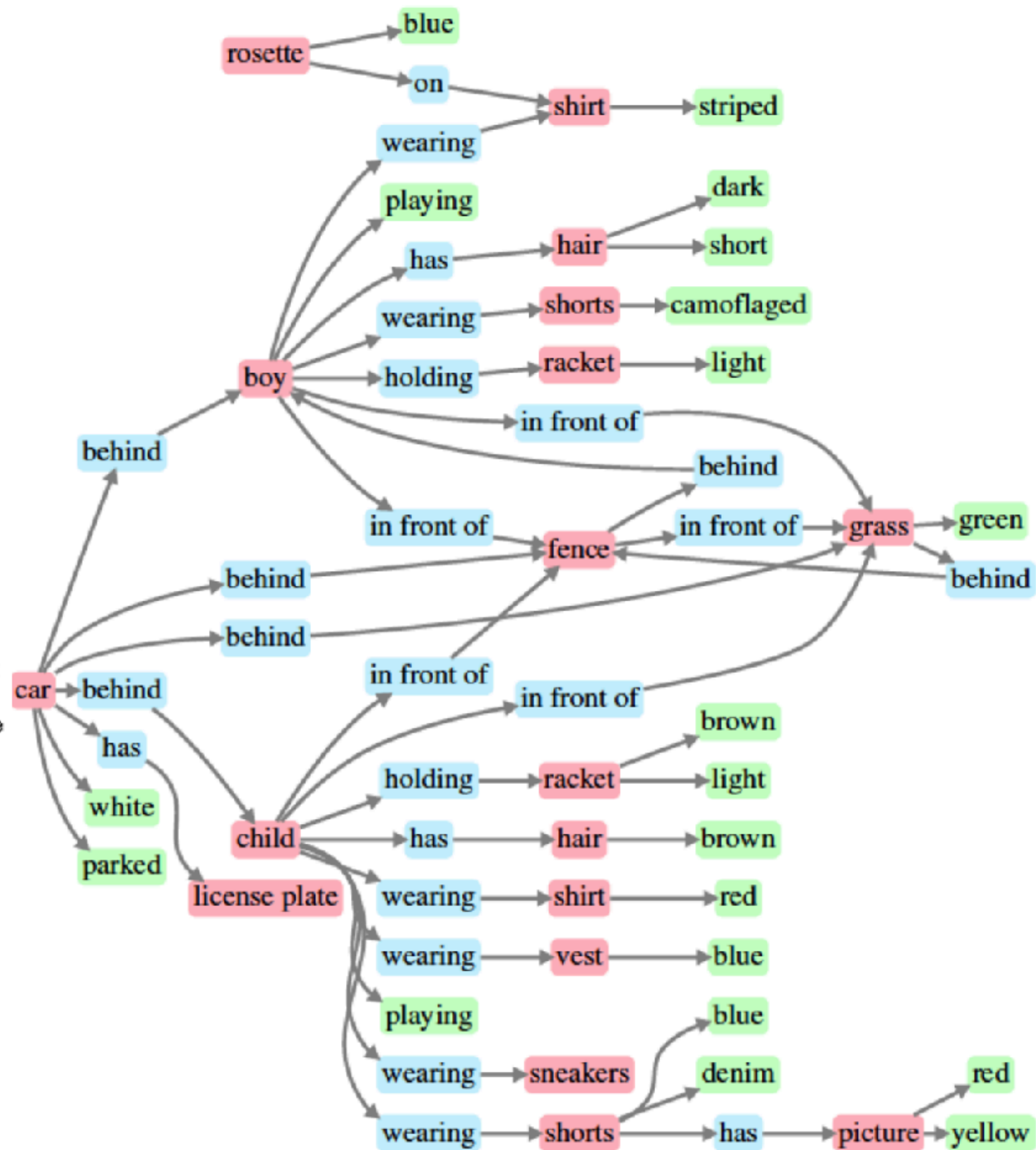
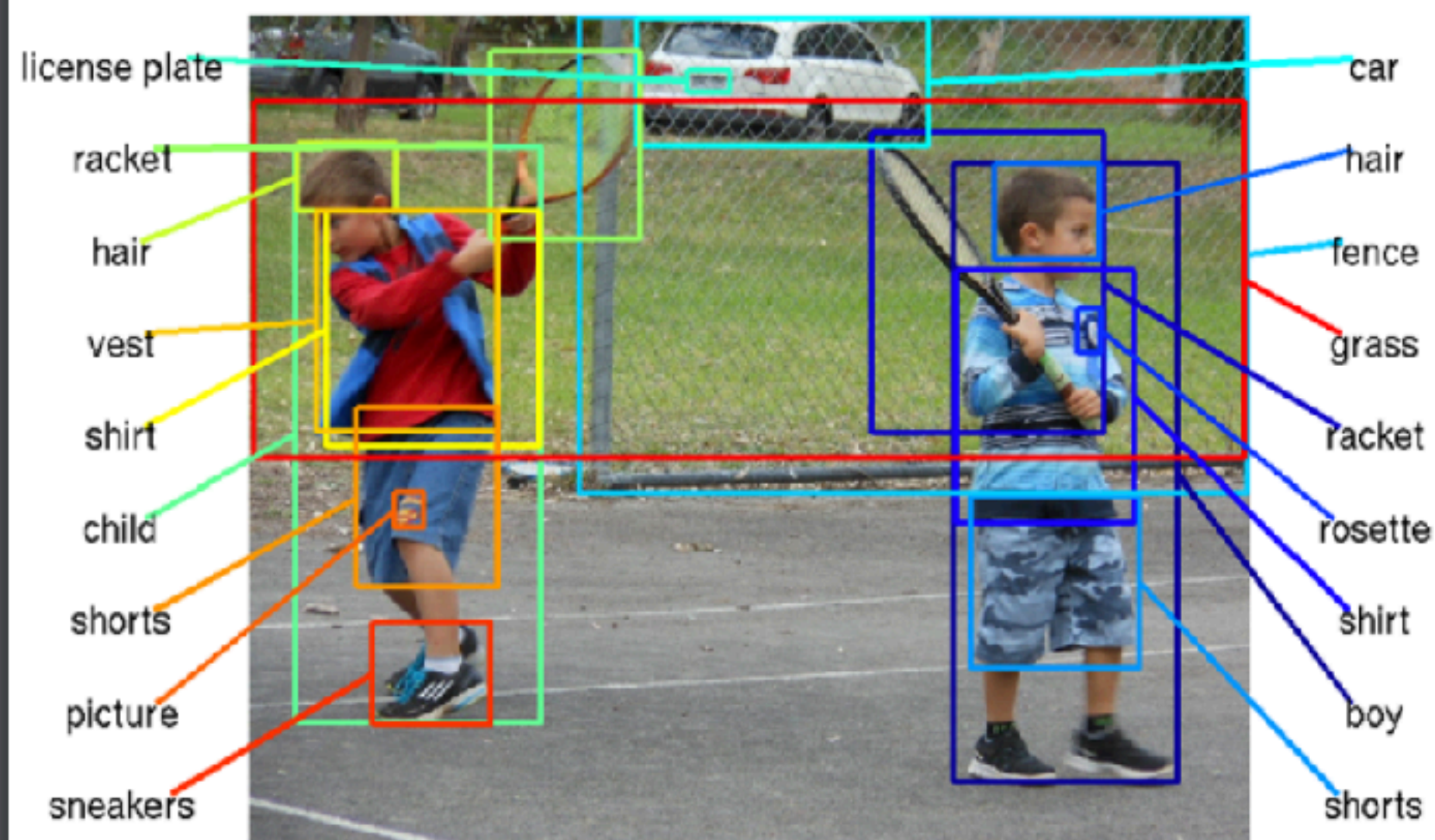


https://pytorch.org/tutorials/beginner/blitz/cifar10_tutorial.html



The following slides were taken from Stanford's CS231:

- <https://cs231n.github.io/>
- <https://www.youtube.com/playlist?list=PL3FW7Lu3i5JvHM8ljYj-zLfQRF3EO8sYv>



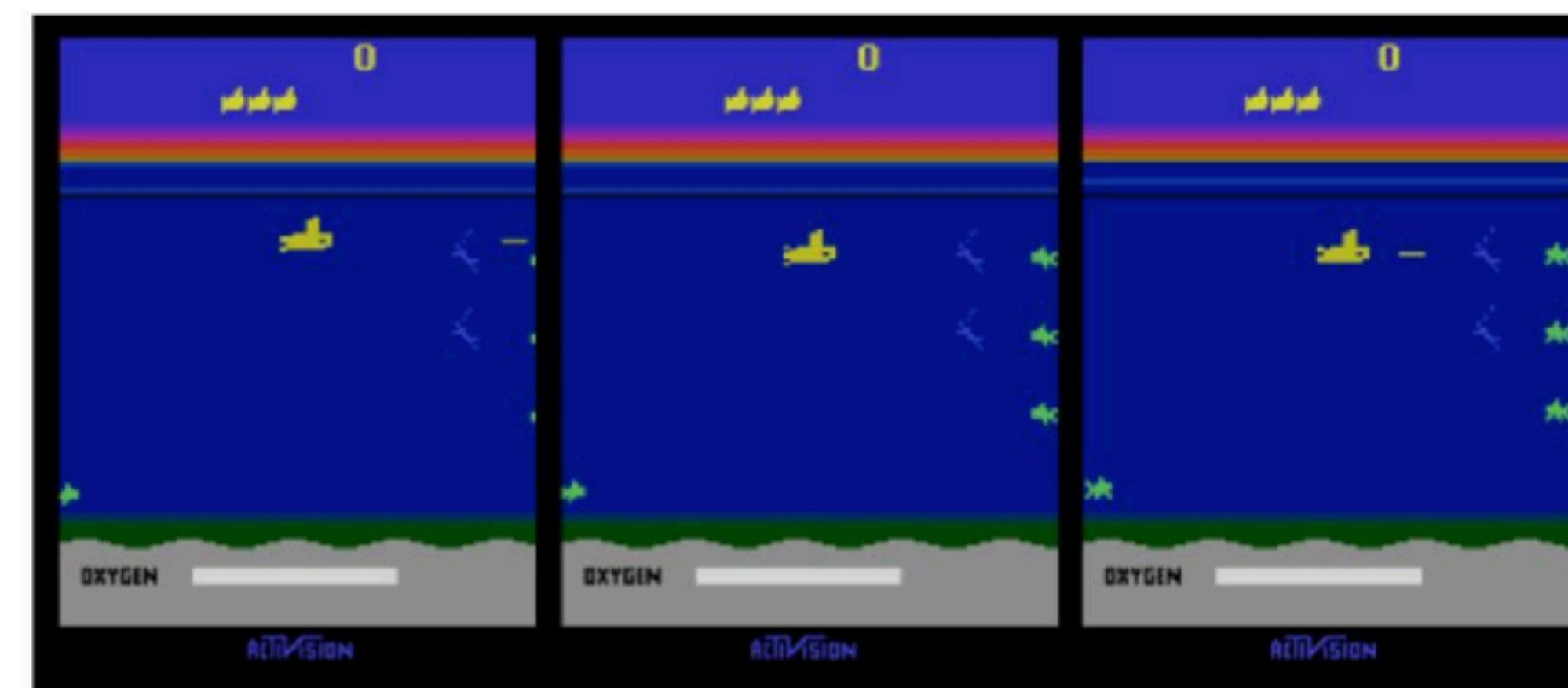
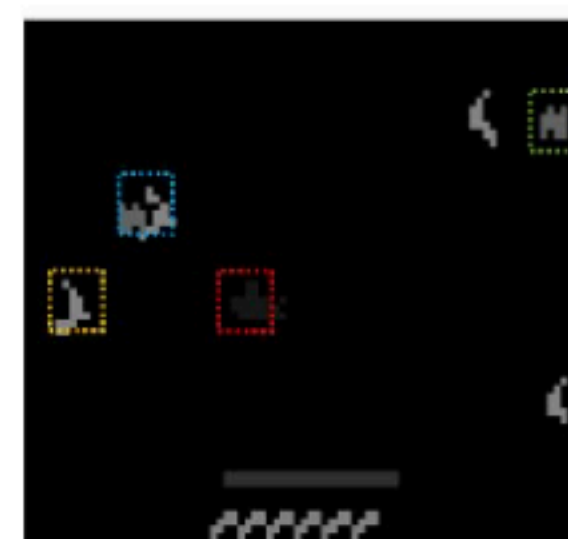
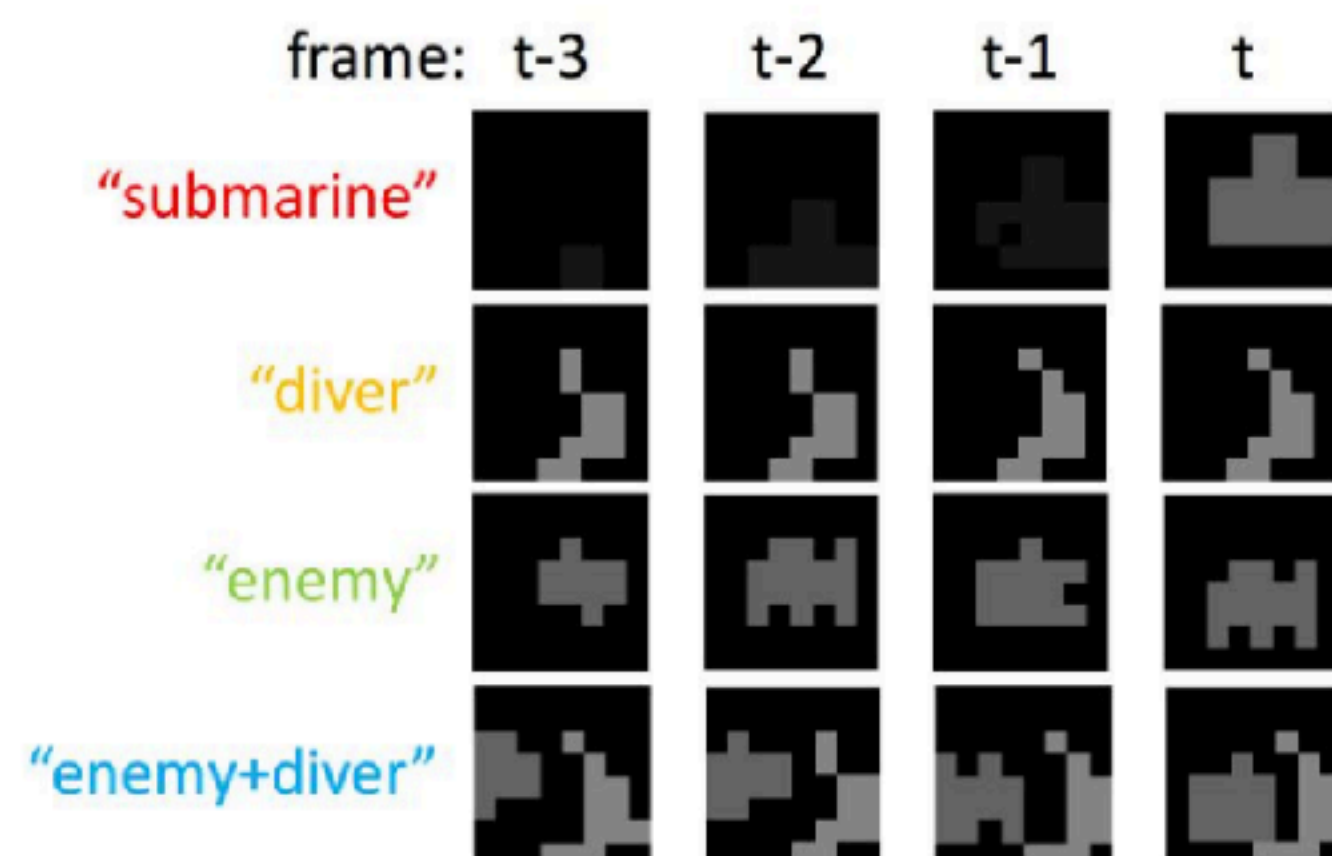
Johnson *et al.*, “Image Retrieval using Scene Graphs”, CVPR 2015

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Images are examples of pose estimation, not actually from Toshev & Szegedy 2014. Copyright Lane McIntosh.

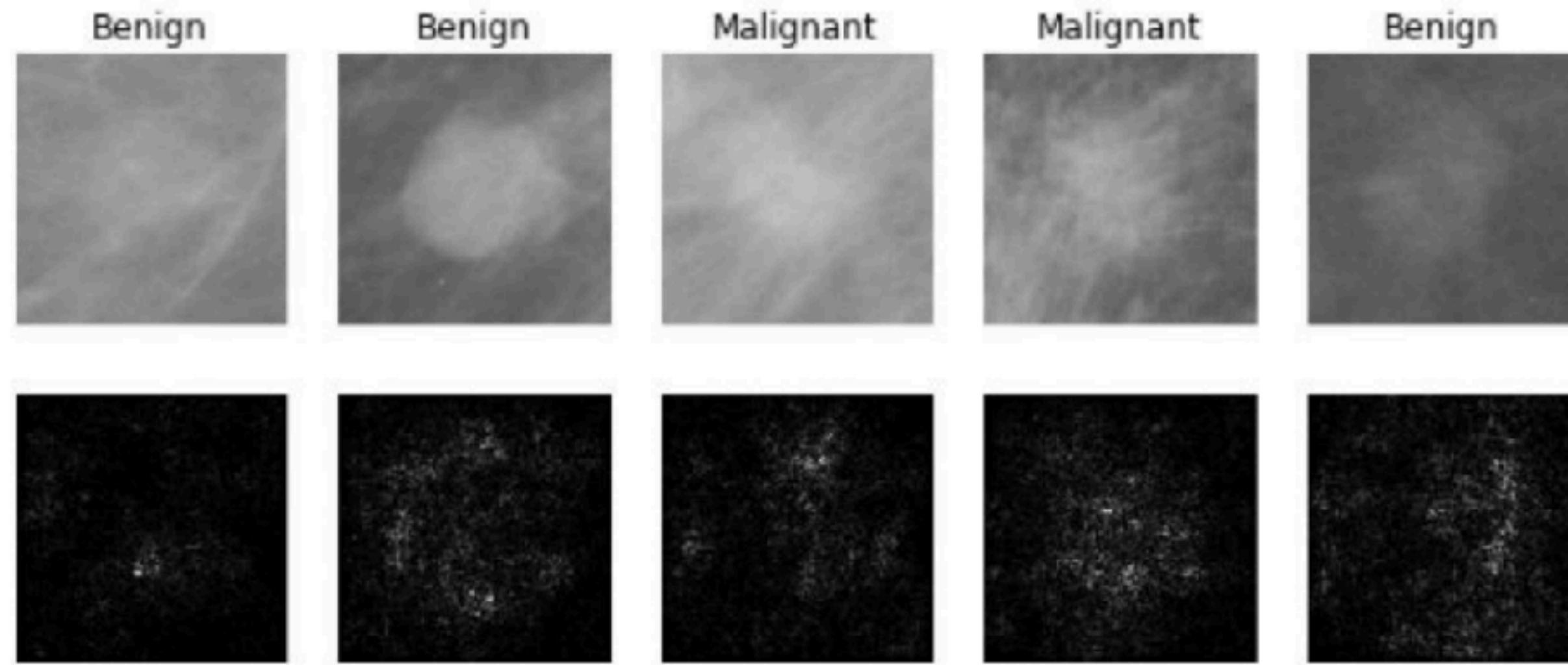
[Toshev, Szegedy 2014]



[Guo et al. 2014]

Figures copyright Xiaoxiao Guo, Satinder Singh, Honglak Lee, Richard Lewis, and Xiaoshi Wang. 2014. Reproduced with permission.

Fast-forward to today: ConvNets are everywhere



[Levy et al. 2016]

Figure copyright Levy et al. 2016.
Reproduced with permission.



[Dieleman et al. 2014]

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[Sermanet et al. 2011]
[Ciresan et al.]

Photos by Lane McIntosh.
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Whale recognition, Kaggle Challenge

Photo and figure by Lane McIntosh; not actual example from Mnih and Hinton, 2010 paper.



Mnih and Hinton, 2010

No errors



A white teddy bear sitting in the grass

Minor errors



A man in a baseball uniform throwing a ball

Somewhat related



A woman is holding a cat in her hand

Image Captioning

*[Vinyals et al., 2015]
[Karpathy and Fei-Fei, 2015]*



A man riding a wave on top of a surfboard



A cat sitting on a suitcase on the floor

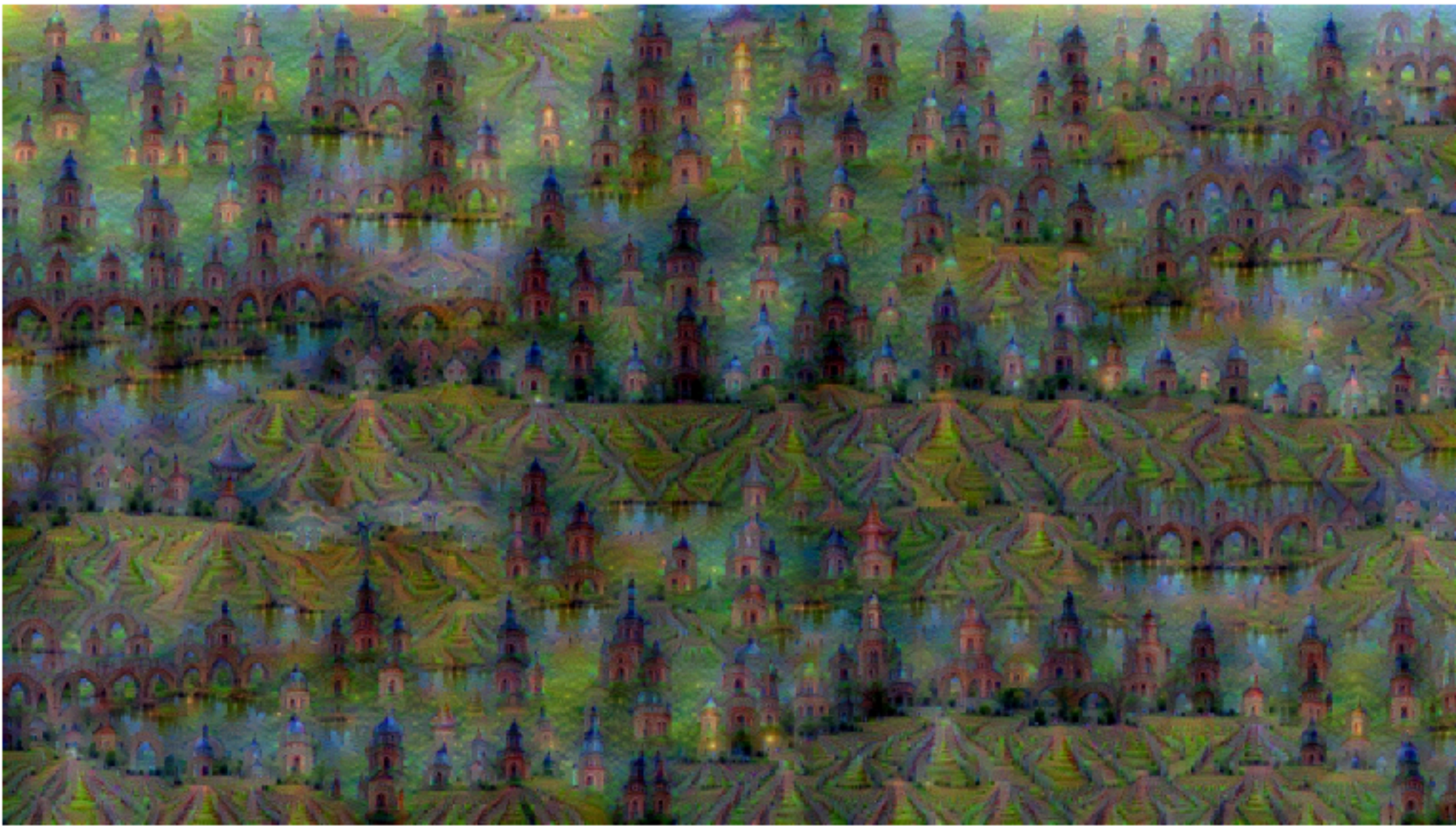
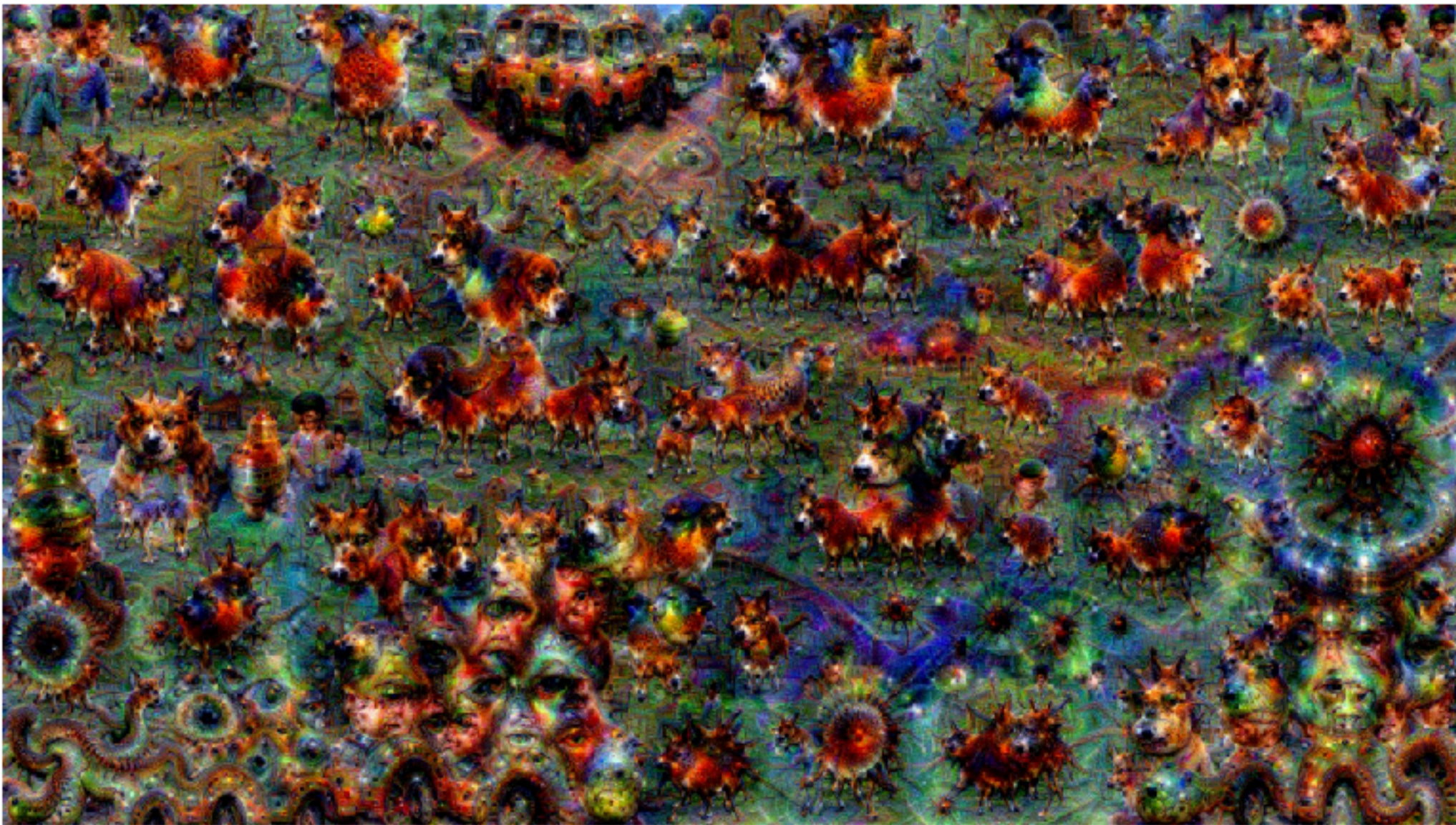


A woman standing on a beach holding a surfboard

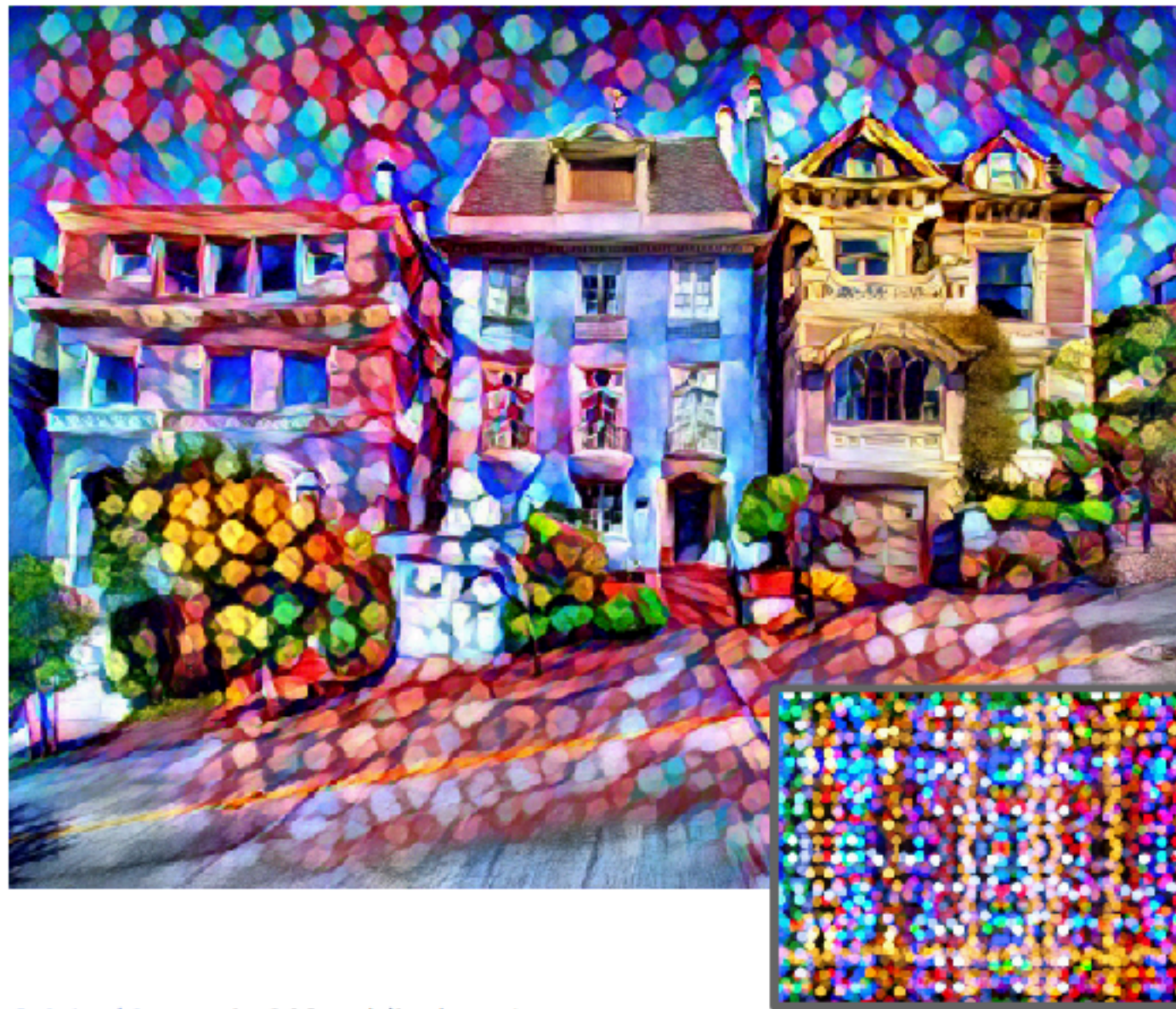
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<https://pixabay.com/en/baseball-player-shortstop-infield-1045263/>

Captions generated by Justin Johnson using [NeuralTalk2](#)



Figures copyright Justin Johnson, 2015. Reproduced with permission. Generated using the Inceptionism approach from a [blog post](#) by Google Research.



[Original image](#) is CC0 public domain
[Starry Night](#) and [Tree Roots](#) by Van Gogh are in the public domain
[Bokeh image](#) is in the public domain
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 reproduced with permission



Gatys et al, "Image Style Transfer using Convolutional Neural Networks", CVPR 2016
 Gatys et al, "Controlling Perceptual Factors in Neural Style Transfer", CVPR 2017

IMAGENET Large Scale Visual Recognition Challenge

Steel drum

The Image Classification Challenge:

1,000 object classes

1,431,167 images



Output:

Scale
T-shirt
Steel drum
Drumstick
Mud turtle



Output:

Scale
T-shirt
Giant panda
Drumstick
Mud turtle

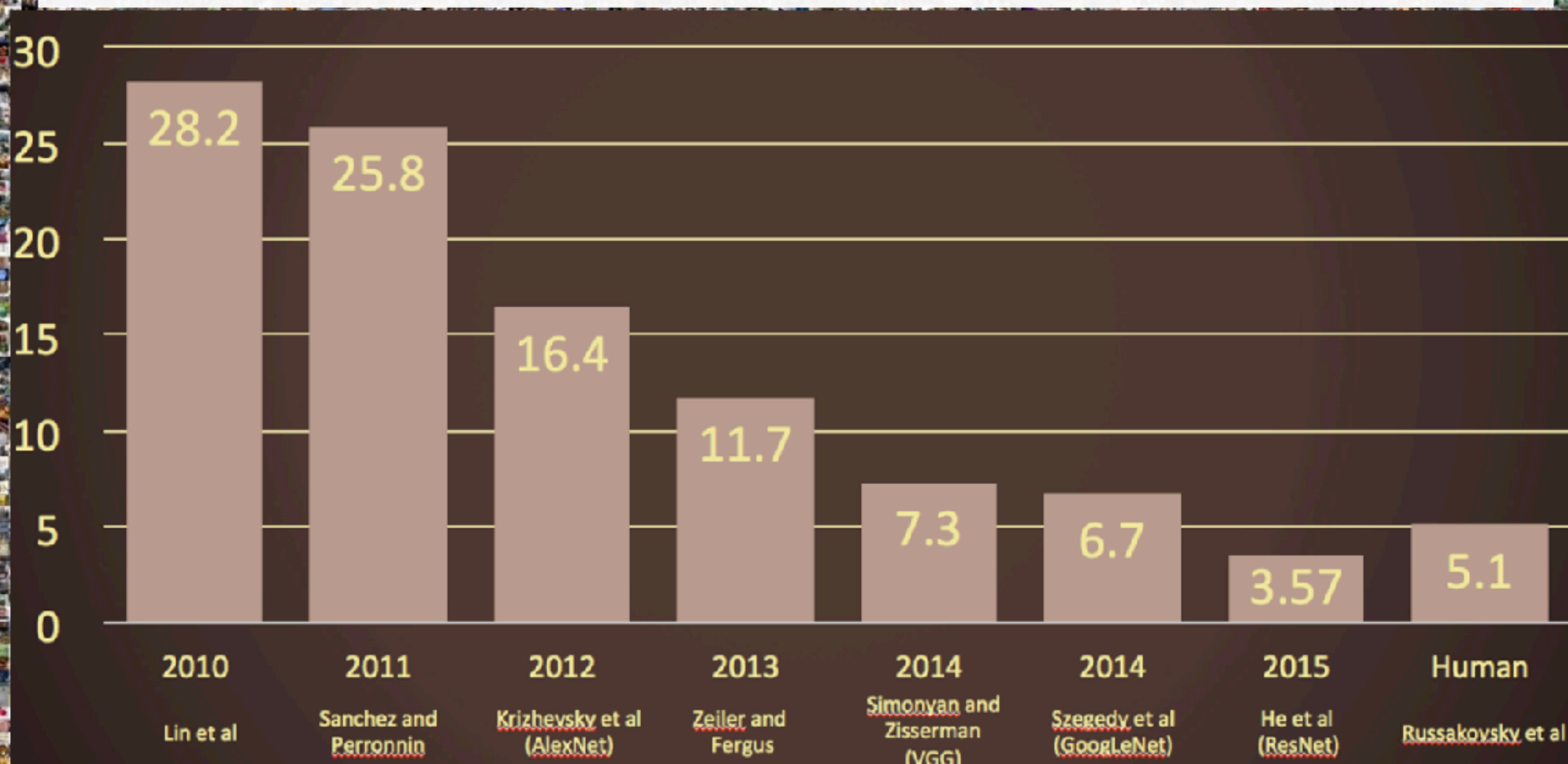


IMAGENET Large Scale Visual Recognition Challenge

The Image Classification Challenge:

1,000 object classes

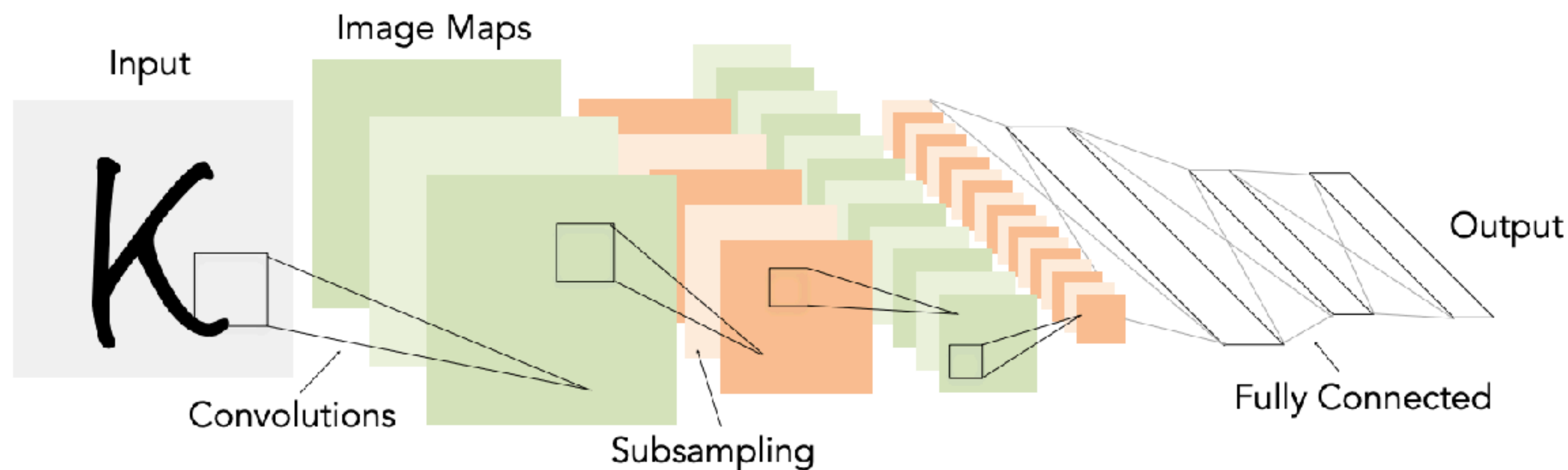
1,431,167 images



Russakovsky et al. arXiv, 2014

1998

LeCun et al.



of transistors



pentium II

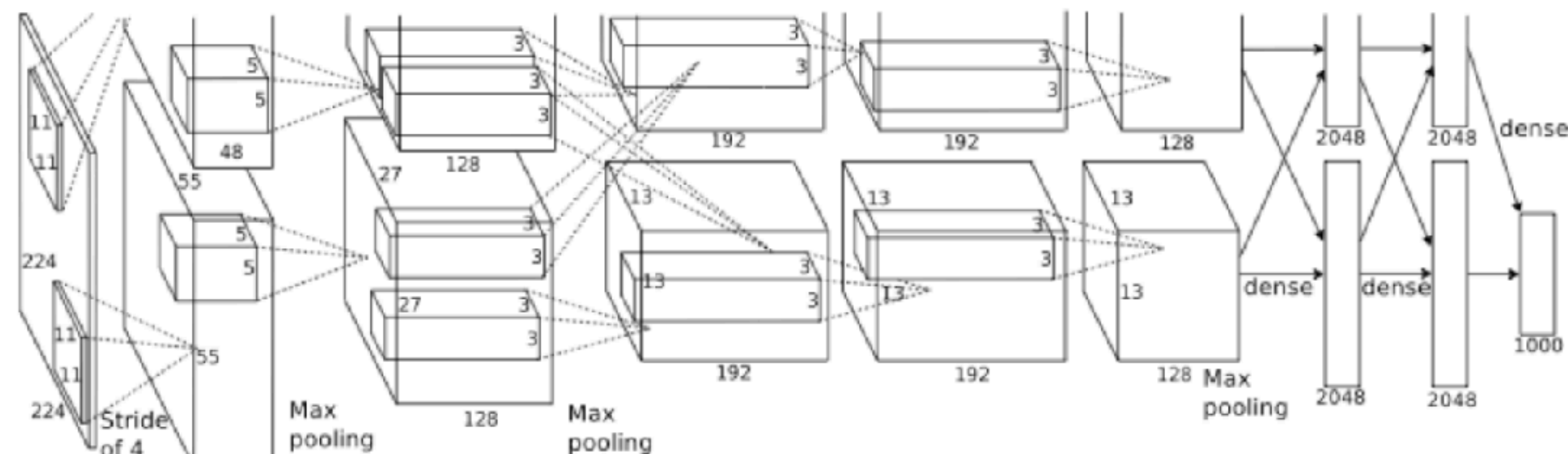
10^6

of pixels used in training

10^7 **NIST**

2012

Krizhevsky et al.



of transistors GPUs



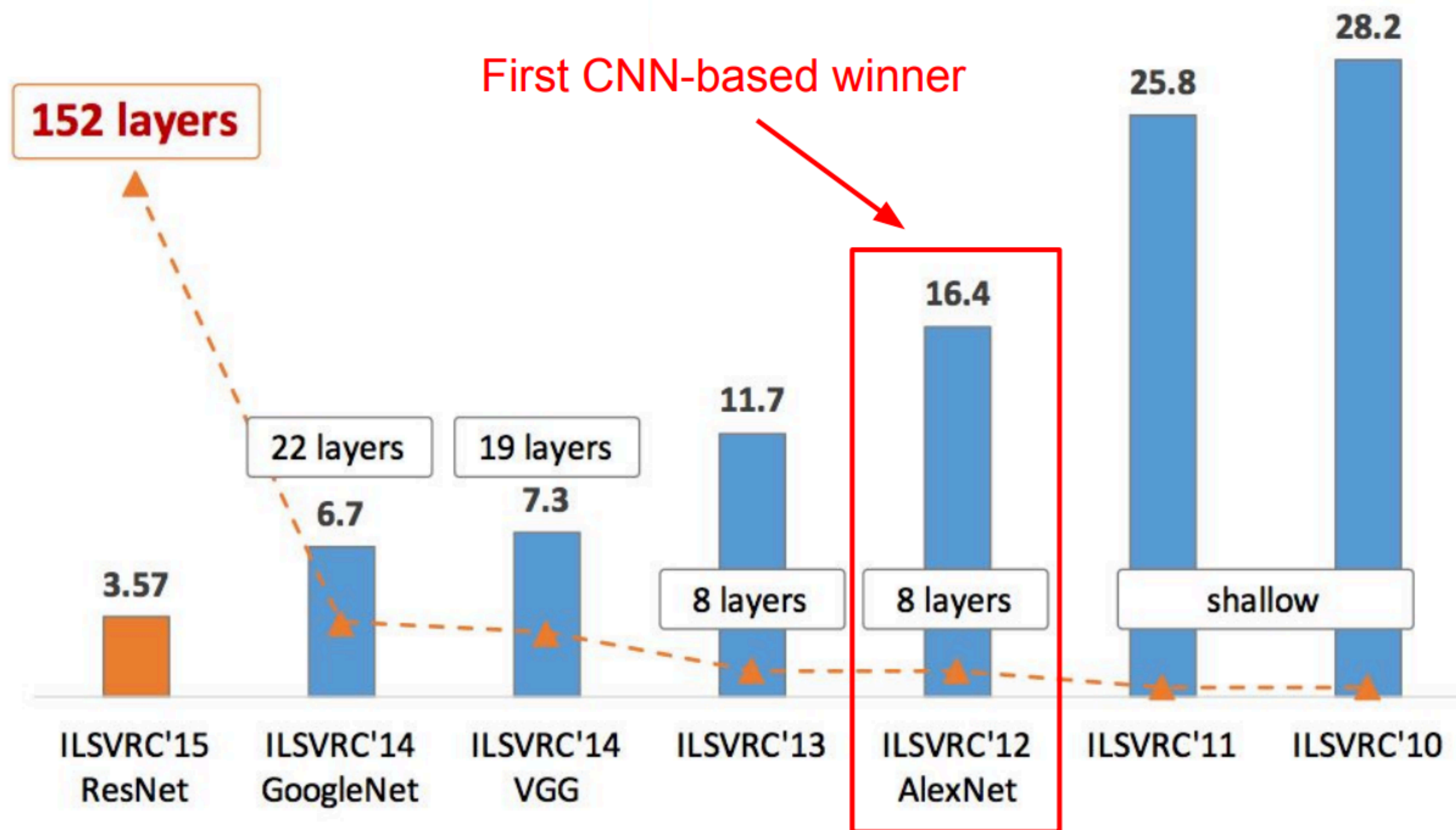
10^9



of pixels used in training

10^{14} **IMAGENET**

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Case Study: AlexNet

[Krizhevsky et al. 2012]

Full (simplified) AlexNet architecture:

[227x227x3] INPUT

[55x55x96] **CONV1**: 96 11x11 filters at stride 4, pad 0

[27x27x96] **MAX POOL1**: 3x3 filters at stride 2

[27x27x96] **NORM1**: Normalization layer

[27x27x256] **CONV2**: 256 5x5 filters at stride 1, pad 2

[13x13x256] **MAX POOL2**: 3x3 filters at stride 2

[13x13x256] **NORM2**: Normalization layer

[13x13x384] **CONV3**: 384 3x3 filters at stride 1, pad 1

[13x13x384] **CONV4**: 384 3x3 filters at stride 1, pad 1

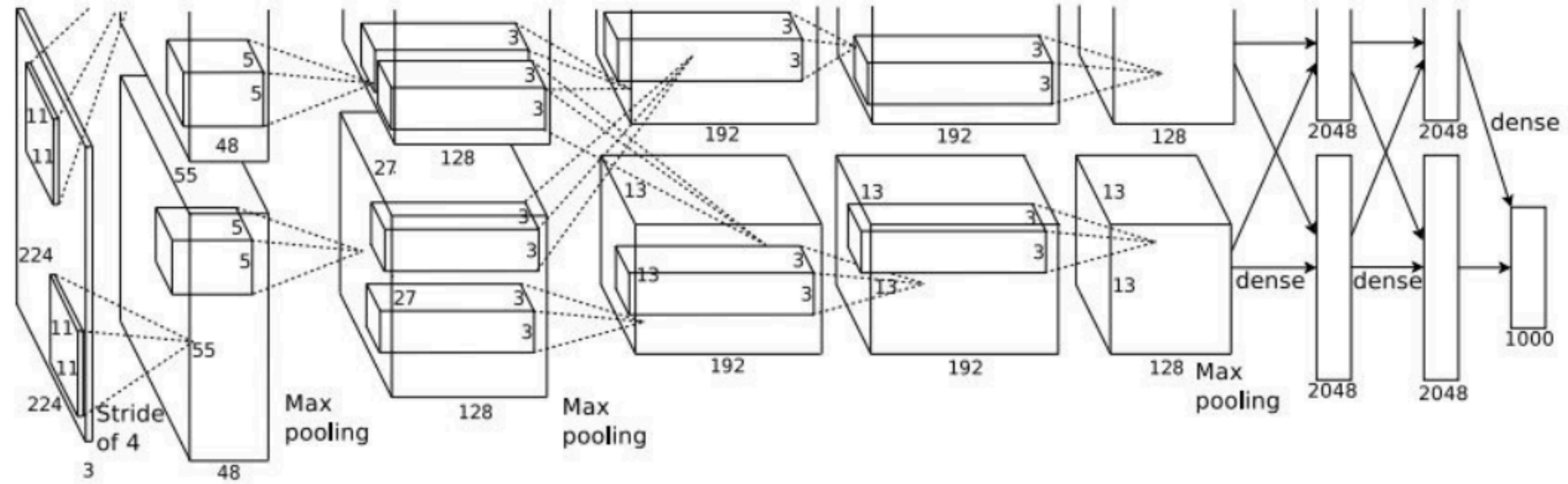
[13x13x256] **CONV5**: 256 3x3 filters at stride 1, pad 1

[6x6x256] **MAX POOL3**: 3x3 filters at stride 2

[4096] **FC6**: 4096 neurons

[4096] **FC7**: 4096 neurons

[1000] **FC8**: 1000 neurons (class scores)



Details/Retrospectives:

- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 5e-4
- 7 CNN ensemble: 18.2% -> 15.4%

Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

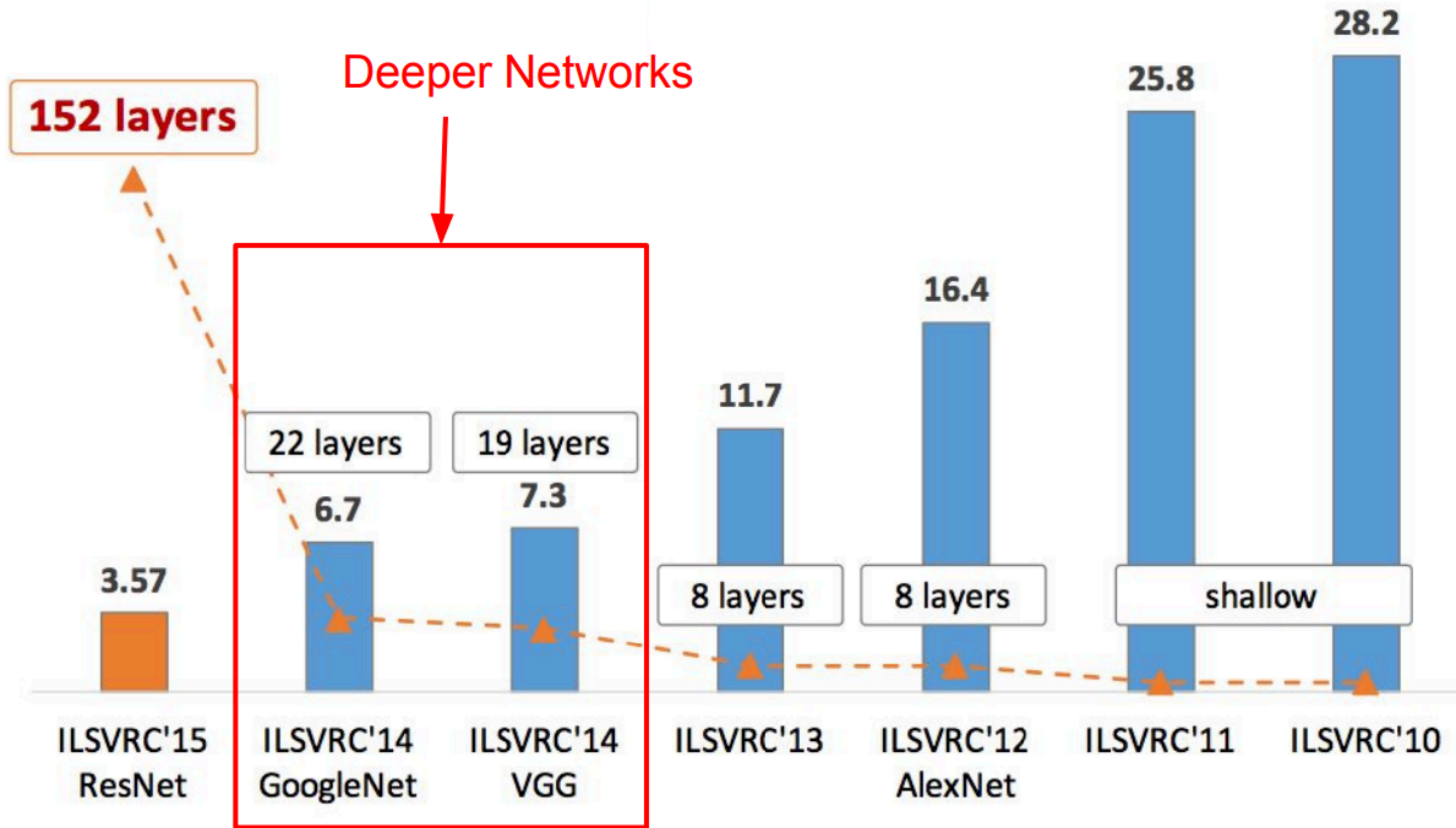


Figure copyright Kaiming He, 2016. Reproduced with permission.

Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Small filters, Deeper networks

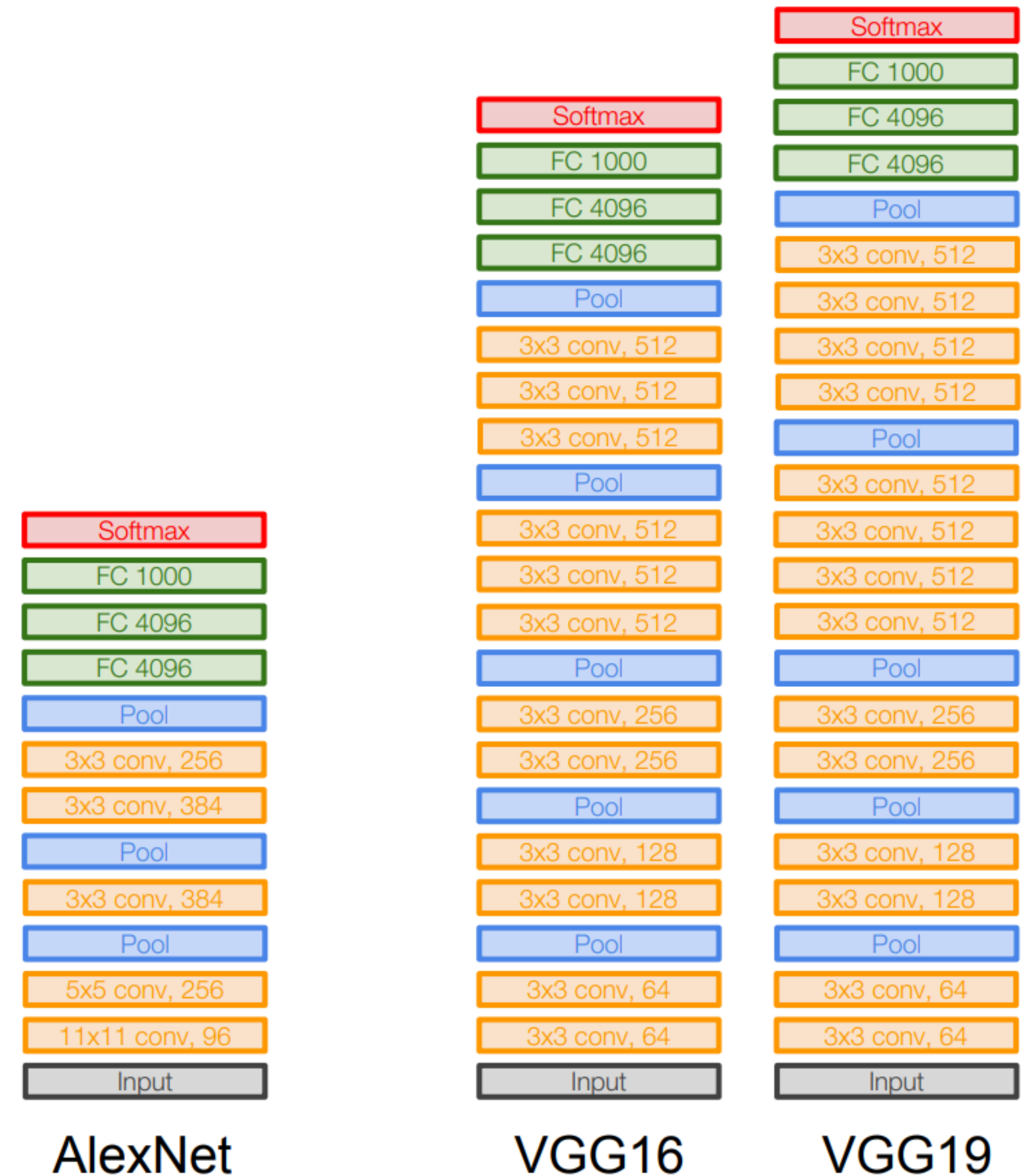
8 layers (AlexNet)

-> 16 - 19 layers (VGG16Net)

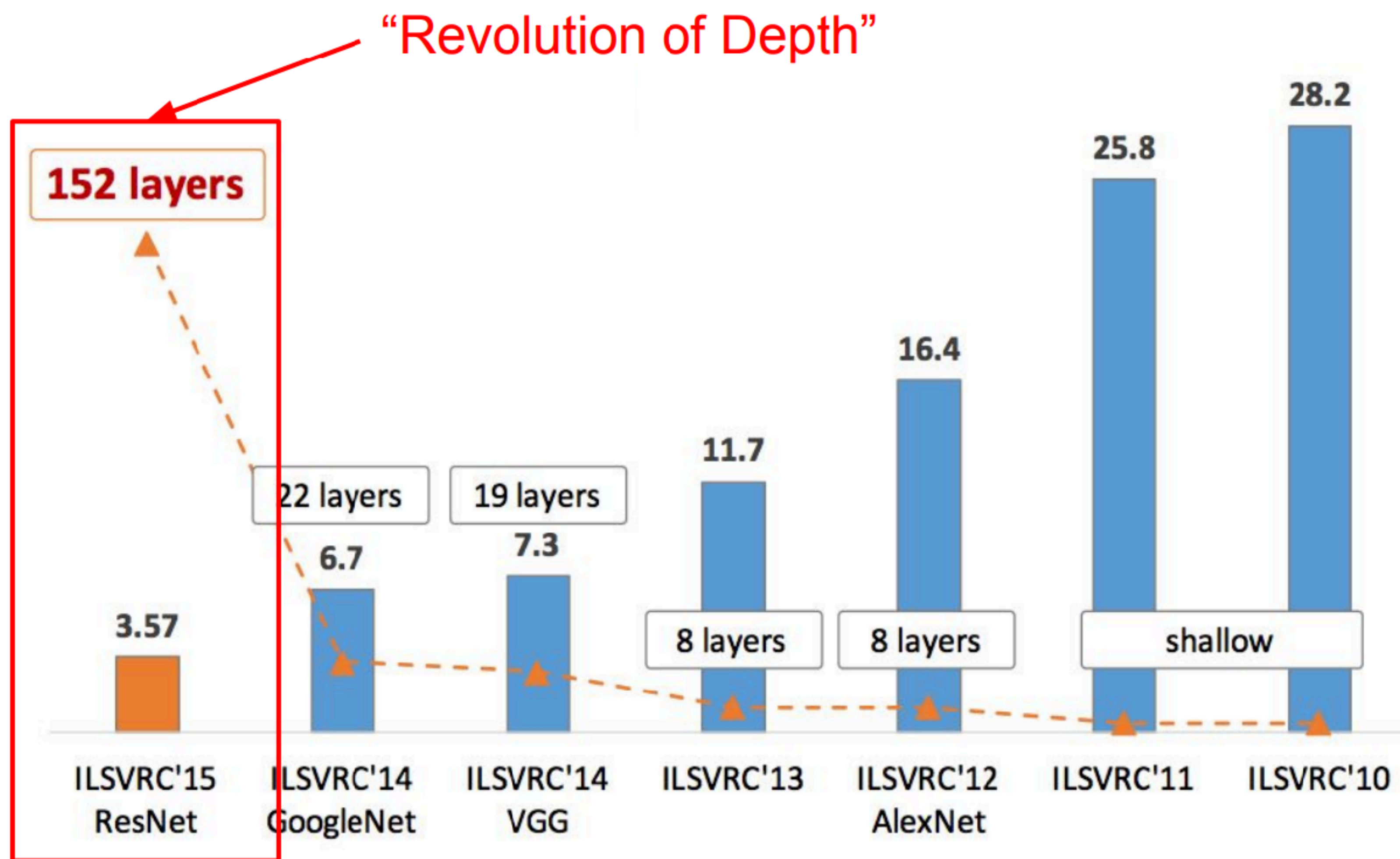
Only 3x3 CONV stride 1, pad 1
and 2x2 MAX POOL stride 2

11.7% top 5 error in ILSVRC'13
(ZFNet)

-> 7.3% top 5 error in ILSVRC'14



ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

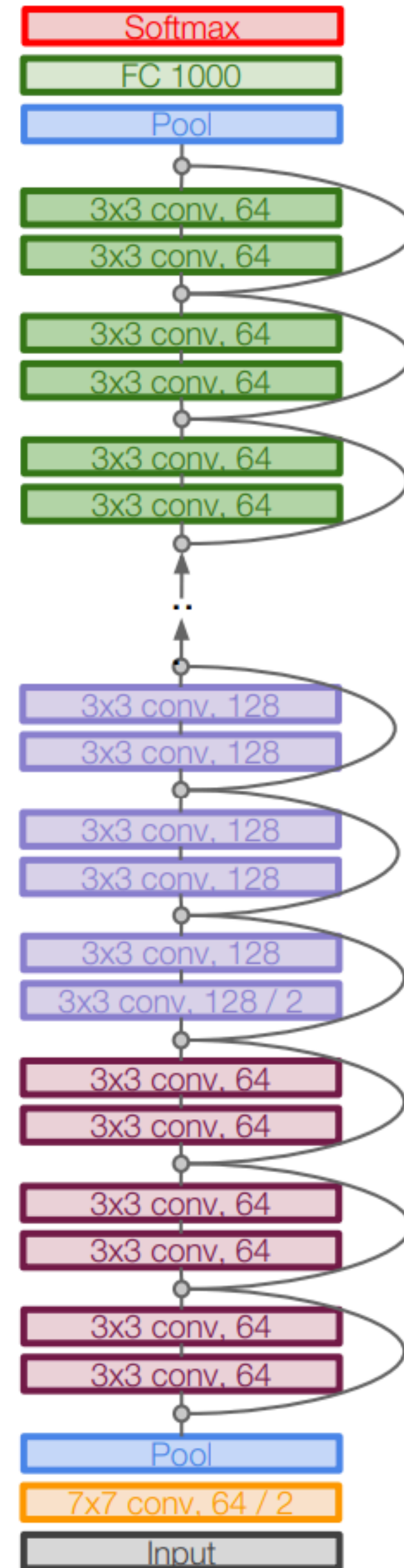
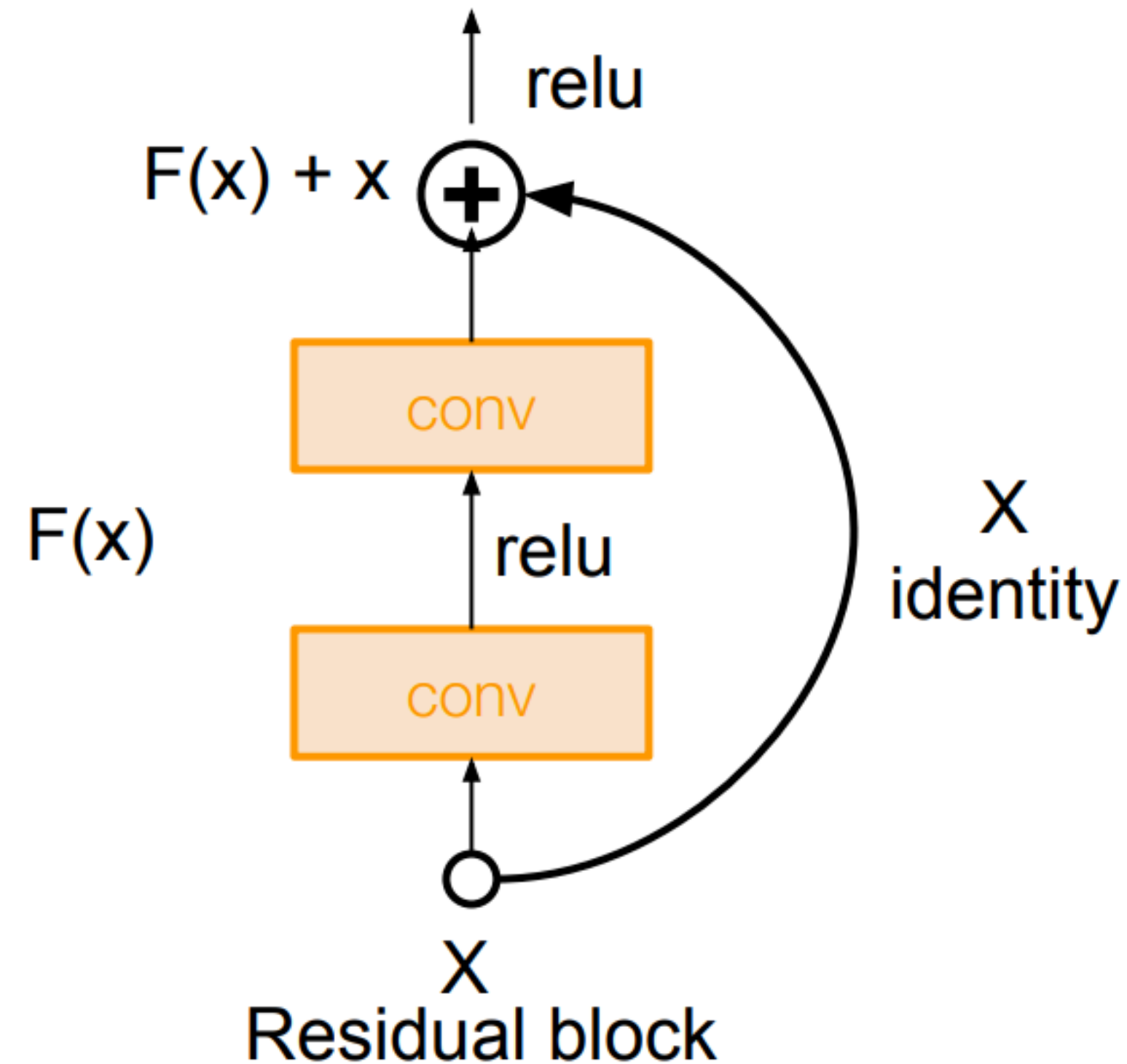


Case Study: ResNet

[He et al., 2015]

Very deep networks using residual connections

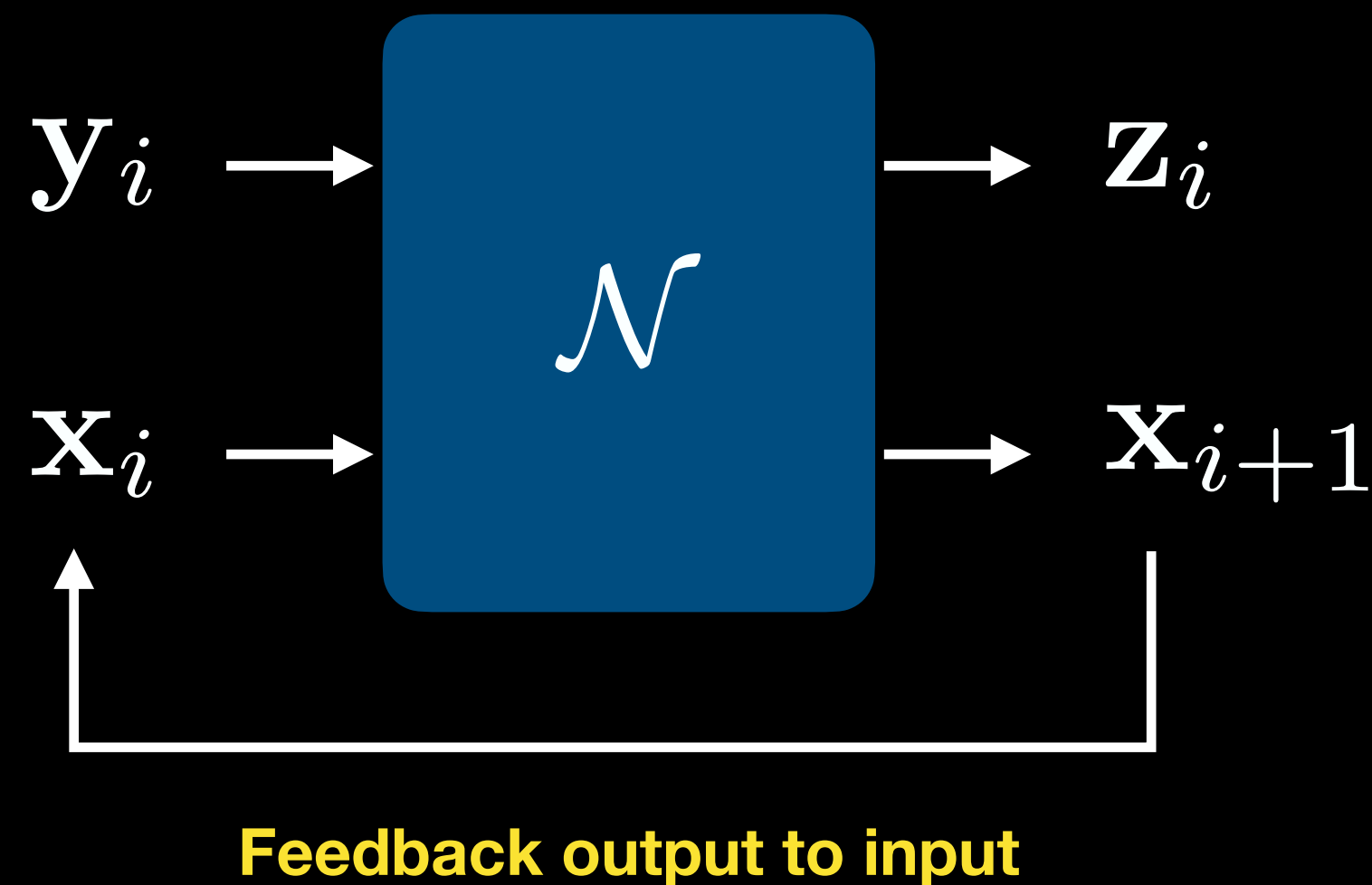
- 152-layer model for ImageNet
- ILSVRC'15 classification winner (3.57% top 5 error)
- Swept all classification and detection competitions in ILSVRC'15 and COCO'15!



Recurrent neural networks

$$\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \dots, \mathbf{x}_i, \mathbf{x}_{i+1}, \dots, \mathbf{x}_n$$

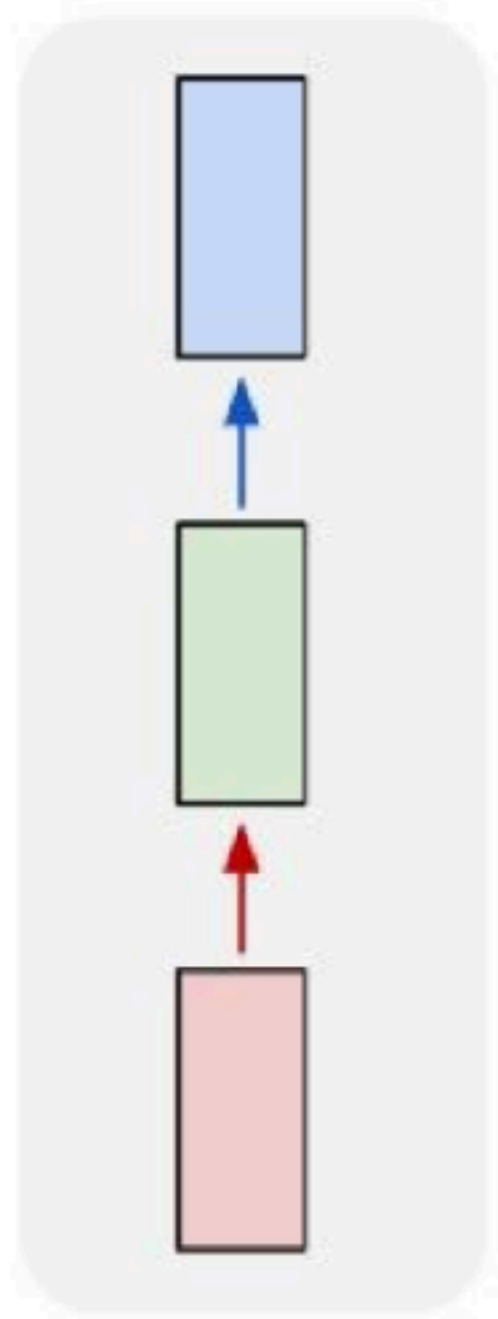
$$[\mathbf{x}_{i+1}, \mathbf{z}_i] = \mathcal{N}(\mathbf{x}_i, \mathbf{y}_i)$$



Numerical solvers are recurrence relations!

“Vanilla” Neural Network

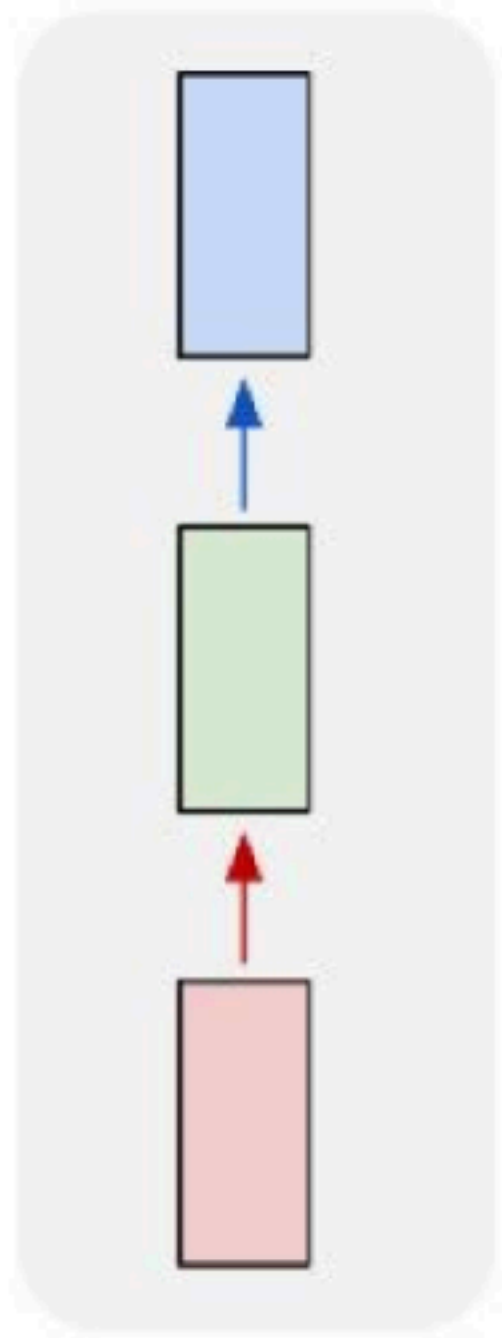
one to one



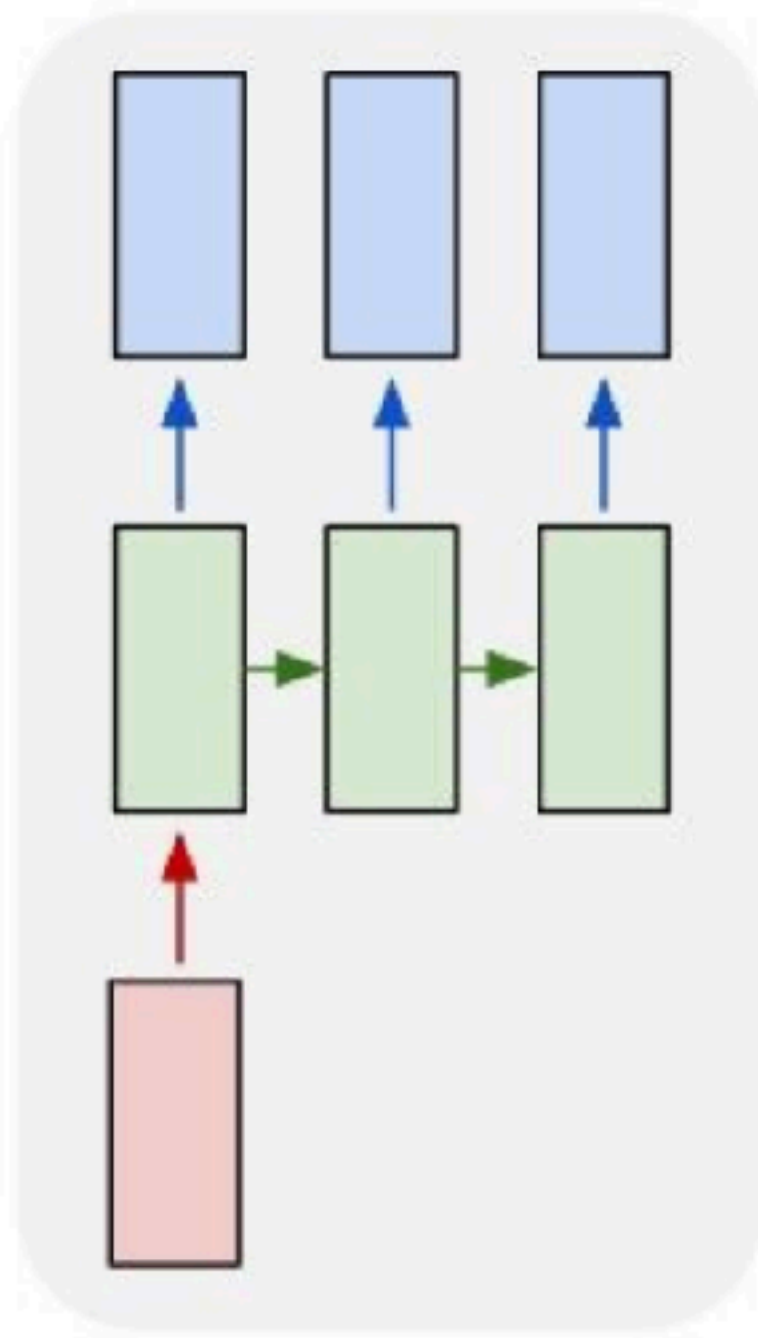
Vanilla Neural Networks

Recurrent Neural Networks: Process Sequences

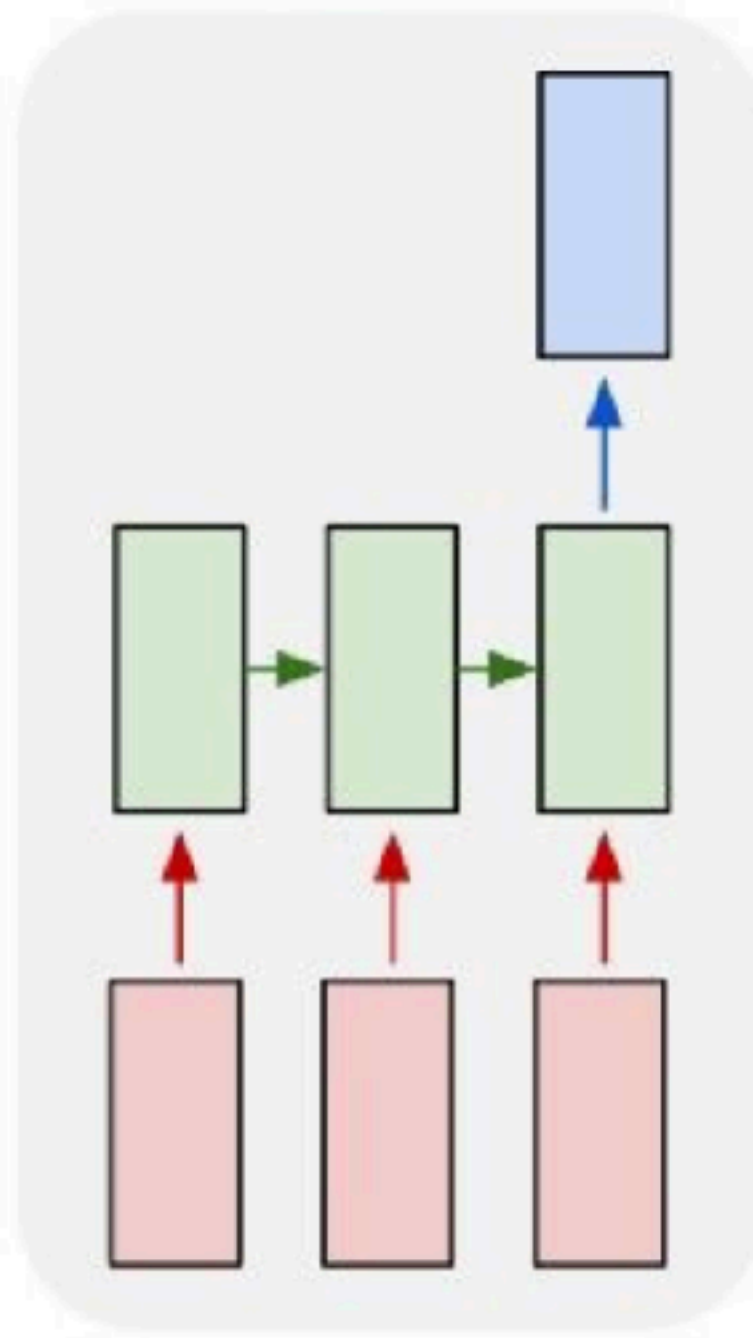
one to one



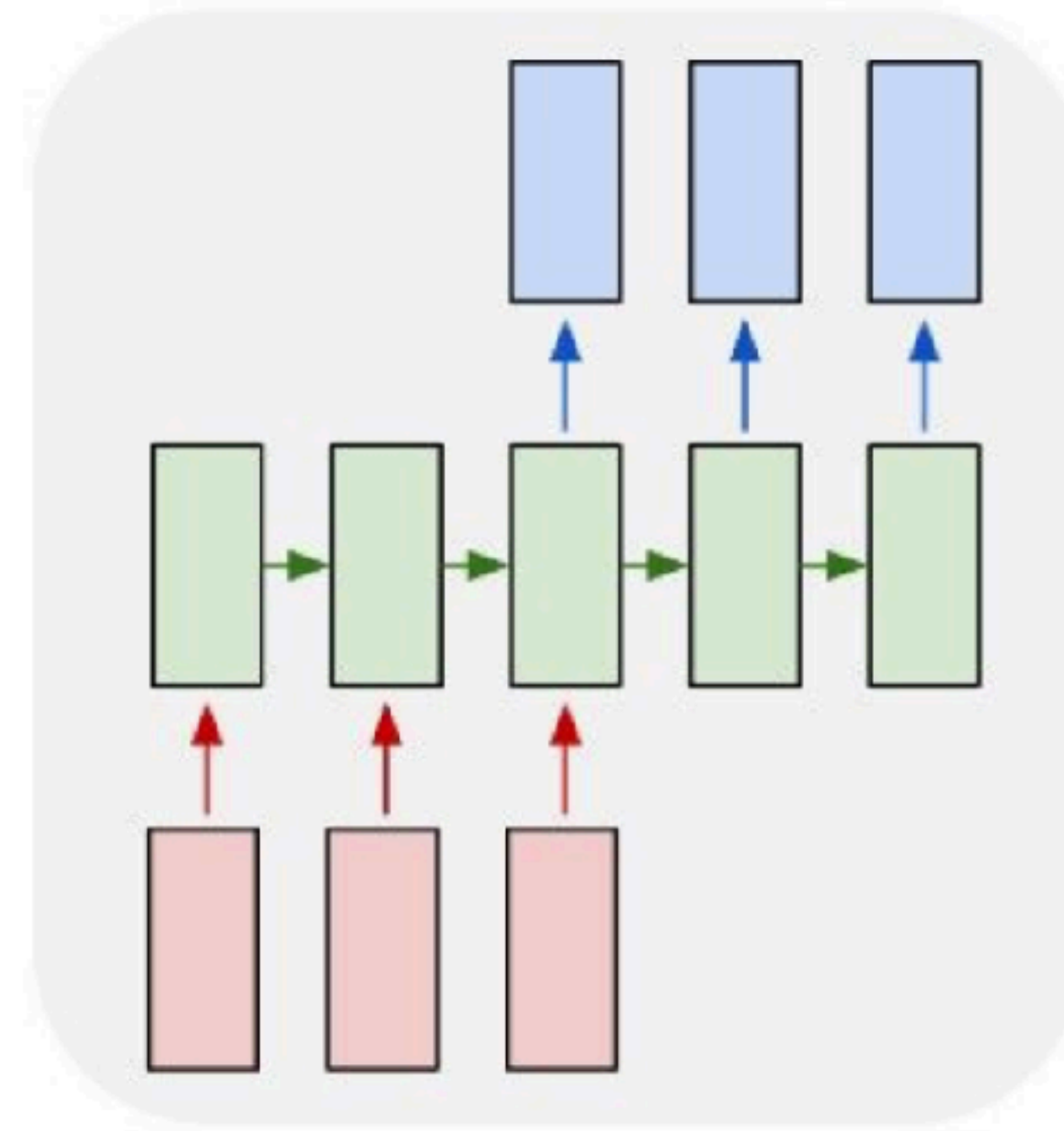
one to many



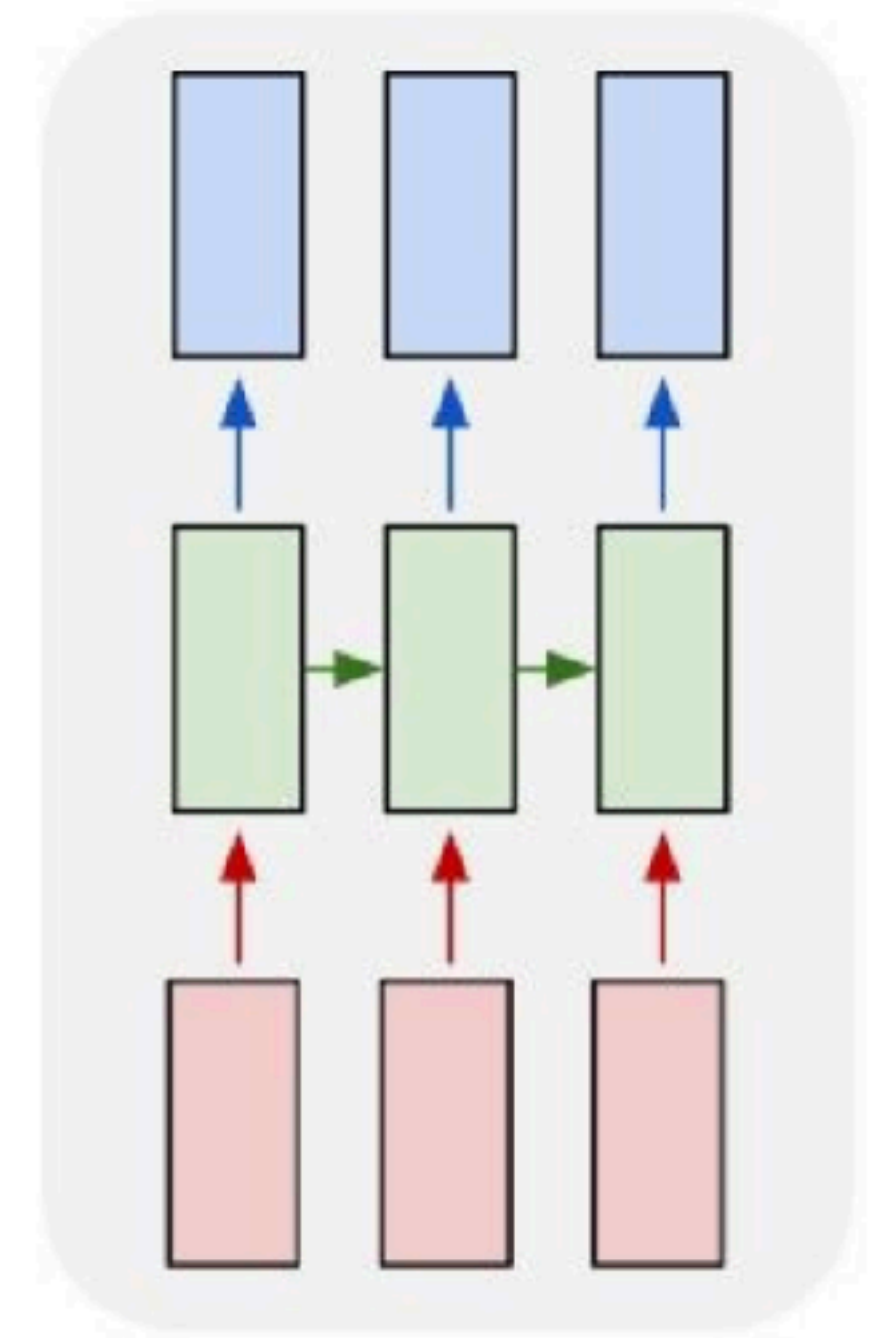
many to one



many to many



many to many

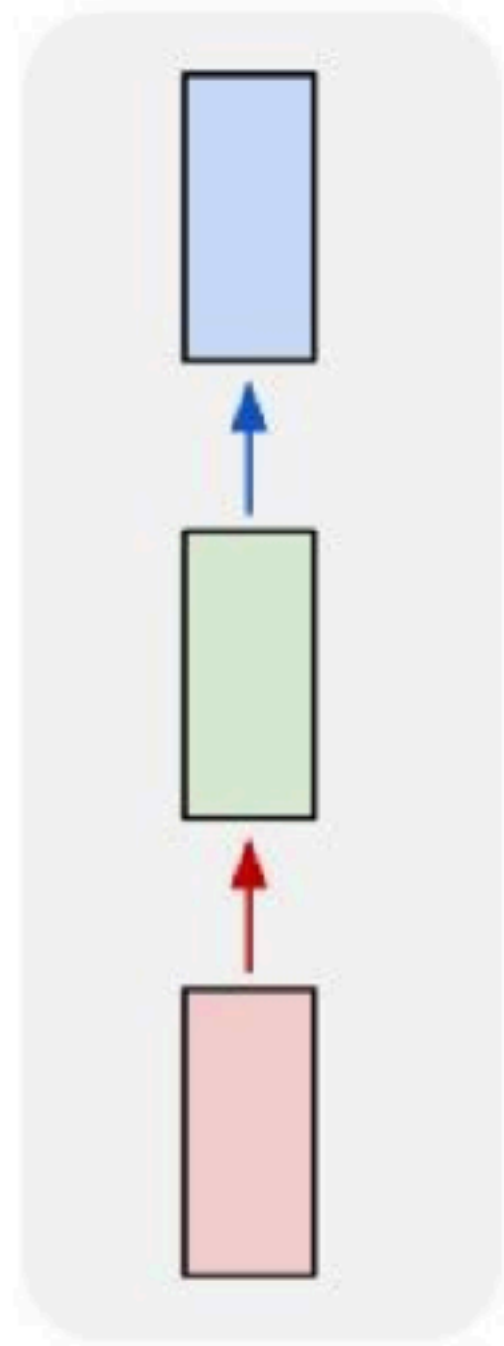


↖ e.g. **Image Captioning**

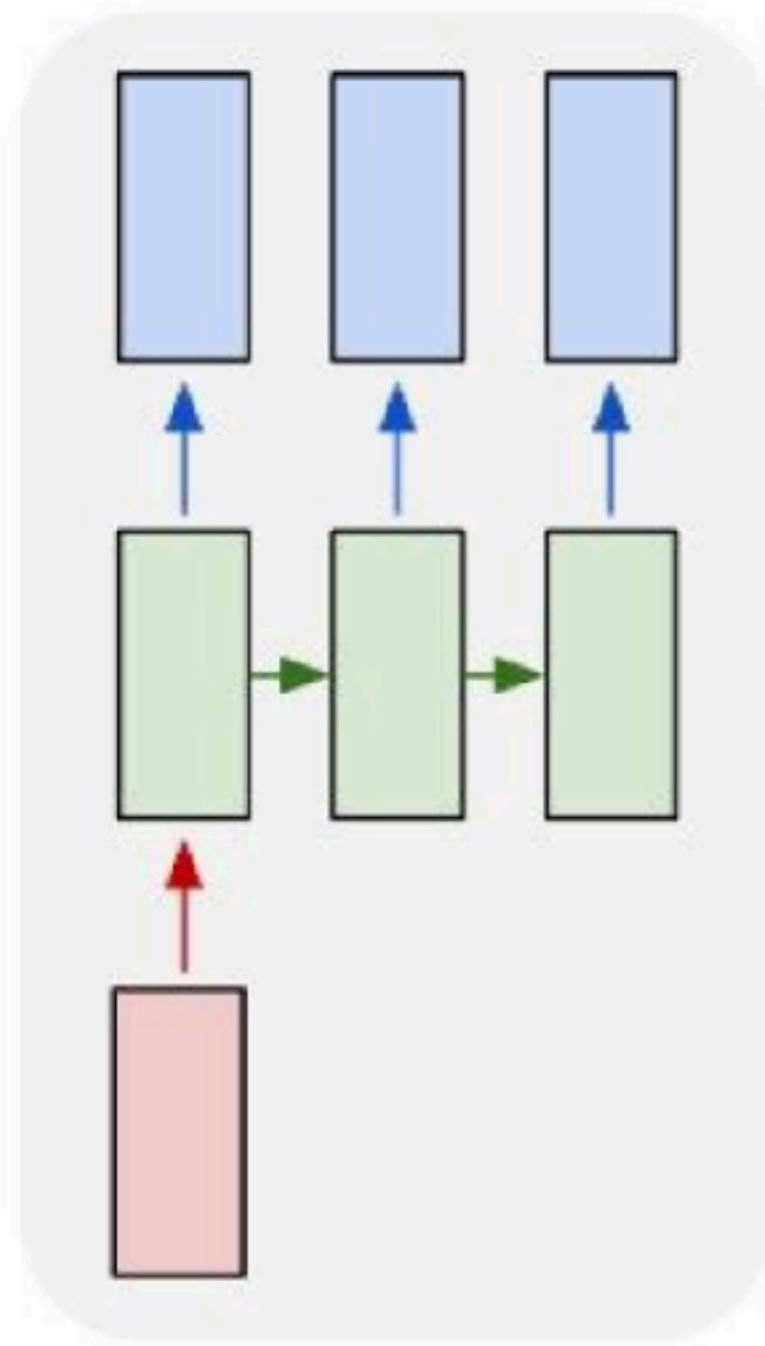
image -> sequence of words

Recurrent Neural Networks: Process Sequences

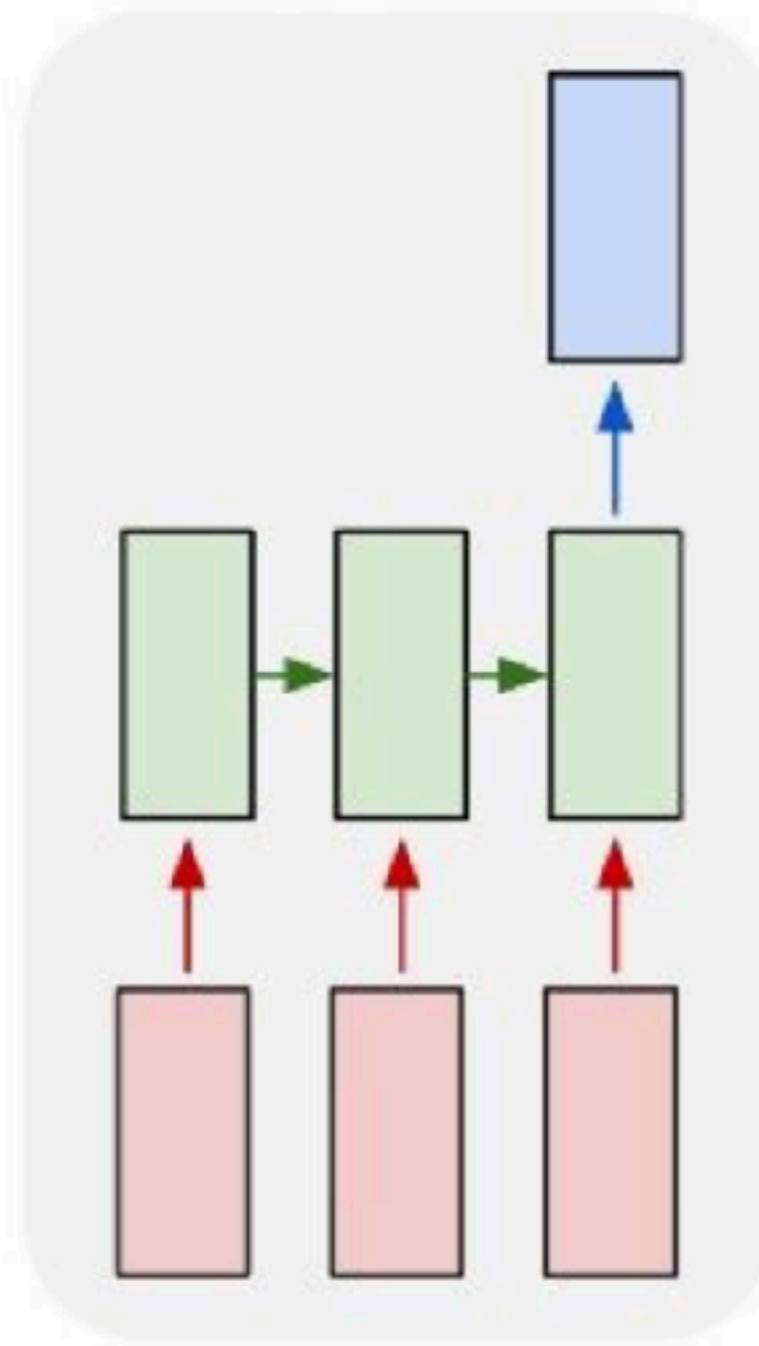
one to one



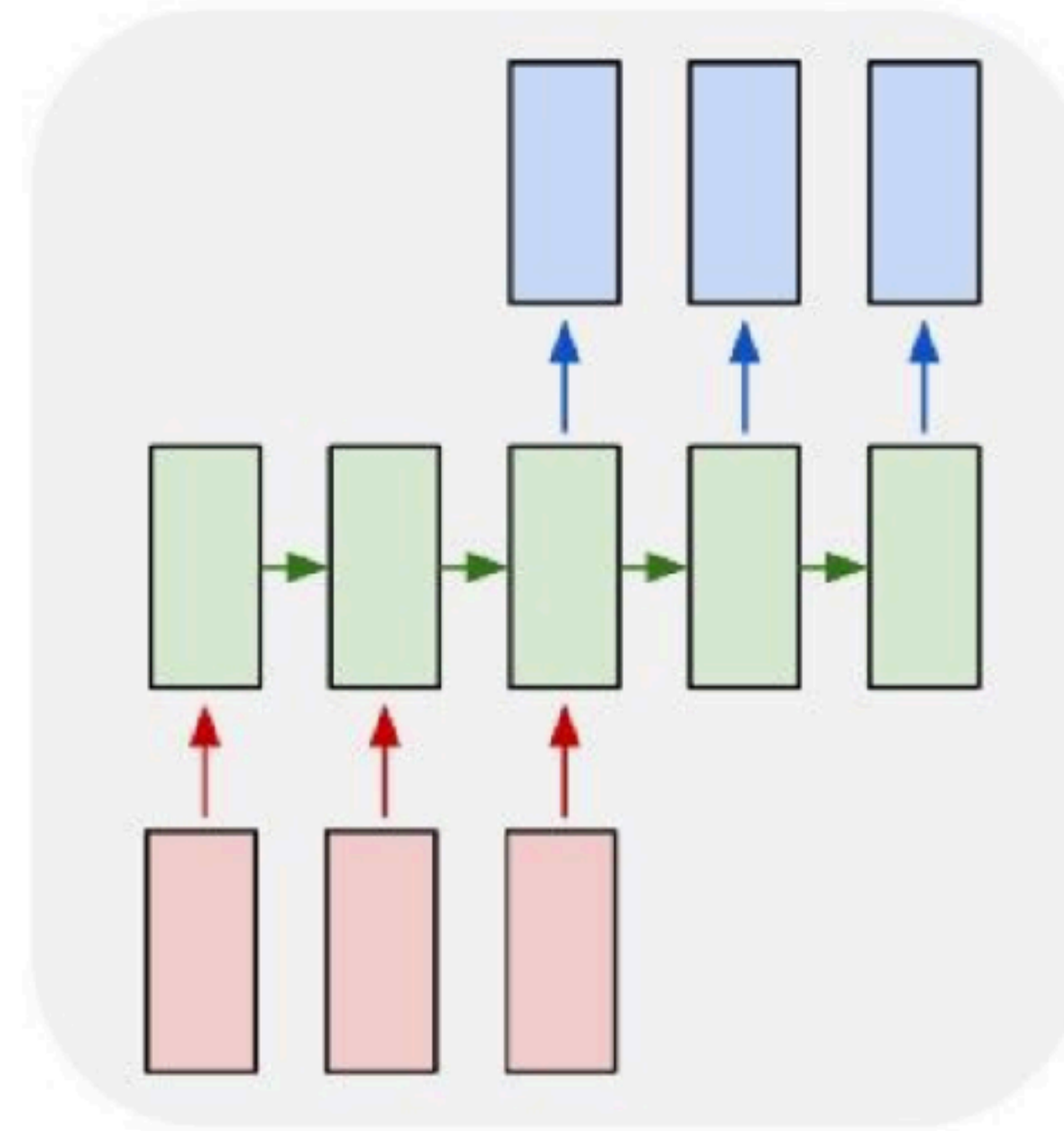
one to many



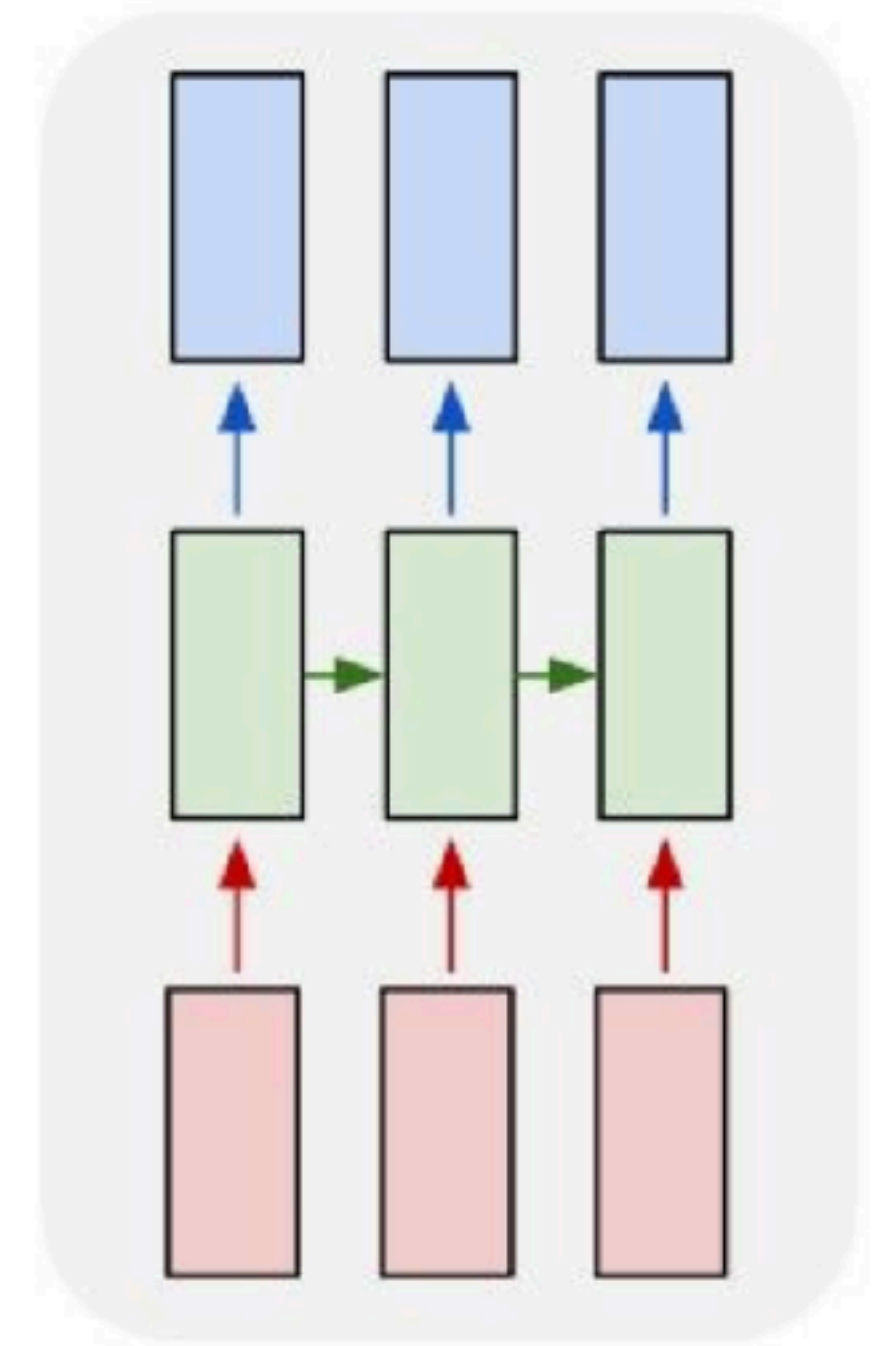
many to one



many to many



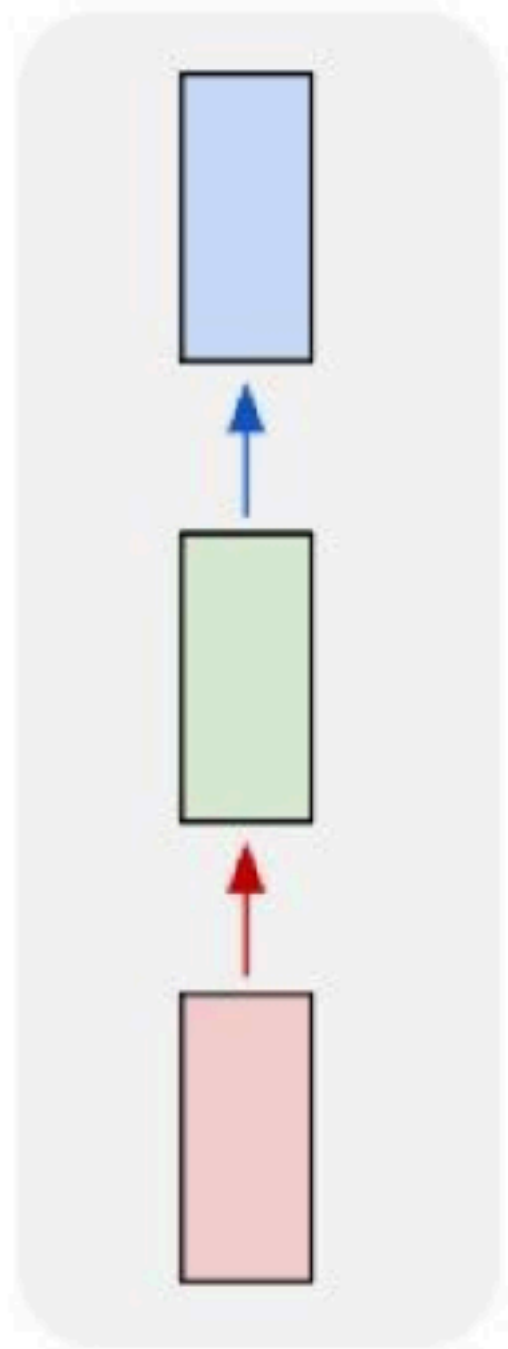
many to many



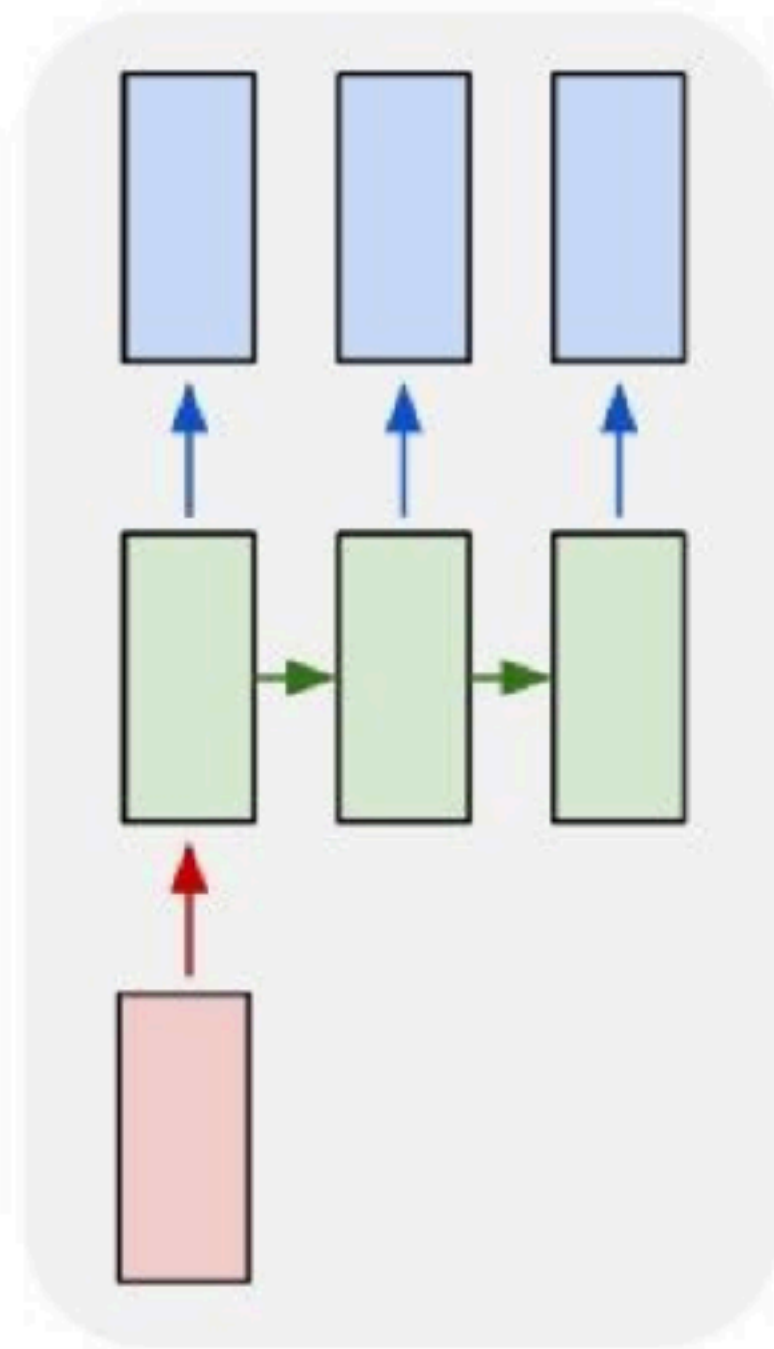
↖ e.g. **Sentiment Classification**
sequence of words -> sentiment

Recurrent Neural Networks: Process Sequences

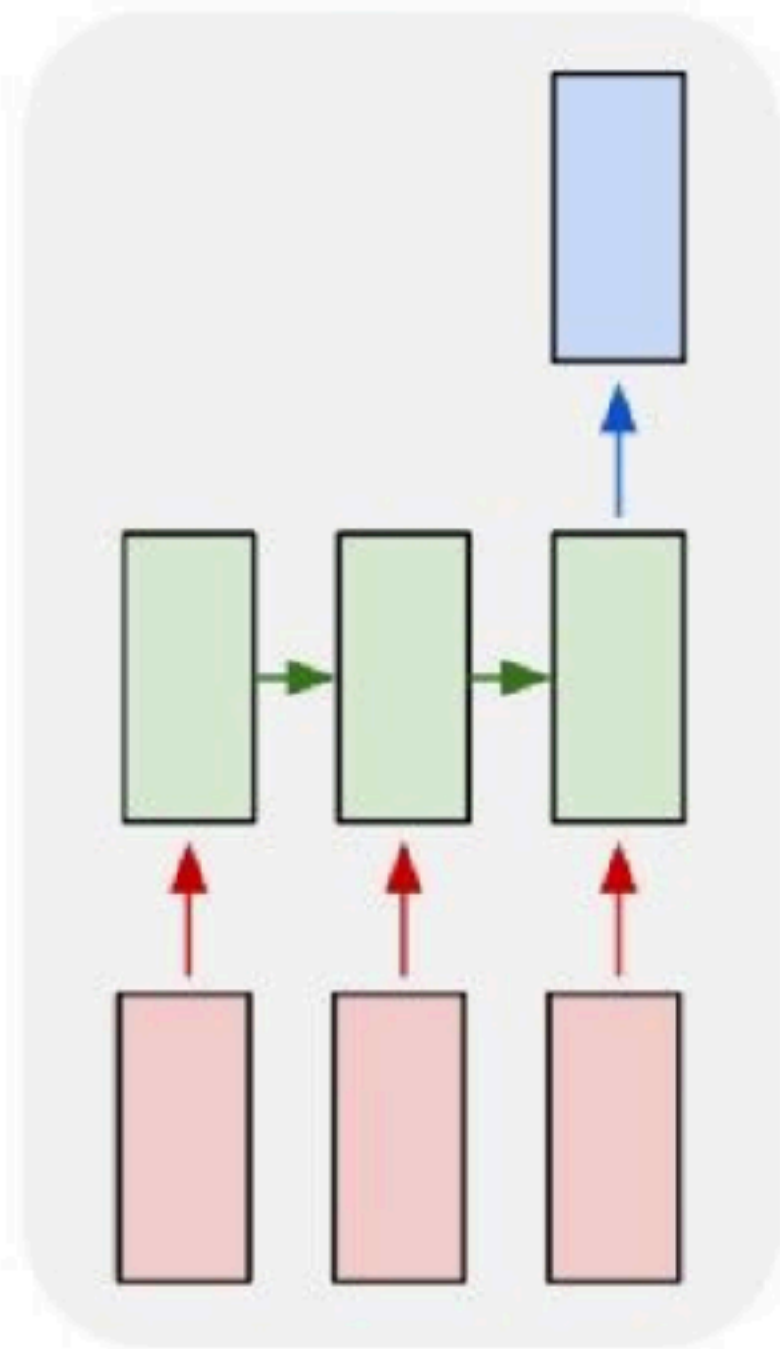
one to one



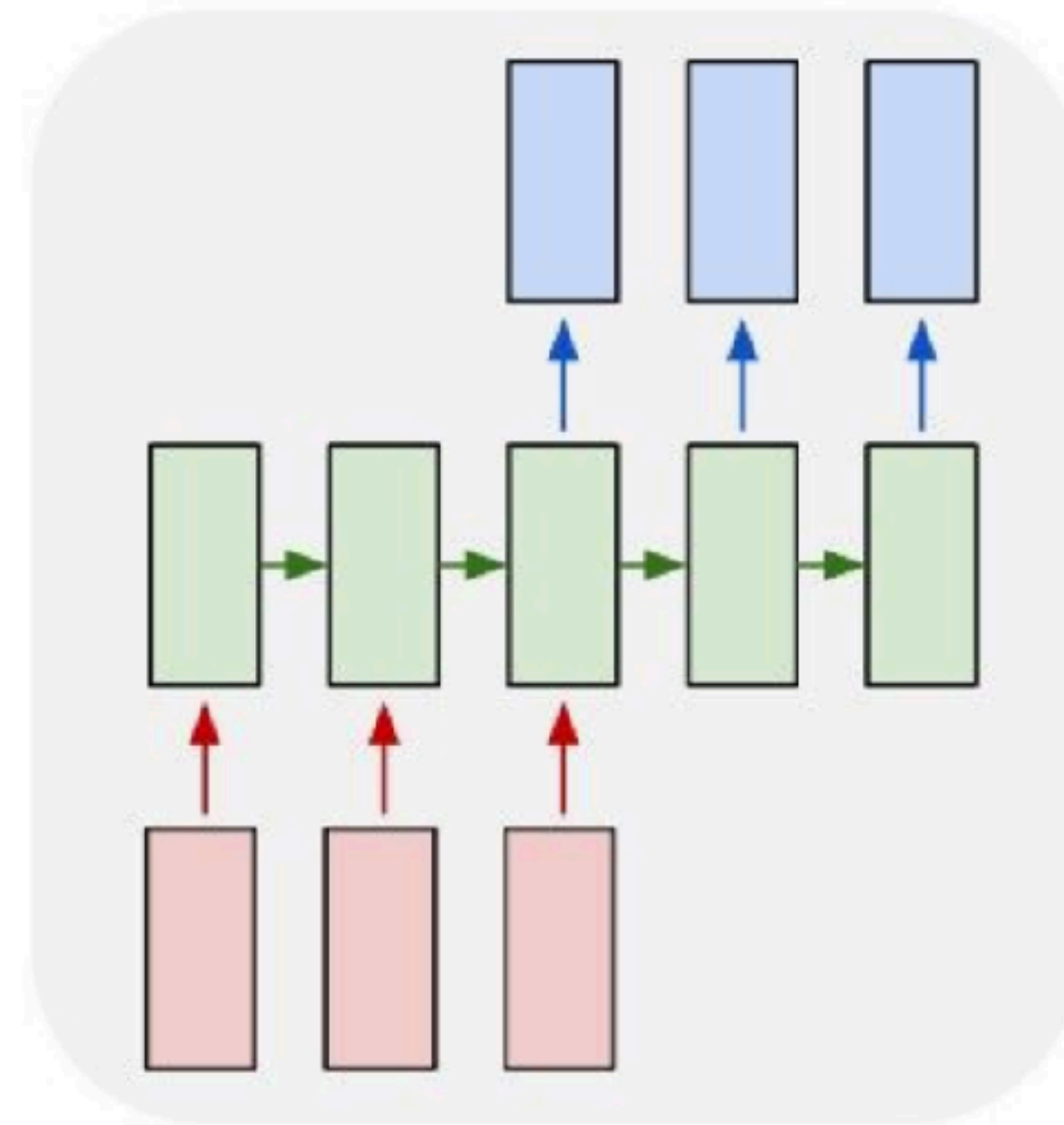
one to many



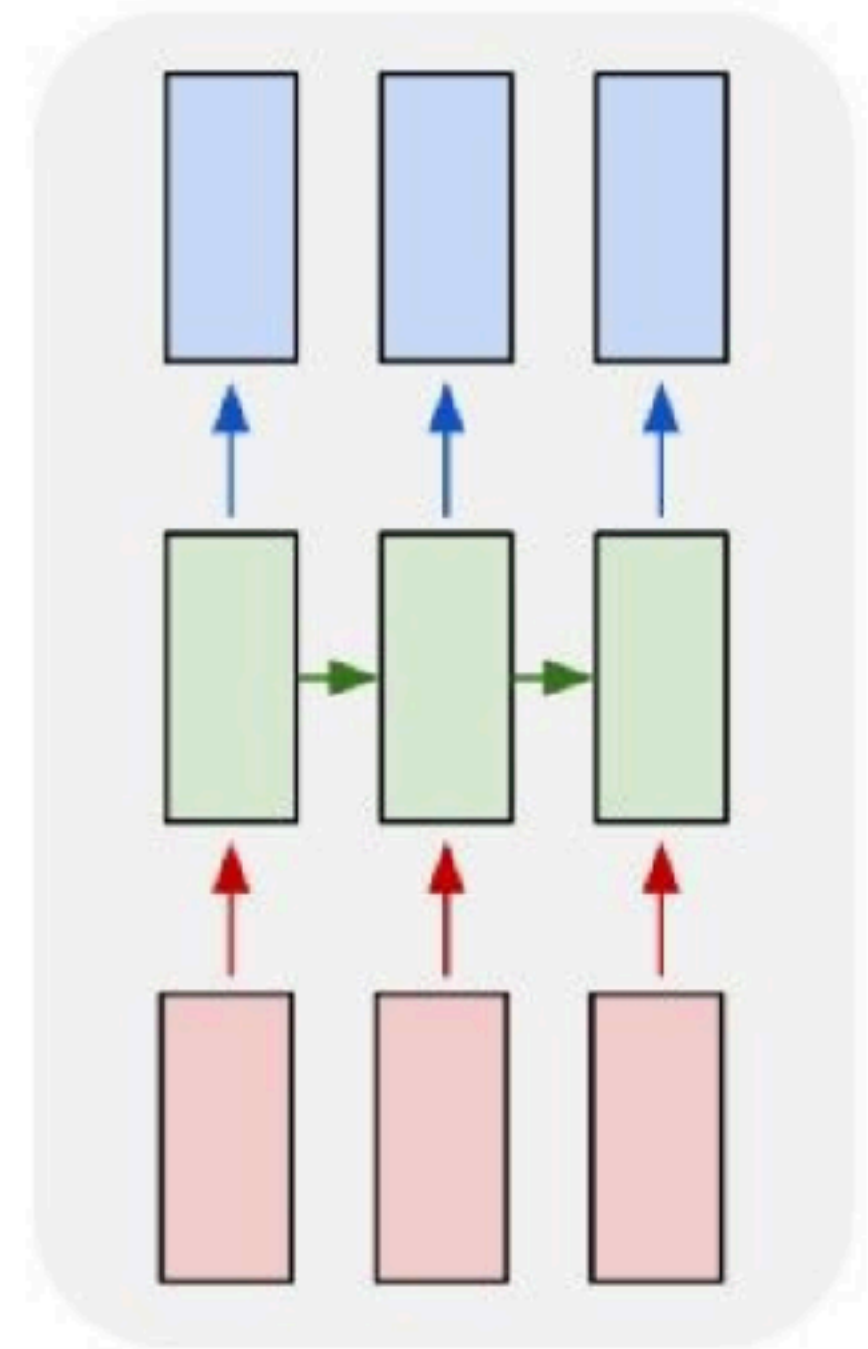
many to one



many to many



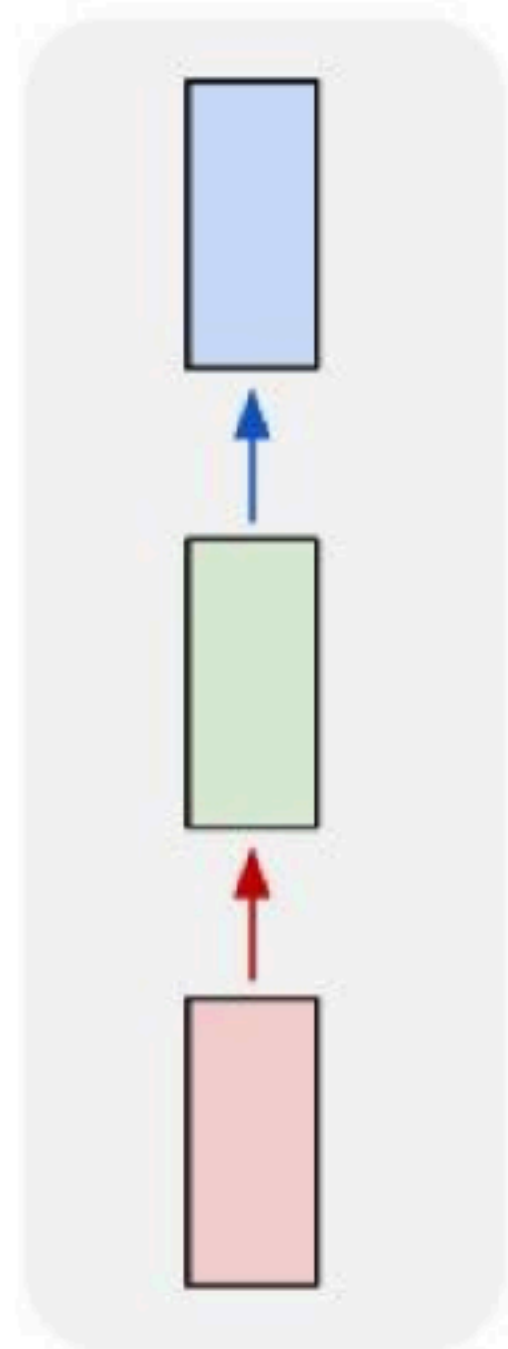
many to many



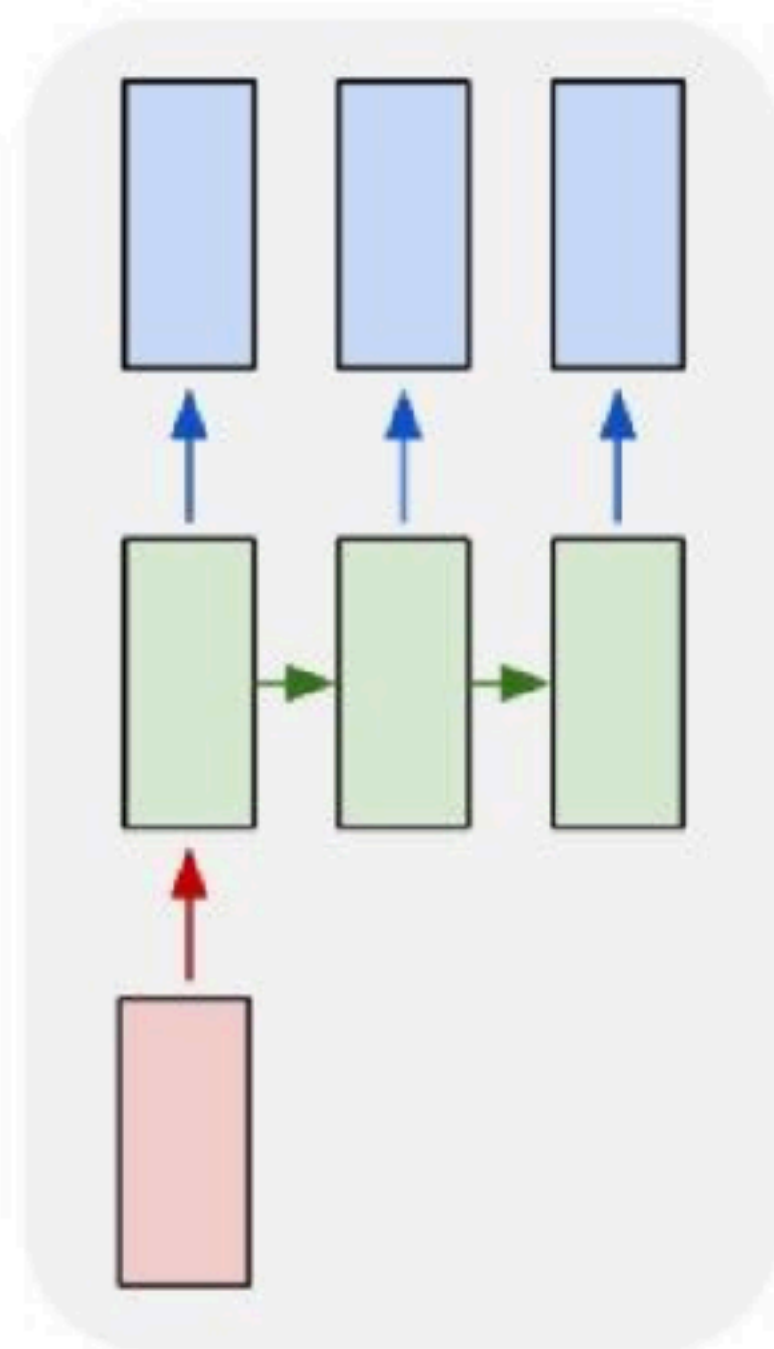
e.g. **Machine Translation**
seq of words -> seq of words

Recurrent Neural Networks: Process Sequences

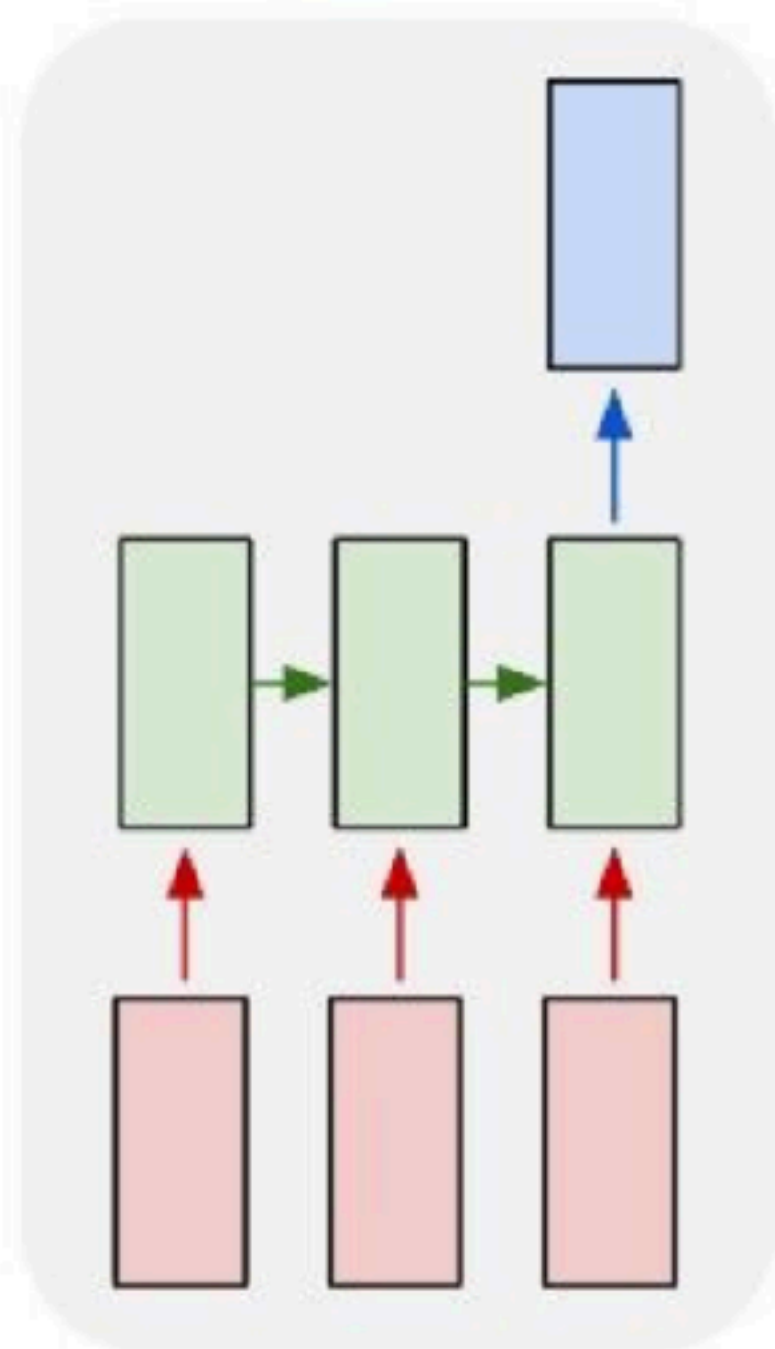
one to one



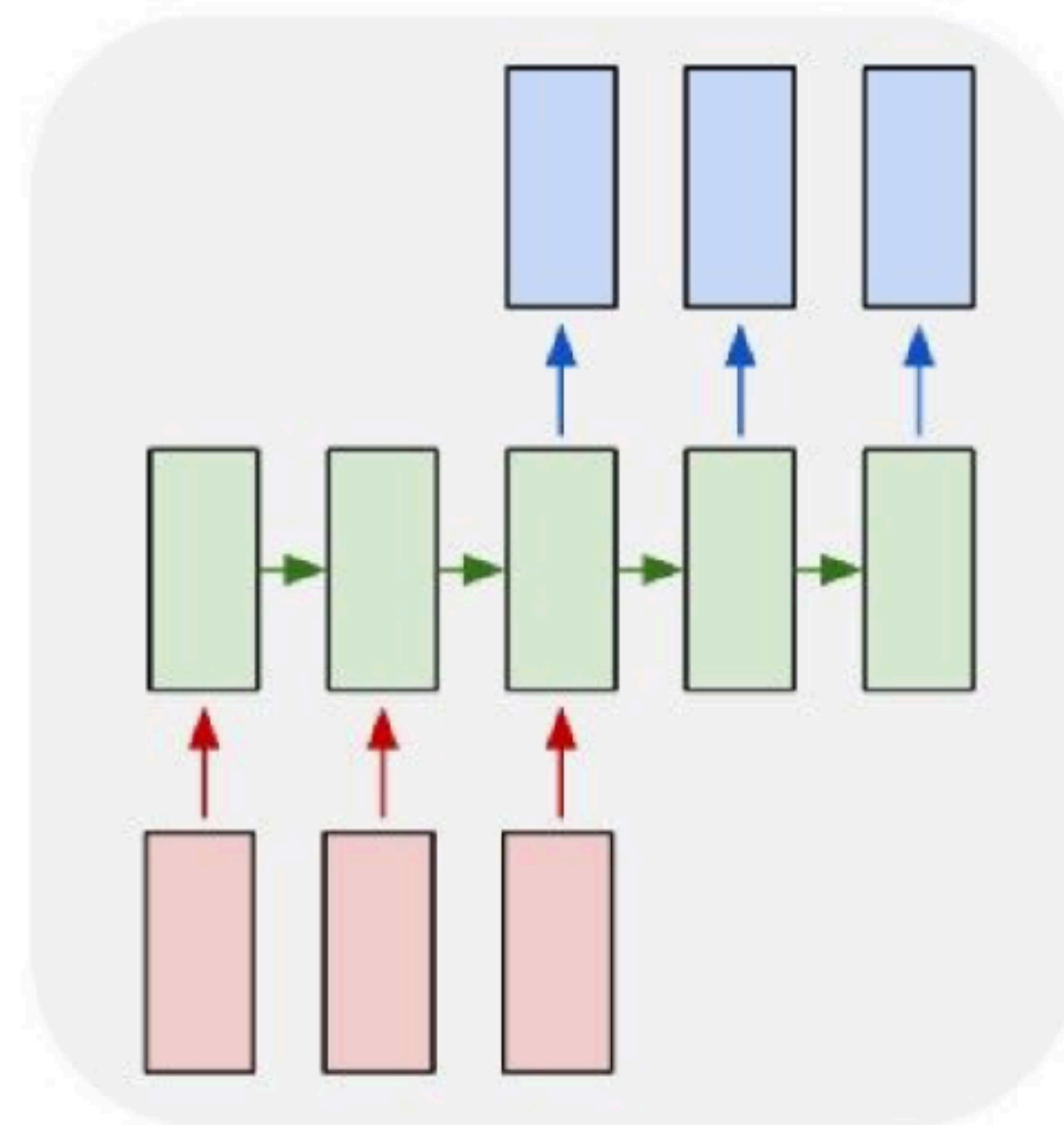
one to many



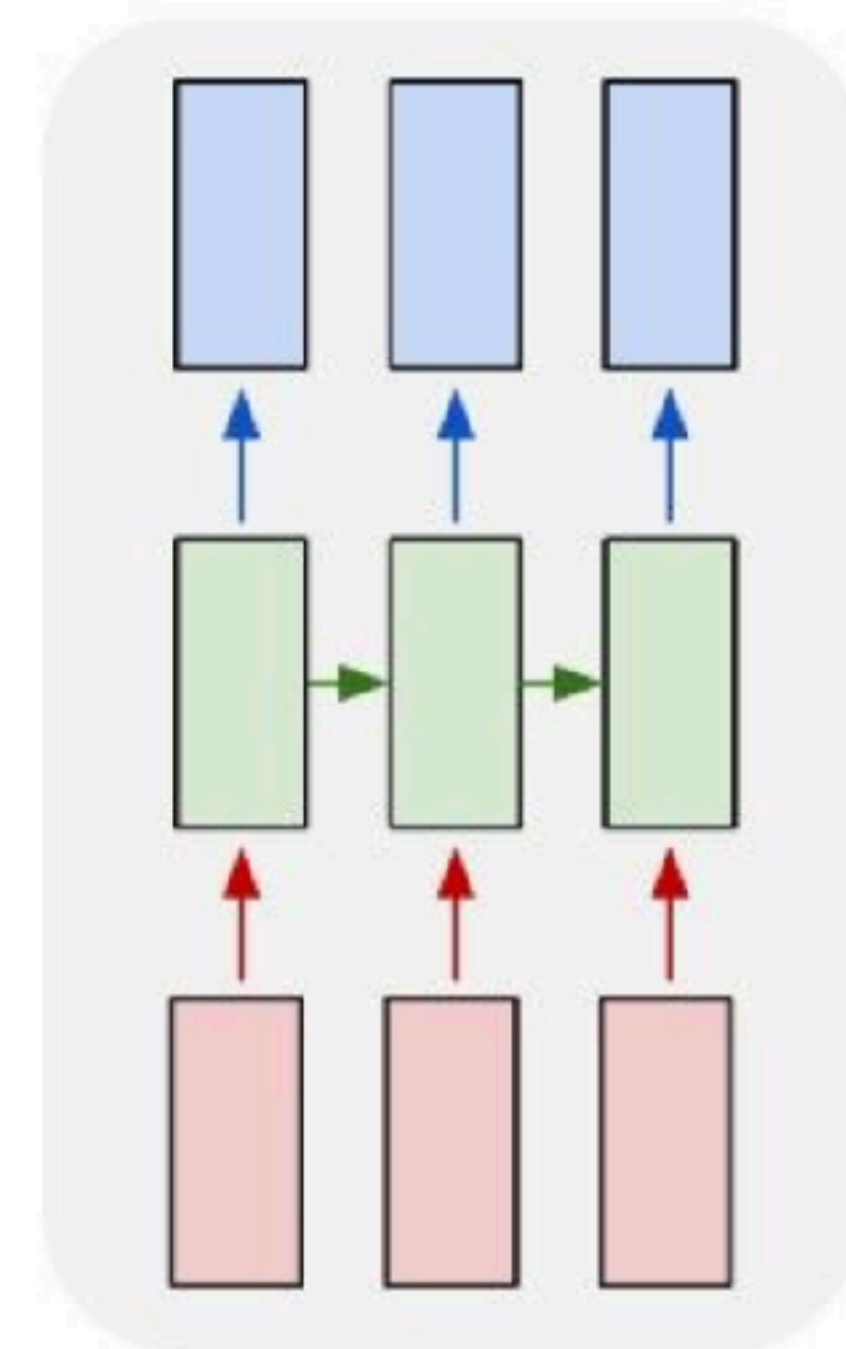
many to one



many to many



many to many



e.g. Video classification on frame level



Recurrent Neural Network

We can process a sequence of vectors $\mathbf{x}$ by applying a **recurrence formula** at every time step:

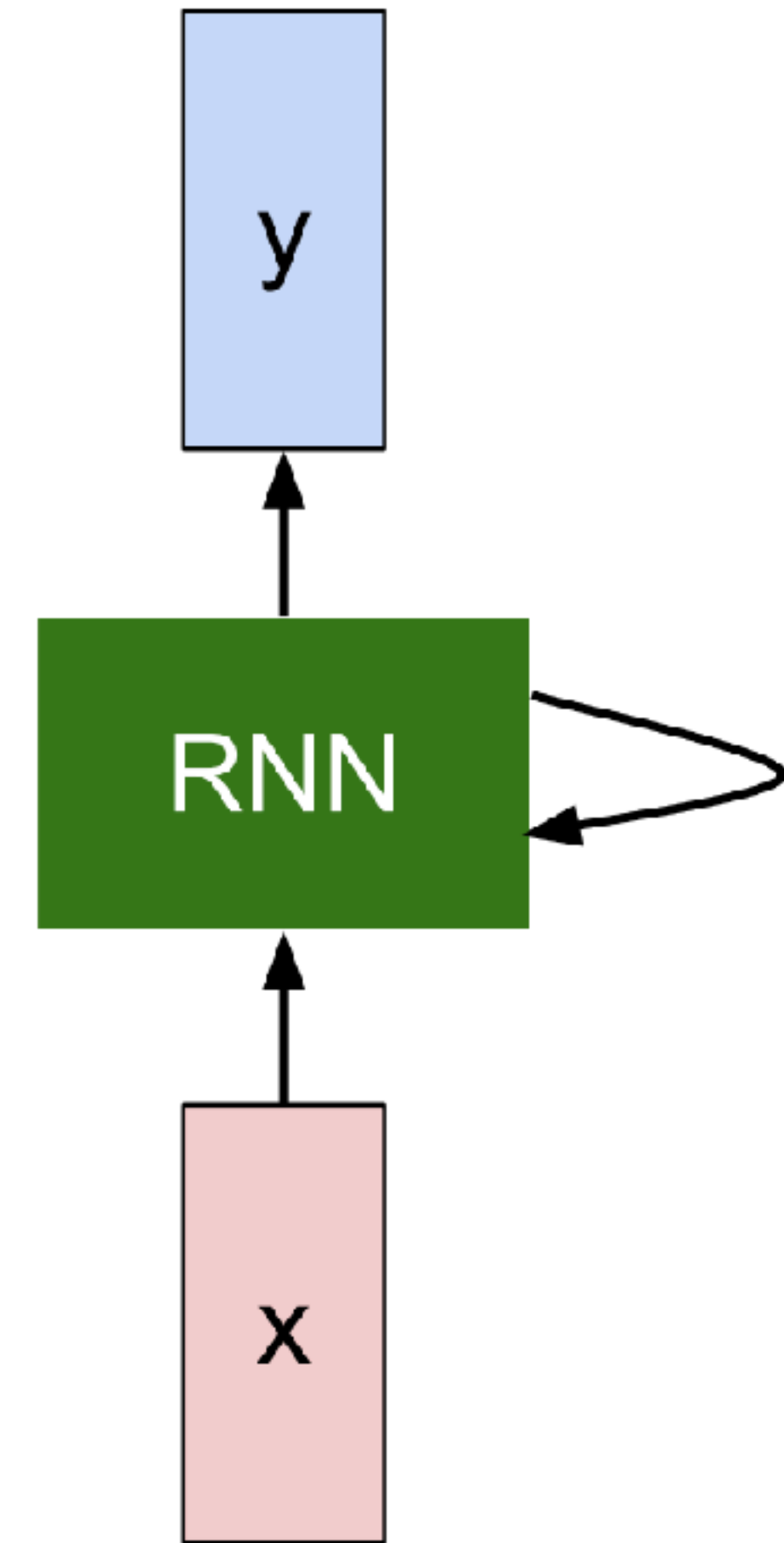
$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

some function with parameters W

old state

input vector at some time step

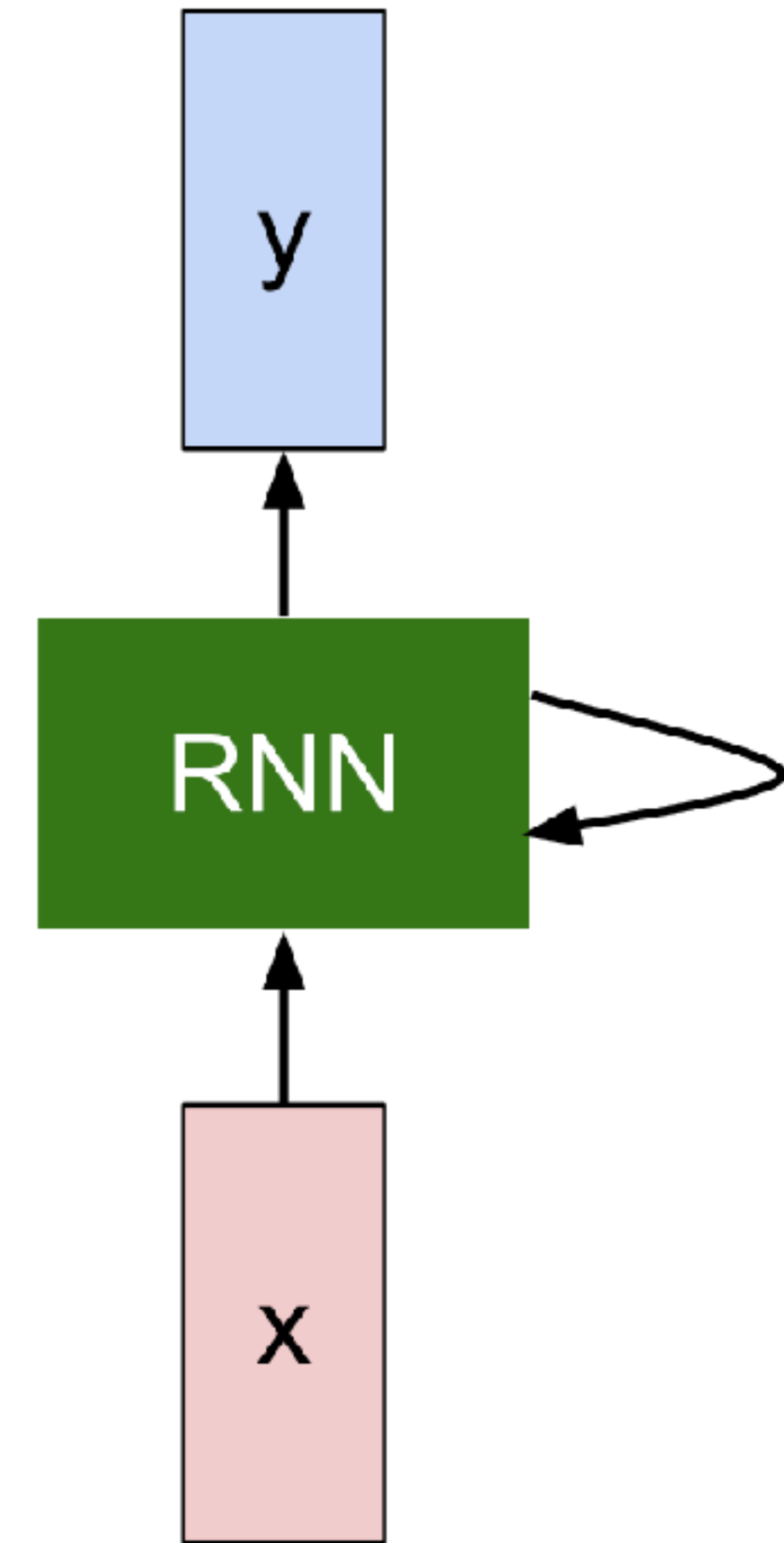


Recurrent Neural Network

We can process a sequence of vectors $\mathbf{x}$ by applying a **recurrence formula** at every time step:

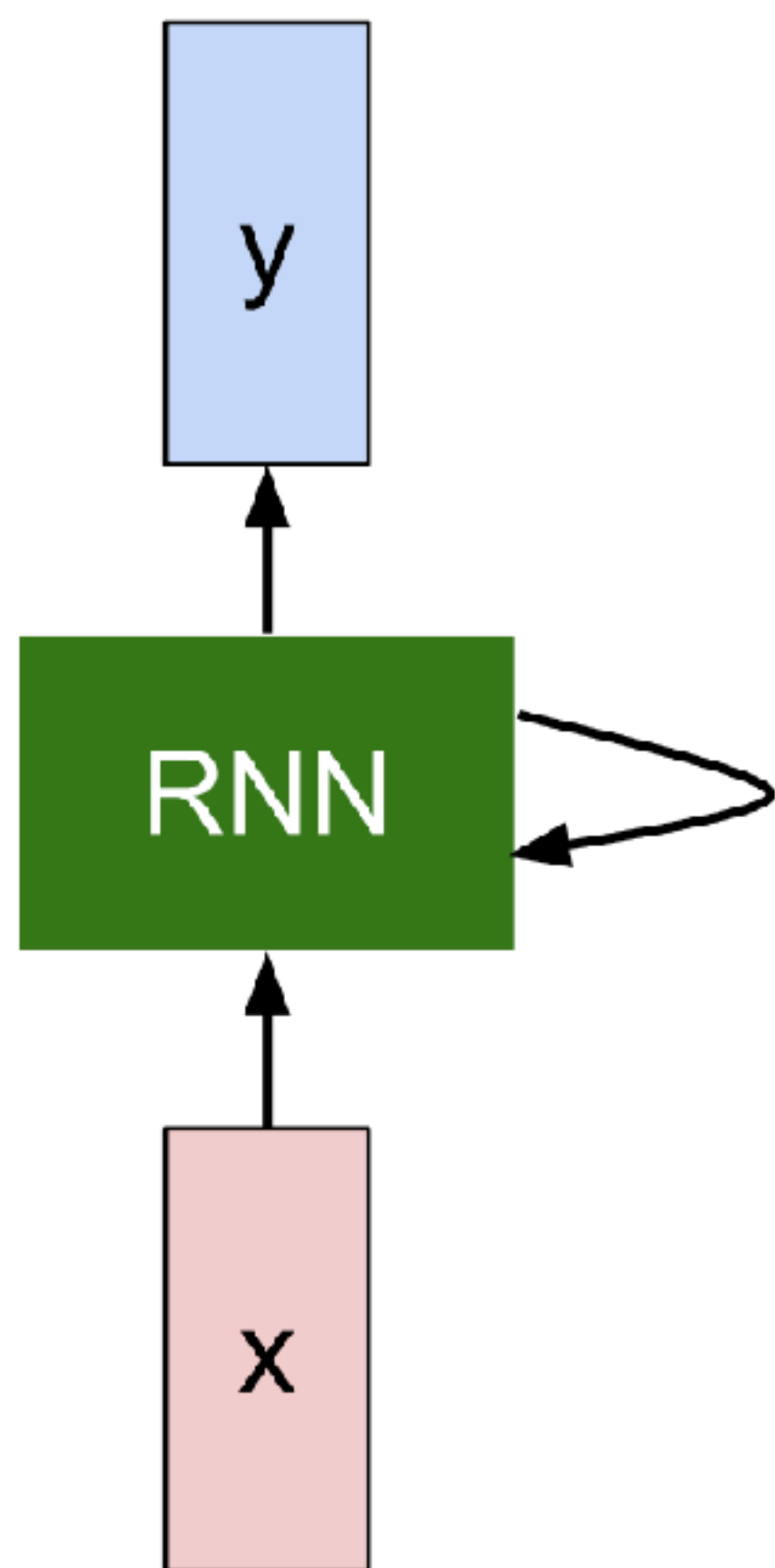
```
class RNN:
    # ...
    def step(self, x):
        # update the hidden state
        self.h = np.tanh(np.dot(self.W_hh, self.h) + np.dot(self.W_xh, x))
        # compute the output vector
        y = np.dot(self.W_hy, self.h)
        return y
```

with parameters W



(Vanilla) Recurrent Neural Network

The state consists of a single “*hidden*” vector h :



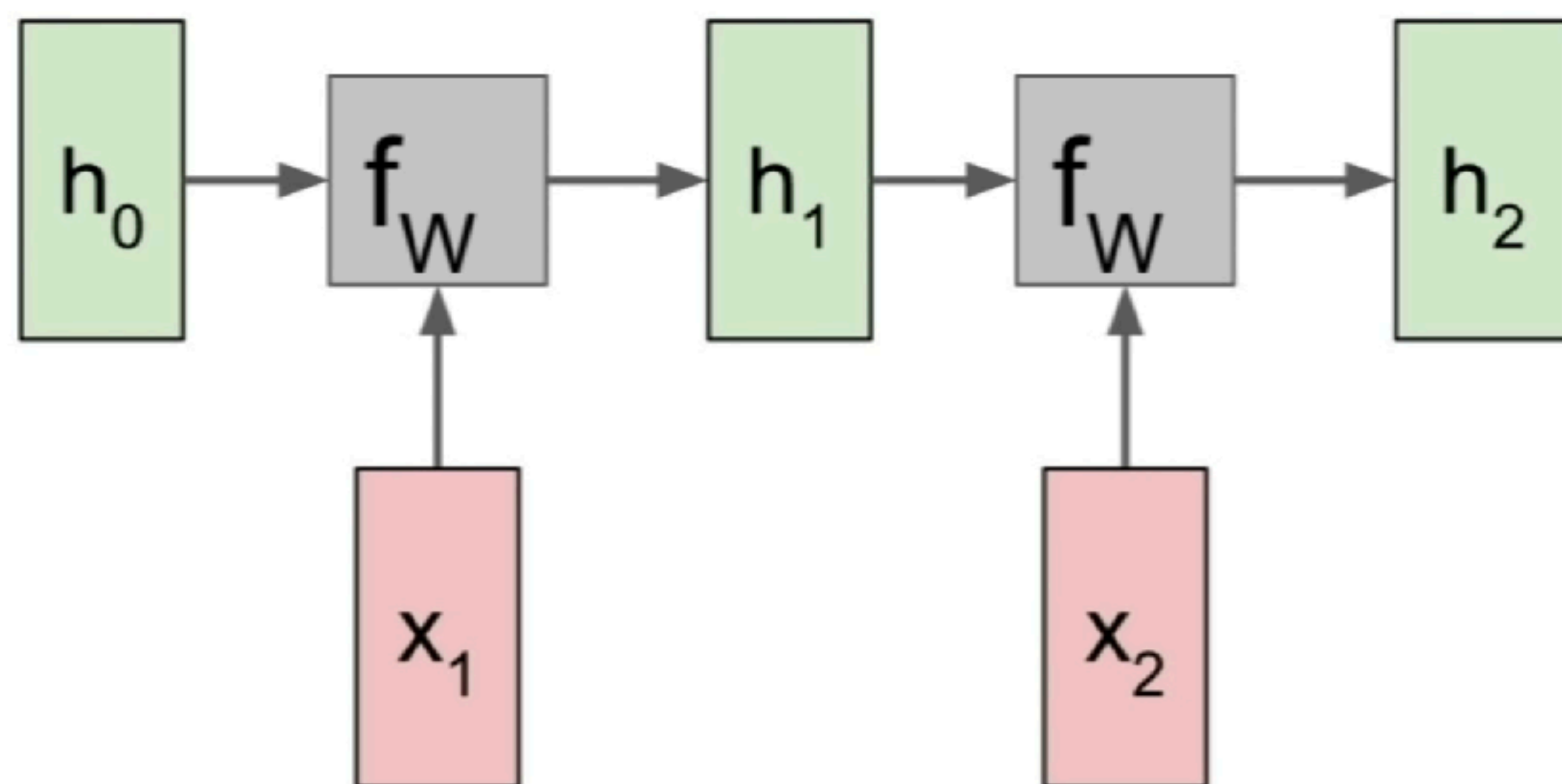
$$h_t = f_W(h_{t-1}, x_t)$$



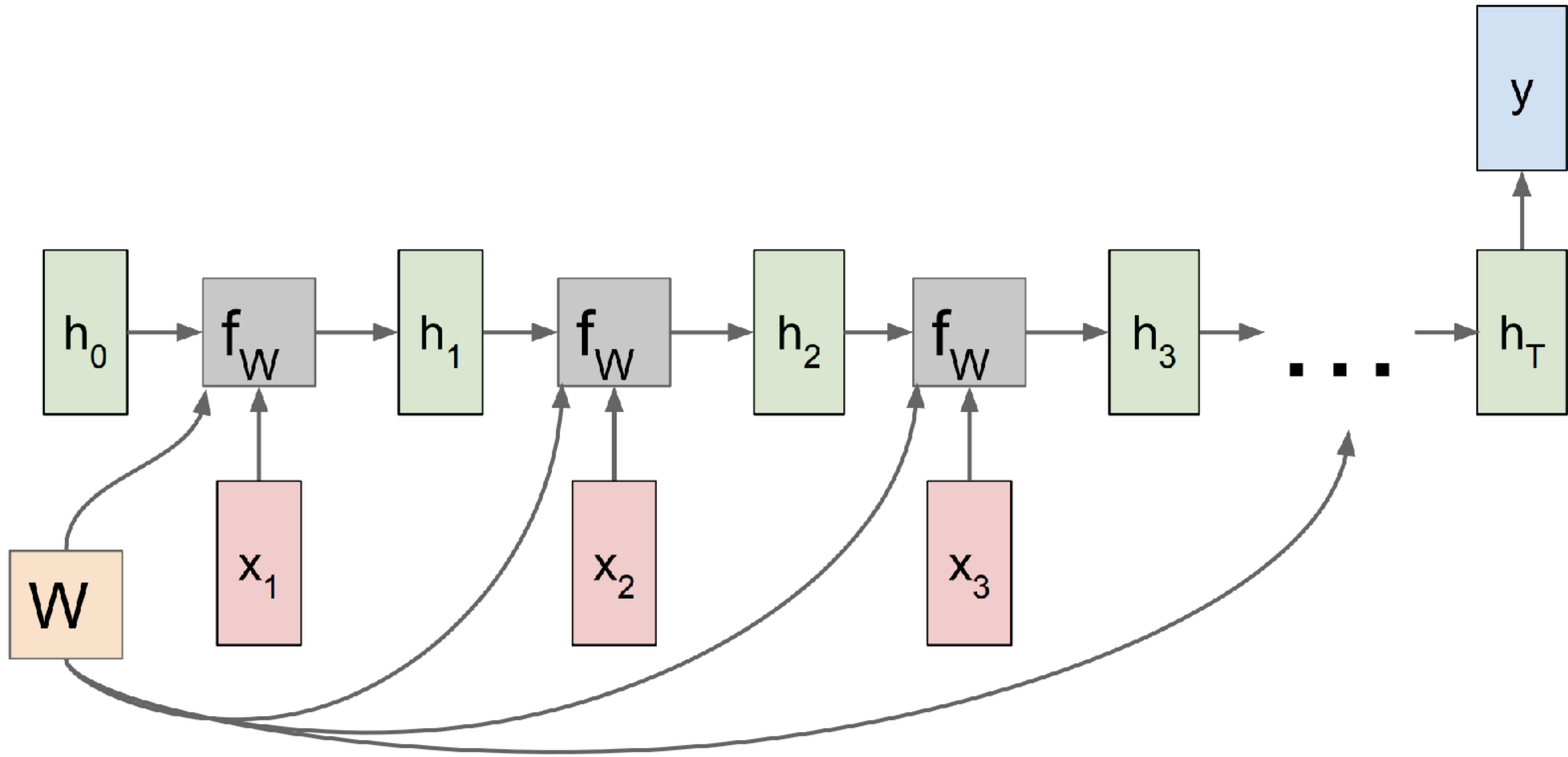
$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

$$y_t = W_{hy}h_t$$

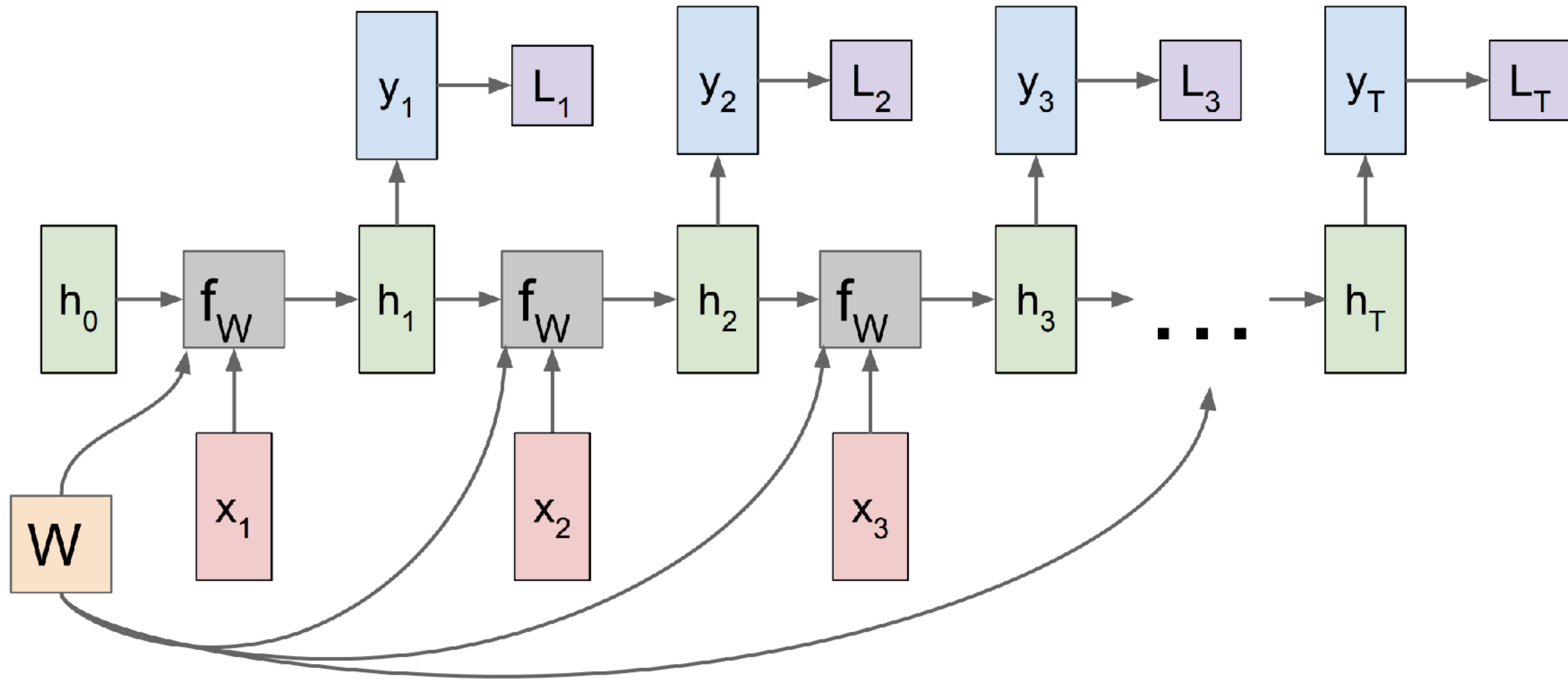
RNN: Computational Graph



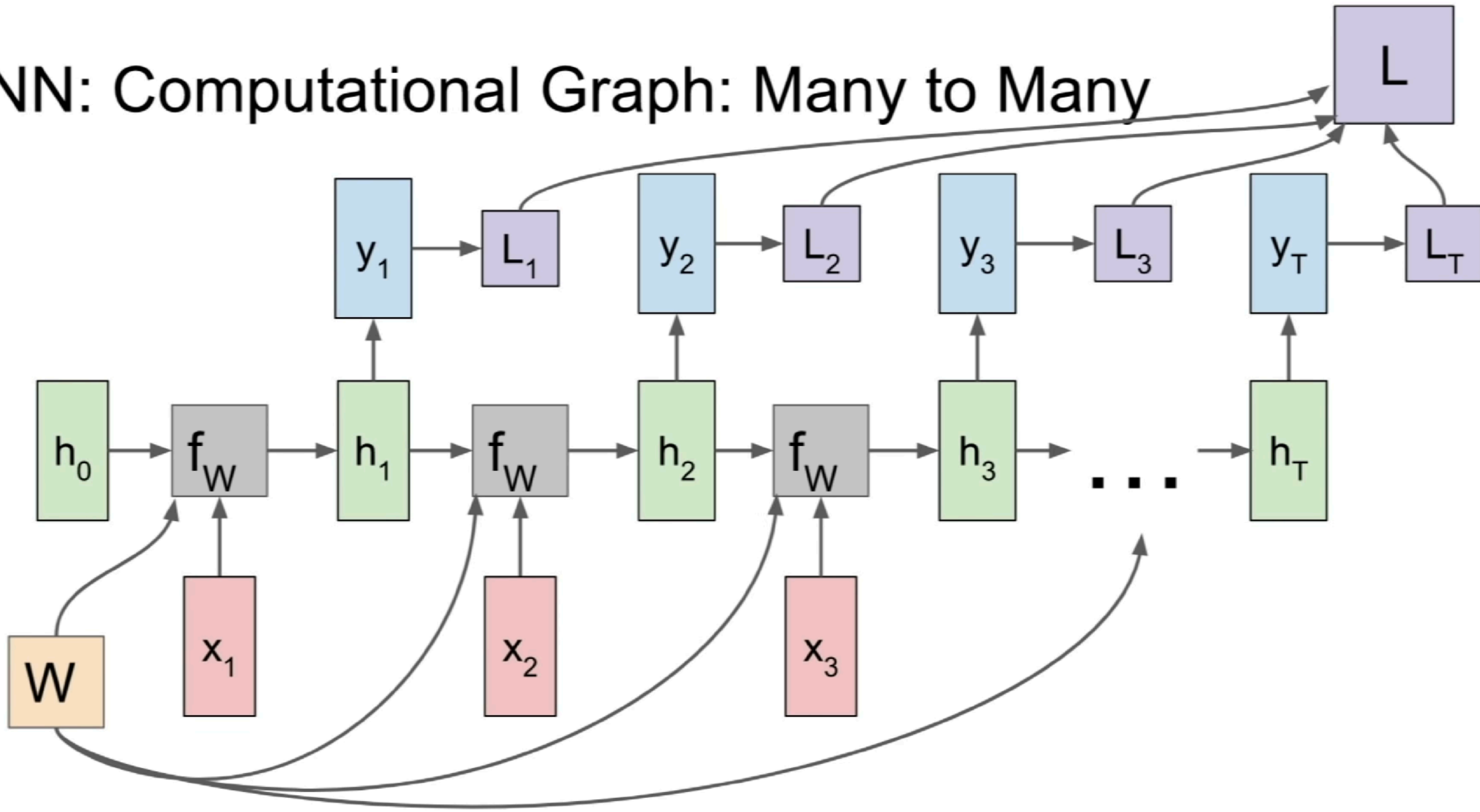
RNN: Computational Graph: Many to One



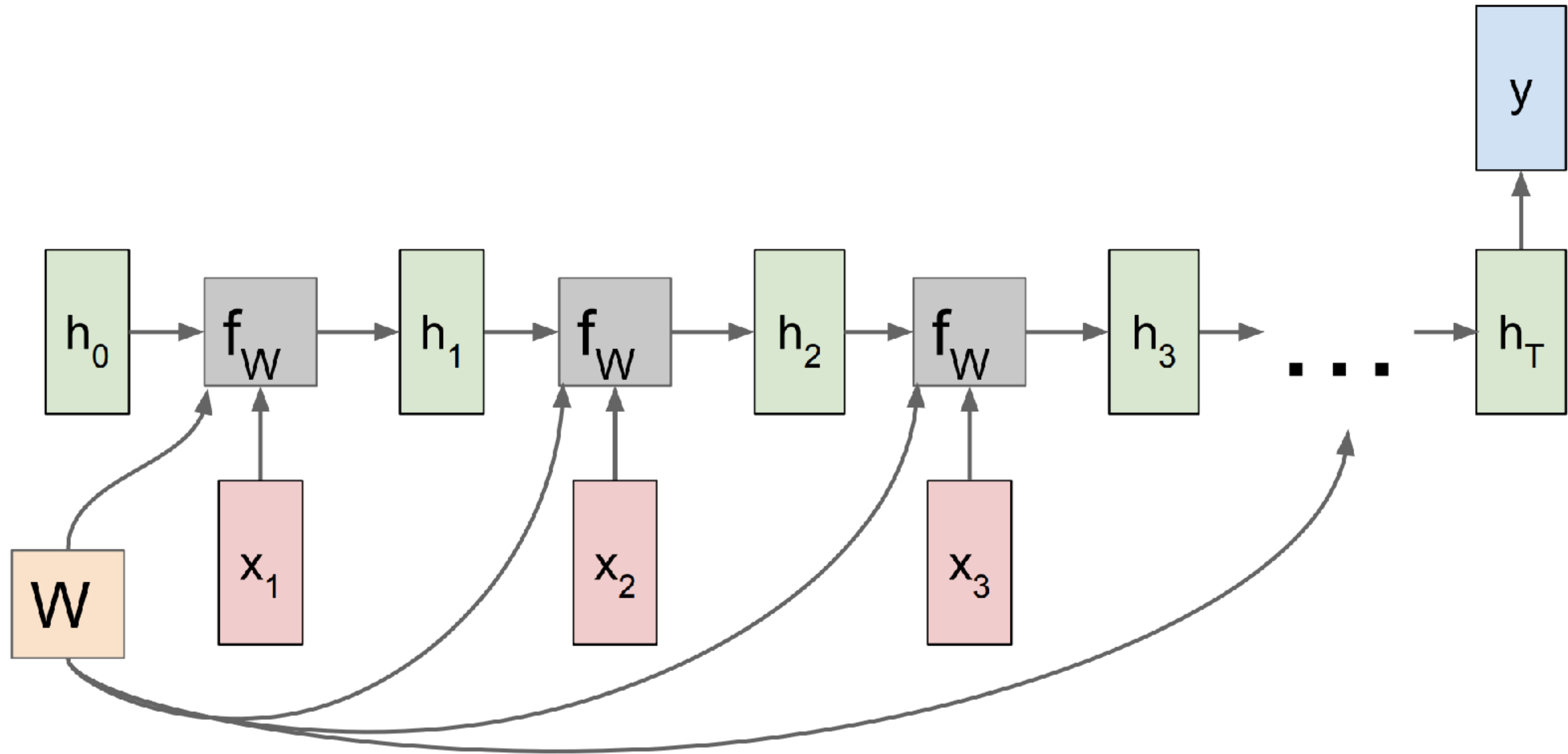
RNN: Computational Graph: Many to Many



RNN: Computational Graph: Many to Many



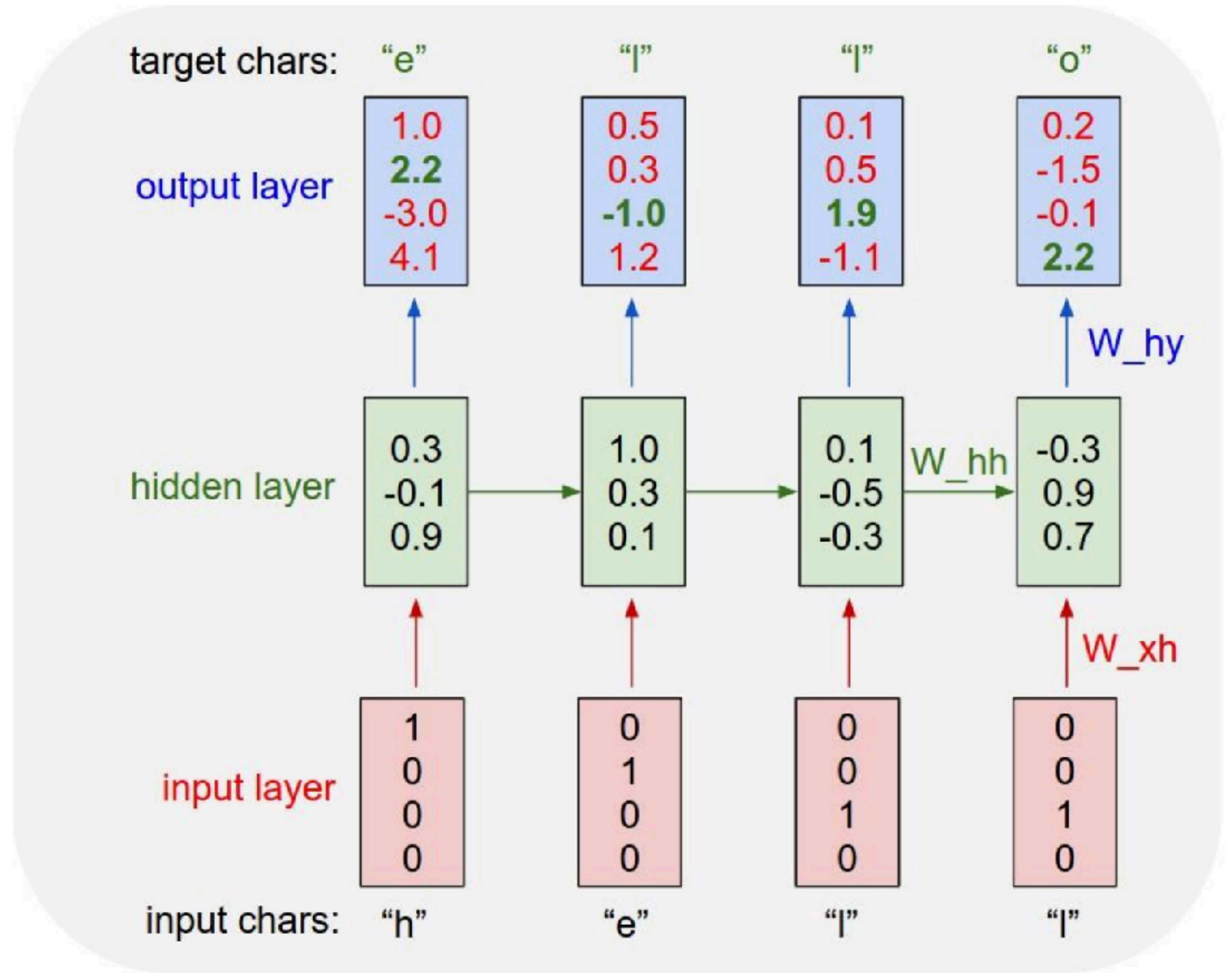
RNN: Computational Graph: Many to One



Example: Character-level Language Model

Vocabulary:
[h,e,l,o]

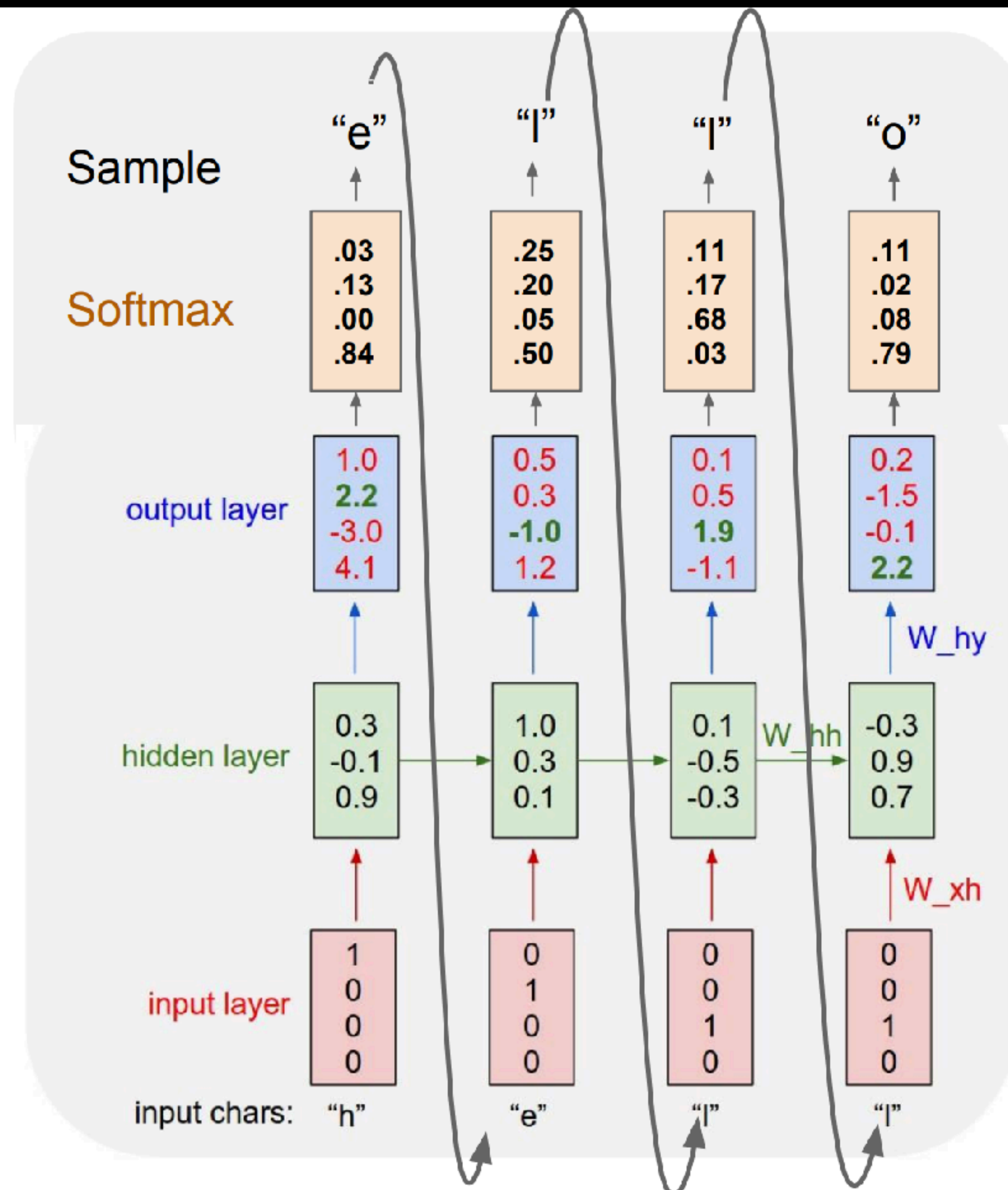
Example training
sequence:
“hello”



Example: Character-level Language Model Sampling

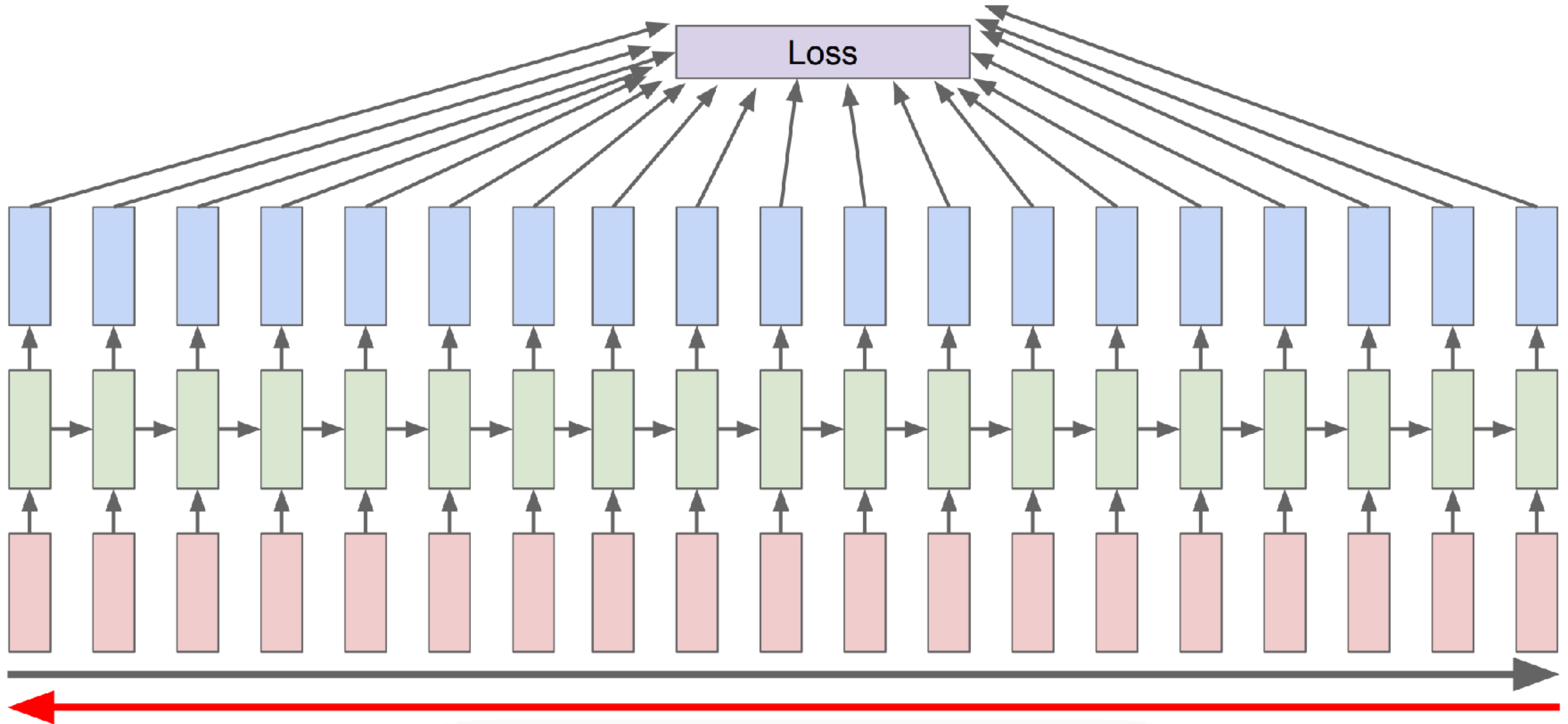
Vocabulary:
[h,e,l,o]

At test-time sample
characters one at a time,
feed back to model

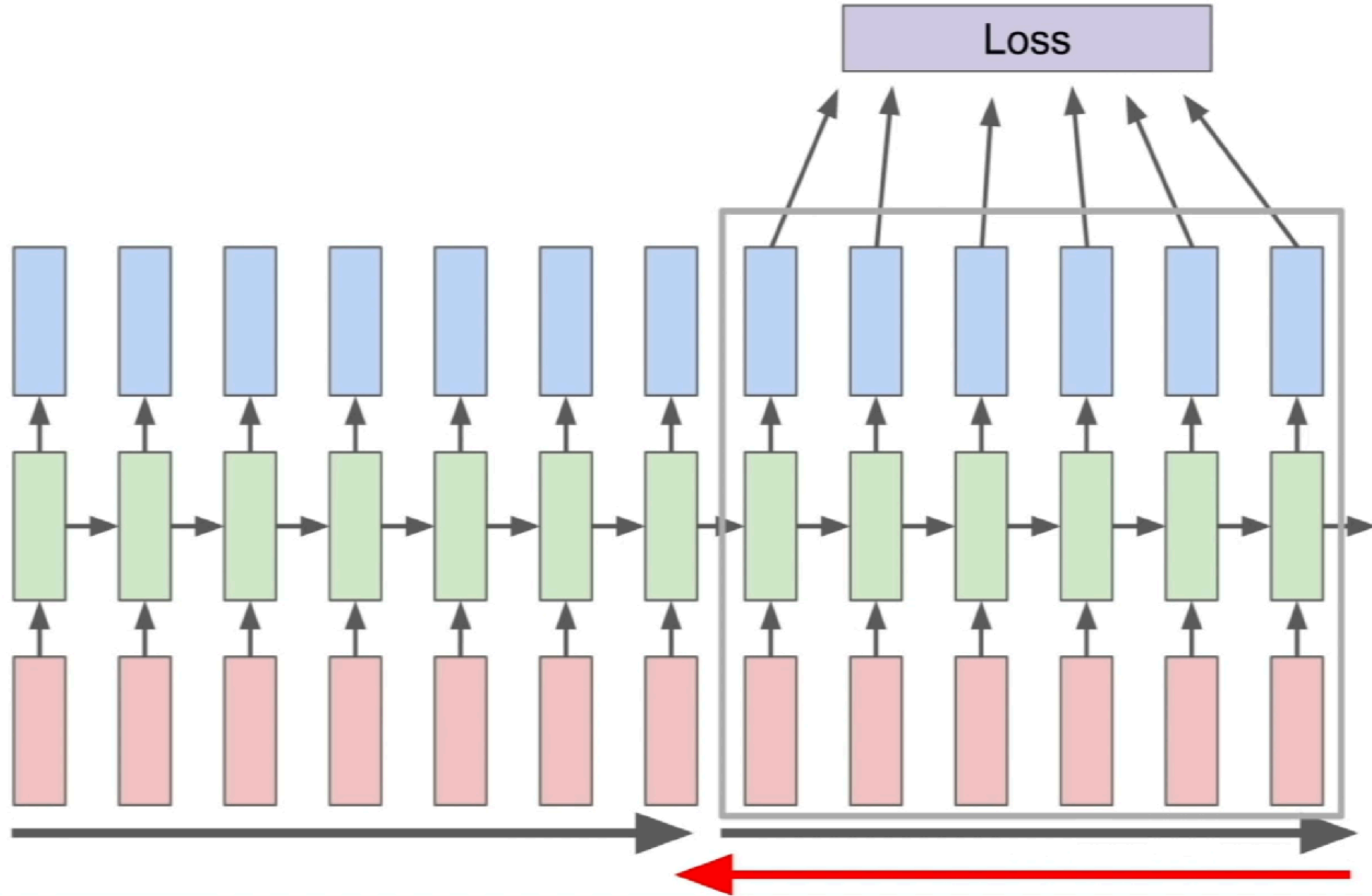


Backpropagation through time

Forward through entire sequence to compute loss, then backward through entire sequence to compute gradient



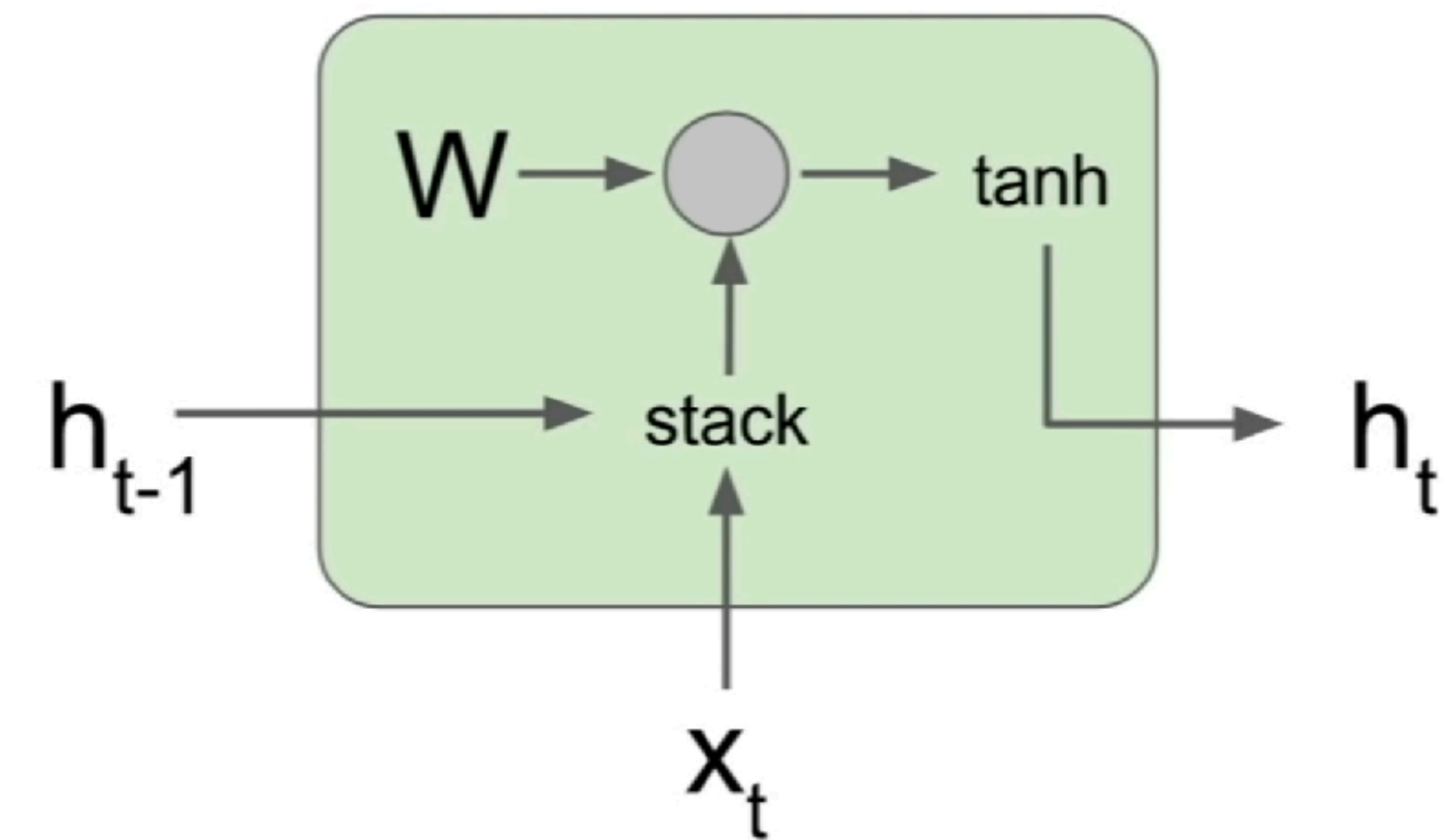
Truncated Backpropagation through time



Carry hidden states forward in time forever, but only backpropagate for some smaller number of steps

Vanilla RNN Gradient Flow

Bengio et al, "Learning long-term dependencies with gradient descent is difficult", IEEE Transactions on Neural Networks, 1994
Pascanu et al, "On the difficulty of training recurrent neural networks", ICML 2013

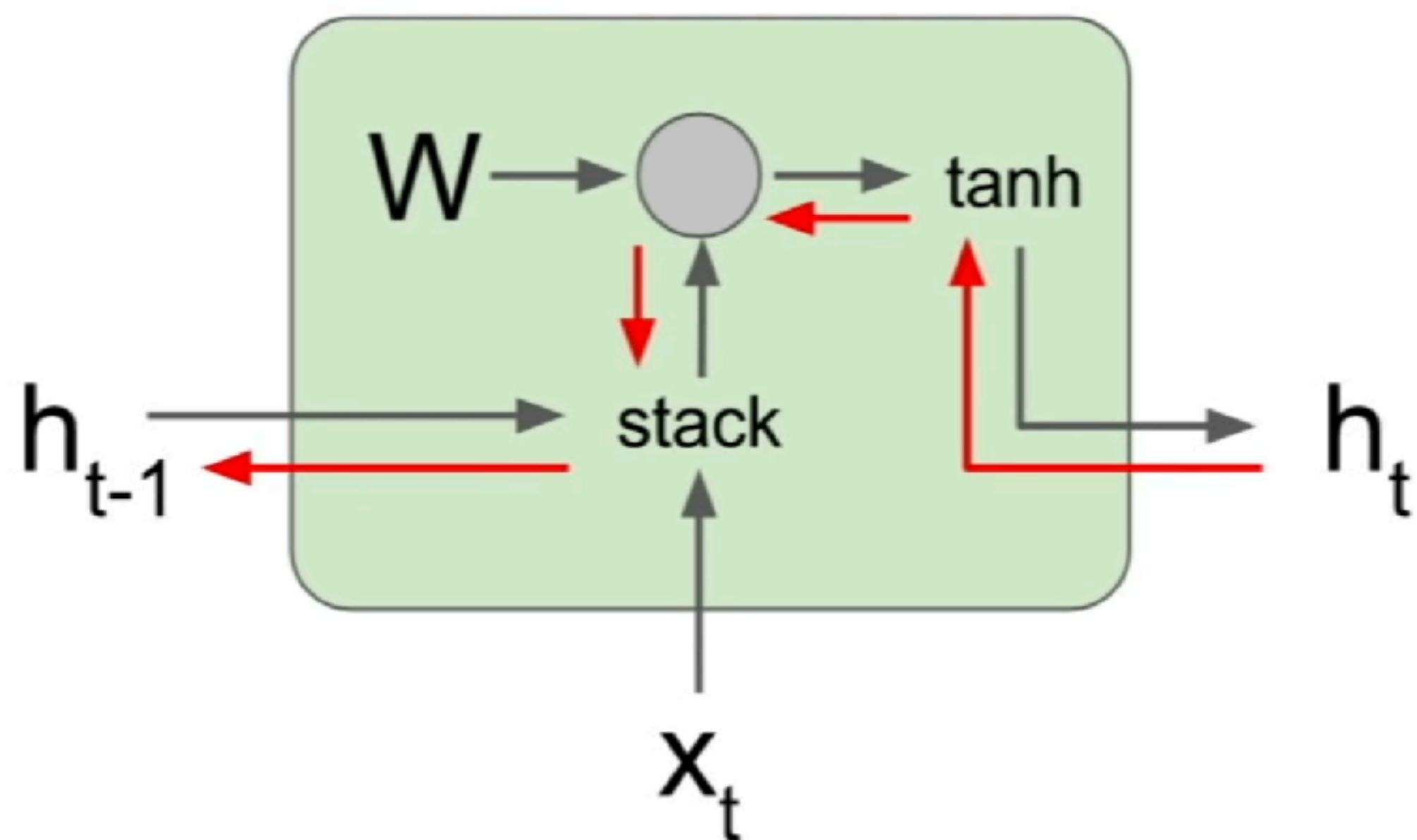


$$\begin{aligned} h_t &= \tanh(W_{hh}h_{t-1} + W_{hx}x_t) \\ &= \tanh\left((W_{hh} \quad W_{hx}) \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right) \\ &= \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right) \end{aligned}$$

Vanilla RNN Gradient Flow

Bengio et al, "Learning long-term dependencies with gradient descent is difficult", IEEE Transactions on Neural Networks, 1994
Pascanu et al, "On the difficulty of training recurrent neural networks", ICML 2013

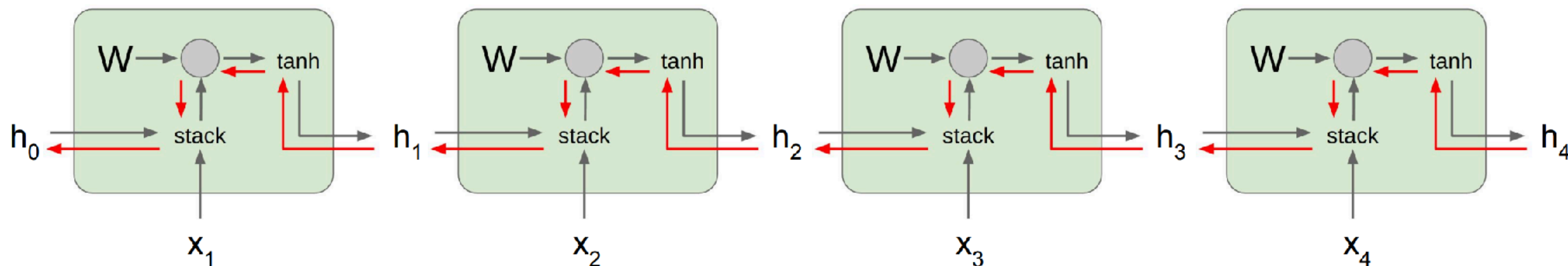
Backpropagation from h_t
to h_{t-1} multiplies by W
(actually W_{hh}^T)



$$\begin{aligned}h_t &= \tanh(W_{hh}h_{t-1} + W_{hx}x_t) \\&= \tanh\left((W_{hh} \quad W_{hx}) \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right) \\&= \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)\end{aligned}$$

Vanilla RNN Gradient Flow

Bengio et al, "Learning long-term dependencies with gradient descent is difficult", IEEE Transactions on Neural Networks, 1994
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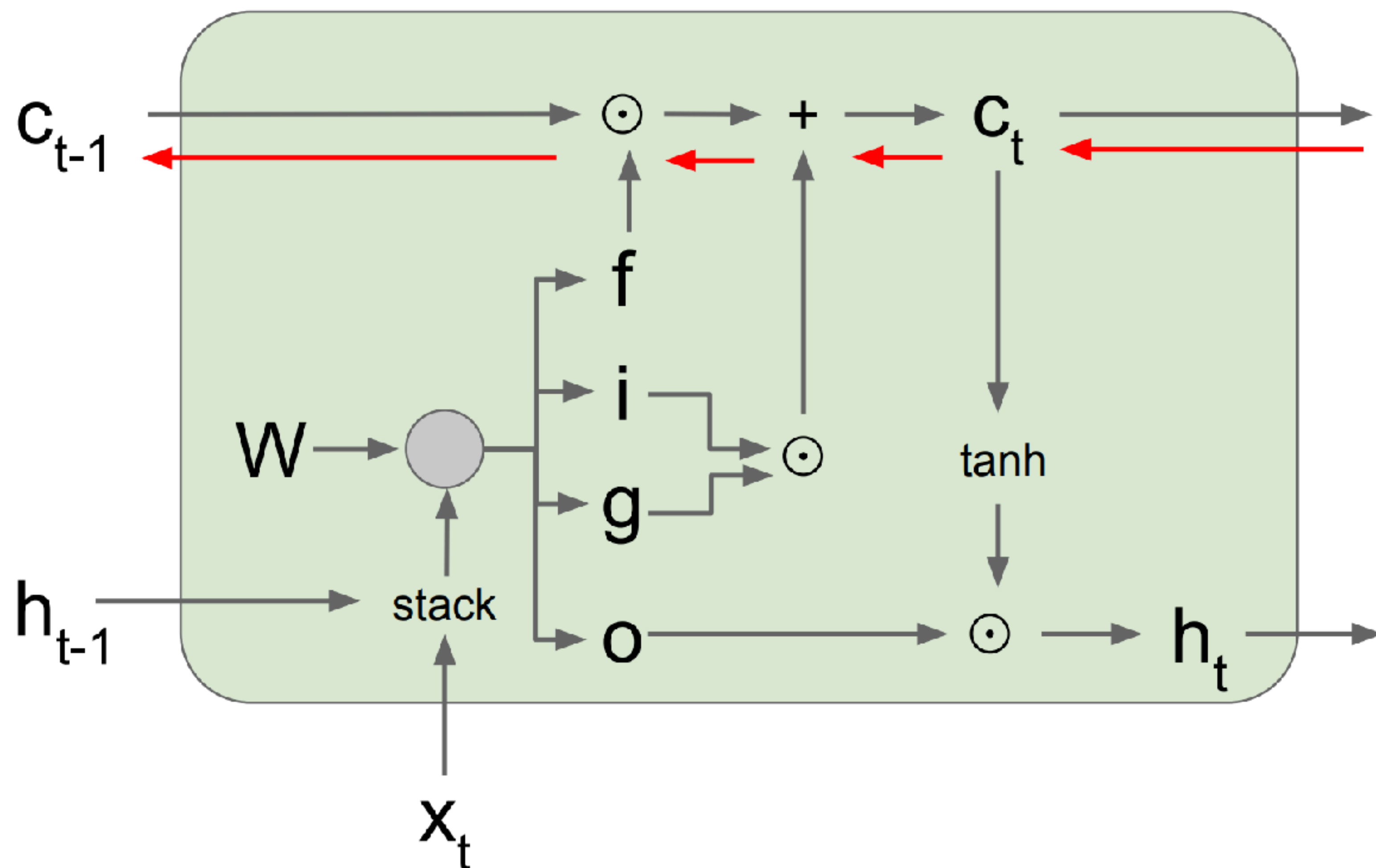
Computing gradient of h_0 involves many factors of W (and repeated $tanh$)

Largest singular value > 1 :
Exploding gradients

Largest singular value < 1 :
Vanishing gradients

Long Short Term Memory (LSTM): Gradient Flow

[Hochreiter et al., 1997]



Backpropagation from c_t to c_{t-1} only elementwise multiplication by f , no matrix multiply by W

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

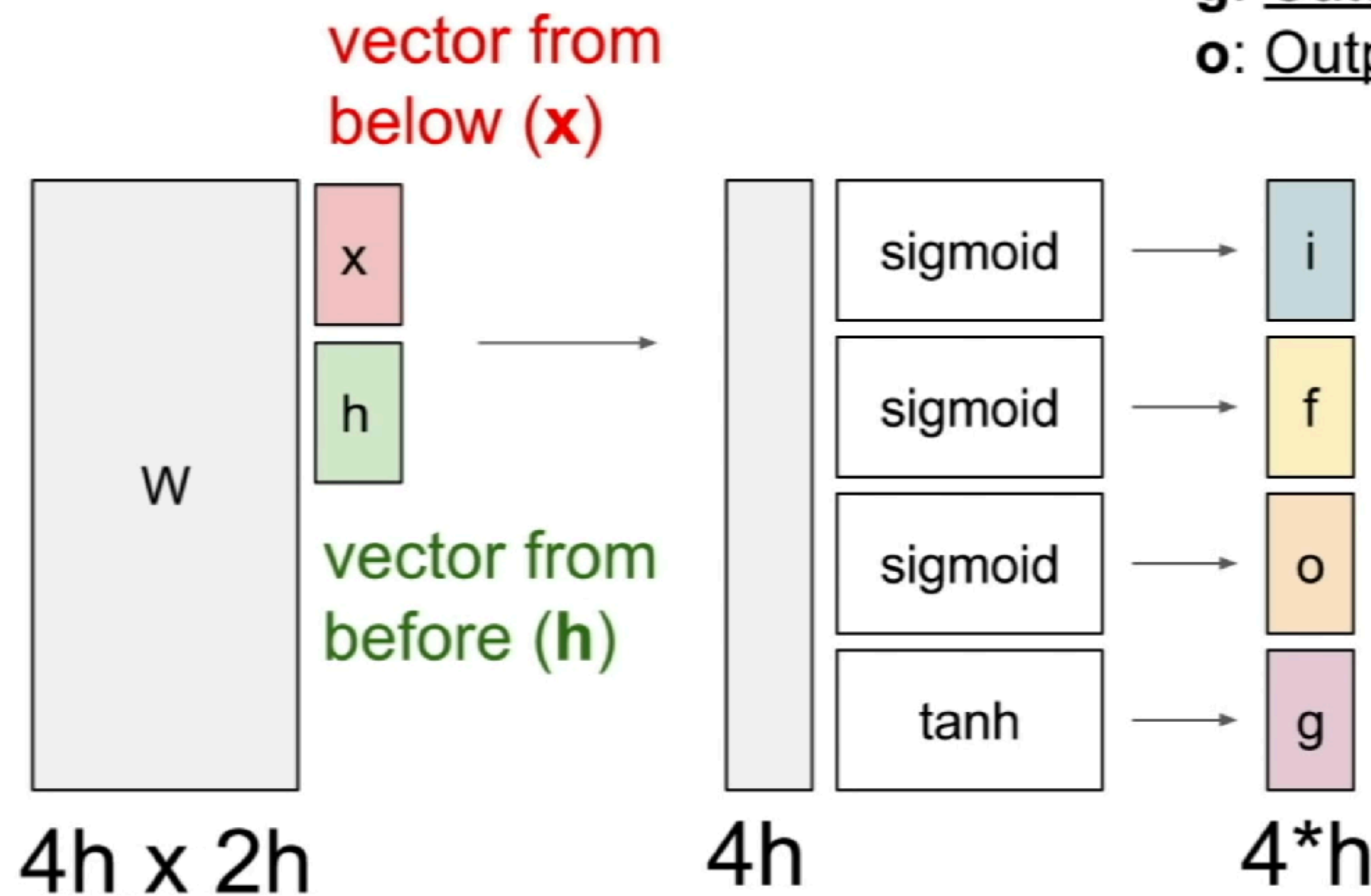
$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

Long Short Term Memory (LSTM)

[Hochreiter et al., 1997]

- f**: Forget gate, Whether to erase cell
- i**: Input gate, whether to write to cell
- g**: Gate gate (?), How much to write to cell
- o**: Output gate, How much to reveal cell



$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

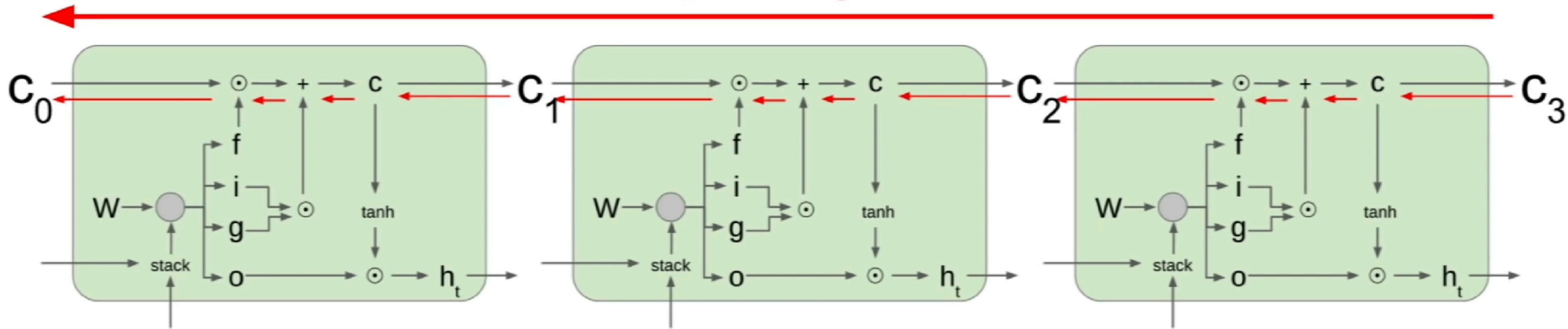
$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

Long Short Term Memory (LSTM): Gradient Flow

[Hochreiter et al., 1997]

Uninterrupted gradient flow!

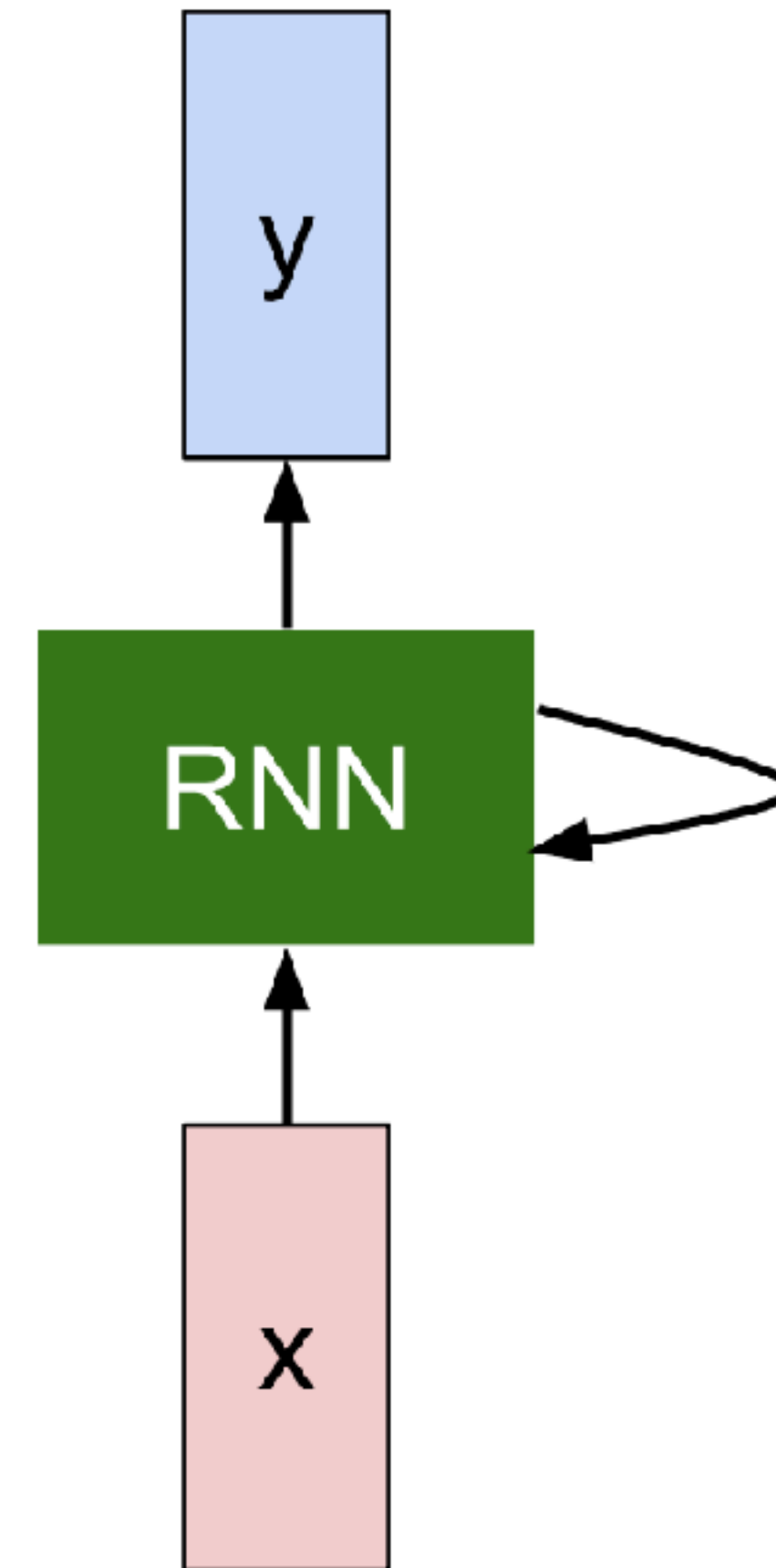


THE SONNETS

by William Shakespeare

From fairest creatures we desire increase,
That thereby beauty's rose might never die,
But as the ripper should by time decease,
His tender heir might bear his memory:
But thou, contracted to thine own bright eyes,
Feed'st thy light's flame with self-substantial fuel,
Making a famine where abundance lies,
Thyself thy foe, to thy sweet self too cruel:
Thou that art now the world's fresh ornament,
And only herald to the gaudy spring,
Within thine own bud buriest thy content,
And tender churl mak'st waste in niggarding:
Pity the world, or else this glutton be,
To eat the world's due, by the grave and thee.

When forty winters shall besiege thy brow,
And dig deep trenches in thy beauty's field,
Thy youth's proud livery so gazed on now,
Will be a tatter'd weed of small worth held:
Then being asked, where all thy beauty lies,
Where all the treasure of thy lusty days;
To say, within thine own deep sunken eyes,
Were an all-eating shame, and thriftless praise.
How much more praise deserv'd thy beauty's use,
If thou couldst answer 'This fair child of mine
Shall sum my count, and make my old excuse,'
Proving his beauty by succession thine!
This were to be new made when thou art old,
And see thy blood warm when thou feel'st it cold.



at first:

tyntd-iafhatawiaoihrdemot lytdws e ,tfti, astai f ogoh eoase rrranbyne 'nhthnee e
plia tklrqd t o idoe ns,smtt h ne etie h,hregtrs nigtike,aoaenns lng

↓
train more

"Tmont thithey" fomesscerliund
Keushey. Thom here
sheulke, anmerenith ol sivh I lalterthend Bleipile shuw y fil on aseterlome
coaniogennc Phe lism thond hon at. MeiDimorotion in ther thize."

↓
train more

Aftair fall unsuch that the hall for Prince Velzonski's that me of
her hearly, and behs to so arwage fiving were to it beloge, pavu say falling misfort
how, and Gogition is so overelical and offer.

↓
train more

"Why do what that day," replied Natasha, and wishing to himself the fact the
princess, Princess Mary was easier, fed in had oftended him.
Pierre aking his soul came to the packs and drove up his father-in-law women.

For $\bigoplus_{n=1,\dots,m} \mathcal{L}_{m,n} = 0$, hence we can find a closed subset $\mathcal{H}$ in $\mathcal{H}$ and any sets $\mathcal{F}$ on X , U is a closed immersion of S , then $U \rightarrow T$ is a separated algebraic space.

Proof. Proof of (1). It also start we get

$$S = \text{Spec}(R) = U \times_X U \times_X U$$

and the comparicoly in the fibre product covering we have to prove the lemma generated by $\coprod Z \times_U U \rightarrow V$. Consider the maps M along the set of points Sch_{fppf} and $U \rightarrow U$ is the fibre category of S in U in Section, ?? and the fact that any U affine, see Morphisms, Lemma ?? . Hence we obtain a scheme S and any open subset $W \subset U$ in $Sh(G)$ such that $\text{Spec}(R') \rightarrow S$ is smooth or an

$$U = \bigcup U_i \times_{S_i} U_i$$

which has a nonzero morphism we may assume that f_i is of finite presentation over S . We claim that $\mathcal{O}_{X,x}$ is a scheme where $x, x', s'' \in S'$ such that $\mathcal{O}_{X,x'} \rightarrow \mathcal{O}'_{X',x'}$ is separated. By Algebra, Lemma ?? we can define a map of complexes $GL_{S'}(x'/S'')$ and we win. $\square$

To prove study we see that $\mathcal{F}|_U$ is a covering of $\mathcal{X}'$, and $\mathcal{T}_i$ is an object of $\mathcal{F}_{X/S}$ for $i > 0$ and $\mathcal{F}_p$ exists and let $\mathcal{F}_i$ be a presheaf of $\mathcal{O}_X$ -modules on $\mathcal{C}$ as a $\mathcal{F}$ -module. In particular $\mathcal{F} = U/\mathcal{F}$ we have to show that

$$\widetilde{M}^\bullet = \mathcal{I}^\bullet \otimes_{\text{Spec}(k)} \mathcal{O}_{S,s} - i_X^{-1} \mathcal{F}$$

is a unique morphism of algebraic stacks. Note that

$$\text{Arrows} = (Sch/S)_{fppf}^{opp}, (Sch/S)_{fppf}$$

and

$$V = \Gamma(S, \mathcal{O}) \mapsto (U, \text{Spec}(A))$$

is an open subset of X . Thus U is affine. This is a continuous map of X is the inverse, the groupoid scheme S .

Proof. See discussion of sheaves of sets. $\square$

The result for prove any open covering follows from the less of Example ?? . It may replace S by $X_{spaces, \acute{e}tale}$ which gives an open subspace of X and T equal to S_{Zar} , see Descent, Lemma ?? . Namely, by Lemma ?? we see that R is geometrically regular over S .

Lemma 0.1. Assume (3) and (3) by the construction in the description.

Suppose $X = \lim |X|$ (by the formal open covering X and a single map $\underline{\text{Proj}}_X(\mathcal{A}) = \text{Spec}(B)$ over U compatible with the complex

$$\text{Set}(\mathcal{A}) = \Gamma(X, \mathcal{O}_{X, \mathcal{O}_X}).$$

When in this case of to show that $\mathcal{Q} \rightarrow \mathcal{C}_{Z/X}$ is stable under the following result in the second conditions of (1), and (3). This finishes the proof. By Definition ?? (without element is when the closed subschemes are catenary. If T is surjective we may assume that T is connected with residue fields of S . Moreover there exists a closed subspace $Z \subset X$ of X where U in X' is proper (some defining as a closed subset of the uniqueness it suffices to check the fact that the following theorem

(1) f is locally of finite type. Since $S = \text{Spec}(R)$ and $Y = \text{Spec}(R)$.

Proof. This is form all sheaves of sheaves on X . But given a scheme U and a surjective étale morphism $U \rightarrow X$. Let $U \cap U = \coprod_{i=1,\dots,n} U_i$ be the scheme X over S at the schemes $X_i \rightarrow X$ and $U = \lim_i X_i$. $\square$

The following lemma surjective restrocomposes of this implies that $\mathcal{F}_{x_0} = \mathcal{F}_{x_0} = \mathcal{F}_{\mathcal{X}, \dots, 0}$.

Lemma 0.2. Let X be a locally Noetherian scheme over S , $E = \mathcal{F}_{X/S}$. Set $\mathcal{I} = \mathcal{I}_1 \subset \mathcal{I}'_n$. Since $\mathcal{I}^n \subset \mathcal{I}^n$ are nonzero over $i_0 \leq \mathfrak{p}$ is a subset of $\mathcal{I}_{n,0} \circ \overline{A}_2$ works.

Lemma 0.3. In Situation ?? . Hence we may assume $q' = 0$.

Proof. We will use the property we see that $\mathfrak{p}$ is the next functor (??). On the other hand, by Lemma ?? we see that

$$D(\mathcal{O}_{X'}) = \mathcal{O}_X(D)$$

where K is an F -algebra where δ_{n+1} is a scheme over S . $\square$


```

static void do_command(struct seq_file *m, void *v)
{
    int column = 32 << (cmd[2] & 0x80);
    if (state)
        cmd = (int)(int_state ^ (in_8(&ch->ch_flags) & Cmd) ? 2 : 1);
    else
        seq = 1;
    for (i = 0; i < 16; i++) {
        if (k & (1 << 1))
            pipe = (in_use & UMXTHREAD_UNCCA) +
                ((count & 0x00000000ffffffff) & 0x0000000f) << 8;
        if (count == 0)
            sub(pid, ppc_md.kexec_handle, 0x20000000);
        pipe_set_bytes(i, 0);
    }
    /* Free our user pages pointer to place camera if all dash */
    subsystem_info = &of_changes[PAGE_SIZE];
    rek_controls(offset, idx, &soffset);
    /* Now we want to deliberately put it to device */
    control_check_polarity(&context, val, 0);
    for (i = 0; i < COUNTER; i++)
        seq_puts(s, "policy ");
}

```

Generated C code

image

conv-64

conv-64

maxpool

conv-128

conv-128

maxpool

conv-256

conv-256

maxpool

conv-512

conv-512

maxpool

conv-512

conv-512

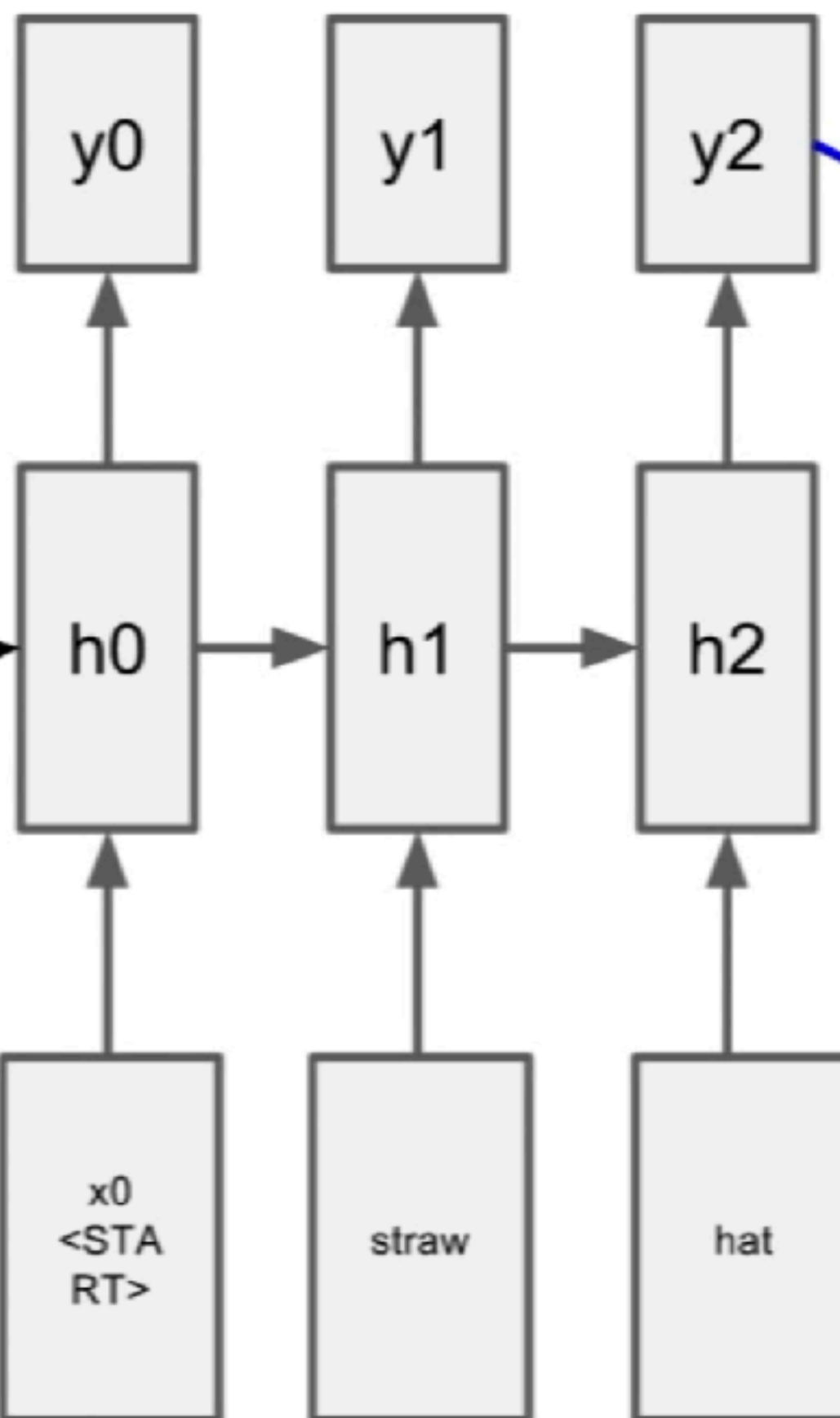
maxpool

FC-4096

FC-4096



test image



sample
<END> token
=> finish.

Image Captioning: Example Results

Captions generated using [neuraltalk2](#)
All images are [CC0 Public domain](#):
[cat suitcase](#), [cat tree](#), [dog](#), [bear](#),
[surfers](#), [tennis](#), [giraffe](#), [motorcycle](#)



A cat sitting on a suitcase on the floor



A cat is sitting on a tree branch



A dog is running in the grass with a frisbee



A white teddy bear sitting in the grass



Two people walking on the beach with surfboards



A tennis player in action on the court



Two giraffes standing in a grassy field



A man riding a dirt bike on a dirt track

Image Captioning: Failure Cases

Captions generated using [neuraltalk2](#)
All images are [CC0 Public domain](#): [fur coat](#), [handstand](#), [spider web](#), [baseball](#)



A woman is holding a cat in her hand



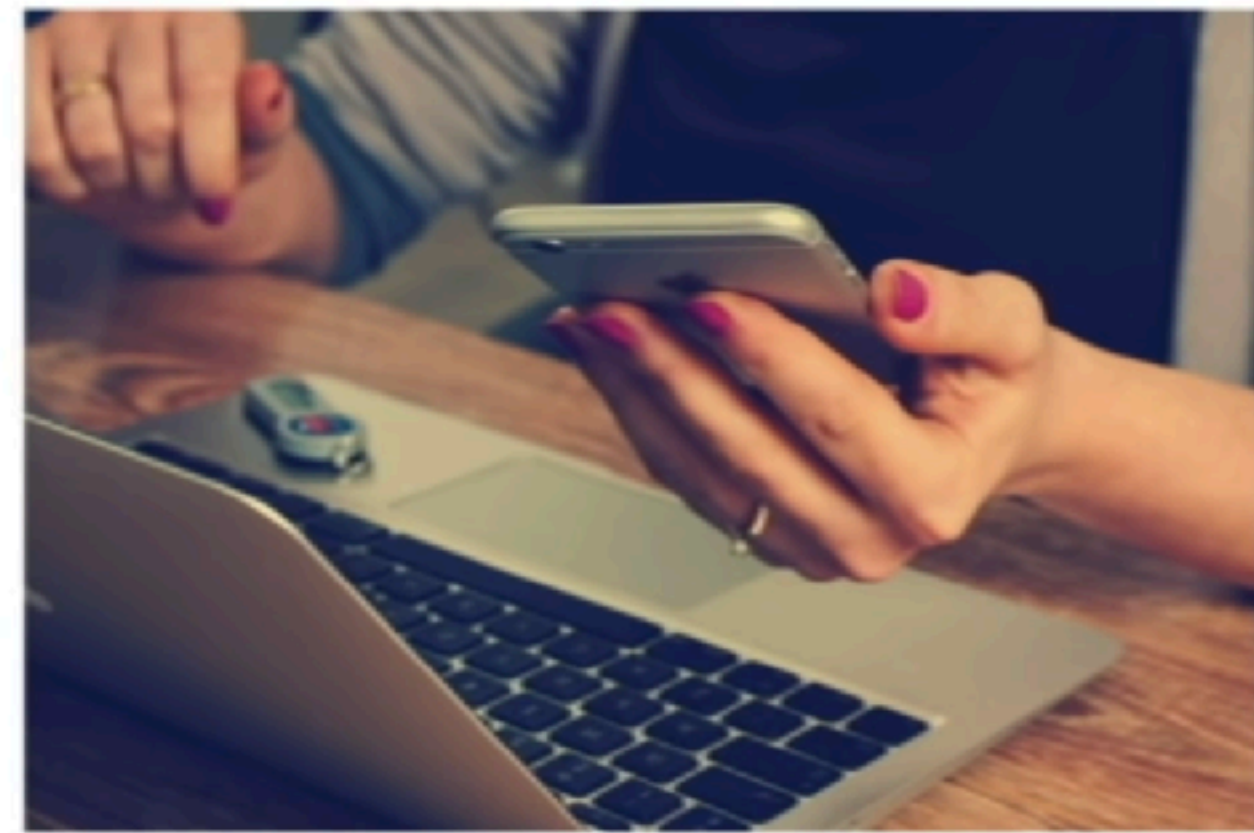
A woman standing on a beach holding a surfboard



A bird is perched on a tree branch



A man in a baseball uniform throwing a ball



A person holding a computer mouse on a desk

Image Captioning with Attention

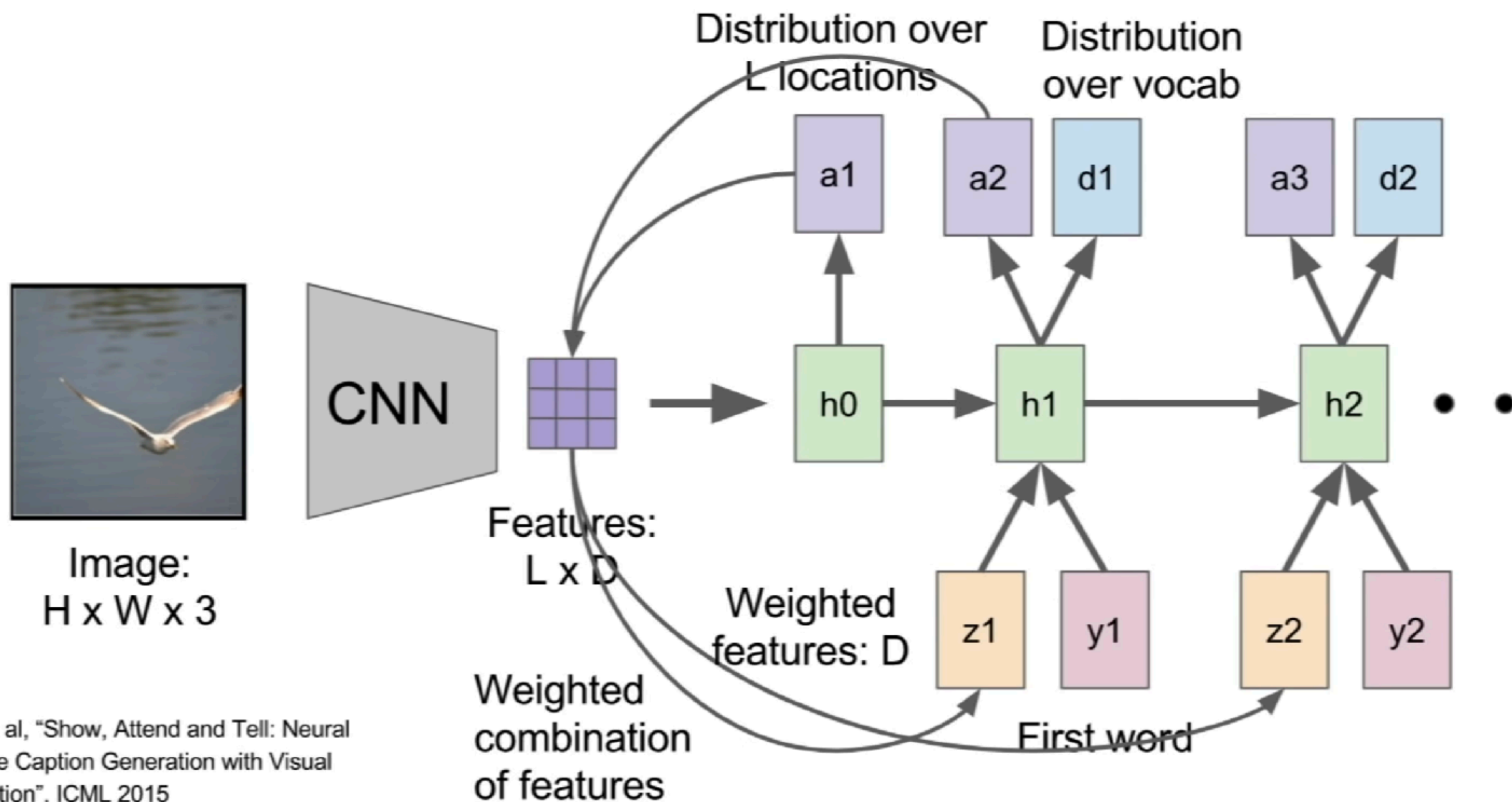
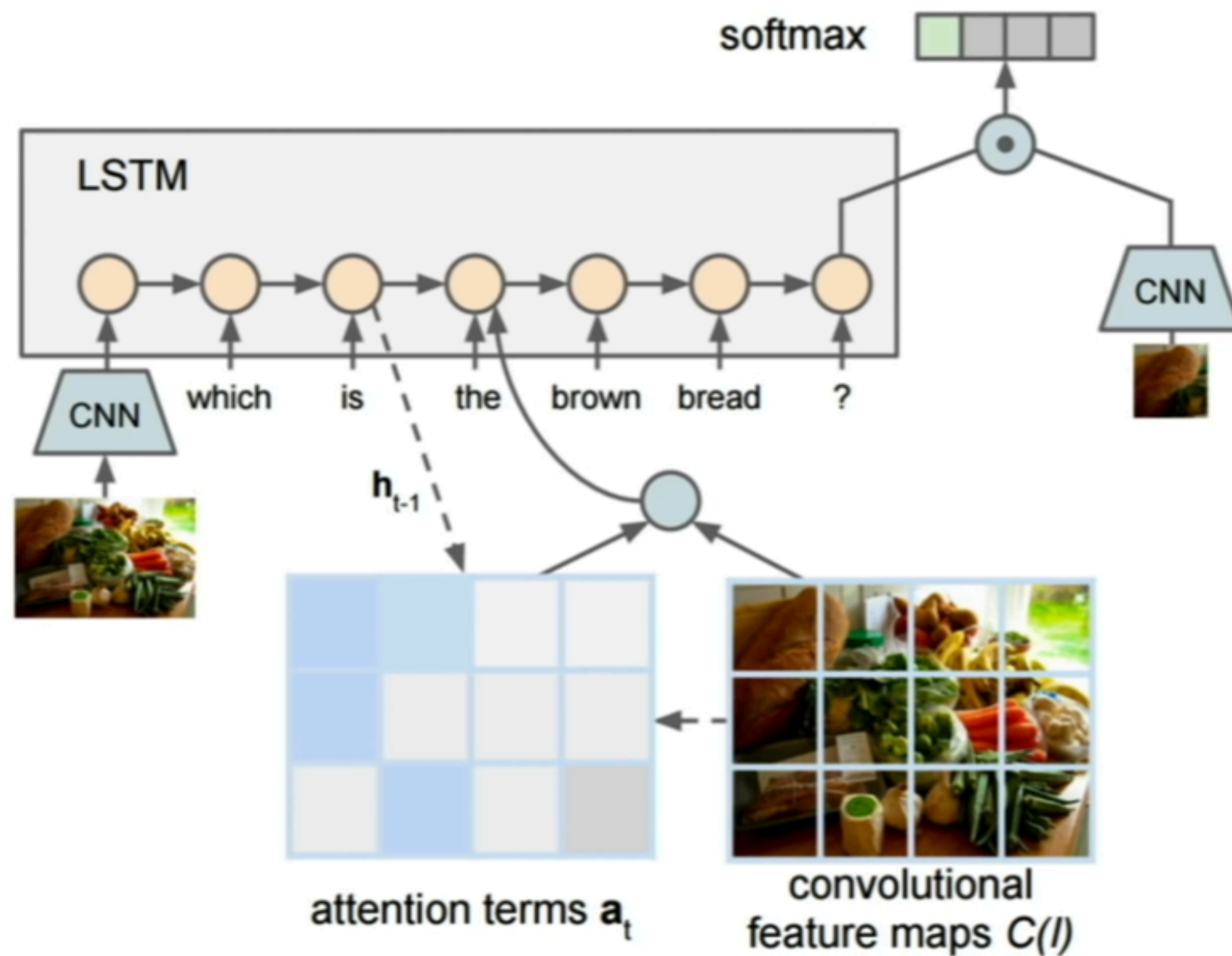
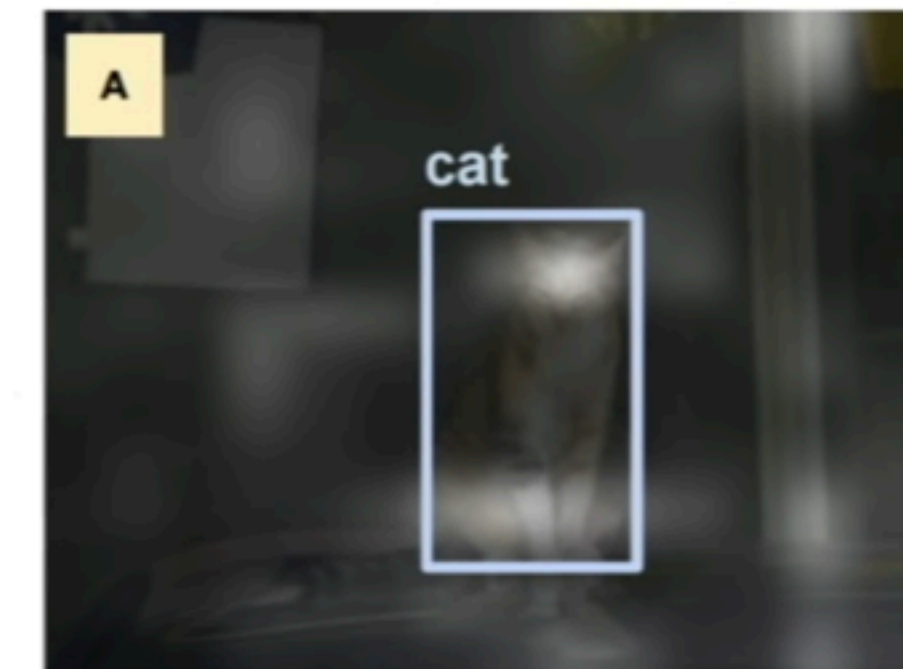


Image Captioning with Attention

Visual Question Answering: RNNs with Attention



Zhu et al, "Visual 7W: Grounded Question Answering in Images", CVPR 2016
Figures from Zhu et al, copyright IEEE 2016. Reproduced for educational purposes.



What kind of animal is in the photo?
A **cat**.



Why is the person holding a knife?
To cut the **cake** with.

Xu et al, "Show, Attend, and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Figure copyright Kelvin Xu, Jimmy Lei Ba, Jamie Kiros, Kyunghyun Cho, Aaron Courville, Ruslan Salakhutdinov, Richard S. Zemel, and Yoshua Bengio, 2015. Reproduced with permission.

Multilayer RNNs

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

$h \in \mathbb{R}^n$.

$W^l [n \times 2n]$

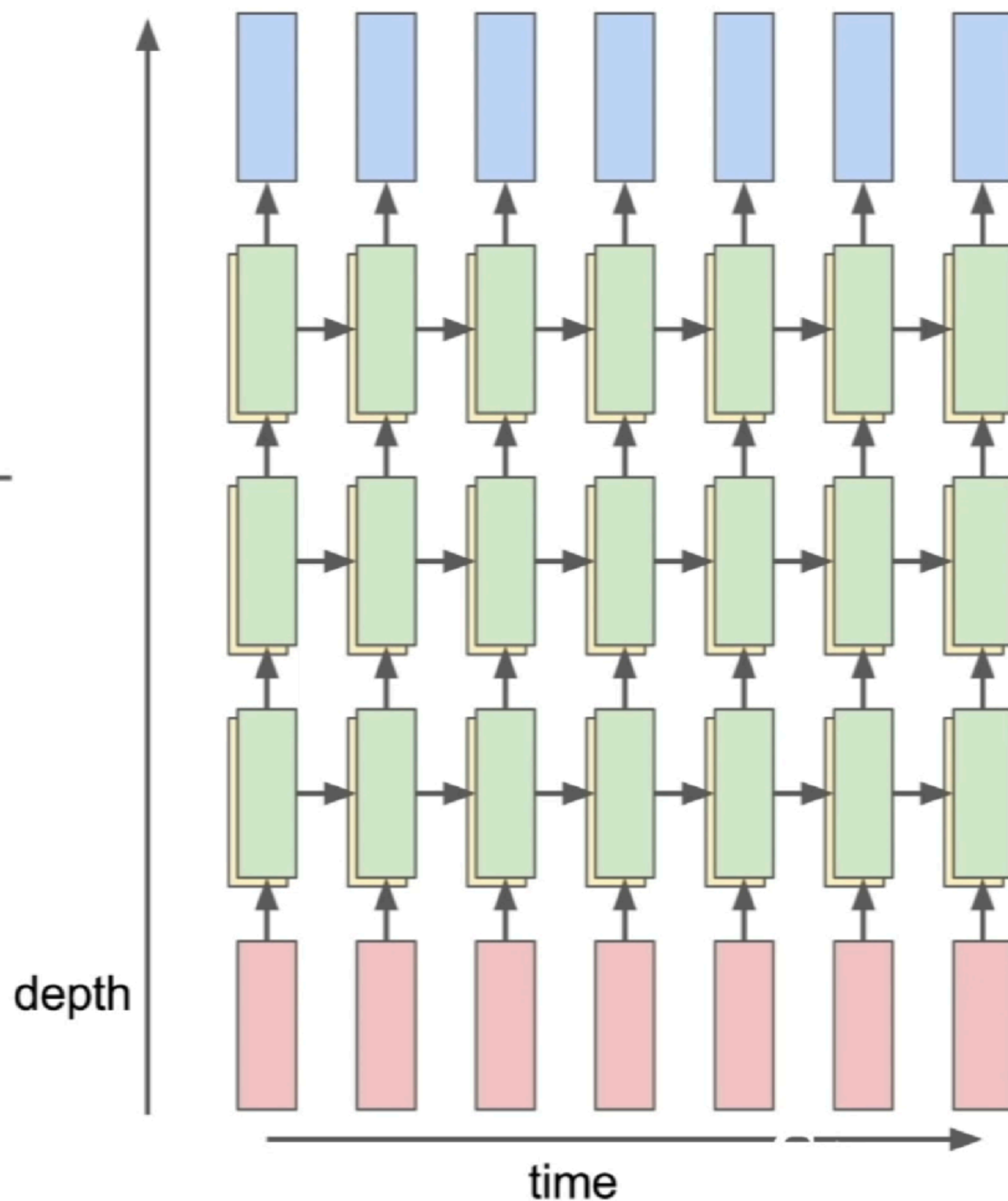
LSTM:

$W^l [4n \times 2n]$

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

$$c_t^l = f \odot c_{t-1}^l + i \odot g$$

$$h_t^l = o \odot \tanh(c_t^l)$$



Other RNN Variants

GRU [*Learning phrase representations using rnn encoder-decoder for statistical machine translation*, Cho et al. 2014]

$$r_t = \sigma(W_{xr}x_t + W_{hr}h_{t-1} + b_r)$$

$$z_t = \sigma(W_{xz}x_t + W_{hz}h_{t-1} + b_z)$$

$$\tilde{h}_t = \tanh(W_{xh}x_t + W_{hh}(r_t \odot h_{t-1}) + b_h)$$

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

[*LSTM: A Search Space Odyssey*, Greff et al., 2015]

[*An Empirical Exploration of Recurrent Network Architectures*, Jozefowicz et al., 2015]

MUT1:

$$z = \text{sigm}(W_{xz}x_t + b_z)$$

$$r = \text{sigm}(W_{xr}x_t + W_{hr}h_t + b_r)$$

$$h_{t+1} = \tanh(W_{hh}(r \odot h_t) + \tanh(x_t) + b_h) \odot z + h_t \odot (1 - z)$$

MUT2:

$$z = \text{sigm}(W_{xz}x_t + W_{hz}h_t + b_z)$$

$$r = \text{sigm}(x_t + W_{hr}h_t + b_r)$$

$$h_{t+1} = \tanh(W_{hh}(r \odot h_t) + W_{xh}x_t + b_h) \odot z + h_t \odot (1 - z)$$

MUT3:

$$z = \text{sigm}(W_{xz}x_t + W_{hz} \tanh(h_t) + b_z)$$

$$r = \text{sigm}(W_{xr}x_t + W_{hr}h_t + b_r)$$

$$h_{t+1} = \tanh(W_{hh}(r \odot h_t) + W_{xh}x_t + b_h) \odot z + h_t \odot (1 - z)$$