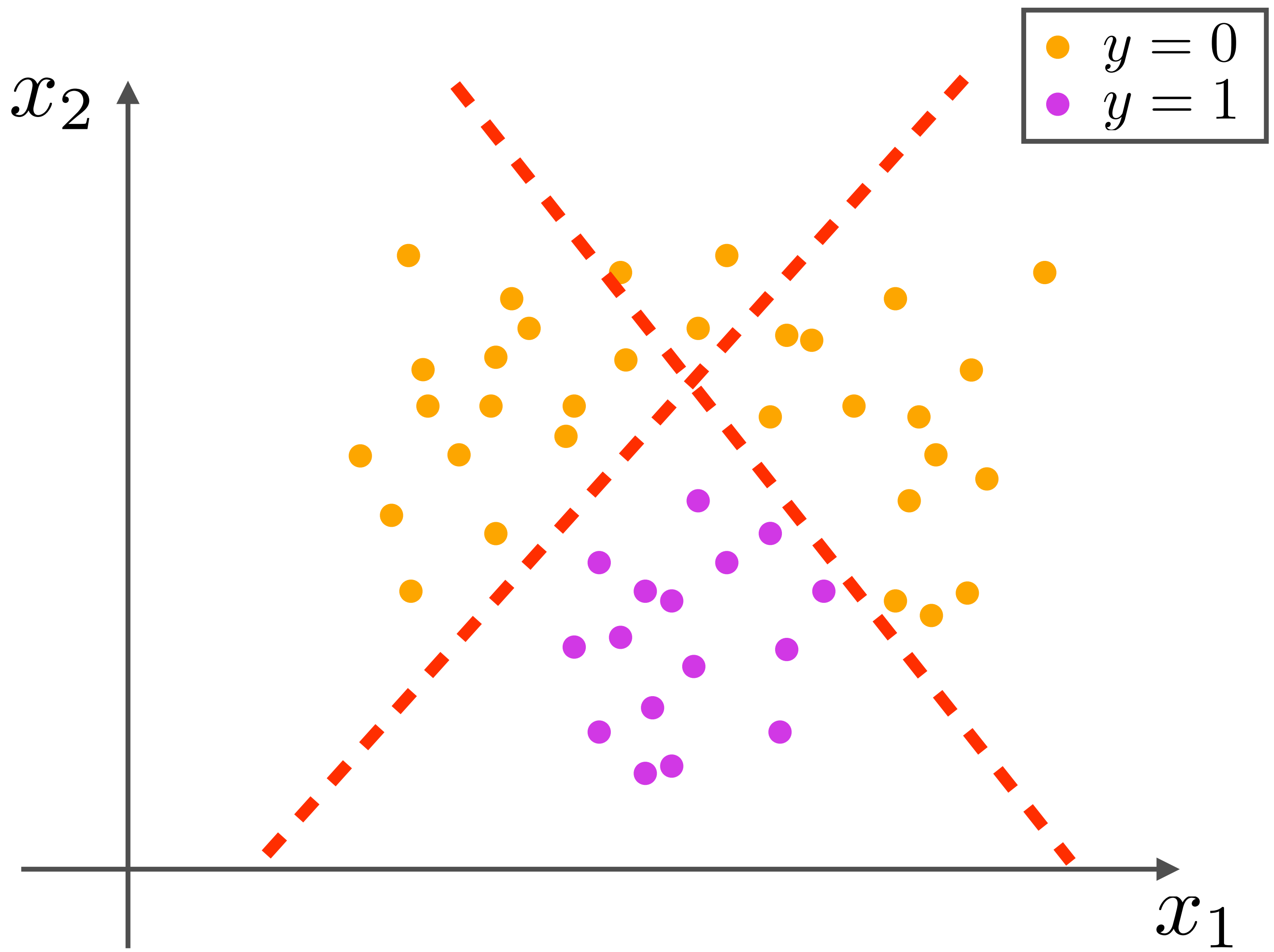
DEEP LEARNING

PART TWO - *CONVOLUTIONAL & RECURRENT NETWORKS*

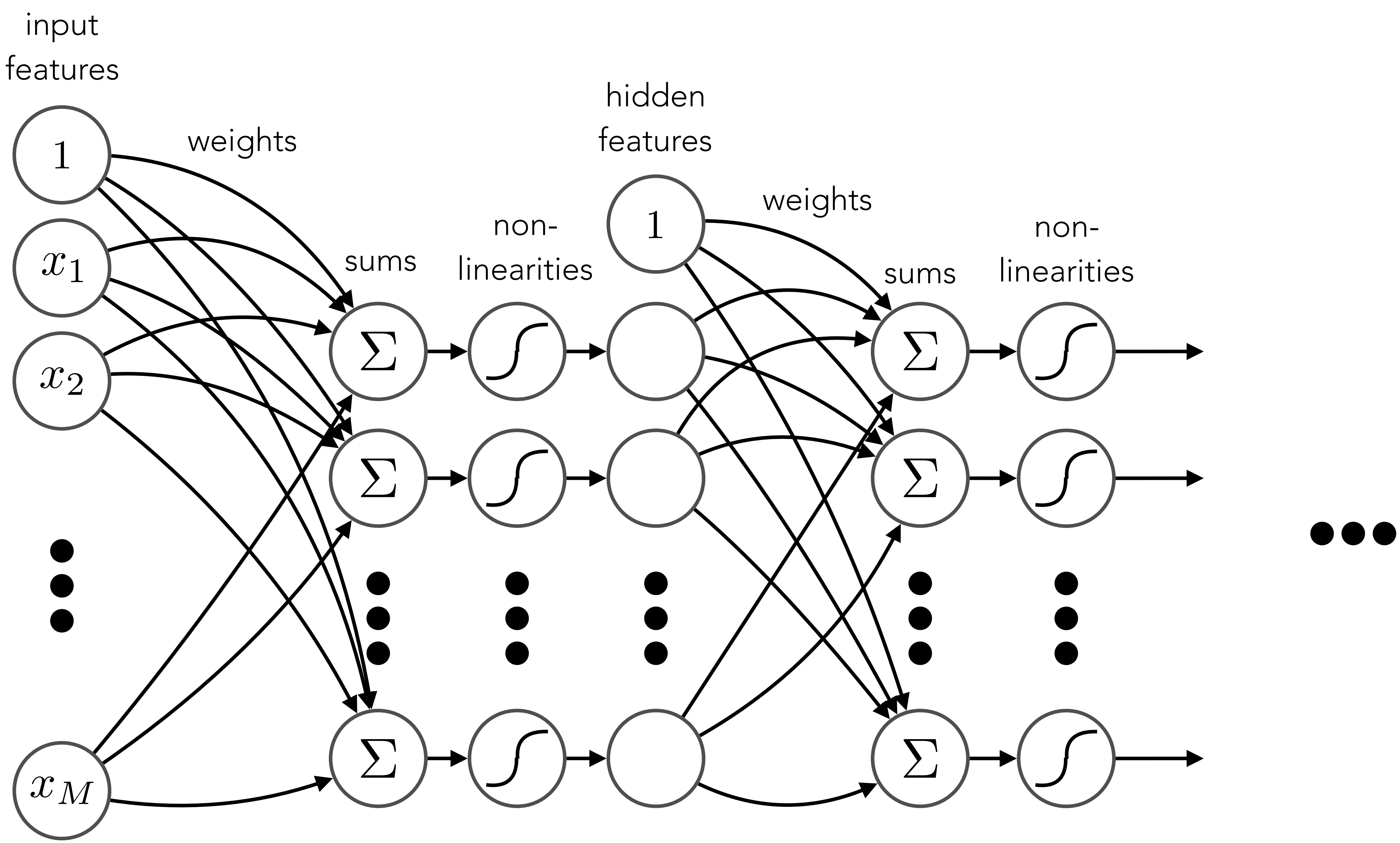
REVIEW

we want to learn ***<u>non-linear</u>*** decision boundaries



$$\mathbf{x} = (x_1, x_2)$$

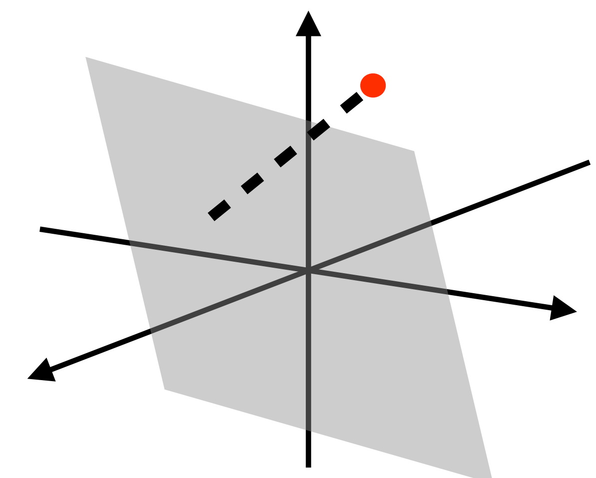
we can do this by composing *linear* decision boundaries neural networks formalize a method for building these composed functions



deep networks are *universal function approximators* the dot product is the shortest distance between a point and a plane

each artificial neuron defines a (hyper)plane:

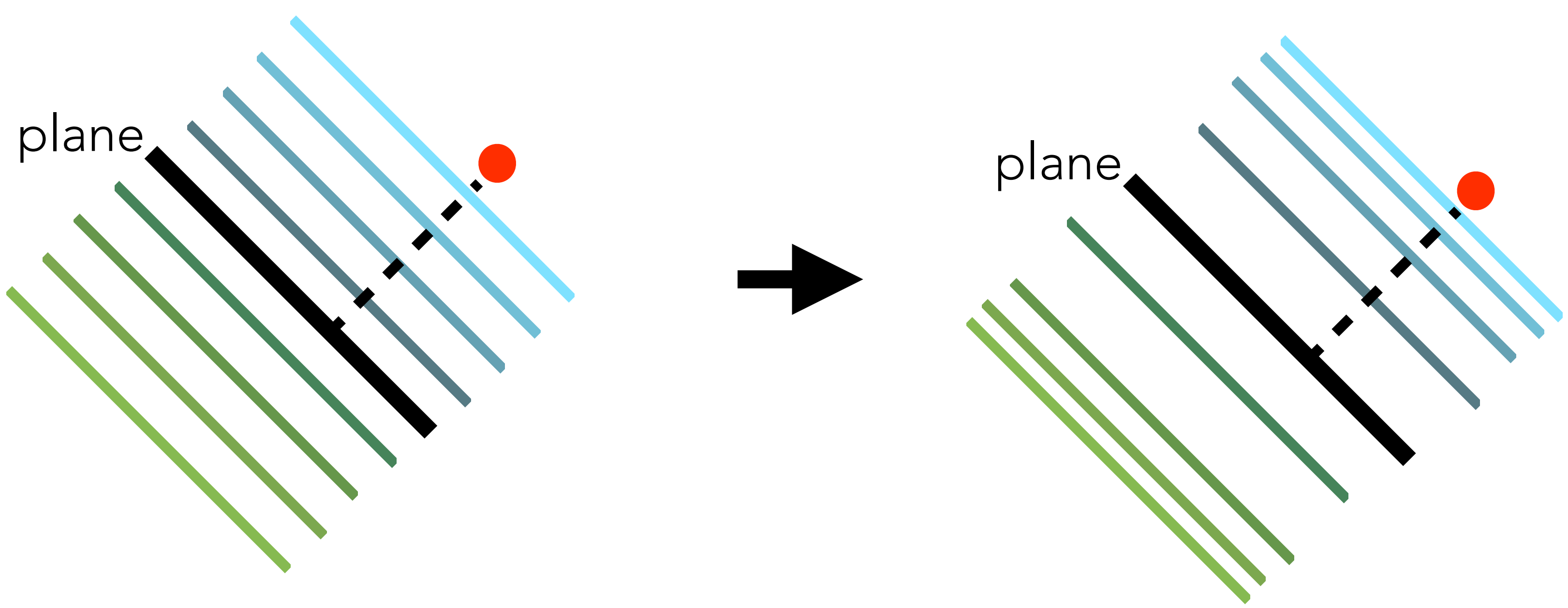
$$0 = w_0 + w_1 x_1 + w_2 x_2 + \ldots w_M x_M$$



summation: distance from plane to input

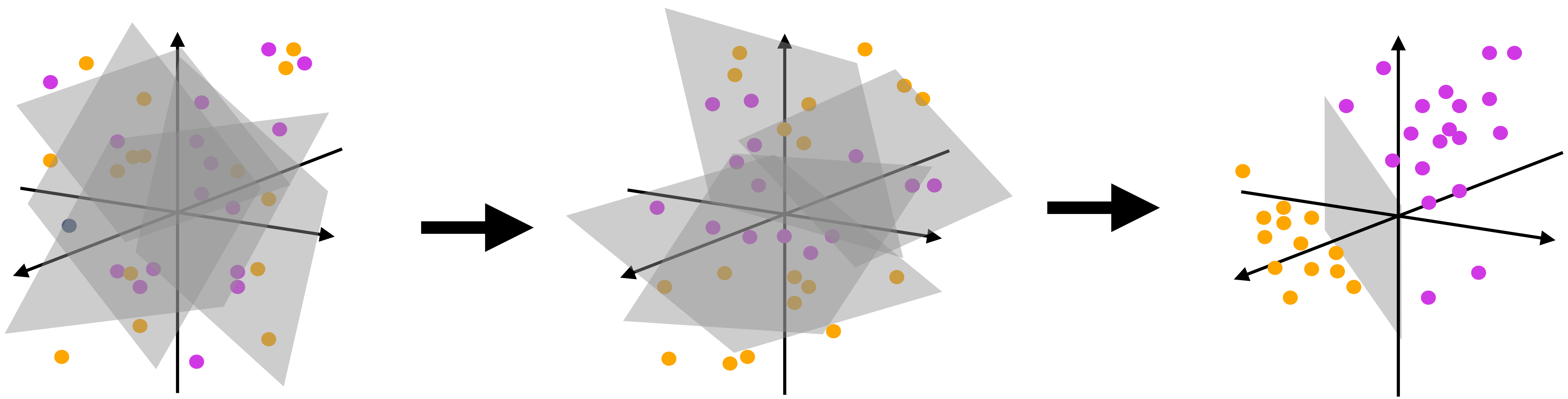
non-linearity: convert distance into non-linear field

distance



example transformed distance

1. cut the space up with hyperplanes
2. evaluate distances of points to hyperplanes
3. non-linearly transform these distances to get new points



repeat until data have been *linearized*

images

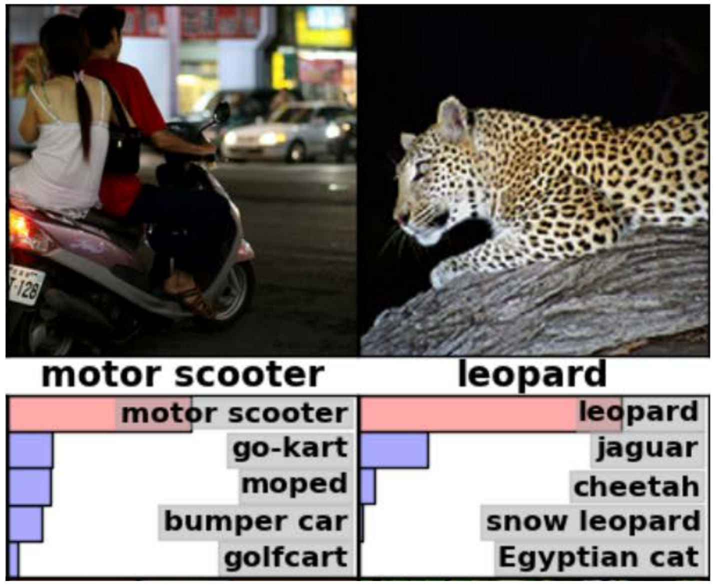
sound & text

virtual/physical control tasks

to scale deep networks to these domains,
we often need to use ***inductive biases***

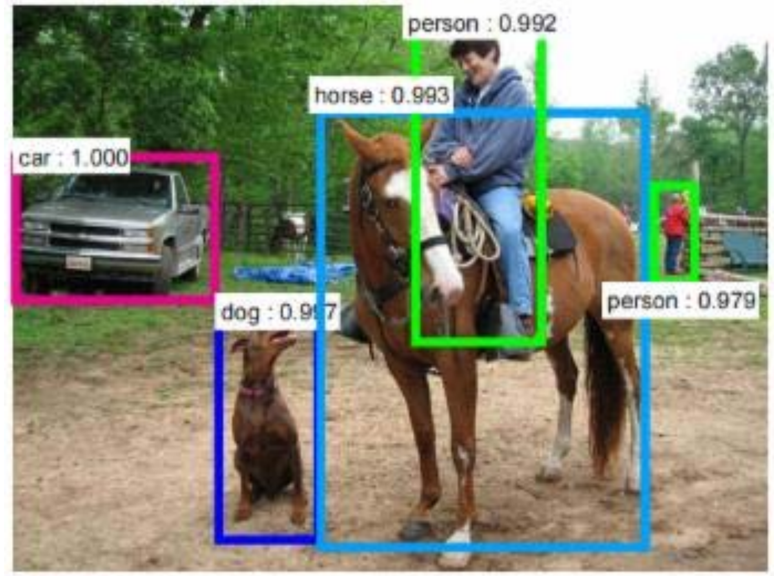
INDUCTIVE BIASES

object recognition



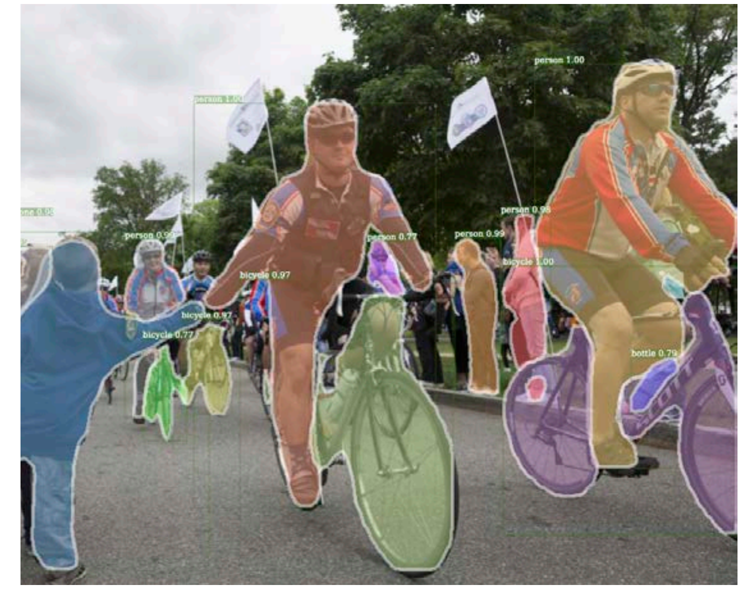
Krizhevsky et al., 2012

object detection



Ren et al., 2016

object segmentation



He et al., 2017

ultimately, we care about *solving tasks*

text translation

Source	Analysts believe the country is unlikely to slide back into full-blown conflict, but recent events have unnerved foreign investors and locals.	
PBMT	Les analystes estiment que le pays a peu de chances de retomber dans un conflit total, mais les événements récents ont inquiété les investisseurs étrangers et locaux.	5.0
GNMT	Selon les analystes, il est peu probable que le pays retombe dans un conflit généralisé, mais les événements récents ont attiré des investisseurs étrangers et des habitants locaux.	2.0
Human	Les analystes pensent que le pays ne devrait pas retomber dans un conflit ouvert, mais les récents évènements ont ébranlé les investisseurs étrangers et la population locale.	5.0

Wu et al., 2016

text question answering

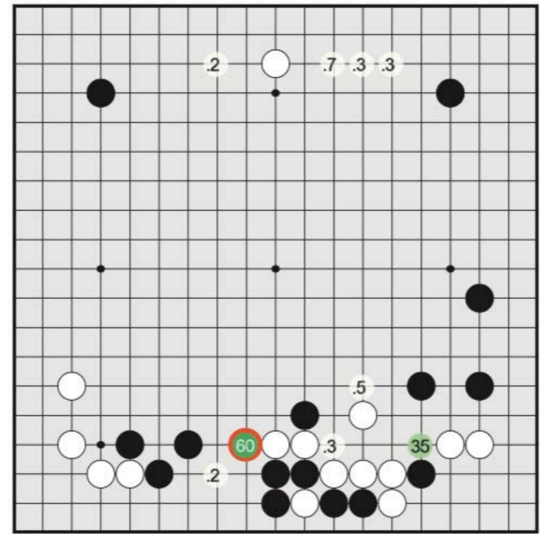
```
1 Mary moved to the bathroom.
2 John went to the hallway.
3 Where is Mary?        bathroom        1
4 Daniel went back to the hallway.
5 Sandra moved to the garden.
6 Where is Daniel?      hallway 4
7 John moved to the office.
8 Sandra journeyed to the bathroom.
9 Where is Daniel?      hallway 4
10 Mary moved to the hallway.
11 Daniel travelled to the office.
12 Where is Daniel?     office  11
13 John went back to the garden.
14 John moved to the bedroom.
15 Where is Sandra?     bathroom        8
1 Sandra travelled to the office.
2 Sandra went to the bathroom.
3 Where is Sandra?      bathroom        2
```

Weston et al., 2015

atari

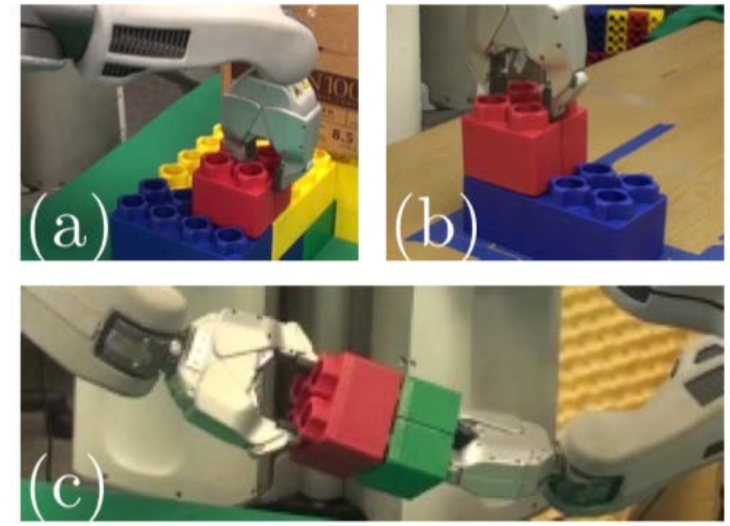
Minh et al., 2013

go



Silver, Huang et al., 2016

object manipulation

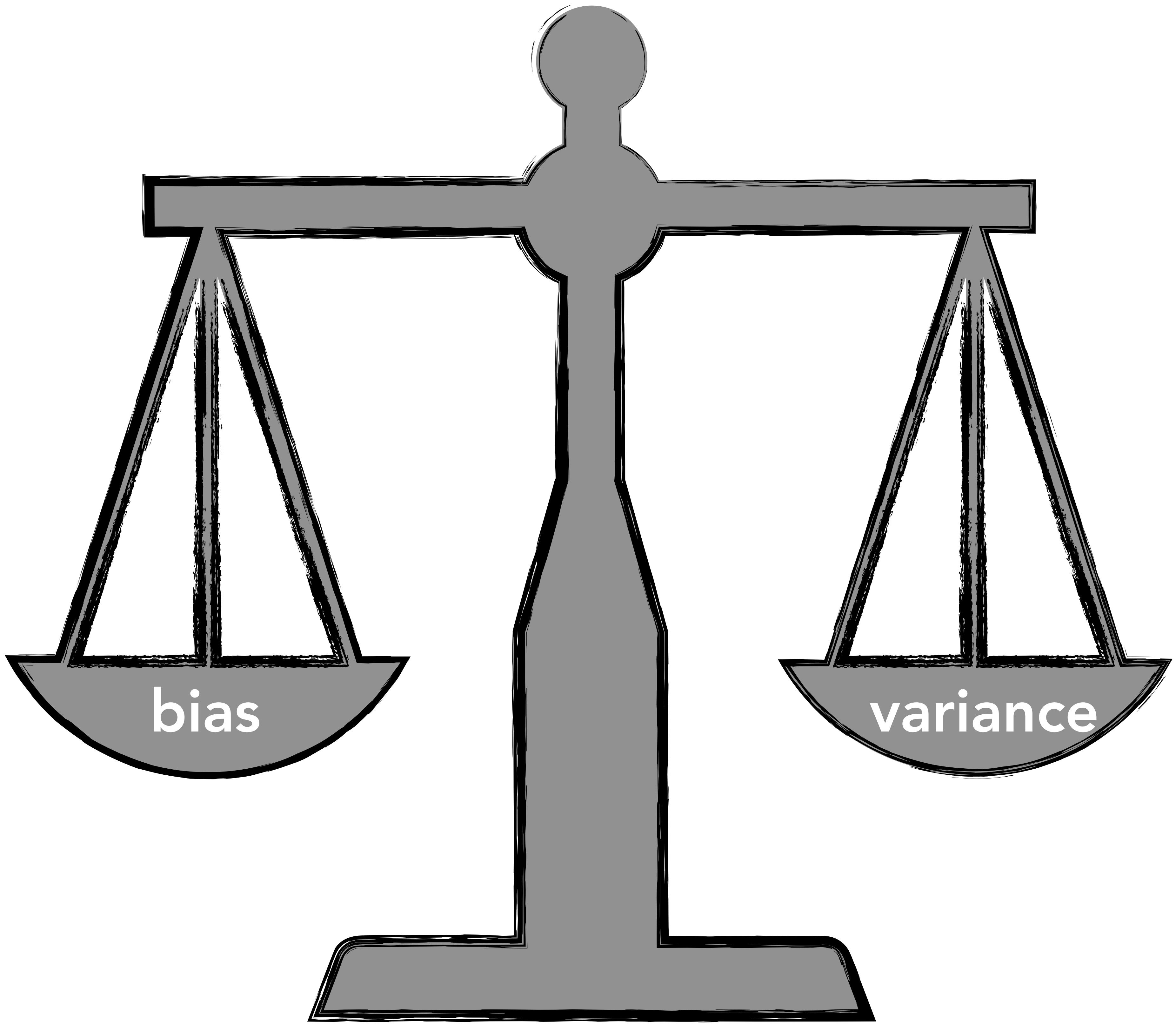


Levine, Finn, et al., 2016

ultimately, we care about *solving tasks*

survival & reproduction

e.g. teaching



performing any task involves a ***bias-variance tradeoff***

<u>*two components*</u> for solving any task

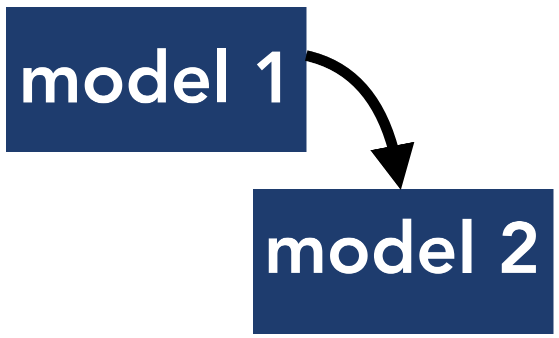
priors

(*bias*)

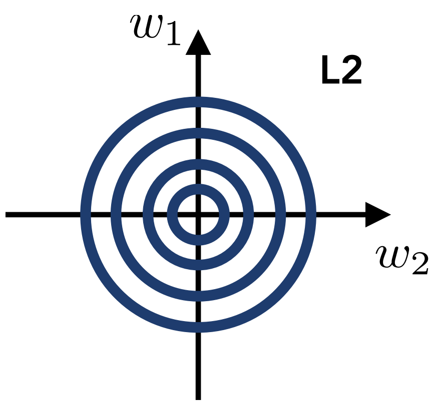
learning

(*variance*)

param. values



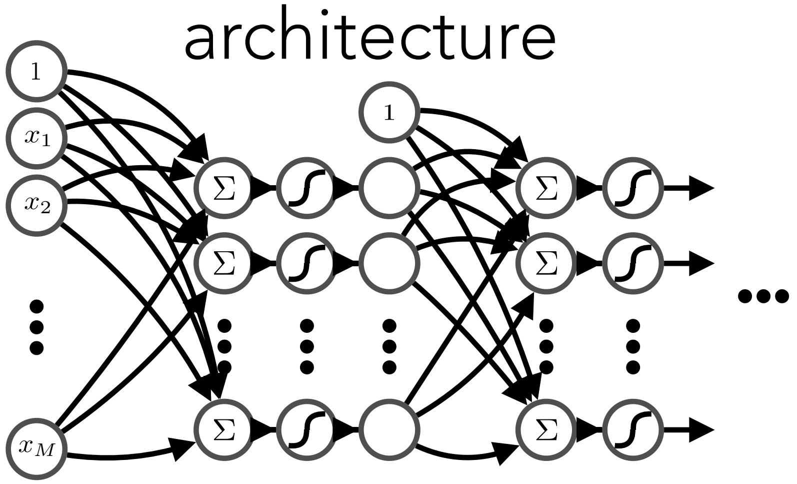
param. constraints



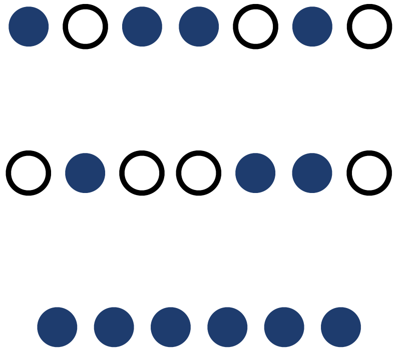
priors

things assumed beforehand

architecture



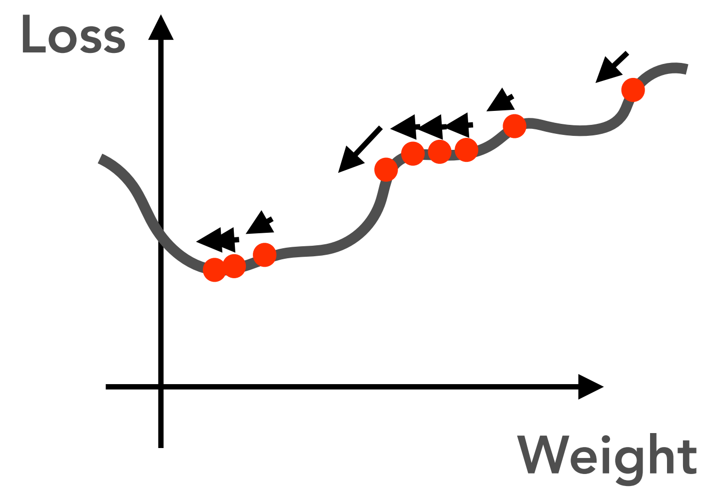
activities, outputs



LOSS/ERROR

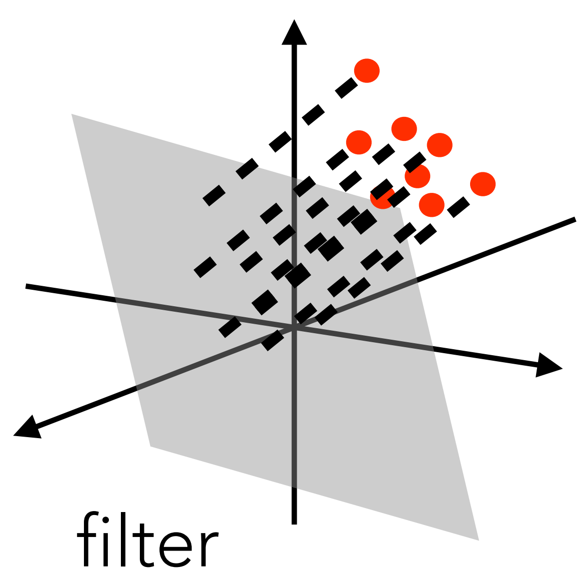
GRADIENT

IMPROVEMENT



learning

things extracted from data

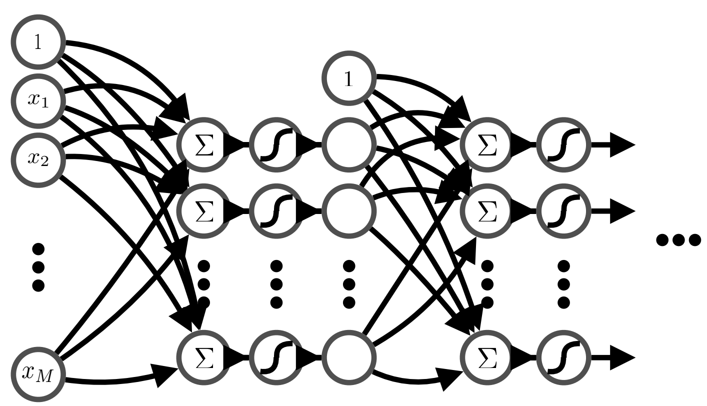


it's a balance! 

strong priors, minimal learning
- fast/easy to learn and deploy
- may be too rigid, unadaptable

weak priors, much learning
- slow/difficult to learn and deploy
- flexible, adaptable

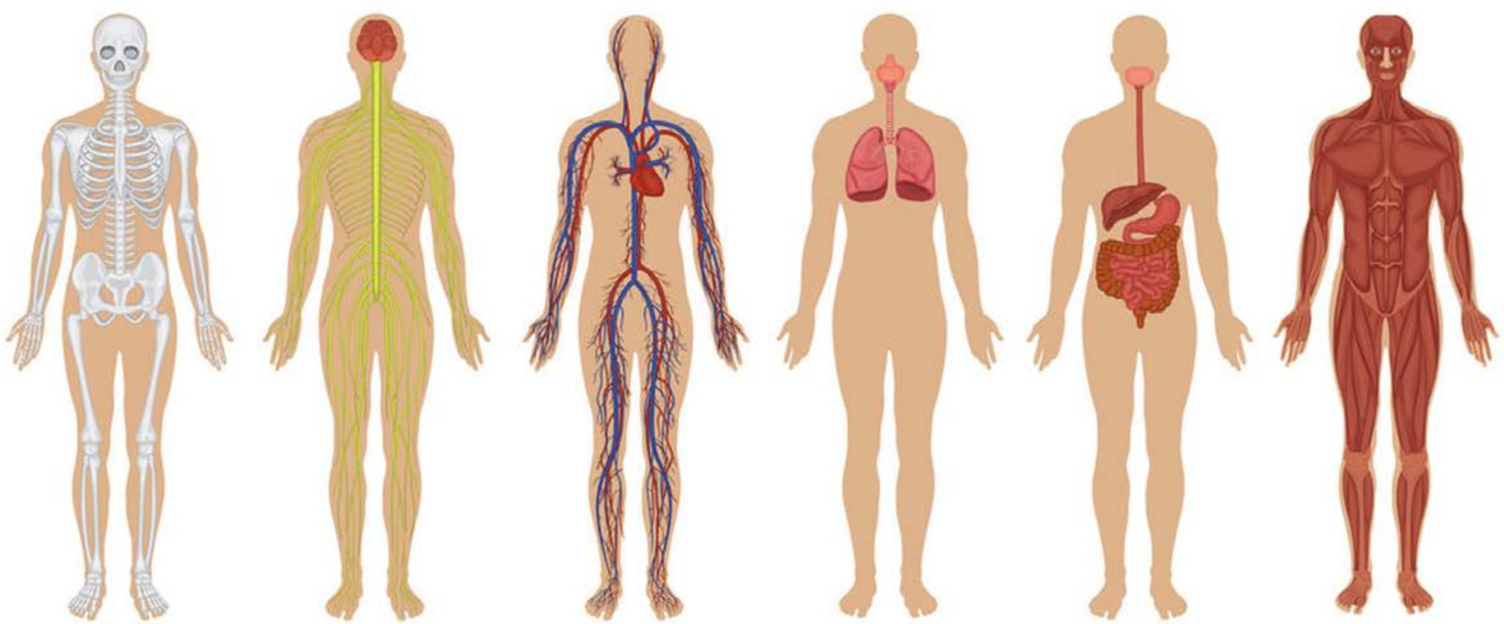
for a desired level of performance on a task…



data

choose priors and collect data to obtain a model
that achieves that performance in the minimal amount of time

priors are *essential* - always have to make some assumptions, cannot integrate over all possible models

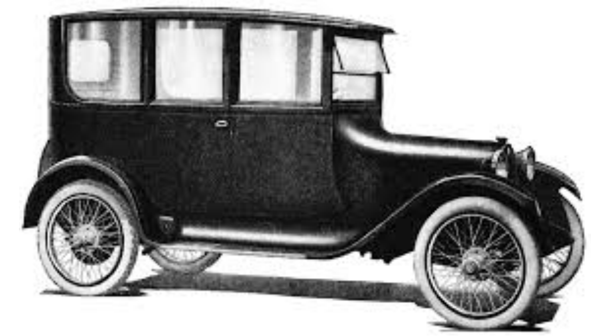


we are all initialized from *evolutionary priors*

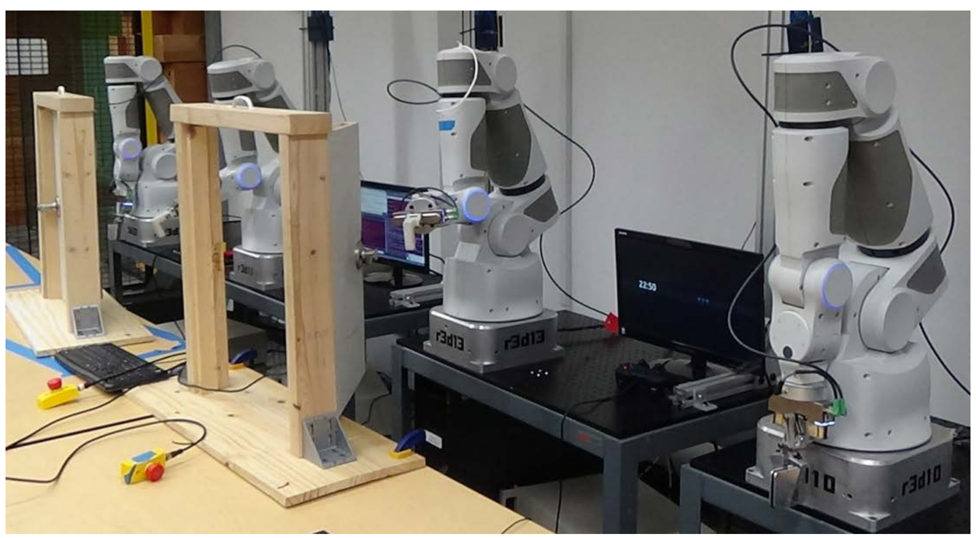
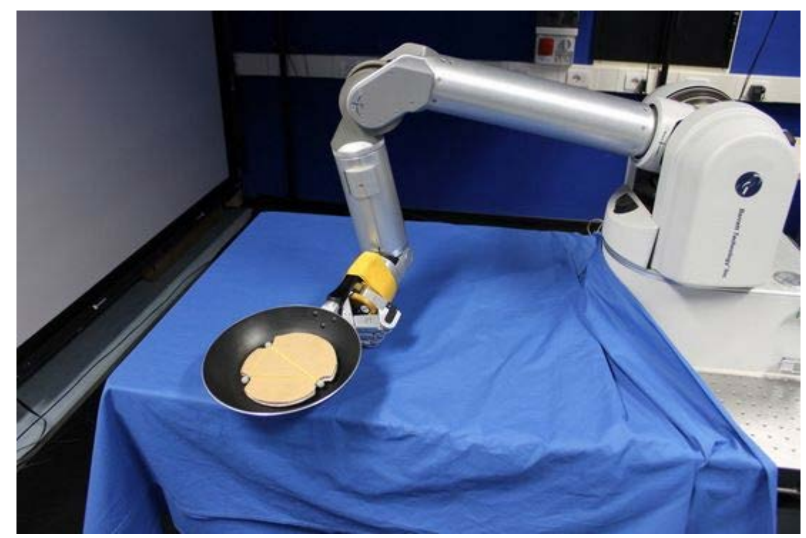
humans seem to have a larger capacity for learning than other organisms

livescience.com

up until now, all of our machines have been purely based on *priors*

for the first time in history, **we can now create machines that also *learn***

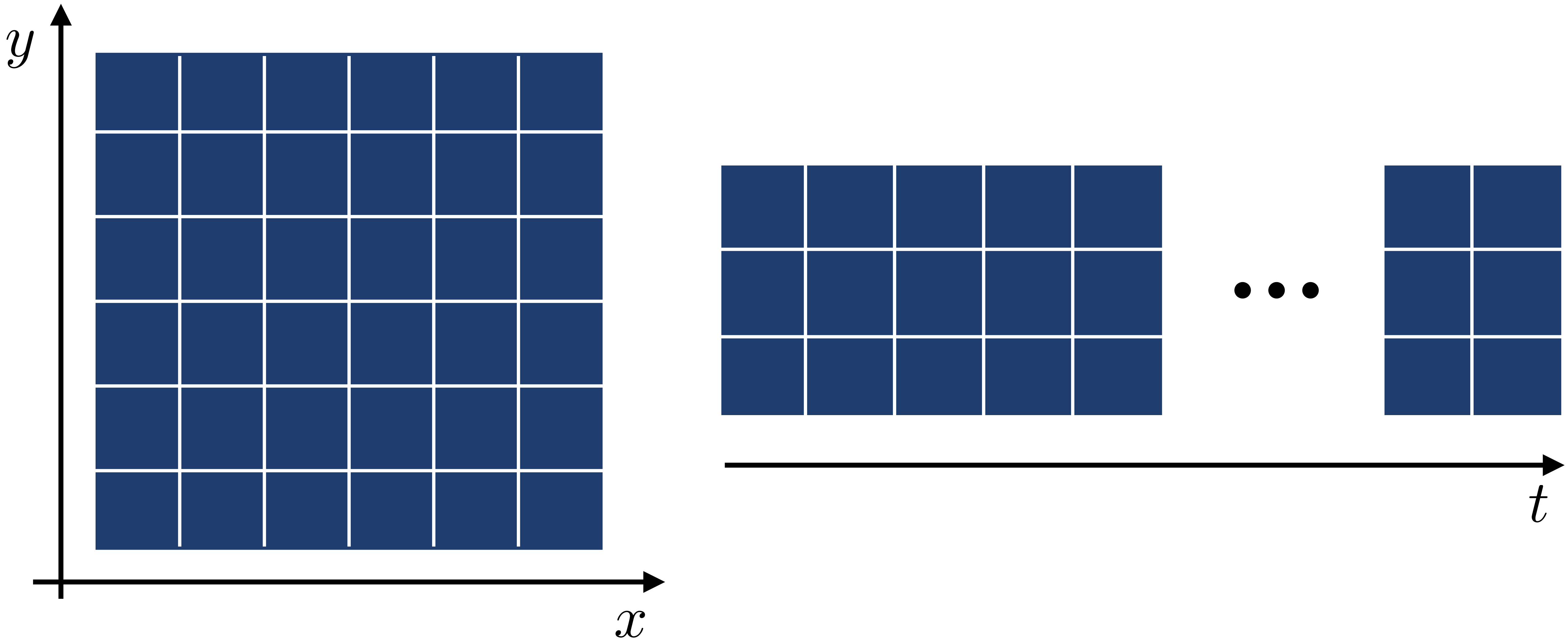
these machines can perform tasks that are impossible to hand-design

…but they are mostly still based on priors!

Kormushev et al.

we can exploit known structure in *spatial* and *sequential* data
to impose priors (i.e. inductive biases) on models

inductive: inferring general laws from examples



this allows us to learn models in complex, high-dimensional domains
while limiting the number of parameters and data examples

CONVOLUTIONAL NEURAL NETWORKS

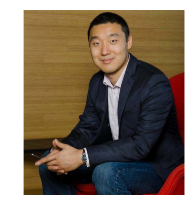
task: *object recognition*

→ *Yisong*

discriminative mapping from image to object identity

images contain all of the information about the binary latent variable *Yisong/Not Yisong*

extract the relevant information about this latent variable to form conditional probability

inference: $p(\text{Yisong}|$  $)$

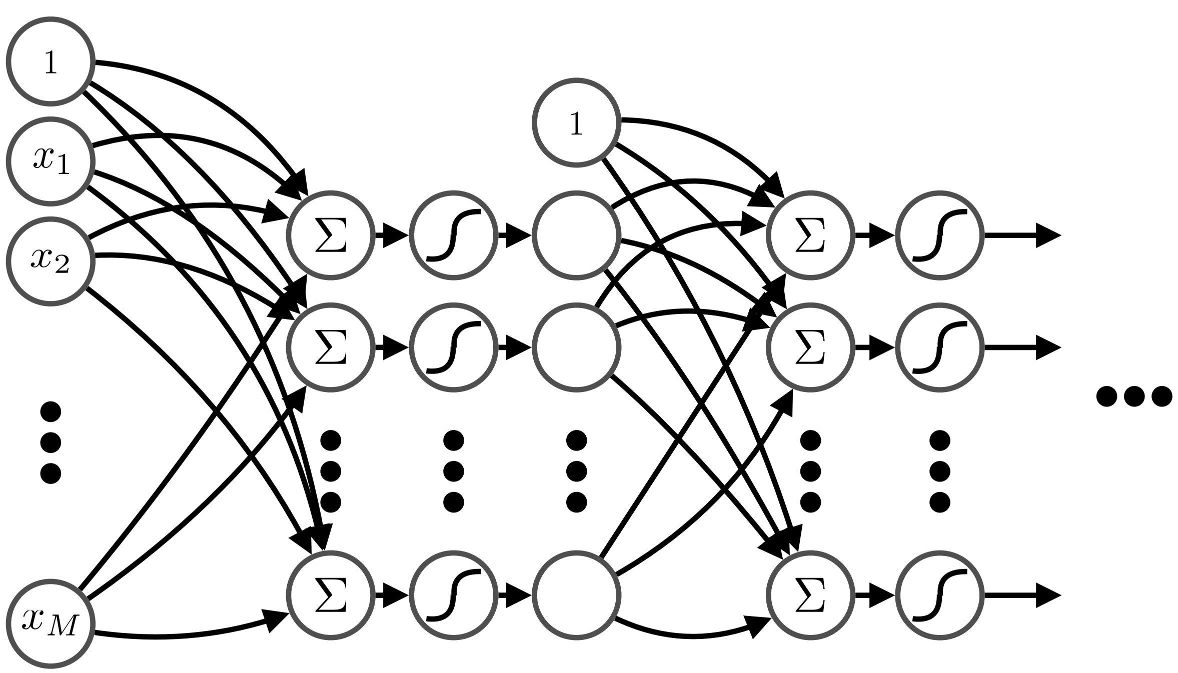
notice that images also contain other *nuisance* information, such as pose, lighting, background, etc.

want to be *invariant* to nuisance information data, label collection

the mapping is too difficult to
define by hand,
need to learn from data

Yisong

Not Yisong



then, we need to choose
a model architecture…

standard neural networks require a fixed input size…

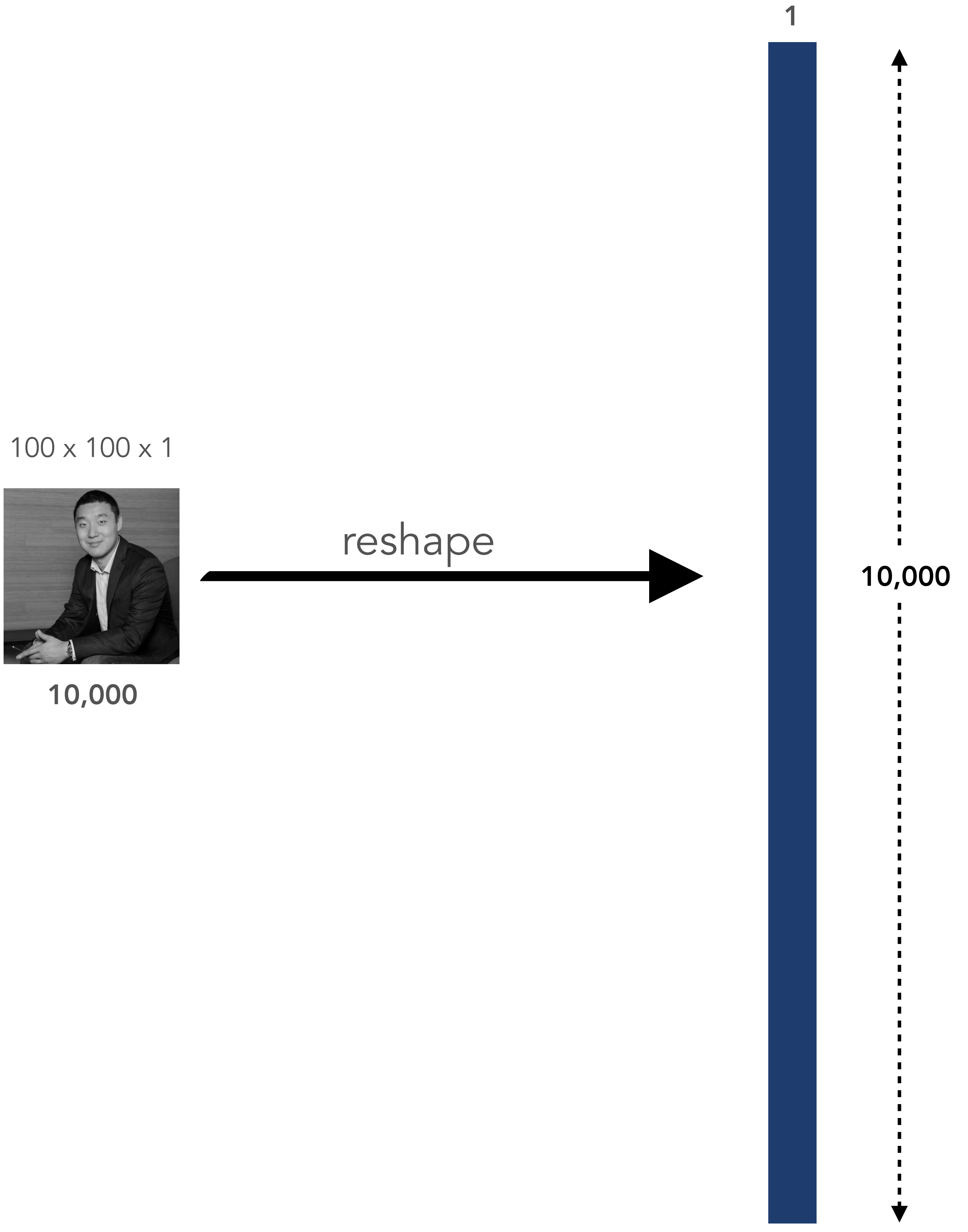
fewer parameters,
but unclear patterns

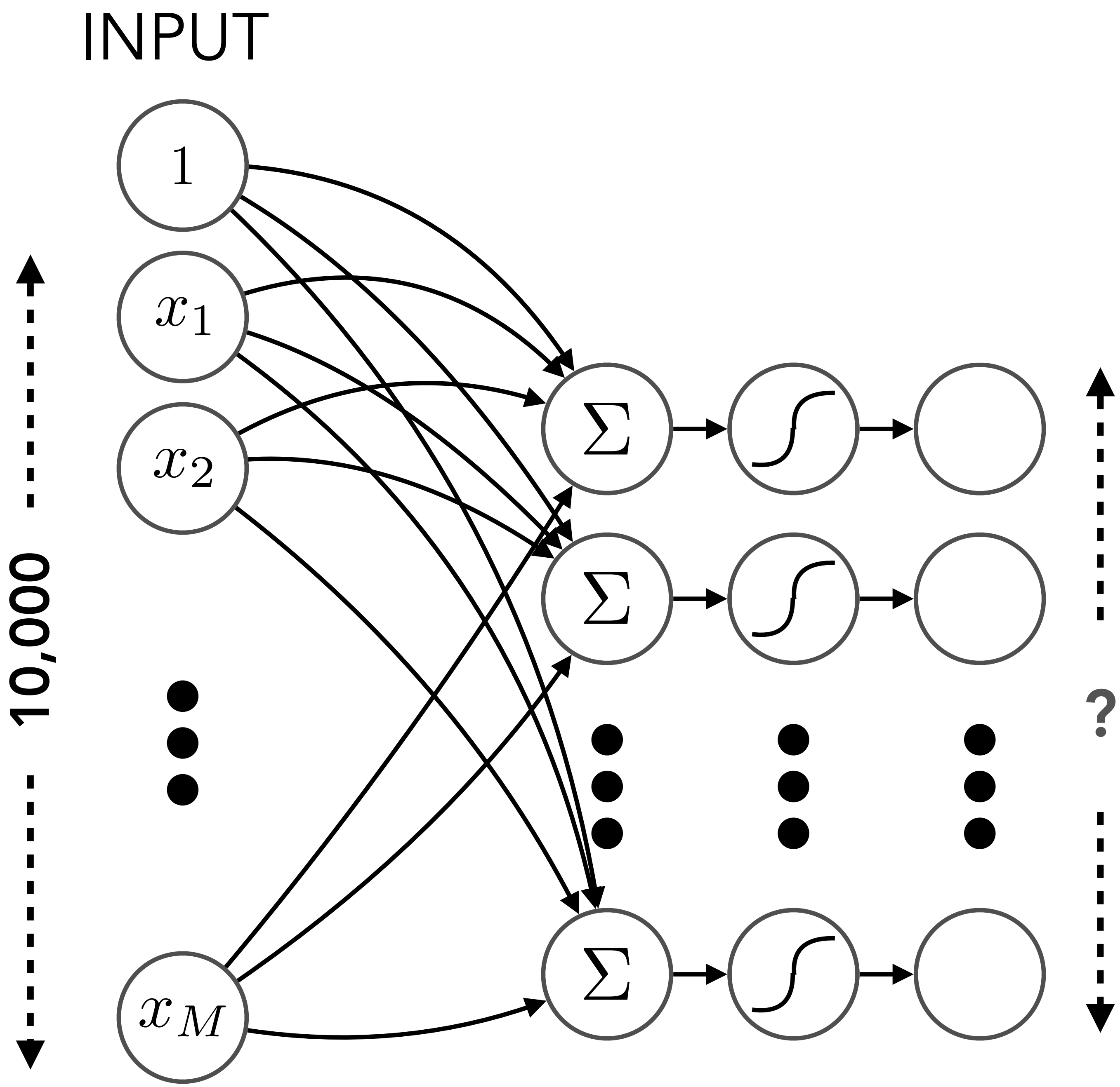
clearer patterns,
but more parameters

convert to grayscale…

fewer parameters,
but unclear patterns

clearer patterns,
but more parameters


100 x 100 x 1
10,000
reshape
1
10,000

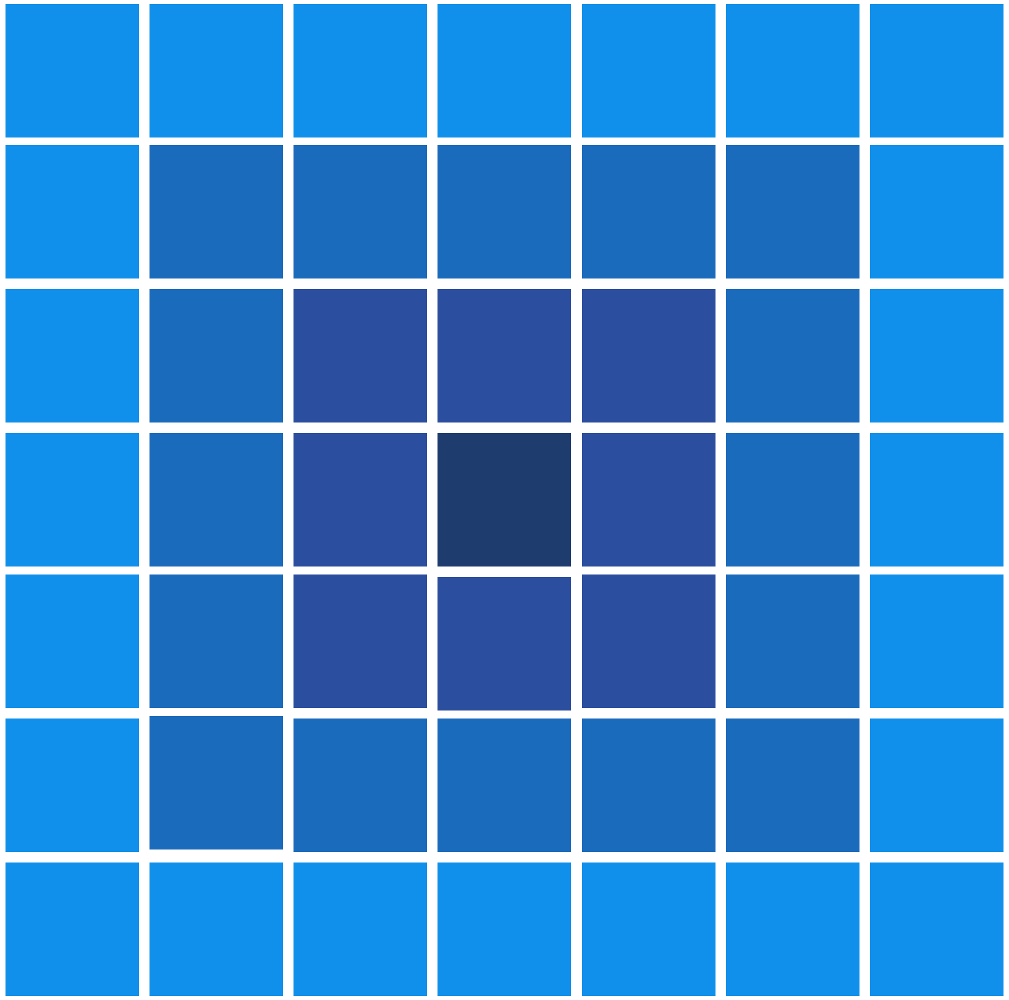


how many units do we need?

# units	x 10,000 =	# weights
1	→	10,000
10	→	100,000
100	→	1,000,000
1,000	→	10,000,000
10,000	→	100,000,000
100,000	→	1,000,000,000
1,000,000	→	10,000,000,000

if we want to recognize even a few basic patterns at each location, the number of parameters will explode!

to reduce the amount of learning,
we can introduce *inductive biases*



exploit the ***spatial structure*** of image data

<u>locality</u>

nearby areas tend to contain stronger patterns

nearby ***pixels*** tend to be similar and vary
in particular ways

nearby ***patches*** tend to share characteristics
and are combined in particular ways

nearby ***regions*** tend to be found
in particular arrangements

translation invariance

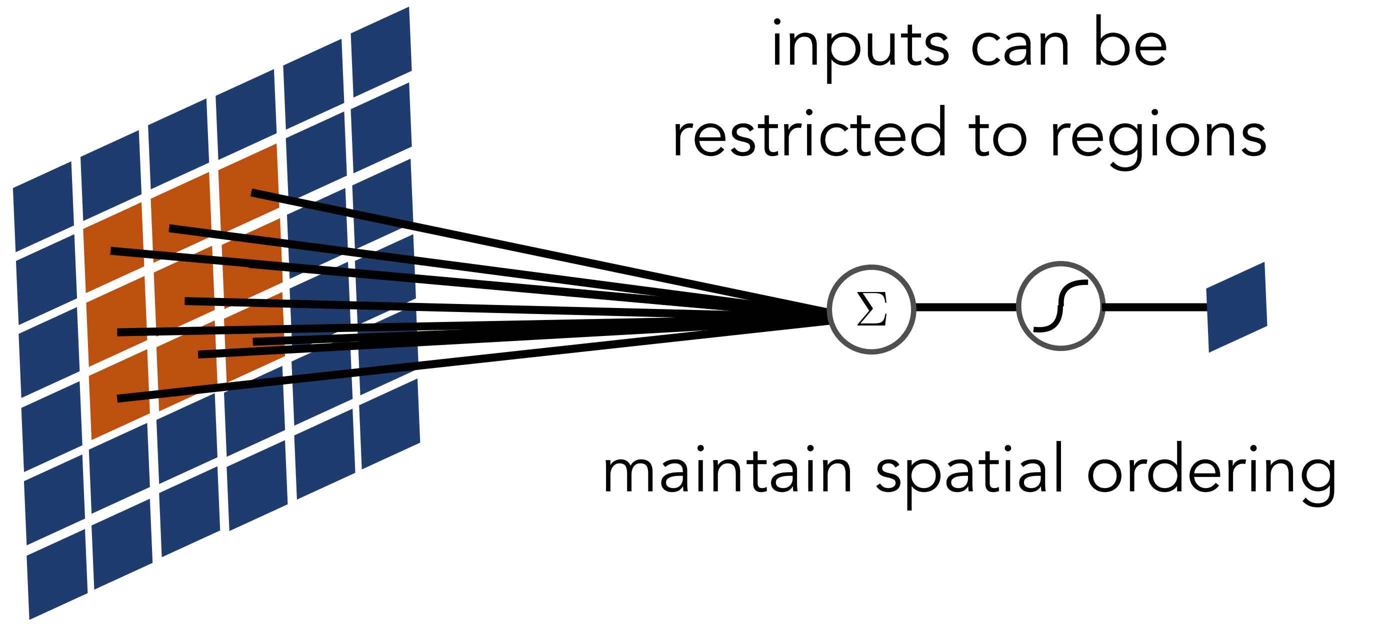
relative (rather than absolute) positions are relevant

Yisong's identity is independent of absolute location of his pixels

let's translate **locality** and **translation invariance** into *inductive biases*

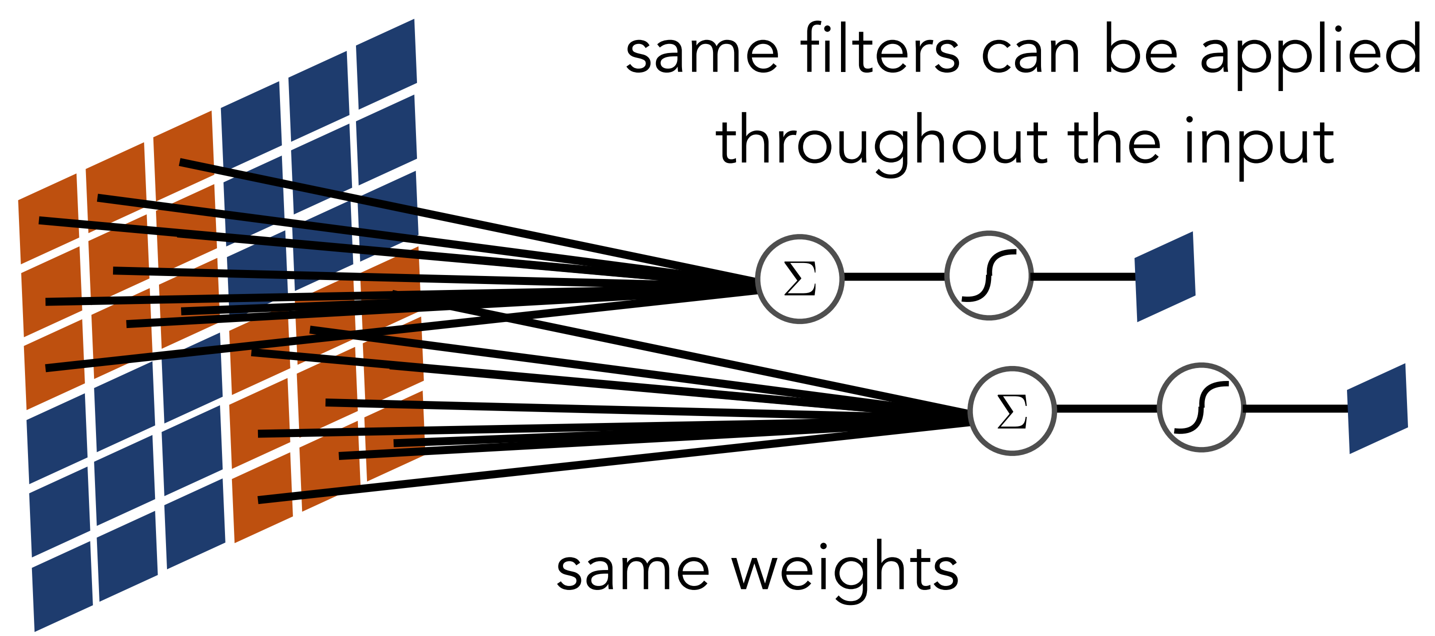
locality

nearby areas tend to contain stronger patterns



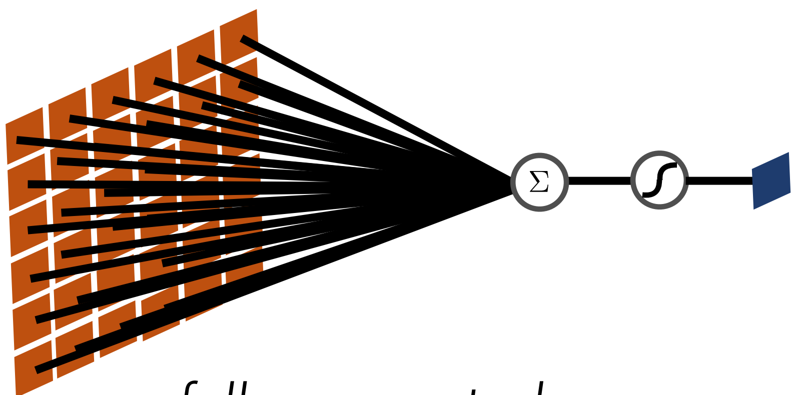
translation invariance

relative positions are relevant

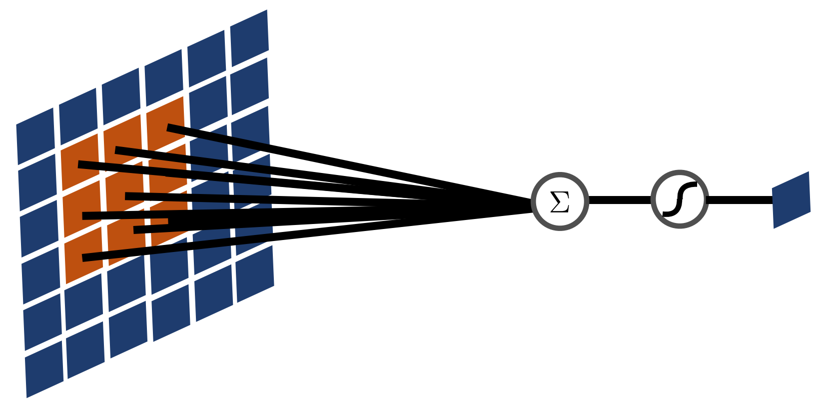


these are the inductive biases of ***convolutional neural networks***

→ special case of standard (fully-connected) neural networks

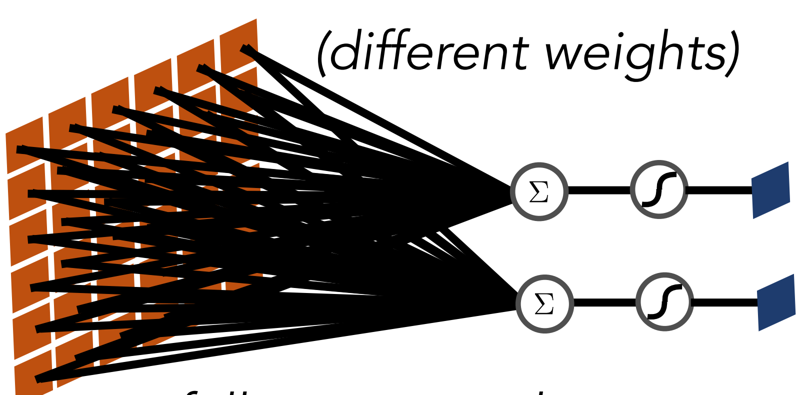


fully-connected

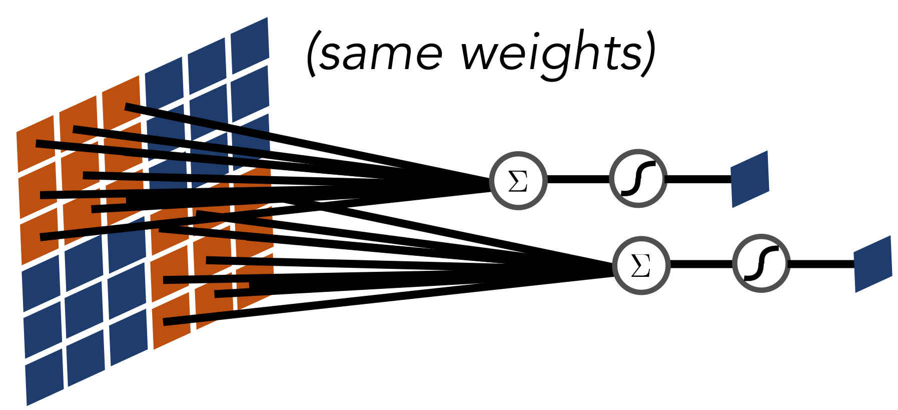


convolutional

weight savings



fully-connected



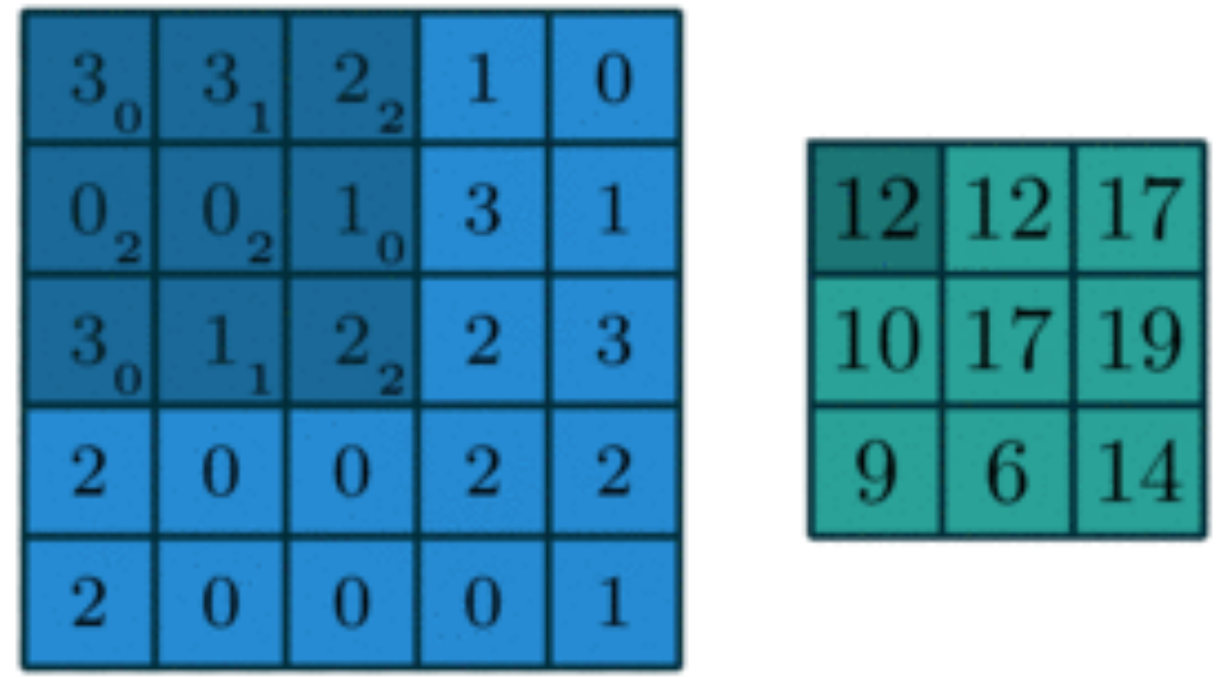
convolutional

weight savings

*these inductive biases make the **number of weights <u>independent</u> of the input size**!*

convolve a set of filters with the input

filter weights: $\begin{pmatrix} 0 & 1 & 2 \\ 2 & 2 & 0 \\ 0 & 1 & 2 \end{pmatrix}$



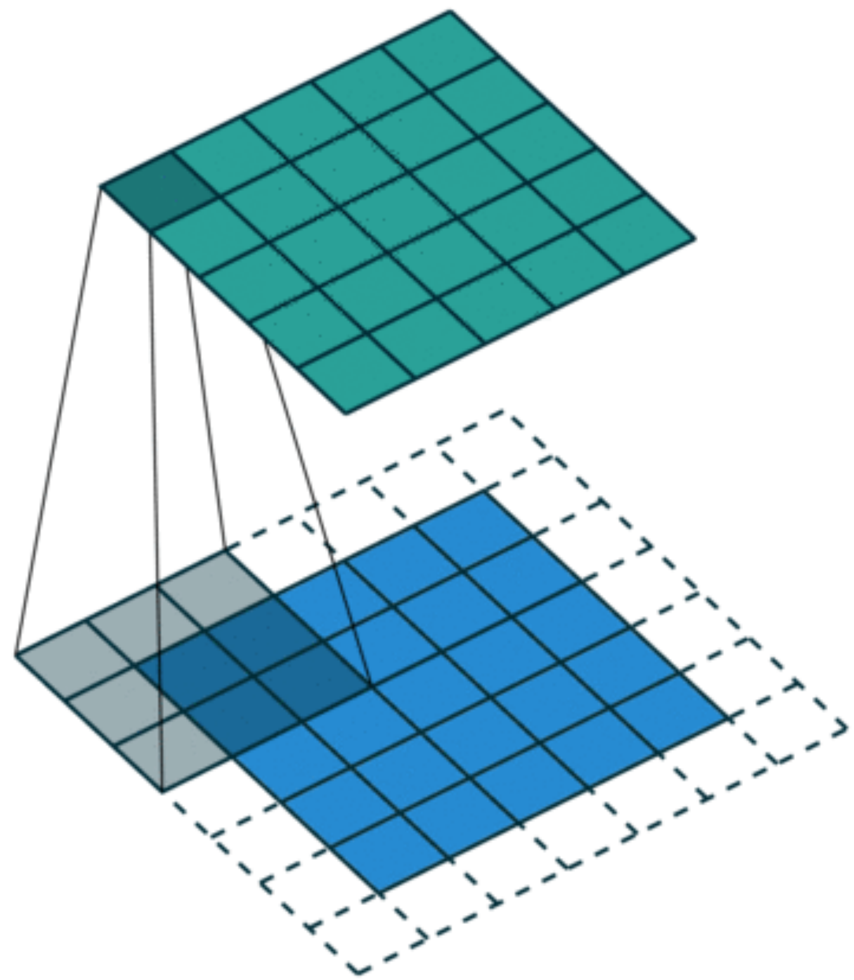
take *<u>inner (dot) product</u>* of filter and each input location

measures degree of filter feature at input location

→ *feature map*

http://deeplearning.net/software/theano_versions/dev/tutorial/conv_arithmetic.html

use ***padding*** to preserve spatial size

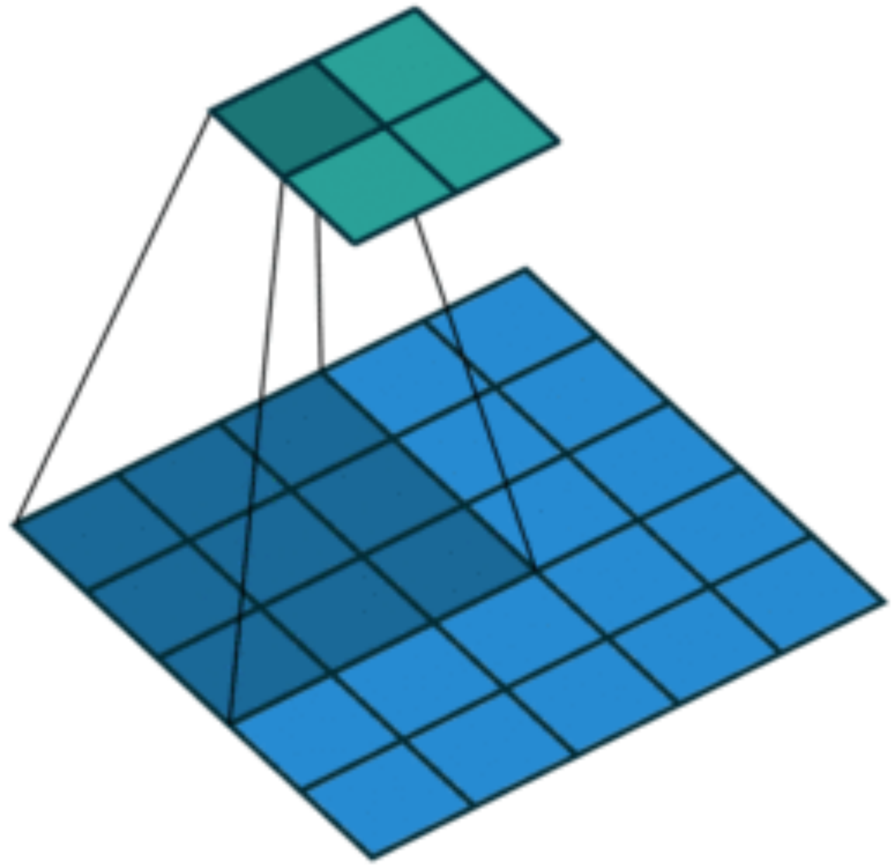


typically add *zeros* around the perimeter

http://deeplearning.net/software/theano_versions/dev/tutorial/conv_arithmetic.html

use ***stride*** to downsample the input

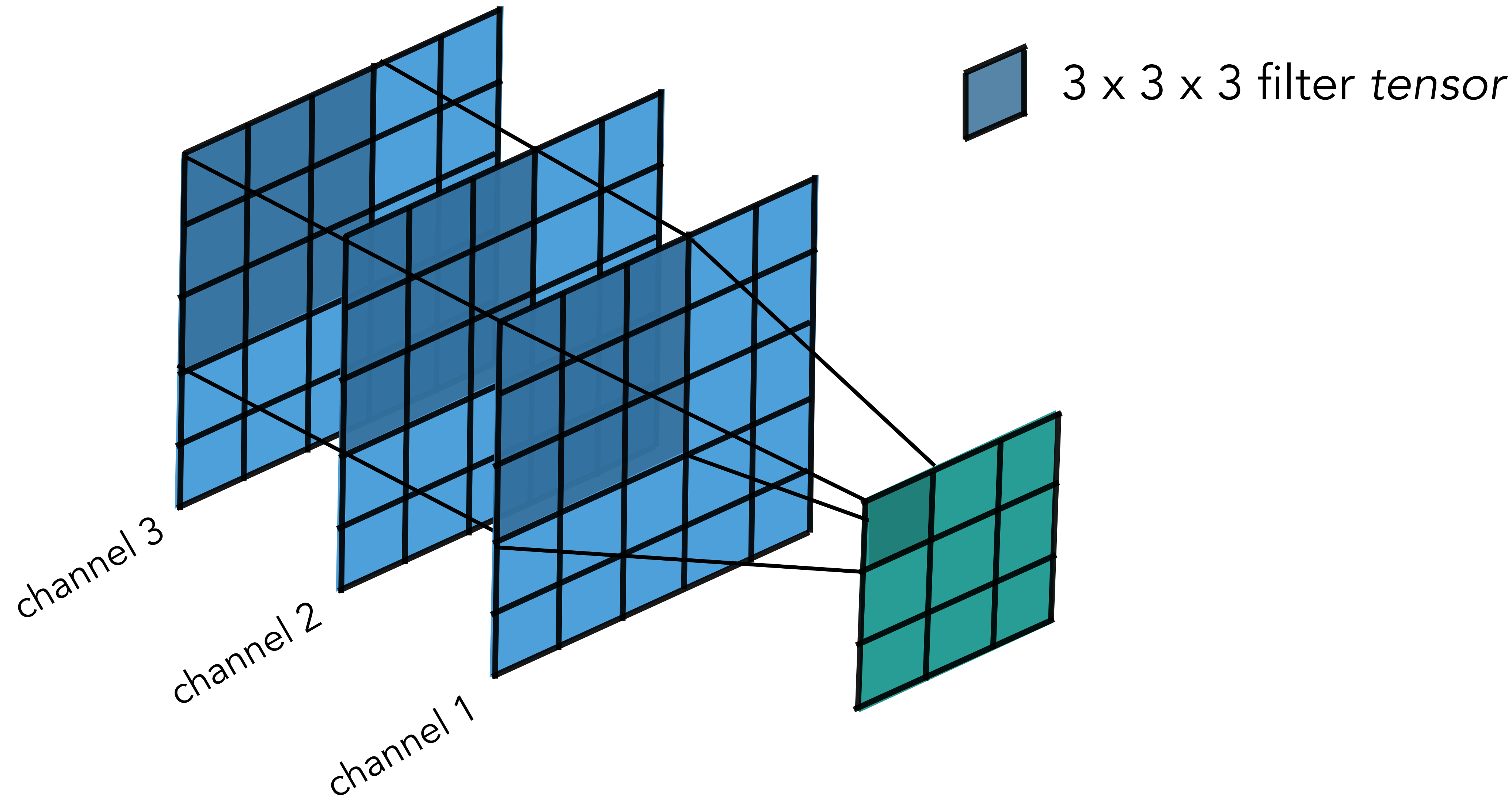
stride = 2



only compute output at some integer interval

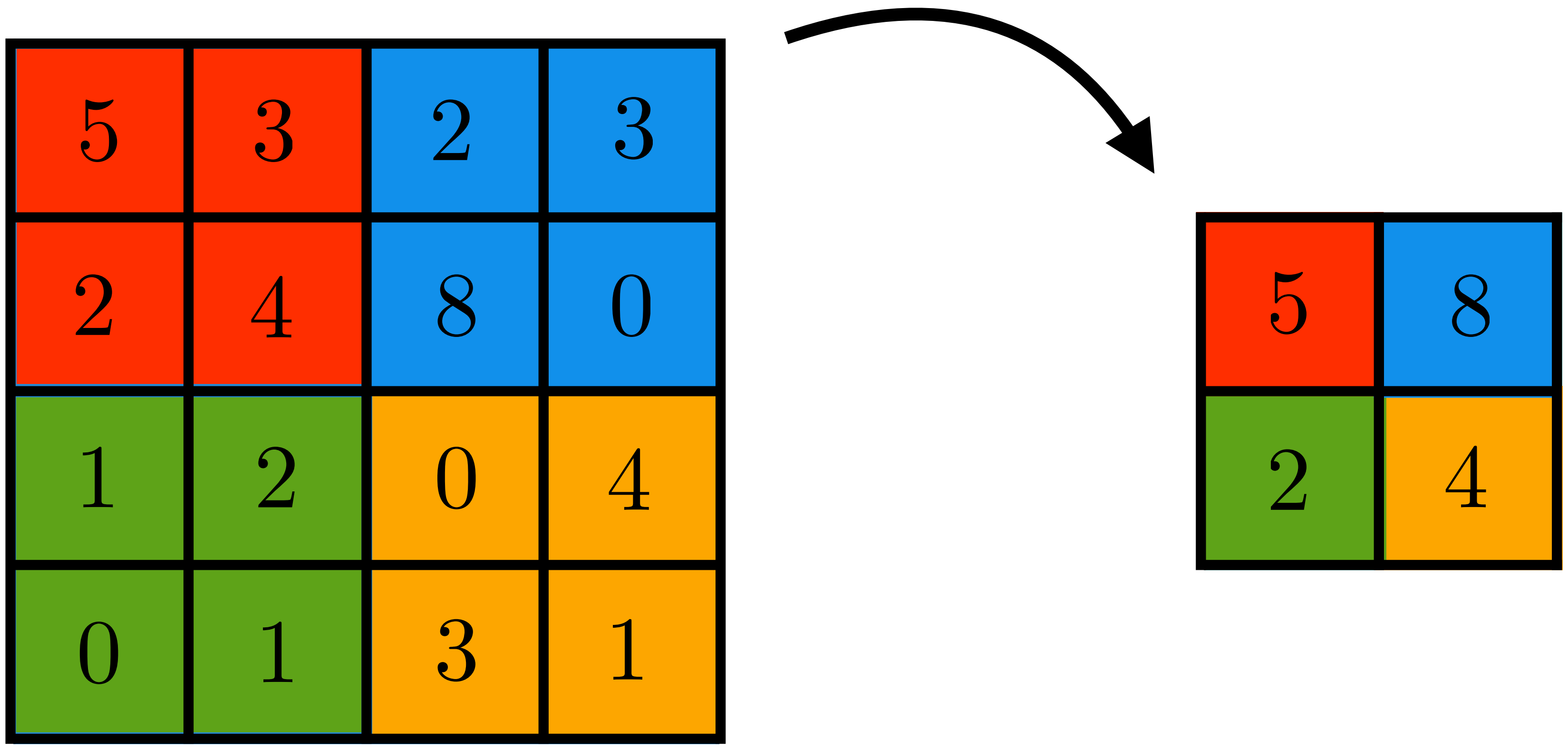
http://deeplearning.net/software/theano_versions/dev/tutorial/conv_arithmetic.html

filters are applied to all input channels



each filter results in a new output channel

pooling locally aggregates values in each feature map

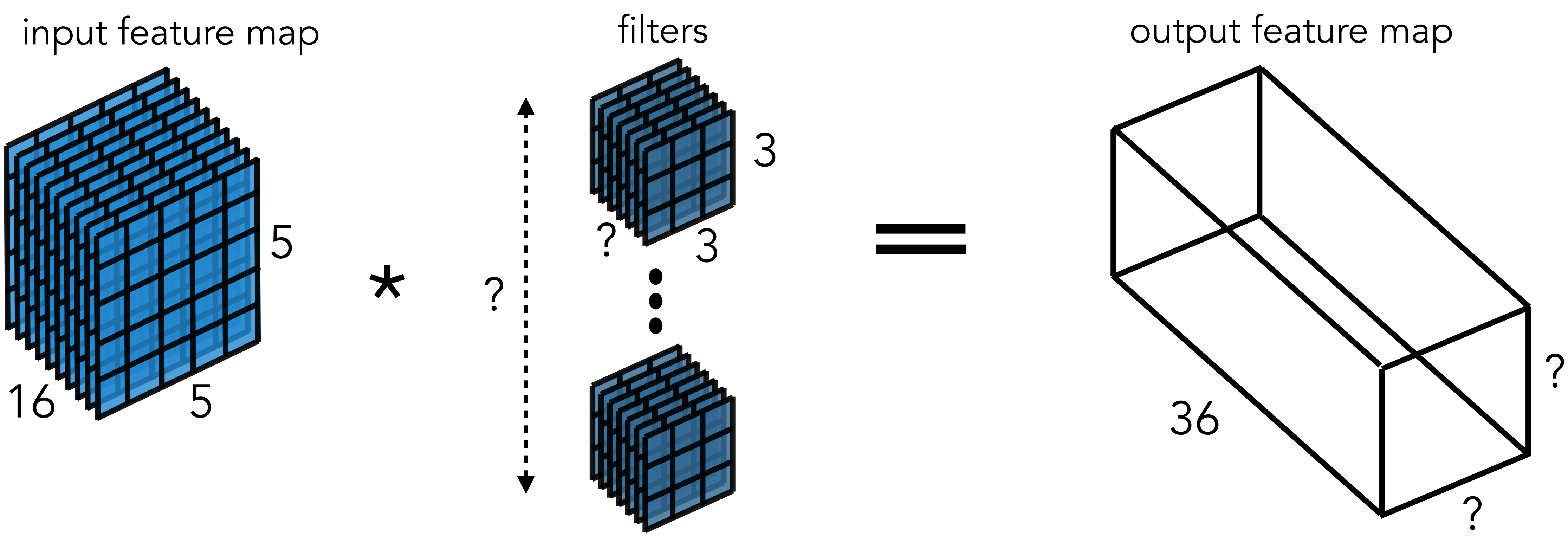


downsampling and invariance

can be applied with *padding* and *stride*

predefined operation: maximum, average, etc.

convolutional pop-quiz



if we use unit stride and no padding then…

how many filters are there? **36** *same as the number of output channels*

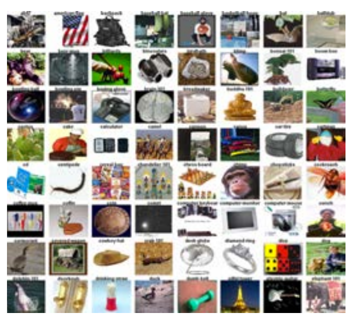
what size is each filter? **3 x 3 x 16** *channels match the number of input channels*

what is the output filter map size? **3 x 3 x 36** *result of only valid convolutions*

natural image datasets

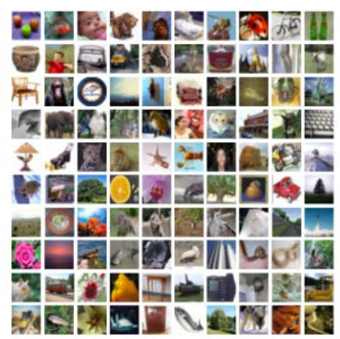
Caltech-101

101 classes,
9,146 images



Caltech-256

256 classes,
30,607 images



CIFAR-10

10 classes,
60,000 images

CIFAR-100

100 classes,
60,000 images

ImageNet

Competition

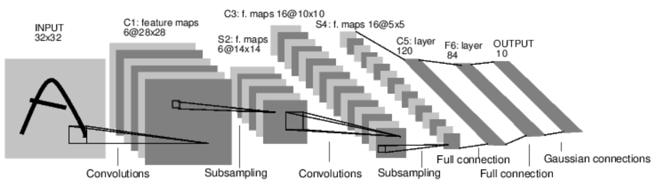
1,000 classes,
1.2 million images

Full

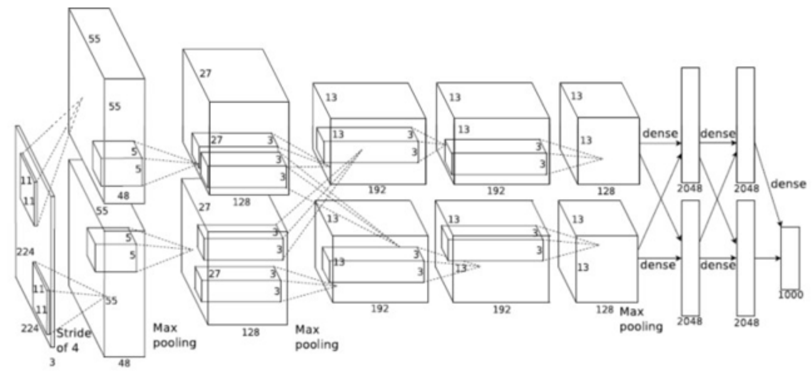
21,841 classes,
14 million images

•••

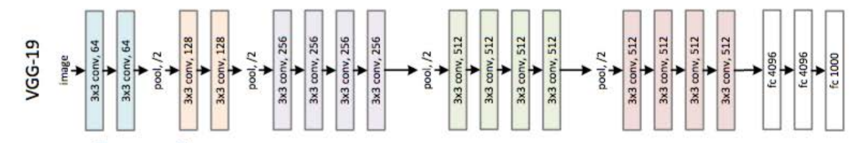
convolutional models for *classification*



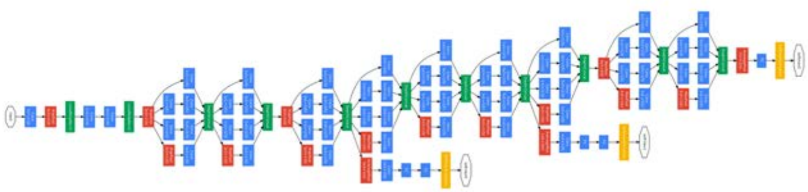
LeNet



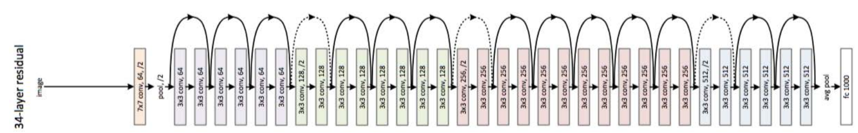
AlexNet



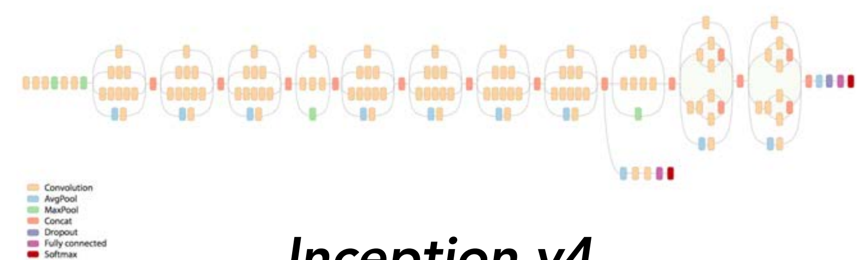
VGG



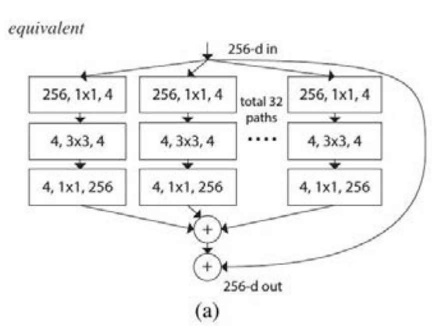
GoogLeNet



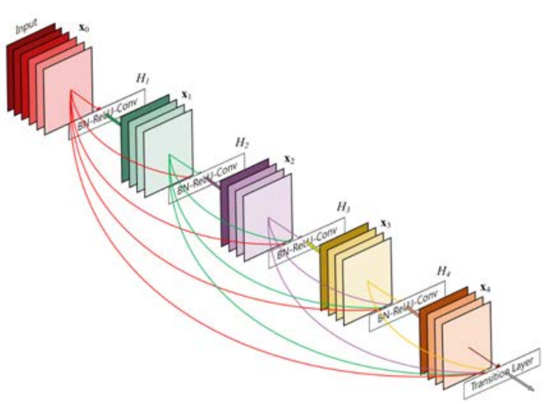
ResNet



Inception v4

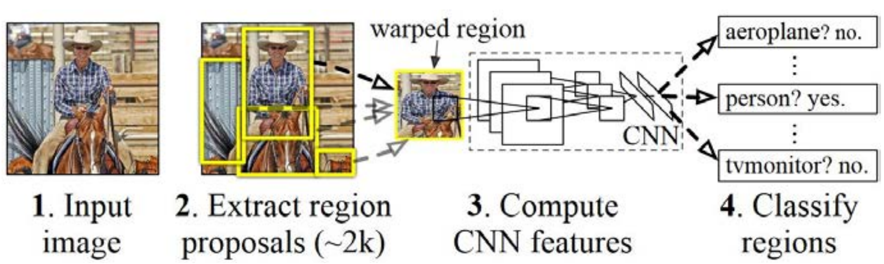


ResNeXt

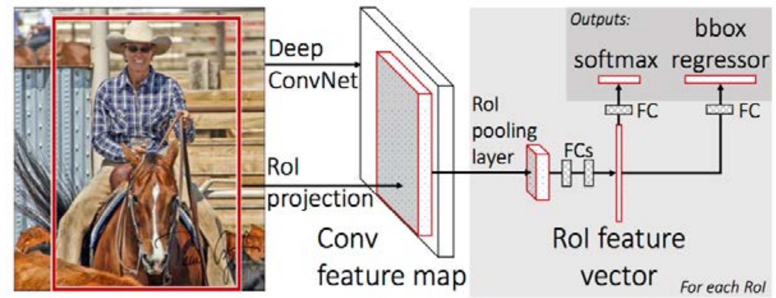


DenseNet

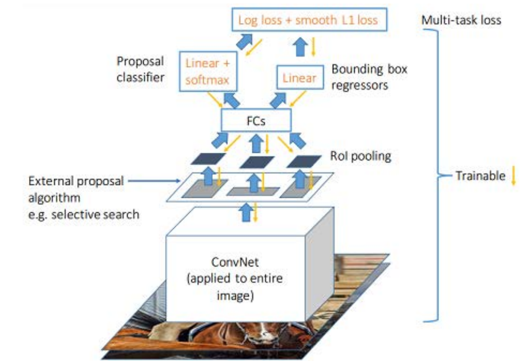
convolutional models for *detection, segmentation, etc.*



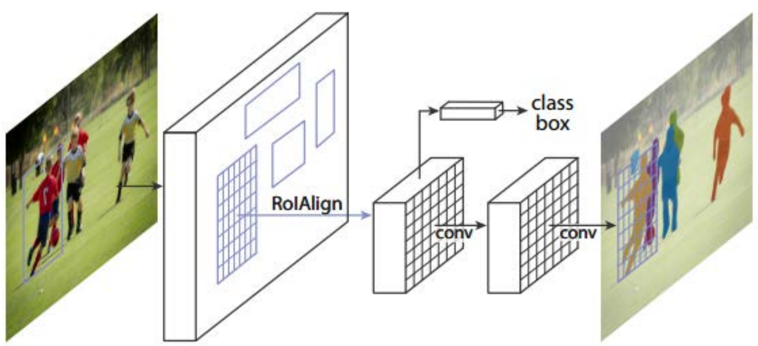
R-CNN



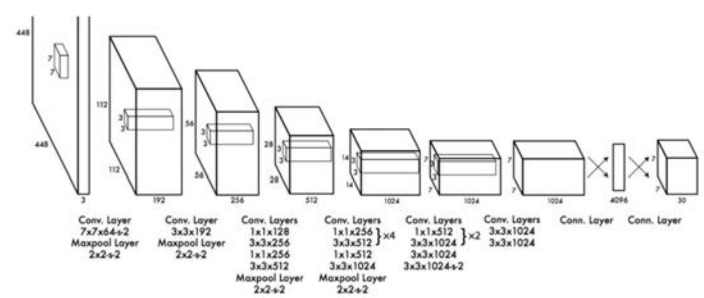
Fast R-CNN



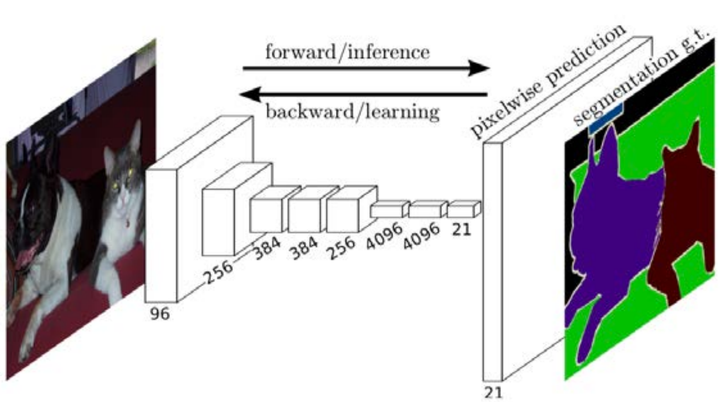
Faster R-CNN



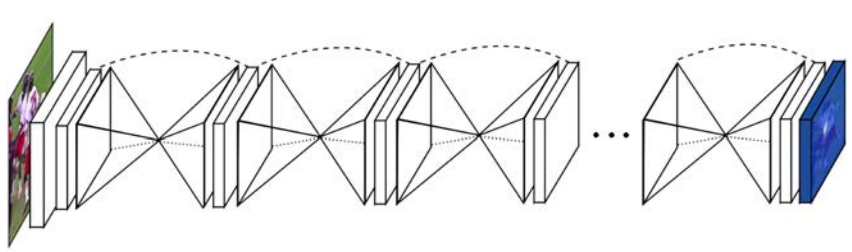
Mask R-CNN



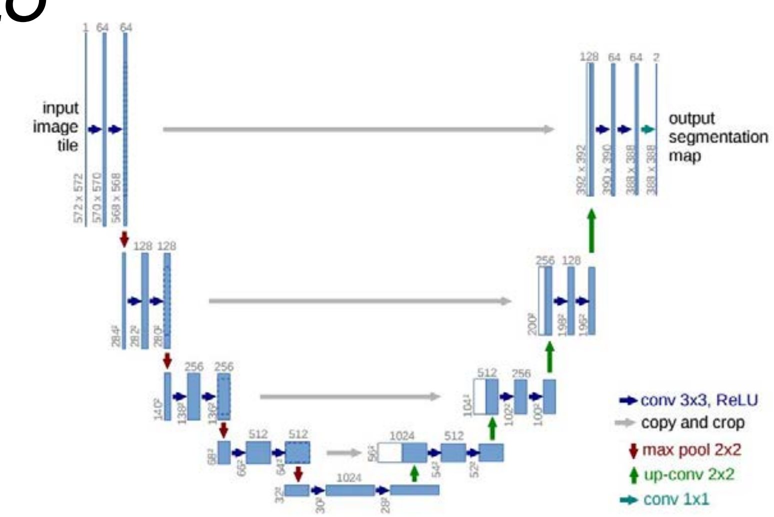
YOLO



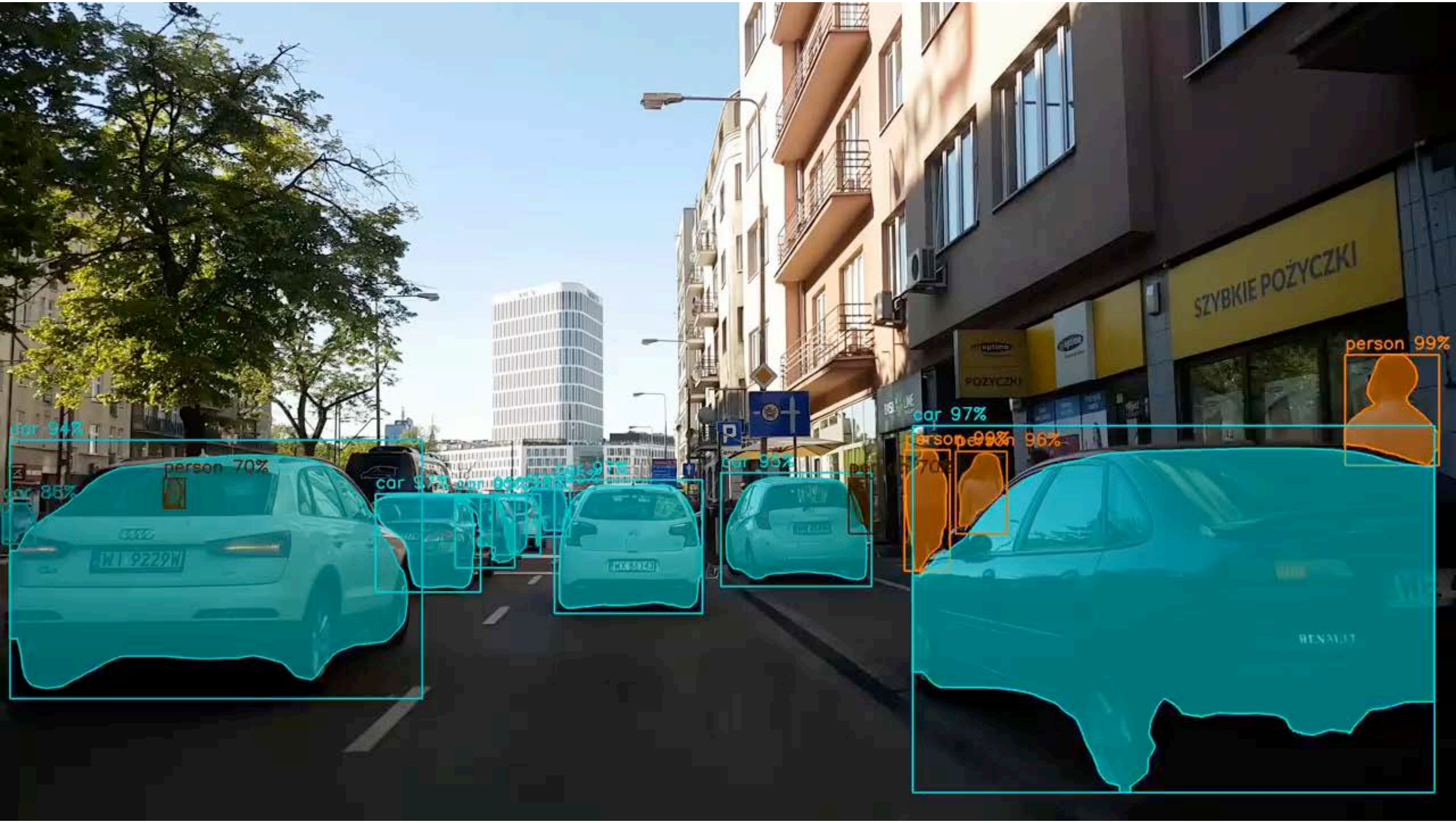
FCN



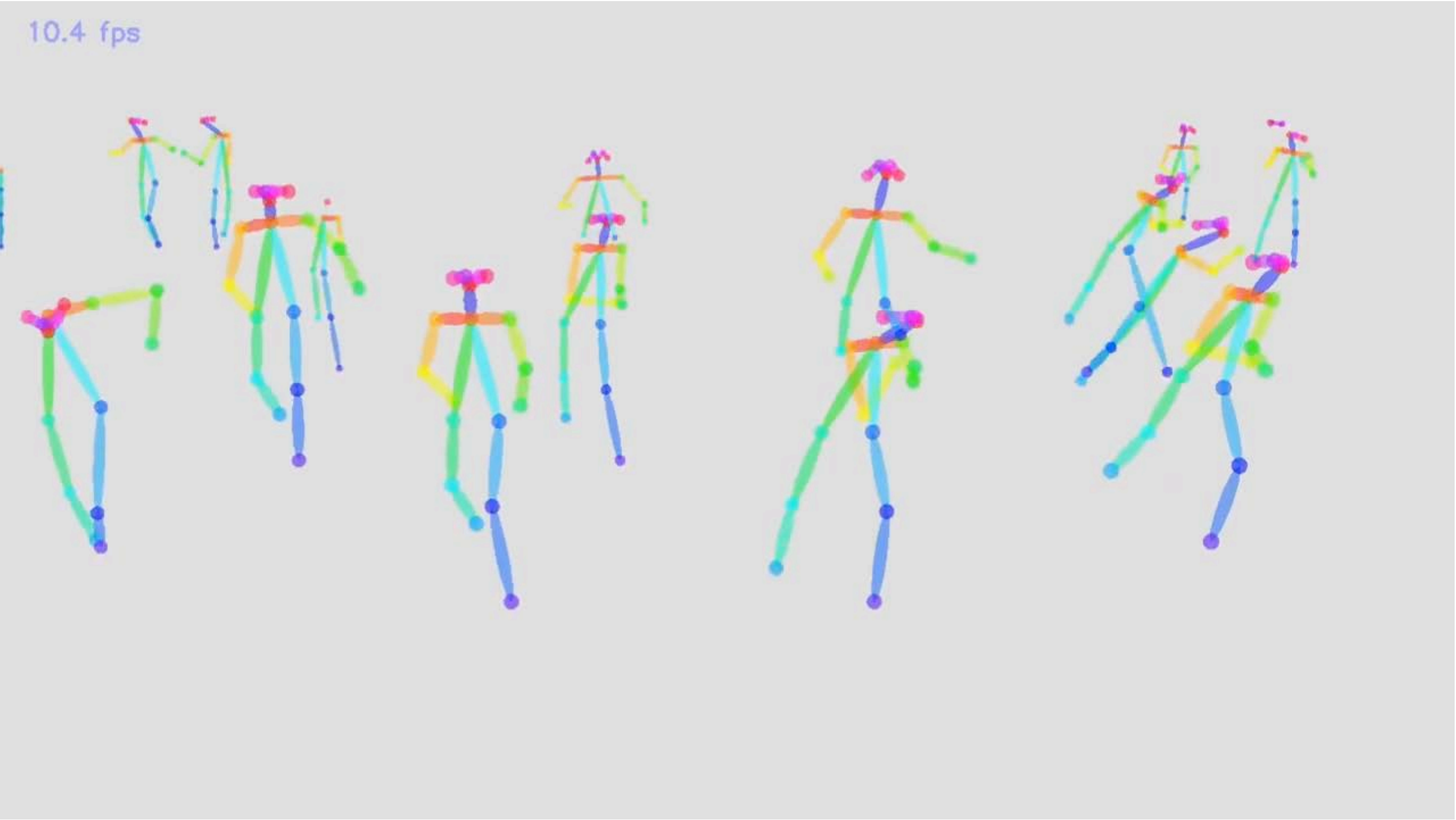
Hourglass



U-Net

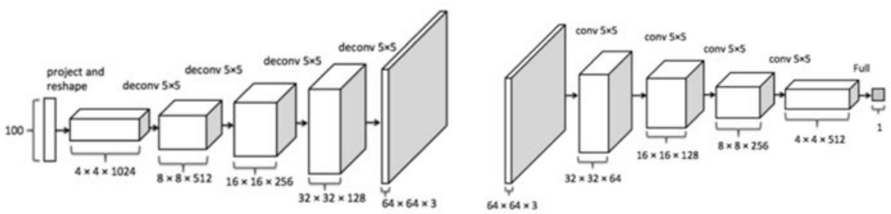


https://www.youtube.com/watch?v=OOT3UIXZztE

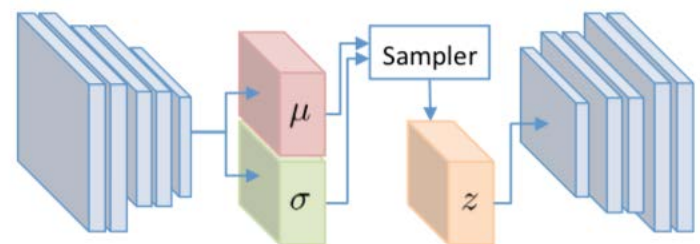


 https://www.youtube.com/watch?v=pW6nZXeWlGM

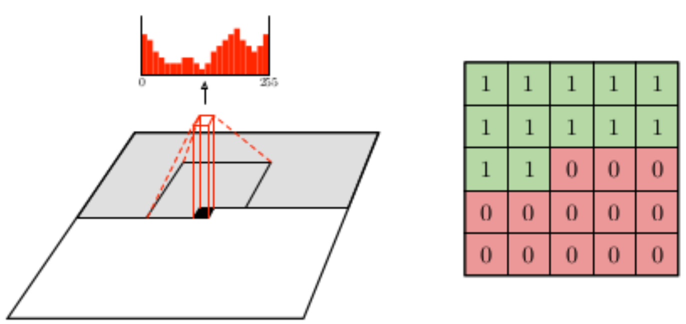
convolutional models for *image generation*



DC-GAN



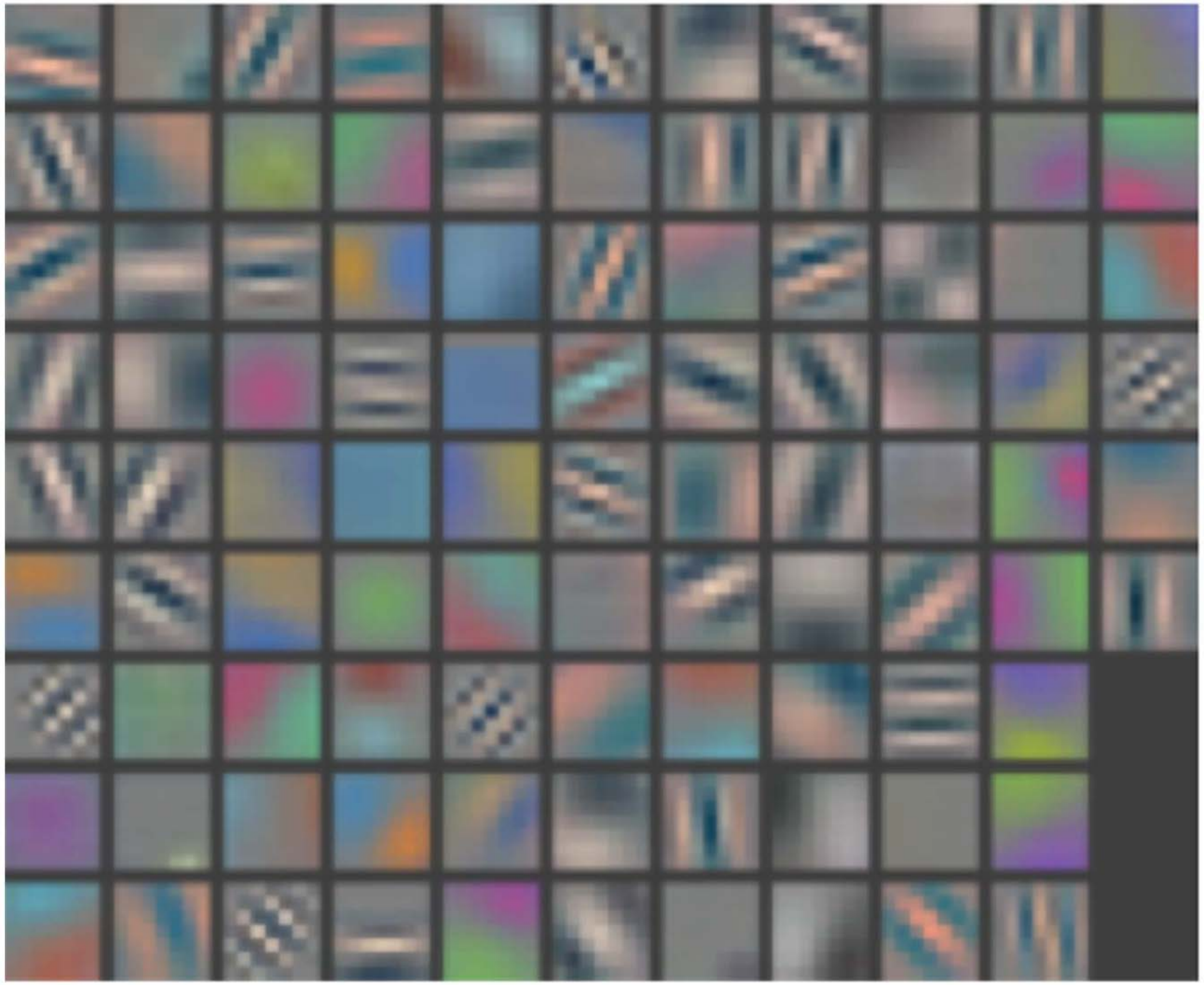
convolutional VAE



Pixel CNN

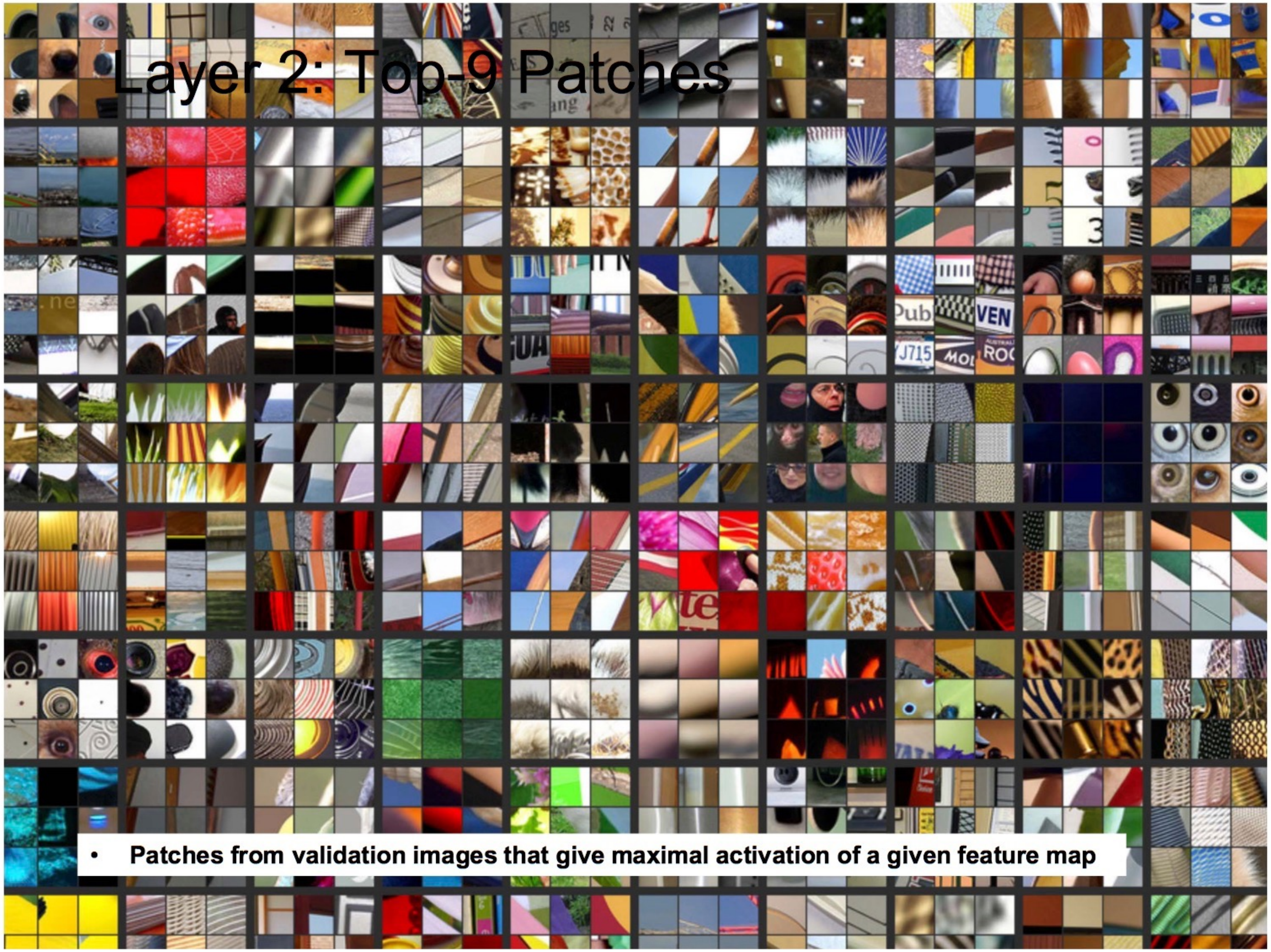
https://www.youtube.com/watch?v=XOxxPcy5Gr4

filter visualization



Zeiler, 2013

filter visualization



Zeiler, 2013

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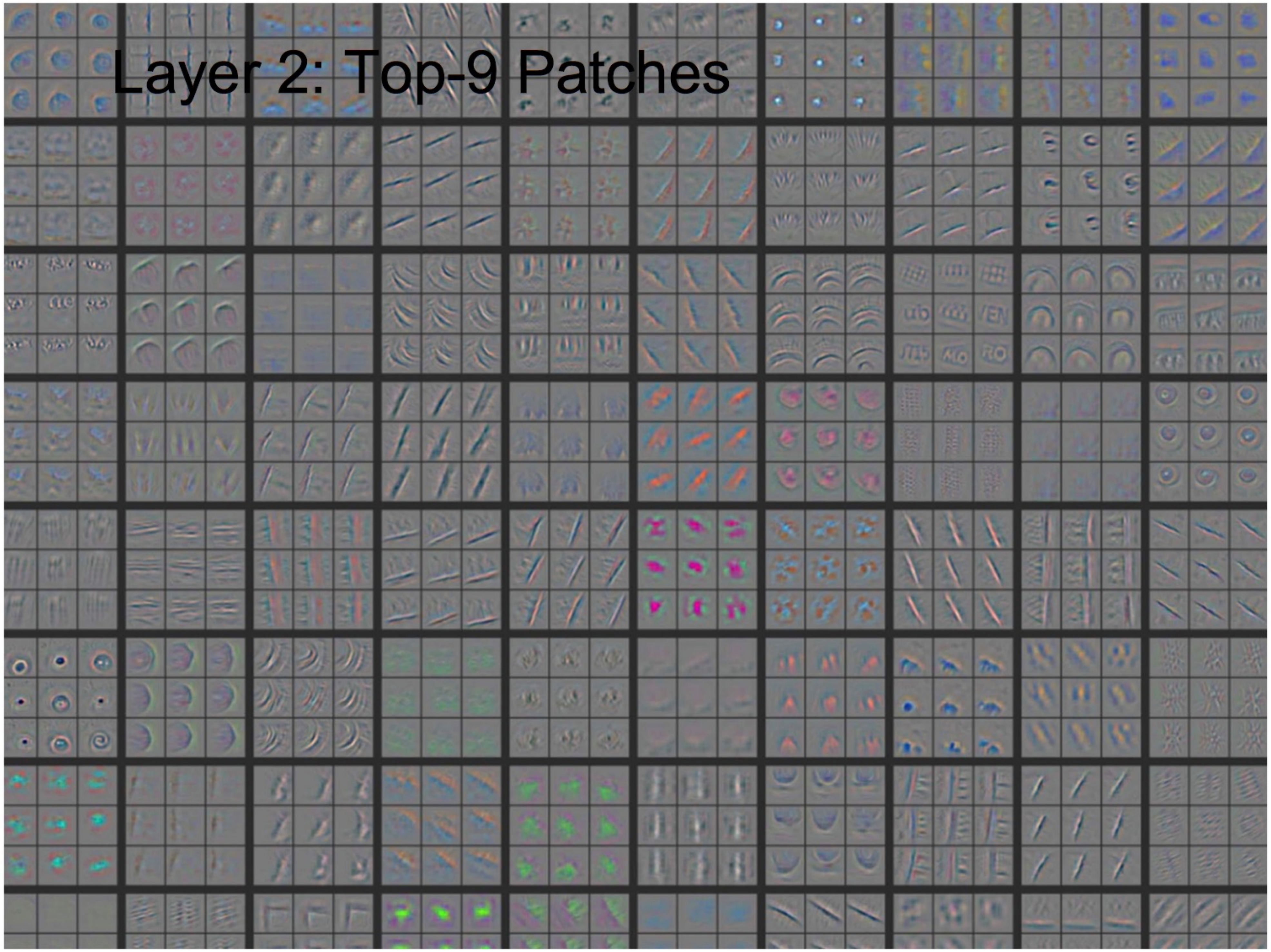

Zeiler, 2013

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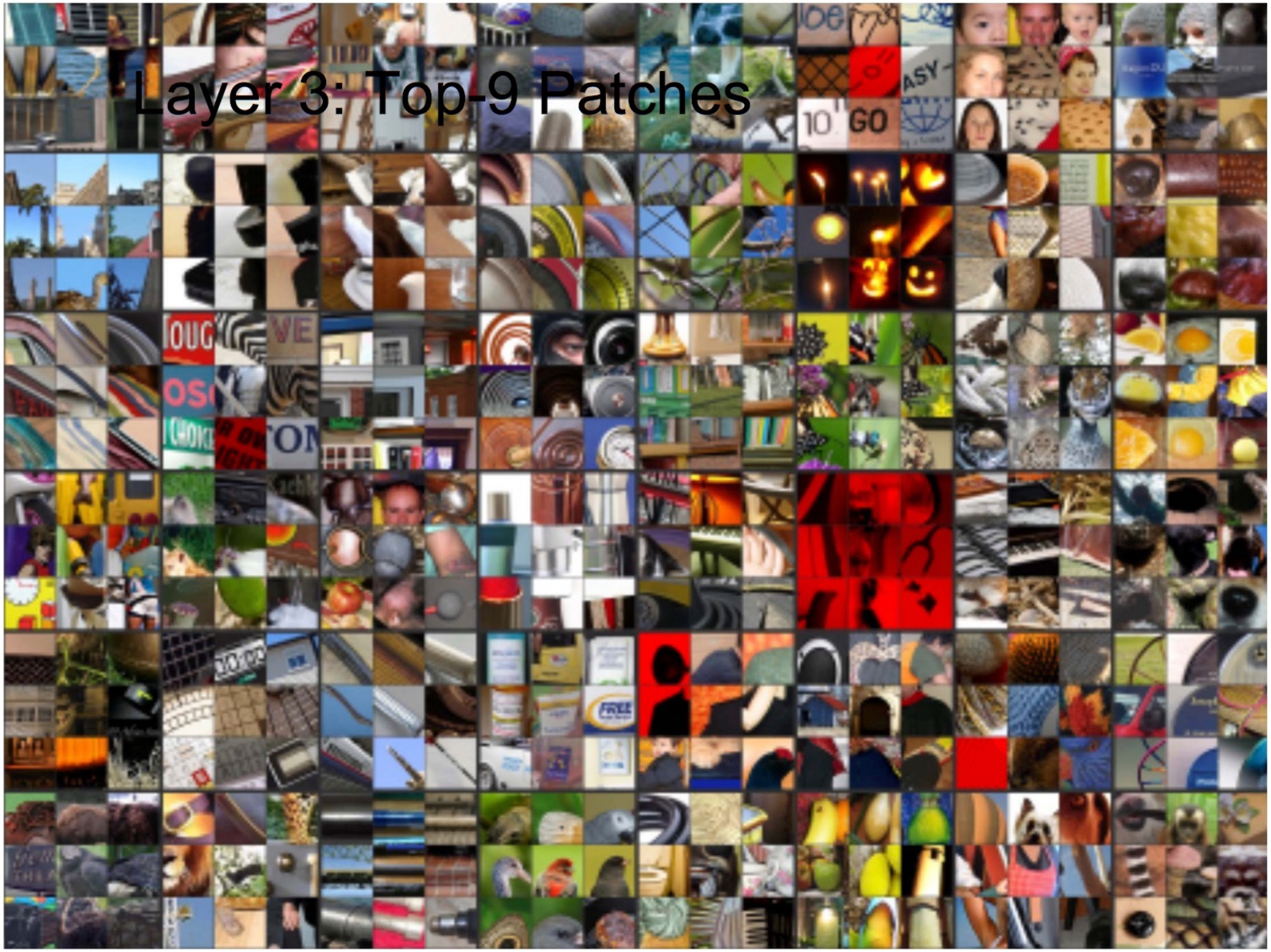

Zeiler, 2013

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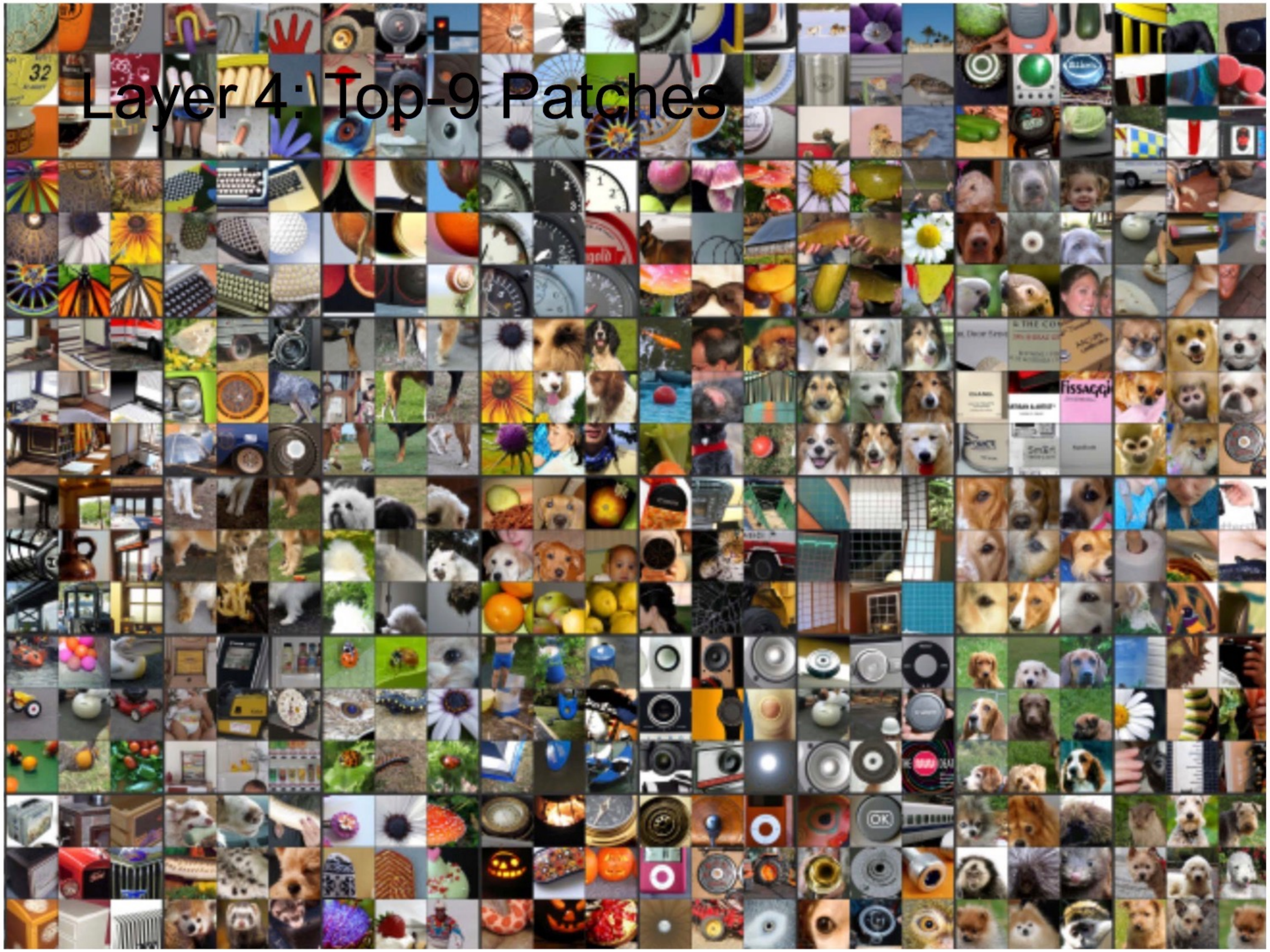

Zeiler, 2013

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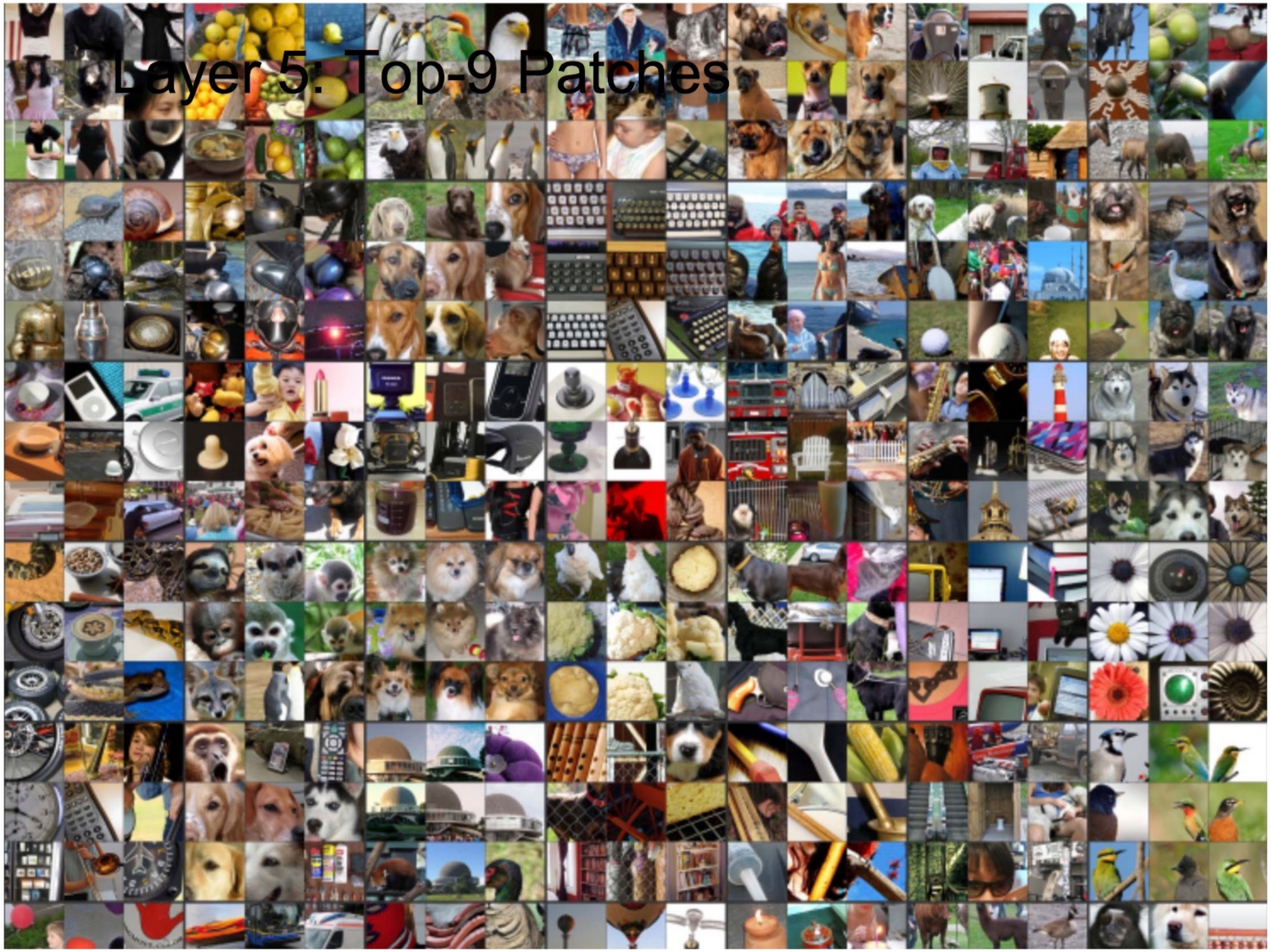

Zeiler, 2013

filter visualization

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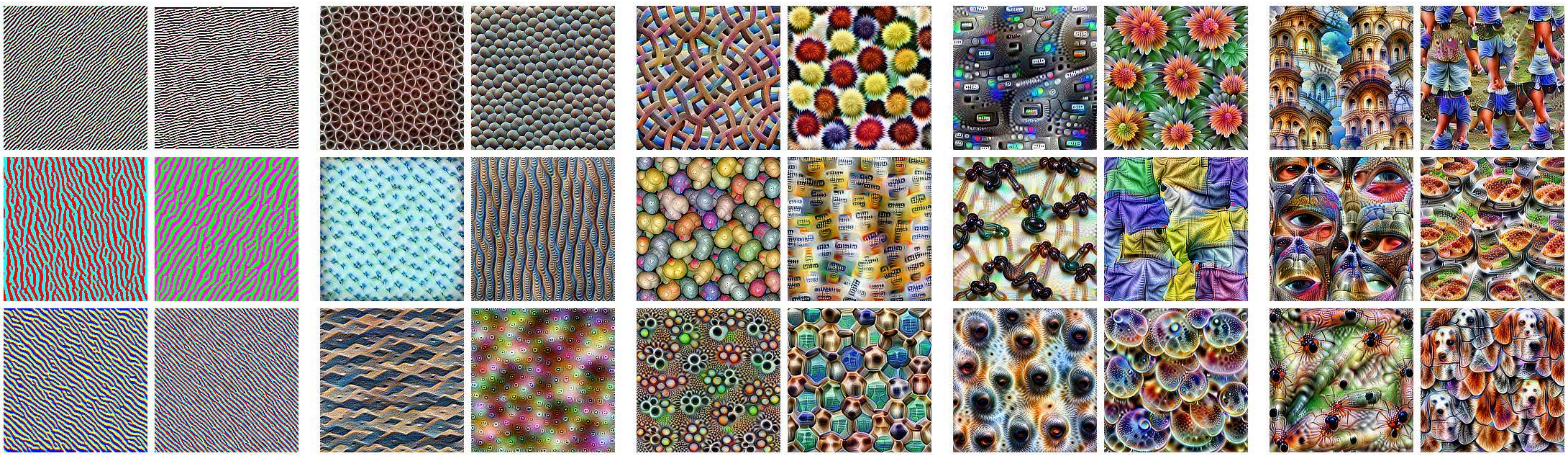
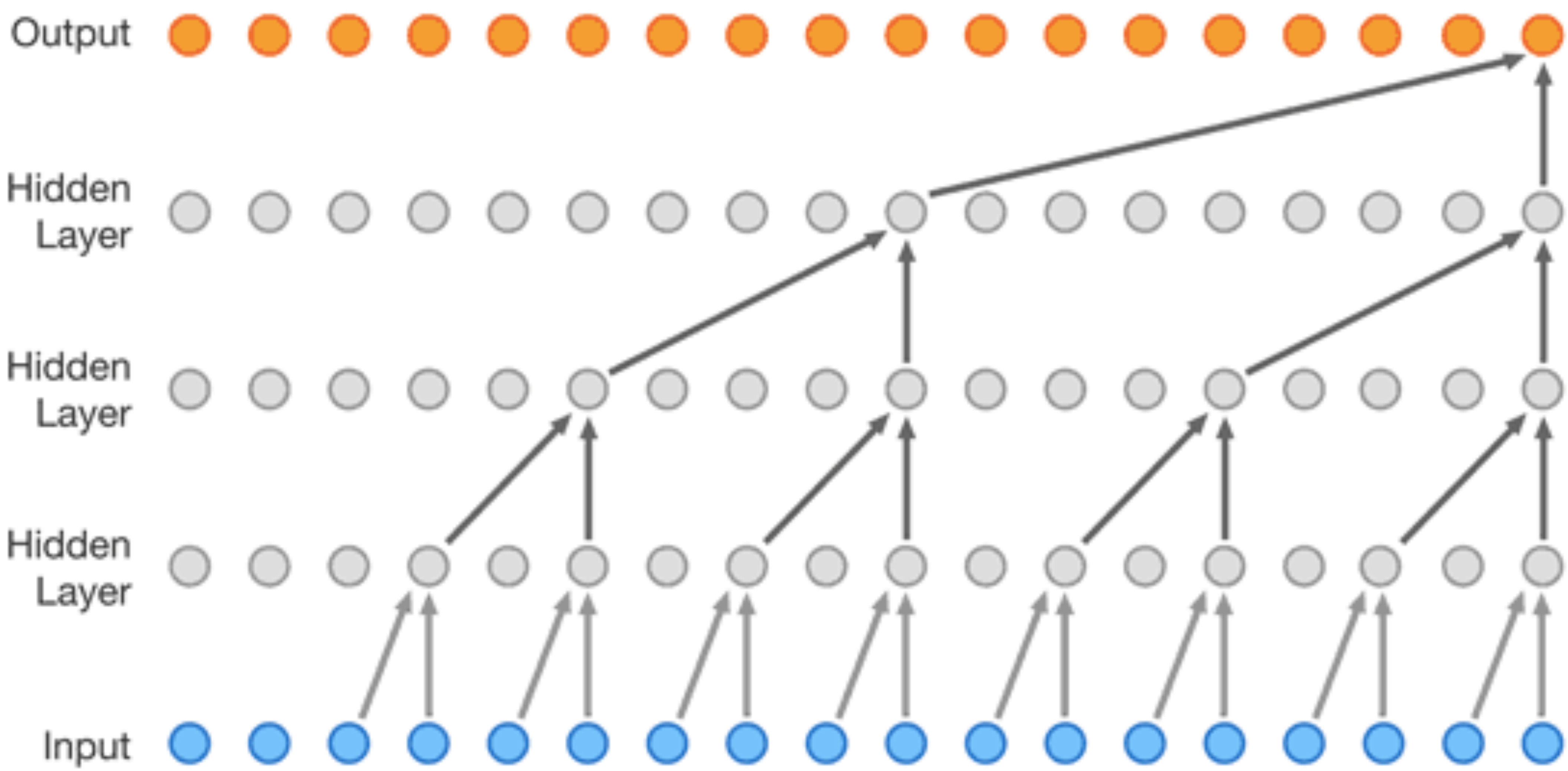


Edges (layer conv2d0) **Textures** (layer mixed3a) **Patterns** (layer mixed4a) **Parts** (layers mixed4b & mixed4c) **Objects** (layers mixed4d & mixed4e)

https://distill.pub/2017/feature-visualization/

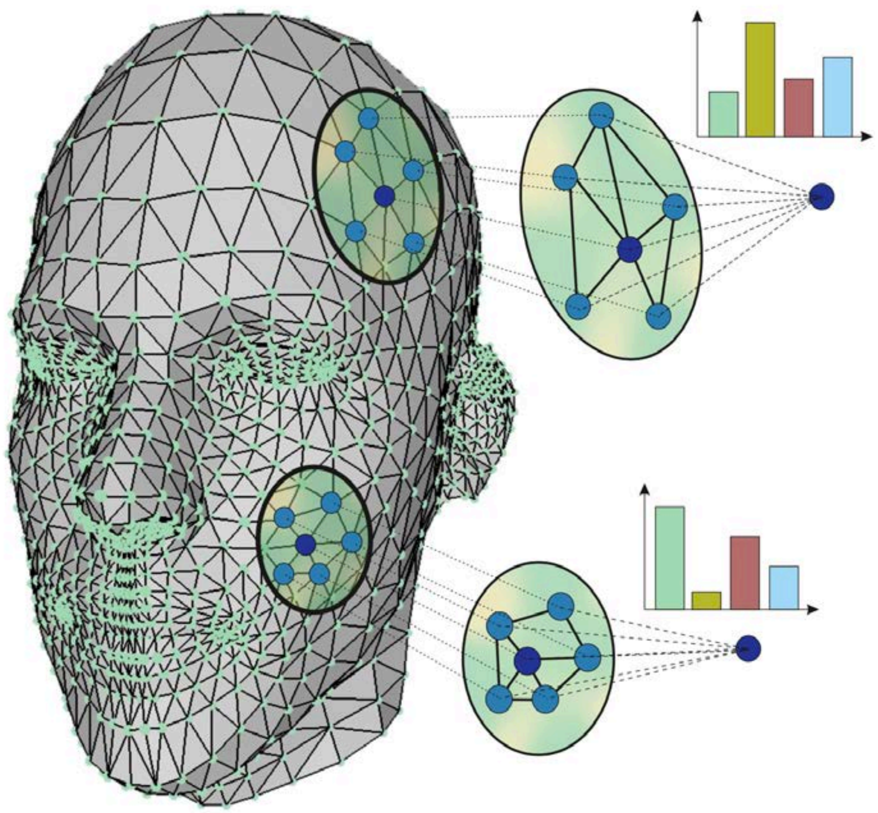
convolutions applied to sequences



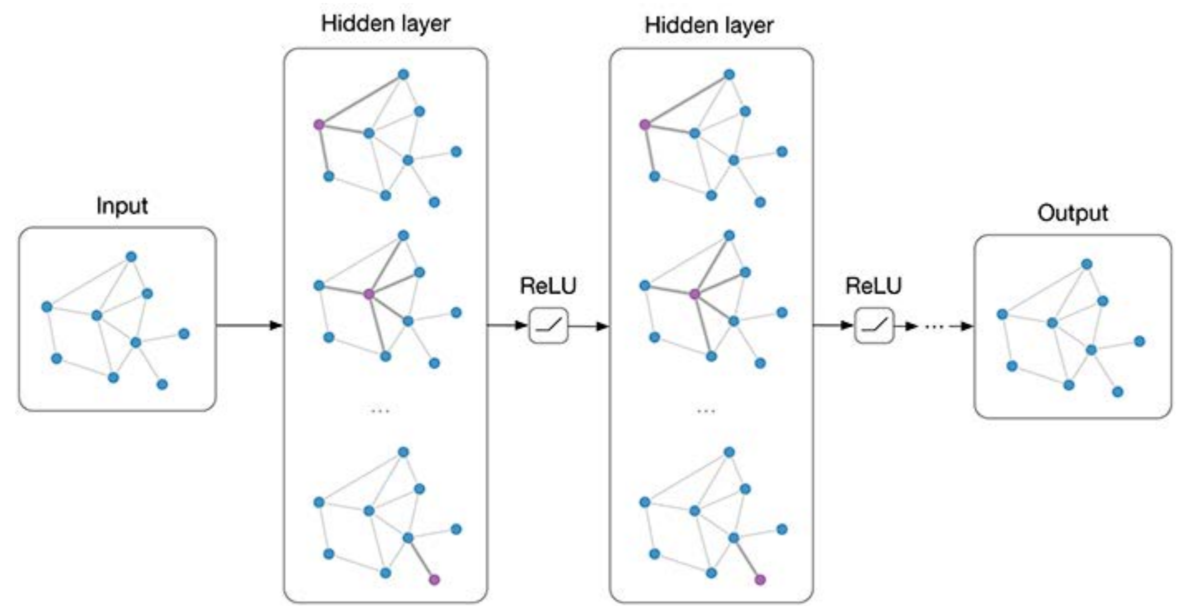
WaveNet

https://deepmind.com/blog/wavenet-launches-google-assistant/

convolutions in non-euclidean spaces



Spline CNN



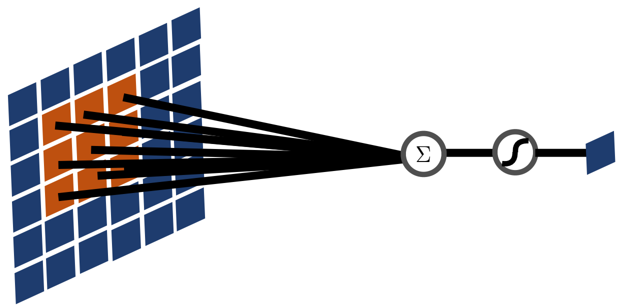
Graph Convolutional Network

Fey et al., 2017

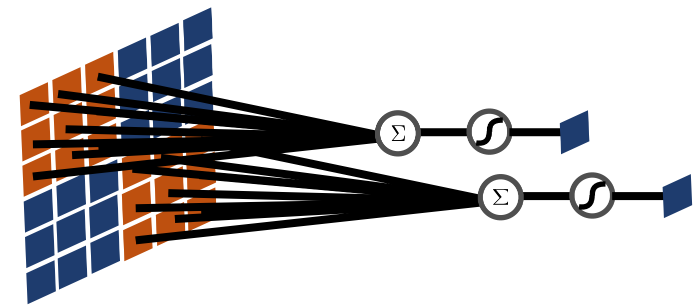
Kipf & Welling, 2016

recapitulation

we can exploit spatial structure to impose inductive biases on the model



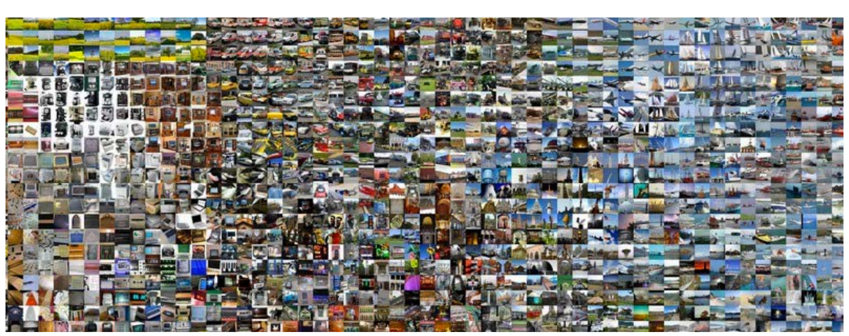
locality



translation invariance

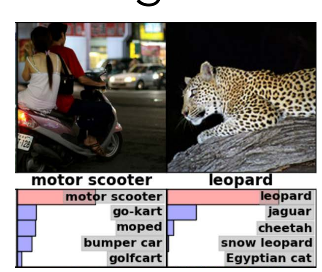
this limits the number of parameters required,
reducing flexibility in reasonable ways

can then scale these models to complex data sets to perform difficult tasks

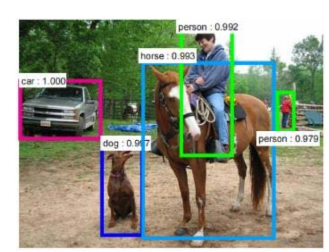


ImageNet

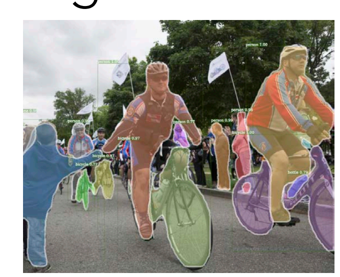
recognition



detection



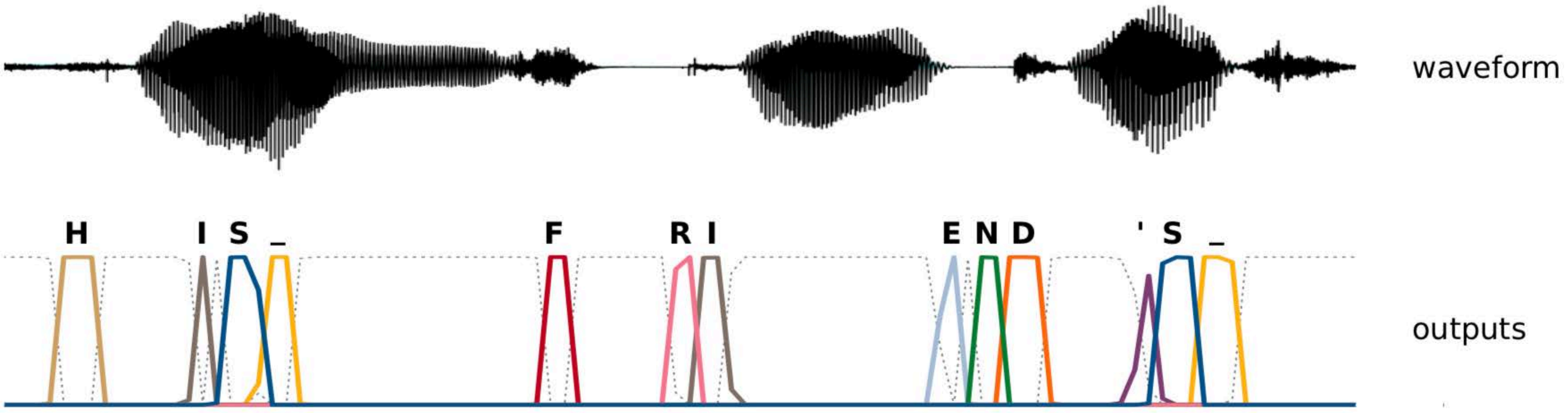
segmentation



generation

RECURRENT NEURAL NETWORKS

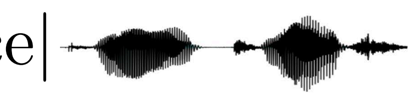
task: *speech recognition*



Graves & Jaitly, 2014

mapping from input waveform to sequence of characters

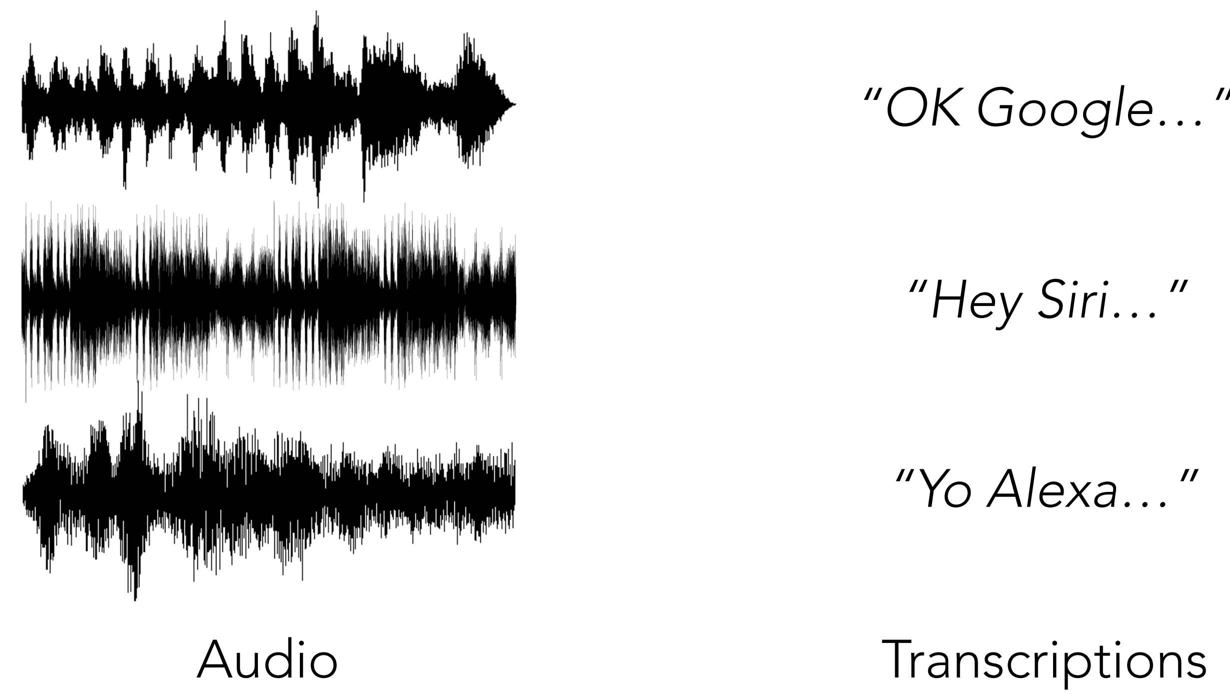
the input waveform contains all of the information
about the corresponding transcribed text

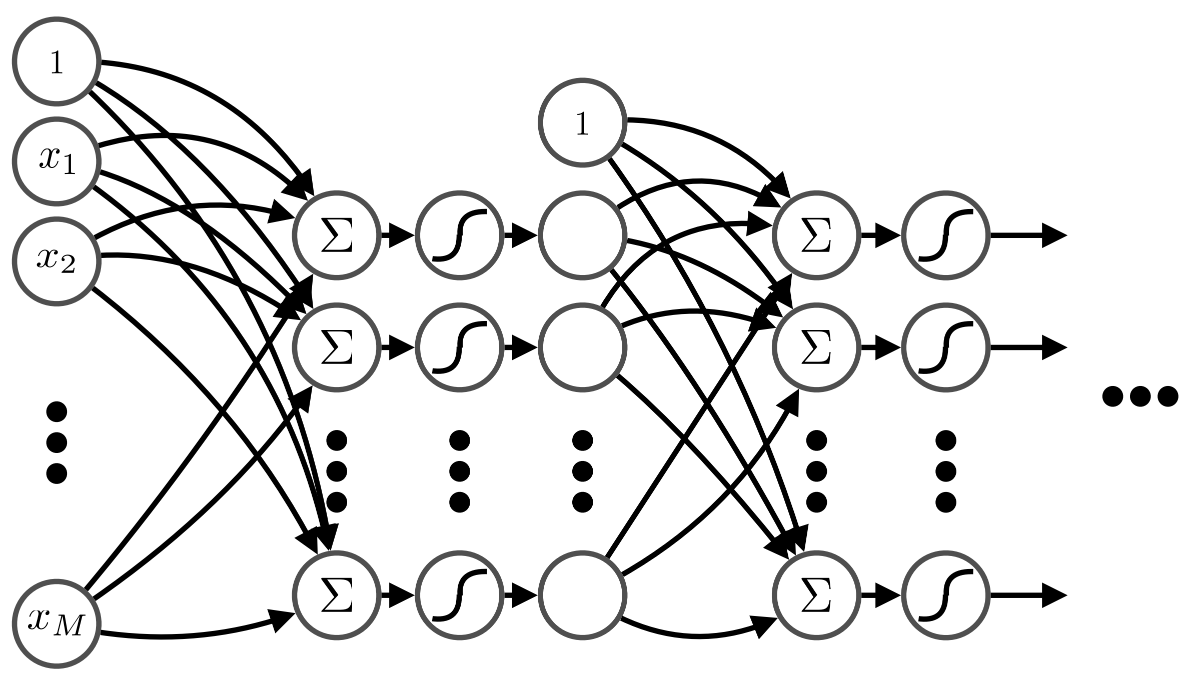
form a discriminative mapping: $p(\text{text sequence}|$  $)$

again, there is *nuisance information* in the waveform coming from the speaker's voice characteristics, volume, background, etc.

data, label collection

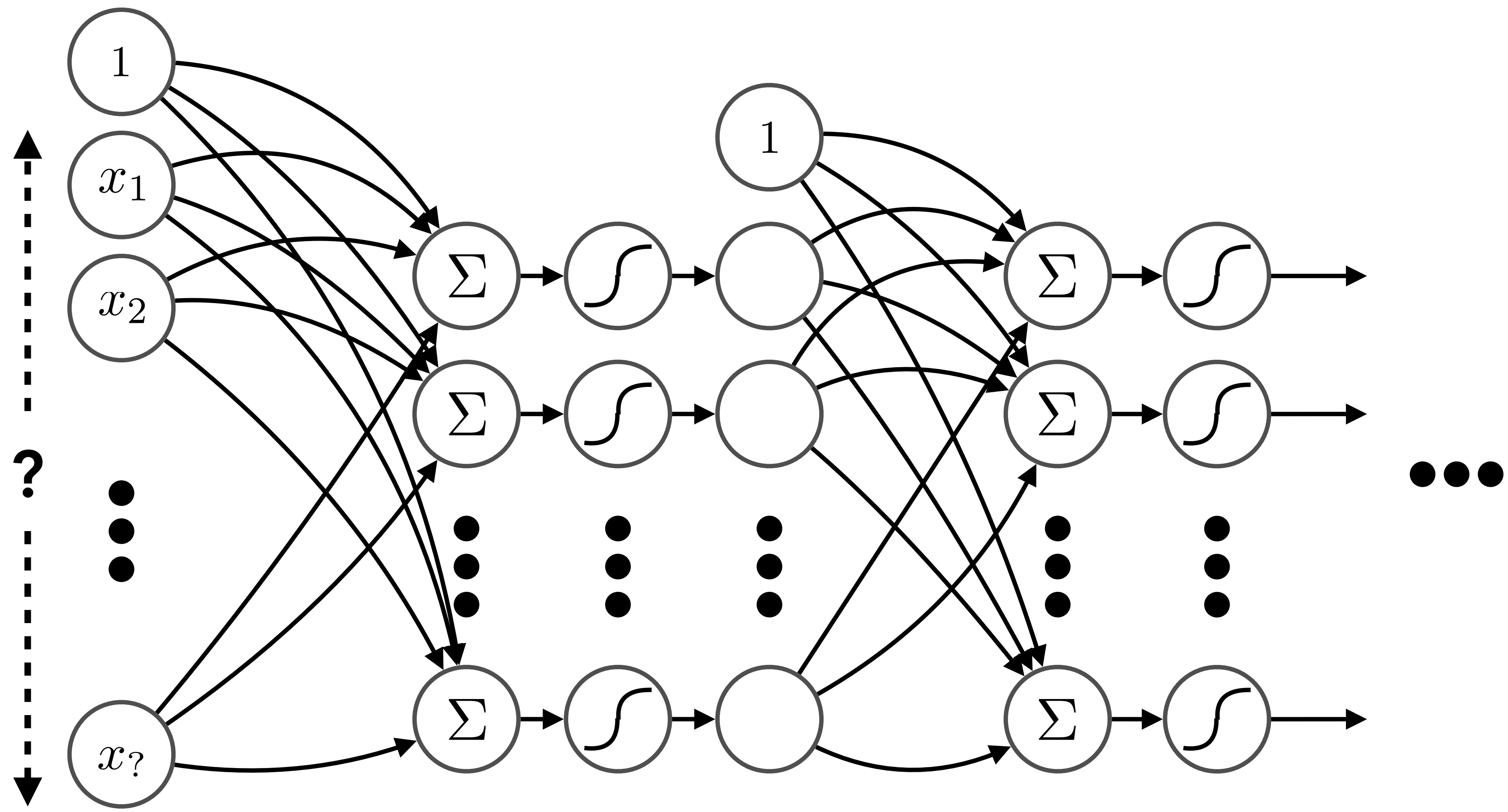
the mapping is too difficult to define by hand,
need to learn from data





but how do we define the network architecture?

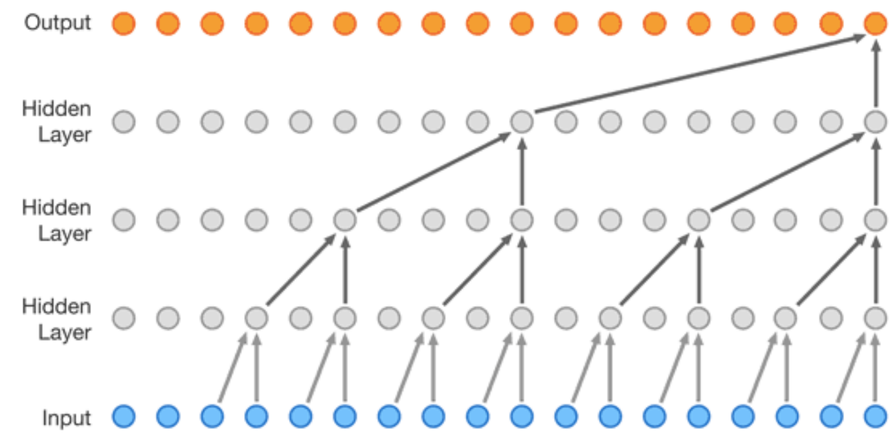
problem: inputs can be of variable size



standard neural networks can only handle data of a fixed input size

wait, but *convolutional networks* can handle variable input sizes…
can't we just use them?

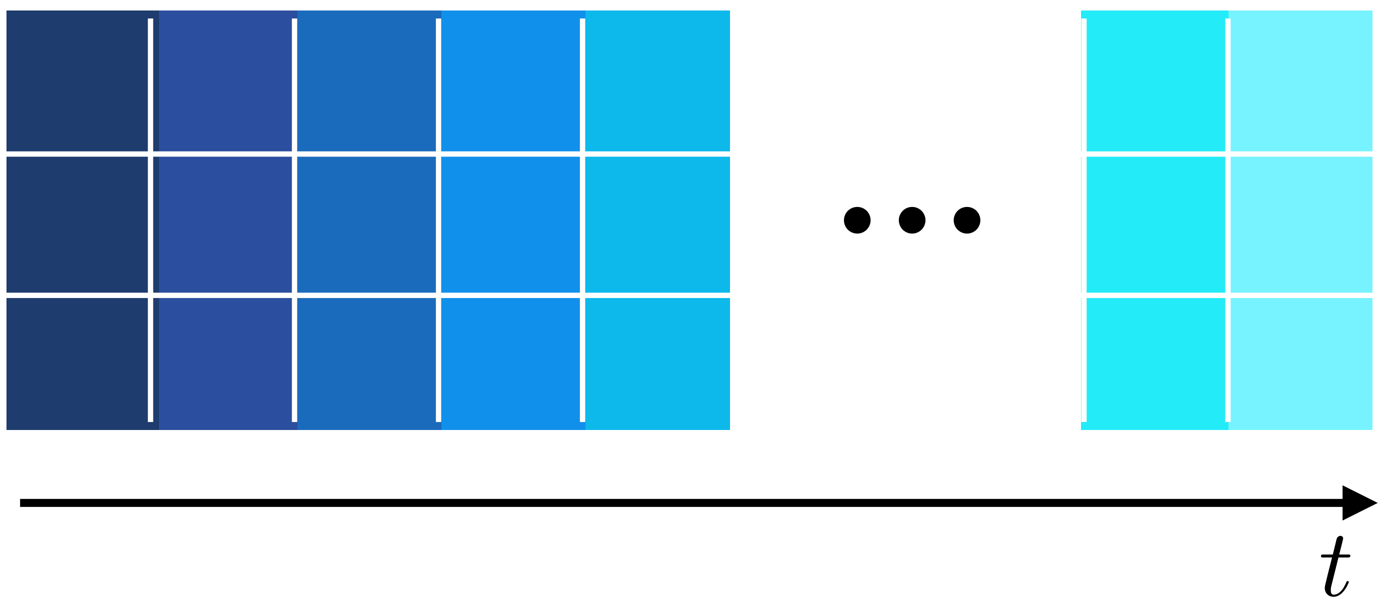
yes, we could



however, this relies on a *fixed input window size*

we may be able to exploit additional structure in sequence data
to impose better inductive biases

the structure of sequence data



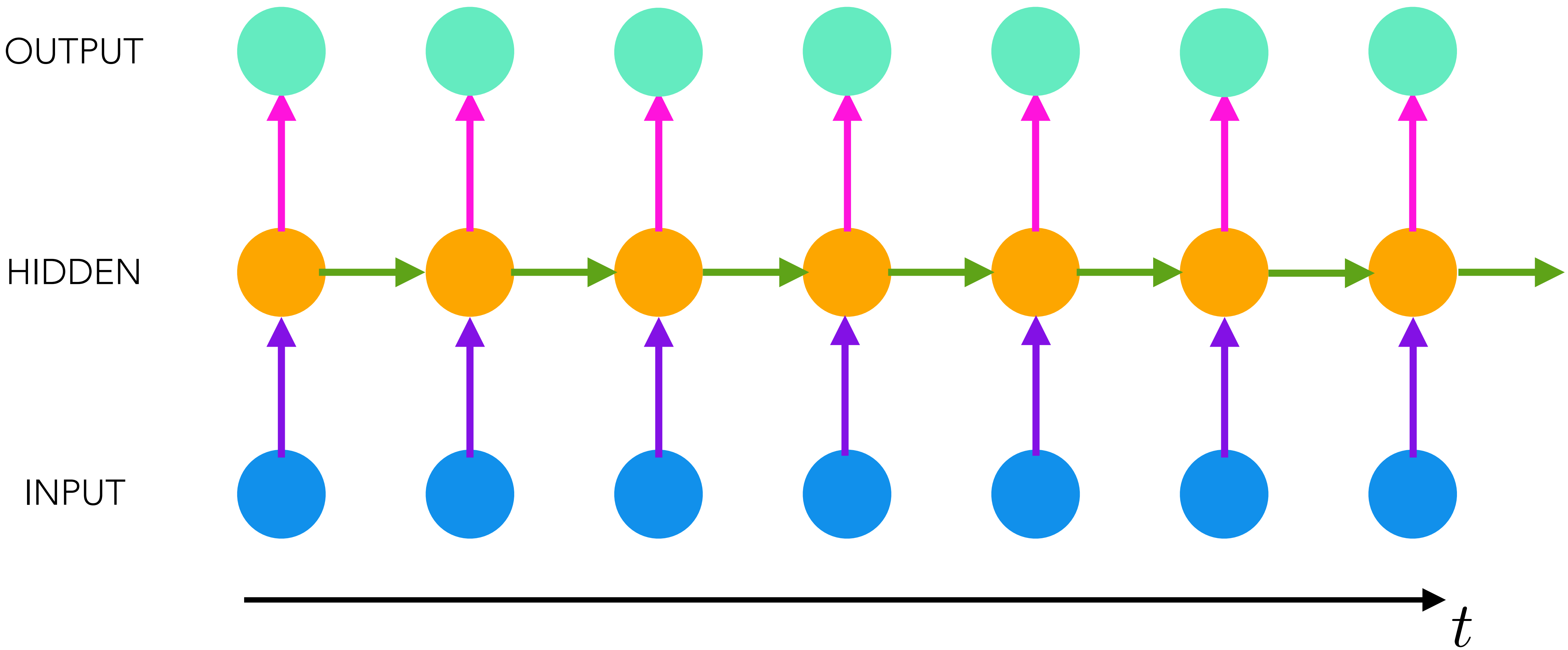
sequence data *also* tends to obey

locality: nearby regions tend to form stronger patterns

translation invariance: patterns are relative rather than absolute

but has a *single* axis on which extended patterns occur to mirror the sequential structure of the data,

we can process the data sequentially



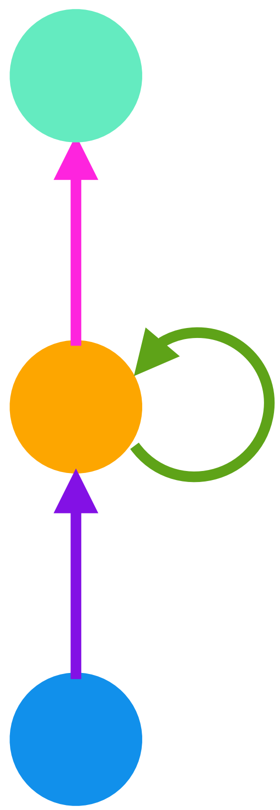
each set of colored arrows denotes shared weights

maintain an *internal representation* during processing

→ potentially *infinite* effective input window

→ fixed number of parameters

a ***recurrent neural network (RNN)*** can be expressed as



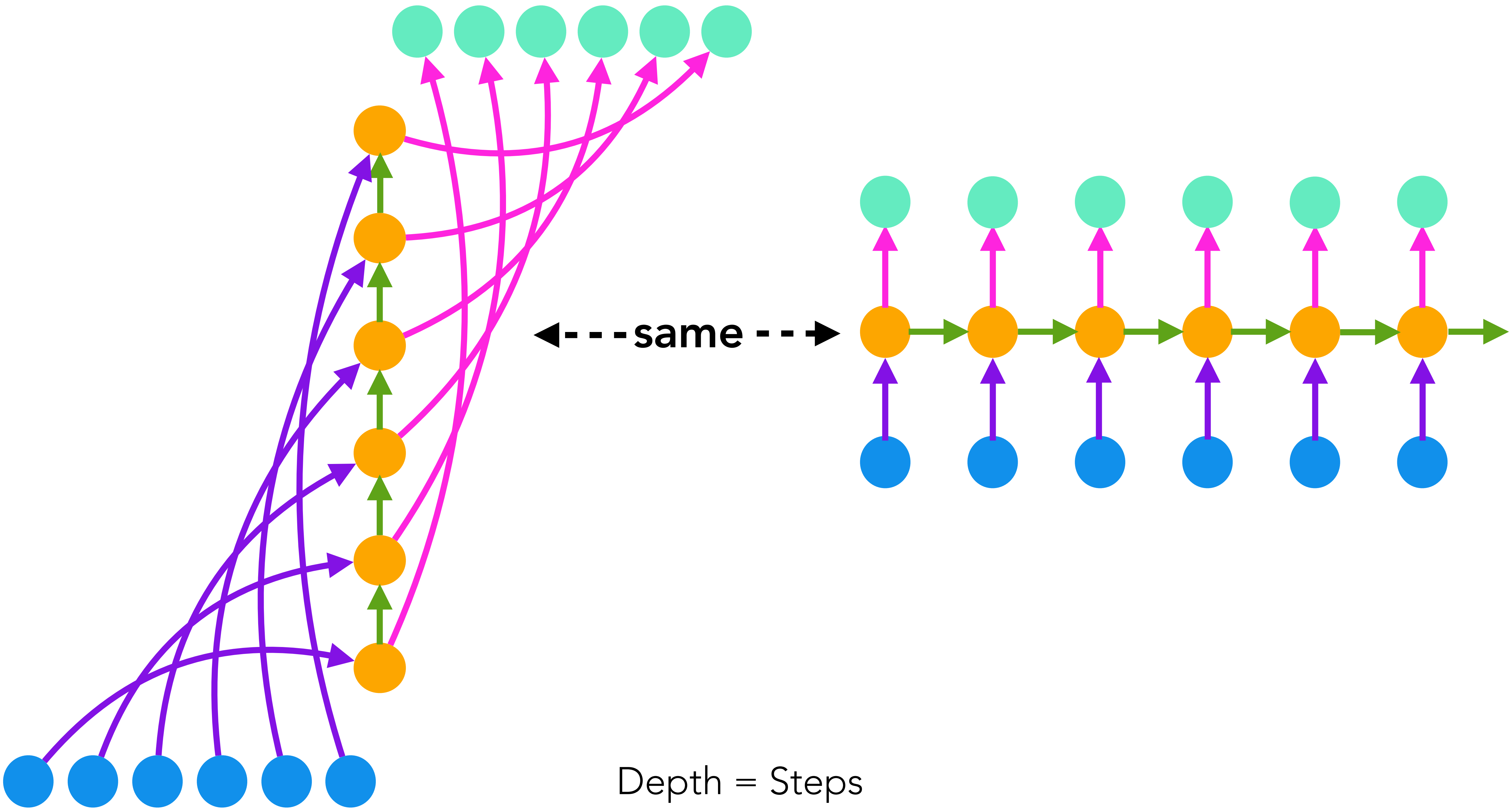
Hidden State

$$\mathbf{h}_t = \sigma(\mathbf{W}_{\mathbf{h}}^\intercal [\mathbf{h}_{t-1}, \mathbf{x}_t])$$

Output

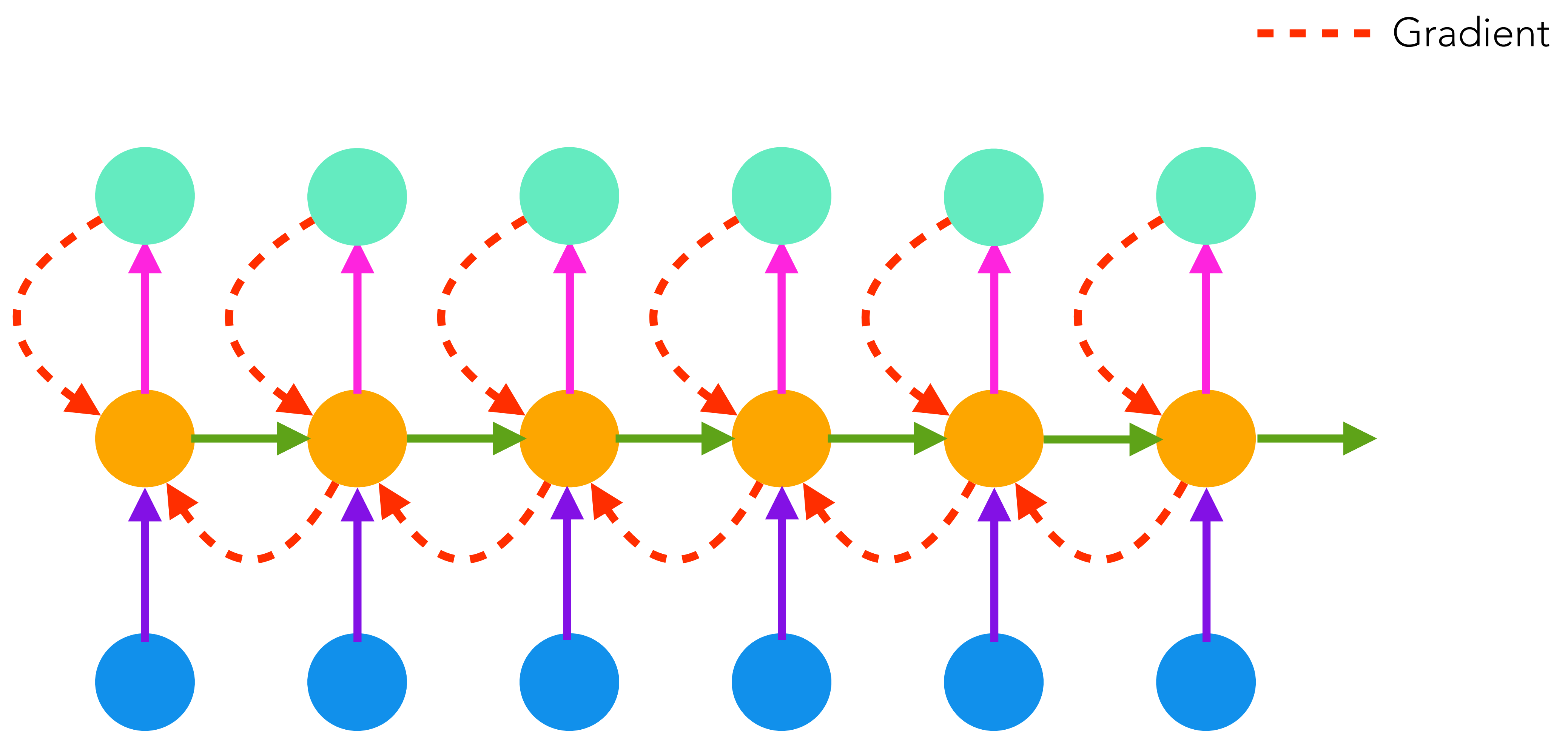
$$\mathbf{y}_t = \sigma(\mathbf{W}_{\mathbf{y}}^\intercal \mathbf{h}_t)$$

basic recurrent networks are also a ***special case***
of standard neural networks with *skip connections* and *shared weights*

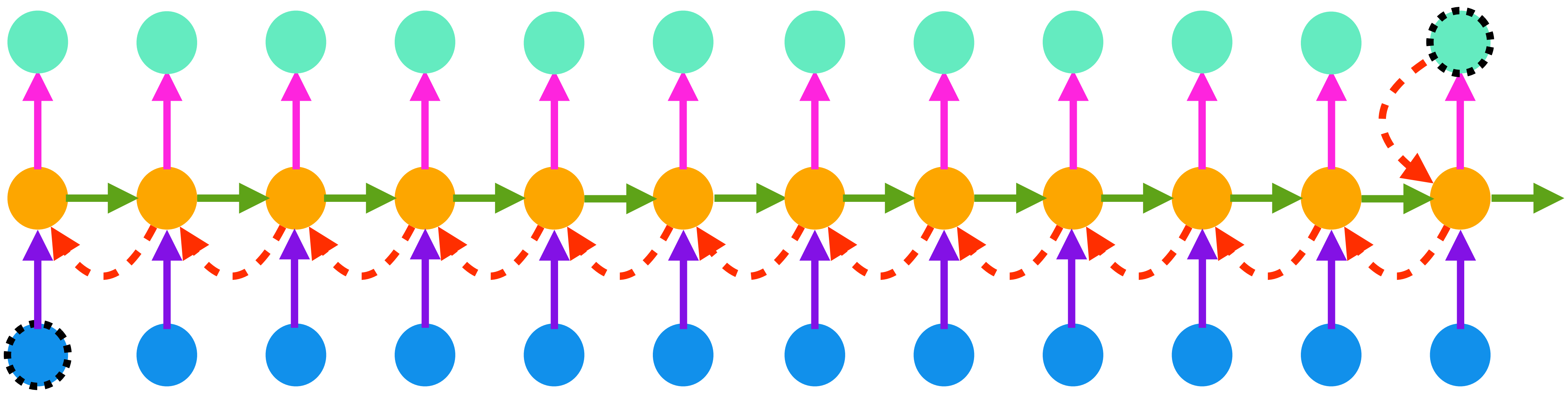


Depth = Steps

therefore, we can use standard backpropagation to train, resulting in ***backpropagation through time (BPTT)***



primary difficulty of training RNNs involves
propagating information over long horizons

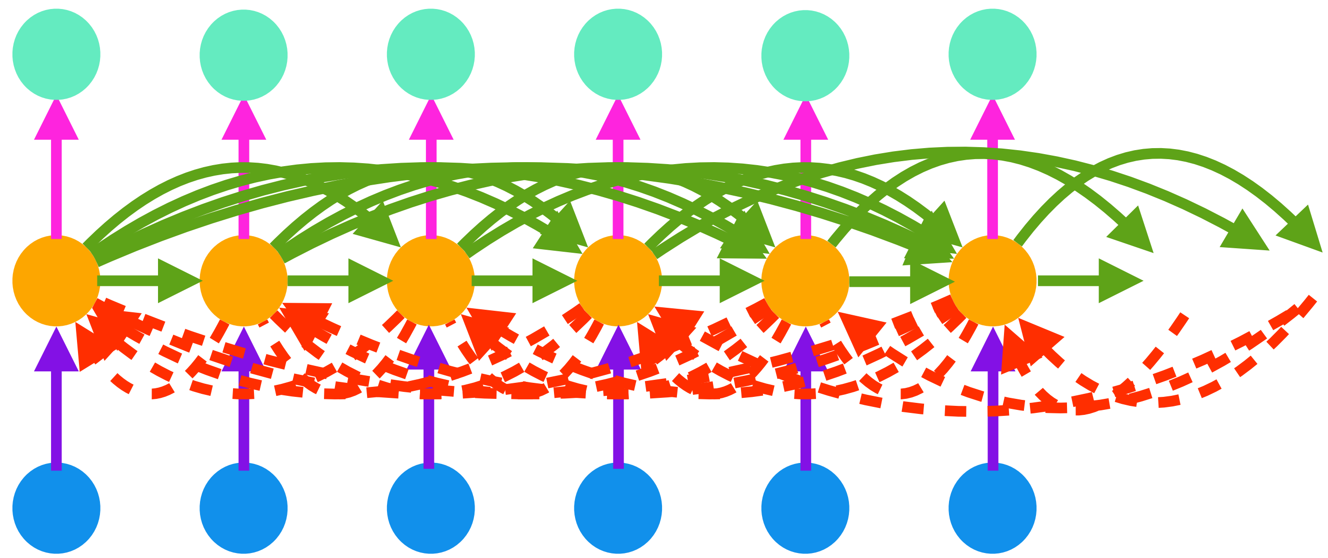


e.g. input at one step is predictive of output at *much later* step

learning extended sequential dependencies
requires propagating gradients over long horizons

- vanishing / exploding gradients
- large memory/computational footprint

naïve attempt to fix information propagation issue



add skip connections across steps

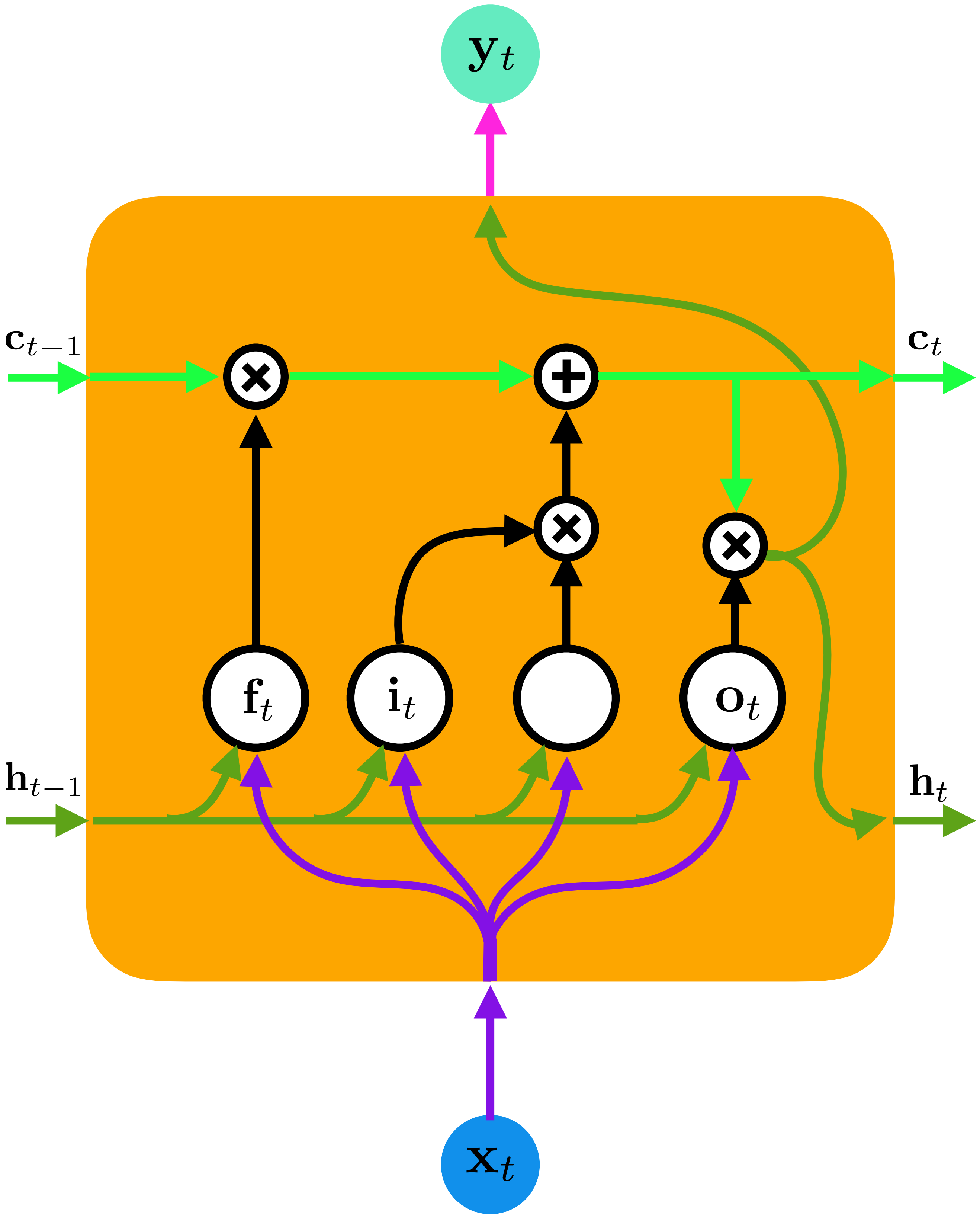
information, gradients can propagate more easily

but…

- increases computation
- must set limit on window size

add trainable ***memory*** to the network

read from and *write* to "***cell***" state



Long Short-Term Memory (LSTM)

Forget Gate

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Input Gate

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Cell State

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tanh(\mathbf{W}_\mathbf{c}^\intercal[\mathbf{h}_{t-1}, \mathbf{x}_t])$$

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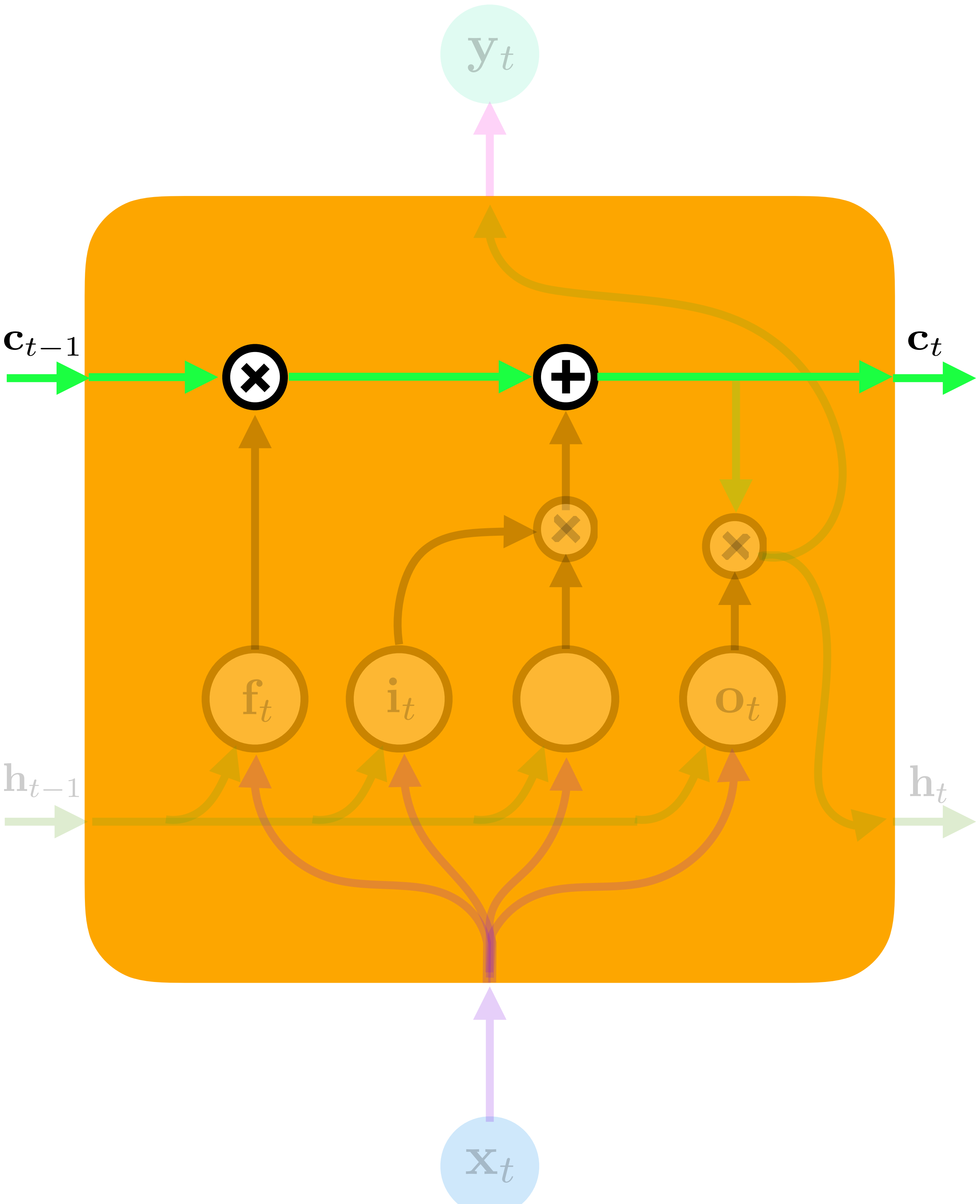

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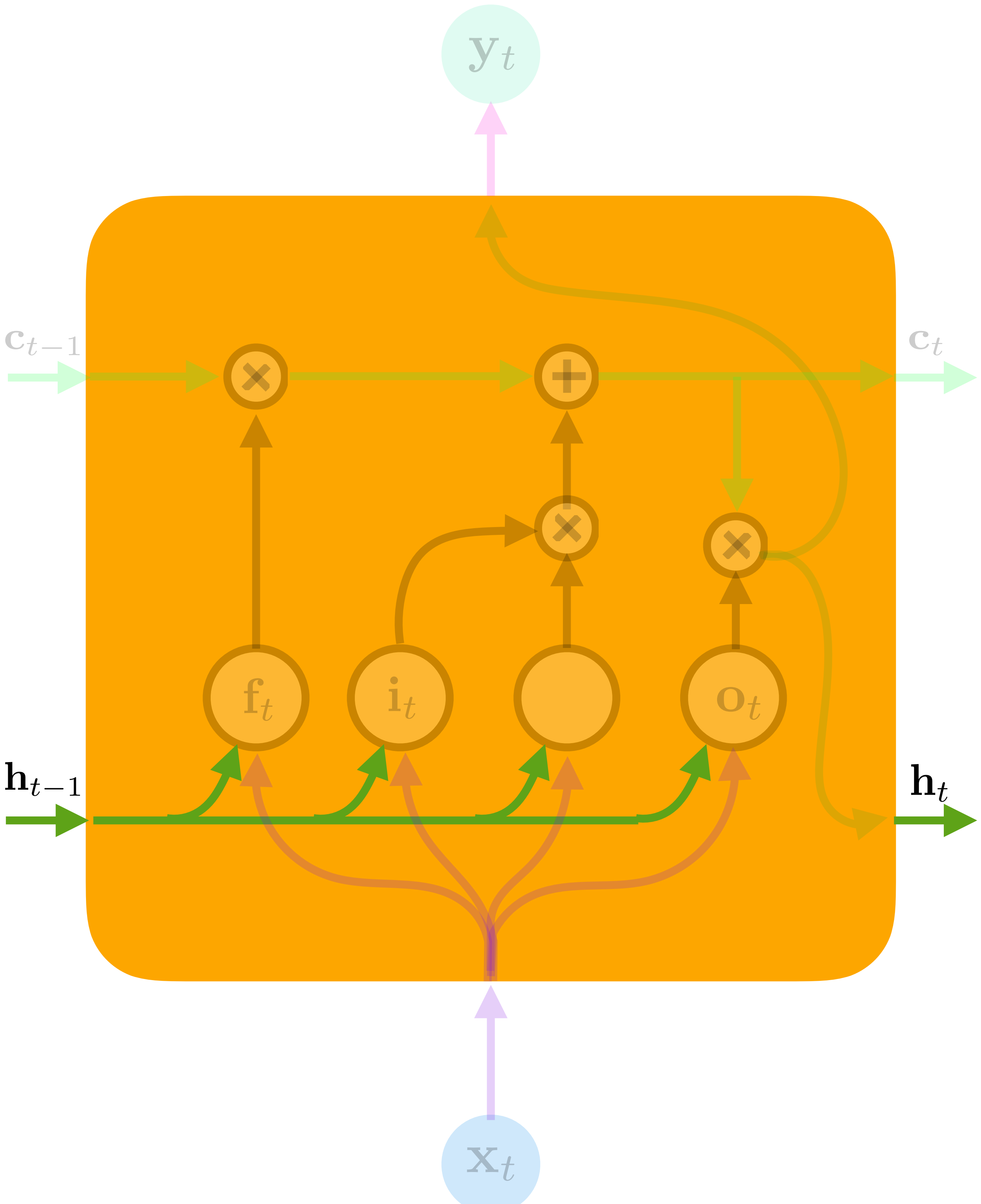

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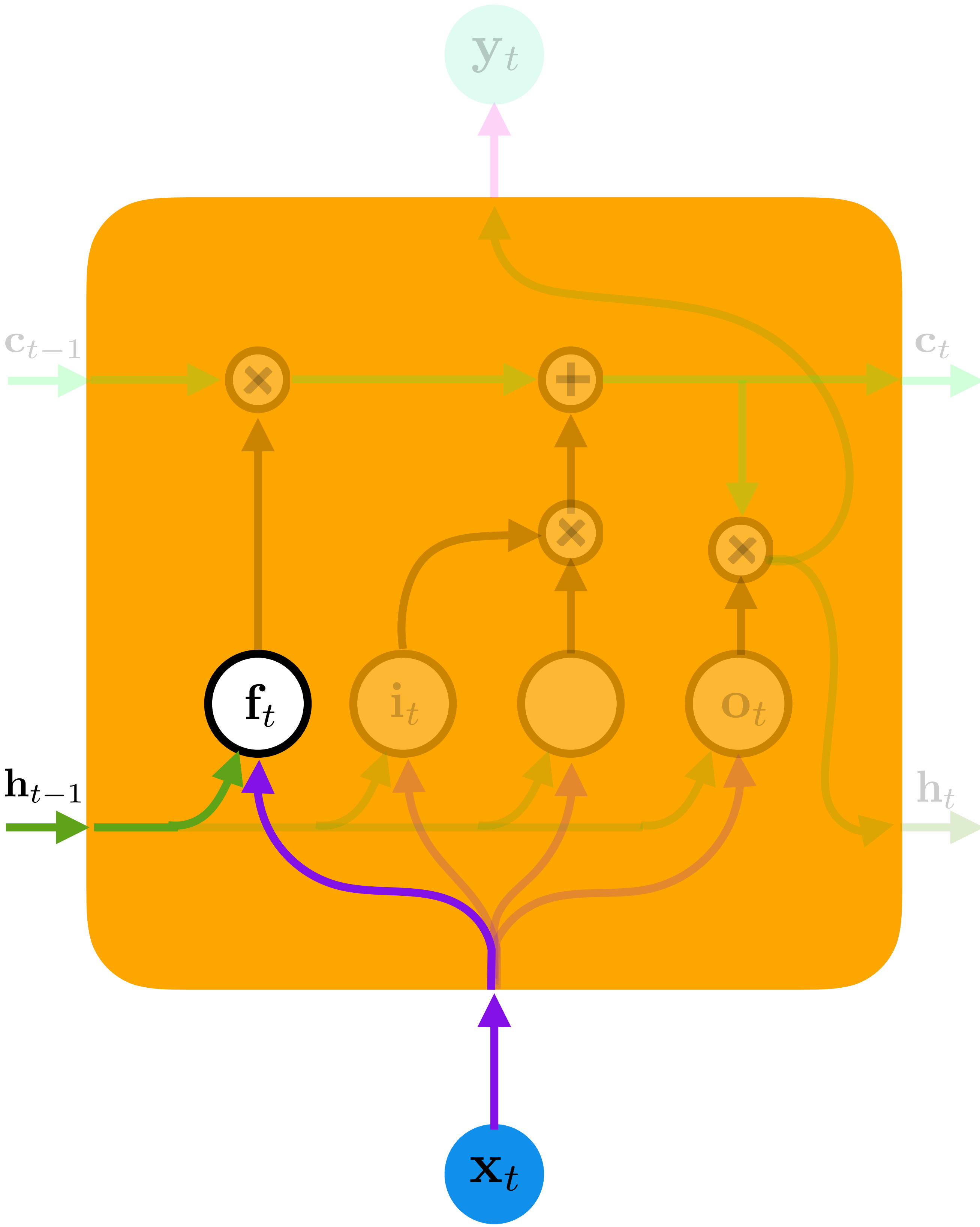

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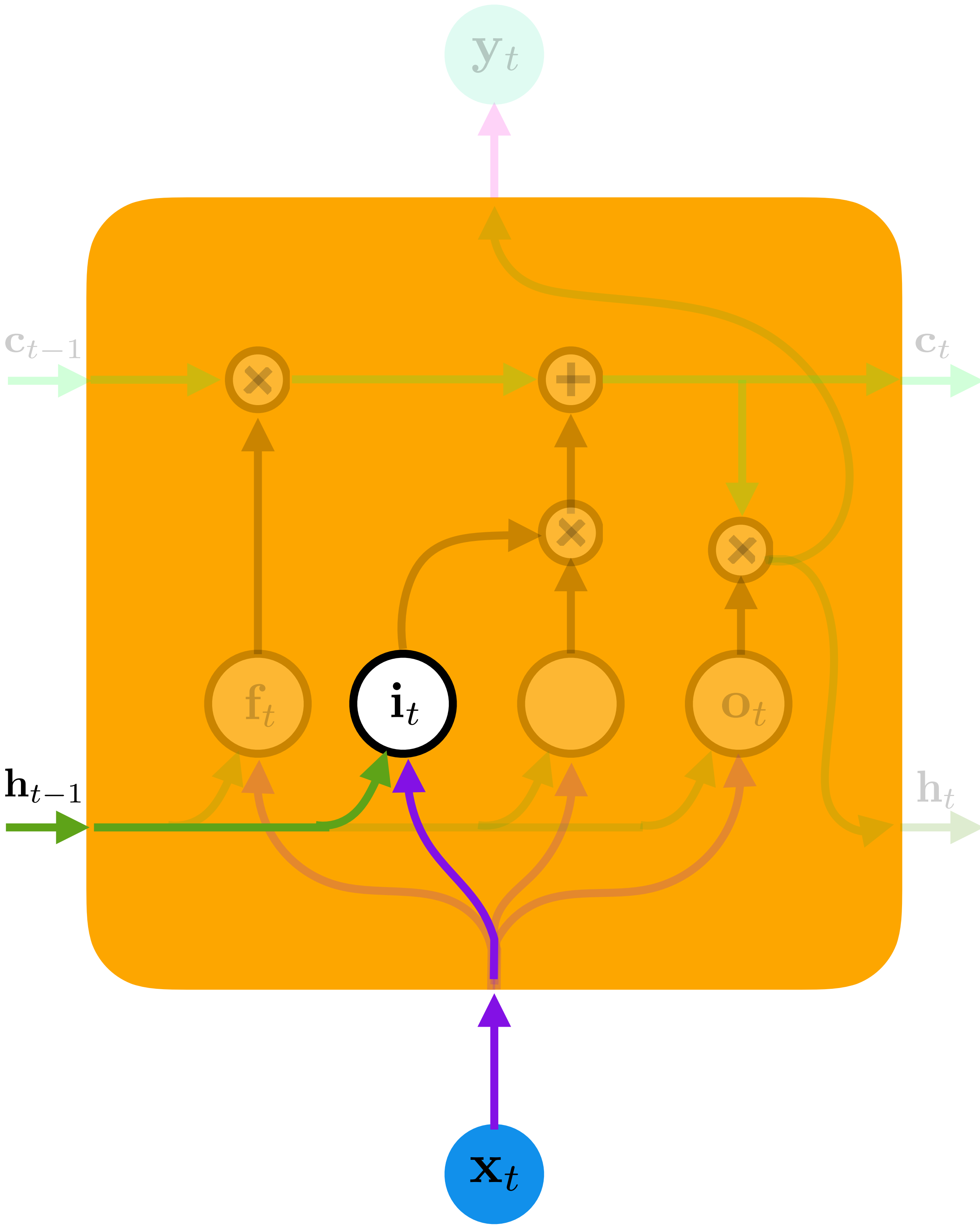

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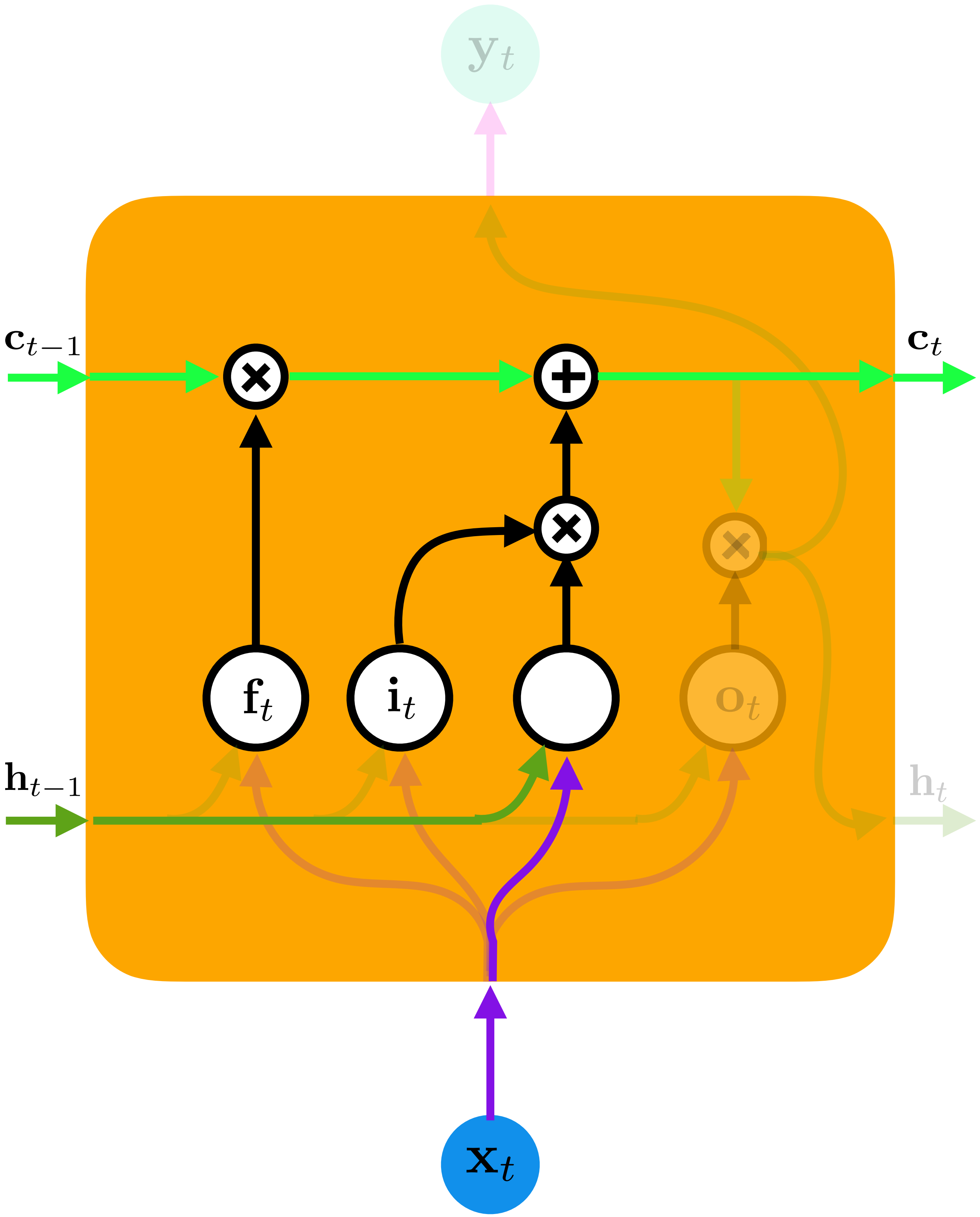

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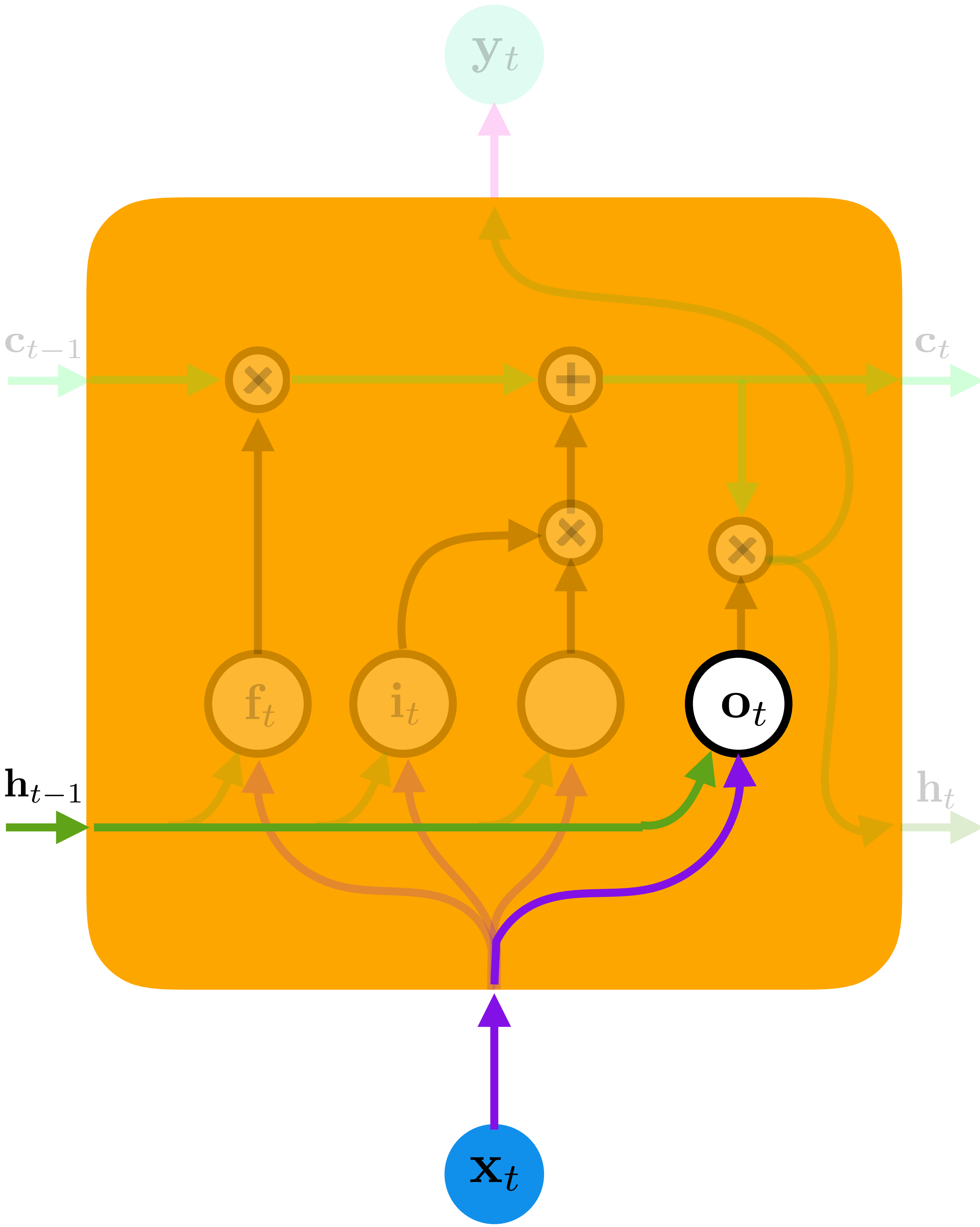

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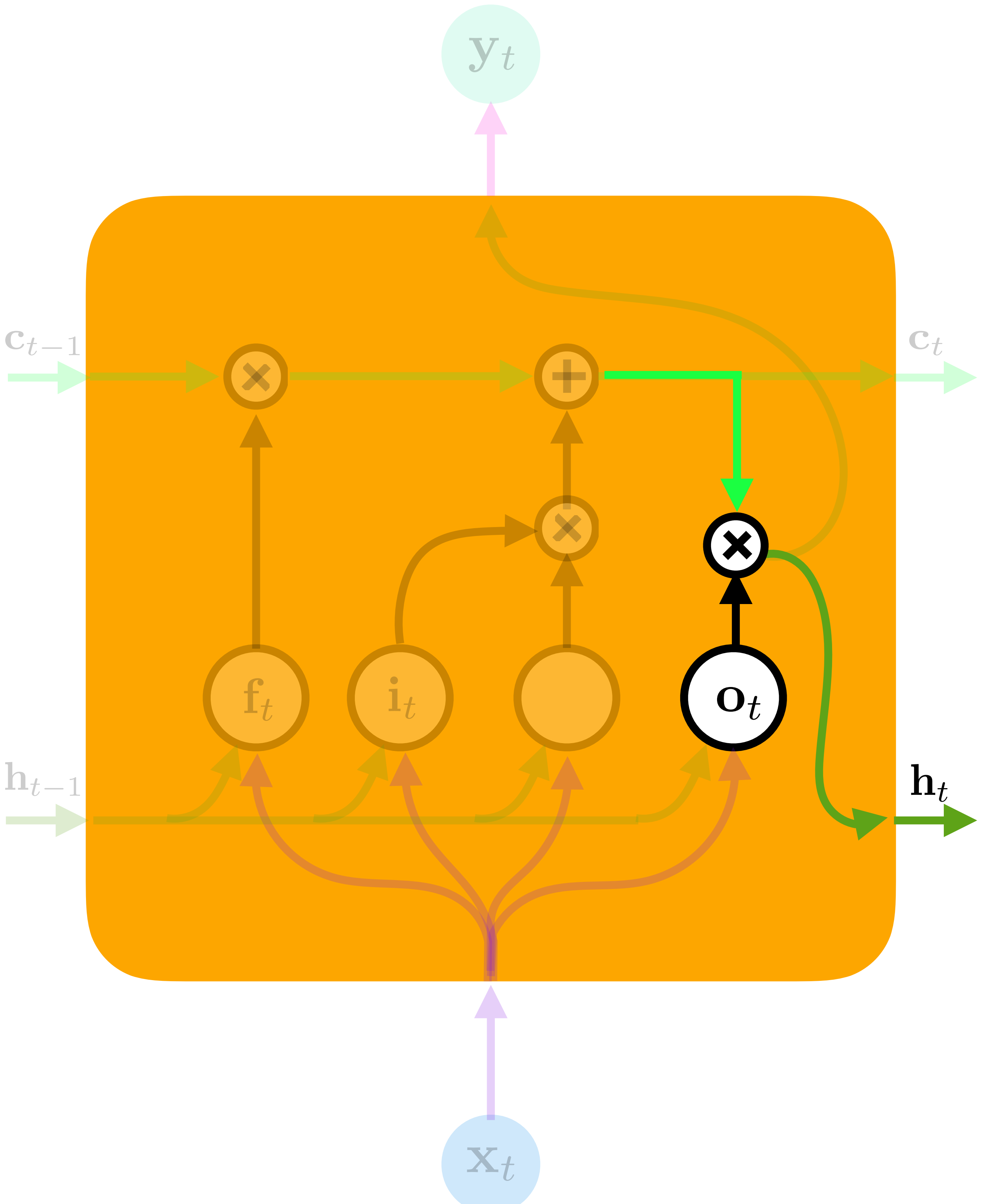

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$$\mathbf{o}_t = \sigma(\mathbf{W}_\mathbf{o}^\intercal[\mathbf{h}_{t-1}, \mathbf{x}_t])$$

Hidden State

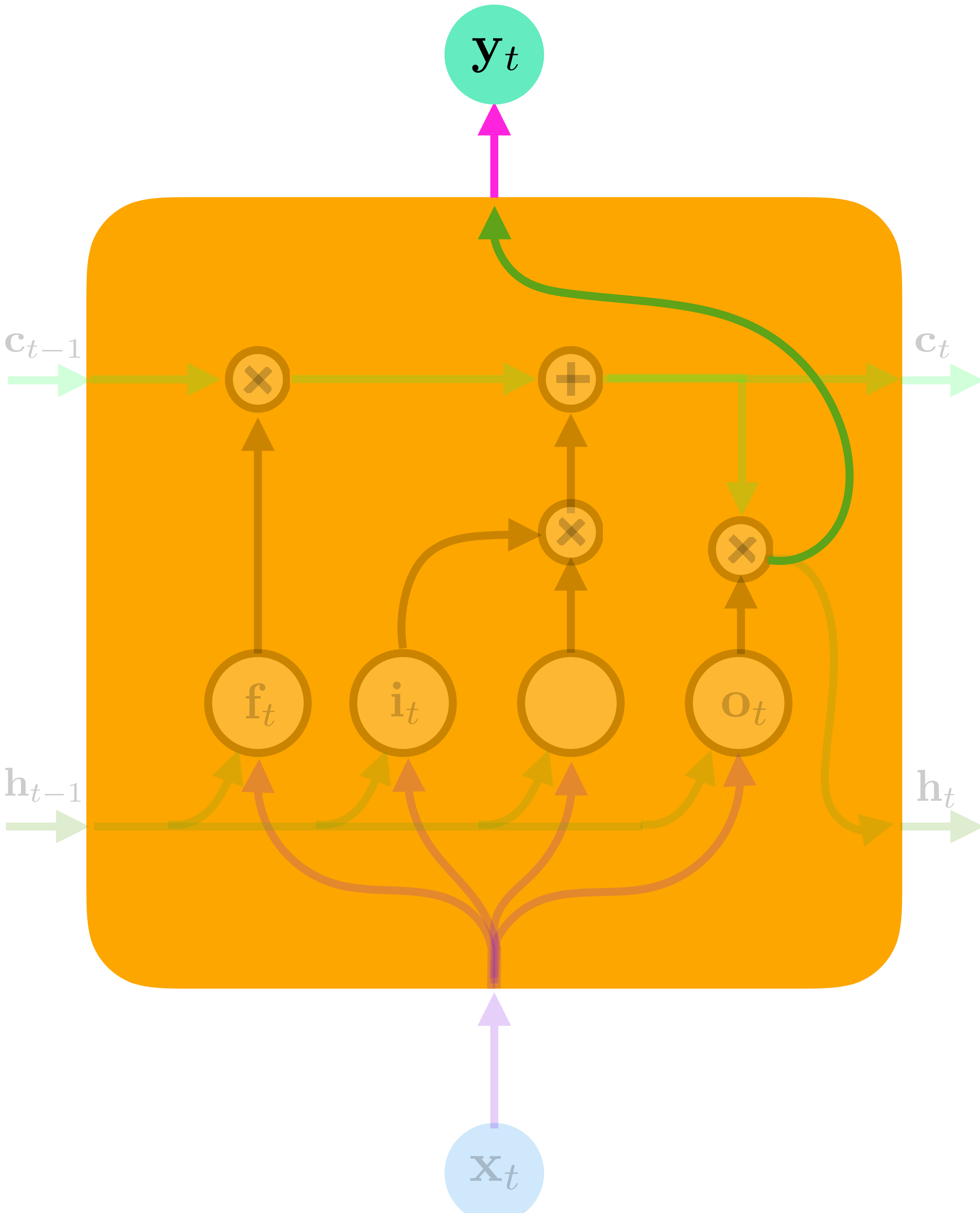
$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$$

Output

$$\mathbf{y}_t = \sigma(\mathbf{W}_\mathbf{y}^\intercal \mathbf{h}_t)$$

add trainable ***memory*** to the network

read from and *write* to "***cell***" state



Long Short-Term Memory (LSTM)

Forget Gate

$$\mathbf{f}_t = \sigma(\mathbf{W}_\mathbf{f}^\intercal[\mathbf{h}_{t-1}, \mathbf{x}_t])$$

Input Gate

$$\mathbf{i}_t = \sigma(\mathbf{W}_\mathbf{i}^\intercal[\mathbf{h}_{t-1}, \mathbf{x}_t])$$

Cell State

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tanh(\mathbf{W}_\mathbf{c}^\intercal[\mathbf{h}_{t-1}, \mathbf{x}_t])$$

Output Gate

$$\mathbf{o}_t = \sigma(\mathbf{W}_\mathbf{o}^\intercal[\mathbf{h}_{t-1}, \mathbf{x}_t])$$

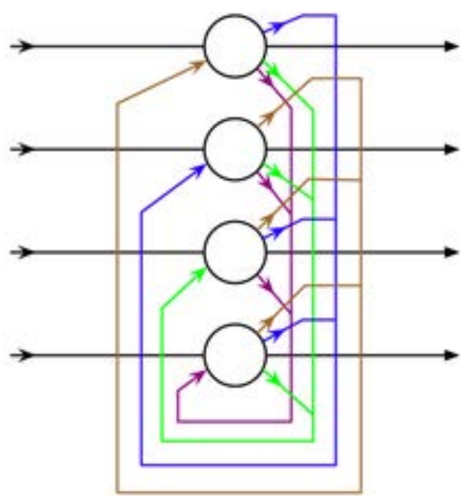
Hidden State

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

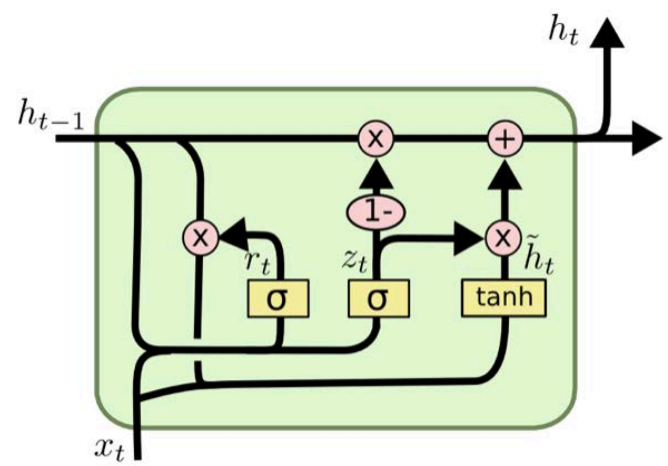
Output

$$\mathbf{y}_t = \sigma(\mathbf{W}_\mathbf{y}^\intercal \mathbf{h}_t)$$

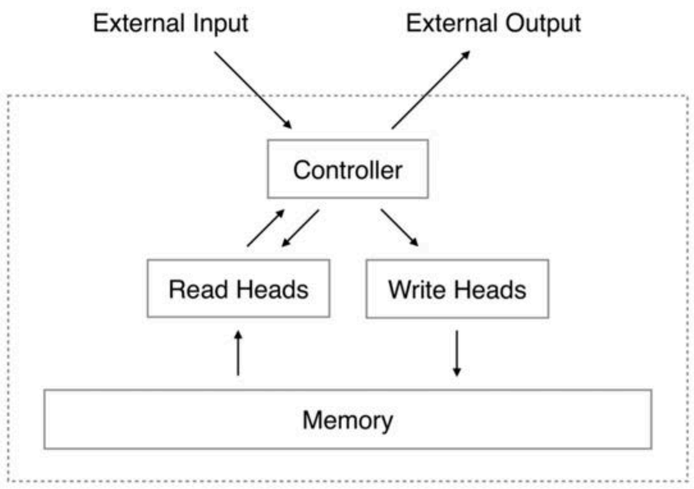
memory networks



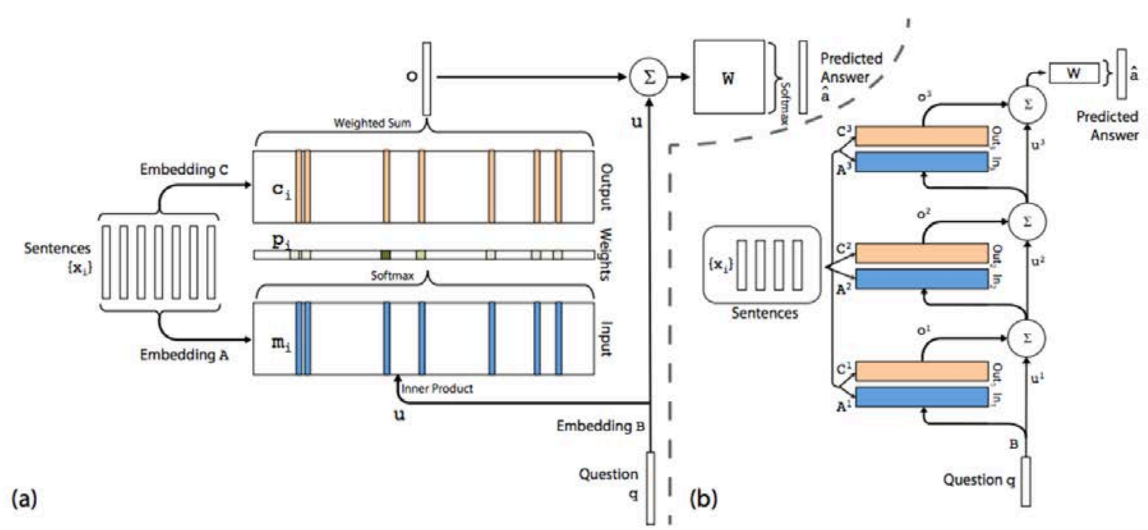
Hopfield Network
Hopfield, 1982



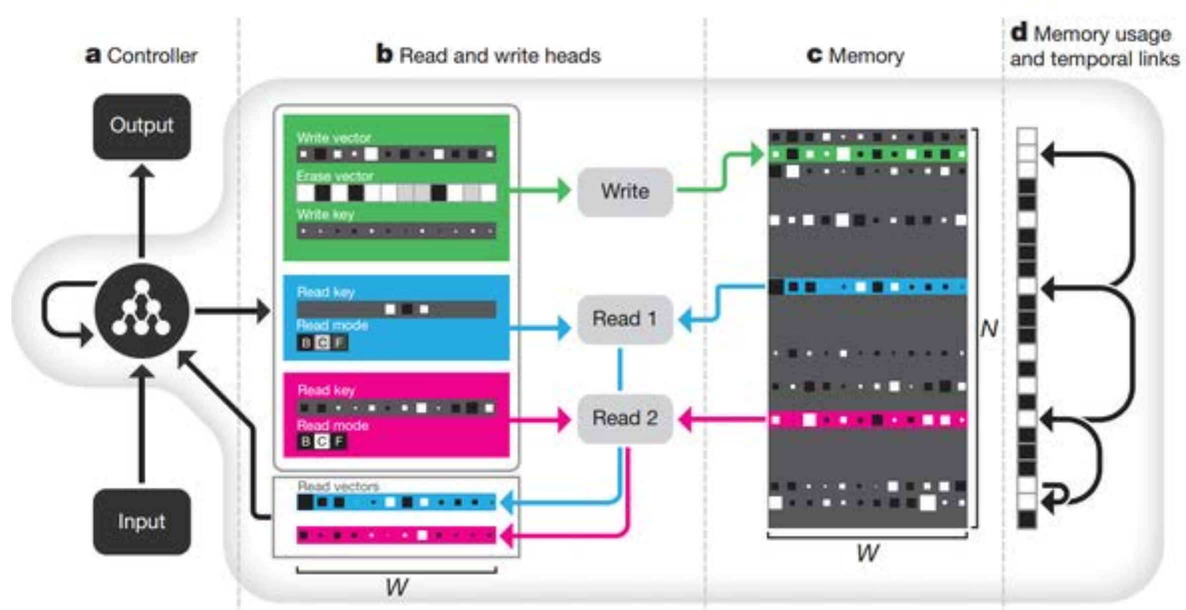
Gated Recurrent Unit (GRU)
Cho et al., 2014



Neural Turing Machine (NTM)
Graves et al., 2014



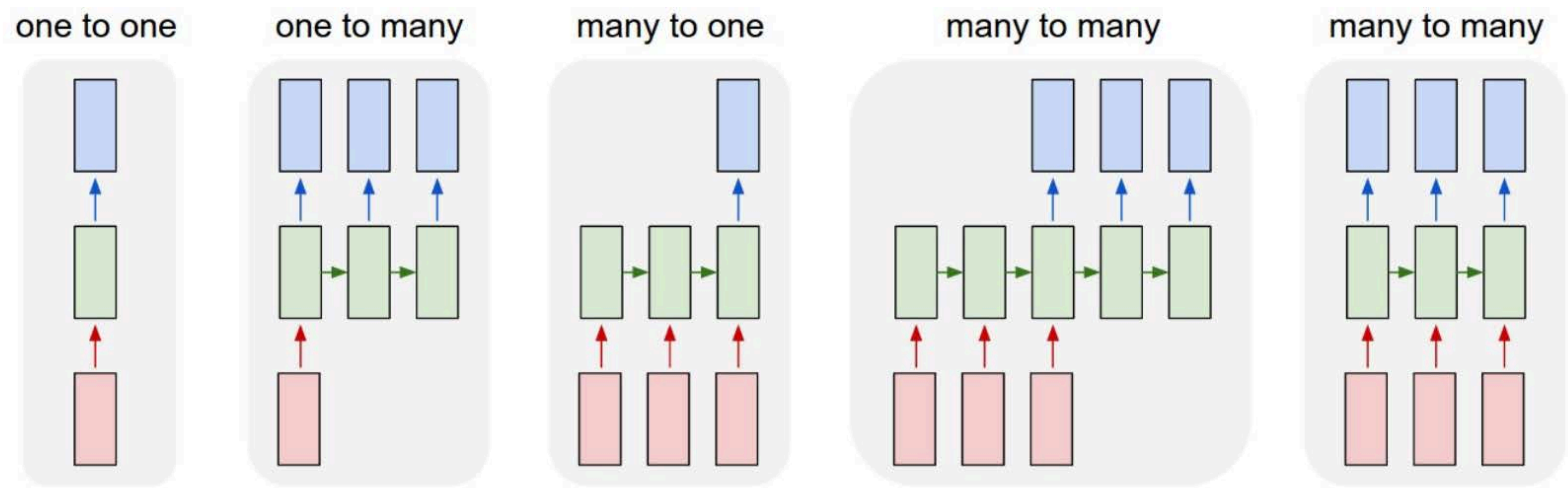
Memory Networks (MemNN)
Weston et al., 2015



Differentiable Neural Computer (DNC)
Graves, Wayne, et al., 2016

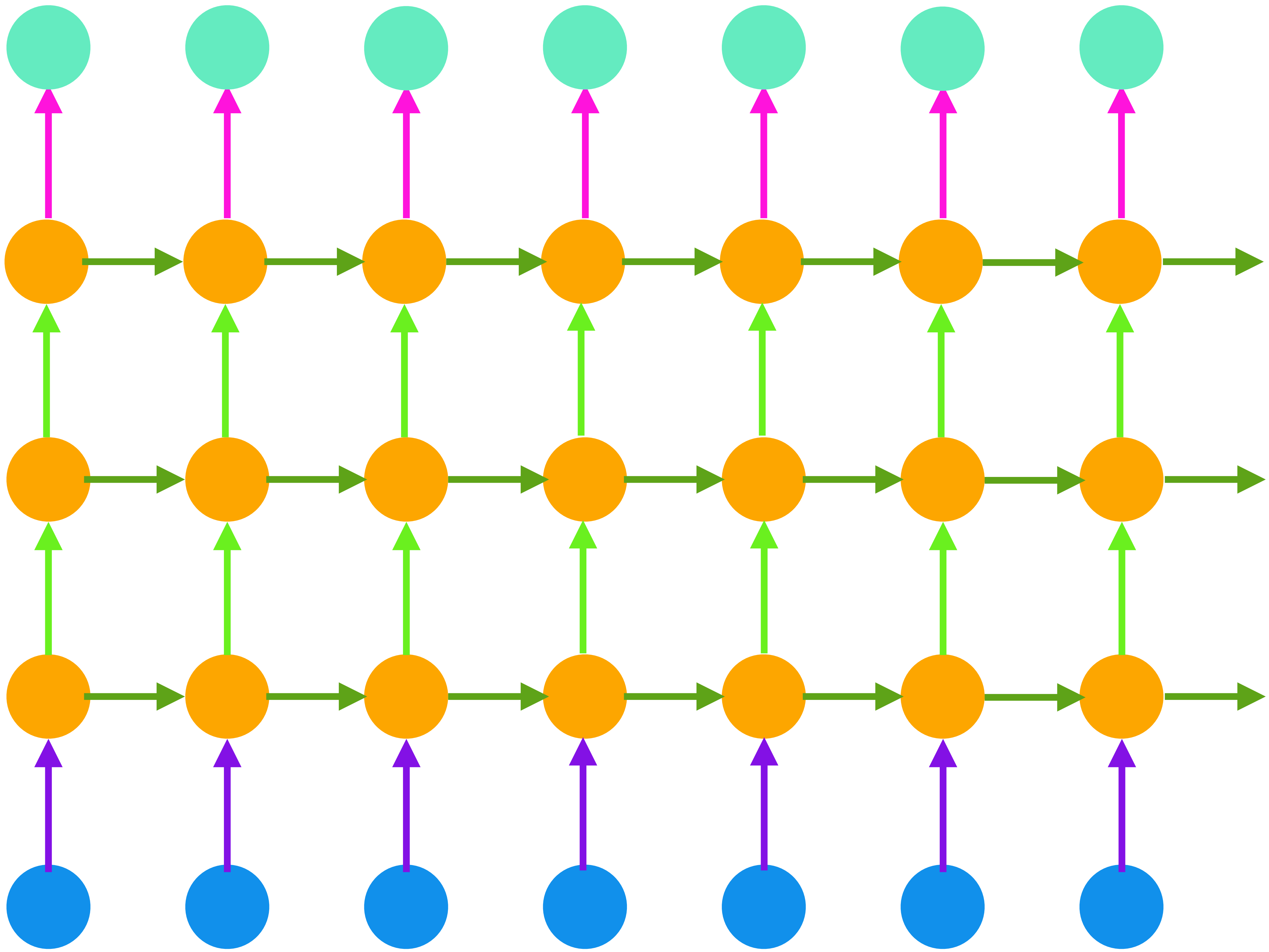
http://colah.github.io/posts/2015-08-Understanding-LSTMs/

tons of options!

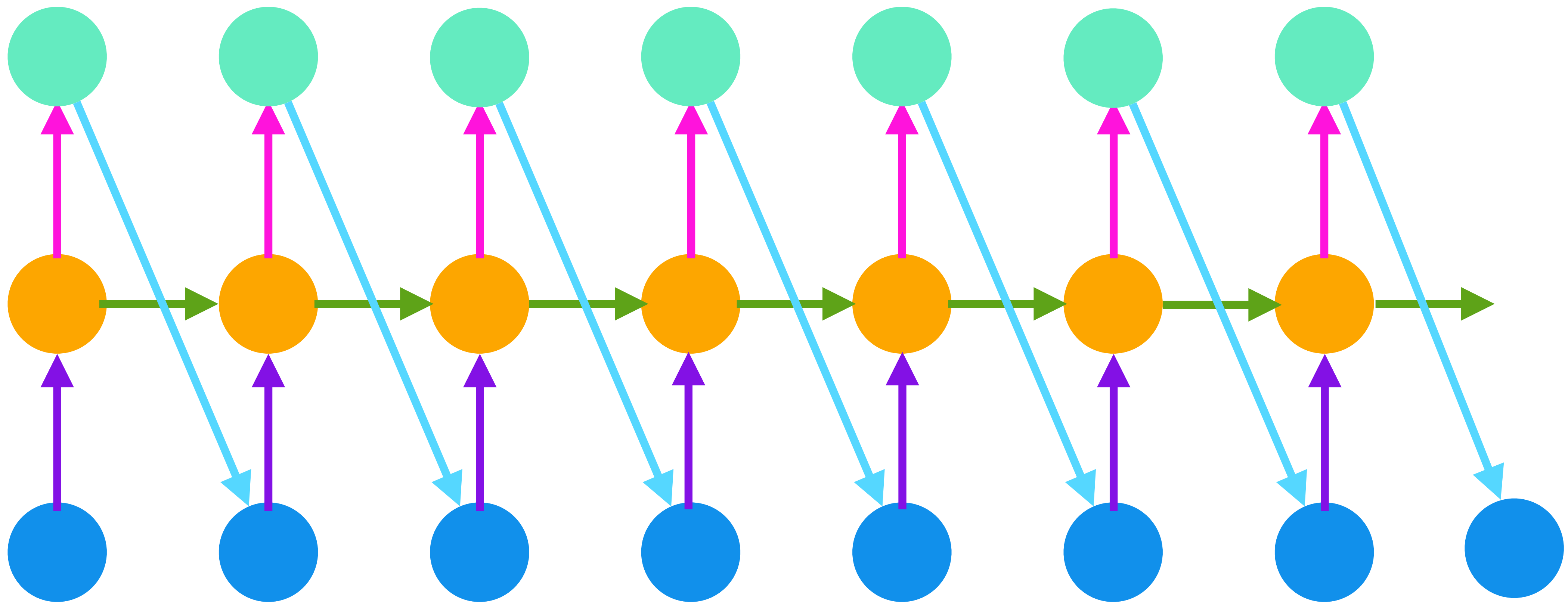


http://karpathy.github.io/2015/05/21/rnn-effectiveness/

deep recurrent neural networks



auto-regressive generative modeling



output becomes next input

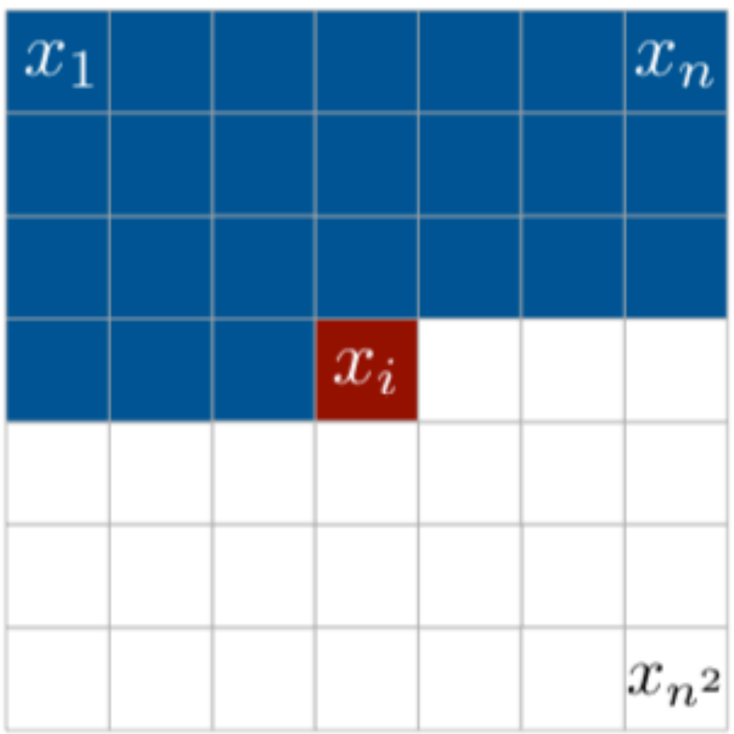
auto-regressive generative language modeling

```
PANDARUS:
Alas, I think he shall be come approached and the day
When little srain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:
They are away this miseries, produced upon my soul,
Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCENTIO:
Well, your wit is in the care of side and that.

Second Lord:
They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.

Clown:
Come, sir, I will make did behold your worship.

VIOLA:
I'll drink it.
```

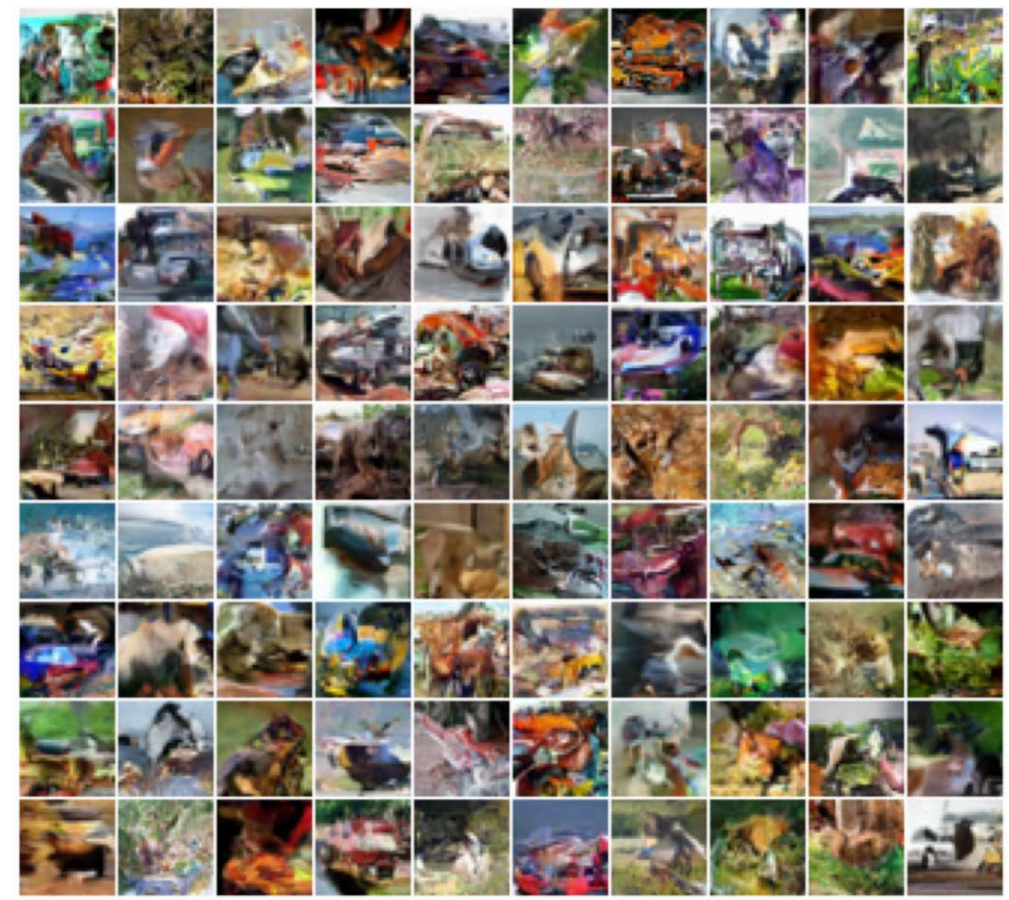

http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Pixel RNN uses recurrent networks to perform auto-regressive image generation

context



generated samples



condition the generation of each pixel on a *sequence* of past pixels

van den Oord et al., 2016

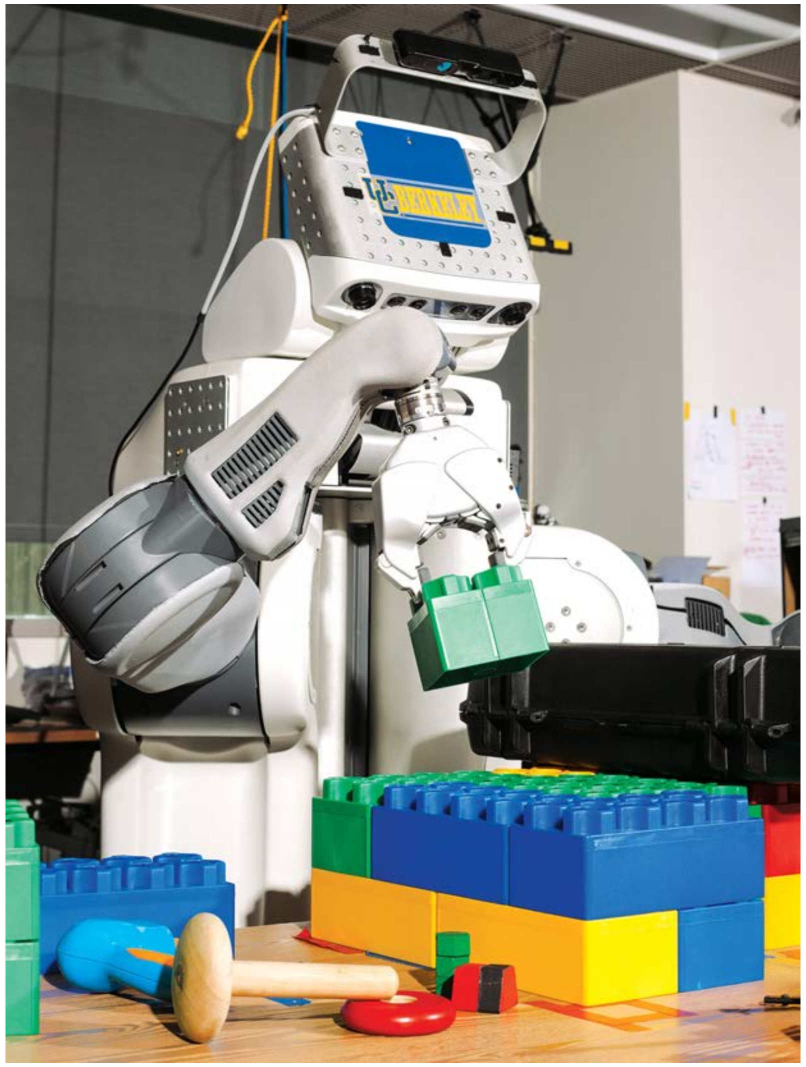
RECAP

we used additional priors (inductive biases) to
scale deep networks up to handle spatial and sequential data

without these priors, we would need
more parameters and data

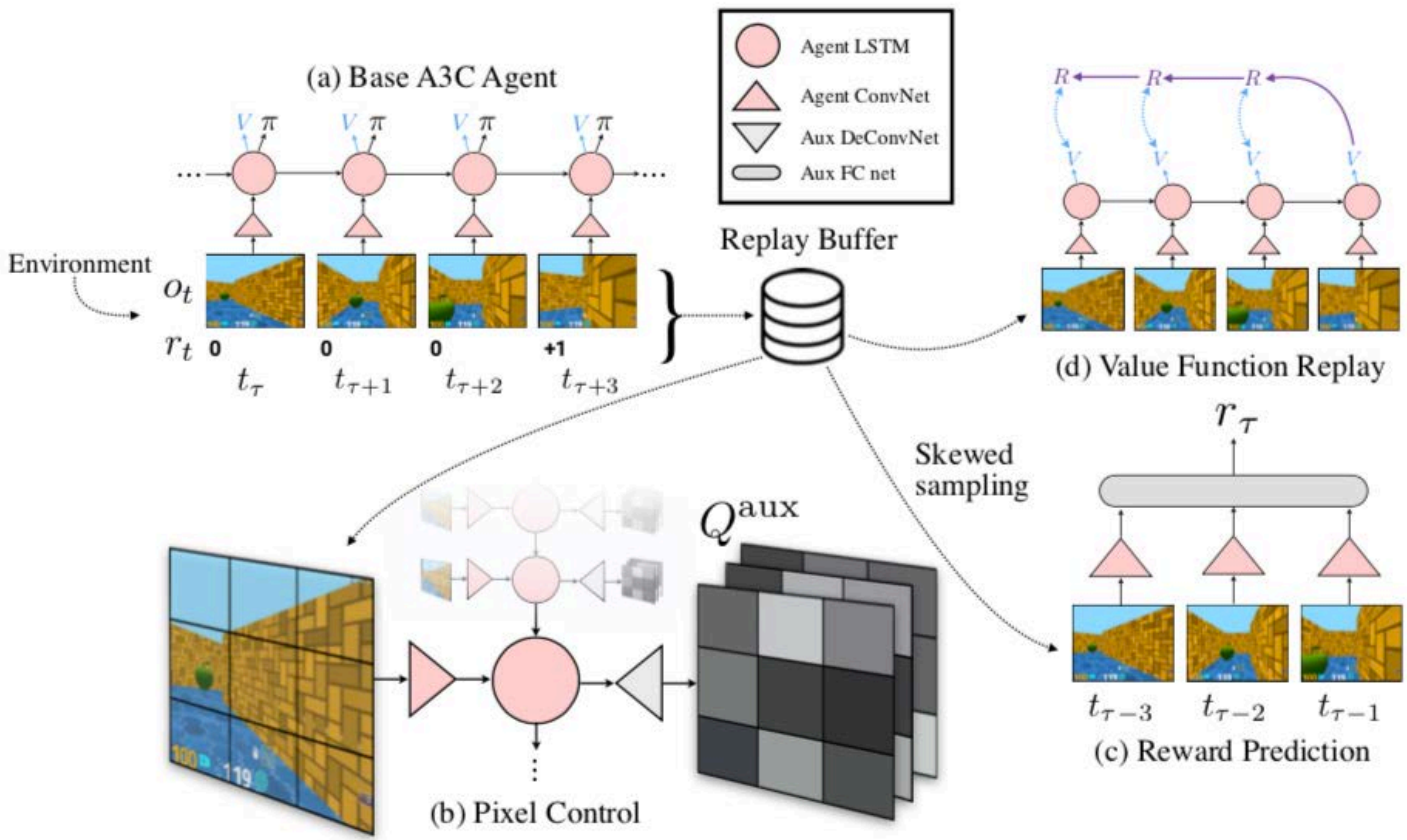
we live in a ***spatiotemporal*** world

we are constantly getting streams of spatial sensory inputs

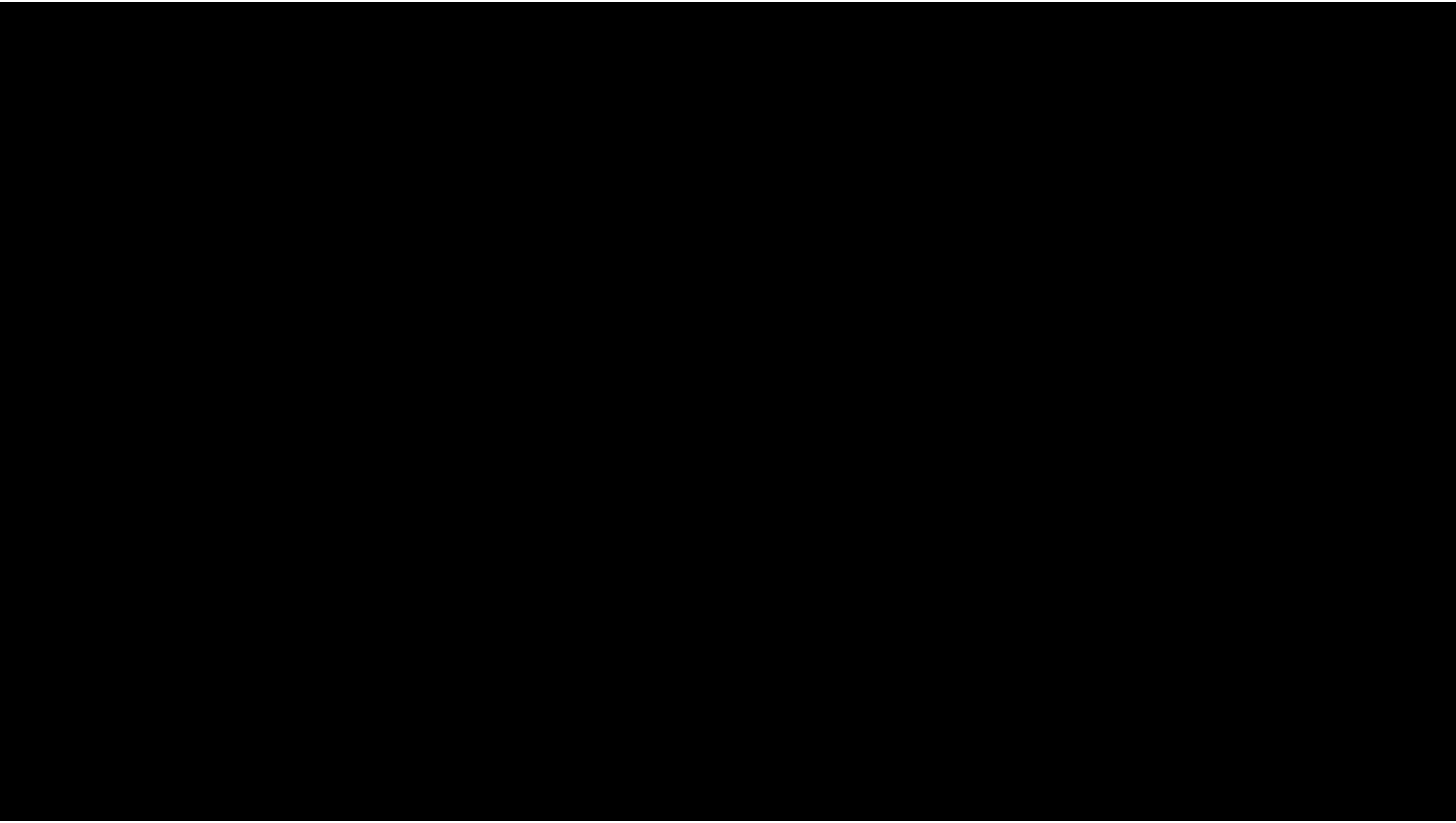


(embodied) intelligent machines need to learn from spatial and temporal patterns

CNNs and RNNs are building blocks for machines that can use spatiotemporal data to solve tasks



Jaderberg, Minh, Czarnecki et al., 2016



Jaderberg, Minh, Czarnecki et al., 2016