UVA CS 6316: Machine Learning

Lecture 15c: Recent Deep Neural Networks: A Quick Overview

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Today

- Deep Learning
  - History
  - A Few Recent trends

    https://qdata.github.io/deep2Read/

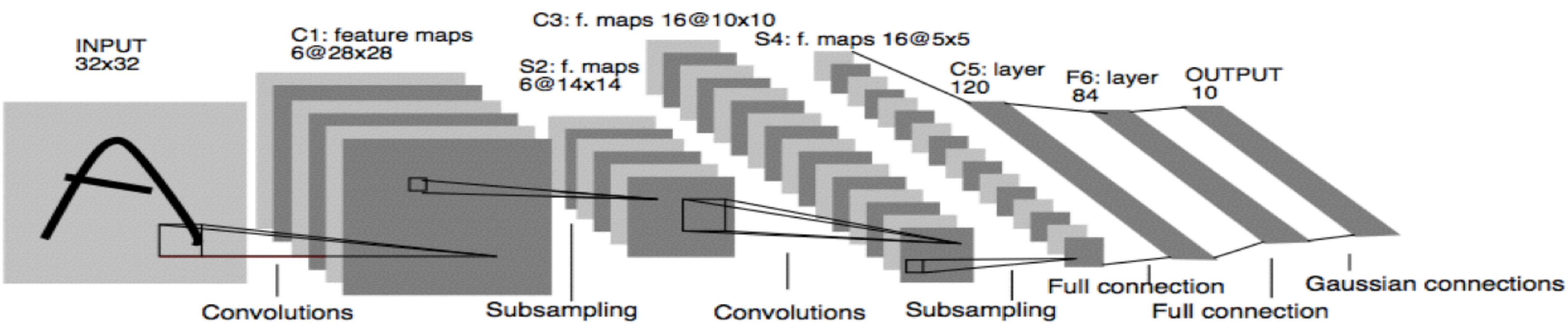
Early History

- In 1950 English mathematician Alan Turing wrote a landmark paper titled "Computing Machinery and Intelligence" that asked the question: "Can machines think?"
- Further work came out of a 1956 workshop at Dartmouth sponsored by John McCarthy. In the proposal for that workshop, he coined the phrase a "study of artificial intelligence"
- 1950s
  - Samuel' s checker player : start of machine learning
  - Selfridge' s Pandemonium
- **1952-1969: Enthusiasm**: Lots of work on neural networks
- 1970s-80s: Expert systems, Knowledge bases to add on rule-based inference, Decision Trees, Bayes Nets
- **1990s : CNN, RNN, ….**
- **2000s :** SVM, Kernel machines, Structured learning, Graphical models, semi-supervised, matrix factorization, …

Adapted From Prof. Raymond J. Mooney's slides

Deep Learning (CNN) in the 90's

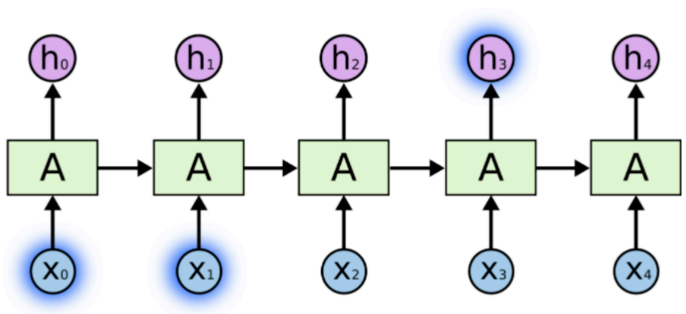
- Prof. Yann LeCun invented Convolutional Neural Networks (CNN) in 1998
- First NN successfully trained with many layers

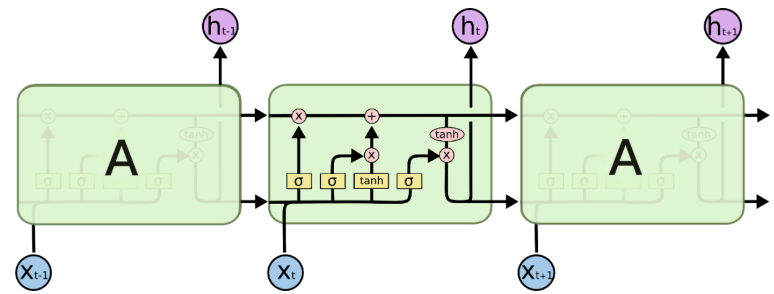


Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86(11): 2278–2324, 1998.

Deep Learning (RNN) in the 90's

- Prof. Schmidhuber invented "Long short-term memory" – Recurrent NN (LSTM-RNN) model in 1997





The repeating module in an LSTM contains four interacting layers.

Sepp Hochreiter; Jürgen Schmidhuber (1997). "Long short-term memory". Neural Computation. 9 (8): 1735–1780.

Image Credits from Christopher Olah

“Winter of Neural Networks” in ~2000s

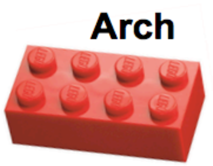
- Non-convex

- Need a lot of tricks to play with
  - How many layers ?
  - How many hidden units per layer ?
  - What topology among layers ? …….

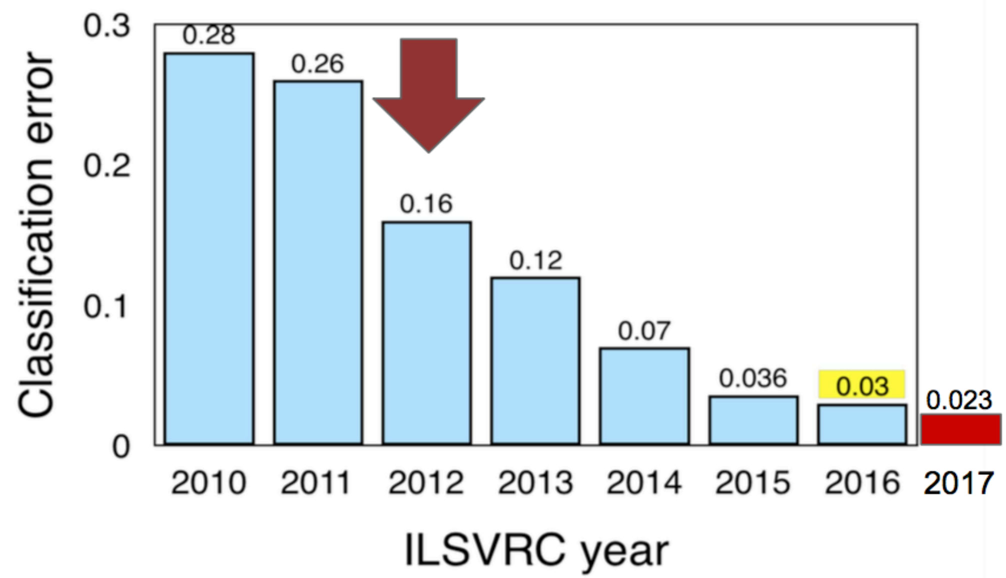
- Hard to perform theoretical analysis

- Large labeled datasets are rare

ImageNet Challenge



- 2010-11: hand-crafted computer vision pipelines
- 2012-2016: ConvNets
  - 2012: AlexNet
    - major deep learning success
  - 2013: ZFNet
    - improvements over AlexNet
  - 2014
    - VGGNet: deeper, simpler
    - InceptionNet: deeper, faster
  - 2015
    - ResNet: even deeper
  - 2016
    - ensembled networks
  - 2017
    - Squeeze and Excitation Network



Adapt from From NIPS 2017 DL Trend Tutorial

MIT Technology Review

10 Breakthrough Technologies 2013

Think of the most frustrating, intractable, or simply annoying problems you can imagine. Now think about what technology is doing to fix them. That's what we did in coming up with our annual list of 10 Breakthrough Technologies. We're looking for technologies that we believe will expand the scope of human possibilities.

Deep Learning

10 Breakthrough Technologies 2017

These technologies all have staying power. They will affect the economy and our politics, improve medicine, or influence our culture. Some are unfolding now; others will take a decade or more to develop. But you should know about all of them right now.

Deep Reinforcement Learning

10 BREAKTHROUGH TECHNOLOGIES 2018

Generative Adversarial Network (GAN)

Why breakthrough ?

DNNs help us build more intelligent computers

- Perceive the world,
  - e.g., objective recognition, speech recognition, …
- Understand the world,
  - e.g., machine translation, text semantic understanding
- Interact with the world,
  - e.g., AlphaGo, AlphaZero, self-driving cars, …
- Being able to think / reason,
  - e.g., learn to code programs, learn to search deepNN, …
- Being able to imagine / to make analogy,
  - e.g., learn to draw with styles, ……

Some Recent Trends

https://qdata.github.io/deep2Read/

- 1. CNN / Residual / Dynamic parameter
- 2. RNN / Attention / Seq2Seq / BERT …
- 3. Neural Architecture with explicit Memory
- 4. Learning to optimize / Learning DNN architectures
- 5. Autoencoder / layer-wise training
- 6. Learning to learn / meta-learning/ few-shots
- 7. DNN on graphs / trees / sets
- 8. NTM 4program induction / sequential decisions
- 9. Generative Adversarial Networks (GAN)
- 10. Deep Generative models, e.g., autoregressive
- 11. Deep reinforcement learning
- 12. Validate / Evade / Test / Understand / Verify DNNs

New Network topology

New Losses

New Inputs

New Tasks

New Model Properties

Machine (Deep) Learning in a Nutshell

Task:

↓

Representation:

↓

Score Function:

↓

Search/Optimization

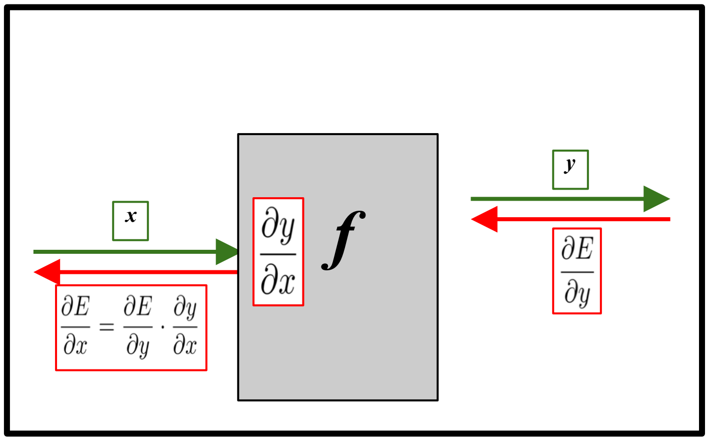
↓

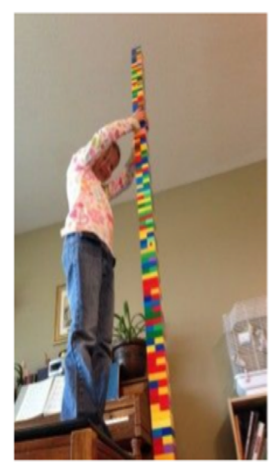
Check / Validate
(Models, Parameters)

A nutshell of Variations in **Deep NN: Five Aspects**

- Tasks:
  - Discriminative prediction / Generative / Reinforce / Reasoning
- Formulate Input / Output:
  - Data representation
- Architecture Design:
  - Network Topology, Network Parameters
- Training / Searching / Learning
  - With new losses
  - With new optimization tricks
  - New formulation of learning
  - Scaling up with GPU, Scaling up with distributed optimization , e.g. Asynchronous SGD
- Validation / Trust / Test / Understand …
  - Software 2.0

Building Deep Neural Nets





http://cs231n.stanford.edu/slides/winter1516_lecture5.pdf

Today's Survey: Trends since ~2011

Inputs and Outputs

Losses

Architectures:

Software 2.0

Validation

Adapt from From NIPS 2017 DL Trend Tutorial

Recent Trend (1):
Convolutional Neural Networks
(aka CNNs and ConvNets)

Architectures:
- Convolutions

Machine (Deep) Learning in a Nutshell

Task:

Representation:

Score Function:

Search/Optimization

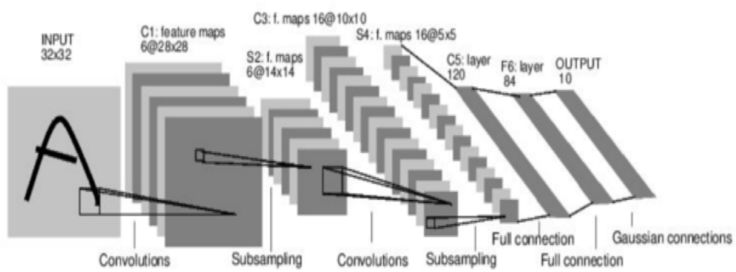
Check / Validate
(Models, Parameters)

- New Network Topology, Network Parameters

History of ConvNets

1998

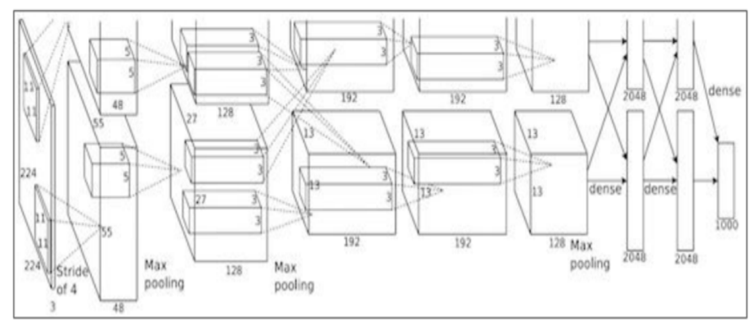
Gradient-based learning applied to document recognition [LeCun, Bottou, Bengio, Haffner]



LeNet-5

2012

ImageNet Classification with Deep Convolutional Neural Networks [Krizhevsky, Sutskever, Hinton, 2012]



“AlexNet”

Important Block: Convolutional Neural Networks (CNN)

- Prof. Yann LeCun invented CNN in 1998
- First NN successfully trained with many layers



The bird occupies a local area and looks the same in different parts of an image.
We should construct neural nets which exploit these properties!

Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86(11): 2278–2324, 1998.

Adapt from From NIPS 2017 DL Trend Tutorial

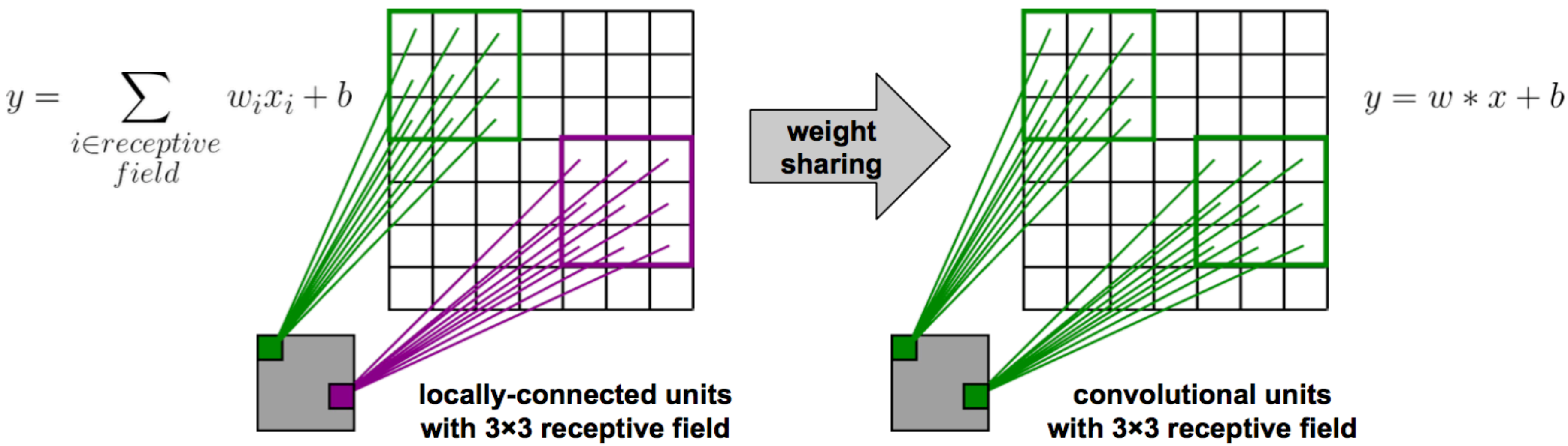
Locality and Translation Invariance

- **Locality**: objects tend to have a local spatial support
- **Translation invariance**: object appearance is independent of location

- Can define these properties since an image lies on a grid/lattice
  - ConvNet machinery applicable to other data with such properties, e.g. audio/text

CNN models Locality and Translation Invariance

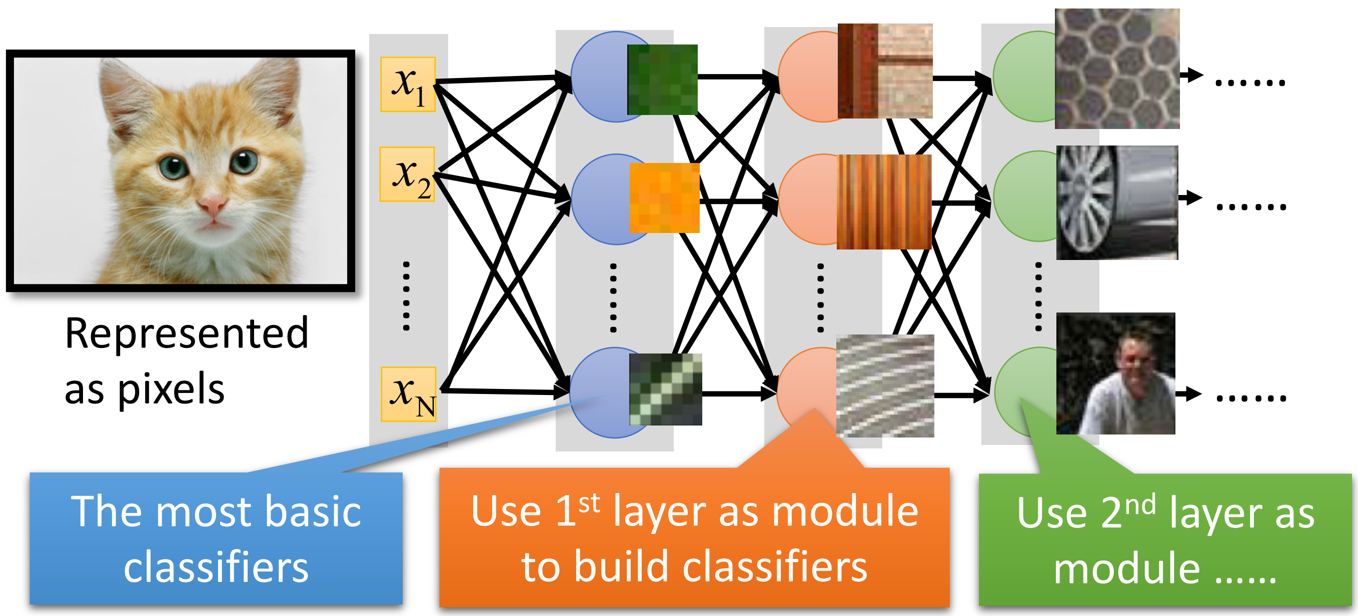
Make fully-connected layer locally-connected and sharing weight



Adapt from From NIPS 2017 DL Trend Tutorial

Why CNN for Image?

[Zeiler, M. D., *ECCV 2014*]



Can the MLP network be simplified by considering the properties of images?

Why CNN for Image

- (1) Locality: Some patterns are much smaller than the whole image

A neuron does not have to see the whole image to discover the pattern.

Connecting to small region with less parameters

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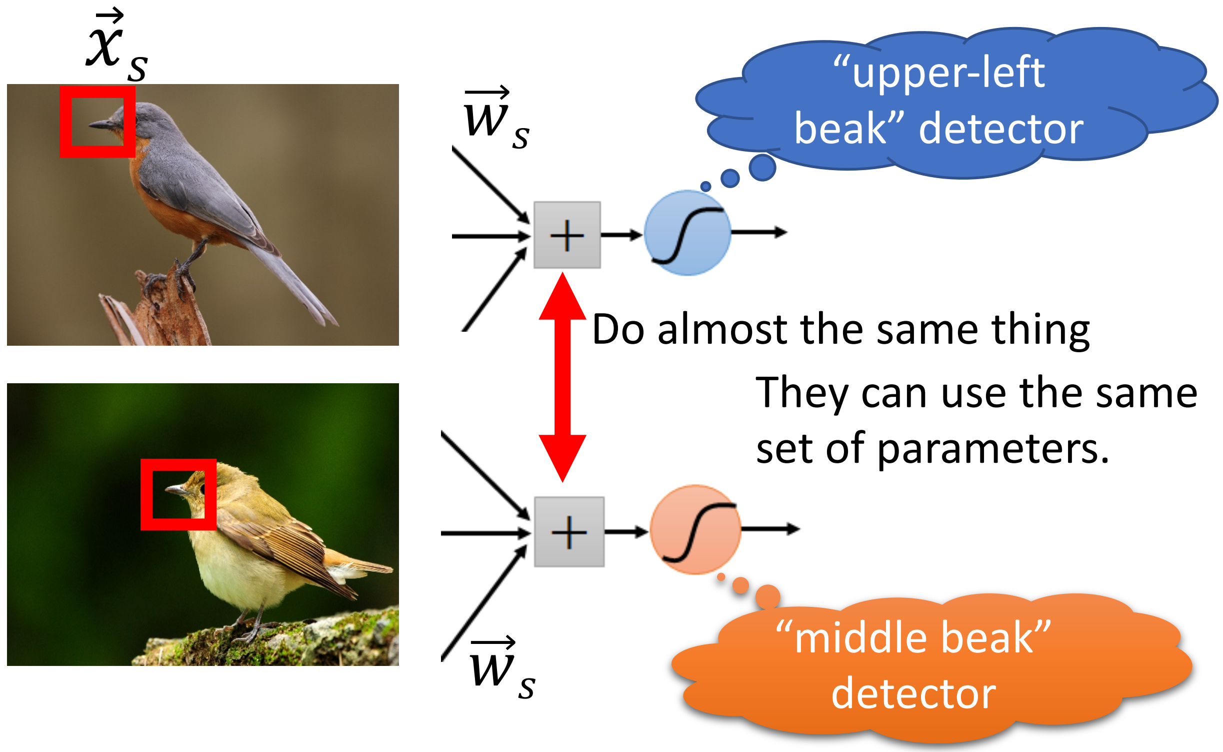
Why CNN for Image

- (2) Translation invariance: The same patterns appear in different regions.



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Why CNN for Image

- (3) Subsampling the pixels will not change the object

bird

subsampling

bird

We can subsample the pixels to make image smaller

➡ Less parameters for the network to process the image

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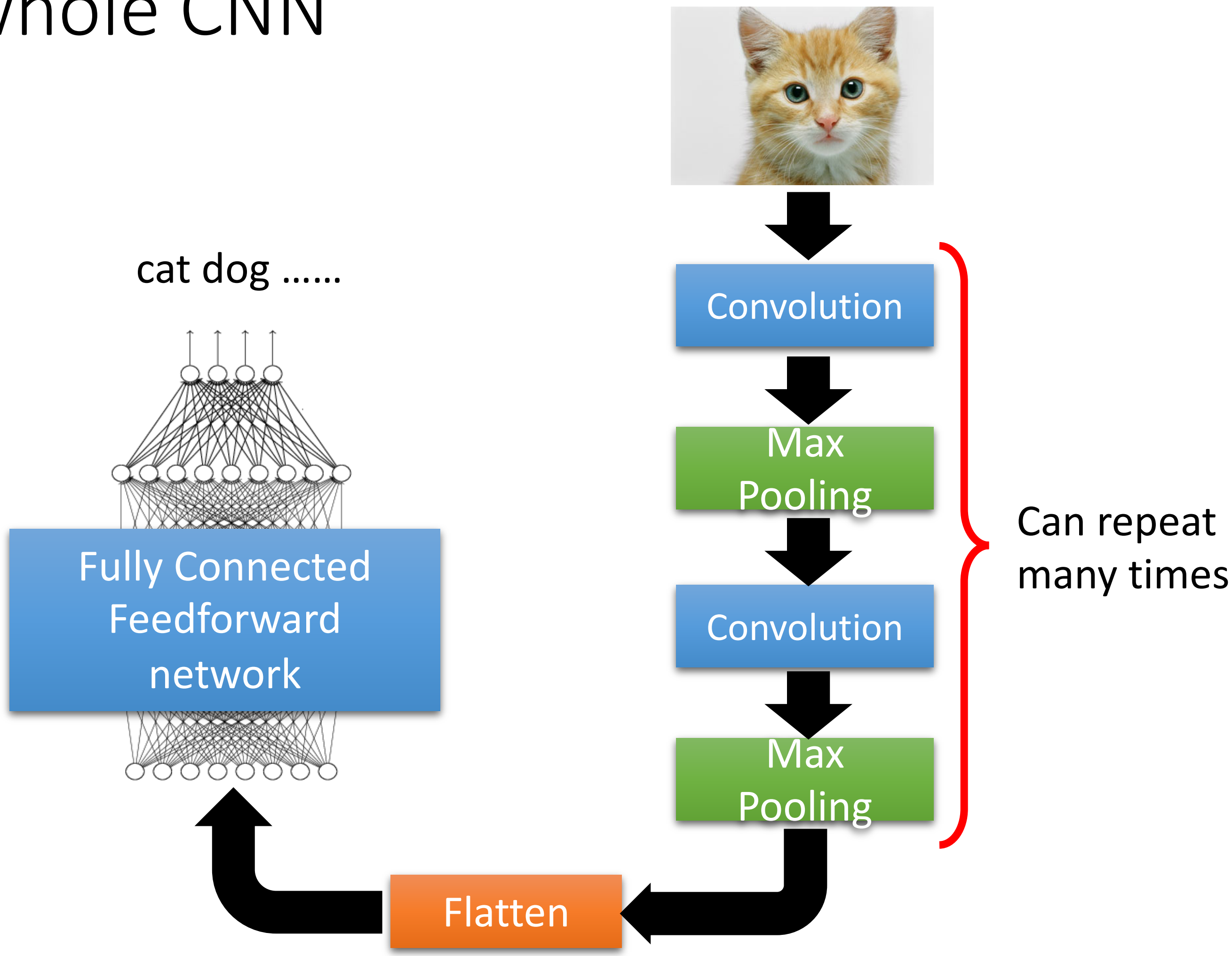
The whole CNN



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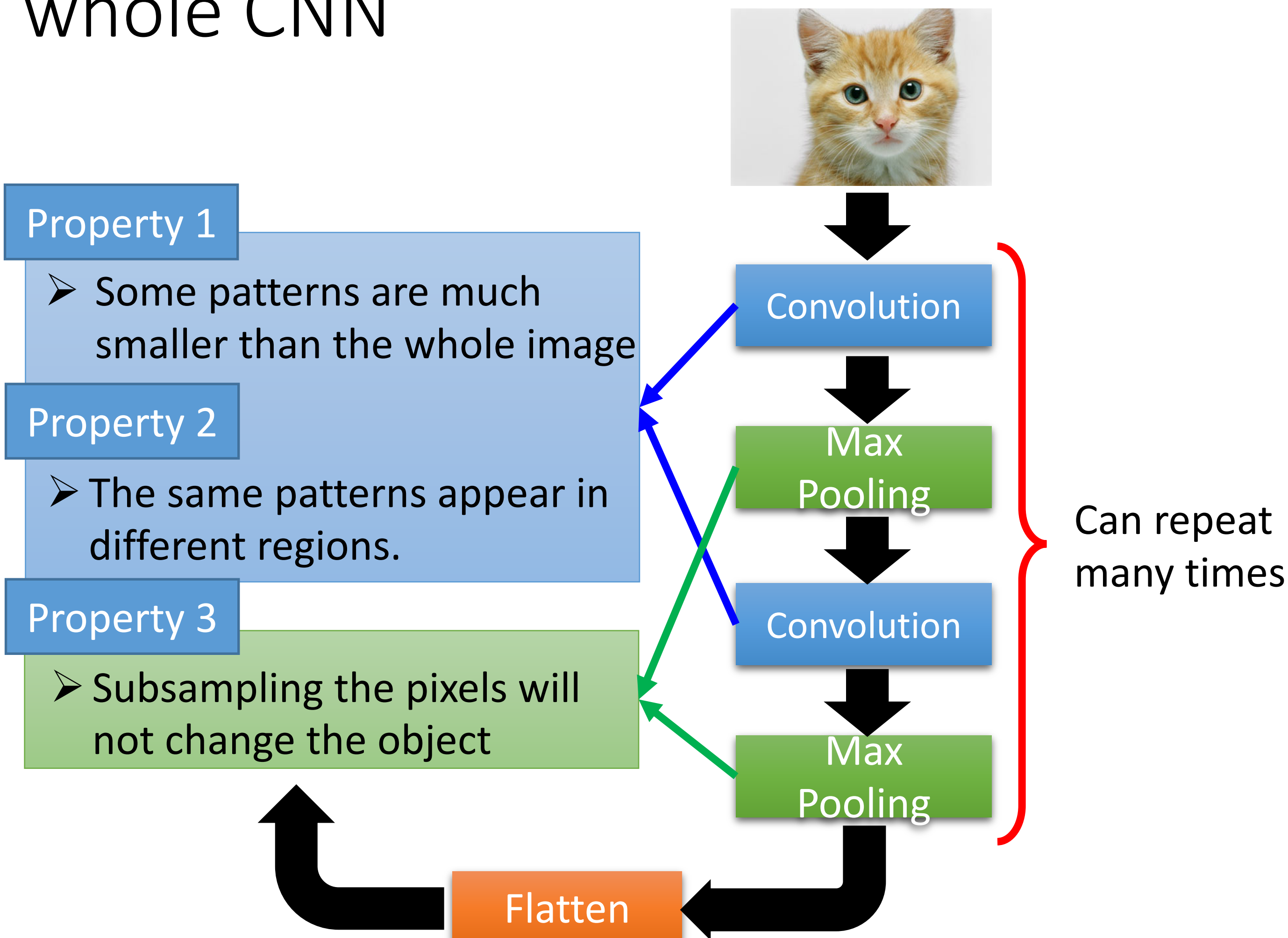
The whole CNN



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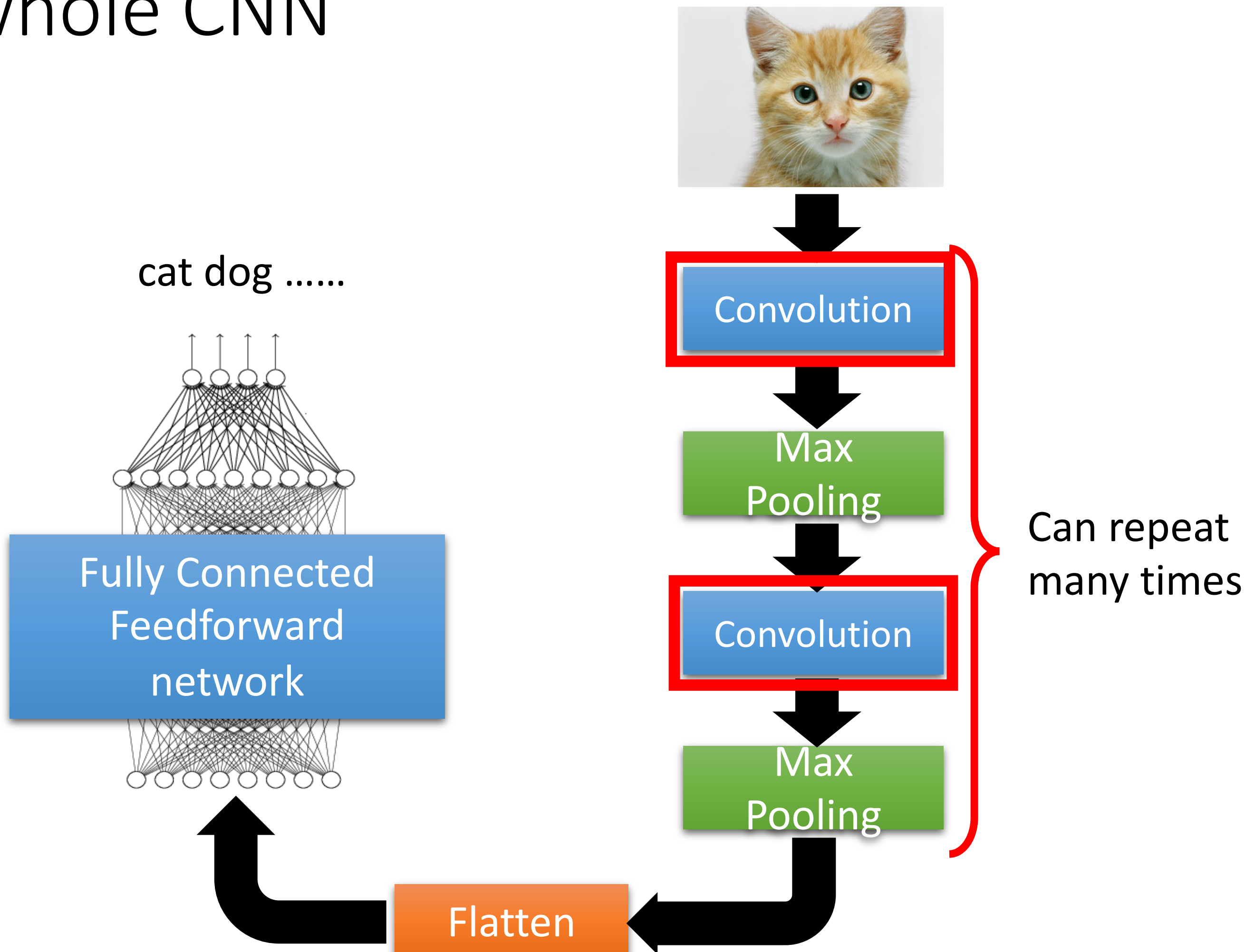
The whole CNN



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CNN – Convolution

Those are the network parameters to be learned.

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

Matrix $\vec{w}_{s1}$

"detector 1"

-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

Matrix $\vec{w}_{s2}$

"detector 2"

⋮ ⋮

Property 1 Each filter detects a small pattern (3 x 3).

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CNN – Convolution

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

3 -1

CNN – Convolution

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

If stride=2

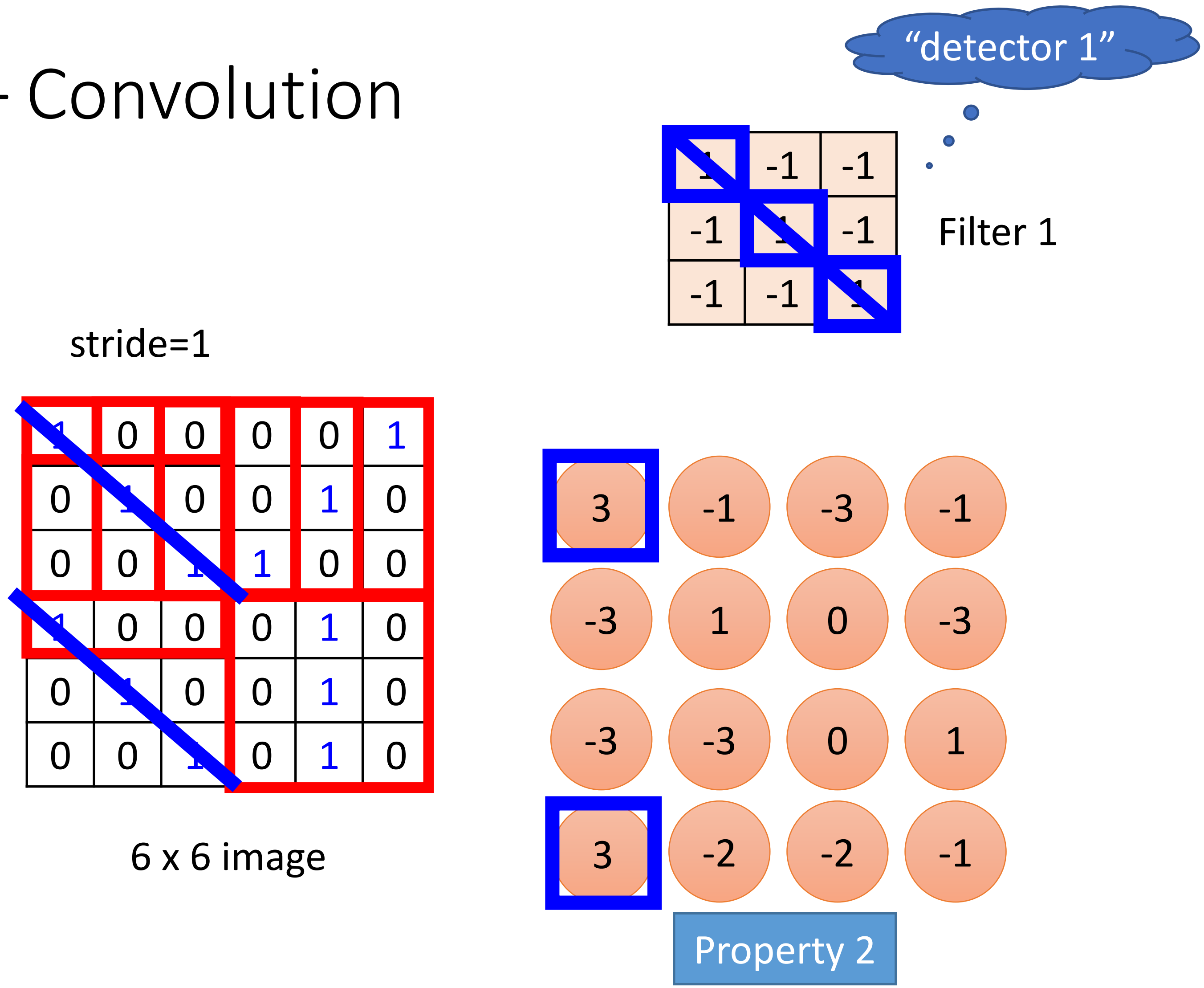
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

3 -3

We set stride=1 below

CNN – Convolution



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CNN – Convolution

“detector 2”

-1	1	-1
-1	1	-1
-1	1	-1

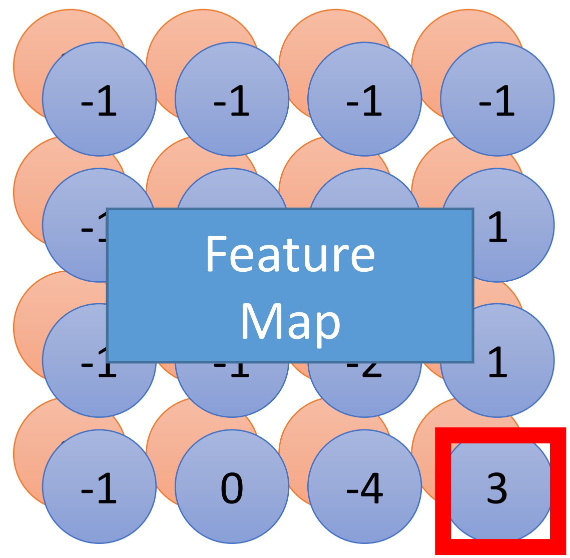
Filter 2

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

Do the same process for every filter



4 x 4 image

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CNN – Convolution

“detector 2”

-1	1	-1
-1	1	-1
-1	1	-1

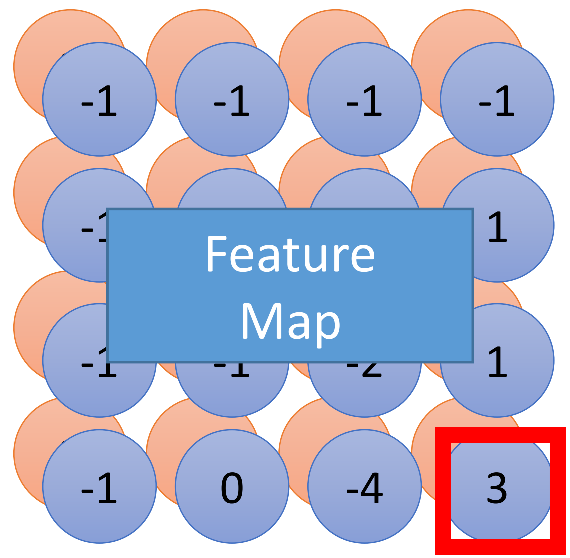
Filter 2

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

Do the same process for every filter



4 x 4 image

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CNN – Convolution

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

-1	1	-1
-1	1	-1
-1	1	-1

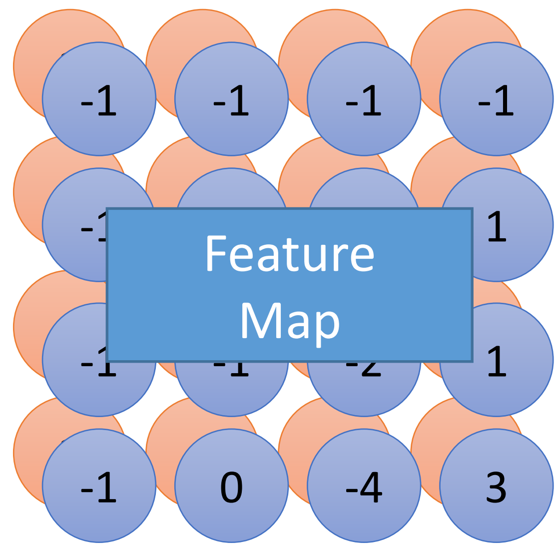
Filter 2

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

You can do the same process for every filter



4 x 4 image

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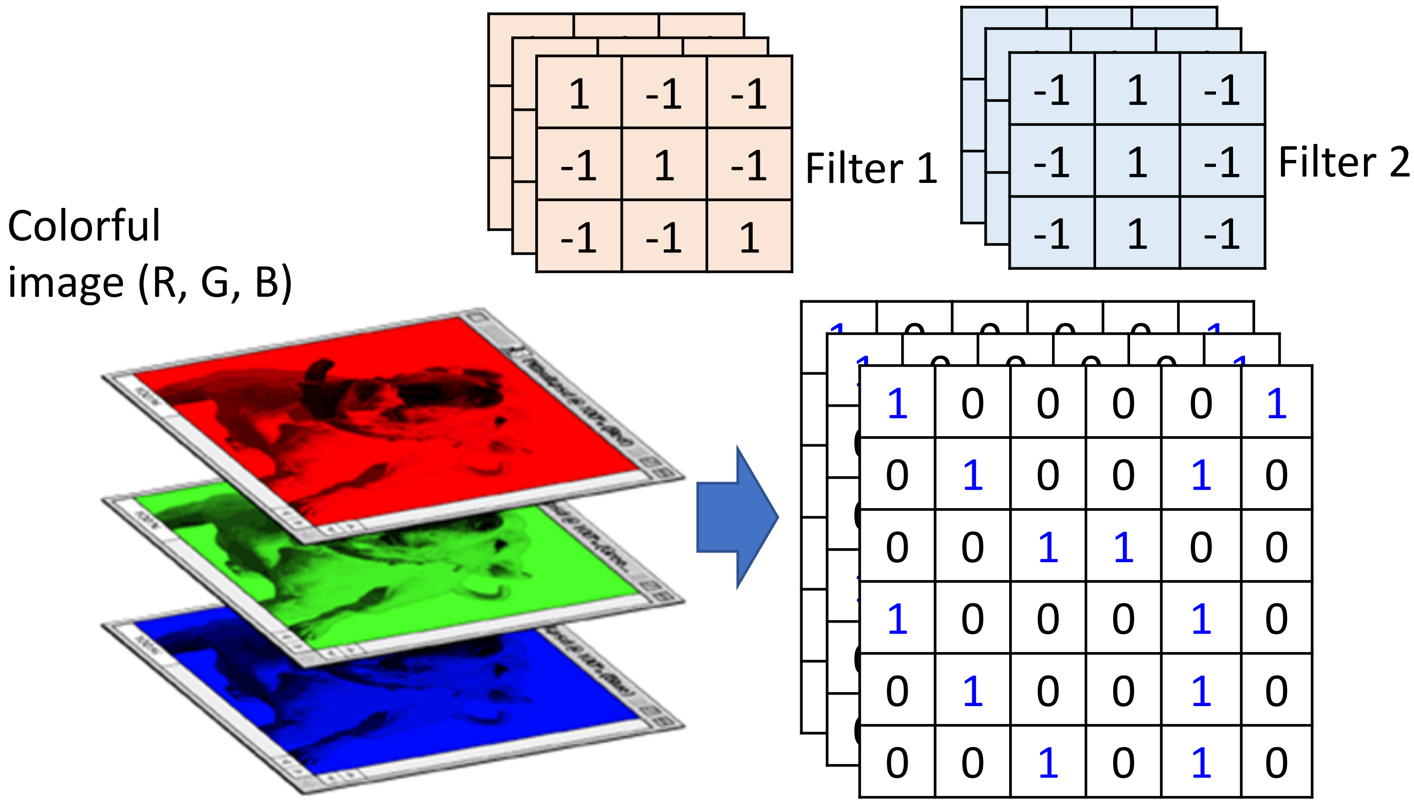
CNN – Colorful image (from matrix to tensor)



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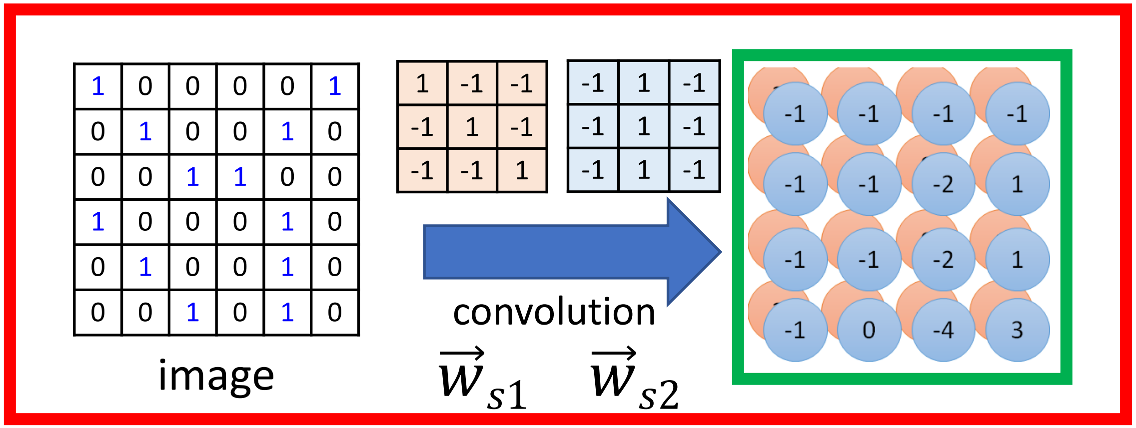
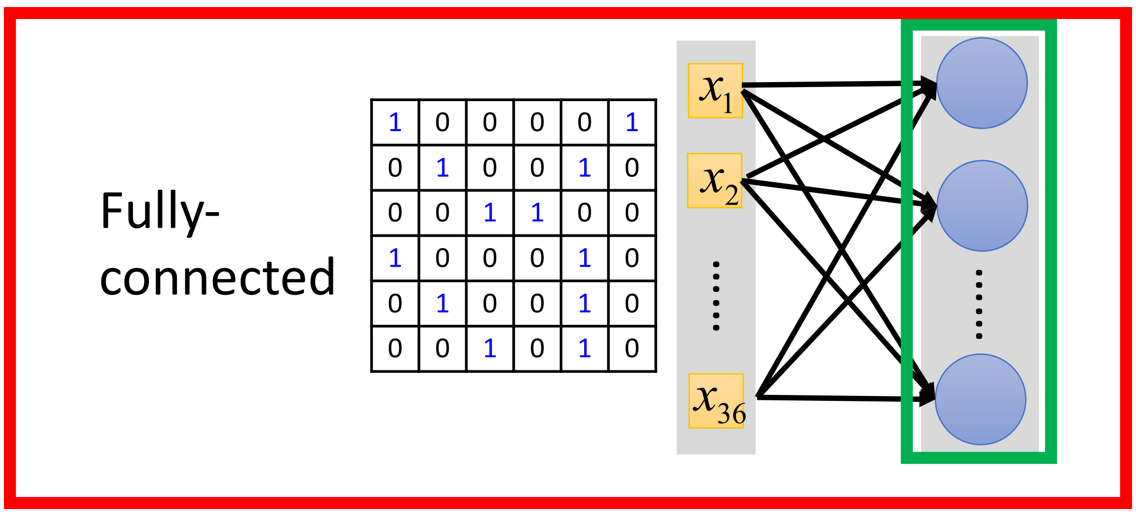
Convolution v.s. Fully Connected





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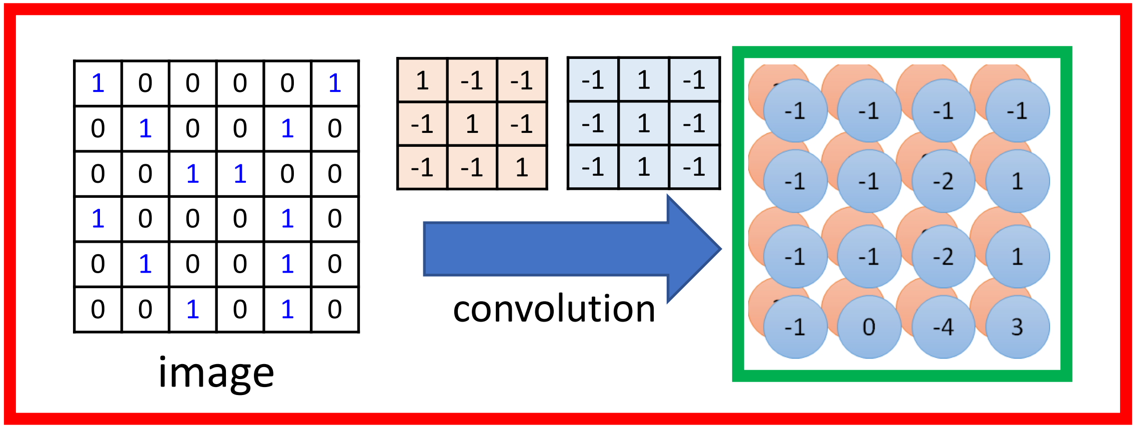
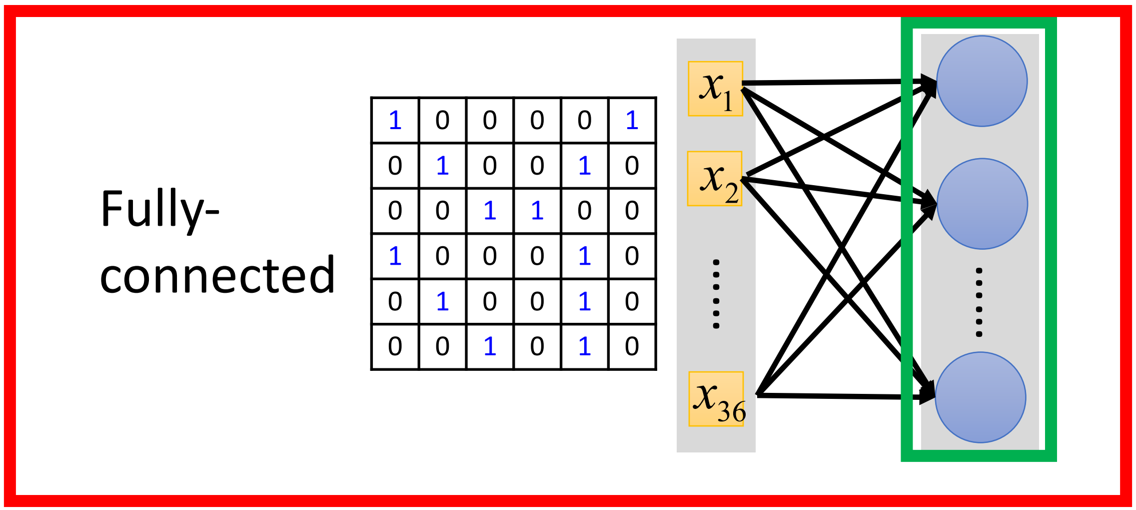
Convolution v.s. Fully Connected

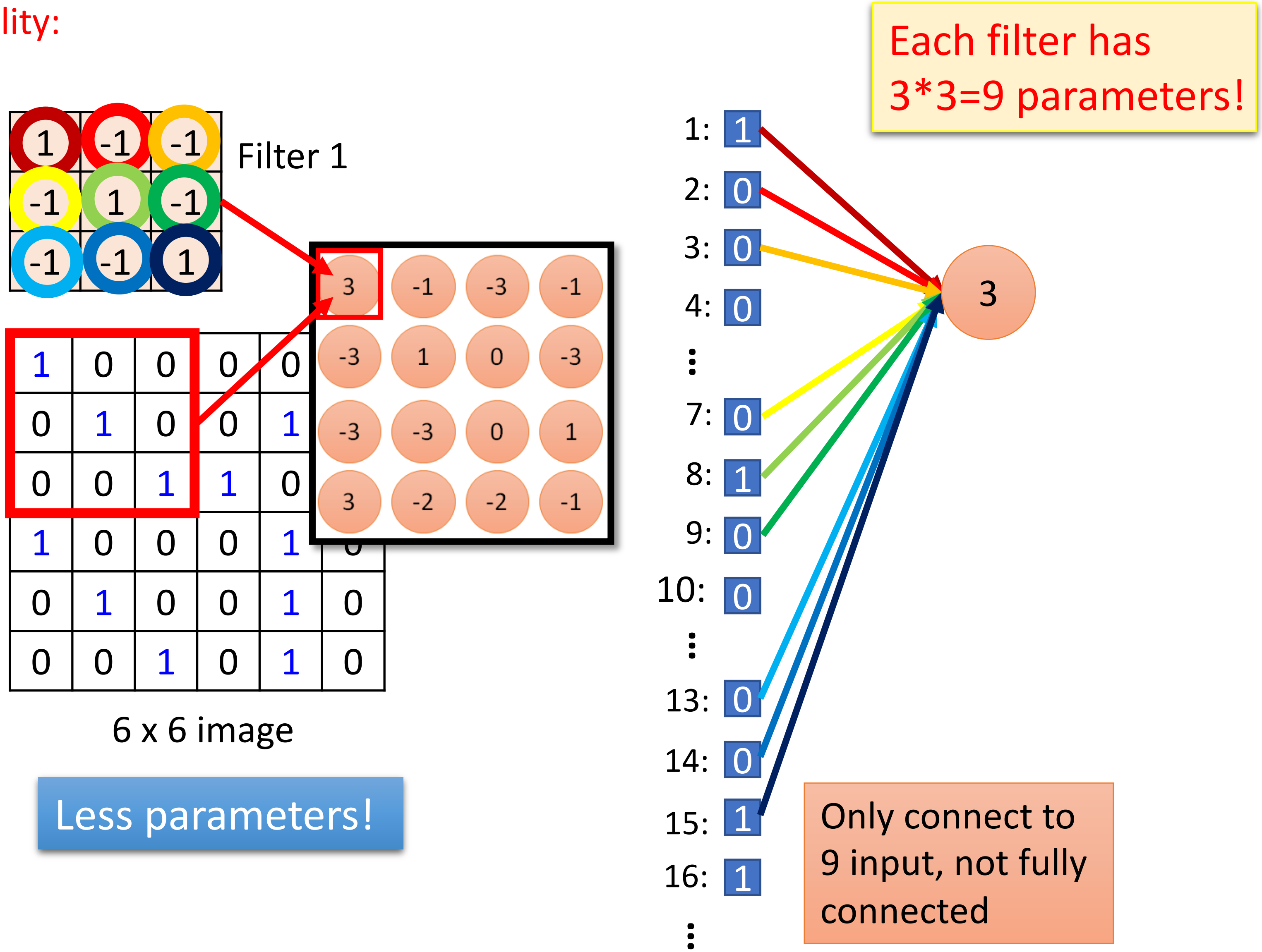
When with 2 filters, 3*3*2=18 parameters!





When 2 filters, 36*2=72 parameters!

(1) Locality:



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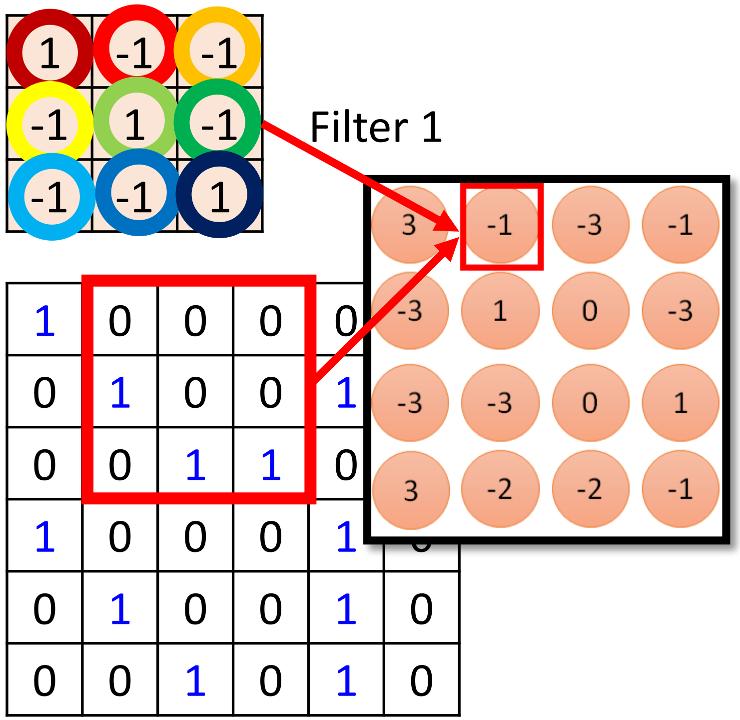
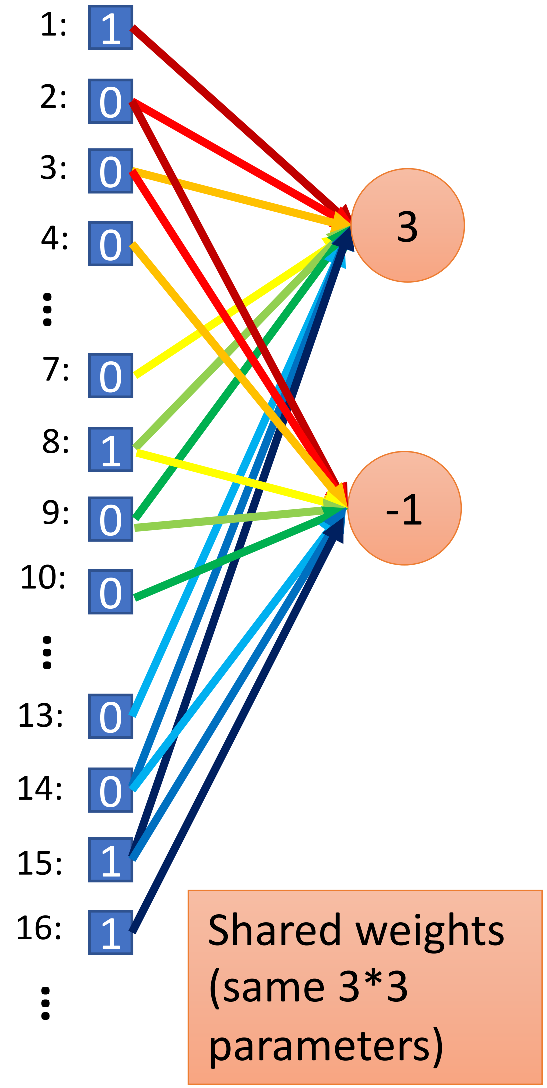
(2) Translation invariance:



6 x 6 image



Less parameters!

Even less parameters! (weight sharing)

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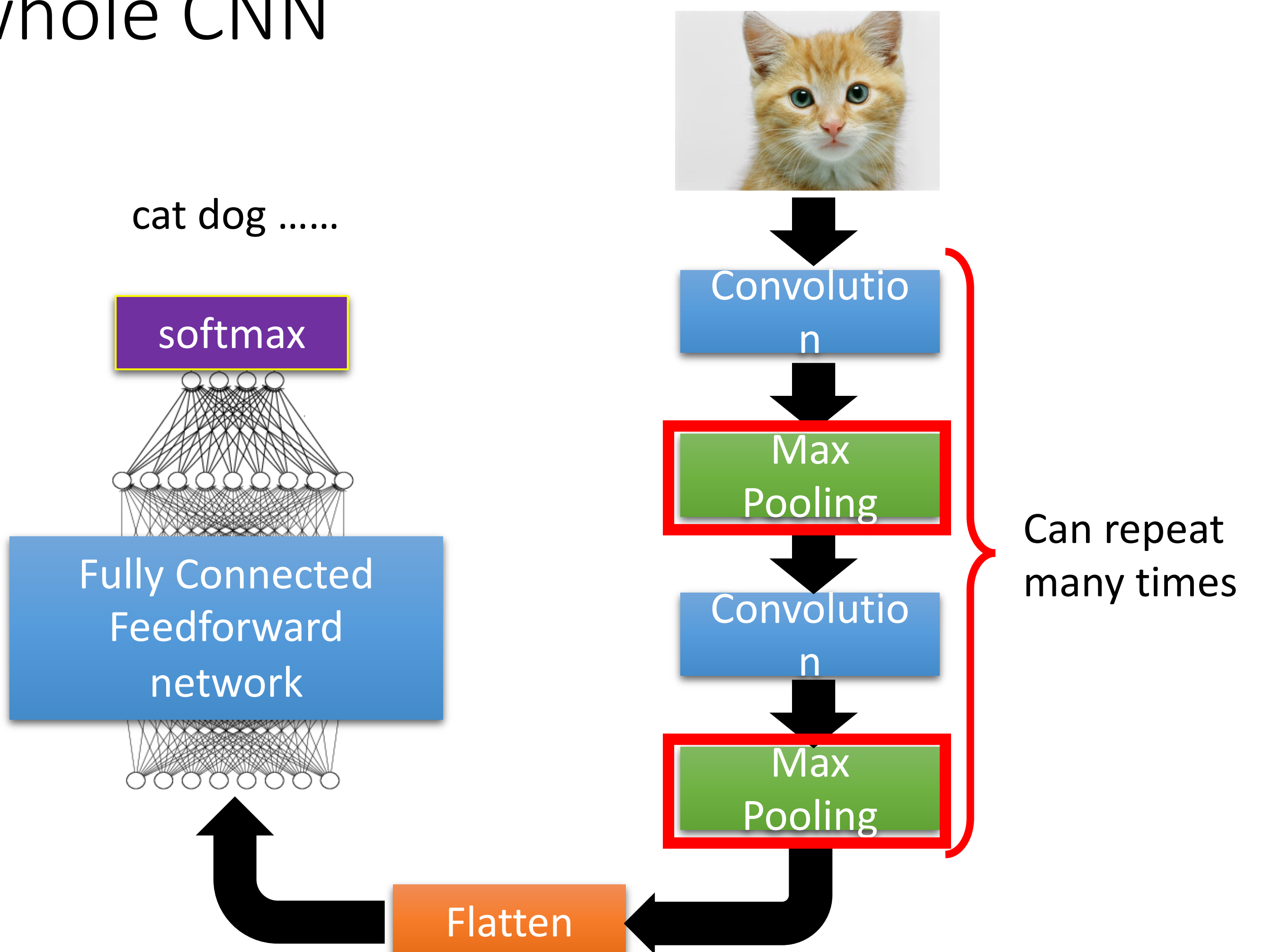
The whole CNN



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(3) Subsampling:

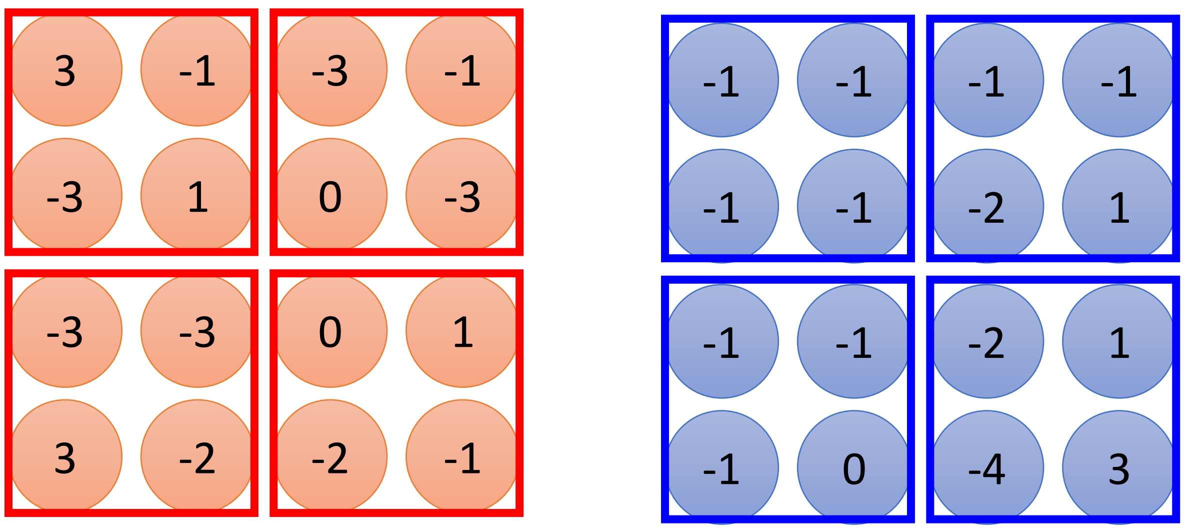
CNN – Max Pooling

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

-1	1	-1
-1	1	-1
-1	1	-1

Filter 2



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(3) Subsampling:

CNN – Max Pooling

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Filter 1

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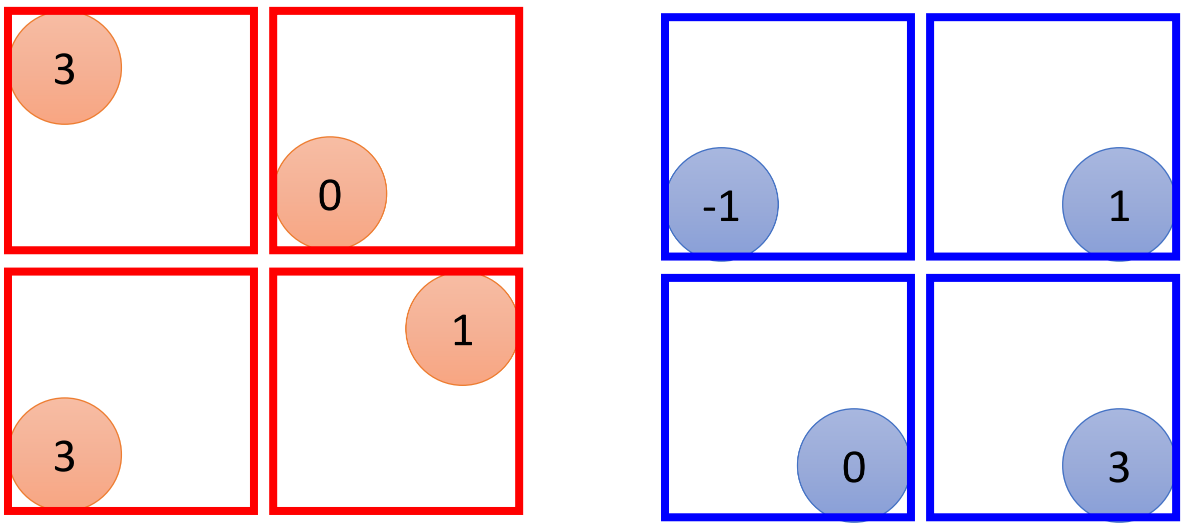
-1	1	-1

Filter 2



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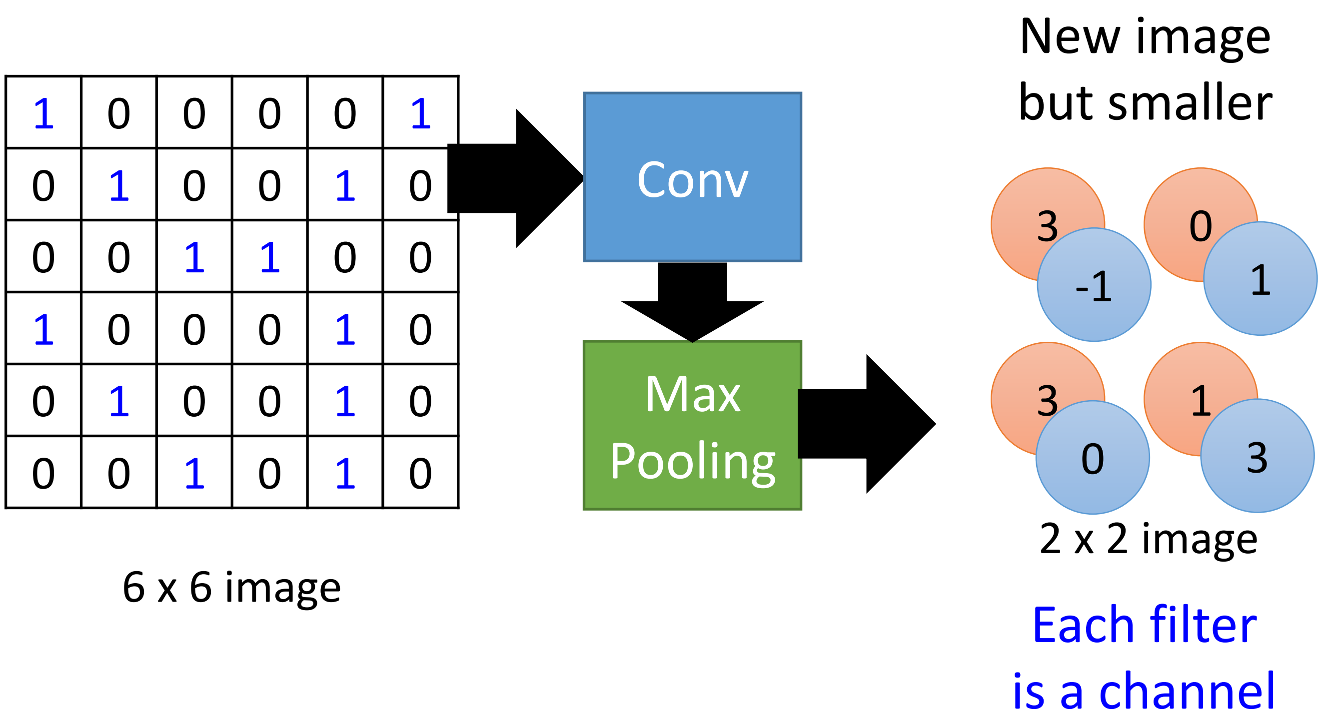
(3) Subsampling:

CNN – Max Pooling



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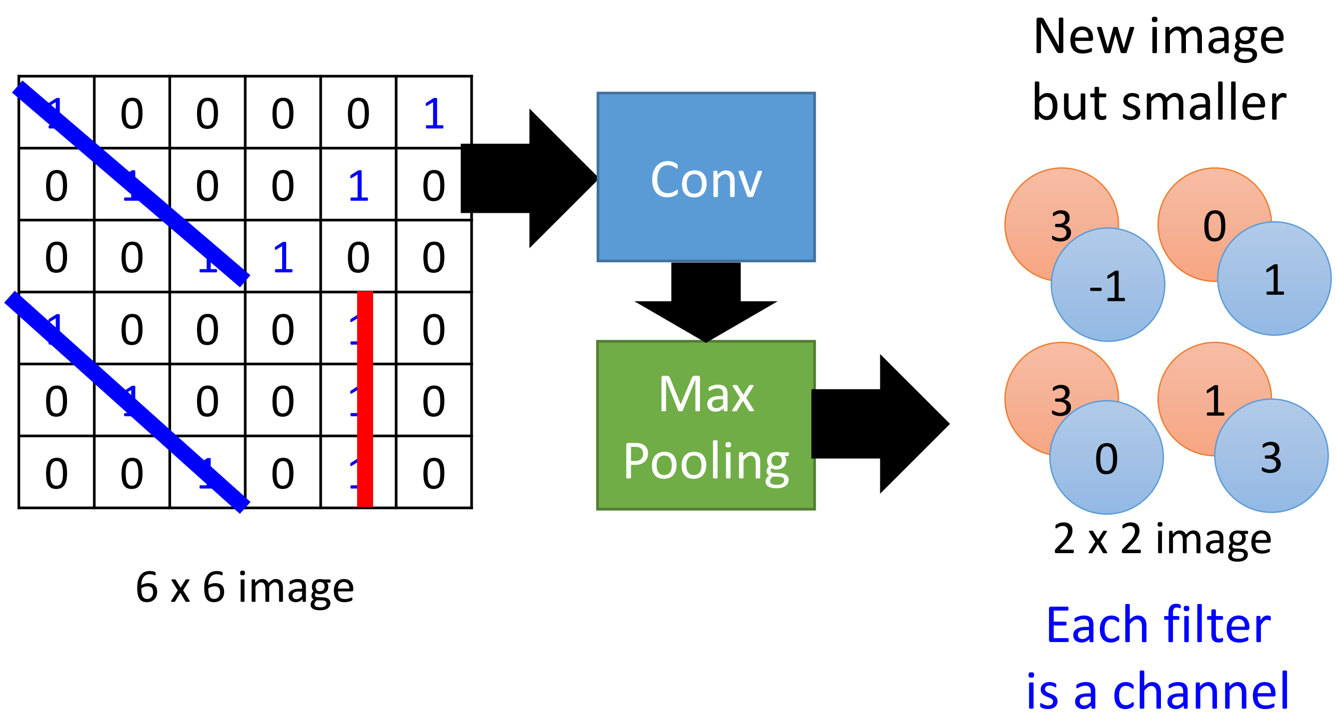
(3) Subsampling:

CNN – Max Pooling



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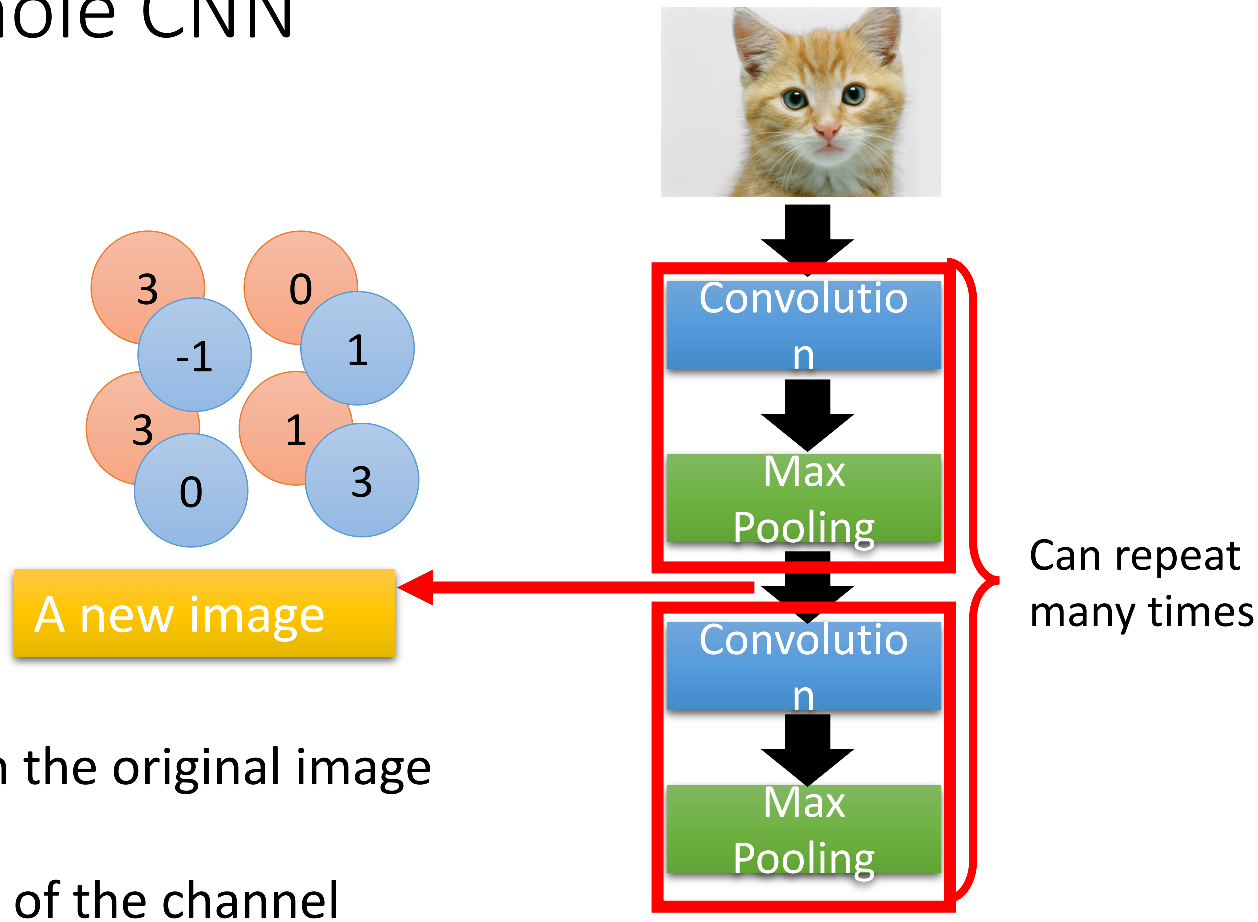
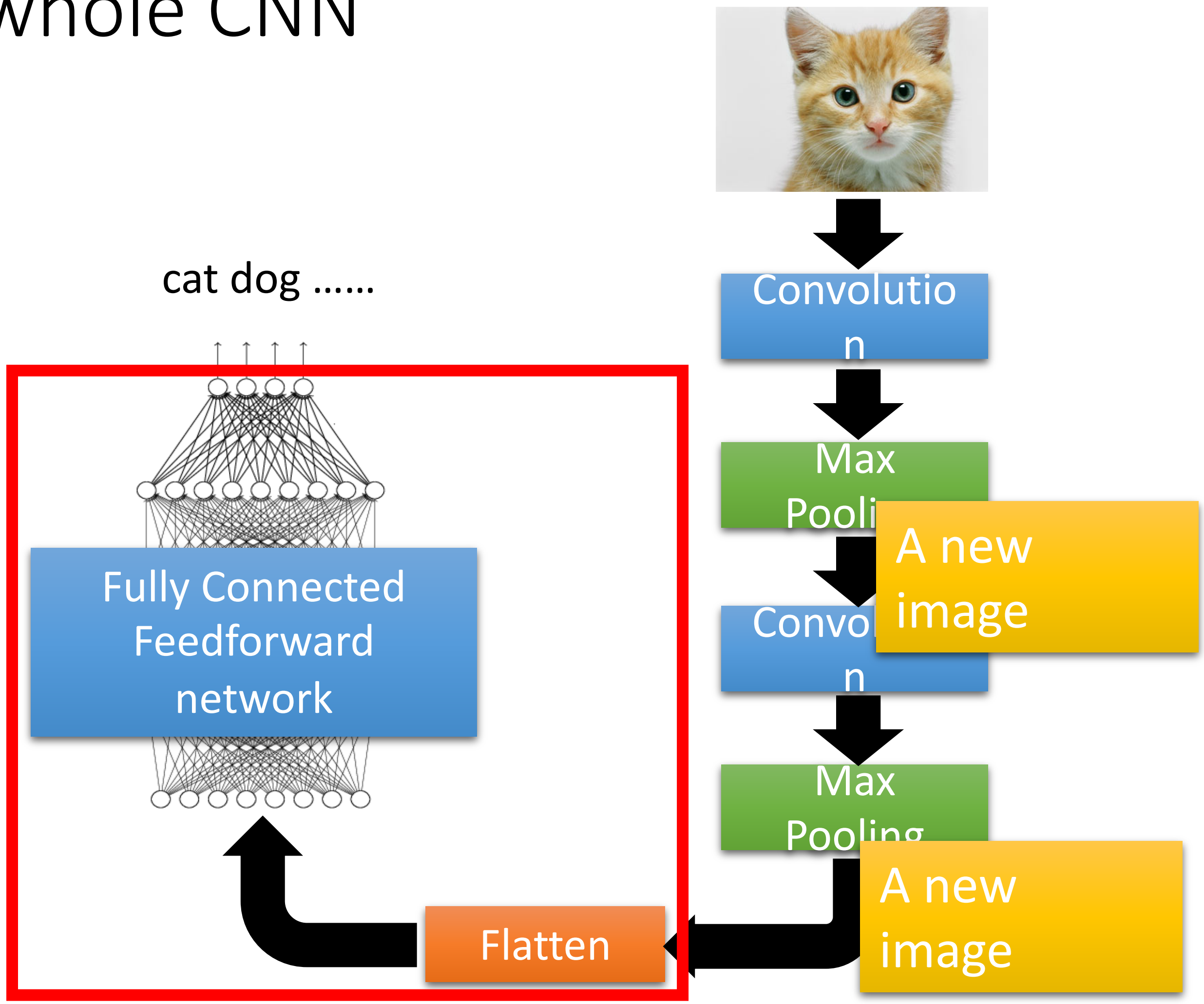
The whole CNN



Smaller than the original image

The number of the channel
is the number of filters

The whole CNN



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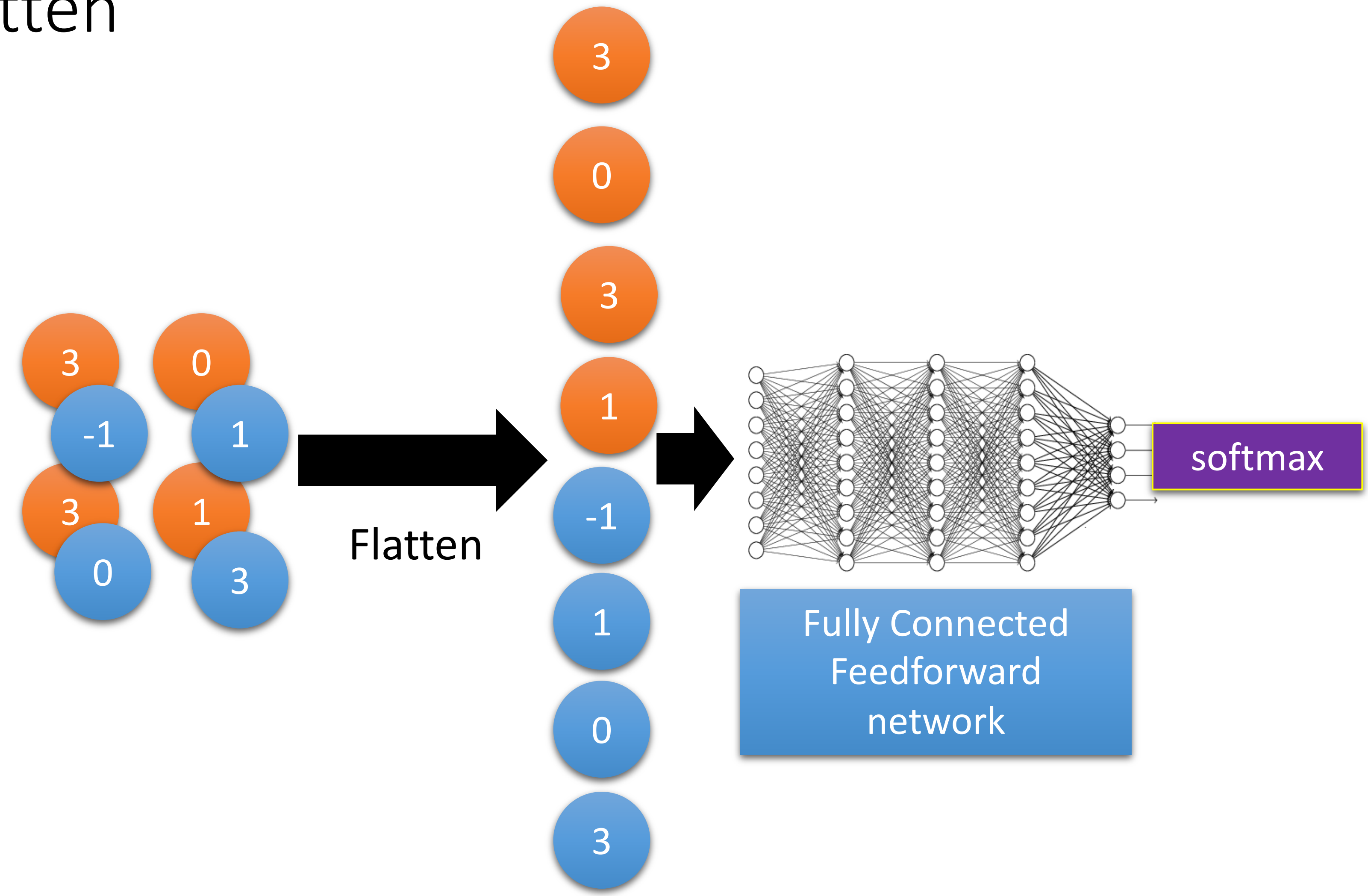
Flatten



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CNN in Keras

network structure and ***input format***
(vector -> 3-D tensor)

```
model2.add( Convolution2D( 25,3,3,
        input_shape=(1,28,28) ) )
```

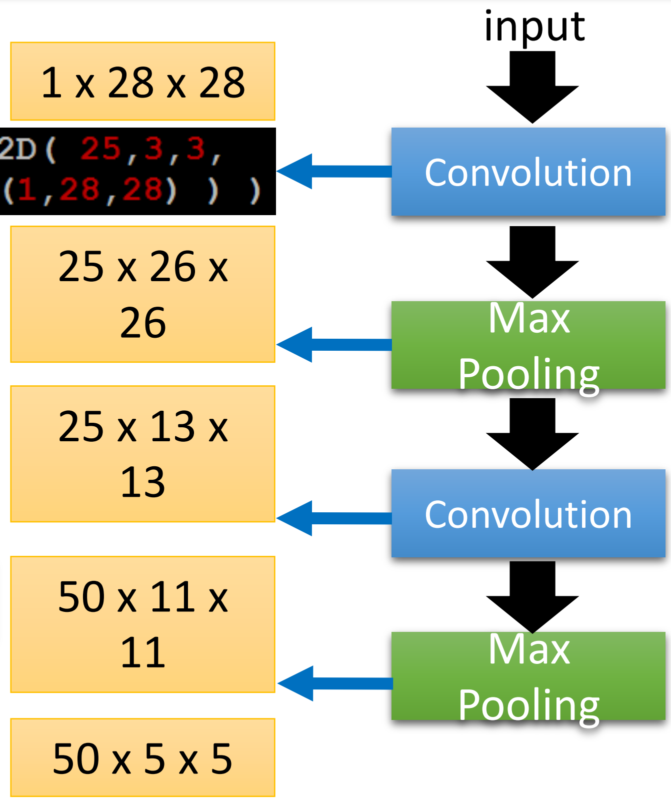
How many parameters for each filter? **9**

```
model2.add(MaxPooling2D((2,2)))
```

```
model2.add(Convolution2D(50,3,3))
```

How many parameters for each filter? **225**

```
model2.add(MaxPooling2D((2,2)))
```



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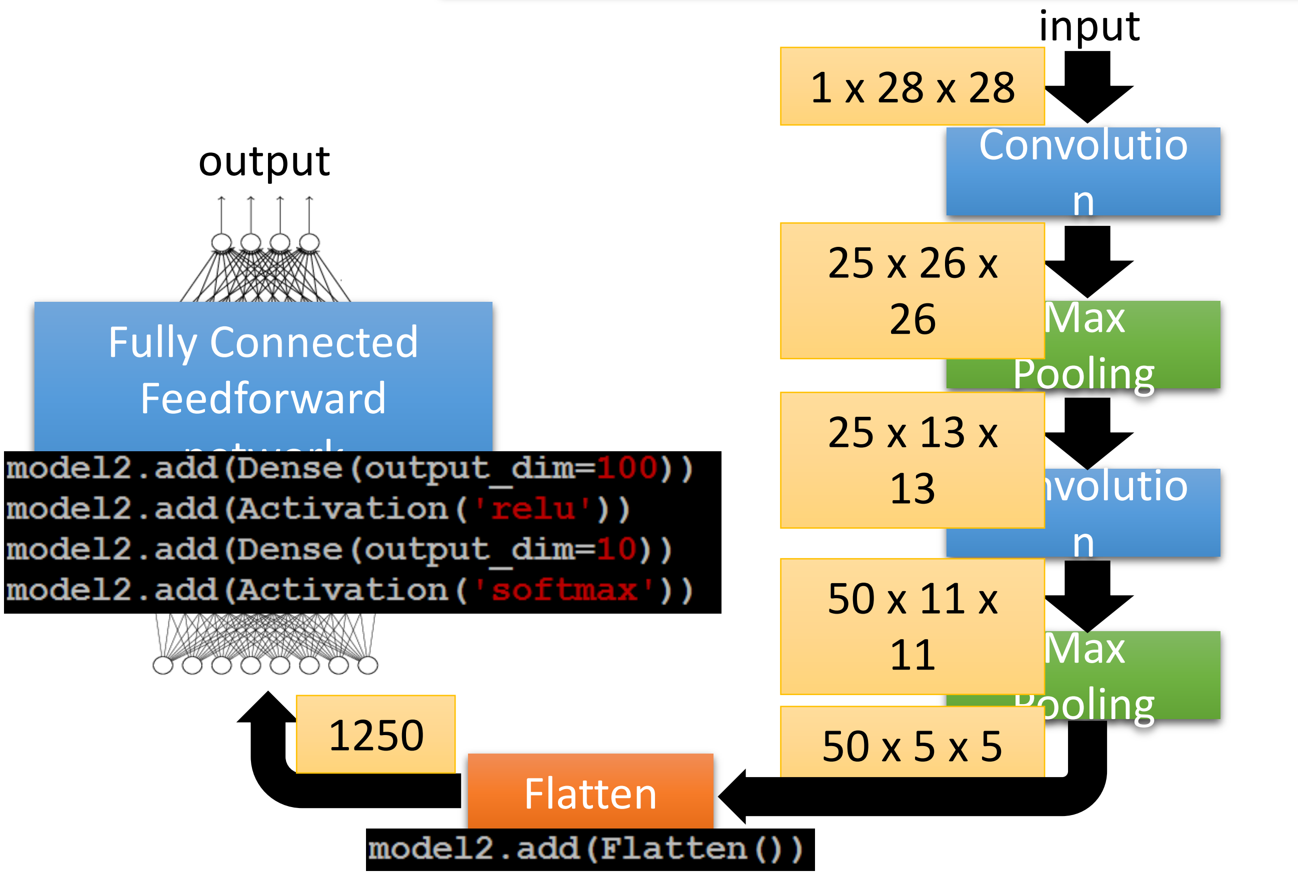
CNN in Keras

Only modified the ***network structure*** and ***input format (vector -> 3-D tensor)***




```
model2.add(Dense(output_dim=100))
model2.add(Activation('relu'))
model2.add(Dense(output_dim=10))
model2.add(Activation('softmax'))
```

```
model2.add(Flatten())
```

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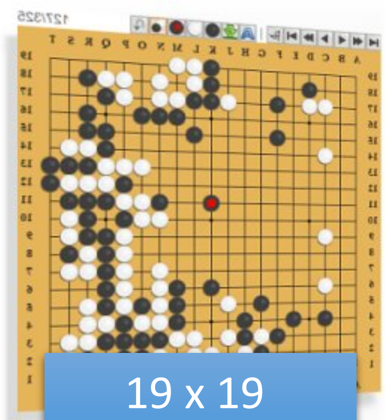
More Application: Playing Go



19 x 19 matrix (image)

Network

Next move (19 x 19 positions)

19 x 19 vector

Black: 1

white: -1

none: 0

Fully-connected feedforward network can be used

But CNN performs much better.

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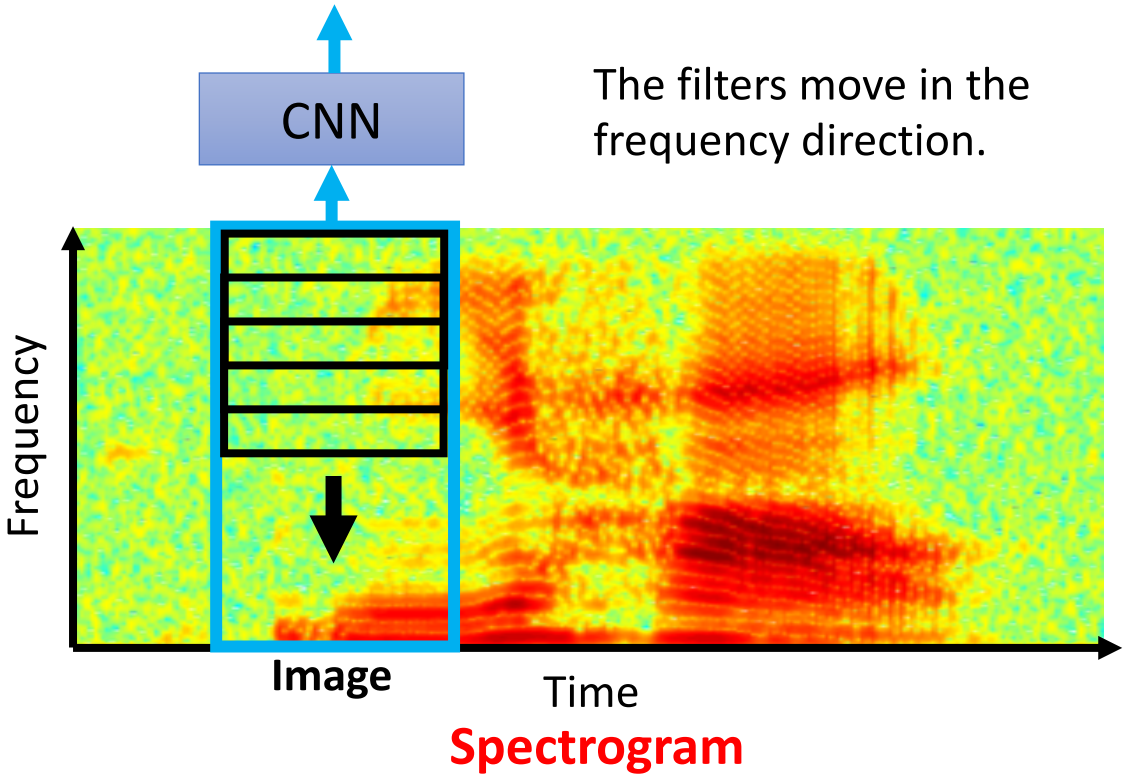
More Application: Speech

The filters move in the frequency direction.



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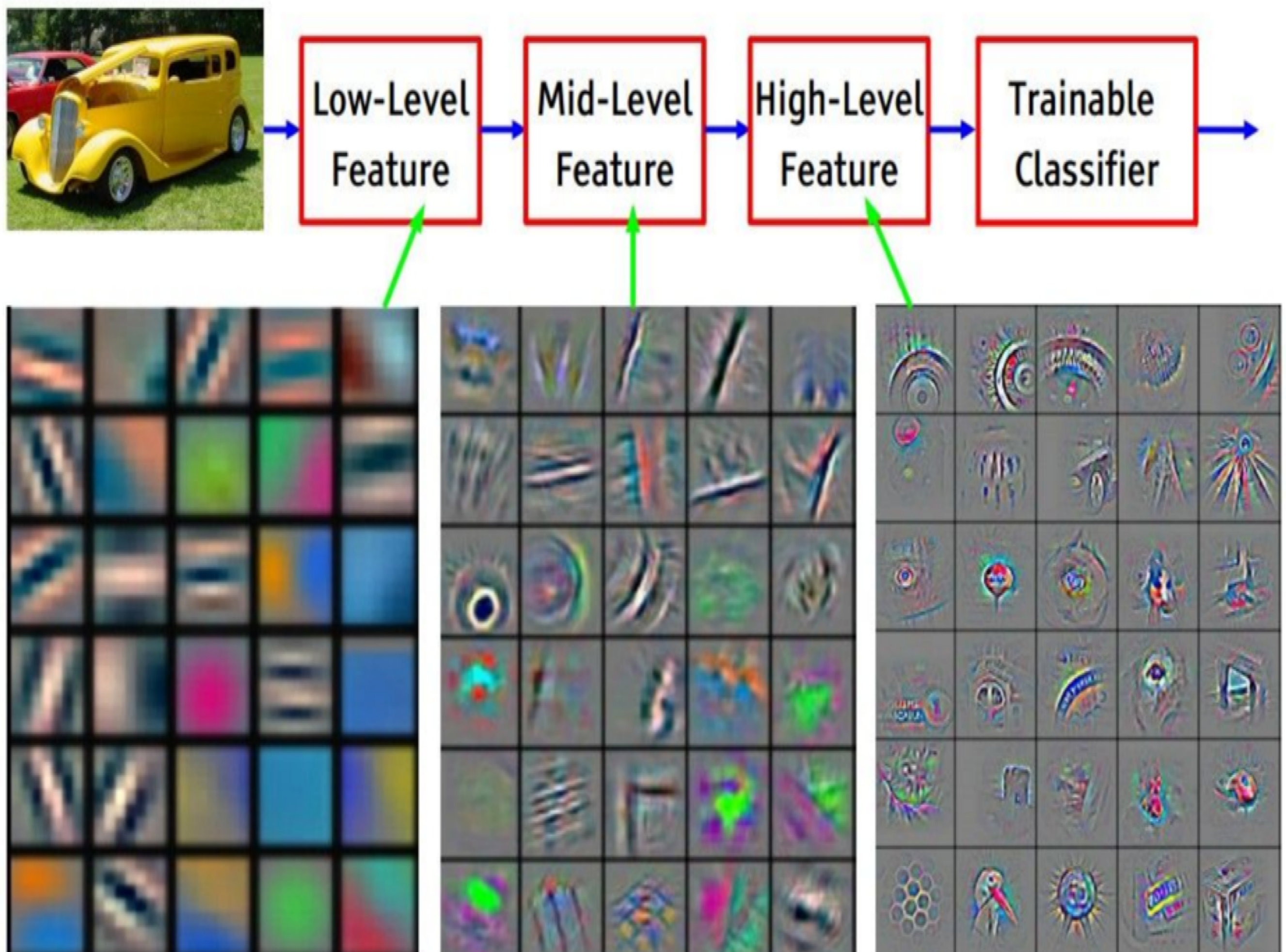
Convolutional Neural Networks

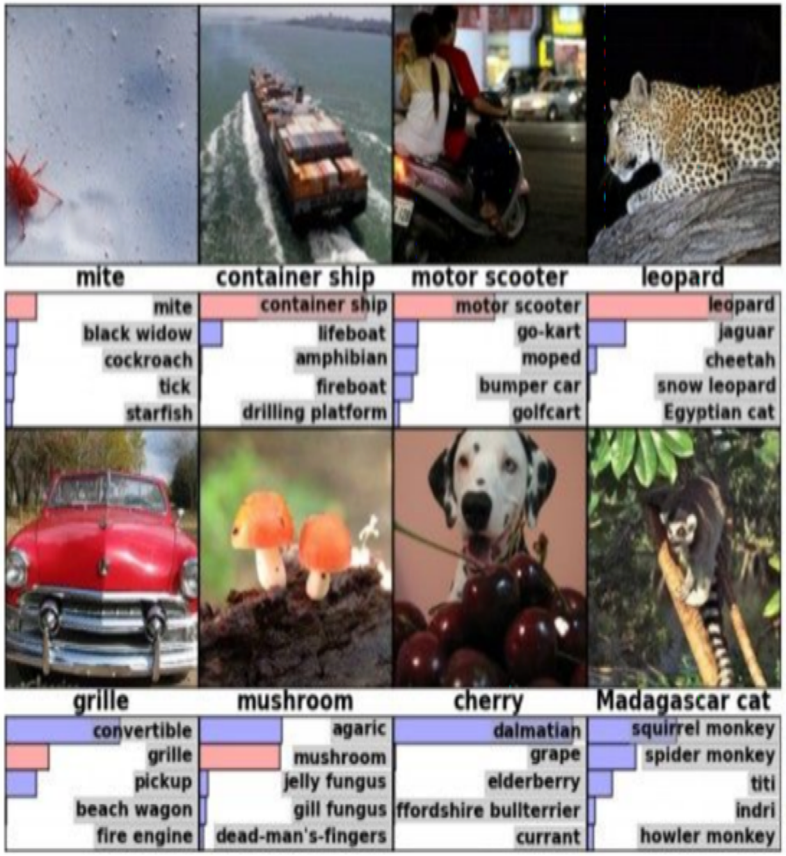
[From recent Yann LeCun slides]



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

Fast-forward to today: ConvNets are everywhere

Classification

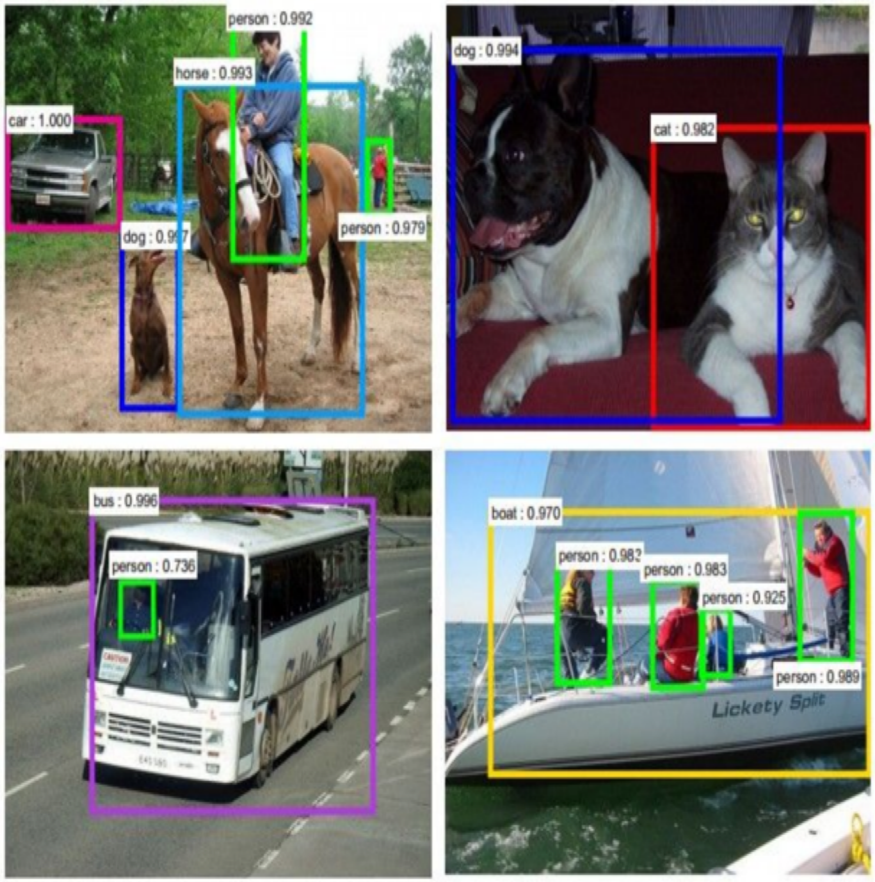


Retrieval

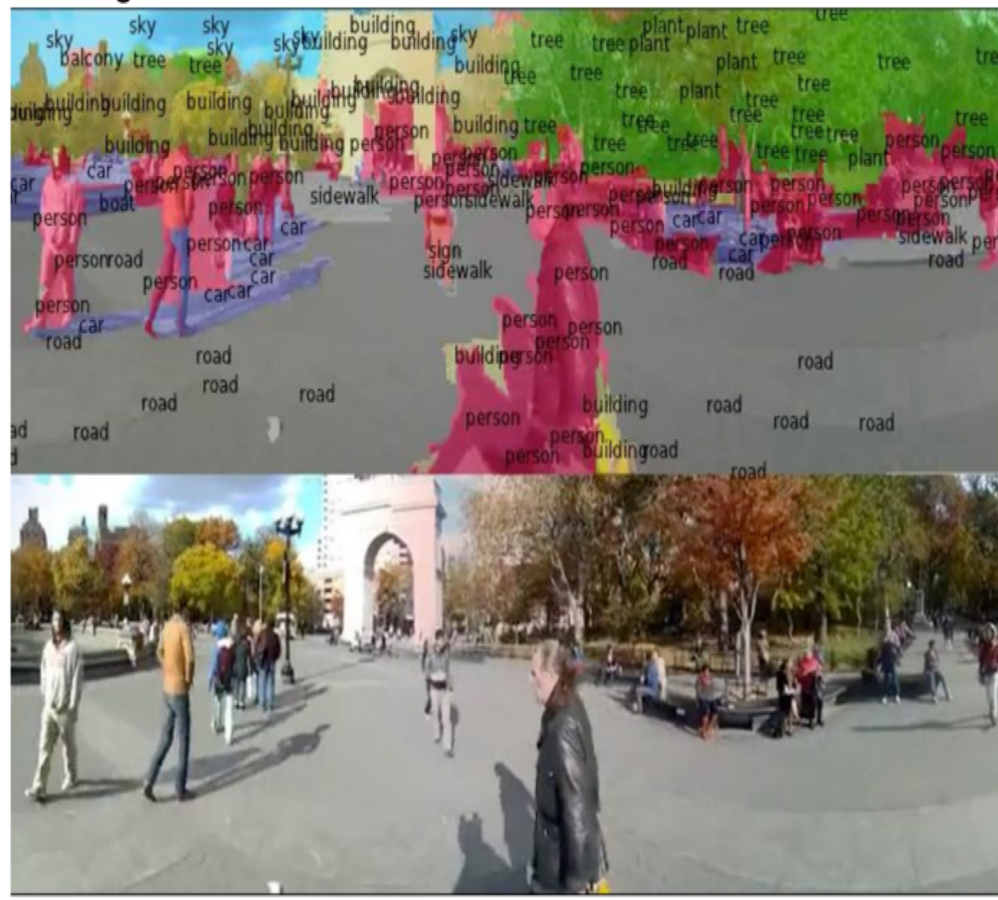
[Krizhevsky 2012]

Fast-forward to today: ConvNets are everywhere

Detection



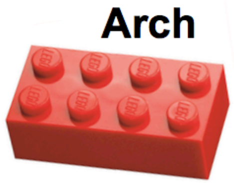
Segmentation



[Faster R-CNN: Ren, He, Girshick, Sun 2015]

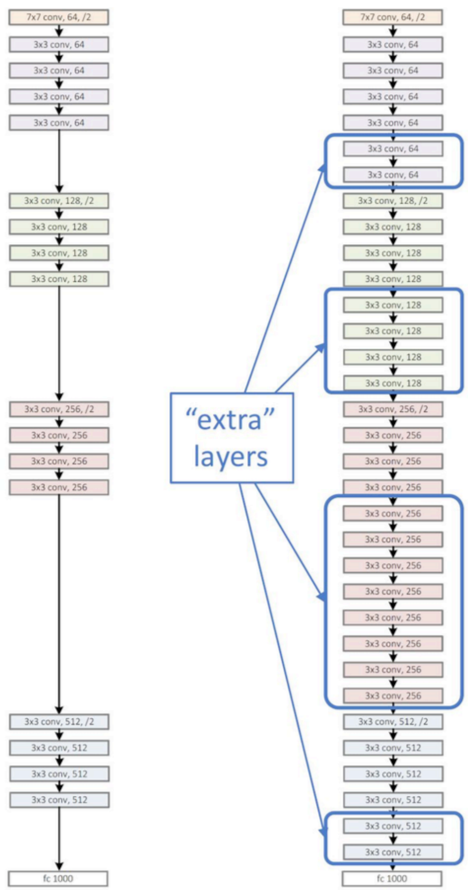
[Farabet et al., 2012]

Residual Trick:



Residual/Skip Connections

a shallower model (18 layers)

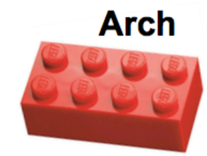


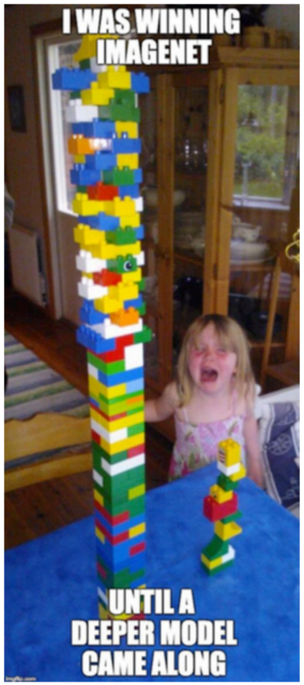
a deeper counterpart (34 layers)

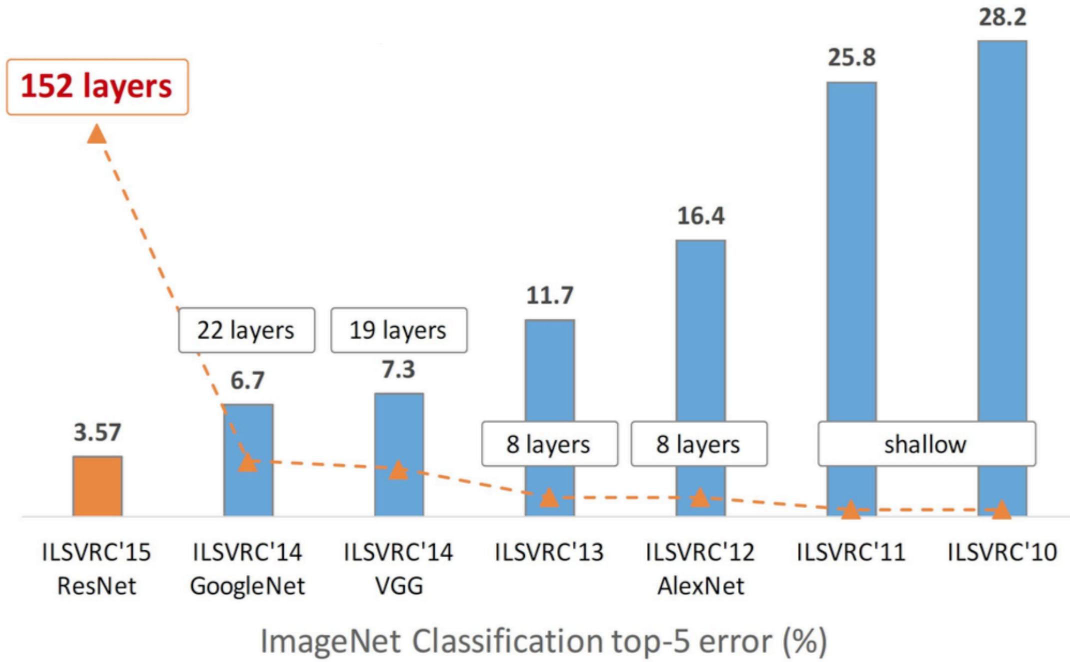
- Richer solution space
- A deeper model should not have **higher training error**
- A solution *by construction*:
  - original layers: copied from a learned shallower model
  - extra layers: set as identity
  - at least the same training error
- Optimization difficulties: solvers cannot find the solution when going deeper…

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Revolution of Depth

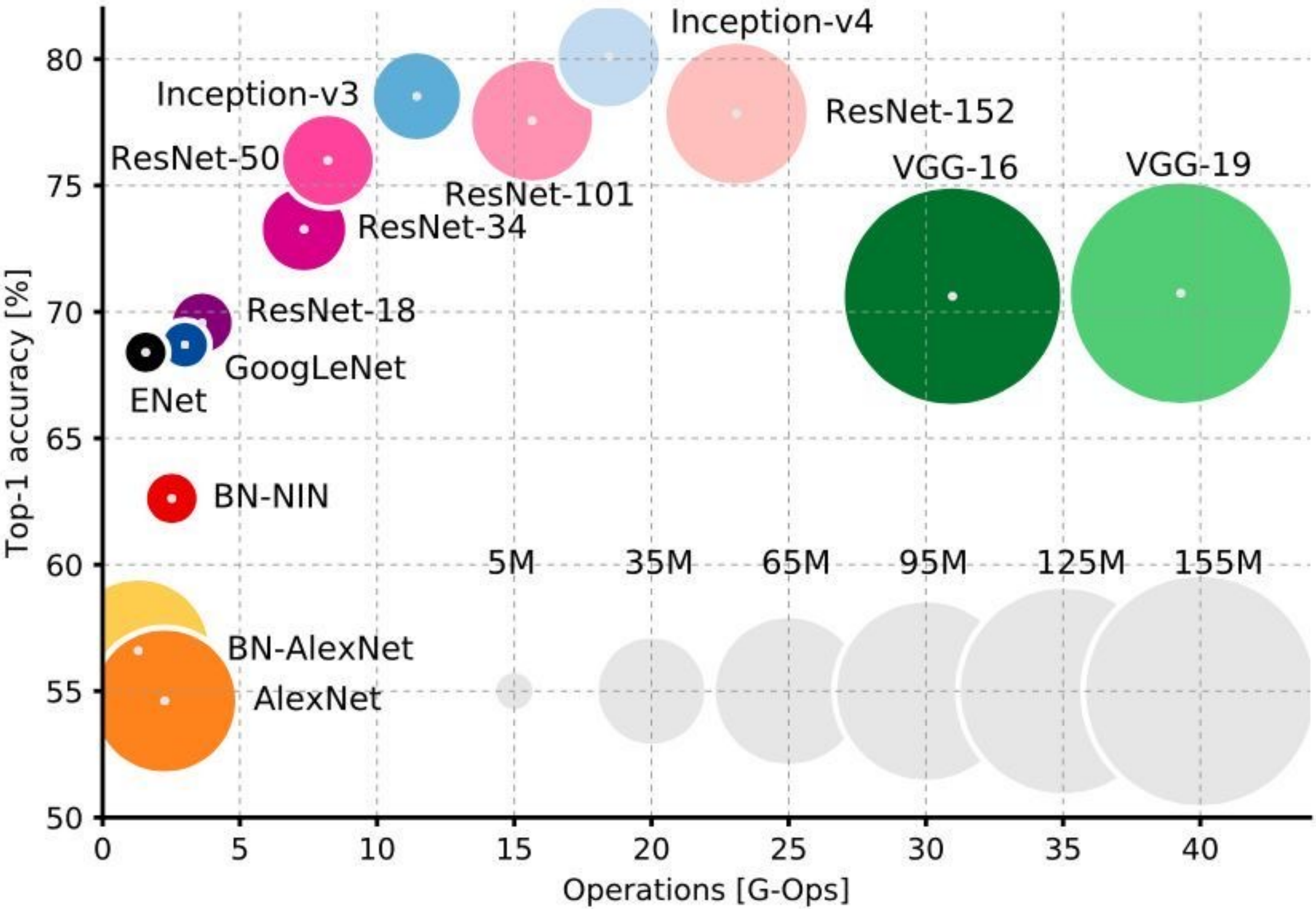






Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Adapt from From NIPS 2017 DL Trend Tutorial



Inception-v4
Inception-v3
ResNet-152
ResNet-50
ResNet-101
VGG-16
VGG-19
ResNet-34
ResNet-18
GoogLeNet
ENet
BN-NIN
5M
35M
65M
95M
125M
155M
BN-AlexNet
AlexNet
Top-1 accuracy [%]
Operations [G-Ops]
50
55
60
65
70
75
80
0
5
10
15
20
25
30
35
40

Adaptive / Dynamic Trick:

- Diet Networks: Thin Parameters for Fat Genomics, ICLR 2017
- Dynamic Filter Networks, NIPS 2016
- Hyper Networks, ICLR 2017
- Optimal Architectures in a Solvable Model of Deep Networks, NIPS16
- AdaNet: Adaptive Structural Learning of Artificial Neural Networks, ICML17
- SplitNet: Learning to Semantically Split Deep Networks for Parameter Reduction and Model Parallelization, ICML17
- Image Question Answering using Convolutional Neural Network with Dynamic Parameter , CVPR 2016
- Many others..

Recent Trend (2): Recurrent Neural Networks

Architectures:

- Recurrent, over space and/or time.
  - + attention
- Attention-only!

Machine (Deep) Learning in a Nutshell

Task:

↓

Representation:

↓

Score Function:

↓

Search/Optimization

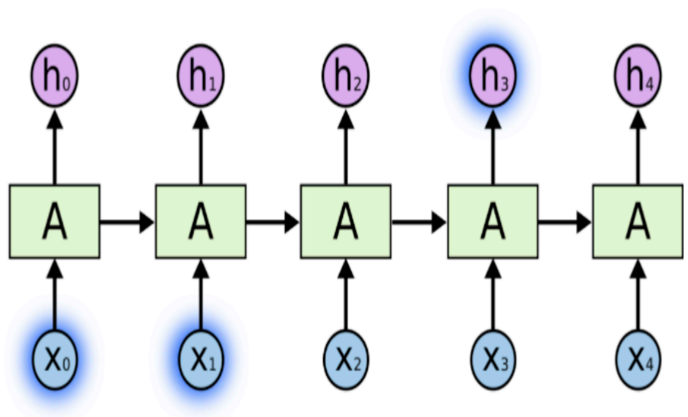
↓

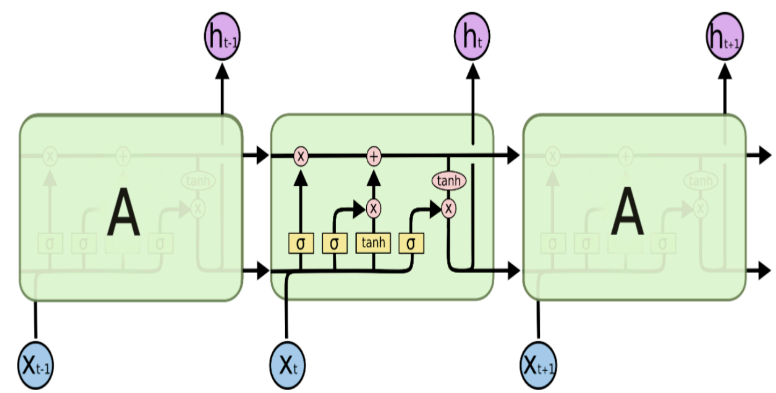
Check / Validate
(Models, Parameters)

- New Network Topology, Network Parameters

Important Block: Recurrent Neural Networks (RNN)

- Prof. Schmidhuber invented "Long short-term memory" – Recurrent NN (LSTM-RNN) model in 1997





The repeating module in an LSTM contains four interacting layers.

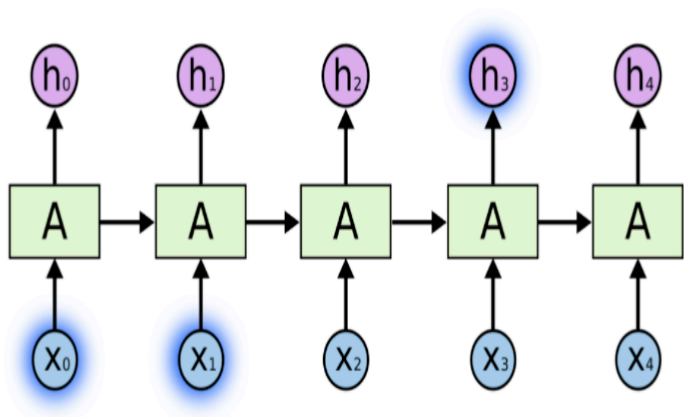
Sepp Hochreiter; Jürgen Schmidhuber (1997). "Long short-term memory". Neural Computation. 9 (8): 1735–1780.

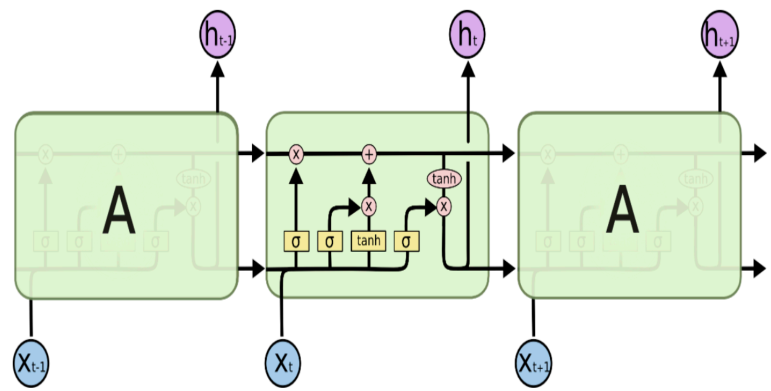
Image Credits from Christoph

Important Block: Recurrent Neural Networks (RNN)

- Prof. Schmidhuber invented "Long short-term memory" – Recurrent NN (LSTM-RNN) model in 1997

$$\mathbf{h}_t = \sigma(\mathbf{W}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{b}) = \overrightarrow{LSTM}(\mathbf{x}_t)$$





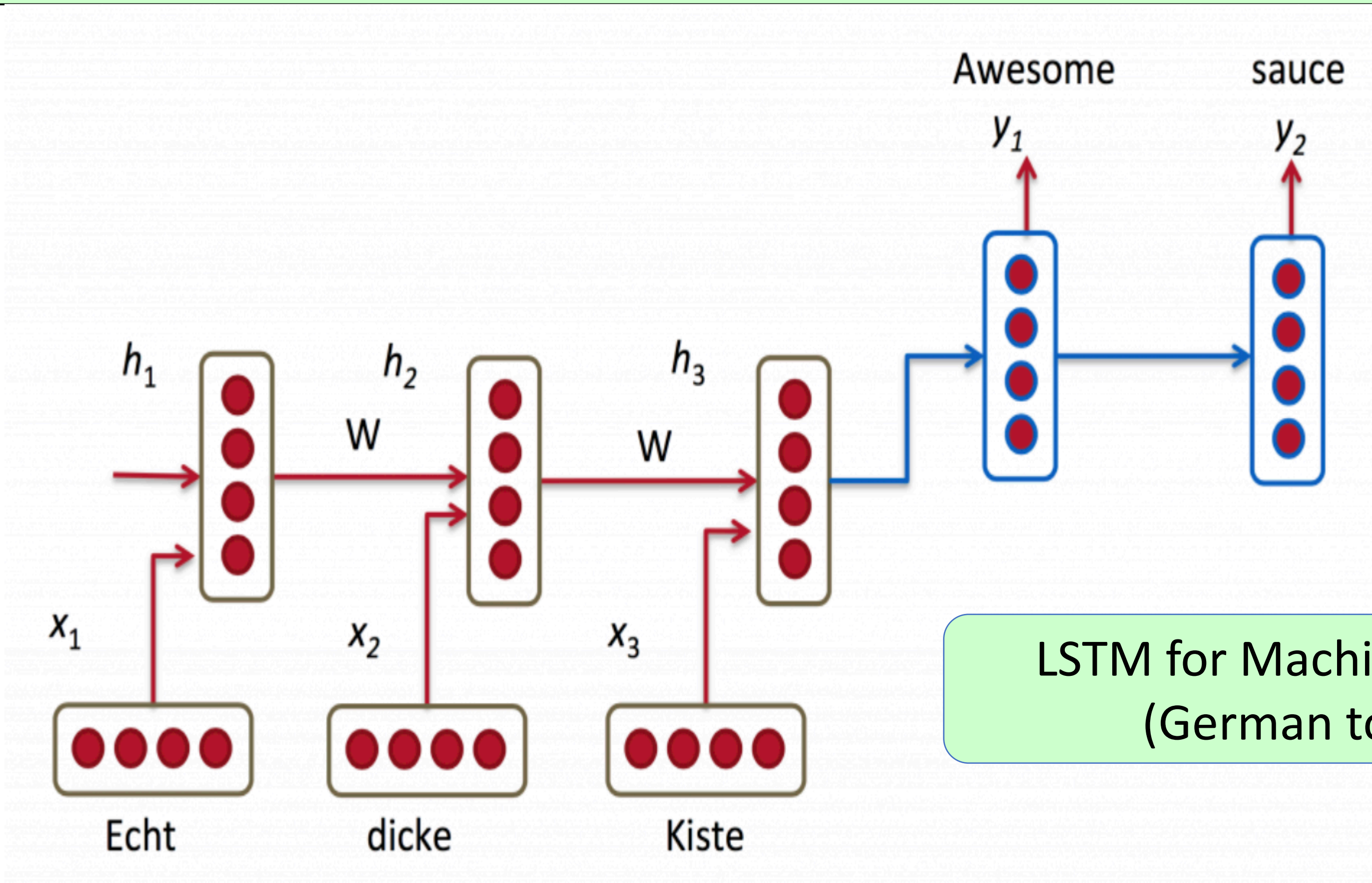
The repeating module in an LSTM contains four interacting layers.

Sepp Hochreiter; Jürgen Schmidhuber (1997). "Long short-term memory". Neural Computation. 9 (8): 1735–1780.

Image Credits from Christoph

RNN models dynamic temporal dependency

- Make fully-connected layer model each unit recurrently
- Units form a directed chain graph along a sequence
- Each unit uses recent history and current input in modeling

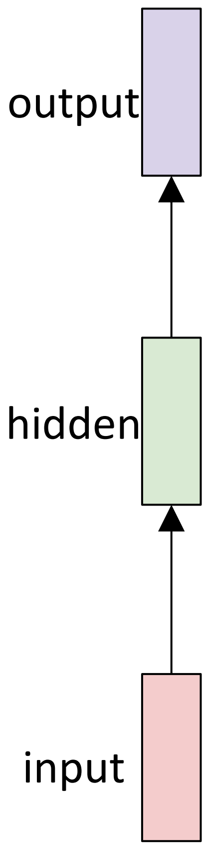


LSTM for Machine Translation
(German to English)

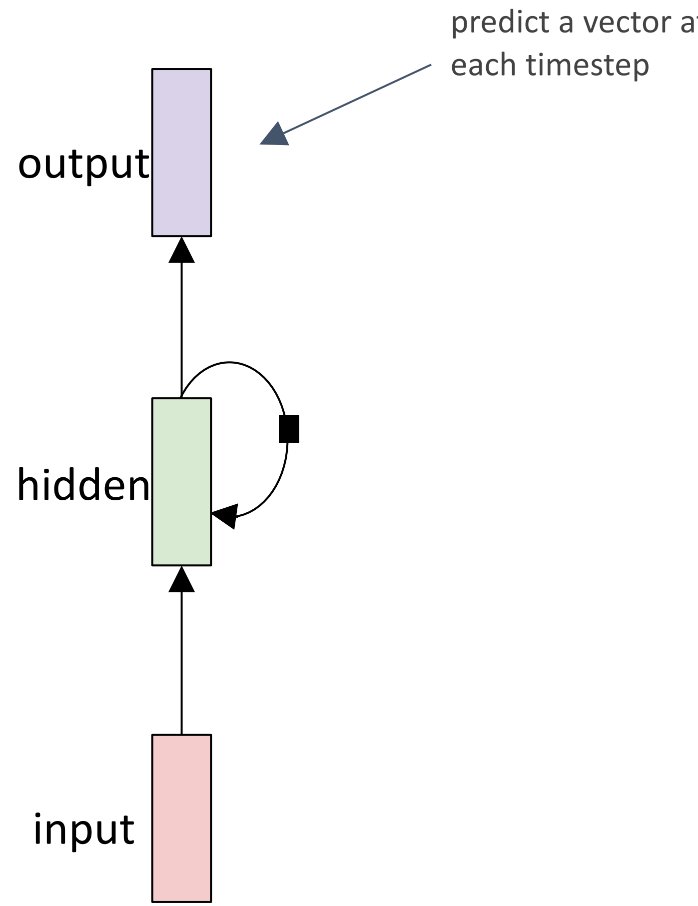
Image credit : wildML

Recurrent Neural Networks (RNNs)

Traditional "Feed Forward" Neural Network

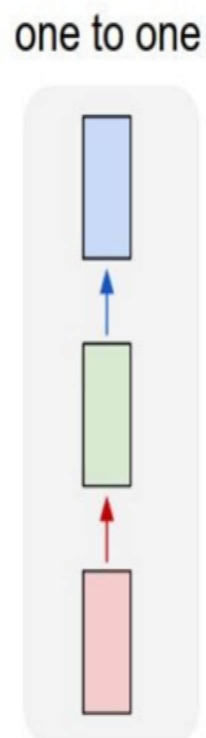


Recurrent Neural Network

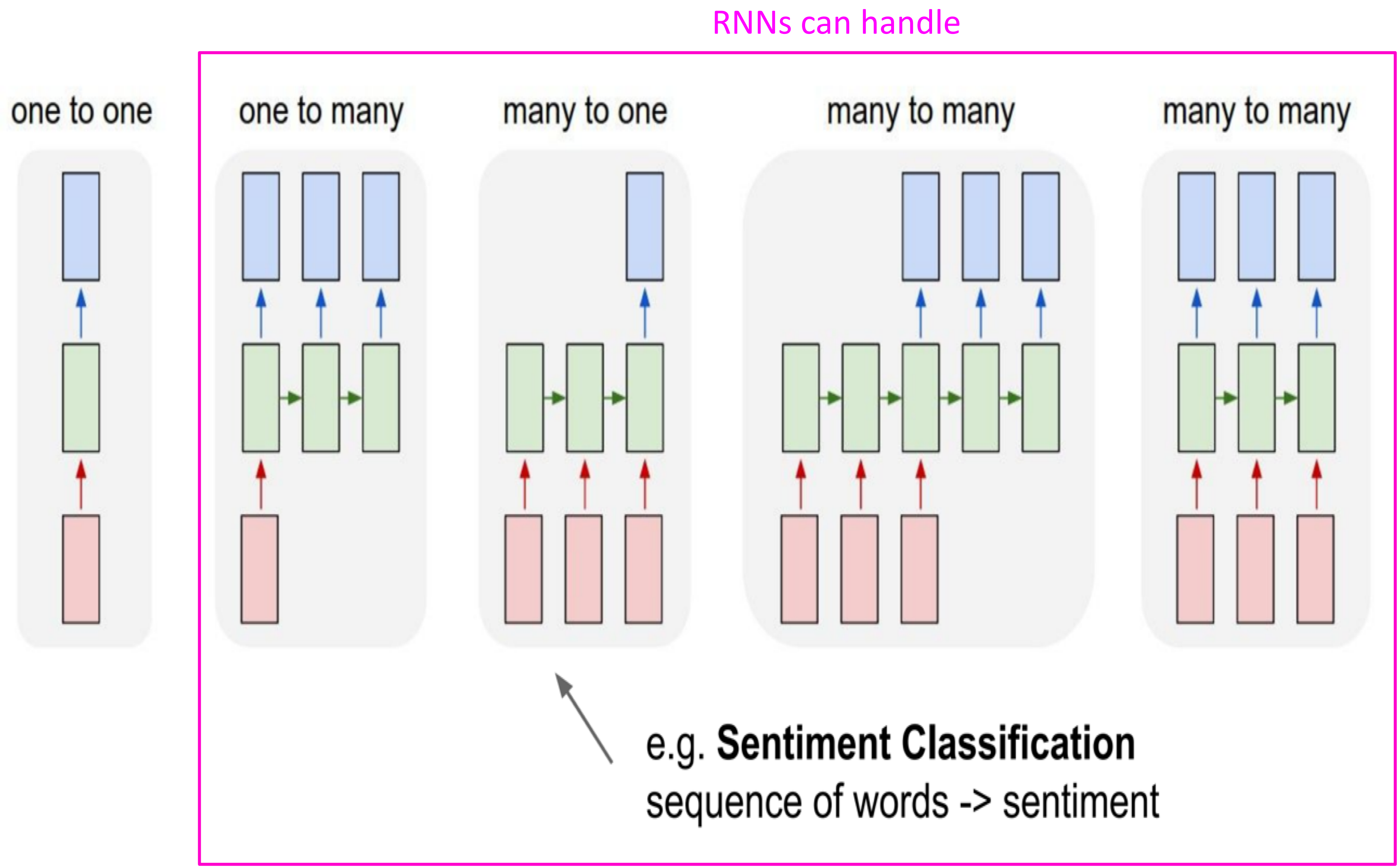


http://cs231n.stanford.edu/slides/

Standard “Feed-Forward” Neural Network



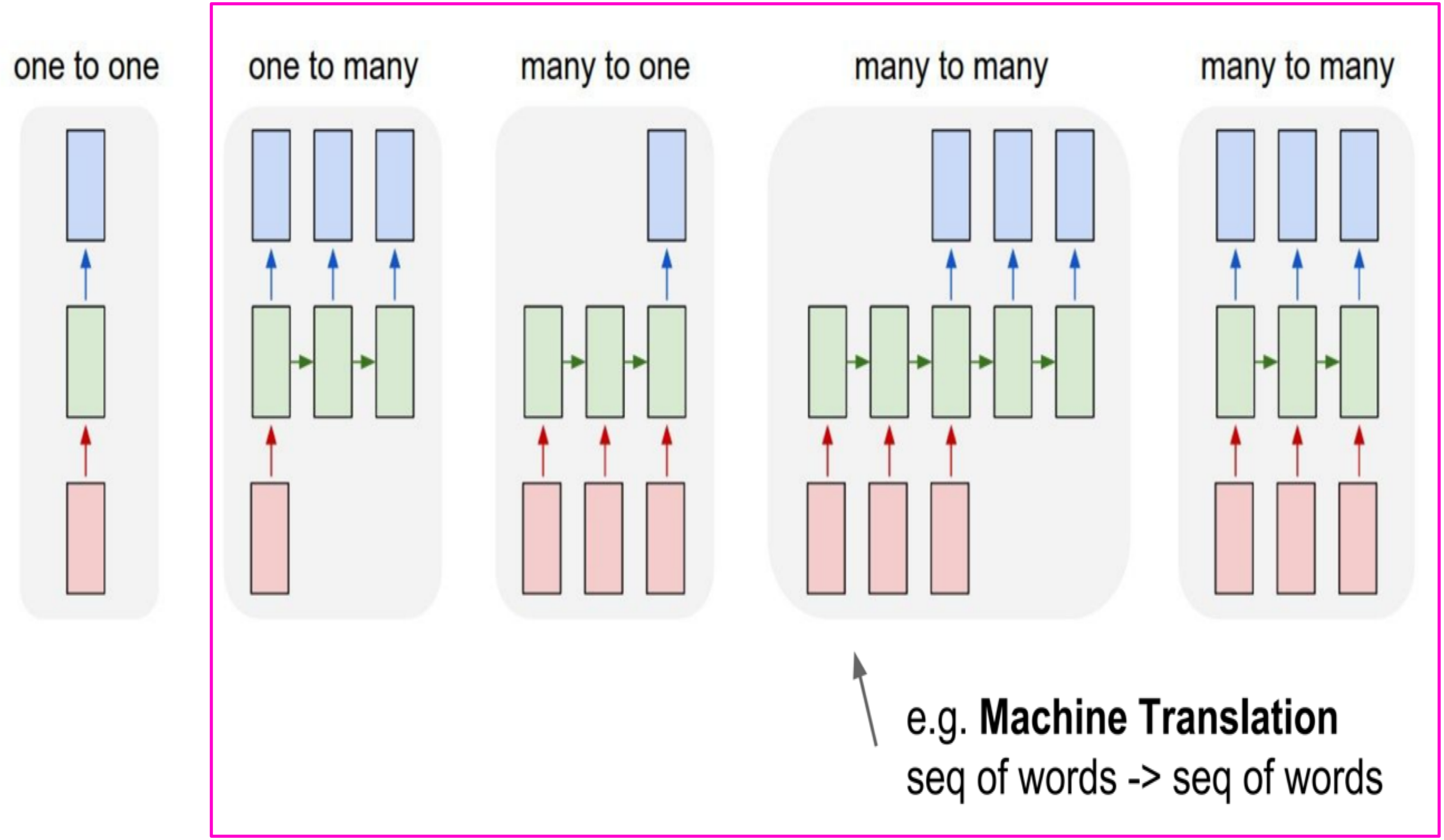
Recurrent Neural Networks (RNNs)



http://cs231n.stanford.edu/slides/

Recurrent Neural Networks (RNNs)

RNNs can handle

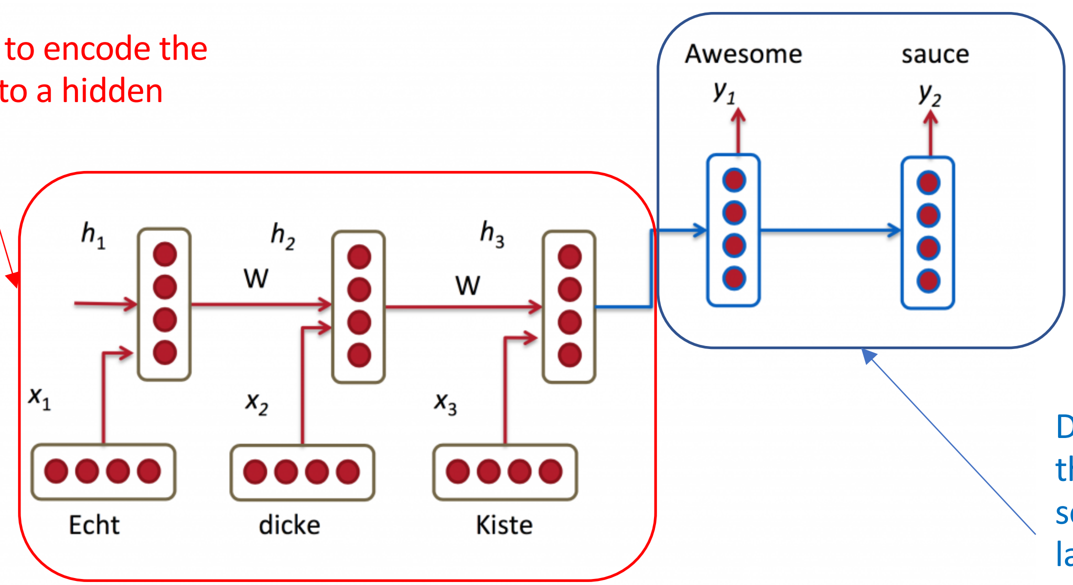


http://cs231n.stanford.edu/slides/

Seq2Seq for Machine Translation

In machine translation, the input is a sequence of words in source language, and the output is a sequence of words in target language.

Encoder: An RNN to encode the input sentence into a hidden state (feature)



Decoder: An RNN with the hidden state of the sentence in source language as the input and output the translated sentence

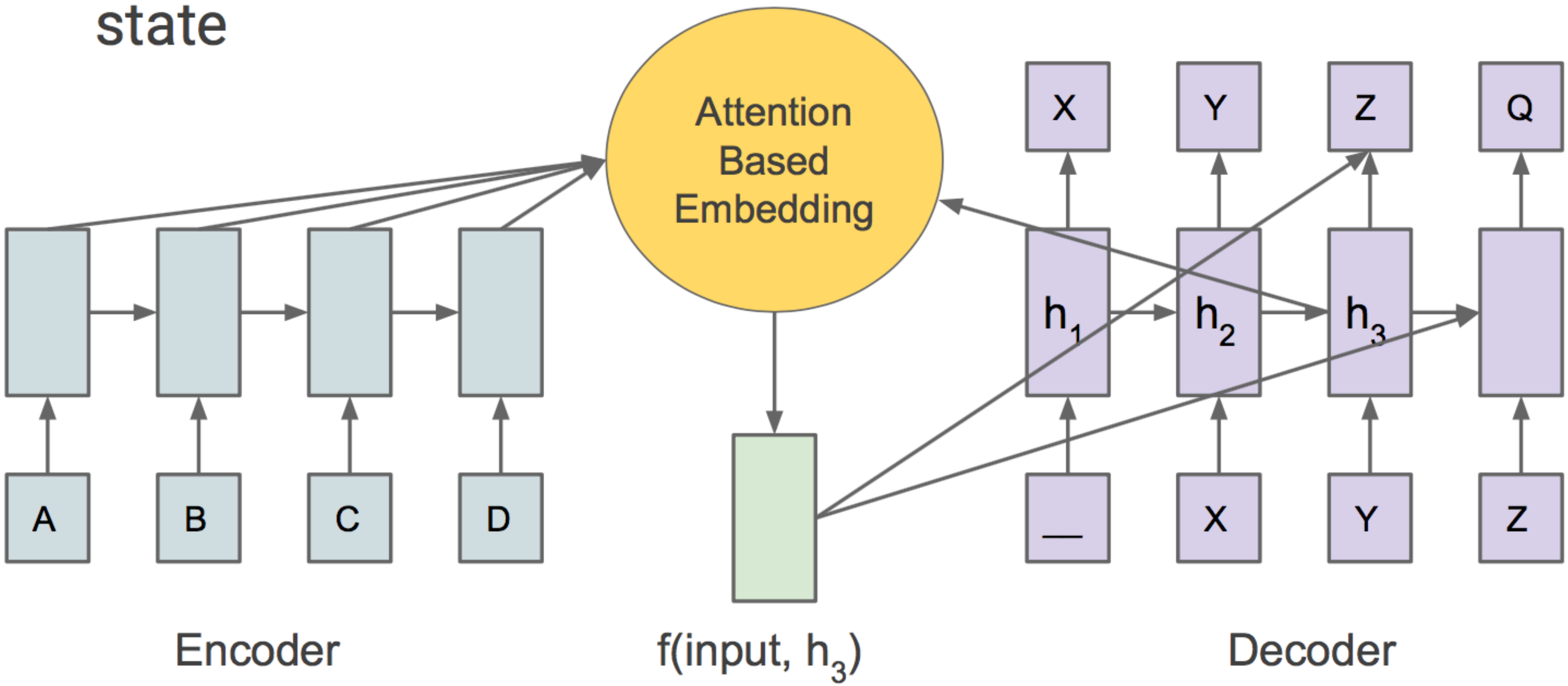
Encoder-decoder architecture for machine translation

Adapt from Professor Qiang Yang of HK UST

Attention Trick:

Seq2Seq with Attention

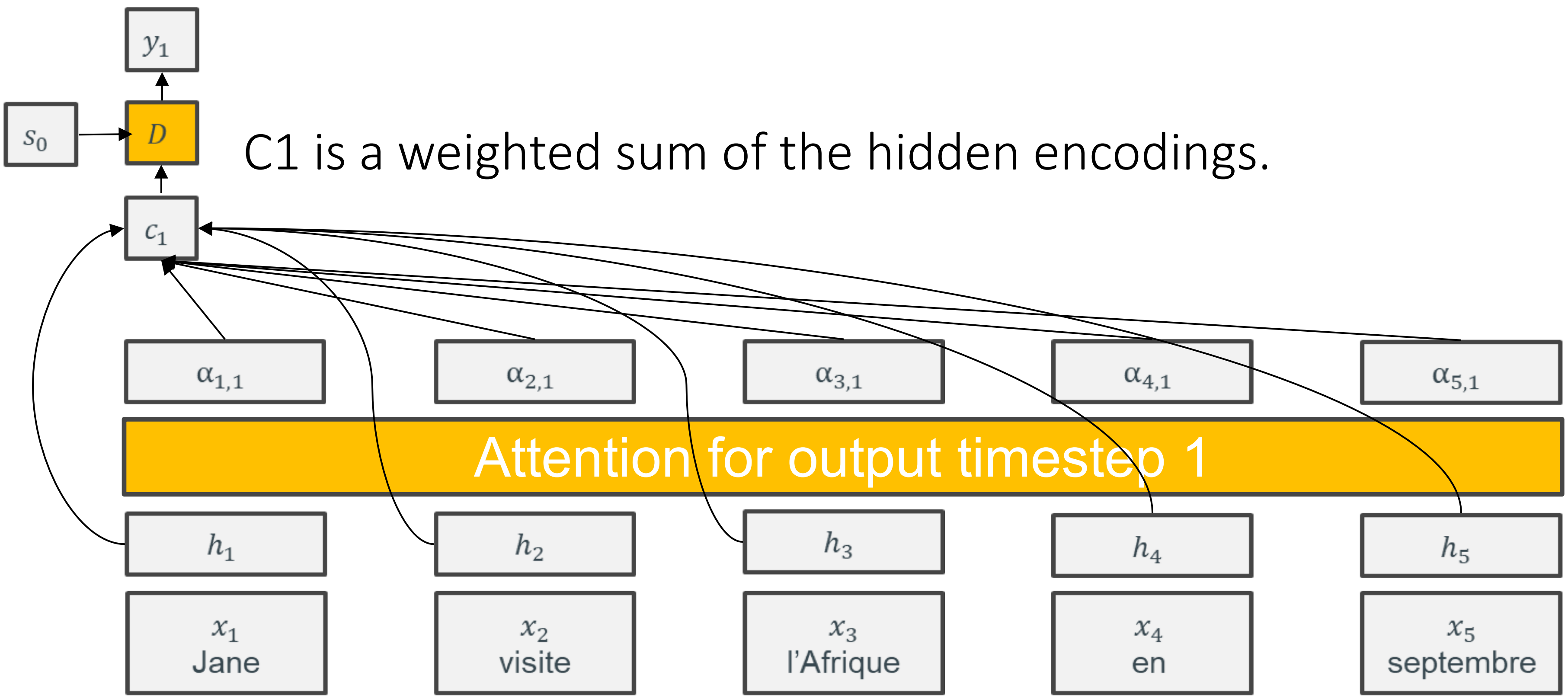
- Embedding used to predict output, and compute next hidden state



Adapt from From NIPS 2017 DL Trend Tutorial

The attention module gives us a weight for each input.

C1 is a weighted sum of the hidden encodings.



Based: Dr. Yangqiu Song's slides

Transformer: Exploiting Self Attentions

- A Google Brain model.
  - Variable-length input
  - Fixed-length output (but typically extended to a variable-length output)
  - **No recurrence**
  - Surprisingly not patented.
- Uses 3 kinds of attention
  - Encoder self-attention.
  - Decoder self-attention.
  - Encoder-decoder multi-head attention.

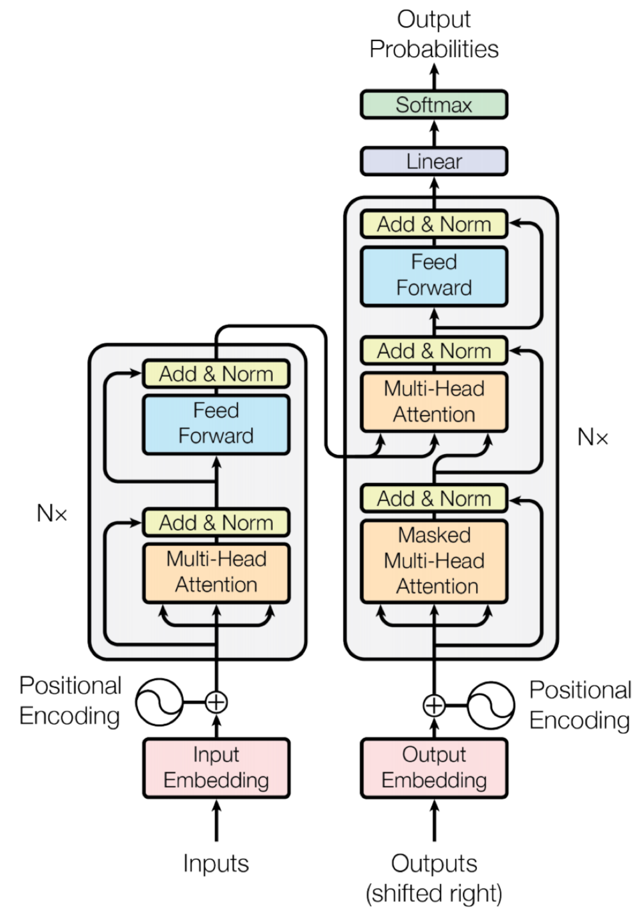
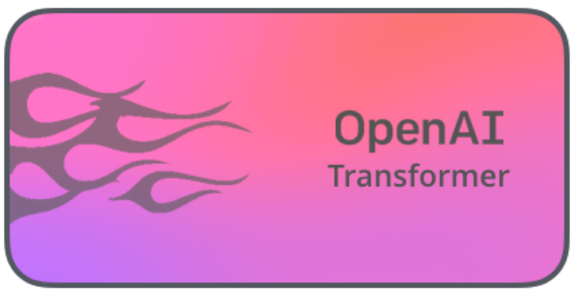


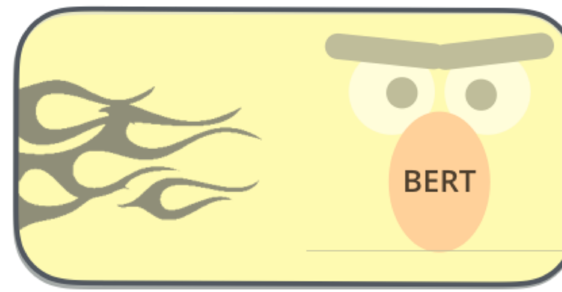
Figure 1: The Transformer - model architecture.

Based: Dr. Yangqiu Song's slides

Notable pre-trained NLP models



BERT: Bidirectional Encoder Representations from Transformers
Pre-trained transformer encode
for sentence embedding

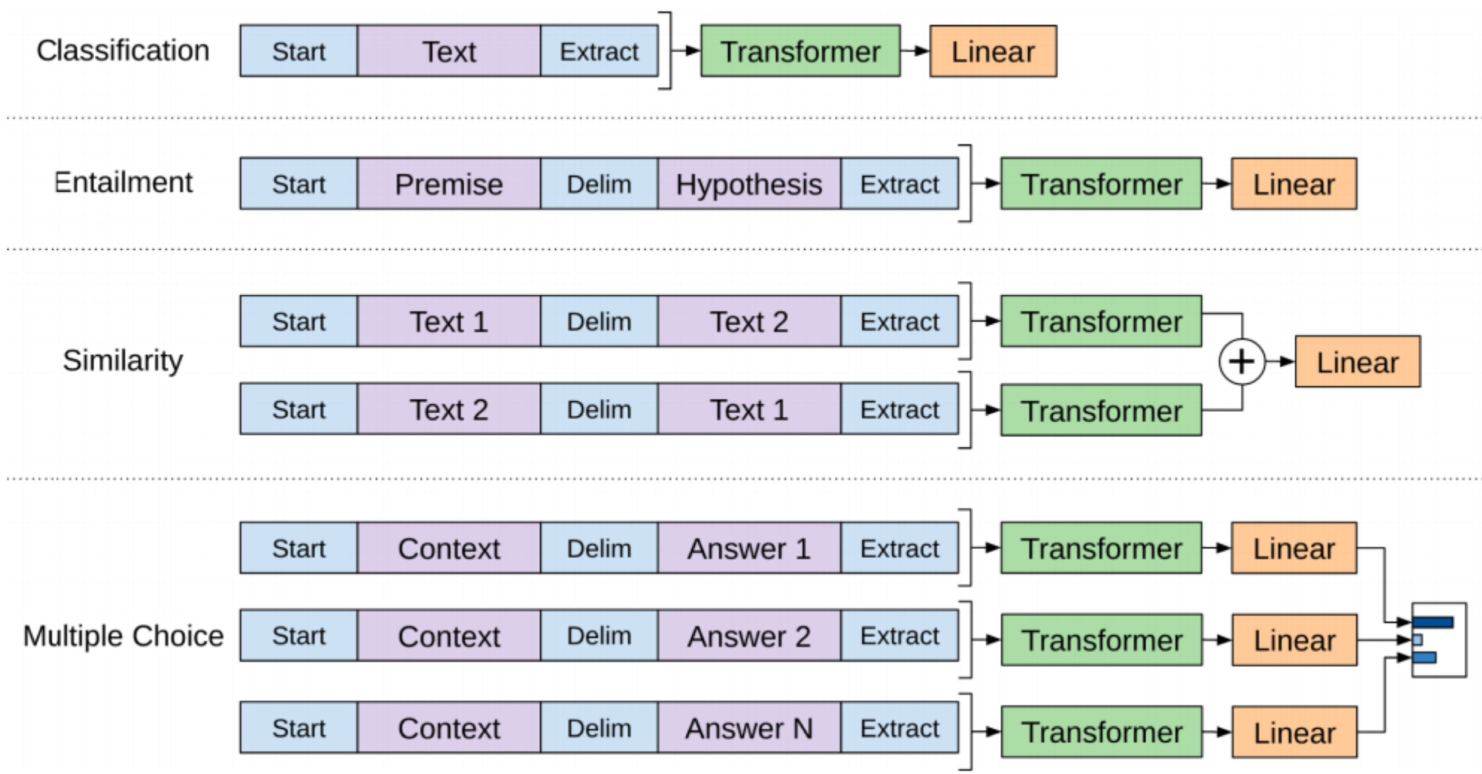


ELMo: Embeddings from Language Models
Pre-trained biLSTM for contextual embedding

Based: Dr. Yangqiu Song's slides

Open AI's GPT-2 is a really large transformer.

Different tasks use the OpenAI transformer in different ways.



Based: Dr. Yangqiu Song's slides

Recent Trend (3):
Neural Architectures with Memory

Architectures:

memory and multi-hop
reasoning to perform AI
tasks better

Machine (Deep) Learning in a Nutshell

Task:

↓

Representation:

↓

Score Function:

↓

Search/Optimization

↓

Check / Validate (Models, Parameters)

- New Network Topology, Network Parameters

e.g. for Story Comprehension

Joe went to the kitchen. Fred went to the kitchen. Joe picked up the milk. Joe travelled to his office. Joe left the milk. Joe went to the bathroom.

Questions from Joe's angry mother:

Q1 : Where is Joe?

Q2 : Where is the milk now?

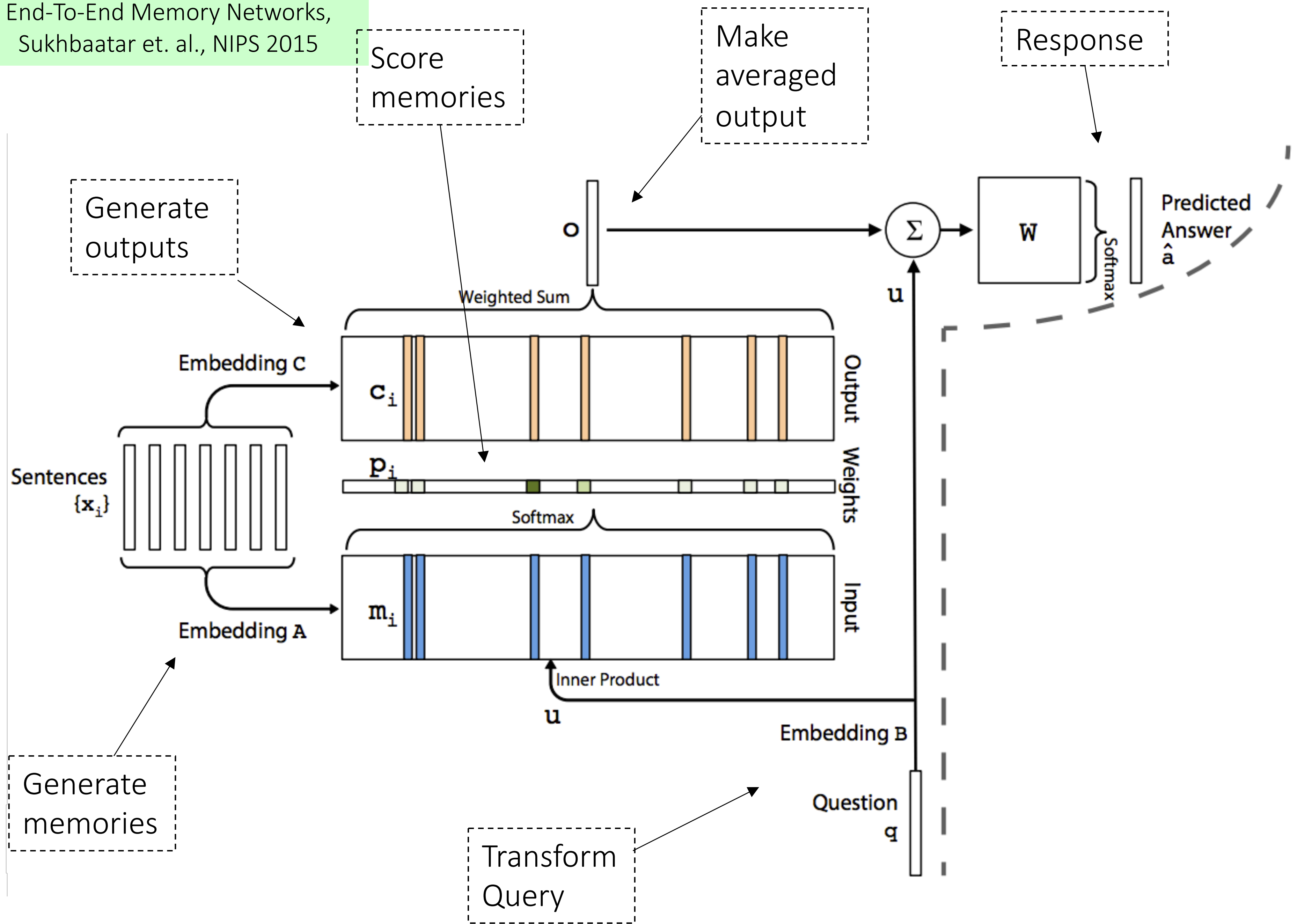
Q3 : Where was Joe before the office?

Need external explicit memory for long-range reasoning

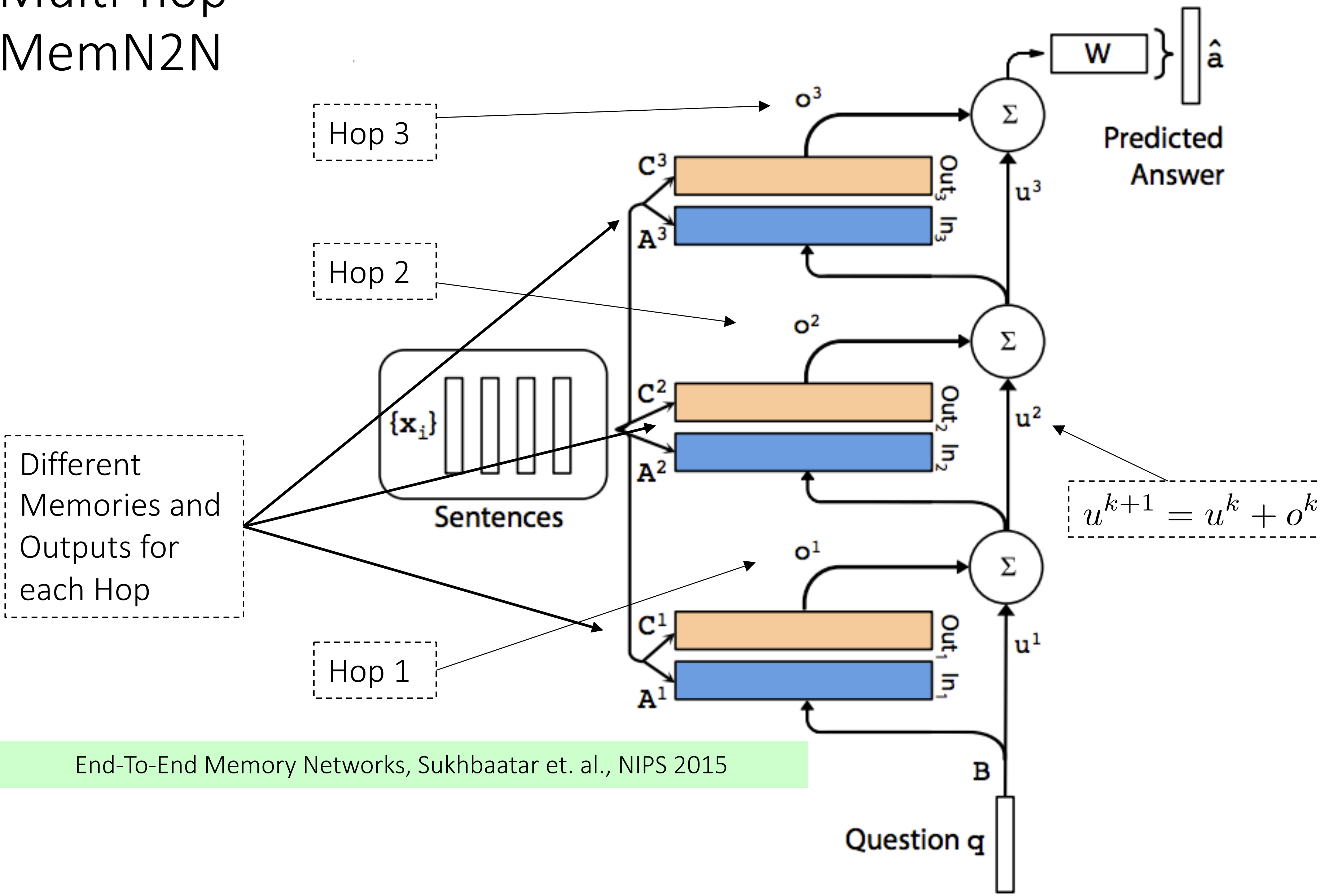
Deeper AI tasks require explicit memory and multi-hop reasoning over it

- RNNs have short memory
- Cannot increase memory without increasing number of parameters
- Need for compartmentalized memory
- Read/Write should be asynchronous

End-To-End Memory Networks, Sukhbaatar et. al., NIPS 2015



Multi-hop MemN2N

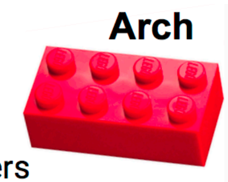


End-To-End Memory Networks, Sukhbaatar et. al., NIPS 2015

Neural Architectures with Memory

- Antoine Bordes, Y-Lan Boureau, Jason Weston, **Learning End-to-End Goal-Oriented Dialog, ICLR 2017**
- Karol Kurach, Marcin Andrychowicz & Ilya Sutskever **Neural Random-Access Machines**, ICLR, 2016
- Emilio Parisotto & Ruslan Salakhutdinov **Neural Map: Structured Memory for Deep Reinforcement Learning**, ArXiv, 2017
- Oriol Vinyals,Meire Fortunato, Navdeep Jaitly **Pointer Networks**, ArXiv, 2017
- Jack W Rae et al., **Scaling Memory-Augmented Neural Networks with Sparse Reads and Writes, ArXiv 2016**
- Junhyuk Oh, Valliappa Chockalingam, Satinder Singh, Honglak Lee, **Control of Memory, Active Perception, and Action in Minecraft, ICML 2016**
- Wojciech Zaremba, Ilya Sutskever, **Reinforcement Learning Neural Turing Machines, ArXiv 2016**

Attention and Memory Toolbox



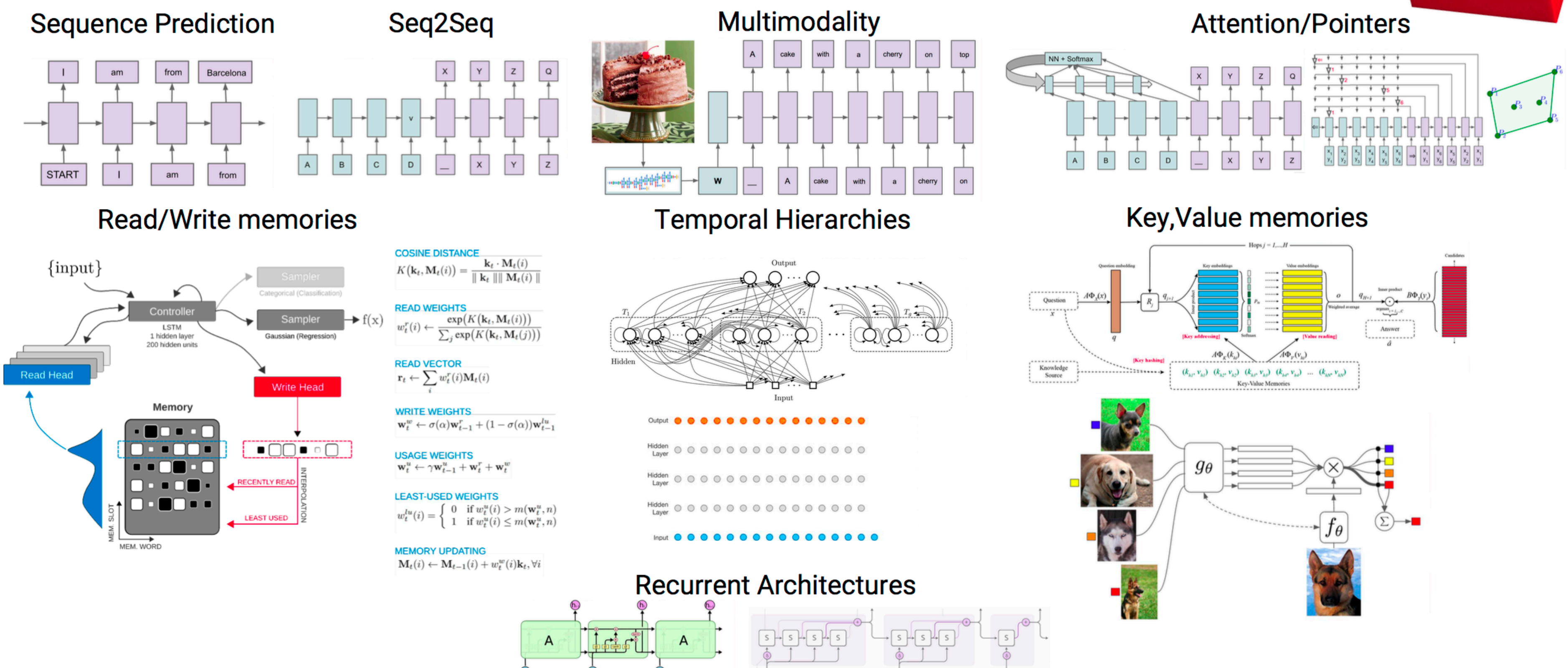
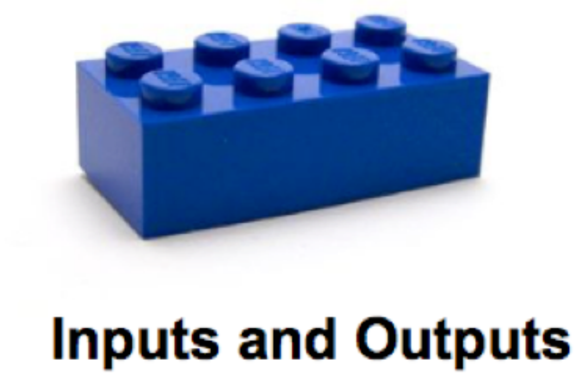


Figure credits: Jeff Dean, Chris Olah, Santoro et al 2016, Koutnik et al 2014, van den Oord et al 2016, Miller et al 2016, Vinyals et al 2016

Adapt from From NIPS 2017 DL Trend Tutorial

Recent Trend (4): Learning to Optimize / Learning to Search DNN architecture



Machine (Deep) Learning in a Nutshell

Task:

Representation:

Score Function:

Search/Optimization

Check / Validate
(Models, Parameters)

Neural Architecture Search with Reinforcement Learning, ICLR17

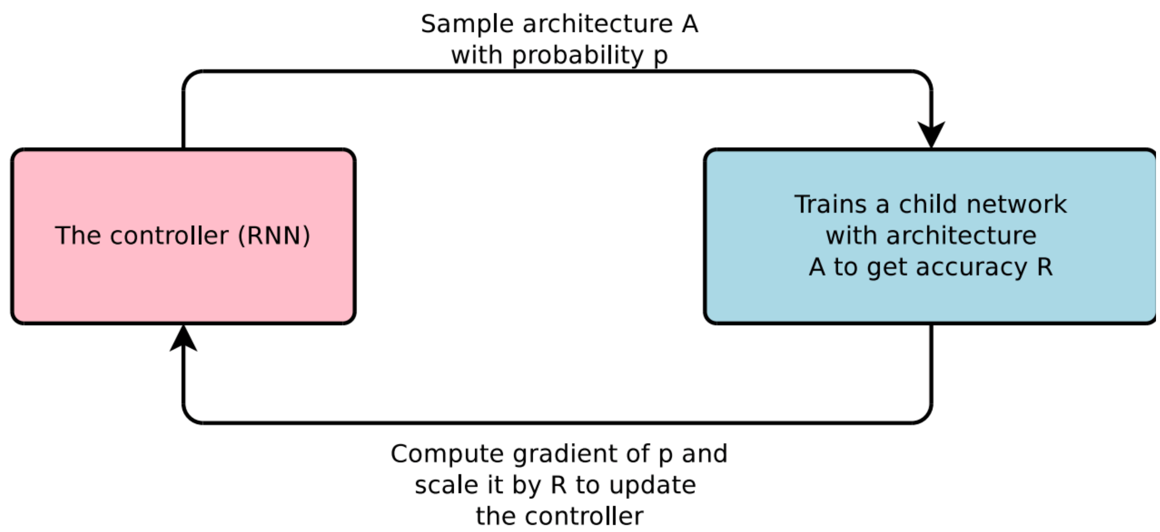
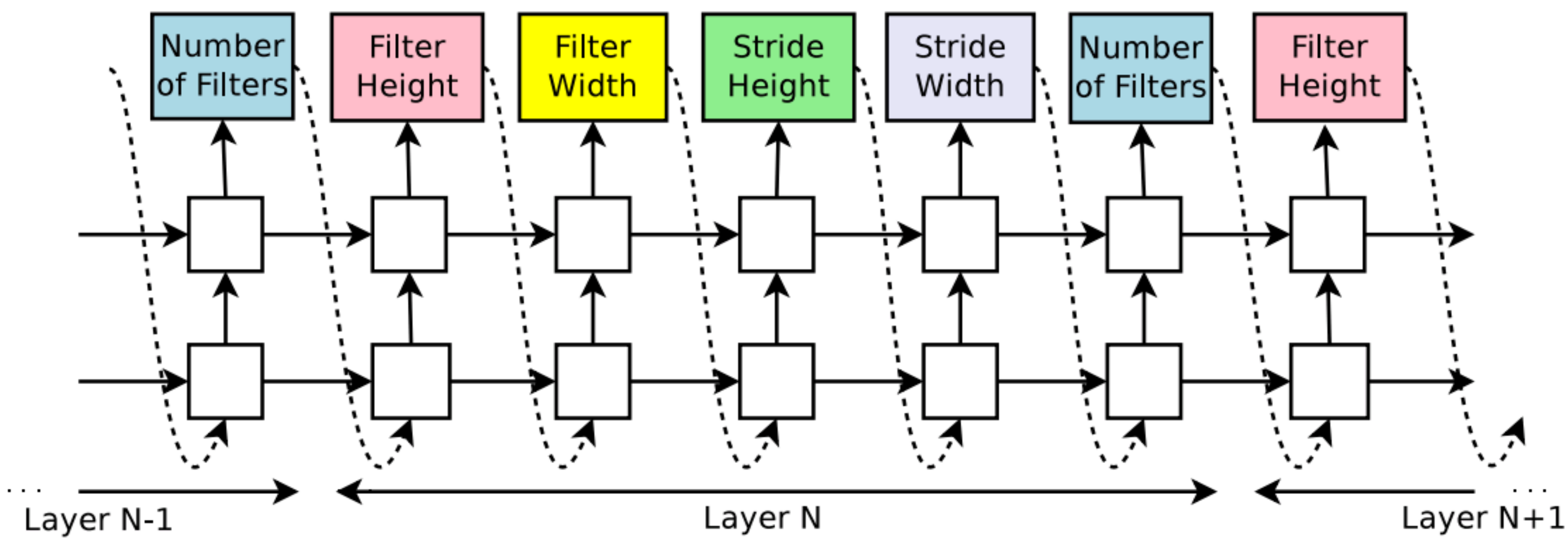


Figure 1: An overview of Neural Architecture Search.



Neural Optimizer Search with Reinforcement Learning, ICML17

- e.g. hyperpara search

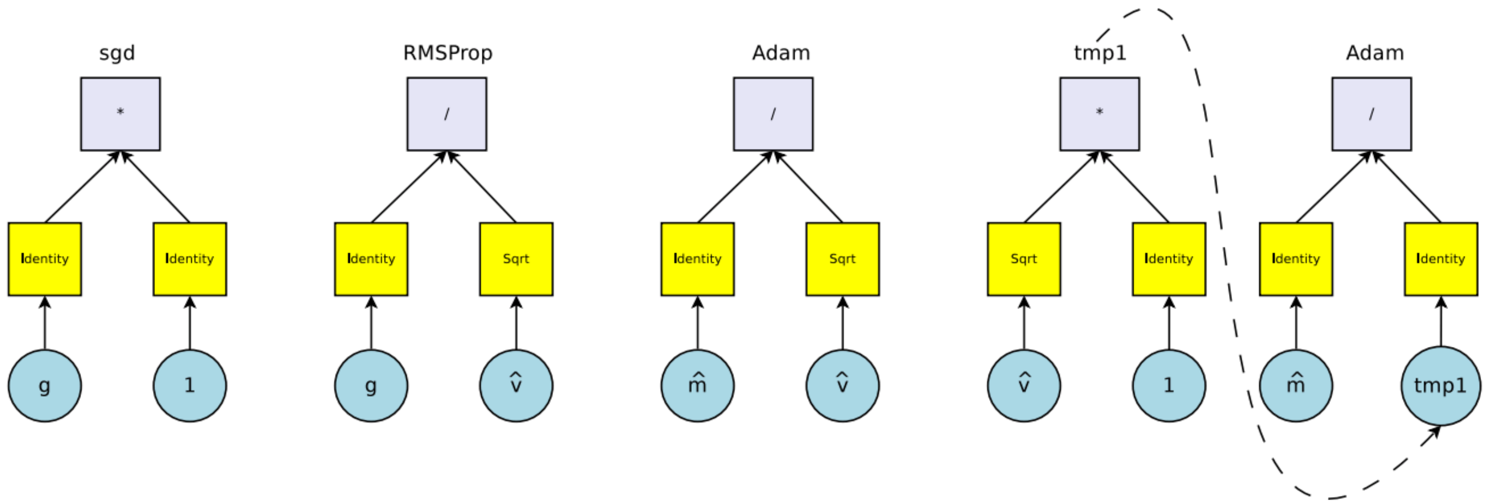


Figure 2. Computation graph of some commonly used optimizers: SGD, RMSProp, Adam. Here, we show the computation of Adam in 1 step and 2 steps. Blue boxes correspond to input primitives or temporary outputs, yellow boxes are unary functions and gray boxes represent binary functions. g is the gradient, $\hat{m}$ is the bias-corrected running estimate of the gradient, and $\hat{v}$ is the bias-corrected running estimate of the squared gradient.

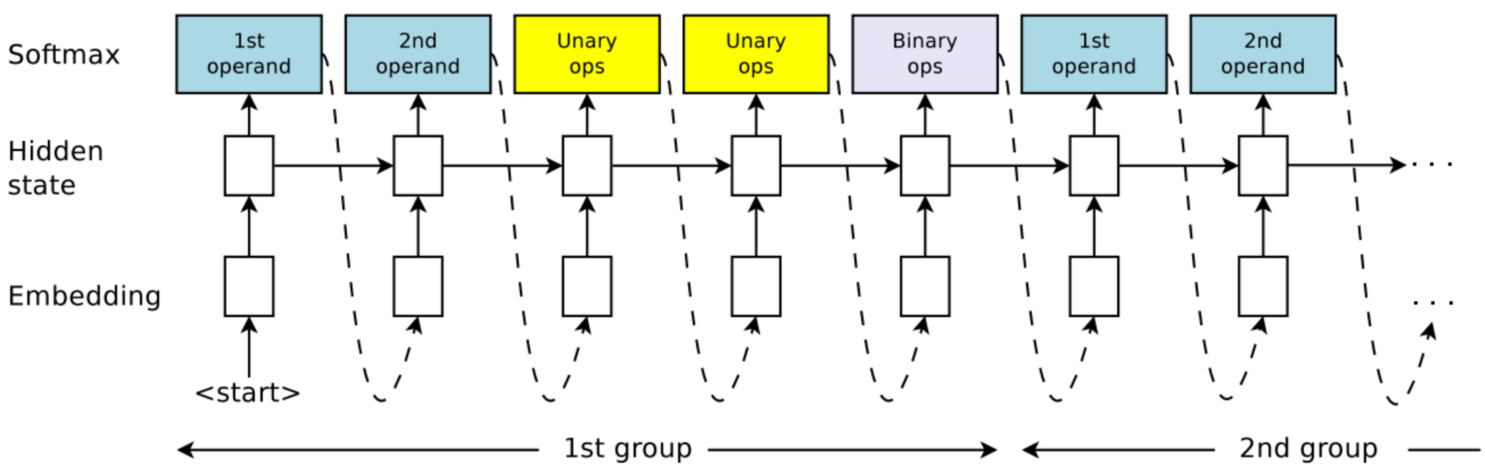
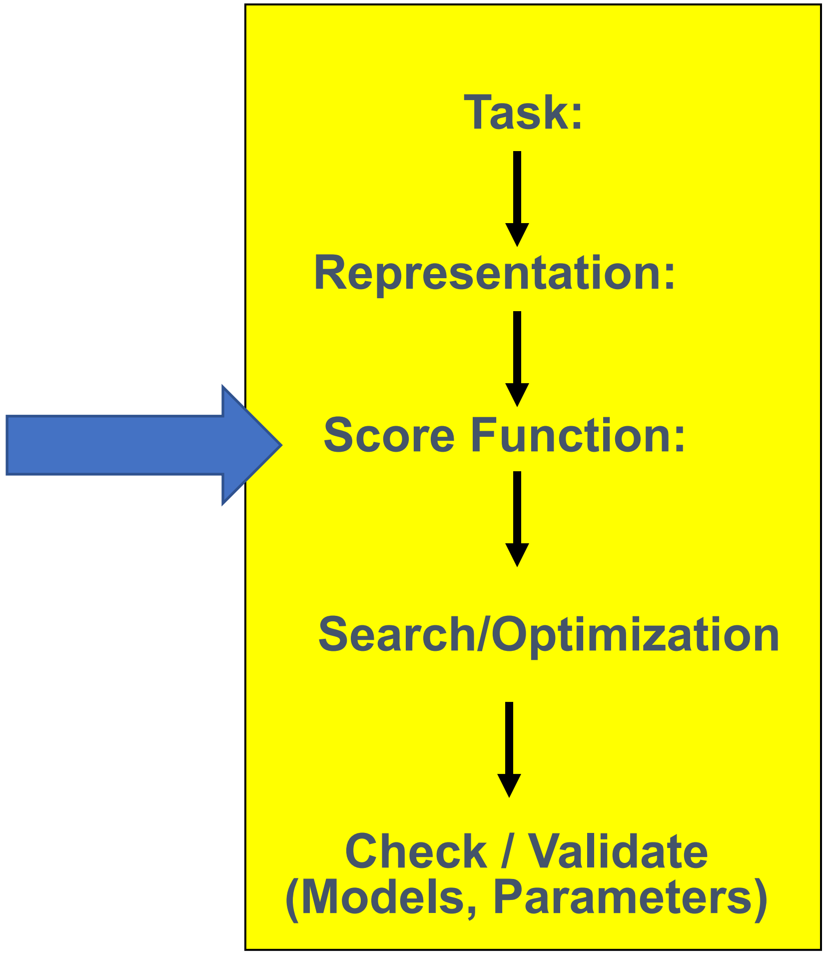


Figure 3. Overview of the controller RNN. The controller iteratively selects subsequences of length 5. It first selects the 1st and 2nd operands op_1 and op_2, then 2 unary functions u_1 and u_2 to apply to the operands and finally a binary function b that combines the outputs of the unary functions. The resulting $b(u_1(op_1), u_2(op_2))$ then becomes an operand that can be selected in the subsequent group of predictions or becomes the update rule. Every prediction is carried out by a softmax classifier and then fed into the next time step as input.

Recent Trend (5): Layer-wise pretraining / Auto-Encoder

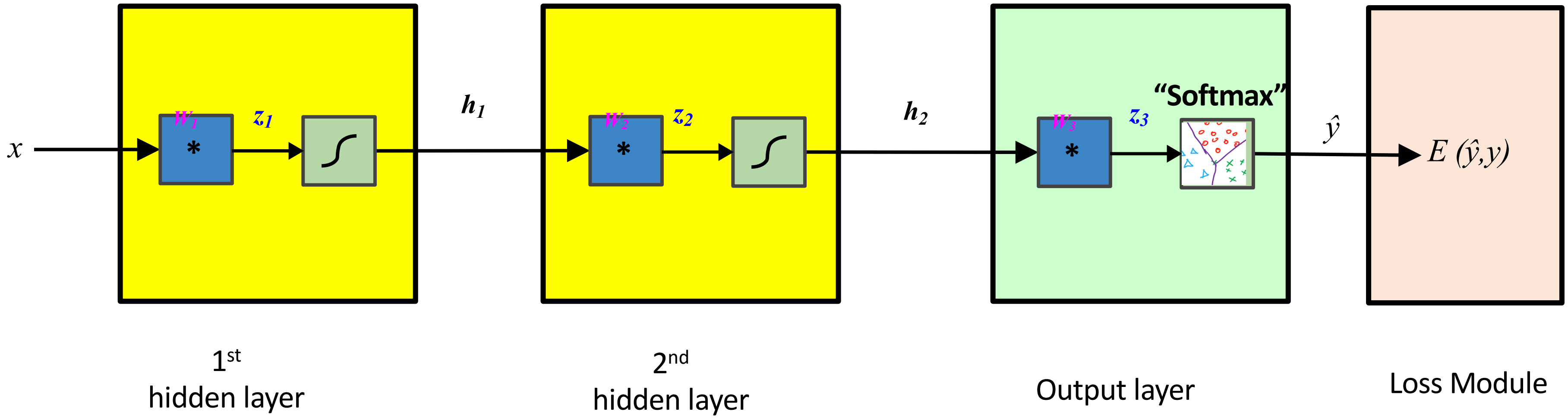
Losses

Machine (Deep) Learning in a Nutshell

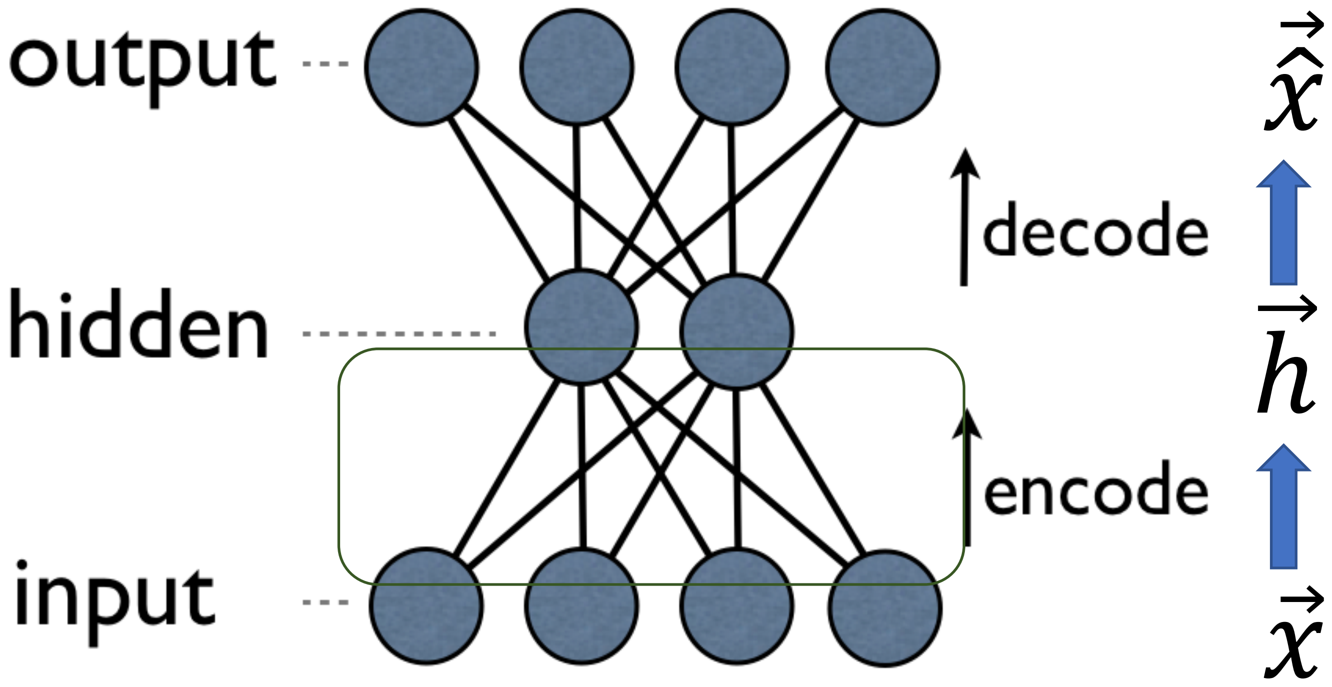


- Training / Searching / Learning
  - With new losses
  - With new optimization tips
  - New formulation of learning
  - Scaling up with GPU, Scaling up with distributed optimization , e.g. Asynchronous SGD

Recap: “Block View”



an auto-encoder-decoder is trained to reproduce the input



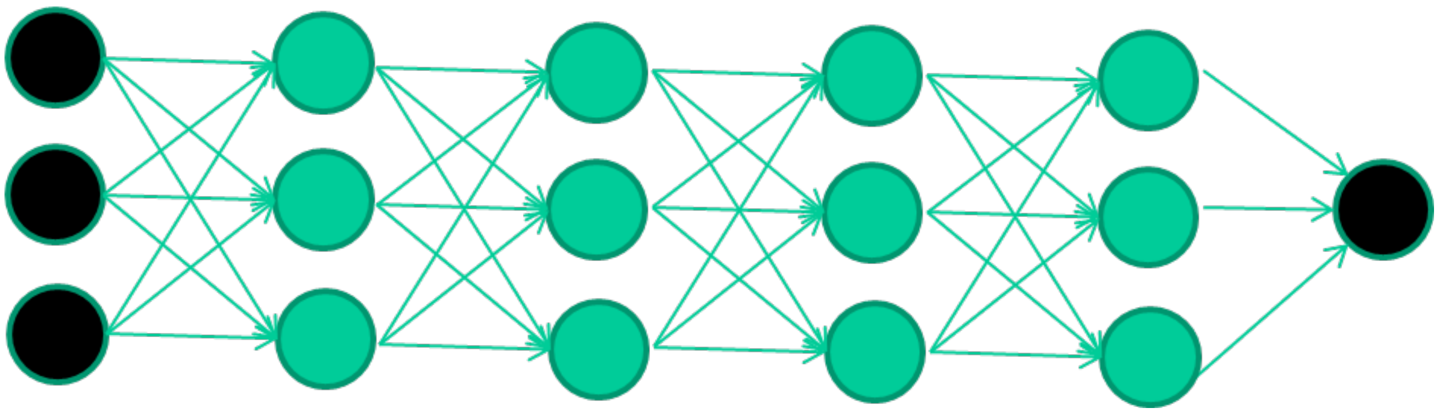
Minimize diff

$$|\vec{\hat{x}} - \vec{x}|$$

Reconstruction Loss: force the 'hidden layer' units to become good / reliable feature detectors

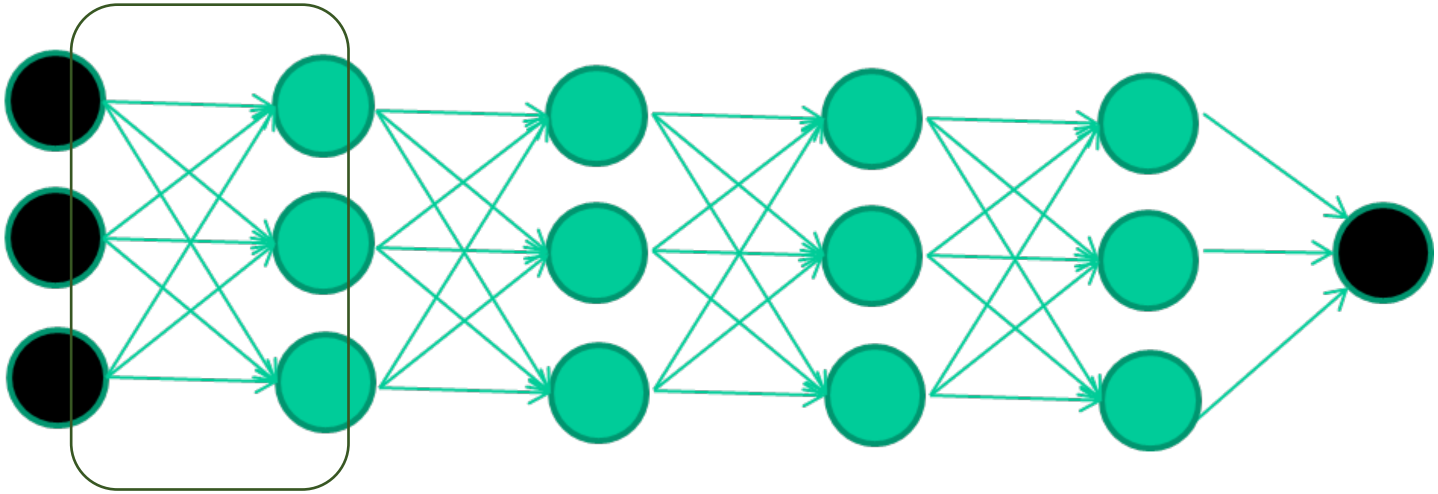
https://www.macs.hw.ac.uk/~dwcorne/Teaching/introdl.ppt

The new way to train multi-layer NNs…



https://www.macs.hw.ac.uk/~dwcorne/Teaching/introdl.ppt

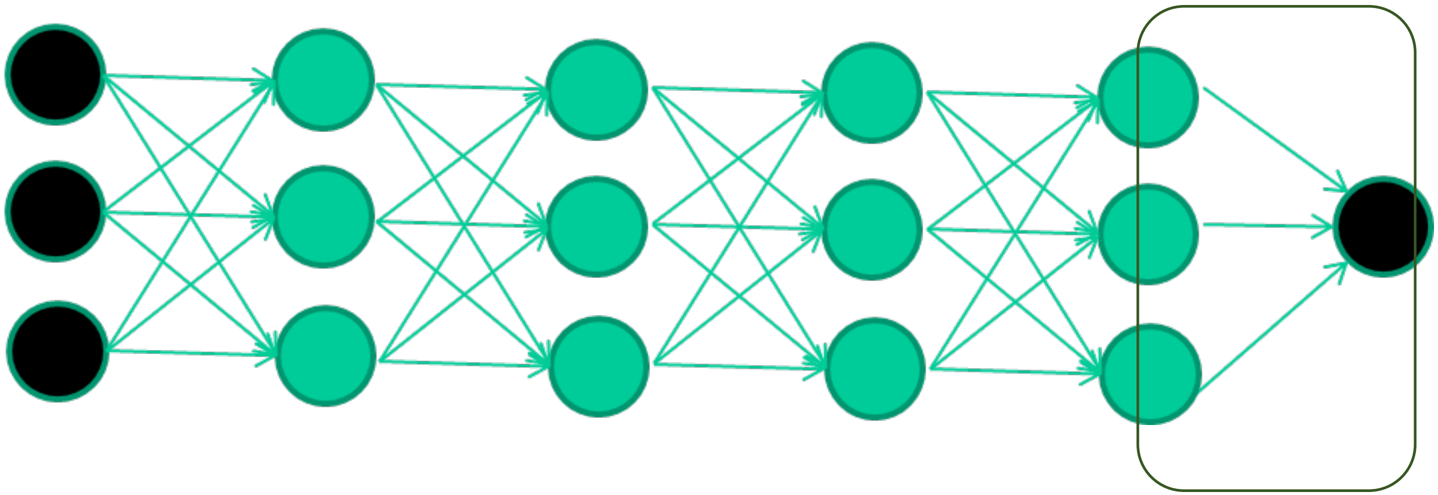
The new way to train multi-layer NNs…



Train **this** layer first

https://www.macs.hw.ac.uk/~dwcorne/Teaching/introdl.ppt

The new way to train multi-layer NNs…



Train **this** layer first

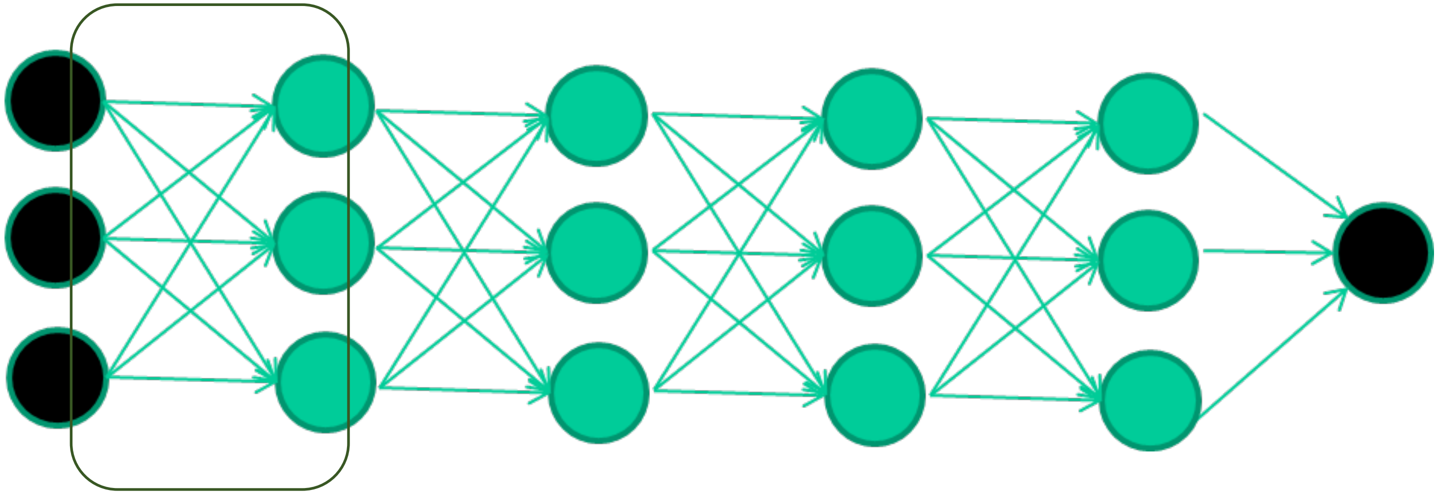
then **this** layer

then **this** layer

then **this** layer

finally **this** layer

The new way to train multi-layer NNs…



Each layer can be trained to be an ***auto-encoder (e.g.,via reconstruction loss)***

Basically, it is forced to learn good features that describe what comes from the previous layer

https://www.macs.hw.ac.uk/~dwcorne/Teaching/introdl.ppt

Recent Trend (6): Learning to Learn

Inputs and Outputs

Losses

Machine (Deep) Learning in a Nutshell

Task:

↓

Representation:

↓

Score Function:

↓

Search/Optimization

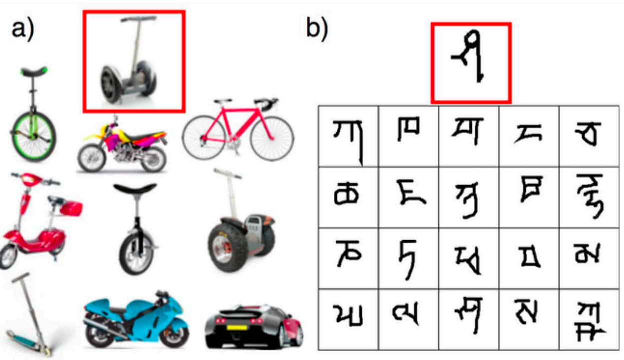
↓

Check / Validate
(Models, Parameters)

Learning to Learn

I/O

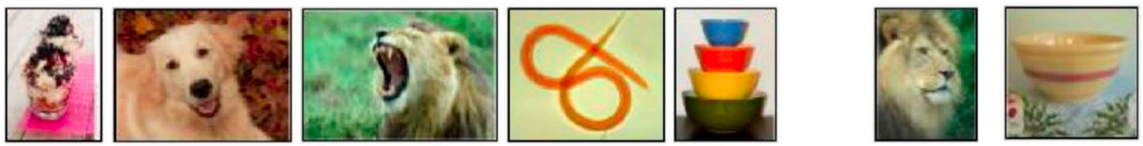
- What is Meta Learning / Learning to Learn?
  - Go beyond train/test from same distribution.
  - Task between train/test changes, so model has to “learn to learn”
- Datasets



Lake et al, 2013, 2015

Image recognition Mini-Imagenet dataset (Vinyals et al.'16)

Given 1 example of 5 classes: Classify new examples



Reinforcement learning

Given a small amount of experience Solve a new task

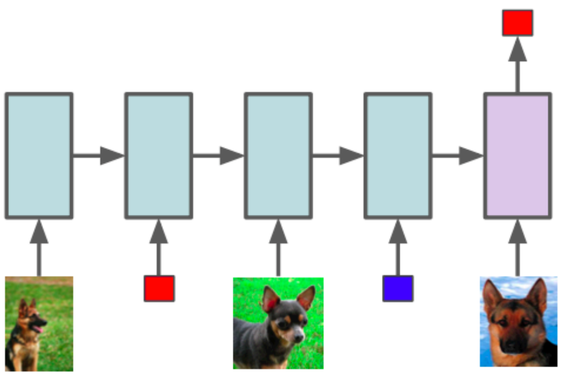
Chelsea Finn, UC Berkeley **How?** learn to learn many other tasks fig. from Duan et al. '17

Adapt from From NIPS 2017 DL Trend Tutorial

Learning to Learn

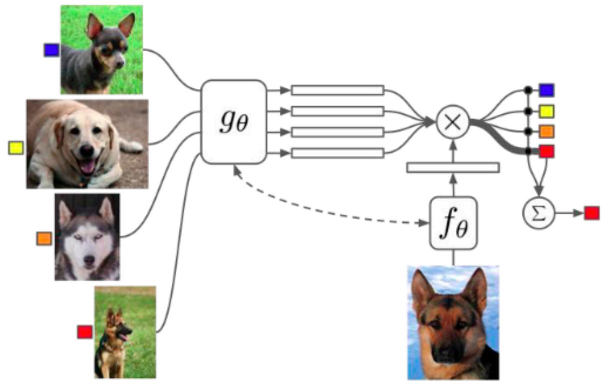
Losses

Model Based



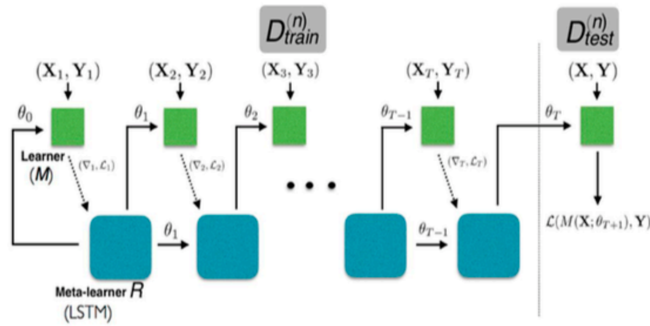
- Santoro et al. '16
- Duan et al. '17
- Wang et al. '17
- Munkhdalai & Yu '17
- Mishra et al. '17

Metric Based



- Koch '15
- Vinyals et al. '16
- Snell et al. '17
- Shyam et al. '17

Optimization Based



- Schmidhuber '87, '92
- Bengio et al. '90, '92
- Hochreiter et al. '01
- Li & Malik '16
- Andrychowicz et al. '16
- Ravi & Larochelle '17
- Finn et al '17

Adapt from From NIPS 2017 DL Trend Tutorial

Recent Trend (7): Variants of Input, e.g., Graphs, Trees, Sets

Inputs and Outputs

Machine (Deep) Learning in a Nutshell

Task:

Representation:

Score Function:

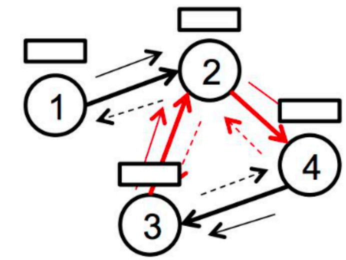
Search/Optimization

Check / Validate (Models, Parameters)

Geometric Deep Learning on Graphs and Manifolds, NIPS 2017 Tutorial

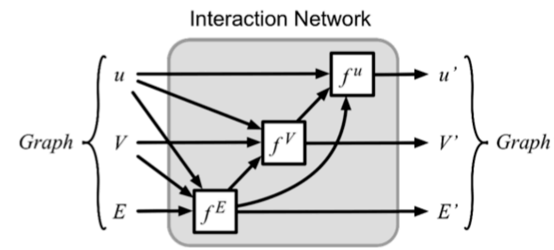
Graph Nets (GNs) are a class of models that:

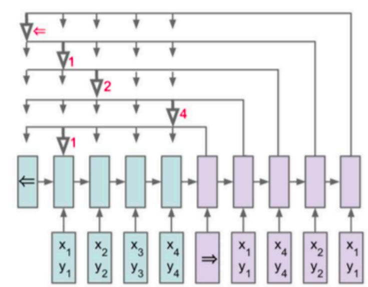
- Use graphs as inputs and/or outputs and/or latent representation
- Manipulate graph-structured representations
- Reflect relational structure
- Share model components across entities and relations



Examples include:

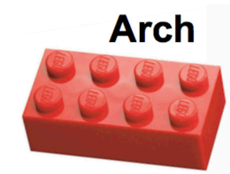
- Graph Neural Networks *(Scarselli et al 07; 08)*
- Recursive Neural Networks *(Goller et al 96)*
- Pointer Networks *(Vinyals et al 2015)*
- Graph Convolutional Networks *(Bruna et al 2013; Duvenaud et al 15; Henaff et al 15; Kipf & Welling 16; Defferrard et al 17)*
- Gated Graph Neural Networks *(Li et al 15)*
- Interaction Networks *(Battaglia et al 2016; Raposo et al 2017;)*
- Message Passing Networks *(Gilmer et al. 2017)*



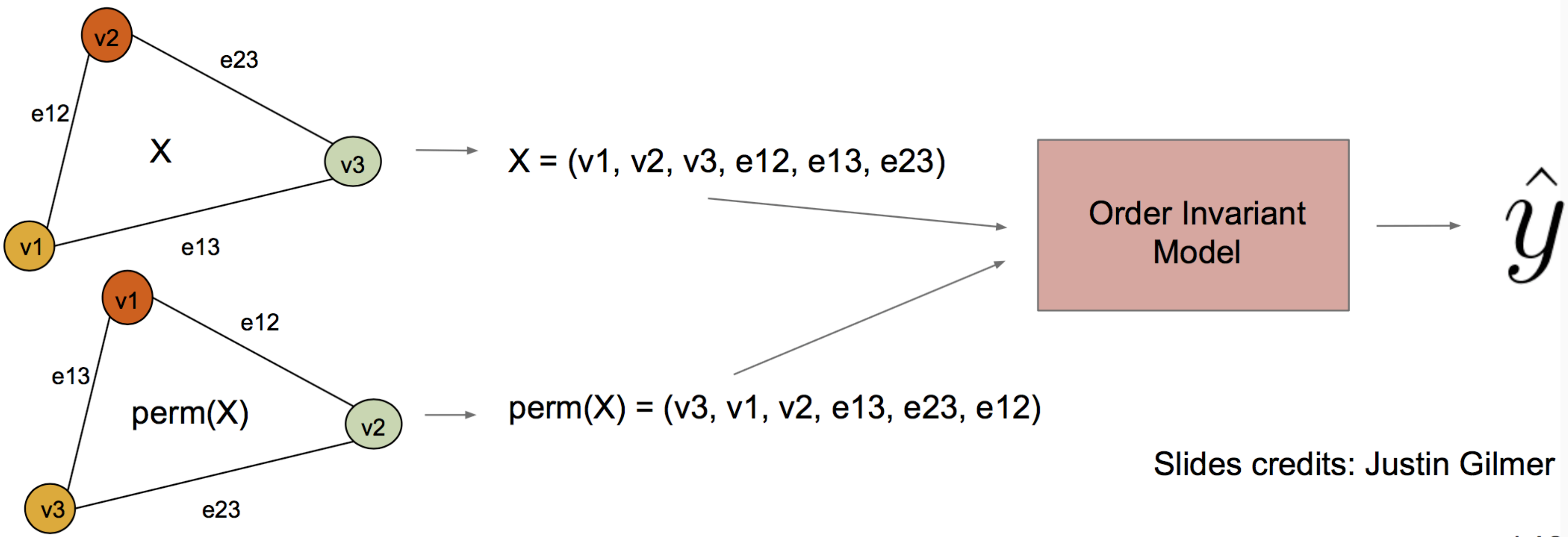


Adapt from From NIPS 2017 DL Trend Tutorial

Inductive Bias for Graphs



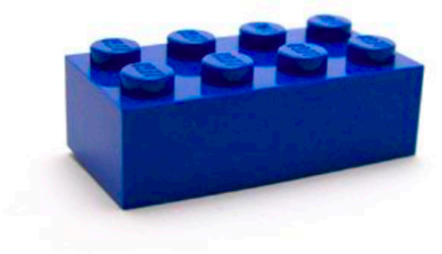
- If we have a graph on N nodes, there are N! possible orderings of the nodes.
- Ideally want a model invariant to the order of nodes.



Slides credits: Justin Gilmer

Adapt from From NIPS 2017 DL Trend Tutorial

Recent Trend (8):
Tasks in the form of Symbolic input/ outputs / Program Induction



Inputs and Outputs:

- Discrete symbols, (e.g. the program itself)
- Program execution traces
- Program I/O pairs

These can also be mixed with perceptual data.

Architectures:

- (Mostly) recurrent
- Sometimes including ConvNets as a visual front-end.

Losses:

- Differentiable, predicting discrete program outputs or code itself: softmax cross entropy.
- Not differentiable: RL

Adapt from From NIPS 2017 DL Trend Tutorial

Machine (Deep) Learning in a Nutshell

Task:

Representation:

Score Function:

Search/Optimization

Check / Validate
(Models, Parameters)

Neural Program Induction - Research Landscape

- Neural network is the program:
  - Learning to Execute, Neural Turing Machine, Neural GPU, Neural RAM, Neural Programmer-Interpreter, Neural Task Programmer, Differentiable Forth Interpreter

2+3
⇩ Network
5

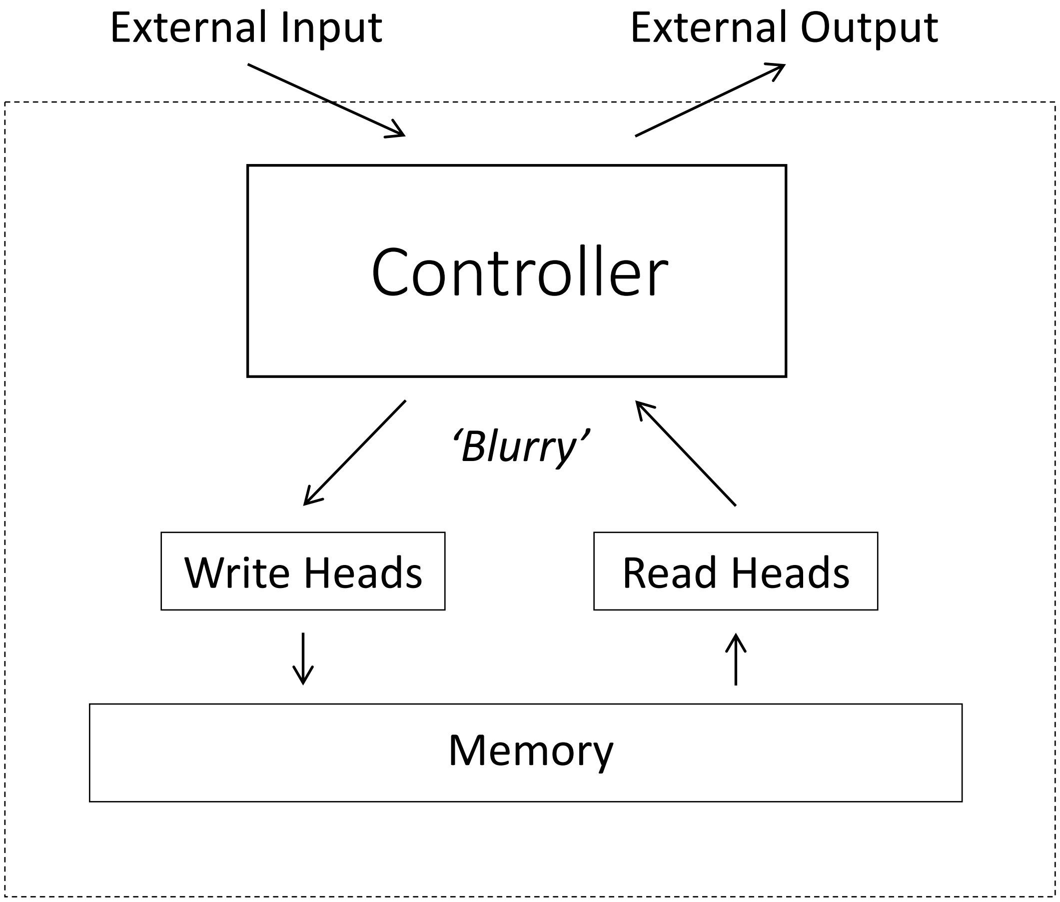
- Neural network generates source code :
  - DeepCoder, RobustFill, Neural Inductive Logic Programming

2,3⇒5
⇩ Network
sum(a,b)

- Probabilistic programming with neural networks:
  - TerpreT, Edward, Picture

Adapt from From NIPS 2017 DL Trend Tutorial

Neural Turing Machines

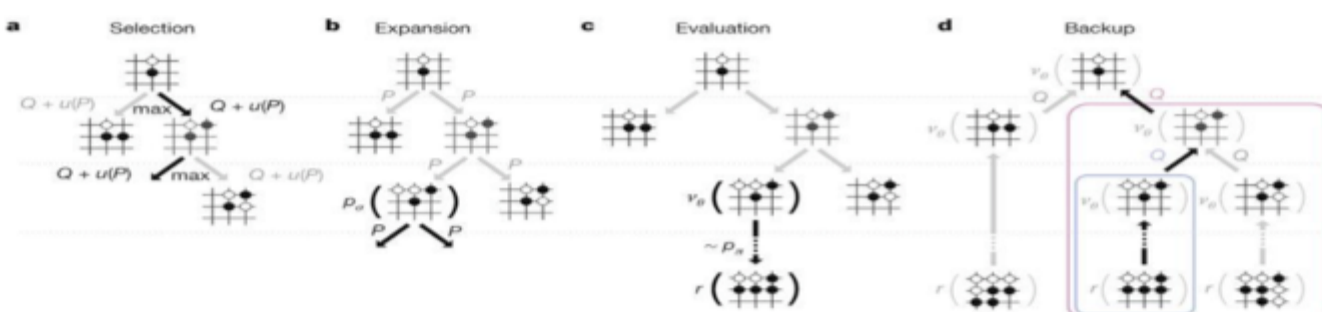


Neural Turing Machines, Graves et. al., arXiv:1410.5401

Task with Sequential Symbolic Form

- Words, letters, strings, ..
- Computer Programs , …
- Sequence decision making, e.g., games, RL

```
while (*d++ = *s++);
```



Recent Trend (9): Generative Adversarial Networks (GAN)

Architectures:

Losses

Machine (Deep) Learning in a Nutshell

Task:

Representation:

Score Function:

Search/Optimization

Check / Validate
(Models, Parameters)

MIT
Technology
Review

Dueling Neural Networks

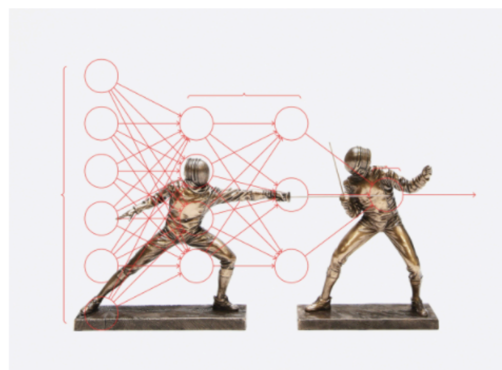
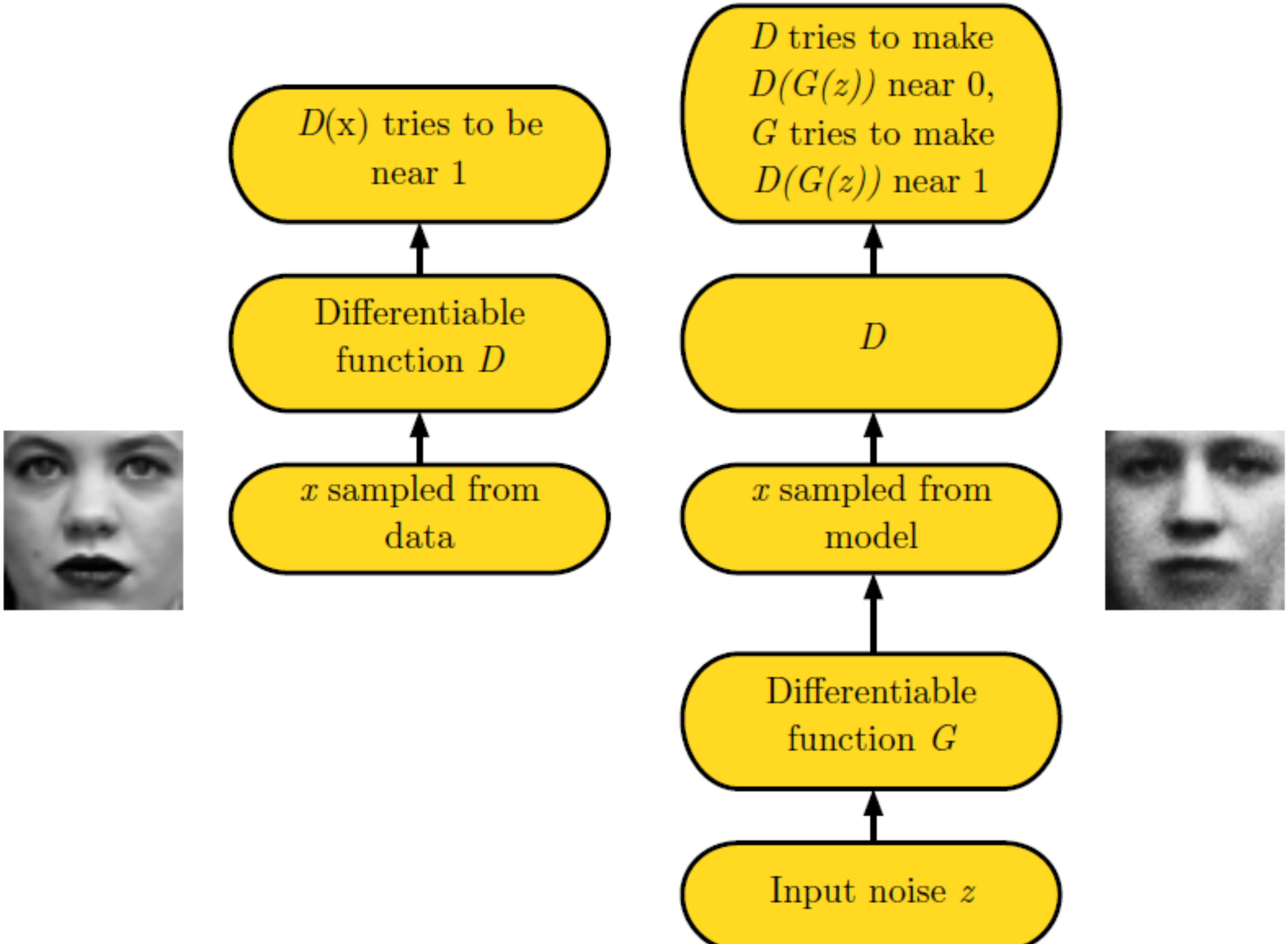


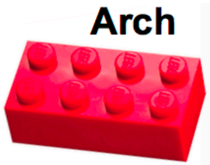
ILLUSTRATION BY DEREK BRAHNEY | DIAGRAM COURTESY OF MICHAEL NIELSEN, "NEURAL NETWORKS AND DEEP LEARNING", DETERMINATION PRESS, 2015

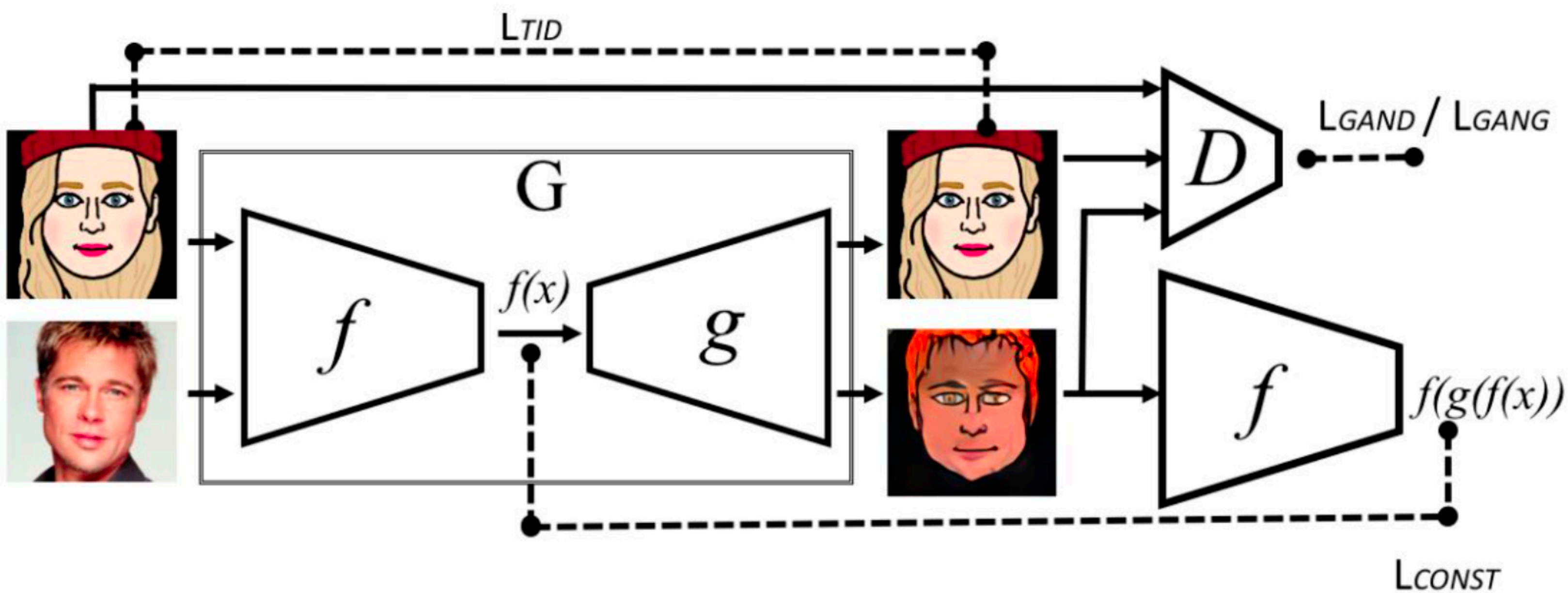
Adversarial Nets Framework



(Goodfellow 2016)

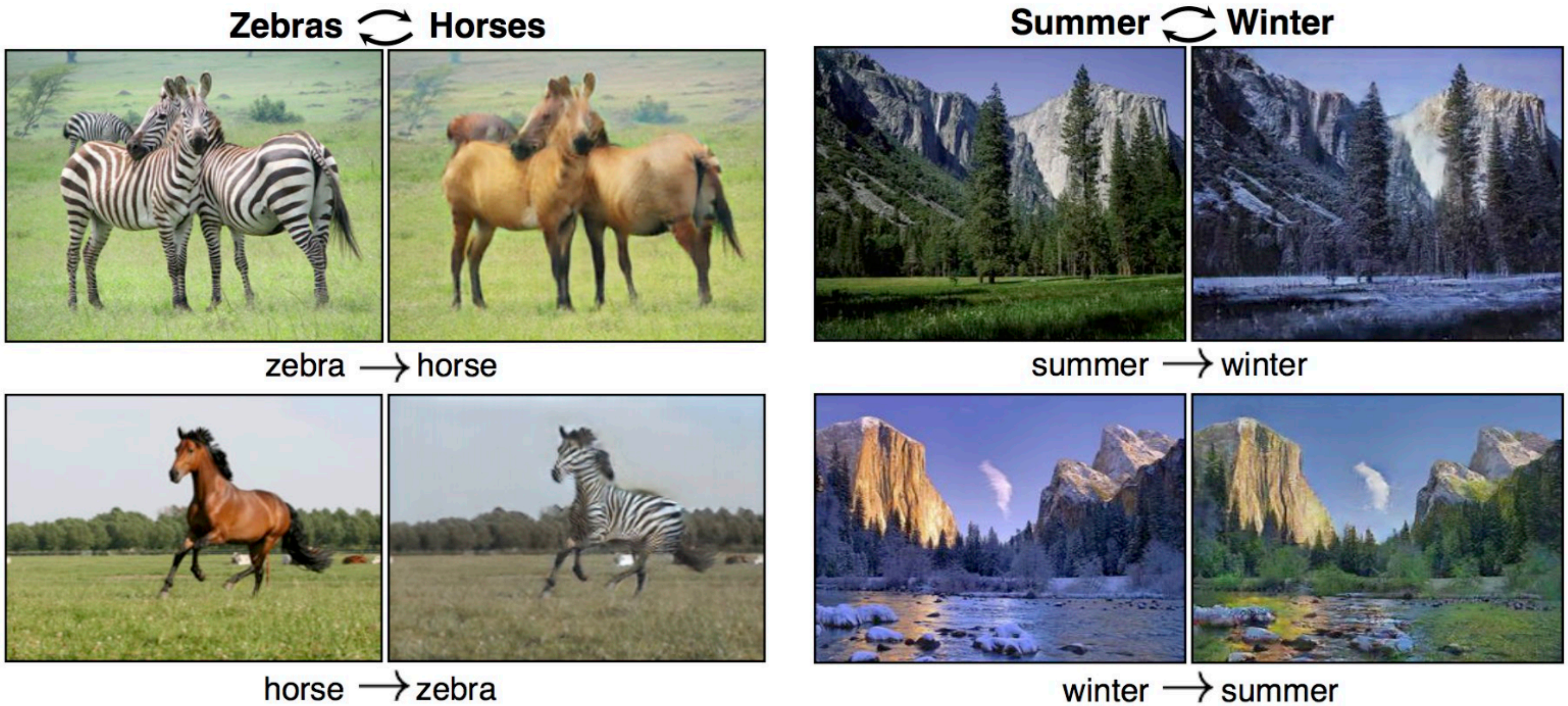
Unsupervised cross-domain image generation





1. Taigmen et al. *"Unsupervised Cross-domain image generation"*. In *ICLR 2017*.

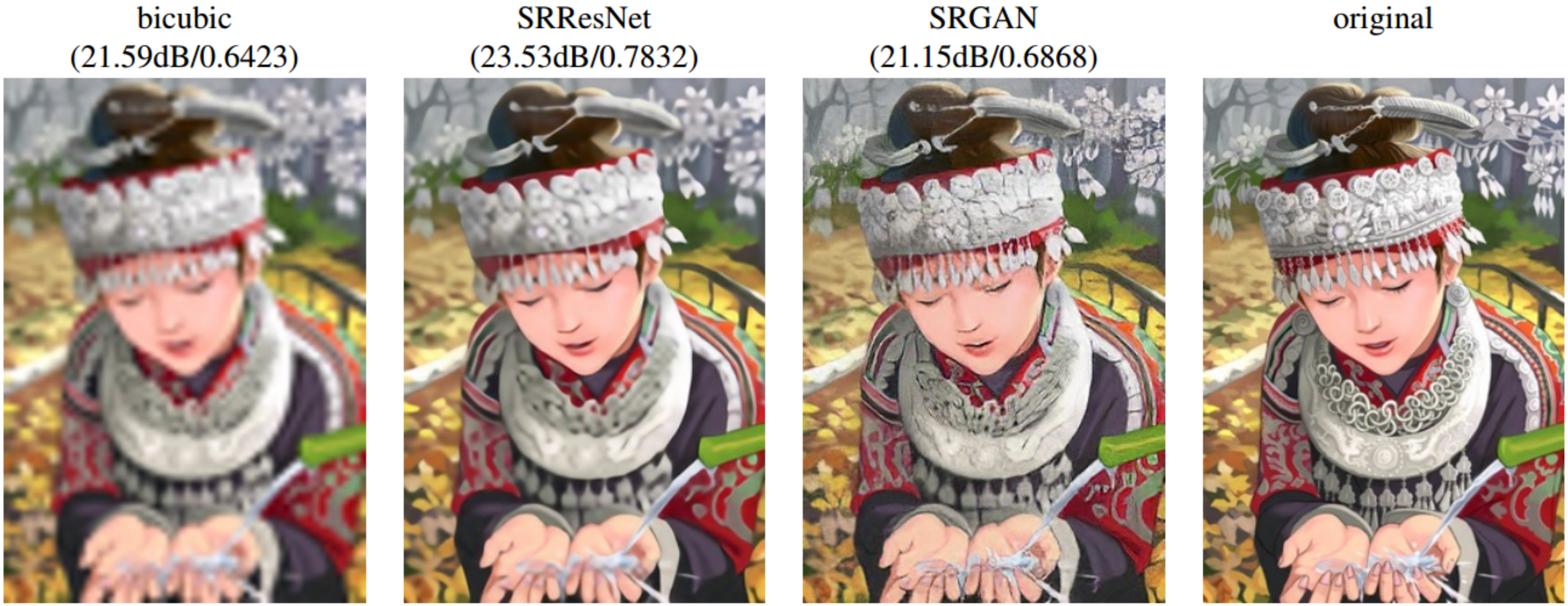
CycleGAN



1. Zhu et al. “Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks”. In ICCV, 2017.

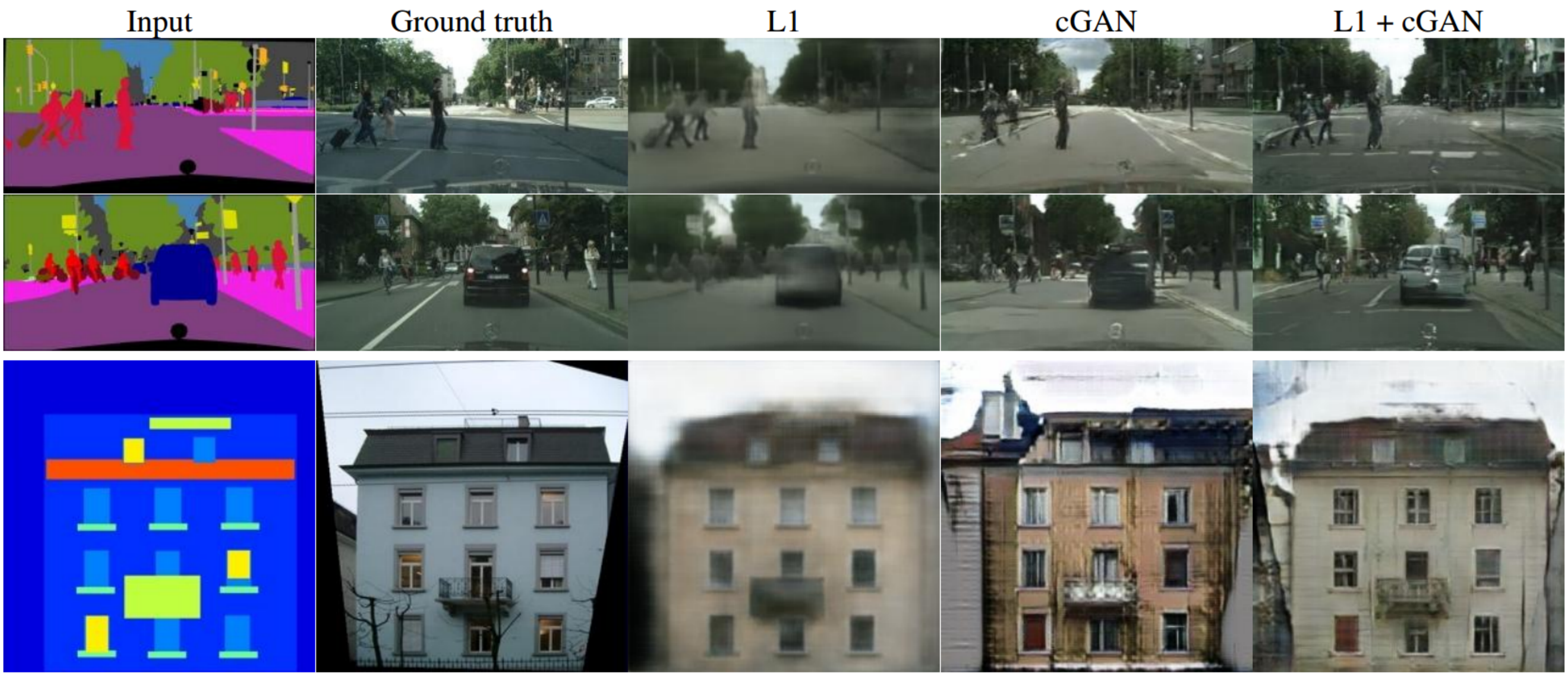
This paper captures special characteristics of one image collection and figures out how these characteristics could be translated into the other image collection, all in the absence of any paired training examples. CycleGANs method can also be applied in variety of applications such as Collection Style Transfer, Object Transfiguration, season transfer and photo enhancement.

Image Super-Resolution



[Ledig et al. CVPR 2017]

Label2Image



[Isola et al. CVPR 2017]

Edges2Image

[Isola et al. CVPR 2017]

Text2Image

this small bird has a pink breast and crown, and black primaries and secondaries.

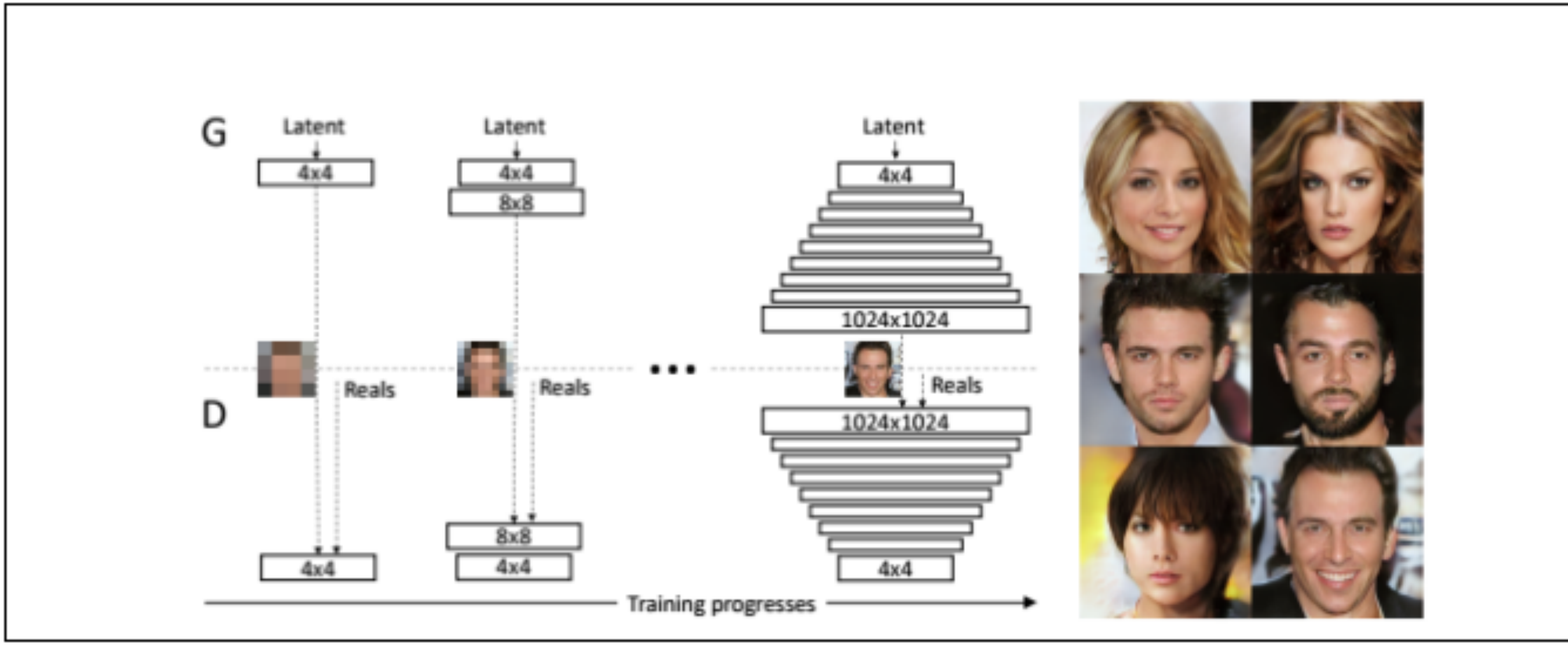
this magnificent fellow is almost all black with a red crest, and white cheek patch.

the flower has petals that are bright pinkish purple with white stigma

this white and yellow flower have thin white petals and a round yellow stamen

[Reed et al. ICML 2016]

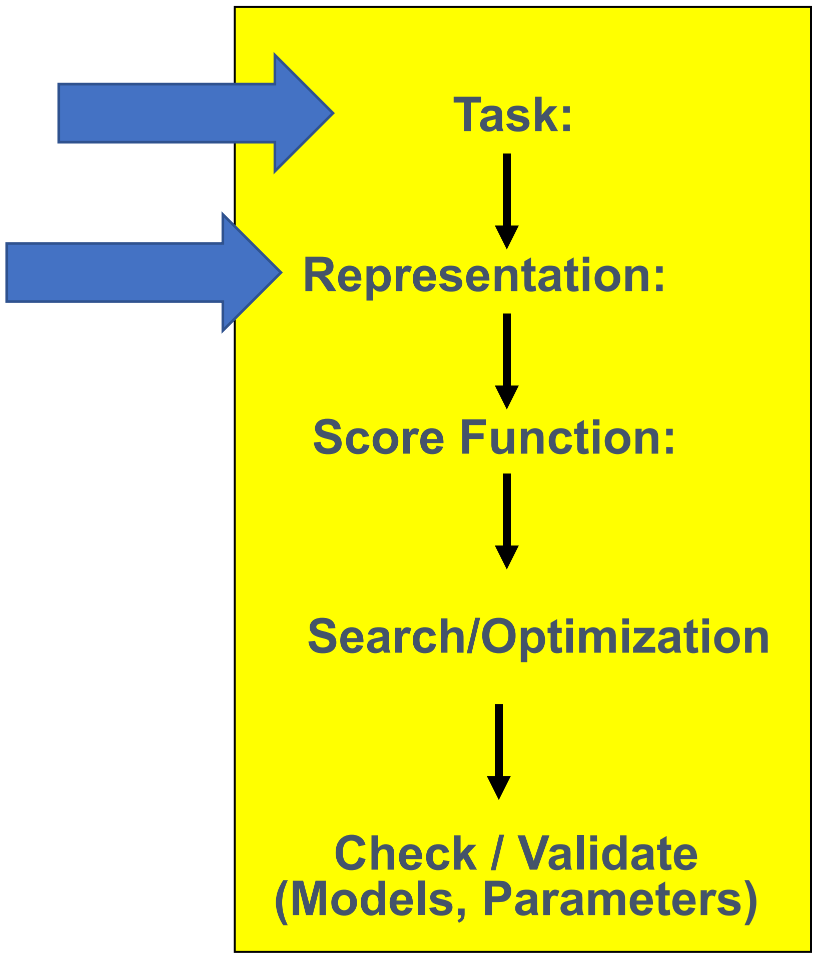
Progressive GAN



PROGRESSIVE GROWING OF GANS FOR IMPROVED QUALITY, STABILITY, AND VARIATION, ICLR 2018

Recent Trend (10):
Deep Generative Models: Autoregressive Kind

Machine (Deep) Learning in a Nutshell



Generative models - Research Landscape

- Latent variable models (VAE, DRAW)
- Implicit (GAN, GMMN, Progressive GAN)
- Transform (NICE, IAF, Real NVP)
- **Autoregressive** (NADE, MADE, RIDE, PixelCNN, WaveNet)

UAI 2017 Tutorial on Deep Generative Models.

NIPS 2016 Tutorial on Generative Adversarial Networks

Adapt from From NIPS 2017 DL Trend Tutorial

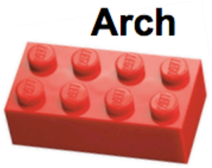
Autoregressive Models

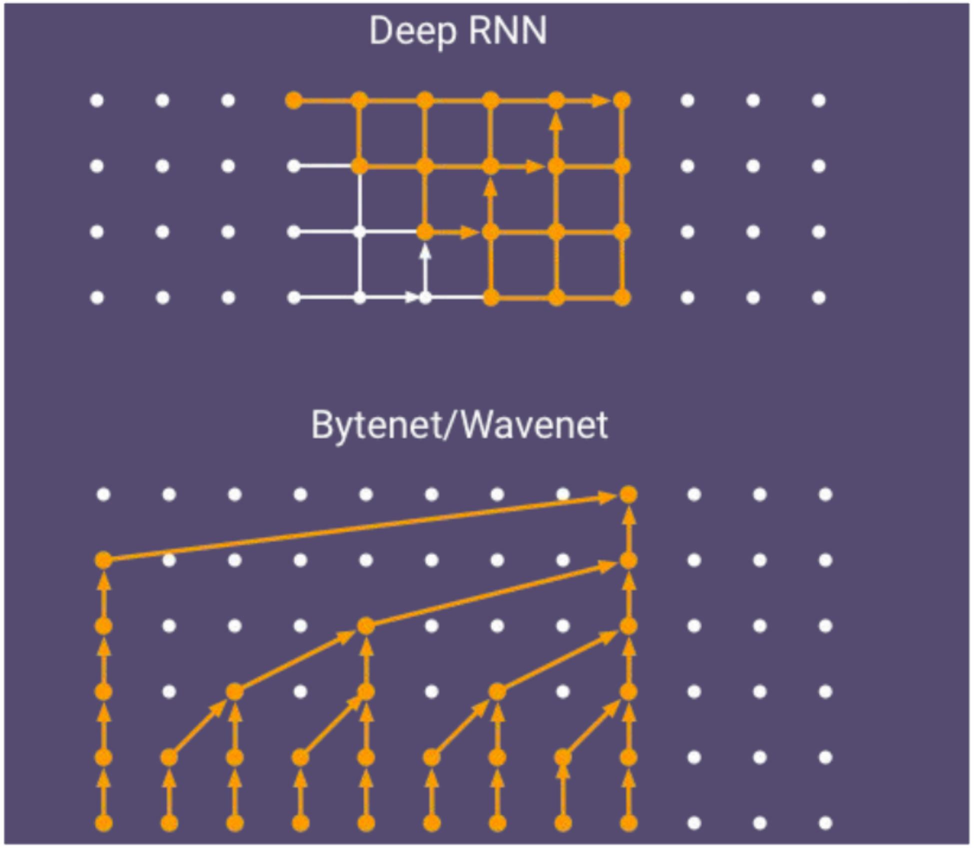
$$P(x;\theta) = \prod_{n=1}^{N} P(x_n | x_{<n}; \theta)$$

- Each factor can be parametrized by θ, which can be shared.
- The variables can be arbitrarily ordered and grouped, as long as the ordering and grouping is consistent.

Adapt from From NIPS 2017 DL Trend Tutorial

Recurrent versus Causal Convolutional Nets





- The architecture is parallelizable along the time dimension (during training or scoring)
- Easy access to many states from the past

Adapt from From NIPS 2017 DL Trend Tutorial

Why Generative Models?

- Excellent test of ability to use high-dimensional, complicated probability distributions
- Simulate possible futures for planning or simulated RL
- Missing data
  - Semi-supervised learning
- Multi-modal outputs
- Realistic generation tasks

(Goodfellow 2016)

Recent Trend (11):
Deep Reinforcement Learning

10 Breakthrough Technologies 2017

These technologies all have staying power. They will affect the economy and our politics, improve medicine, or influence our culture. Some are unfolding now; others will take a decade or more to develop. But you should know about all of them right now.

MIT Technology Review

Machine (Deep) Learning in a Nutshell

Task:

↓

Representation:

↓

Score Function:

↓

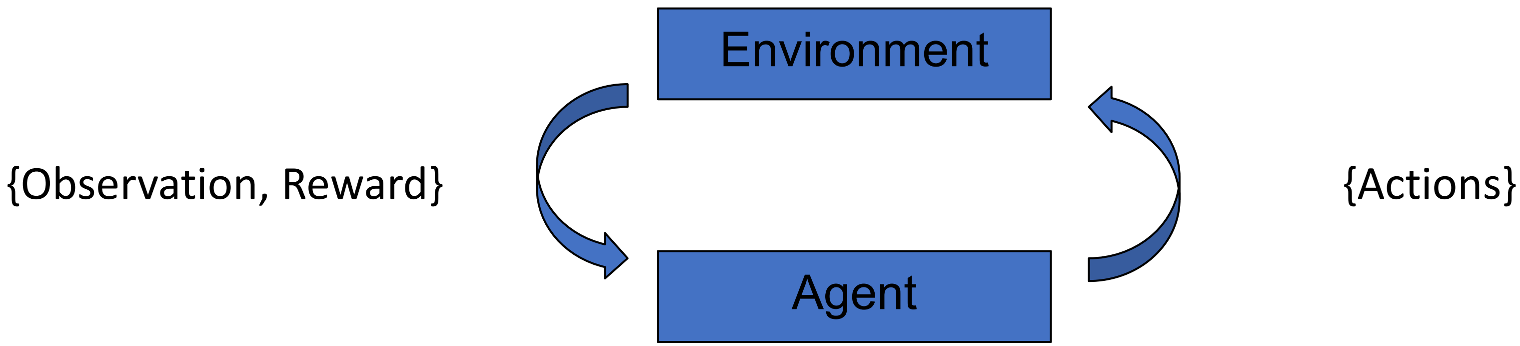
Search/Optimization

↓

Check / Validate
(Models, Parameters)

Reinforcement Learning (RL)

- What's Reinforcement Learning?

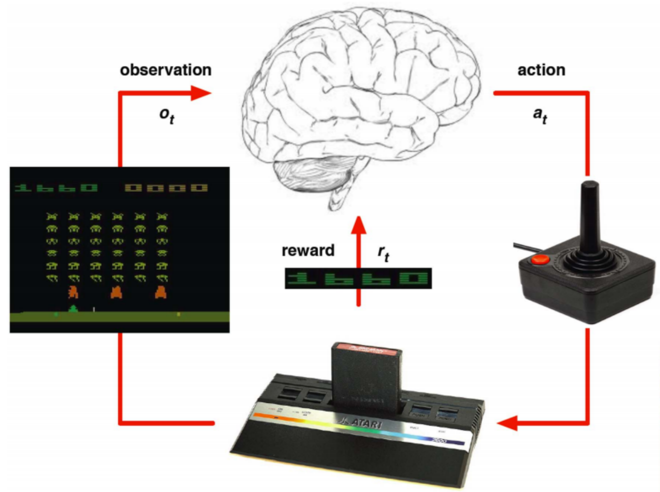


- Agent interacts with an environment and learns by maximizing a scalar reward signal
- No labels or any other supervision signal.
- Previously suffering from hand-craft states or representation.

Adapt from Professor Qiang Yang of HK UST

Deep Reinforcement Learning

- Human

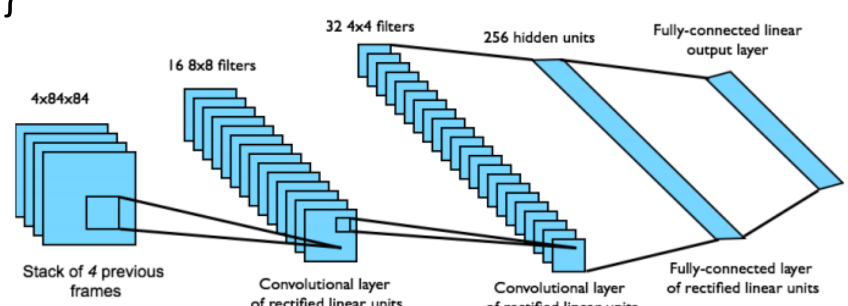


- So what's **DEEP** RL?

Environment

{Raw Observation, Reward}

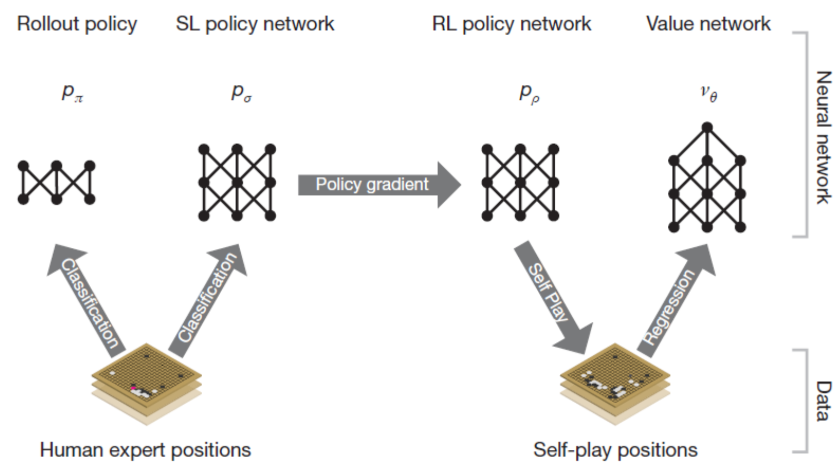
{Actions}



Adapt from Professor Qiang Yang of HK UST

AlphaGO: Learning Pipeline

- Combine Supervised Learning (SL) and RL to learn the search direction in Monte Carlo Tree Search



Silver, David, et al. 2016.

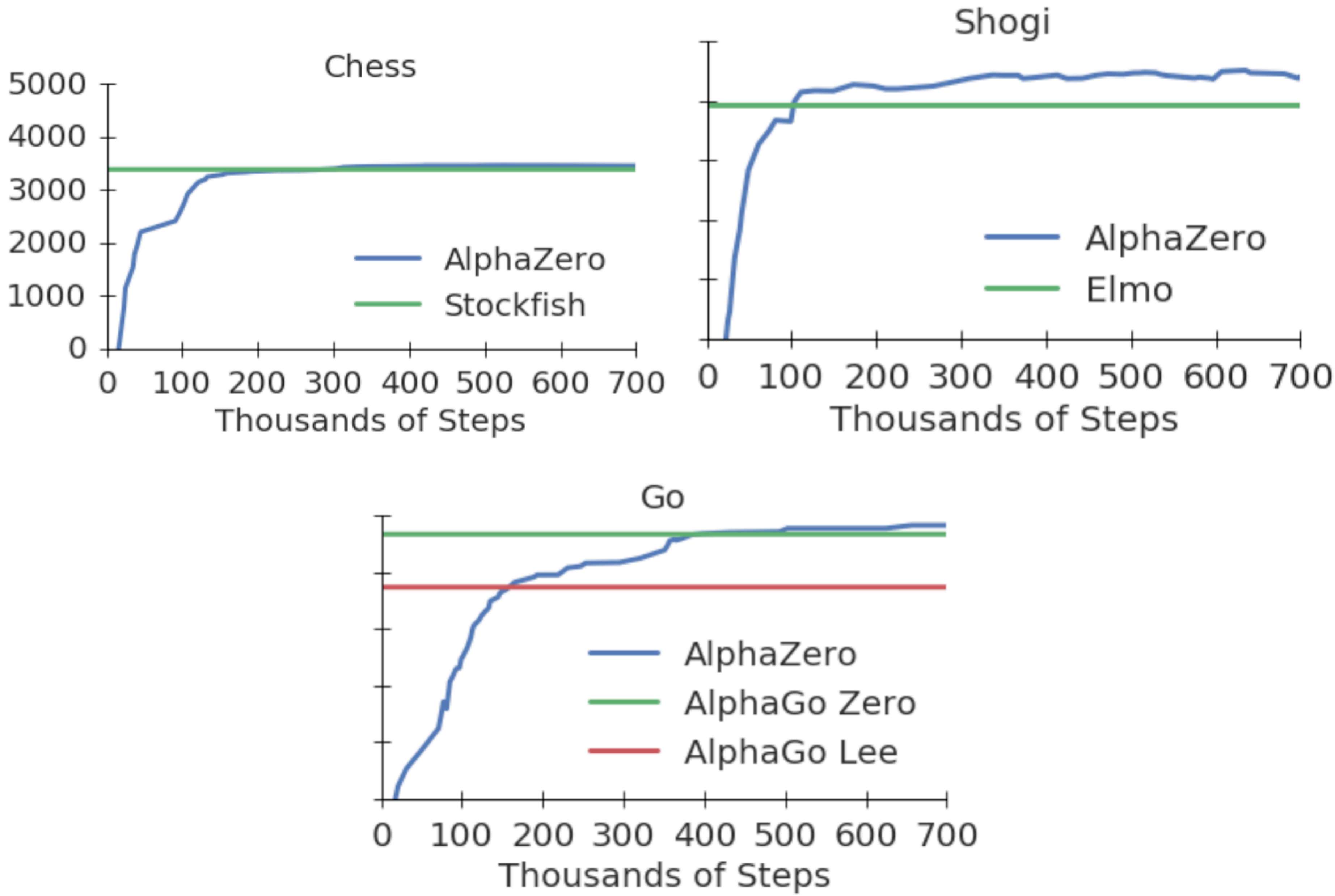
- SL policy Network
  - Prior search probability or potential
- Rollout:
  - combine with MCTS for quick simulation on leaf node
- Value Network:
  - Build the Global feeling on the leaf node situation

Silver, David, et al. "Mastering the game of Go with deep neural networks and tree search." *Nature* 529.7587 (2016): 484-489.

AlphaGo {Fan, Lee, Master} $\times$ AlphaGo Zero:

- supervised learning from human expert positions $\times$ from scratch by self-play reinforcement learning ("tabula rasa")
- additional (auxialiary) input features $\times$ only the black and white stones from the board as input features
- separate policy and value networks $\times$ single neural network
- tree search using also Monte Carlo rollouts $\times$ simpler tree search using only the single neural network to both evaluate positions and sample moves
- (AlphaGo Lee) distributed machines + 48 tensor processing units (TPUs) $\times$ single machines + 4 TPUs
- (AlphaGo Lee) several months of training time $\times$ 72 h of training time (outperforming AlphaGo Lee after 36 h)

Silver, David et al. (2017b). "Mastering the Game of Go without Human Knowledge". In: Nature 550.7676, pp. 354–359.



Silver, David et al. (2017b). “Mastering the Game of Go without Human Knowledge”. In: Nature 550.7676, pp. 354–359.

Recent Trend (12): Robustness / Trustworthiness / Understand / Verify / Test / Evade / Detect Bias / Protect DNN

Validation

Machine (Deep) Learning in a Nutshell

Task:

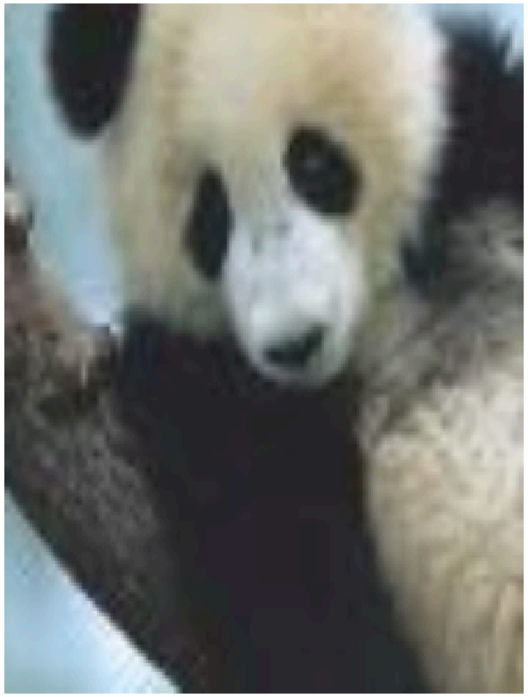
Representation:

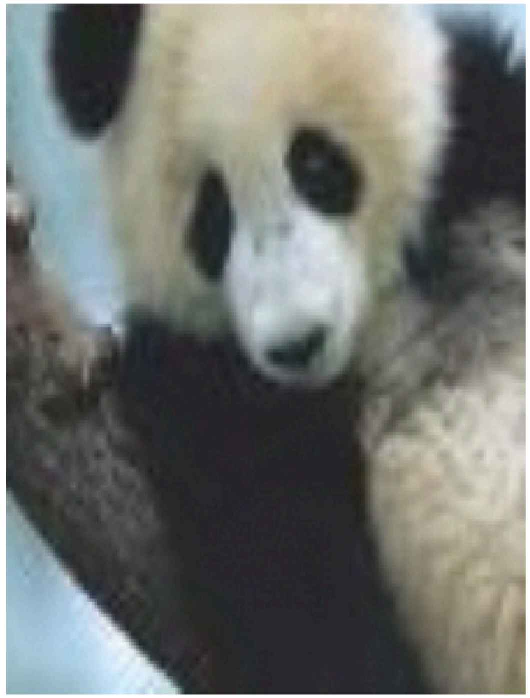
Score Function:

Search/Optimization

Check / Validate
(Models, Parameters)

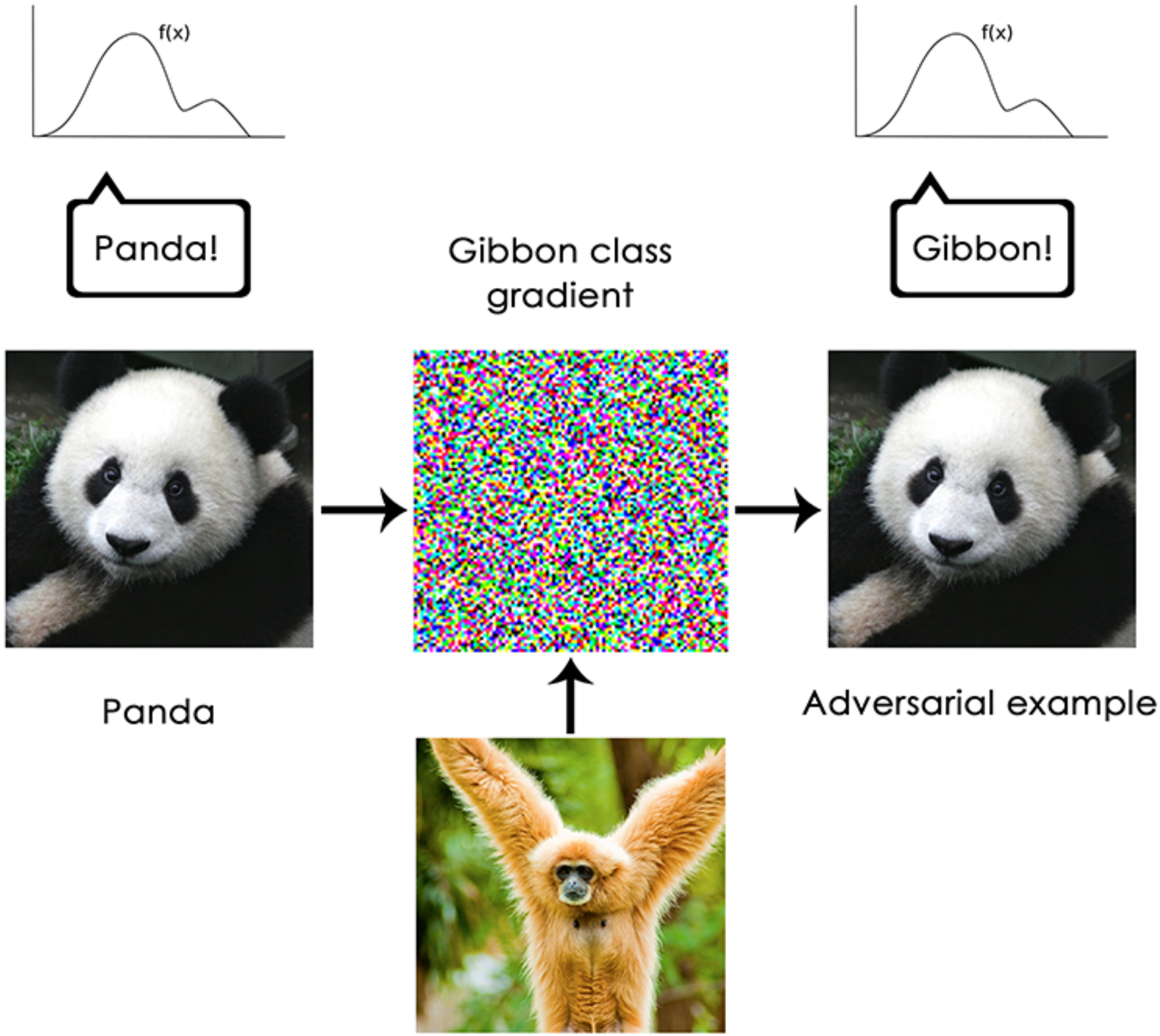
Evade DNN, e.g. Adversarial Examples (AE)





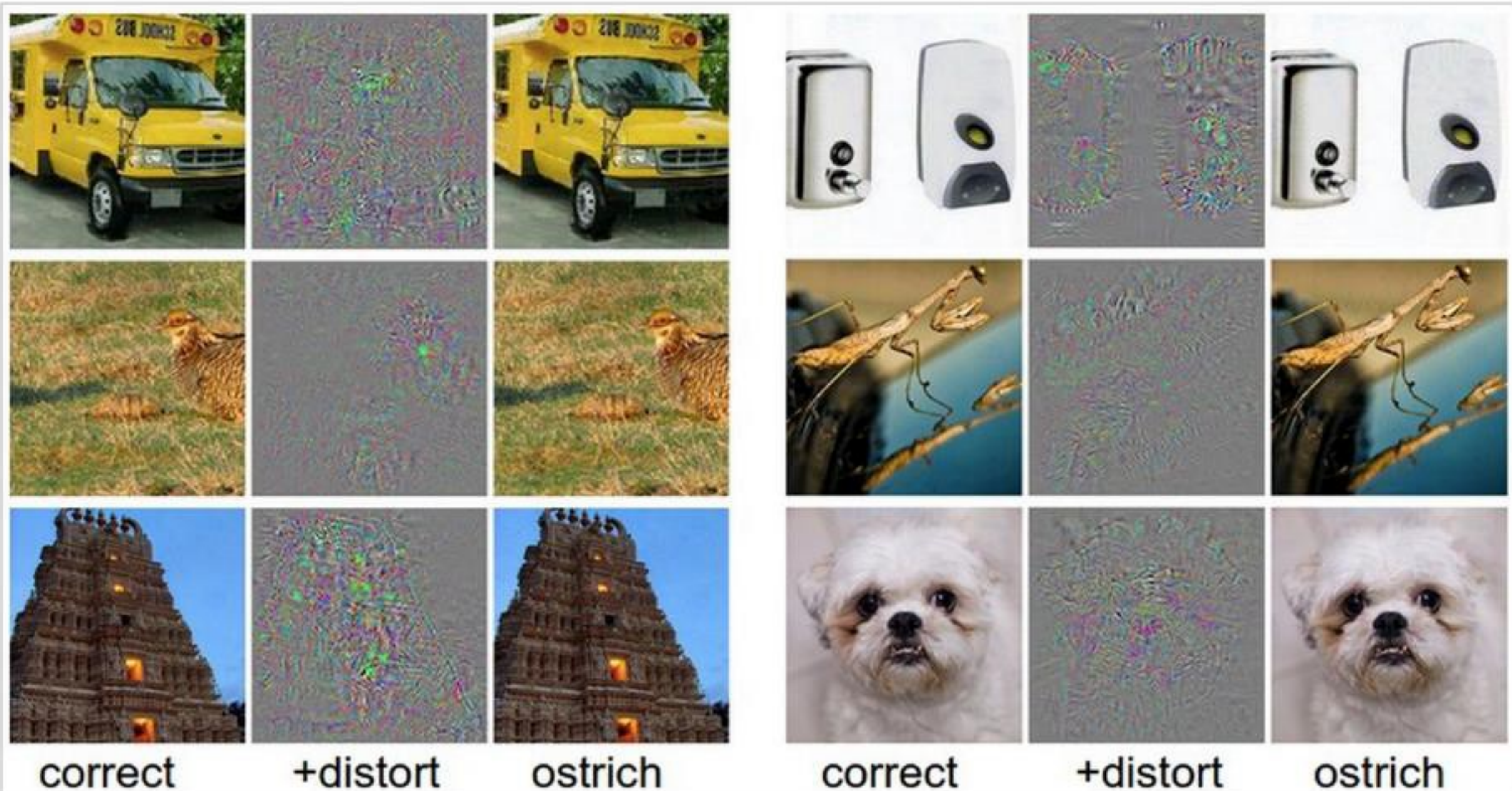
“panda” $+$ $0.007 \times [noise]$ $=$ “gibbon”

Example from: Ian J. Goodfellow, Jonathon Shlens, Christian Szegedy. *Explaining and Harnessing Adversarial Examples*. ICLR 2015.



Francois Chollet - https://blog.keras.io/the-limitations-of-deep-learning.html

Breaking CNNs

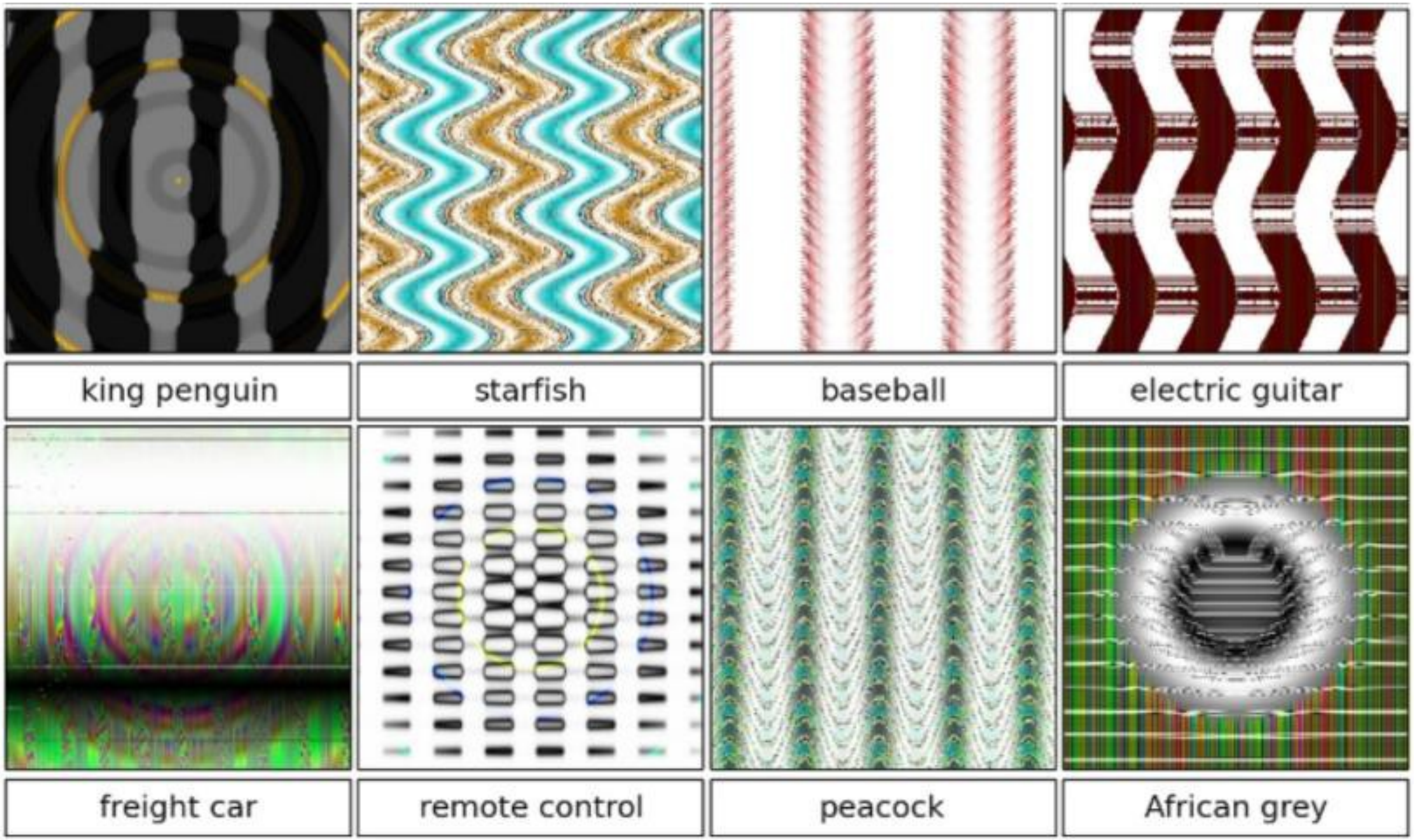


Take a correctly classified image (left image in both columns), and add a tiny distortion (middle) to fool the ConvNet with the resulting image (right).

Intriguing properties of neural networks [Szegedy ICLR 2014]

Andrej Karpathy

Breaking CNNs



Deep Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images [Nguyen et al. CVPR 2015]

Cat-and-mouse game

[Szegedy+ 2014]: first discover adversarial examples

[Goodfellow+ 2015]: Adversarial training (AT) against FGSM

[Papernot+ 2015]: defensive distillation

[Calini & Wagner 2016]: distillation is not secure

[Papernot+ 2017]: better distillation

[Carlini & Wagner 2017]: All detection strategies fail

[Madry+ 2017]: AT against PGD, informal argument about optimality

[Lu+ July 12 2017]: "NO Need to Worry about Adversarial Examples in Object Detection in Autonomous Vehicles"

[Athalye & Sutskever July 17 2017]: break defense with AT on PGD with transformed examples

From: Ian J. Goodfellow

Bias in DNN: e.g. Men Also Like Shopping: Reducing Gender Bias Amplification using Corpus-level Constraints, EMNLP 2017

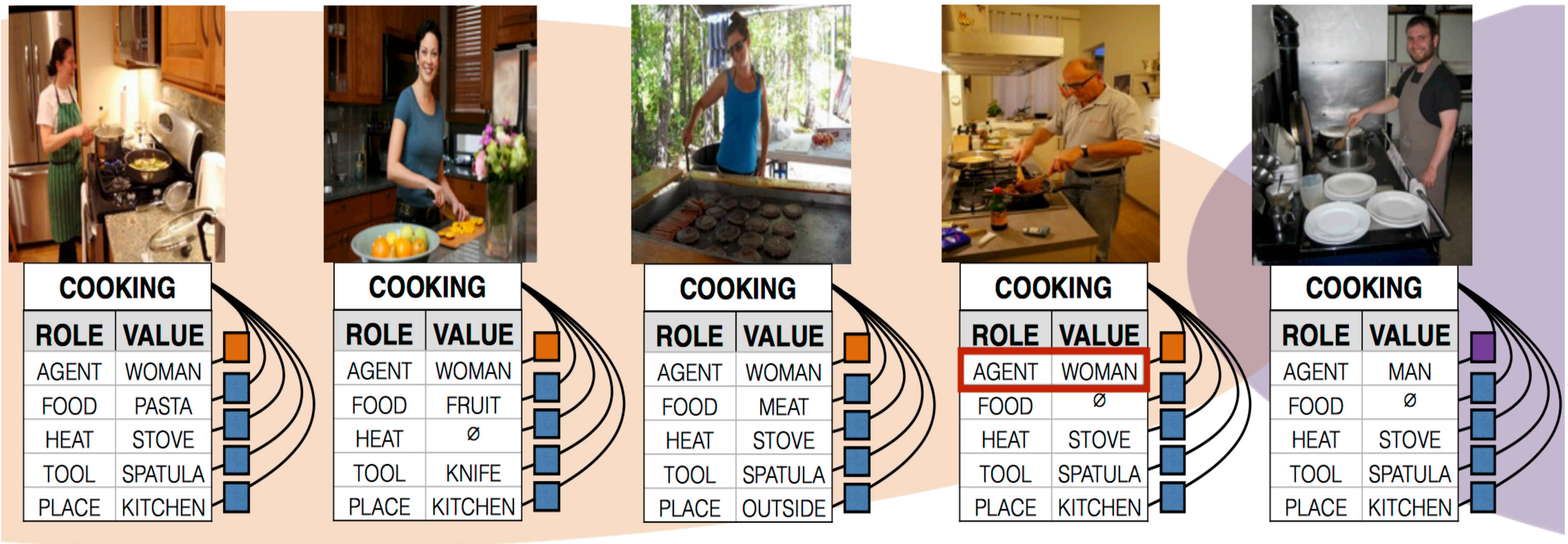


Figure 1: Five example images from the imSitu visual semantic role labeling (vSRL) dataset. Each image is paired with a table describing a situation: the verb, `cooking`, its semantic roles, i.e `agent`, and noun values filling that role, i.e. `woman`. In the imSitu training set, 33% of `cooking` images have `man`

Verify DNN, e.g. "Reluplex: An efficient SMT solver for verifying deep neural networks." International Conference on Computer Aided Verification. 2017.

Provably robust?

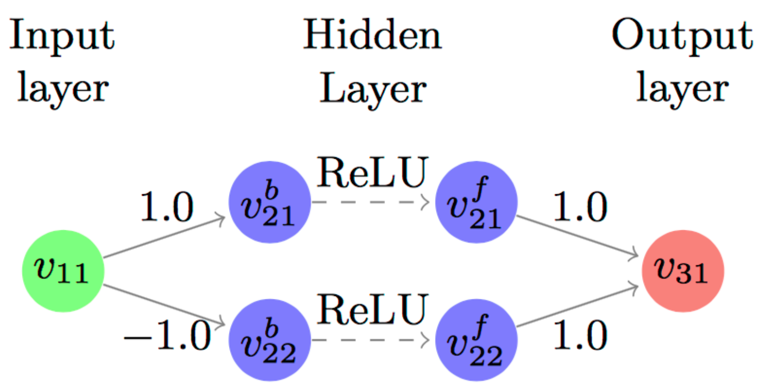


Table 3: Local adversarial robustness tests. All times are in seconds.

	$\delta = 0.1$		$\delta = 0.075$		$\delta = 0.05$		$\delta = 0.025$		$\delta = 0.01$		Total
	Result	Time	Result	Time	Result	Time	Result	Time	Result	Time	Time
Point 1	SAT	135	SAT	239	SAT	24	UNSAT	609	UNSAT	57	1064
Point 2	UNSAT	5880	UNSAT	1167	UNSAT	285	UNSAT	57	UNSAT	5	7394
Point 3	UNSAT	863	UNSAT	436	UNSAT	99	UNSAT	53	UNSAT	1	1452
Point 4	SAT	2	SAT	977	SAT	1168	UNSAT	656	UNSAT	7	2810
Point 5	UNSAT	14560	UNSAT	4344	UNSAT	1331	UNSAT	221	UNSAT	6	20462

Today Recap: Some Recent Trends

- 1. CNN / Residual / Dynamic parameter
- 2. RNN / Attention / Seq2Seq / BERT …
- 3. Neural Architecture with explicit Memory
- 4. Learning to optimize / Learning DNN architectures

New Network topology

- 5. Autoencoder / layer-wise training
- 6. Learning to learn / meta-learning/ few-shots

New Losses

- 7. DNN on graphs / trees / sets
- 8. NTM 4program induction / sequential decisions

New Inputs

- 9. Generative Adversarial Networks (GAN)
- 10. Deep Generative models, e.g., autoregressive

New Tasks

- 11. Deep reinforcement learning
- 12. Validate / Evade / Test / Understand / Verify DNNs

New Model Properties

- (Many more exciting trends not covered here!)

References

- Dr. Yann Lecun's deep learning tutorials
- Dr. Li Deng's ICML 2014 Deep Learning Tutorial
- Dr. Kai Yu's deep learning tutorial
- Dr. Rob Fergus' deep learning tutorial
- Prof. Nando de Freitas' slides
- Olivier Grisel's talk at Paris Data Geeks / Open World Forum
- Hastie, Trevor, et al. *The elements of statistical learning*. Vol. 2. No. 1. New York: Springer, 2009.
- Dr. Hung-yi Lee's CNN slides
- NIPS 2017 DL Trend Tutorial