



Deep Learning Like Magic, but Real!



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Outline

- Chapter 1: Motivation (King)
- Chapter 2: State of the Art Architectures (Xing)

Machine Learning



Making the machines sentient and intelligent. It'll take away all the jobs -- It's an existential threat to humanity -- it will lead to the SINGULARITY!

Programing: Human imposes the rules on Machine

Learning: Machine *infers* the rules (from data) for Human



Chapter 1: It's Magic!



Gee Whiz #1: Infer Color

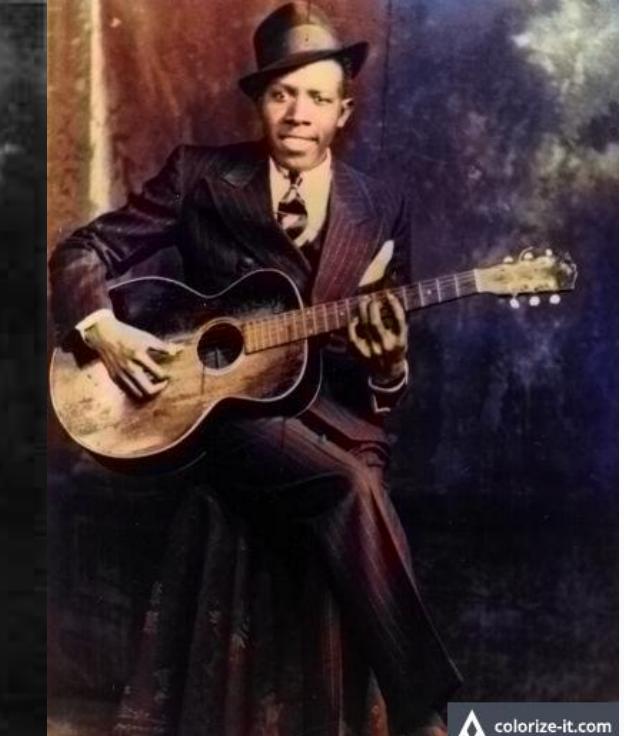


<https://arxiv.org/pdf/1603.08511.pdf>
<https://github.com/richzhang/colorization>



<http://demos.algorithmia.com/colorize-photos/>

Gee Whiz #1: Infer Color



Gee Whiz #2: Capturing Style



<http://dizajnsvakidan.com/kad-umjetna-neuronska-mreza-generira-tipografiju/>

Original Paper: <https://arxiv.org/abs/1703.07511>

Gee Whiz #2: Capturing Style



Also useful for Propaganda



Gee Whiz #3: Robust Image Classification/Captioning



<http://www.boredpanda.com/camouflage-owl-photography/>

PREDICTED CONCEPT	PROBABILITY
tree	0.998
bark	0.998
nature	0.997
wood	0.994
owl	0.986
trunk	0.985
no person	0.965
log	0.951

<https://www.clarifai.com/demo>

Gee Whiz #3: Robust Image Classification/Captioning



a bird sitting on a ledge looking out the window
logprob: -9.87



a pair of scissors and a pair of shears
logprob: -6.00



a large elephant standing in a field of grass
logprob: -7.93



a man riding a horse drawn carriage down a street
logprob: -7.29



a man is standing on a beach with a surfboard
logprob: -10.07



a man riding a bike down a street next to a woman
logprob: -9.47

Gee Whiz #4 : Voice Synthesis

<https://lyrebird.ai/demo>

Chapter 2: It's Real.

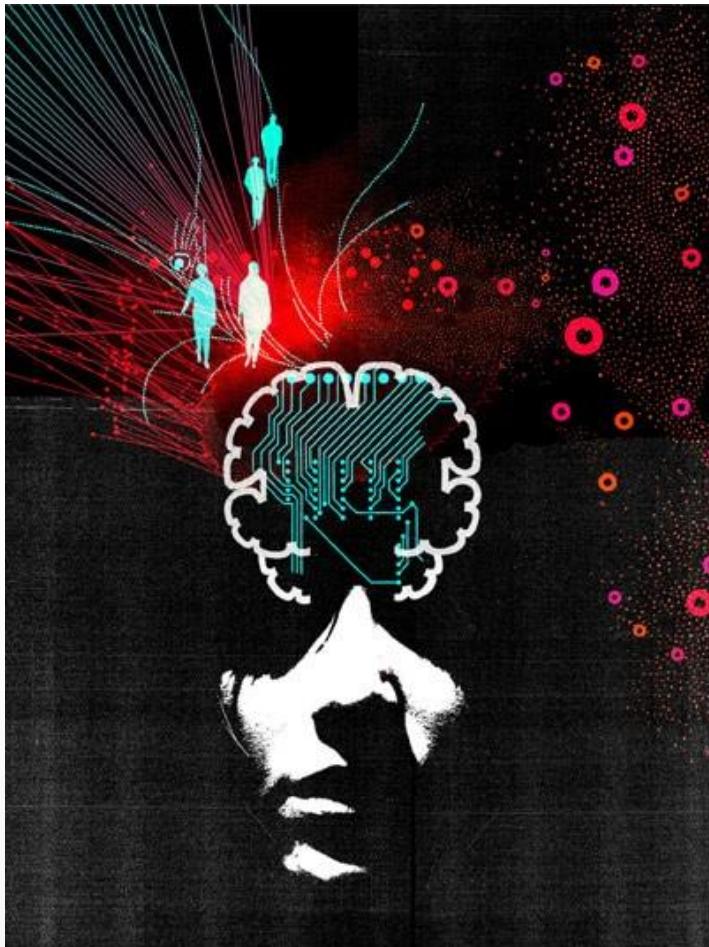
Ok—Maybe it's this much magic...



Deep Learning is A Breakthrough Technology

- MIT Technology Review: 10 breakthrough technologies

2013: Deep learning



2017: Paying with your face



Why Deep Learning?



PINTEREST

SOCIAL SITE
THAT IS ALL ABOUT
DISCOVERY

LARGEST
OPPORTUNITIES



USERS ARE:

20% MALE

80% FEMALE

150
MILLION
ACTIVE USERS



TWITTER

MICRO BLOGGING
SOCIAL SITE
THAT LIMITS EACH
POST TO **140**
CHARACTERS

THERE ARE OVER
67 MILLION
TWITTER USERS



6,000 TWEETS
ON AVERAGE
HAPPEN
EVERY
SECOND

328
MILLION
ACTIVE USERS



FACEBOOK

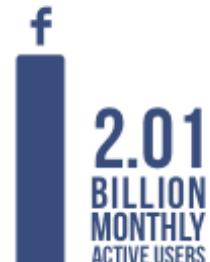
MOBILE IS
FACEBOOK'S
CASH COW



1.15
BILLION
DAILY ACTIVE
MOBILE USERS

AGE 25 TO 34
AT **29.7%** OF USERS
IS THE MOST COMMON
AGE DEMOGRAPHIC

USERS
1 MILLION LINKS
EVERY 20 MINUTES



INSTAGRAM

SOCIAL SHARING
APP ALL AROUND
PICTURES
AND NOW 60 SECOND
VIDEOS

MANY BRANDS
ARE PARTICIPATING
THROUGH THE USE OF
HASHTAGS
AND POSTING

PICTURES
CONSUMERS
CAN RELATE TO

MOST FOLLOWED BRAND IS
 NATIONAL GEOGRAPHIC



SNAPCHAT

APP FOR SENDING
VIDEOS AND
PICTURES
THAT DISAPPEAR
AFTER BEING VIEWED

10+
BILLION
VIDEO VIEWS DAILY

ROUGHLY
70% OF
USERS ARE FEMALE

MOST USED
PLATFORM
AMONG **12 - 24**
YEAR OLDS



LINKEDIN

BUSINESS
ORIENTED
SOCIAL NETWORKING SITE

BRANDS THAT ARE
PARTICIPATING
ARE **CORPORATE**
BRANDS
GIVING POTENTIAL AND
CURRENT ASSOCIATES
A PLACE TO **NETWORK**
& **CONNECT**



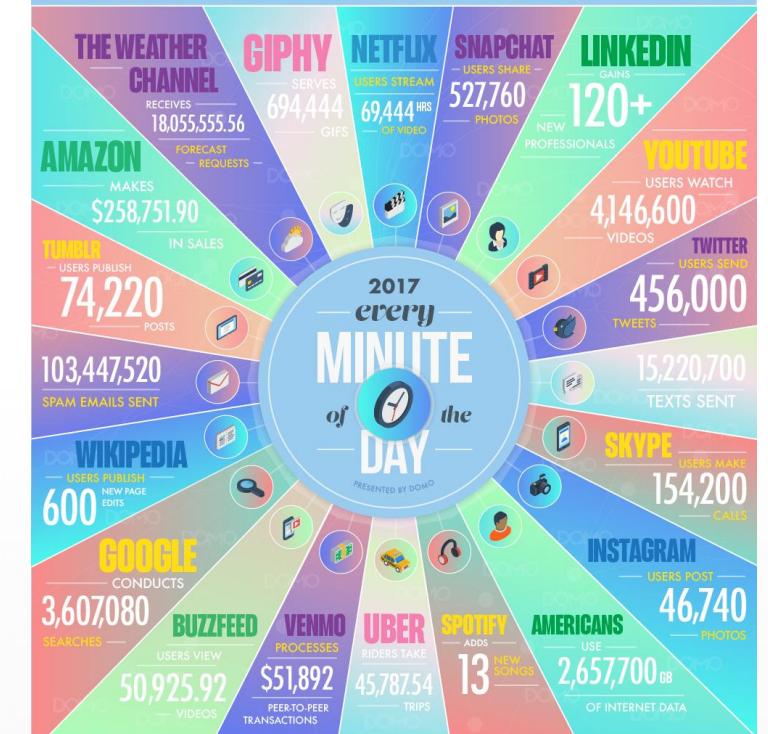
70% OF USERS
ARE OUTSIDE
THE U.S.



DATA NEVER SLEEPS 5.0

How much data is generated *every minute*?

90% of all data today was created in the last two years—that's 2.5 quintillion bytes of data per day. In our 5th edition of Data Never Sleeps, we bring you the latest stats on just how much data is being created in the digital sphere—and the numbers are staggering.



The world internet population has grown 7.5% from 2016 and now represents 3.7 billion people.

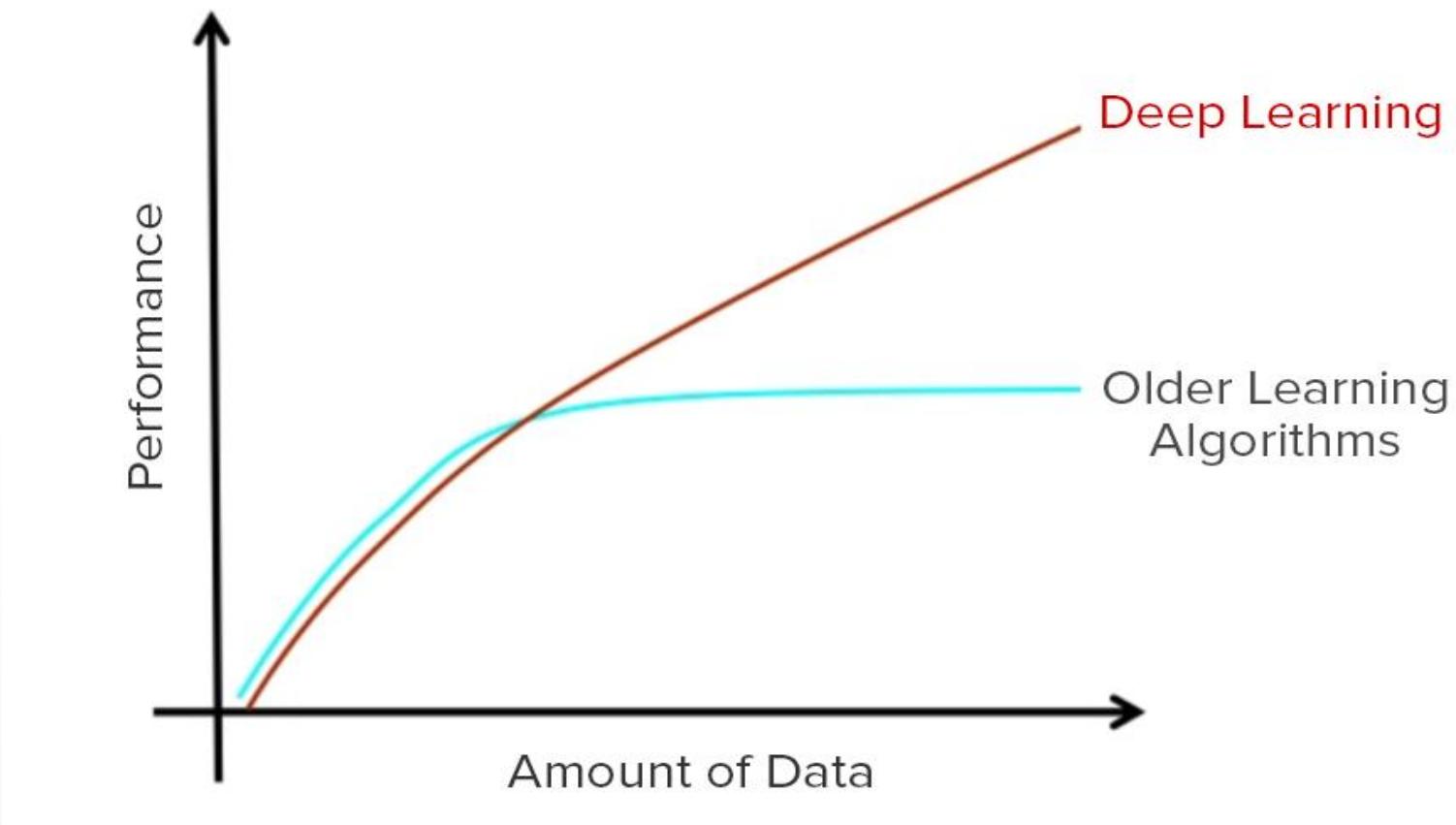
2012 2014 2016 2017

GLOBAL INTERNET POPULATION GROWTH 2012-2017 (IN BILLIONS)

With each click, swipe, share, and like, businesses are using data to make decisions about the future. Domo gives everyone in your business real-time access to data from virtually any data source in a single platform for smarter decision-making at any moment.

Learn more at domo.com

Why Deep Learning?



Why Deep Learning is Taking Off?

- Data
- Computing resources
- Algorithms

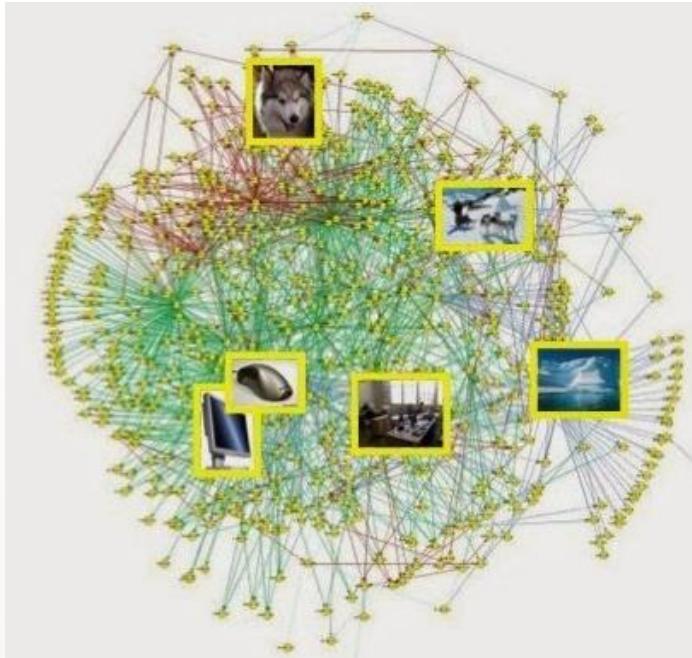
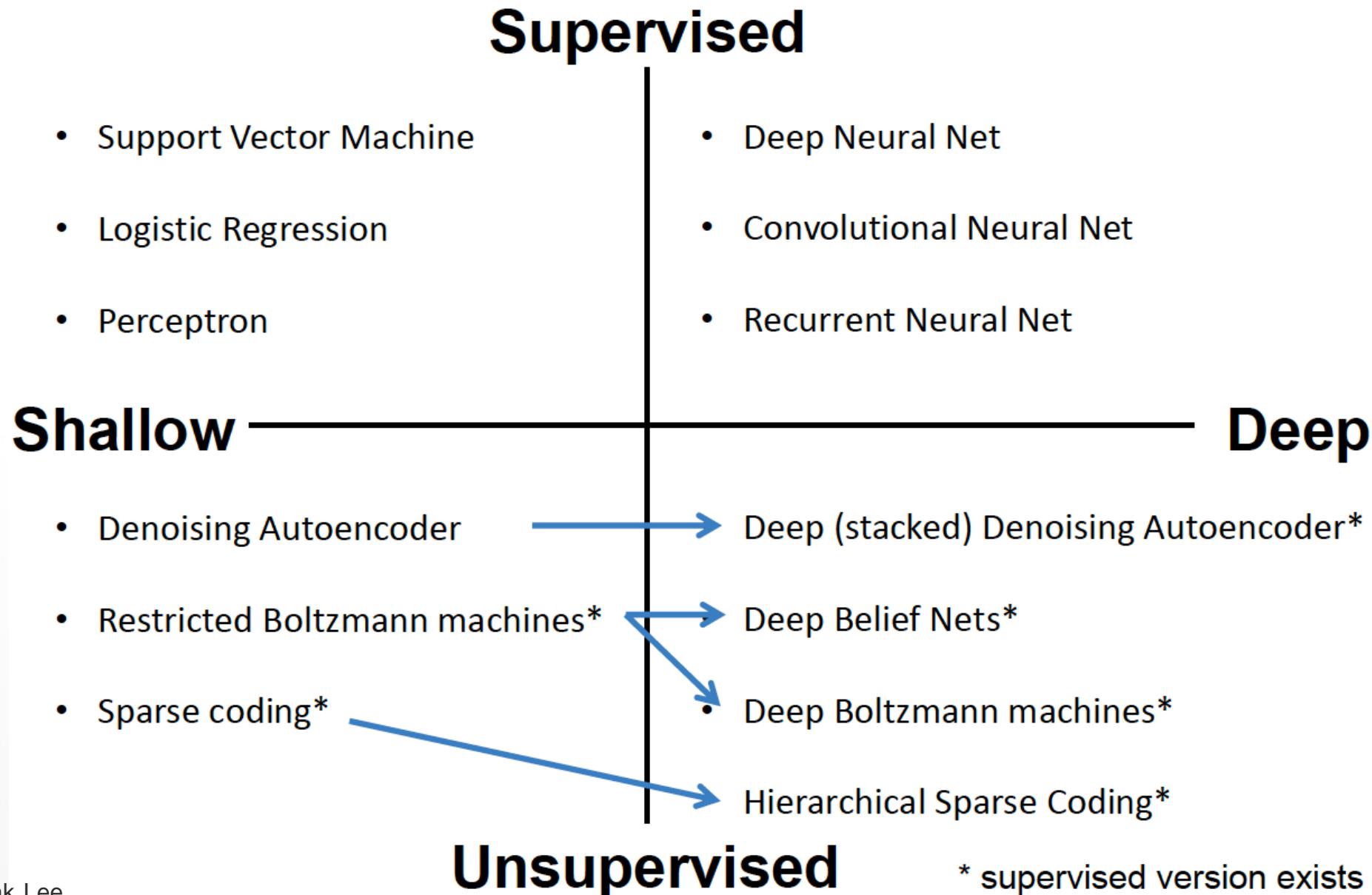


Image credit:

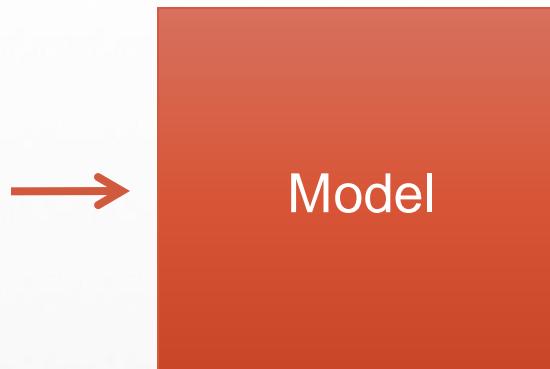
1. <https://www.nasa.gov>
2. <http://www.computervisionblog.com/2015/05/deep-learning-vs-big-data-who-owns-what.html>
3. <https://www.nvidia.com>

Taxonomy of Machine Learning Methods



Supervised Machine Learning

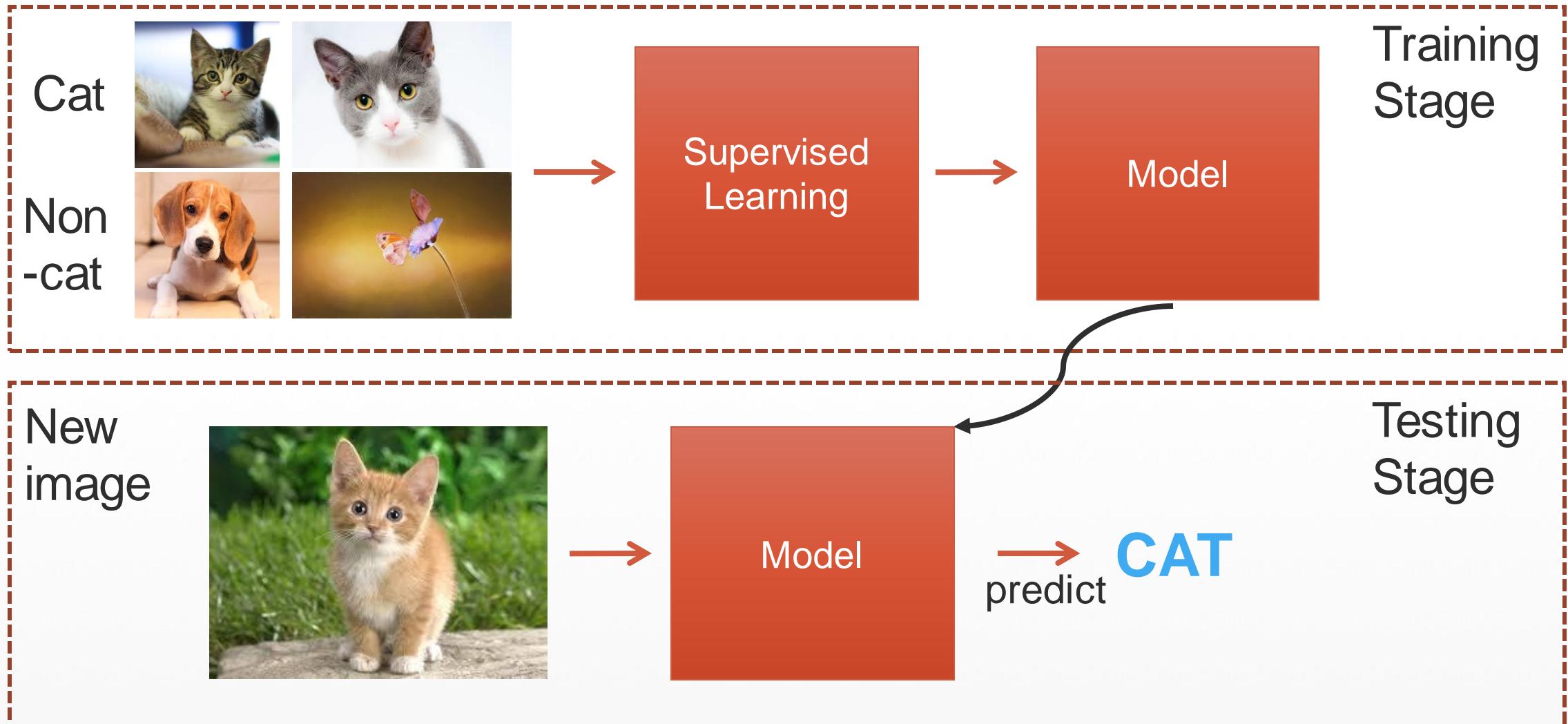
- What is this picture?



→ Model
predict CAT

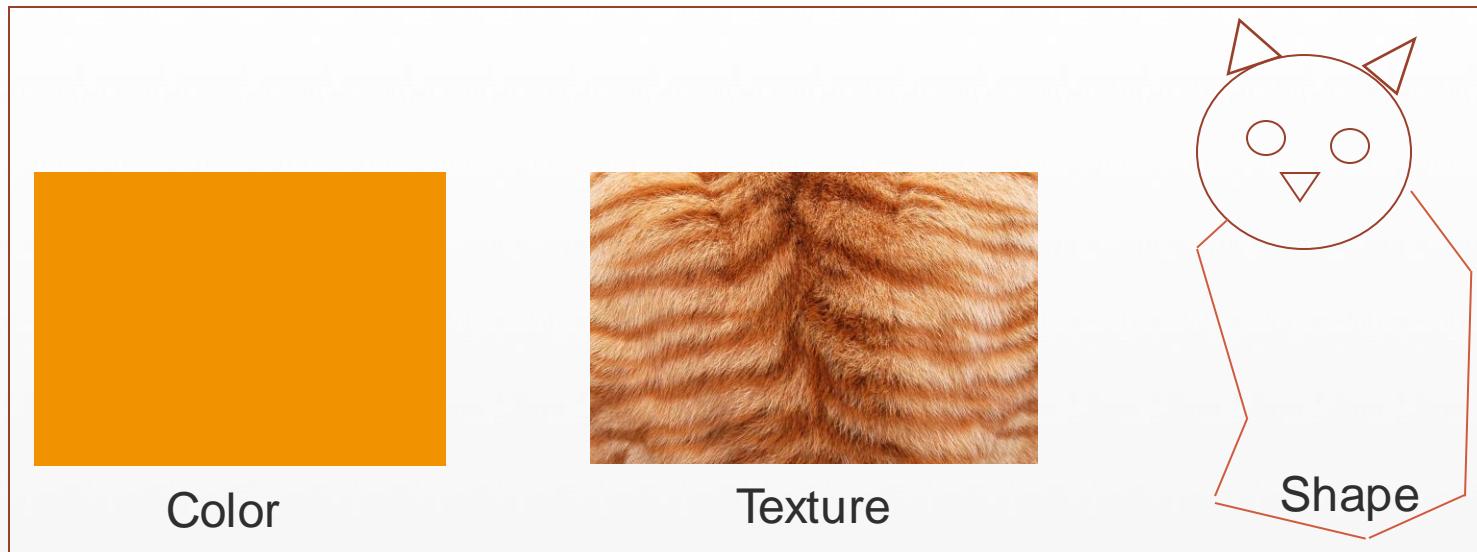
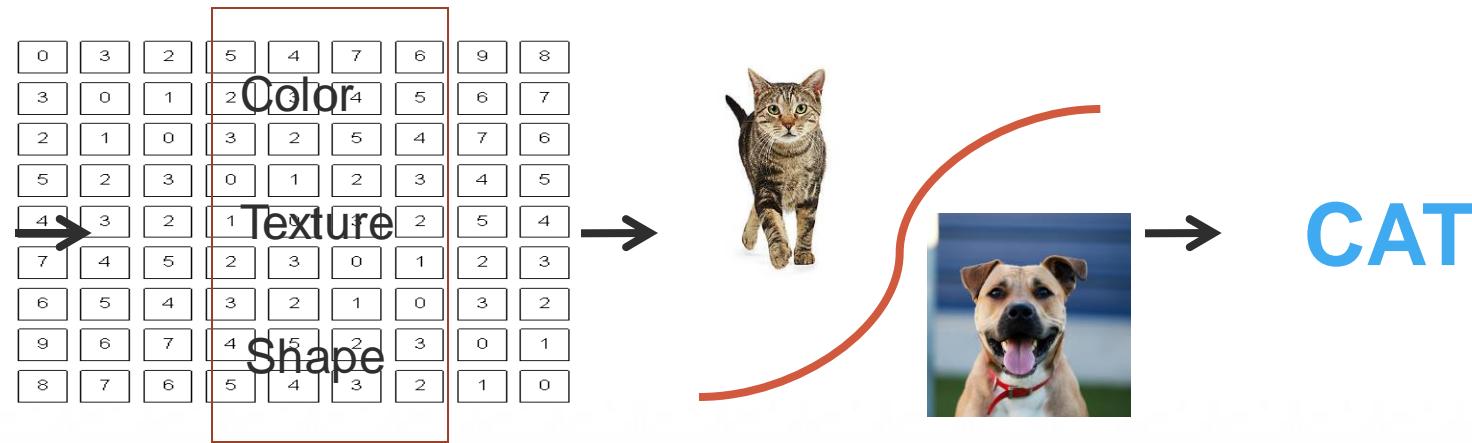
Supervised Machine Learning

- Supervised learning: training and testing.



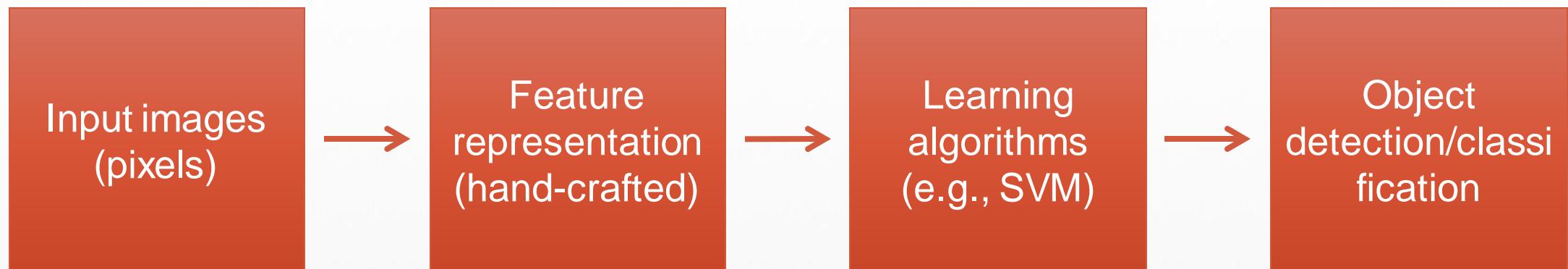
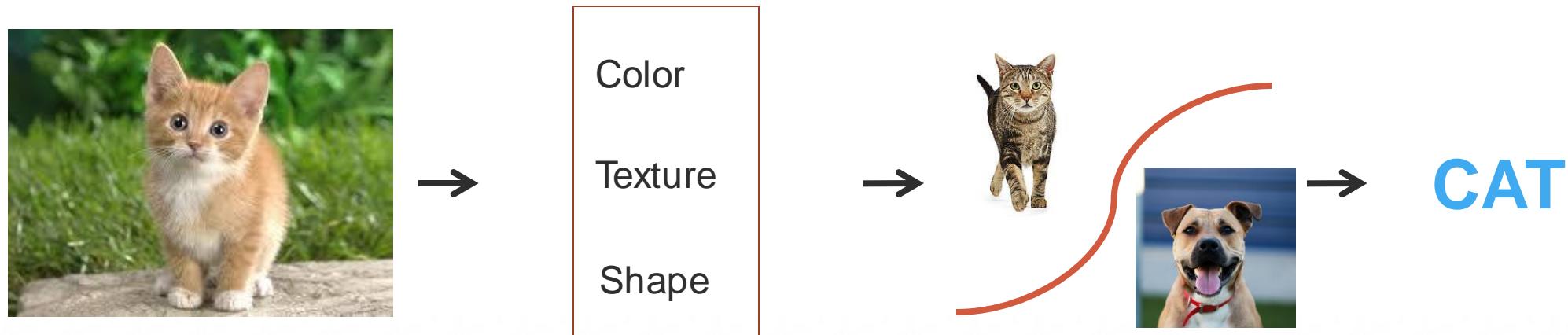
Traditional Machine Learning Recognition

- What is this picture?



Traditional Machine Learning Recognition

- What is this picture?



Traditional Machine Learning Recognition



Design Swan

Deep Learning Recognition

- Deep neural networks: representation learning from raw image data.



Input images
(pixels)



Deep neural networks
(representation learning)

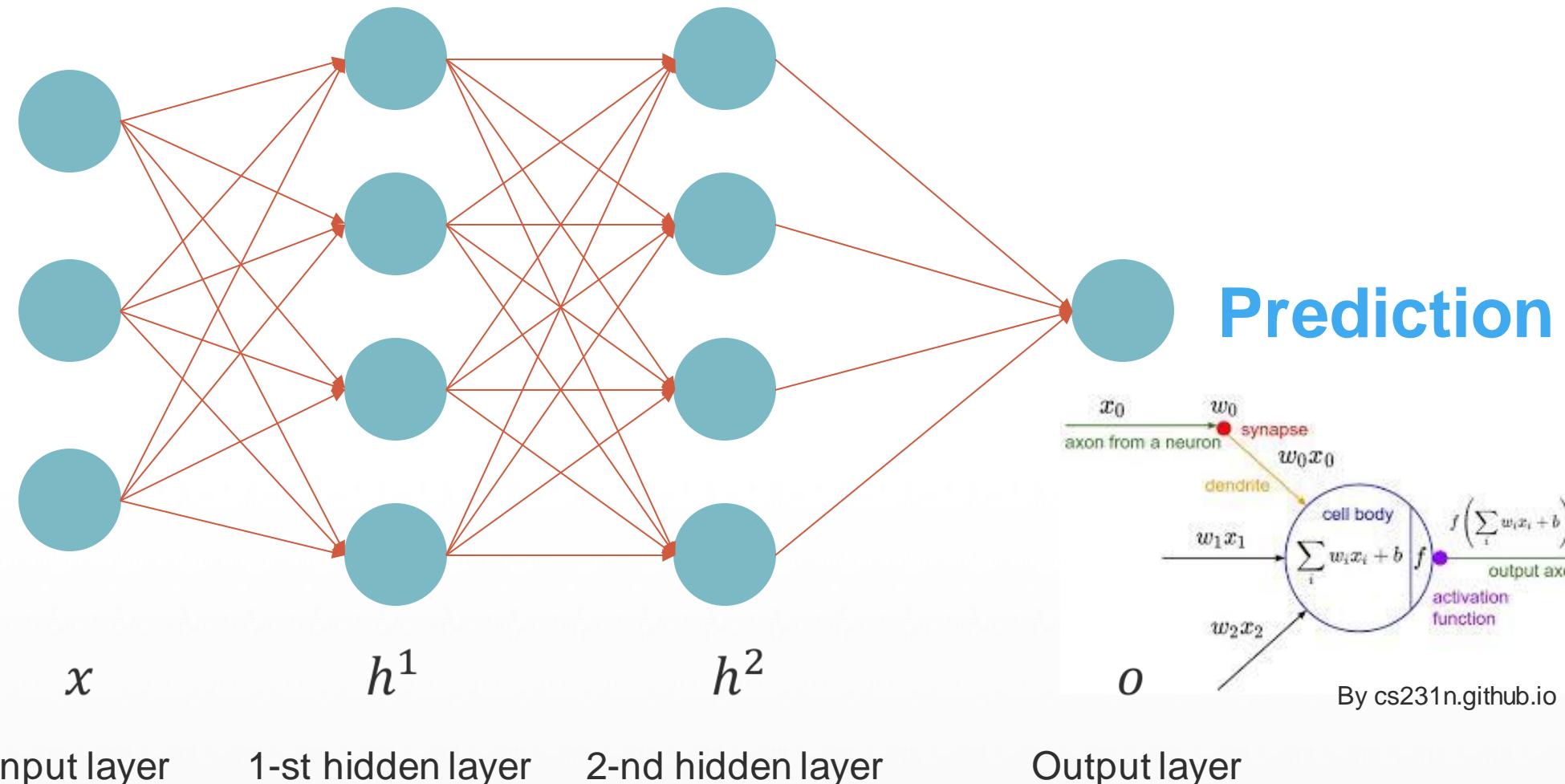


???



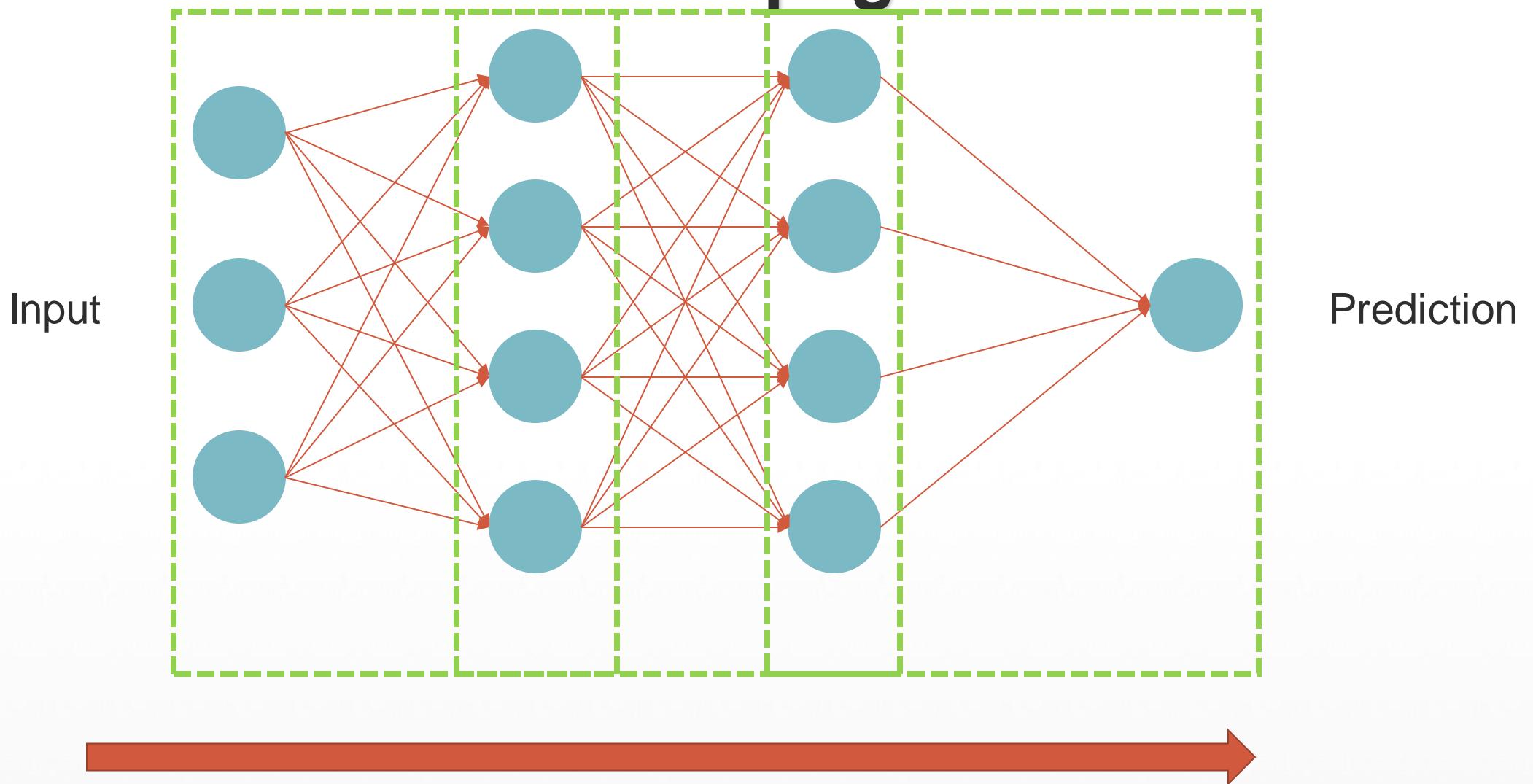
Prediction

Deep Fully-connected Neural Network

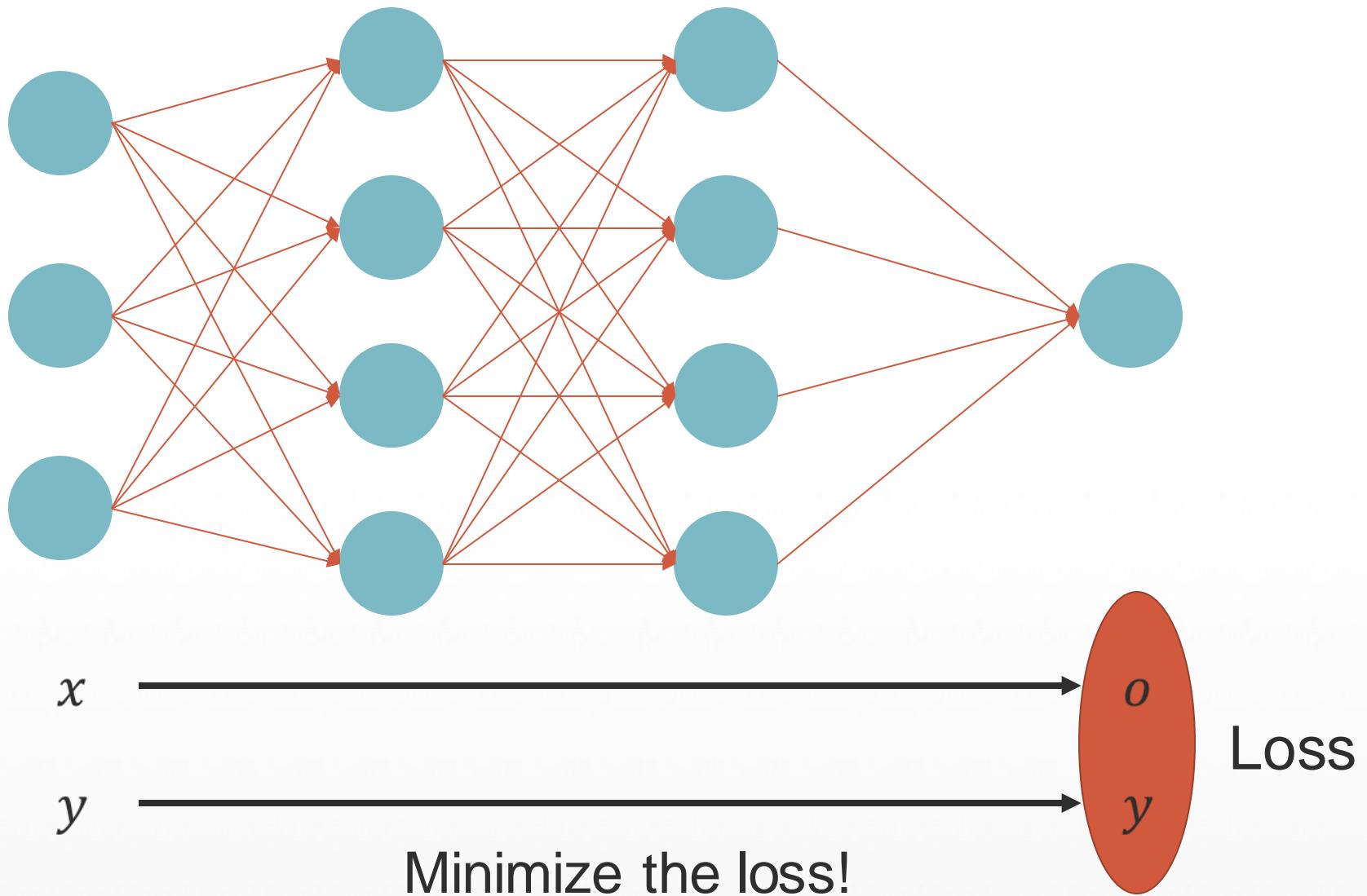


- Model training: 1) forward propagation, 2) loss computation, 3) backpropagation and parameter update.

Forward Propagation

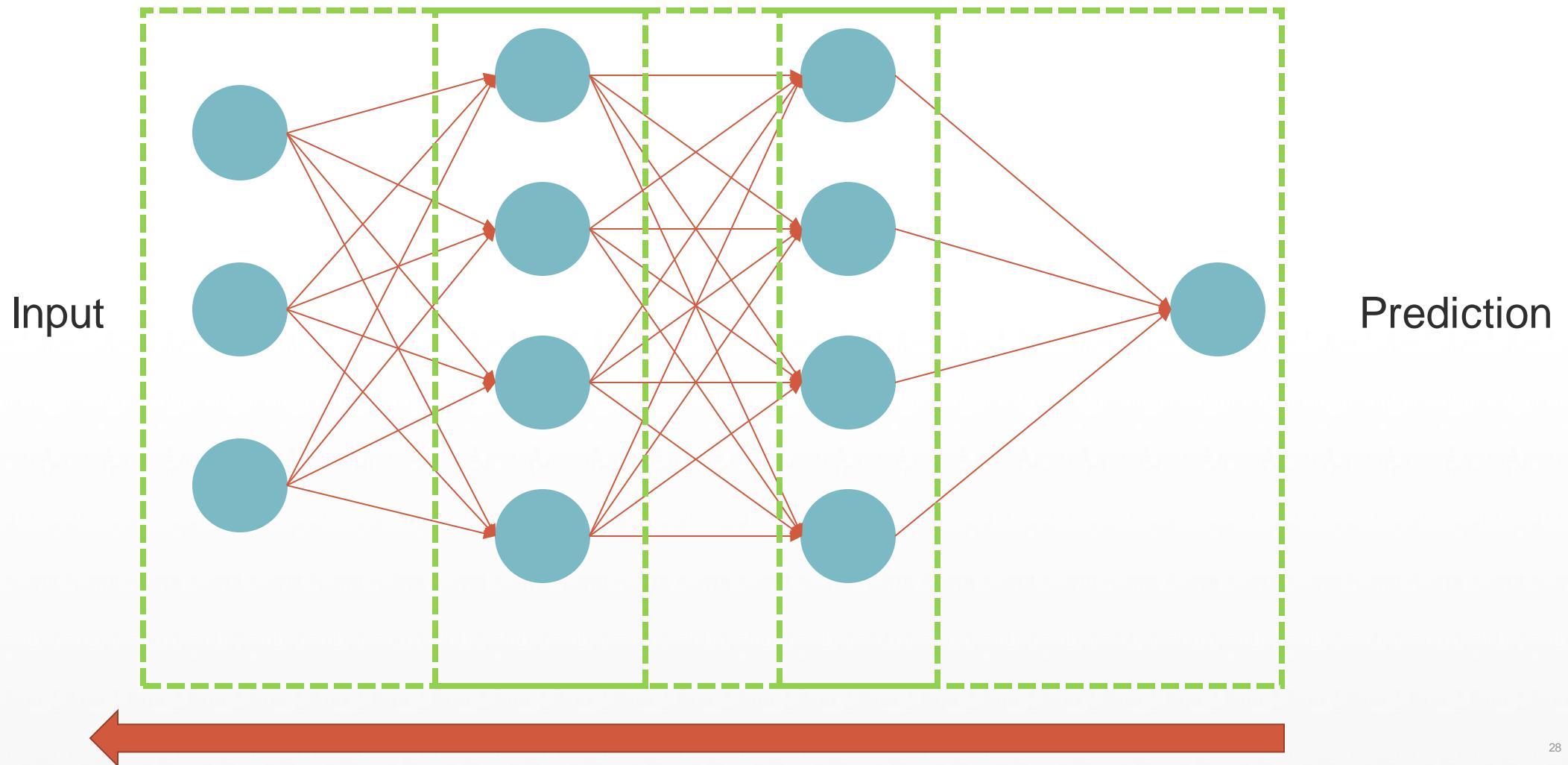


Loss Computation



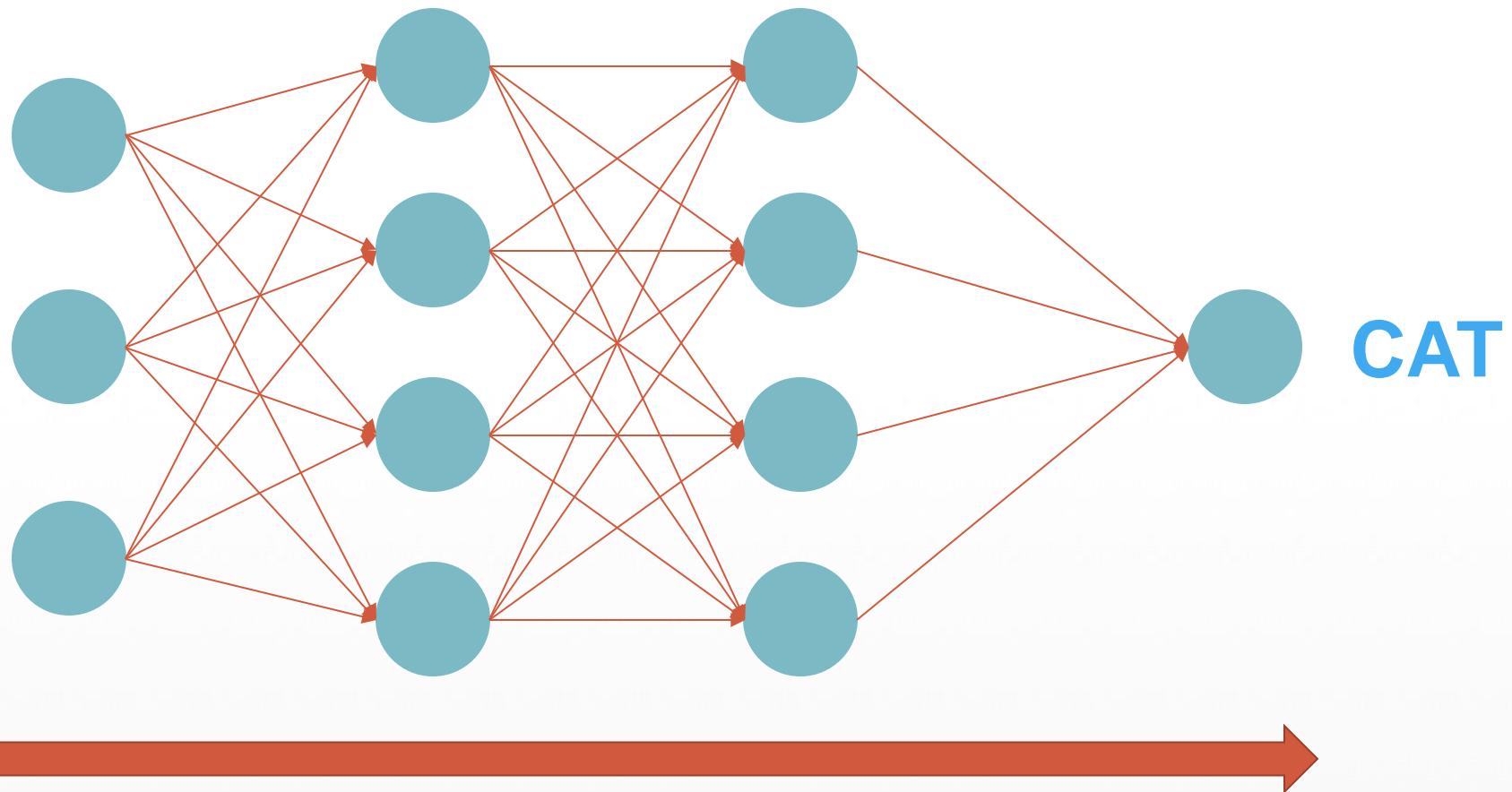
Backpropagation

- Compute gradients of loss w.r.t. to parameters using the chain rule.



Testing

- Model inference or testing: only conduct forward propagation



Forward propagation

Convolutional Neural network (CNN)

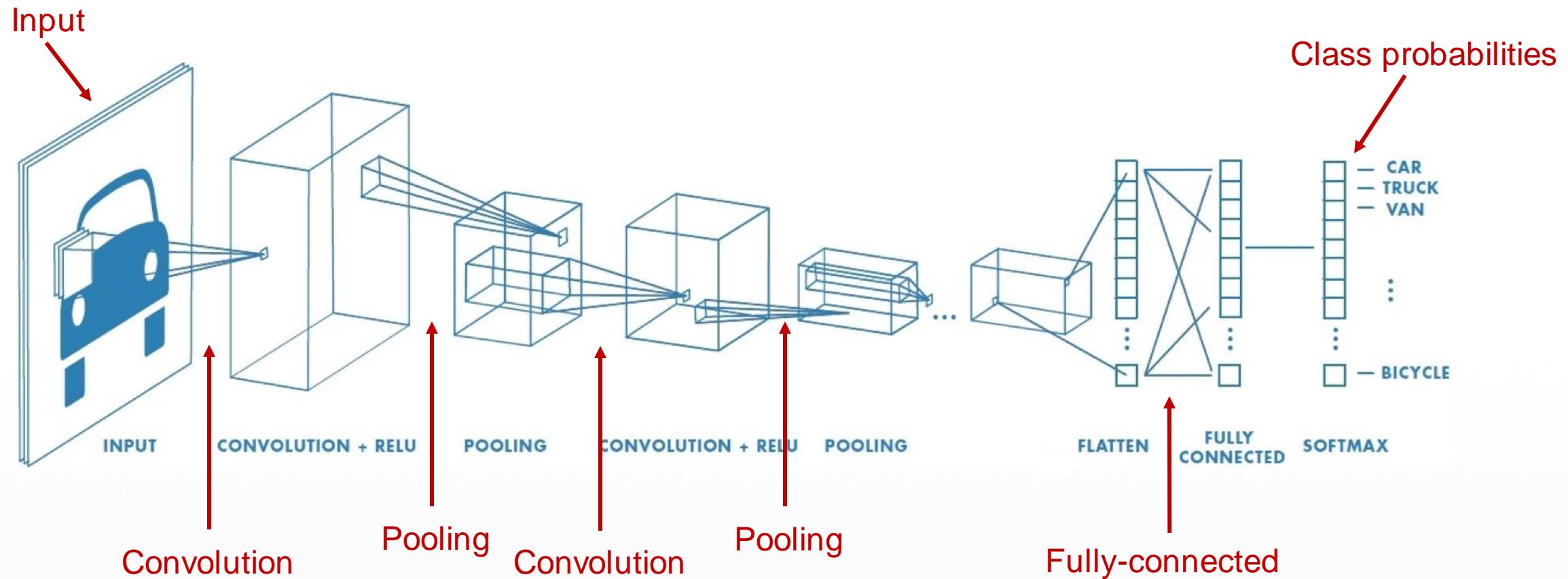


Image credit: Mathworks

Convolutional Neural network (CNN)

- Fully connected: each unit in the current layer connects all units in the previous layer.
- For a 200 x 200 image with 40000 hidden units
 - **1.6 billion** parameters
- A deep neural network would have multiple layers.
- **One solution: weight sharing!**

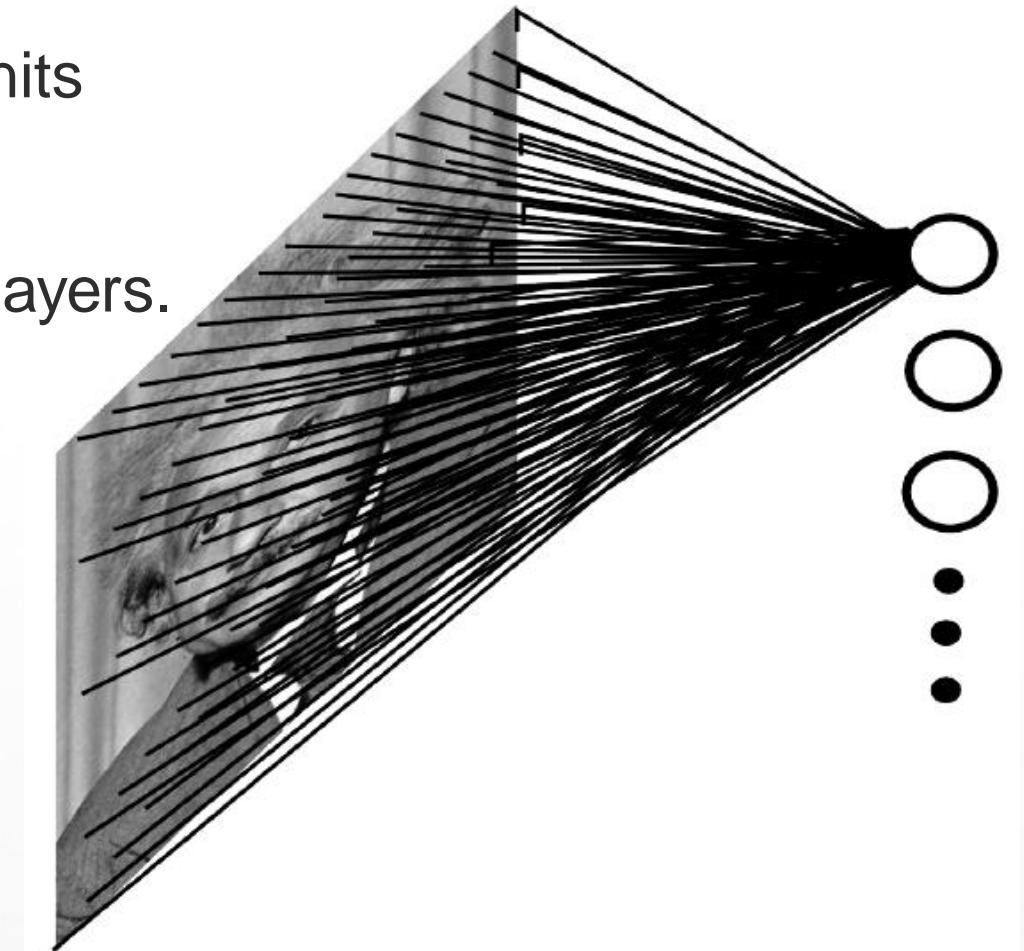


Image credit: LeCun Yann and Marc'Aurelio Ranzato¹

Convolutional Layer

- Convolutional layer: share parameters across different locations.

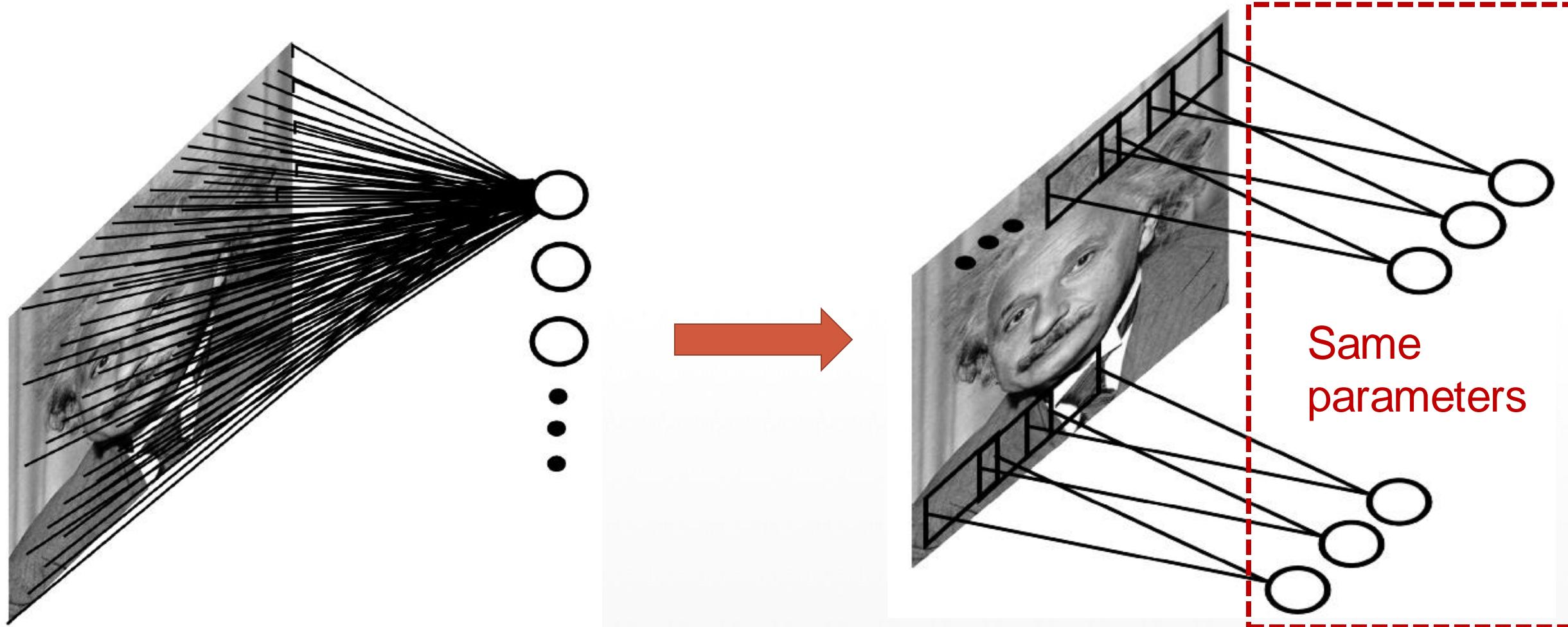


Image credit: LeCun Yann and Marc'Aurelio Ranzato³²

Convolutional Layer

1	0	1
0	1	0
1	0	1

Kernel

1 _{x1}	1 _{x0}	1 _{x1}	0	0
0 _{x0}	1 _{x1}	1 _{x0}	1	0
0 _{x1}	0 _{x0}	1 _{x1}	1	1
0	0	1	1	0
0	1	1	0	0

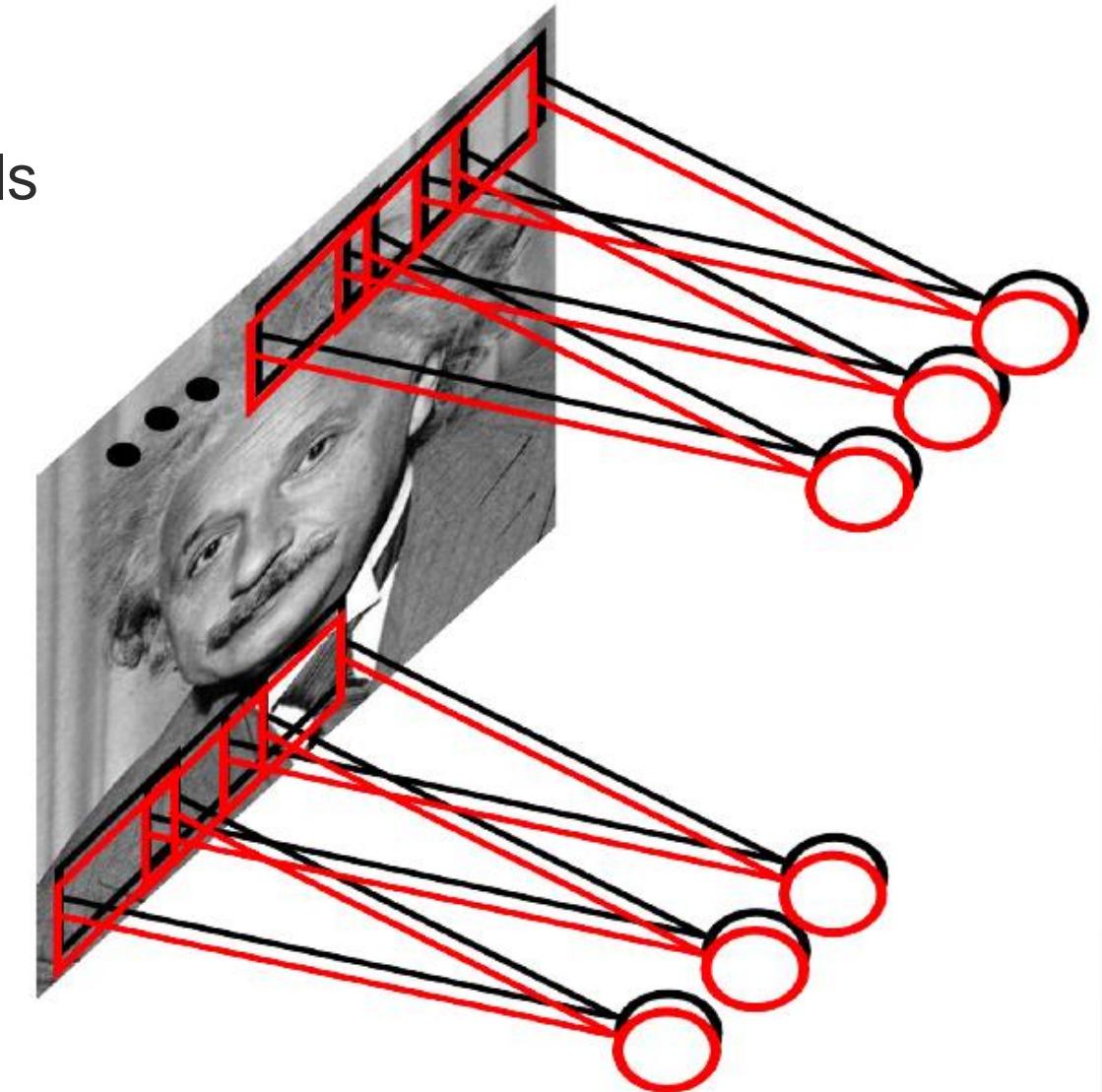
Image

4		

Convolved Feature

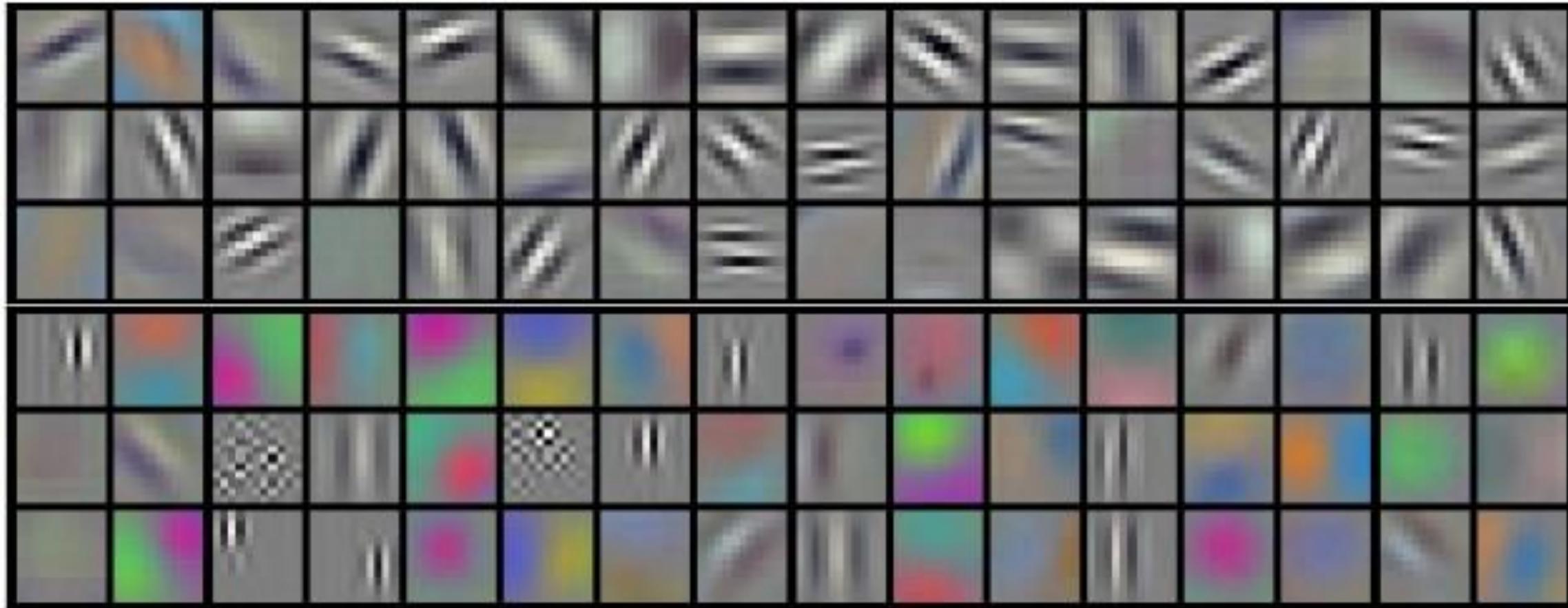
Convolutional Layer

- Learn multiple kernels.
- For a 200×200 image with 100 kernels
 - Filter size: 10×10
 - Parameters: 10K



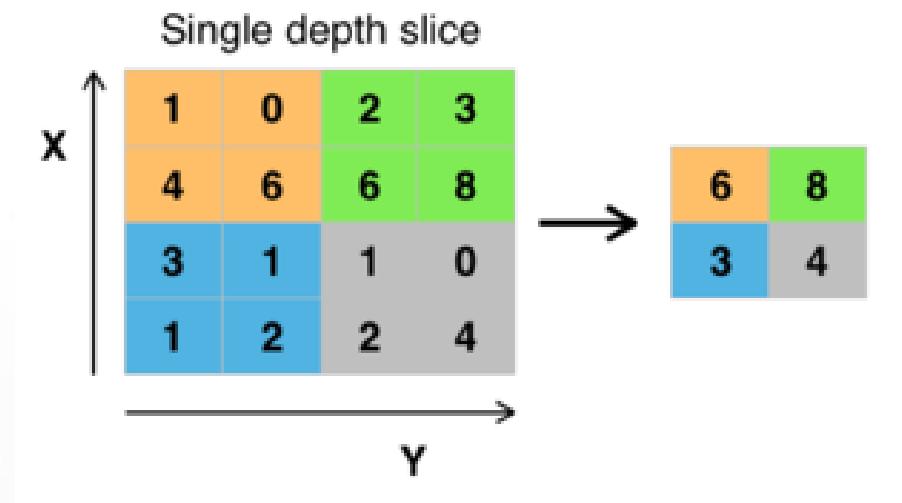
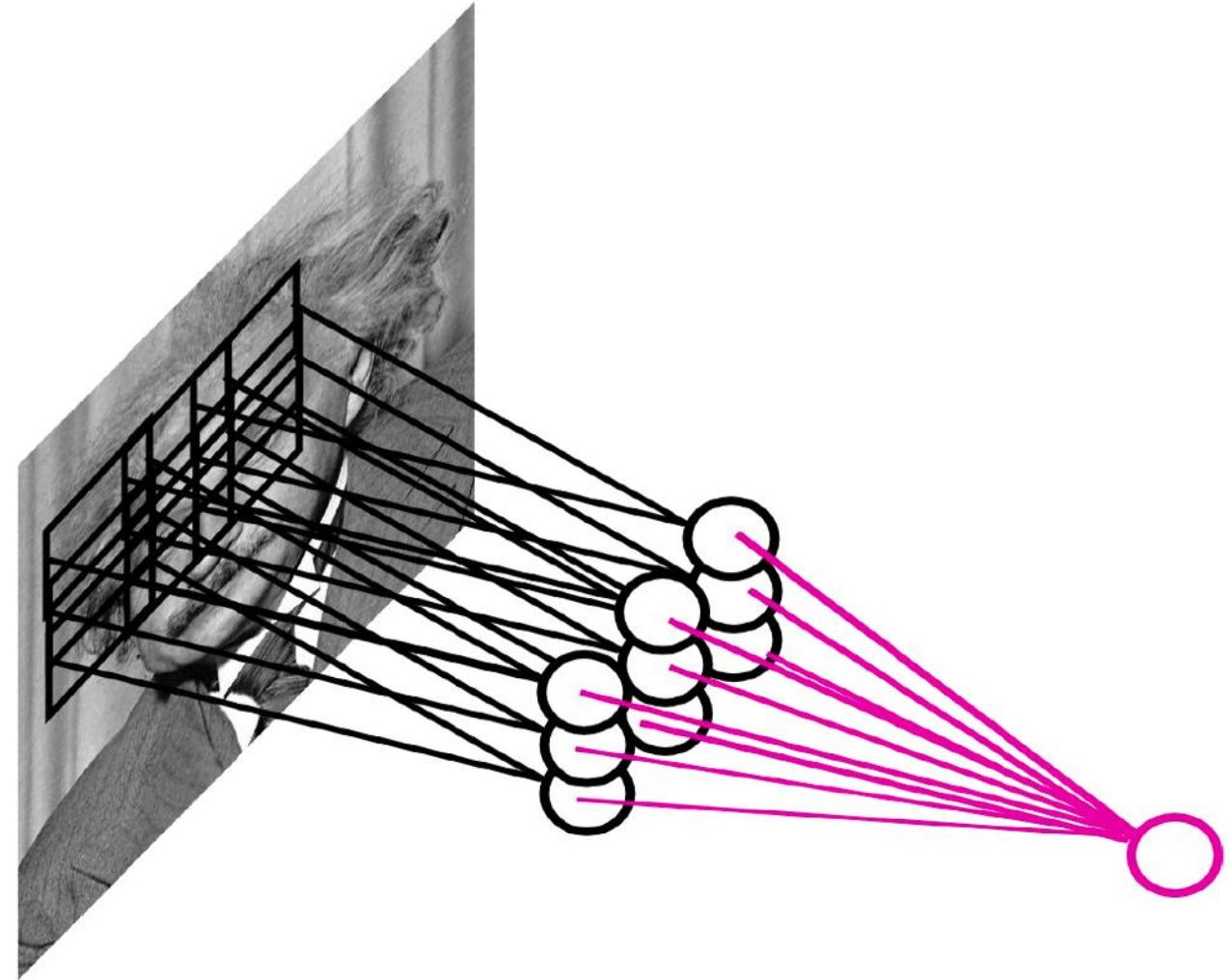
Convolutional Layer

- Filters learned in the first convolutional layer in CNN (AlexNet).



Pooling Layer

- Pooling: robust to small distortions and reduce number of units.



CNN Achievements

- LeNet
- AlexNet
- VGGNet
- GoogLeNet (and variants)
- ResNet

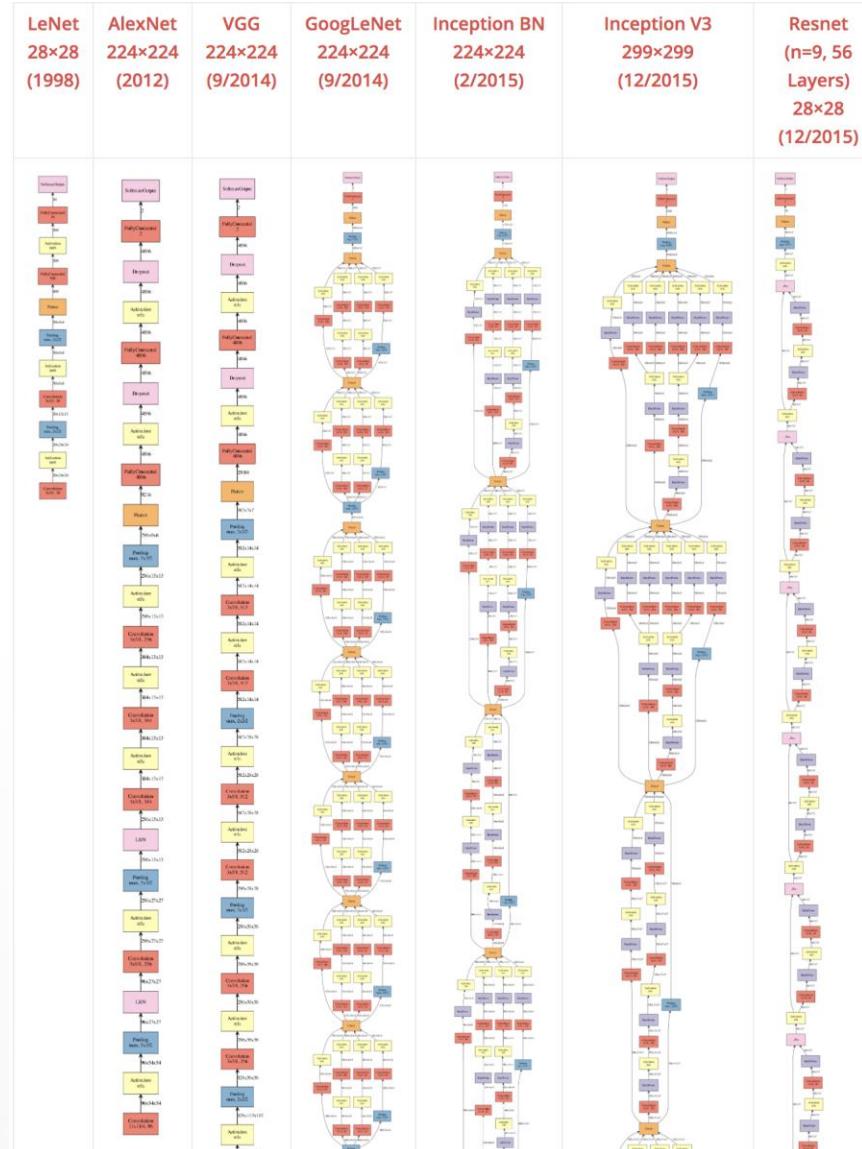
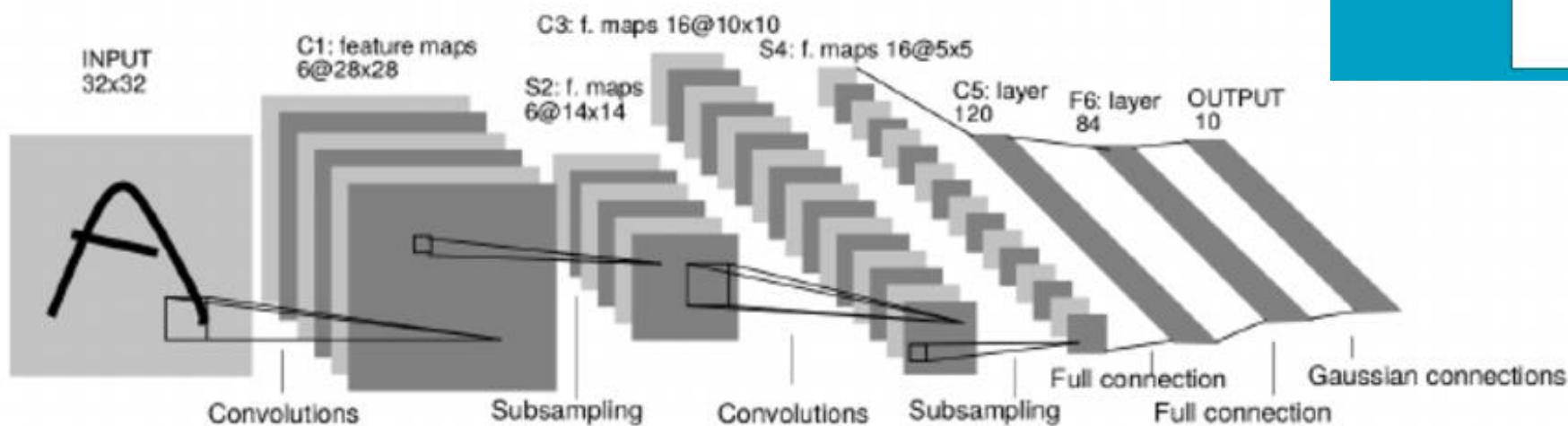


Image credit: <http://josephpcohen.com/w/visualizing-cnn-architectures-side-by-side-with-mxnet/>

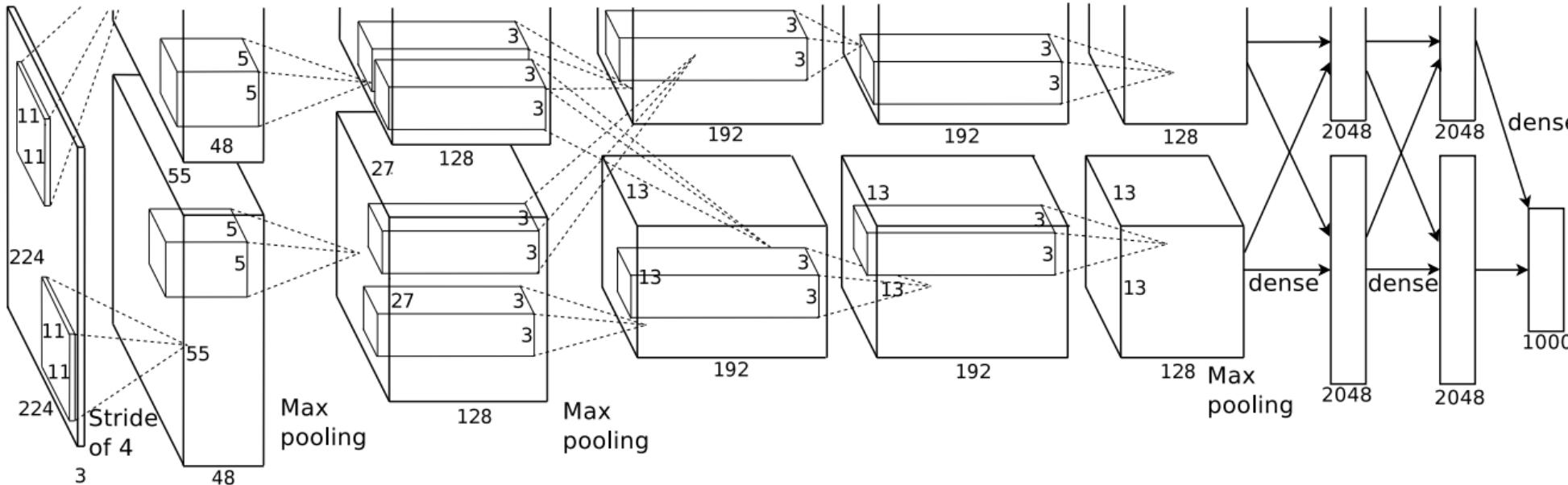
CNN Achievements

- LeNet: handwritten digit recognition



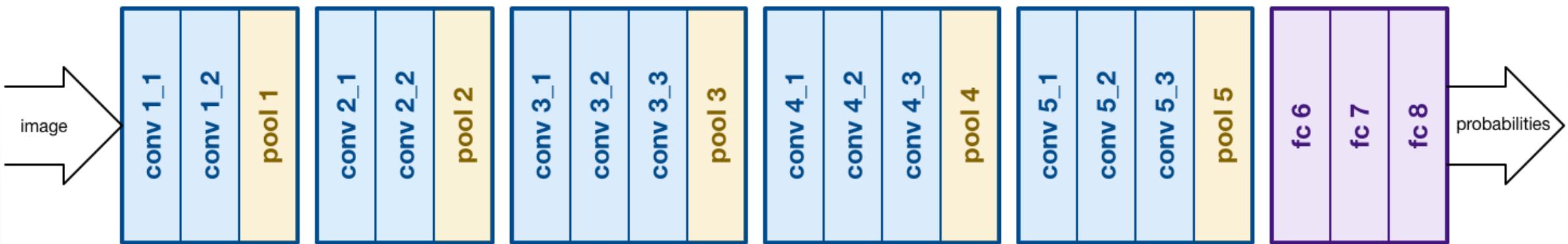
CNN Achievements

- AlexNet: image classification
- Winner of ImageNet ILSVRC 2012: top-5 error is **15.3% (8 layers)**.
- Second place: top-5 error is **26.2%**.



CNN Achievements

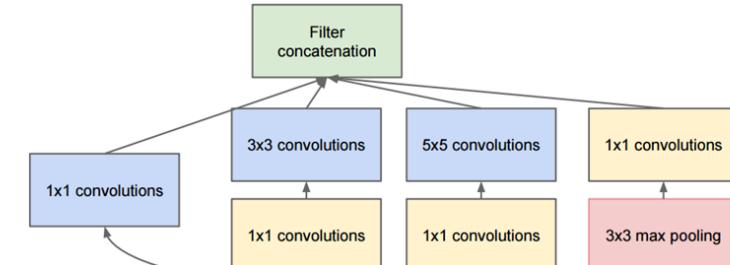
- VGGNet: image classification
- Simple and deep: only 3×3 kernels
- Top-5 error: 7.3% (19 layers)



1. K. Simonyan, A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition", *arXiv*, 2014
2. Image credit: <http://machinethink.net/blog/convolutional-neural-networks-on-the-iphone-with-vggnet/>

CNN Achievements

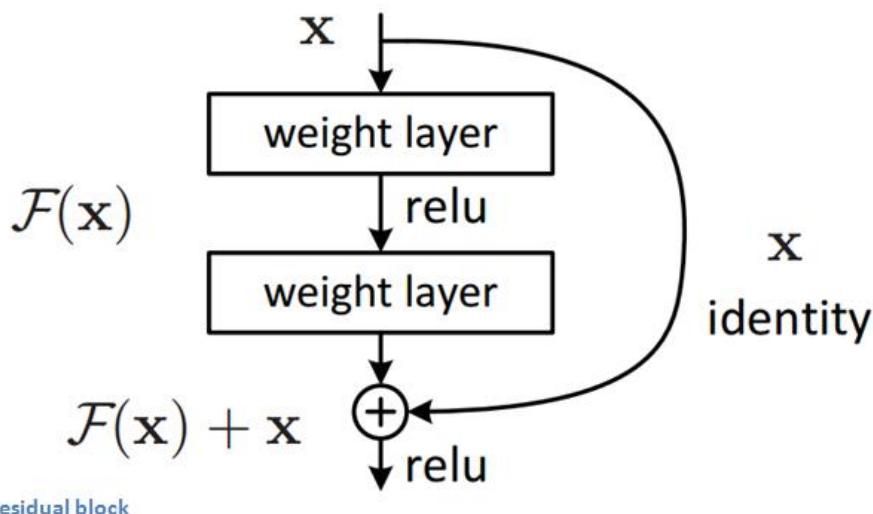
- GoogLeNet: image classification
- Winner of ILSVRC 2014
- Top-5 error: 6.7% (22 layers)



1. C. Szegedy et al., "Going Deeper with Convolutions", CVPR, 2015
2. <http://knowyourmeme.com/memes/we-need-to-go-deeper>

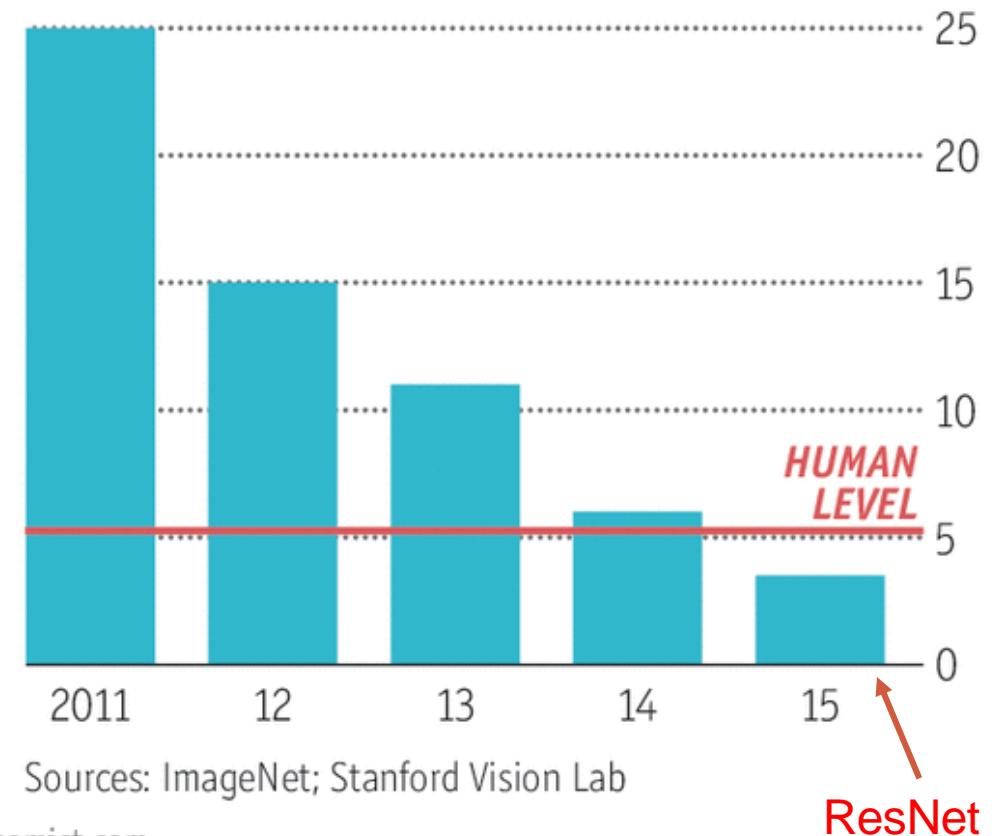
CNN Achievements

- ResNet: image classification
- Winner of ILSVRC 2015
- Best Paper Award in CVPR 2016
- Top-5 error: 3.6% (152 layers)



Ever cleverer

Error rates on ImageNet Visual Recognition Challenge, %



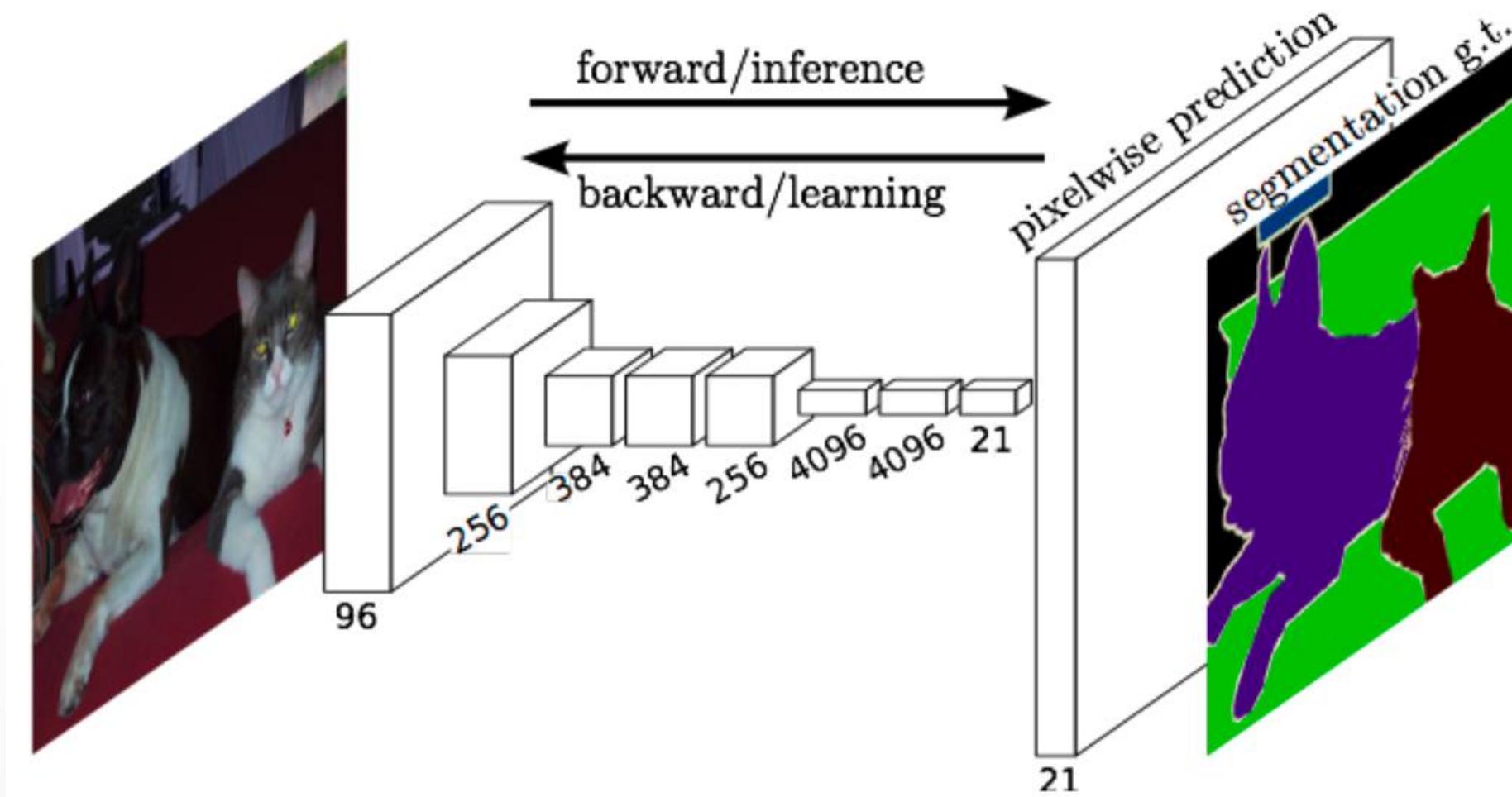
Deep Learning Segmentation

- Image Segmentation: pixel-wise labeling.



Fully Convolutional Network (FCN)

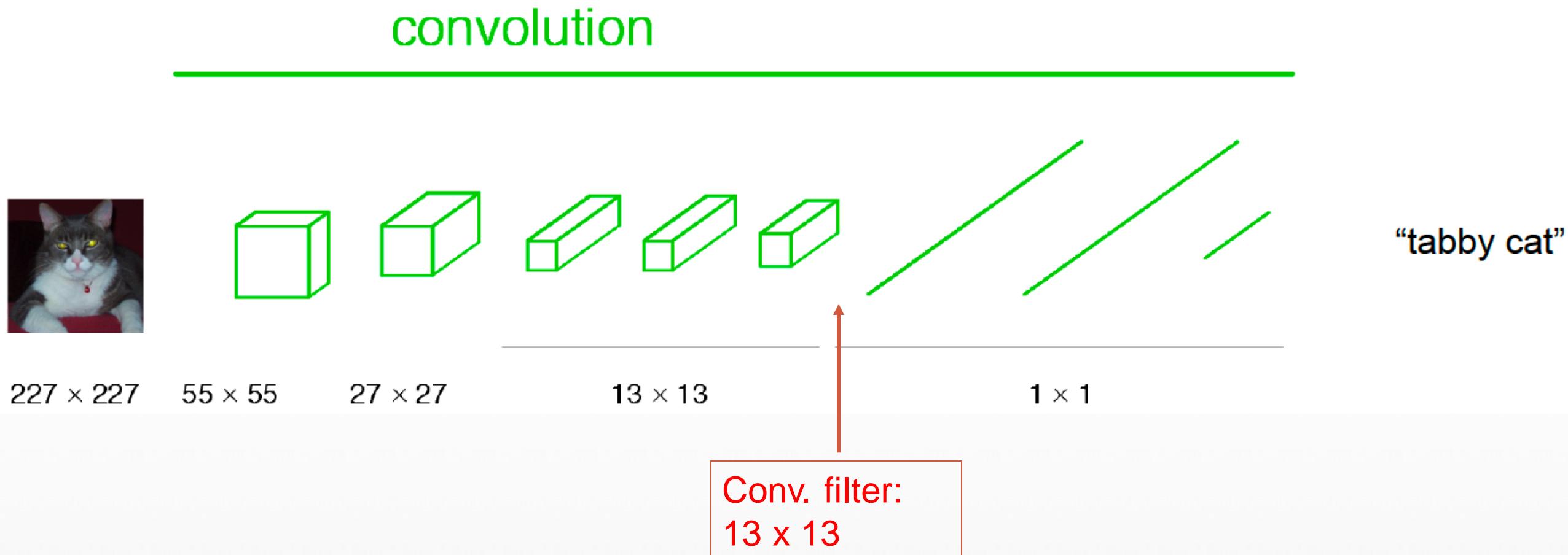
- FCN: end-to-end, pixels-to-pixels modeling.



1. J. Long, et al., "Fully Convolutional Networks for Semantic Segmentation", CVPR, 2015

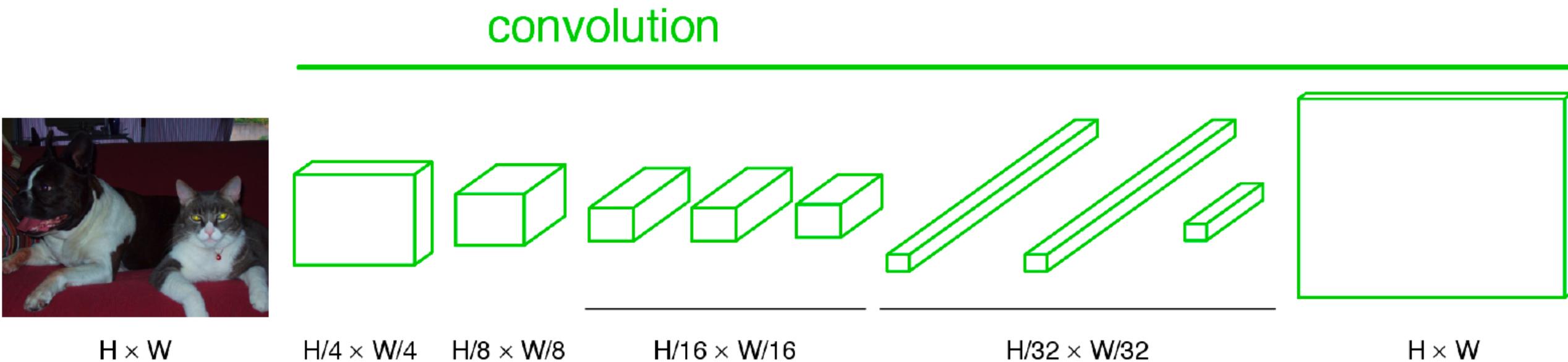
Fully Convolutional Network (FCN)

- CNN → FCN.



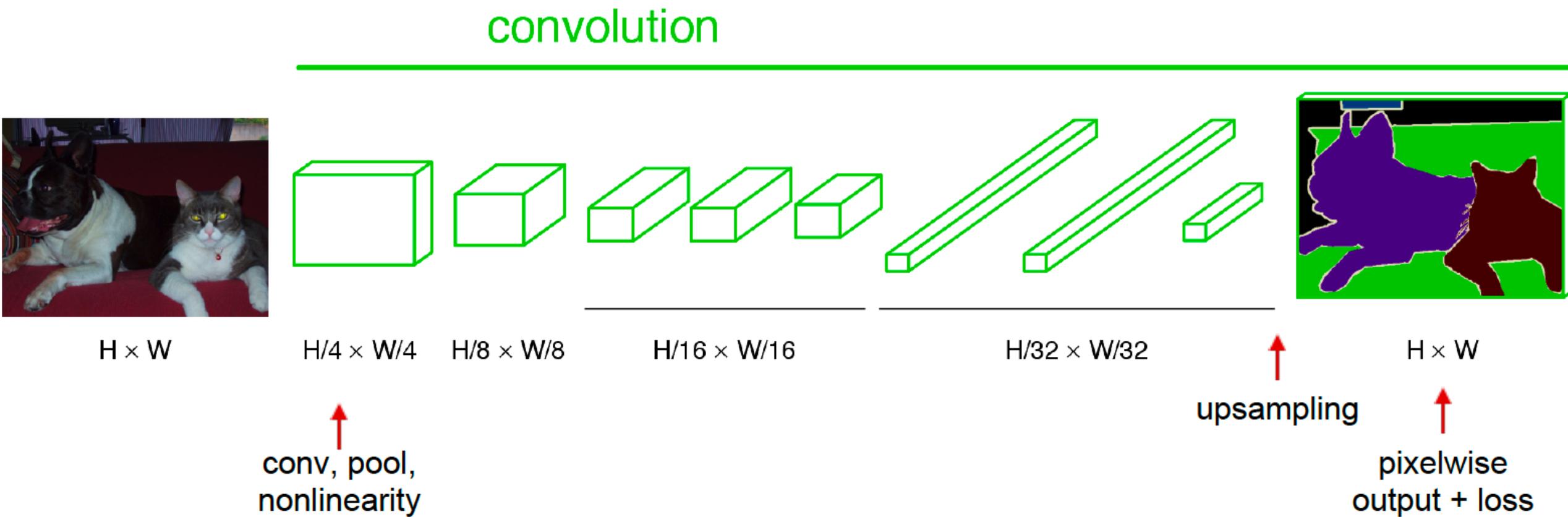
Fully Convolutional Network (FCN)

- FCN: arbitrary-sized input.



Fully Convolutional Network (FCN)

- FCN: arbitrary-sized input.



Deep Learning in Biomedical Image Computing

- Deep learning has improved biomedical image analysis in many tasks.



Original Investigation | Innovations in Health Care Delivery

FREE

December 13, 2016

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

Varun Gulshan, PhD¹; Lily Peng, MD, PhD¹; Marc Coram, PhD¹; et al

» Author Affiliations | Article Information

JAMA. 2016;316(22):2402-2410. doi:10.1001/jama.2016.17216

Editorial Comment

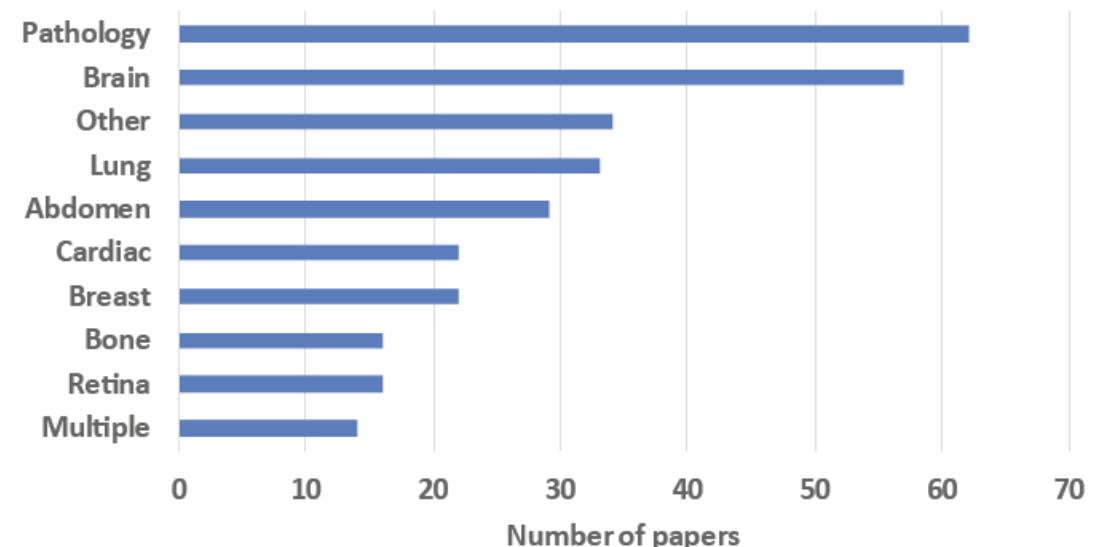
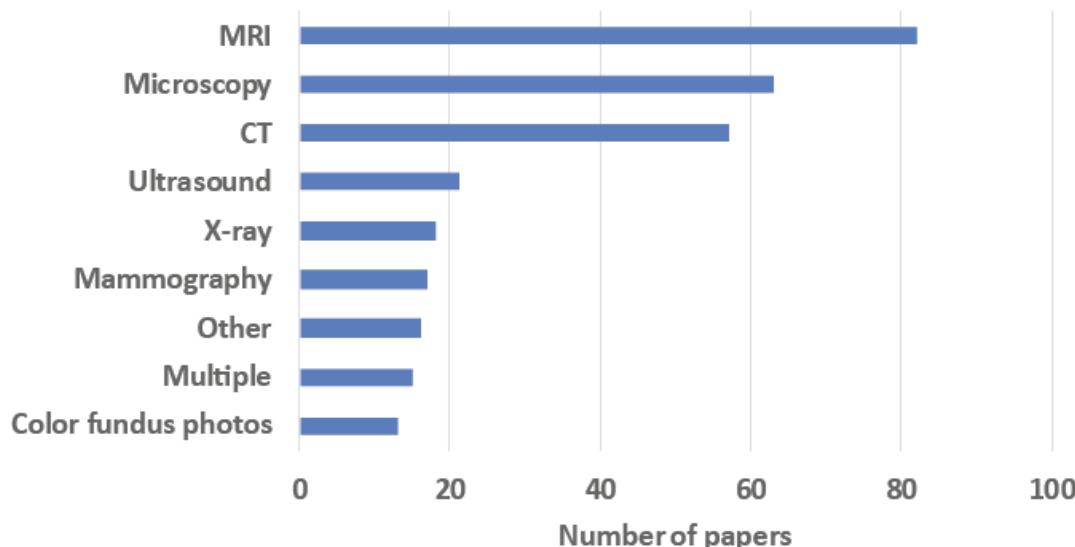
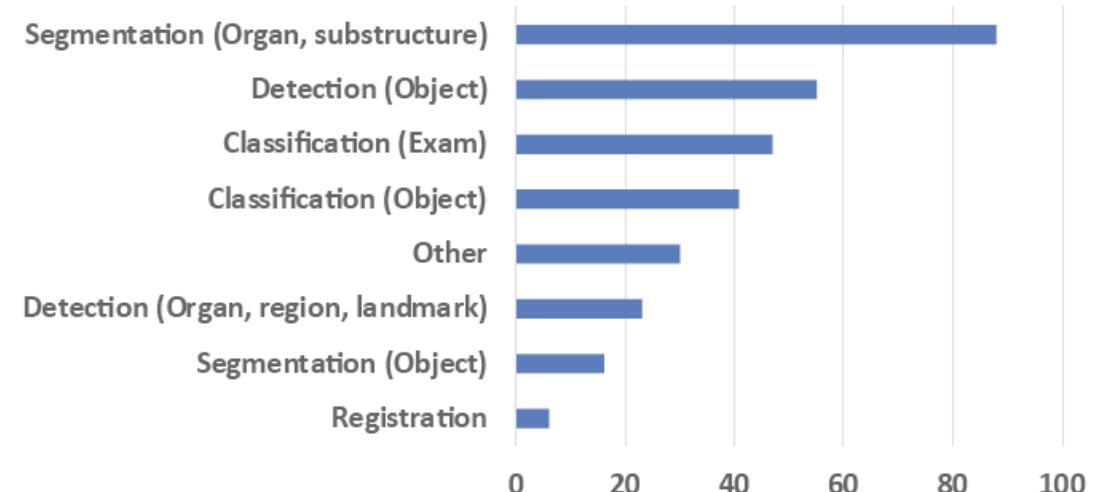
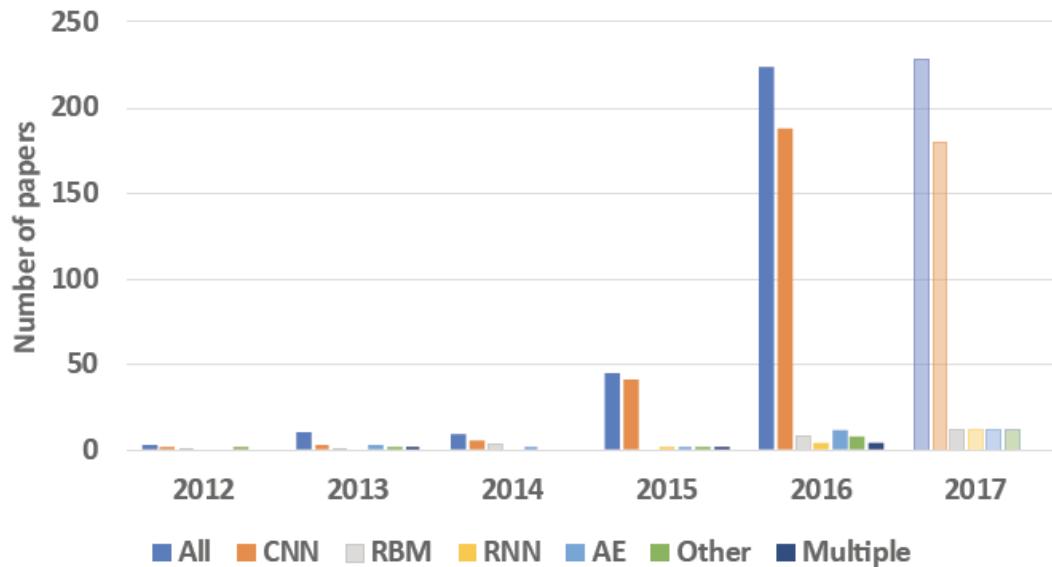
Key Points

Question How does the performance of an automated deep learning algorithm compare with manual grading by ophthalmologists for identifying diabetic retinopathy in retinal fundus photographs?

Finding In 2 validation sets of 9963 images and 1748 images, at the operating point selected for high specificity, the algorithm had 90.3% and 87.0% sensitivity and 98.1% and 98.5% specificity for detecting referable diabetic retinopathy, defined as moderate or worse diabetic retinopathy or referable macular edema by the majority decision of a panel of at least 7 US board-certified ophthalmologists. At the operating point selected for high sensitivity, the algorithm had 97.5% and 96.1% sensitivity and 93.4% and 93.9% specificity in the 2 validation sets.

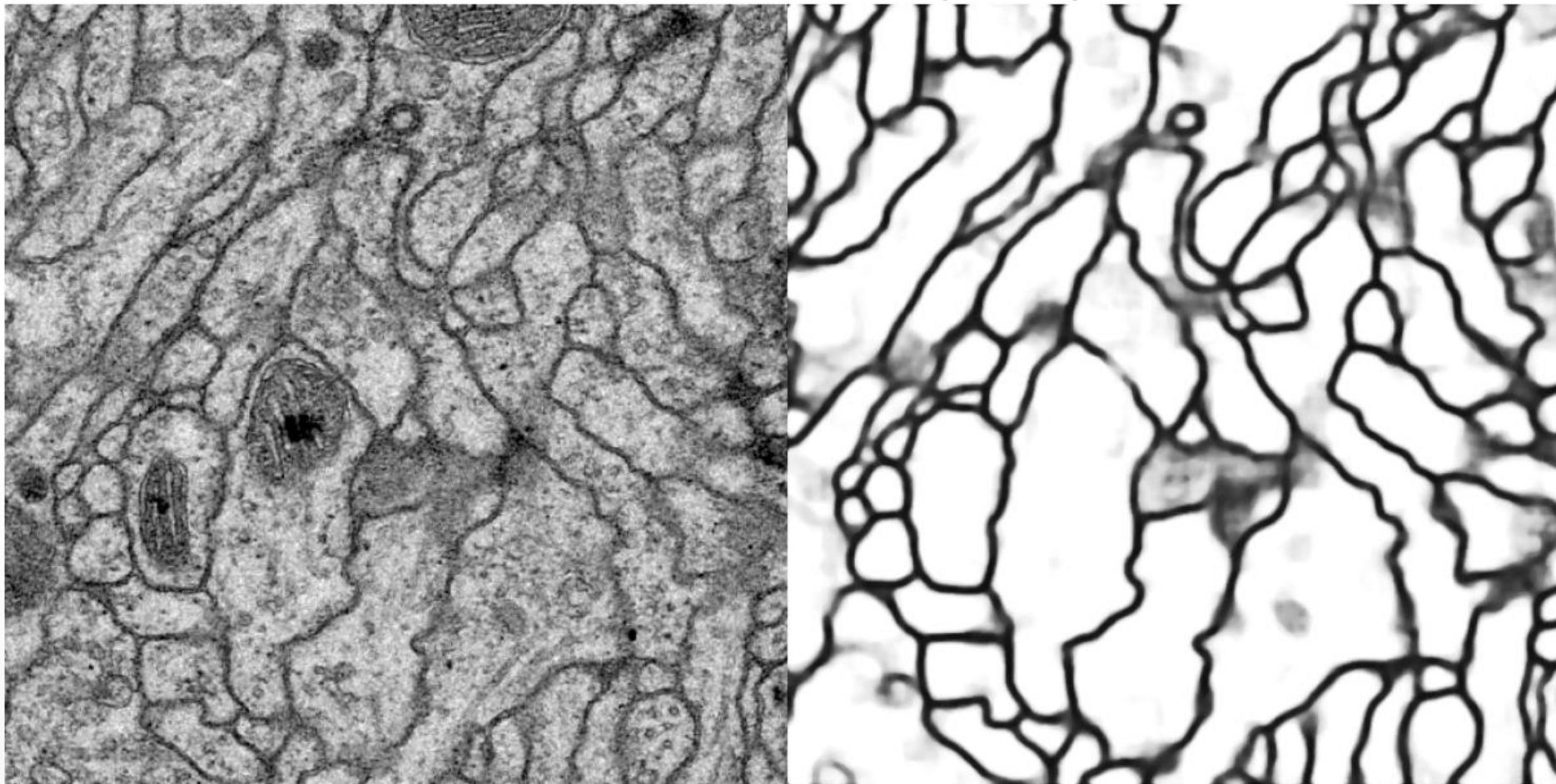
Meaning Deep learning algorithms had high sensitivity and specificity for detecting diabetic retinopathy and macular edema in retinal fundus photographs.

Deep Learning in Biomedical Image Computing



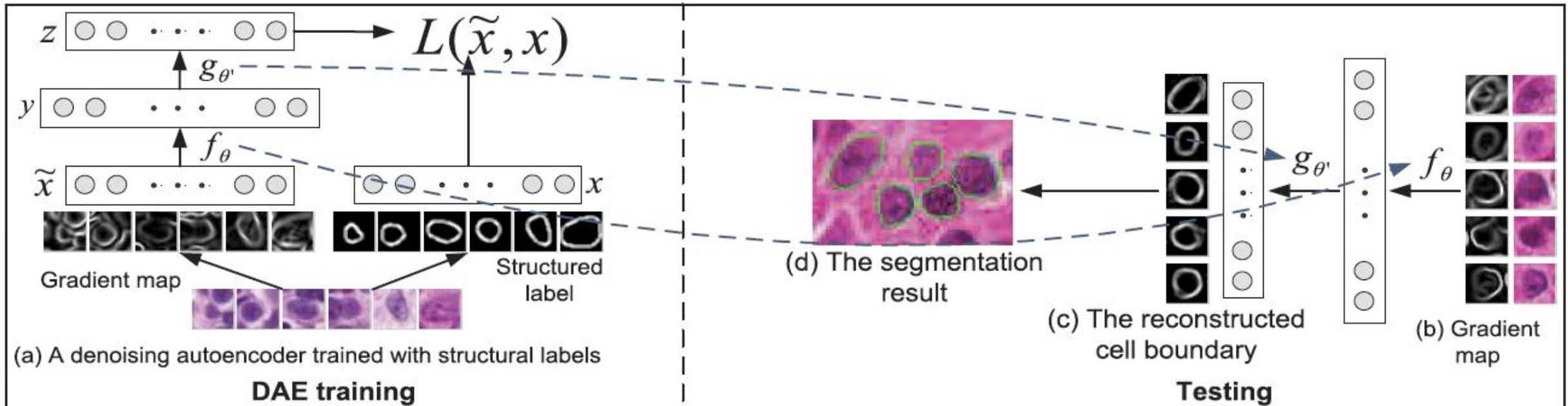
Biomedical Image Segmentation

- CNN: neuronal membrane segmentation of 3D volumetric images.
- Winner of ISBI 2012 electron microscopy image segmentation.



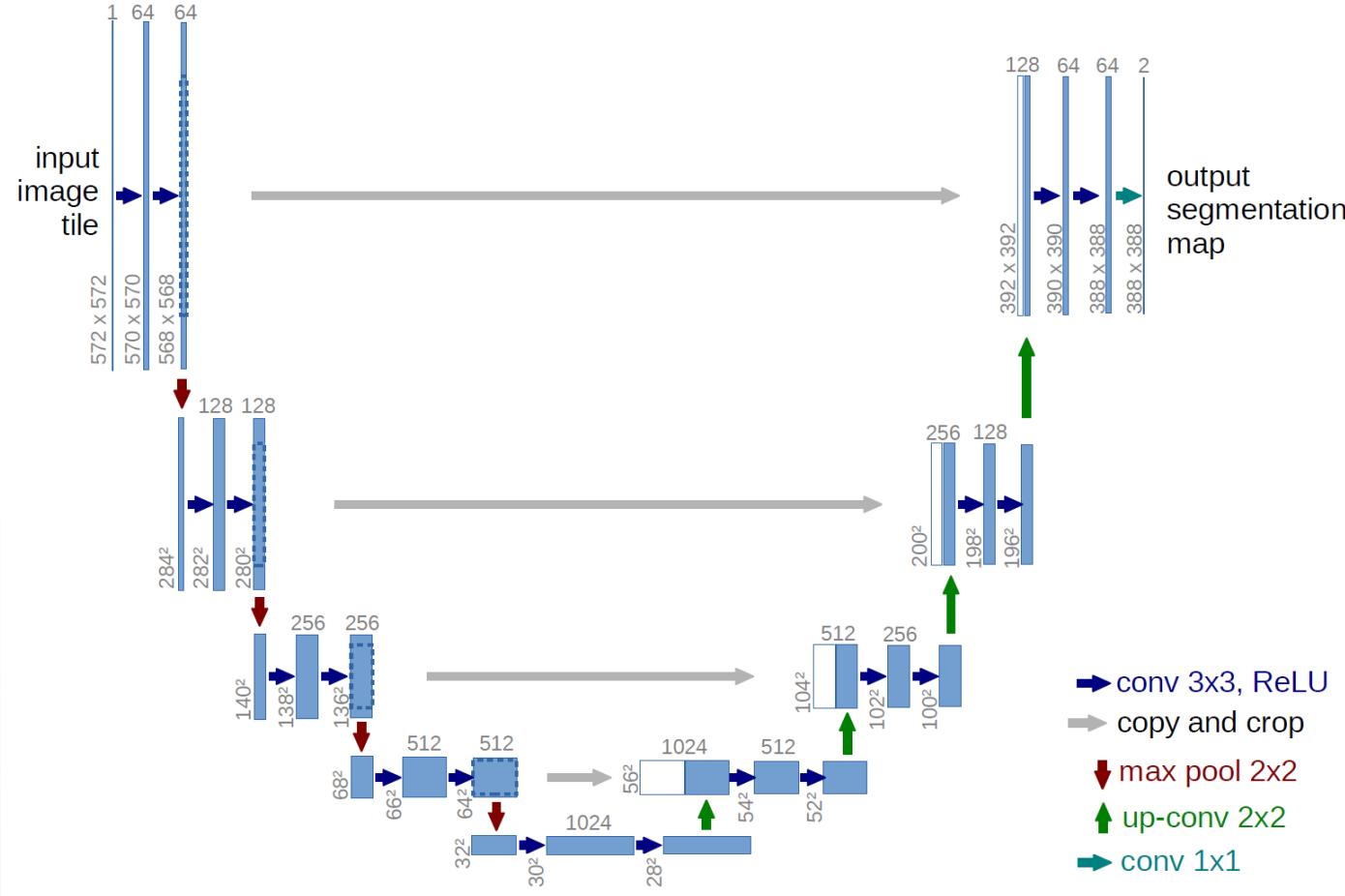
Biomedical Image Segmentation

- Stacked denoising autoencoder (sDAE): nucleus segmentation in histopathology images.
- Runners Up for Young Scientist Awards in MICCAI 2015.



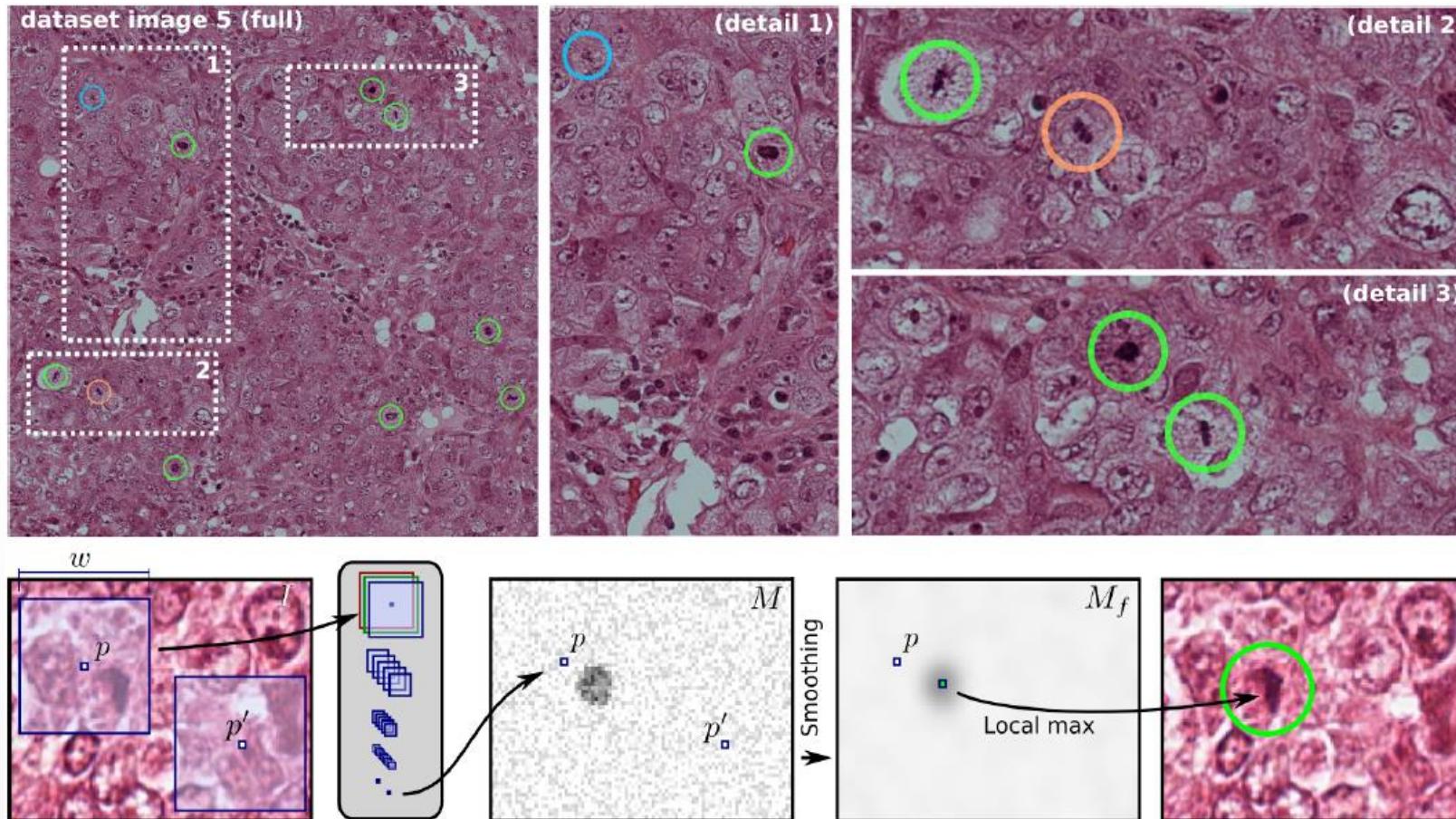
Biomedical Image Segmentation

- U-Net: introduces an expansion path and concatenation connection.
- Winner of ISBI 2015 challenges (dental X-ray image segmentation and cell tracking).



Detection in Biomedical Images

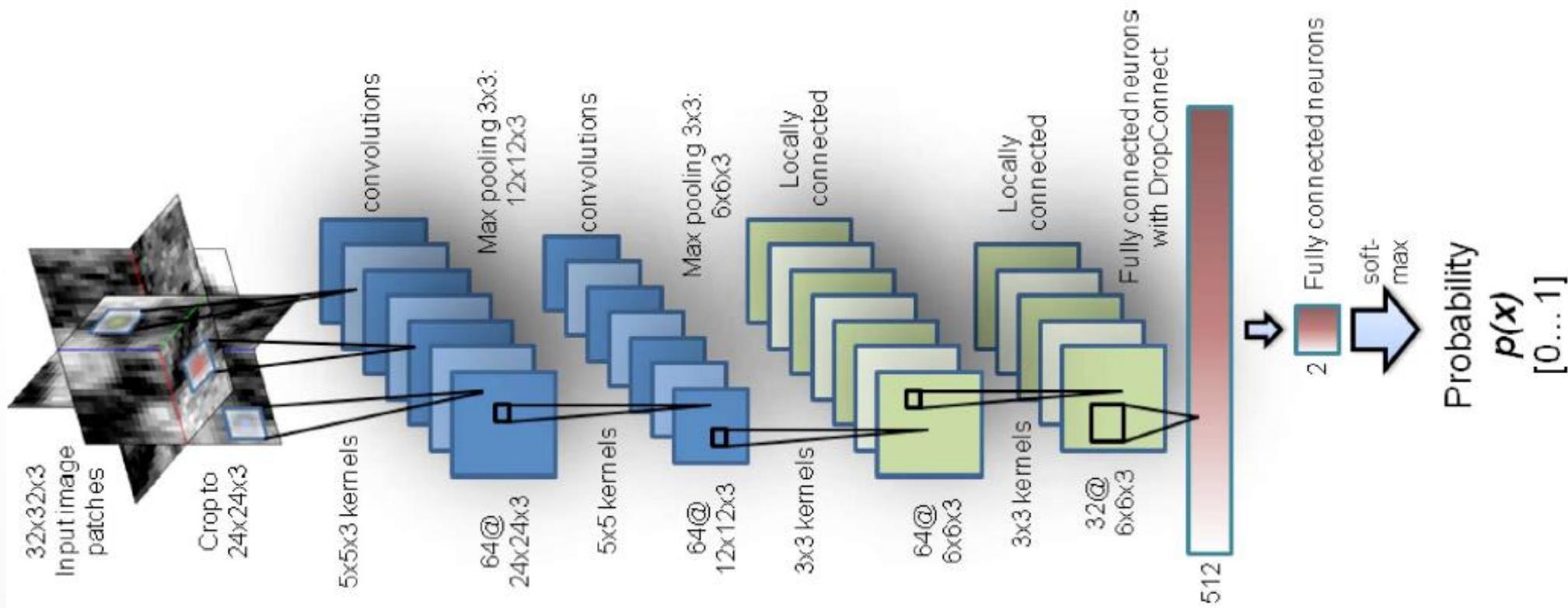
- CNN: mitosis detection in breast cancer histology images.
- Winner of MICCAI 2013 Grand Challenge.



1. D.C. Ciresan, et al., "Mitosis Detection in Breast Cancer Histology Images with Deep Neural Networks", *MICCAI*, 2013

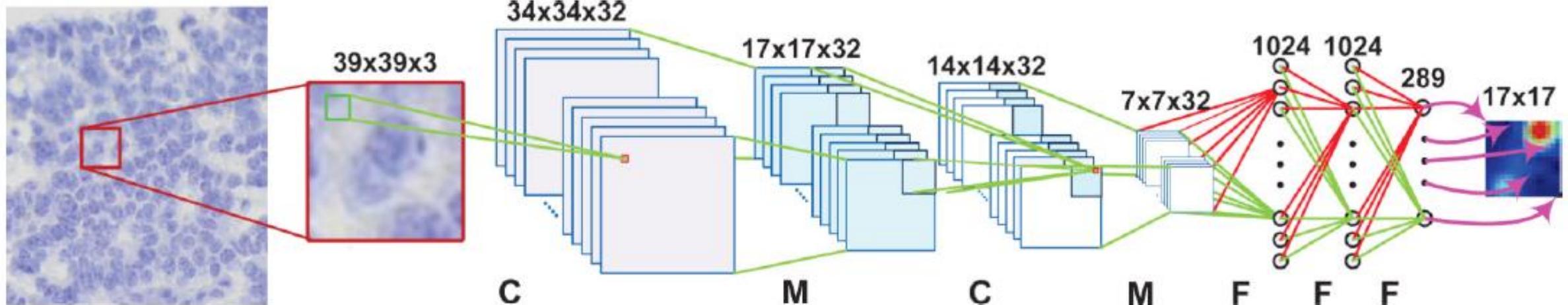
Detection in Biomedical Images

- CNN: lesion detection in CT images.



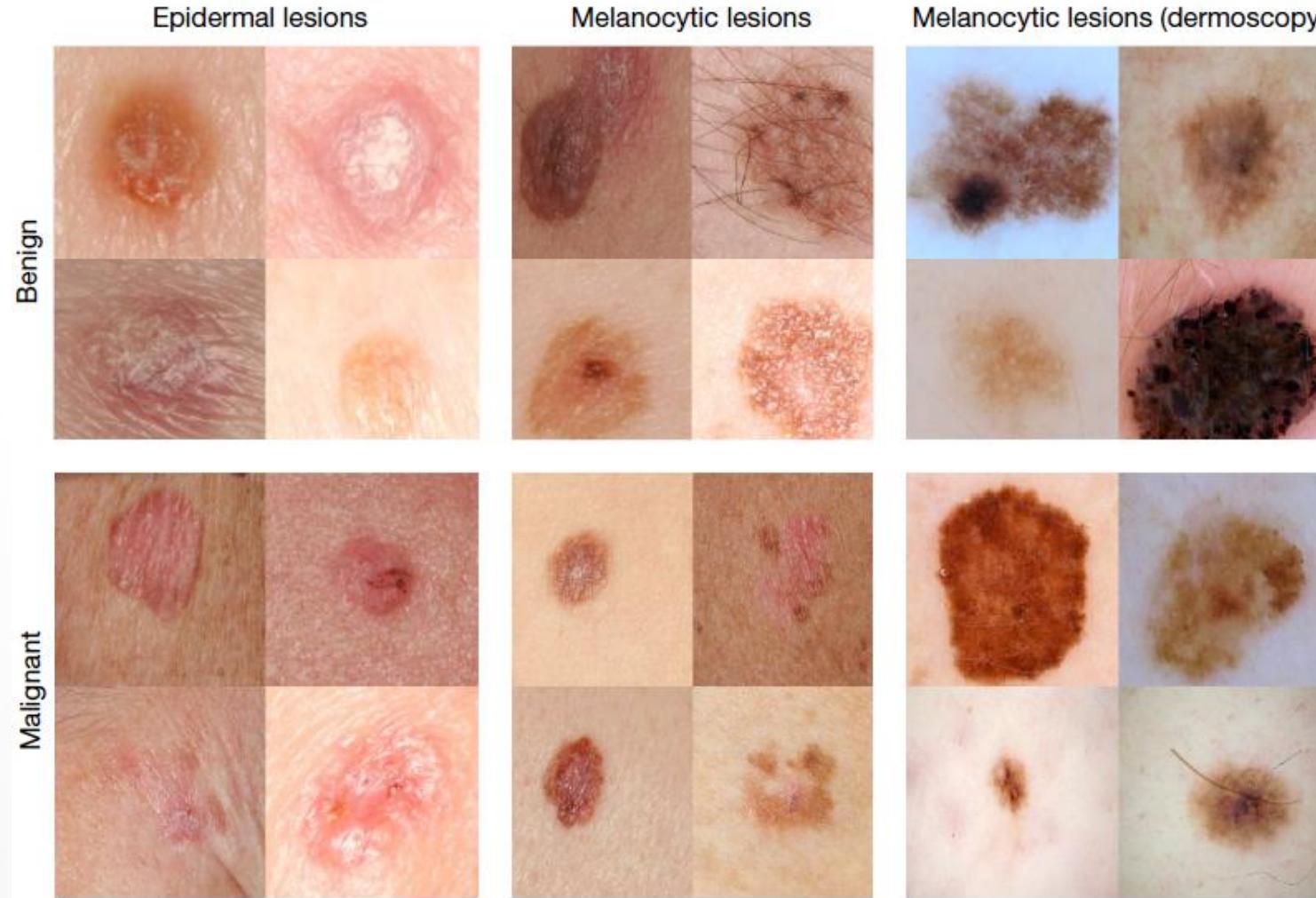
Detection in Biomedical Images

- CNN: structured regression for cell detection in microscopy images.
- Runners Up for Young Scientist Awards in MICCAI 2015



Biomedical Image Classification

- CNN (GoogLeNet Inception-v3): skin cancer classification.

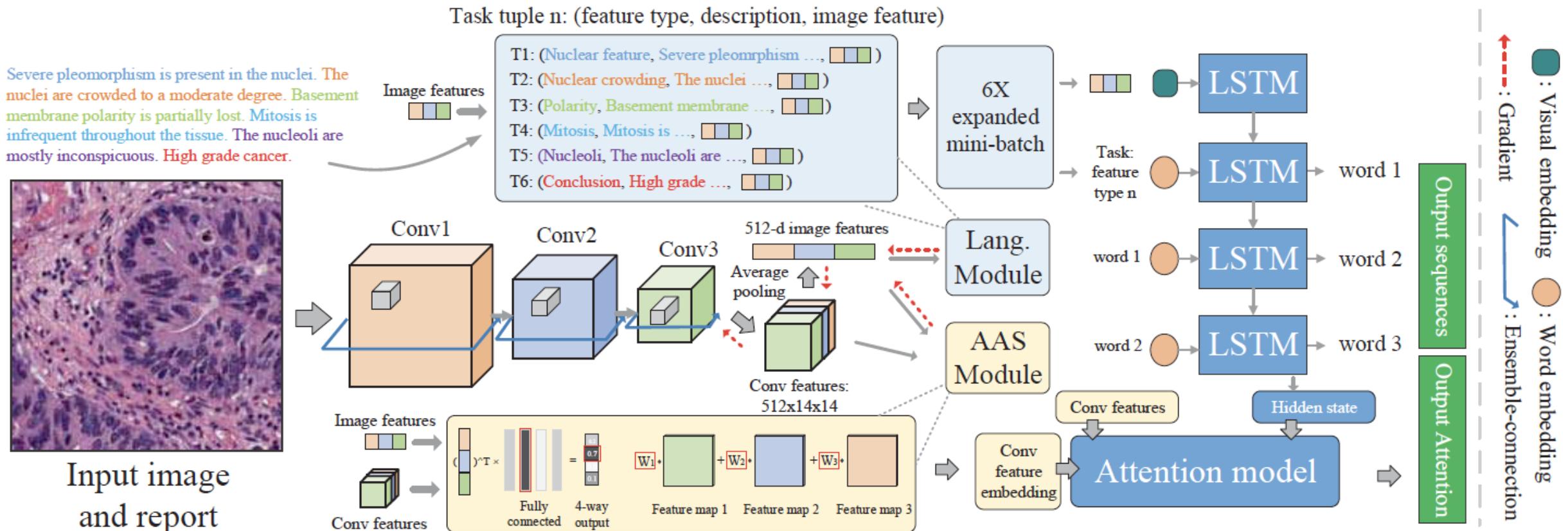


1. A. Esteva, et al., "Dermatologist-level classification of skin cancer with deep neural networks", *Nature*, 2017

Text Generation From Biomedical Images

- CNN + RNN: descriptive paragraph generation.

Link: <https://www.youtube.com/watch?v=yy7NUrc3KI0>



Deep Learning Frameworks



DEEPMLEARNING4J



CNTK theano Caffe TensorFlow

K Keras

MatConvNet



References

- General Review/Survey/Book:
 - Deep learning (2015), Y. LeCun, Y. Bengio and G. Hinton
 - Deep learning in neural networks: An overview (2015), J. Schmidhuber
 - Deep learning (Book, 2016), I. Goodfellow et al.
- Deep learning in biomedical informatics:
 - Deep learning in bioinformatics (2017), S. Min et al.
 - A survey on deep learning in medical image analysis (2017), G. Litjens et al.
 - Deep learning in microscopy image analysis: A survey (2017), F. Xing et al.