ML classifiers: Artificial Neural Networks and Deep Learning

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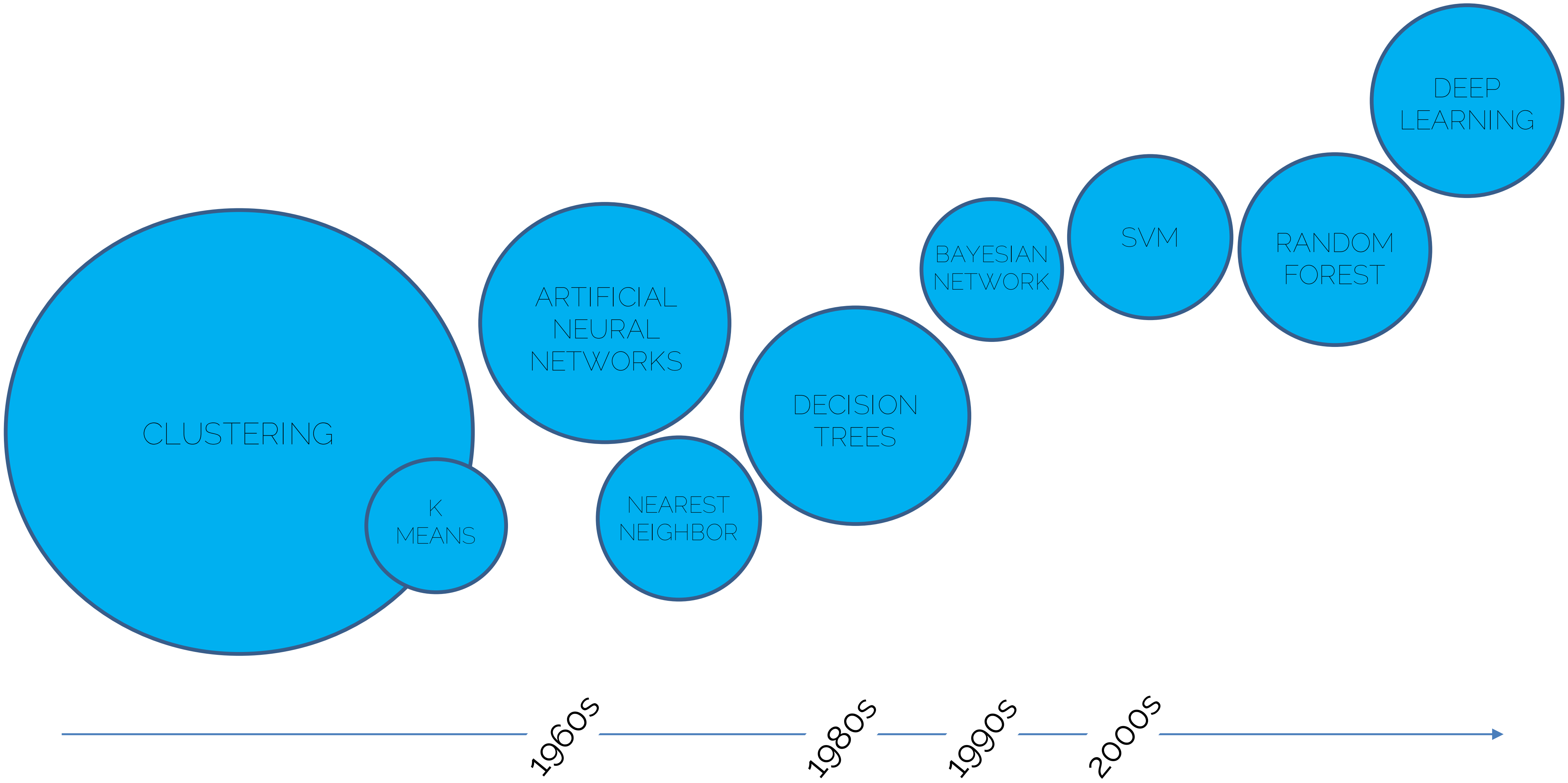
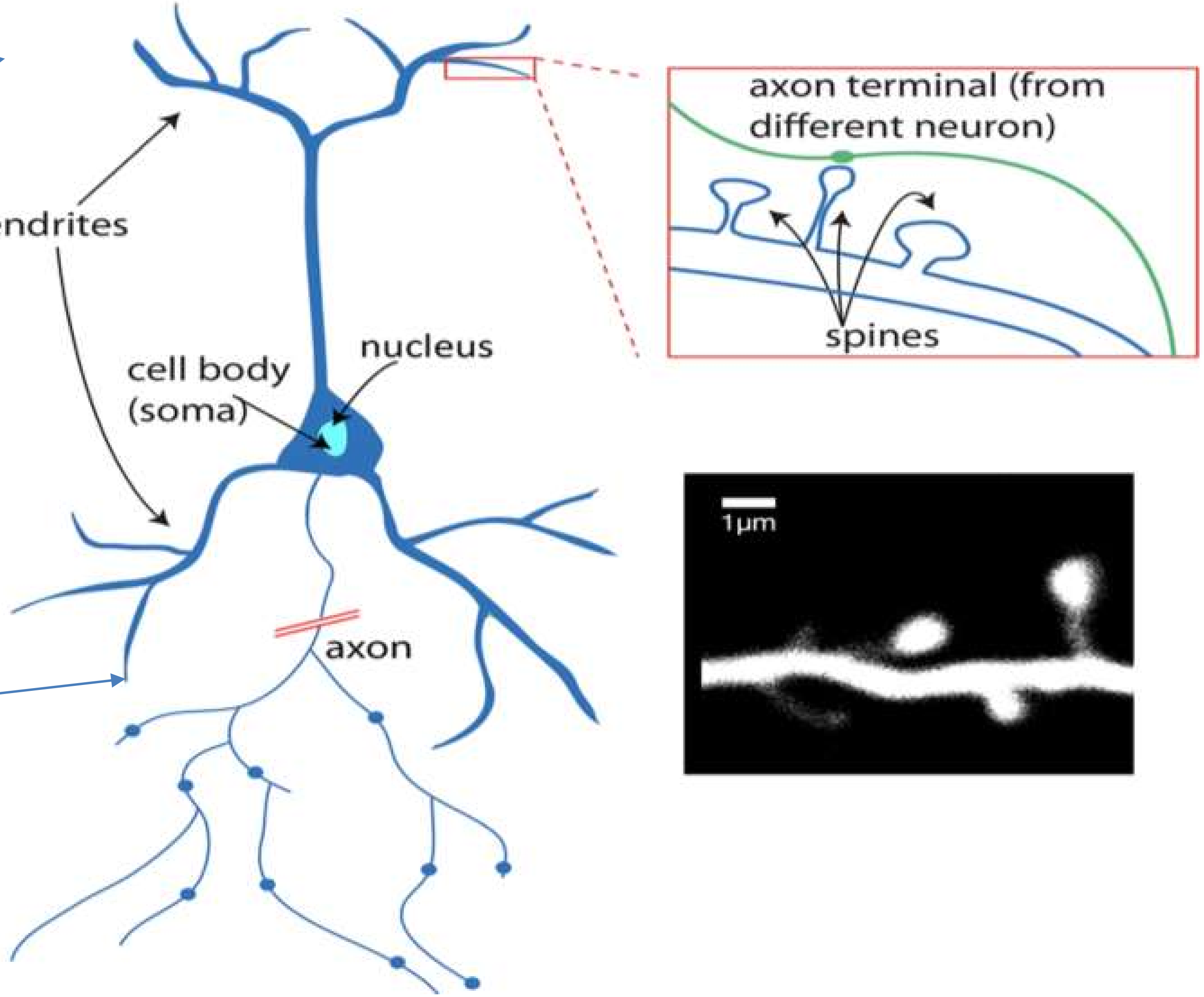
Machine learning



NEURAL NETWORKS

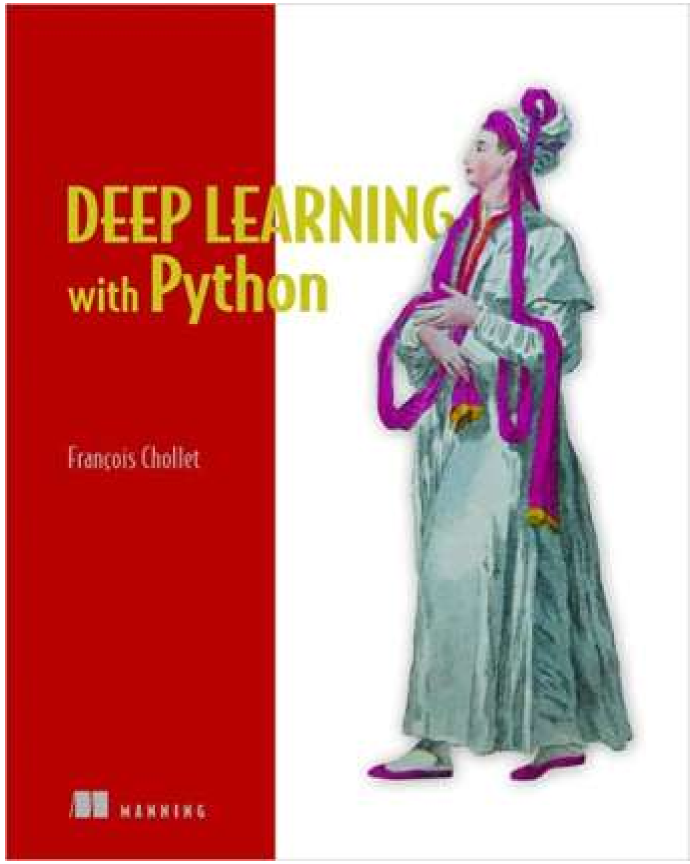
A Biological Neuron

Input
from
other
neurons



output
propagated to
other neurons
(activations)

Artificial Neural Networks



CS231n Convolutional Neural Networks for Visual Recognition

These notes accompany the Stanford CS class CS231n: Convolutional Neural Networks for Visual Recognition. For questions/concerns/bug reports, please submit a pull request directly to our git repo.

Spring 2023 Assignments

Assignment #1: Image Classification, kNN, SVM, Softmax, Fully Connected Neural Network

Assignment #2: Fully Connected and Convolutional Nets, Batch Normalization, Dropout, Pytorch & Network Visualization

(To be released) Assignment #3: Image Captioning with RNNs and Transformers, Network Visualization, Generative Adversarial Networks, Self-Supervised Contrastive Learning

Module 0: Preparation

Software Setup

Python / Numpy Tutorial (with Jupyter and Colab)

Module 1: Neural Networks

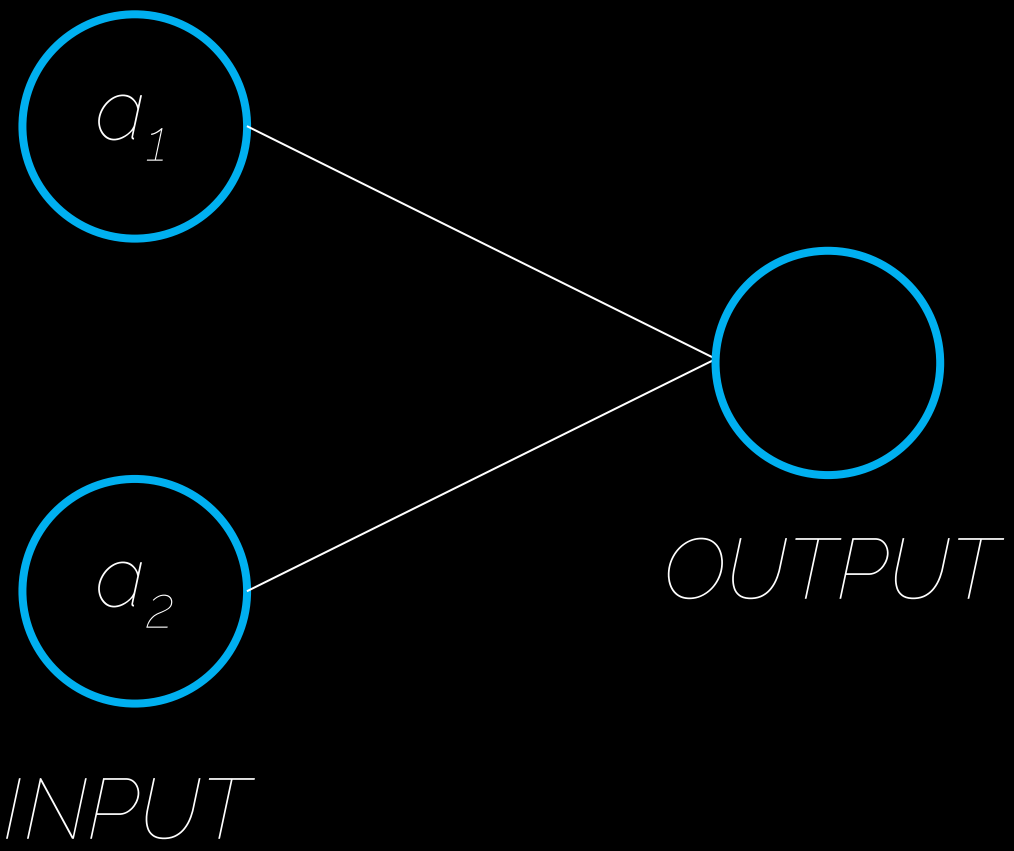
Image Classification: Data-driven Approach, k-Nearest Neighbor, train/val/test splits
L1/L2 distances, hyperparameter search, cross-validation

Linear classification: Support Vector Machine, Softmax
parameteric approach, bias trick, hinge loss, cross-entropy loss, L2 regularization, web demo

Optimization: Stochastic Gradient Descent
optimization landscapes, local search, learning rate, analytic/numerical gradient

https://cs231n.github.io/

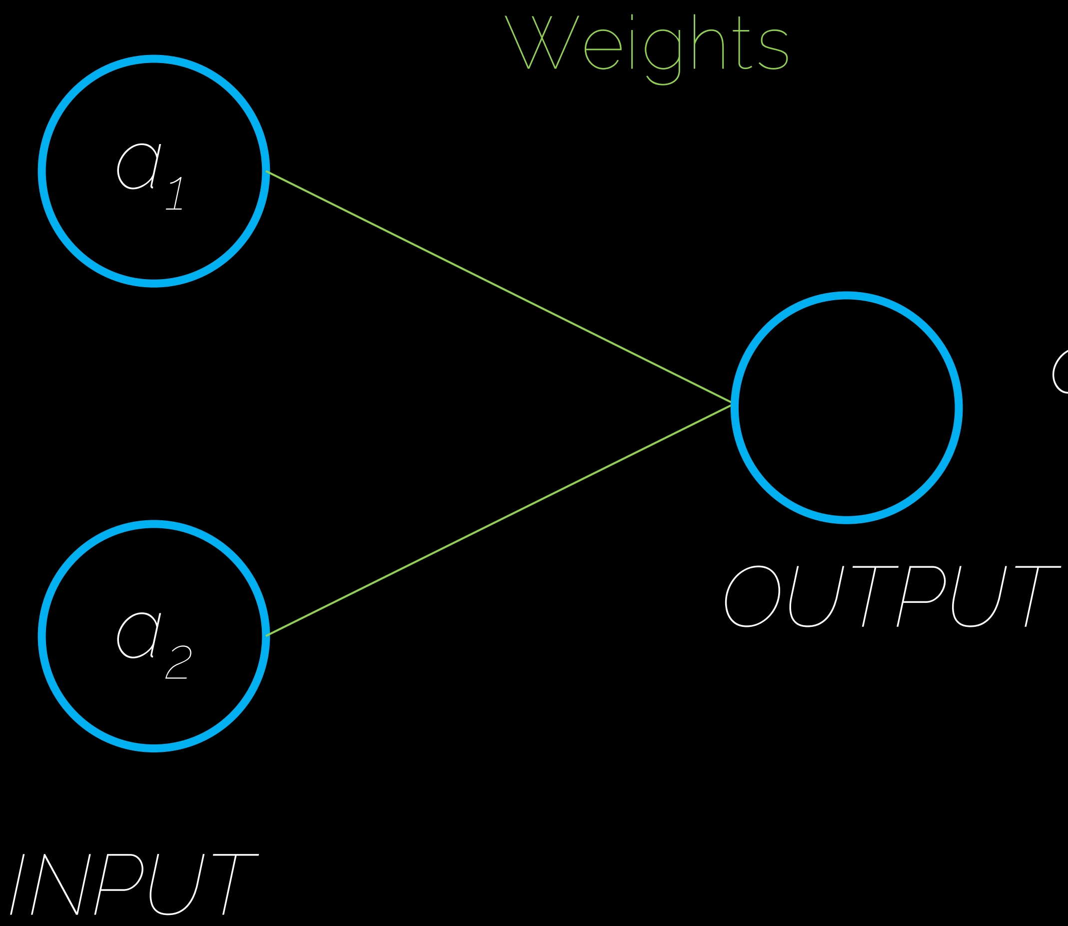
Neural Network



OUTPUT = f (INPUT)

0 1

Neural Network | Weights and Bias

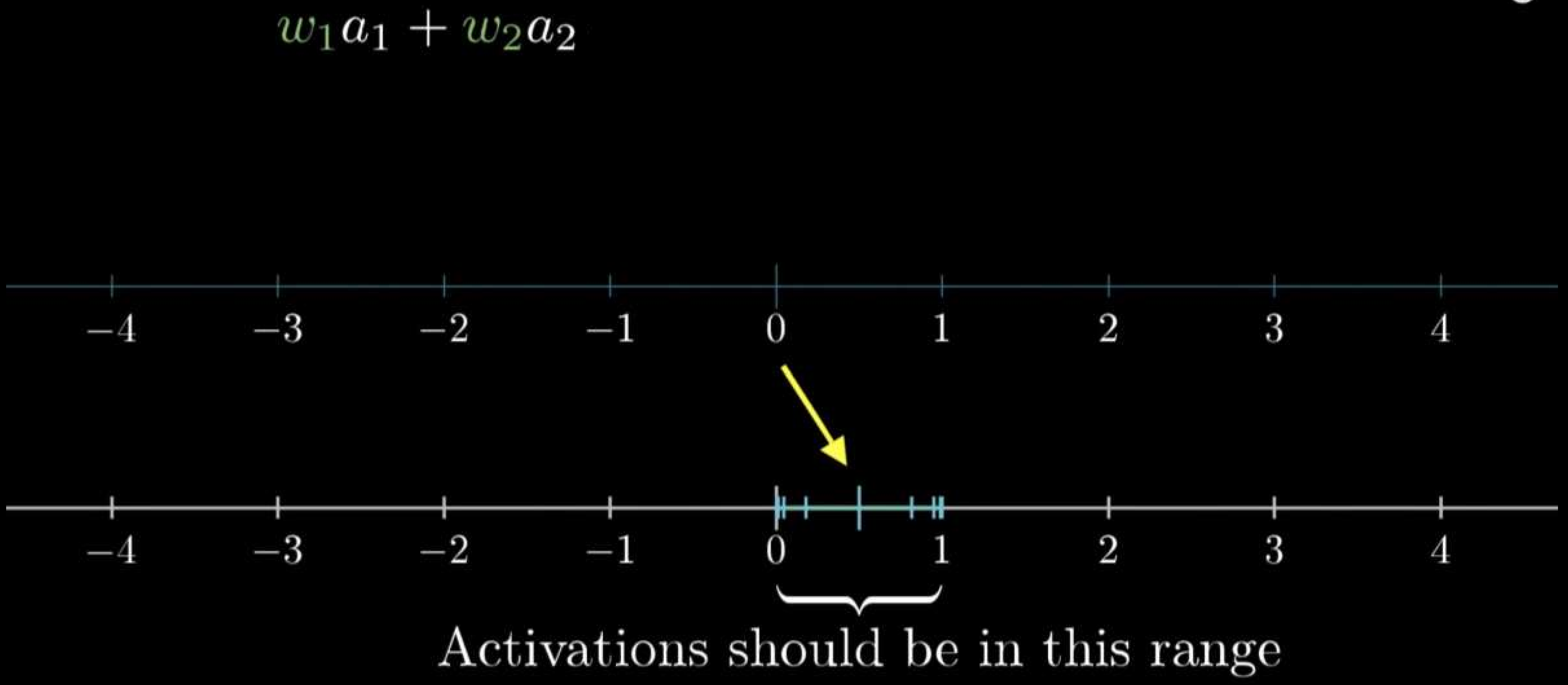


Bias (for inactivity)

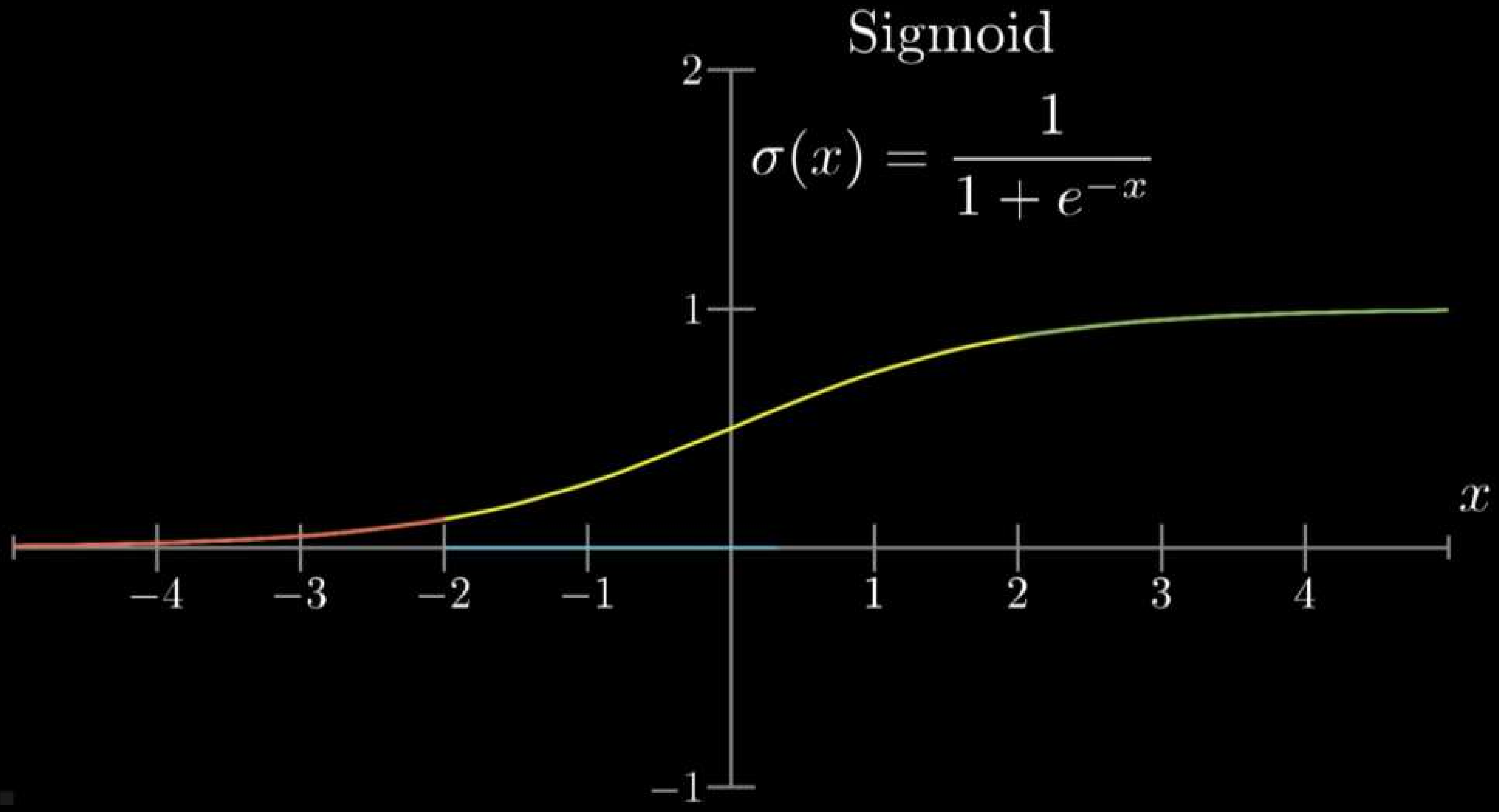
$$a_1 w_1 + a_2 w_2 + b$$

$$OUTPUT = f\,(INPUT)$$

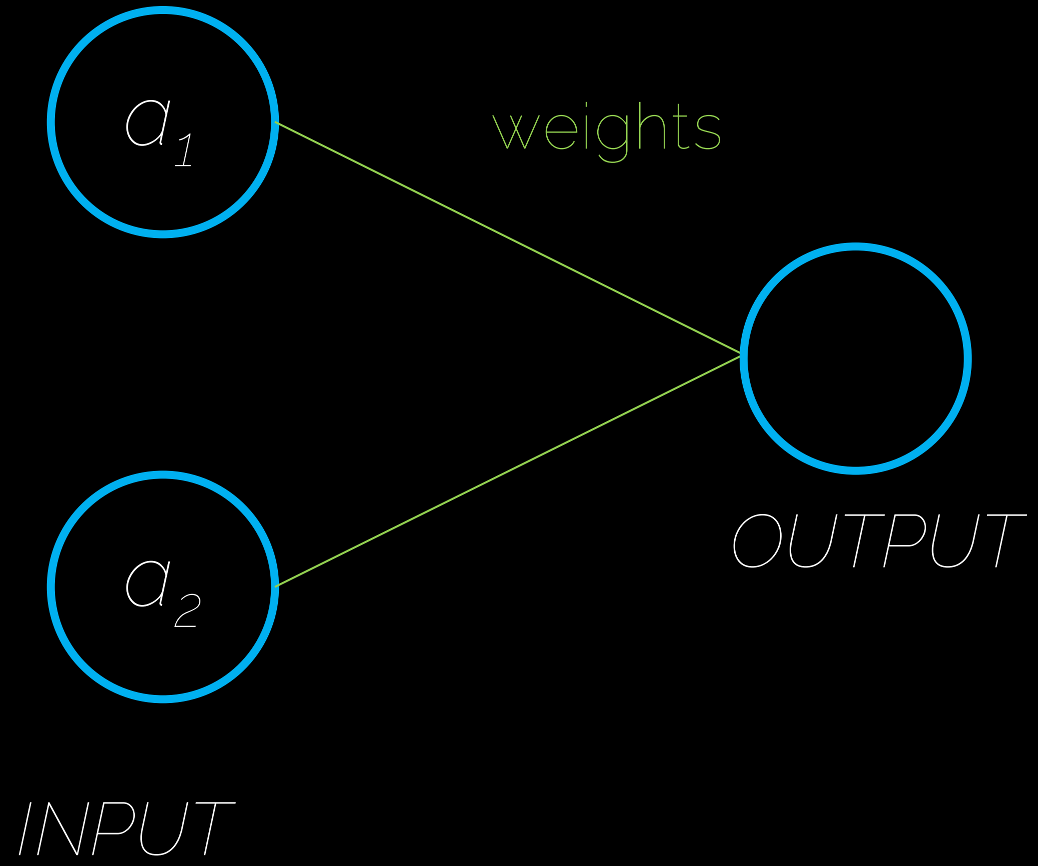
Neural Network | Activation function



Neural Network | Activation function



Neural Network | Activation function



Forward propagation

Activation function

$$Sigmoid\,(a_1 w_1 + a_2 w_2 + b)$$

$$OUTPUT = f\,(INPUT)$$

w_1 ? w_2 ? b ?

Neural Network

INPUT

a_1 a_2

Cost Function?

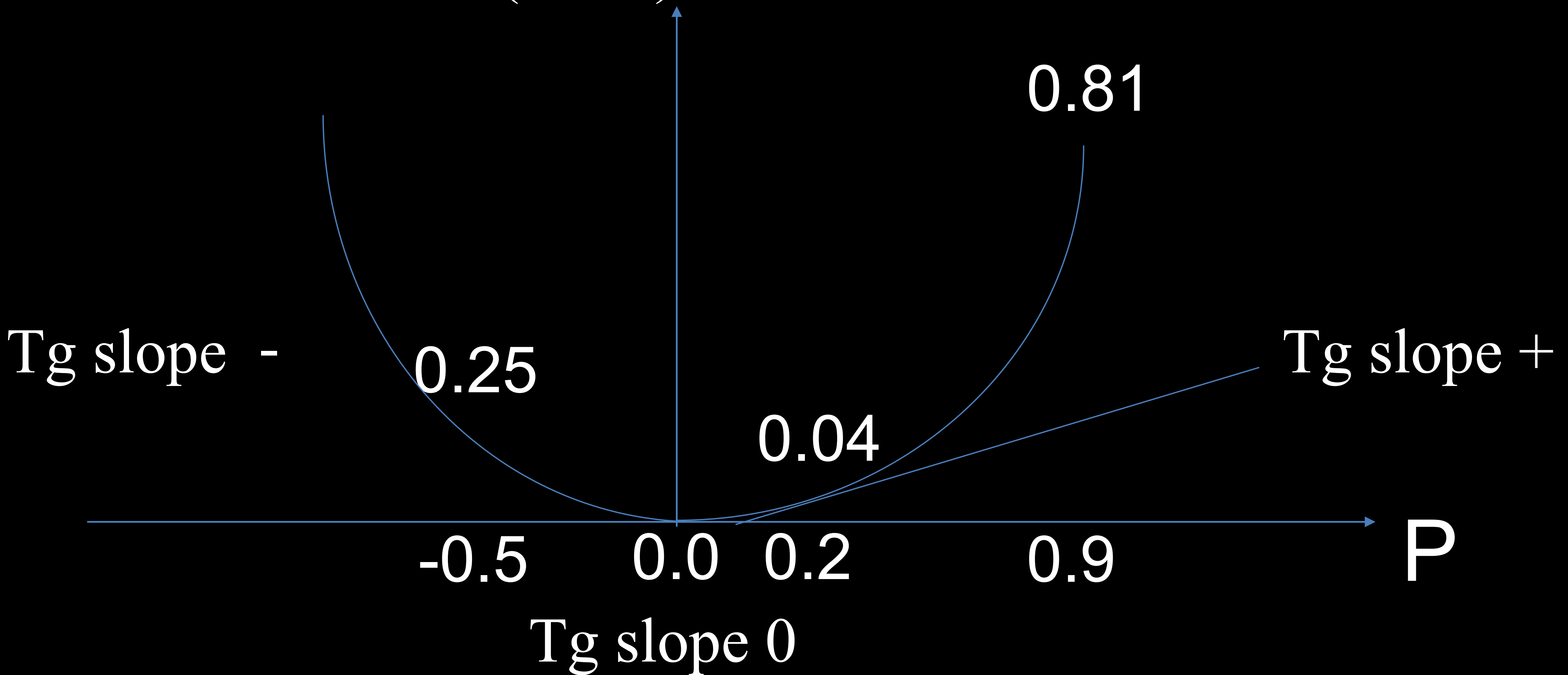
$\mathit{Sigmoid}\ (a_1 w_1 + a_2 w_2 + b)$

OUTPUT

Cost Function = $(\text{Predicted}-\text{Expected})^2$

Squared error cost

The Cost Function = $(P-0.0)^2$



Neural Network

If the slope is + we must decrease P of a fraction of the slope

If the slope is - we must increase P of a fraction of the slope

If the slope is 0 we have the solution

Training a single-neuron neural network

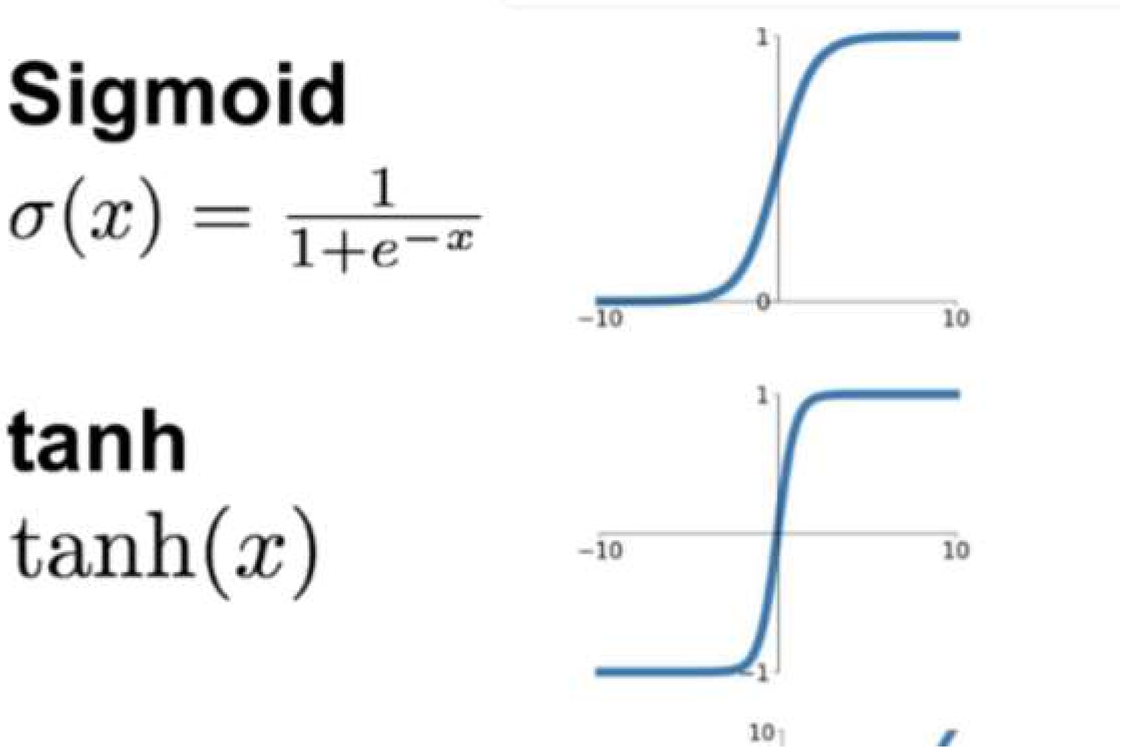
-> backward propagation

pdf / part 1

Neural Network

Other functions that progressively change from 0 to 1 with no discontinuity

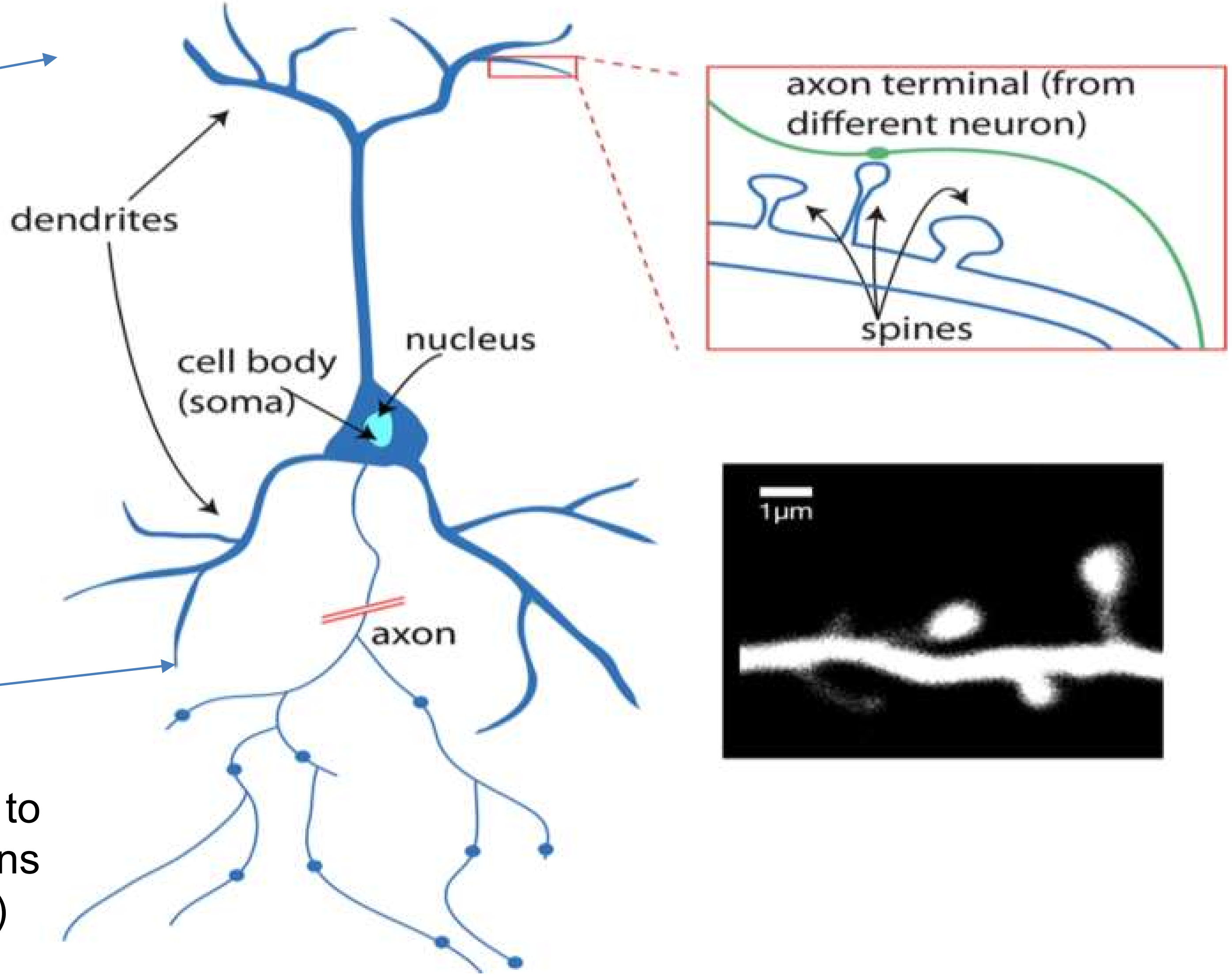
Hyperbolic tangent function



DEEP NEURAL NETWORKS (Deep Learning)

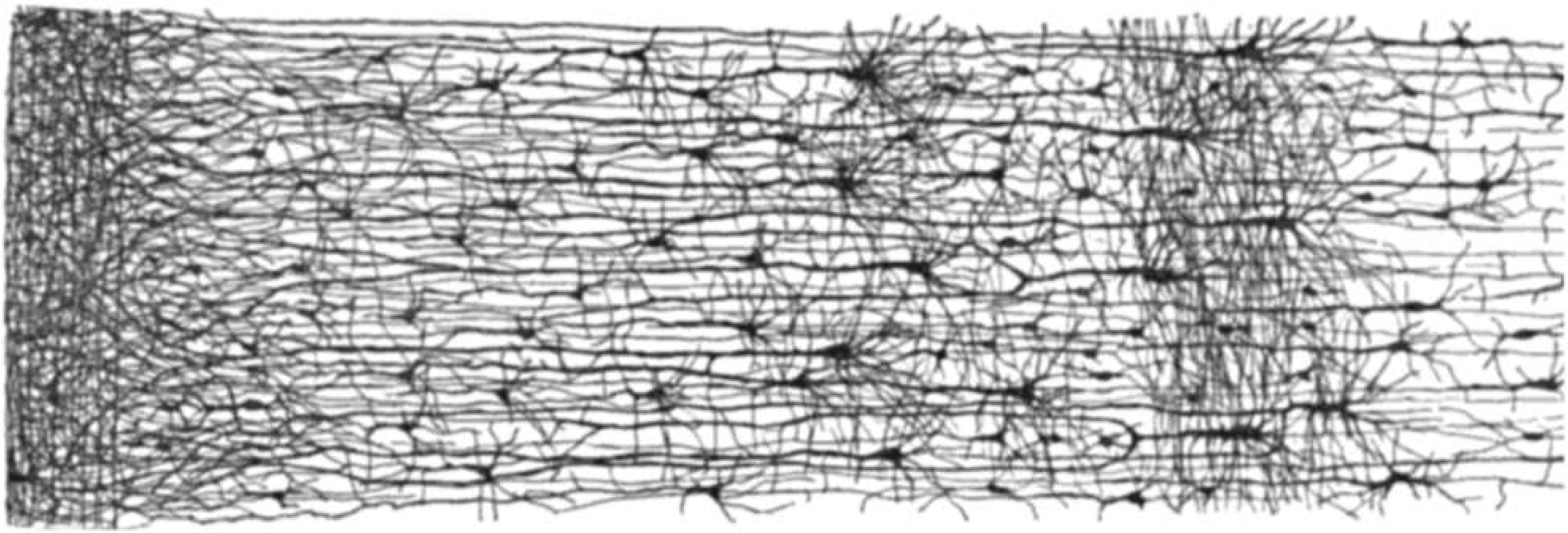
A Biological Neuron

Input
from
other
neurons



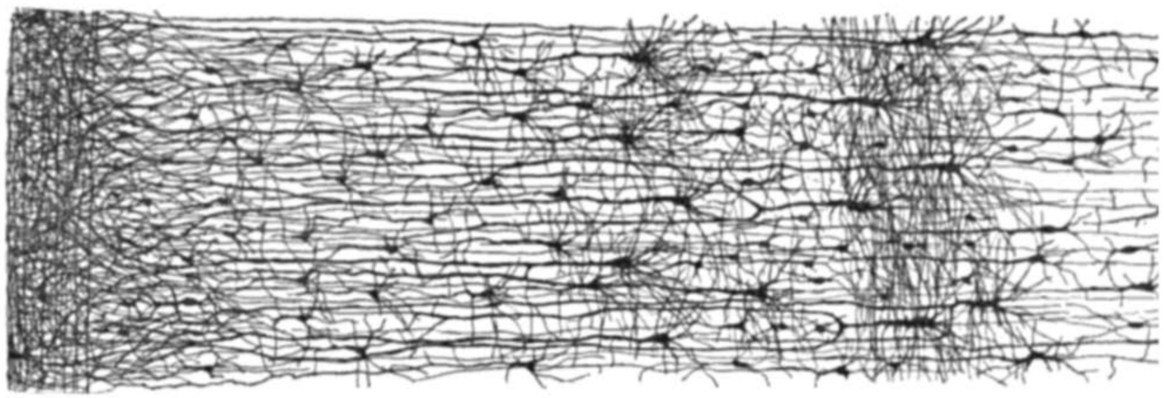
output
propagated to
other neurons
(activations)

A Biological Neuron Network

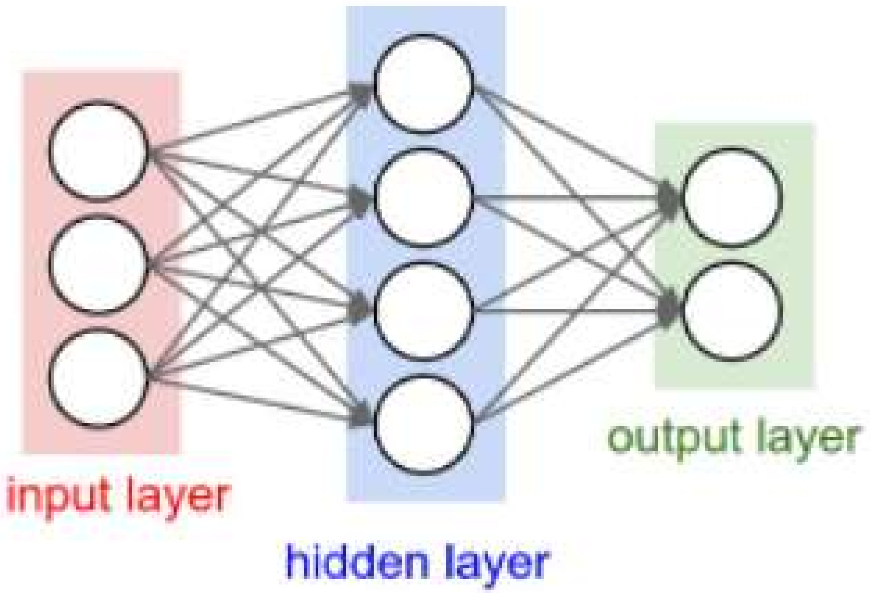


100 B neurons

A Biological Neuron Network



100 B neurons



Neural Network

Training a multi-layer / deep neural network

-> generalized backward propagation

pdf / part 2

Problems in training performance

-Vanishing Gradient

-Overfitting

-Computational load

Vanishing gradients

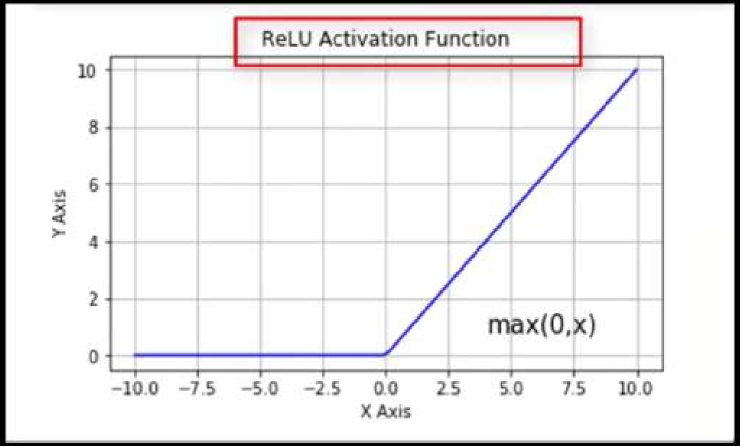
During training each weight receives an update proportional to the partial derivative of the error function with respect to the current weight in each iteration of training.

In some cases, the gradient will be vanishingly small, effectively preventing the weight from changing its value. In the worst case, this may completely stop the neural network from further training.

As one example of the problem cause, traditional activation functions such as the hyperbolic tangent function have gradients in the range (-1, 1), and backpropagation computes gradients by the chain rule. This has the effect of multiplying n of these small numbers to compute gradients of the "front" layers in an n-layer network, meaning that the gradient (error signal) decreases exponentially with n while the front layers train very slowly.

Vanishing gradients

Can be solved using Rectified Linear Unit function (ReLU) and its derivative as activation function



$$\varphi(x) = \begin{cases} x, & x > 0 \\ 0, & x \le 0 \end{cases}$$

$$= \max(0,\ x)$$

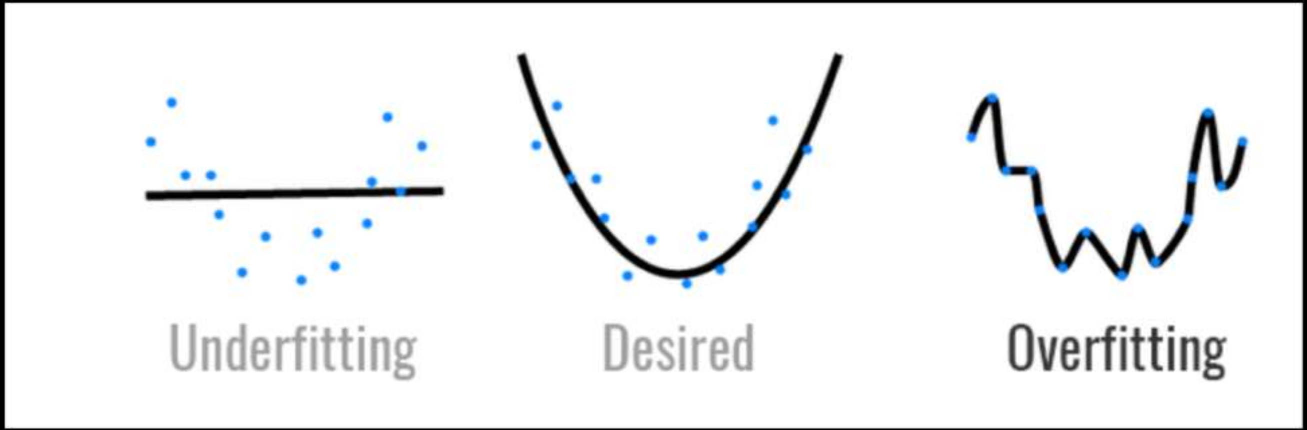
$$\boxed{\varphi'(x) = \begin{cases} 1, & x > 0 \\ 0, & x \le 0 \end{cases}}$$

Computational load

Can be solved by GPU, Batch Normalization method

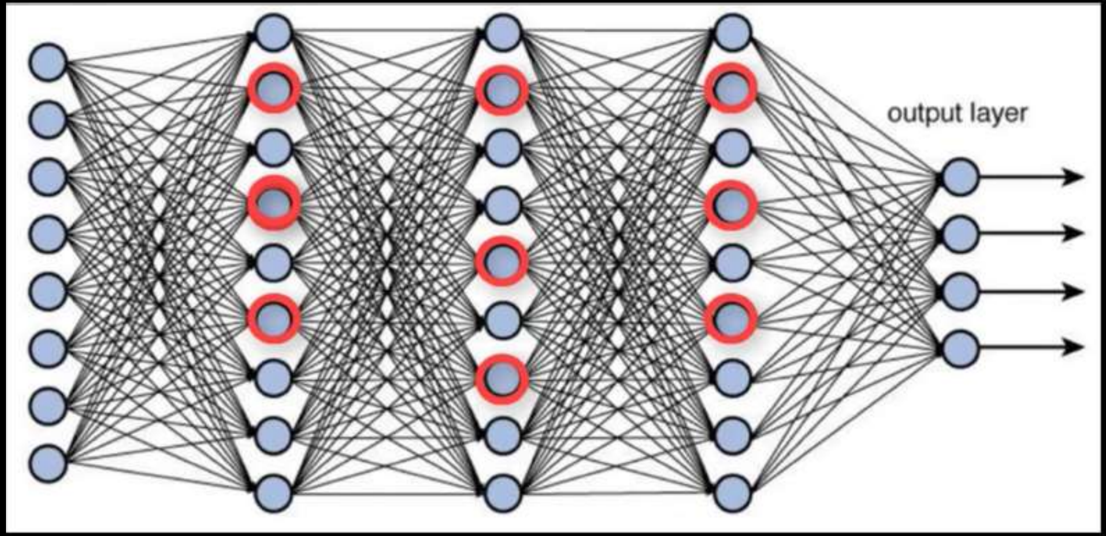
Overfitting

It refers to a model that models the training data too well. Instead of learning the genral **distribution** of the data, the model learns the *expected output* for every data point.

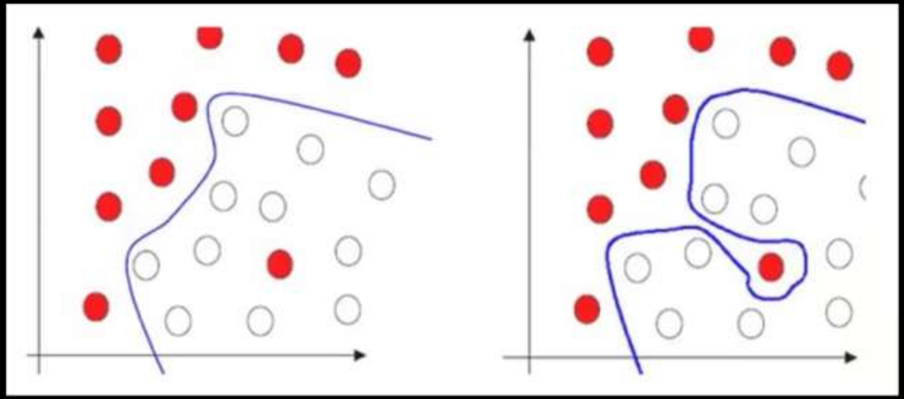


Overfitting

Can be solved using Dropout or Regularization

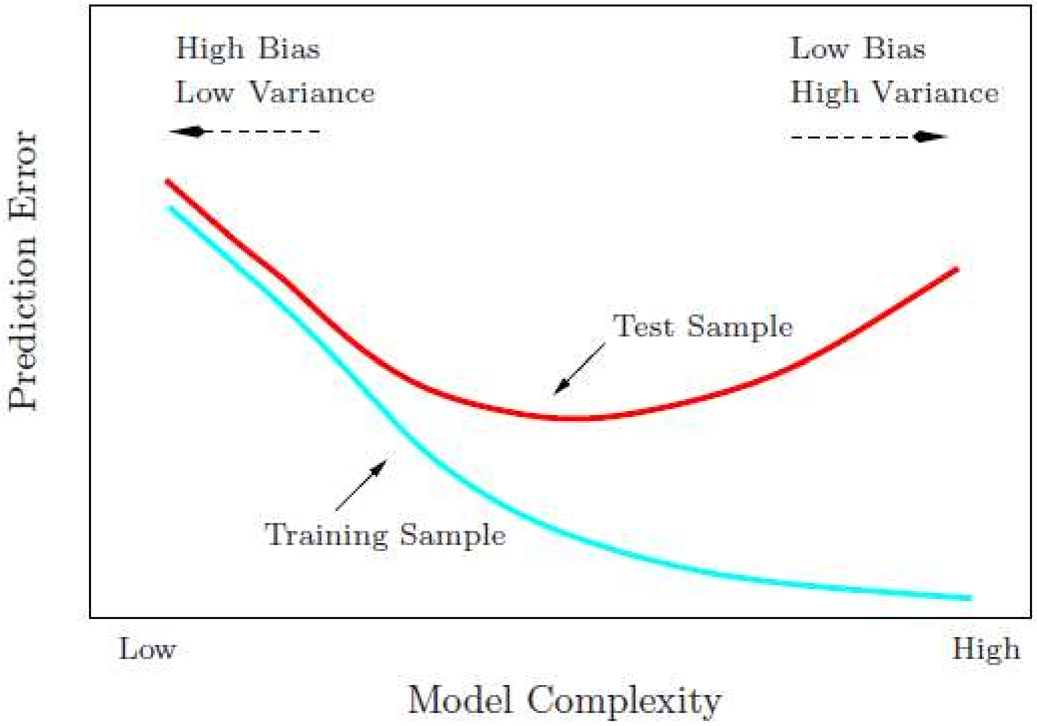


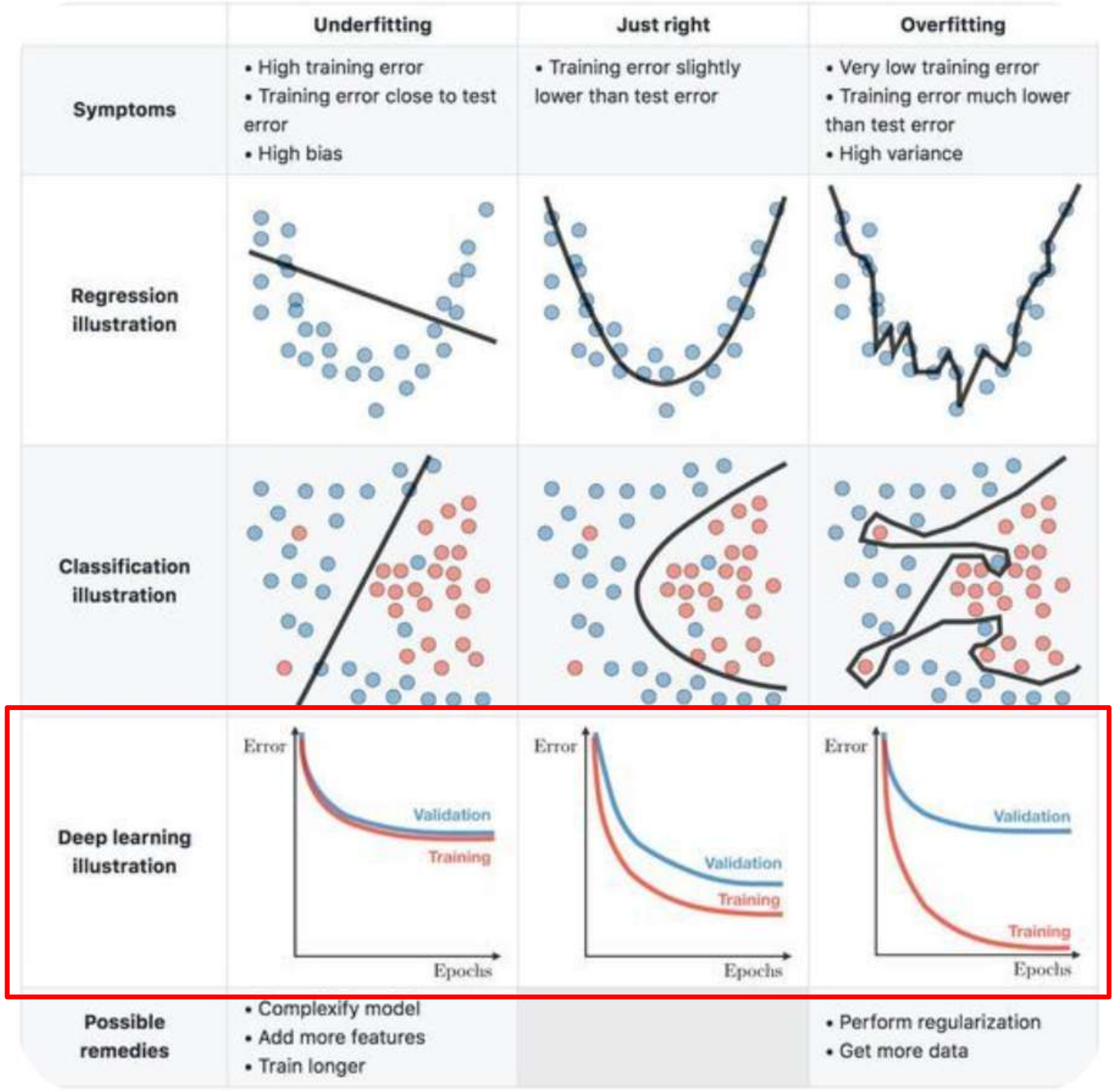
Dropout



Regulariztion

Deep Learning





When weight update should be calculated?

Batch: error is calculated for all training data, each of the weight updates are calculated but the avarage of all weight updates are used only once in each epoch.

In **Stochastic Gradient Descent**, error is calculated for each training data, weights updated immediately.

With **Mini-Batch Gradient Descent**, we have a mix of the previous situations.

Mini-Batch method

1-10

11-20

21-40

41-60

61-80

5 weight update will be performed to complete the training process

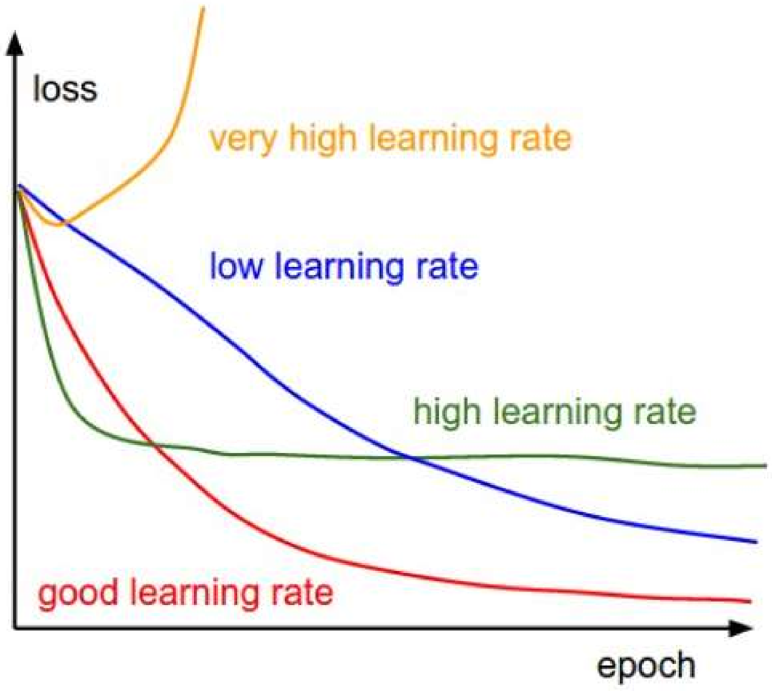
Robusteness of SGD
Efficiency of batch

Neural Network

Learning rate and optimizer for weight update

Learning rate determines how much weights are changed every time
Too high→ output wanders around the expected solution
Too low → output fails to converge to acceptable solution

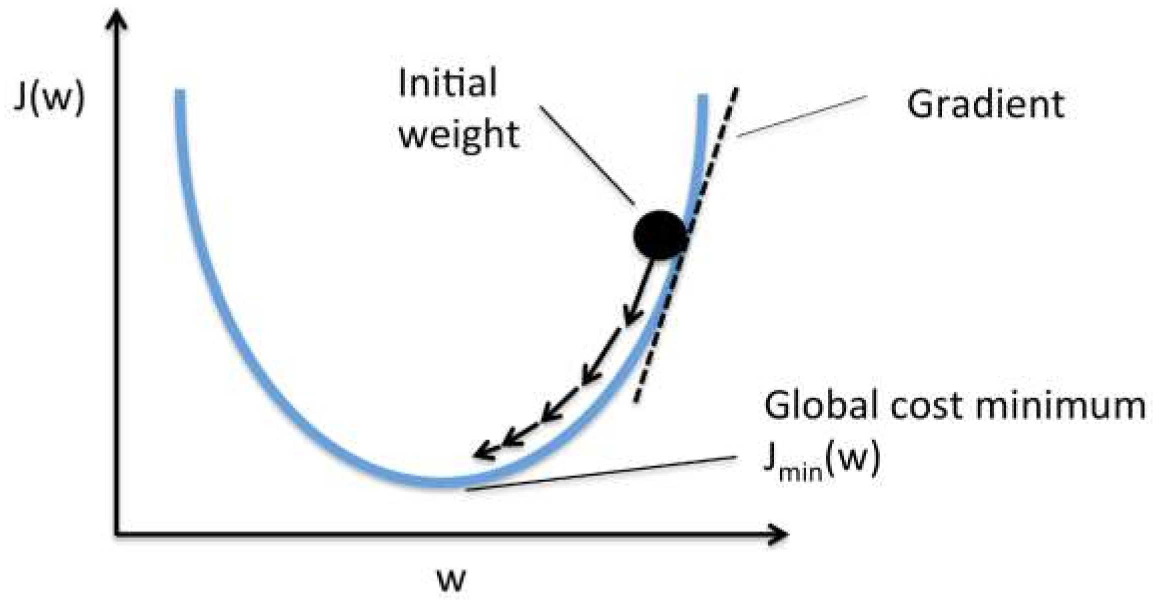
-> Constant learning rate
-> Learning rate schedule
  - (constant) step decay
  - exponential decay $\alpha = \alpha_0 e^{-kt}$
  - 1/t decay $\alpha = \alpha_0 / (1 + kt)$



Optimization methods are techniques used to improve the weight update in order to improve the performance of the network (for example, by reaching a solution in a faster way)

Stochastic Gradient Descent is the one described above

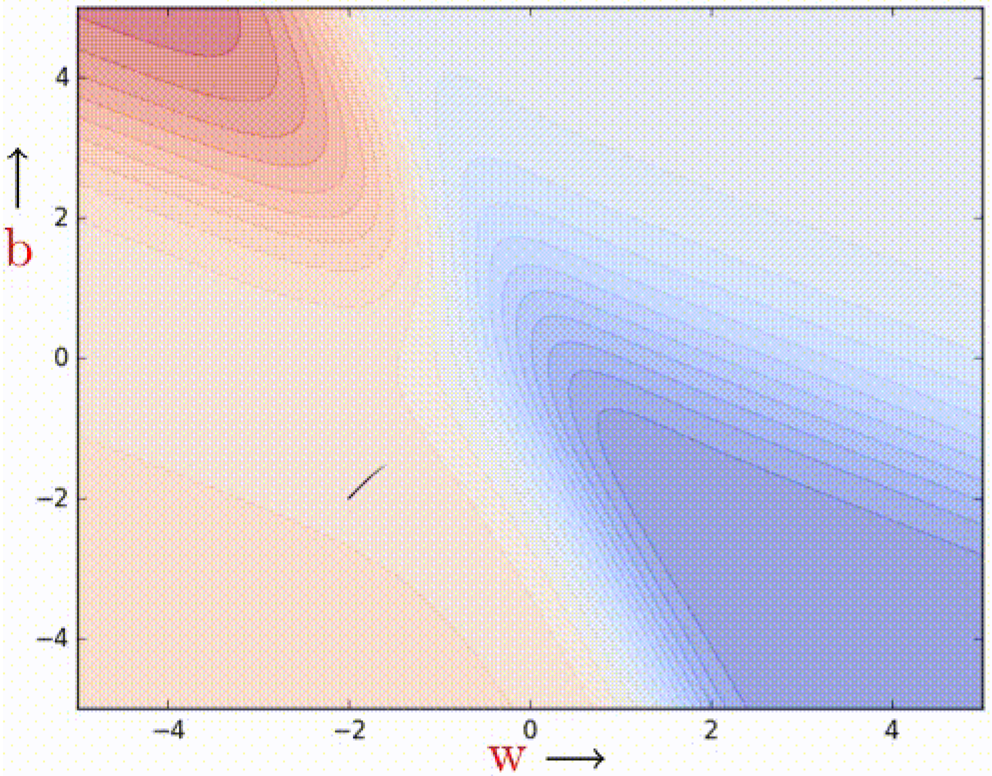
-> parameters are updated along the negative gradient direction



Momentum

Parameters are updated as a function not only of the present gradient, but also of previous steps (introducing a sort of "velocity" parameters)

```
# Momentum update
v = mu * v - learning_rate * dx # integrate velocity
x += v # integrate position
```



Vanilla SDG vs Momentum, 100 iterations

Momentum

Parameters are updated as a function not only of the present gradient, but also of previous steps (introducing a sort of "velocity" parameters)

```
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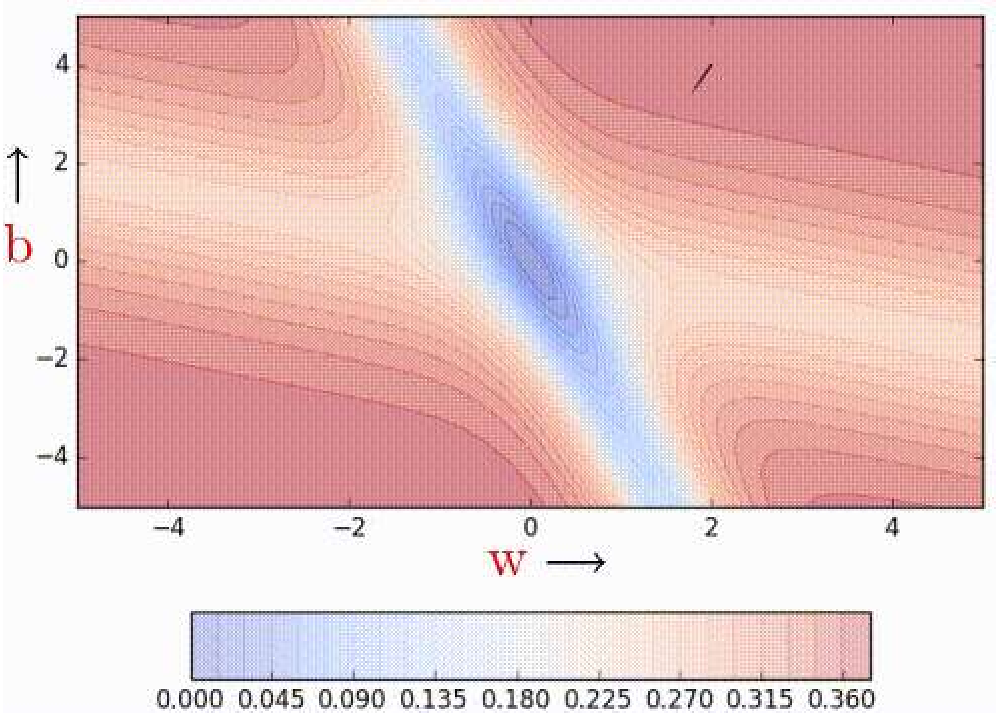
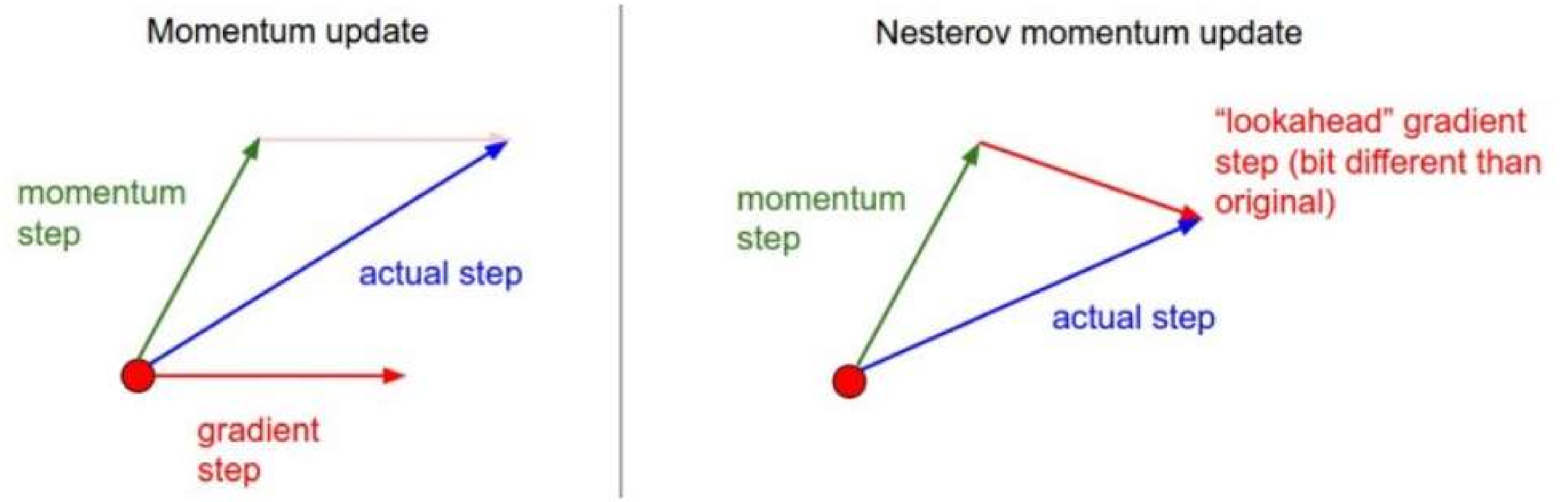


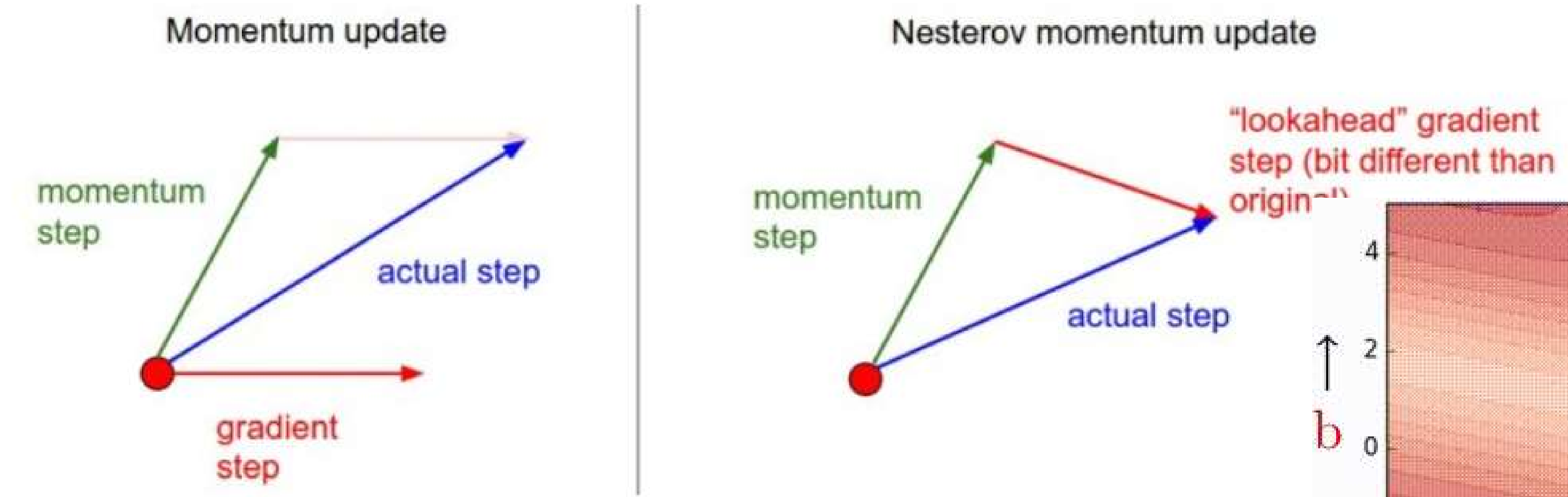
Vanilla SDG vs Momentum, 100 iterations

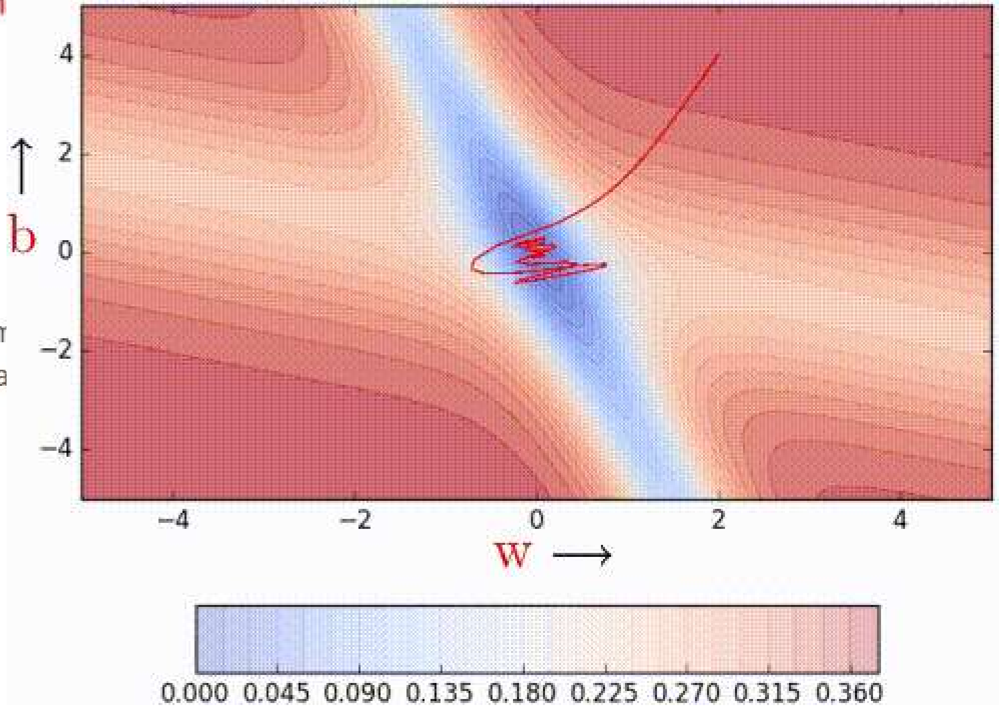
Nesterov Accelerated Gradient



Nesterov momentum. Instead of evaluating gradient at the current position (red circle), we know that our momentum is about to carry us to the tip of the green arrow. With Nesterov momentum we therefore instead evaluate the gradient at this "looked-ahead" position.

Nesterov Accelerated Gradient





Nesterov momentum. Instead of evaluating gradient at the current position (red circle), we know that our m carry us to the tip of the green arrow. With Nesterov momentum we therefore instead evaluate the gra ahead" position.

Adagrad

```
cache += dx**2
x += - learning_rate * dx / (np.sqrt(cache) + eps)
```

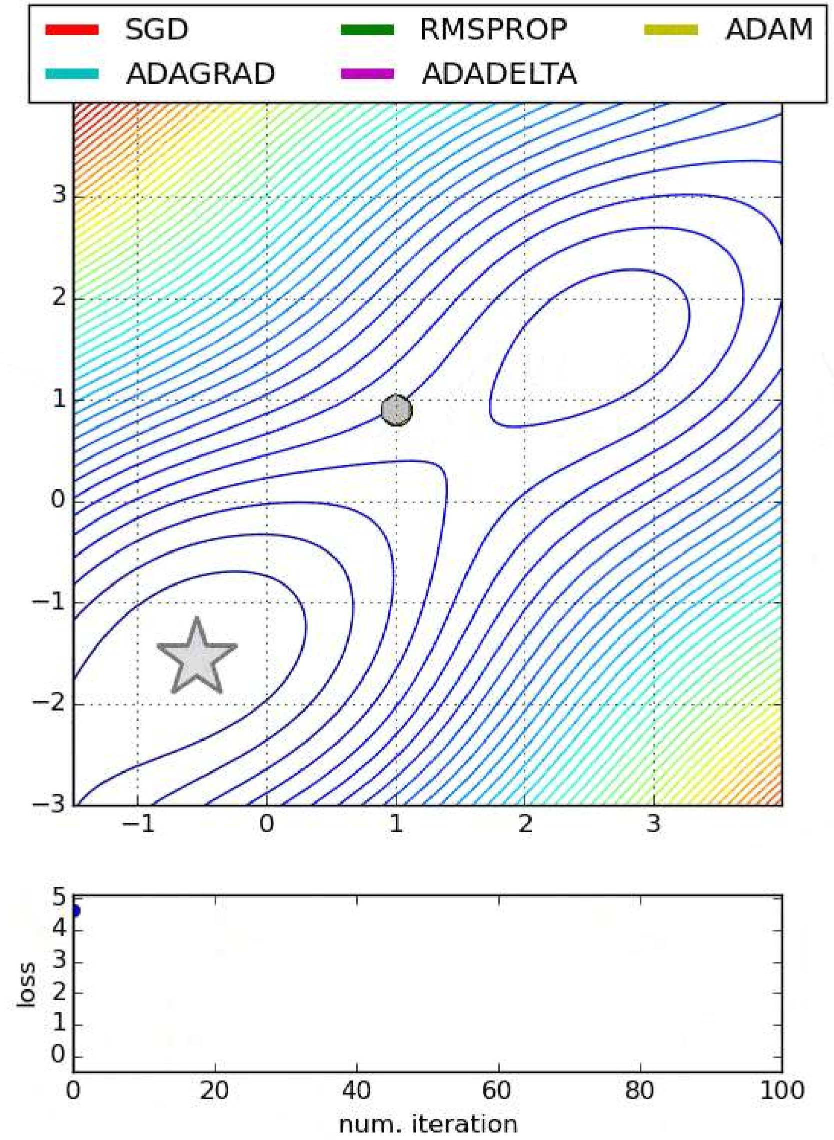
RMSprop

```
cache = decay_rate * cache + (1 - decay_rate) * dx**2
x += - learning_rate * dx / (np.sqrt(cache) + eps)
```

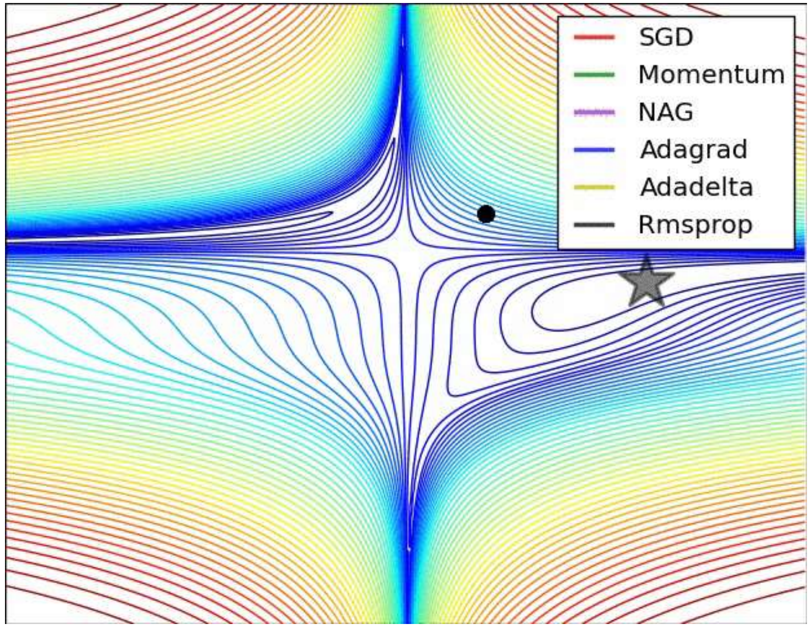
Adam (Adaptive Moment Estimation)

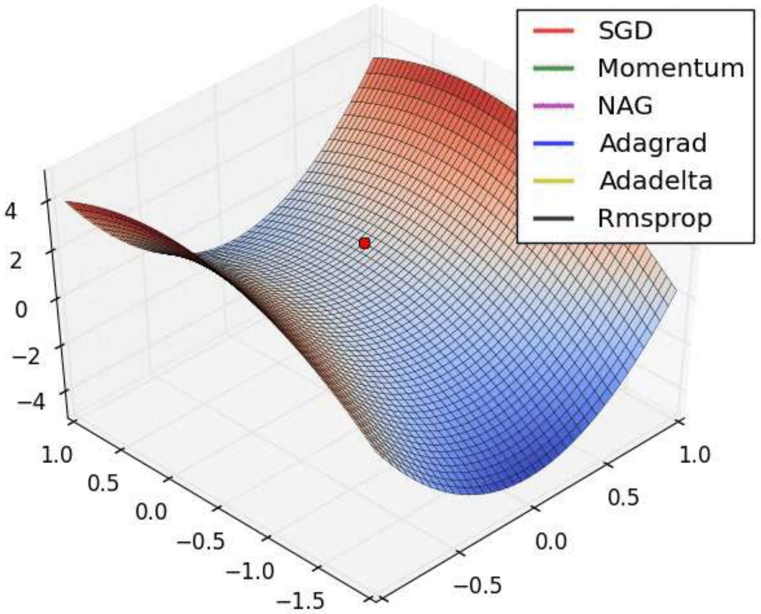
```
m = beta1*m + (1-beta1)*dx
v = beta2*v + (1-beta2)*(dx**2)
x += - learning_rate * m / (np.sqrt(v) + eps)
```

Optimizer


SGD
RMSPROP
ADAM
ADAGRAD
ADADELTA
3
2
1
0
−1
−2
−3
−1
0
1
2
3
5
4
3
2
1
0
loss
0
20
40
60
80
100
num. iteration

Optimizer

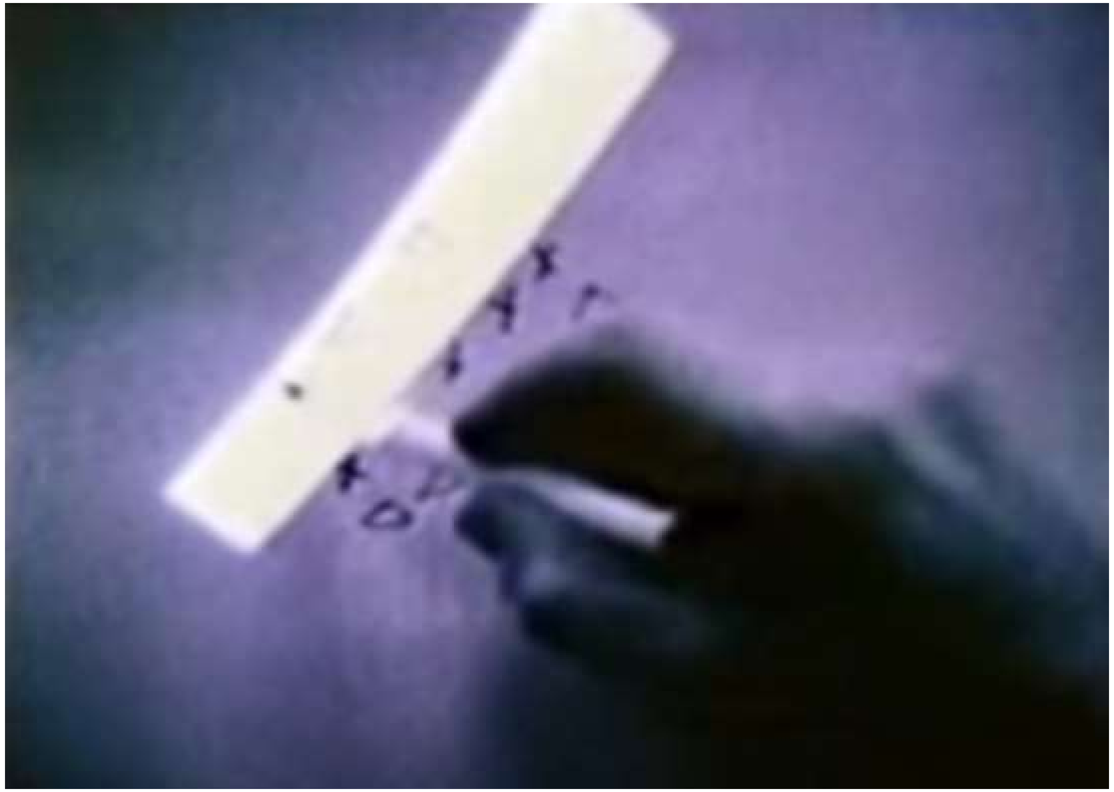




Animations that may help your intuitions about the learning process dynamics. **Left:** Contours of a loss surface and time evolution of different optimization algorithms. Notice the "overshooting" behavior of momentum-based methods, which make the optimization look like a ball rolling down the hill. **Right:** A visualization of a saddle point in the optimization landscape, where the curvature along different dimension has different signs (one dimension curves up and another down). Notice that SGD has a very hard time breaking symmetry and gets stuck on the top. Conversely, algorithms such as RMSprop will see very low gradients in the saddle direction. Due to the denominator term in the RMSprop update, this will increase the effective learning rate along this direction, helping RMSProp proceed. Images credit: Alec Radford.

(Deep) CONVOLUTIONAL NEURAL NETWORKS

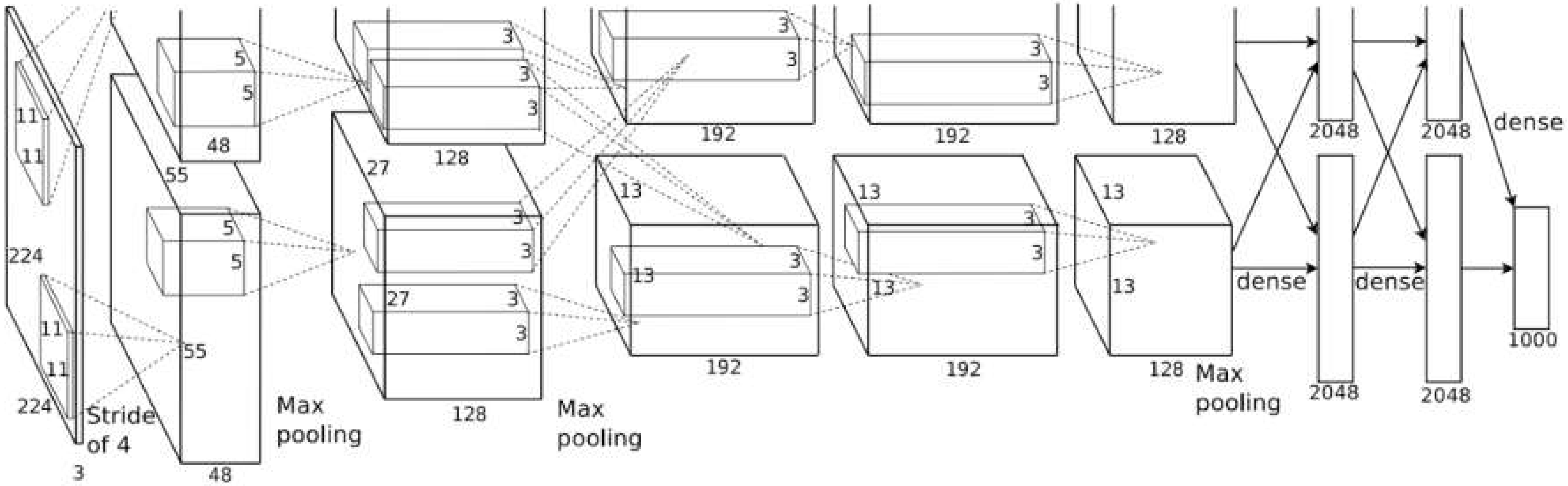
Convolutional Neural Networks



Hubel and Wiesel

https://www.youtube.com/watch?v=Cw5PKV9Rj3o

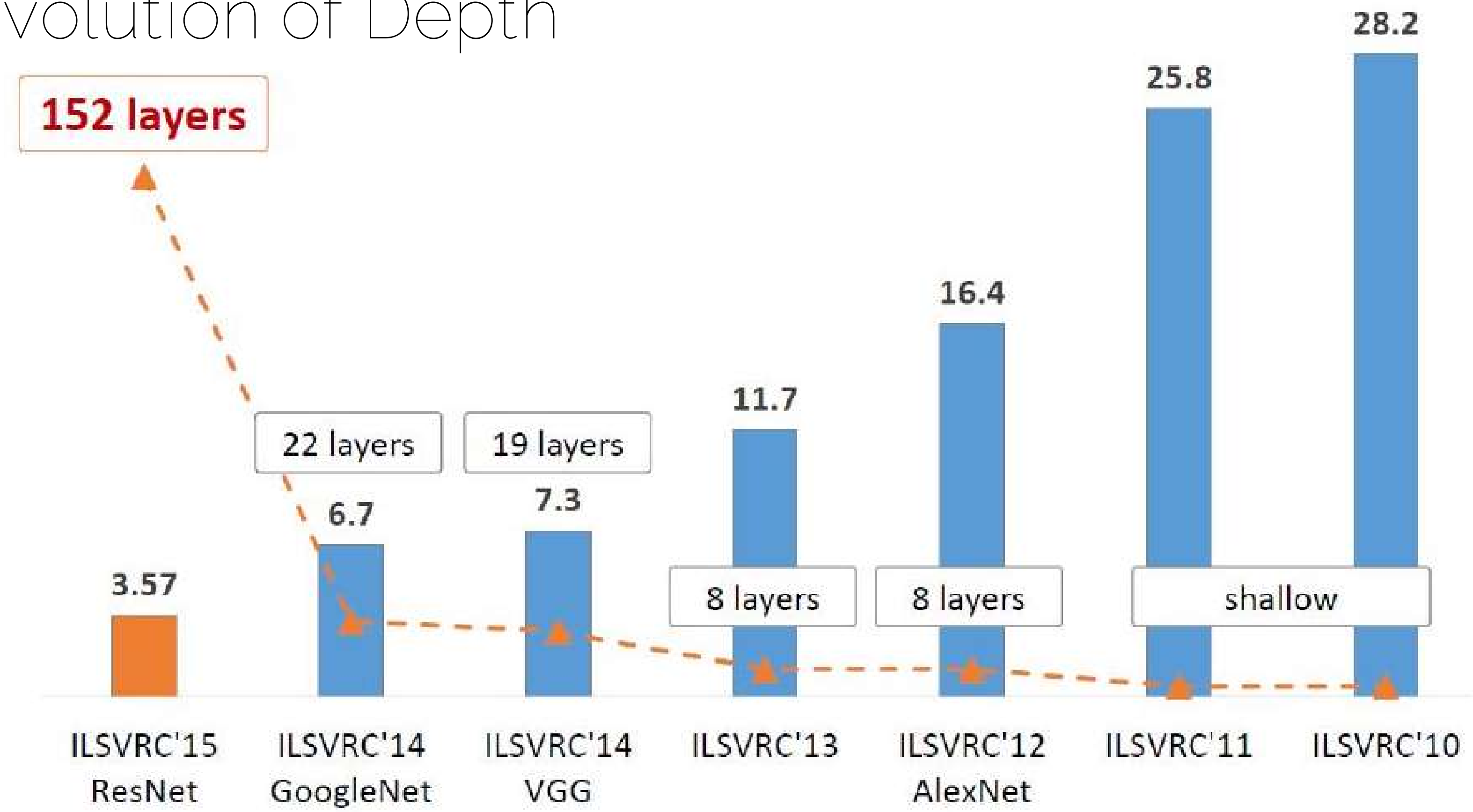
Convolutional Neural Networks



Krizhevsky, Sutskever, and Hinton, 2012

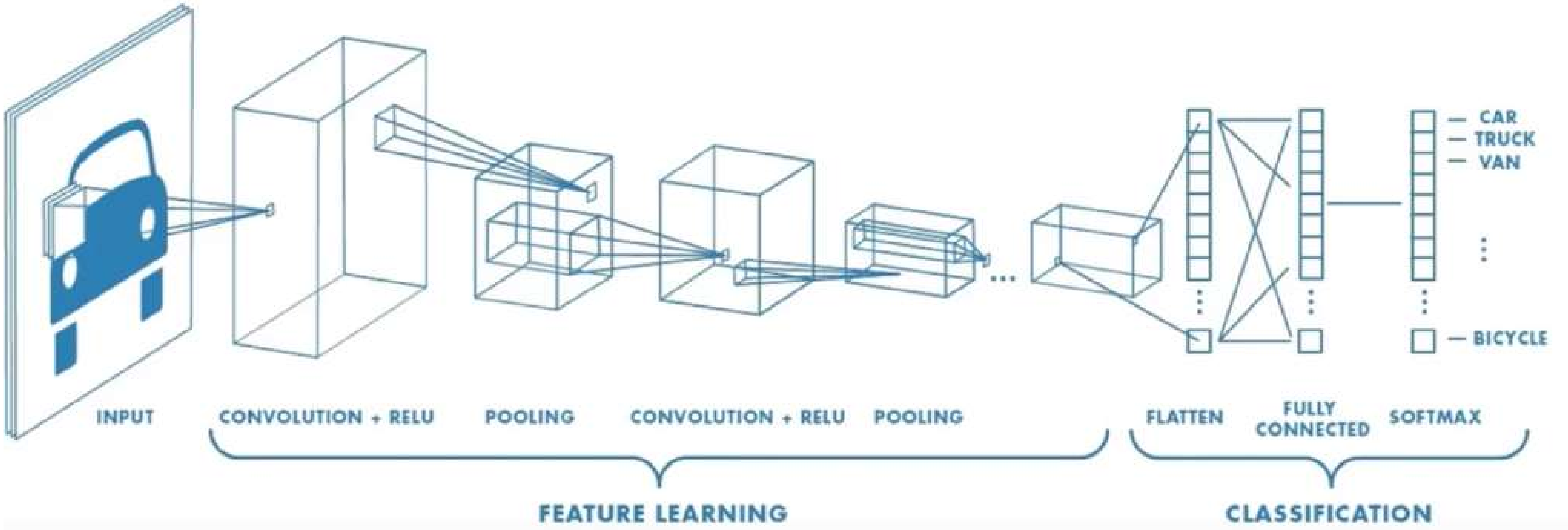
Convolutional Neural Networks

Revolution of Depth



ImageNet Classification top-5 error (%)

Convolutional Neural Networks



Convolutional Neural Networks

Convolution operation: a collection of digital filters (2D)

They convert images into feature maps

Different (convolutional) filters convert images into different feature maps

N convolutional layers by M convolutional filters
-> N by M feature maps

$$\begin{bmatrix} 1 & 1 & 1 & 3 \\ 4 & 6 & 4 & 8 \\ 30 & 0 & 1 & 5 \\ 0 & 2 & 2 & 4 \end{bmatrix} * \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

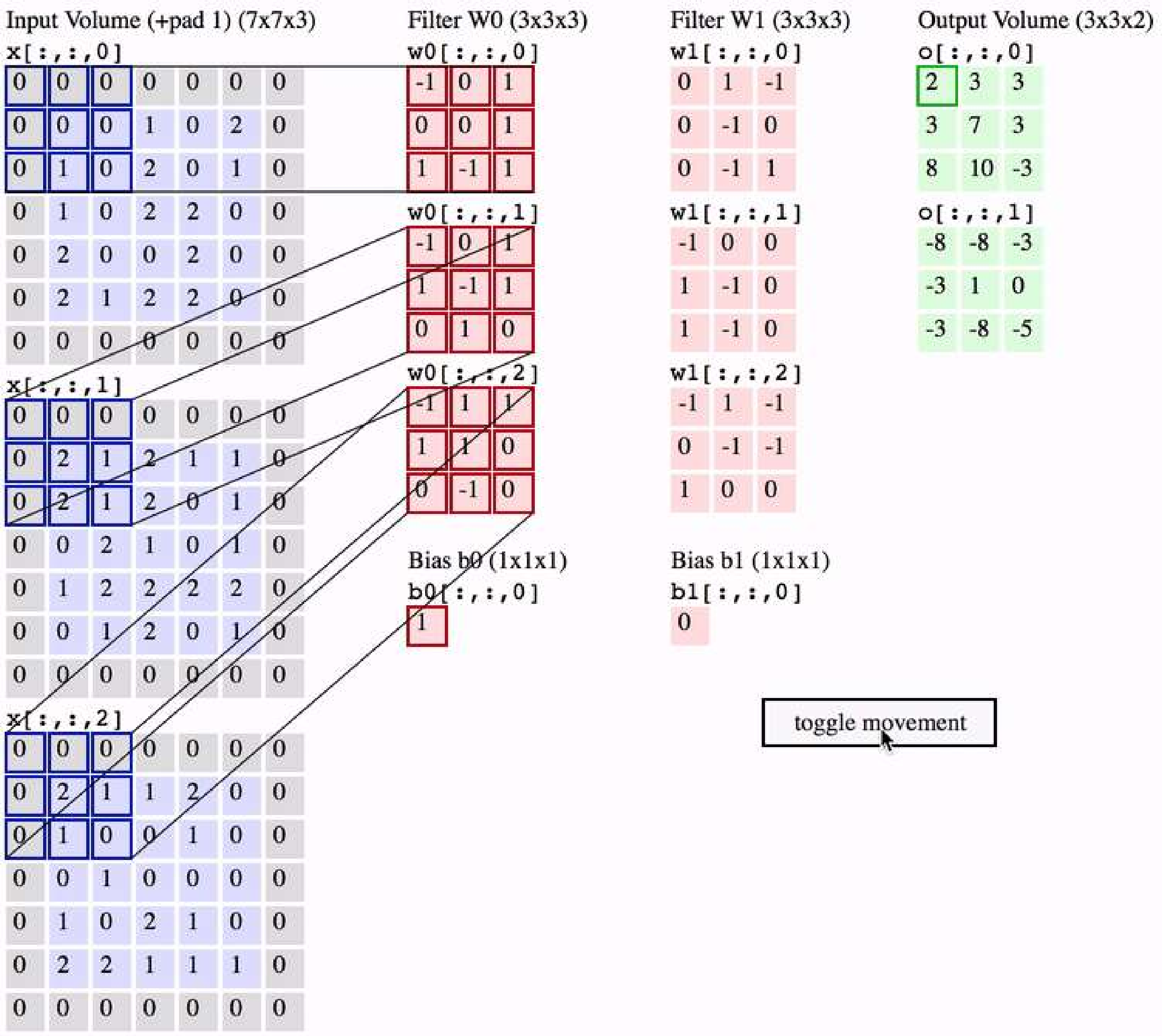
Convolution filter

$$\boxed{1x1 + 1x0 + 4x0 + 6x1 = 7}$$

$$\begin{bmatrix} 1 & 1 & 1 & 3 \\ 4 & 6 & 4 & 8 \\ 30 & 0 & 1 & 5 \\ 0 & 2 & 2 & 4 \end{bmatrix} * \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 7 & \boxed{5} & \\ & & \\ & & \end{bmatrix} \qquad \begin{bmatrix} 1 & 1 & 1 & 3 \\ 4 & 6 & 4 & 8 \\ 30 & 0 & 1 & 5 \\ 0 & 2 & 2 & 4 \end{bmatrix} * \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 7 & 5 & \boxed{9} \\ & & \\ & & \end{bmatrix}$$

$$\begin{bmatrix} 1 & 1 & 1 & 3 \\ 4 & 6 & 4 & 8 \\ 30 & 0 & 1 & 5 \\ 0 & 2 & 2 & 4 \end{bmatrix} * \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 7 & 5 & 9 \\ \boxed{4} & & \\ & & \end{bmatrix} \dashrightarrow \begin{bmatrix} 1 & 1 & 1 & 3 \\ 4 & 6 & 4 & 8 \\ 30 & 0 & 1 & 5 \\ 0 & 2 & 2 & 4 \end{bmatrix} * \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 7 & 5 & 9 \\ 4 & 7 & 9 \\ 32 & 2 & \boxed{5} \end{bmatrix}$$

Convolutional Neural Networks



Convolutional Neural Networks

Convolution filter: first example

$$\begin{bmatrix} 1 & 1 & 1 & 3 \\ 4 & 6 & 4 & 8 \\ 30 & 0 & 1 & 5 \\ 0 & 2 & 2 & 4 \end{bmatrix} * \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 7 & 5 & 9 \\ 4 & 7 & 9 \\ \boxed{32} & 2 & 5 \end{bmatrix}$$

High value when filter match image patch

$$\begin{bmatrix} 1 & 1 & 1 & 3 \\ 4 & 6 & 4 & 8 \\ 30 & 0 & 1 & 5 \\ 0 & 2 & 2 & 4 \end{bmatrix} * \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 7 & 5 & 9 \\ \boxed{4} & 7 & 9 \\ 32 & 2 & 5 \end{bmatrix}$$

Low value when filter does not match image patch

Convolutional Neural Networks

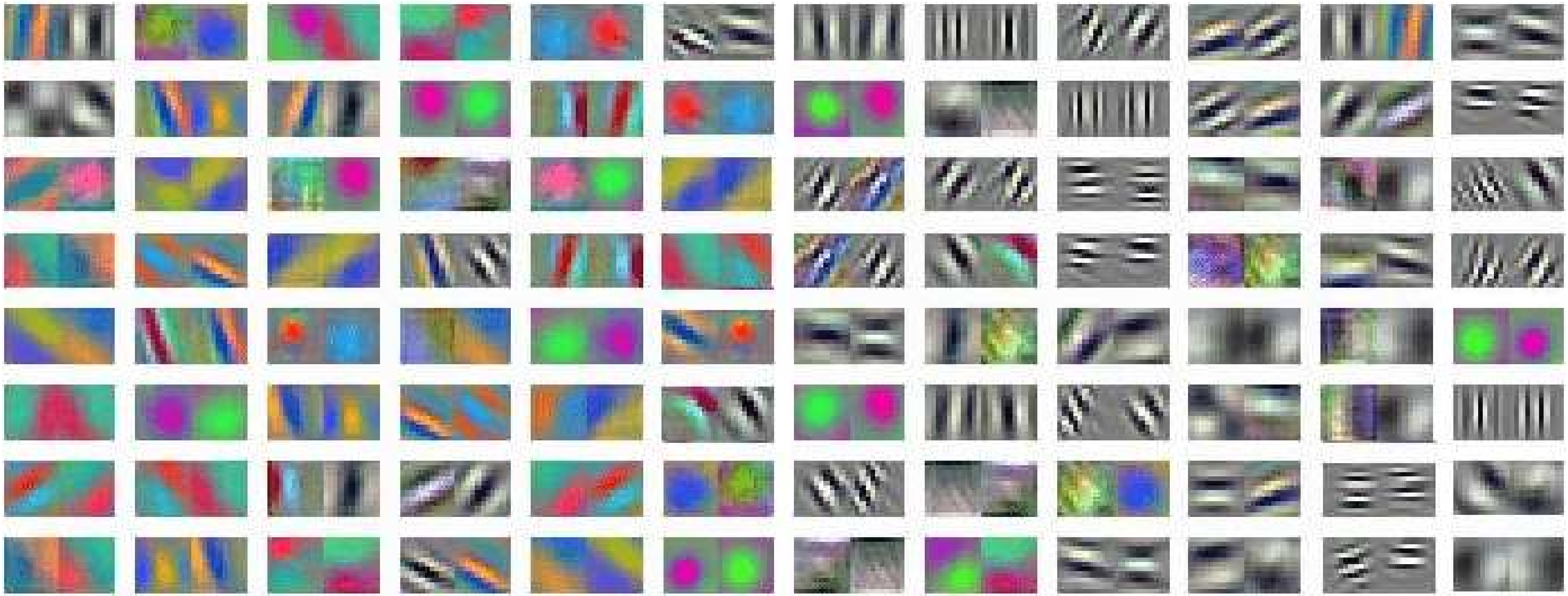
Convolution filter: second example

$$\begin{bmatrix} 1 & 1 & 1 & 3 \\ 4 & 6 & 4 & 8 \\ 30 & 0 & 1 & 5 \\ 0 & 2 & 2 & 4 \end{bmatrix} * \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 5 & 7 & 7 \\ 36 & 4 & 9 \\ 0 & 3 & 7 \end{bmatrix}$$

High value when filter match image patch
Low value when filter does not match image patch

Convolutional Neural Networks

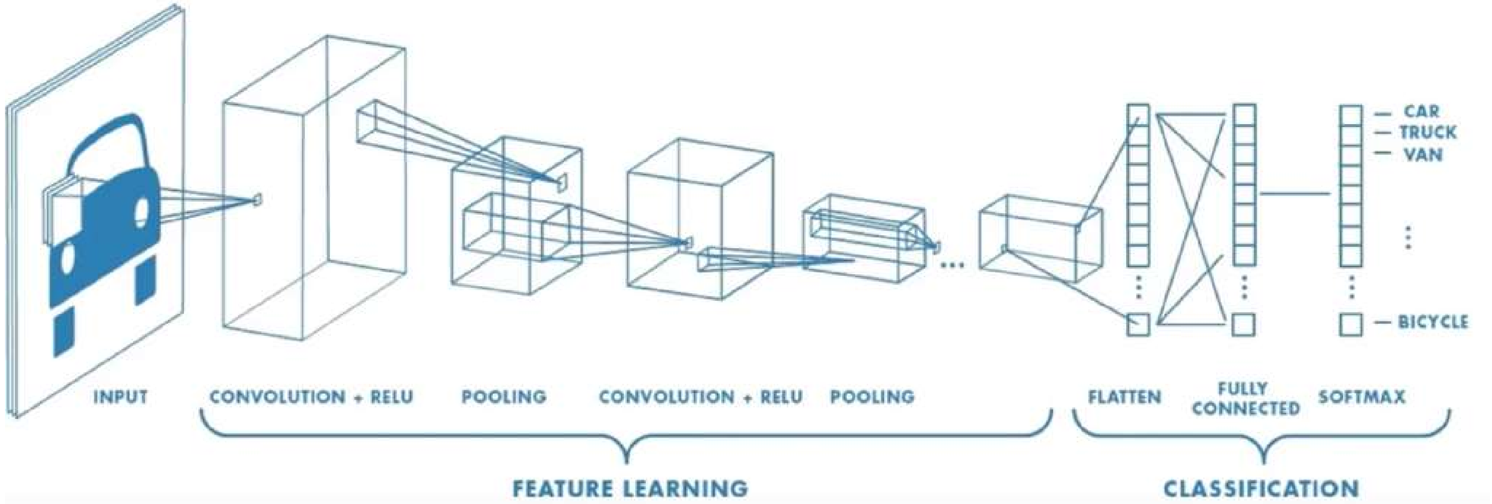
ALEXNET CONV1 LEARNED FILTERS



Convolutional Neural Networks

TYPES OF LAYERS

- Convolutional layer
- Pooling layer
- Dropout layer
- Flatten layer
- Fully-connected layer
- Activation layer



TYPES OF LAYERS

- Convolutional layer
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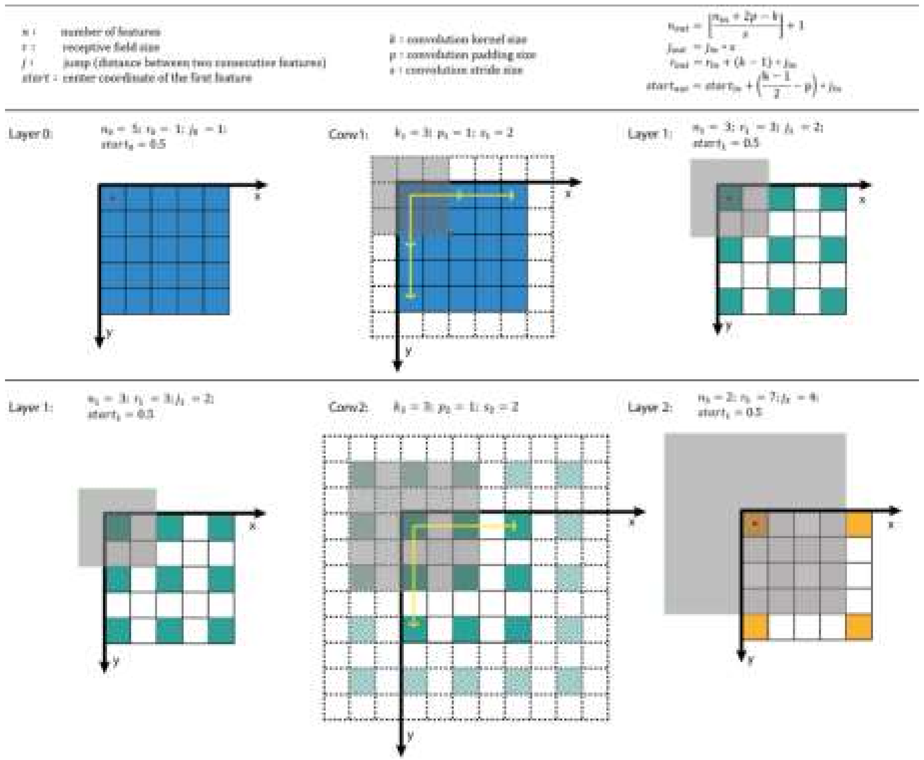
CONVOLUTION HYPERPARAMETERS

DEPTH / STRIDE / ZERO-PADDING



TYPES OF LAYERS

- Convolutional layer
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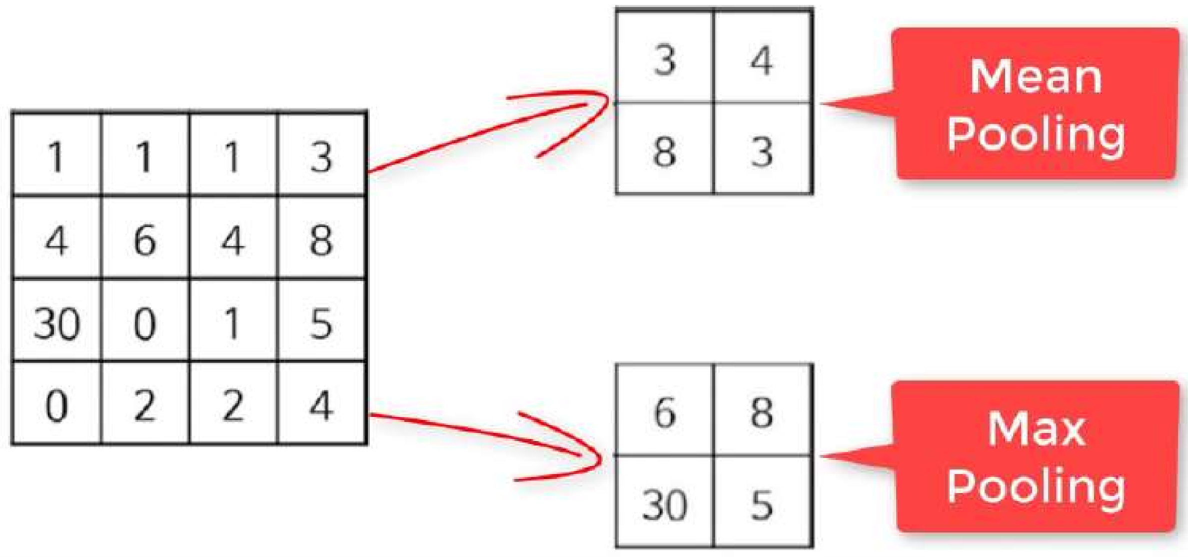
- Activation layer

Pooling operation combines adjacent pixels into one pixel (2D) (to reduce the size of the image)



Convolutional Neural Networks

TYPES OF LAYERS

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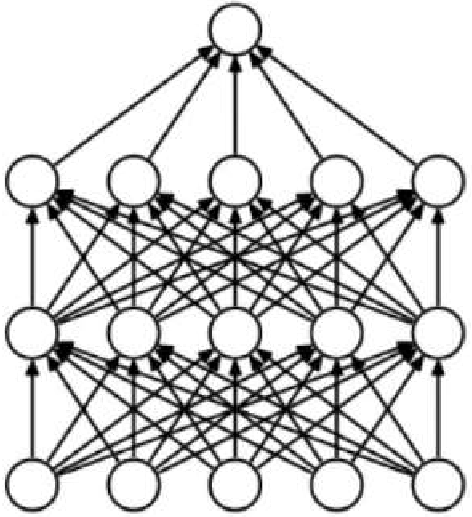
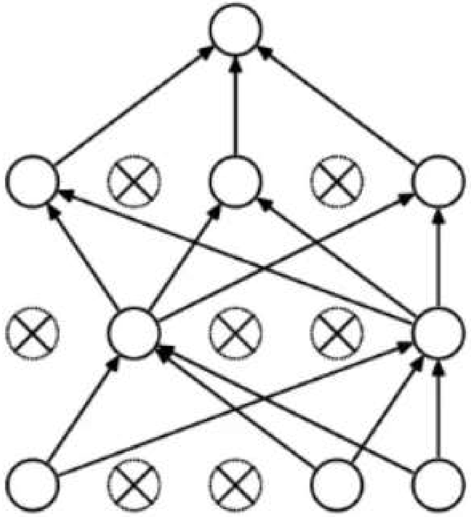


(a) Standard Neural Net



(b) After applying dropout.

Convolutional Neural Networks

TYPES OF LAYERS

- Convolutional layer
- Pooling layer
- Dropout layer
- Flatten layer
- Fully-connected layer
- Activation layer

Flattening is converting the data into a 1-dimensional array for inputting it to the next **layer**

TYPES OF LAYERS

- Convolutional layer
- Pooling layer
- Dropout layer
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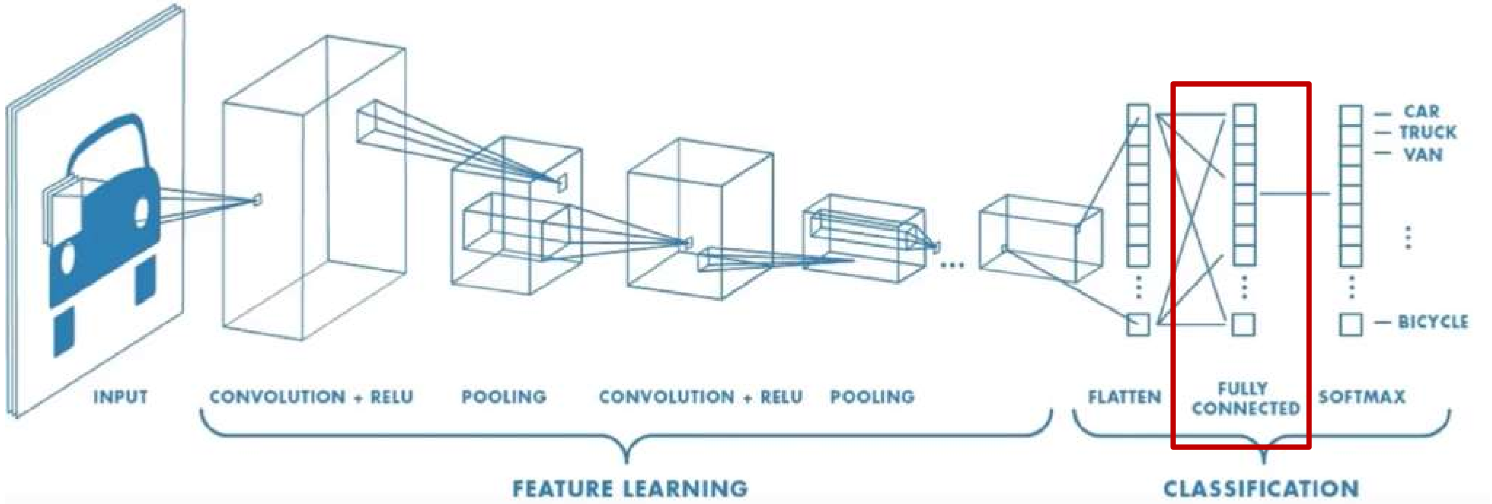
- Fully-connected layer
- Activation layer



TYPES OF LAYERS

- Convolutional layer
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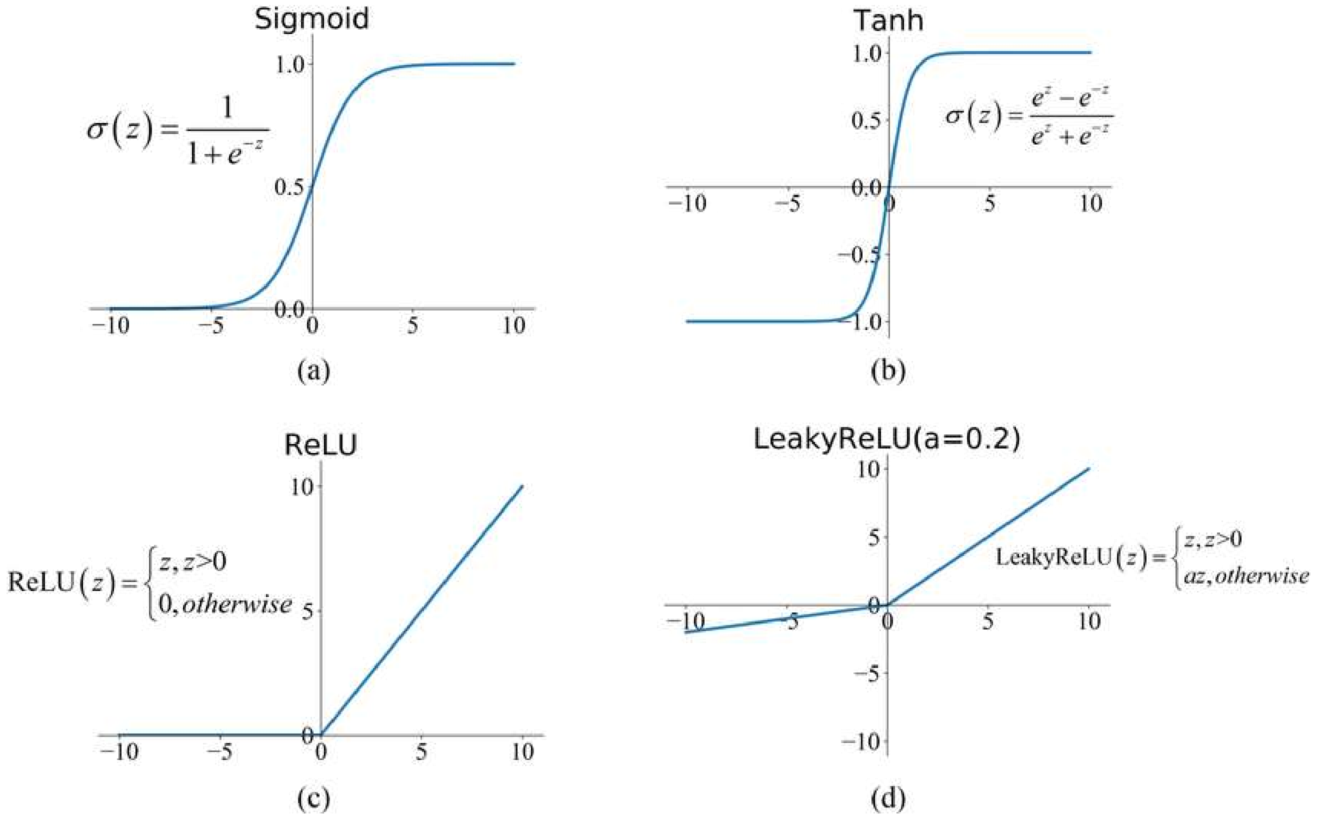


Convolutional Neural Networks

<u>TYPES OF LAYERS</u>

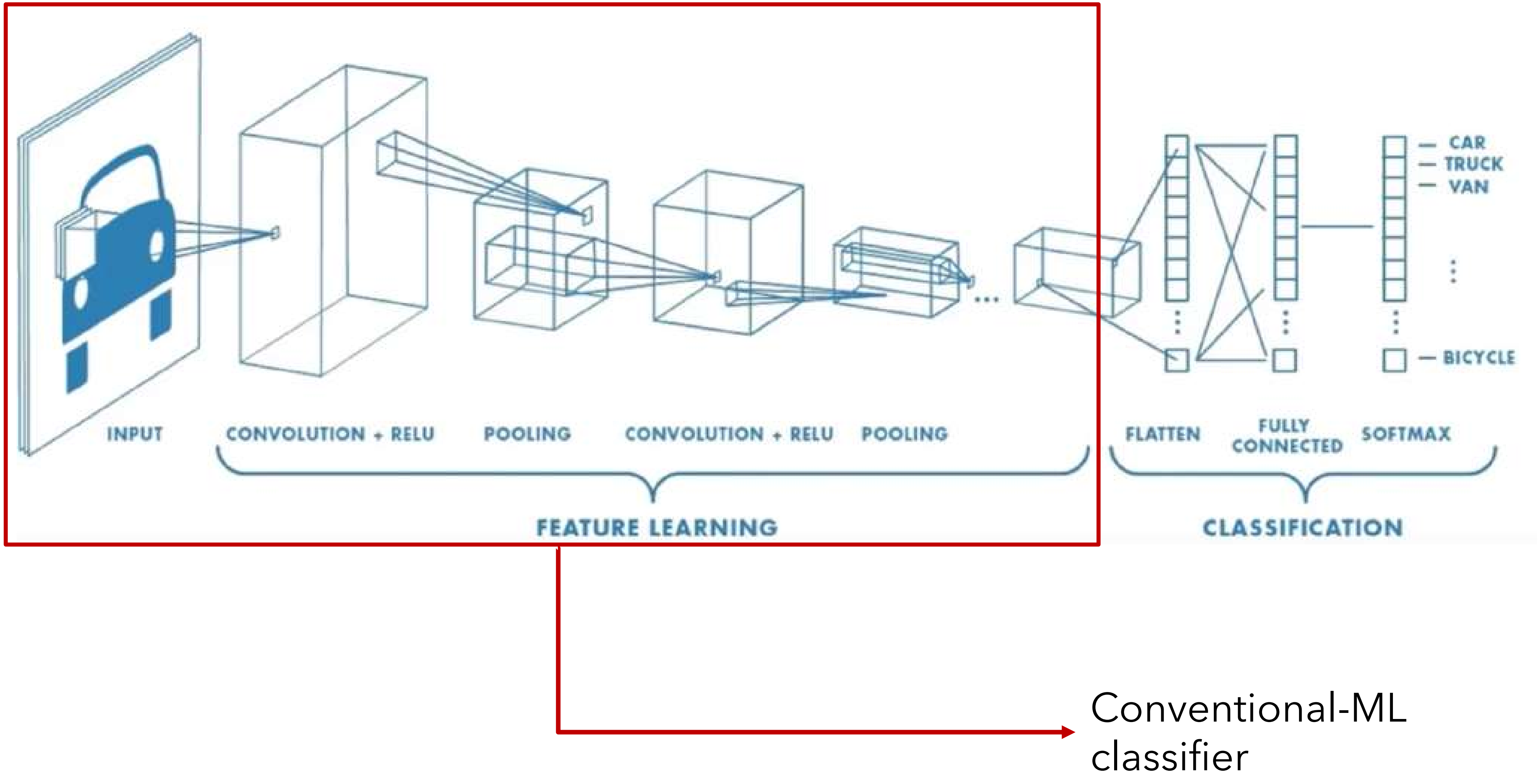
- Convolutional layer
- Pooling layer
- Dropout layer
- Flatten layer
- Fully-connected layer
- Activation layer

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

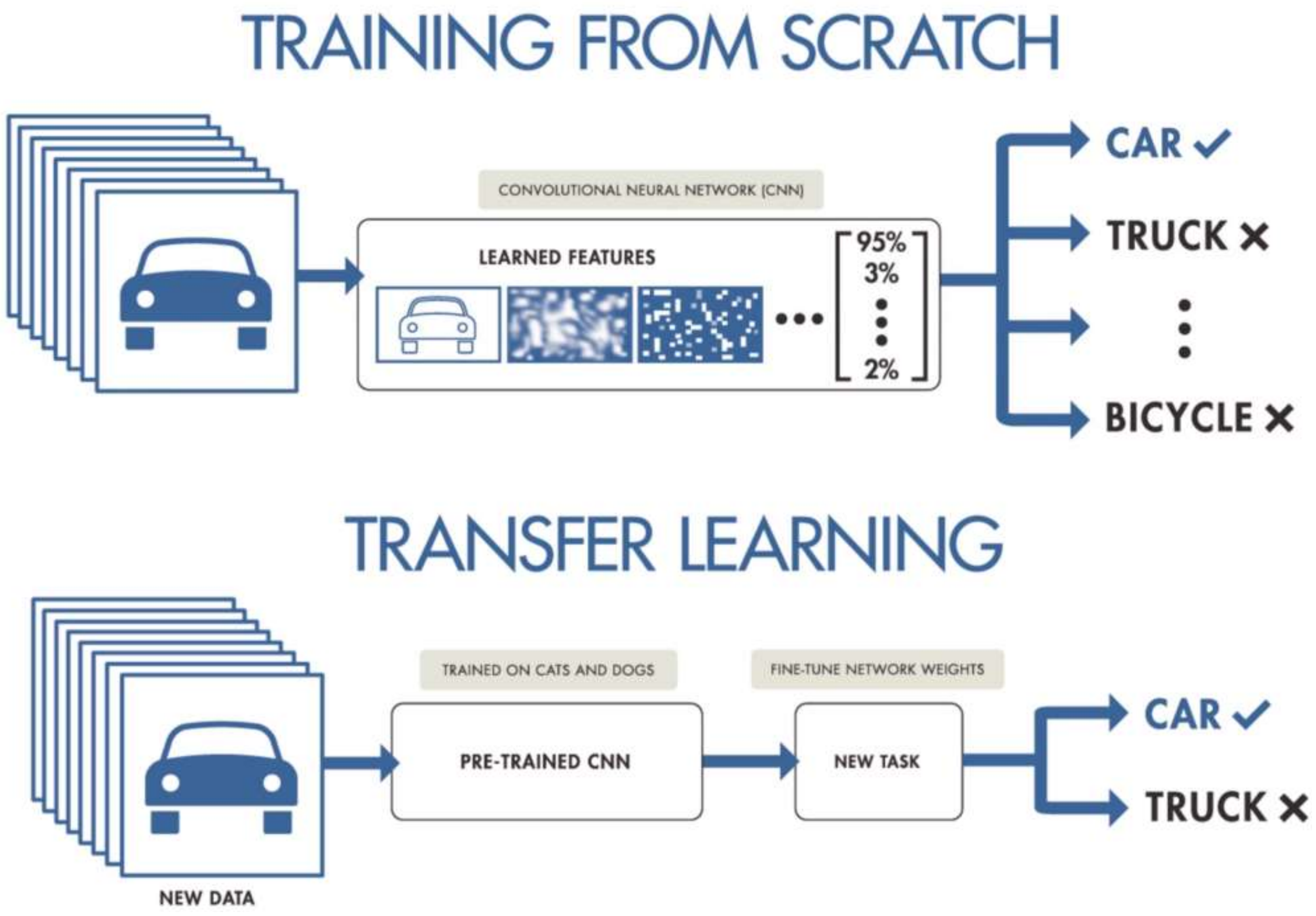
Softmax

+ loss
calculation

Convolutional Neural Networks as feature extractors

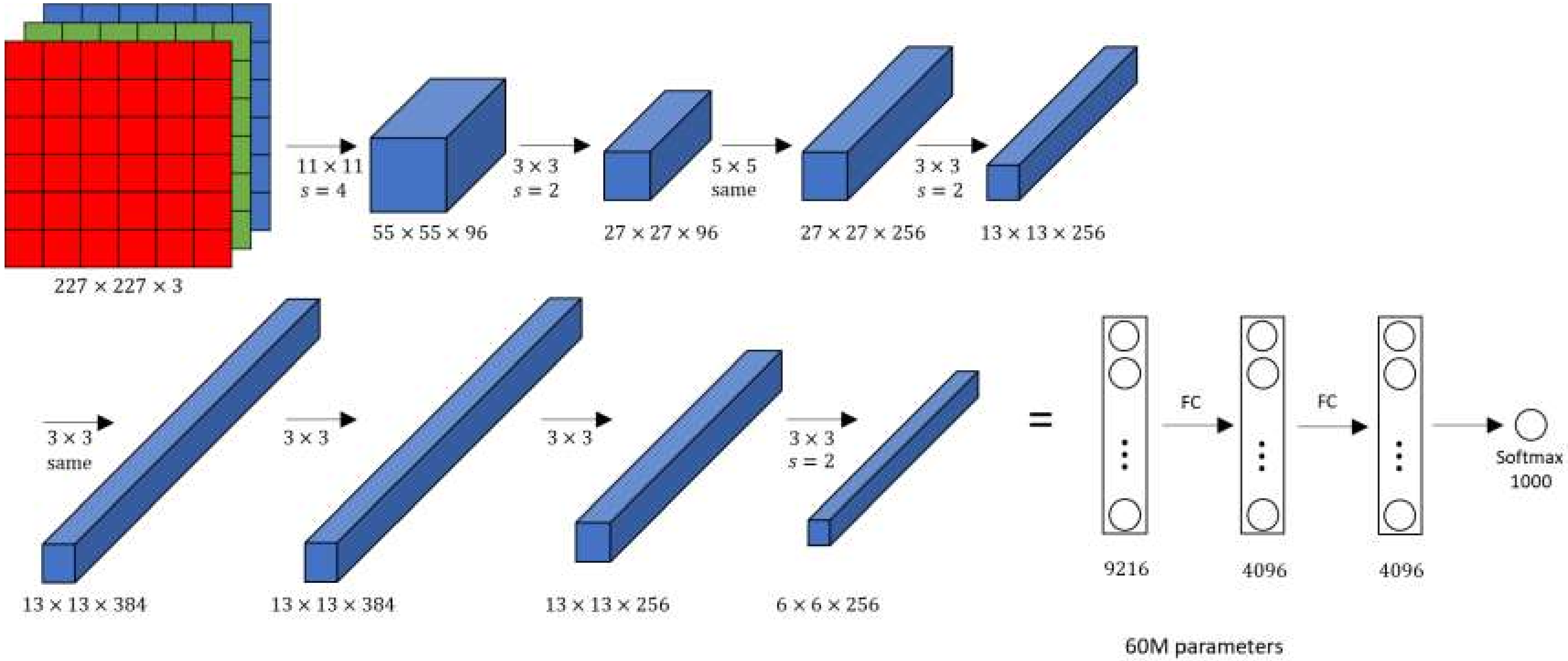


Convolutional Neural Networks | Transfer learning

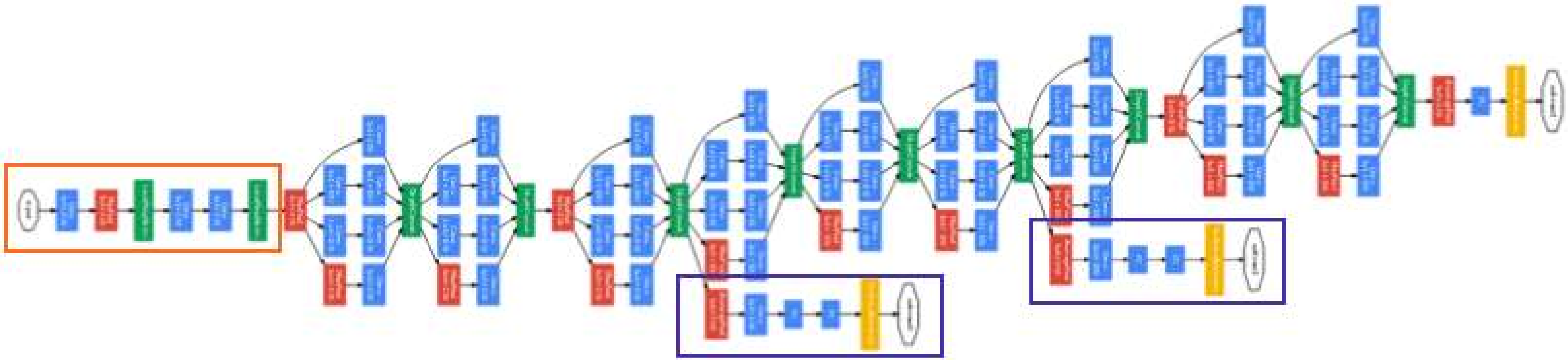


Convolutional Neural Networks | From LeNet to . . .

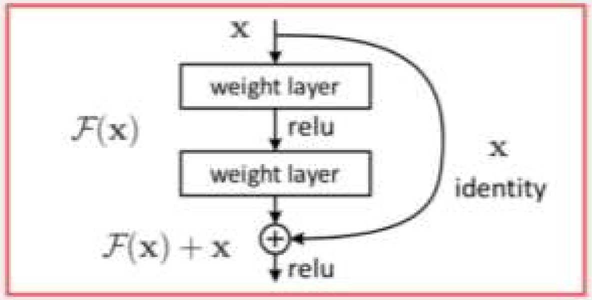
AlexNet [winner of the ImageNet ILSVRS challenge in 2012; (17)] is composed of both stacked and connected layers and includes five convolutional layers followed by three fully-connected layers, with max-pooling layers in between. A rectified linear unit nonlinearity is applied to each convolutional layer along with a fully-connected layer to enable faster training.



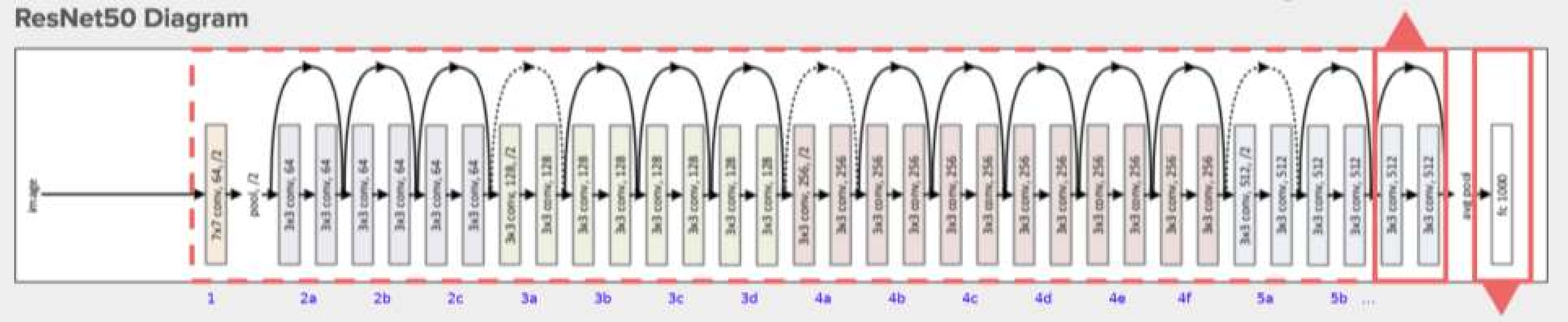
GoogleNet [winner of the ImageNet ILSVRS challenge in 2014; (41)] is the deep-learning algorithm whose design introduced the so-called Inception module, a subnetwork consisting of parallel convolutional filters whose outputs are concatenated. Inception greatly reduces the number of required parameters. GoogleNet is composed by 22 layers that require training (for a total of 27 layers when including the pooling layers).



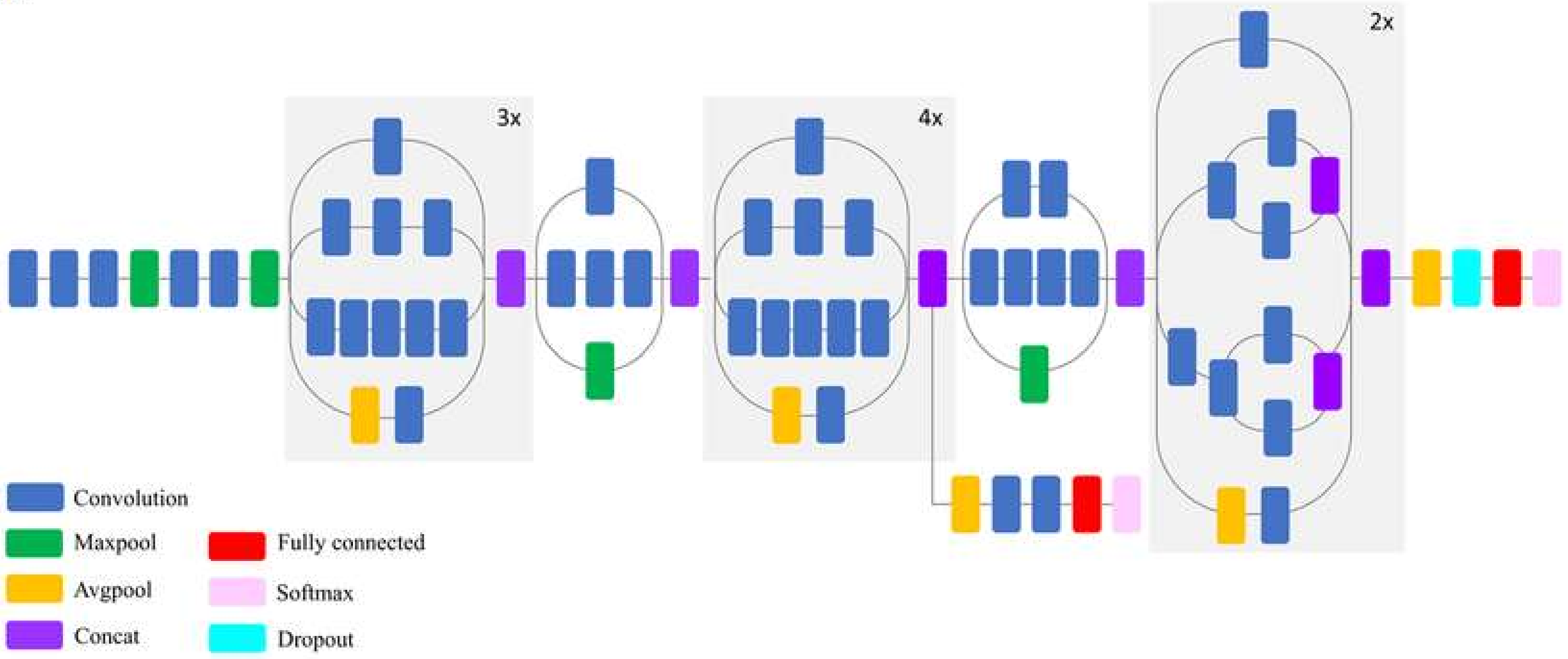
ResNet [winner of ILSVRC 2015; (42)], an architecture that is approximately twenty times deeper than AlexNet; its main novelty is the introduction of residual layers, a kind of network-in-network architecture that forms building blocks to construct the network. ResNet uses special skip connections and batch normalization, and the fully-connected layers at the end of the network are substituted by global average pooling. Instead of learning unreferenced functions, ResNet explicitly reformulates layers as learning residual functions with reference to the input layer, which makes the model smaller in size and thus easier to optimize than other architectures.



Residual Learning Block

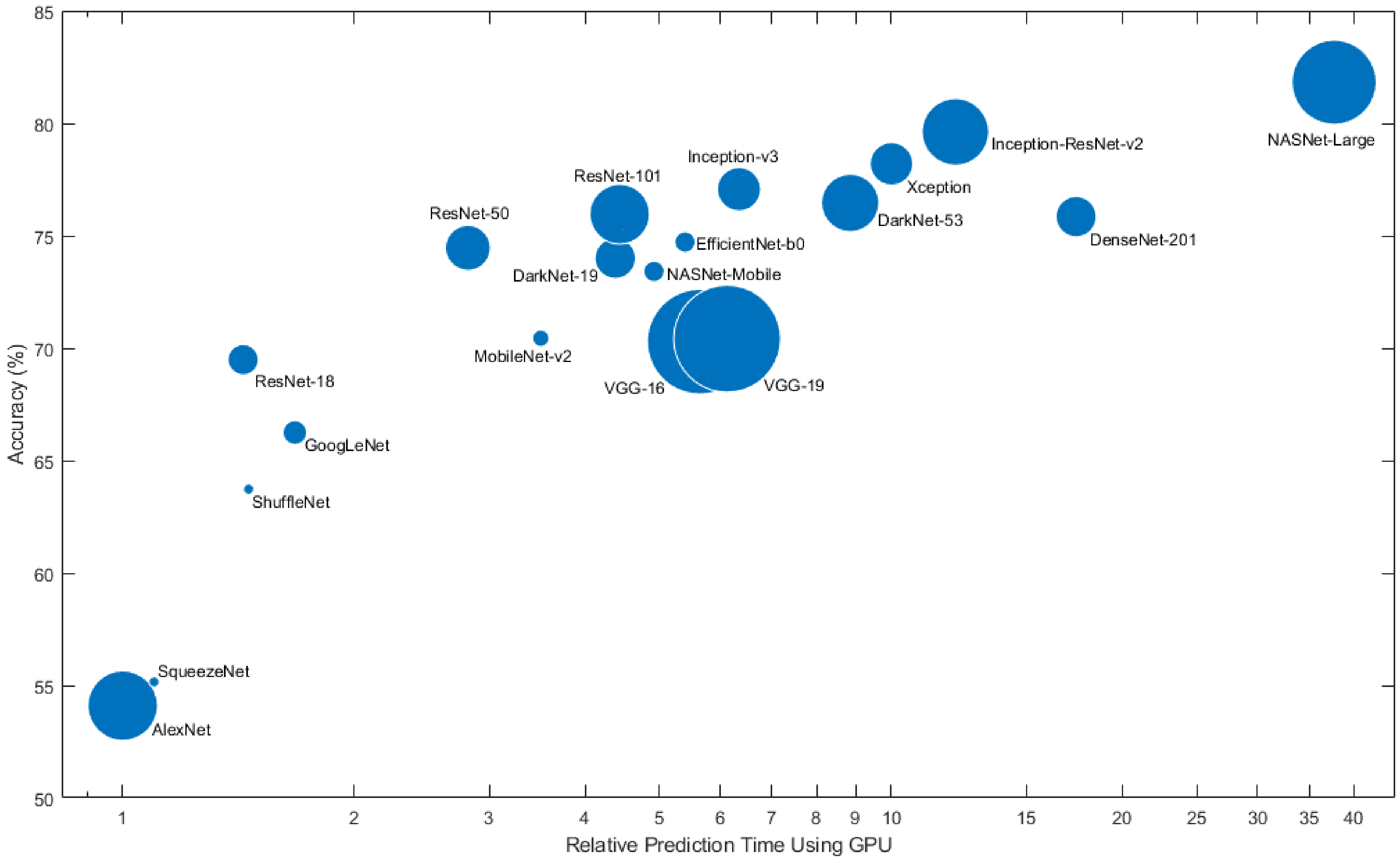


Inception-v3 (43), a deep architecture of 48 layers able to classify images into 1,000 object categories; the net was trained on more than a million images obtained from the ImageNet database (resulting in a rich feature representation for a wide range of images). Inception-v3 classified as the first runner up for the ImageNet ILSVRC challenge in 2015.



Convolutional Neural Networks | From LeNet to . . .

https://it.mathworks.com/help/deeplearning/ug/pretrained-convolutional-neural-networks.html

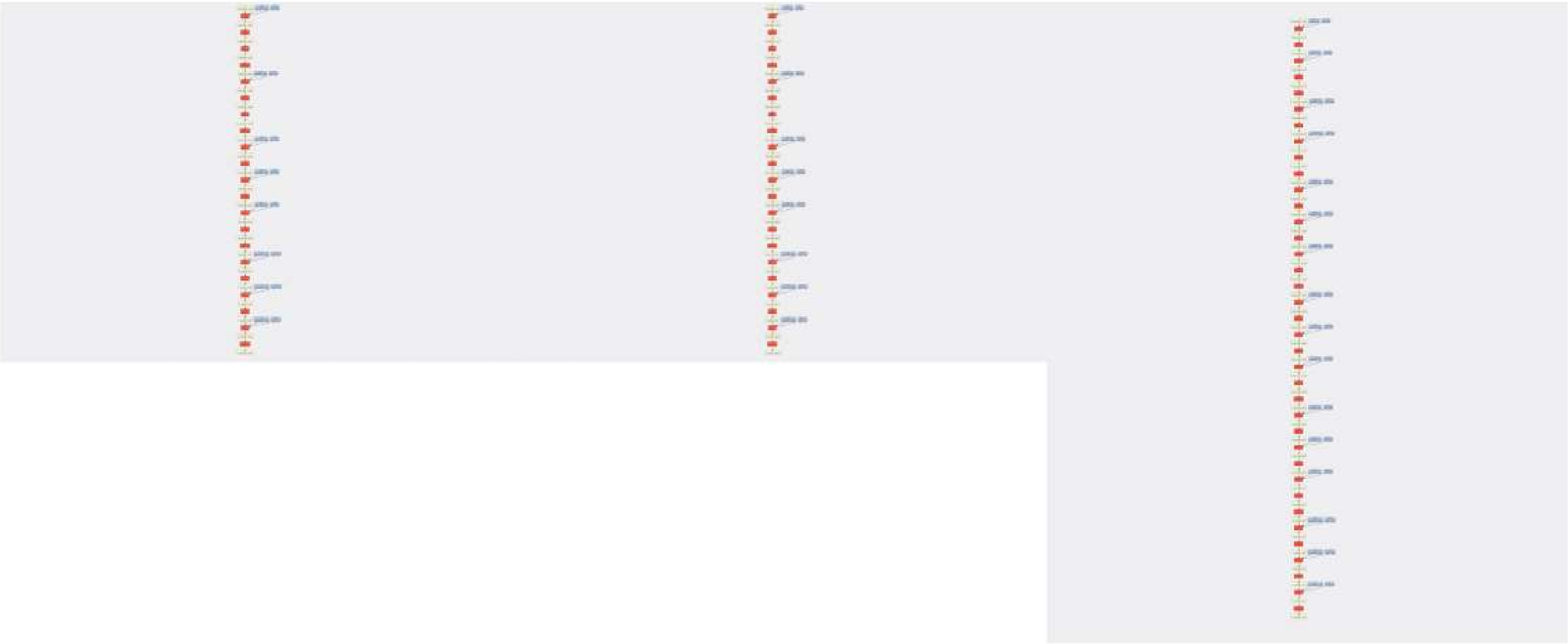


Convolutional Neural Networks | From LeNet to . . .

Network	Depth	Size	Parameters (Millions)	Image Input Size
squeezenet	18	5.2 MB	1.24	227-by-227
googlenet	22	27 MB	7.0	224-by-224
inceptionv3	48	89 MB	23.9	299-by-299
densenet201	201	77 MB	20.0	224-by-224
mobilenetv2	53	13 MB	3.5	224-by-224
resnet18	18	44 MB	11.7	224-by-224
resnet50	50	96 MB	25.6	224-by-224
resnet101	101	167 MB	44.6	224-by-224
xception	71	85 MB	22.9	299-by-299
inceptionresnetv2	164	209 MB	55.9	299-by-299
shufflenet	50	5.4 MB	1.4	224-by-224
nasnetmobile	*	20 MB	5.3	224-by-224
nasnetlarge	*	332 MB	88.9	331-by-331
darknet19	19	78 MB	20.8	256-by-256
darknet53	53	155 MB	41.6	256-by-256
efficientnetb0	82	20 MB	5.3	224-by-224
alexnet	8	227 MB	61.0	227-by-227
vgg16	16	515 MB	138	224-by-224
vgg19	19	535 MB	144	224-by-224

Convolutional Neural Networks | From LeNet to . . .

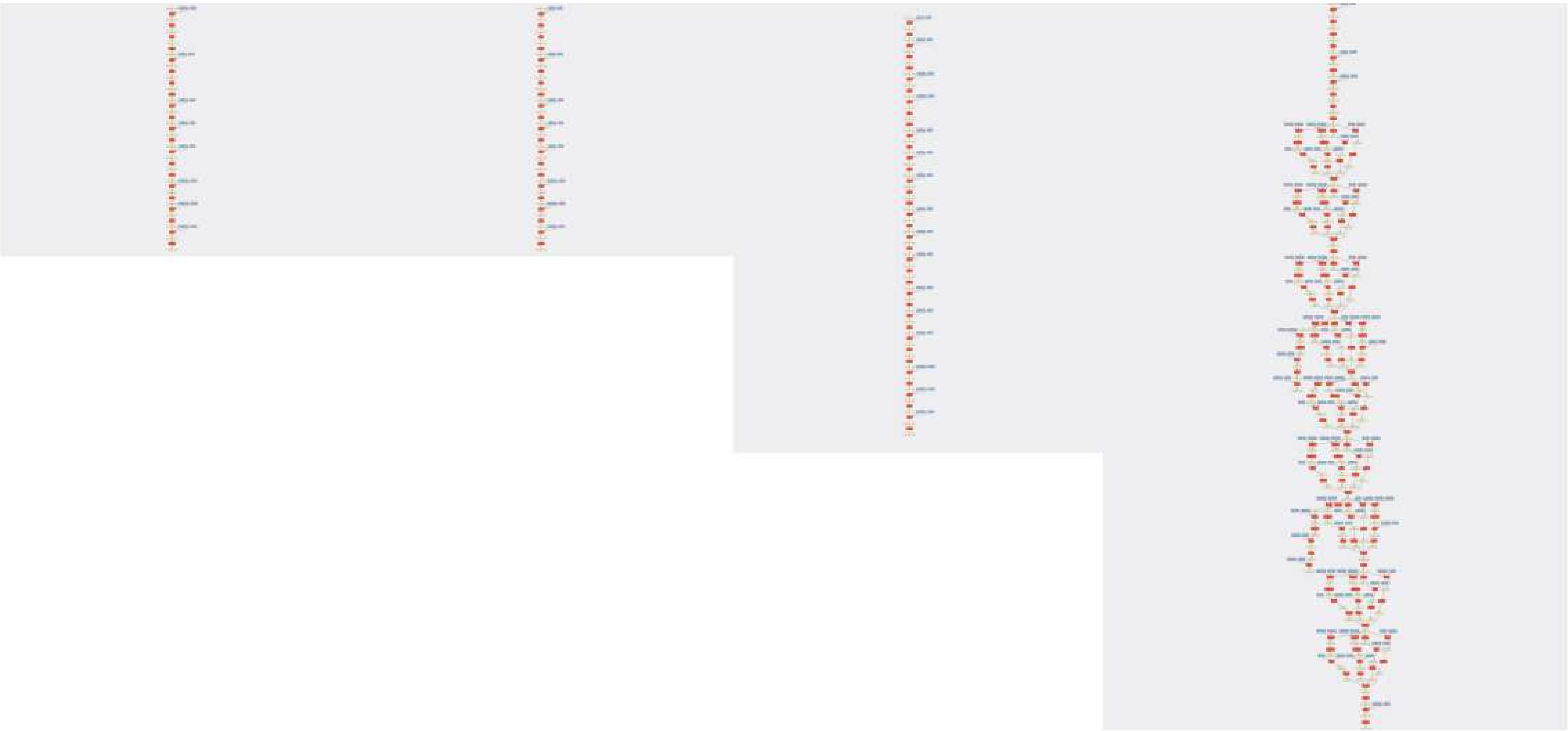
AlexNet (2012) VGG-M (2013) VGG-VD-16 (2014)



FROM A. VEDALDI

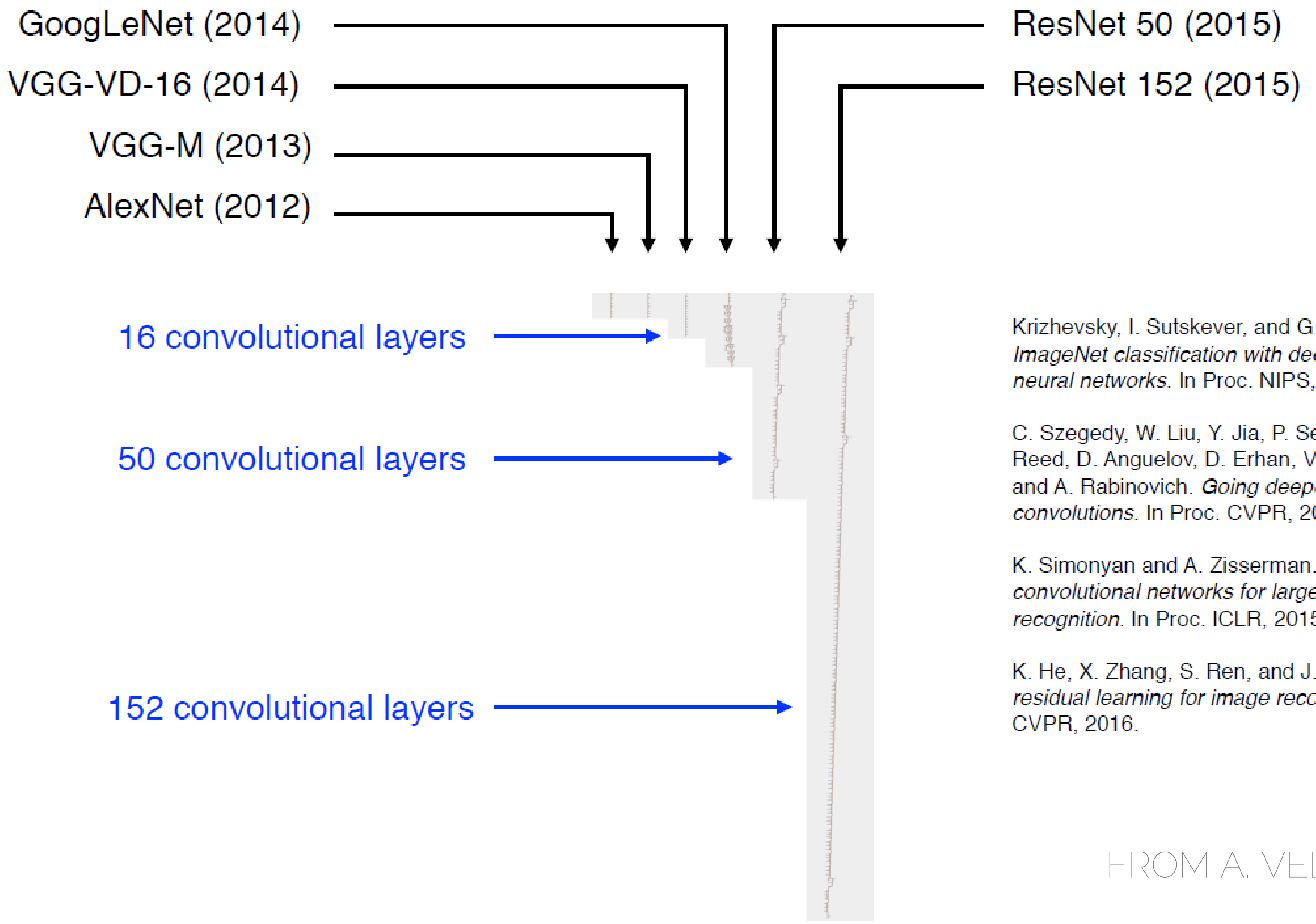
Convolutional Neural Networks | From LeNet to . . .

AlexNet (2012) VGG-M (2013) VGG-VD-16 (2014) GoogLeNet (2014)



FROM A. VEDALDI

Convolutional Neural Networks | From LeNet to . . .



Krizhevsky, I. Sutskever, and G. E. Hinton. *ImageNet classification with deep convolutional neural networks*. In Proc. NIPS, 2012.

C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. *Going deeper with convolutions*. In Proc. CVPR, 2015.

K. Simonyan and A. Zisserman. *Very deep convolutional networks for large-scale image recognition*. In Proc. ICLR, 2015.

K. He, X. Zhang, S. Ren, and J. Sun. *Deep residual learning for image recognition*. In Proc. CVPR, 2016.

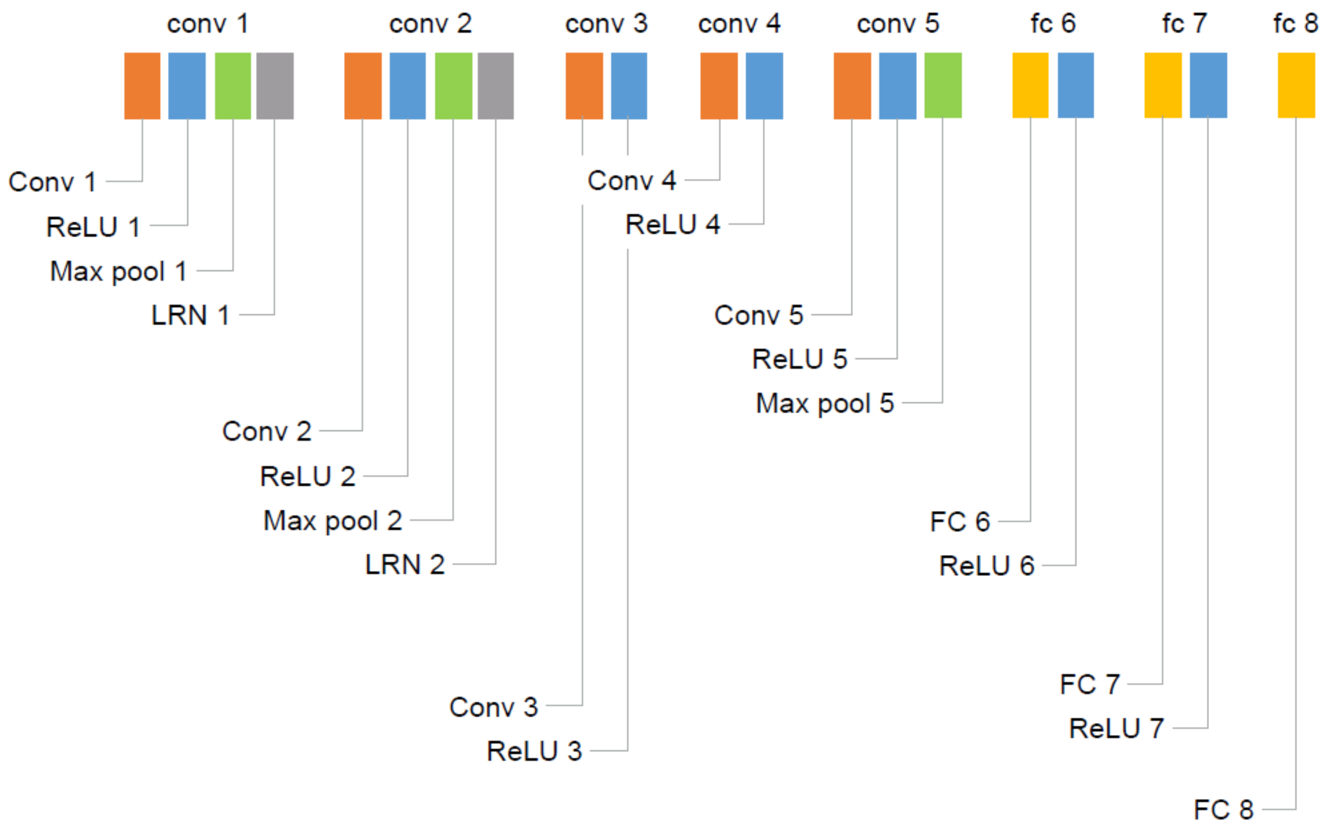
FROM A. VEDALDI

A CONSIDERATION ON EXPLAINABILITY AND (OVER)FITTING

FROM A. VEDALDI

Inversion

10



AlexNet
[Krizhevsky et al. 2012]

UNDERFITTING, OVERFITTING AND BEST FITTING

Inversion

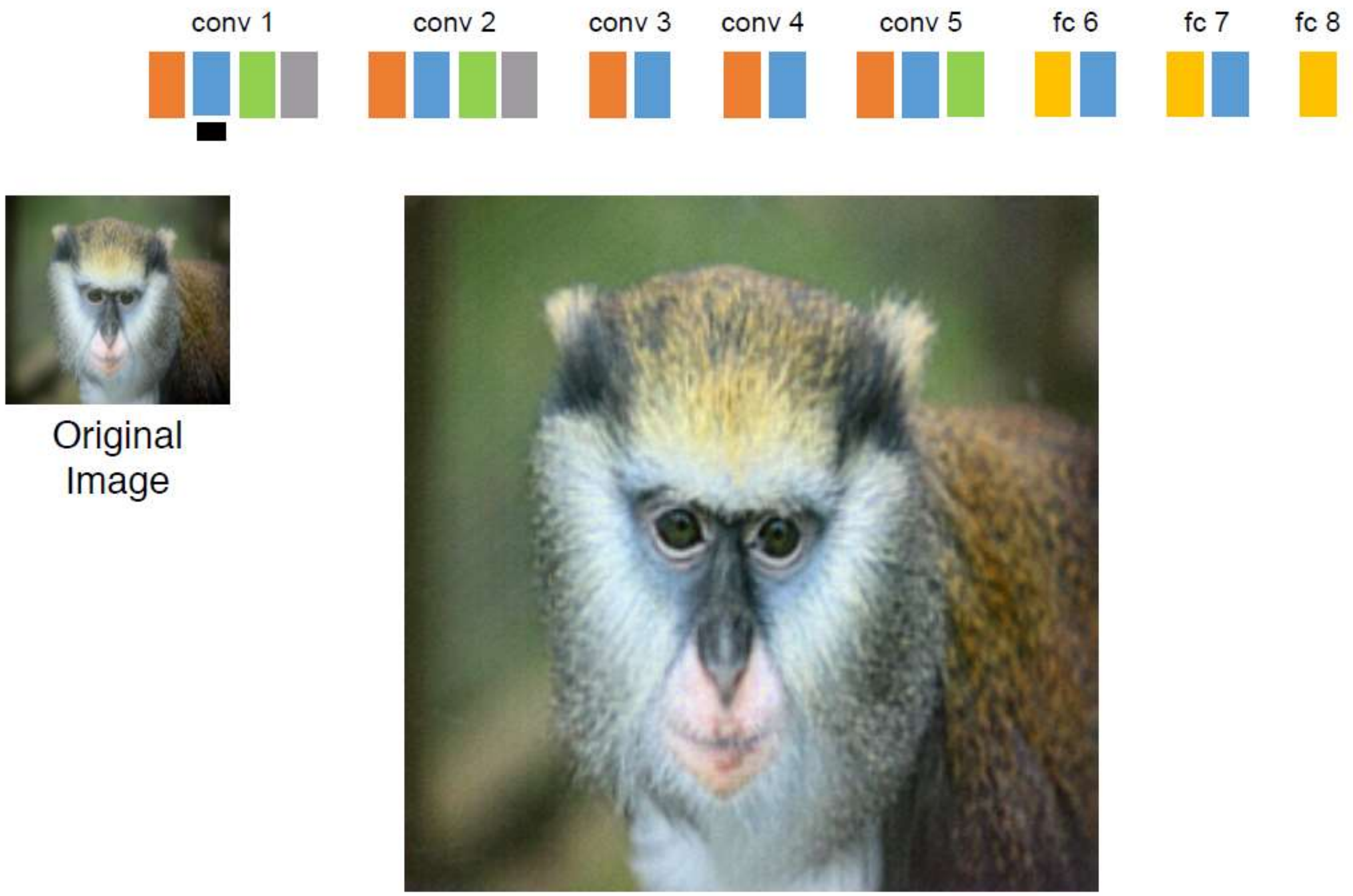
11

Original Image

FROM A. VEDALDI

UNDERFITTING, OVERFITTING AND BEST FITTING

Inversion



FROM A. VEDALDI

UNDERFITTING, OVERFITTING AND BEST FITTING

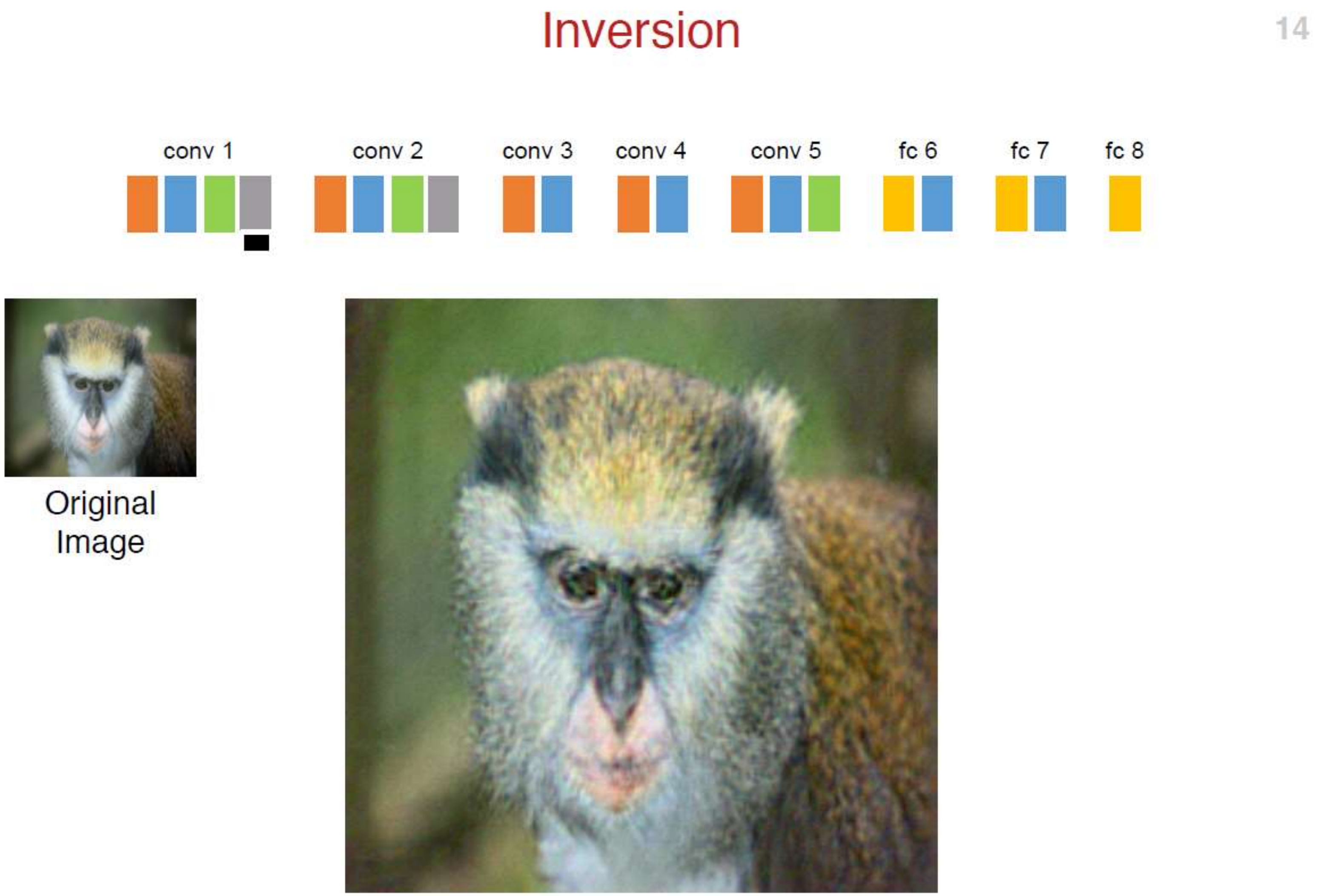
FROM A. VEDALDI

Inversion

13

Original Image

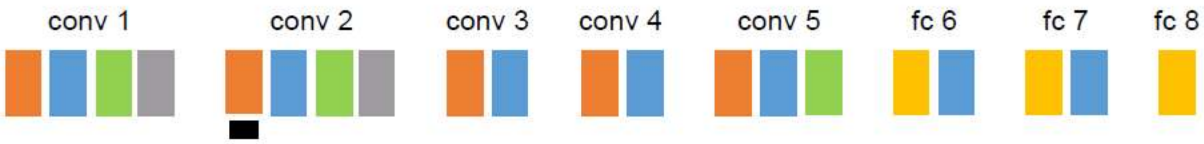
UNDERFITTING, OVERFITTING AND BEST FITTING



FROM A. VEDALDI

FROM A. VEDALDI

Inversion



Original Image

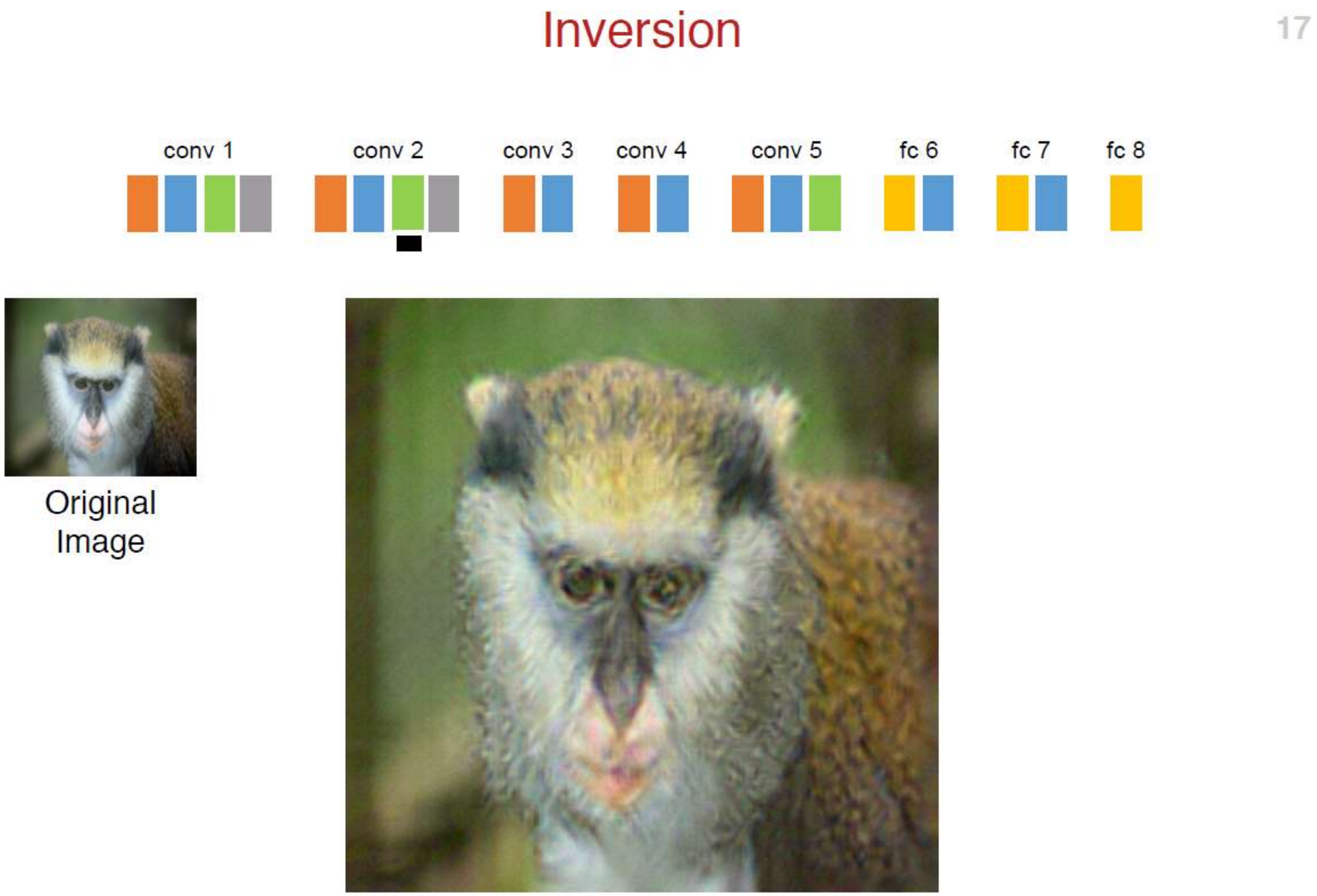
FROM A. VEDALDI

Inversion

16

Original Image

UNDERFITTING, OVERFITTING AND BEST FITTING



FROM A. VEDALDI

UNDERFITTING, OVERFITTING AND BEST FITTING

Inversion

18

Original Image

FROM A. VEDALDI

UNDERFITTING, OVERFITTING AND BEST FITTING

FROM A. VEDALDI

Inversion

19

Original Image

UNDERFITTING, OVERFITTING AND BEST FITTING

Inversion

FROM A. VEDALDI

Original Image

UNDERFITTING, OVERFITTING AND BEST FITTING

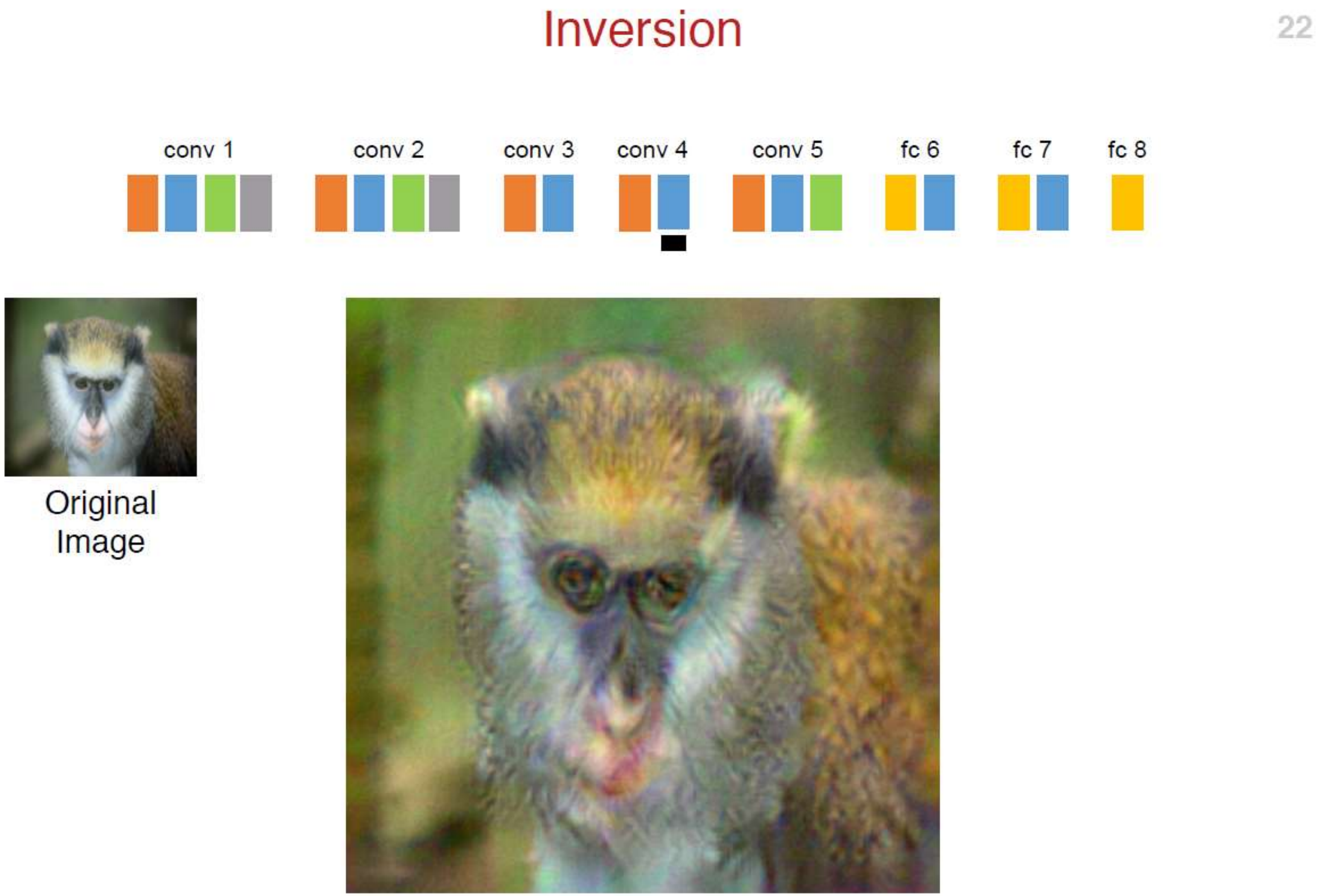
FROM A. VEDALDI

Inversion

21

Original Image

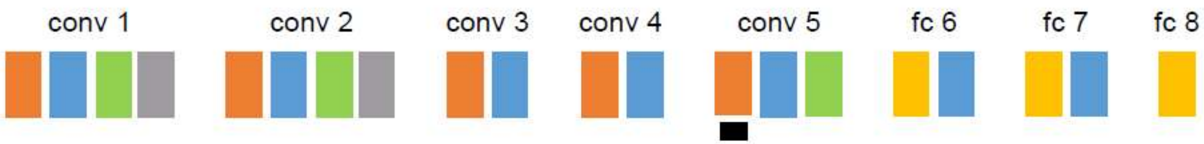
UNDERFITTING, OVERFITTING AND BEST FITTING



FROM A. VEDALDI

FROM A. VEDALDI

Inversion



Original Image

UNDERFITTING, OVERFITTING AND BEST FITTING

FROM A. VEDALDI

Inversion

Original Image

UNDERFITTING, OVERFITTING AND BEST FITTING

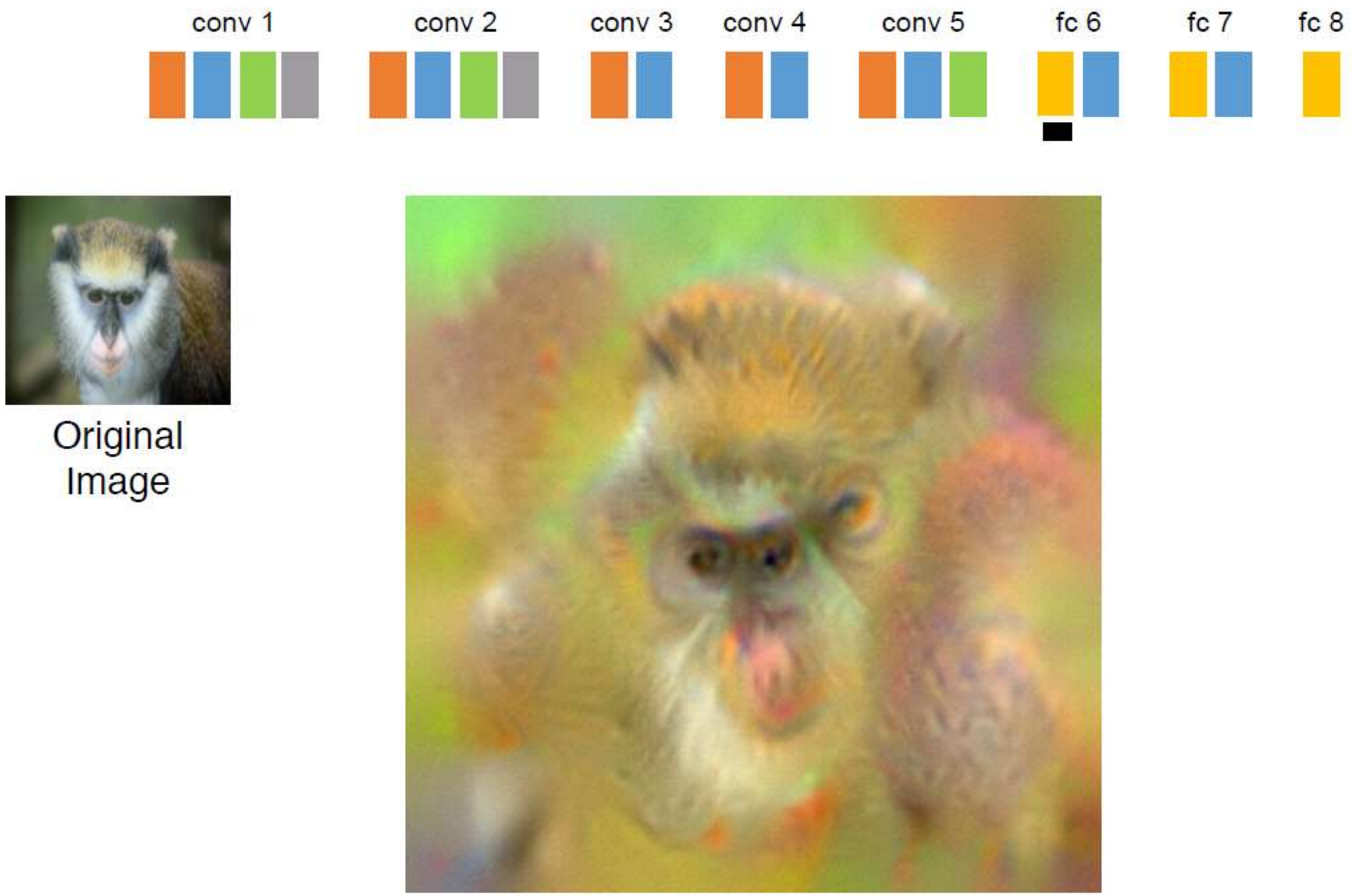
FROM A. VEDALDI

Inversion

25

Original Image

Inversion



FROM A. VEDALDI

FROM A. VEDALDI

Inversion

27

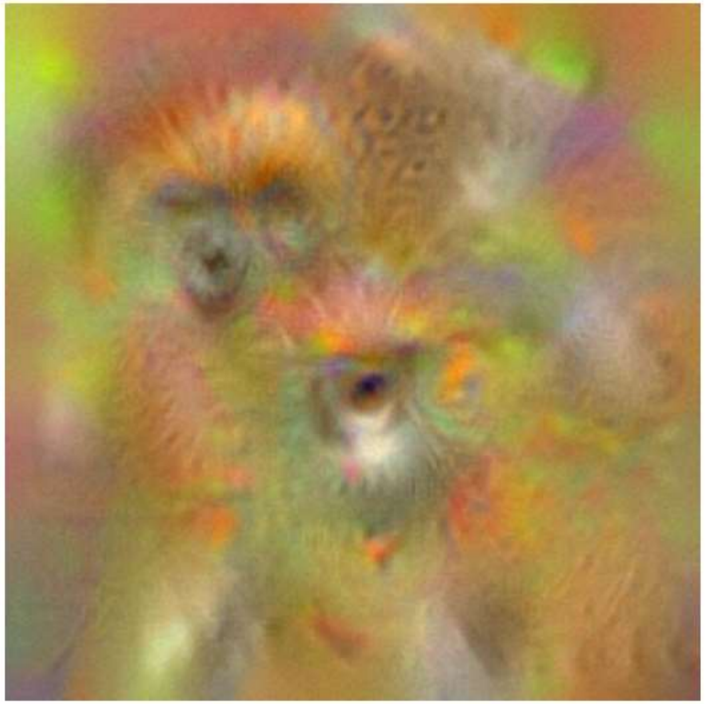
Original Image

UNDERFITTING, OVERFITTING AND BEST FITTING

Inversion

28

Original
Image



FROM A. VEDALDI

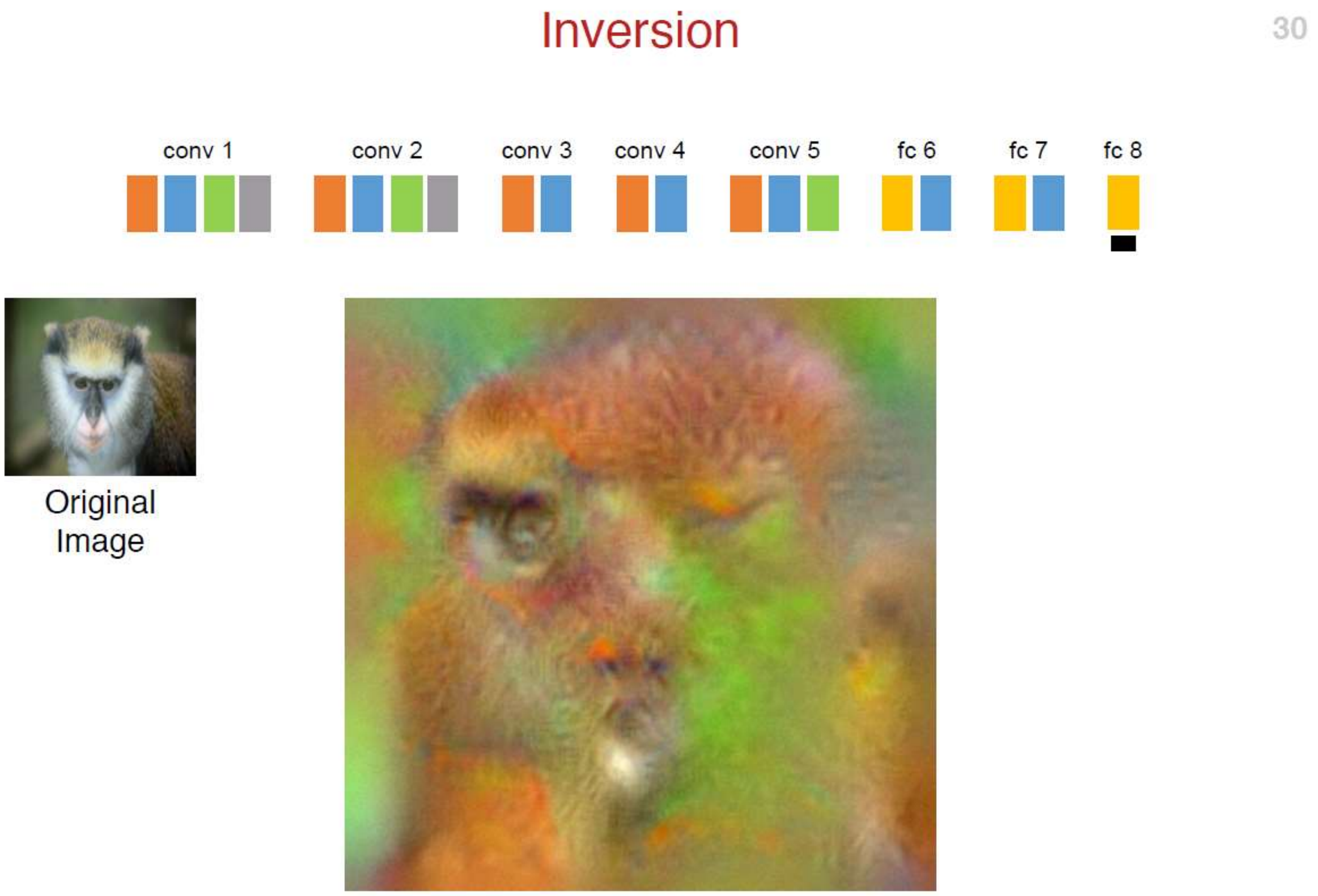
UNDERFITTING, OVERFITTING AND BEST FITTING

Inversion


Original Image

FROM A. VEDALDI

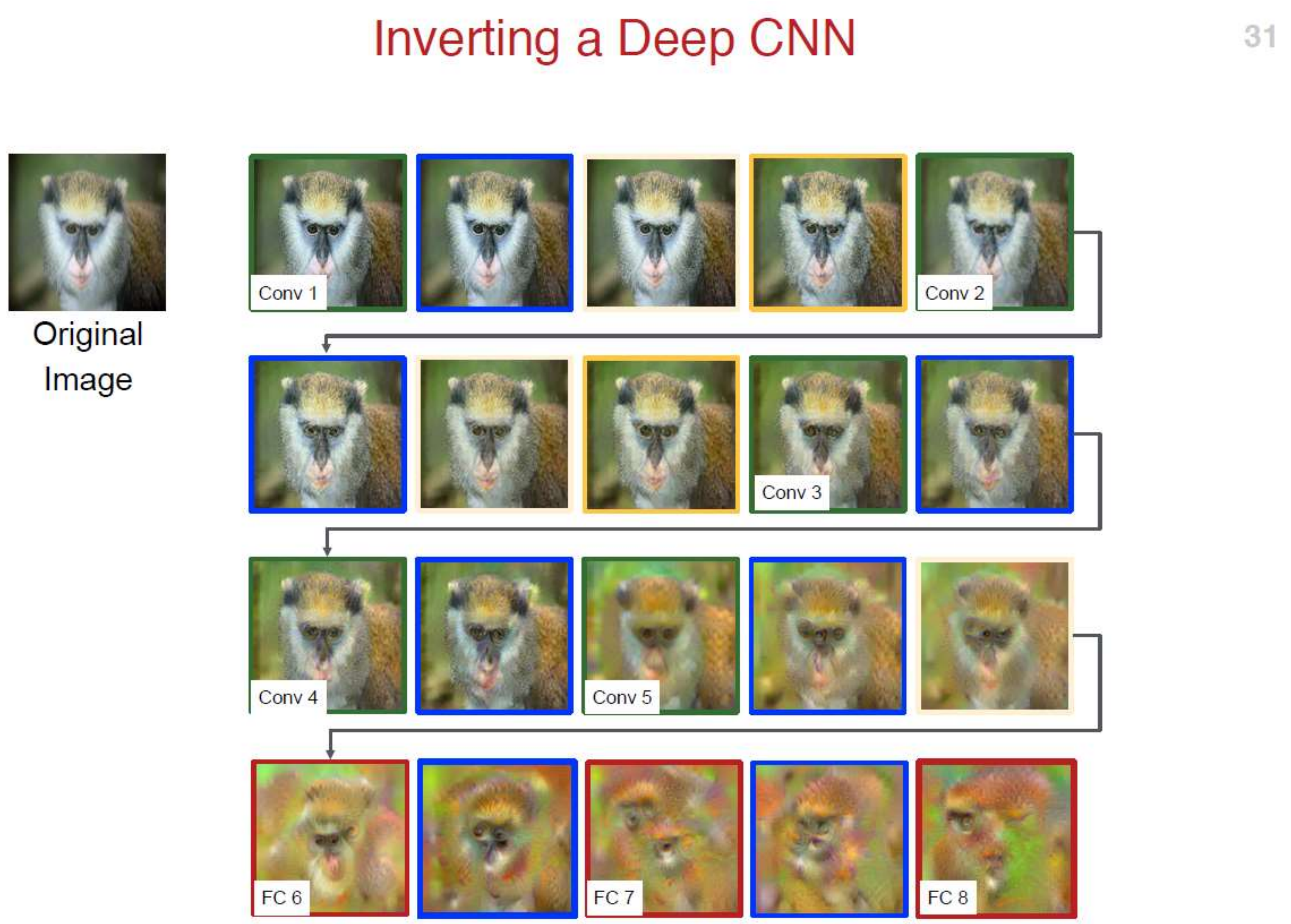
UNDERFITTING, OVERFITTING AND BEST FITTING



FROM A. VEDALDI

UNDERFITTING, OVERFITTING AND BEST FITTING

FROM A. VEDALDI



UNDERFITTING, OVERFITTING AND BEST FITTING

Another interesting source:

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