Convolutional Neural Networks

Danna Gurari

University of Texas at Austin

Spring 2020

Zoom Overview & New Policies

- Class is recorded and will be shared only with students in this course
  - In case of technical glitches, etc.
- Zoom viewing options: e.g., gallery view
- Interactive zoom functionalities we will use today and going forward:
  - Unmute/mute your connection
  - Raise your hand if: “You are a student in this class”
  - Say yes or no to: “This is my first class in Zoom ever”
  - Send chat message sharing: “What city you are connecting from”
  - Submit response to poll question
  - Share in a breakout room about “a current success/struggle with the shelter-in-place lifestyle”
- Beyond class:
  - Student Resources: https://www.ischool.utexas.edu/ischool-student-town-hall-03262020
  - Student Resources: https://onestop.utexas.edu/keep-learning/

Review

- Last class:
  - History of Neural Networks
  - Neural Network Architecture – Hidden Layers and Solving XOR Problem
  - Neural Network Architecture – Output Units
  - Training a Neural Network – Optimization
  - Training a Neural Network – Activation Functions & Loss Functions
- Assignments (Canvas):
  - Lab assignment 3 due yesterday
  - Project pre-proposal due next week (email me if you want help to find partner)
- Questions?

Today’s Topics

- History of Convolutional Neural Networks (CNNs)
- CNNs – Convolutional Layers
- CNNs – Pooling Layers
- Deep Features
- Guest Speaker: Dr. Peter Anderson, Research Scientist at Google

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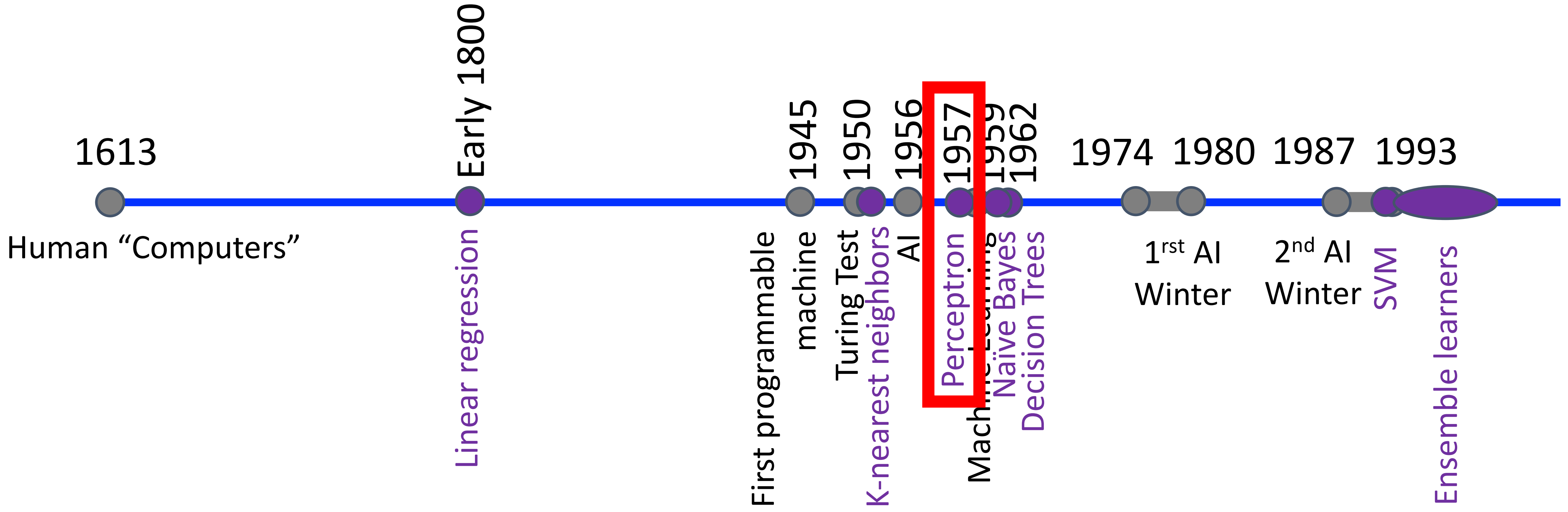
Recall:


1613
Human "Computers"
Early 1800
Linear regression
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SVM
Ensemble learners

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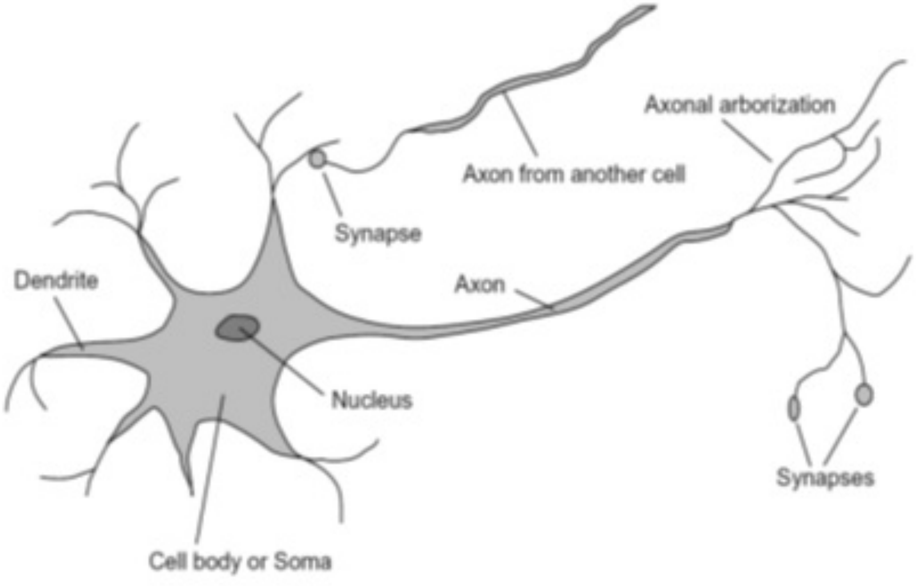
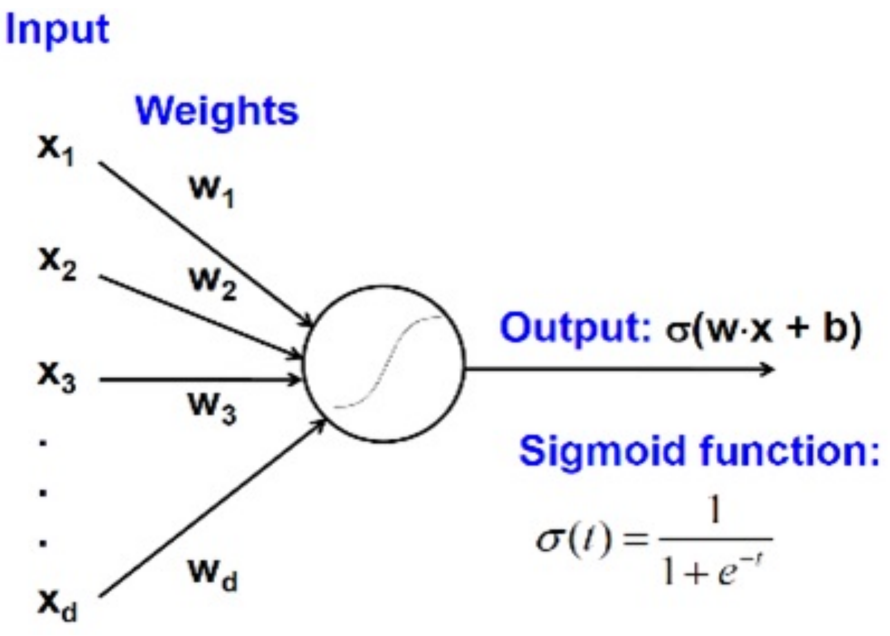


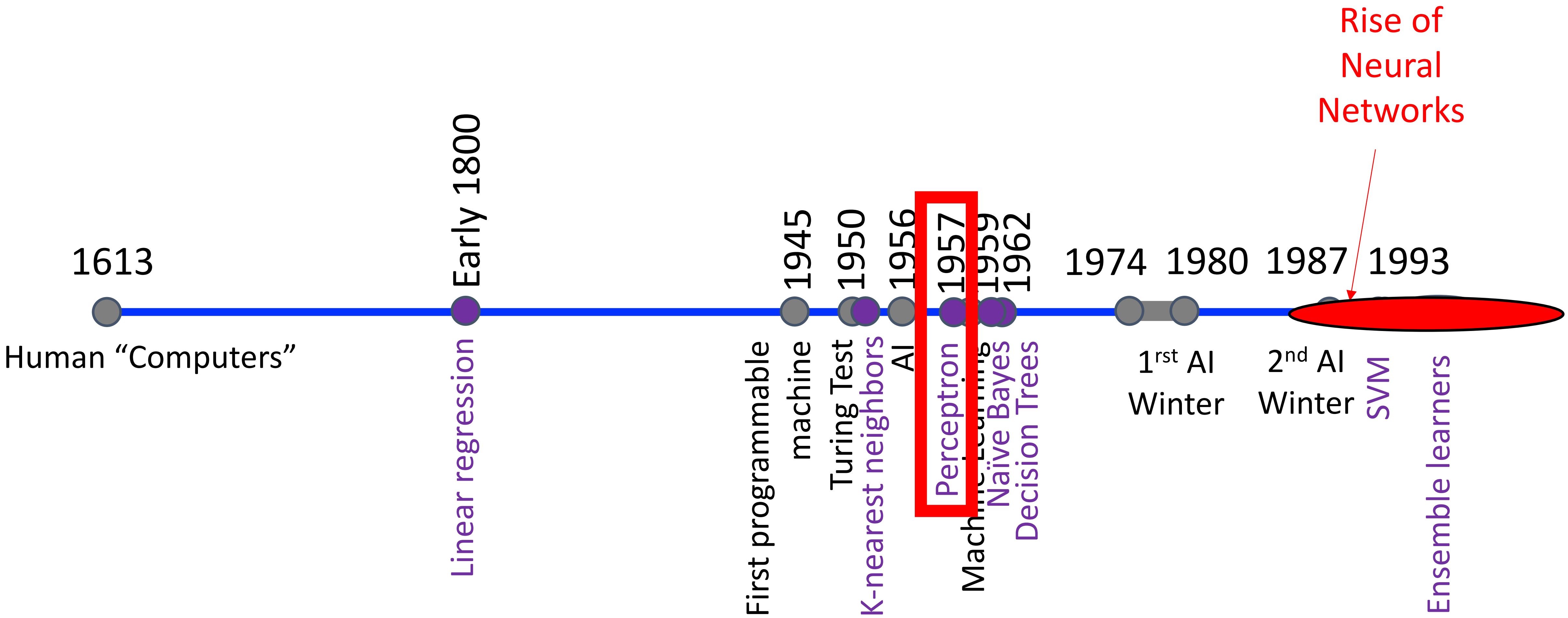
A biological neuron



An artificial neuron (Perceptron)
- a linear classifier

Slide credit: Jia-Bin Huang

Recall: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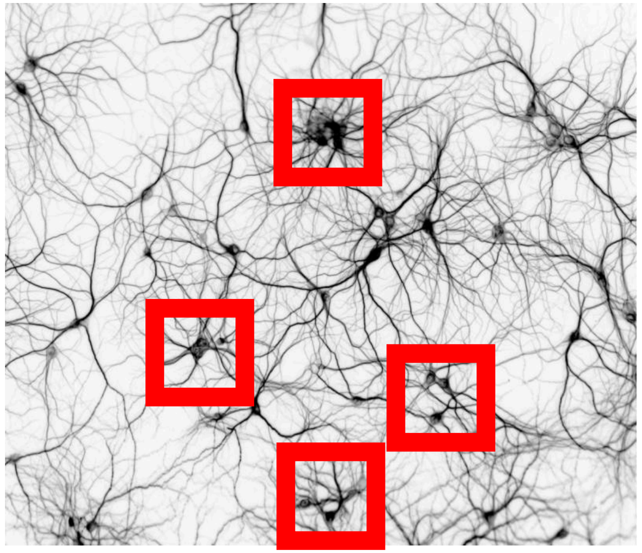
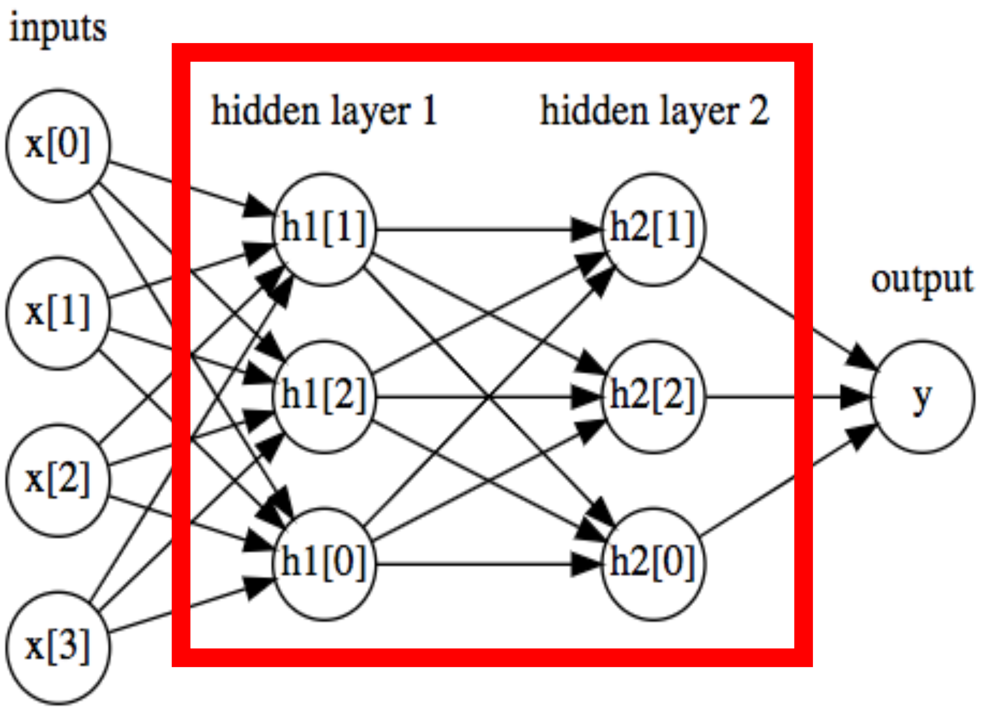
Recall:

Biological Neural Network:



http://www.rzagabe.com/2014/11/03/an-introduction-to-artificial-neural-networks.html

Artificial Neural Network:



https://github.com/amueller/introduction_to_ml_with_python/blob/master/02-supervised-learning.ipynb

Motivation: How Vision System Works

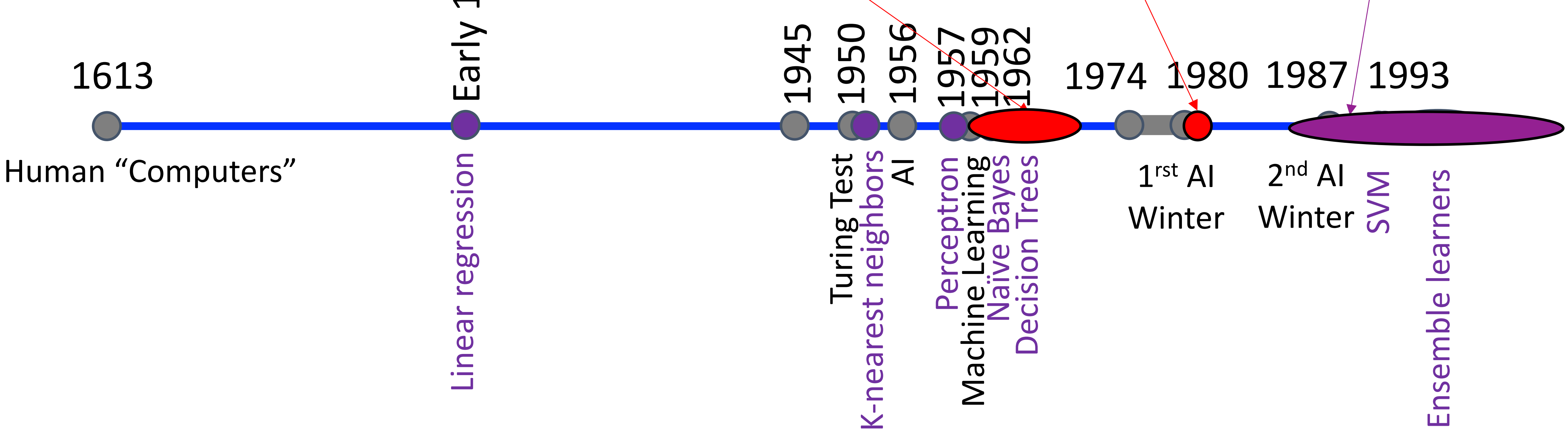
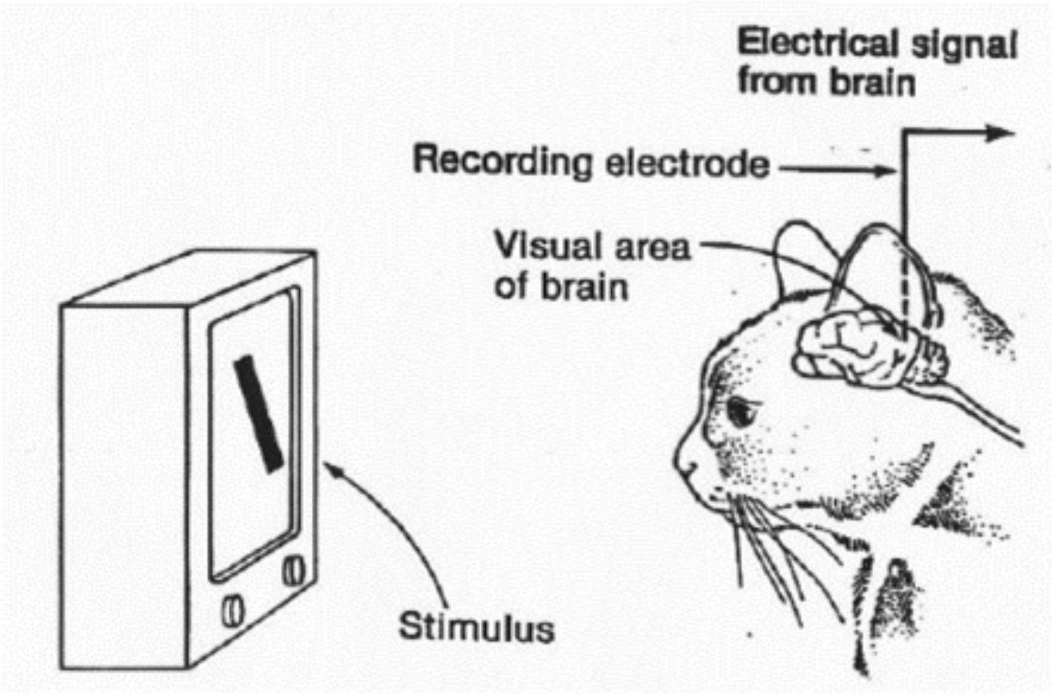


Image Source: https://braintour.harvard.edu/archives/portfolio-items/hubel-and-wiesel

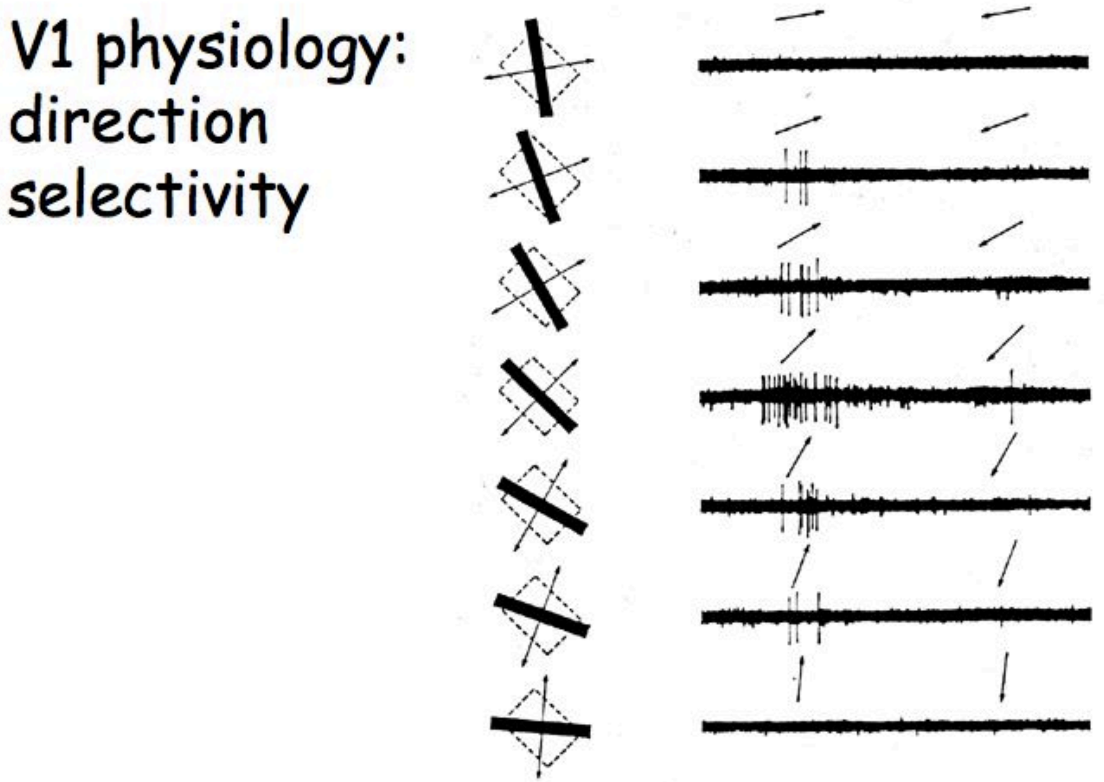
Motivation: How Vision System Works

Experiment Set-up:



https://www.esantus.com/blog/2019/1/31/convolutional-neural-networks-a-quick-guide-for-newbies

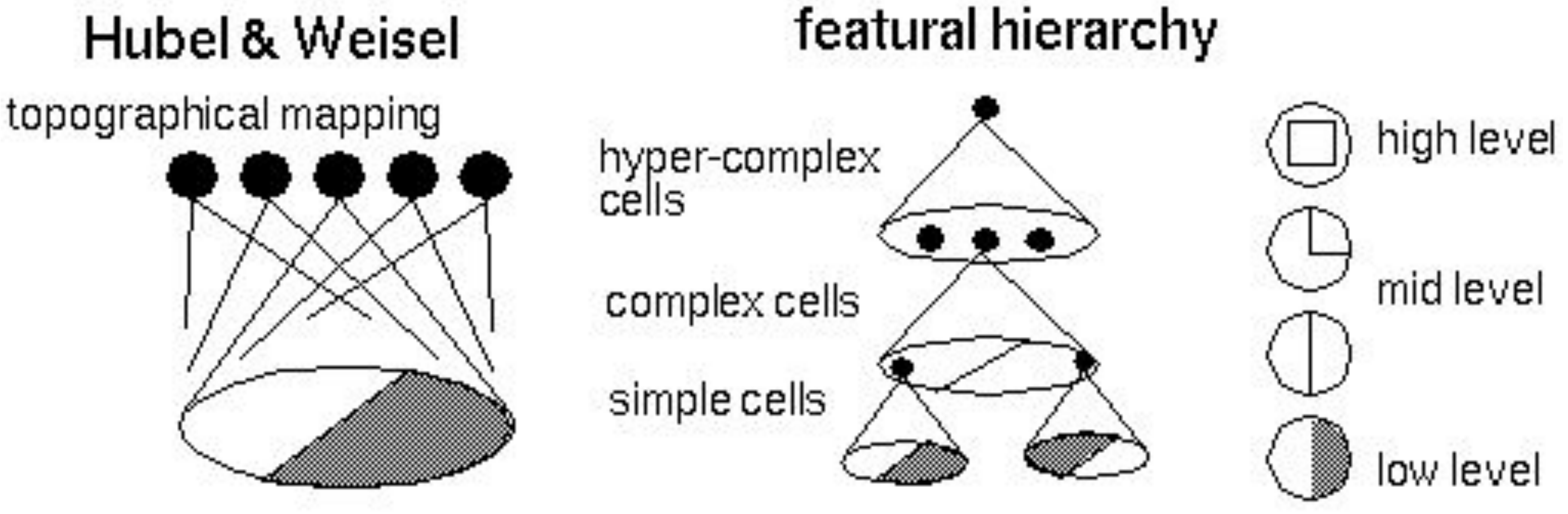
Key Finding: response based on orientation of light stimulus



https://www.cns.nyu.edu/~david/courses/perception/lecturenotes/V1/lgn-V1.html

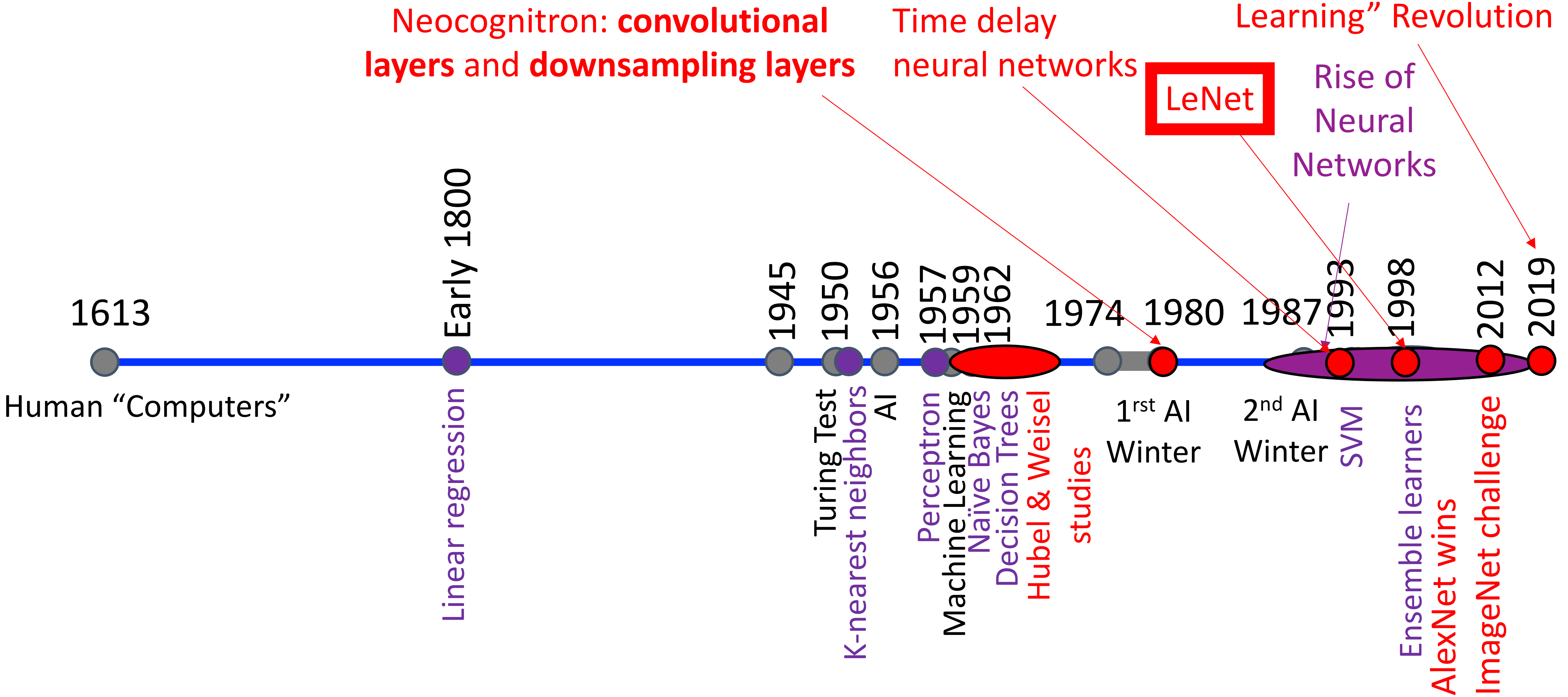
Motivation: How Vision System Works

Key Finding: cells are organized as a hierarchy of feature detectors, with higher level features responding to patterns of activation in lower level cells



Source: https://bruceoutdoors.files.wordpress.com/2017/08/hubel.jpg

CNN: Modeling Vision System



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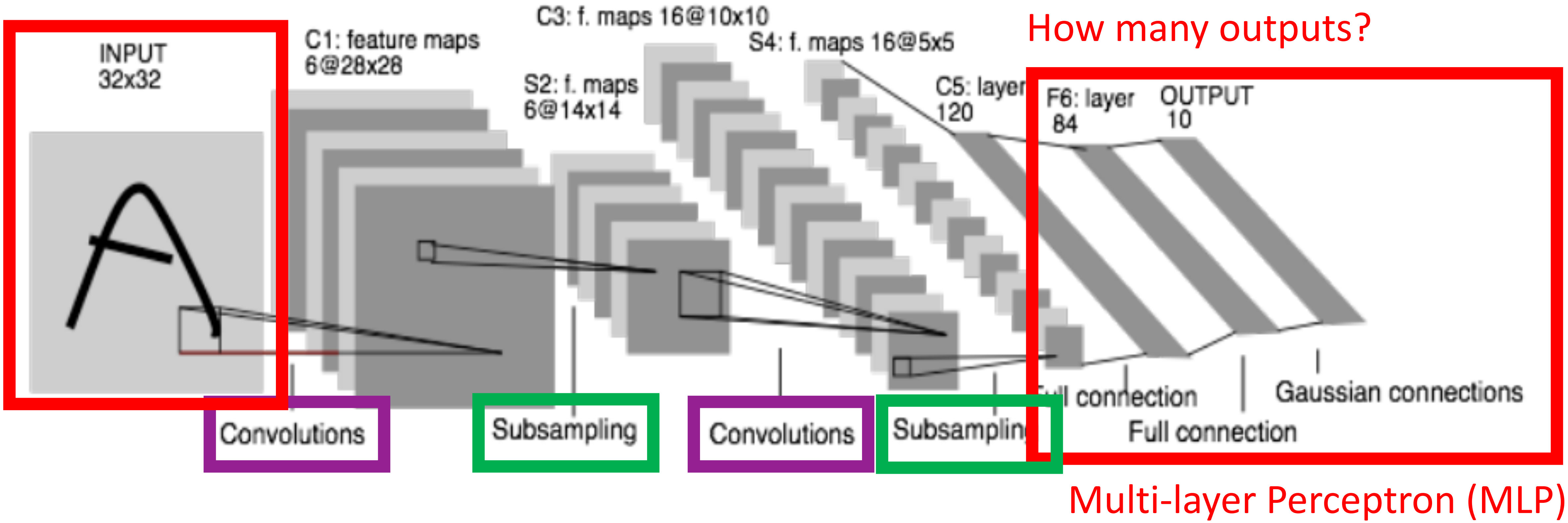
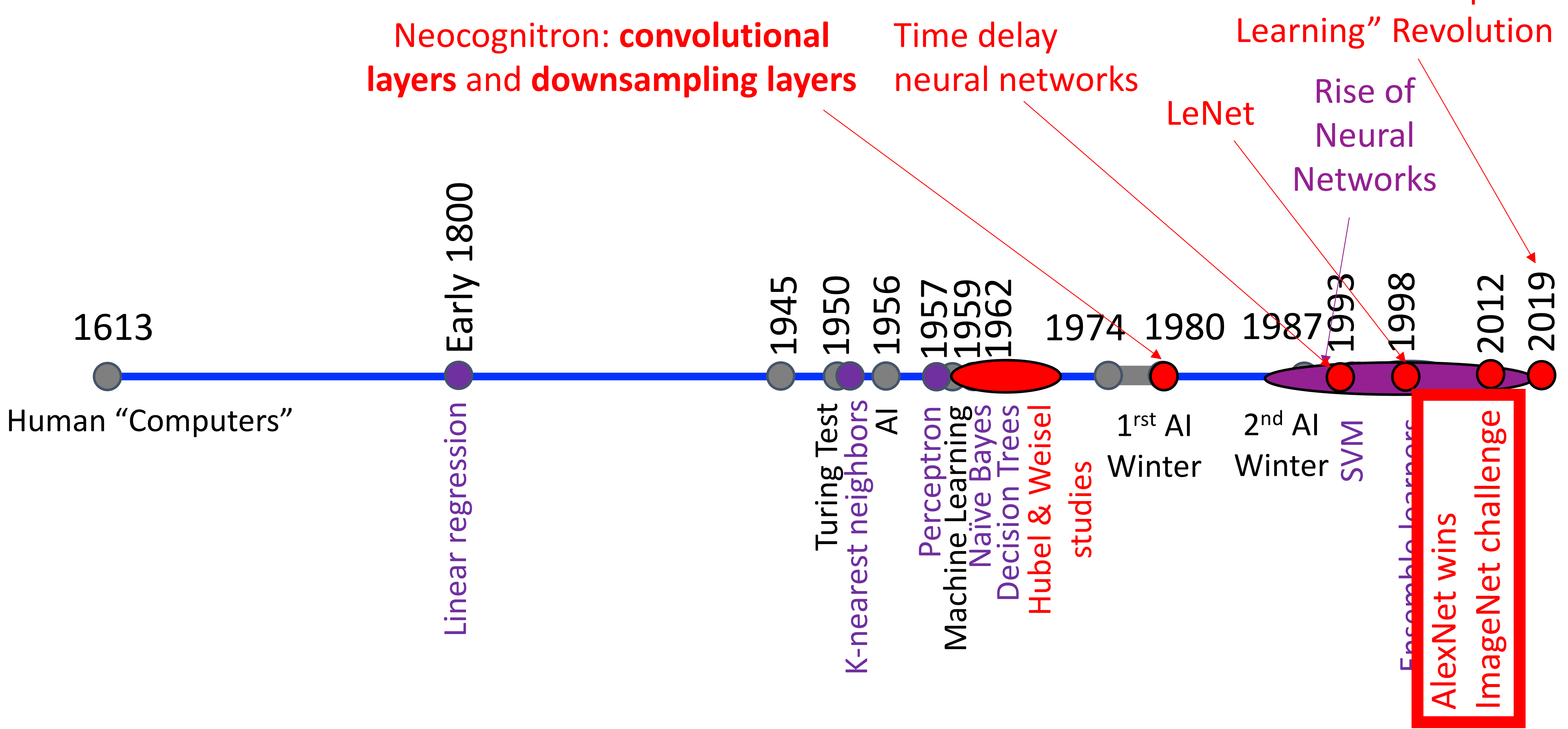


Slide Credit: https://people.eecs.berkeley.edu/~jrs/189/lec/cnn.pdf

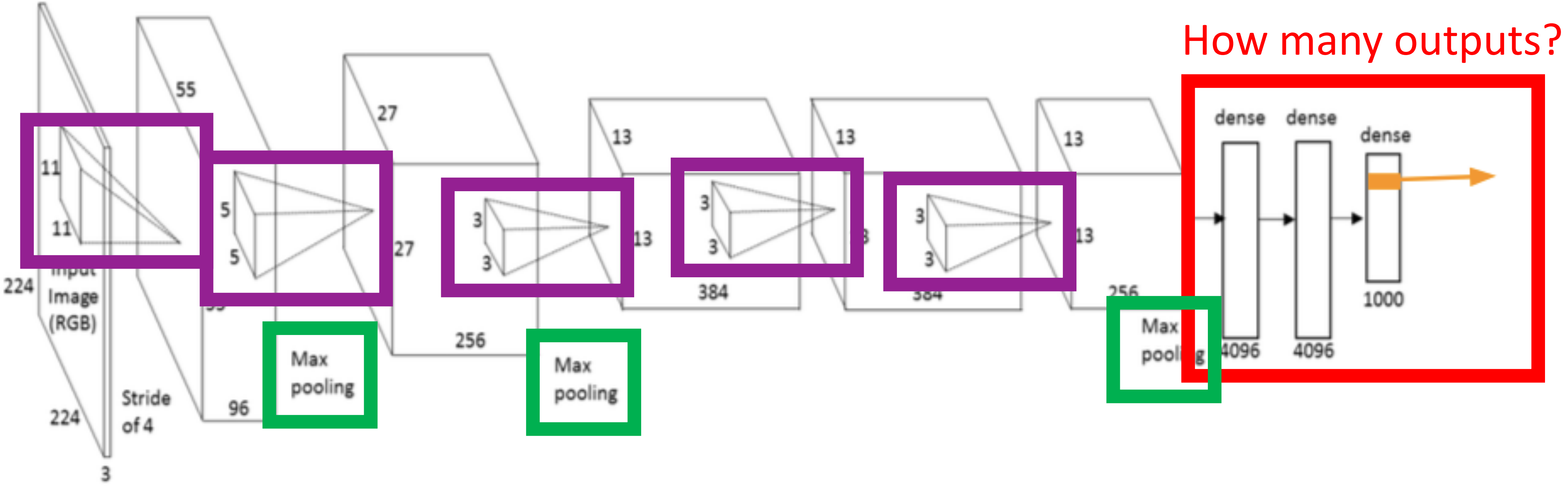
Y. Lecun ; L. Bottou ; Y. Bengio ; P. Haffner; Gradient-based learning applied to document recognition; 1998

CNN: Modeling Vision System



CNN: Modeling Vision System

- AlexNet extracts useful features of lower dimension prior to passing it to MLP with:
  - Convolutional layers
  - Pooling Layers



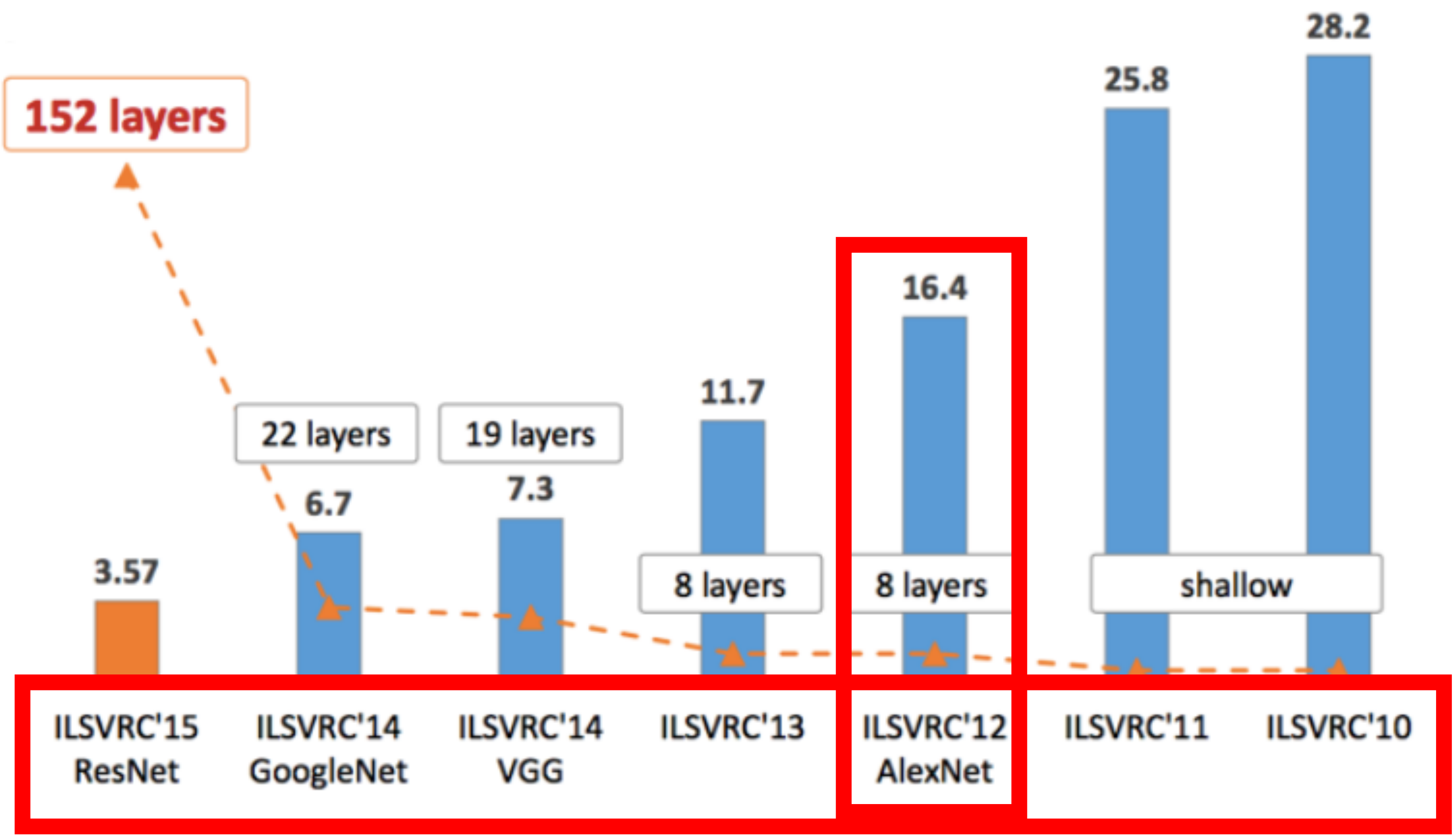
Slide Credit: https://www.slideshare.net/xavigiro/saliency-prediction-using-deep-learning-techniques

A. Krizhevsky, I. Sutskever, G. E. Hinton "ImageNet classification with deep convolutional neural networks"

ImageNet: Predict Category from 1000 Options

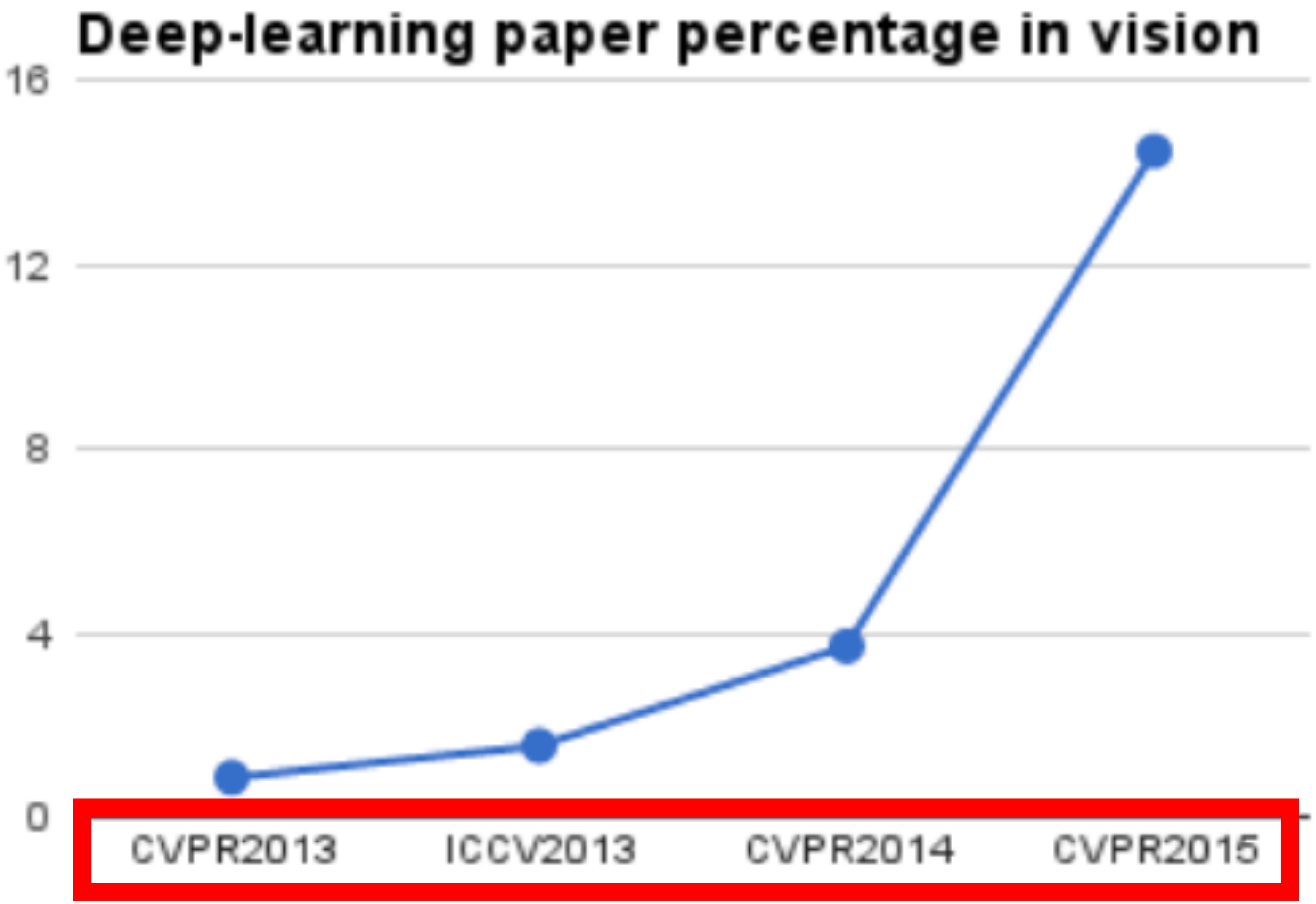
https://medium.com/coinmonks/paper-review-of-vggnet-1st-runner-up-of-ilsvlc-2014-image-classification-d02355543a11

ILSVRC: Top CNN Models Over Time



https://medium.com/@sidereal/cnns-architectures-lenet-alexnet-vgg-googlenet-resnet-and-more-666091488df5

CNN: Modeling Vision System



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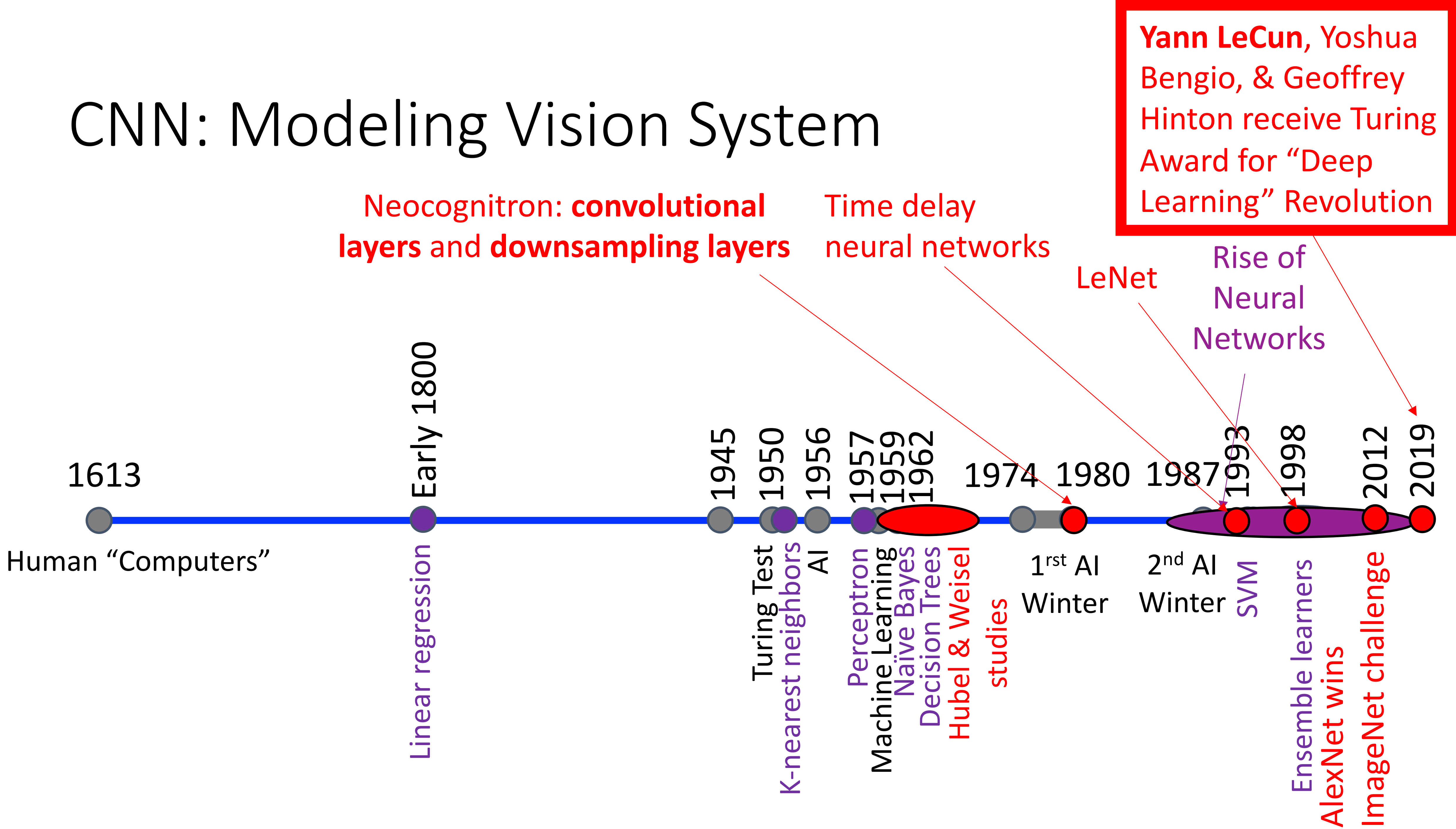


Note: Initial Resistance to this "Revolution"

Yann LeCun's letter to CVPR organizer about 2012 submission:
(*Paper ratings: "Definitely Reject," "Borderline", "Weakly Reject")*

"… I was very sure that this paper was going to get good reviews because: 1) it has two simple and generally applicable ideas for segmentation ("purity tree" and "optimal cover"); **2) it uses no hand-crafted features (it's all learned all the way through. Incredibly, this was seen as a negative point by the reviewers!); 3) it beats all published results on 3 standard datasets for scene parsing; 4) it's an order of magnitude faster than the competing methods.**

If that is not enough to get good reviews, I just don't know what is.

"*Scene Parsing with Multiscale Feature Learning, Purity Trees, and Optimal Covers*" rejected by CVPR but accepted by ICML'12

Note: Initial Resistance to this “Revolution”

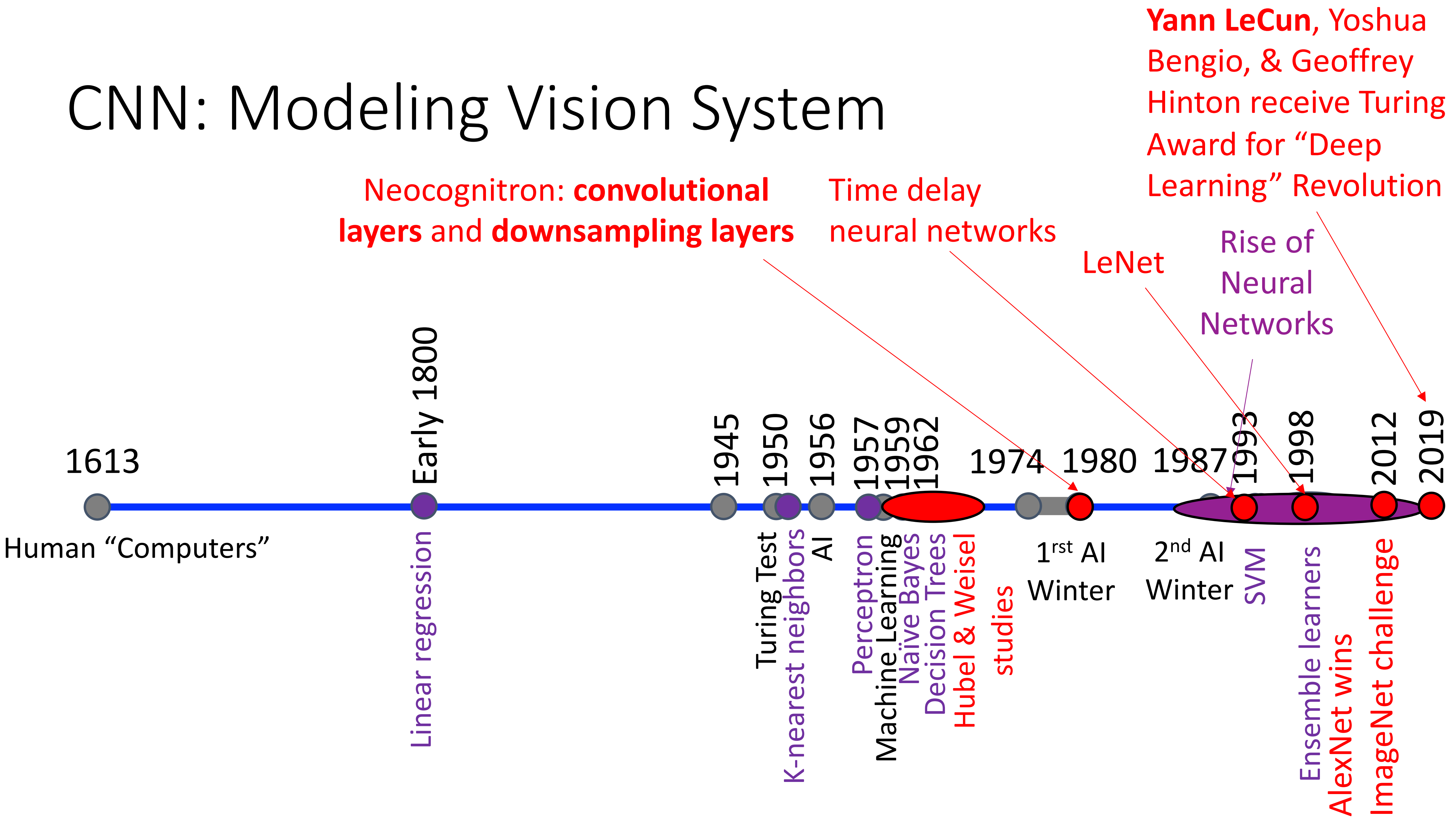
Yann LeCun’s Facebook post on March 28, 2019:

“The injustice of any award is that it has to pick a small number of winners. **But the winners are merely the visible part of an iceberg and wouldn't come to the surface without the much-larger submerged part that supports it…**

I am very thankful to all my mentors, collaborators, postdocs and students over the years. To a large extent, it is their work that the Turing Award rewards… I have been very fortunate to work with incredibly talented people over the years…

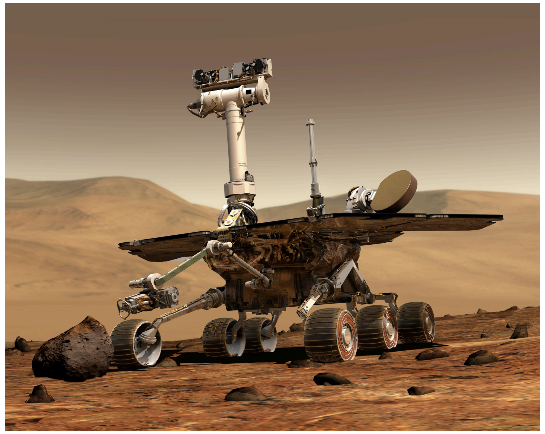
Mentors include Maurice Milgram & Françoise Soulié-Fogelman, my PhD advisors, Geoff Hinton with whom I did my postdoc, Larry Jackel and Rich Howard who hired me at Bell Labs, and Lawrence Rabiner my lab director at AT&T Labs…”

CNN: Modeling Vision System



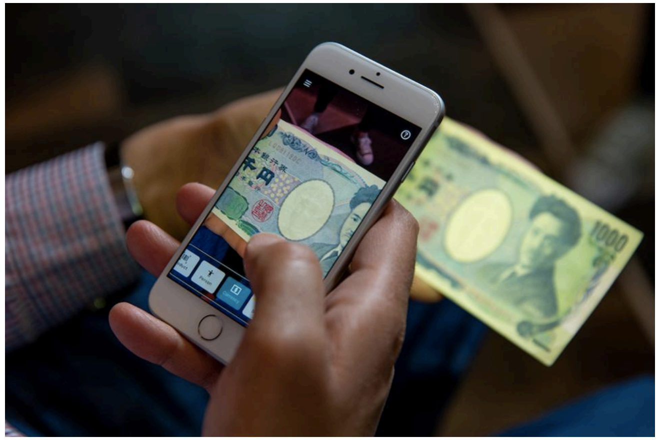
CNN: Catalyst for Computer Vision Industry Boom

Self-driving cars

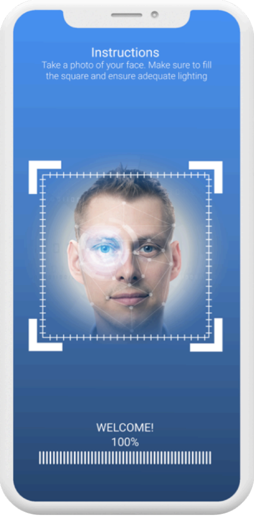


Self-driving vehicle on Mars

Guided surgery



Visual assistance for people who are blind



Security

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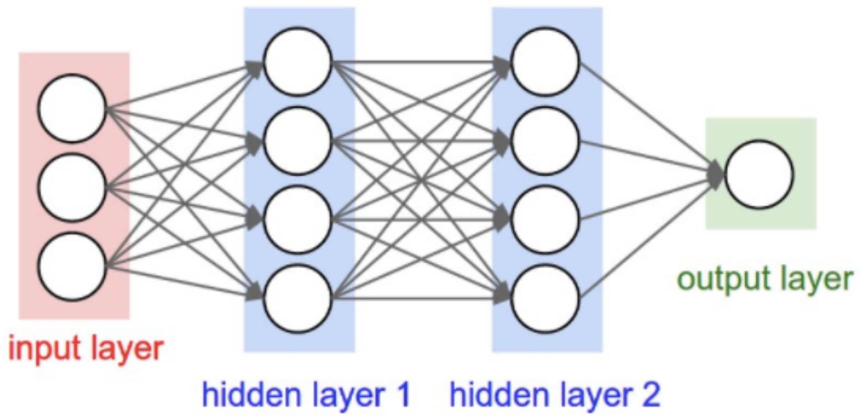
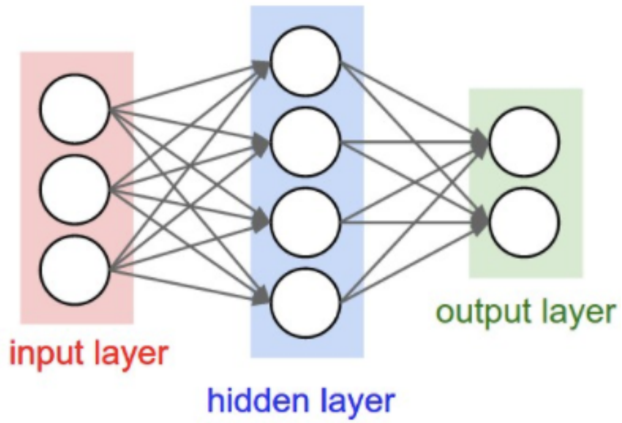
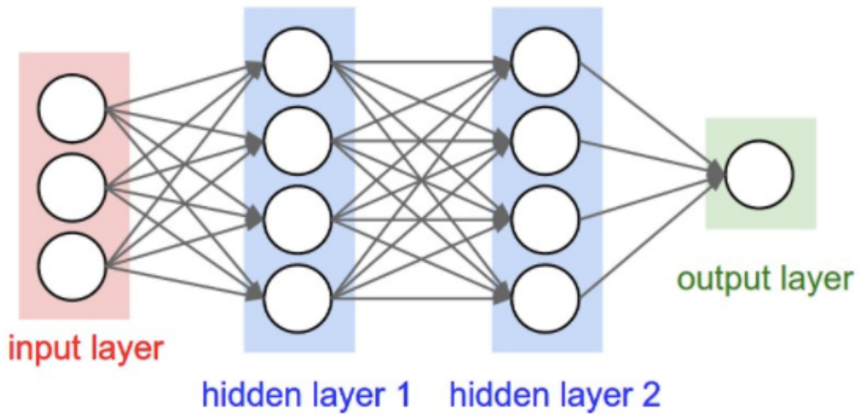
Recall: Fully-Connected Neural Networks

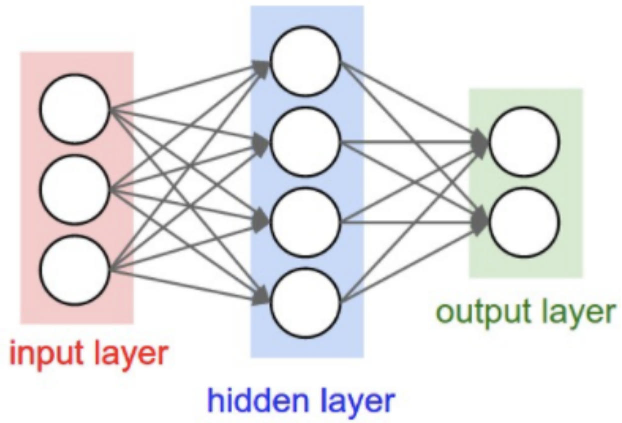




Each node provides input to each node in the next layer

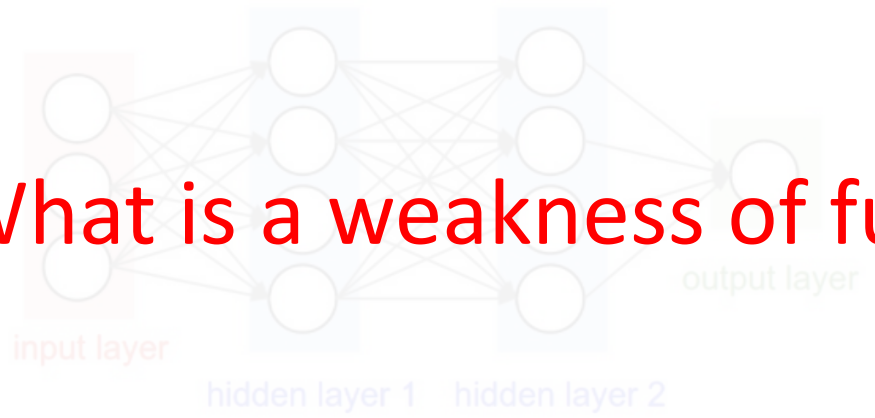
Recall: Fully-Connected Neural Networks

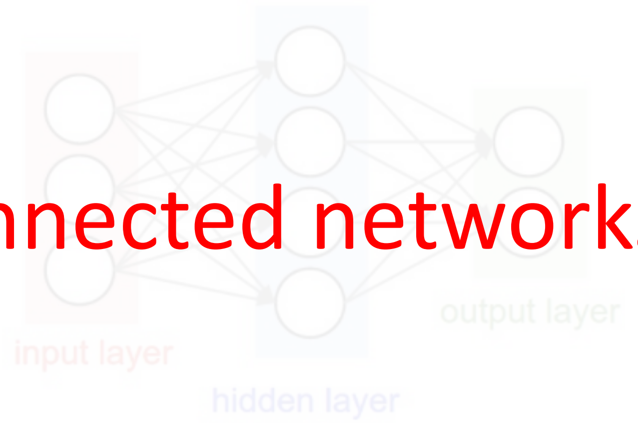




- Assume 2 layer model with 100 nodes per layer
  - e.g., how many weights are in a 640x480 image?
    - 640x480x3x100 + 100x100 + 100x1 = 92,170,100
  - e.g., how many weights are in a 2048X1536 image (3.1 Megapixel image)?
    - 2048x1536x3x100 + 100x100 + 100x1 = 943,728,500

Recall: Fully-Connected Neural Networks





What is a weakness of fully-connected networks?

- Assume 2 layer model with 100 nodes per layer
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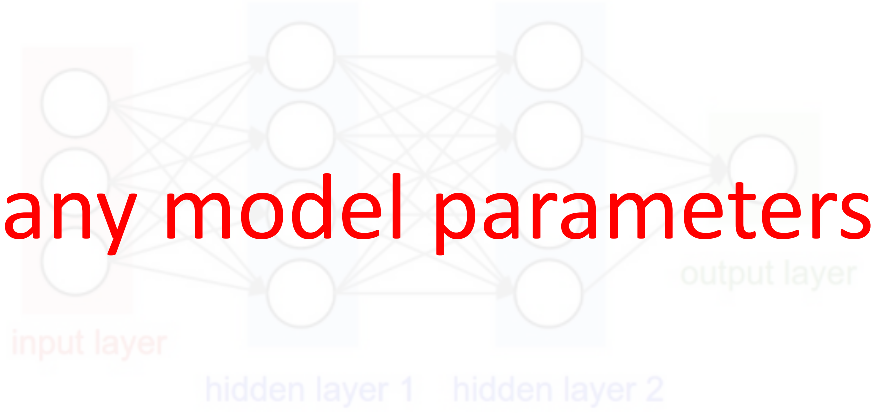

Many model parameters in fully connected networks

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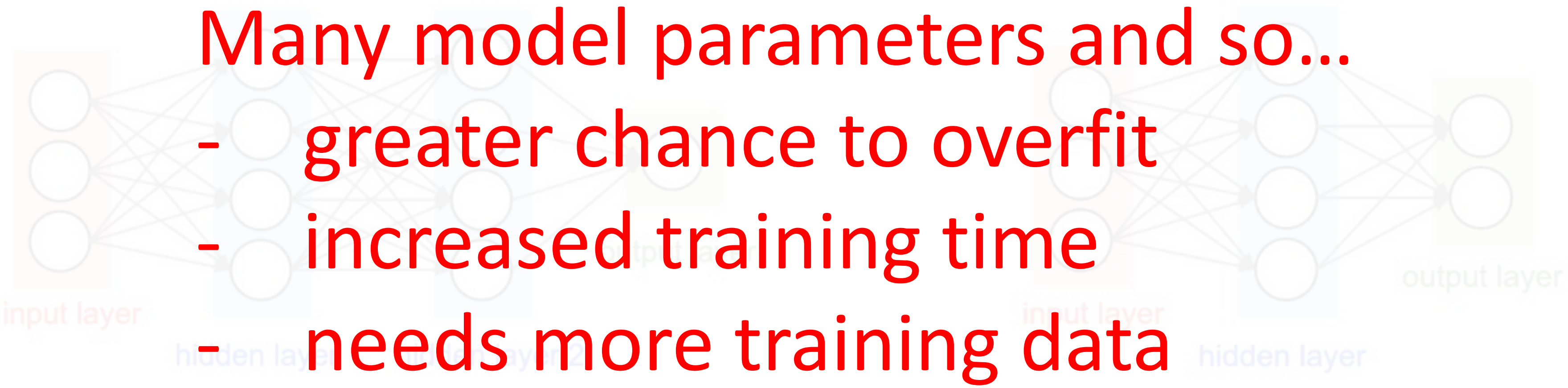

Many model parameters and so…

- greater chance to overfit
- increased training time
- needs more training data

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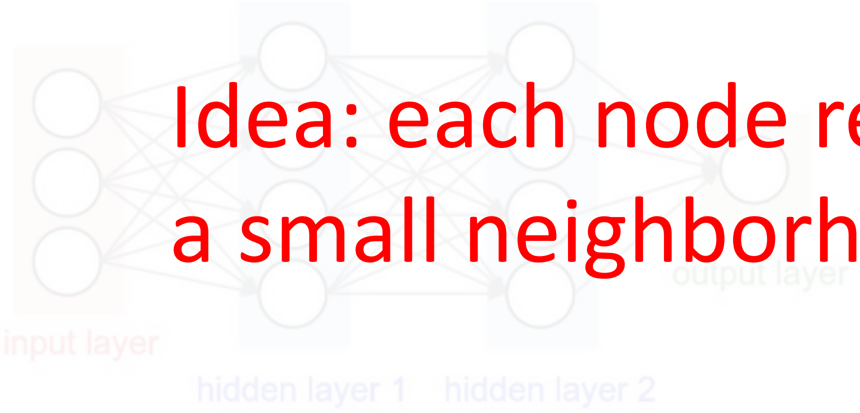
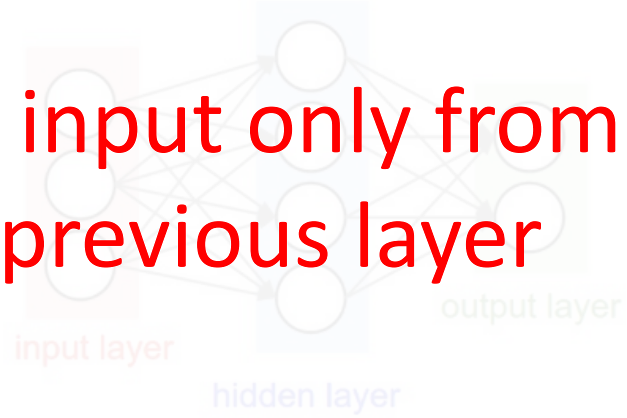
Convolutional Layer





Idea: each node receives input only from a small neighborhood in previous layer

- Assume 2 layer model with 100 nodes per layer
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    - 640x480x3x100 + 100x100 + 100x1 = 92,170,100
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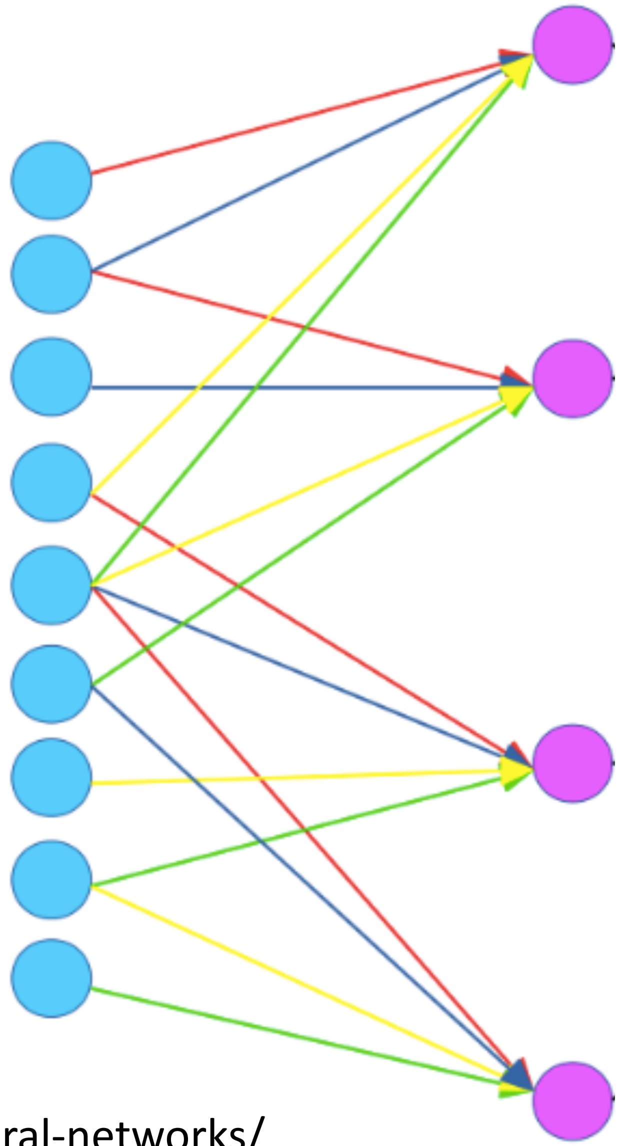
Convolutional Layer: Parameters to Learn

- For example, how many weights must be learned?
  - 4 (red, blue, yellow, and green values in the filter)
- If we instead used a fully connected layer, how many weights would need to be learned?
  - 36 (9 blue x 4 magenta)
- For example, how many parameters must be learned?
  - 5 (4 weights + 1 bias)
- If we instead used a fully connected layer, how many parameters would need to be learned?
  - 40 (36 weights + 4 bias)

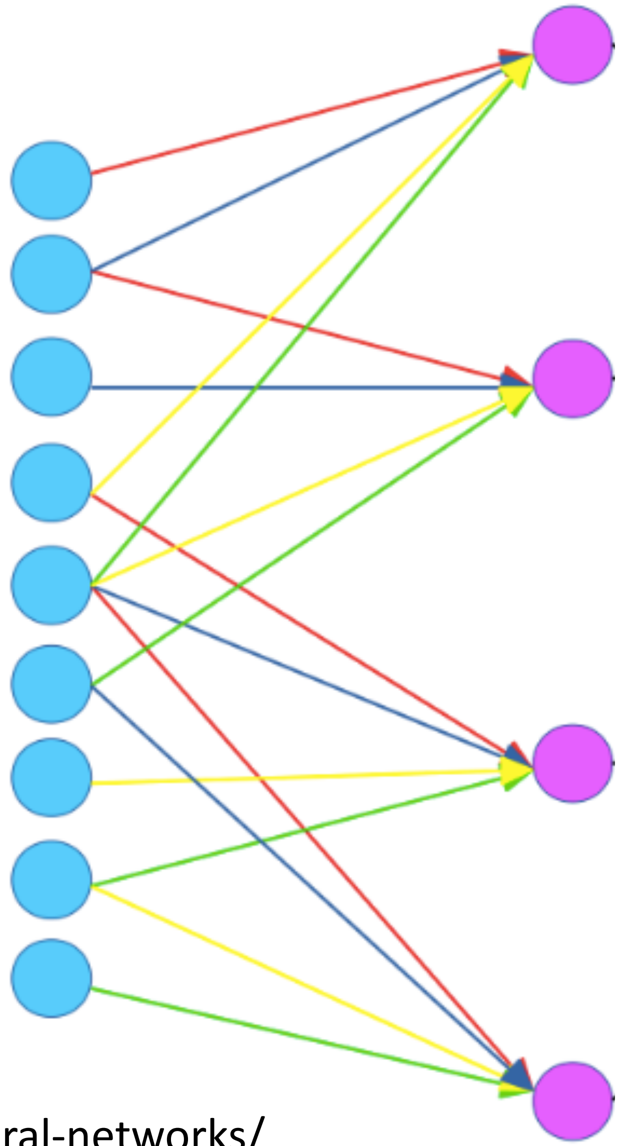


https://www.jefkine.com/general/2016/09/05/backpropagation-in-convolutional-neural-networks/

Convolutional Layer: Parameters to Learn

- Parameter sharing significantly reduces number of weights to learn and so storage requirements

- Sparse (rather than full) connectivity also significantly reduces the number of computational operations required



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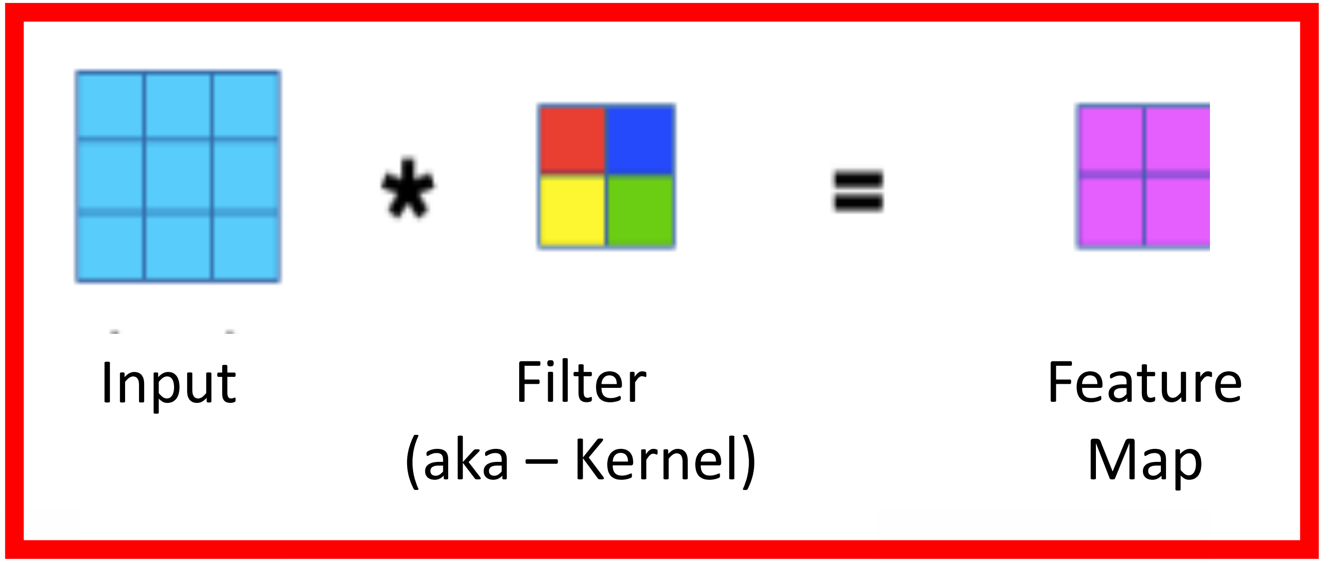
Convolutional Layer: Applies Linear Filter



Way to Interpret Neural Network

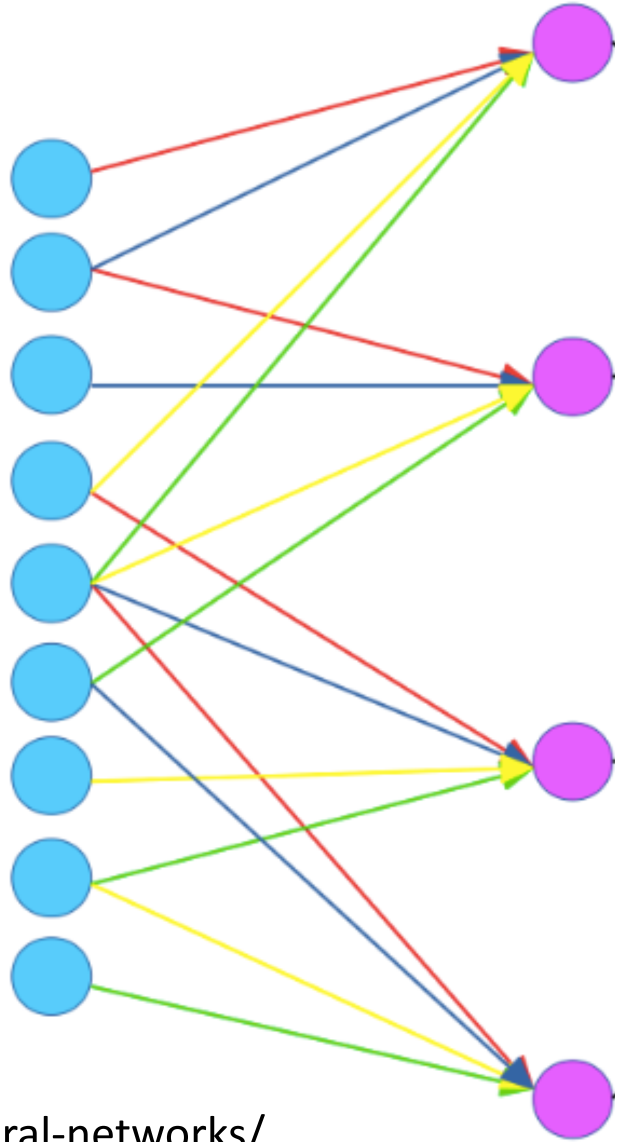


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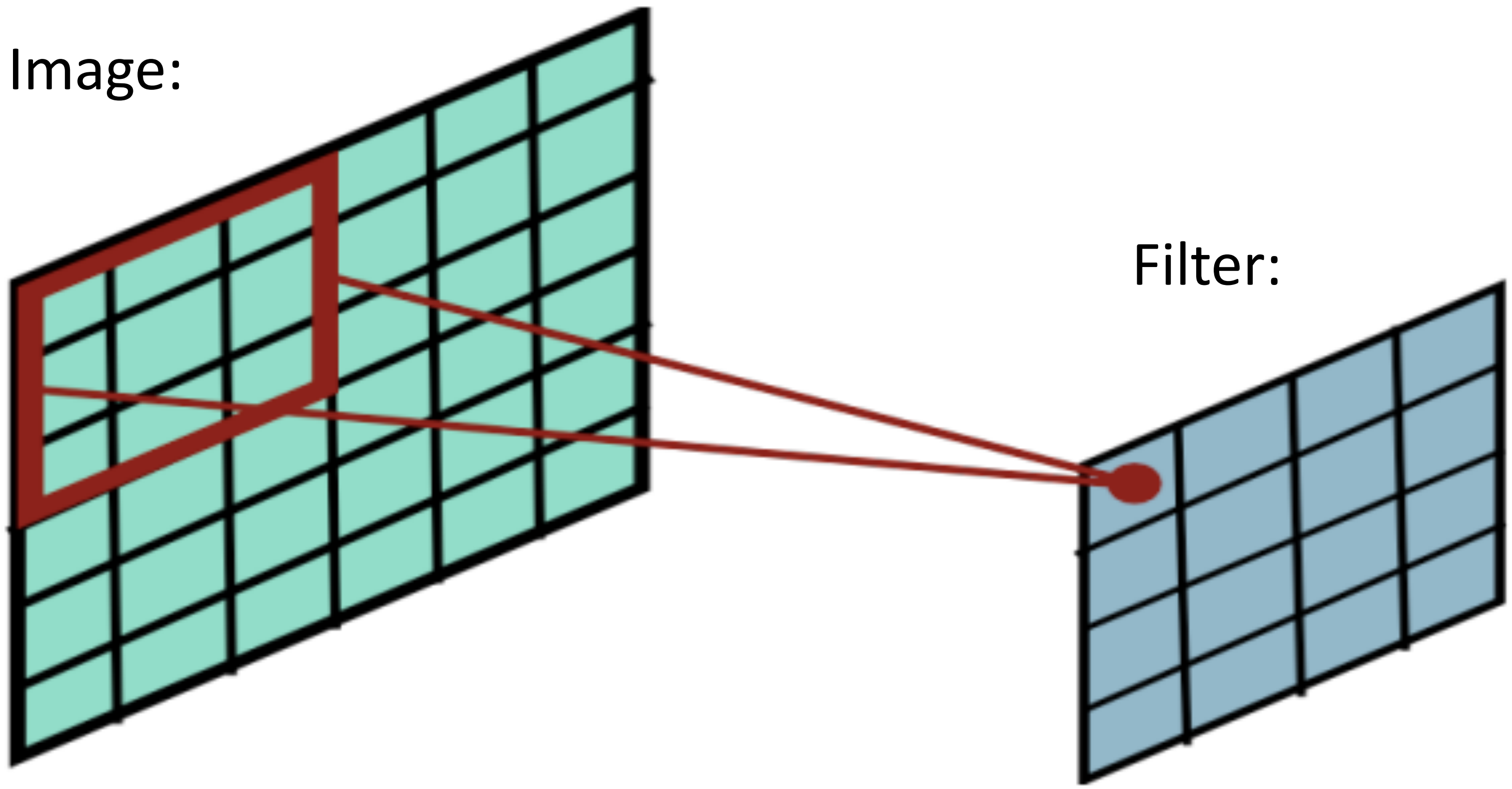
Image Filtering

- Compute a function of local neighborhood for each pixel in the image
- A filter specifies the function for how to combine neighbors’ values

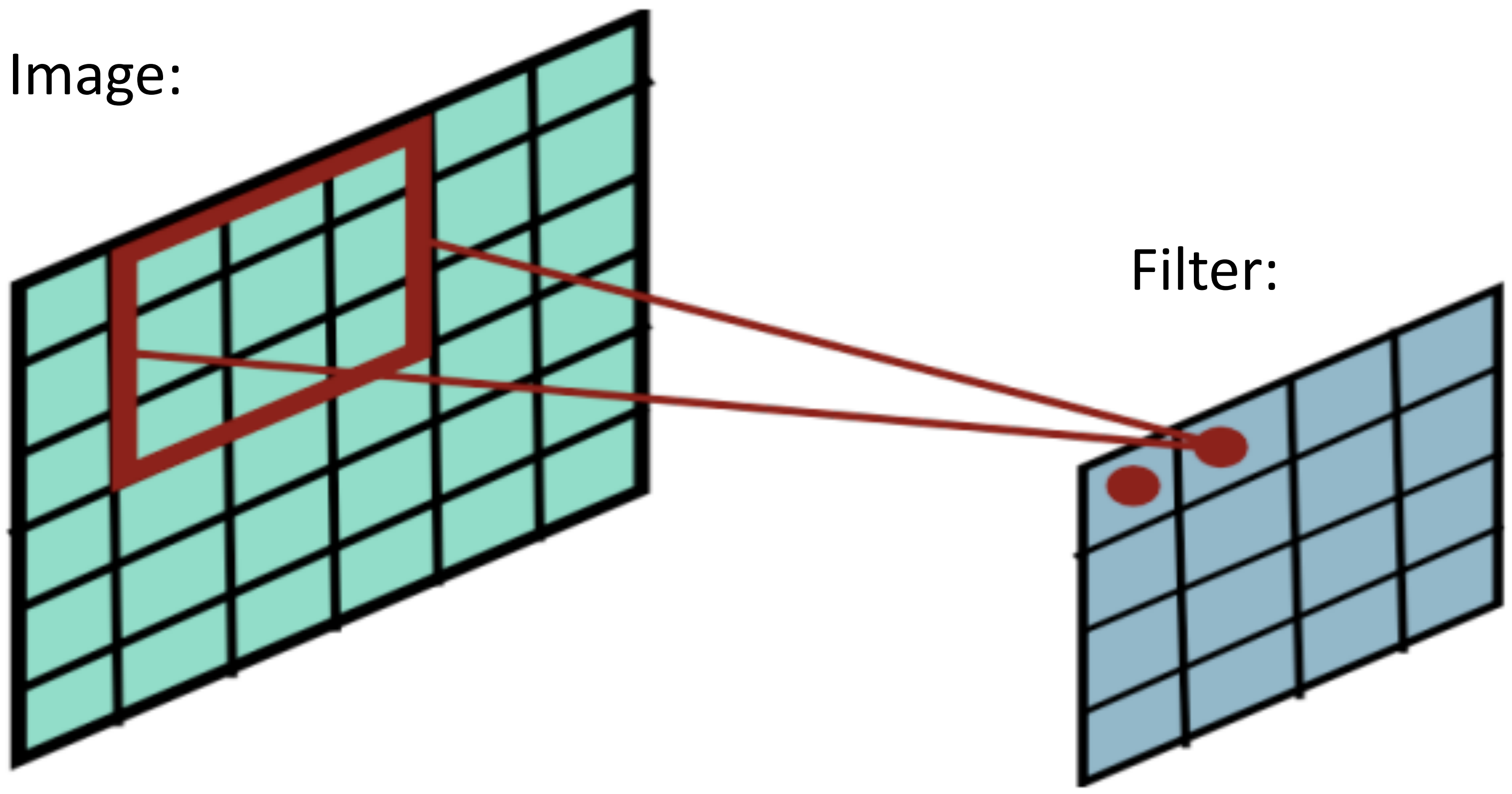
Image Filtering



Slides filter over the image and computes dot products

https://people.eecs.berkeley.edu/~jrs/189/lec/cnn.pdf

Image Filtering



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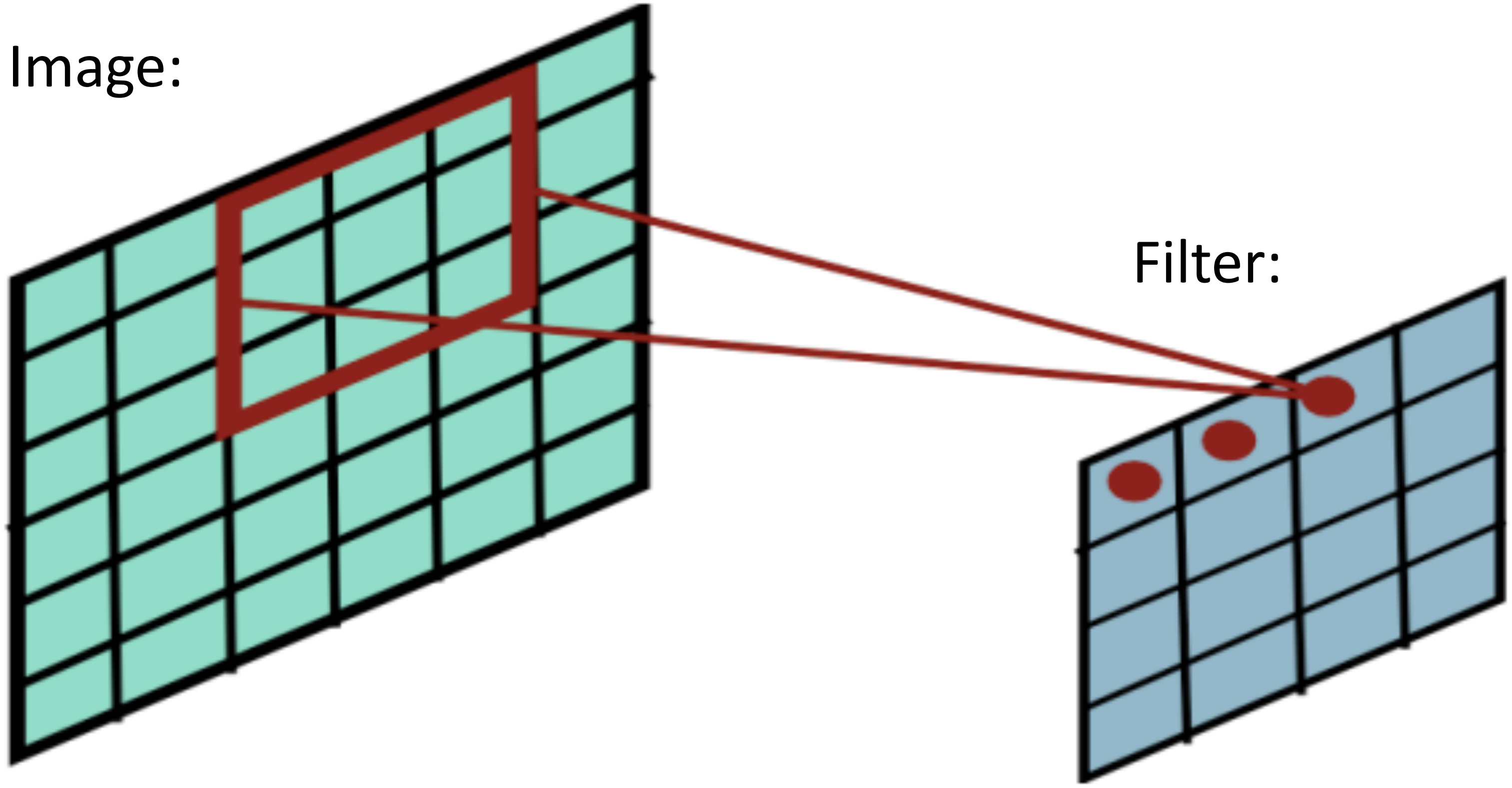

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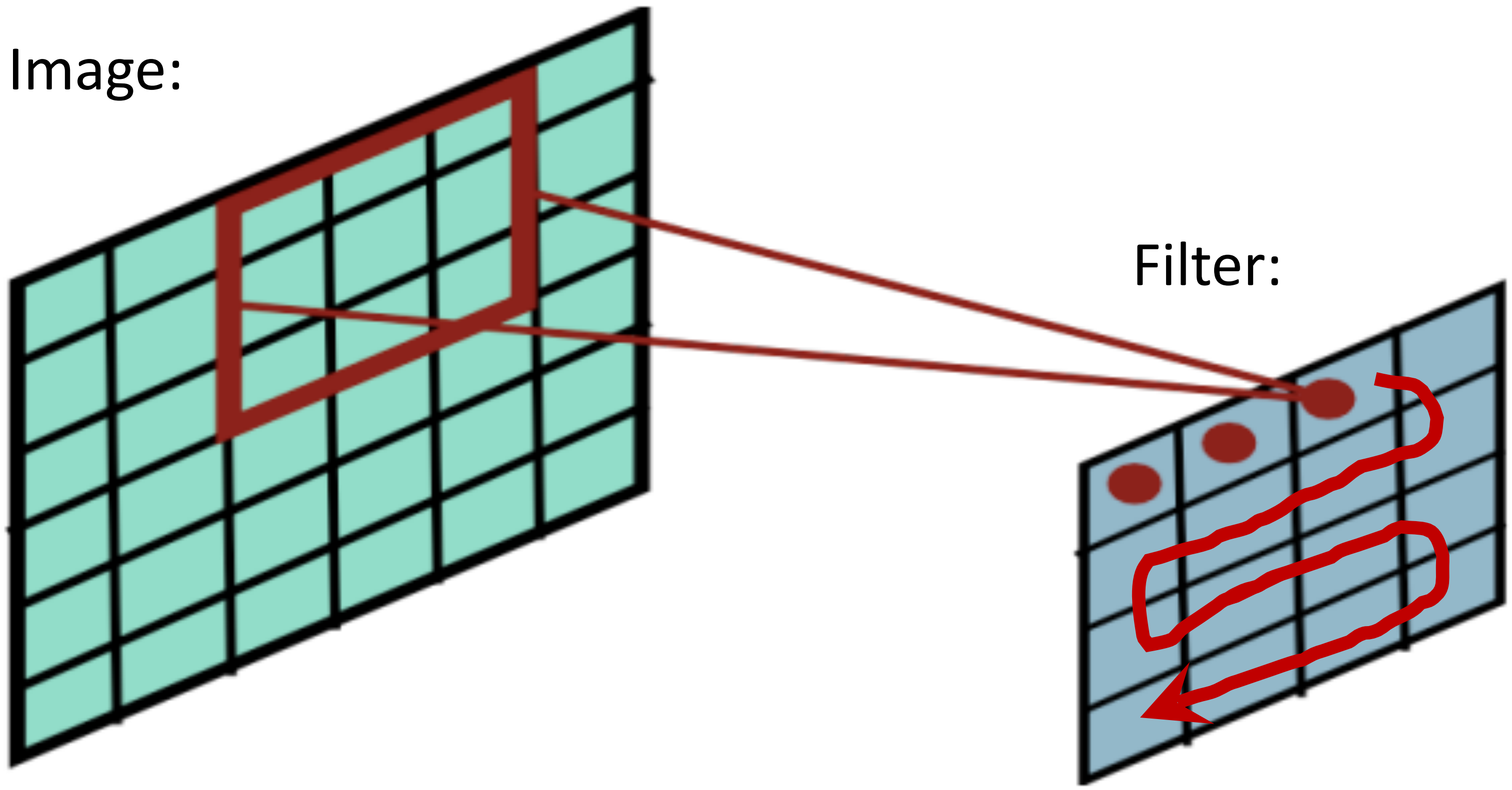

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Image Filtering: Toy Example

Image

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

Filter

1	0	1
0	1	0
1	0	1

Feature Map

?	?	?
?	?	?
?	?	?

Dot Product = 1*1 + 1*0 + 1*1 + 0*0 + 1*1 + 1*0 + 0*1 + 0*1 + 0*0 + 0*0 + 1*1

Dot Product = 4

Image Filtering: Toy Example

Image

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

Filter

1	0	1
0	1	0
1	0	1

Feature Map

4	?	?
?	?	?
?	?	?

Image Filtering: Toy Example

Image

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

Filter

1	0	1
0	1	0
1	0	1

Feature Map

4	3	?
?	?	?
?	?	?

Image Filtering: Toy Example

Image

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

Filter

1	0	1
0	1	0
1	0	1

Feature Map

4	3	4
?	?	?
?	?	?

Image Filtering: Toy Example

Image

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

Filter

1	0	1
0	1	0
1	0	1

Feature Map

4	3	4
2	?	?
?	?	?

Image Filtering: Toy Example

Image

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

Filter

1	0	1
0	1	0
1	0	1

Feature Map

4	3	4
2	4	?
?	?	?

Image Filtering: Toy Example

Image

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

Filter

1	0	1
0	1	0
1	0	1

Feature Map

4	3	4
2	4	3
?	?	?

Image Filtering: Toy Example

Image

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

Filter

1	0	1
0	1	0
1	0	1

Feature Map

4	3	4
2	4	3
2	?	?

Image Filtering: Toy Example

Image

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

Filter

1	0	1
0	1	0
1	0	1

Feature Map

4	3	4
2	4	3
2	3	?

Image Filtering: Toy Example

Image

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

Filter

1	0	1
0	1	0
1	0	1

Feature Map

4	3	4
2	4	3
2	3	4

Image Filter: What Does It Do? (Where's Waldo?)

Filter

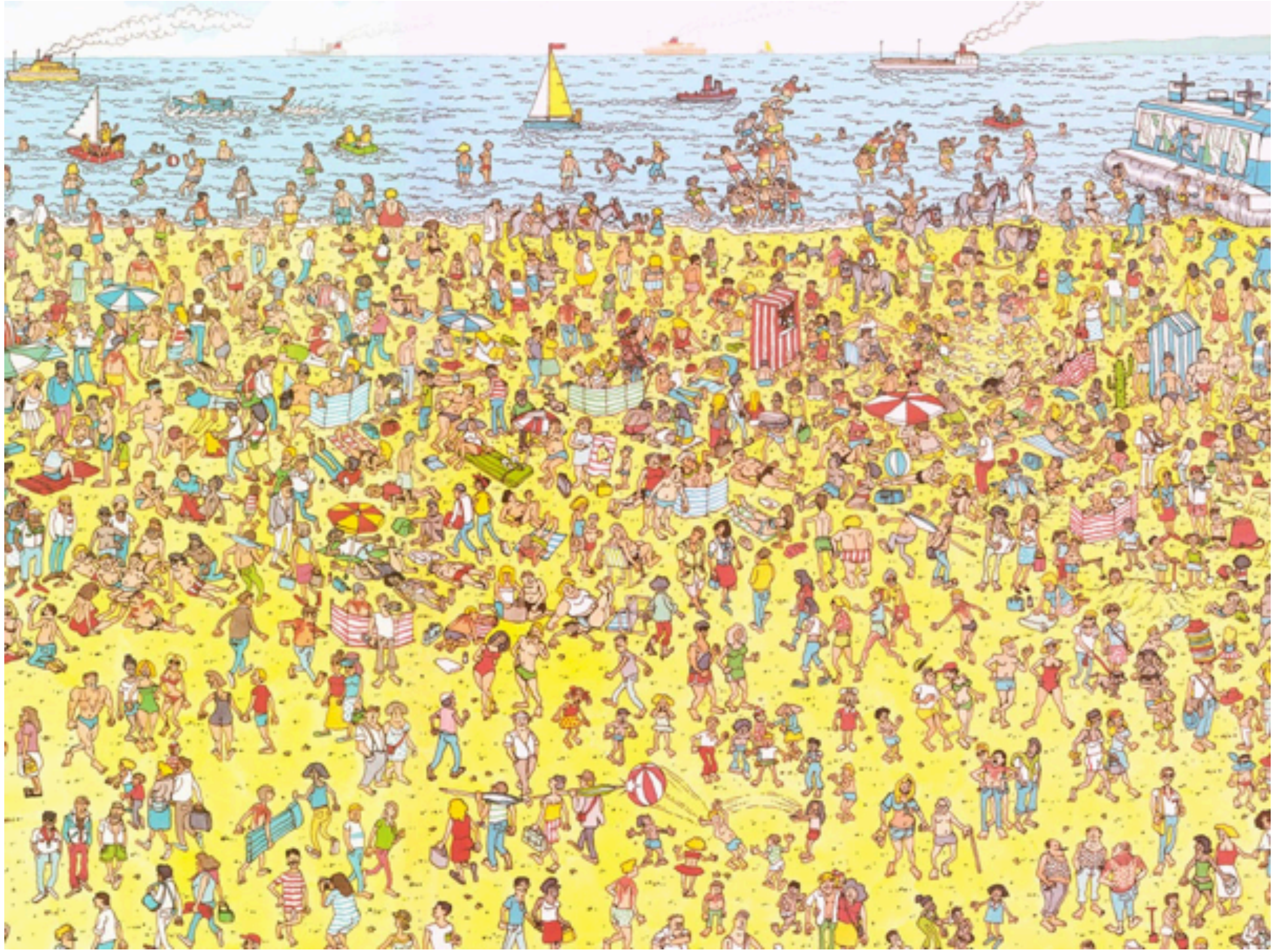


Image Filter: What Does It Do?

- e.g.,

Filter

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Visualization of Filter

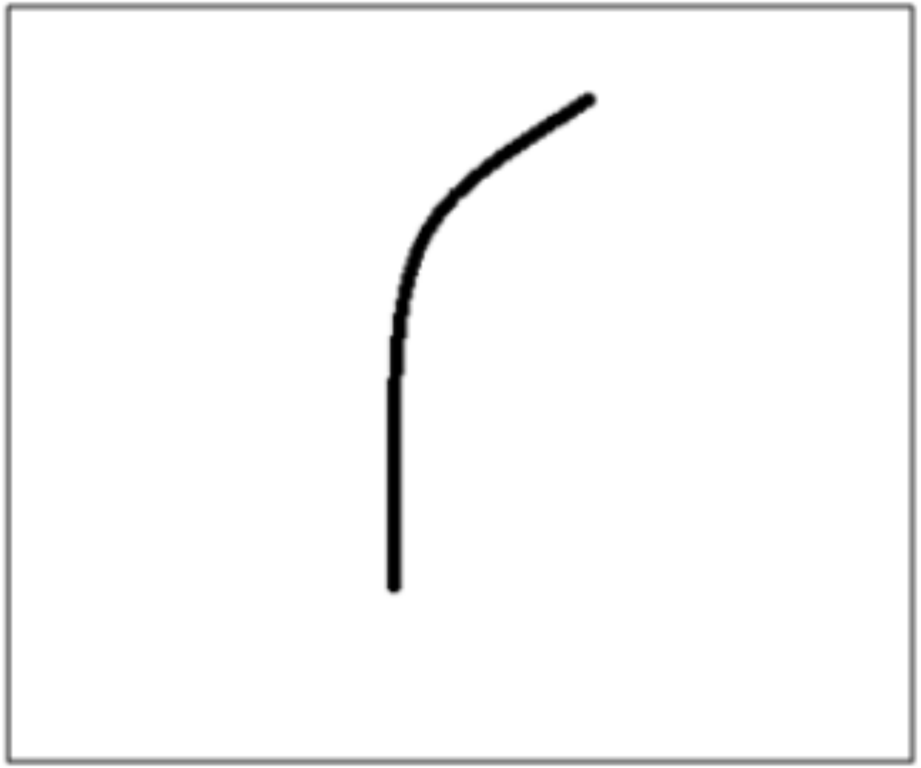
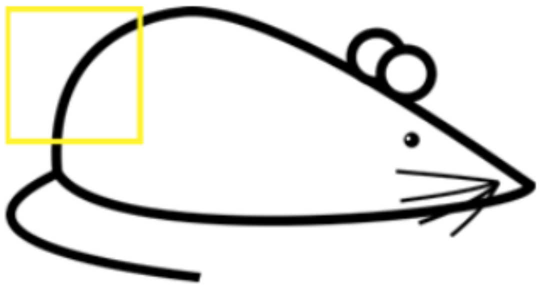


Image Credit: https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/

Image Filter: What Does It Do?

- e.g.,

Filter Overlaid on Image



Image

0	0	0	0	0	0	30
0	0	0	0	50	50	50
0	0	0	20	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0

*

Filter

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Weighted Sum = ?

Weighted Sum = (50x30) + (20x30) + (50x30) + (50x3) + (50x30)

Weighted Sum = 6600 **(Large Number!!)**

Image Credit: https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/

Image Filter: What Does It Do?

- e.g.,

Filter Overlaid on Image

Image

0	0	0	0	0	0	0
0	40	0	0	0	0	0
40	0	40	0	0	0	0
40	20	0	0	0	0	0
0	50	0	0	0	0	0
0	0	50	0	0	0	0
25	25	0	50	0	0	0

$*$

Filter

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Weighted Sum = ?

Weighted Sum = 0 **(Small Number!!)**

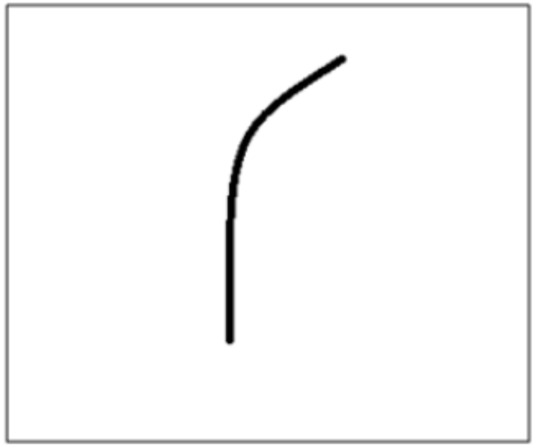
Image Credit: https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/

Image Filter: What Does It Do?

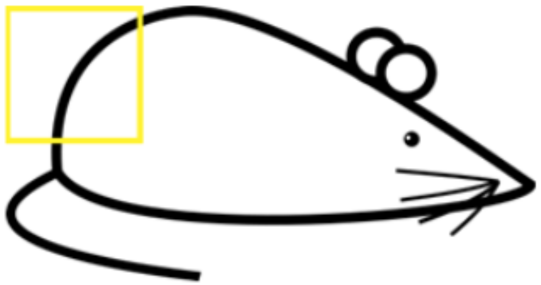
- e.g.,

This Filter is a Curve Detector!

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0



Filter Overlaid on Image (Big Response!)



Filter Overlaid on Image (Small Response!)

Image Credit: https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/

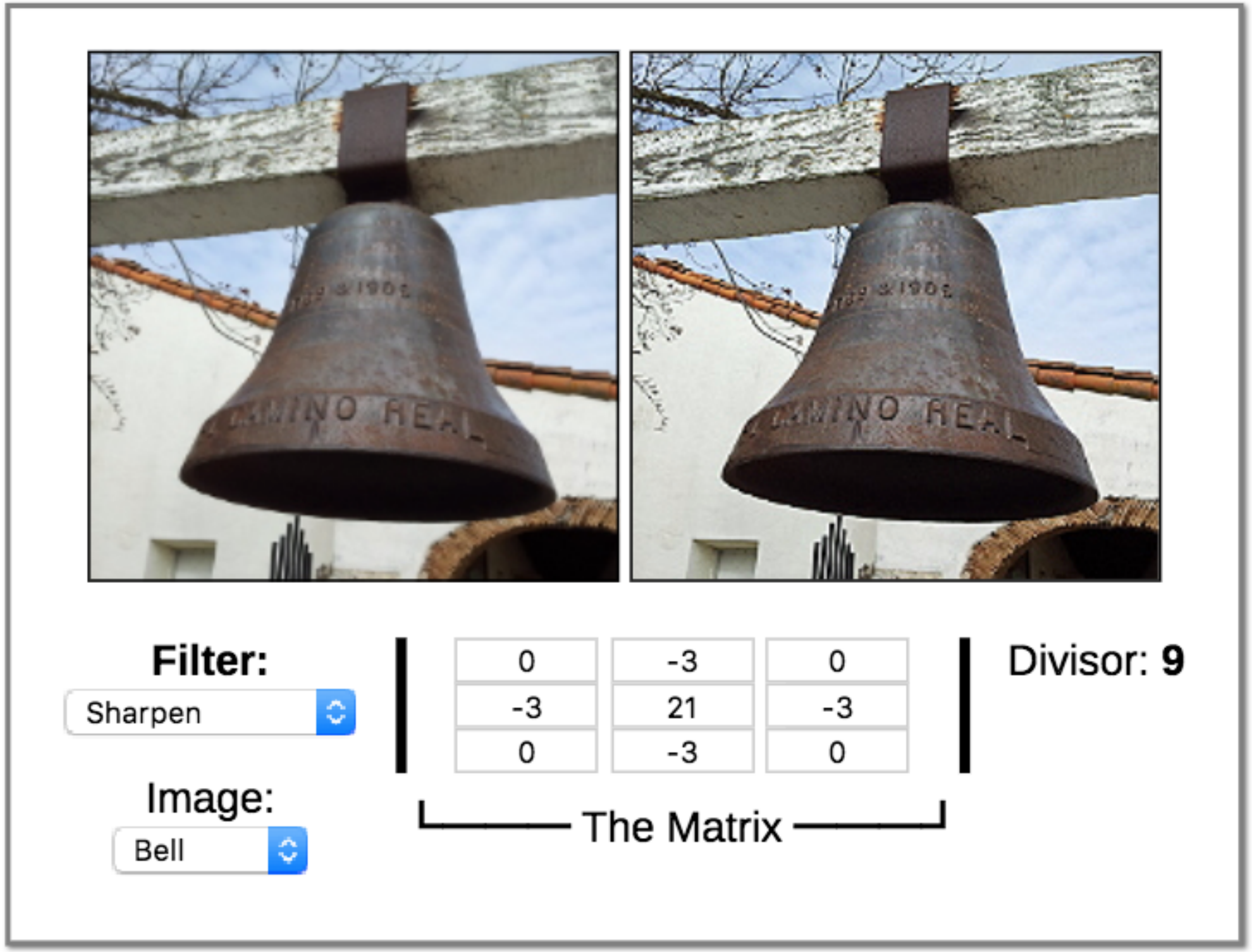
Different Filters Detect Different Features

	Filter	Feature Map
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	

	Filter	Feature Map
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
Gaussian blur (approximation)	$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	

https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/

Different Filters Detect Different Features

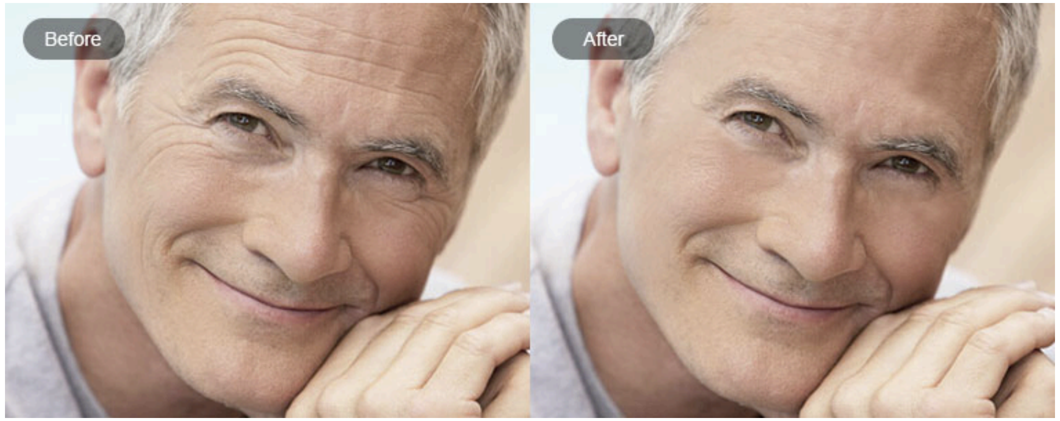


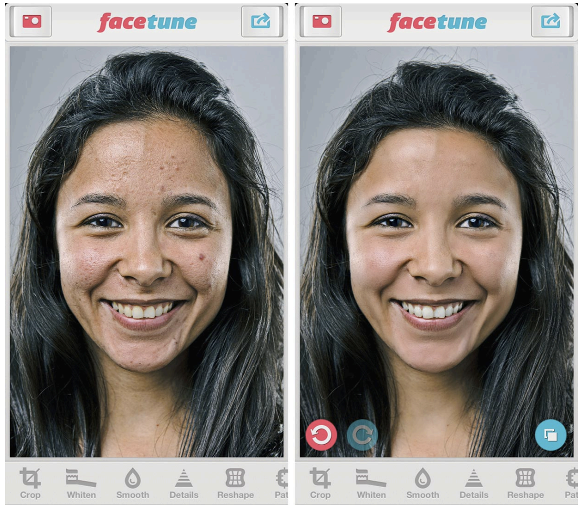
Demo: http://beej.us/blog/data/convolution-image-processing/

Group Discussion

1. How would you design a linear filter to "brighten" an image

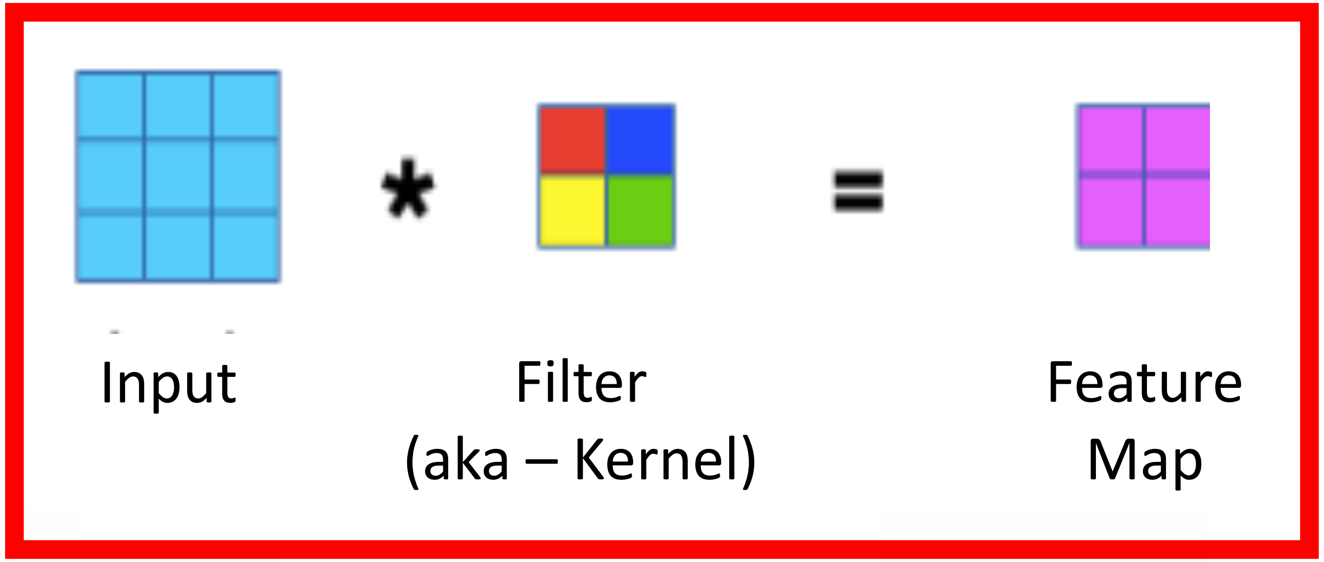
2. How would you design a linear filter to remove wrinkles/blemishes?



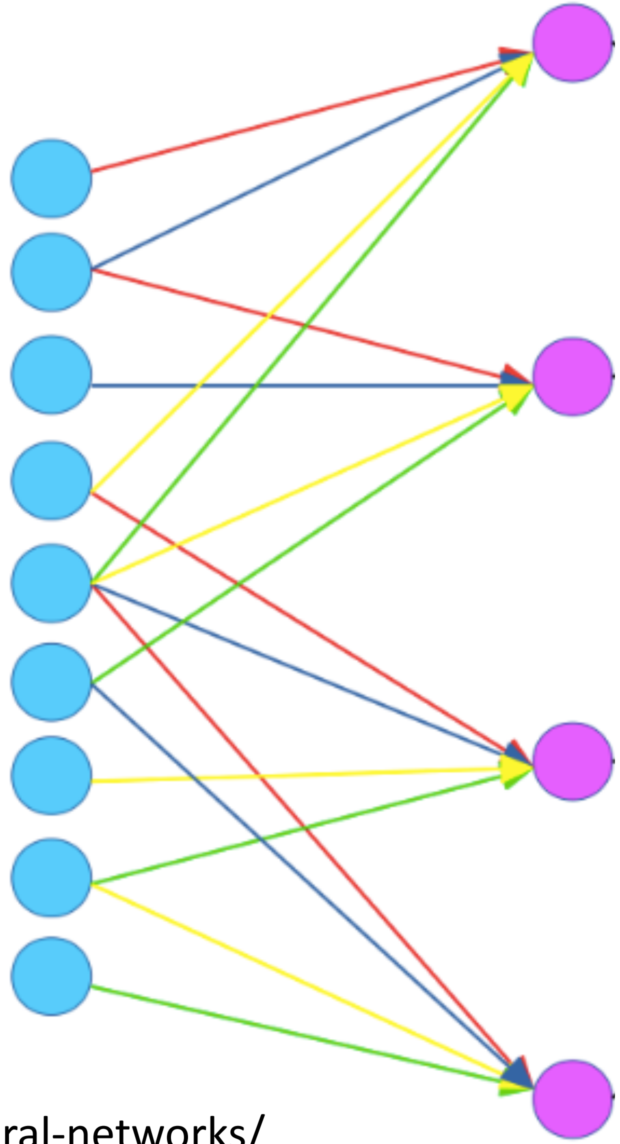


Convolutional Layer: Applies Linear Filter

- Note, previous examples show the “cross-correlation” function
- Many neural network libraries use “cross correlation” interchangeably with “convolution”; for mathematicians, these are technically different



Way to Interpret Neural Network



https://www.jefkine.com/general/2016/09/05/backpropagation-in-convolutional-neural-networks/

Convolutional Layer: Implementation Details

- **Padding**: add values at the image boundaries to preserve image size

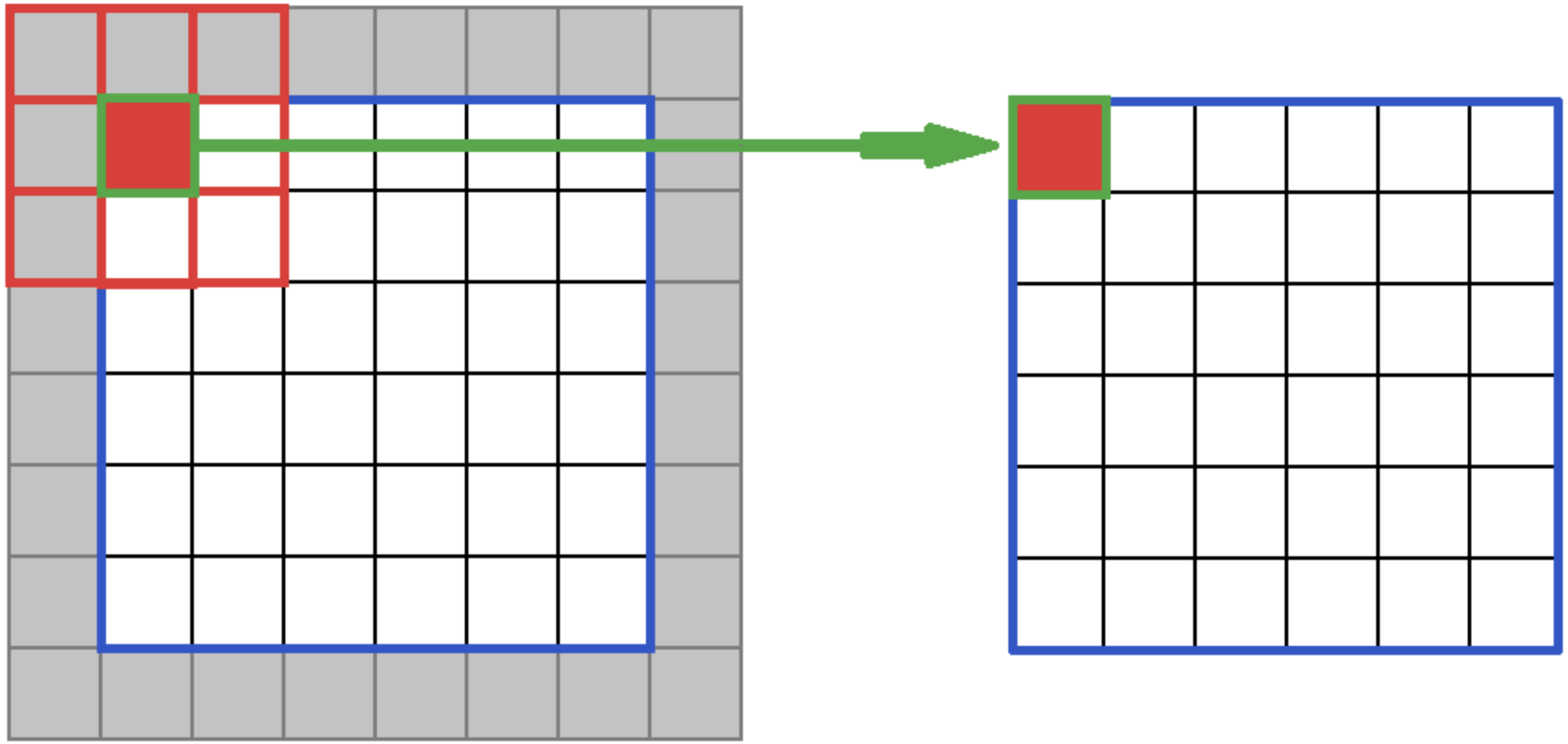


Image Credit: https://software.intel.com/en-us/node/586159

Convolutional Layer: Implementation Details

- **Stride**: how many steps taken spatially before applying a filter
  - e.g., 2x2

Image

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

Filter

1	0	1
0	1	0
1	0	1

Feature Map

4	4
2	4

http://deeplearning.net/software/theano/tutorial/conv_arithmetic.html

Convolutional Layer: Implementation Details

- Demo:

http://deeplearning.net/software/theano/tutorial/conv_arithmetic.html

Group Discussion

1. Why would you choose a larger versus a smaller filter?

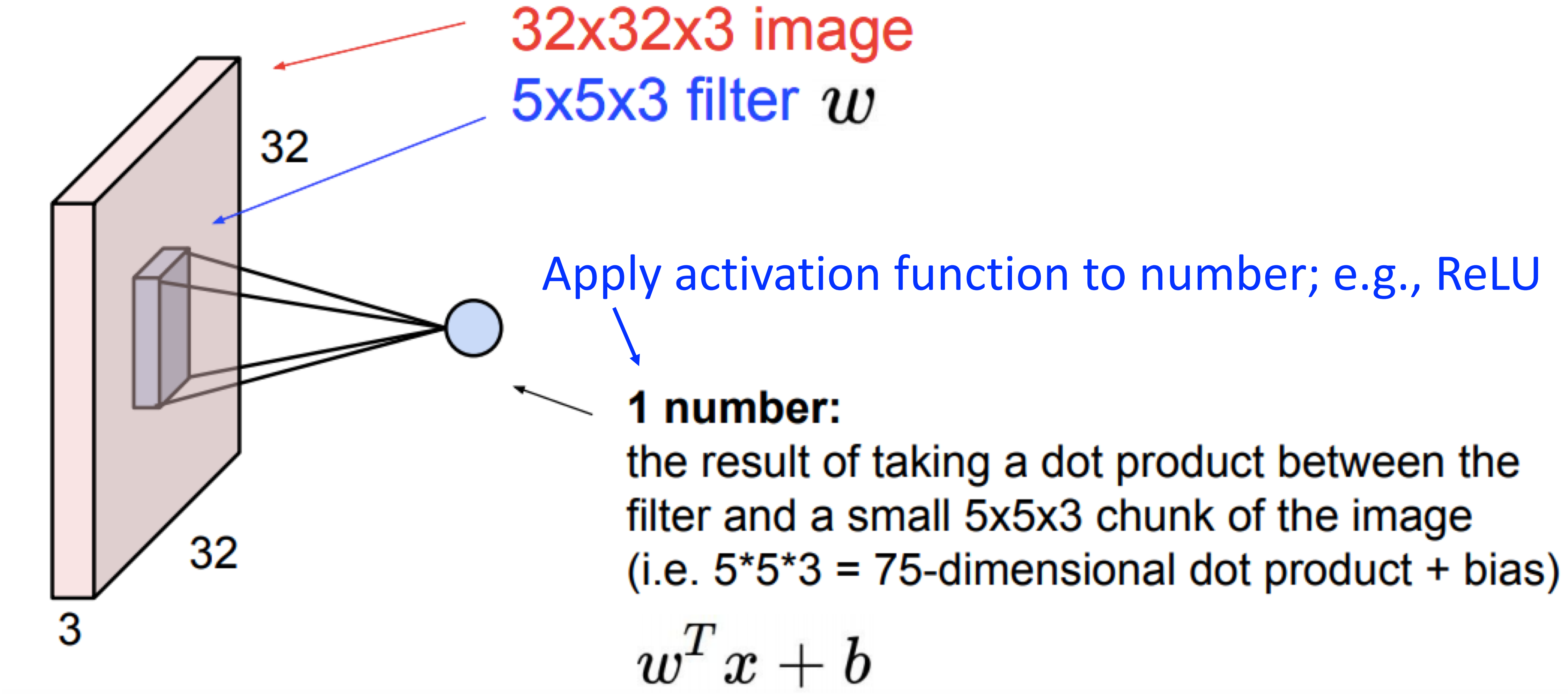
1	1	1
1	1	1
1	1	1

1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1

1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1

2. Why choose a larger versus smaller stride size?

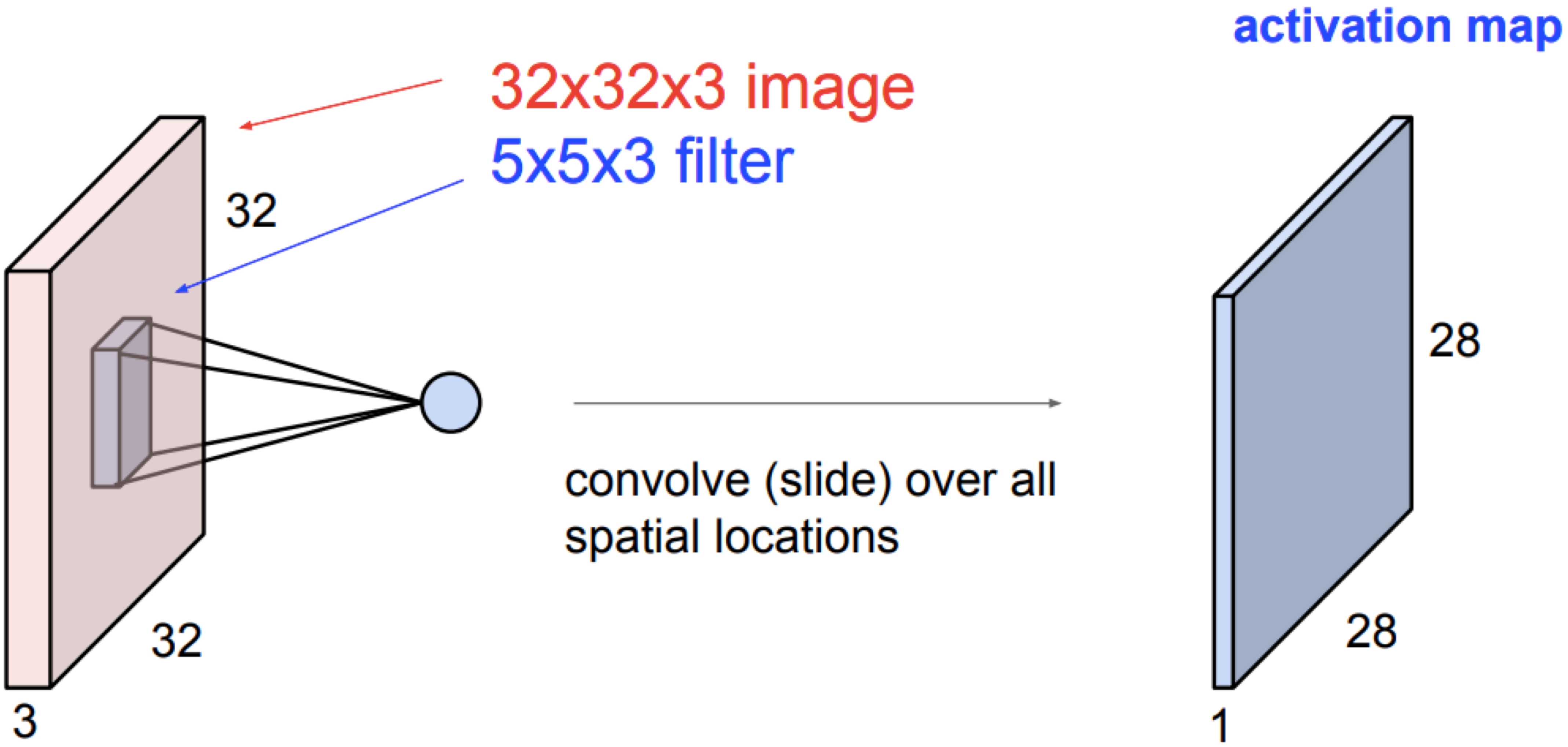
Convolutional Layer: Introduce Non-Linearity



Apply activation function to number; e.g., ReLU

Slide Credit: http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture05.pdf

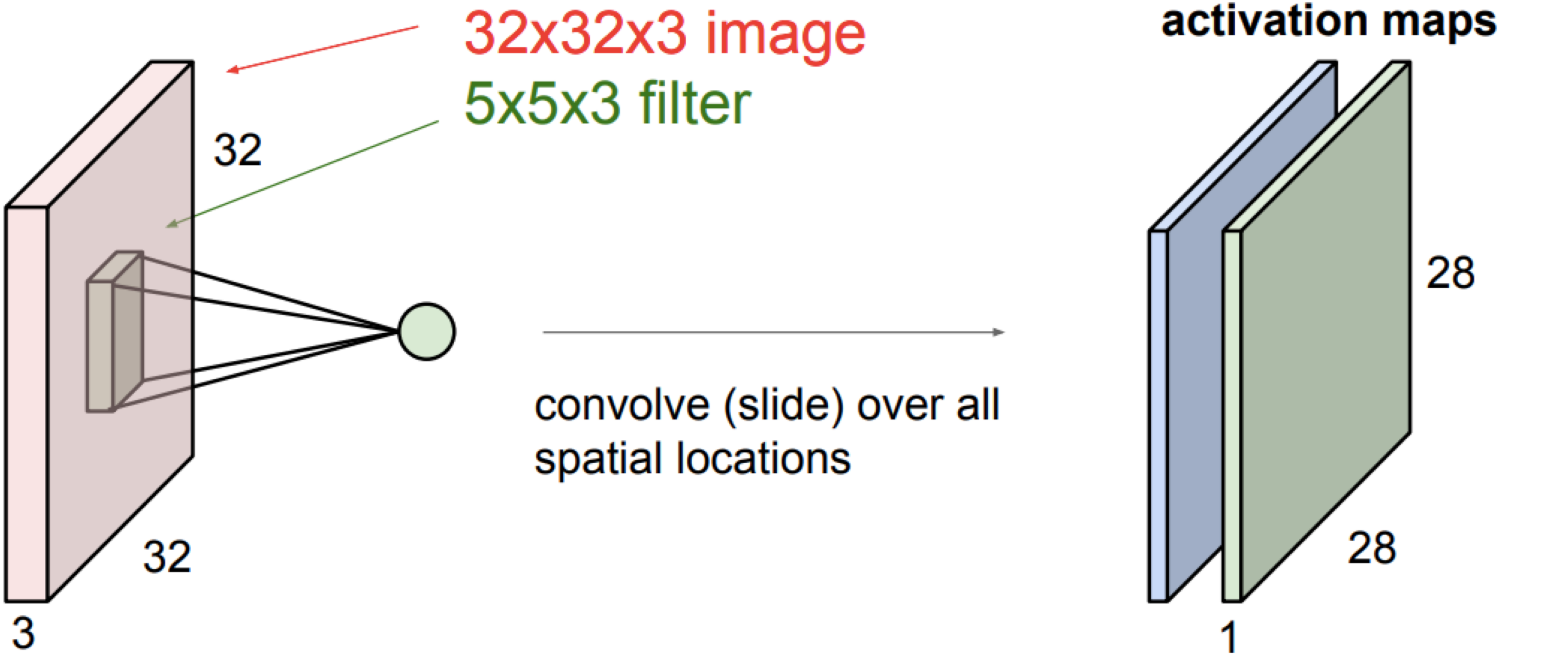
Convolutional Layer



Slide Credit: http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture05.pdf

consider a second, green filter

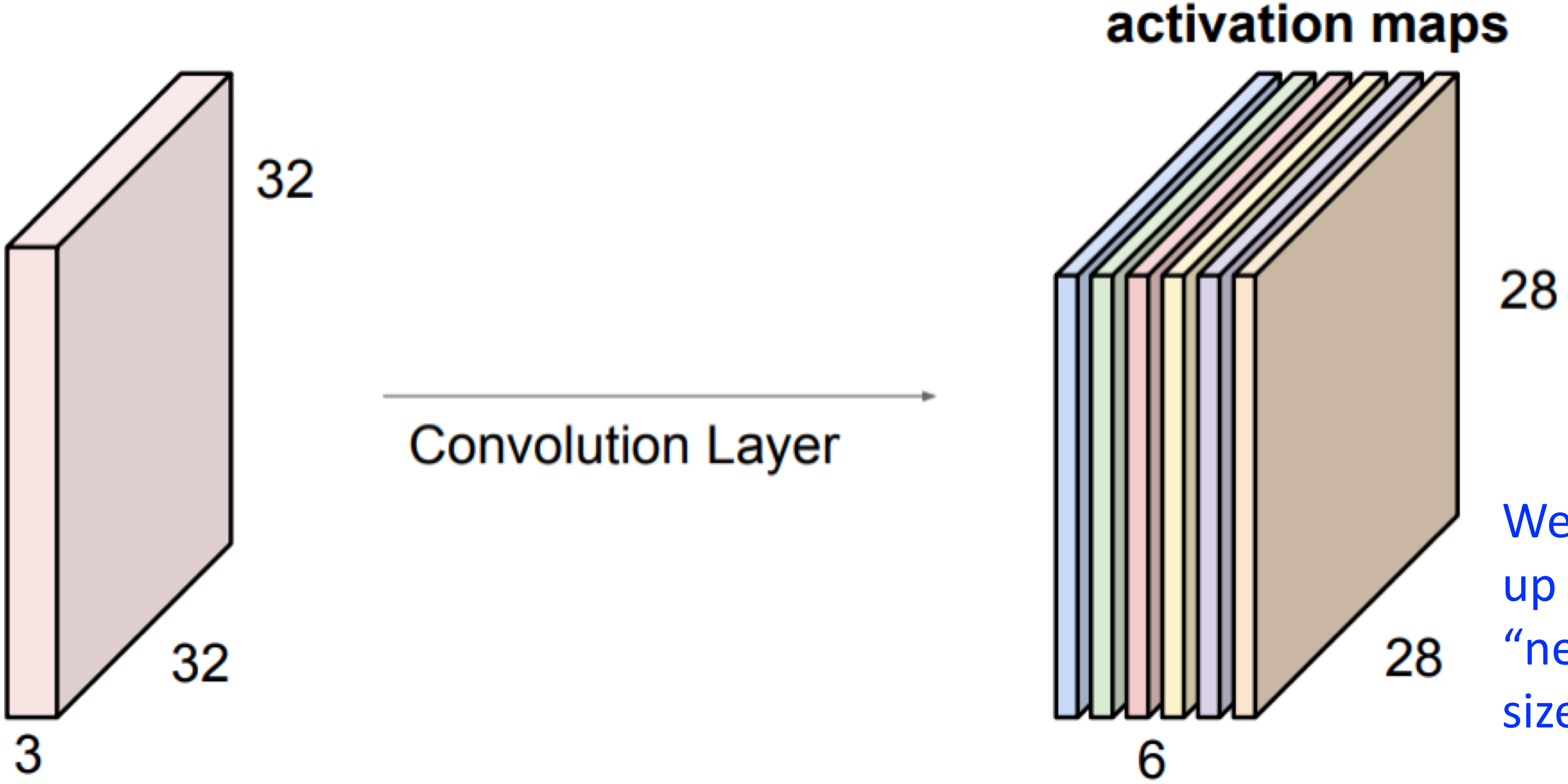
Convolutional Layer



Slide Credit: http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture05.pdf

Convolutional Layer

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

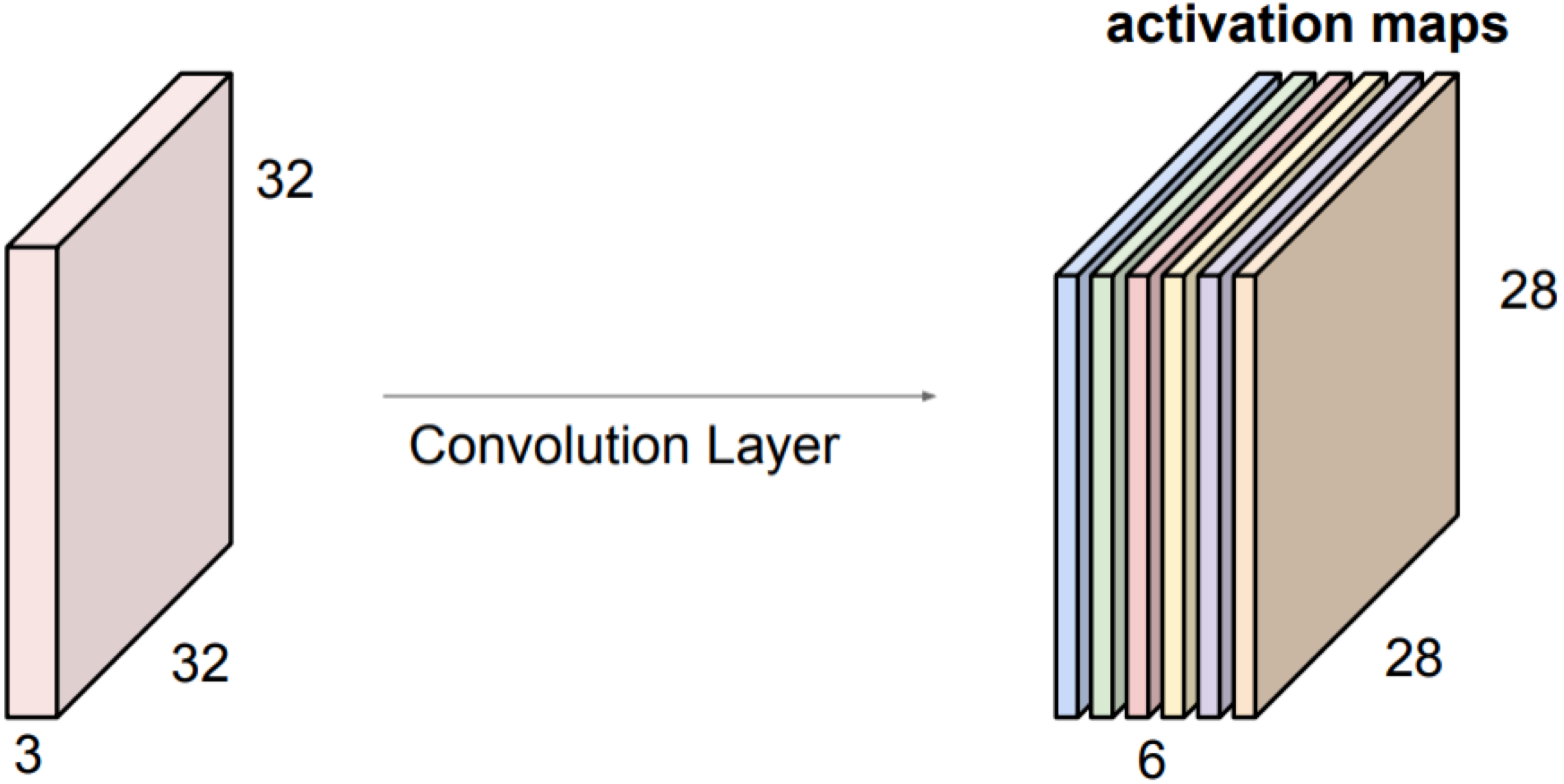


We stack these up to get a "new image" of size 28x28x6!

Slide Credit: http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture05.pdf

Convolutional Layer: Parameters to Learn

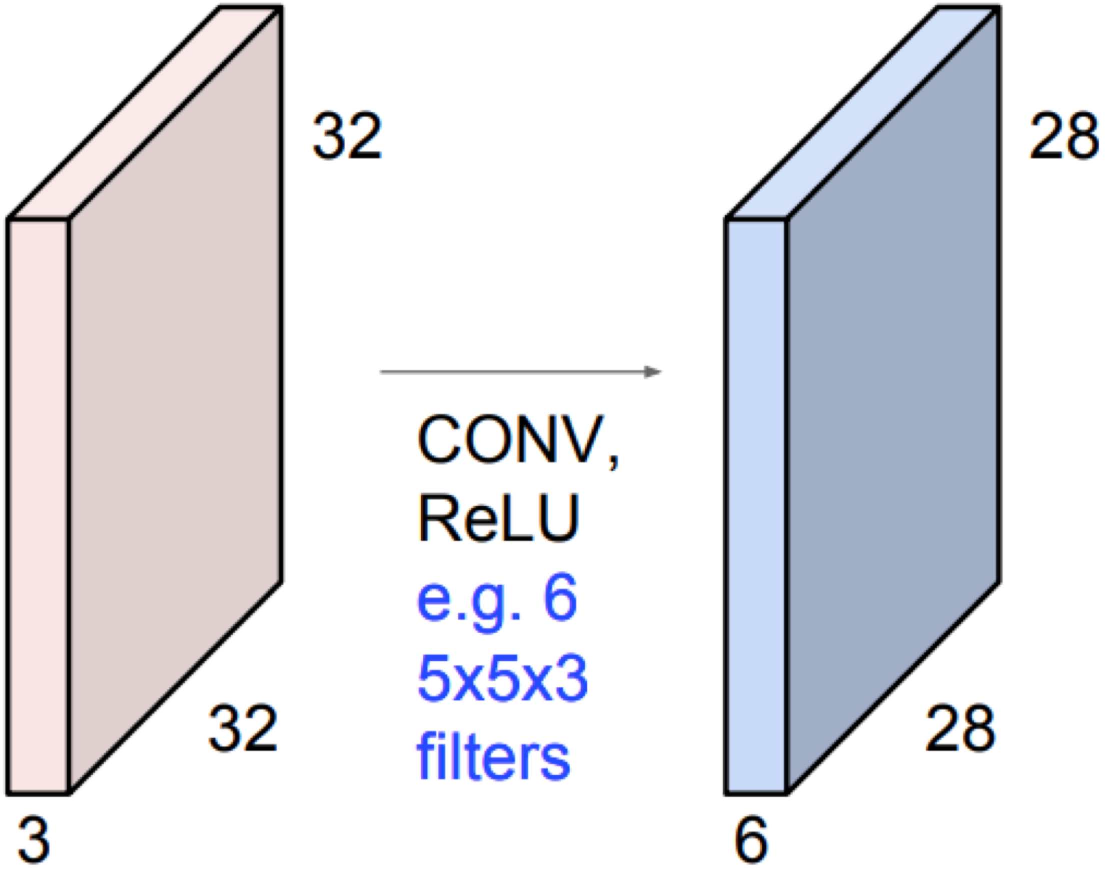
Parameters: bank of filters and biases used to create the activation maps (aka – feature maps)



Slide Credit: http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture05.pdf

Convolutional Neural Networks (CNNs)

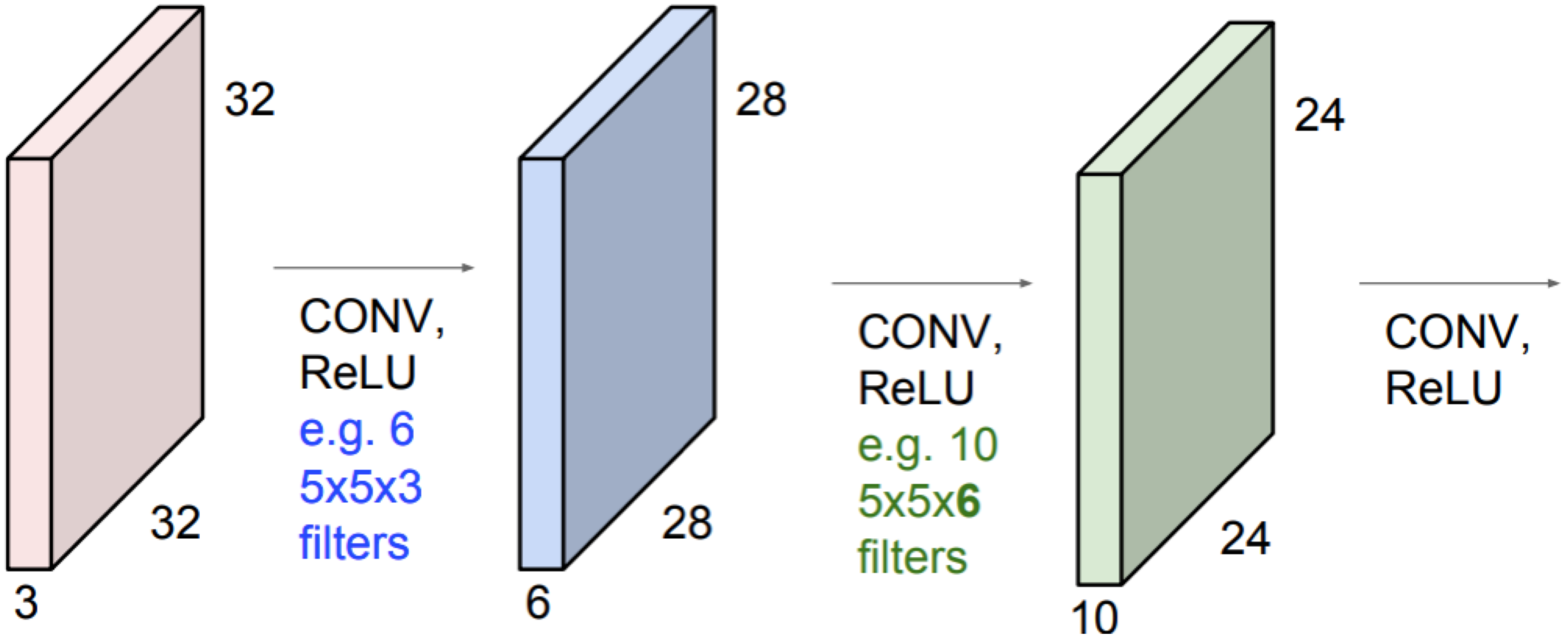
Can then stack a sequence of convolution layers, interspersed with activation functions:



[Slide Credit: http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture05.pdf](http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture05.pdf)

Convolutional Neural Networks (CNNs)

Can then stack a sequence of convolution layers, interspersed with activation functions:

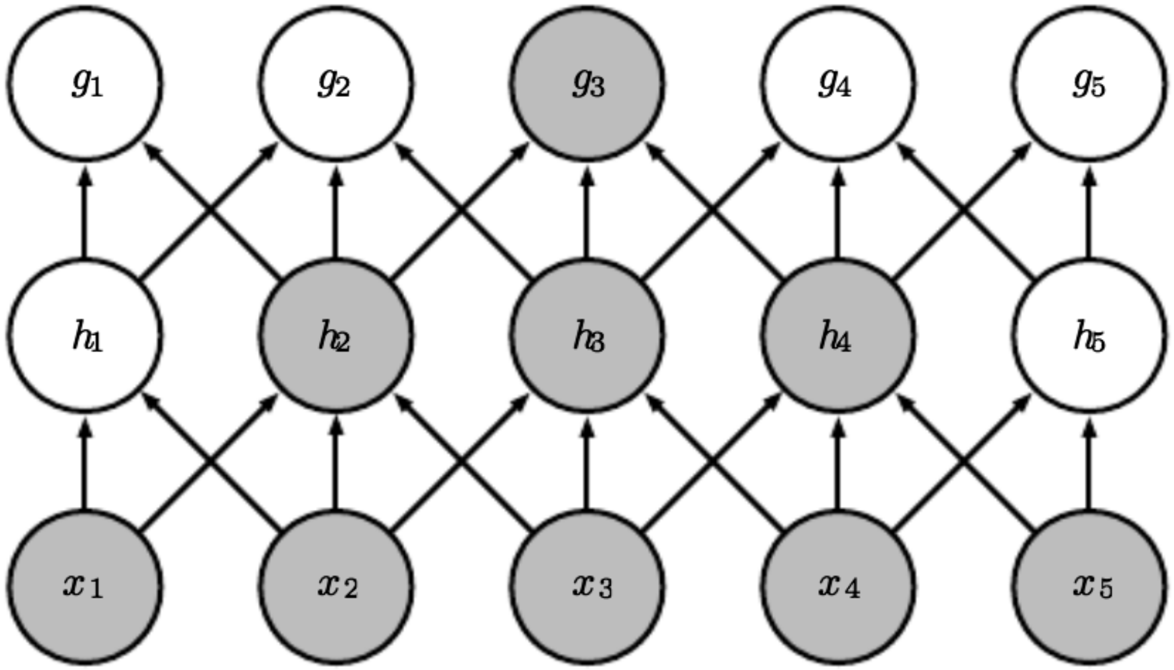


Slide Credit: http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture05.pdf

Convolutional Neural Networks (CNNs)

Can then stack a sequence of convolution layers, interspersed with activation functions:

Stacking many convolutional layers leads to learning patterns in increasingly **larger regions of the input (e.g., pixel) space.**



https://www.deeplearningbook.org/contents/convnets.html

Convolutional Layer: Training

1. Forward Pass:
    - For convolutional layers:
        1. Apply convolution operation with each filter
        2. Add biases (one per each output image)
        3. Apply an activation function to all the pixels of the output images

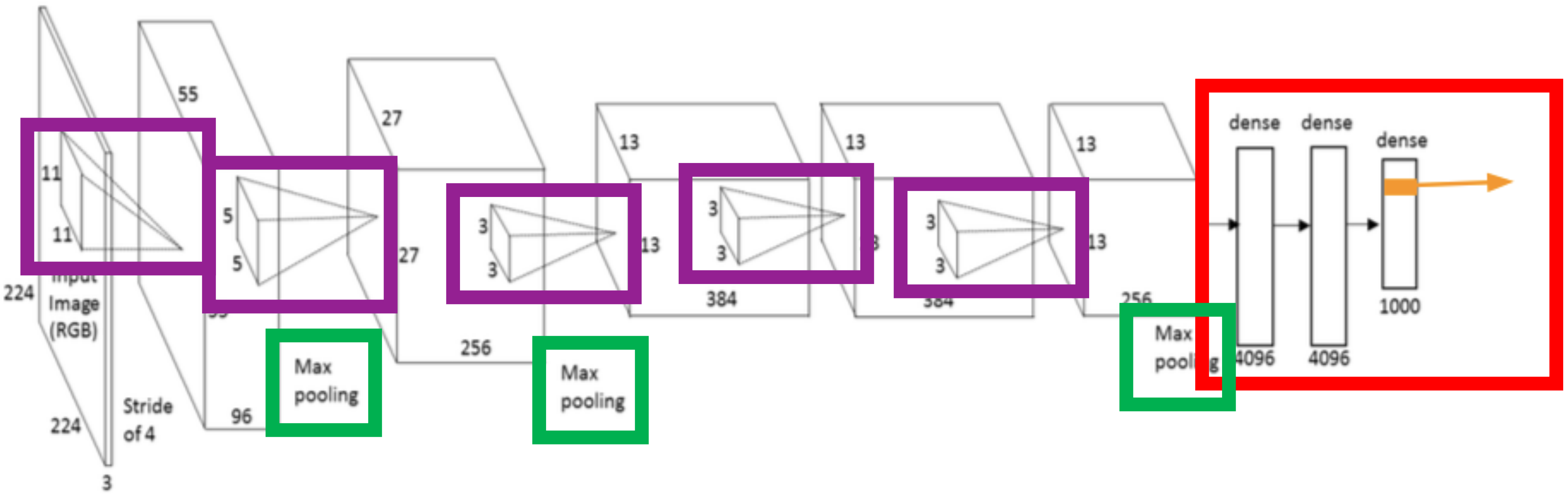
2. Compute prediction error (with respect to a loss function)

3. Backpropagate error to all model parameters (determine how changing a single pixel in the weight kernel affects the loss function)

4. Update all model parameters (kernel weights, biases)

CNN: Summary of Convolution Layers

- e.g., AlexNet extracts useful features of lower dimension prior to passing it to MLP with:
  - **Convolutional layers**
  - Pooling Layers



Slide Credit: https://www.slideshare.net/xavigiro/saliency-prediction-using-deep-learning-techniques

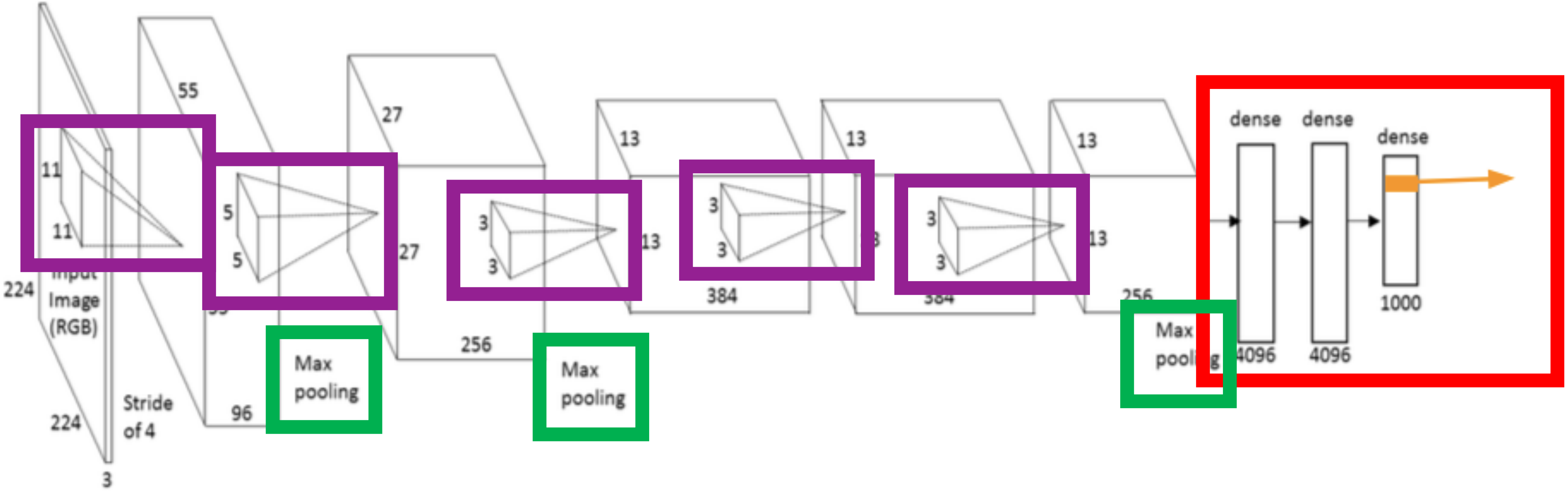
A. Krizhevsky, I. Sutskever, G. E. Hinton "ImageNet classification with deep convolutional neural networks"

Today’s Topics

- History of Convolutional Neural Networks (CNNs)
- CNNs – Convolutional Layers
- CNNs – Pooling Layers
- Deep Features
- Guest Speaker: Dr. Peter Anderson, Research Scientist at Google

CNN: Pooling Layers

- AlexNet extracts useful features of lower dimension prior to passing it to MLP with:
  - Convolutional layers
  - Pooling Layers

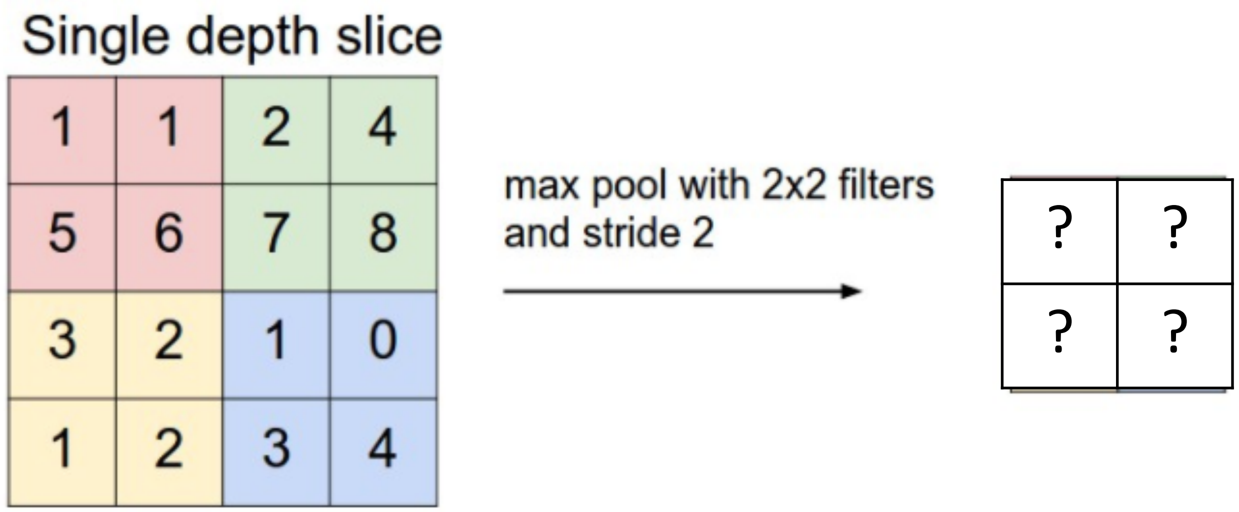


Slide Credit: https://www.slideshare.net/xavigiro/saliency-prediction-using-deep-learning-techniques

A. Krizhevsky, I. Sutskever, G. E. Hinton "ImageNet classification with deep convolutional neural networks"

Pooling Layer: Summarizes Neighborhood

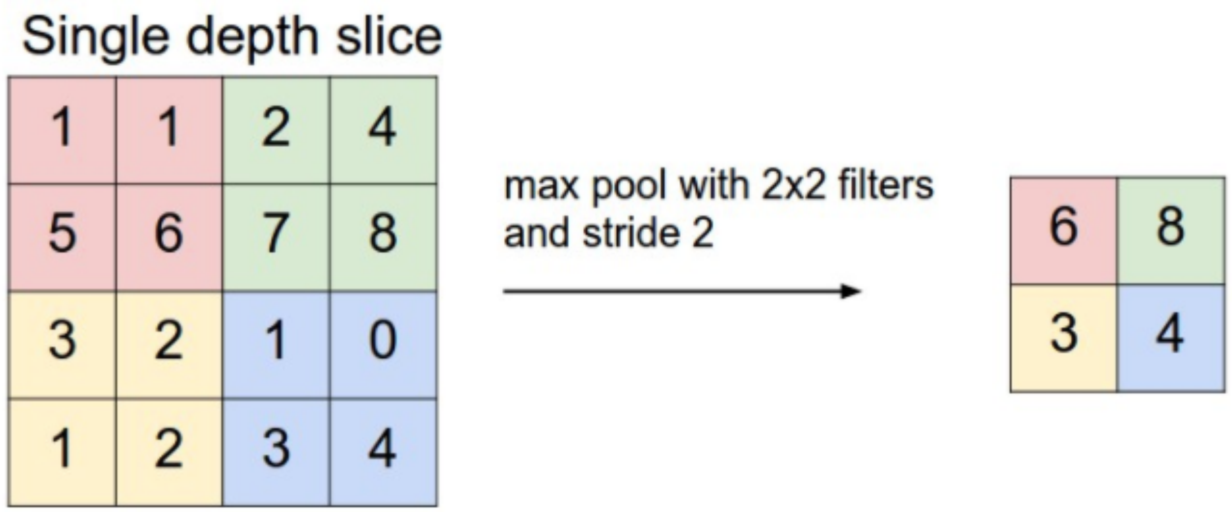
- **Max-pooling***:* partitions input into a set of non-overlapping rectangles and outputs the maximum value for each chunk



http://cs231n.github.io/convolutional-networks/#pool

Pooling Layer: Summarizes Neighborhood

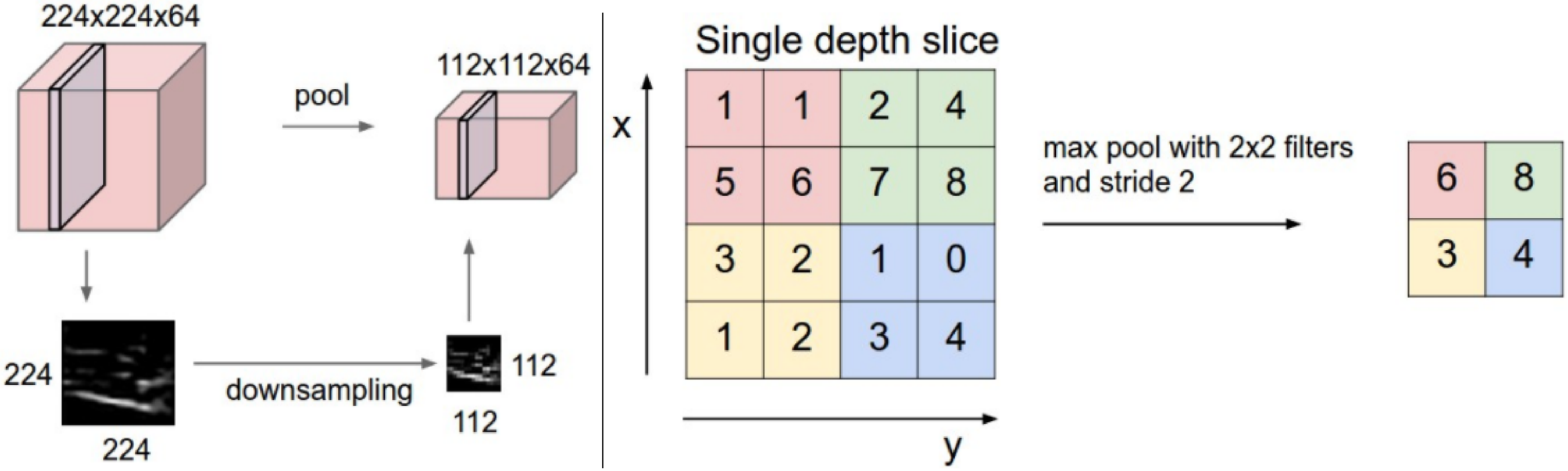
- **Max-pooling***:* partitions input into a set of non-overlapping rectangles and outputs the maximum value for each chunk



http://cs231n.github.io/convolutional-networks/#pool

Pooling Layer: Summarizes Neighborhood

- **Max-pooling***:* partitions input into a set of non-overlapping rectangles and outputs the maximum value for each chunk

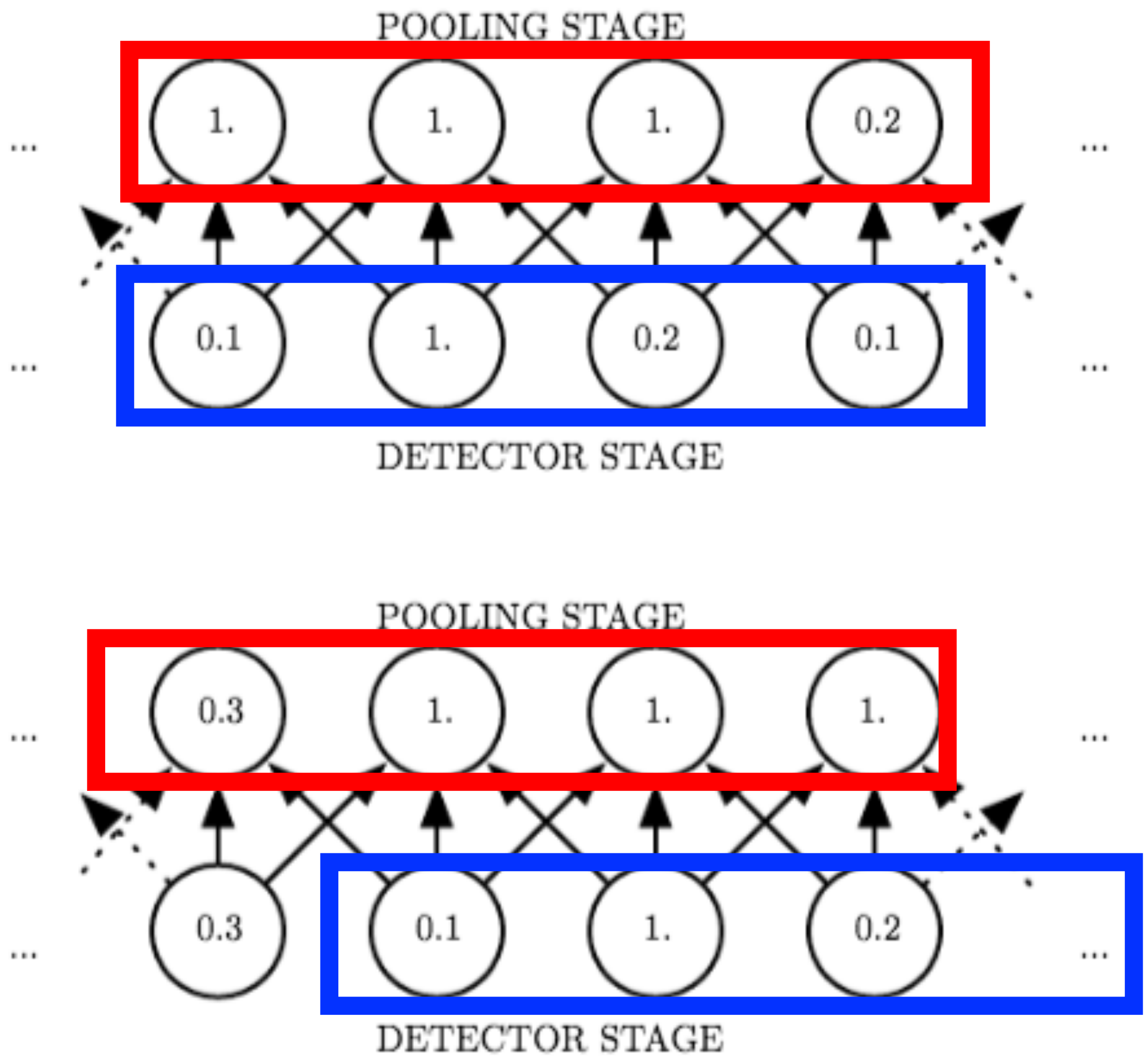


http://cs231n.github.io/convolutional-networks/#pool

Pooling Layer

- Resilient to small translations

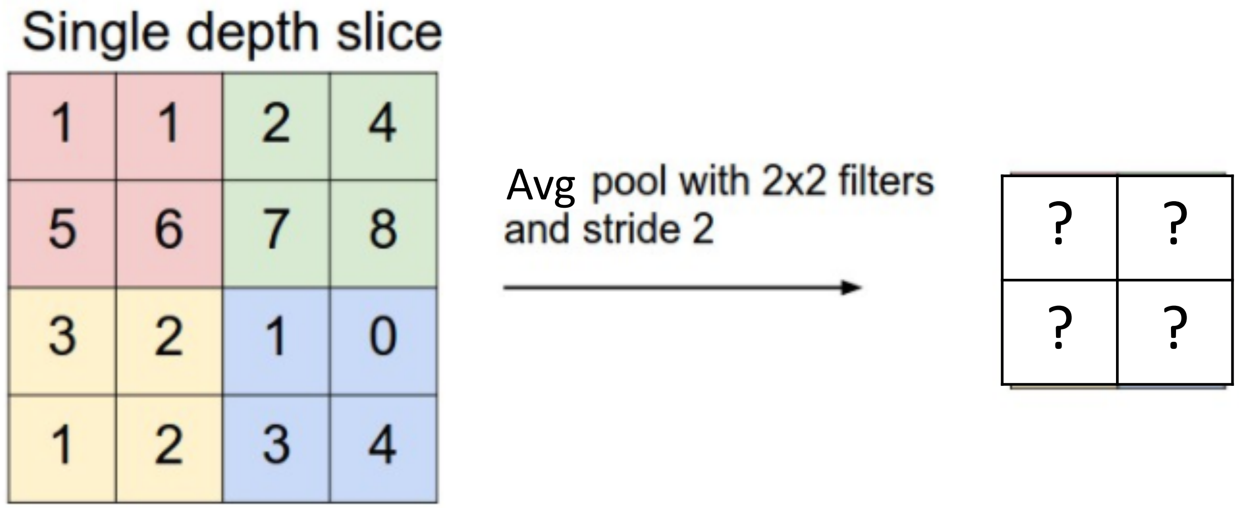
- e.g.,
  - Input: all values change (shift right)
  - Output: only half the values change



https://www.deeplearningbook.org/contents/convnets.html

Pooling Layer: Summarizes Neighborhood

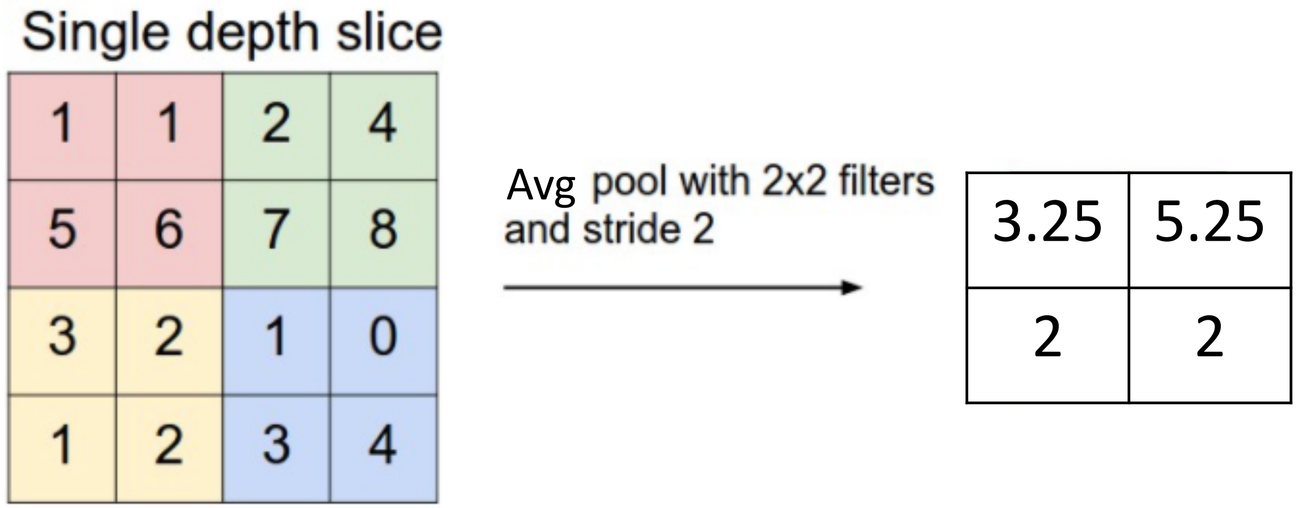
- **Max-pooling**: partitions input into a set of non-overlapping rectangles and outputs the maximum value for each chunk
- **Average-pooling**: partitions input into a set of non-overlapping rectangles and outputs the average value for each chunk



http://cs231n.github.io/convolutional-networks/#pool

Pooling Layer: Summarizes Neighborhood

- **Max-pooling***:* partitions input into a set of non-overlapping rectangles and outputs the maximum value for each chunk
- **Average-pooling***:* partitions input into a set of non-overlapping rectangles and outputs the average value for each chunk



http://cs231n.github.io/convolutional-networks/#pool

Pooling Layer: Benefits

- How many parameters must be learned?
  - None
- Benefits?
  - Builds in invariance to translations of the input
  - Reduces memory requirements
  - Reduces computational requirements

Today’s Topics

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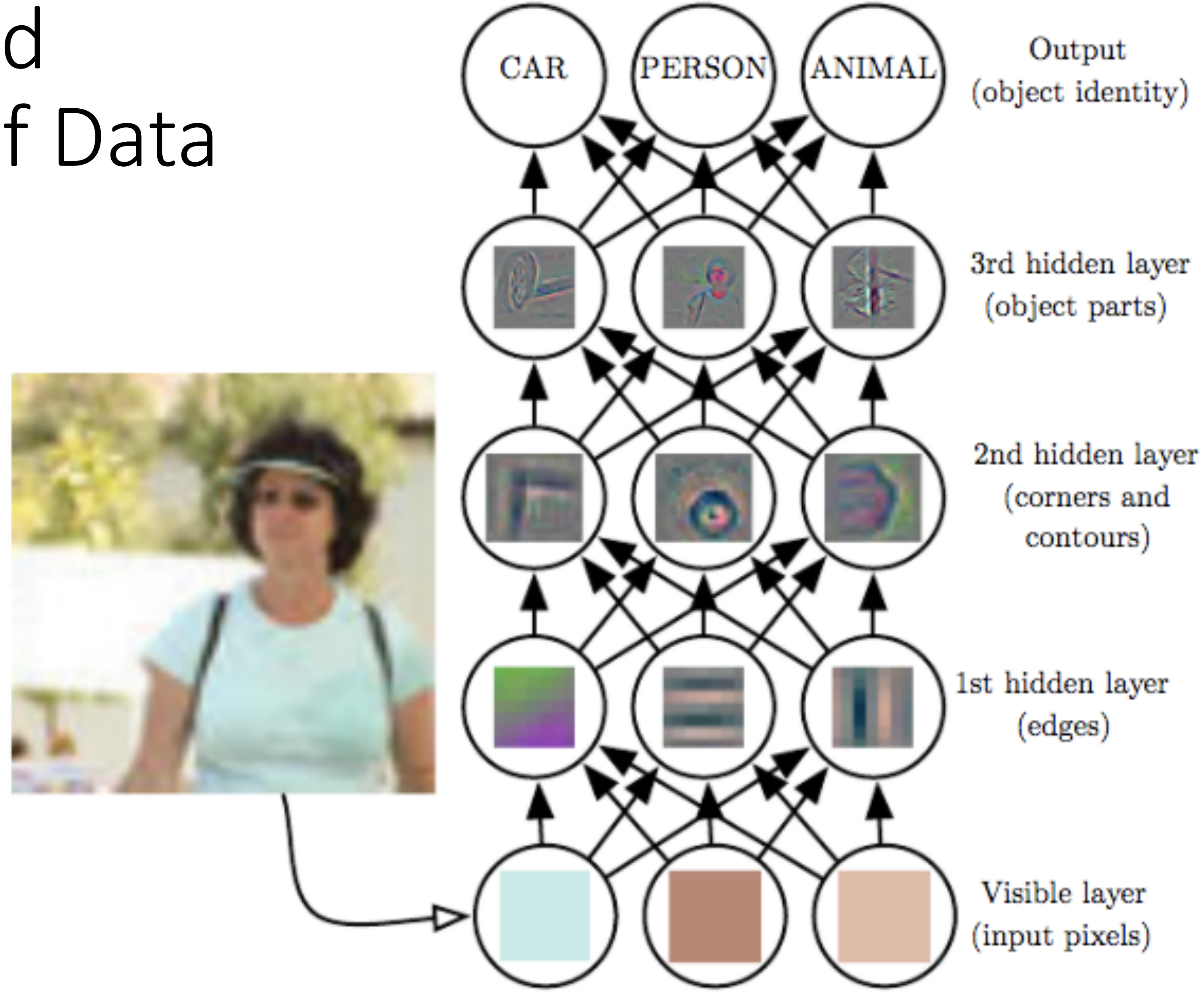
CNN: Learns Good Representation of Data

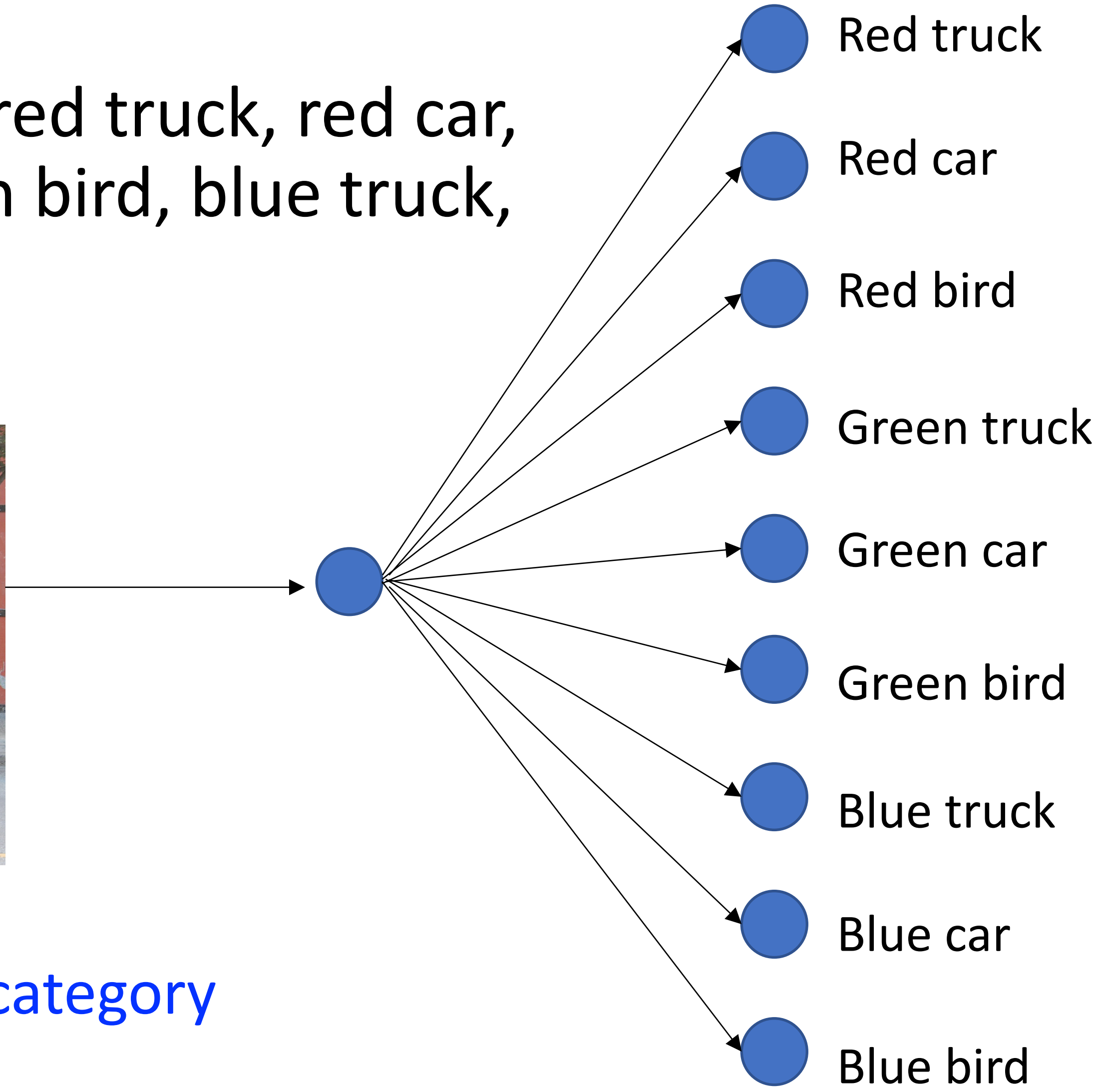


Deep Learning, Ian Goodfellow, Yoshua Bengio, and Aaron Courville

How to Efficiently Describe/Represent Images?

- e.g., predict for given image if it is a: red truck, red car, red bird, green truck, green car, green bird, blue truck, blue car, & blue bird

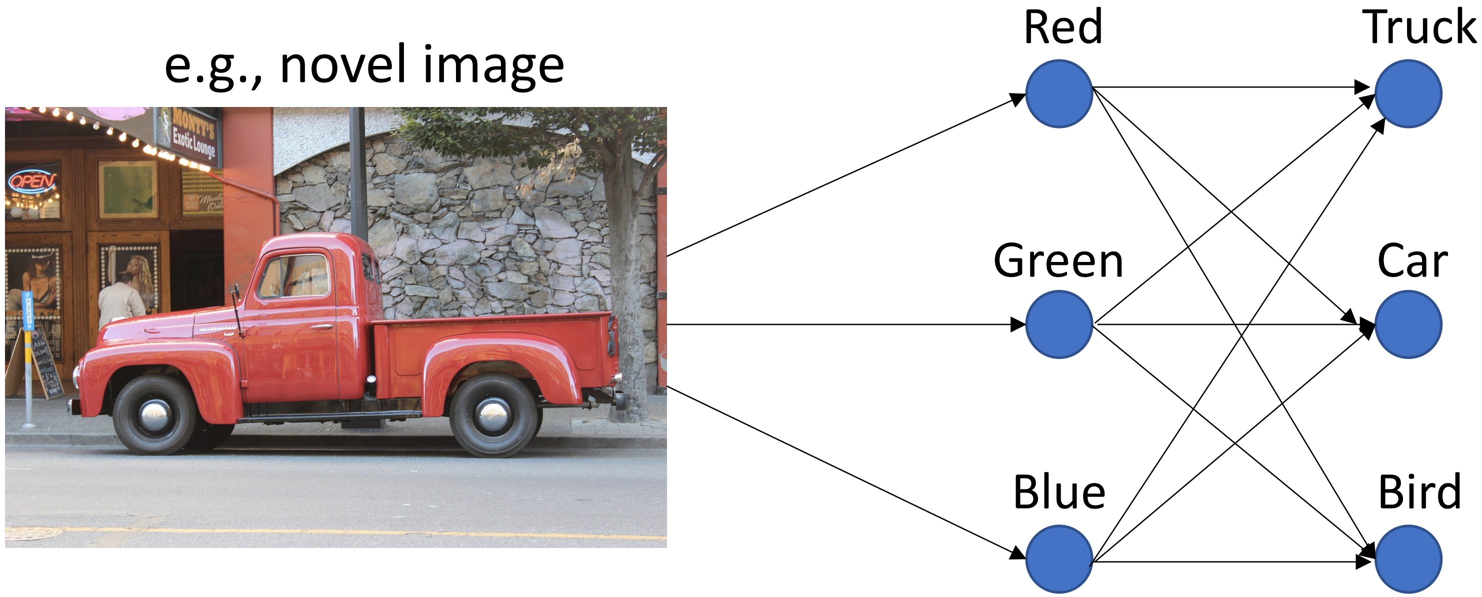
e.g., novel image



Can train a model to predict each category

How to Efficiently Describe/Represent Images?

- e.g., predict for given image if it is a: red truck, red car, red bird, green truck, green car, green bird, blue truck, blue car, & blue bird



Can design a more efficient model to first capture color and then objects (greater parameter efficiency using hierarchical layers of features)!

CNN: Learns Good Representation of Data

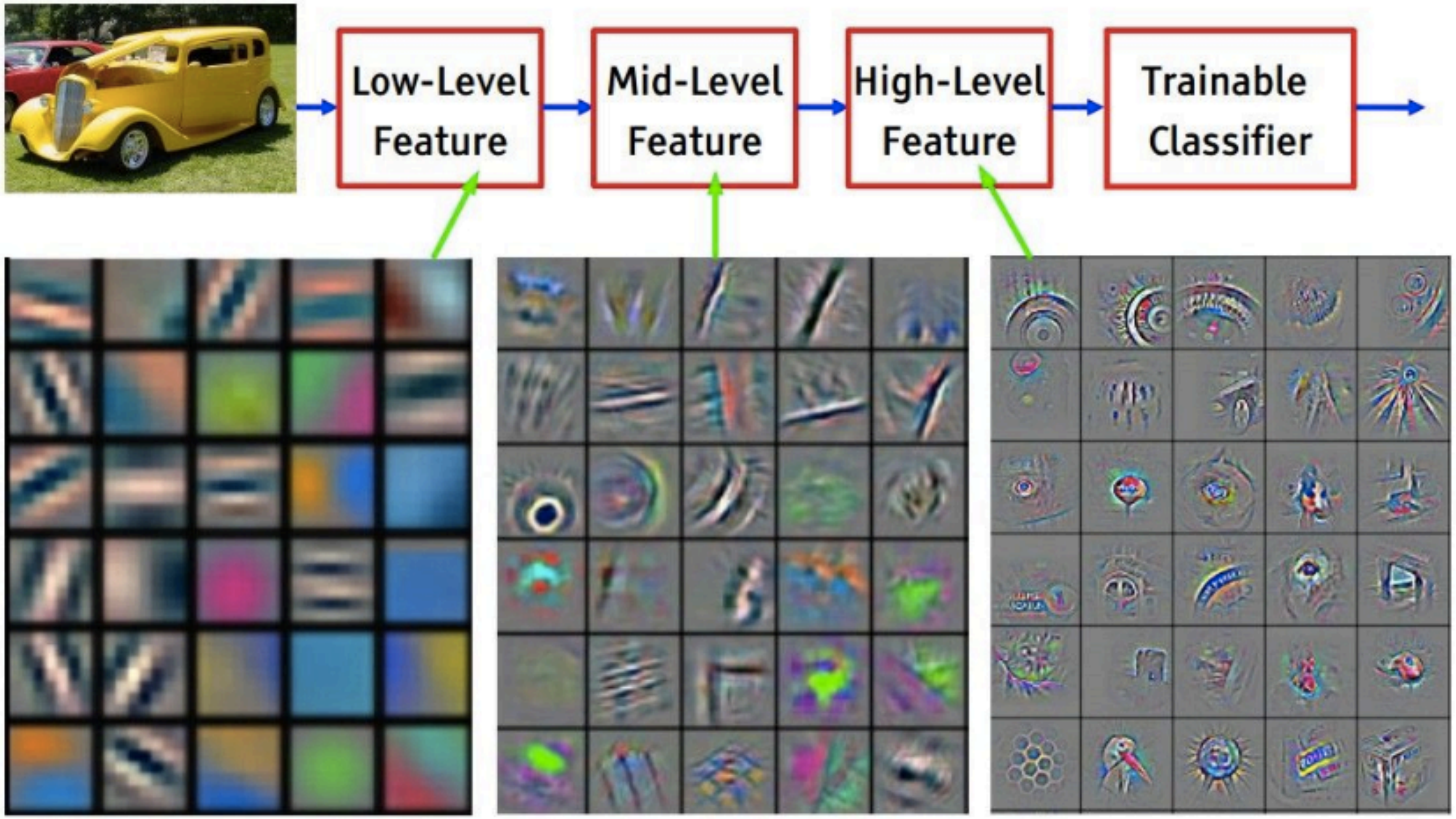
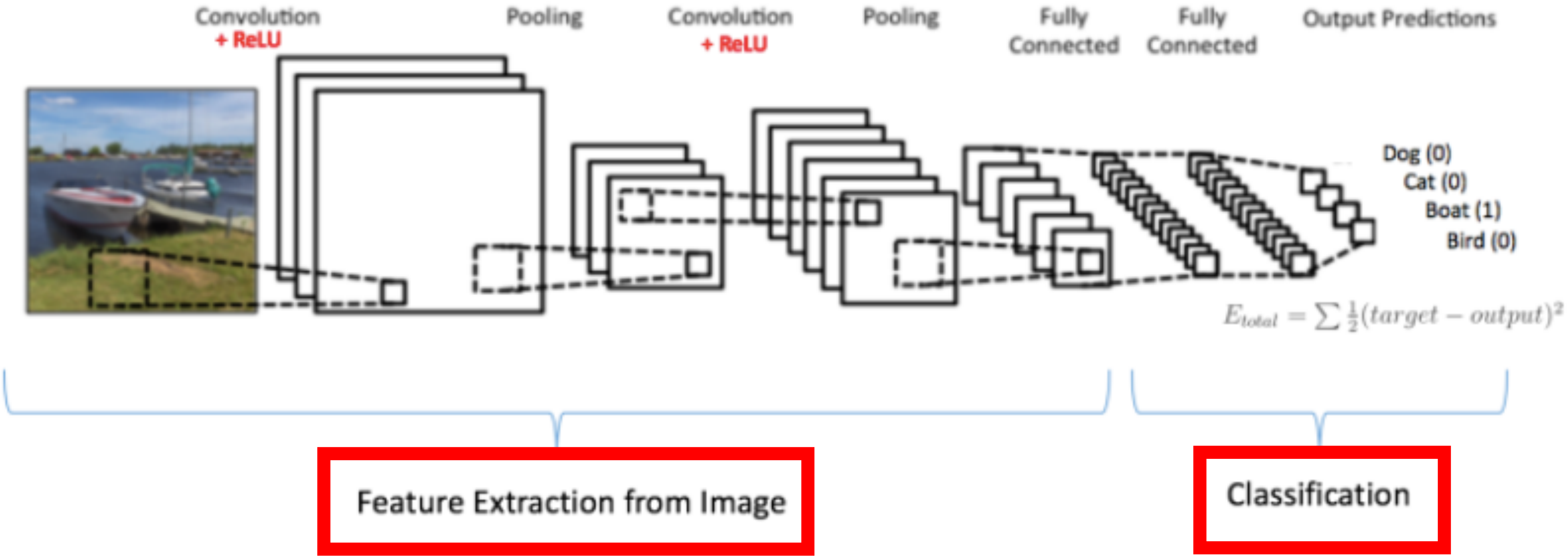


Figure Credit: Yann LeCun

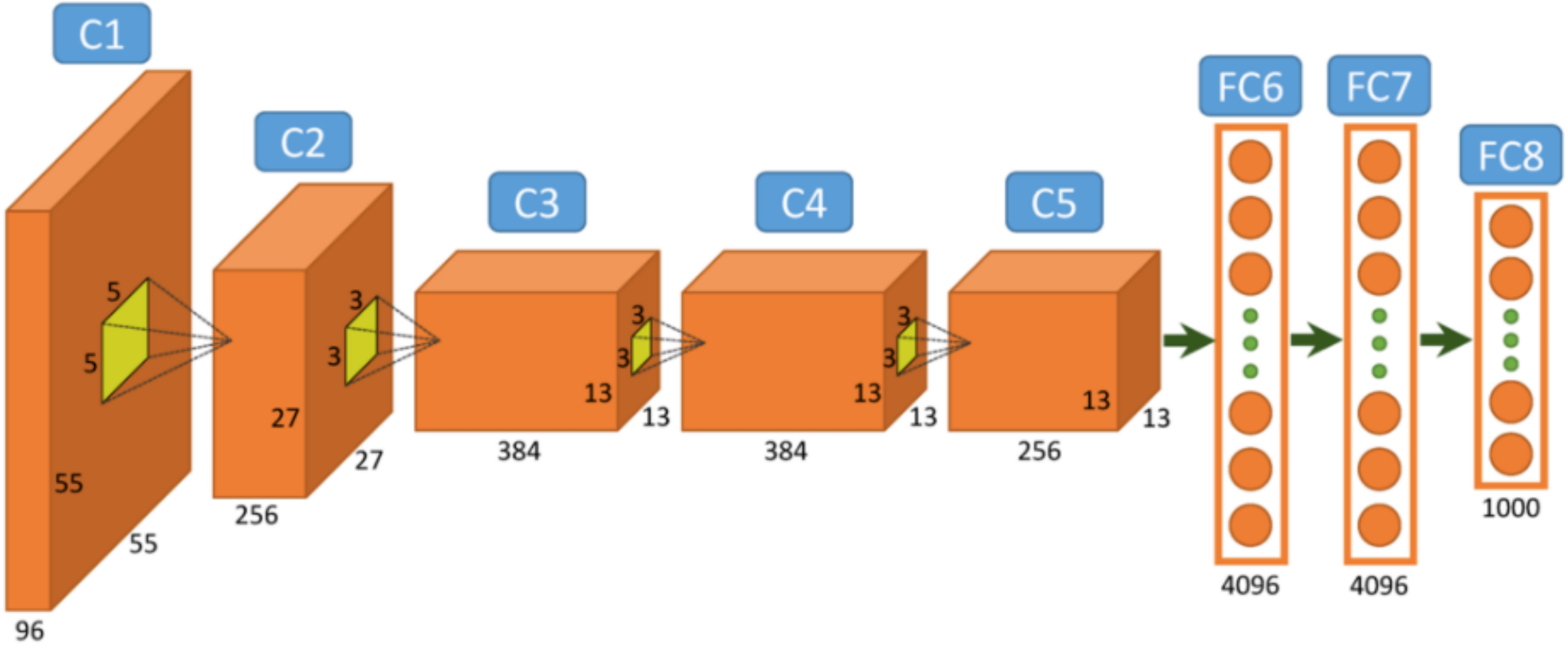
CNN: Intuition of Different Layers



https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/

AlexNet Deep Features

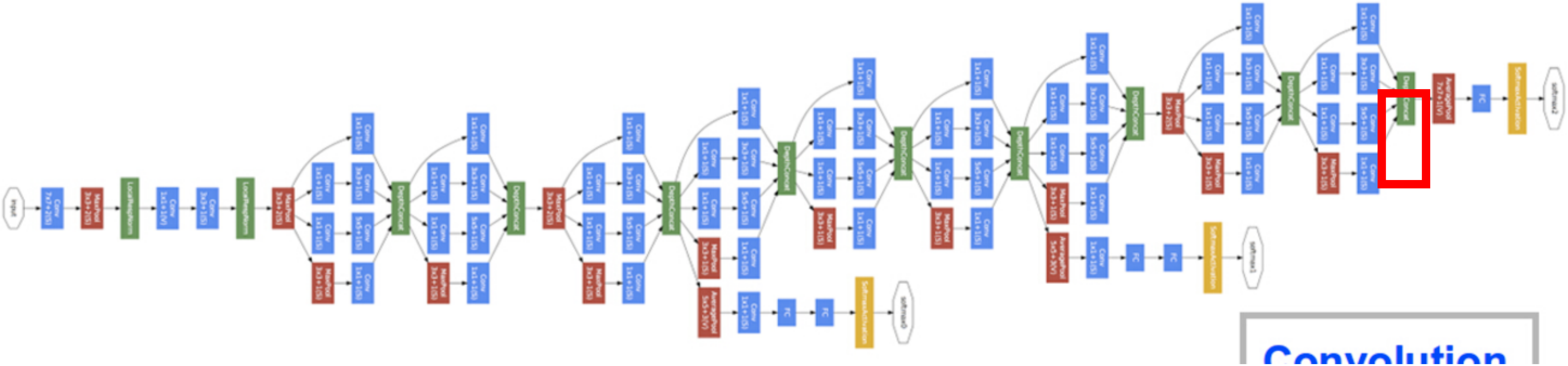
- What is the dimensionality of the fc6 feature?
- What is the dimensionality of the fc7 feature?



https://www.researchgate.net/figure/Architecture-of-Alexnet-From-left-to-right-input-to-output-five-convolutional-layers_fig2_312303454

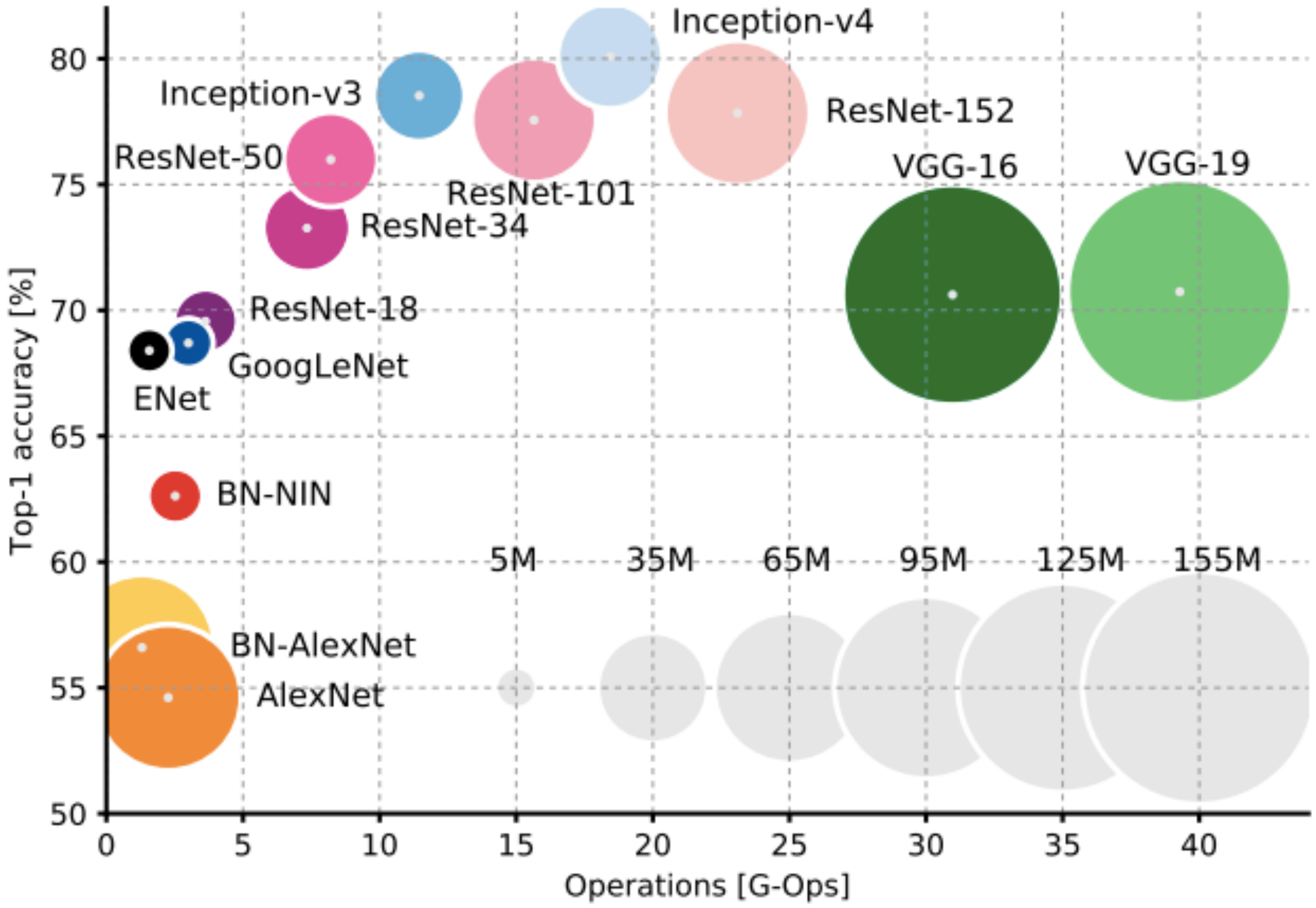
GoogleNet (Inception) Deep Features

- What is the dimensionality of the inception features?



http://joelouismarino.github.io/blog_posts/blog_googlenet_keras.html

And Many More Features From…



- VGG16
- VGG19
- ResNet
- Enet
- …

CNN Architectures: Input Beyond Images…

- Acoustic/Speech: input treated as an image, with one axis corresponding to time and the other to frequency of spectral components

- Video: one axis corresponds to time, one to the height of the video frame, and one to the width of the video frame

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