Lecture 12

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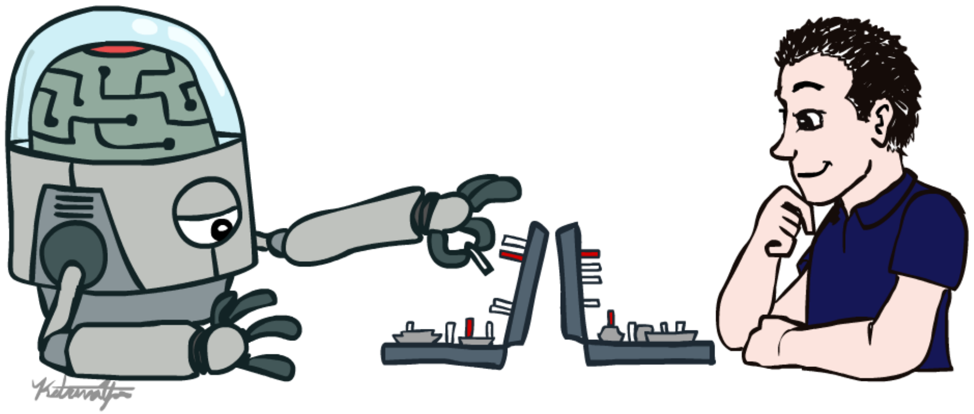
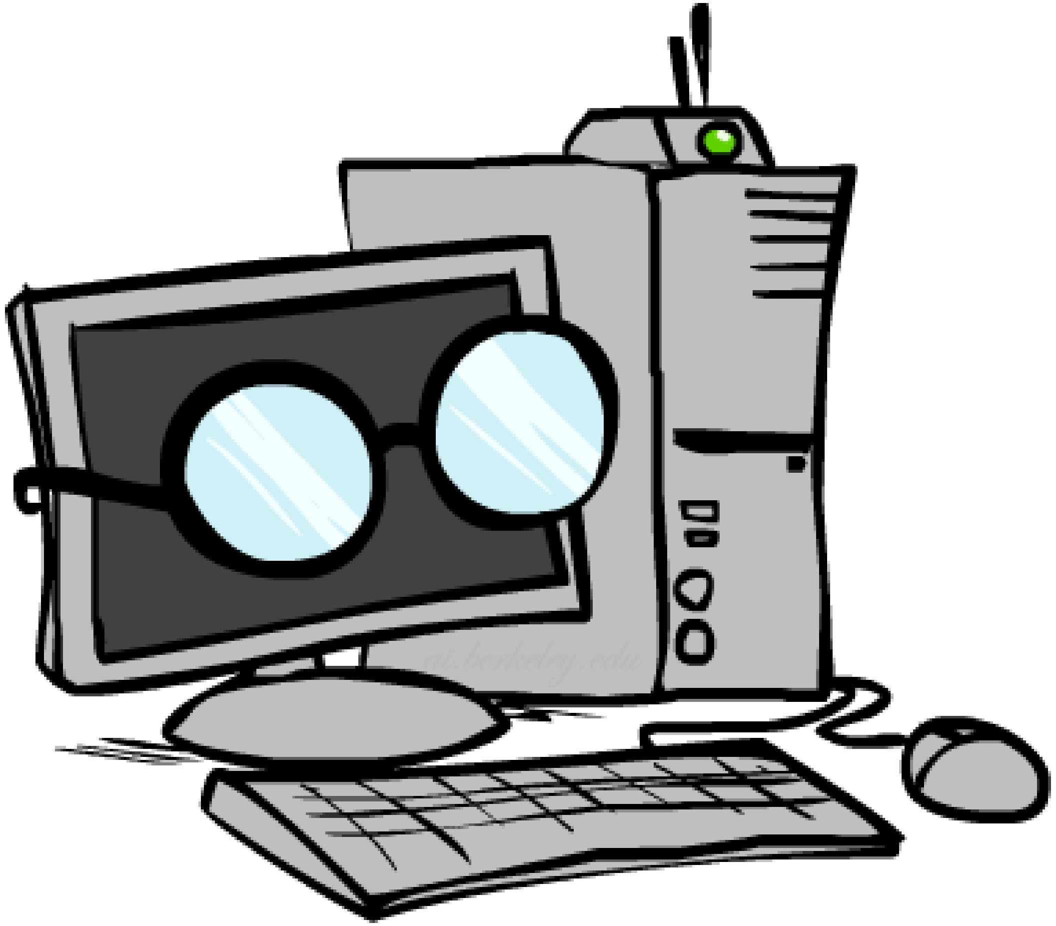


Rowan University

Computer Vision



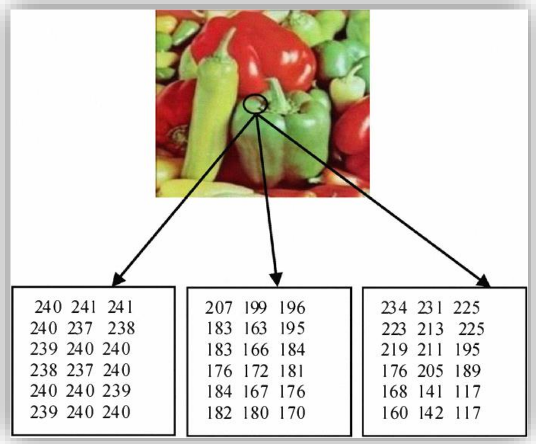
Computer Vision

Grayscale Image

6 x 6

6 x 6

1	0	4	2	125	67
8	2	5	4	34	12
20	13	25	15	240	2
76	8	6	6	100	76
34	66	134	223	201	3
255	123	89	55	32	2



Picture data is stored in RGB format

Structured data

Computer Vision Problems

Image Classification

64x64

→ Cat? (0/1)

Object detection

Neural Style Transfer


Introduction

Two types of image classification:

- Object (i.e., cat, dog) [background doesn’t matter]
- Background (i.e., grassland, living room)

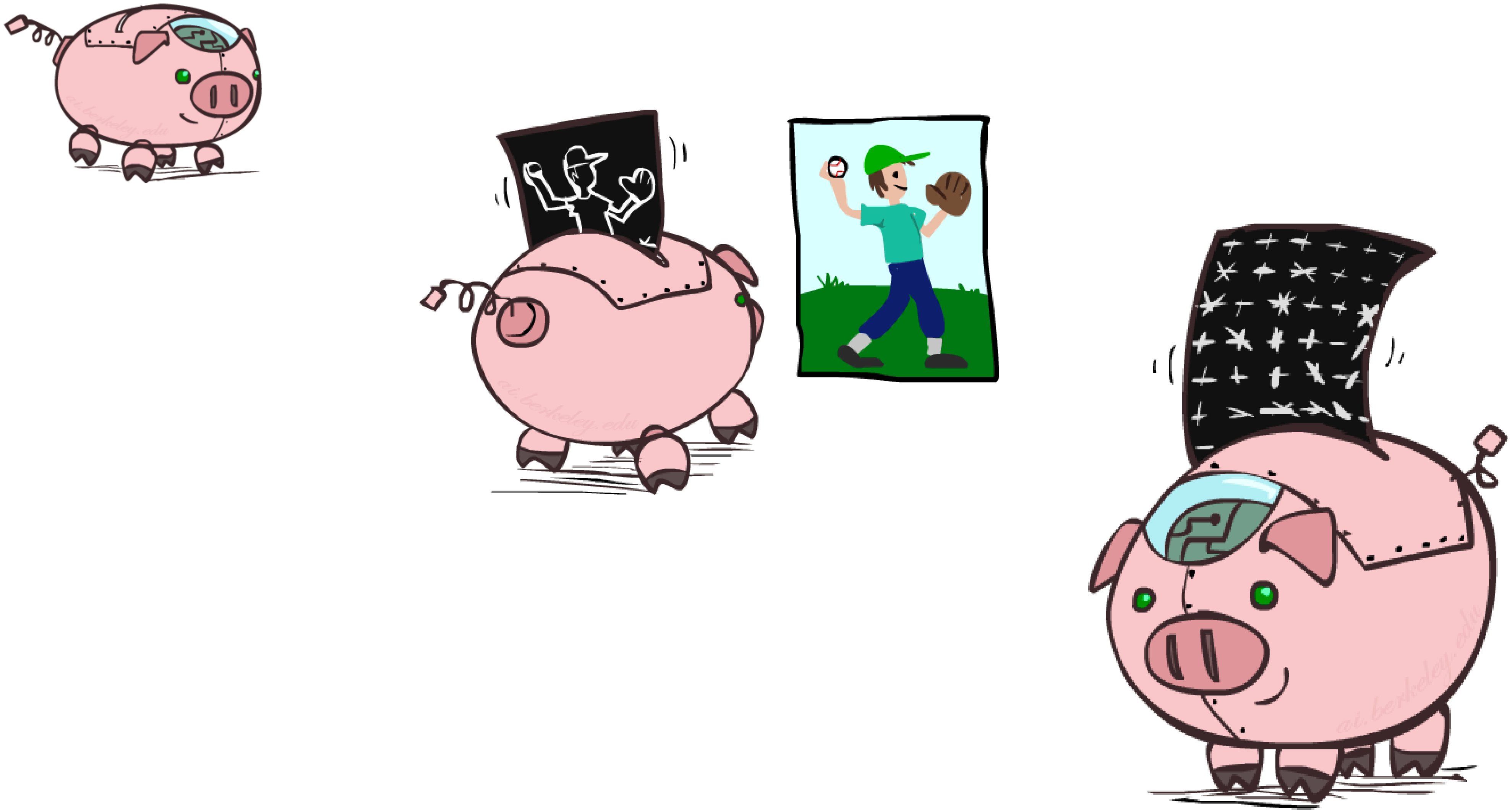
- Effects on images:
  - Lighting: which changes the brightness and color of the image.
  - Aspect: which causes objects to look different when seen from different directions.
  - Occlusion: where some parts of the object are hidden.
  - Deformation: where the object changes its shape.

Introduction

Figure 2. Deformation and scaling problem in product images

Figure 3. Occlusion problem in product images

Manual Feature Design



Introduction

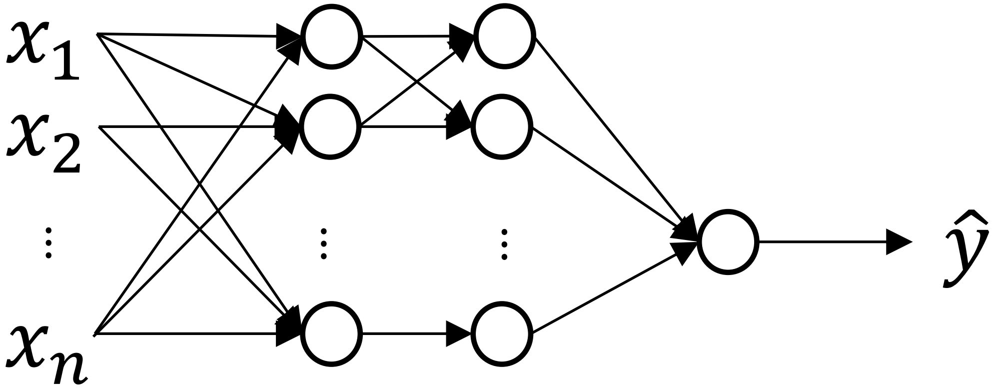
- Individual pixel values are not important.
- Local patterns can be quite informative.
    - The digits 0, 6, 8, 9 have loops.
    - The digits 4, and 8 have crosses.
    - The digits 1, 2, 3, 5, 7 have lines.

- How do we learn about the patterns?

NN on images


64x64

→ Cat? (0/1)



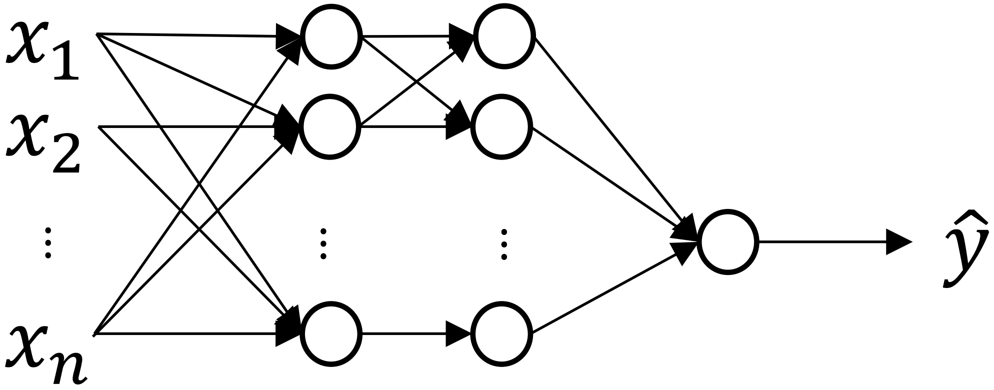
NN on images

64x64×3

→ Cat? (0/1)

12288

1000 x 1000 x 3 = ?



NN on images: problems

64x64x3

Cat? (0/1)

12288

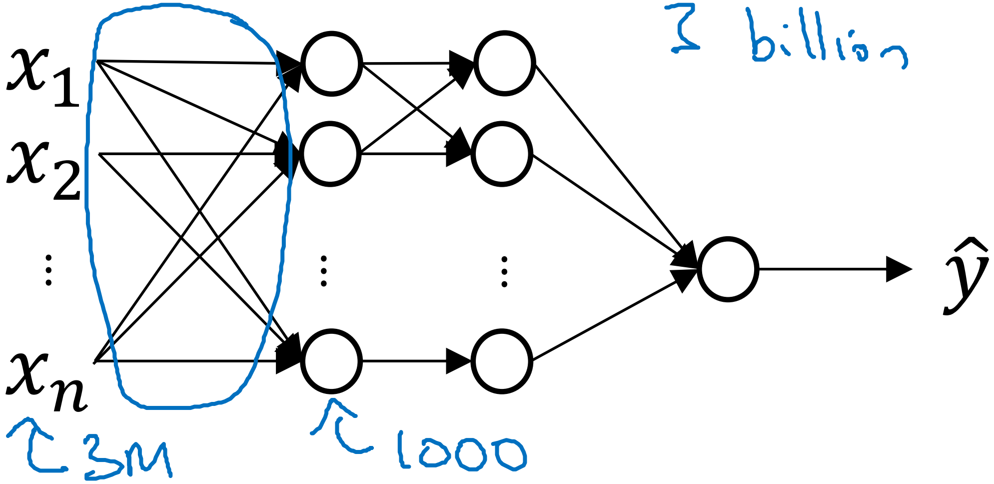
1000x1000x3

= 3 million

$x \in \mathbb{R}^{3M}$

$W^{[1]}$ (1000, 3M)

3 billion



Idea: Reading frame by frame

64x64 × 3

→ Cat? (0/1)

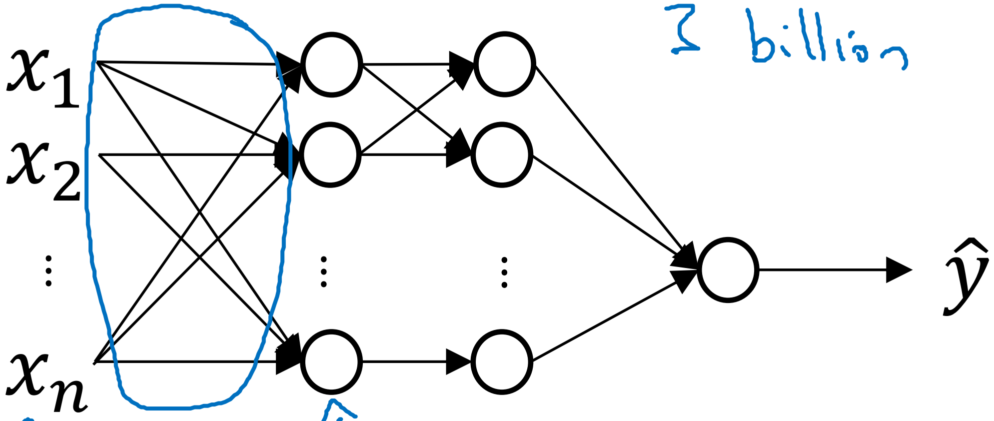
12288

1000 × 1000 × 3
= 3 million

$x \in \mathbb{R}^{3M}$

$W^{[1]}$ (1000, 3M)

3 billion



3M

1000

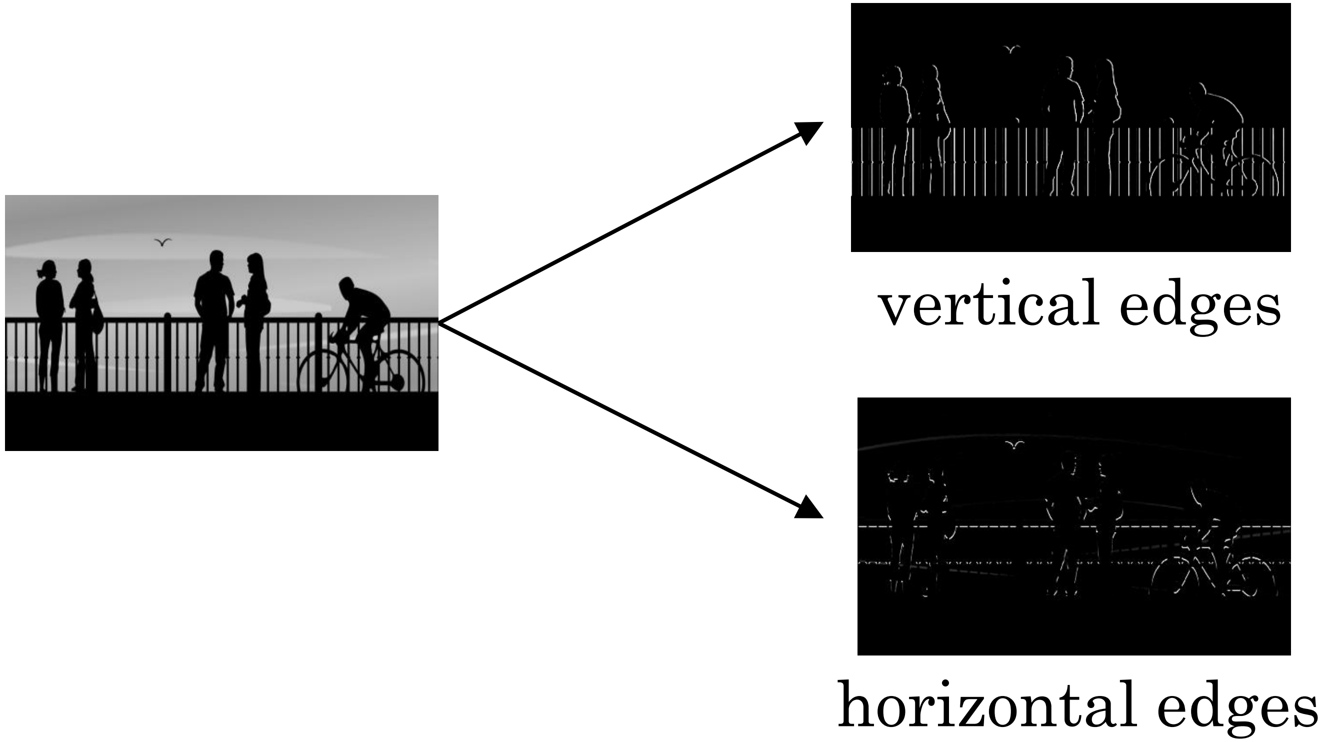
Types of layer in a convolutional network:

- Convolution
- Pooling
- Fully connected

Convolution layer
Edge detection example

Slides adapted from Andrew Ng

Computer Vision Problem



Vertical edge detection

$$
\begin{bmatrix}
3 & 0 & 1 & 2 & 7 & 4 \\
1 & 5 & 8 & 9 & 3 & 1 \\
2 & 7 & 2 & 5 & 1 & 3 \\
0 & 1 & 3 & 1 & 7 & 8 \\
4 & 2 & 1 & 6 & 2 & 8 \\
2 & 4 & 5 & 2 & 3 & 9
\end{bmatrix}
*
\begin{bmatrix}
1 & 0 & -1 \\
1 & 0 & -1 \\
1 & 0 & -1
\end{bmatrix}
=
\begin{bmatrix}
-5 & -4 & 0 & 8 \\
-10 & -2 & 2 & 3 \\
0 & -2 & -4 & -7 \\
-3 & -2 & -3 & -16
\end{bmatrix}
$$

Filter/Kernel
Small region to scan

Stride: the number of gap to slide the filter

Spatial size: [(W – F)/S] +1

Zero padding: adding extra zero column & rows in input to make a desirable output matrix

Vertical edge detection

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

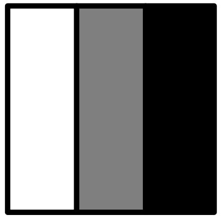
$*$

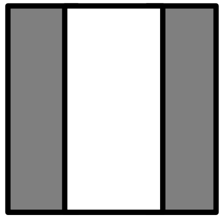
1	0	-1
1	0	-1
1	0	-1

$=$

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

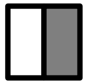
$*$

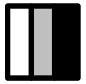


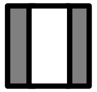


Vertical edge detection examples

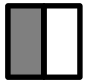
$$\begin{bmatrix} 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \end{bmatrix} * \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} = \begin{bmatrix} 0 & 30 & 30 & 0 \\ 0 & 30 & 30 & 0 \\ 0 & 30 & 30 & 0 \\ 0 & 30 & 30 & 0 \end{bmatrix}$$

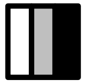


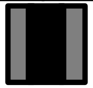




$$\begin{bmatrix} 0 & 0 & 0 & 10 & 10 & 10 \\ 0 & 0 & 0 & 10 & 10 & 10 \\ 0 & 0 & 0 & 10 & 10 & 10 \\ 0 & 0 & 0 & 10 & 10 & 10 \\ 0 & 0 & 0 & 10 & 10 & 10 \\ 0 & 0 & 0 & 10 & 10 & 10 \end{bmatrix} * \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} = \begin{bmatrix} 0 & -30 & -30 & 0 \\ 0 & -30 & -30 & 0 \\ 0 & -30 & -30 & 0 \\ 0 & -30 & -30 & 0 \end{bmatrix}$$







Vertical and Horizontal Edge Detection

1	0	-1
1	0	-1
1	0	-1

Vertical

1	1	1
0	0	0
-1	-1	-1

Horizontal

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10

$*$

1	1	1
0	0	0
-1	-1	-1

$=$

0	0	0	0
30	10	-10	-30
30	10	-10	-30
0	0	0	0

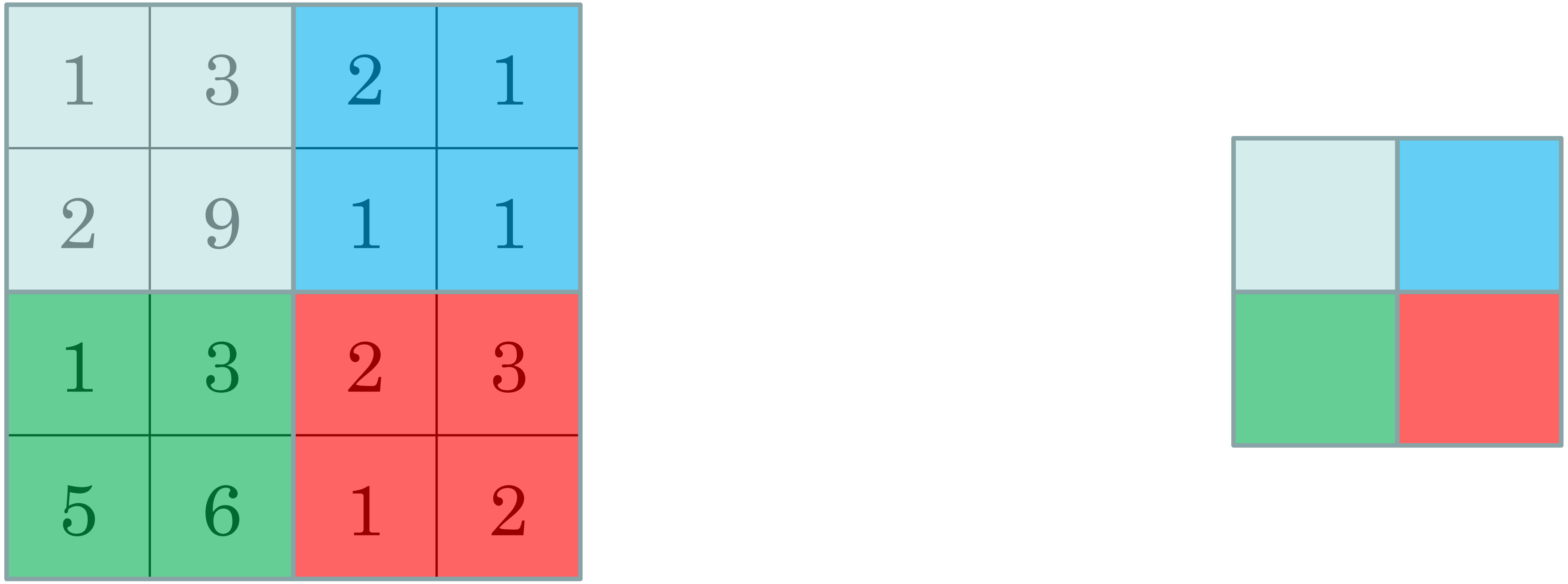
Vertical and Horizontal Edge Detection

(a) Lenna (b) Horizontal edge (c) Vertical edge

Figure : The Lenna image and the effect of different convolution kernels.

Pooling layer

Pooling layer: Max pooling



Reduce the spatial size (Idea: adjacent cells have same similar property)

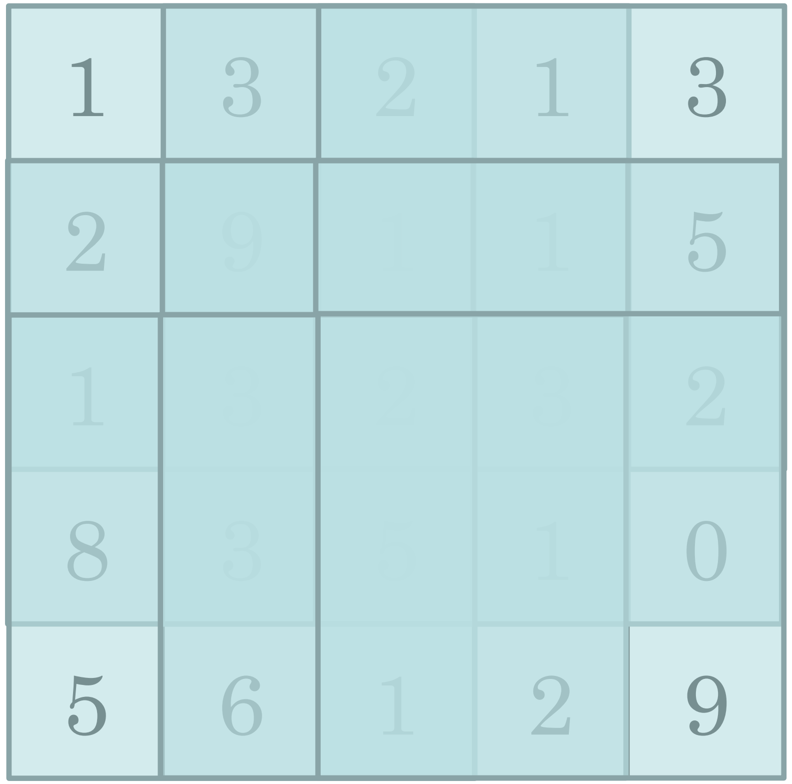
Pooling layer: Max pooling

1	3	2	1	3
2	9	1	1	5
1	3	2	3	2
8	3	5	1	0
5	6	1	2	9

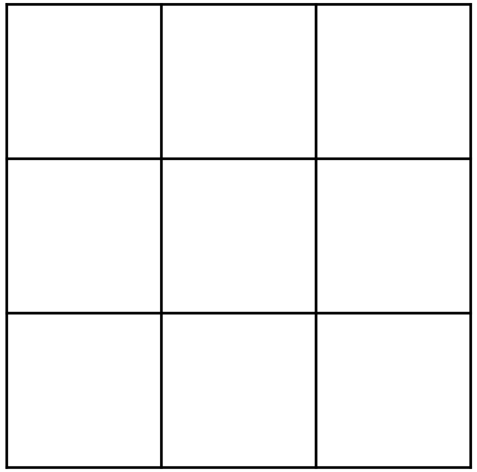
5 * 5

Kernel size is 3 * 3
F = 3
Stride, S = 1

Pooling layer: Max pooling

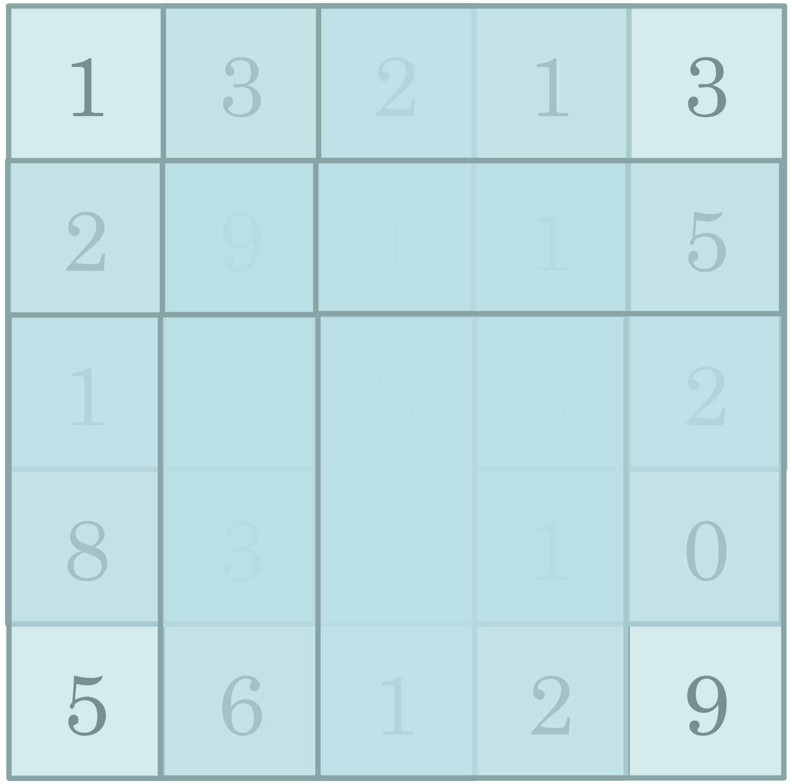


5 * 5



Kernel size is 3 * 3
F = 3
Stride, S = 1

Pooling layer: Max pooling

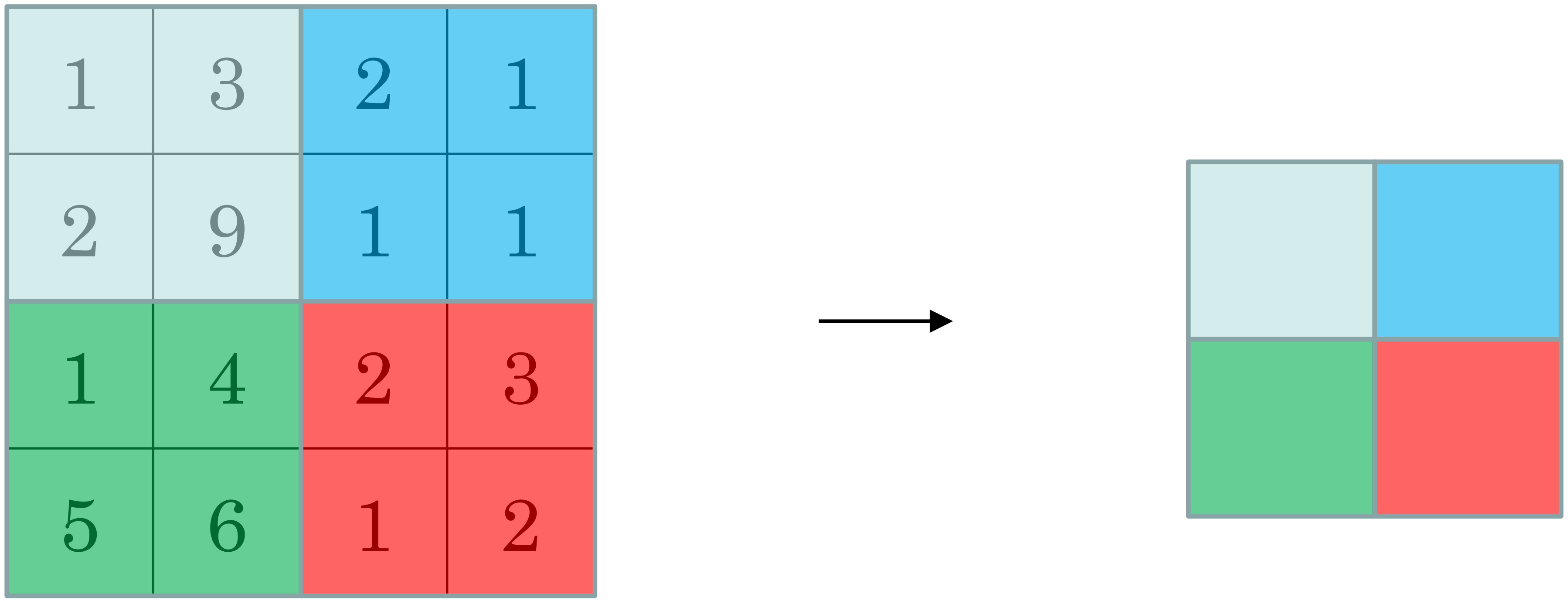


5 * 5

9	9	5
9	9	5
8	6	4

Kernel size is 3 * 3
F = 3
Stride, S = 1

Pooling layer: Average pooling



Kernel size is 2 * 2
F = 2
Stride, S = 2

Summary of pooling

Hyperparameters:

f : filter size

s : stride

Max or average pooling

- Reduce spatial size (memory size)
- Reduce computation cost
- Reduce overfitting

Dropout

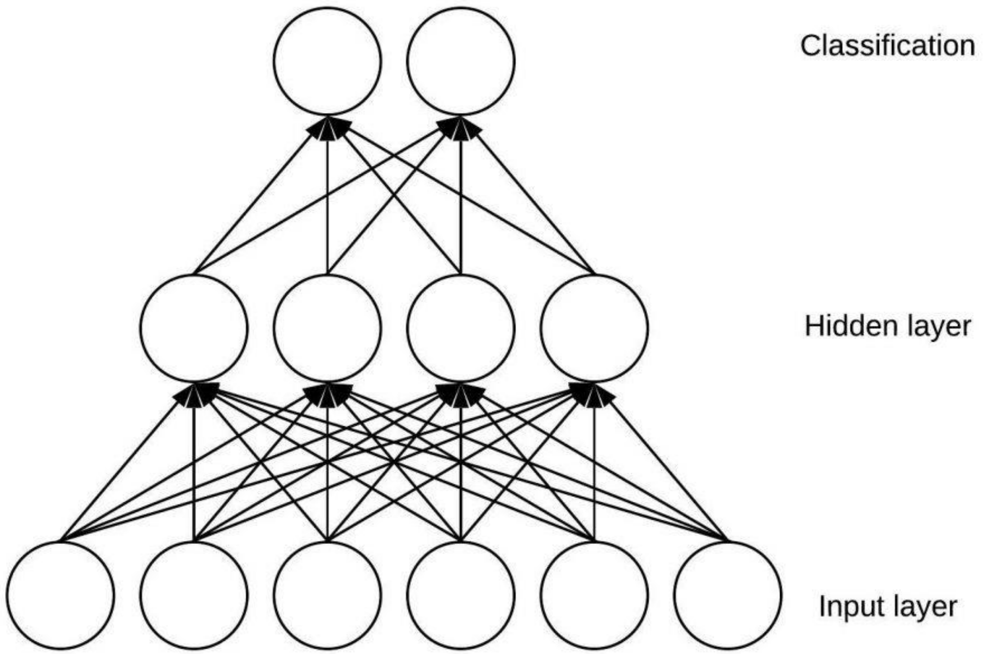
- During training, some number of layer outputs are randomly ignored or "dropped out."

- Dropout is a regularization method.

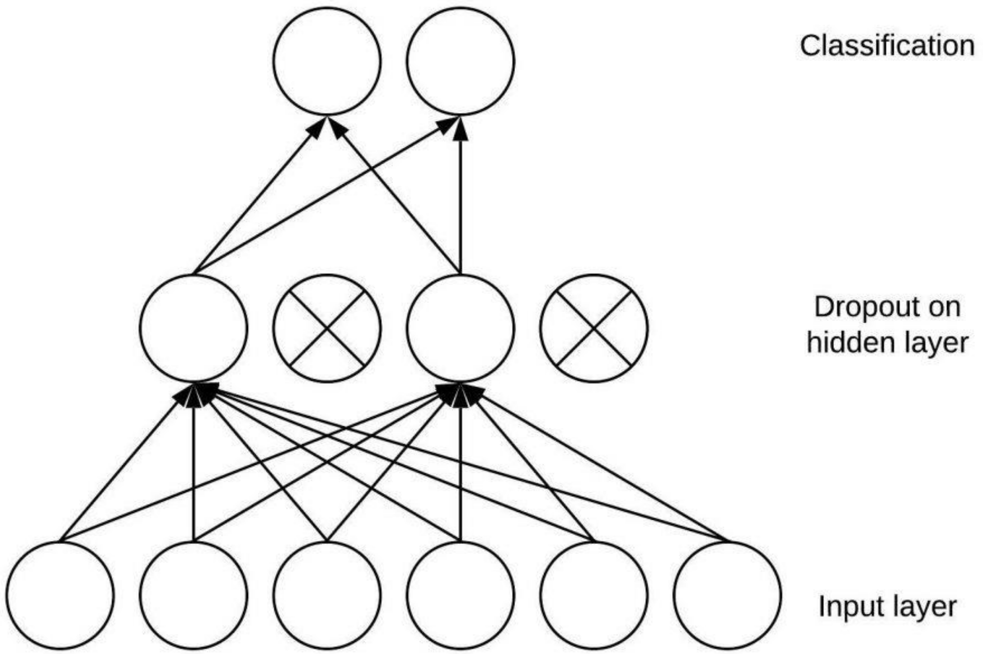
- Dropout is not used after training when making a prediction with the fit network.

- A new hyperparameter is introduced that specifies the probability at which outputs of the layer are dropped out.

Dropout

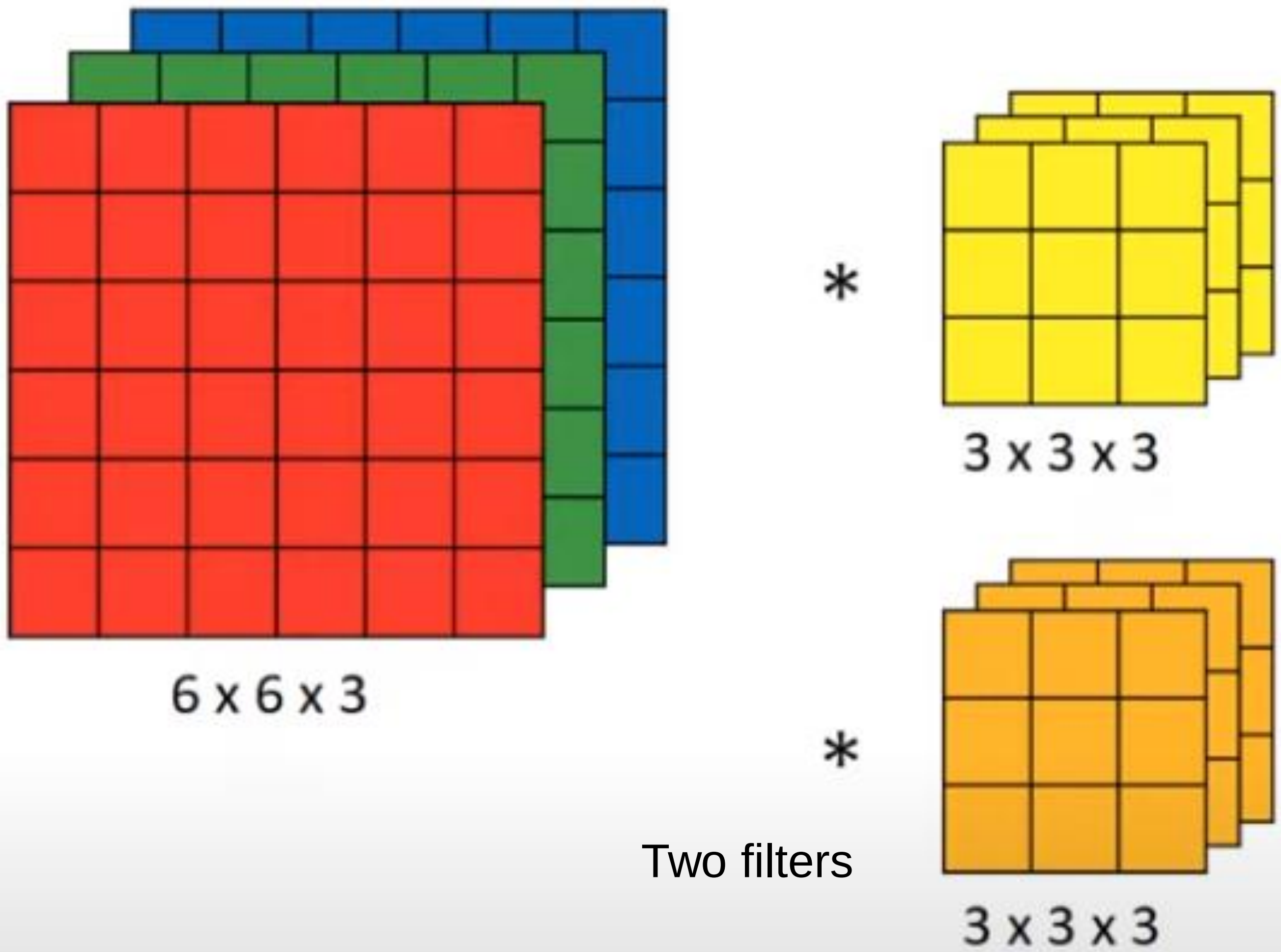


Without Dropout



With Dropout

Example of a layer



Two filters

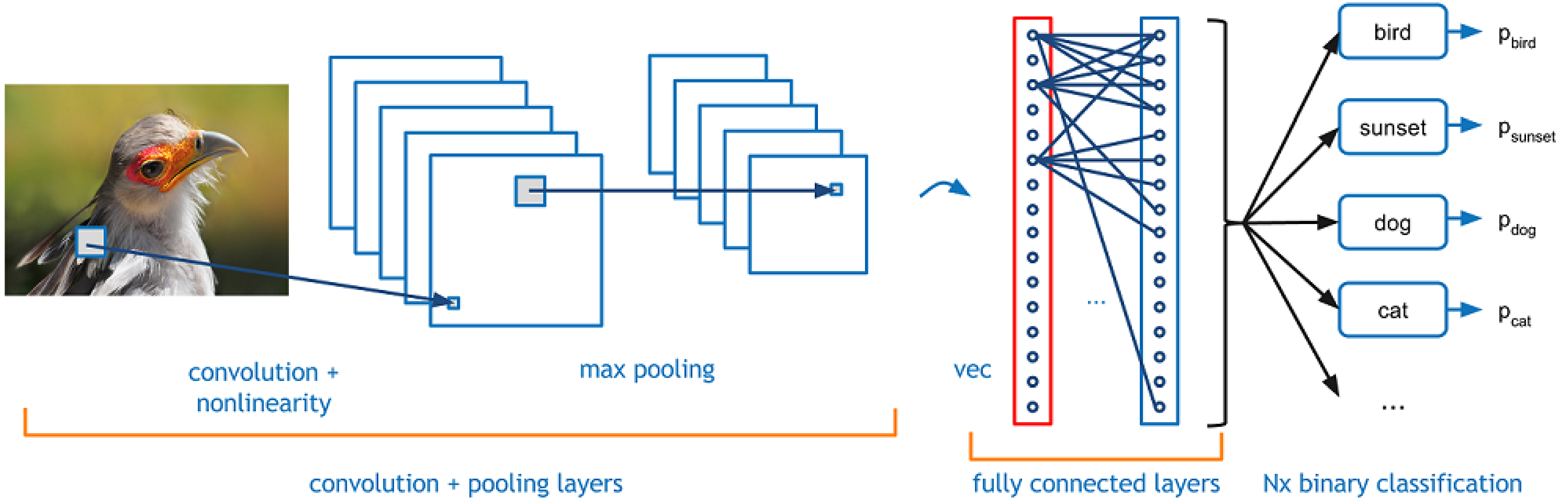
Spatial size: [(W – F)/S] +1
[(6-3)/1] + 1
4

4 by 4

(4 by 4) * 2

4 by 4

CNN: simple architecture



Last layer:
Use sigmoid for binary classification
Use softmax for multi-class problem

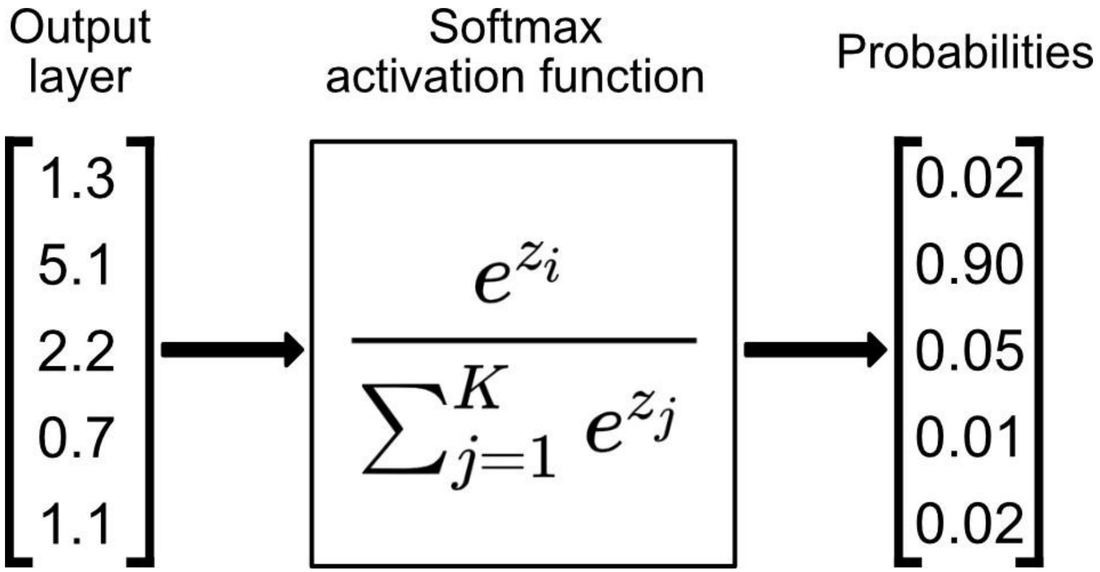
Last/Output layer

$$z = w \cdot x + b$$

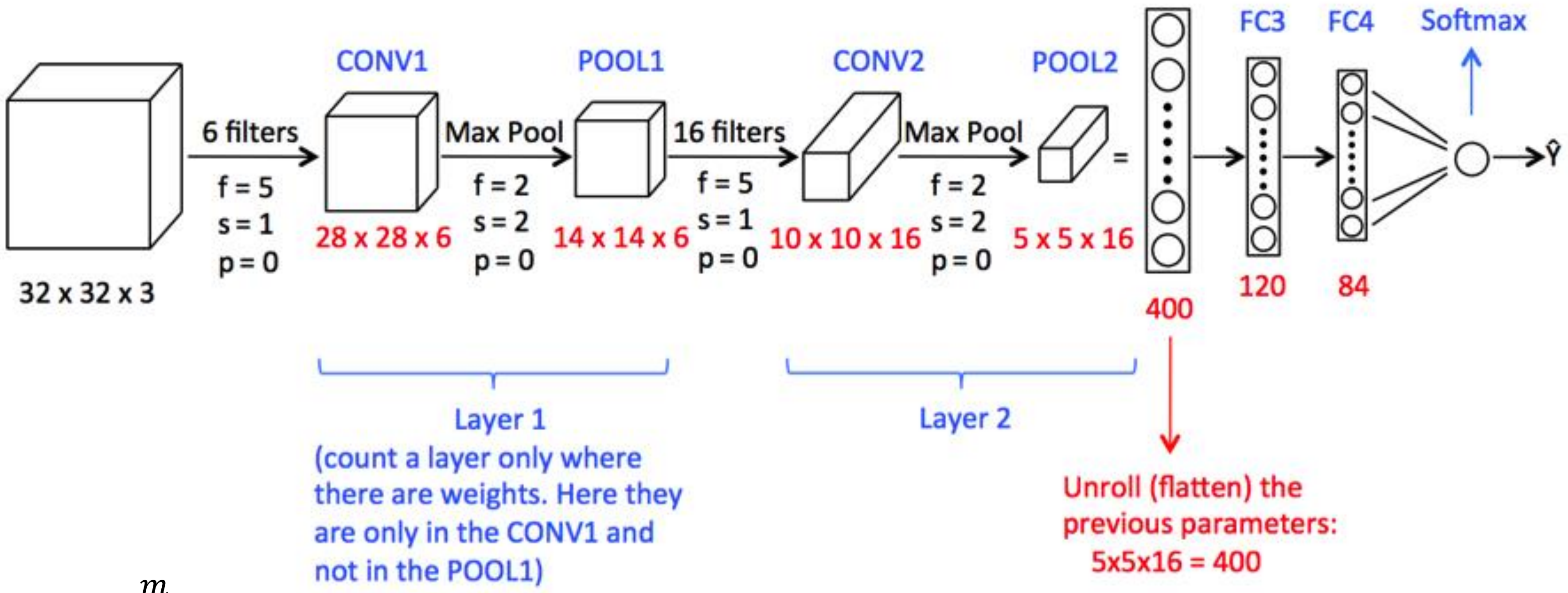
- Solution 1: Sigmoid (use a function of z that goes from 0 to 1)

$$y = s(z) = \frac{1}{1 + e^{-z}} = \frac{1}{1 + \exp(-z)}$$

- Solution 2: Softmax



CNN: adding more layers



$$\text{Cost } J = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

Use gradient descent to optimize parameters to reduce J

Why convolutions

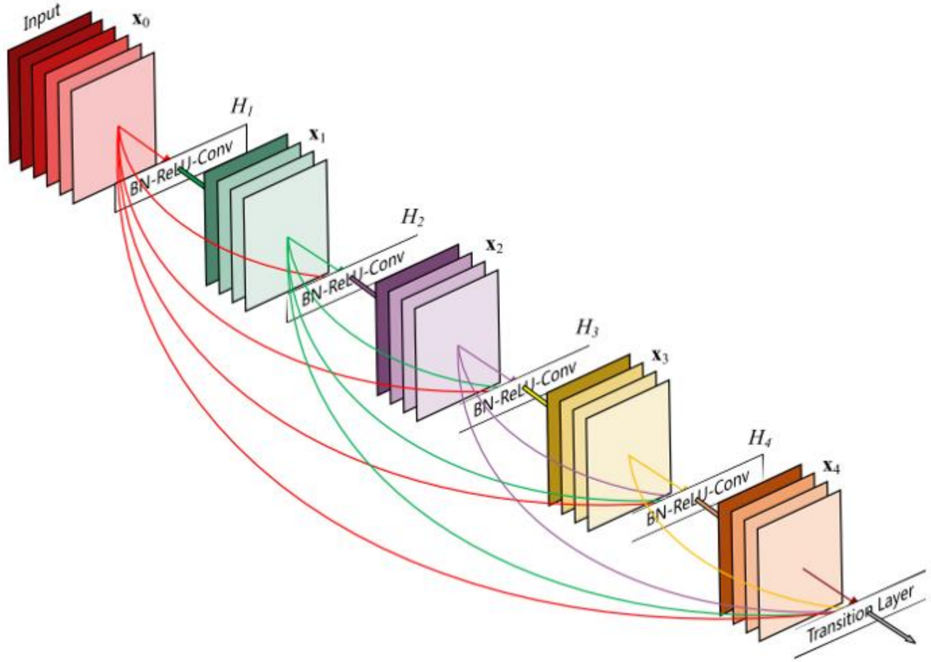
$$\begin{bmatrix} 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \\ 10 & 10 & 10 & 0 & 0 & 0 \end{bmatrix} * \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} = \begin{bmatrix} 0 & 30 & 30 & 0 \\ 0 & 30 & 30 & 0 \\ 0 & 30 & 30 & 0 \\ 0 & 30 & 30 & 0 \end{bmatrix}$$

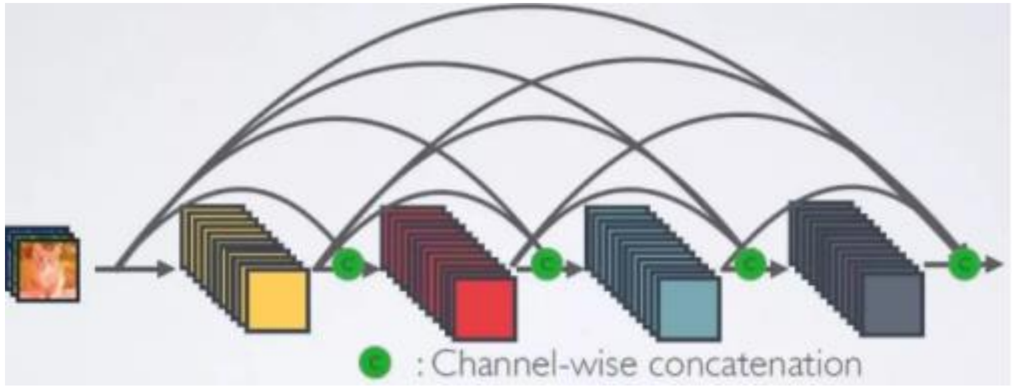
Parameter sharing: A feature detector (such as a vertical edge detector) that's useful in one part of the image is probably useful in another part of the image.

Sparsity of connections: In each layer, each output value depends only on a small number of inputs.

Deep CNN Model

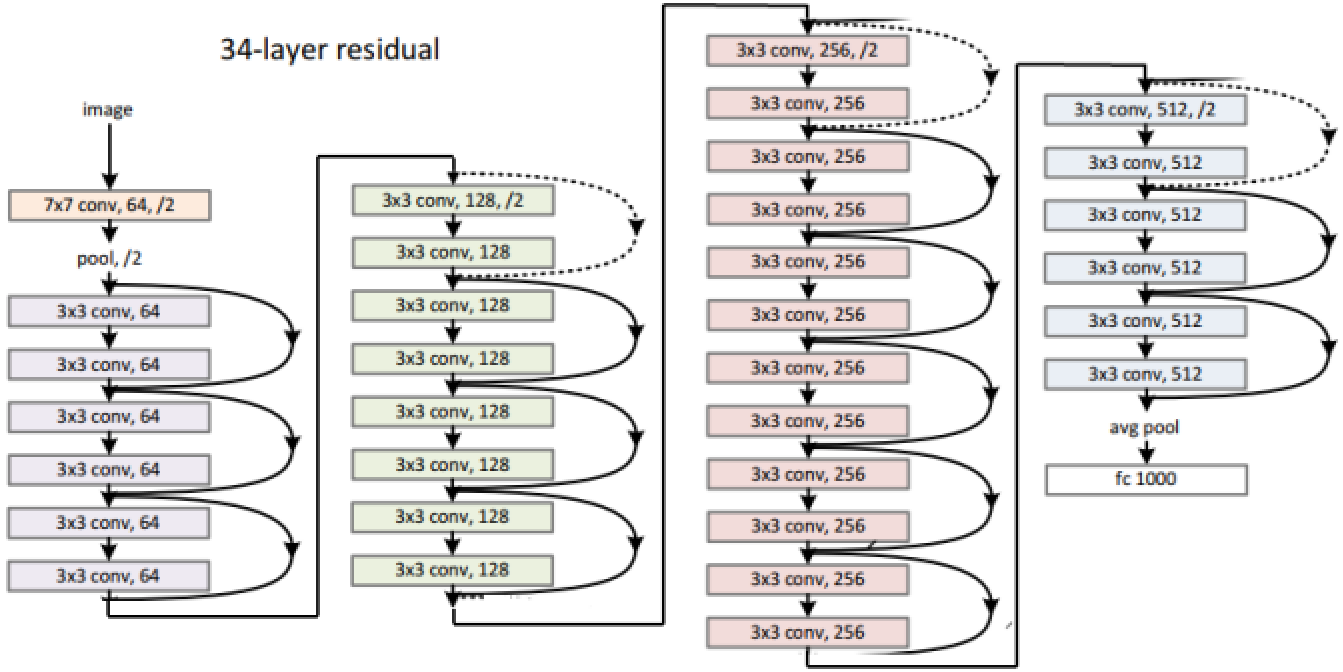
- DenseNet





Deep CNN Model

- Residual Network (ResNet)

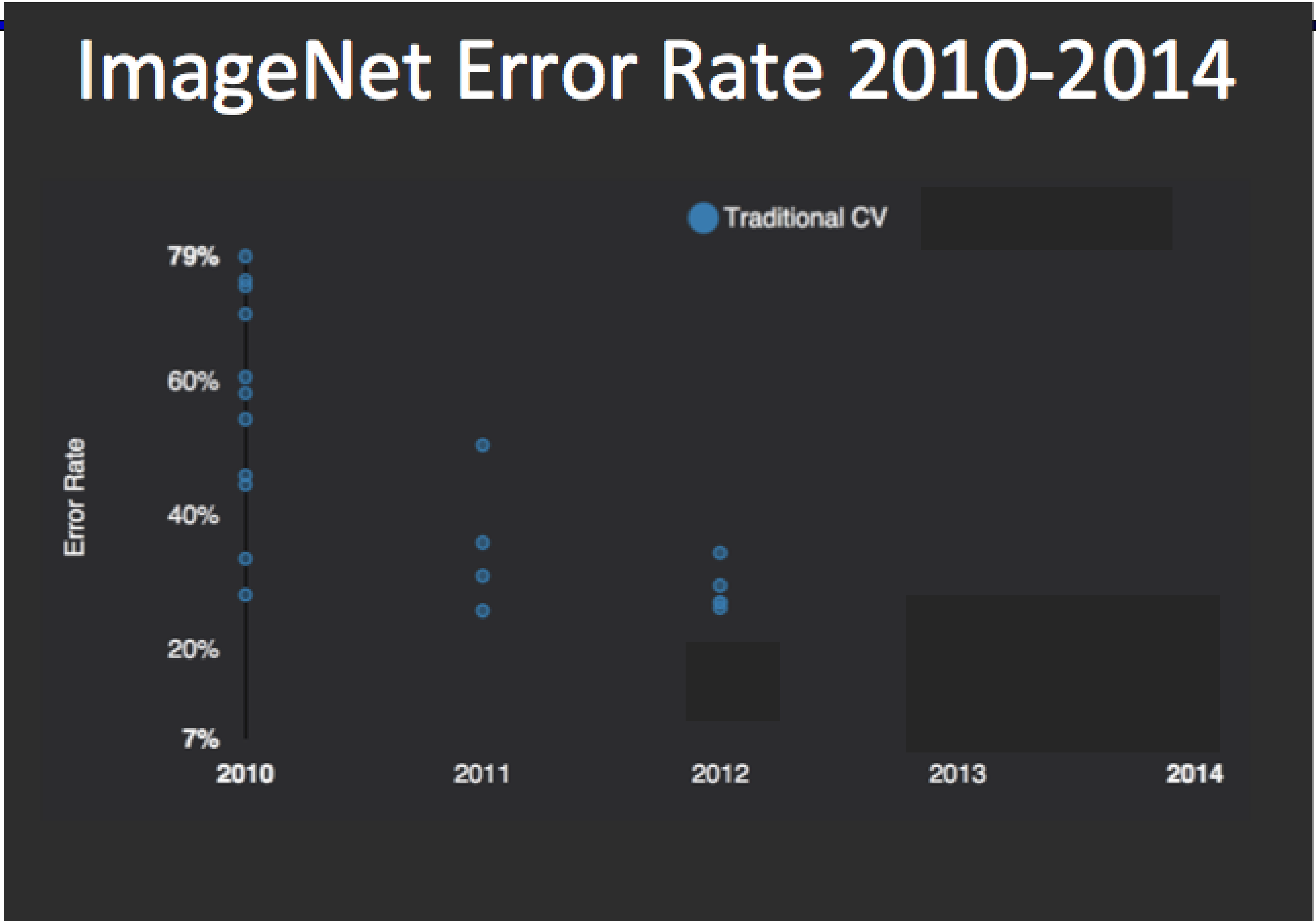


Simplest resNet example given in paper - 34 layers

Deep learning in Image Classification

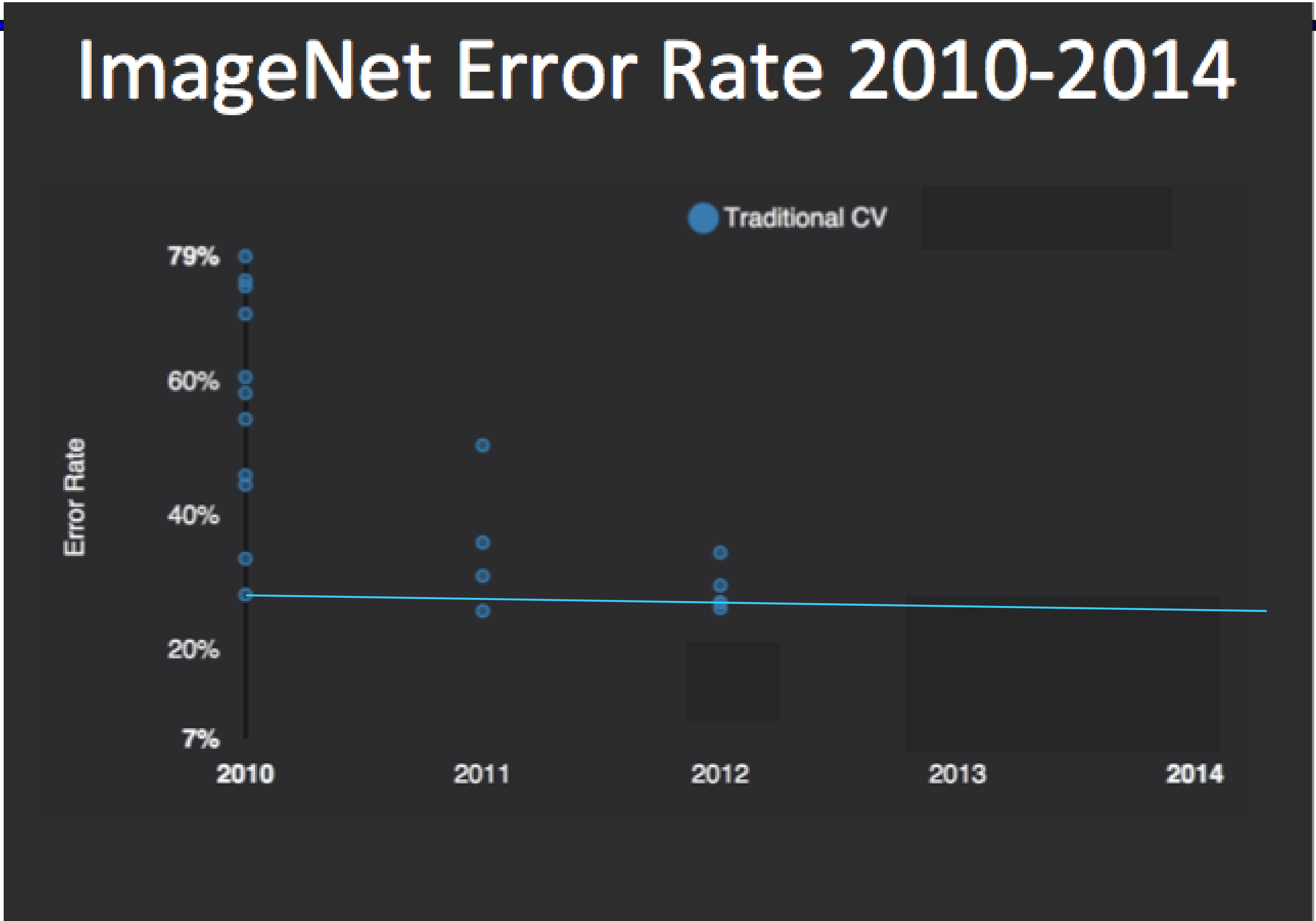
A real example

ImageNet: 14 million images; 30,000 categories



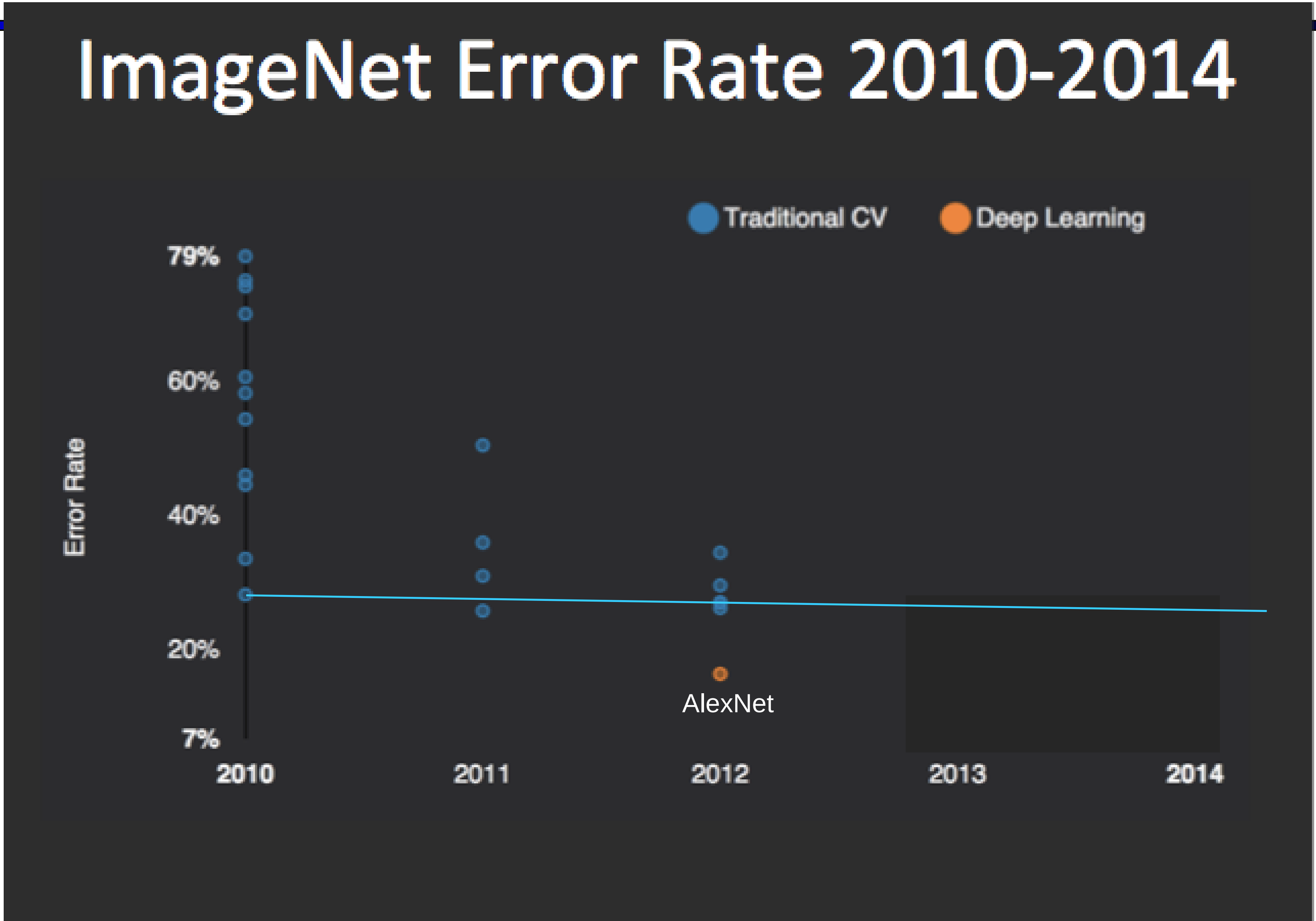
graph credit Matt Zeiler, Clarifai

Performance



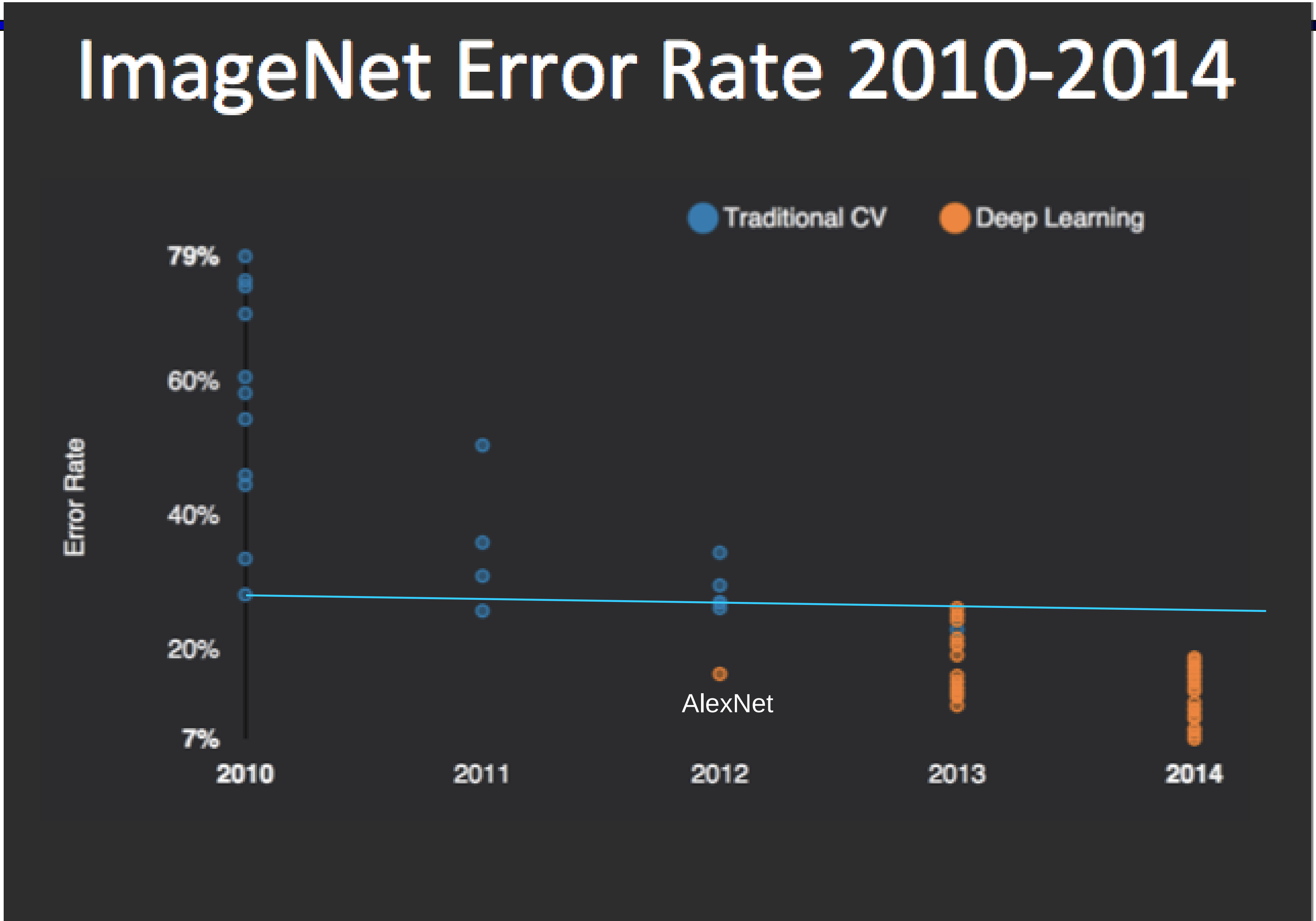
graph credit Matt Zeiler, Clarifai

Performance



graph credit Matt Zeiler, Clarifai

Performance



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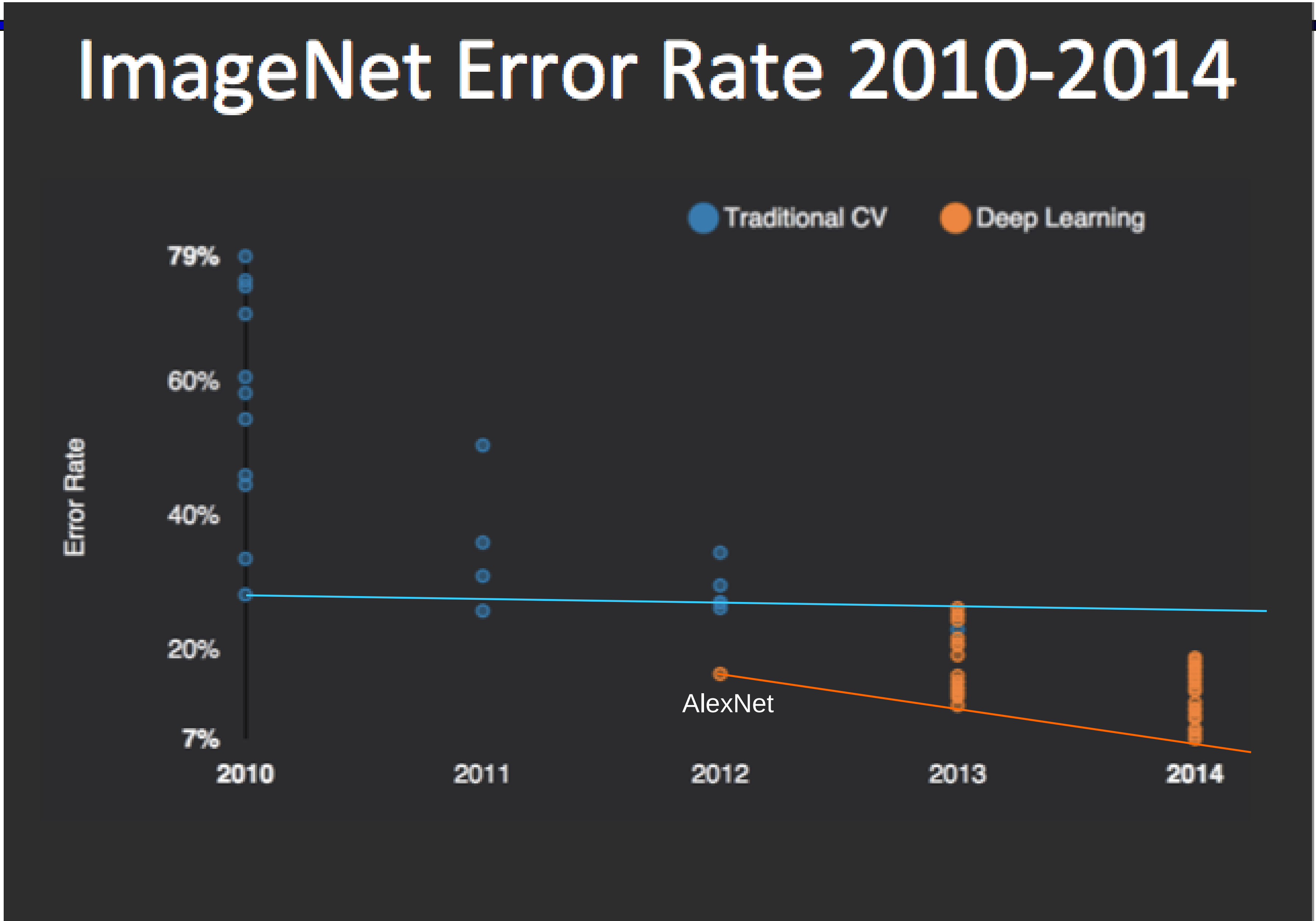
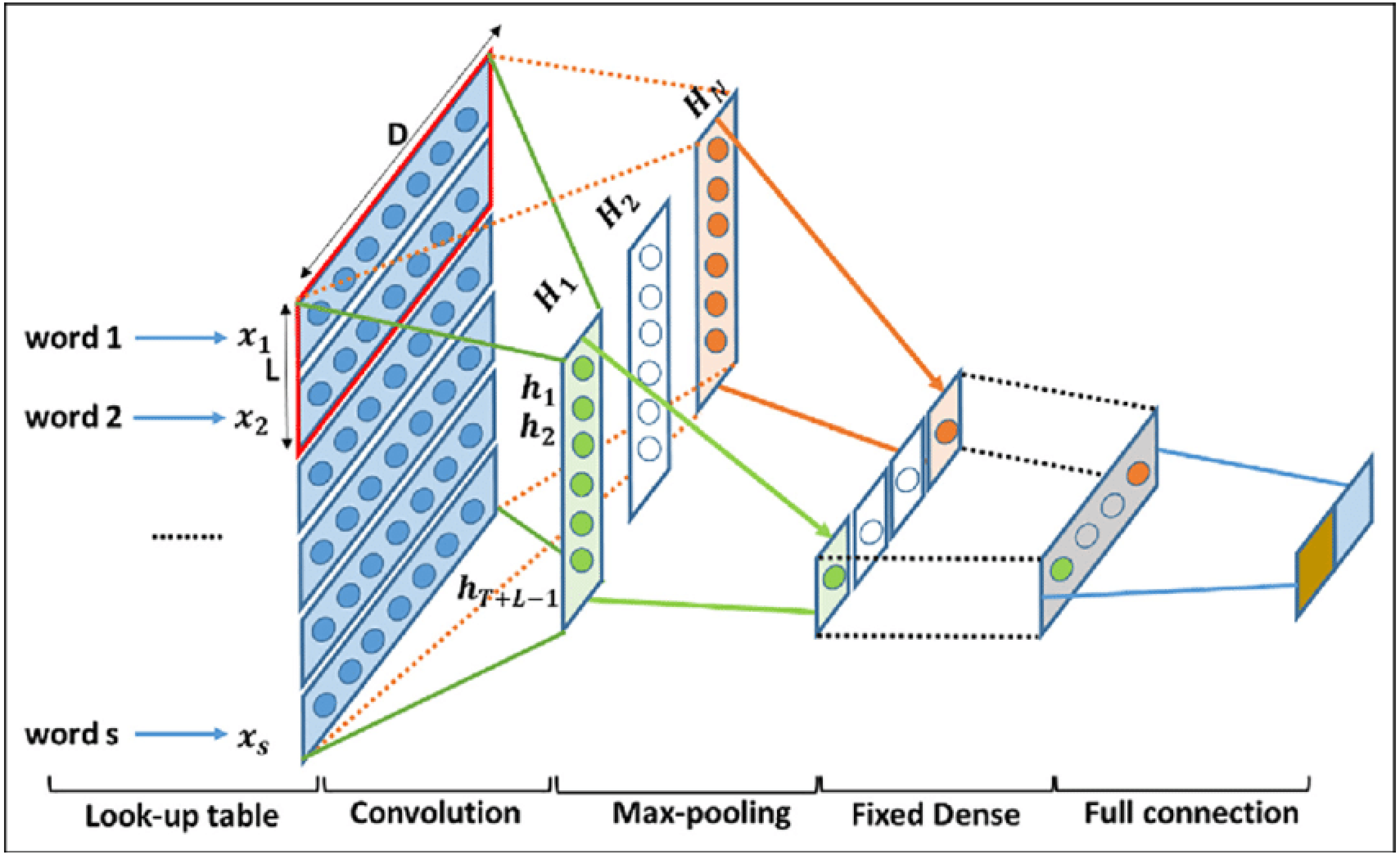
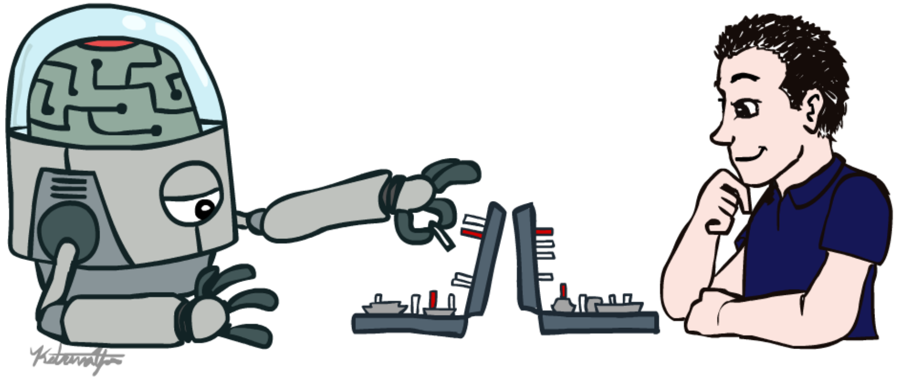
Performance



graph credit Matt Zeiler, Clarifai

CNN in Text Analysis





Thanks!