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Exploring Deep Neural Networks

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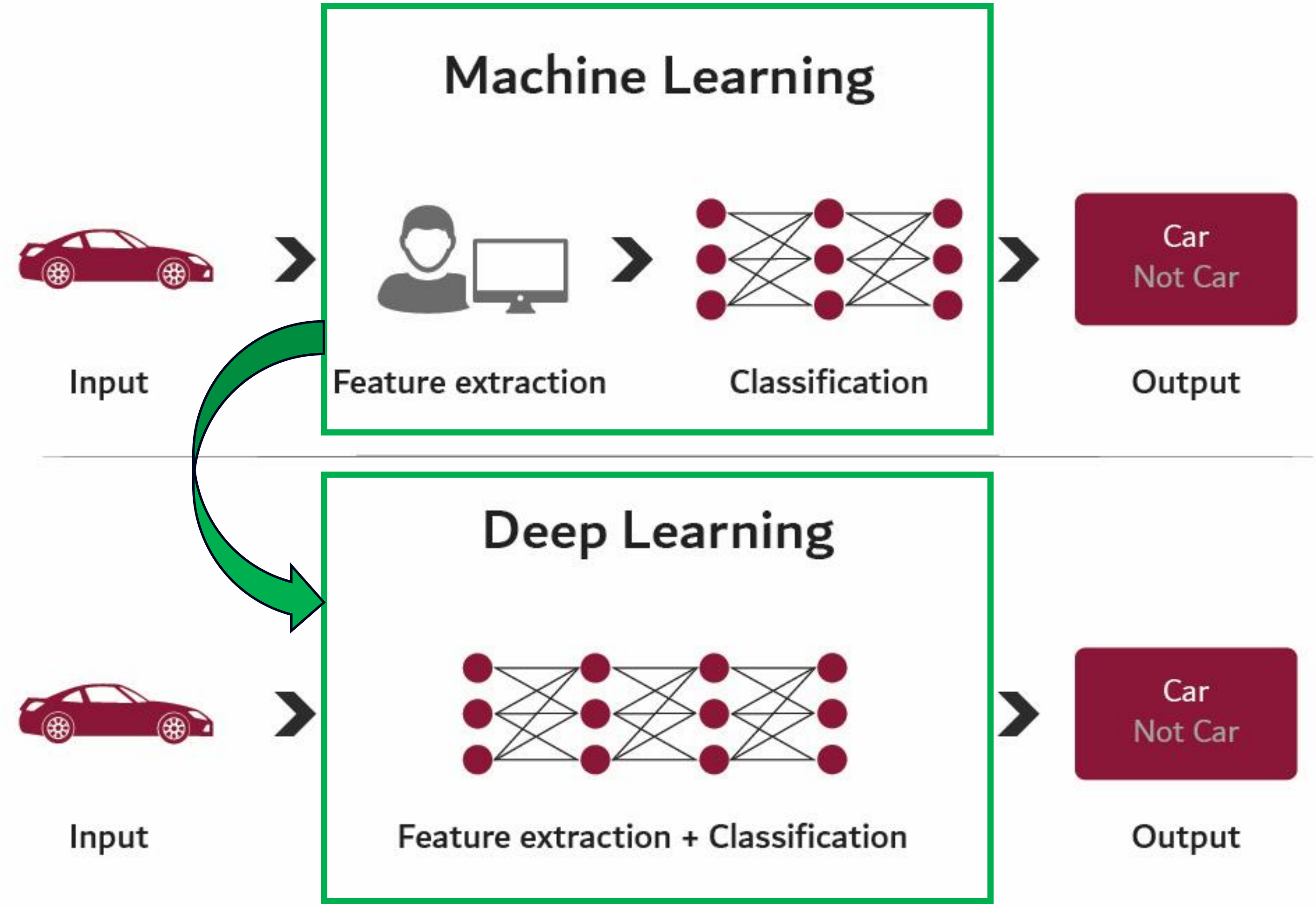
Outline

- Machine Learning vs Deep Learning
- Why Deep Learning and Convolutional Neural Networks (CNN)
- Convolutional Neural Networks
- State-Of-Arts CNN models
- Recurrent Neural Networks (RNN)
- Regularizing Deep Neural Networks (DNN)
- Fine Tuning DNN
- Demos
- Conclusion

Classic Machine Learning vs Deep Learning



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Why Deep Learning and Convolutional Neural Networks (CNN)

What’s wrong with Fully Connected NN?

Data

1D grid: sequential data, e.g. univariate time series, tabular data

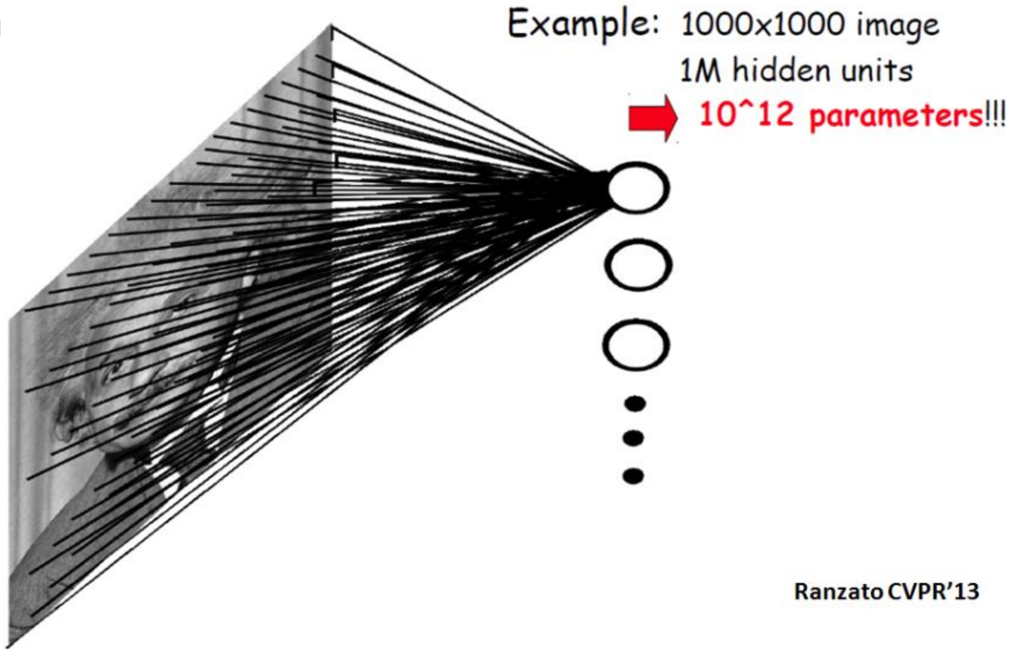
2D grid: natural images

3D grid: video, 3D image volumes (multi/hyper spectral images)

Loss of spacial information

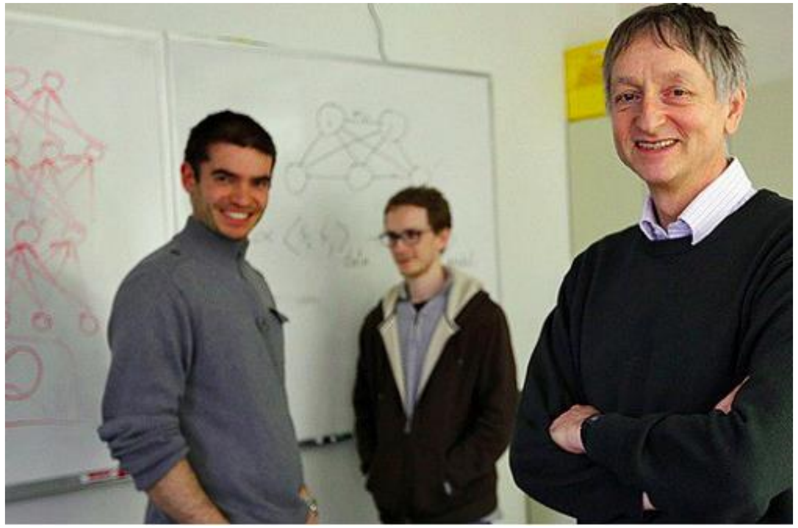
Distant pixels are less correlated

Larger input size ➔ Higher # params



Ranzato CVPR’13

Why deep learning and Convolutional NN?



Deep learning

- Has won numerous pattern recognition competitions
- Does so with minimal feature engineering

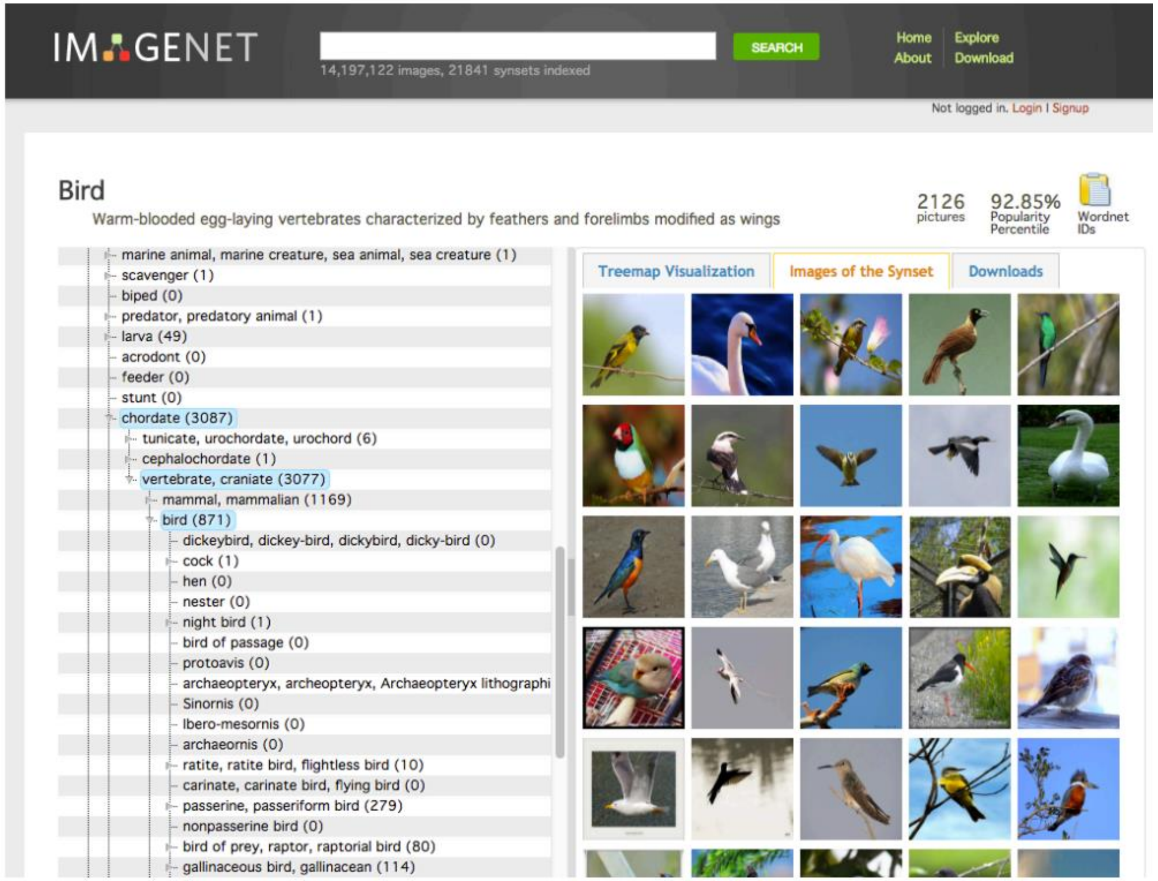
Billions of $ are invested in it

DeepMind: Acquired by Google for $400 million

DNNResearch: Three-person startup (including Geoff Hinton) acquired by Google for unknown price tag

Data are heterogeneous, (image, video, sequential, speech …)

IMAGENET and ILSVRC



14 million annotated images

Over 20.000 categories

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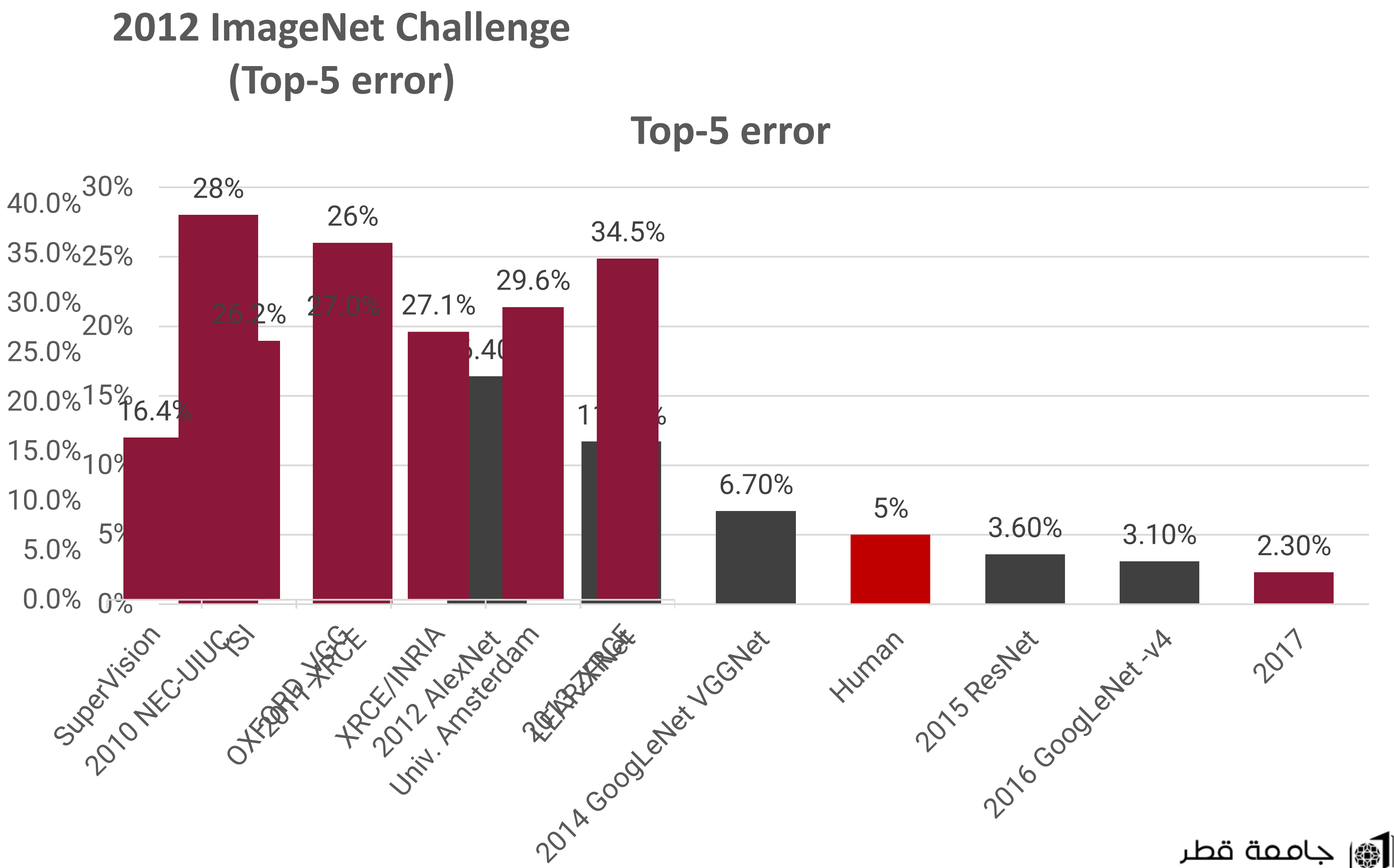
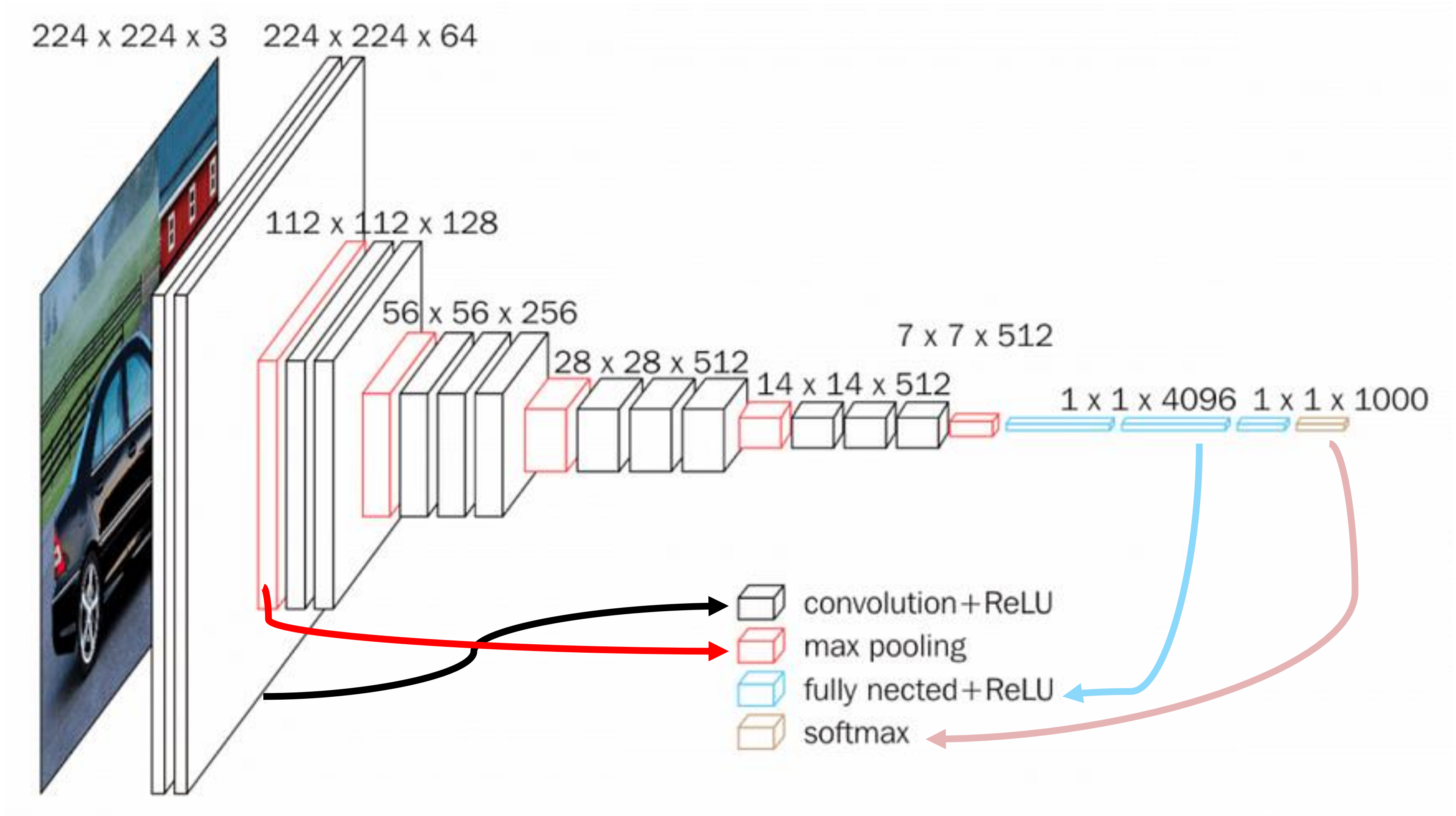
IMAGENET and ILSVRC



Convolutional Neural Networks (CNN)

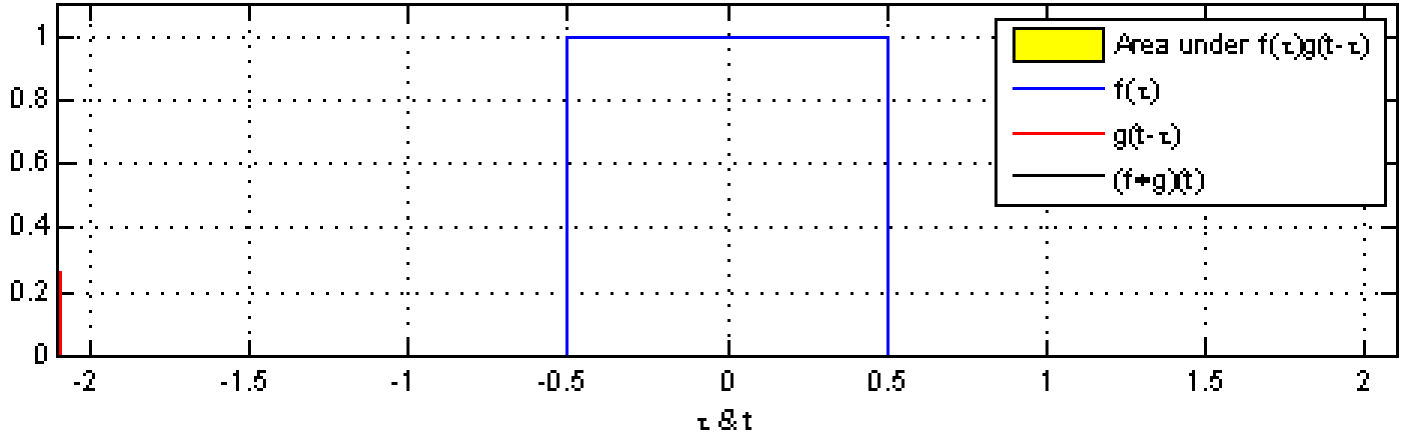
Convolutional Neural Network



Convolution

- To “convolve” means to roll together.
- Is an integral measuring how much two functions overlap as one passes over the other.

$$(f * g)(t) = \int f(\tau)g(t - \tau)d\tau$$



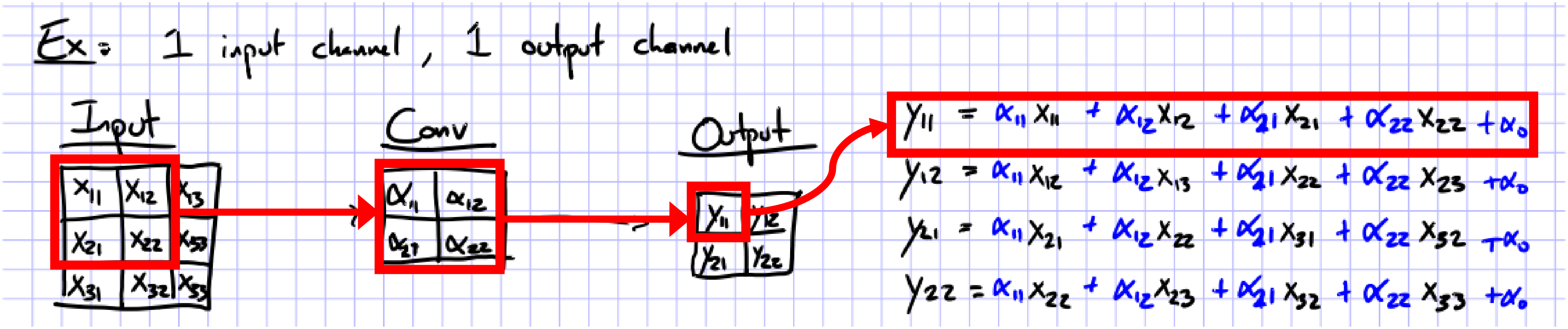
2D Convolution

Basic idea

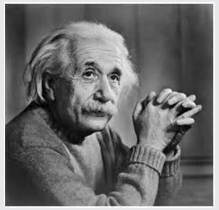
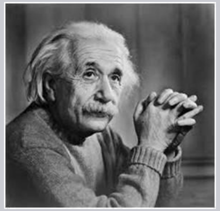
- Pick a 2x2 (for example) matrix (a.k.a kernel) F of weights
- Slide this over an image and compute the “inner product” (similarity) of F and the corresponding field of the image, and replace the pixel in the center of the field with the output of the inner product operation

Key point

- Different convolutions extract different types of low-level “features” from an image
- All that we need to vary to generate these different features is the weights of F



2D Convolutional Kernels

Kernel	Operation	Result (demo 1)
$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	Identity	
$\begin{bmatrix} -1 & -2 & -1 \\ 0 & 1 & 0 \\ 1 & 2 & 1 \end{bmatrix}$	Sobel-Horizontal	 
$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$	Sobel-Vertical	 
$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	Sharpen	 

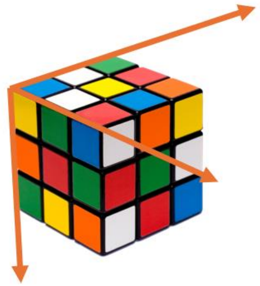
Side note about tensor

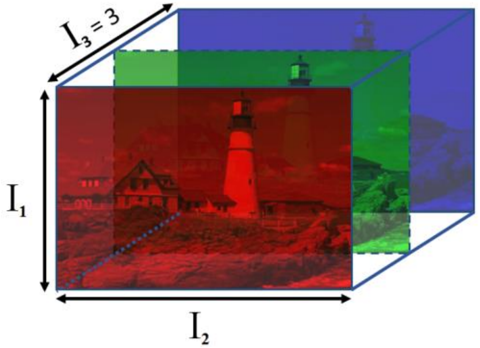
Scalar: $[a]$

Vector: $\begin{bmatrix} a \\ b \\ c \end{bmatrix}$

Matrix: $\begin{bmatrix} a_{11} & \cdots & a_{1N} \\ \vdots & \ddots & \vdots \\ a_{M1} & \cdots & a_{MN} \end{bmatrix}$

3D matrix:





A tensor is a general representation of data in any number of dimension

2D Convolution

Demo 2 (color image/tensor)

Input size: $W_1 \times H_1 \times D_1$

Filters:

K filters of size $F \times F$

Stride S

Zero Padding amount P

Output size: $W_2 \times H_2 \times D_2$

$W_2 = (W_1 - F + 2P)/S + 1$

$H_2 = (H_1 - F + 2P)/S + 1$

$D_2 = K$

Example

Input: $5 \times 5 \times 3$

Filter $3 \times 3 \times 2$

Padding $P = 1$

Stride $S = 2$

$$W_1 = \frac{5 - 3 + 2 \times 1}{2} + 1 = 3 = H_1$$

$D_1 = 2$

➔ Output size: $3 \times 3 \times 2$

CNN: Convolutional Layer

Input Image

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

Learned Convolution

θ_{11}	θ_{12}	θ_{13}
θ_{21}	θ_{22}	θ_{23}
θ_{31}	θ_{32}	θ_{33}

Key Idea: The convolution kernel parameters are learned

Convolved Image

.4	.5	.5	.5	.4
.4	.2	.3	.6	.3
.5	.4	.4	.2	.1
.5	.6	.2	.1	0
.4	.3	.1	0	0

CNN Activation Function

- Real world data is inherently non-linear.
- For instance, the process of recognizing objects in an image involves understanding shapes, textures, and patterns that do not have a linear relationship with the pixel intensities.

Non-linear activation functions enable neural networks to capture these complex, non-linear mappings between inputs and outputs.

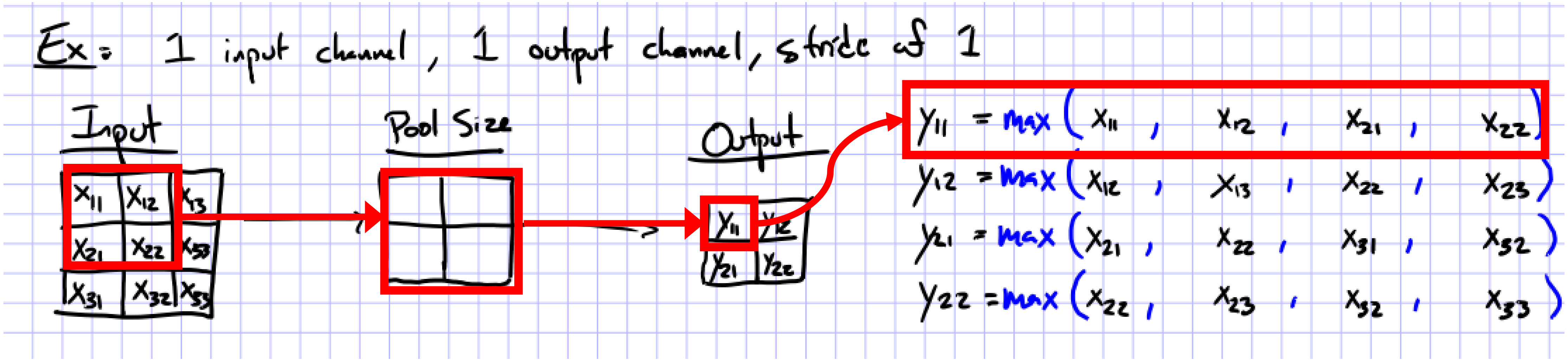
sigmoid	$\boldsymbol{1/(1+e^{-x})}$
Hyperbolic Tangent (tanh)	$\boldsymbol{(e^{x}-e^{-x})/(e^{x}+e^{-x})}$
Rectified Linear Unit (ReLU)	$\boldsymbol{max(0,x)}$
Leaky ReLU	$\begin{cases} x & if\ x>0 \\ \alpha x & otherwise \end{cases}$
Exponential Linear unit (ELU)	$\begin{cases} x & if\ x>0 \\ \alpha(e^{x}-1) & otherwise \end{cases}$
Softmax	$e^{x_j} \Big/ \sum_j e^{x_j}$

CNN Downsampling: Max-Pooling

Used to reduce the input size

Take the max value within the range of the kernel size

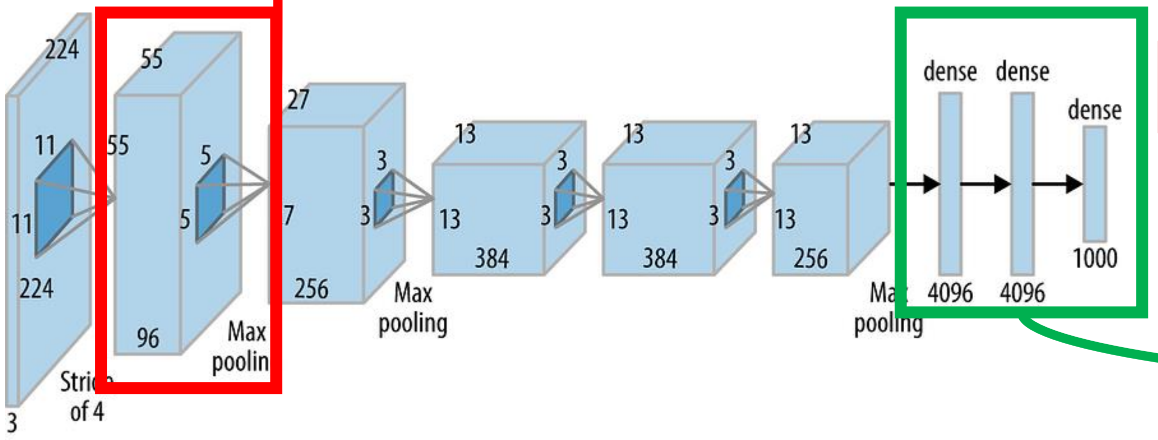
For Stride S = 2:



State-of-arts CNN

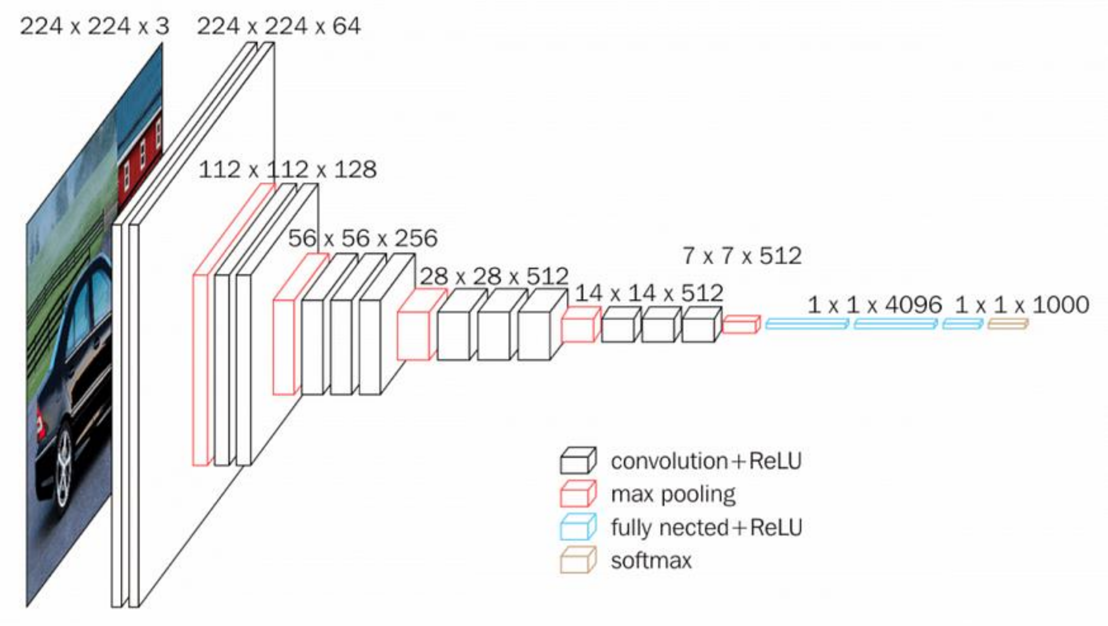
19

SOTA Deep Learning Models: AlexNet



AlexNet Network - Structural Details													
Input			Output			Layer	Stride	Pad	Kernel size		in	out	# of Param
227	227	3	55	55	96	conv1	4	0	11	11	3	96	34944
55	55	96	27	27	96	maxpool1	2	0	3	3	96	96	0
27	27	96	27	27	256	conv2	1	2	5	5	96	256	614656
27	27	256	13	13	256	maxpool2	2	0	3	3	256	256	0
13	13	256	13	13	384	conv3	1	1	3	3	256	384	885120
13	13	384	13	13	384	conv4	1	1	3	3	384	384	1327488
13	13	384	13	13	256	conv5	1	1	3	3	384	256	884992
13	13	256	6	6	256	maxpool5	2	0	3	3	256	256	0
						fc6			1	1	9216	4096	37752832
						fc7			1	1	4096	4096	16781312
						fc8			1	1	4096	1000	4097000
						Total							62,378,344

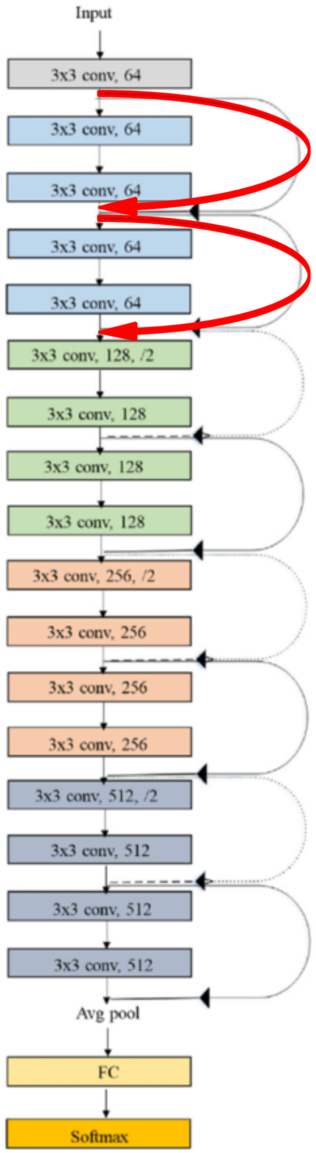
SOTA Deep Learning Models: VGG-16



VGG16 - Structural Details

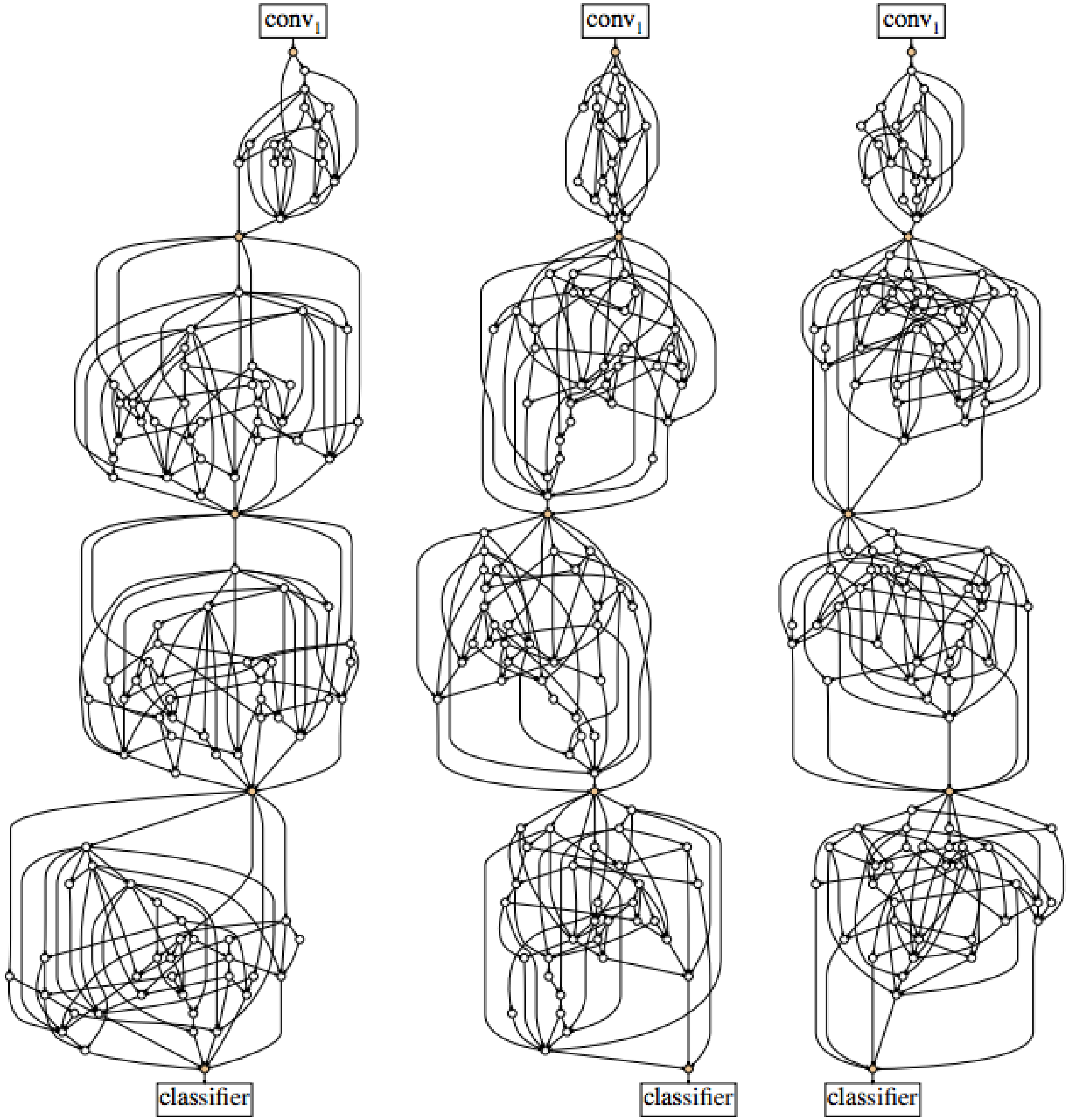
#	Input Image			output			Layer	Stride	Kernel		in	out	Param
1	224	224	3	224	224	64	conv3-64	1	3	3	3	64	1792
2	224	224	64	224	224	64	conv3064	1	3	3	64	64	36928
	224	224	64	112	112	64	maxpool	2	2	2	64	64	0
3	112	112	64	112	112	128	conv3-128	1	3	3	64	128	73856
4	112	112	128	112	112	128	conv3-128	1	3	3	128	128	147584
	112	112	128	56	56	128	maxpool	2	2	2	128	128	65664
5	56	56	128	56	56	256	conv3-256	1	3	3	128	256	295168
6	56	56	256	56	56	256	conv3-256	1	3	3	256	256	590080
7	56	56	256	56	56	256	conv3-256	1	3	3	256	256	590080
	56	56	256	28	28	256	maxpool	2	2	2	256	256	0
8	28	28	256	28	28	512	conv3-512	1	3	3	256	512	1180160
9	28	28	512	28	28	512	conv3-512	1	3	3	512	512	2359808
10	28	28	512	28	28	512	conv3-512	1	3	3	512	512	2359808
	28	28	512	14	14	512	maxpool	2	2	2	512	512	0
11	14	14	512	14	14	512	conv3-512	1	3	3	512	512	2359808
12	14	14	512	14	14	512	conv3-512	1	3	3	512	512	2359808
13	14	14	512	14	14	512	conv3-512	1	3	3	512	512	2359808
	14	14	512	7	7	512	maxpool	2	2	2	512	512	0
14	1	1	25088	1	1	4096	fc		1	1	25088	4096	102764544
15	1	1	4096	1	1	4096	fc		1	1	4096	4096	16781312
16	1	1	4096	1	1	1000	fc		1	1	4096	1000	4097000
							Total						138,423,208

SOTA Deep Learning Models: ResNet-18(34, 50, 101, 152 ..)



ResNet18 - Structural Details															
#	Input Image			output			Layer	Stride	Pad	Kernel		in	out	Param
1	227	227	3	112	112	64	conv1	2	1	7	7	3	64	9472
	112	112	64	56	56	64	maxpool	2	0.5	3	3	64	64	0
2	56	56	64	56	56	64	conv2-1	1	1	3	3	64	64	36928
3	56	56	64	56	56	64	conv2-2	1	1	3	3	64	64	36928
4	56	56	64	56	56	64	conv2-3	1	1	3	3	64	64	36928
5	56	56	64	56	56	64	conv2-4	1	1	3	3	64	64	36928
6	56	56	64	28	28	128	conv3-1	2	0.5	3	3	64	128	73856
7	28	28	128	28	28	128	conv3-2	1	1	3	3	128	128	147584
8	28	28	128	28	28	128	conv3-3	1	1	3	3	128	128	147584
9	28	28	128	28	28	128	conv3-4	1	1	3	3	128	128	147584
10	28	28	128	14	14	256	conv4-1	2	0.5	3	3	128	256	295168
11	14	14	256	14	14	256	conv4-2	1	1	3	3	256	256	590080
12	14	14	256	14	14	256	conv4-3	1	1	3	3	256	256	590080
13	14	14	256	14	14	256	conv4-4	1	1	3	3	256	256	590080
14	14	14	256	7	7	512	conv5-1	2	0.5	3	3	256	512	1180160
15	7	7	512	7	7	512	conv5-2	1	1	3	3	512	512	2359808
16	7	7	512	7	7	512	conv5-3	1	1	3	3	512	512	2359808
17	7	7	512	7	7	512	conv5-4	1	1	3	3	512	512	2359808
	7	7	512	1	1	512	avg pool	7	0	7	7	512	512	0
18	1	1	512	1	1	1000	fc					512	1000	513000
Total														11,511,784

SOTA Deep Learning Models: Neural Architecture Search



Recurrent Neural Networks (RNN)

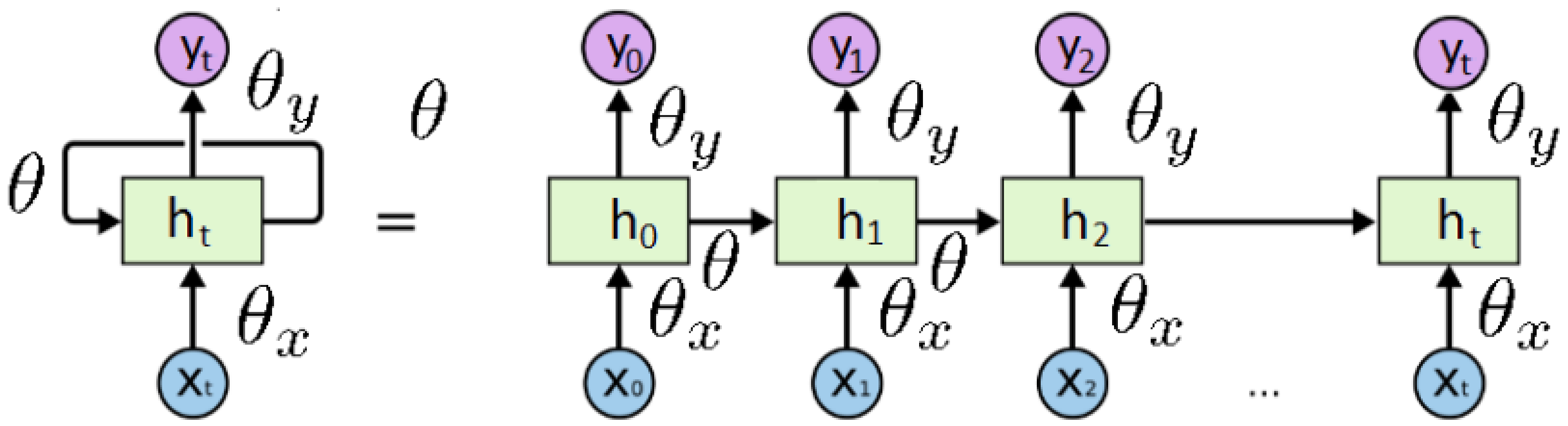
24

Recurrent Neural Networks (RNN)

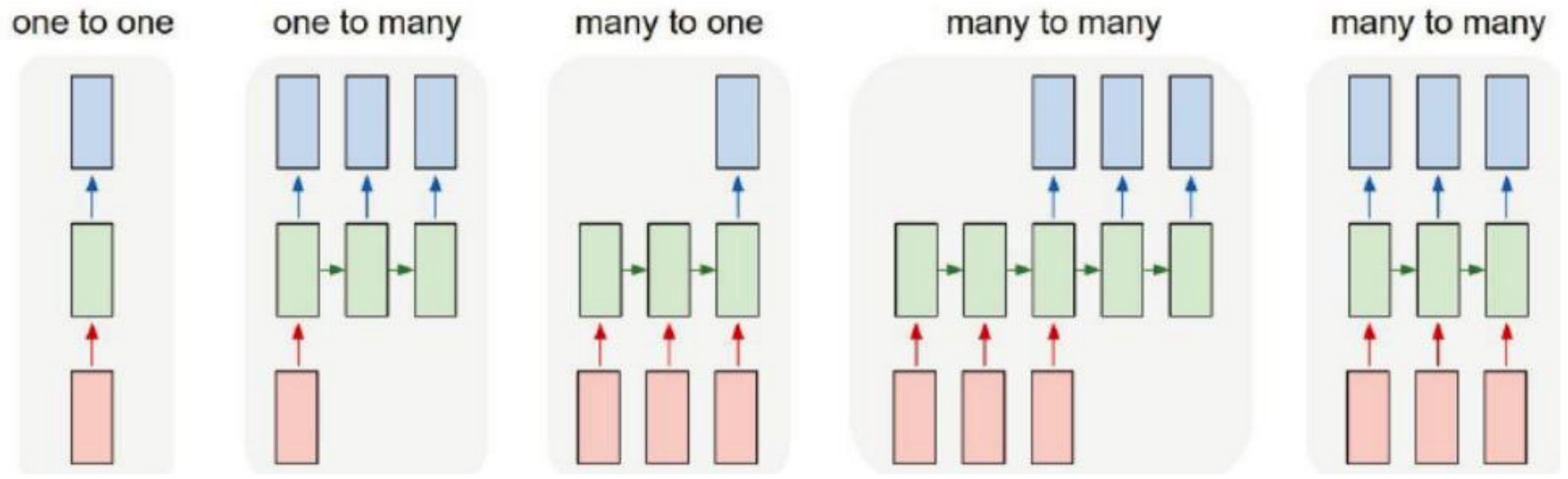
- Motivation:
  - Some data are sequential e.g., time series, text, speech
  - The sequence matters i.e., knowledge about the previous information matters:
  - The clouds are in the …?
    - Sky
  - Issues with simple NN for sequential data:
    - Fixed input/Fixed Output
    - Hard/Impossible to choose a fixed context window

Recurrent Neural Networks (RNN)

- RNNs can be thought of as multiple copies of the same network, each passing a message to a successor.
- The same function and the same set of parameters are used at every time step.
- Are called recurrent because they perform the same task for each input.



Recurrent Neural Networks (RNN)



Vanilla NN: Fixed I/O i.e. image classification	Sequence Output e.g., image captioning: image to sequence of words	Sequence Input e.g., sentiment classification: sequence of words to sentiment	Sequence I/O e.g., machine translation: sequence of words to sequence of words	Synced sequence I/O e.g. video frame classification

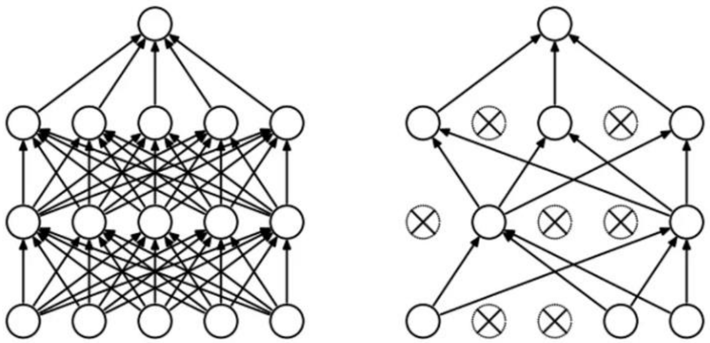
Regularizing Neural Networks

Regularizing deep neural networks

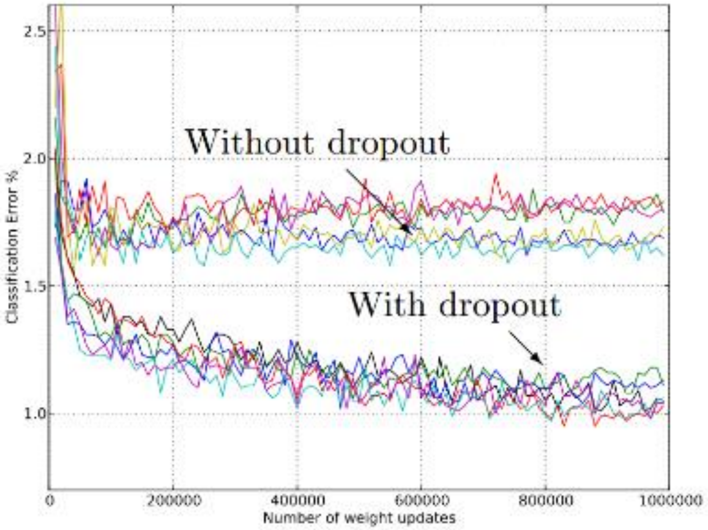
Why?

- Avoid Overfitting
- Noisy data
- Reduce model complexity

Dropout



(a) Standard Neural Net (b) After applying dropout.



Batch Normalization

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1 \ldots m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

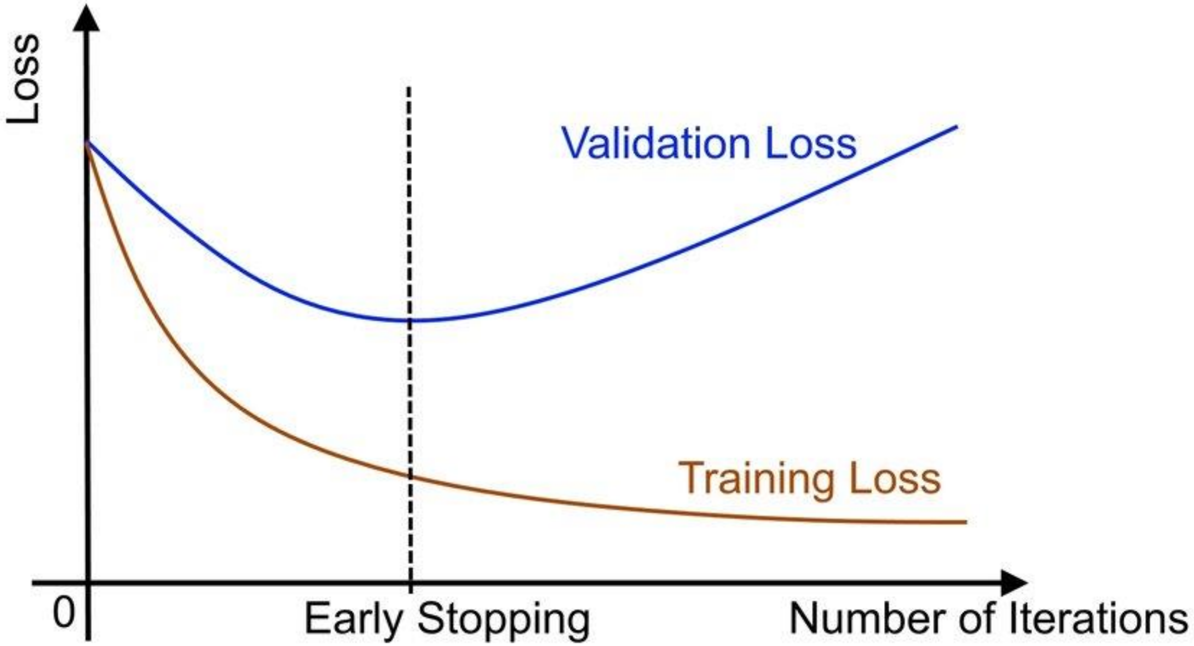
$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

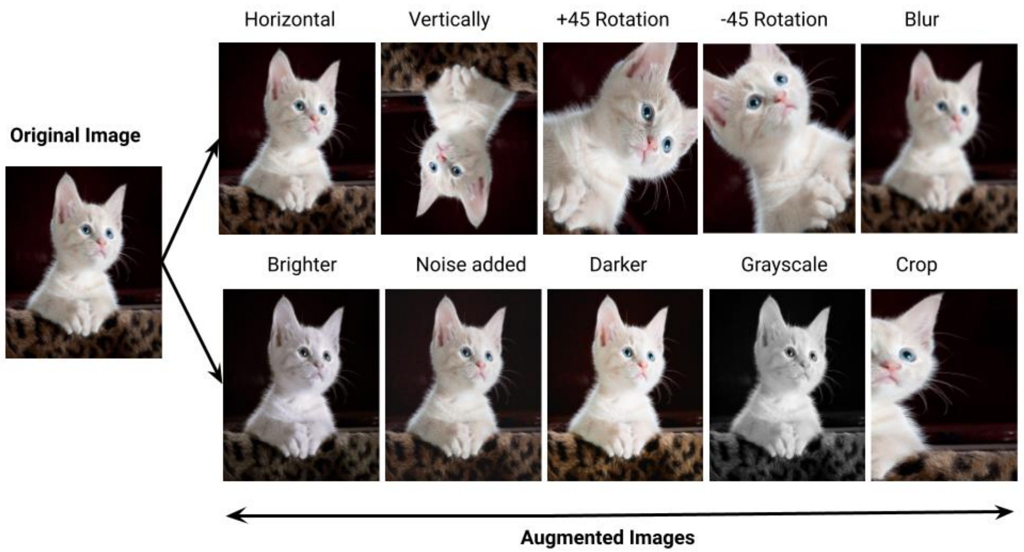
$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Regularizing deep neural networks

Early Stopping



Data Augmentation



Demo

Demo

Fine Tuning

33

Fine Tuning

Motivation:

- Goal: Recognize chair types from images and recommend purchase links.
- Method: Identify 100 common chairs, take 1000 images per chair, train classification model.
- Dataset smaller than ImageNet, risking overfitting of complex models.
- Limited training examples may result in insufficient accuracy for practical use.

➔ Let’s collect more data ➔ Collecting and labeling data can take a lot of time and money.

Or:

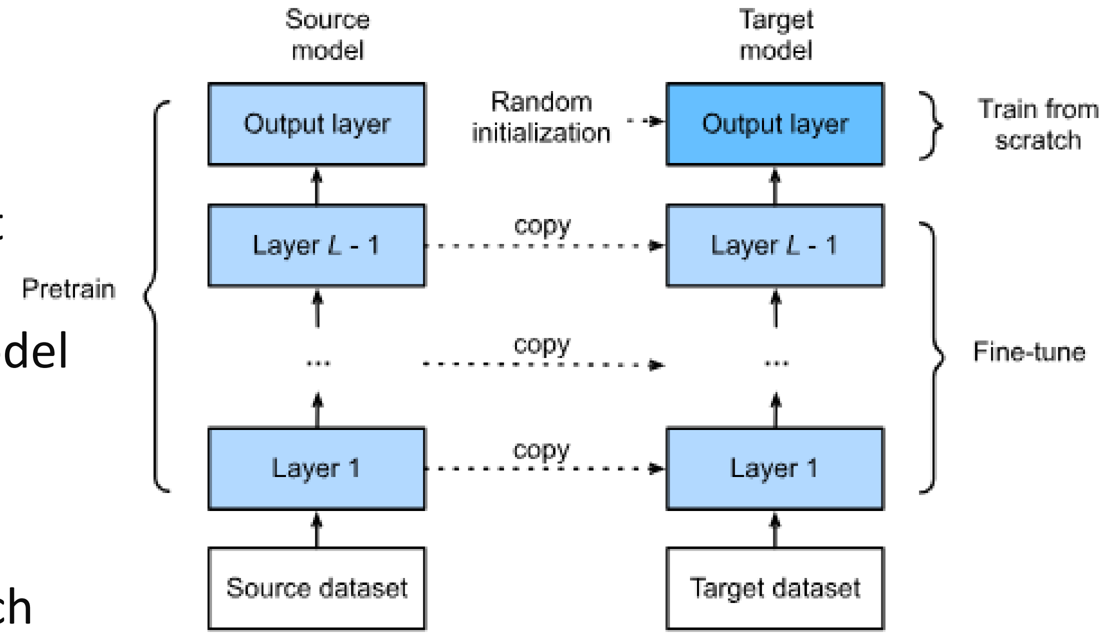
➔ Apply knowledge from source dataset to target dataset.

➔ ImageNet features (edges, textures, shapes, object composition) can help recognize chairs.

➔ Leverages pre-trained models (models already trained) to improve performance on chair recognition task.

Fine Tuning- How?

- Pre-train source model on source dataset (e.g., ImageNet)
- Create target model, copying source model except output layer
- Add randomly initialized output layer to target model based on target dataset categories (how many classes you have)
- Train target model on target dataset, fine-tuning copied layers and training output layer from scratch




```
from torchvision.models import resnet50, ResNet50_Weights

# Old weights with accuracy 76.130%
resnet50(weights=ResNet50_Weights.IMAGENET1K_V1)

# New weights with accuracy 80.858%
resnet50(weights=ResNet50_Weights.IMAGENET1K_V2)

# Best available weights (currently alias for IMAGENET1K_V2)
# Note that these weights may change across versions
resnet50(weights=ResNet50_Weights.DEFAULT)

# Strings are also supported
resnet50(weights="IMAGENET1K_V2")

# No weights - random initialization
resnet50(weights=None)
```

Conclusion: Things to keep in mind

- Classic ML algorithms work better for tabular data (so far)

- Training Deep NN:
    - Data augmentation
    - Dropout
    - Monitor your loss
    - Early stopping

- We didn't even scratch the surface

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Thank you