Deep Learning for CV

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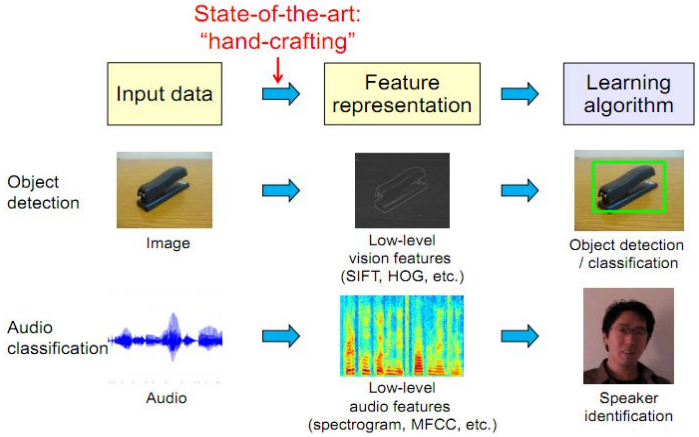
SOICT, HUST

Content

- Introduction
- ML for image classification
- CNN
  - Architectures
  - Training

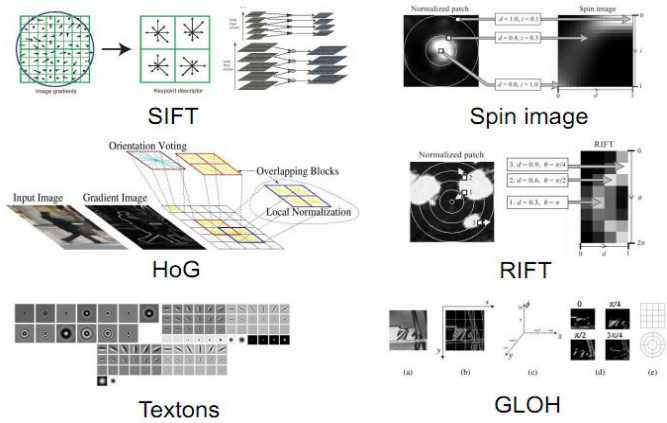
Computer Vision

Traditional machine perception



Computer Vision

Computer vision features



Computer Vision

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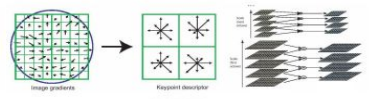
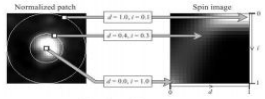
Computer vision features



SIFT



Spin image

Hand-crafted features:
1. Needs expert knowledge
2. Requires time-consuming hand-tuning
3. (Arguably) one of the limiting factors of computer vision systems

Deep Learning

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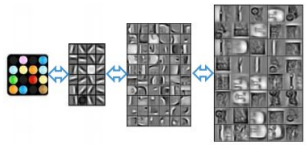
Deep learning approach



Train:

Errors

MODEL

Dog
Cat
Raccoon

Deploy:

MODEL

Dog

Deep Learning

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DEEP LEARNING EVERYWHERE

INTERNET & CLOUD	MEDICINE & BIOLOGY	MEDIA & ENTERTAINMENT	SECURITY & DEFENSE	AUTONOMOUS MACHINES
Image Classification Speech Recognition Language Translation Language Processing Sentiment Analysis Recommendation	Cancer Cell Detection Diabetic Grading Drug Discovery	Video Captioning Video Search Real Time Translation	Face Detection Video Surveillance Satellite Imagery	Pedestrian Detection Lane Tracking Recognize Traffic Sign

Deep Learning

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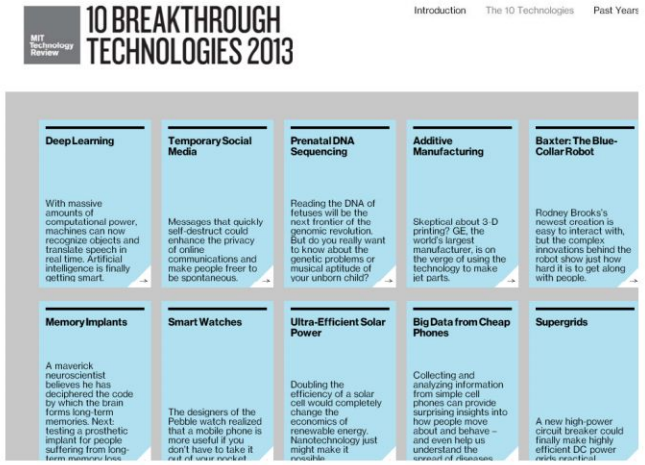

MIT Technology Review

10 BREAKTHROUGH TECHNOLOGIES 2013

Introduction The 10 Technologies Past Years

Deep Learning
With massive amounts of computational power, machines can now recognize objects and translate speech in real time. Artificial intelligence is finally getting smart.

Temporary Social Media
Messages that quickly self-destruct could enhance the privacy of online communications and make people freer to be spontaneous.

Prenatal DNA Sequencing
Reading the DNA of fetuses will be the next frontier of the genomic revolution. But do you really want to know about the genetic problems or musical aptitude of your unborn child?

Additive Manufacturing
Skeptical about 3-D printing? GE, the world's largest manufacturer, is on the verge of using the technology to make jet parts.

Baxter: The Blue-Collar Robot
Rodney Brooks's newest creation is easy to interact with, but the complex innovations behind the robot show just how hard it is to get along with people.

Memory Implants
A maverick neuroscientist believes he has deciphered the code by which the brain forms long-term memories. Next: testing a prosthetic implant for people suffering from long-

Smart Watches
The designers of the Pebble watch realized that a mobile phone is more useful if you don't have to take it

Ultra-Efficient Solar Power
Doubling the efficiency of a solar cell would completely change the economics of renewable energy. Nanotechnology just might make it

Big Data from Cheap Phones
Collecting and analyzing information from simple cell phones can provide surprising insights into how people move about and behave – and even help us understand the

Supergrids
A new high-power circuit breaker could finally make highly efficient DC power

Deep Learning vs Human

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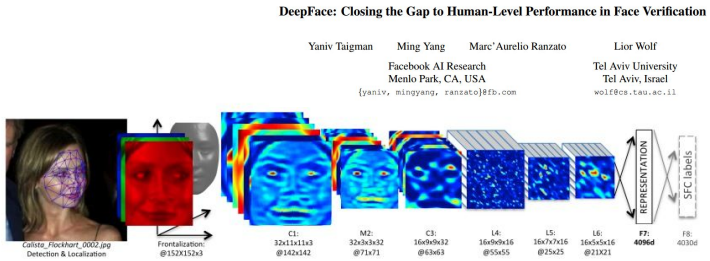

DeepFace 2014

Closing the Gap to **Human** Level **Performance** in **Face** Verification

Accuracy

DeepFace: 97.35%

Human: 97.5%

Deep Learning vs Human

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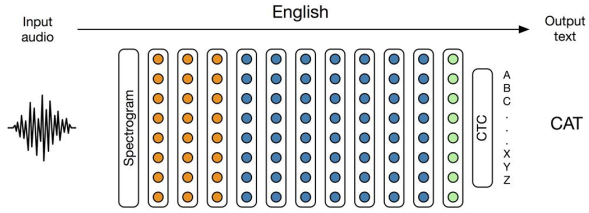

Deep Speech 2015

Baidu has developed a voice system that can recognize English and Mandarin speech **better than people**, in some cases.

"For short phrases, out of context, we seem to be **surpassing human levels of recognition**"- Andrew Ng

Deep Learning vs Human

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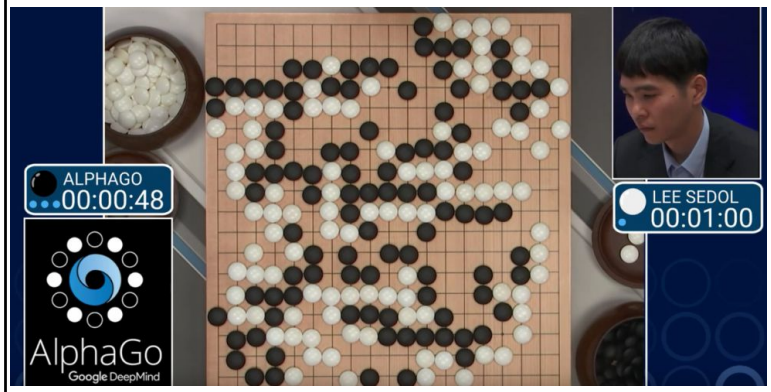

AlphaGo vs Human: 9-1

What is Deep Learning?

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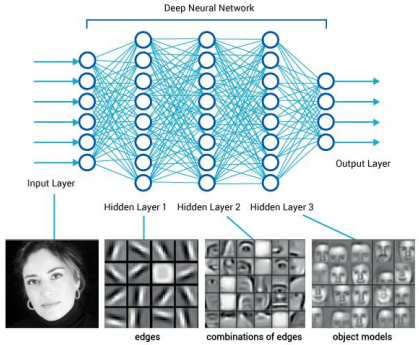
Deep learning is a branch of machine learning based on a set of algorithms that attempt to model high-level abstractions in data by using a deep graph with multiple processing layers, composed of multiple non-linear transformations.



Content

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- Introduction
- ML for image classification
- CNN
  - Architectures
  - Training

Convolution

14

12	3	19
25	10	1
9	7	17

*

1	2
3	4

=

133	75
100	101

$$f[n,m] * h[n,m] = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} f[k,l]\, h[n-k, m-l]$$

Why they are useful

15

Allow us to find **interesting insights/features** from images!

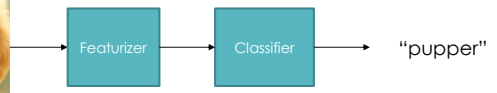
*

0	-½	0
0	0	0
0	½	0

=

Recall Image Classification…

16



Allow us to use features to put **images in categories**!

Wait a Minute…

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Convolution = Image -> Features

Classification Algorithm = Features -> Category

➔ **Let's put 'em together!**

In Specific…

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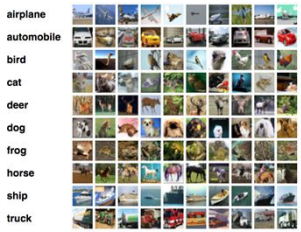
Let's build a **convolution-based** classification algorithm for the CIFAR-10 dataset (10 classes, 32x32 images):



Feature Extractor

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Feature Extractor

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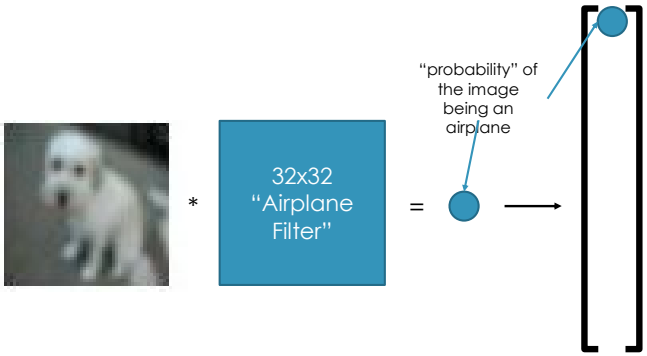
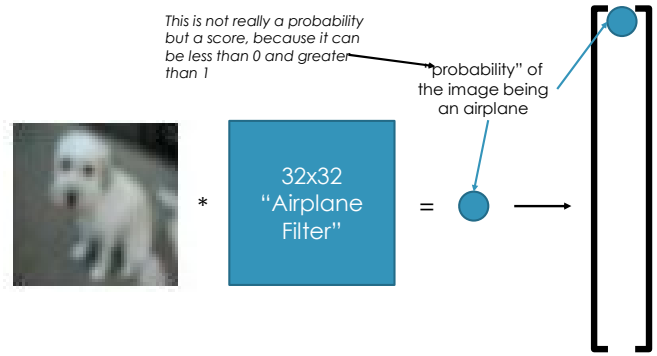
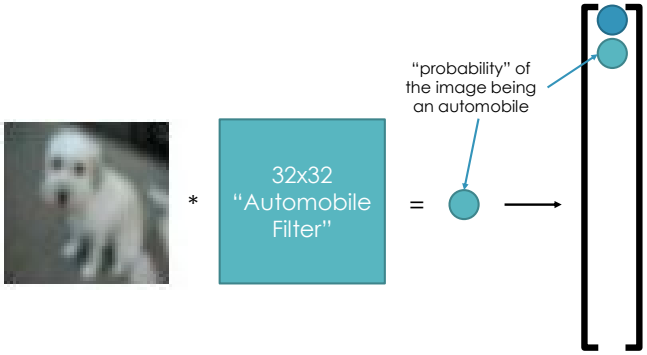
Feature Extractor 21



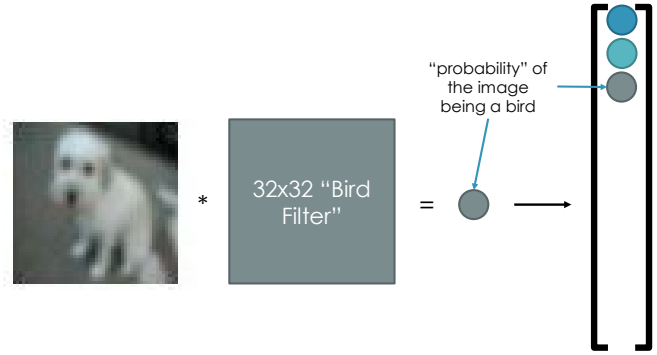
Feature Extractor 22



Feature Extractor 23

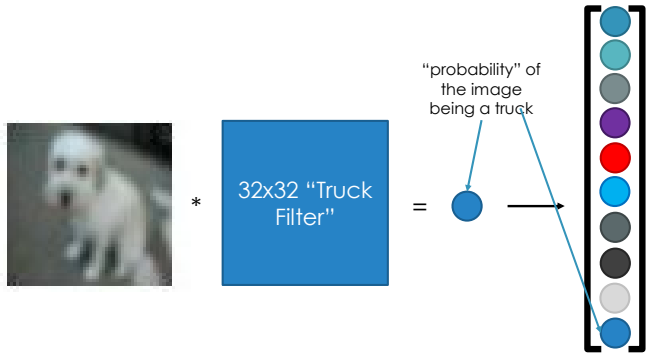


Feature Extractor 24



Feature Extractor

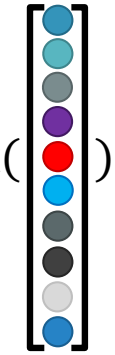
25



Classifier

26

$$c_{pred} = \arg\max(\quad)$$



We predict the class that has the highest probability!

The Whole Shebang

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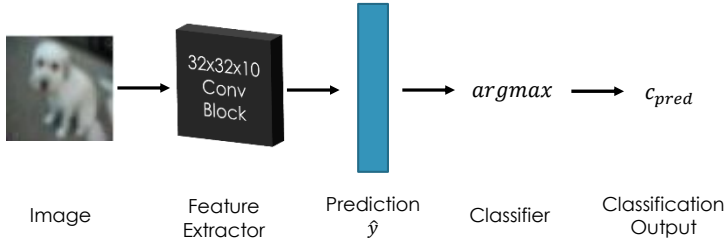
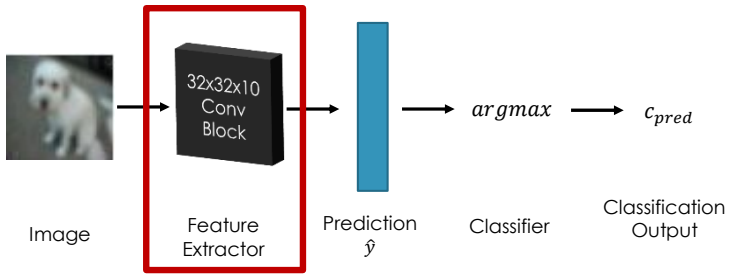


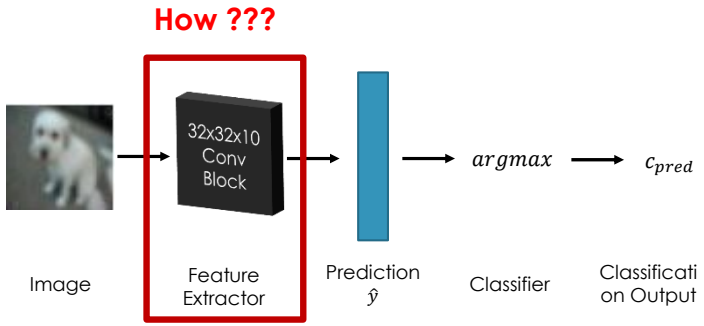
The Whole Shebang

28



The Whole Shebang

29



Reframing convolution

30

12	21
18	31

$*$

1	2
3	4

$= \begin{bmatrix} 12 \\ 21 \\ 18 \\ 31 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix}$

Reframed Feature Extractor

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Reframed Feature Extractor

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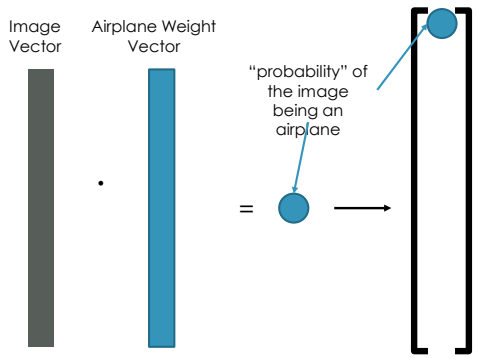
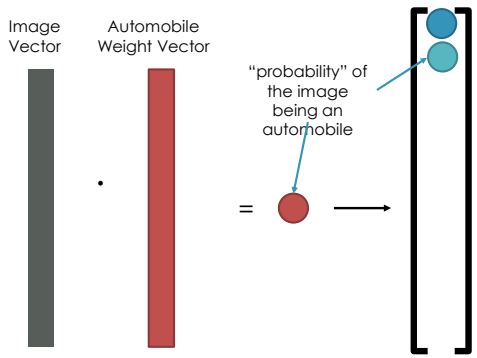
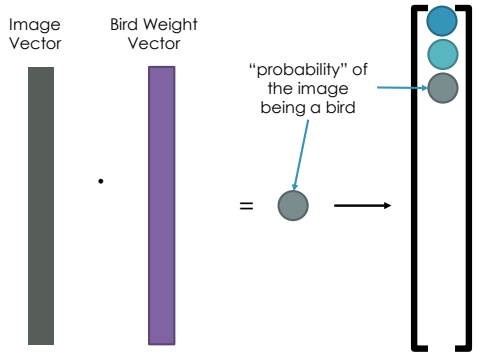
New Feature Extractor 33



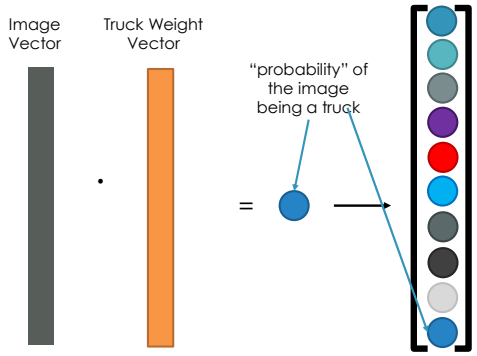
New Feature Extractor 34



New Feature Extractor

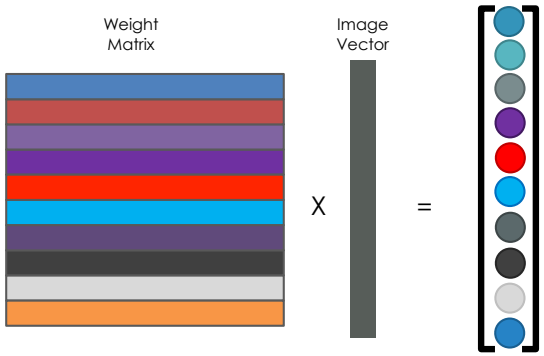


New Feature Extractor 36



New Feature Extractor

37



New Feature Extractor

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$$Wx = \hat{y}$$

W: the (10x1024) matrix of weight vectors

x: the (1024x1) image vector

$\hat{y}$: the (10x1) vector of class "probabilities"

New Feature Extractor

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This simple computation is called a *fully-connected layer*!

$$Wx = \hat{y}$$

W: the (10x1024) matrix of weight vectors

x: the (1024x1) image vector

$\hat{y}$: the (10x1) vector of class "probabilities"

Aside: Fully-Connected Neural Networks

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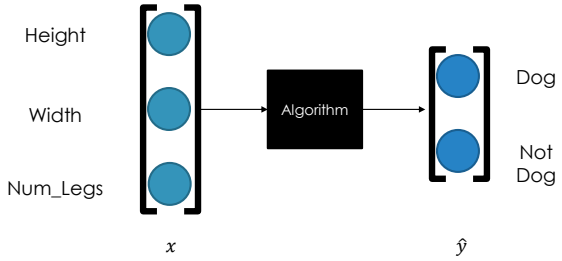

Aside: Fully-Connected Neural Networks

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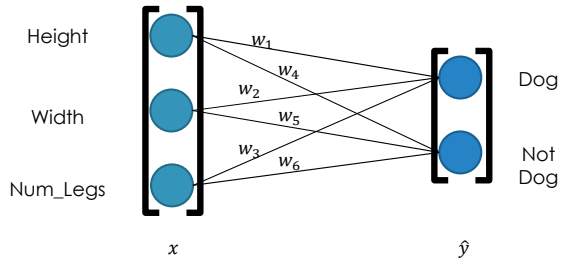

Aside: Fully-Connected Neural Networks

42

$$\begin{bmatrix} w_1 & w_2 & w_3 \\ w_4 & w_5 & w_6 \end{bmatrix} \cdot \quad = \quad$$

W x $\hat{y}$

$$Wx = \hat{y}$$

Aside: Fully-Connected Neural Networks

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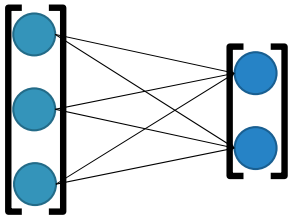
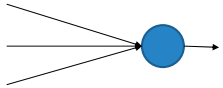
"Fully-Connected"



Every node is connected to every other node

"Neural Network"



Kinda looks like a neuron!

New Feature Extractor

44

$$Wx = \hat{y}$$

W: the (10x1024) matrix of weight vectors

x: the (1024x1) image vector

$\hat{y}$: the (10x1) vector of class "probabilities"

New Feature Extractor

45

$$Wx = \hat{y}$$

W: the (10x1024) matrix of weight vectors

x: the (1024x1) image vector

$\hat{y}$: the (10x1) vector of class "probabilities"?

Class Probability Vector

46

- Must have values between 0 and 1
- Must sum to 1
- There's no guarantee either requirement is satisfied!

$$\hat{y} = Wx$$

Softmax Function

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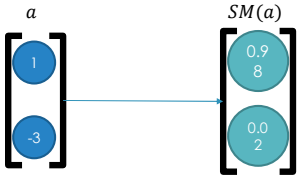


Softmax: $a(x)_i = \frac{e^{x_i}}{\sum_j e^{x_j}}$

Class Probability Vector

48

- Must have values between 0 and 1
- Must sum to 1

$$\hat{y} = Wx$$

- Must have values between 0 and 1
- Must sum to 1

$$\hat{y} = SM(Wx)$$

System so far… 49

- Feature extractor:
- Classifier: $\hat{y} = SM(Wx)$

$$c_{pred} = \arg\max(\hat{y})$$

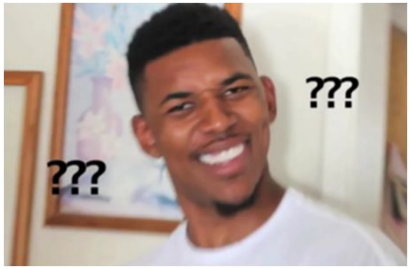
System so far… 50

- Feature extractor:
- Classifier: $\hat{y} = SM(Wx)$

$$c_{pred} = \arg\max(\hat{y})$$

System so far… 51

- Feature extractor:
- Classifier:



Using the label 52

Let's compare our prediction with the real answer! For each image, we have the label y which tells us the true class:

X

y

$$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Dog class index

Key Insight:

53

We want:

$$\arg\max(\hat{y}) = \arg\max(y)$$

Key Insight:

54

We want:

$$\arg\max(\hat{y}) = \arg\max(y)$$

Which we can accomplish by:

$$W^* = \arg\min_W \left(-\sum_{x,y} \log(p_c) \right)$$

Where p_c is the probability of the true class in $\hat{y}$

Cross-Entropy Loss

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Our loss function represents *how bad we are currently doing*:

$$L = -\log(p_c)$$

Examples:

$p_c = 0 \rightarrow L = -\log(0) = \infty$
$p_c = 0.1 \rightarrow L = -\log(0.1) = 2.3$
$p_c = 0.9 \rightarrow L = -\log(0.9) = 0.1$
$p_c = 1 \rightarrow L = -\log(1) = 0$

The larger the loss, the worse our prediction. We want to minimize L!

Minimizing Loss

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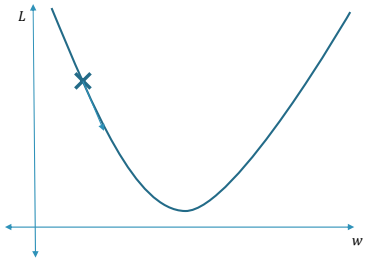
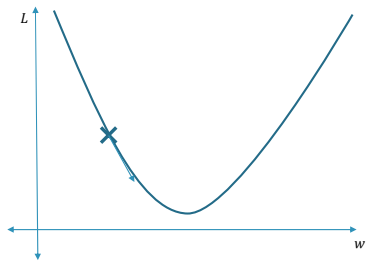
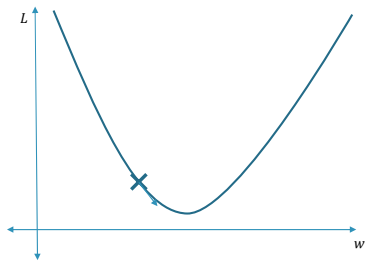


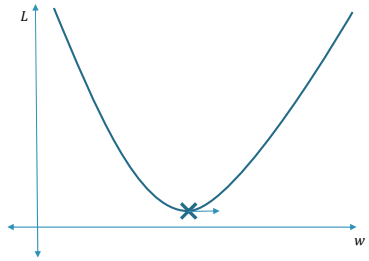
Minimizing Loss 57



Minimizing Loss 58



Minimizing Loss 59



Minimizing Loss 60

Gradient Descent Pseudocode

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```
for i in {0,…,num_epochs}:
    for x, y in data:
```

$\hat{y} = SM(Wx)$

$L = CE(\hat{y}, y)$

$\frac{dL}{dW} = ???$

$W := W - \alpha \frac{dL}{dW}$

Getting the Gradient

62

$$z = Wx$$
$$L = SCE(z, y)$$

$$\frac{dL}{dW} = \frac{dL}{dz}\frac{dz}{dW}$$

Getting the Gradient

63

$$z = Wx$$
$$L = SCE(z, y)$$

$$\frac{dL}{dW} = \frac{dL}{dz}(x)$$

Getting the Gradient

64

$$z = Wx$$
$$L = SCE(z, y)$$

$$\frac{dL}{dW} = (SM(z) - y)(x)$$

Getting the Gradient

65

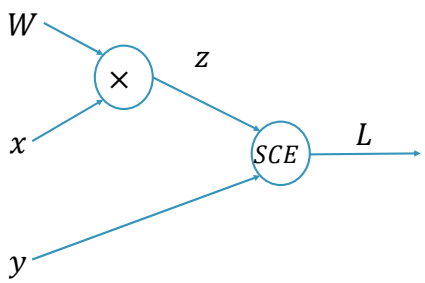
$$z = Wx$$
$$L = SCE(z, y)$$

$$\frac{dL}{dW} = (SM(z) - y)(x^T)$$

BACKPROPAGATION!

What is Backprop?

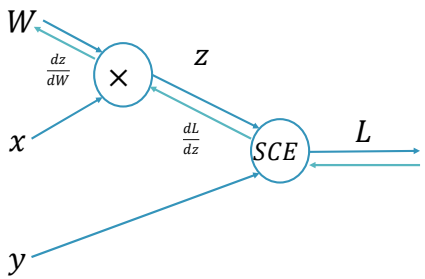
66



$$z = Wx$$
$$L = SCE(z, y)$$
$$\frac{dL}{dW} = \frac{dL}{dz}\frac{dz}{dW}$$

What is Backprop?

67



$$z = Wx$$
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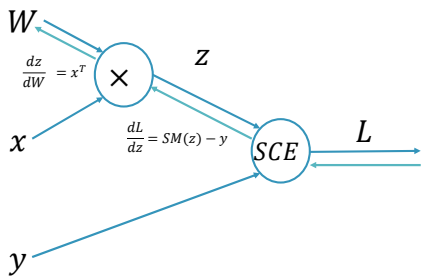
$$\frac{dL}{dW} = \frac{dL}{dz}\frac{dz}{dW}$$

What is Backprop?

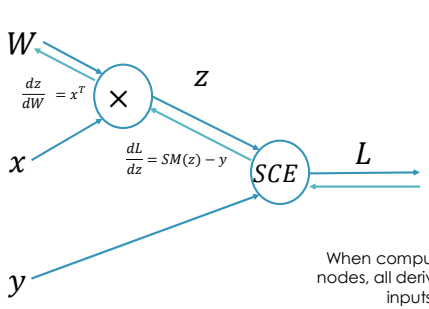
68



$$z = Wx$$
$$L = SCE(z, y)$$
$$\frac{dL}{dW} = \frac{dL}{dz}\frac{dz}{dW}$$

What is Backprop?

69

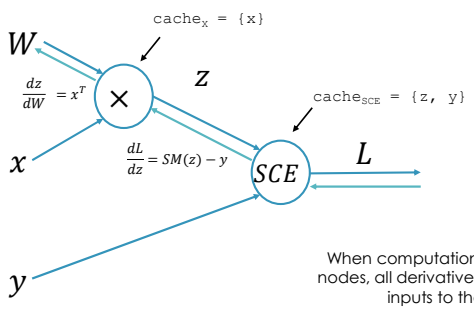


$$z = Wx$$
$$L = SCE(z, y)$$
$$\frac{dL}{dW} = \frac{dL}{dz}\frac{dz}{dW}$$

When computations are treated as nodes, all derivatives depend only on inputs to that node.

What is Backprop?

70



$$z = Wx$$
$$L = SCE(z, y)$$
$$\frac{dL}{dW} = \frac{dL}{dz}\frac{dz}{dW}$$

When computations are treated as nodes, all derivatives depend only on inputs to that node.

So, we can cache the initial computation and reuse!

Gradient Descent Pseudocode (Updated)

71

```
for i in {0,…,num_epochs}:
    for x, y in data:
```
$\hat{y} = SM(Wx)$

$L = CE(\hat{y}, y)$

$\frac{dL}{dW} =$ **backprop(L)**

$W := W - \alpha \frac{dL}{dW}$

Gradient Descent Pseudocode (Updated)

72

```
for i in {0,…,num_epochs}:
    for x, y in data:
```
$\hat{y} = SM(Wx)$

$L = CE(\hat{y}, y)$

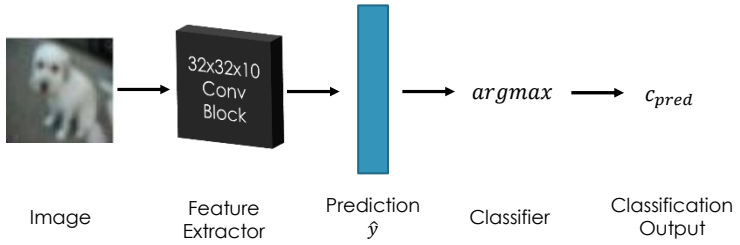
$\frac{dL}{dW} =$ **backprop(L)**

$W := W - \alpha \frac{dL}{dW}$

MACHINE LEARNING!

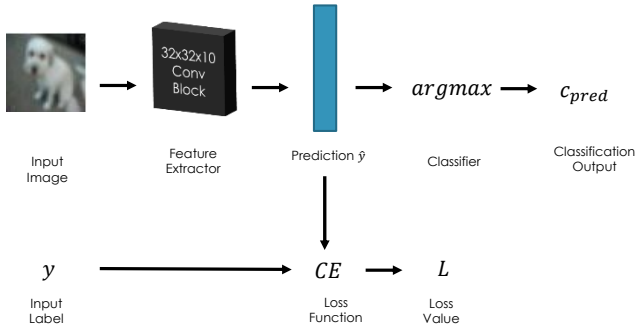
Simple Classification System

73



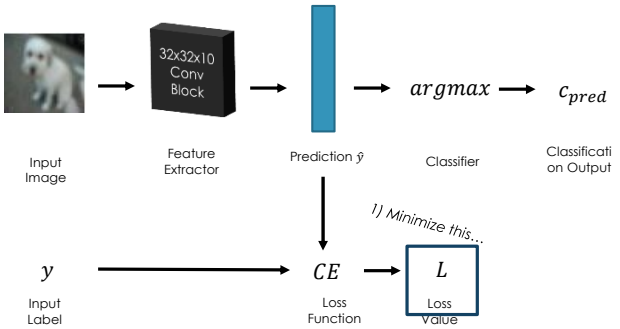
Simple Classification System (modified)

74



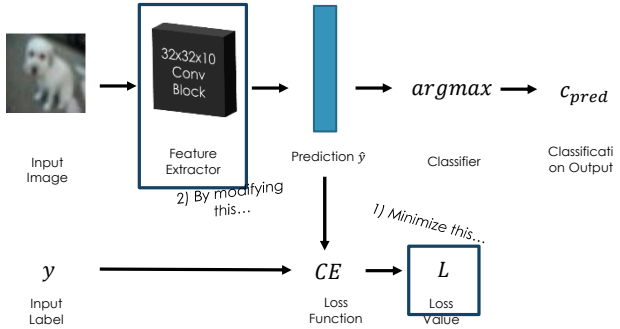
Simple Classification System (modified)

75



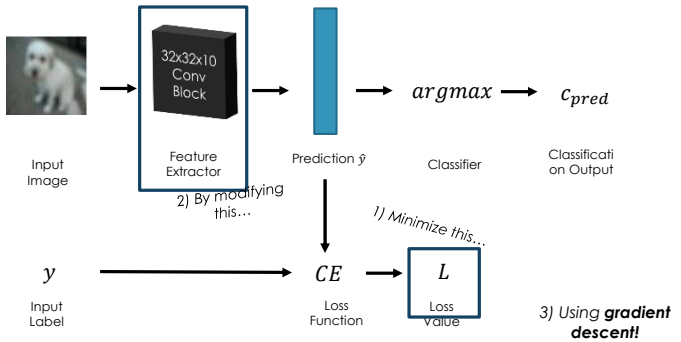
Simple Classification System (modified)

76



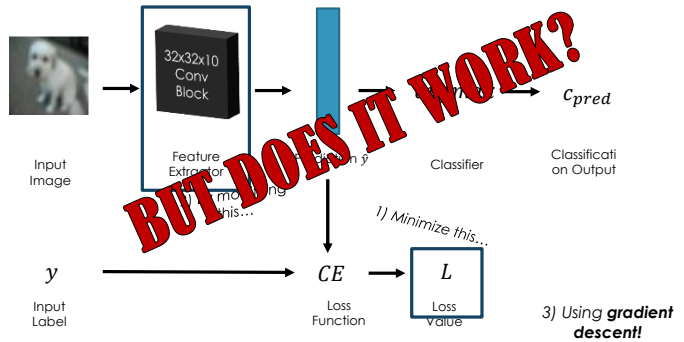
Simple Classification System (modified)

77



Simple Classification System (modified)

78



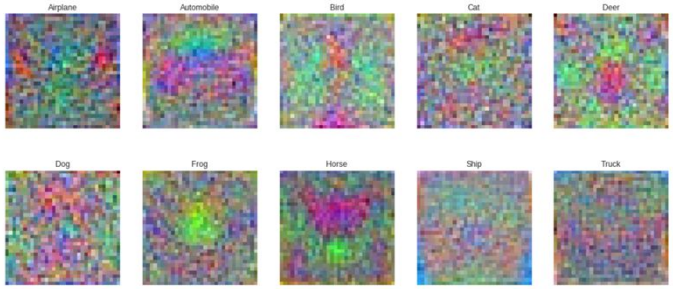
Simple System's Performance

79

- ~40% accuracy on CIFAR-10 test
  - Best class: Truck (~60%)
  - Worst class: Horse (~16%)
- Check out the model at: **https://tinyurl.com/cifar10**
- What about the filters? What do they look like?

Visualizing the Filters

80



Content 81

- Introduction
- Computer Vision & ML
- CNN
  - Architectures
  - Training

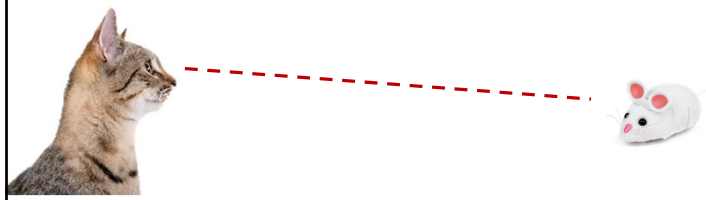
Convolutions 82

Building a stronger convolution-based feature extractor ??

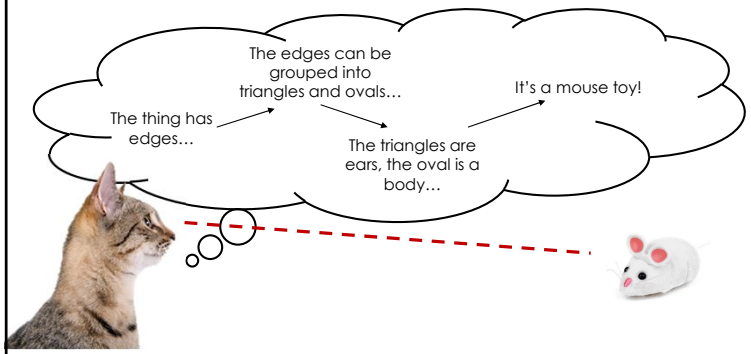
Convolutions = Insights

More Convolutions = More Insights?

Recall Hubel and Weisel… 83

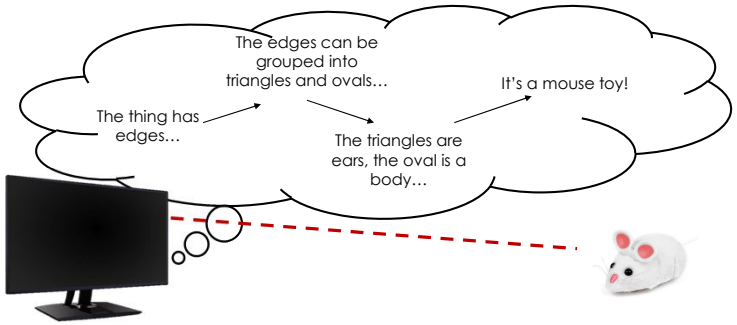


Recall Hubel and Weisel… 84



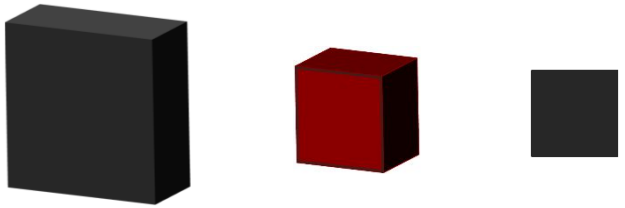
Recall Hubel and Weisel…

85



Convolutions Across Channels

86



$28 \times 28 \times 3$
Image

$15 \times 15 \times 3$
Filter

$14 \times 14 \times 1$
Output

Convolutions Across Channels

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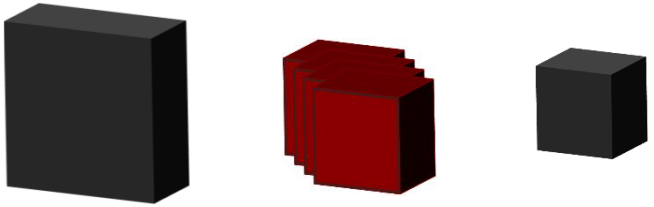


$28 \times 28 \times 3$
Image

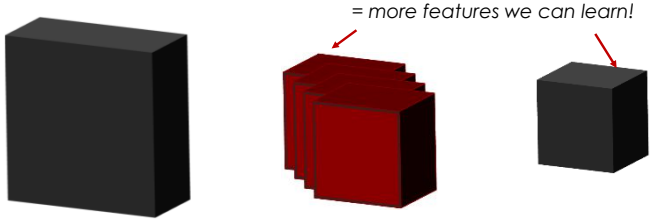
$15 \times 15 \times 3 \times 4$
Filter

$14 \times 14 \times 4$
Output

Convolutions Across Channels

88

more output channels
= more filters
= more features we can learn!



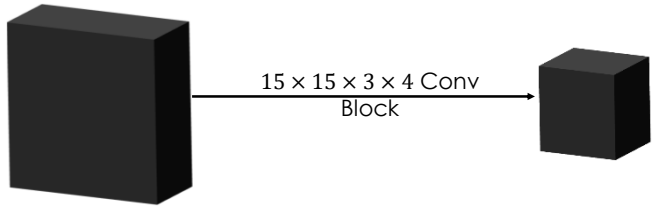
$28 \times 28 \times 3$
Image

$15 \times 15 \times 3 \times 4$
Filter

$14 \times 14 \times 4$
Output

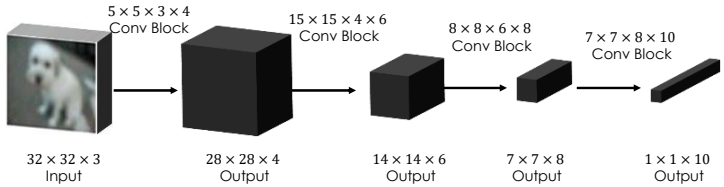
Convolutions Across Channels

89



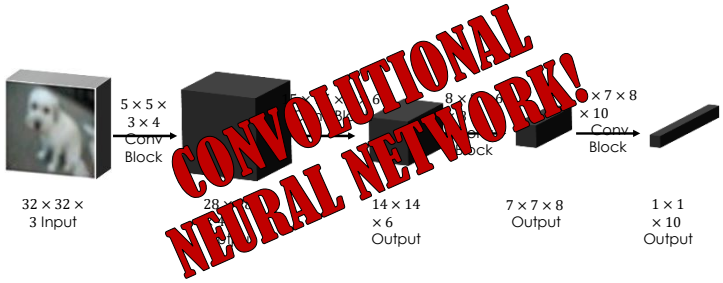
Stacking Convolutions

90



Stacking Convolutions

91

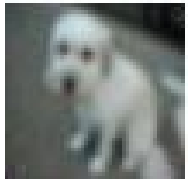


Convolutional Neural Networks (ConvNets)

92

- Neural networks which involve the stacking of multiple convolutional layers to produce output
- Often times end in fully-connected layers as the "classifier"

Why Do They Work So Well?



Why Do They Work So Well?

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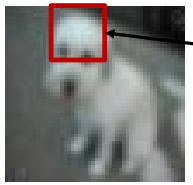


This is the neural network's "receptive field"—it's able to see!

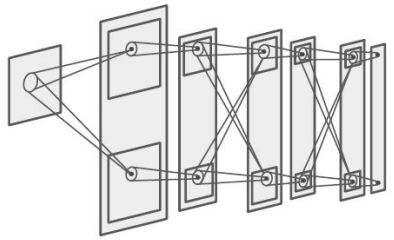
History of ConvNets

98

A bit of history:

Neocognitron
[Fukushima 1980]

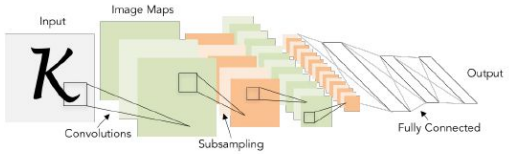
"sandwich" architecture (SCSCSC…)
simple cells: modifiable parameters
complex cells: perform pooling



History of ConvNets

99

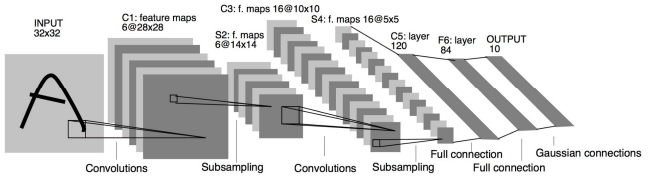
A bit of history:
Gradient-based learning applied to document recognition
[LeCun, Bottou, Bengio, Haffner 1998]



LeNet-5

History of ConvNets

100



LeNet – 1998

MNIST is 0-9
0.7% test accuracy on MNIST

History of ConvNets

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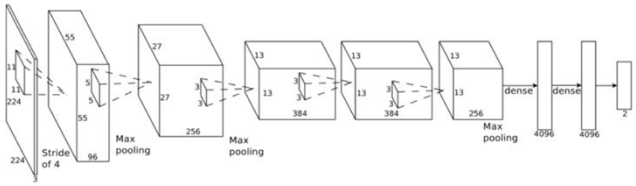

AlexNet – 2012

History of ConvNets

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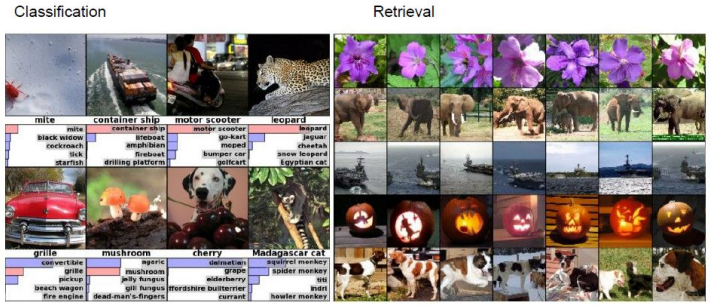
Fast-forward to today: ConvNets are everywhere



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History of ConvNets

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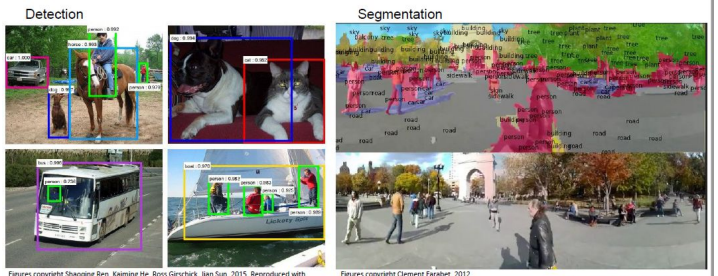
Fast-forward to today: ConvNets are everywhere



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[Faster R-CNN: Ren, He, Girshick, Sun 2015]

Figures copyright Clement Farabet, 2012. Reproduced with permission.

[Farabet et al., 2012]

History of ConvNets

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Fast-forward to today: ConvNets are everywhere

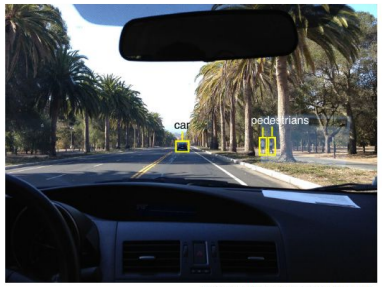

Photo by Lane McIntosh. Copyright CS231n 2017.

self-driving cars

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NVIDIA Tesla line
(these are the GPUs on rye01.stanford.edu)

Note that for embedded systems a typical setup would involve NVIDIA Tegras, with integrated GPU and ARM-based CPU cores.

History of ConvNets

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History of ConvNets

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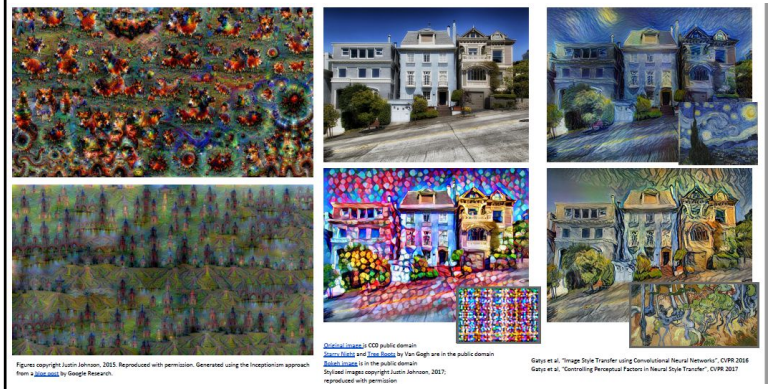

NN vs CNN

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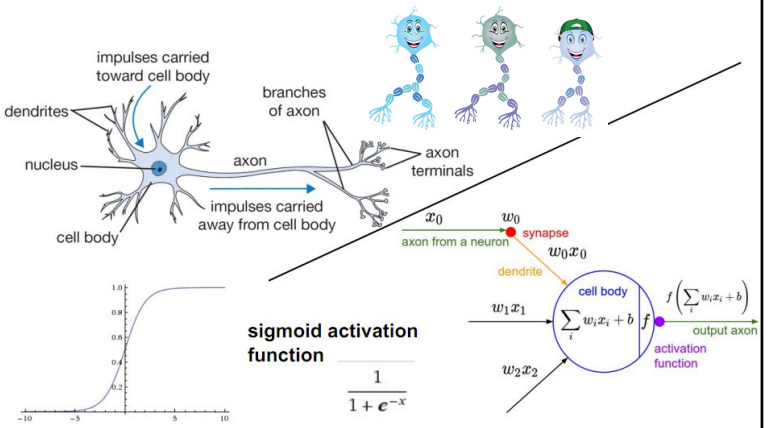
Neuron

110



Neural Networks

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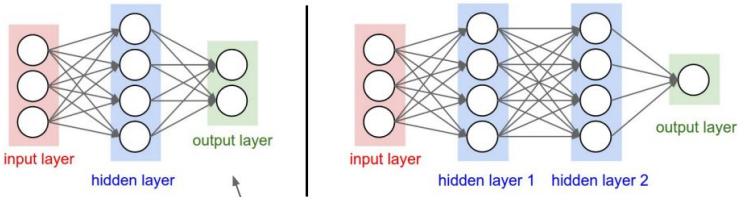
Neural Networks: Architectures



"2-layer Neural Net", or
"1-hidden-layer Neural Net"

"3-layer Neural Net", or
"2-hidden-layer Neural Net"

"Fully-connected" layers

ConvNets

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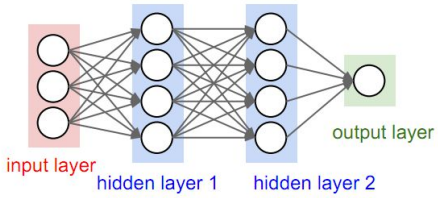
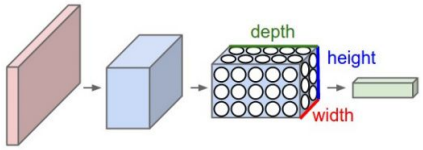
before:



now:



ConvNets

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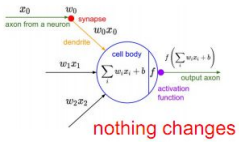
Convolutional Neural Networks are just Neural Networks BUT:

Local connectivity



nothing changes

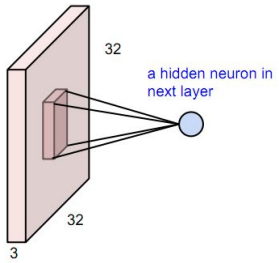


image: 32x32x3 volume
before: full connectivity: 32x32x3 weights

now: one neuron will connect to, e.g. 5x5x3 chunk and only have 5x5x3 weights.

note that connectivity is:
- local in space (5x5 inside 32x32)
- but full in depth (all 3 depth channels)

ConvNets

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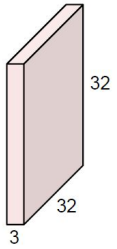
Convolution Layer

Filters always extend the full depth of the input volume

32x32x3 image

5x5x3 filter



Convolve the filter with the image i.e. "slide over the image spatially, computing dot products"

ConvNets

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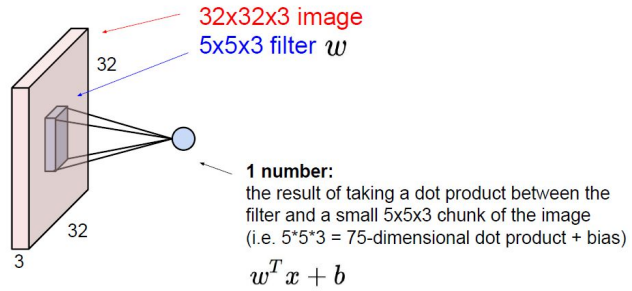
Convolution Layer



ConvNets

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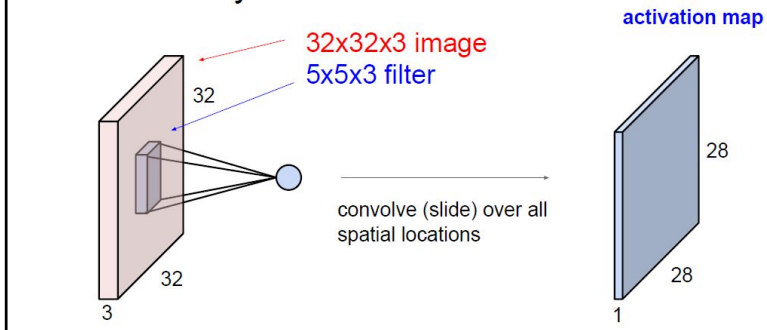
Convolution Layer



ConvNets

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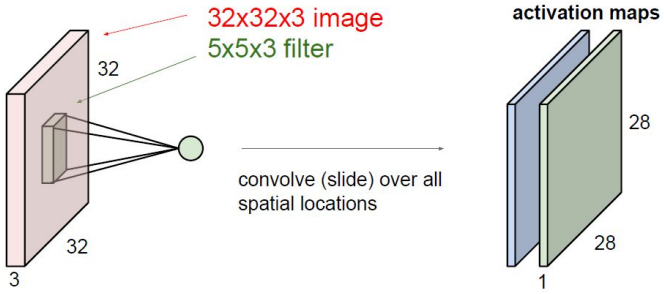
Convolution Layer

consider a second, green filter



ConvNets

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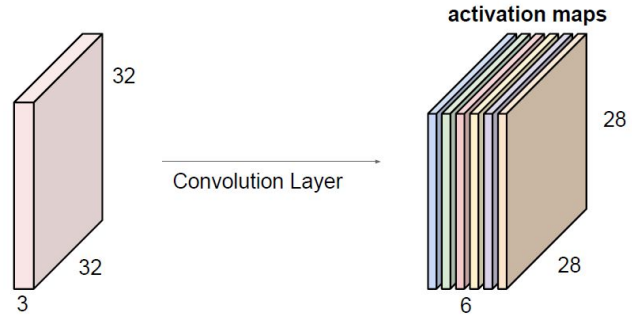
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



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

ConvNets

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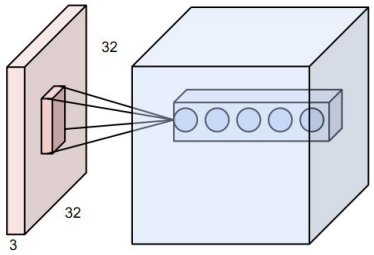
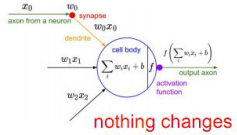
Convolutional Neural Networks are just Neural Networks BUT:

Local connectivity





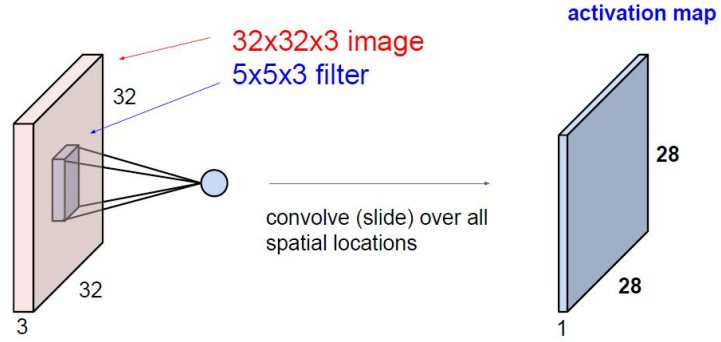
nothing changes

These form a single [1 x 1 x depth] "depth column" in the output volume

ConvNets

120

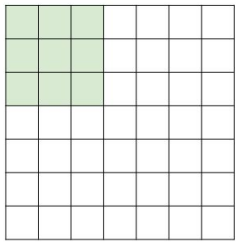
A closer look at spatial dimensions:



ConvNets

121

Replicate this column of hidden neurons across space, with some **stride.**

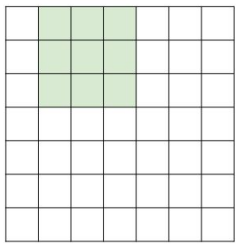


7x7 input
assume 3x3 connectivity, stride 1

ConvNets

122

Replicate this column of hidden neurons across space, with some **stride.**

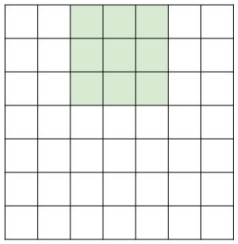


7x7 input
assume 3x3 connectivity, stride 1

ConvNets

123

Replicate this column of hidden neurons across space, with some **stride.**

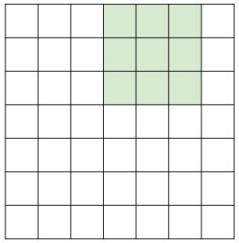


7x7 input
assume 3x3 connectivity, stride 1

ConvNets

124

Replicate this column of hidden neurons across space, with some **stride.**

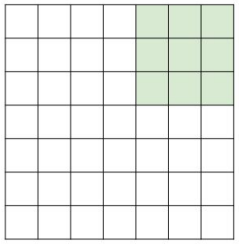


7x7 input
assume 3x3 connectivity, stride 1

ConvNets

125

Replicate this column of hidden neurons across space, with some **stride.**



7x7 input
assume 3x3 connectivity, stride 1
=> **5x5 output**

ConvNets

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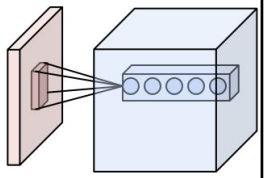
Examples time:



Input volume: **32x32x3**
Receptive fields: **5x5**, **stride 1**
Number of neurons: **5**

Output volume: (32 - 5) / 1 + 1 = 28, so: **28x28x5**
How many weights for each of the 28x28x5 neurons?

ConvNets

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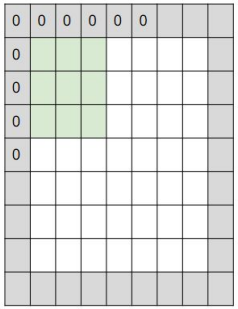
In practice: Common to zero pad the border

(in each channel)



e.g. input 7x7
neuron with receptive field 3x3, stride 1
pad with 1 pixel border => what is the output?

7x7 => preserved size!

in general, common to see stride 1, size F, and zero-padding with (F-1)/2.
(Will preserve input size spatially)

ConvNets

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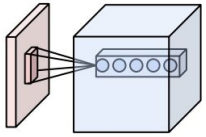
There's one more problem…

Assume input **[32 x 32 x3]**
30 neurons with receptive fields **5x5**, applied at **stride 1/pad1:**
=> Output volume: [32 x 32 x 30] (32*32*30 = 30720 neurons)
Each neuron has 5*5*3 (=75) weights
=> Number of weights in such layer: 30720 * 75 ~= **3 million :**



Example trained weights

IDEA: lets not learn the same thing across all spatial locations

ConvNets

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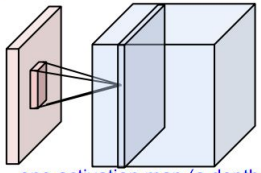
These layers are called **Convolutional Layers**

1. Connect neurons only to local receptive fields
2. Use the same neuron weight parameters for neurons in each "depth slice" (i.e. across spatial positions)



one activation map (a depth slice), computed with one set of weights

ConvNets

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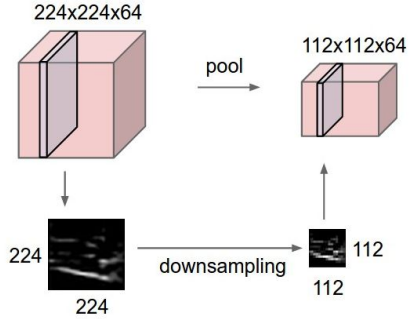
In ConvNet architectures, **Conv** layers are often followed by **Pool** layers

- convenience layer: makes the representations smaller and more manageable without losing too much information. Computes MAX operation (most common)



ConvNets

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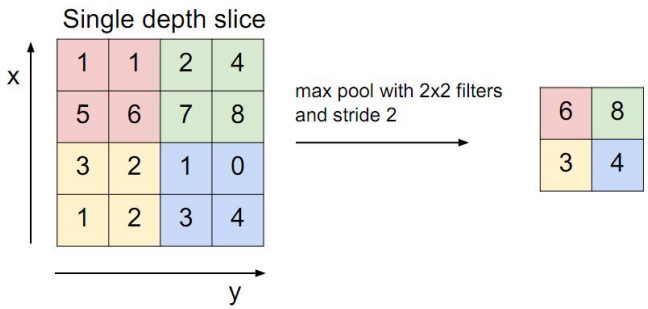
MAX POOLING



ConvNets

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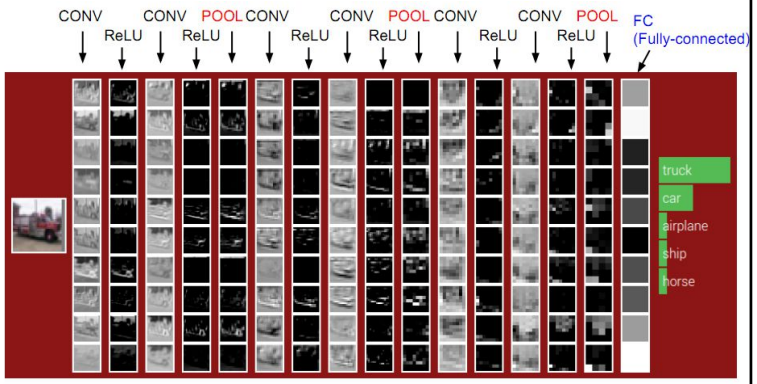

ConvNets

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Modern CNNs:

- use **filter sizes of 3x3** (maybe even 2x2 or 1x1!)
- use **pooling sizes of 2x2** (maybe even less - e.g. fractional pooling!)
- **stride 1**
- **very deep**

INPUT -> [[CONV -> RELU]*N -> POOL?]*M -> [FC -> RELU]*K -> FC
where the * indicates repetition, and the POOL? indicates an optional pooling layer.
N >= 0 (and usually N <= 3), M >= 0, K >= 0 (and usually K < 3).

ConvNets

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Case study: VGGNet / OxfordNet
(runner-up winner of ILSVRC 2014)
[Simonyan and Zisserman]

best model

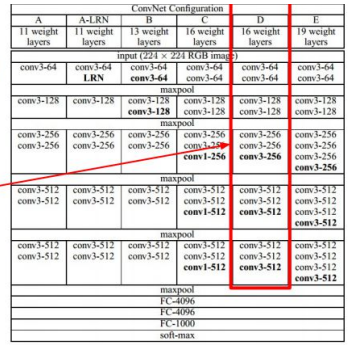

Table 2: **Number of parameters** (in millions).

Network	A,A-LRN	B	C	D	E
Number of parameters	133	133	134	138	144

Training ConvNets

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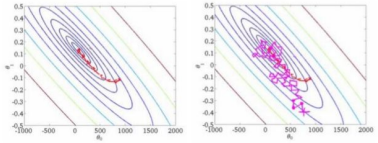
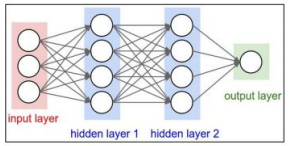
Mini-batch SGD



Loop:

1. **Sample** a batch of data
2. **Forward** prop it through the graph, get loss
3. **Backprop** to calculate the gradients
4. **Update** the parameters using the gradient



Training ConvNets

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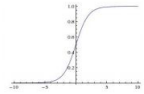
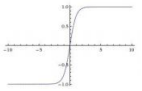
Activation Functions

Sigmoid

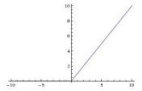
$\sigma(x) = 1/(1+e^{-x})$



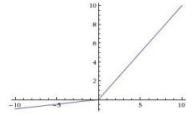
tanh tanh(x)



ReLU max(0,x)

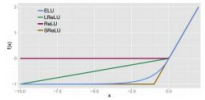


Leaky ReLU
max(0.1x, x)



Maxout $\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU $f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha(\exp(x) - 1) & \text{if } x \le 0 \end{cases}$



Data Augmentation

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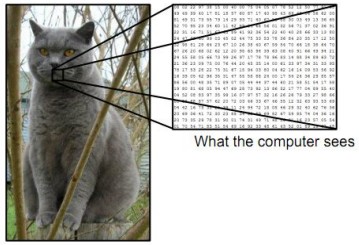
Data Augmentation

- i.e. simulating “fake” data
- explicitly encoding image transformations that shouldn’t change object identity.



Data Augmentation

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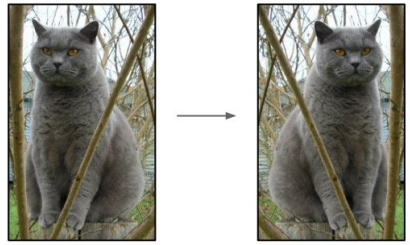
Data Augmentation

1. Flip horizontally



Data Augmentation

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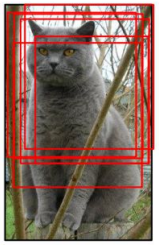
Data Augmentation
2. Random crops/scales



Sample these during training
(also helps a lot during test time)

e.g. common to see even up to 150 crops used

Data Augmentation

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Data Augmentation
3.

Random mix/combinations of :
- translation
- rotation
- stretching
- shearing,
- lens distortions, … (go crazy)

Data Augmentation

141

Data Augmentation
4. Color jittering
(maybe even contrast jittering, etc.)

- Simple: Change contrast small amounts, jitter the color distributions, etc.
- Vignette,... (go crazy)

Transfer learning

142

"You need a lot of a data if you want to train/use CNNs"

Transfer learning 143

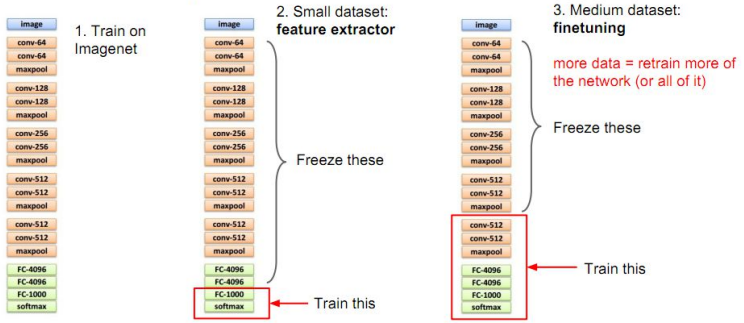
Transfer Learning

"You need a lot of data if you want to train/use CNNs"

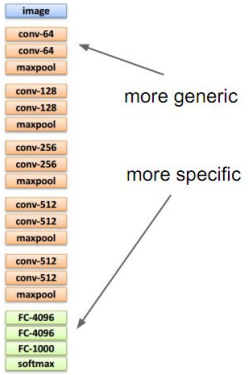
BUSTED

Transfer learning 144

Transfer Learning with CNNs

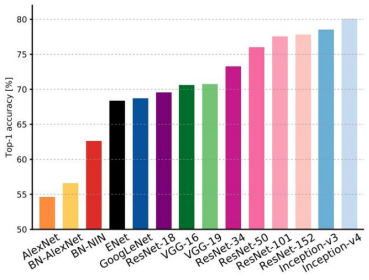


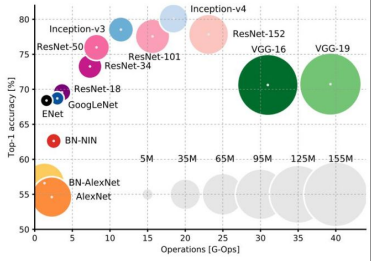
Transfer learning 145



	very similar dataset	very different dataset
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

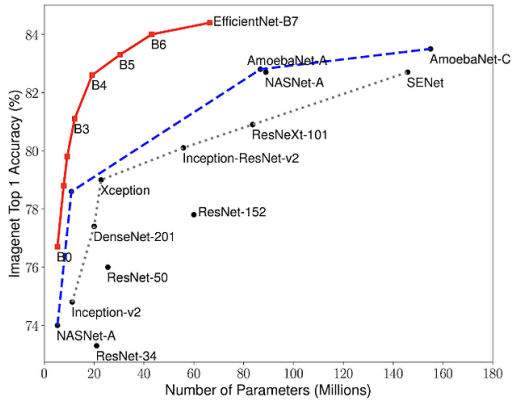
CNN Performances 146





CNN Performances

147



EfficientNet: Improving Accuracy and Efficiency through AutoML and Model Scaling, 5/2019

What is CNN dev?

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- Define the objective
  - What is the input/output?
  - What is the loss/objective function?
- Create the architecture
  - How many conv layers?
  - What size are the convolutions?
  - How many fully-connected layers?
- Define hyperparameters
  - What is the learning rate?
- Train and evaluate
  - How did we do?
  - How can we do better?

CPU vs GPU

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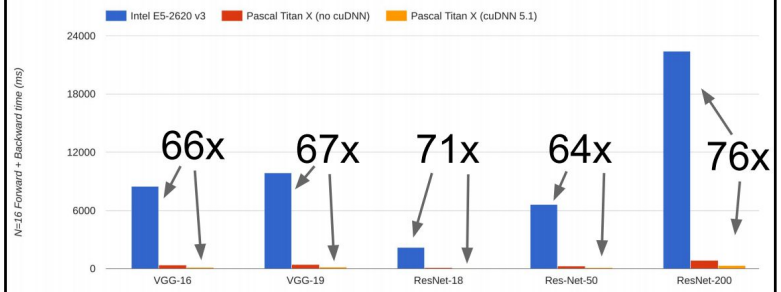
CPU vs GPU in practice

(CPU performance not well-optimized, a little unfair)



CPU vs GPU

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	Cores	Clock Speed	Memory	Price	Speed
CPU (Intel Core i7-7700k)	4 (8 threads with hyperthreading)	4.2 GHz	System RAM	$339	~540 GFLOPs FP32
GPU (NVIDIA GTX 1080 Ti)	3584	1.6 GHz	11 GB GDDR5 X	$699	~11.4 TFLOPs FP32
TPU NVIDIA TITAN V	5120 CUDA, 640 Tensor	1.5 GHz	12GB HBM2	$2999	~14 TFLOPs FP32 ~112 TFLOP FP16
TPU Google Cloud TPU	?	?	64 GB HBM	$6.50 per hour	~180 TFLOP

CPU: Fewer cores, but each core is much faster and much more capable; great at sequential tasks

GPU: More cores, but each core is much slower and "dumber"; great for parallel tasks

TPU: Specialized hardware for deep learning

A zoo of frameworks

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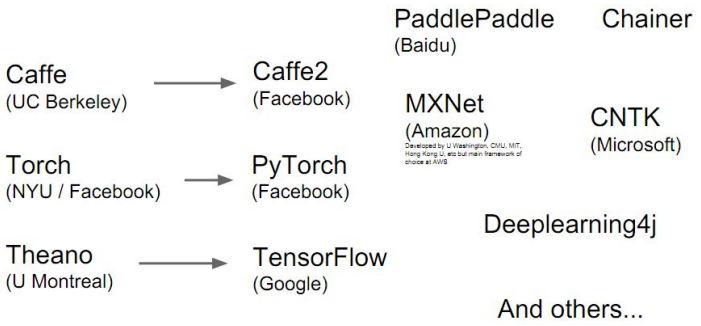

References

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- Fei-Fei Li & Justin Johnson & Serena Yeung. *CS231n – 2019 - lecture 4, lecture 5*
- Shubhang Desai, Ranjay Krishna, and Juan Carlos Niebles. *Lecture: Computer Vision and Machine Learning*. CS131 Stanford Vision and Learning Lab