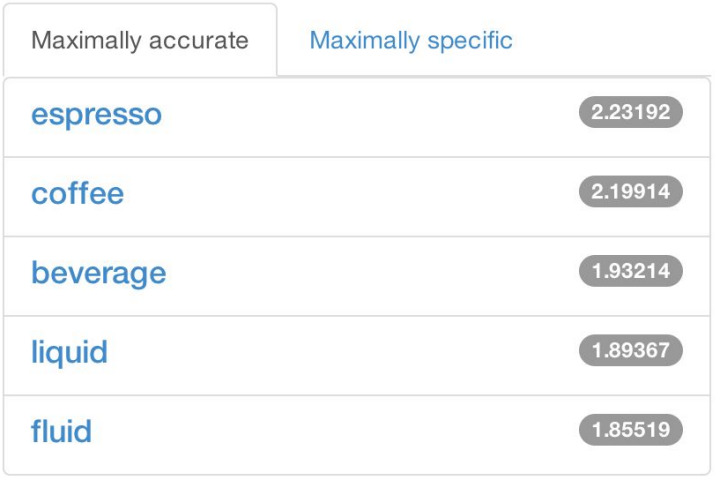
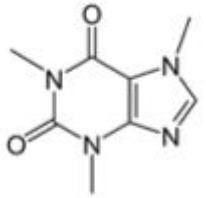
DIY Deep Learning for Vision: A Full-Day Caffe Tutorial





caffe.berkeleyvision.org

github.com/BVLC/caffe

BAIR
BERKELEY ARTIFICIAL INTELLIGENCE RESEARCH

embedded VISION ALLIANCE

Evan Shelhamer, Jeff Donahue, Jon Long

The Highest Bandwidth Input Channel

Machines are useful mainly to the extent that they **interact with the physical world**

Visual information is the richest source of information about the real world

Vision is the highest-bandwidth mode for machines to obtain real-world info

Embedded vision enables our things to be:

- **More responsive**
- **More personal and secure**
- **Safer, more autonomous**
- **Easier to use**

subaru.com

Tutorial Organization

Part 1 (Morning)

Introduction to Deep Learning and Convolutional Networks:

A Theoretical and *Practical Discussion*

Part 2 (Afternoon)

Hands-On Introduction to the Caffe Framework:

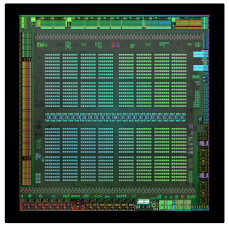
Brewing Networks with Caffe

Part 1: Deep Learning for Vision

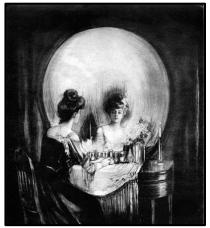
Why Deep Learning?

Dive into Deep Learning

What is DL? Why Now?



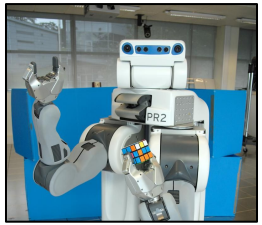
The Challenge of Recognition



Learning & Optimization

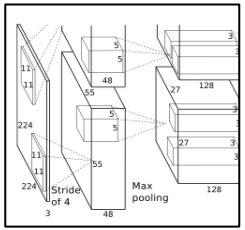
$$\nabla_\theta L$$

Applications



Caffe First Sip

Network Tour

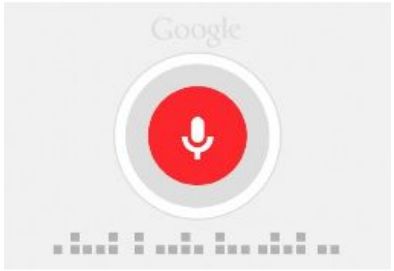


Transfer Learning

Why Deep Learning?

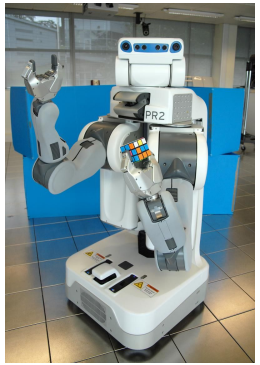
End-to-End Learning for Many Tasks

vision



speech

text



control

Visual Recognition Tasks

Classification

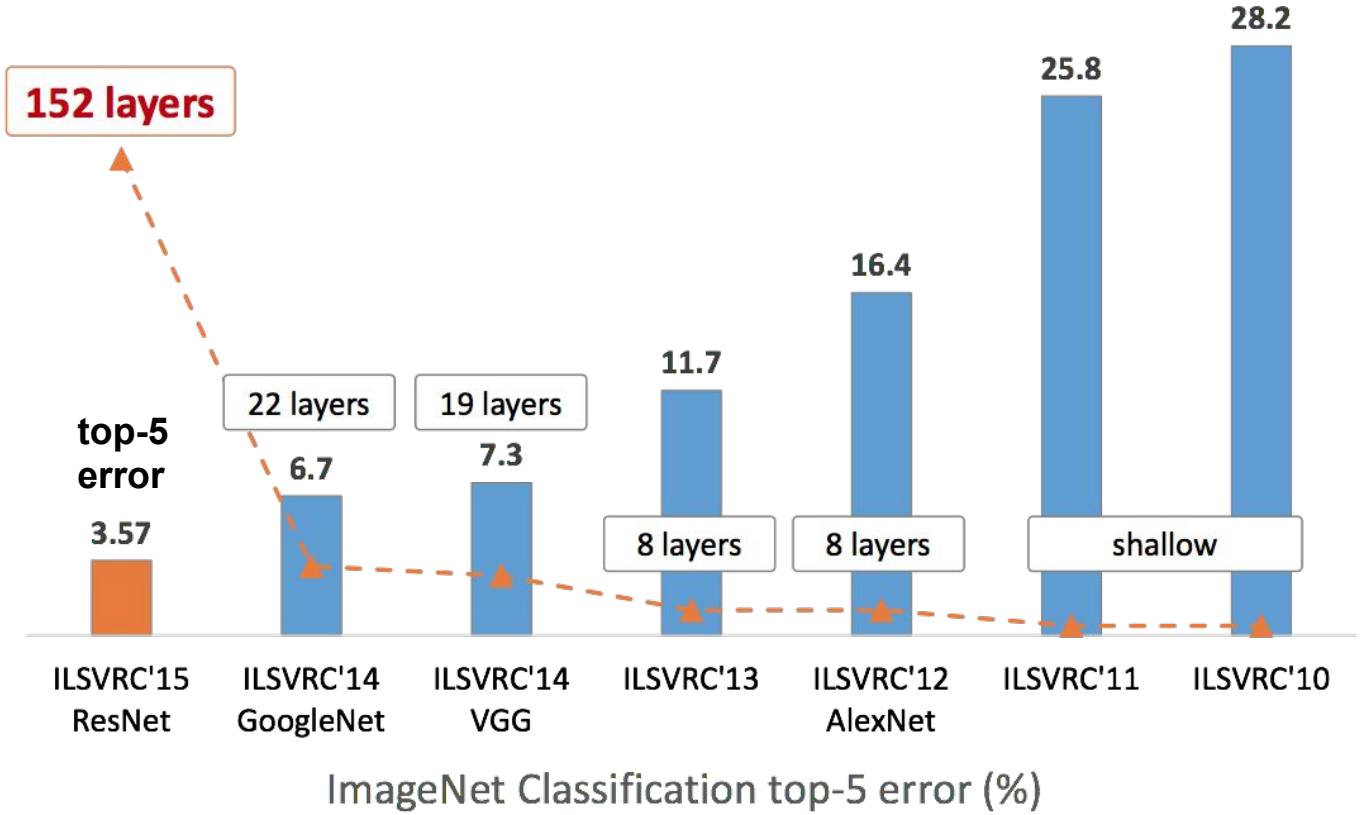
- what kind of image?
- which kind(s) of objects?

Challenges

- appearance varies by lighting, pose, context, ...
- clutter
- fine-grained categorization (horse or exact species)

- ❑ dog
- ☑ car
- ☑ horse
- ❑ bike
- ❑ cat
- ❑ bottle
- ☑ person

Image Classification: ILSVRC 2010-2015



- ☐ dog
- ☑ car
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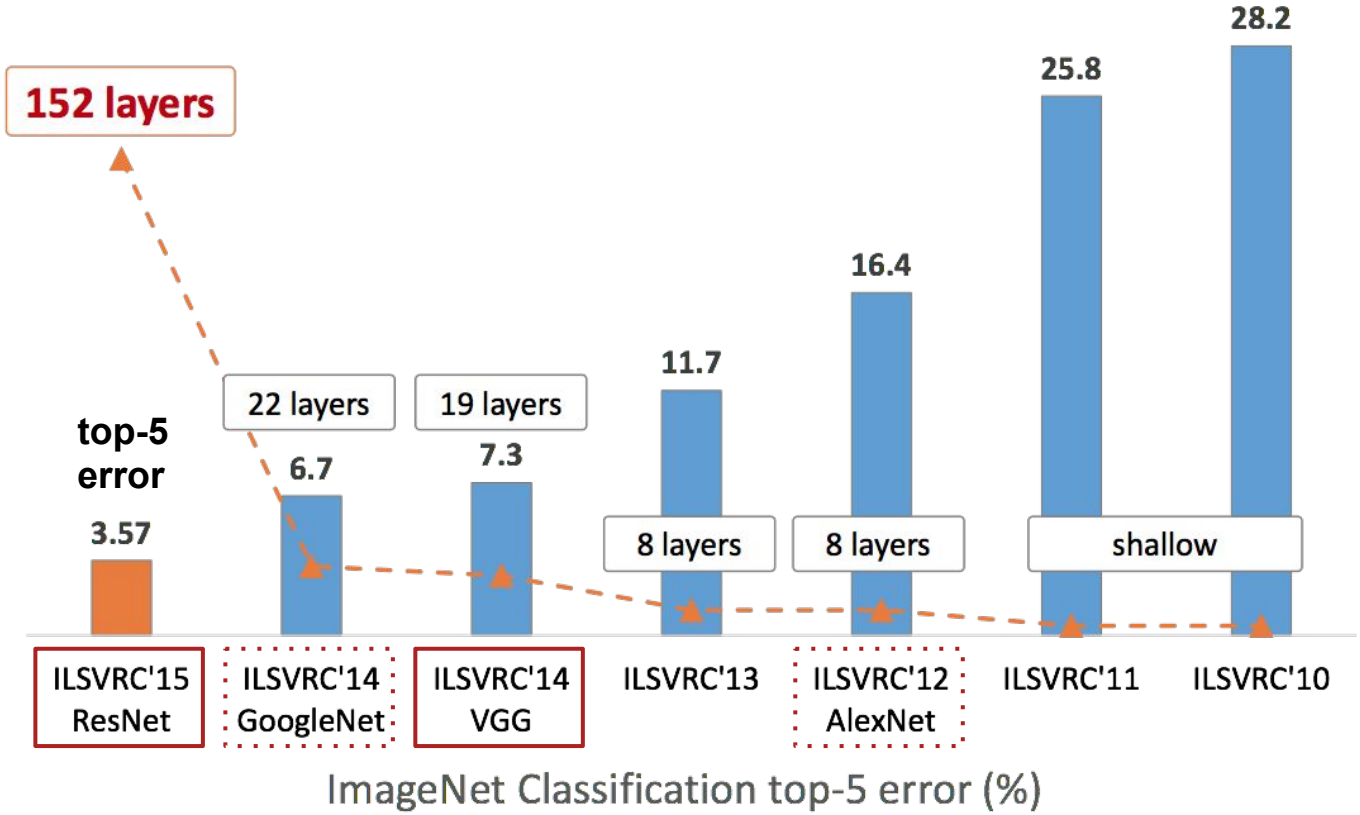
- ☐ bike
- ☐ cat
- ☐ bottle
- ☑ person

[graph credit K. He]

Image Classification: ILSVRC 2010-2015



- ❑ dog
- ☑ car
- ☑ horse
- ❑ bike
- ❑ cat
- ❑ bottle
- ☑ person

[graph credit K. He]

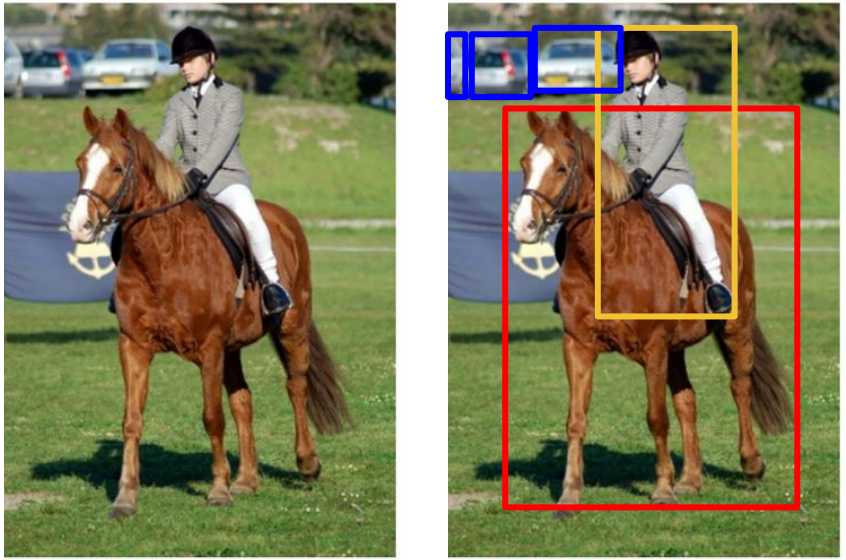
Visual Recognition Tasks

Detection

- what objects are there?
- where are the objects?

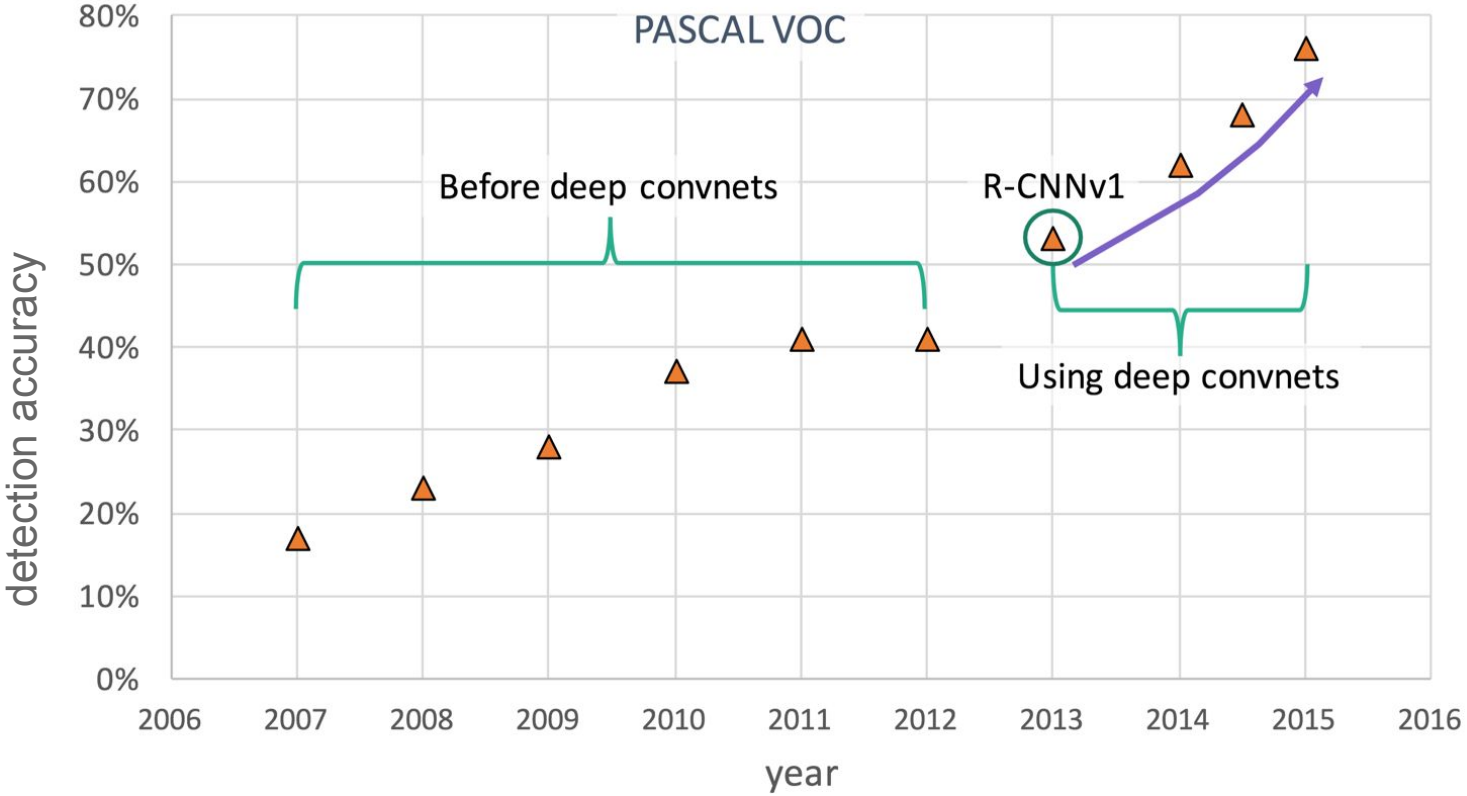
Challenges

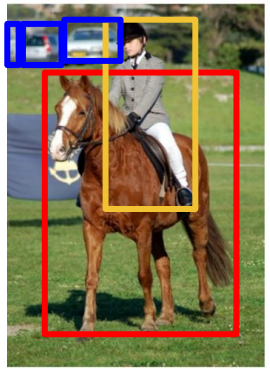
- localization
- multiple instances
- small objects



car person horse

Detection: PASCAL VOC





R-CNN:
regions + convnets

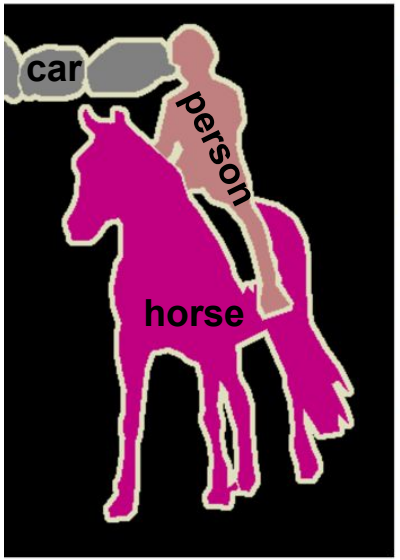
state-of-the-art, in Caffe

[graph credit R. Girshick]

Visual Recognition Tasks

Semantic Segmentation

- what kind of thing
  is each pixel part of?
- what kind of stuff
  is each pixel?



Challenges

- tension between
  recognition and localization
- amount of computation

Segmentation: PASCAL VOC

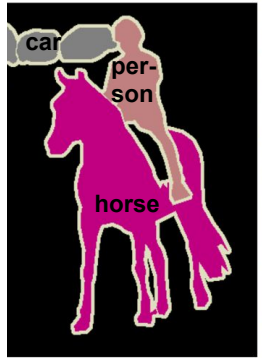
Leaderboard

MSRA_BoxSup [?]	75.2
Oxford_TVG_CRF_RNN_COCO [?]	74.7
DeepLab-MSc-CRF-LargeFOV-COCO-CrossJoint [?]	73.9
Adelaide_Context_CNN_CRF_VOC [?]	72.9
DeepLab-CRF-COCO-LargeFOV [?]	72.7
POSTECH_EDeconvNet_CRF_VOC [?]	72.5
Oxford_TVG_CRF_RNN_VOC [?]	72.0
DeepLab-MSc-CRF-LargeFOV [?]	71.6
MSRA_BoxSup [?]	71.0
DeepLab-CRF-COCO-Strong [?]	70.4
DeepLab-CRF-LargeFOV [?]	70.3
TTI_zoomout_v2 [?]	69.6
DeepLab-CRF-MSc [?]	67.1
DeepLab-CRF [?]	66.4
CRF_RNN [?]	65.2
TTI_zoomout_16 [?]	64.4
Hypercolumn [?]	62.6
FCN-8s [?]	62.2
MSRA_CFM [?]	61.8
TTI_zoomout [?]	58.4
SDS [?]	51.6
NUS_UDS [?]	50.0
TTIC-divmbest-rerank [?]	48.1
BONN_O2PCPMC_FGT_SEGM [?]	47.8
BONN_O2PCPMC_FGT_SEGM [?]	47.5
BONNGC_O2P_CPMC_CSI [?]	46.8
BONN_CMBR_O2P_CPMC_LIN [?]	46.7

deep learning with Caffe

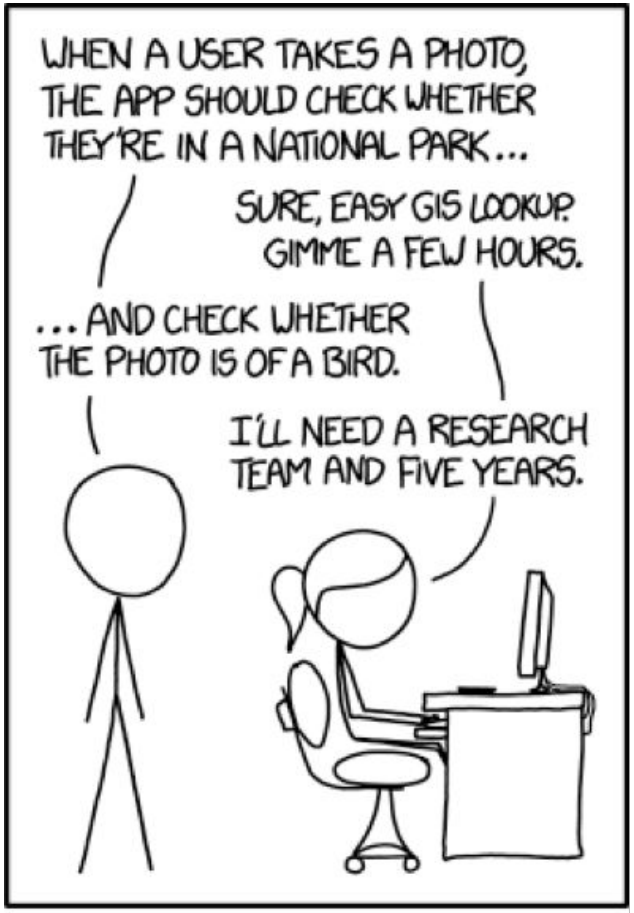
end-to-end networks lead to
30 points absolute or 50% relative improvement
and >100x speedup in 1 year!

(papers published for +1 or +2 points)



FCN:
pixelwise
convnet

state-of-the-art,
in Caffe



xkcd: Tasks

"The Virtually Impossible"

EXAMPLE PHOTOS



Photo credits

PARK or BIRD

Want to know if your photo is from a U.S. national park? Want to know if it contains a bird? Just drag it into the box to the left, and we'll tell you. We'll use the GPS embedded in your photo (if it's there) to see whether it's from a park, and we'll use our super-cool computer vision skills to try to see whether it's a bird (which is a hard problem, but we do a pretty good job at it).

To try it out, just drag any photo from your desktop into the upload box, or try dragging any of our example images. We'll give you your answers below!

Want to know more about PARK or BIRD, including why the heck we did this? Just click here for more info →

PARK?

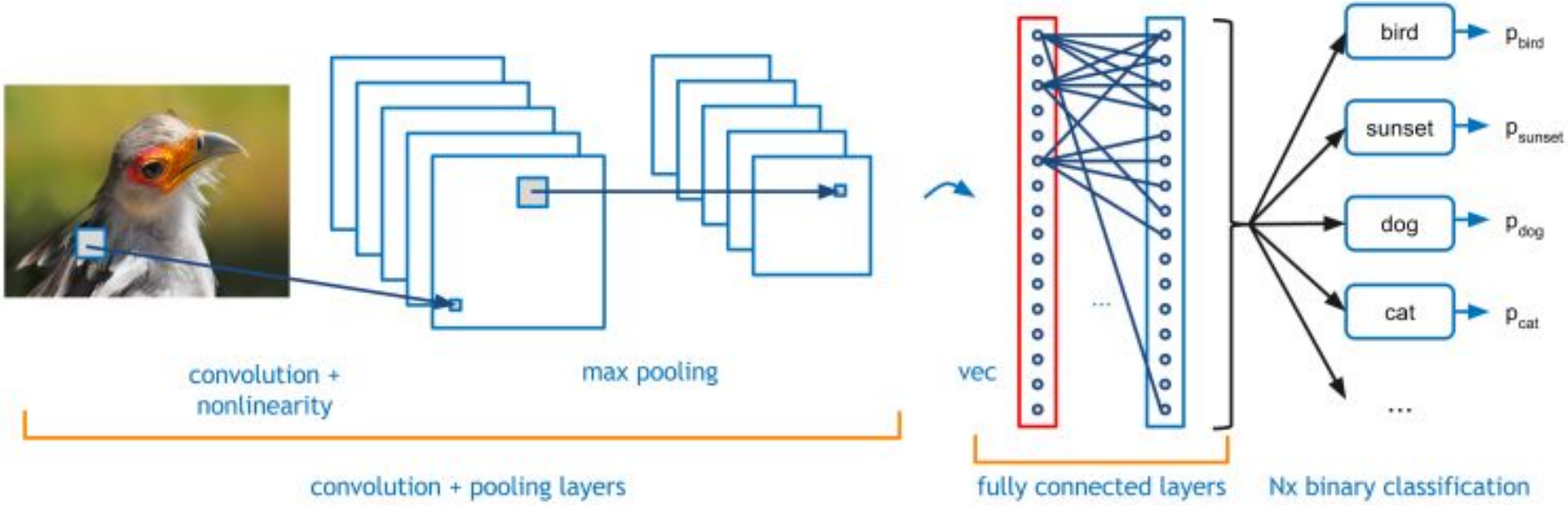
YES

Ah yes, Everglades is truly beautiful.

BIRD?

YES

Dude, that is such a bird.



All in a day's work with Caffe

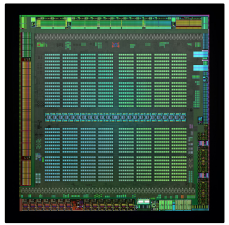
http://code.flickr.net/2014/10/20/introducing-flickr-park-or-bird/

Part 1: Deep Learning for Vision

Why Deep Learning?

Dive into Deep Learning

What is DL? Why Now?



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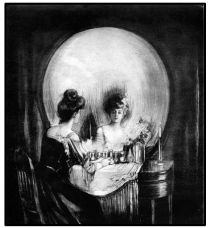
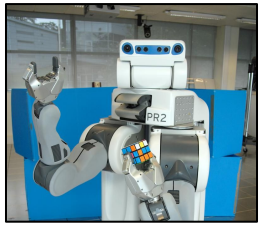


Learning & Optimization

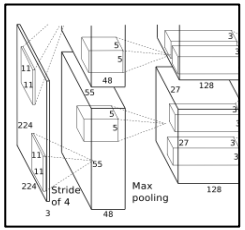
$$\nabla_\theta L$$

Applications



Caffe First Sip

Network Tour



Transfer Learning

First Dive Into Deep Learning

Deep Learning is

Stacking **Layers**

and

Learning **End-to-End**

Stacking Layers

A **layer** is a transformation

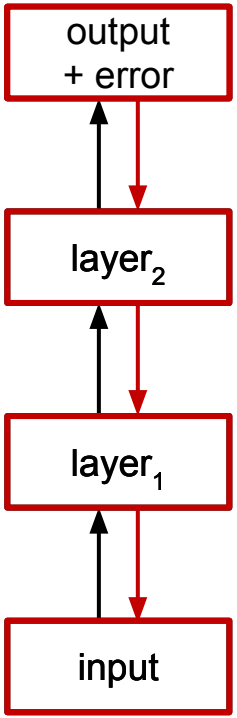
$x' = \mathbf{layer}(x)$

Deep networks are layered models made by stacking different types of transformation

$x_2 = \mathbf{layer_1}(x_1)$
$x_3 = \mathbf{layer_2}(x_2)$
...

How do layers stack?

Layered Networks



Networks run layer-by-layer, composing the input-output transformation of each layer

$$x_1 = \mathbf{layer_1}(input)$$
$$out = \mathbf{layer_2}(x_1)$$

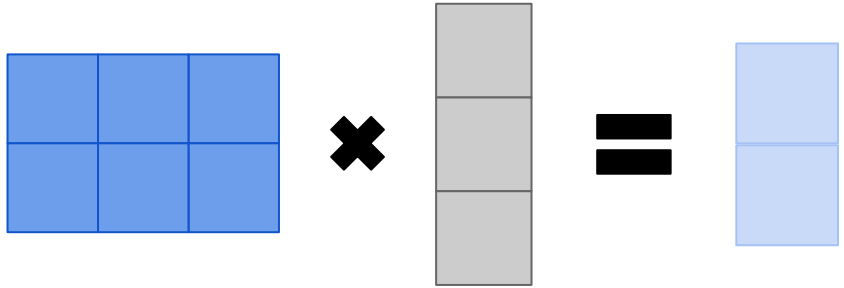
During learning, the error is passed back layer-by-layer to tune the transformations

What kind of layers should we stack?

The Simplest Layers

Matrix Multiplication

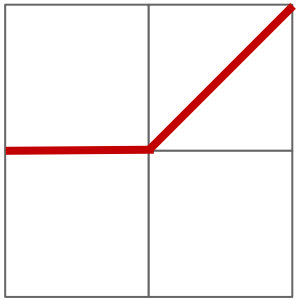
$$x' = Wx + b$$



Non-linearity

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

(for example)

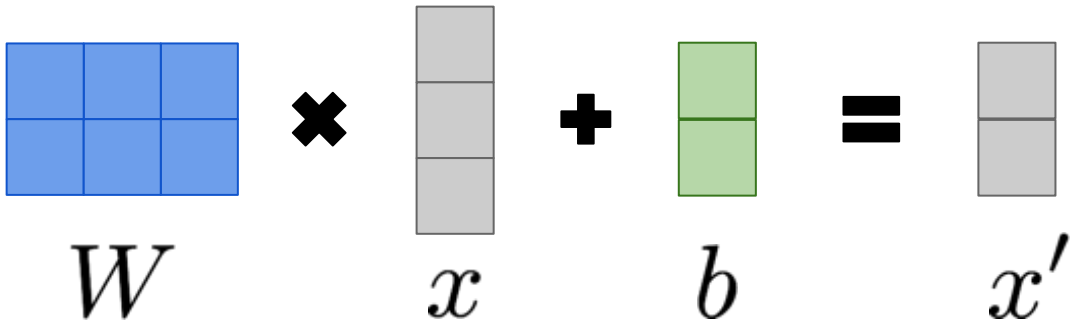


Matrix Multiplication

Multiply input *x* by weights *W* and add bias *b*

Learns linear transformations

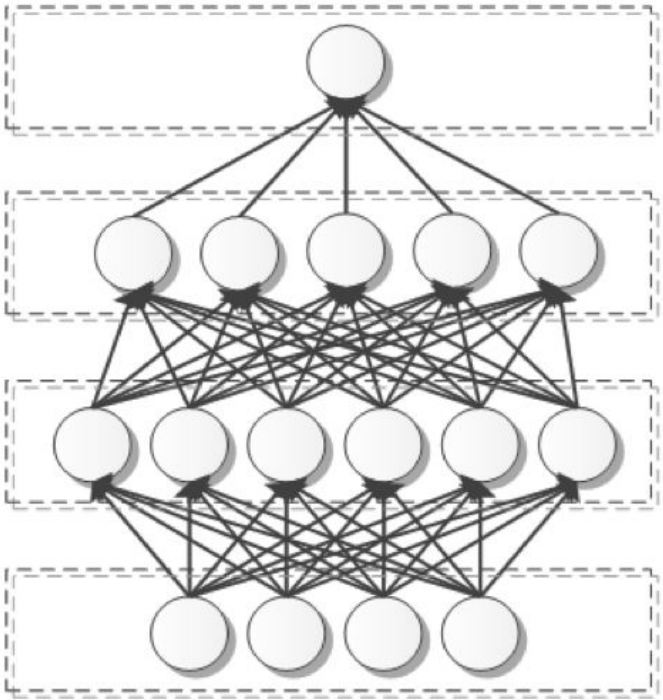
$$x' = Wx + b$$



W K x O dimensional
K inputs
O outputs

b O outputs

Matrix Multiplication == Fully Connected Layer



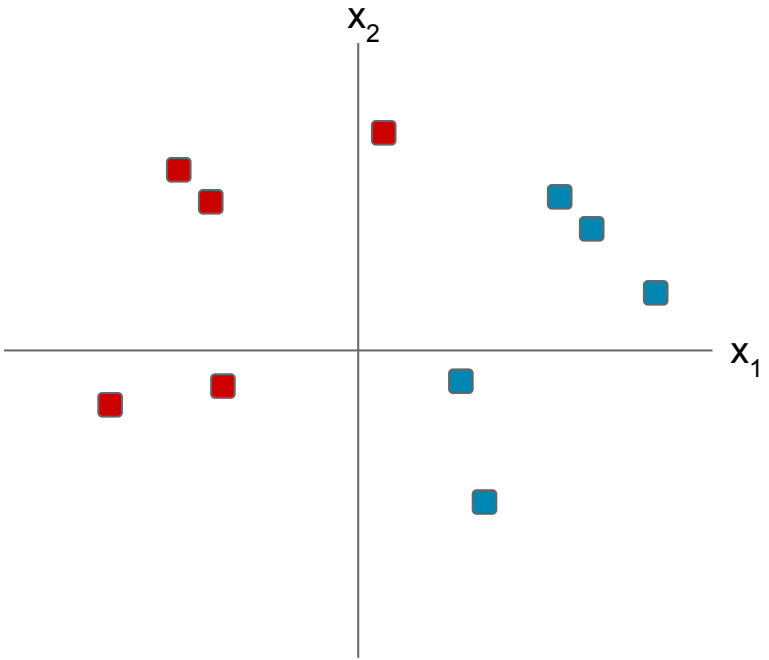
Output is a function of every input, or the input and output are "fully connected"

Abbreviated as **FC**

[figure credit BDTI]

Linear Classification

To classify we need to separate the data into red vs. blue



- Suppose our data points (**x**) are 2D and each comes with a label y, where y = -1 or y = 1
- Learn a weight vector $\mathbf{w} = [w_1; w_2]$
- Predict the class of a given **x** by $\text{sign}(\mathbf{w}^T\mathbf{x}) = \text{sign}(w_1x_1 + w_2x_2)$

?

Linear Classification

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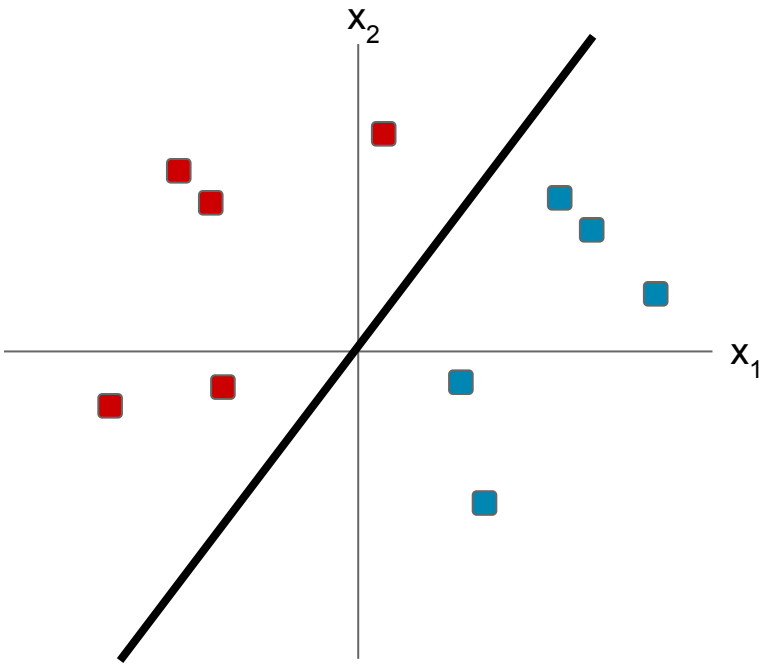

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Linearity is Not Enough

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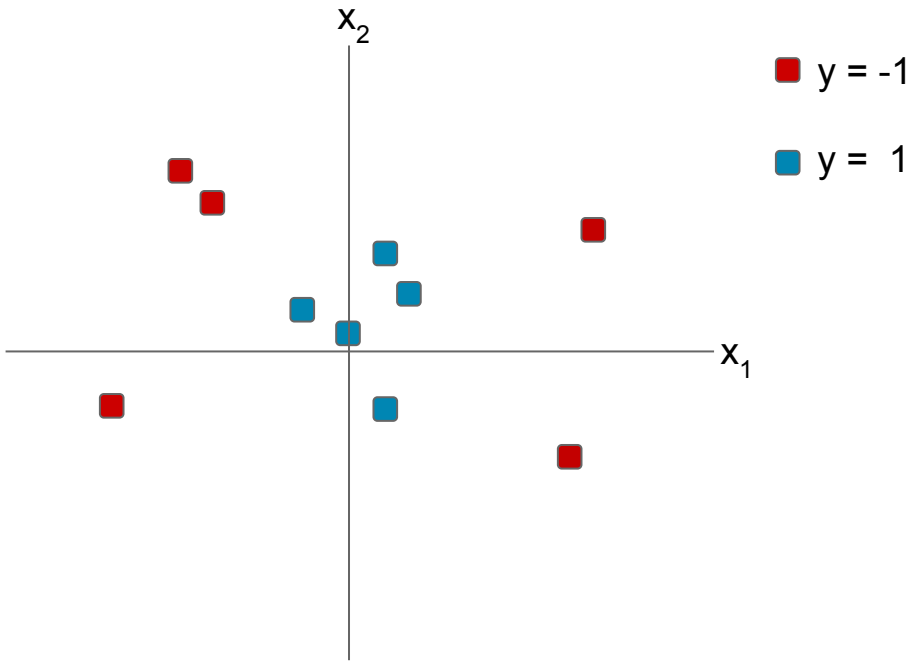

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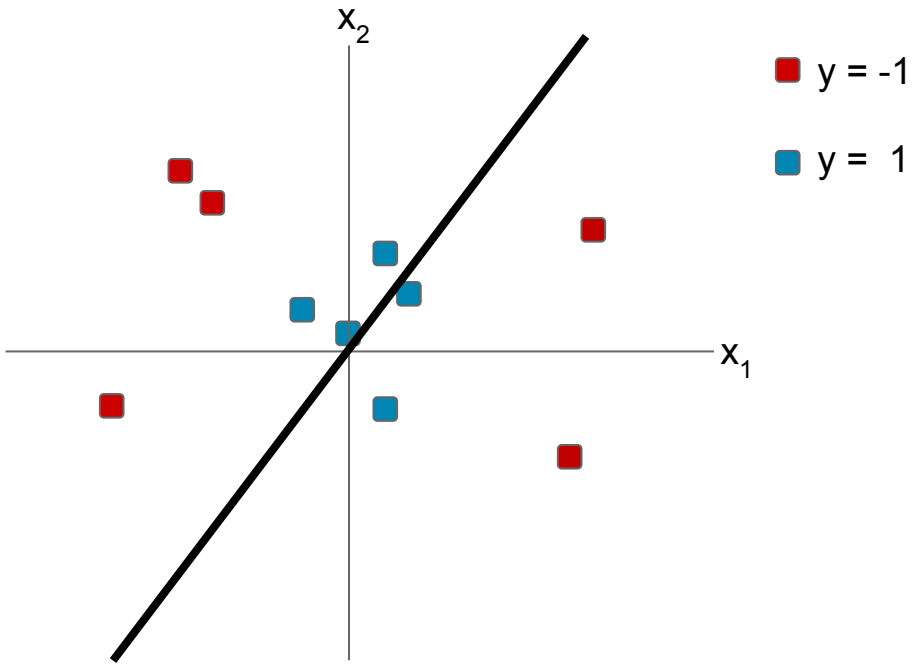

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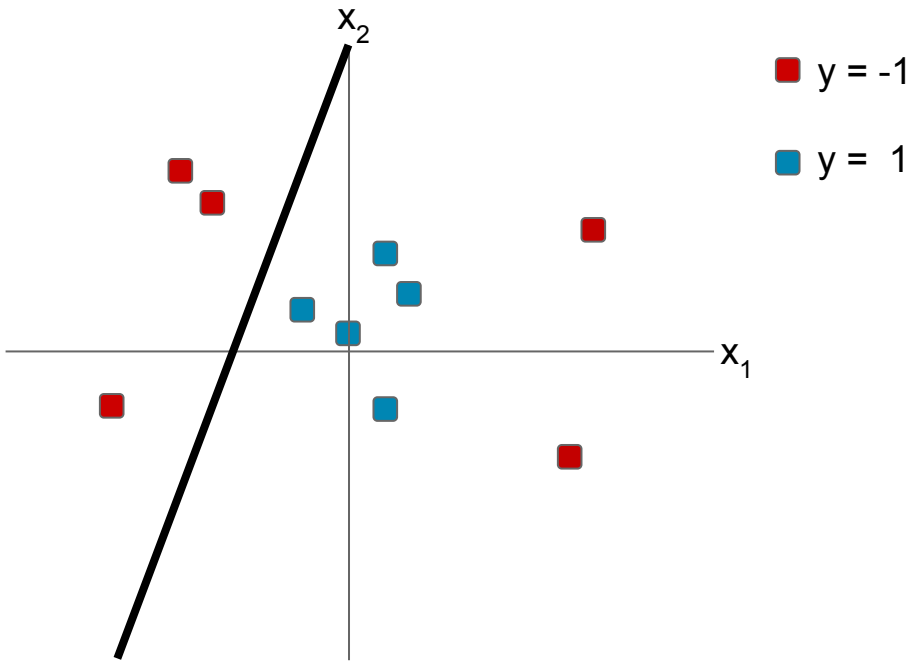

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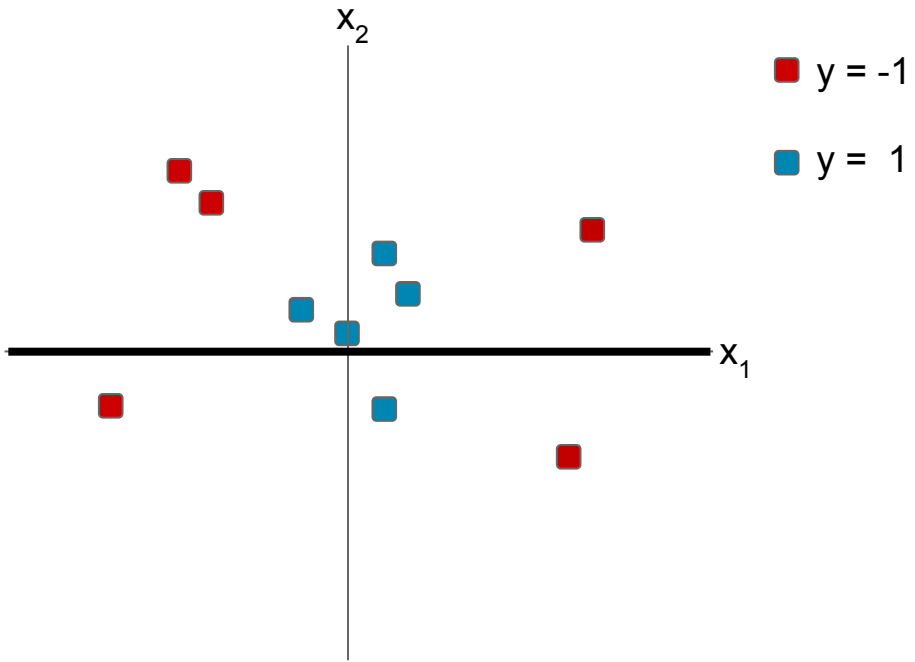

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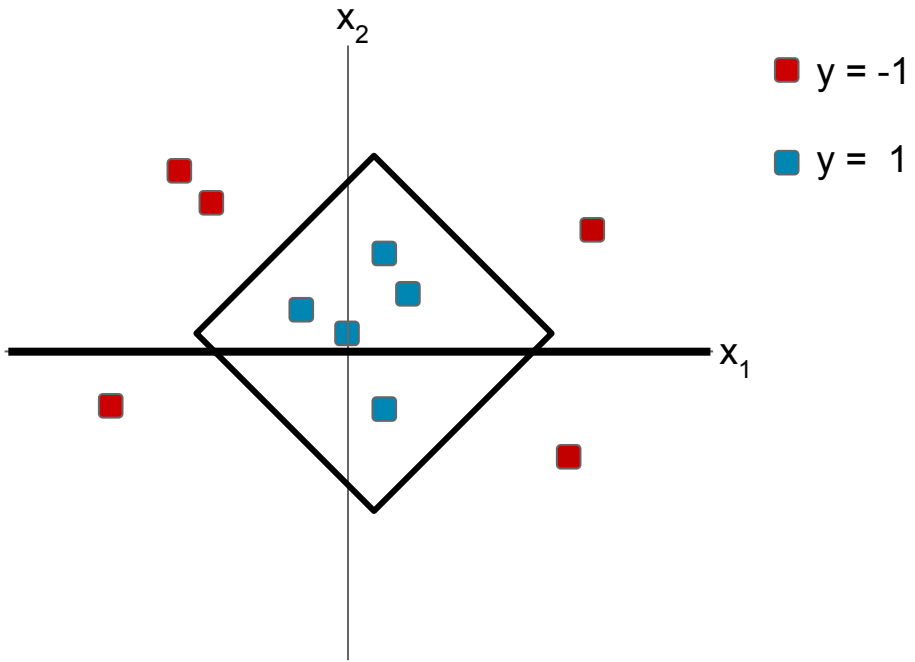

YES

Non-linearity!

Linearity is Not Enough

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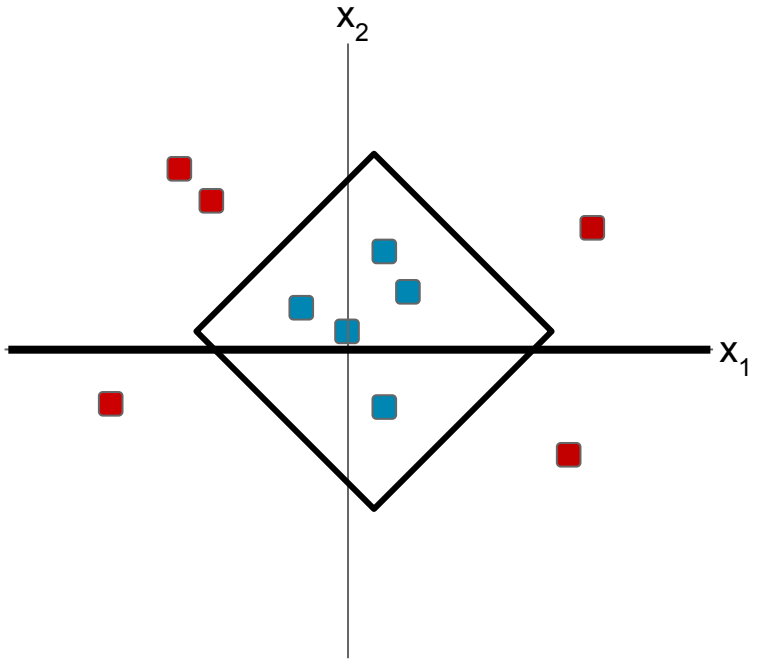


YES

Non-linearity!

$$y = W_2 \max(0, (W_1(x)))$$

The Limits of Linearity

Linear steps **collapse** and stay linear

$$x_2 = W_1 x_1$$
$$x_3 = W_2 x_2$$

$$\longrightarrow \quad x_3 = W_{\text{both}} x_1$$

$$W_{\text{both}} = W_2 \times W_1$$

Linear layers alone do not meaningfully stack

The Shallowest Deep Net

Deep nets are made by stacking learned linear layers and simple pointwise **non-linear** layers

Linear

$$x_2 = W_1 x_1$$
$$x_3 = W_2 x_2$$

add ReLU

Non-linear, Deep

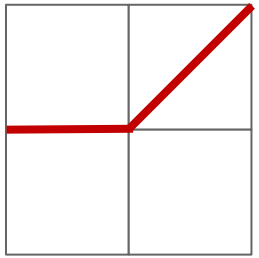
$$x_2 = W_1 x_1$$
$$x_2^\circ = \max(0, x_2)$$
$$x_3 = W_2 x_2^\circ$$

Due to the Rectified Linear Unit (ReLU) non-linearity **max(0, x)**, x_3 cannot be computed as a linear function of

Non-linearity

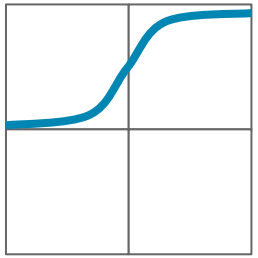
ReLU

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



Sigmoid

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

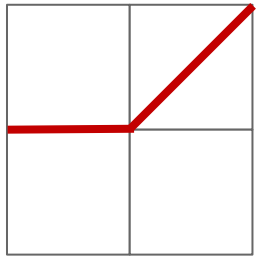


Non-linearity is needed to deepen the representation
Many non-linearities or *activations* to choose from

Yet More Non-linearities

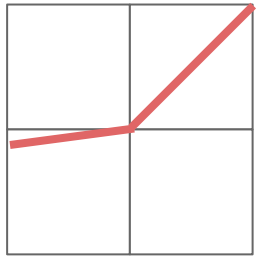
ReLU

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



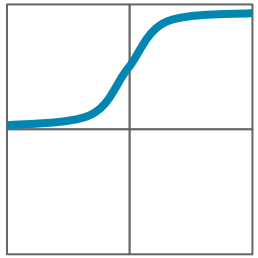
Leaky ReLU

$$x' = \max(0.1x, x)$$



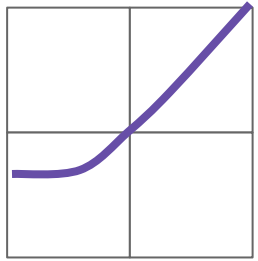
Sigmoid

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



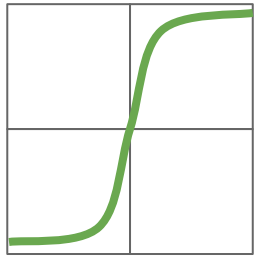
ELU

$$x' = \begin{cases} x & x > 0 \\ \alpha(e^x - 1) & x \leq 0 \end{cases}$$



TanH

$$x' = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$



When in doubt, **ReLU**

Worth trying Leaky ReLU, ELU

Avoid Sigmoid

Define Your First Net

Let’s go non-linear on
a classification problem

Try It Out

Designing for Sight

Convolutional Networks or convnets are nets for vision

- functional fit for the visual world
  by compositionality and feature sharing

- learned end-to-end to handle visual detail
  for more accuracy and less engineering

Convnets are the dominant architectures for visual tasks

Visual Structure

Local Processing: pixels close together go together

receptive fields capture local detail

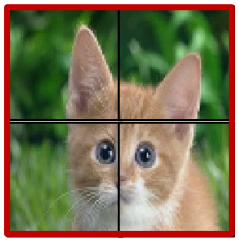
Across Space: the same what, no matter where

recognize the same input in different places

Visual Structure

Local Processing: pixels close together go together

receptive fields capture local detail



Can rely on spatial coherence

This is not a cat

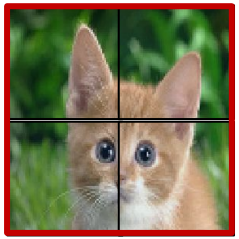
Across Space: the same what, no matter where

recognize the same input in different places

Visual Structure

Local Processing: pixels close together go together

receptive fields capture local detail



Can rely on spatial coherence

This is not a cat

Across Space: the same what, no matter where

recognize the same input in different places

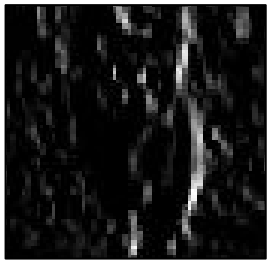
All of these are cats

Vision Layers

Convolution/Filtering

linear layer for vision

Learned Filter



Pooling

spatial summarization

1	1	2	4
5	6	7	8
3	2	1	0
1	2	3	4

max pool 2x2
with stride 2

6	8
3	4

[figure credit A. Karpathy, cs231n course]

Convolution: A Linear Layer for Vision

Images have *translation invariant* semantics: these are all equally squirrels

So use the same weights between nodes with the same *spatial* relationship

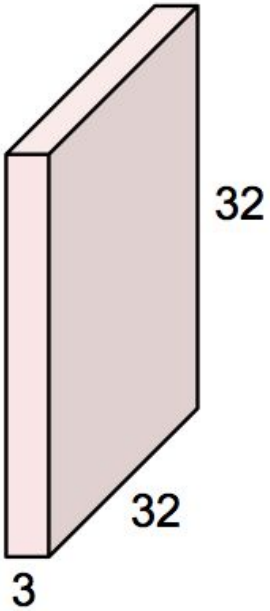
$$\text{output}(x, y) = \sum_{i,j} \text{weight}(i, j) \cdot \text{input}(x + i, y + j)$$

This is **convolution** (or correlation—used interchangeably in vision)

Convolution means *fewer parameters* for *more efficient learning*

A Filter

A filter is a **spatially local** and **cross-channel** template
Convnet filters are **learned**



input is **3**x32x32 data
a color image (3 RGB channels) and square (32x32)

[figure adapted from A. Karpathy]

A Filter

A filter is a **spatially local** and **cross-channel** template
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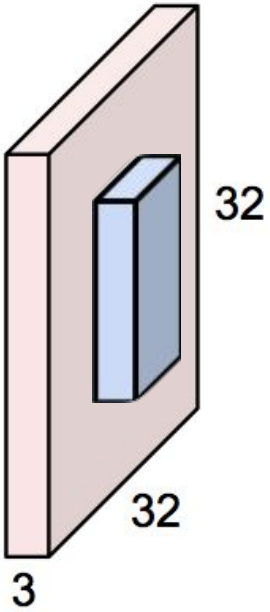


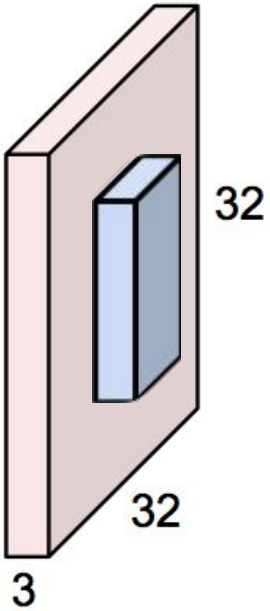
input is **3**x32x32 data
a color image (3 RGB channels) and square (32x32)

filter is **3**x5x5 weights
- spatially local: kernel size is 5x5
- cross-channel: connected across all input channels

[figure adapted from A. Karpathy]

A Filter

A filter is a **spatially local** and **cross-channel** template
Convnet filters are **learned**



input is **3**x32x32 data
a color image (3 RGB channels) and square (32x32)

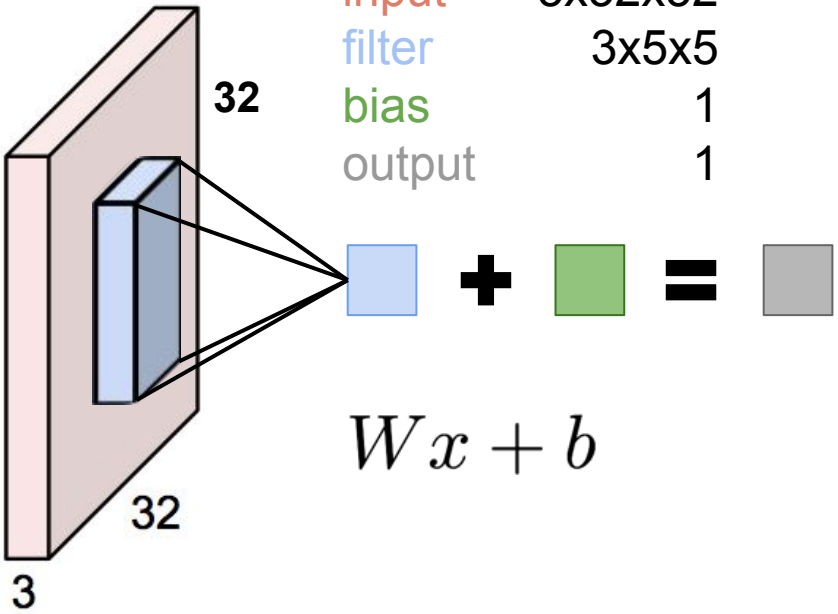
filter is **3**x5x5 weights
- spatially local: kernel size is 5x5
- cross-channel: connected across all input channels

total parameters:
$3*5^2$ = 75 filter weights + 1 bias

[figure adapted from A. Karpathy]

Convolution

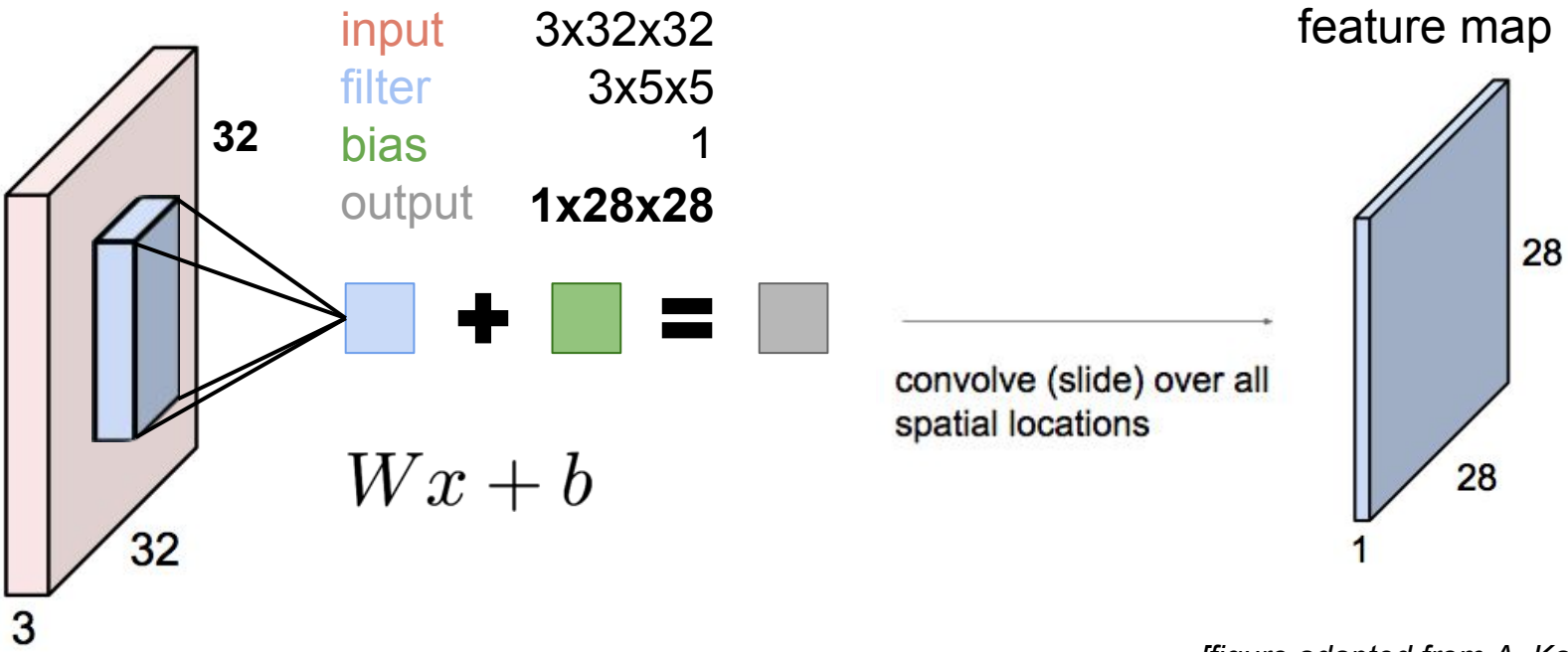
One filter evaluation is a dot product between the input window and weights + bias



[figure adapted from A. Karpathy]

Convolution

Convolving the filter with the input gives a **feature map**.



[figure adapted from A. Karpathy]

Convolution

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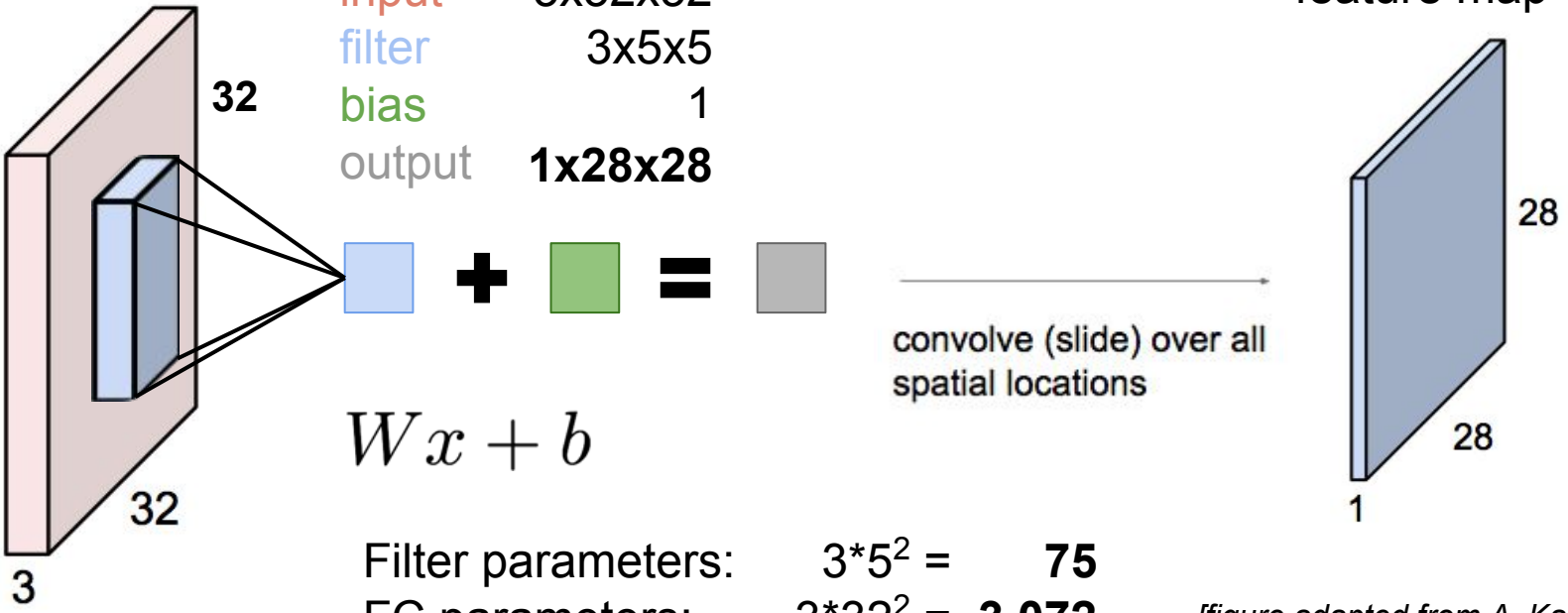


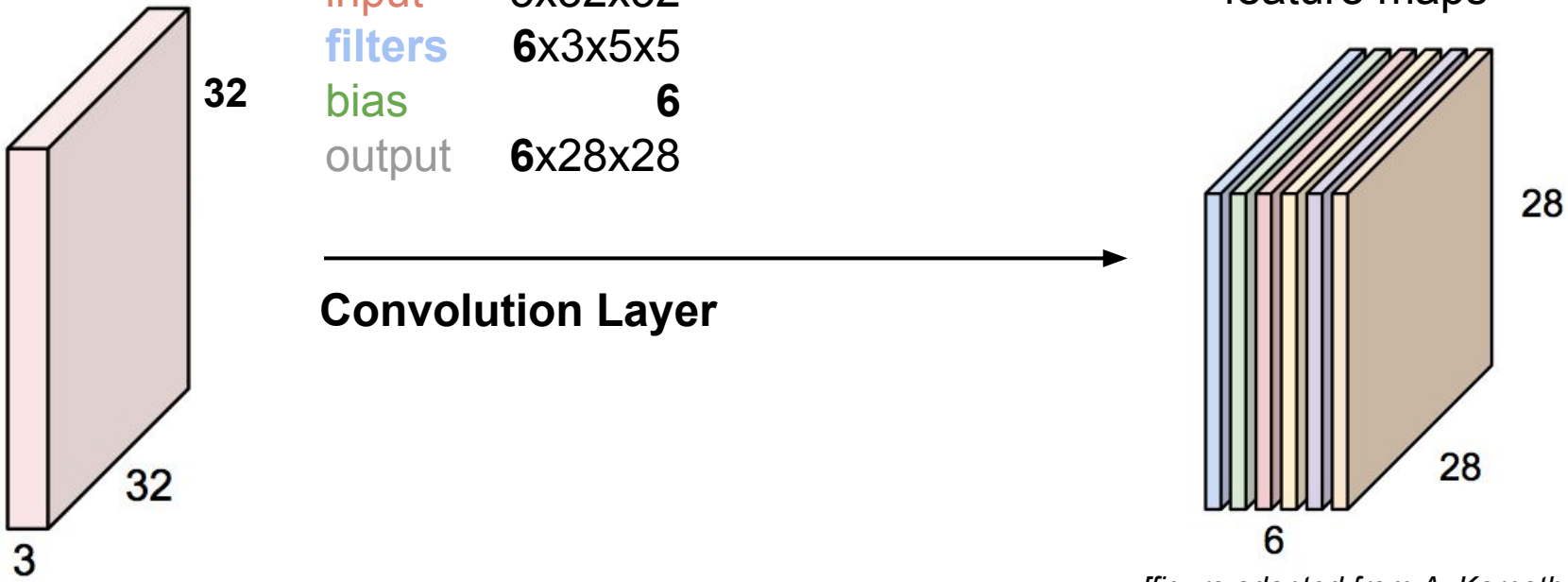
Filter parameters: $3*5^2 =$ **75**

FC parameters: $3*32^2 =$ **3,072**

[figure adapted from A. Karpathy]

Convolution Layer (conv)

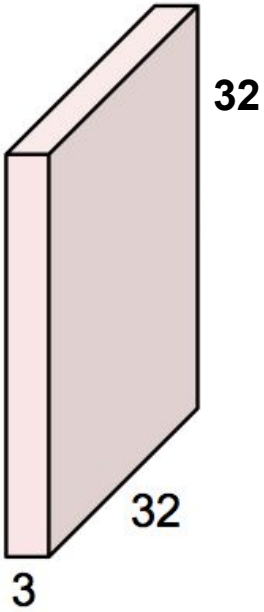
Convolution layers have multiple **filters** for more modeling capacity



[figure adapted from A. Karpathy]

Convolution Layer (conv)

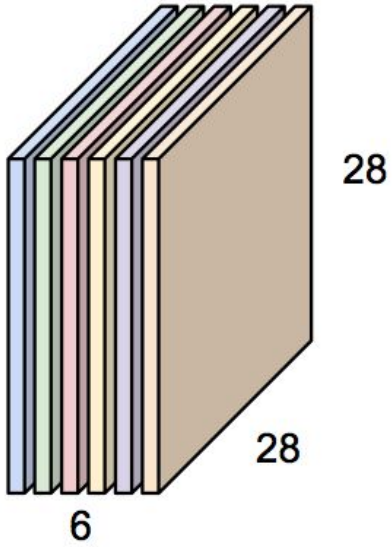
Convolution layers have multiple **filters** for more modeling capacity

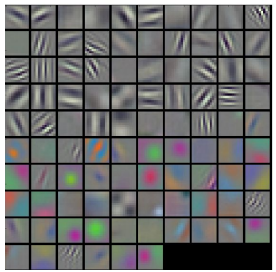


input 3x32x32
filters **6**x3x5x5
bias **6**
output **6**x28x28

Convolution Layer

feature maps





Learned Filters from AlexNet `conv`$_1$

`conv`$_1$ has 96 filters for edge, color, and frequency

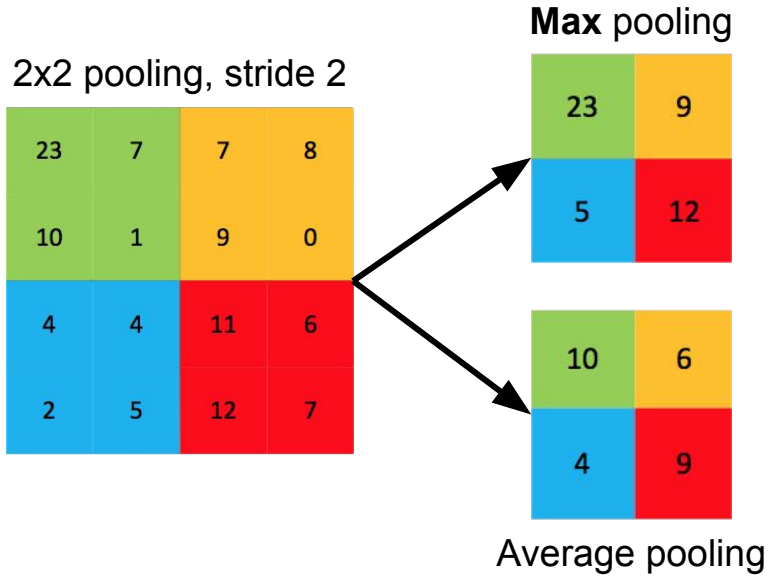
richer than 3D RGB

[figure adapted from A. Karpathy]

Pooling (pool)

Spatial summary by computing **operation** over **window** with **stride**

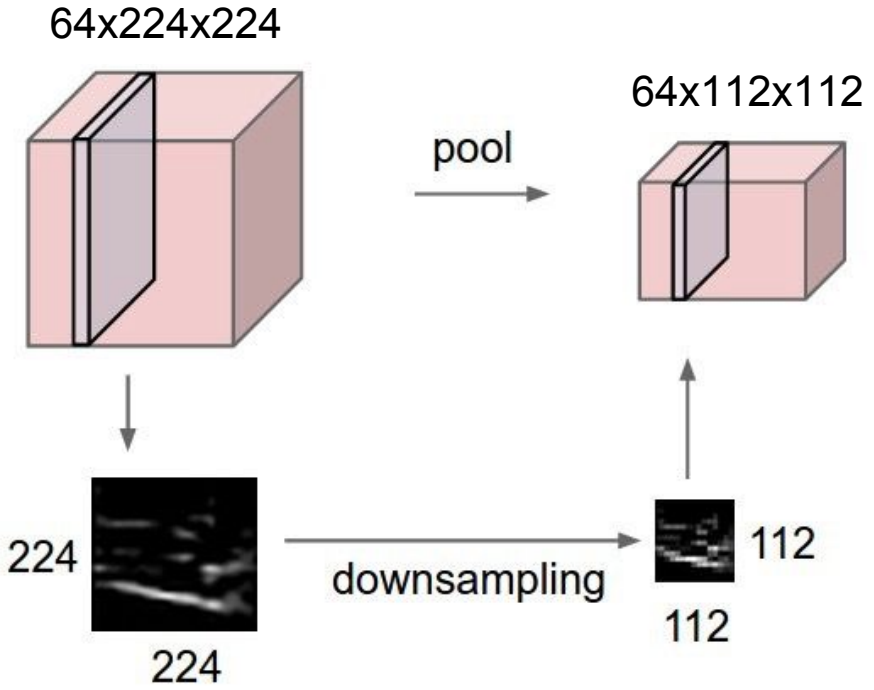
- overlapping or non-overlapping
- separate across channels
- Current fashion:
  3x3 max pooling
  with stride 2



[figure credit BDTI]

Pooling

- reduce resolution
- increase receptive field size for later layers
- save computation
- add invariance to translation/noise within pooling window



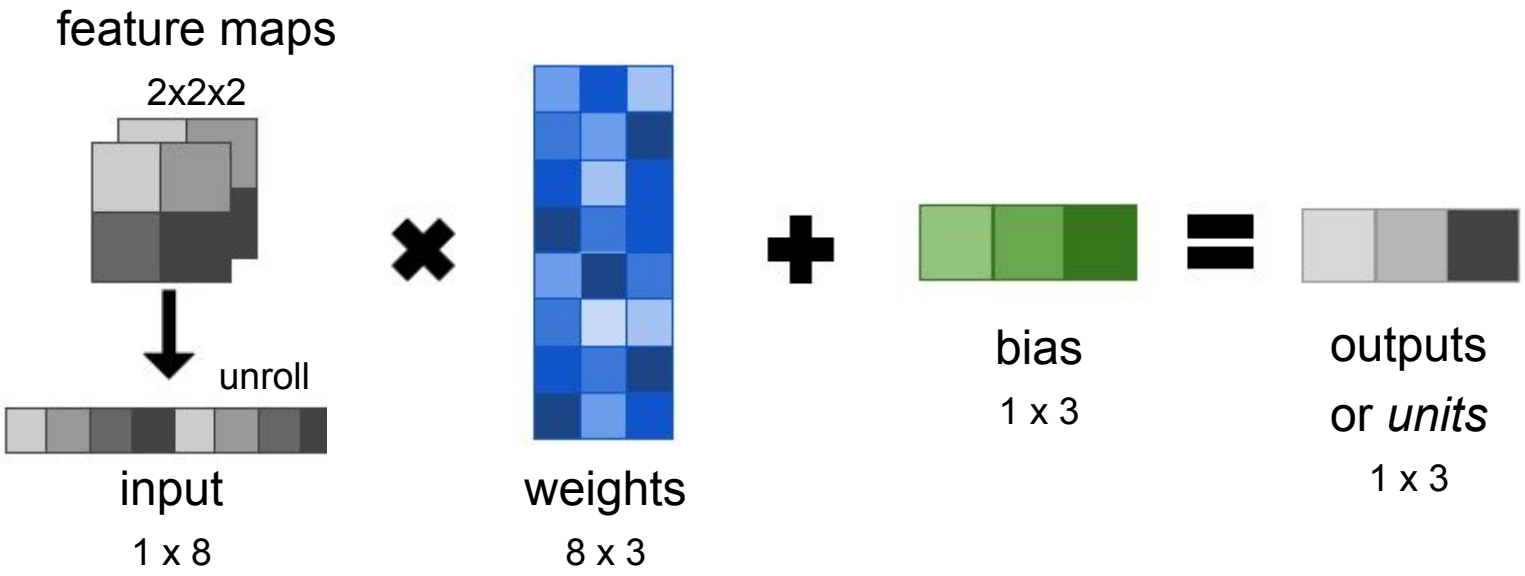
[figure credit A. Karpathy]

Fully Connected Layers (FC)

Learn a global feature from the full feature maps

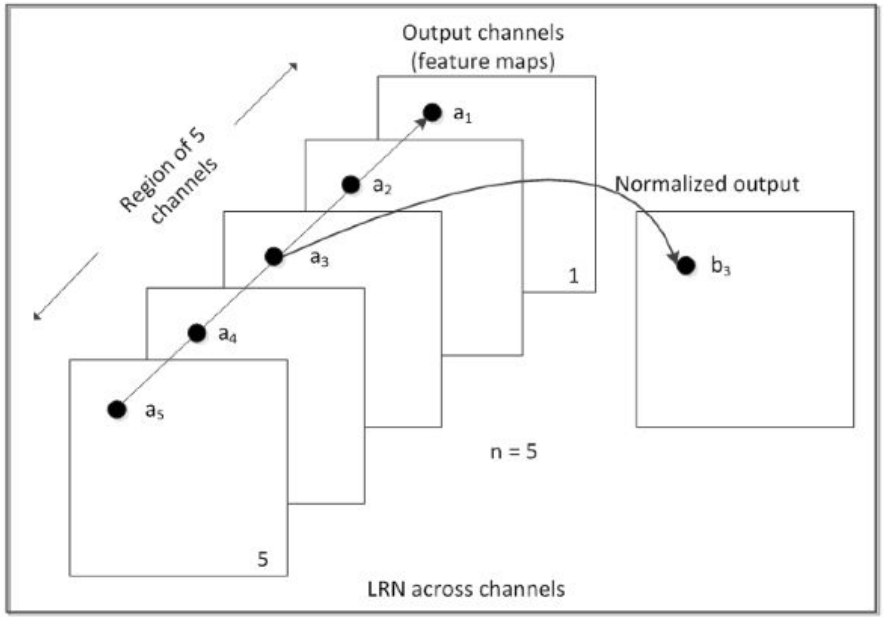
Often found at the end of convnets

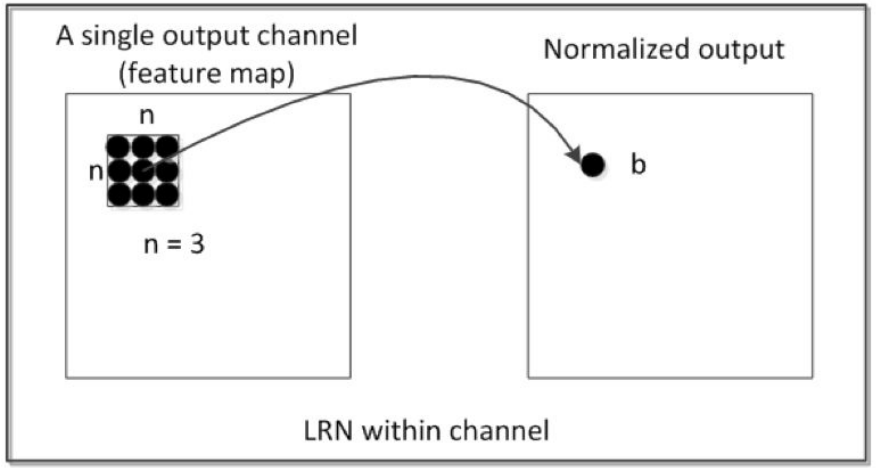
Note: this could likewise be done by a large convolution kernel



Normalization Layers (Deprecated)

Local response normalization was popular for a time but is now deprecated; more recent networks do not include these layers





[figure credit BDTI]

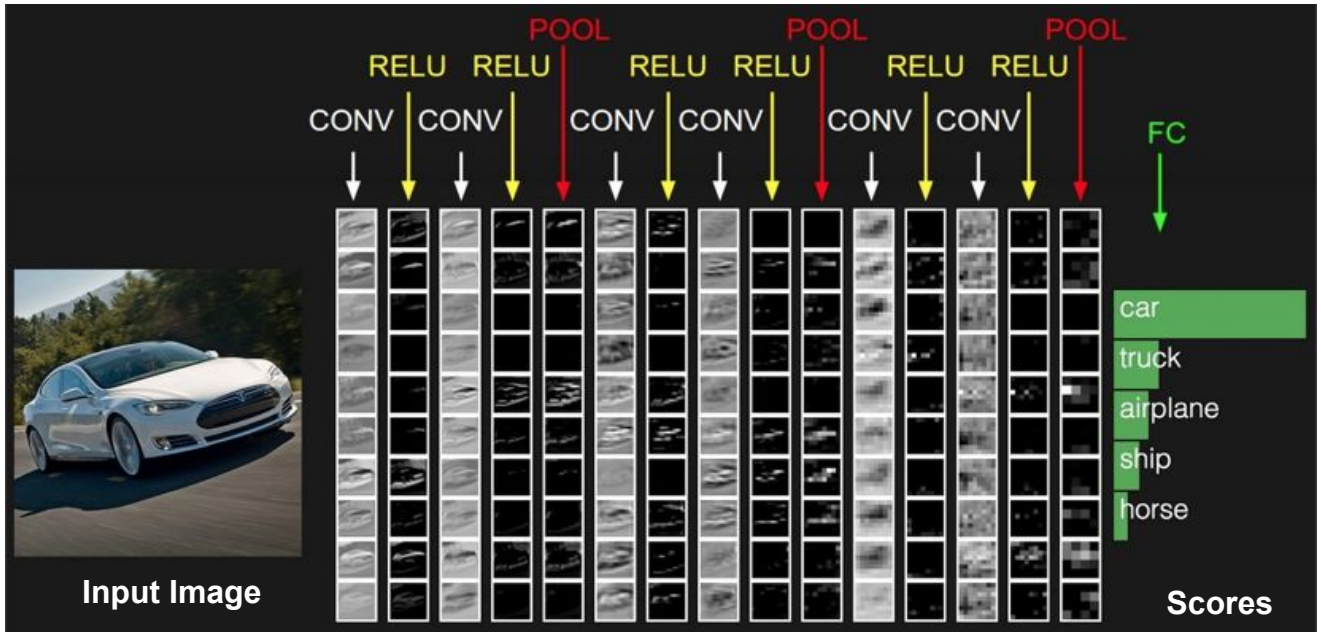
Layer Review

- layers compute differentiable transformations
- types of layers: **conv**, **ReLU**, pool, FC
- parameters (conv, FC) or not (pool, ReLU)
- arguments like kernel size, stride, etc. (conv, pool) or not (Sigmoid)

Convnet Architecture

Stack convolution, non-linearity, and pooling until global FC layer classifier

Conv 3x3s1, 10 / ReLU **Type**: Conv **Kernel Size**: 3x3 **Stride**: 1 **Channels**:10 **Activation**: ReLU



FC 10
Max Pool 3x3s1
Conv 3x3s1, 10 / ReLU
Conv 3x3s1, 10 / ReLU
Max Pool 3x3s1
Conv 3x3s1, 10 / ReLU
Conv 3x3s1, 10 / ReLU
Max Pool 3x3s1
Conv 3x3s1, 10 / ReLU
Conv 3x3s1, 10 / ReLU

[figure credit A. Karpathy]

See a Net Learn to See

Let’s watch a convnet as it learns
how to recognize objects in images

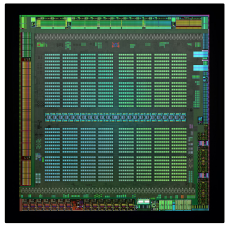
Try It Out

Part 1: Deep Learning for Vision

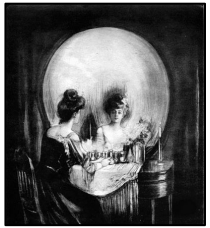
Why Deep Learning?

Dive into Deep Learning

What is DL? Why Now?



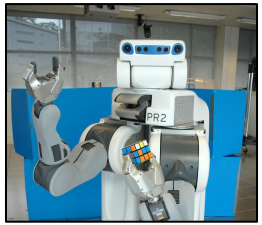
The Challenge of Recognition



Learning & Optimization

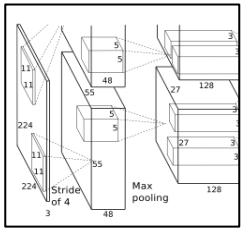
$$\nabla_\theta L$$

Applications



Caffe First Sip

Network Tour



Transfer Learning

Share a Sip of Brewed Models

demo.caffe.berkeleyvision.org

demo code open-source and bundled

Maximally accurate | Maximally specific

cat	1.80727
domestic cat	1.74727
feline	1.72787
tabby	0.99133
domestic animal	0.78542

Scene Recognition http://places.csail.mit.edu/

Predictions:

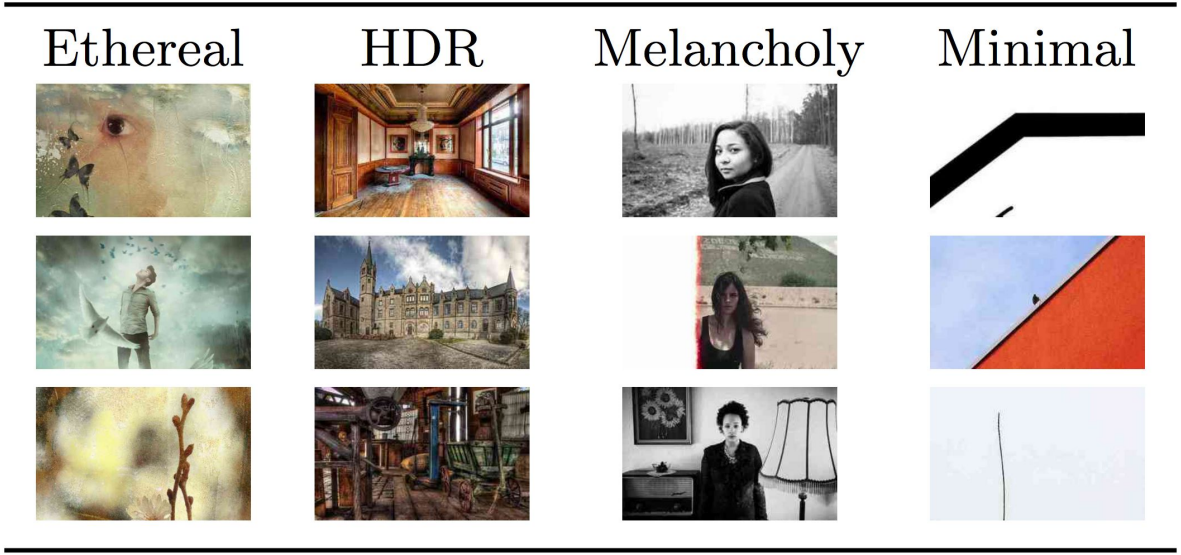
- **Type of environment:** outdoor
- **Semantic categories:** skyscraper:0.69, tower:0.16, office_building:0.11,
- **SUN scene attributes:** man-made, vertical components, natural light, open area, nohorizon, glossy, metal, wire, clouds, far-away horizon

B. Zhou et al. NIPS 14

Visual Style Recognition

Karayev et al. *Recognizing Image Style*. BMVC14. Caffe fine-tuning example.

Demo online at http://demo.vislab.berkeleyvision.org/ (see Results Explorer).



[Image-Style]

Other Styles:

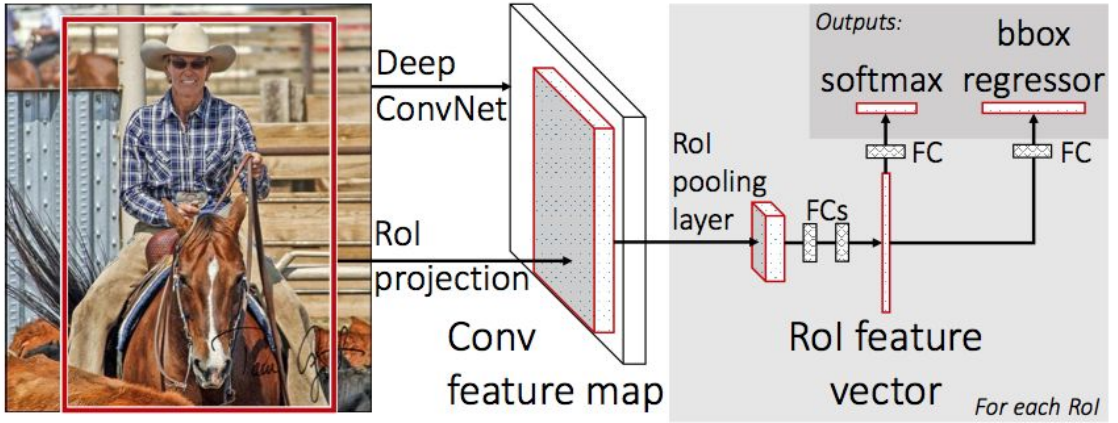
Vintage
Long Exposure
Noir
Pastel
Macro
… and so on.

Object Detection

R-CNNs: Region-based Convolutional Networks

Fast R-CNN

- convnet for features
- proposals for detection



Faster R-CNN

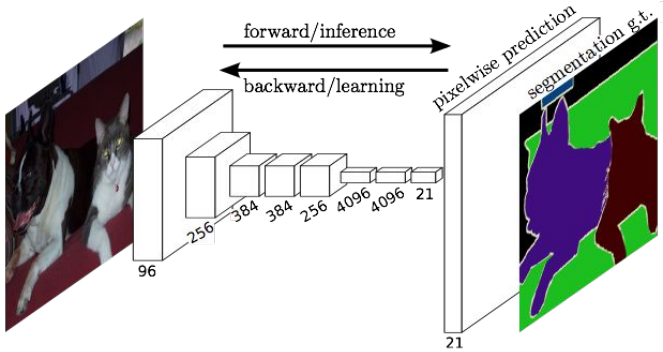
- end-to-end proposals and detection
- image inference in 200 ms
- Region Proposal Net + Fast R-CNN

papers + code online

Pixelwise Prediction

Fully convolutional networks for pixel prediction in particular semantic segmentation

- end-to-end learning
- efficient inference and learning
  100 ms per-image prediction
- multi-modal, multi-task



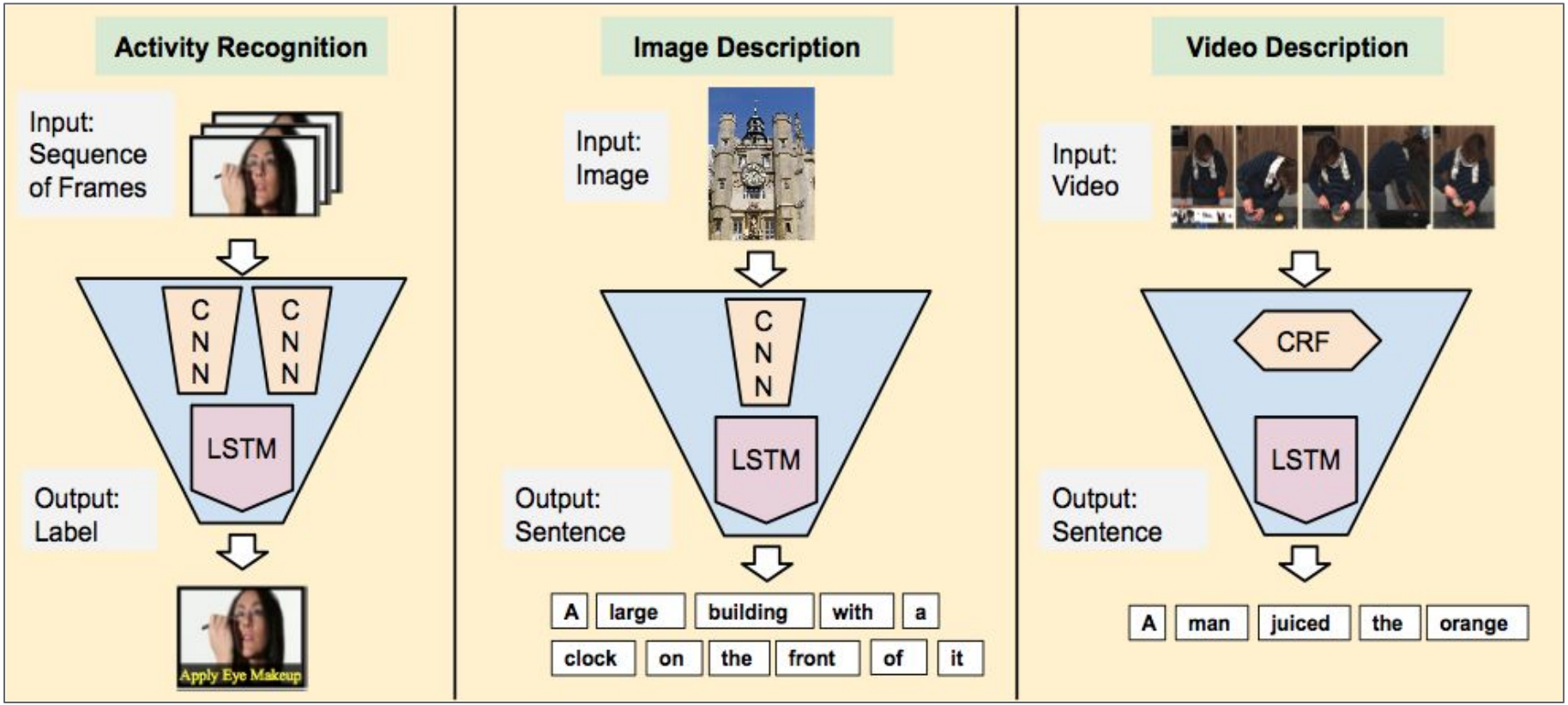
Applications

- semantic segmentation
- denoising
- depth estimation
- optical flow

Jon Long & Evan Shelhamer*, Trevor Darrell. CVPR'15*

CVPR'15 paper and code + models

Visual Sequence Tasks

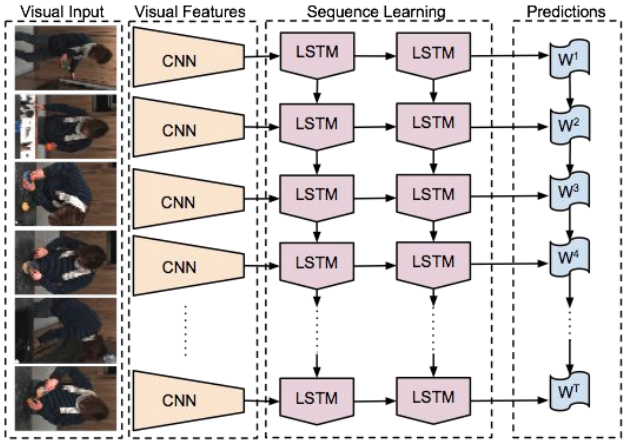


Recurrent Networks for Sequences

Recurrent Nets and Long Short Term Memories (LSTM) are sequential models

- video
- language
- dynamics

learned by backpropagation through time



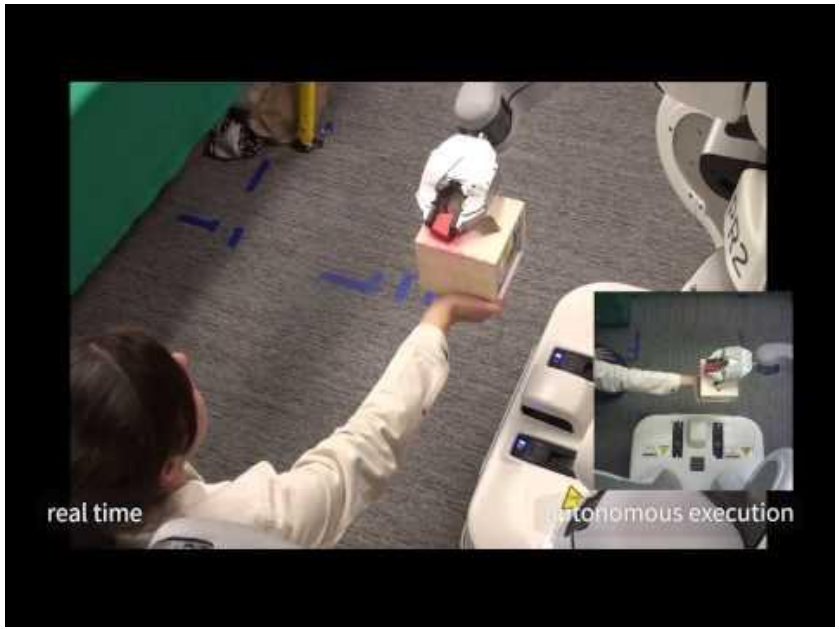
LRCN: Long-term Recurrent Convolutional Network

- activity recognition (sequence-in)
- image captioning (sequence-out)
- video captioning (sequence-to-sequence)

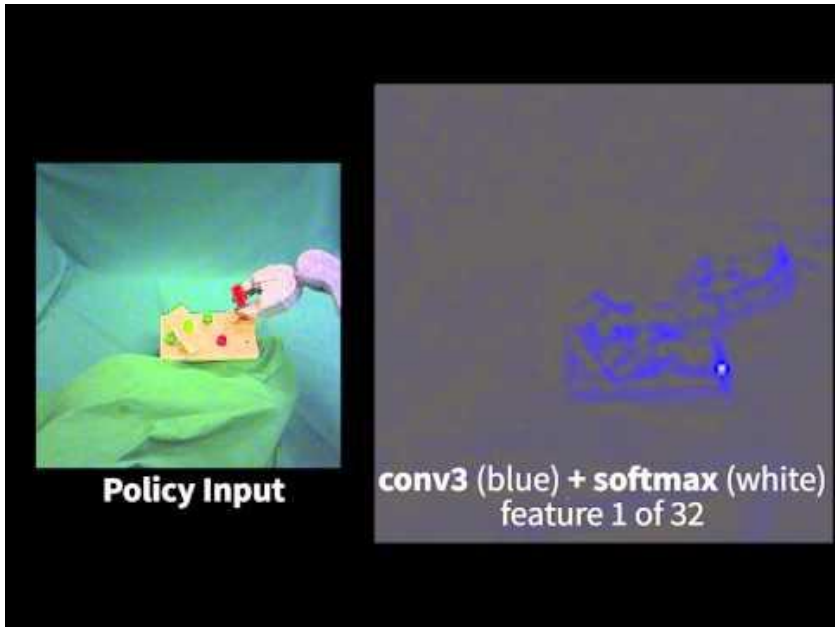
LRCN:
recurrent + convolutional
for visual sequences

CVPR'15 paper and code + models

Deep Visuomotor Control



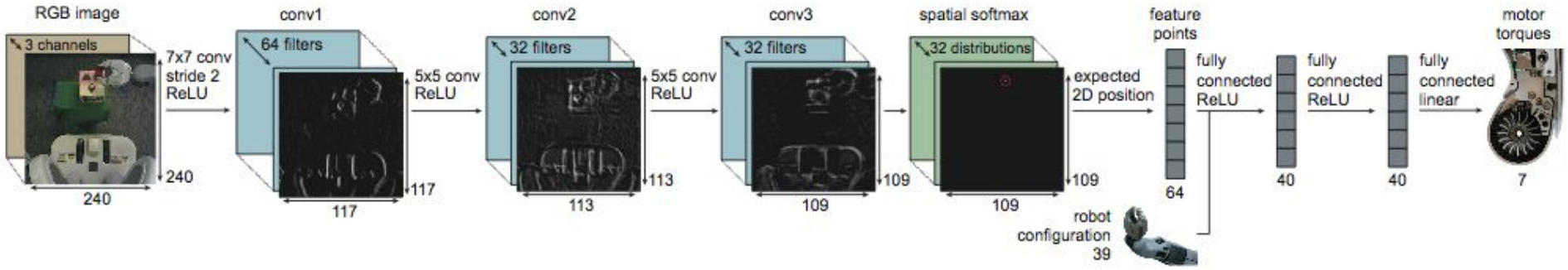
example experiments



feature visualization

Sergey Levine & Chelsea Finn*,*
Trevor Darrell, and Pieter Abbeel

Deep Visuomotor Control Architecture



- multimodal (images & robot configuration)
- runs at 20 Hz - mixed GPU & CPU
  for real-time control

paper + code for guided policy search

Sergey Levine & Chelsea Finn*,*
Trevor Darrell, and Pieter Abbeel

Embedded Caffe

Caffe runs on embedded CUDA hardware and mobile devices

- same model weights,
  same framework interface
- out-of-the-box on
  CUDA platforms
- OpenCL port
  thanks Fabian Tschopp!
  + AMD, Intel, and the community
- community Android port
  thanks sh1r0!

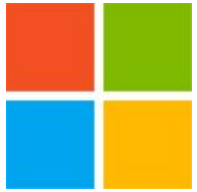
CUDA Jetson TX1, TK1

OpenCL branch

Android lib, demo

Ristretto toolkit
for approximation

Caffeinated Companies


… startups, big companies, more ...

Caffe at Facebook

- in production for vision at scale: uploaded photos run through Caffe
- Automatic Alt Text for the blind
- On This Day for surfacing memories
- objectionable content detection
- contributing back to the community: inference tuning, tools, code review include fb-caffe-exts thanks Andrew!

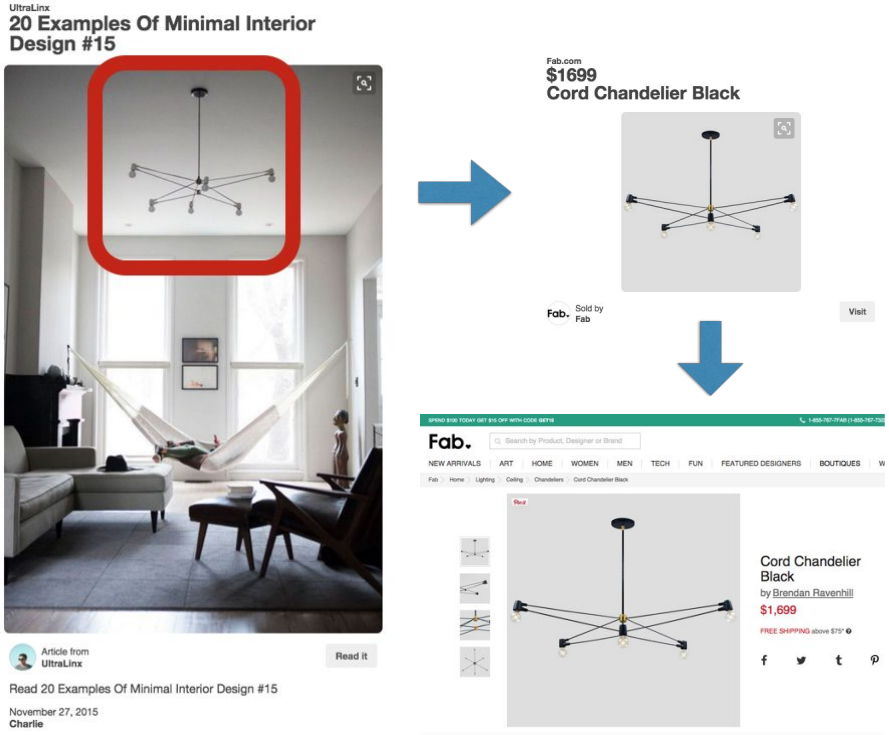
On This Day
highlight content

Automatic Alt Text
recognize photo content for accessibility

[example credit Facebook]

Caffe at Pinterest

- in production for vision at scale: uploaded photos run through Caffe
- deep learning for visual search: retrieval over billions of images in <250 ms
- ~4 million requests/day
- built on an open platform of Caffe, FLANN, Thrift, ...



[example credit Andrew Zhai, Pinterest]

Caffe at Yahoo! Japan

- curate news and restaurant photos for recommendation

- arrange user photo albums

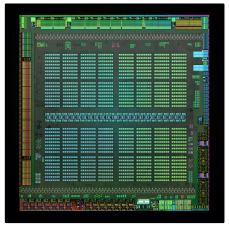
News Image Recommendation
select and crop images for news

Part 1: Deep Learning for Vision

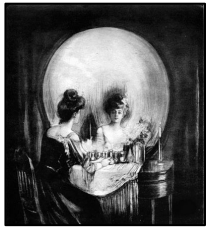
Why Deep Learning?

Dive into Deep Learning

What is DL? Why Now?



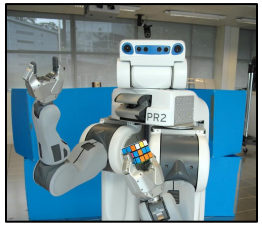
The Challenge of Recognition



Learning & Optimization

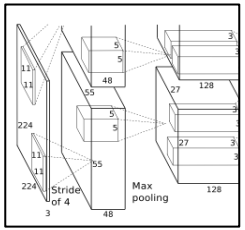
$$\nabla_\theta L$$

Applications



Caffe First Sip

Network Tour



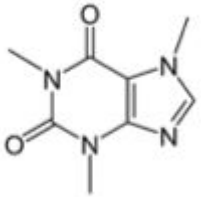
Transfer Learning

First Sip of Caffe

We'll be using **Caffe** for our hands-on experience

see notebook

Coffee Break (15 minutes)



caffe.berkeleyvision.org

github.com/BVLC/caffe

BERKELEY ARTIFICIAL INTELLIGENCE RESEARCH

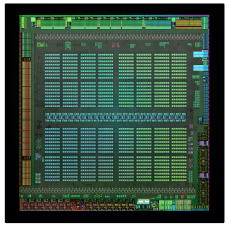
embedded VISION ALLIANCE

Part 1: Deep Learning for Vision

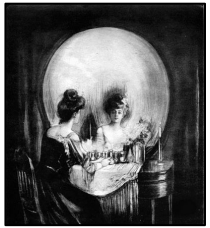
Why Deep Learning?

Dive into Deep Learning

What is DL? Why Now?



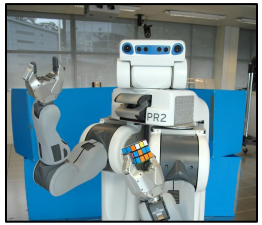
The Challenge of Recognition



Learning & Optimization

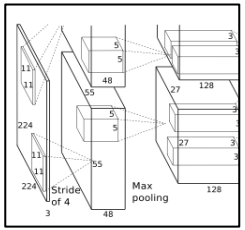
$$\nabla_\theta L$$

Applications



Caffe First Sip

Network Tour



Transfer Learning

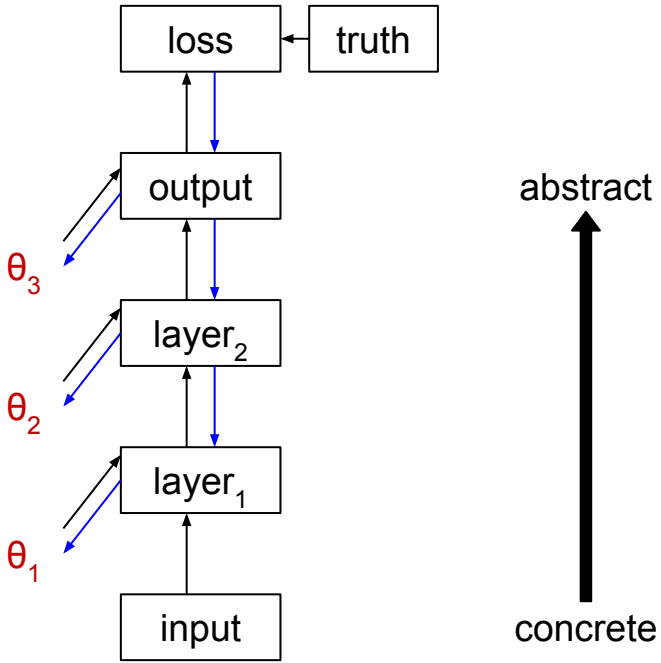
What is Deep Learning?

Compositional Models

Learned End-to-End

Hierarchy of Representations

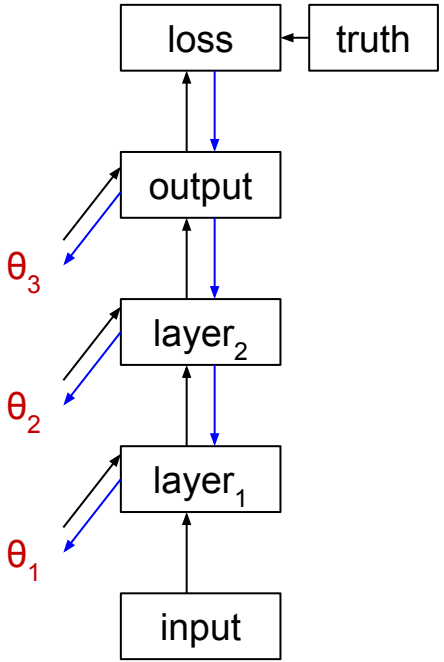
- vision: pixel, motif, part, object
- text: character, word, clause, sentence
- speech: audio, band, phone, word



What is Deep Learning?

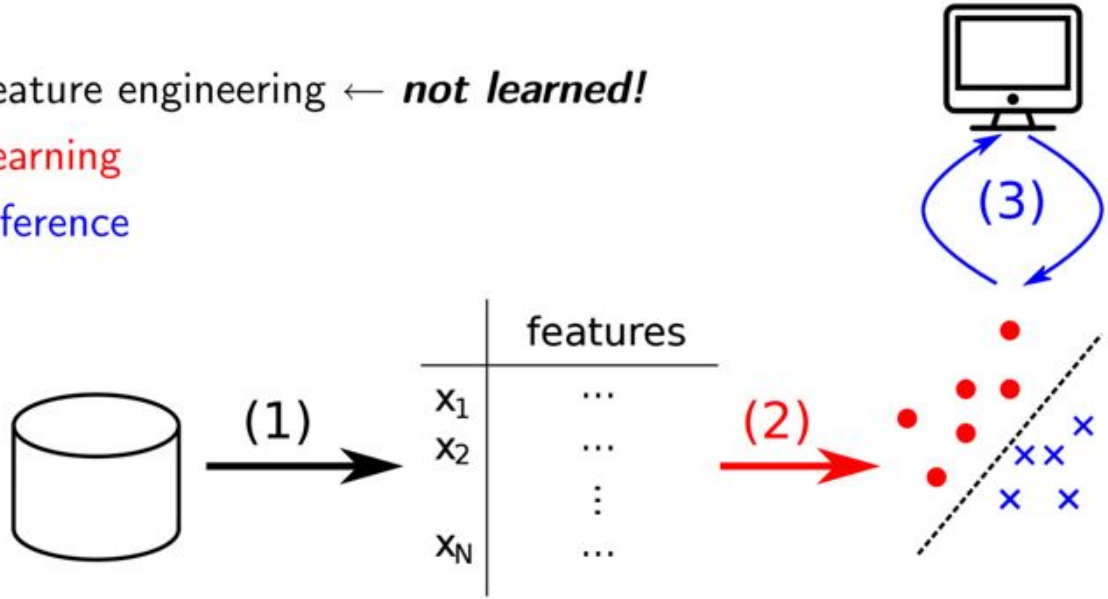
Compositional Models
Learned End-to-End

Back-propagation jointly learns all of the model parameters to optimize the output for the task —more on this later!



Shallow Learning

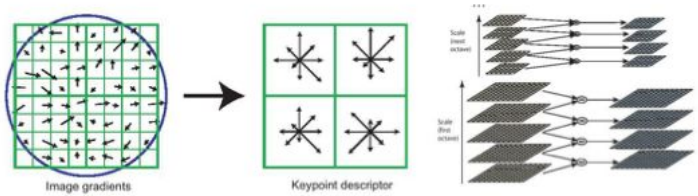
1. Feature engineering ← ***not learned!***
2. Learning
3. Inference



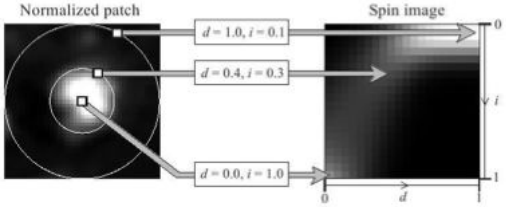
Separation of hand engineering and machine learning

[slide credit K. Cho]

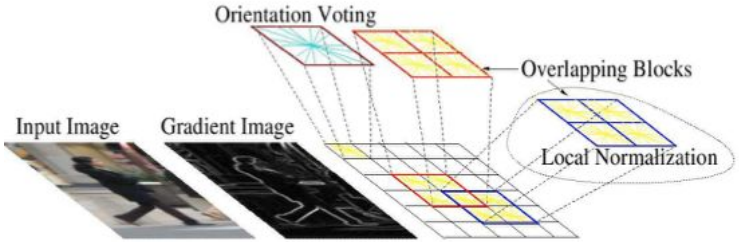
Hand-Engineered Features



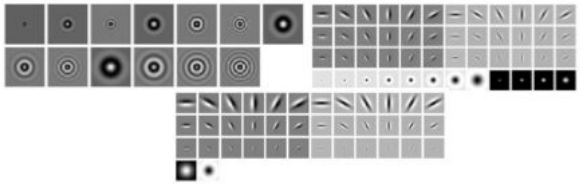
SIFT



Spin image



HoG

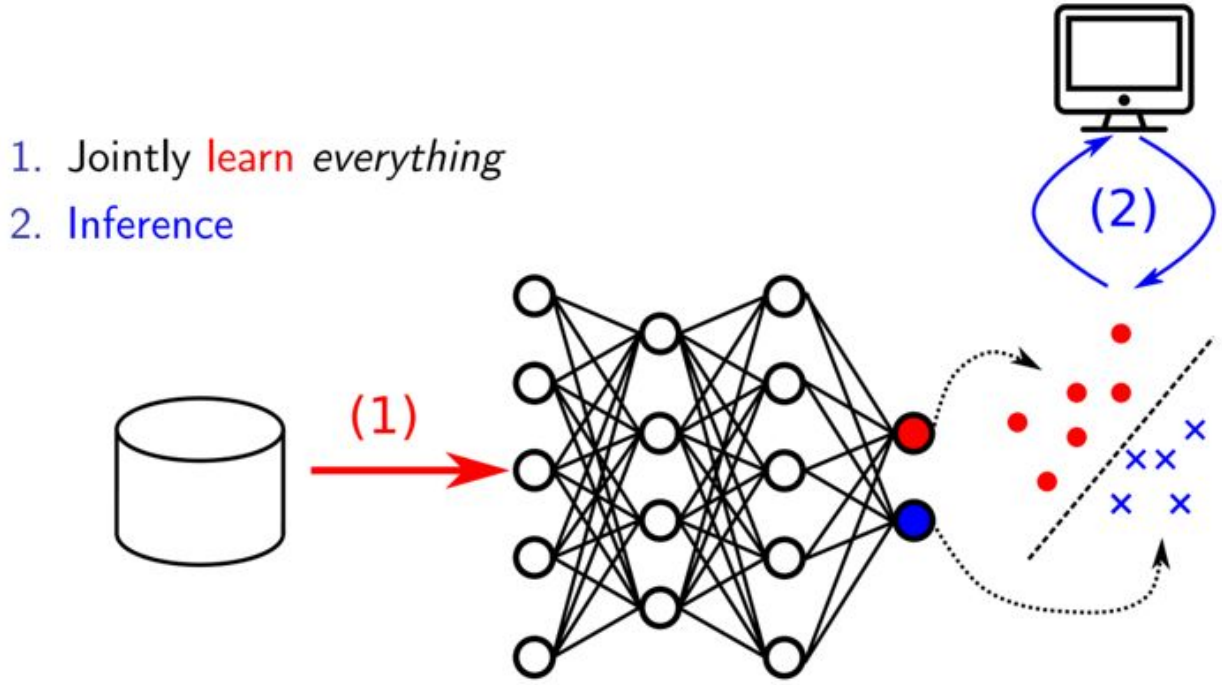


Textons

[figure credit R. Fergus]

Features from years of vision expertise by the whole community are now surpassed by *learned* representations and these *transfer across tasks*

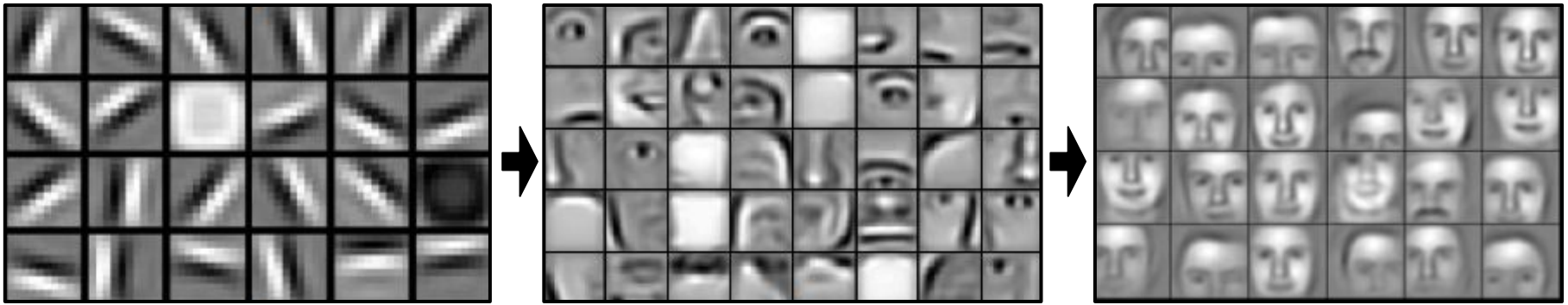
Deep Learning



[slide credit K. Cho]

End-to-End Learning Representations

The visual world is too vast and varied
to fully describe by hand



local appearance | parts and texture | objects and semantics

Learn the representation from data

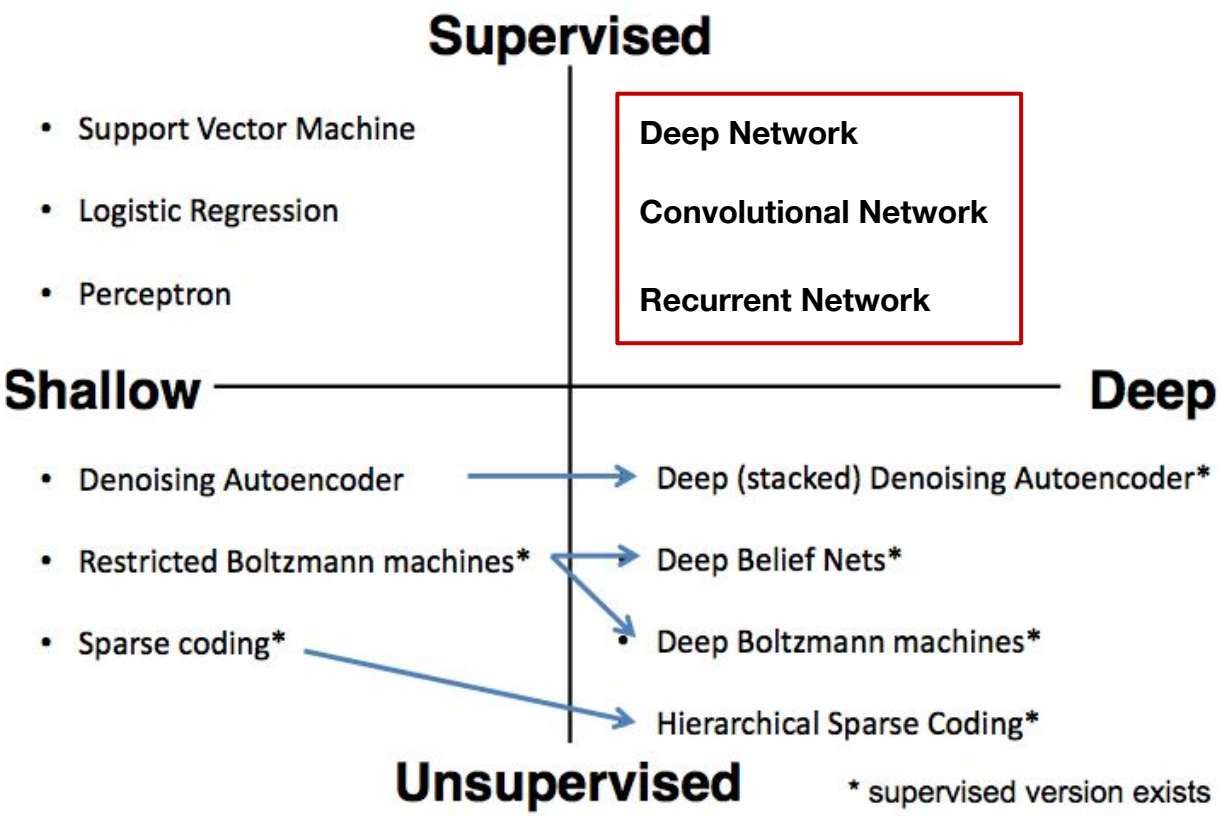
[figure credit H. Lee]

End-to-End Learning Tasks

The visual world is too vast and varied
to fully describe by hand

Learn the task from data

Types of Learning

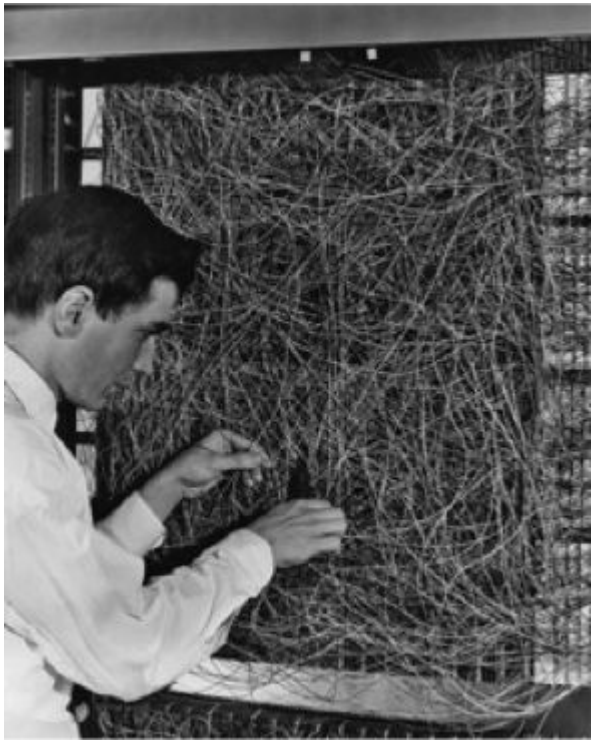


Vast space of models!

[figure credit Marc'aurelio Ranzato, CVPR 2014 tutorial]

History

1958 Rosenblatt proposed perceptrons
1980 Neocognitron (Fukushima, 1980)
1982 Hopfield network, SOM (Kohonen, 1982), Neural PCA (Oja, 1982)
1985 Boltzmann machines (Ackley et al., 1985)
1986 Multilayer perceptrons and backpropagation (Rumelhart et al., 1986)
1988 RBF networks (Broomhead&Lowe, 1988)
1989 Autoencoders (Baldi&Hornik, 1989), Convolutional network (LeCun, 1989)
1992 Sigmoid belief network (Neal, 1992)
1993 Sparse coding (Field, 1993)
2000s Sparse, Probabilistic, and Layer-wise models (Hinton, Bengio, Ng)
2012 DL popularized in vision by contest victory (Krizhevsky et al. 2012)



Rosenblatt's Perceptron

Is deep learning 4, 20, or 50 years old? What's changed?

Why Now?

1. Data

   ImageNet et al.: millions of *labeled* (crowdsourced) images
2. Compute

   GPUs: terabytes/s memory bandwidth, teraflops compute
3. Technique

   new optimization know-how,

   new variants on old architectures,

   new tools for rapid experimentation

Why Now? Data

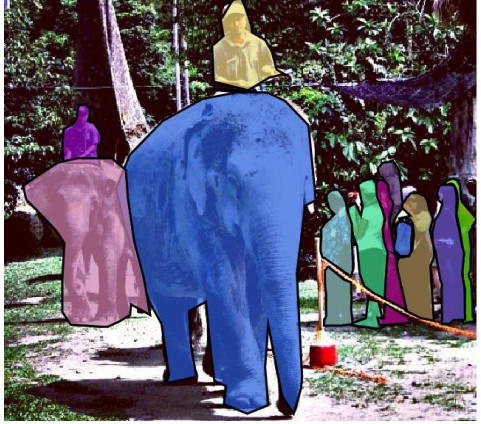
For example:

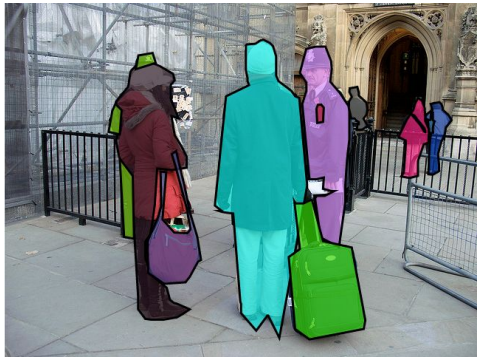
IMAGENET

>10 million labeled images
>1 million with *bounding boxes*

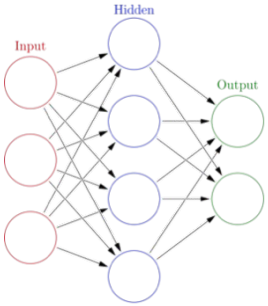
Microsoft
Common Objects in Context

>300,000 images with *labeled and segmented* objects





Why Now? GPUs



Parallel processors
for parallel models:

Inherent Parallelism

same op, different data

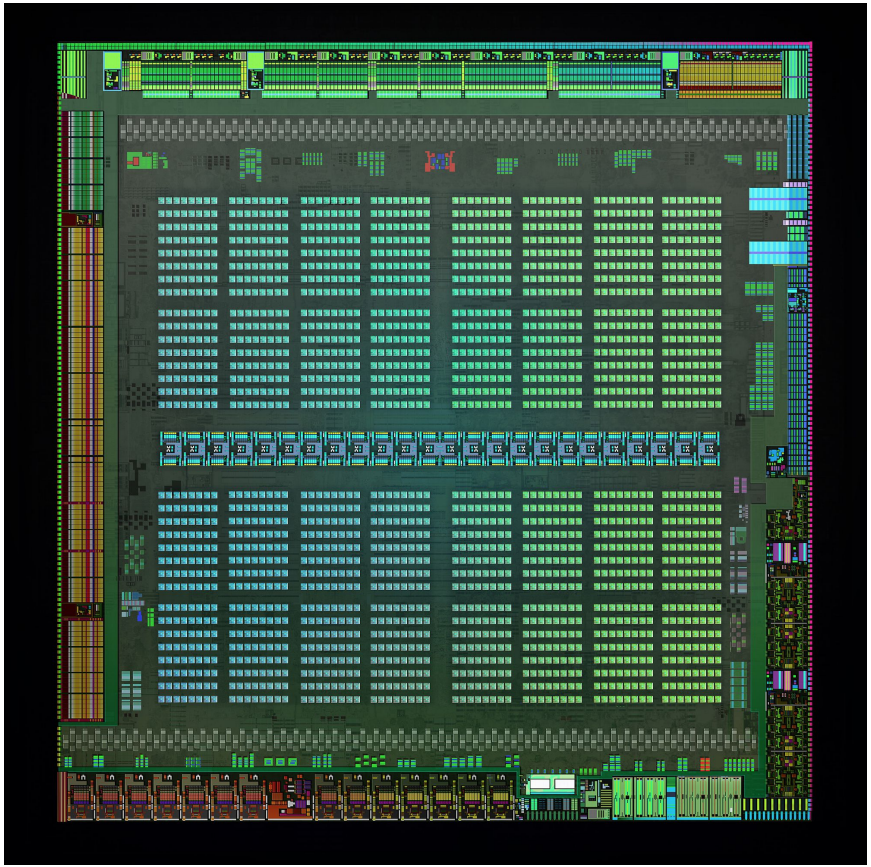
Bandwidth

lots of data in and out

Tuned Primitives

cuDNN and cuBLAS

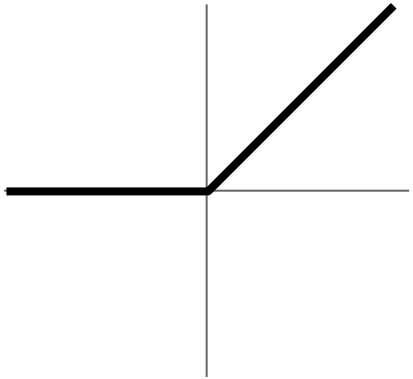
for deep nets for matrices



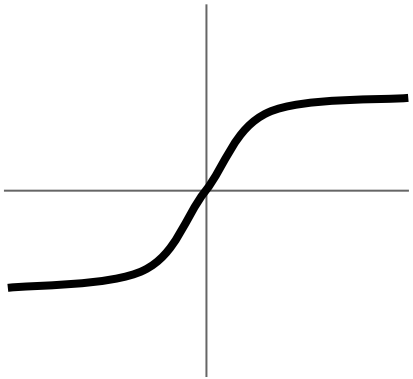
Why Now? Technique

Non-convex and high-dimensional learning is okay with the right design choices

e.g. non-saturating non-linearities

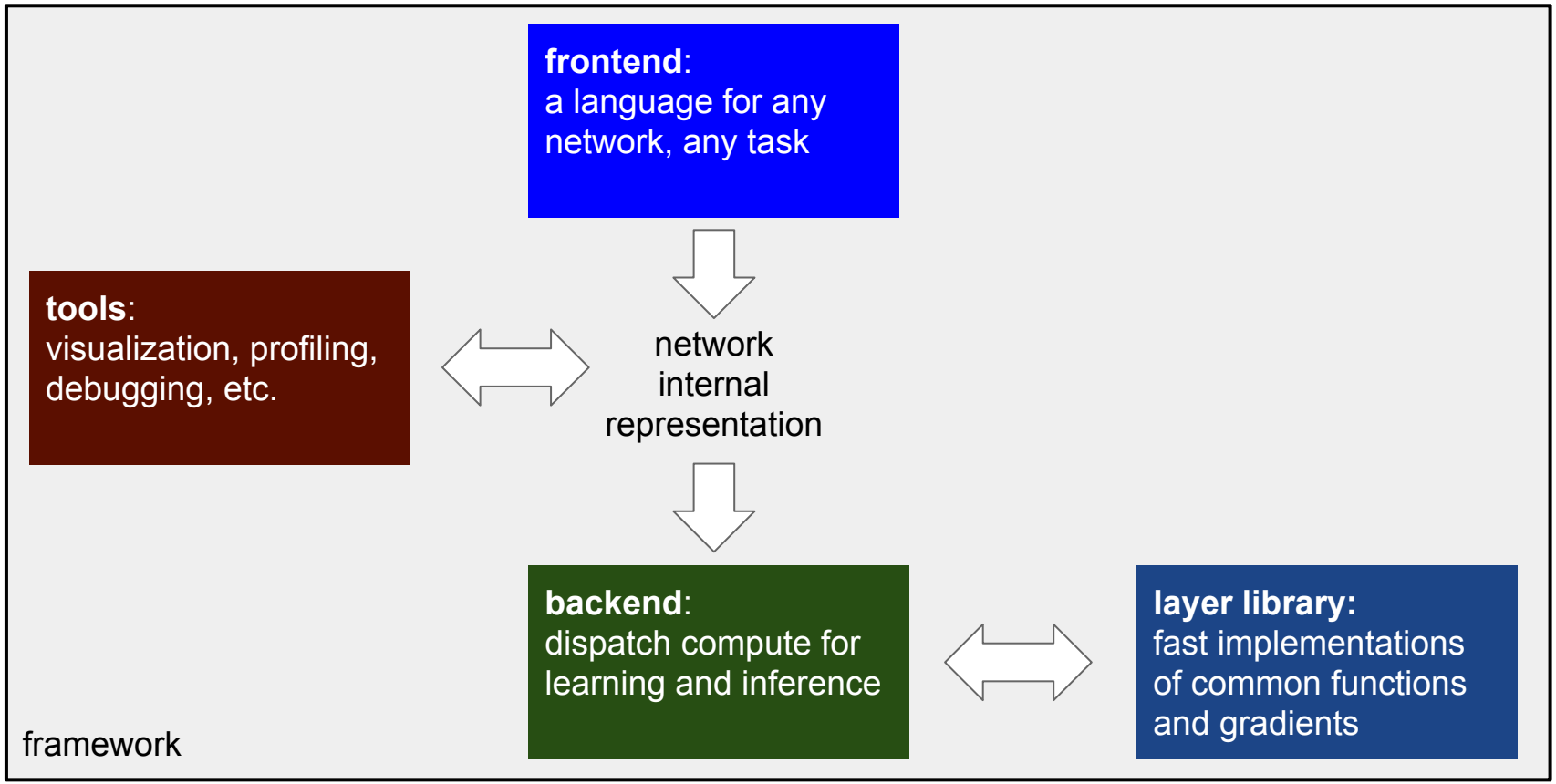


instead of

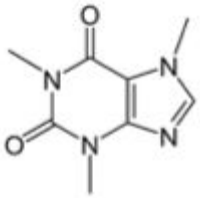


Learning by Stochastic Gradient Descent (SGD) with momentum and other variants — more later!

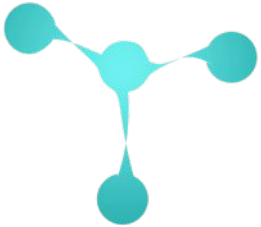
Why Now? Deep Learning Frameworks



Deep Learning Frameworks



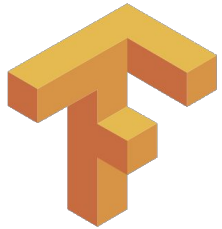
Caffe
Berkeley / BVLC
C++ / CUDA,
Python, MATLAB



Torch
Facebook + NYU
Lua (C++)

theano

Theano
U. Montreal
Python



TensorFlow
Google
Python (C++)

all open source
we like to brew our networks with **Caffe**

Not So “Neural”

These models are not how the brain works

We don’t know how the brain works!

- This isn’t a problem (except for neuroscientists)

- Be wary of neural realism hype or “it just works because it’s like the brain”

- **network**, not neural network
  unit, not neuron

Part 1: Deep Learning for Vision

Why Deep Learning?

Dive into Deep Learning

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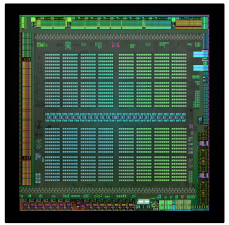
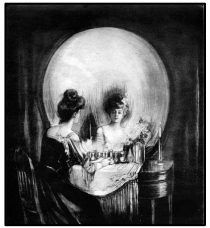


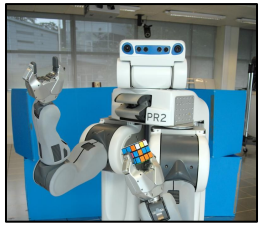
The Challenge of Recognition



Learning & Optimization

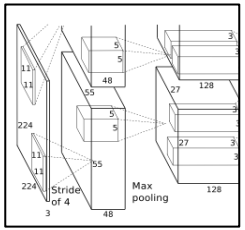
$$\nabla_\theta L$$

Applications



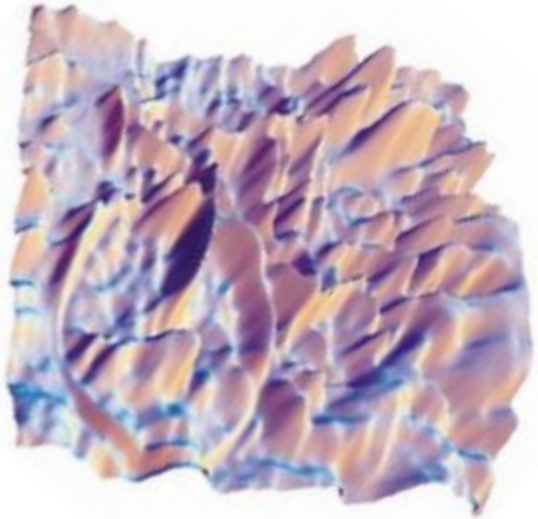
Caffe First Sip

Network Tour



Transfer Learning

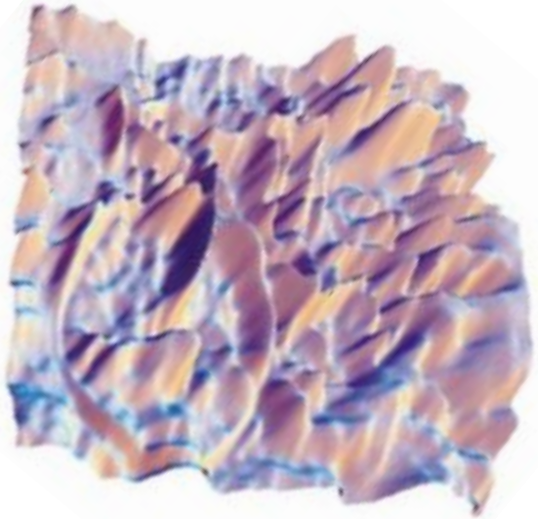
The Challenge of Recognition



What does this pattern depict?

[Kersten & Yuille, 2003]

The Challenge of Recognition

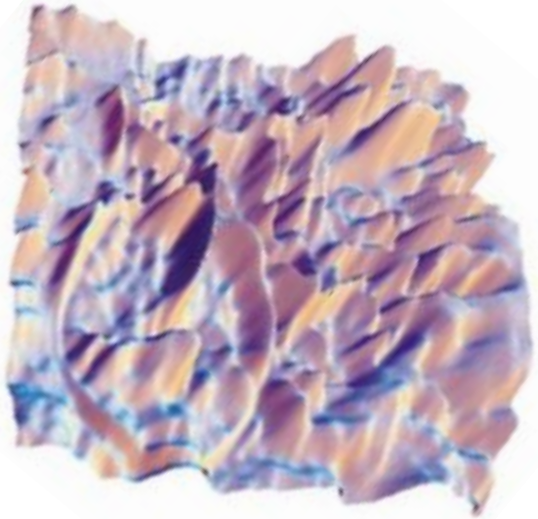


What does this pattern depict?

Same data!

[Kersten & Yuille, 2003]

The Challenge of Recognition



What does this pattern depict?

intensity as elevation

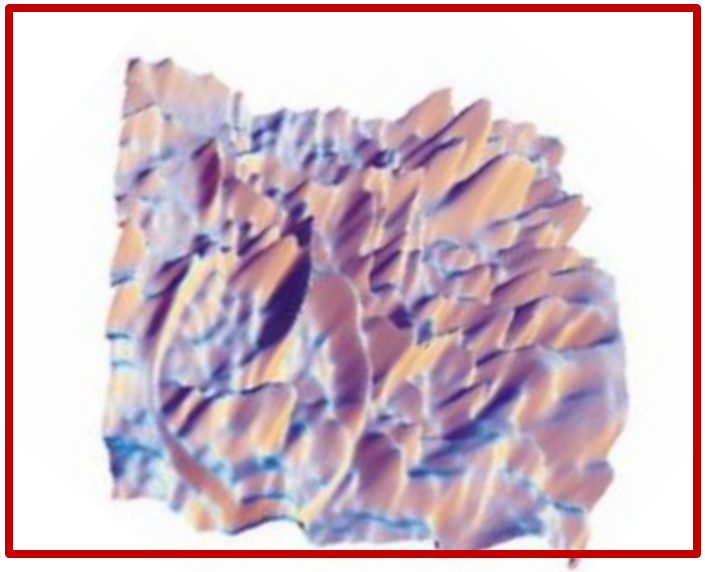
Same data!

intensity as brightness

[Kersten & Yuille, 2003]

The Challenge of Recognition

Machine Recognition



What does this pattern depict?

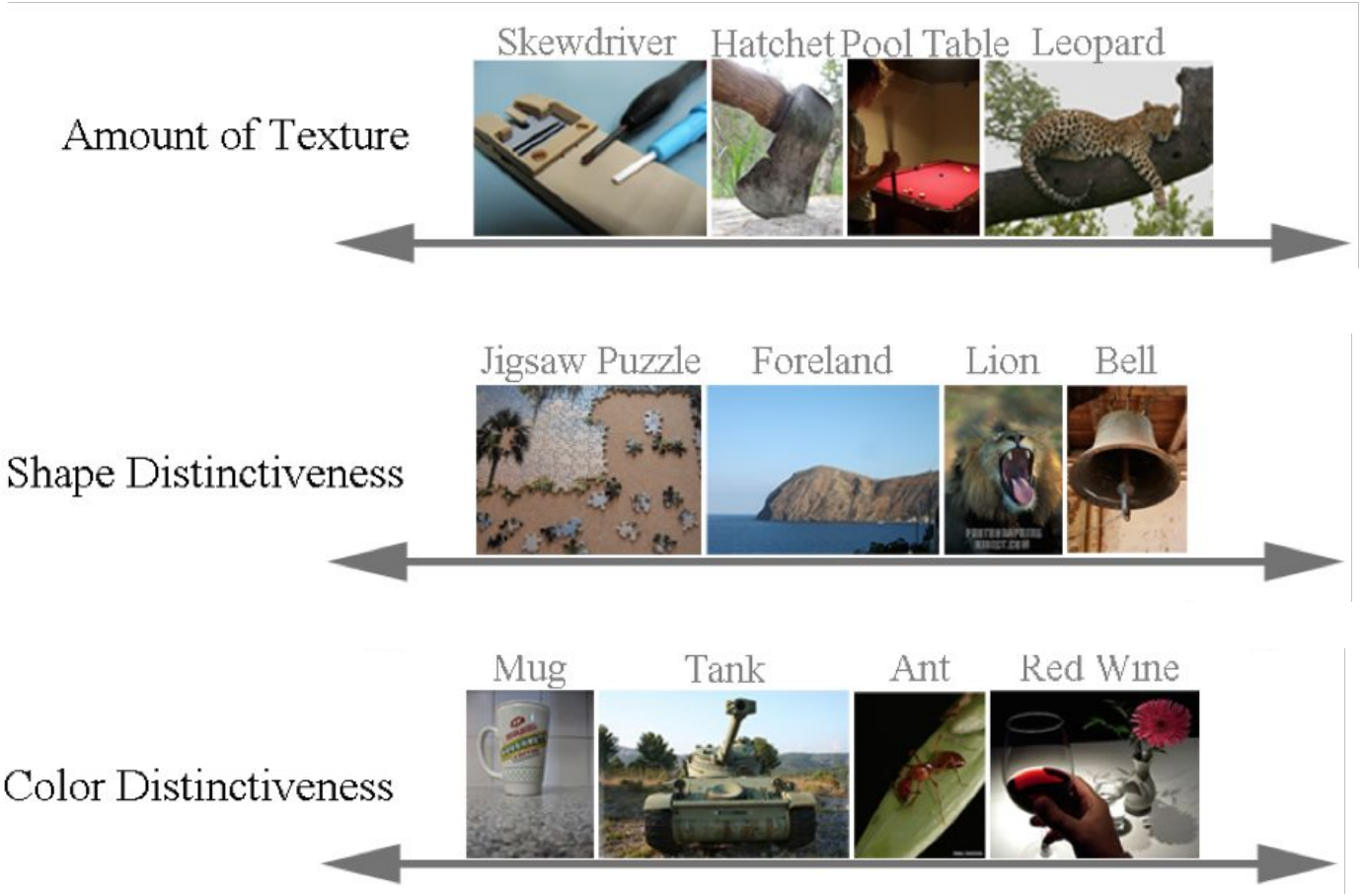
intensity as elevation

Same data!

intensity as brightness

[Kersten & Yuille, 2003]

[Russakovsky15]



[Russakovsky15]

PASCAL

ILSVRC

birds

bird

flamingo

cock

ruffed grouse

quail

partridge

...

cats

cat

Egyptian cat

Persian cat

Siamese cat

tabby

lynx

...

dogs

dog

dalmatian

keeshond

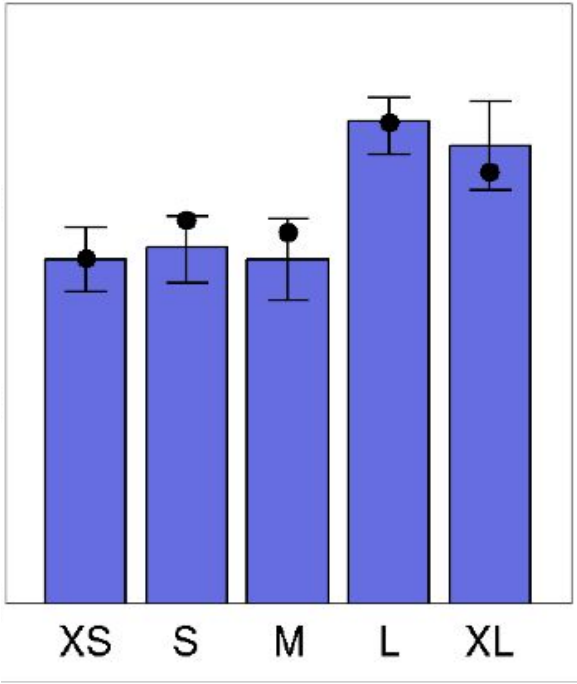
miniature schnauzer

standard schnauzer

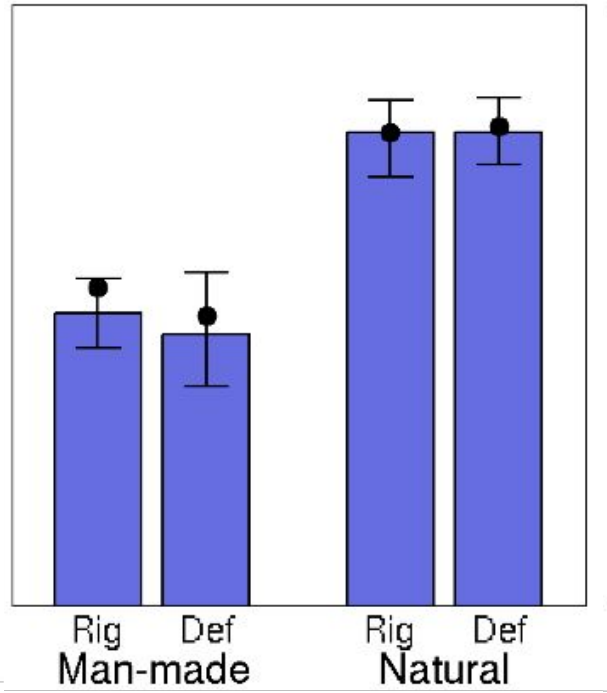
giant schnauzer

[Russakovsky15]

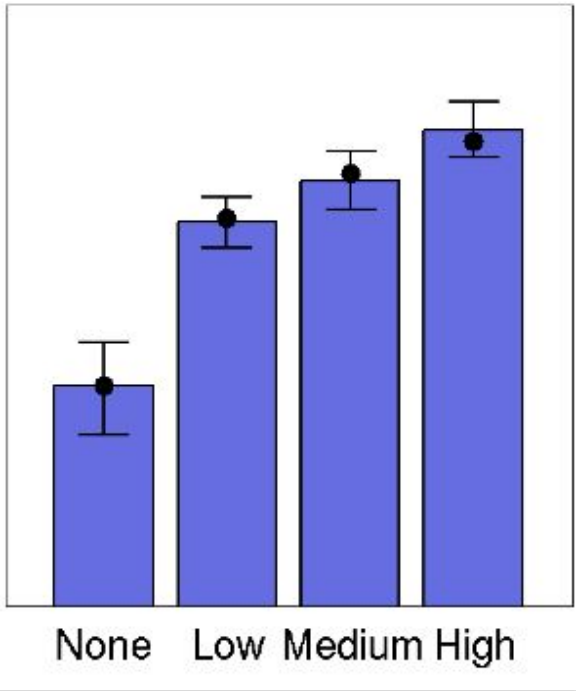
Image Classification Accuracy (on ILSVRC)



Size



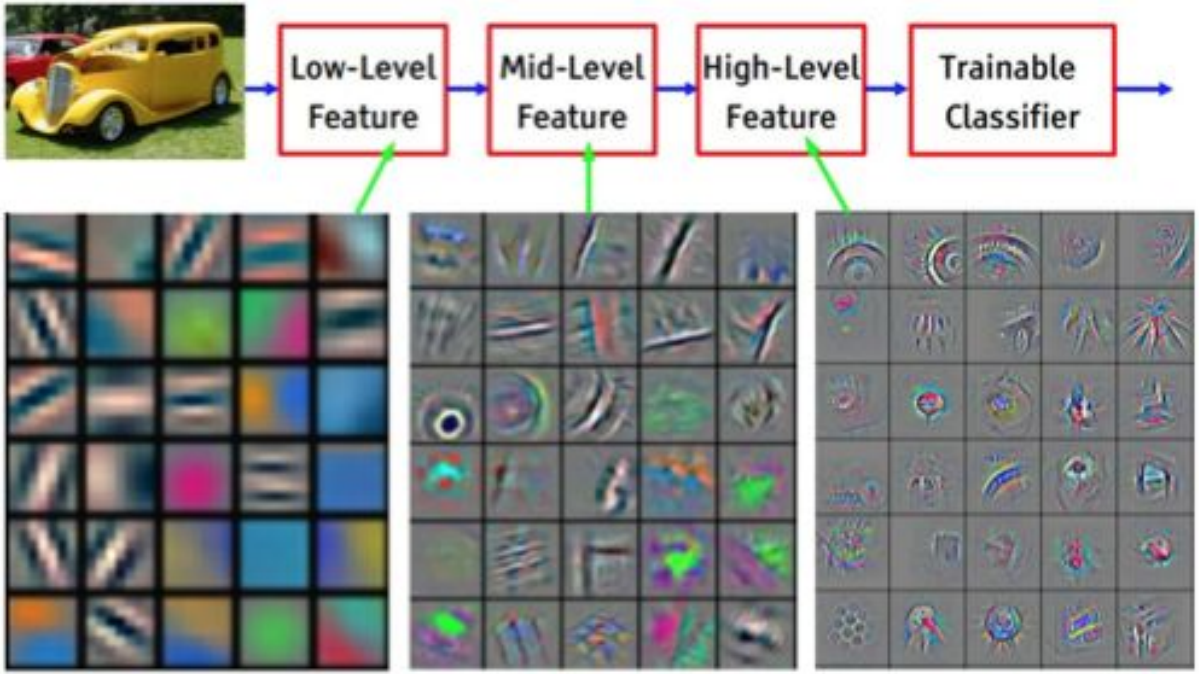
Rigid / Deformable



Texture

[Russakovsky15]

What Does a Deep Net Learn?

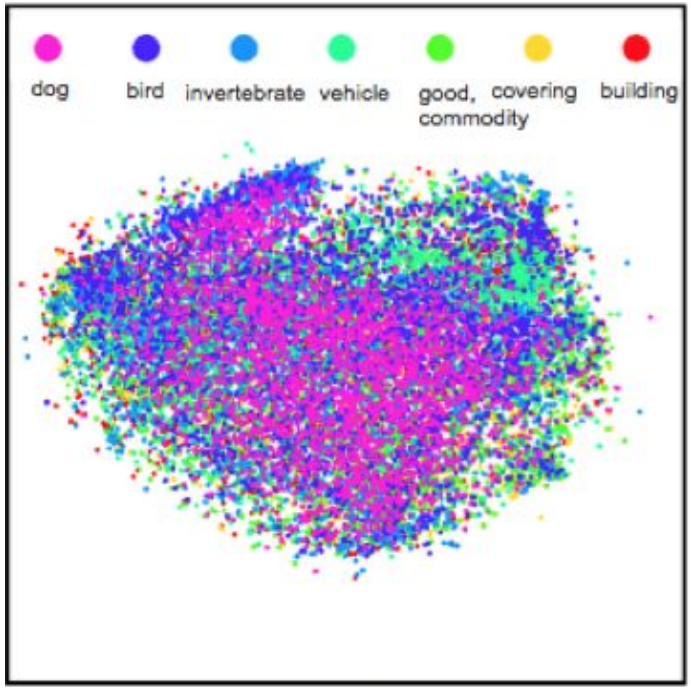


Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

[figure credit Y. LeCun, ICML13 tutorial]

Feature Embedding

The Unreasonable Effectiveness of Deep Features



Low-level: $Pool_1$

High-level: FC_6

Classes separate in the deep representations and transfer to many tasks.

[DeCAF] [Zeiler-Fergus]

Feature Mining

Strongest Feature Responses are Visually Rich

Maximal activations of $\texttt{pool}_5$ units *[R-CNN]*

$\texttt{conv}_5$ "deconv" visualization *[Zeiler-Fergus]*

Rich visual structure of features deep in hierarchy

Shallow Layers Learn Simple Features

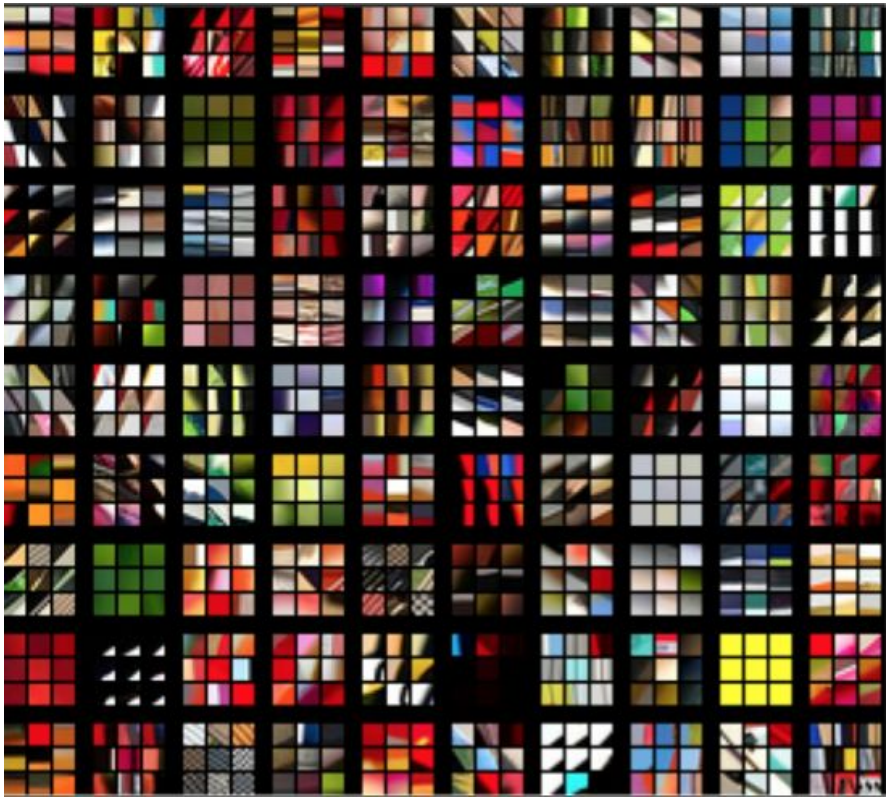
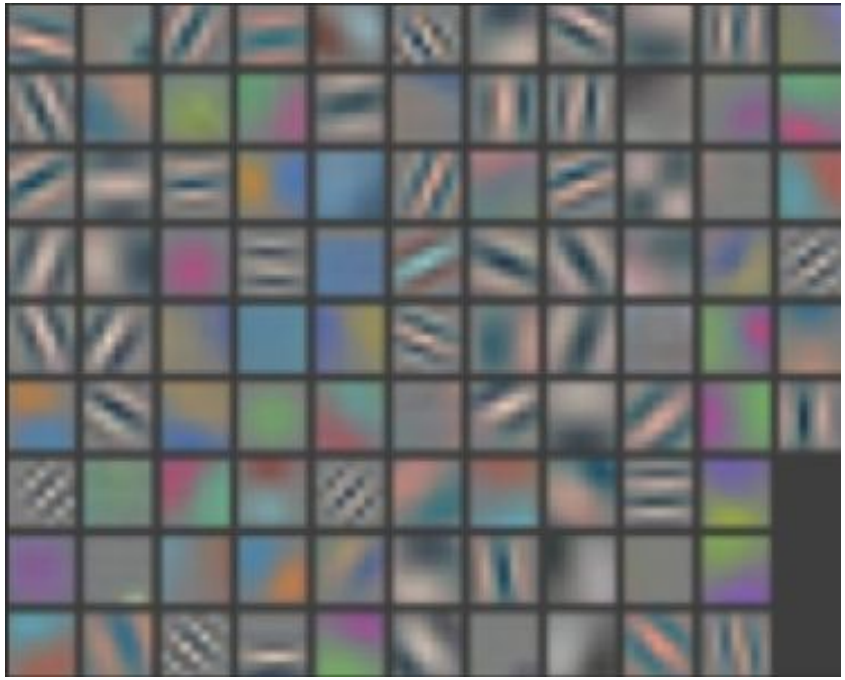
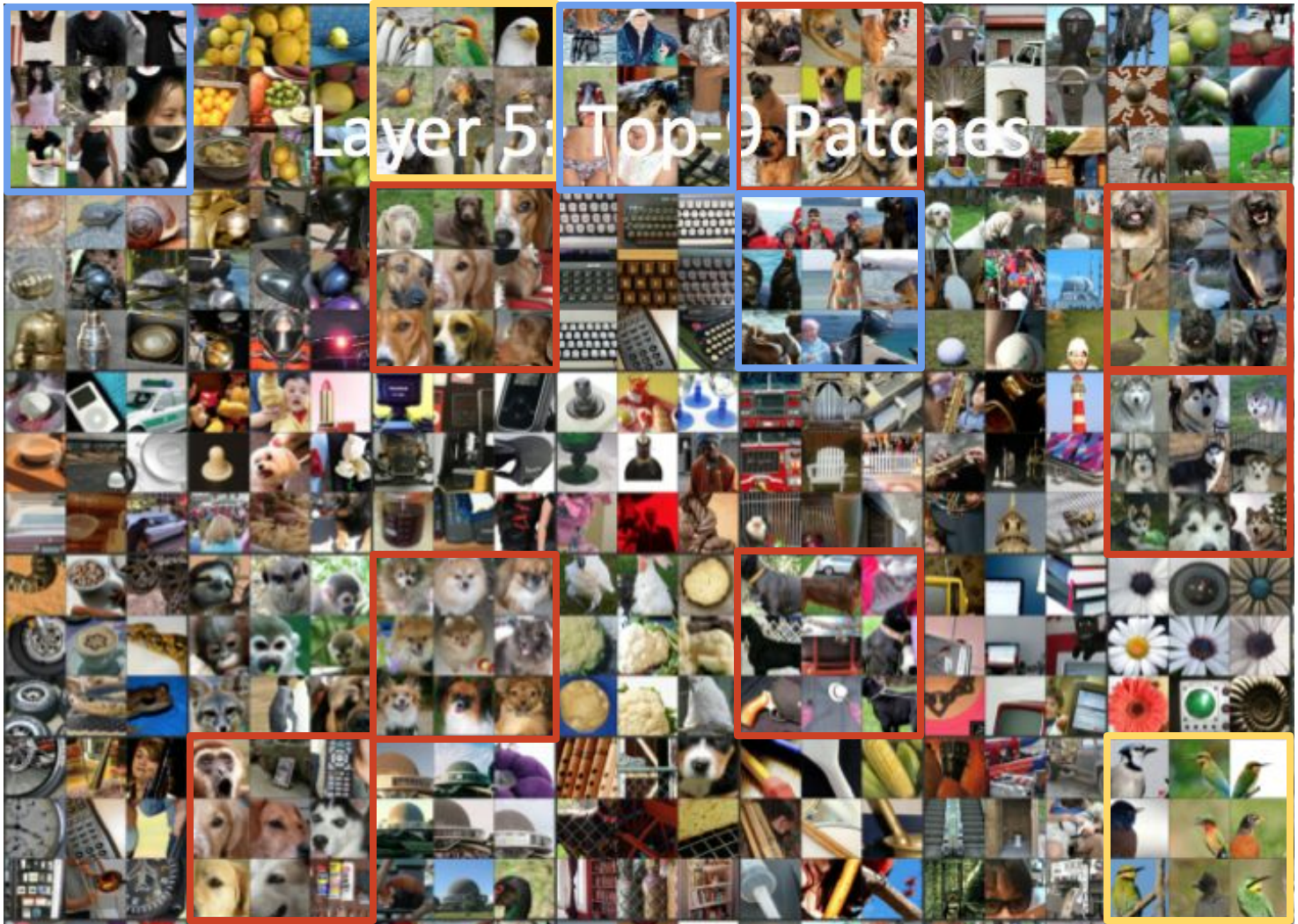


image patches that strongly activate 1st layer filters



$\texttt{conv}_1$ 1st layer filters

[figure credit M. Zeiler]



$conv_5$

visual complexity increases from "shallow" to "deep"

dog **person** **bird**

deep responses have *semantic* consistency

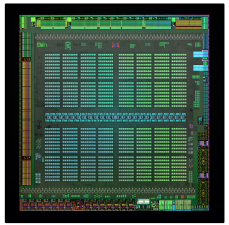
[figure credit M. Zeiler]

Part 1: Deep Learning for Vision

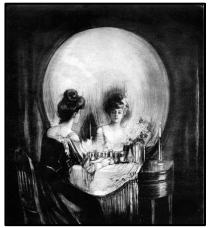
Why Deep Learning?

Dive into Deep Learning

What is DL? Why Now?



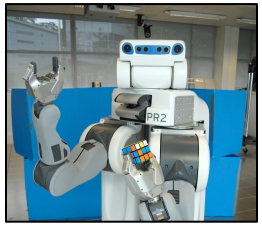
The Challenge of Recognition



Learning & Optimization

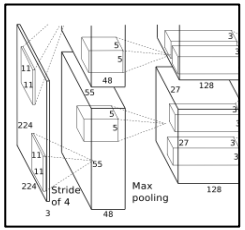
$$\nabla_\theta L$$

Applications



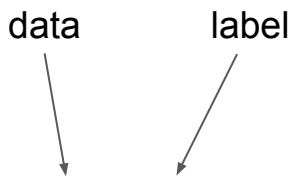
Caffe First Sip

Network Tour



Transfer Learning

Supervised Learning



Given labeled data:

$$(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)$$

Goal: find a function f such that

$$y_n = f(x_n)$$

for all n, “as well as possible”

Supervised Loss

What does “as well as possible” mean?

Pick a *loss function* $\ell(y, \hat{y})$: how wrong is it to predict $\hat{y}$ when the true label is y?

Minimize the total loss over all data:

$$L = \sum_n \ell(y_n, \hat{y}_n)$$

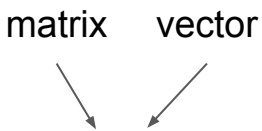
E.g. $\ell(y, \hat{y}) = \|y - \hat{y}\|^2$ “Euclidean Loss” or everyday linear regression

Parametric Learning

How do we find the label-prediction function f?

Parametric answer: pick it from a family determined by a set of *parameters* θ:

$$f(x) = f(x; \theta)$$

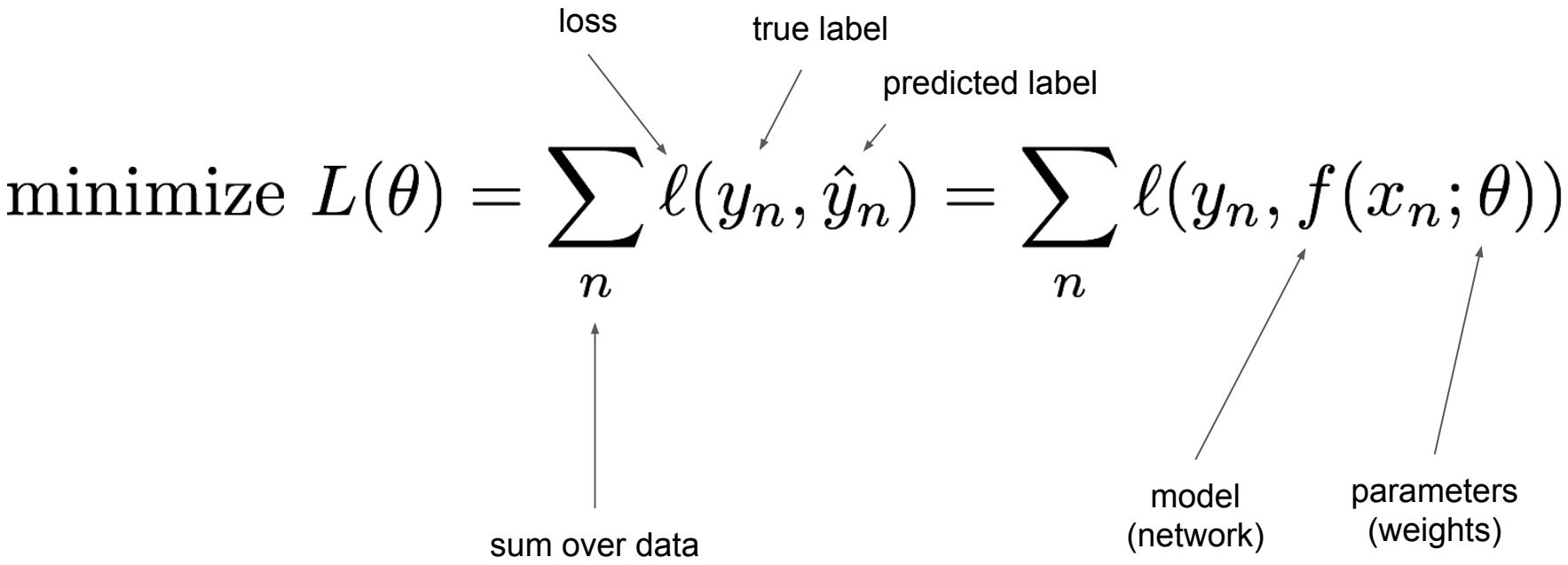


E.g. $f(x; \theta) = \theta x$ “linear prediction”

For us: f is a *network*, θ is a set of *weights*

Parametric Supervised Learning

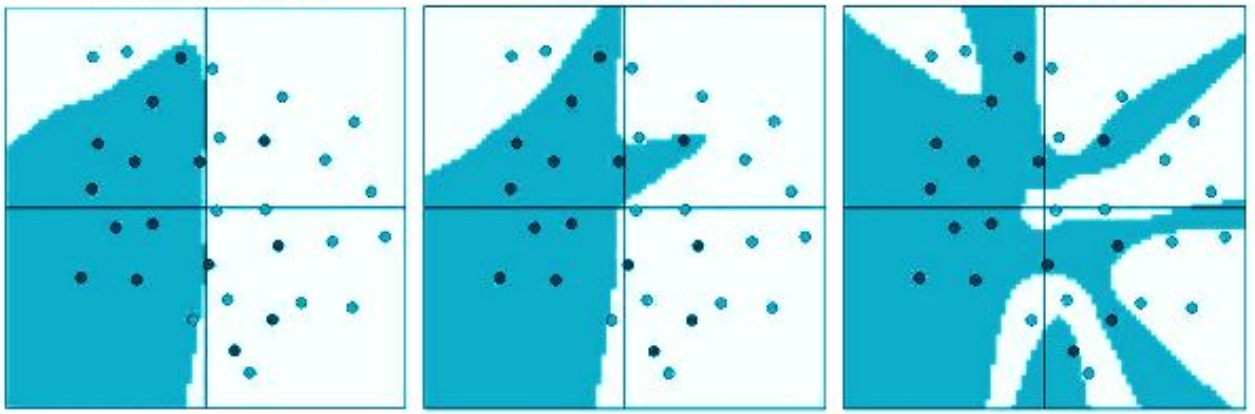
Altogether: our goal is to find θ in order to



Underfitting and Overfitting

fewer parameters

more parameters



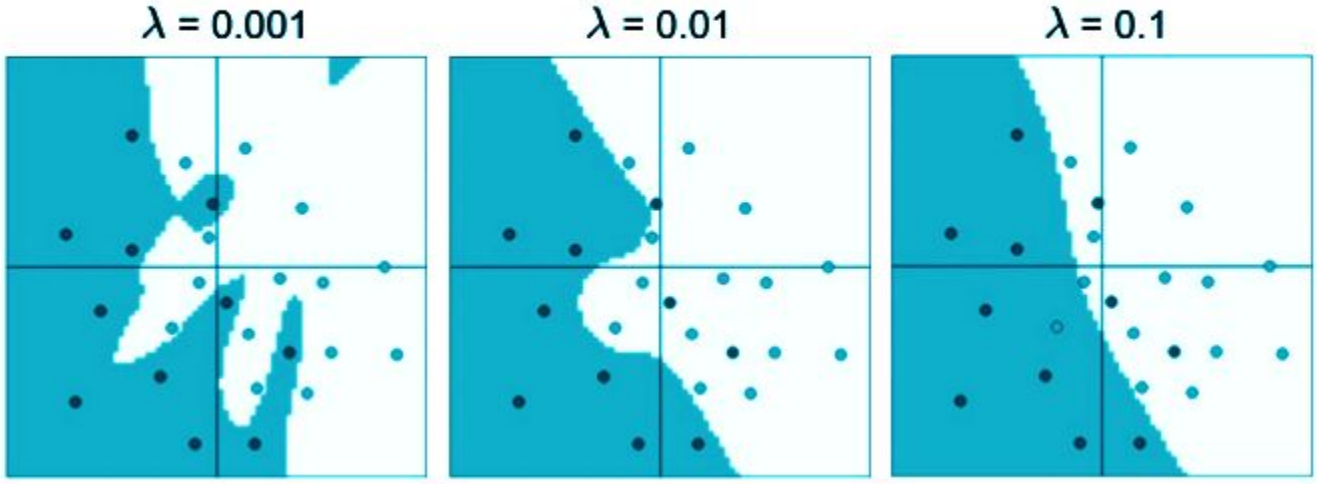
underfitting:
not enough parameters
to model the data

overfitting:
enough parameters to
memorize the training
set without generalizing

[figure credit A. Karpathy]

Regularization

How can we prevent overfitting without reducing the number of parameters?



Add a *regularization penalty* to our loss: “complicated” solutions are worse

[figure credit A. Karpathy]

Regularization: Weight Decay and Dropout

Weight Decay: minimize $L(\theta) + \lambda\|\theta\|^2$ to pull weights toward zero

- λ (scalar) is an optimization setting… pick it empirically
- aka "L^2 regularization"

Dropout: during training, randomly set a fraction p of activations to zero

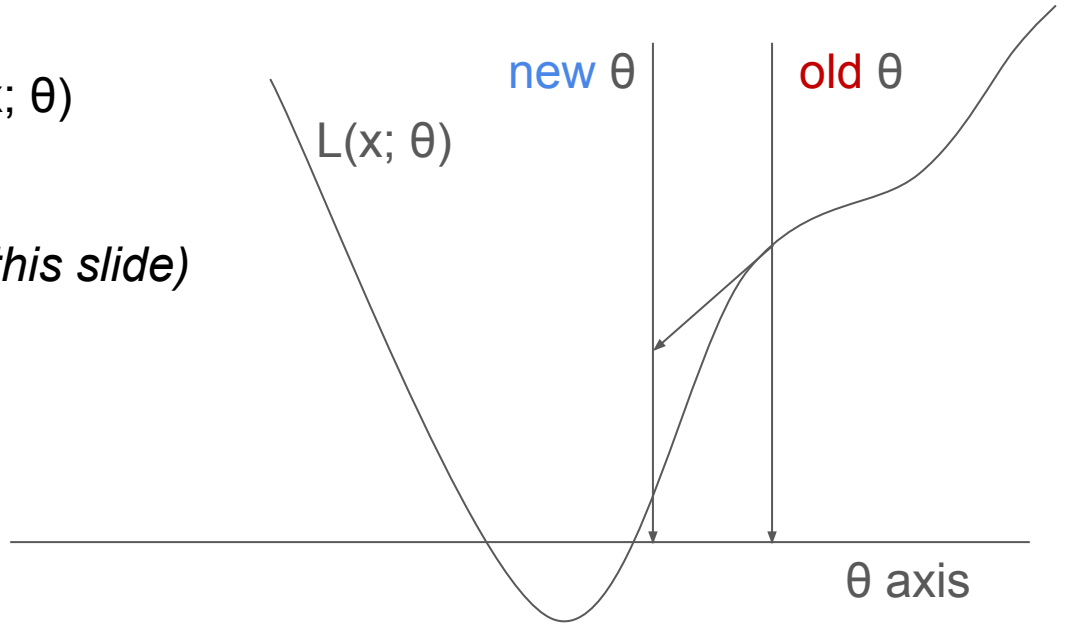
- p is an optimization setting (often 0.5)
- forces model to be robust to noise

Gradient Descent: Intuition

Want to minimize “loss” function L(x; θ)

θ (vector): parameter to update

x (vector): input data *(fixed on this slide)*

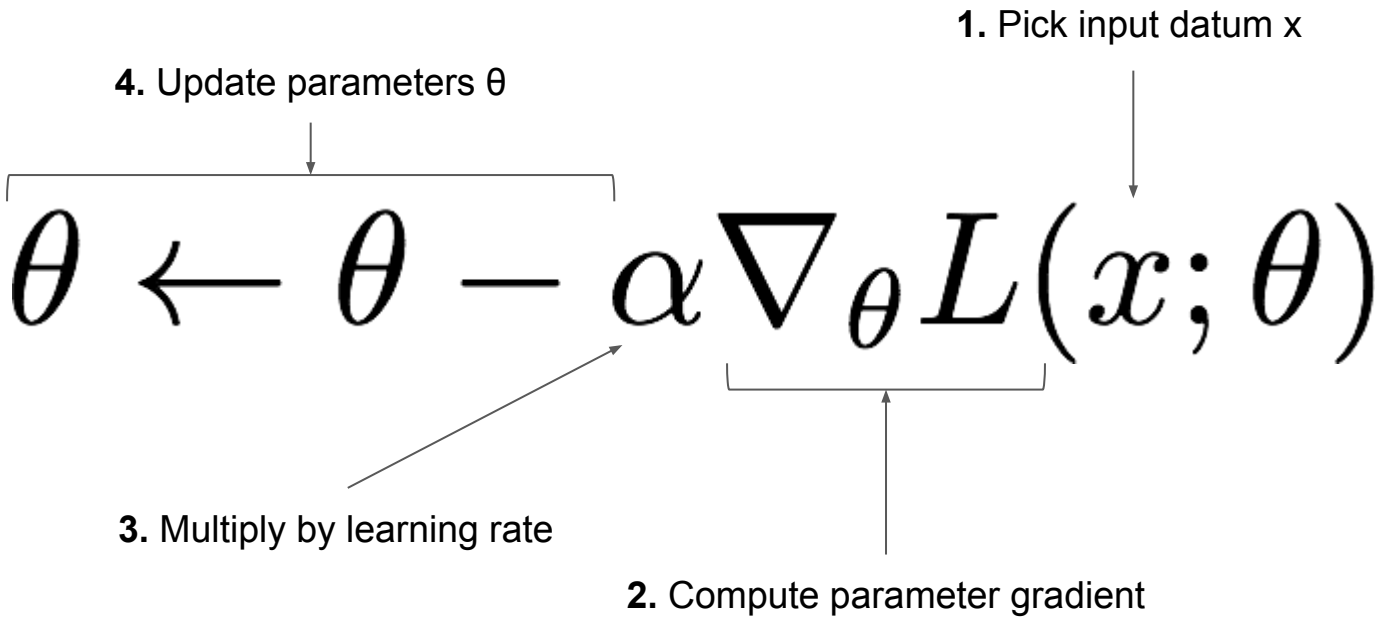


Move in the direction of the gradient

The gradient tells you, for each element of the network parameters, how the loss changes in response to a change in that parameter.

Stochastic Gradient Descent (SGD)

Want to minimize “loss” function L(x; θ)



Why “Stochastic”?

The gradient depends on the choice of input datum x

Choose x *randomly* (or just cycle through all data in a fixed order)

(The alternative is to average the gradient over all available data, “batch gradient descent”:

$$\theta \leftarrow \theta - \alpha \sum_i \nabla_\theta L(x_i; \theta)$$

That’s too slow for big data!)

SGD with Weight Decay and Momentum

$$\theta \leftarrow \theta - \alpha \ \ \nabla_\theta L(x;\theta)$$

SGD with Weight Decay and Momentum

$$\theta \leftarrow \theta - \alpha \left(\nabla_\theta L(x; \theta) - \lambda \theta \right)$$

weight decay
(*regularization*)

SGD with Weight Decay and Momentum

$$\theta \leftarrow \theta - \alpha \left(\nabla_\theta L(x;\theta) - \lambda\theta\right) + p[\text{last update}]$$

weight decay
(*regularization*)

momentum
(p is a number less than 1)

There are many other variants:
Adam, RMSprop, AdaDelta, AdaGrad, Nesterov, ...

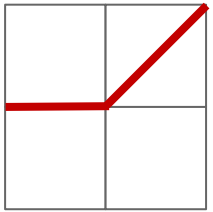
Layer Gradients

Matrix Multiply

$$y_i = \sum_j A_{ij} x_j$$

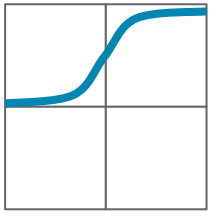
ReLU

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



Sigmoid

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



Gradients

$$\frac{\partial y_i}{\partial x_j} = A_{ij} \qquad \frac{\partial y_i}{\partial A_{ij}} = x_j$$

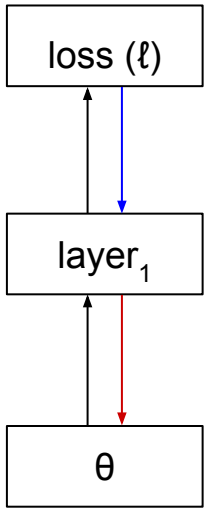
$$\frac{dy}{dx} = \begin{cases} 0 & x < 0 \\ 1 & x > 0 \end{cases}$$

$$\frac{dy}{dx} = e^{-x} y^2$$

Back-propagation: The Chain Rule

A net is a composition of layer functions

The gradient of a net is the product of layer gradients



$= L(\theta) = \ell(\text{layer}_1(\theta))$

$\frac{dL}{d\theta} = \frac{d\ell}{d\,\text{layer}_1} \frac{d\,\text{layer}_1}{d\theta}$

$\text{layer}_1(\theta)$

$\frac{d\ell}{d\,\text{layer}_1}$

$\frac{d\ell}{d\,\text{layer}_1} \frac{d\,\text{layer}_1}{d\theta}$

Back-propagation in a Bigger Net

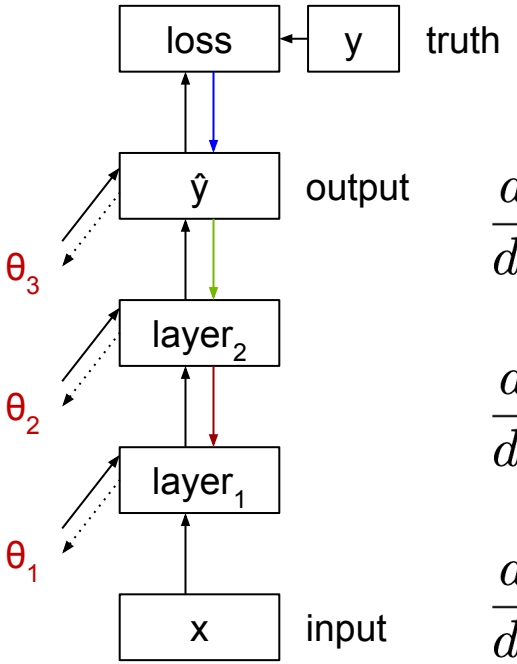
Forward pass

$$L = \text{loss}(\hat{y}, y)$$

$$\hat{y} = \text{layer}_3(x_2; \theta_3)$$

$$x_2 = \text{layer}_2(x_1; \theta_2)$$

$$x_1 = \text{layer}_1(x; \theta_1)$$



Backward pass

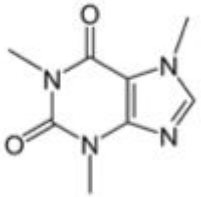
$$\frac{dL}{d\hat{y}}$$

$$\frac{dL}{d\theta_3} = \frac{dL}{d\hat{y}}\frac{d\hat{y}}{d\theta_3} \qquad \frac{dL}{dx_2} = \frac{dL}{d\hat{y}}\frac{d\hat{y}}{dx_2}$$

$$\frac{dL}{d\theta_2} = \frac{dL}{dx_2}\frac{dx_2}{d\theta_2} \qquad \frac{dL}{dx_1} = \frac{dL}{dx_2}\frac{dx_2}{dx_1}$$

$$\frac{dL}{d\theta_1} = \frac{dL}{dx_1}\frac{dx_1}{d\theta_1}$$

Lunch Break (45 minutes)



caffe.berkeleyvision.org

github.com/BVLC/caffe

BAIR

BERKELEY ARTIFICIAL INTELLIGENCE RESEARCH

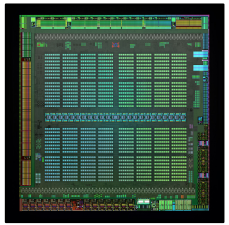
embedded VISION ALLIANCE

Part 1: Deep Learning for Vision

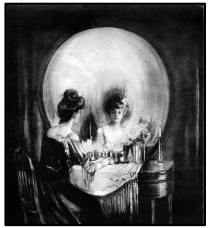
Why Deep Learning?

Dive into Deep Learning

What is DL? Why Now?



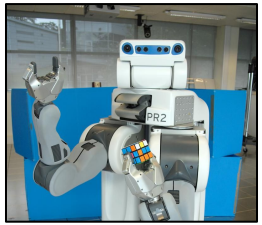
The Challenge of Recognition



Learning & Optimization

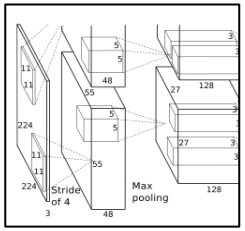
$$\nabla_\theta L$$

Applications



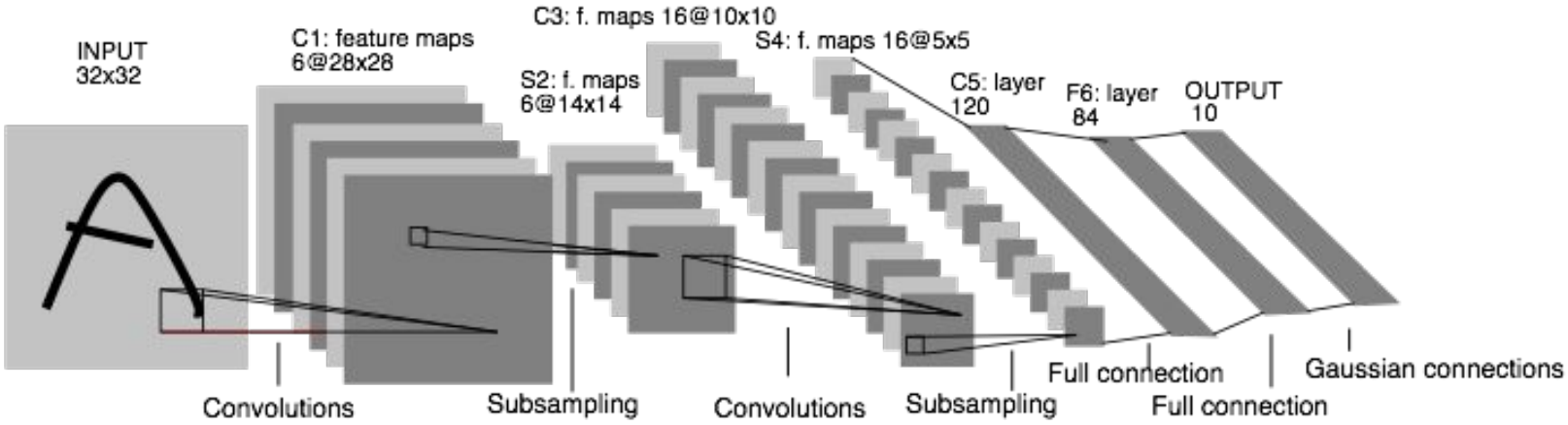
Caffe First Sip

Network Tour



Transfer Learning

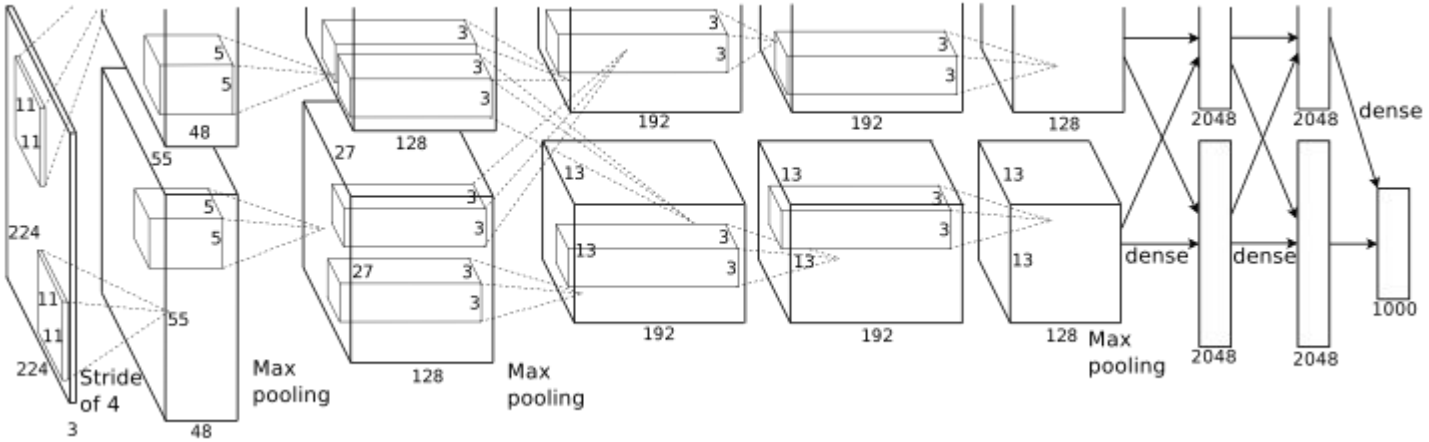
Convolutional Networks: 1989



LeNet: a layered model composed of convolution and subsampling layers followed by a holistic representation and ultimately a classifier for handwritten digits [LeNet]

Note: channel dimension goes up as spatial dimension goes down... still a common pattern today

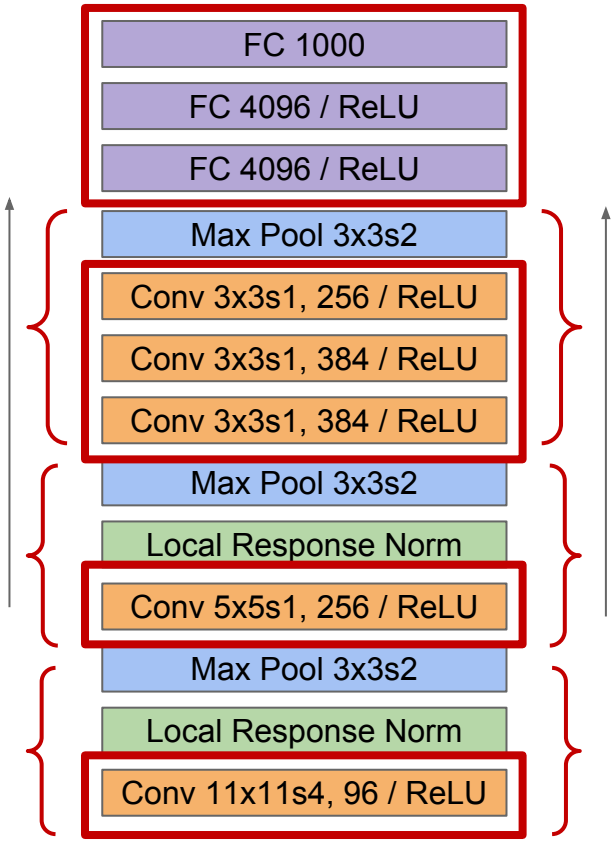
Convolutional Networks: 2012



AlexNet: a layered model composed of convolution, subsampling, and further operations followed by a holistic representation and all-in-all a landmark classifier on ILSVRC12 [AlexNet]

+ data
+ gpu
+ non-saturating non-linearity
+ regularization

Convnet Design Patterns

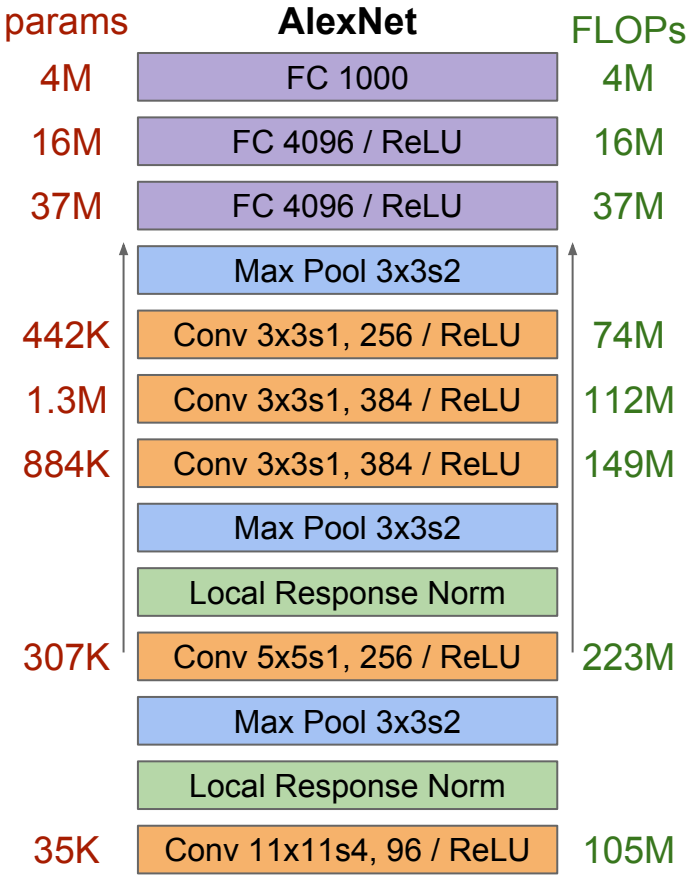


FC-ReLU:
stack at end of the net to learn output
majority of the learned parameters

Conv-Pool:
1+ conv are followed by pooling to subsample
spatial size shrinks; receptive field grows

Conv-ReLU:
all conv are followed by non-linearity
in this case ReLU

Convnet Computation: 2012 & 2014



AlexNet inference for a single image (3x227x227 input):

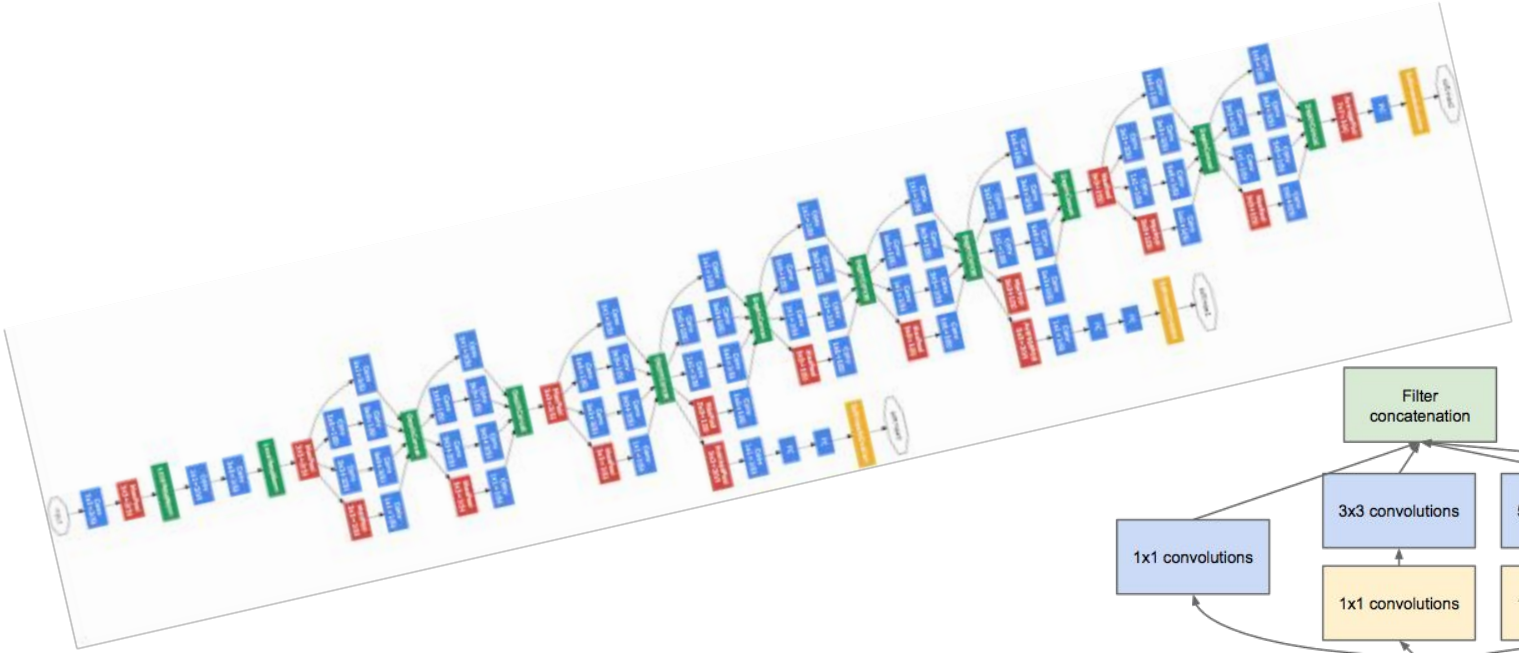
- **725M** FLOPS
- **60M** parameters (60,965,224 to be exact)
- **408 mb** GPU memory in Caffe
  <12 gb for batch size of 1,500
- **<1ms / image** on Titan X with cuDNN v4
  for batch size >= 256

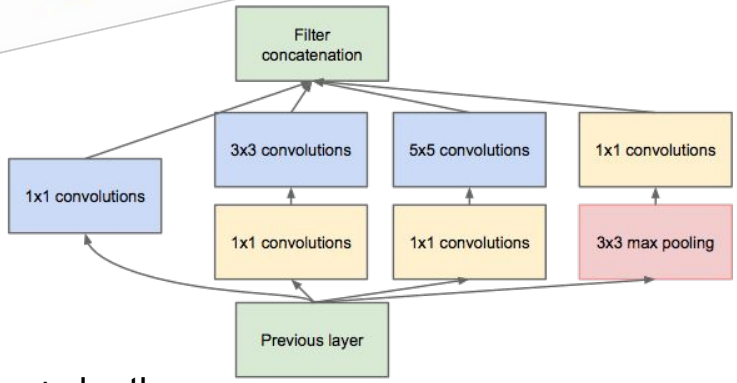
Compare GoogleNet (ILSVRC14 winner):

- **2x** FLOPs
- **0.1x** the parameters
- **14%** more accurate

Architecture matters!
But the computational primitives are the same.

Convolutional Nets: 2014





GoogLeNet ILSVRC14 Winner: ~6.6% Top-5 error

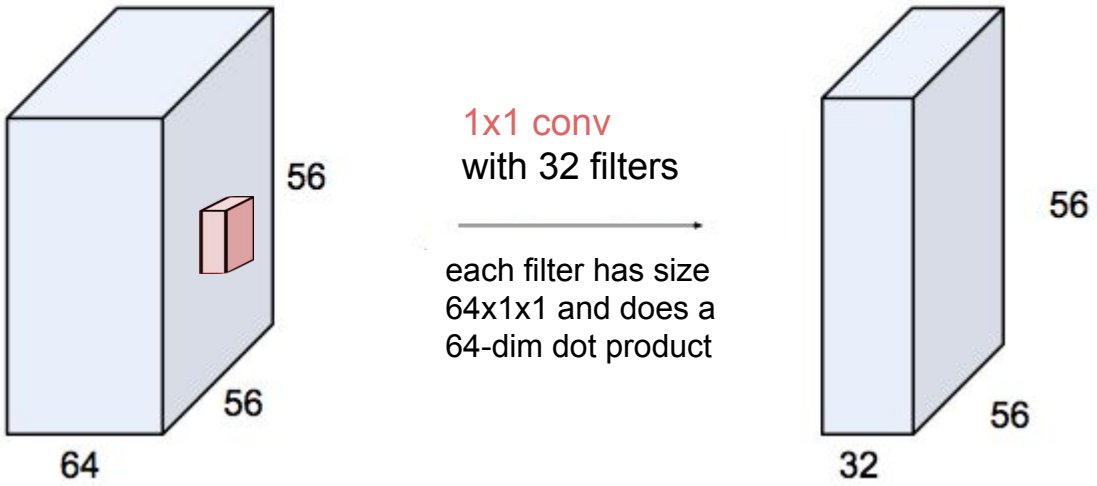
- composition of multi-scale dimension-reduced "Inception" modules
- no FC layers and only 5 million parameters

+ depth
+ auxiliary classifiers
+ dimensionality reduction

[Szegedy15]

1x1 Convolution

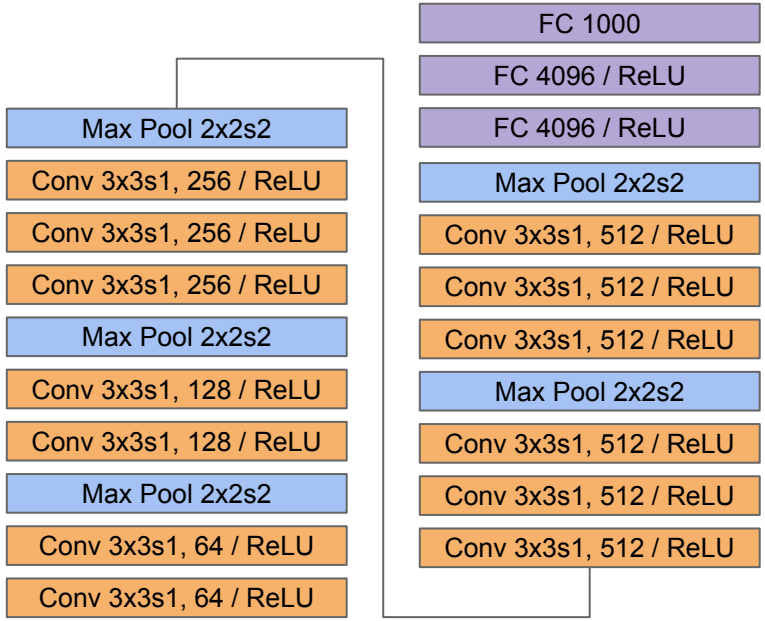
- reduce channel dimension to control 1. parameter count 2. computation
- stack with non-linearity for deeper net
- found in many of the latest nets



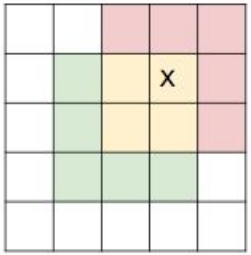
[figure credit A. Karpathy]

Convolutional Nets: 2014

A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					



stack 2
3x3 conv



for a 5x5
receptive field

[figure credit A. Karpathy]

VGG16 ILSVRC14 Runner-up: ~7.3% Top-5 error

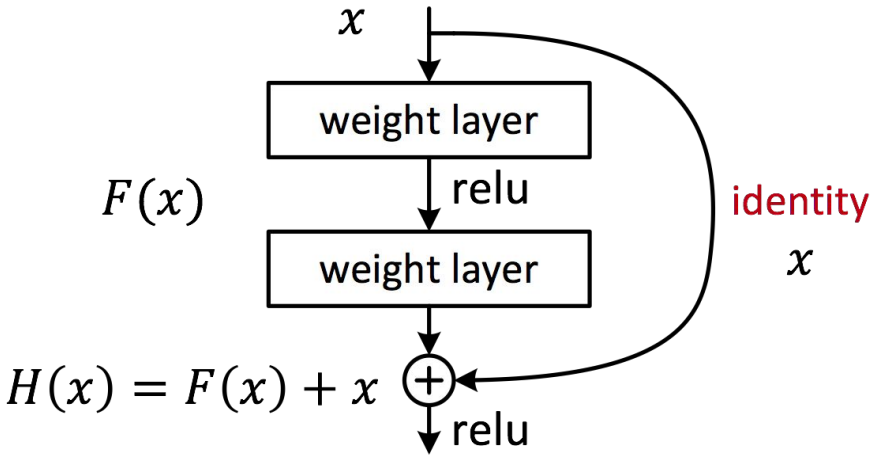
- 13 layers of 3x3 convolution interleaved with max pooling + 3 fully-connected layers
- simple architecture, *good for transfer learning*
- 155 million params and more expensive to compute

+ depth
+ fine-tuning deeper and deeper
+ stacking small filters

[Simonyan15]

Convolutional Nets: 2015

Learn **residual** mapping w.r.t. **identity**



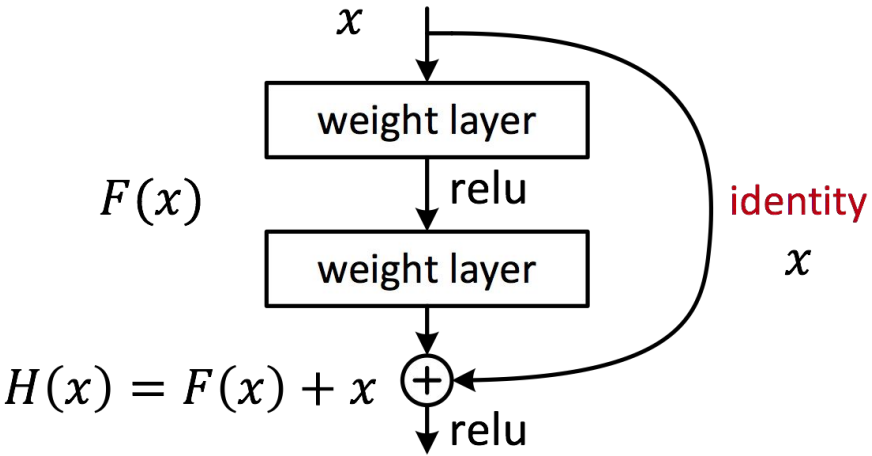
ILSVRC15 and COCO15 Winner: **MSRA ResNet**
- classification
- detection
- segmentation

- very deep 100+ layer nets
- skip connections across layers
- batch normalization

Kaiming He, et al.
Deep Residual Learning for Image Recognition
arXiv 1512.03385. Dec. 2015.

[He15]

Convolutional Nets: 2015

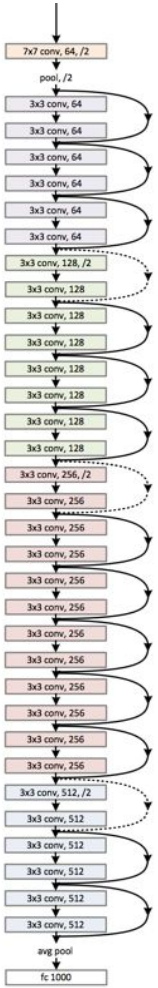


ILSVRC15 Winner **3.5% Top-5 error** and
COCO15 Winner with **>10% lead** for detection and segmentation

- MSRA Residual Net (ResNet): **101 and 152 layer networks**
- skip and sum layers to form residuals
- batch normalization (optimization trick)

MSRA ResNet

(~5x the layers shown here)



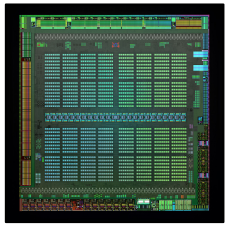
[He15]

Part 1: Deep Learning for Vision

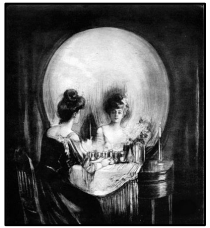
Why Deep Learning?

Dive into Deep Learning

What is DL? Why Now?



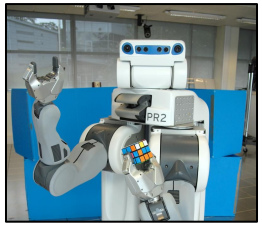
The Challenge of Recognition



Learning & Optimization

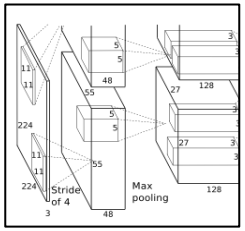
$$\nabla_\theta L$$

Applications



Caffe First Sip

Network Tour

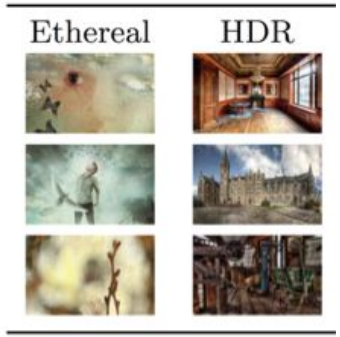


Transfer Learning

Take a Pre-trained Model and Fine-tune to New Datasets...

Lots of Data

Your Data



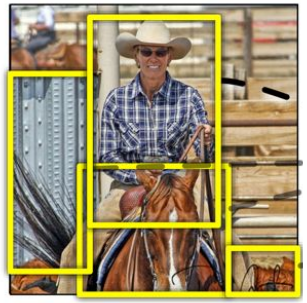
Style Recognition

© kaggle.com

Dogs vs. Cats
top 10 in 10 minutes

Take a Pre-trained Model and Fine-tune to New Tasks...

Lots of Data



Detection

Segmentation

Your Task

Take a Pre-trained Model and Fine-tune to New Modalities...

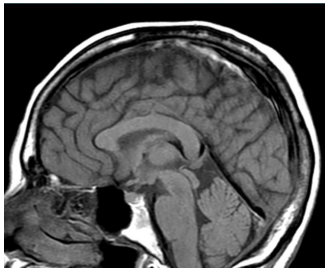
Lots of Data

IMAGENET

Your Modality

Depth/ Range

Remote Sensing



Medical Imaging

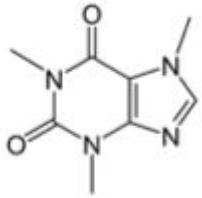
End of Part 1

To learn more:

- Deep Learning Intro by Nielsen
- Stanford cs231n Convnet Class
- Deep Learning Book (draft)
  by Goodfellow, Bengio, Courville

- caffe.berkeleyvision.org

Part 2:
Hands-On Introduction to the Caffe Framework:
Brewing Networks with Caffe



caffe.berkeleyvision.org

github.com/BVLC/caffe

BAIR
BERKELEY ARTIFICIAL INTELLIGENCE RESEARCH

embedded VISION ALLIANCE

What is caffe?
Running a pre-trained network
Defining, learning, and testing networks
Fine-tuning for transfer learning

What is Caffe?

Open framework, models, and worked examples
for deep learning

- 3 years old
- 4000+ citations, 250+ contributors, 17,000+ stars
- 10,000+ forks, >1 pull request / day average
- focus has been vision, but branching out: sequences, reinforcement learning, speech + text

Prototype

Train

Deploy

What is Caffe?

Open framework, models, and worked examples
for deep learning

- Pure C++ / CUDA architecture for deep learning
- Command line, Python, MATLAB interfaces
- Fast, well-tested code
- Tools, reference models, demos, and recipes
- Seamless switch between CPU and GPU

Prototype

Train

Deploy

Caffe is a Community

[project pulse]

BVLC / caffe

Unwatch 1,205 | Unstar 8,498 | Fork 4,821

January 19, 2016 – February 19, 2016

Period: **1 month**

Overview

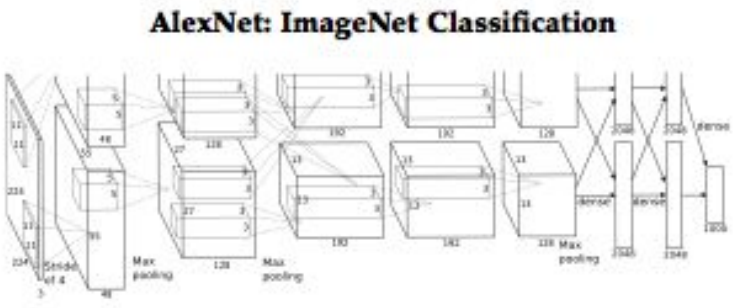
45 Active Pull Requests

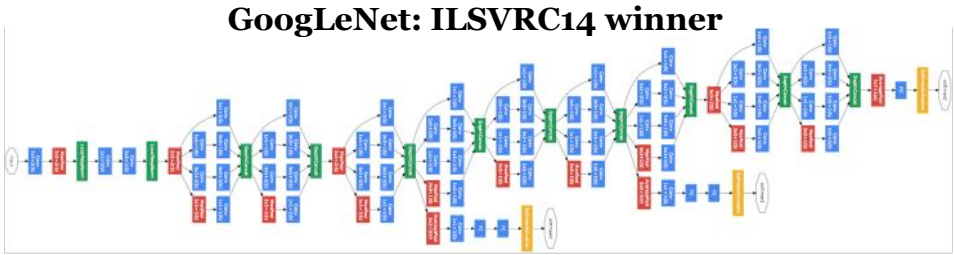
90 Active Issues

22 Merged Pull Requests	**23** Proposed Pull Requests	**52** Closed Issues	**38** New Issues

Excluding merges, **20 authors** have pushed **19 commits** to master and **53 commits** to all branches. On master, **44 files** have changed and there have been **2,268 additions** and **162 deletions**.

Reference Models





Caffe offers the
- model definitions
- optimization settings
- pre-trained weights

so you can start right away

The BVLC models are licensed for unrestricted use

The community shares models in our Model Zoo

Open Model Collection

The Caffe Model Zoo open collection of deep models to share innovation

- MSRA ResNet ILSVRC15 winner in the zoo
- VGG ILSVRC14 + Devil models in the zoo
- MIT Places scene recognition model in the zoo
- Network-in-Network / CCCP model in the zoo

help disseminate and reproduce research

bundled tools for loading and publishing models

Share Your Models! with your citation + license of course

Brewing by the Numbers...

Speed with Krizhevsky's 2012 model:

- 2 ms/image on K40 GPU
- <1 ms inference with Caffe + cuDNN v4 on Titan X
- 72 million images/day with batched IO
- 8-core CPU: ~20 ms/image Intel optimization in progress

9k lines of C++ code (20k with tests)

System Requirements

Linux or OS X

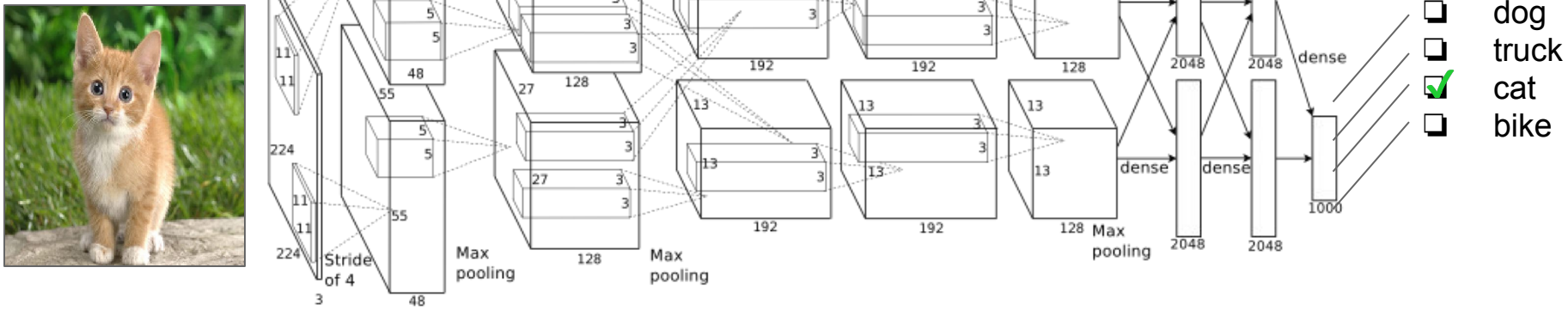
- Ubuntu best, RHEL ok
- Apt and Homebrew packaging in-progress

GPU

- CUDA >3.0 capability Titan X, K80, K40, GTX980, …
- CPU-only mode for deployment

Windows and OpenCL ports—see installation guide

Classification



Before we get into the details, let's take a peek at image classification using deep convnets in Caffe [AlexNet]

Classification

Instant recognition the Caffe way
see notebook

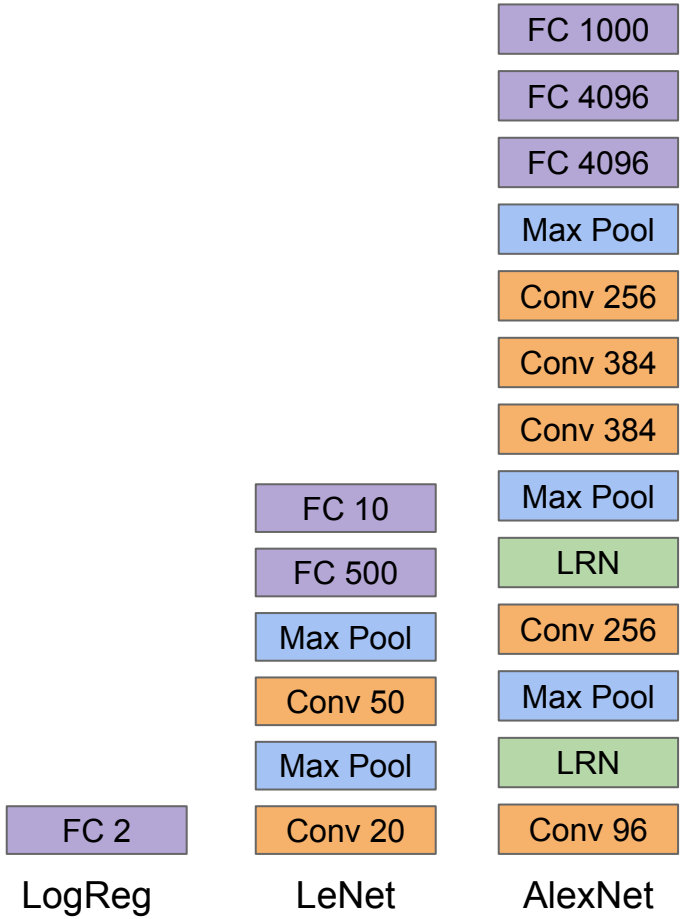
1. Load pre-trained network (CaffeNet)
2. Classify an image
3. Explore output and intermediate features
4. Compare CPU and GPU computation

Net

A network is a set of layers and their connections:

```
name: "dummy-net"
layer { name: "data" …}
layer { name: "conv" …}
layer { name: "pool" …}
    … more layers …
layer { name: "loss" …}
```

- Caffe creates and checks the net from the definition.
- Data and derivatives flow through the net as *blobs* – an array interface



Layer Protocol

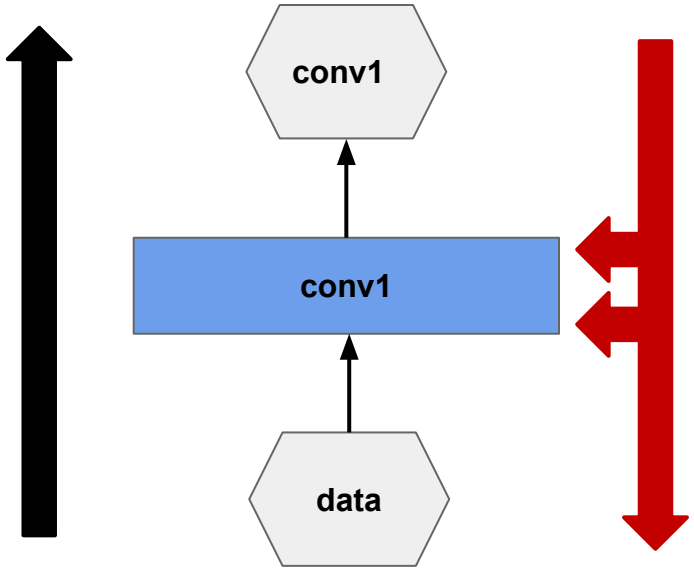
Forward: make output given input.

Backward: make gradient of output
- w.r.t. bottom
- w.r.t. parameters (if needed)

Setup: run once for initialization.

Reshape: set dimensions.

Compositional Modeling
The Net's forward and backward passes are composed of the layers' steps



Layer Development Checklist

```python
import caffe
import numpy as np

class EuclideanLoss(caffe.Layer):

    def setup(self, bottom, top):
        # check input pair
        if len(bottom) != 2:
            raise Exception("Need two inputs to compute distance.")

    def reshape(self, bottom, top):
        # check input dimensions match
        if bottom[0].count != bottom[1].count:
            raise Exception("Inputs must have the same dimension.")
        # difference is shape of inputs
        self.diff = np.zeros_like(bottom[0].data, dtype=np.float32)
        # loss output is scalar
        top[0].reshape(1)

    def forward(self, bottom, top):
        self.diff[...] = bottom[0].data - bottom[1].data
        top[0].data[...] = np.sum(self.diff**2) / bottom[0].num / 2.

    def backward(self, top, propagate_down, bottom):
        for i in range(2):
            if not propagate_down[i]:
                continue
            if i == 0:
                sign = 1
            else:
                sign = -1
            bottom[i].diff[...] = sign * self.diff / bottom[i].num
```

Layer Protocol == Class Interface

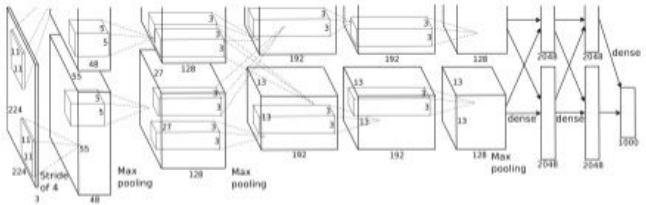
Define a class in C++ or Python to extend `Layer`

Include your new layer type in a network and keep brewing

```
layer {
type: "Python"
python_param {
  module: "layers"
  layer: "EuclideanLoss"
} }
```

Forward / Backward The Essential Net Computations

Forward: inference $f_W(x)$



"espresso" + loss

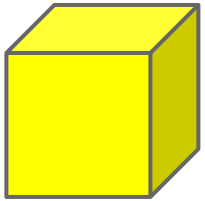
$\nabla f_W(x)$ Backward: learning

Caffe models are complete machine learning systems for inference and learning
The computation follows from the model definition: define the model and run

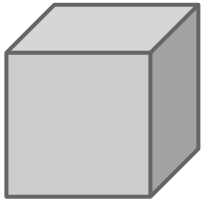
Memory Interface: Blob

Blobs are N-D arrays for storing and communicating information

- hold data, derivatives, and parameters
- lazily allocate memory
- shuttle between CPU and GPU



Data
*N*umber x *K* Channel x *H*eight x *W*idth
256 x 3 x 227 x 227 for ImageNet train input

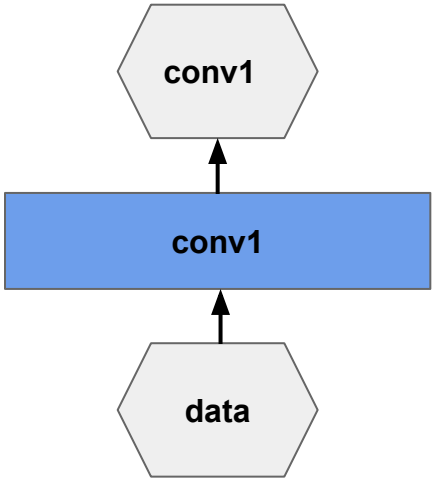


Parameter: Convolution Weight
N Output x *K* Input x *H*eight x *W*idth
96 x 3 x 11 x 11 for CaffeNet conv1

Parameter: Convolution Bias
96 x 1 x 1 x 1 for CaffeNet conv1

```
name: "conv1"
type: "Convolution"
bottom: "data"
top: "conv1"
… definition …
```

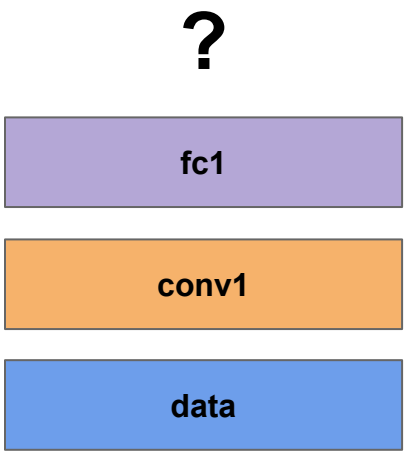
top
blob



bottom
blob

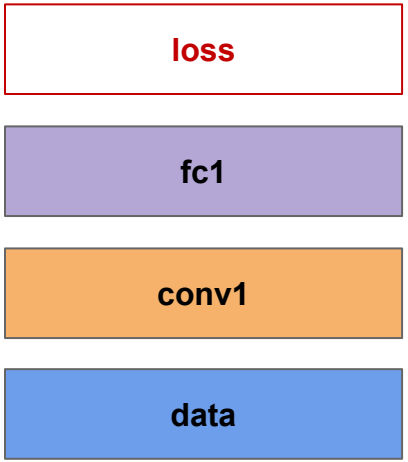
Loss Defines the Task

What kind of model is this?



Loss Defines the Task

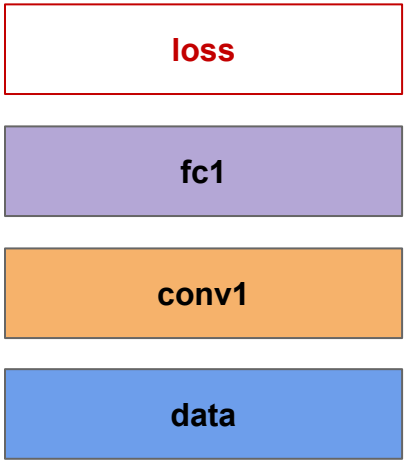
What kind of model is this?



Define the task by the **loss**

Loss Defines the Task

What kind of model is this?



Classification
`SoftmaxWithLoss`
`HingeLoss`

Linear Regression
`EuclideanLoss`

Attributes / Multiclassification
`SigmoidCrossEntropyLoss`

Others…

New Task
`NewLoss`

Define the task by the **loss**

Solving: Training a Net

Optimization like model definition is configuration

```
train_net: "lenet_train.prototxt"
type: SGD
base_lr: 0.01
momentum: 0.9
weight_decay: 0.0005
max_iter: 10000
snapshot_prefix: "lenet_snapshot"
```

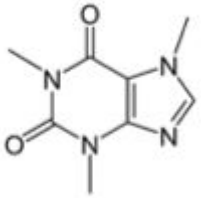
All you need to run things on the GPU

```
> caffe train -solver lenet_solver.prototxt -gpu 0
```

SGD + momentum **`SGD`** · Nesterov's Accelerated Gradient `Nesterov`

Adaptive Solvers **`Adam`** · `RMSProp` · `AdaDelta` · `AdaGrad`

Coffee Break (15 minutes)

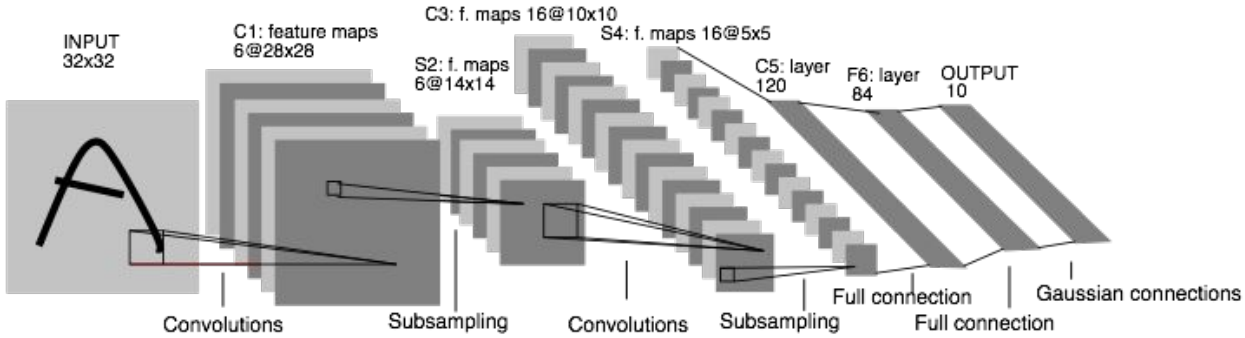


caffe.berkeleyvision.org

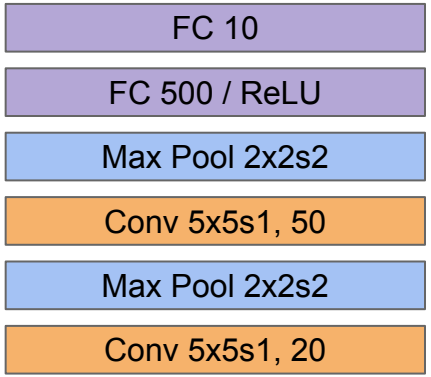
github.com/BVLC/caffe

embedded VISION ALLIANCE

Learning LeNet



The original LeNet: a typical conv-pool to FC architecture
in 1989 style with small channel dimensions and sigmoid non-linearity



our LeNet
in 60 seconds

Define, train, and test a handwritten digit classifier like the famous LeNet convnet [LeNet]

Learning LeNet

Back to the future of visual recognition
see notebook

1. Define and instantiate the network and solver
2. Train the net on MNIST data to recognize digits
3. Examine progress during learning

Model Format: Protobuf

- Strongly typed format
- Auto-generates code
- Developed by Google
- Defines Net / Layer / Solver schemas in **caffe.proto**

```
message ConvolutionParameter {
 // The number of outputs for the layer
 optional uint32 num_output = 1;
 // whether to have bias terms
 optional bool bias_term = 2 [default = true];
}
```

```
layer {
name: "conv1"
type: "Convolution"
bottom: "data"
top: "conv1"
convolution_param {
    num_output: 20
    kernel_size: 5
    stride: 1
    weight_filler {
        type: "xavier"
    }
}}
```

Model Zoo Format

readme.md Raw

name: FCN-32s Fully Convolutional Semantic Segmentation on PASCAL-Context caffemodel: fcn-32s-pascalcontext.caffemodel caffemodel_url: http://dl.caffe.berkeleyvision.org/fcn-32s-pascalcontext.caffemodel sha1: adbbd504c280e2b8966fc32e32ada2a2ecf13603

gist_id: 80667189b218ad570e82

This is a model from the paper:

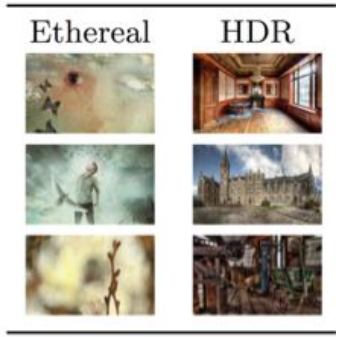
```
Fully Convolutional Networks for Semantic Segmentation
Jonathan Long, Evan Shelhamer, Trevor Darrell
arXiv:1411.4038
```

Gists on github hold model definition, license, url for weights, and hash of Caffe commit that guarantees compatibility

Take a Pre-trained Model and Fine-tune to New Tasks

[DeCAF, Zeiler-Fergus, R-CNN, OverFeat]

Lots of Data



Style Recognition

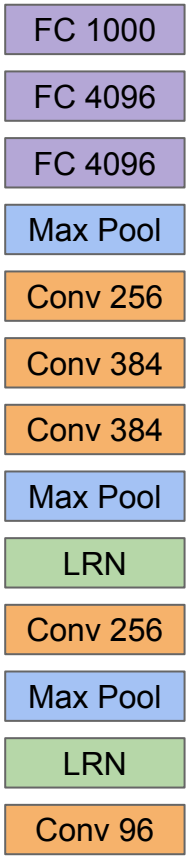
© kaggle.com

Dogs vs. Cats
top 10 in 10 minutes

Your Task

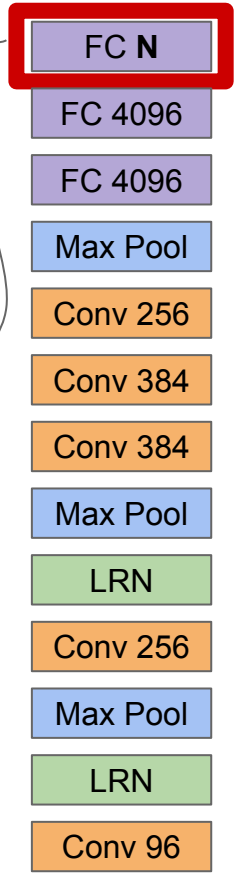
Transfer Learning With Convnets

(1) Train on ImageNet



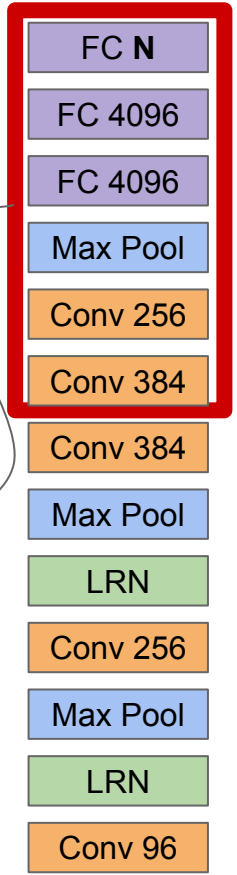
(2a) *Small dataset*. Fix all weights (treat convnet as a feature extractor); retrain only the classifier

Swap the softmax layer at the end, replace with appropriate number of classes **N**



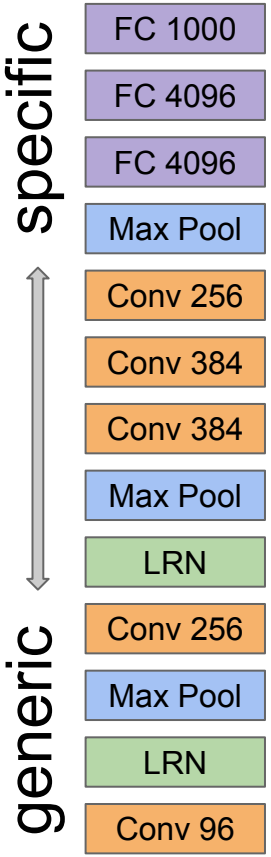
(2b) *Medium-sized or larger dataset*. **Fine-tune** the network. Using the ImageNet-learned weights as an initialization, train the full network, or just some of the last layers

Retrain a bigger portion of the network, or even all of it



Tip: use only ~1/10th the original learning rate when fine-tuning the top (output) layer and ~1/100th for other layers

From the Source to Other Tasks

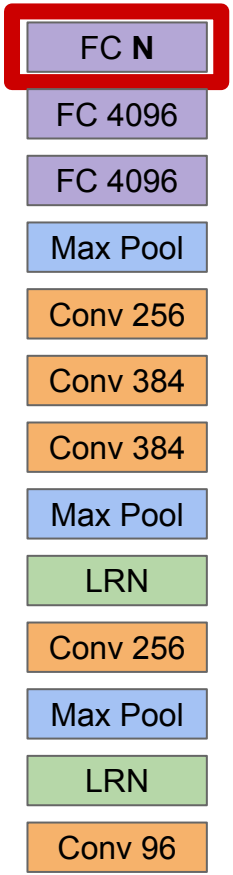


compared with the source, the **target** dataset is a...

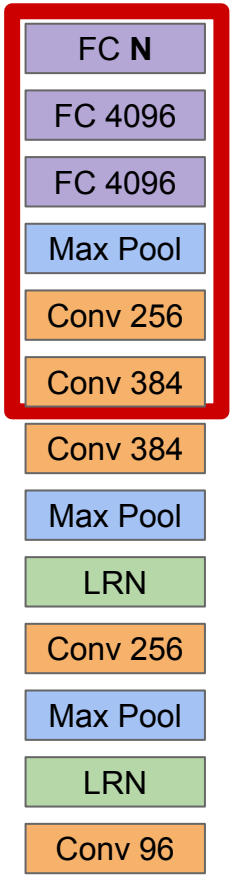
the **target** dataset has...	**very similar dataset**	**very different dataset**
very little data	Learn linear classifier on features from top layer(s)	You're in trouble … try a linear classifier on different layers
lots of data	Finetune a few layers	Finetune more layers

A Two-stage Approach to Fine-tuning

(1) First, train only the new classifier to convergence, without modifying the network or weights otherwise



(2) *Then*, train more of the network, or even all of it



- (1) prevents the pretrained network from being subjected to noisy updates from the randomly initialized classifier, so that in
- (2), the rest of the network can be usefully tuned for the target task

From ImageNet to Style (1/2)

Simply change a few lines in the model definition

```
layer {
  name: "data"
  type: "Data"
  data_param {
    source: "ilsvrc12_train_lmdb"
    mean_file: "../../data/ilsvrc12"
    ...
  }
  ...
}
...
layer {
  name: "fc8"
  type: "InnerProduct"
  inner_product_param {
    num_output: 1000
    ...
  }
}
```

```
layer {
  name: "data"
  type: "Data"
  data_param {
    source: "style_train_lmdb"
    mean_file: "../../data/ilsvrc12"
    ...
  }
  ...
}
...
layer {
  name: "fc8-style"
  type: "InnerProduct"
  inner_product_param {
    num_output: 20
    ...
  }
}
```

new name =
new params

Input:
A different source

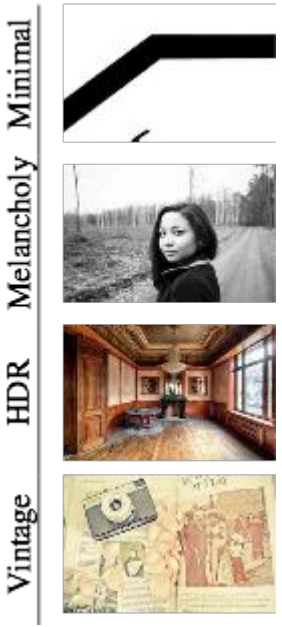
Last Layer:
A different classifier

From ImageNet to Style (2/2)

```
> caffe train -solver models/finetune_flickr_style/solver.prototxt
              -weights bvlc_reference_caffenet.caffemodel
```

Step-by-step in pycaffe:

```
pretrained_net = caffe.Net(
  "net.prototxt", "net.caffemodel")
solver = caffe.SGDSolver("solver.prototxt")
solver.net.copy_from(pretrained_net)
solver.solve()
```



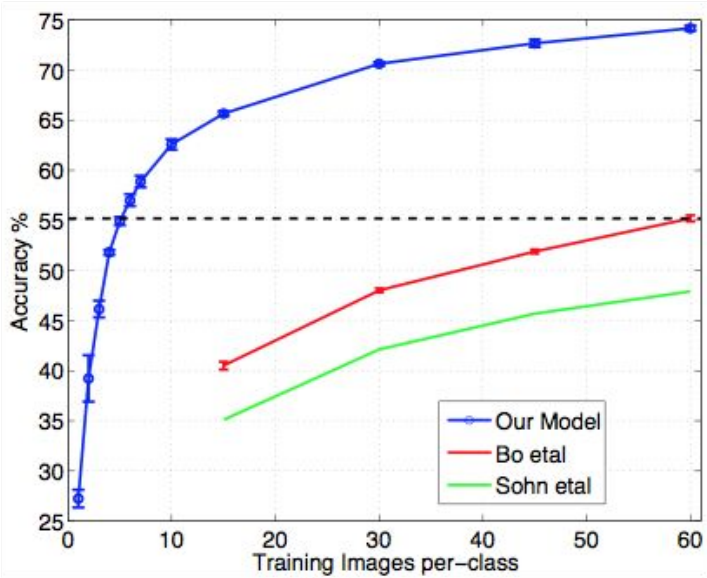
When to Fine-tune?

Almost always

- More robust optimization – good initialization helps
- Needs less data
- Faster learning

State-of-the-art results in

- classification
- detection
- segmentation
- more



[Zeiler-Fergus]

Fine-tuning Tricks

Learn the last layer first

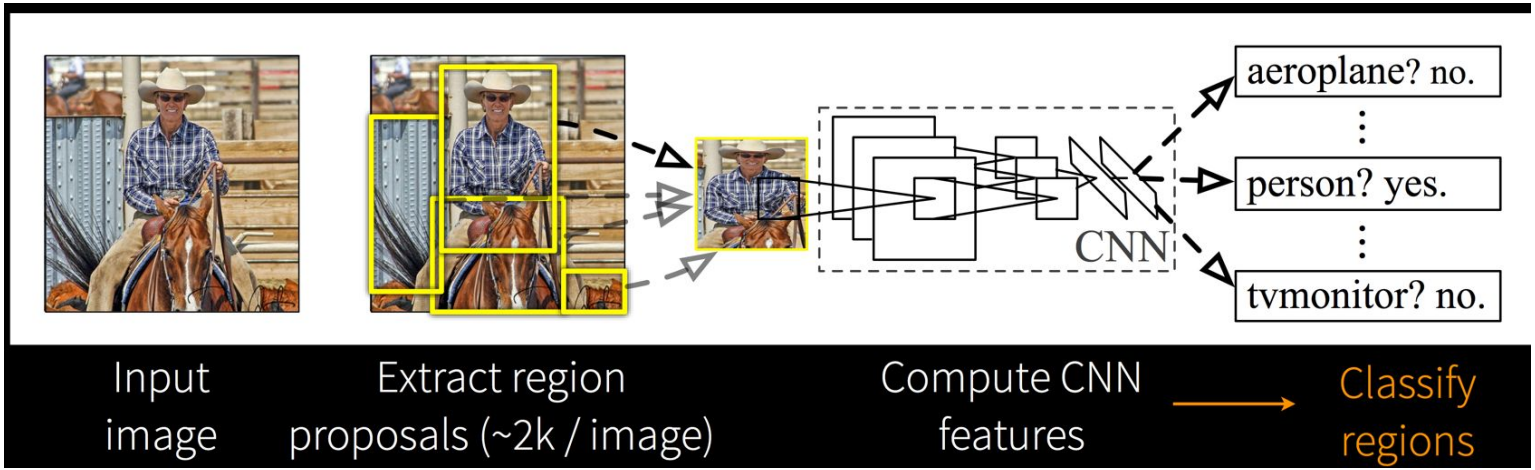
- Caffe layers have local learning rates: `param { lr_mult: 1 }`
- Freeze all but the last layer for fast optimization and avoiding divergence by setting `lr_mult: 0` to fix a parameter
- Stop if good enough, or keep fine-tuning

Reduce the learning rate

- Drop the solver learning rate by 10x, 100x
- Preserve the initialization from pre-training and avoid divergence

Fine-tuning for Detection

R-CNN approach: cast detection into classification of *region proposals*; fine-tune as usual

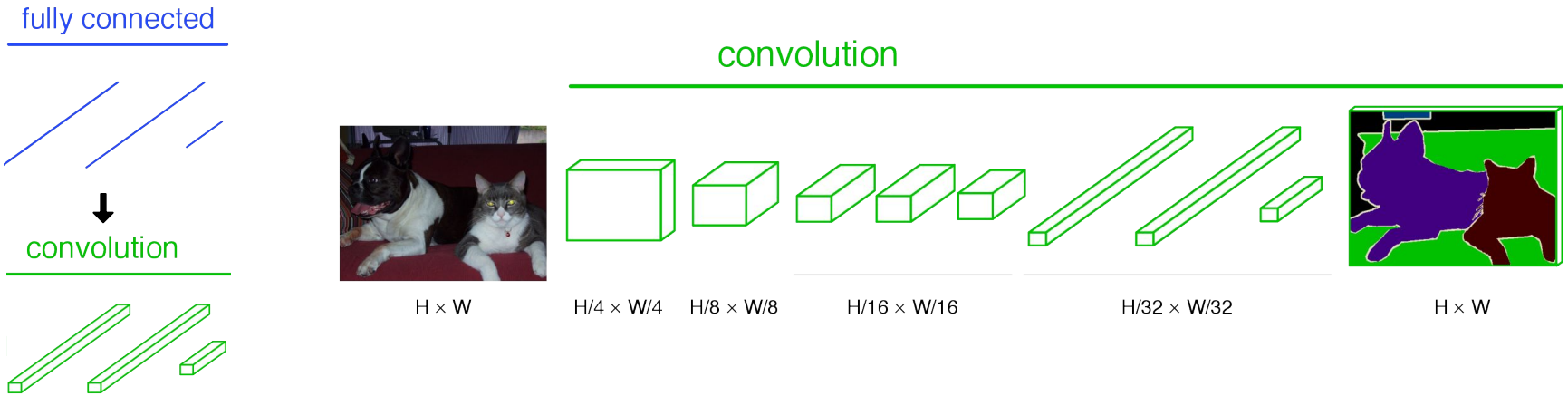


Later work (*Faster R-CNN*) incorporates region proposals into net: end-to-end approach is faster and more accurate

Ross Girshick, Jeff Donahue, Trevor Darrell, Jitendra Malik. "Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation." CVPR 2014.

Fine-tuning for Segmentation

FCN approach: cast net in *spatially dense* “fully convolutional” form; fine-tune as usual



Infer and learn on whole images at a time:
end-to-end approach is faster and more accurate

Jon Long, Evan Shelhamer*, Trevor Darrell. “Fully Convolutional Networks for Semantic Segmentation.” CVPR 2015.*

Fine-tuning

Transferring features to style recognition

see notebook

1. Learn a classifier on pre-trained features
2. Fine-tune by end-to-end optimization
3. Compare from scratch and fine-tuned nets

Recipe for Brewing

- Convert the data to Caffe-format

  python layer, lmdb, leveldb, hdf5 / .mat, list of images, etc.
- Define the Net
- Configure the Solver
- caffe train -solver solver.prototxt -gpu 0

- Examples are your friends

  `caffe/examples/mnist,cifar10,imagenet`

  `caffe/examples/*.ipynb`

  `caffe/models/*`

Contents of the `caffe` Directory

- **model schema**

  src/caffe/proto/**caffe.proto**
- **layers**

  src/caffe/layers/*.{cpp, cu}

  include/caffe/layers/*.hpp
- **solvers**

  src/caffe/solvers/*.{cpp, cu}

  include/caffe/sgd_solvers.hpp

- **examples** notebooks + scripts

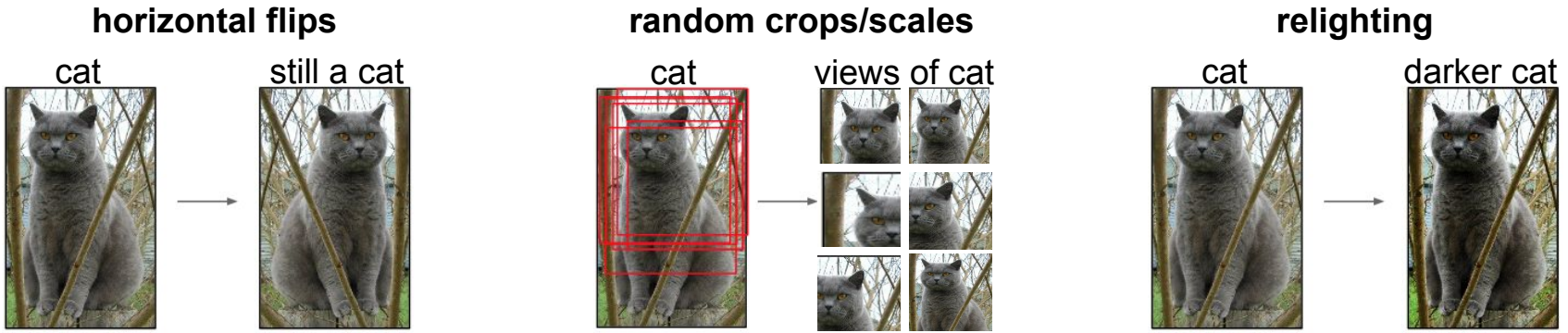
  examples/*.ipynb for hands-on notebooks

  examples/mnist for quick-start scripts

- **docs** local edition of tour, API, web site
- **models** reference models + model zoo
- **tools, scripts**
  - command line tool
  - visualization

Data Augmentation

transform the training data, without changing its truth



… and anything else you can come up with! (random combinations of the above, or shearing, rotations, …)

[figure adapted from A. Karpathy]

Debugging Training (Sanity Checks)

- my loss is **diverging** or **getting stuck**!
- verify these sanity checks before exploring optimization tricks on next slides
  - check your **input data** and labels
    - look at the values actually being fed into the net (reasonable mean/variance? zero mean = probably good; zero variance = almost certainly bad)
    - if the data and/or labels are images (or image-like), **visualize** them
  - did you initialize multiplicative weights to non-zero values?
    - if not, you may see that the loss is exactly constant
    - add `debug_info: true` to a Caffe solver: prints the mean of absolute activation (output) values for each layer
      - if any of these values is 0, you may have initialized weights to 0 in one or more layers
  - if you wrote any new layers, use a **gradient checker** to ensure their "backward" implementation is correct

Debugging Training (Diverging Loss)

- what should I do if...
- ...my **loss diverges**? (increases by order of magnitude, goes to inf. or NaN)
  - lower the learning rate
  - raise momentum (with corresponding learning rate drop)
  - raise weight decay
  - raise batch size
  - use gradient clipping (limit the L2 norm of the gradient to a particular value at each iteration; shrink it to that norm if greater)
  - try another solver: momentum SGD, ADAM, RMSProp, ...
  - try a smaller initialization (e.g., for a Gaussian init., lower the stdev.)

Debugging Training (Static Loss 1/3)

- what should I do if...
- ...my **loss doesn't improve / gets stuck / drops slowly**?
  - raise the learning rate
  - (maybe) lower momentum, weight decay, and/or batch size
  - try another solver: momentum SGD, ADAM, RMSProp, ...
  - transfer a pre-trained (e.g. on ImageNet) initialization, if possible
  - use a larger initialization (in particular, *make sure you didn't **zero**-initialize any multiplicative weights* in intermediate layers)
  - use a "smarter" initialization (e.g., for linear layers followed by ReLUs, try the `msra` initialization in Caffe)

Debugging Training (Static Loss 2/3)

- what should I do if...
- ...my **loss doesn’t improve / gets stuck / drops slowly**?
  - remove some layers to make the network shallower
    - at least to start!
    - a strategy for model design: begin with a simple, trainable network; “deepen” it by adding new layers one-by-one
  - modify the architecture to improve gradient flow:
    - batch normalization
    - residual learning [ResNet]
    - intermediate losses [GoogLeNet]
    - other tricks

Debugging Training (Static Loss 3/3)

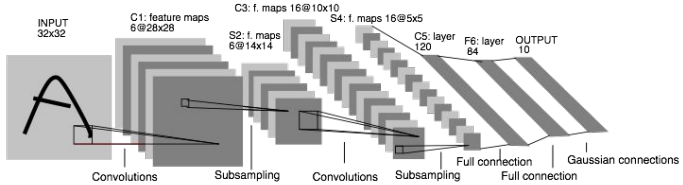
- what should I do if...
- ...my **loss doesn't improve / gets stuck / drops slowly**?
  - be patient! (go outside?)
    - deep learning can take a long time
      - training AlexNet in 2012: 12 days
        although this is down to 1 day in 2015!
        - loss hovers around the chance value of ln(1000) ≅ 6.908 for the first 1000+ iterations (~1 hour on 2012 GPU)
      - training ResNet-152 in 2015: 1-2 months (on 8 GPUs!)
    - the best configurations (net architectures, solvers) at convergence are often *not* the ones that train fastest early on
      - some tricks to speed up learning can be "greedy" rather than ultimately beneficial

Debugging Training (Overfitting/Underfitting)

- what should I do if...
- ...my **net overfits**? (train accuracy is much higher than test accuracy)
  - ideally, collect (and label) more data! but this can be expensive, so…
  - use data augmentation (and if possible, generate data)
  - in a word, **regularize**! specifically…
    - increase weight decay (and/or other weight regularization)
    - use dropout (or increase proportion of activations dropped out)
    - try a shallower/simpler model
      - fewer layers
      - fewer units in each layer
      - (for convnets) restrict (reduce) receptive field sizes
- ...my **net underfits**? (train accuracy is much lower than expected)
  - use less regularization (reverse any above regularization suggestions)
  - try a deeper/larger model (more layers, more units, …)

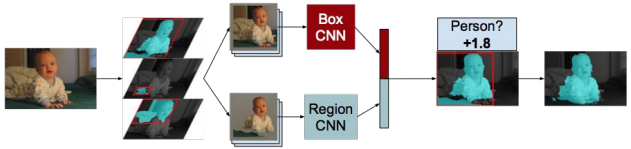
Network Graph

Many current deep models have linear structure

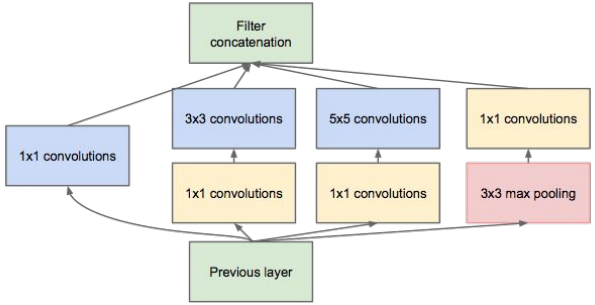


but Caffe nets can have any directed acyclic graph (DAG) structure

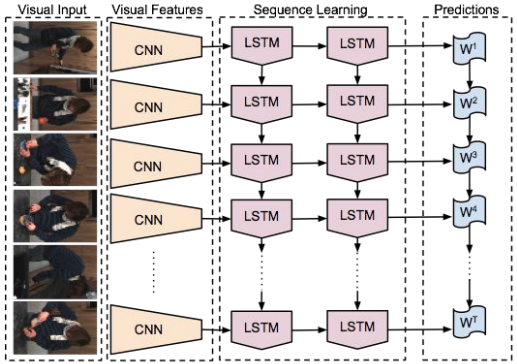
Define `bottoms` and `tops` and Caffe will connect the net



two-stream detection + segmentation



GoogLeNet Inception Module



LRCN joint vision-sequence model

Weight Sharing

- Just give the parameter blobs explicit names using the `param` field

- Layers specifying the same `param` name will share that parameter, accumulating gradients accordingly

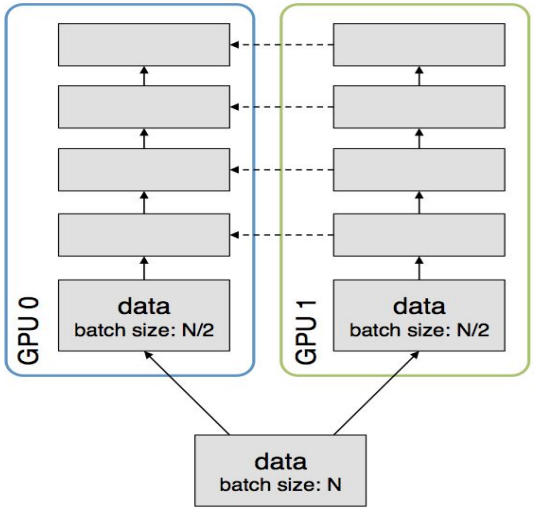
```
layer {
  name: 'innerproduct1'
  type: 'InnerProduct'
  inner_product_param {
    num_output: 10
    bias_term: false
    weight_filler {
      type: 'gaussian'
      std: 10
    }
  }
  param { name: 'sharedweights' }
  bottom: 'data1'
  top: 'innerproduct1'
}
layer: {
  name: 'innerproduct2'
  type: 'InnerProduct'
  inner_product_param {
    num_output: 10
    bias_term: false
  }
  param { name: 'sharedweights' }
  bottom: 'data2'
  top: 'innerproduct2'
}
```

Parallelism

Train in parallel across GPUs

- data-parallelism included
  `caffe train -gpu 0,1 ...`

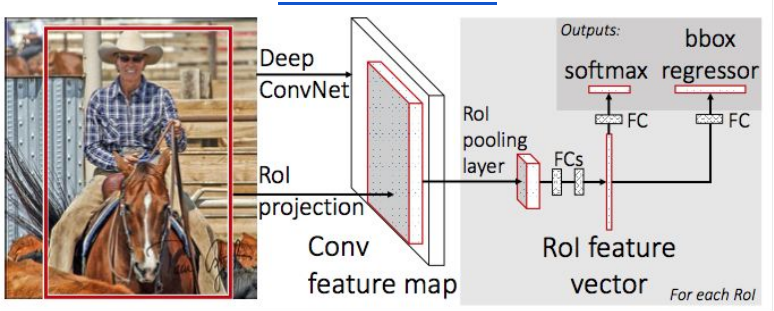
- further parallelism possible, with effort



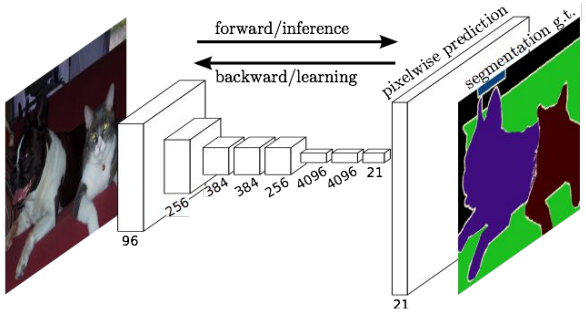
data parallelism
split data across processors

Extensions Tasks and Future

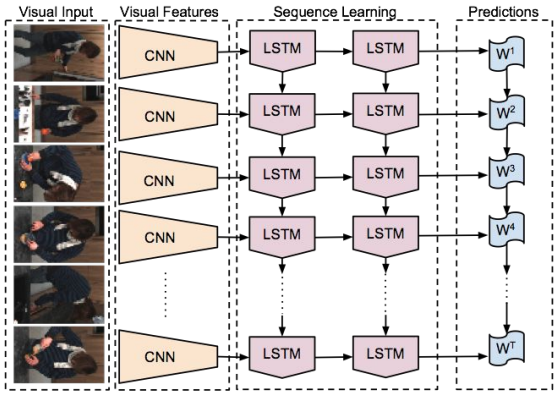
Detection



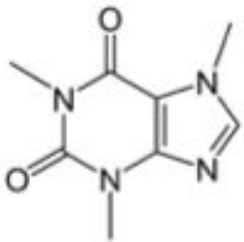
Pixelwise Prediction



Sequences



Framework Future



Framework Future

1.0 is coming stability, documentation, packaging

Dedicated Branches for OpenCL and Windows

Halide and Module interface for prototyping and experimenting

Performance Tuning for GPU (CUB) and CPU (nnpack)

Widening the Circle continued and closer collaborative development

Help Brewing

Documentation

- tutorial documentation
- hands-on examples

Modeling, Usage, and Installation

- caffe-users group
- gitter.im chat

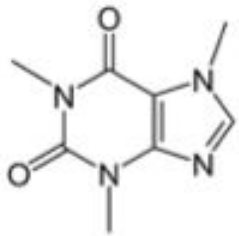
Convolutional Nets

- CS231n online convnet class
  by Andrej Karpathy and Fei-Fei Li
- Deep Learning Online
  by Michael Nielsen
- Deep Learning Book
  by Goodfellow, Bengio, Courville

Next Steps

Today you've seen the essentials of deep learning for vision with convolutional networks and Caffe

Next Up:



caffe.berkeleyvision.org

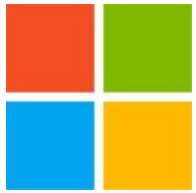
github.com/BVLC/caffe

Check out Caffe on github

Run Caffe through Docker and NVIDIA Docker for GPU

Reach out to Caffe Coldpress for R&D consulting

Acknowledgements


Thank you to the Berkeley Vision and Learning Center and its sponsors

Thank you to NVIDIA
for GPUs, cuDNN collaboration,
and hands-on cloud instances

Thank you to our 250+
open source contributors
and vibrant community!

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Yangqing Jia, Evan Shelhamer, Jeff Donahue, Jonathan Long,
Sergey Karayev, Ross Girshick, Sergio Guadarrama, Ronghang Hu, Trevor Darrell

and our open source contributors!

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END