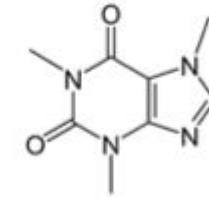


DIY Deep Learning for Vision: a Hands-On Tutorial with Caffe



Maximally accurate	Maximally specific
espresso	2.23192
coffee	2.19914
beverage	1.93214
liquid	1.89367
fluid	1.85519



caffe.berkeleyvision.org



github.com/BVLC/caffe

Evan Shelhamer, Jeff Donahue, Jon Long,
Yangqing Jia, and Ross Girshick

Look for further
details in the
outline notes



BERKELEY ARTIFICIAL INTELLIGENCE RESEARCH

Tutorial Schedule

Caffe tour and latest roast

Caffe Tour

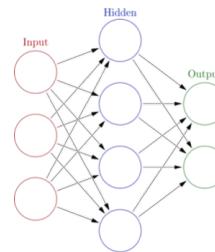
- the why and how of Caffe
- highlight reel of examples + applications
- do-it-yourself notebooks

Latest Roast

- detection *Ross Girshick*
- sequences and vision + language *Jeff Donahue*
- pixelwise prediction *Jon Long and Evan Shelhamer*
- framework future *Yangqing Jia*

Why Deep Learning?

End-to-End Learning for Many Tasks



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

concrete  learning abstract

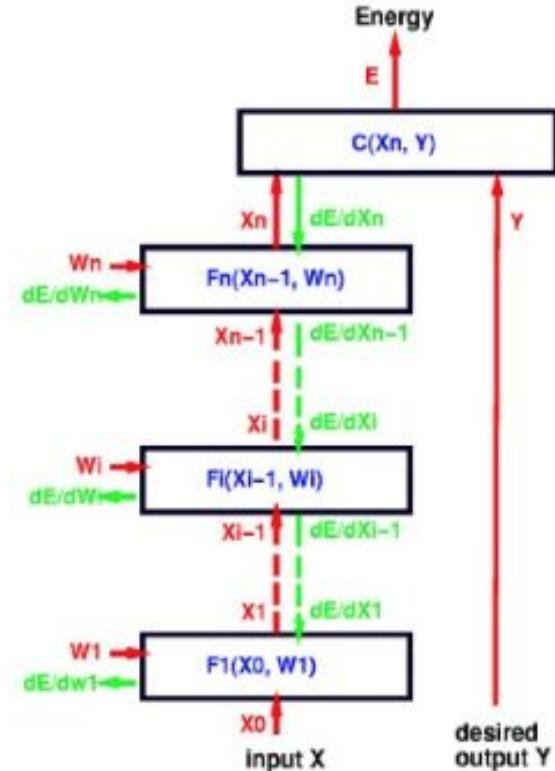


figure credit Yann LeCun, ICML '13 tutorial

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.

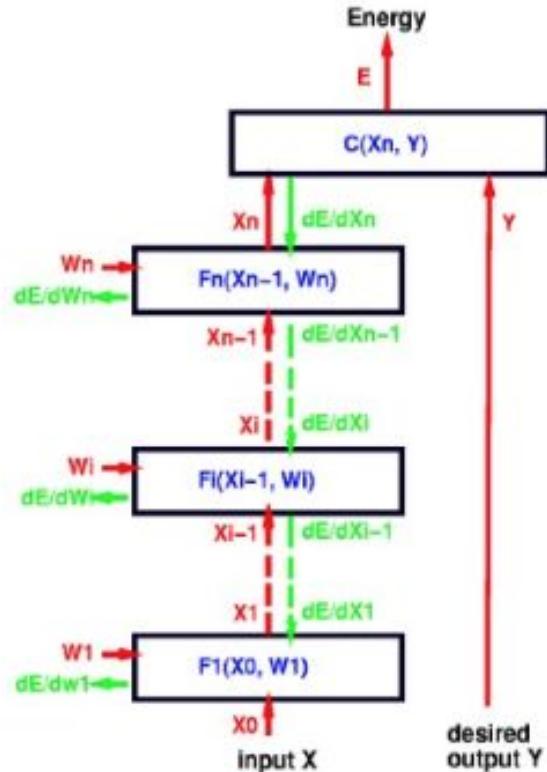


figure credit Yann LeCun, ICML '13 tutorial

WHEN A USER TAKES A PHOTO,
THE APP SHOULD CHECK WHETHER
THEY'RE IN A NATIONAL PARK...

SURE, EASY GIS LOOKUP.
GIMME A FEW HOURS.

... AND CHECK WHETHER
THE PHOTO IS OF A BIRD.

I'LL NEED A RESEARCH
TEAM AND FIVE YEARS.



xkcd: Tasks

“The Virtually Impossible”

IN CS, IT CAN BE HARD TO EXPLAIN
THE DIFFERENCE BETWEEN THE EASY
AND THE VIRTUALLY IMPOSSIBLE.



EXAMPLE PHOTOS



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 → [i](#)

PARK?

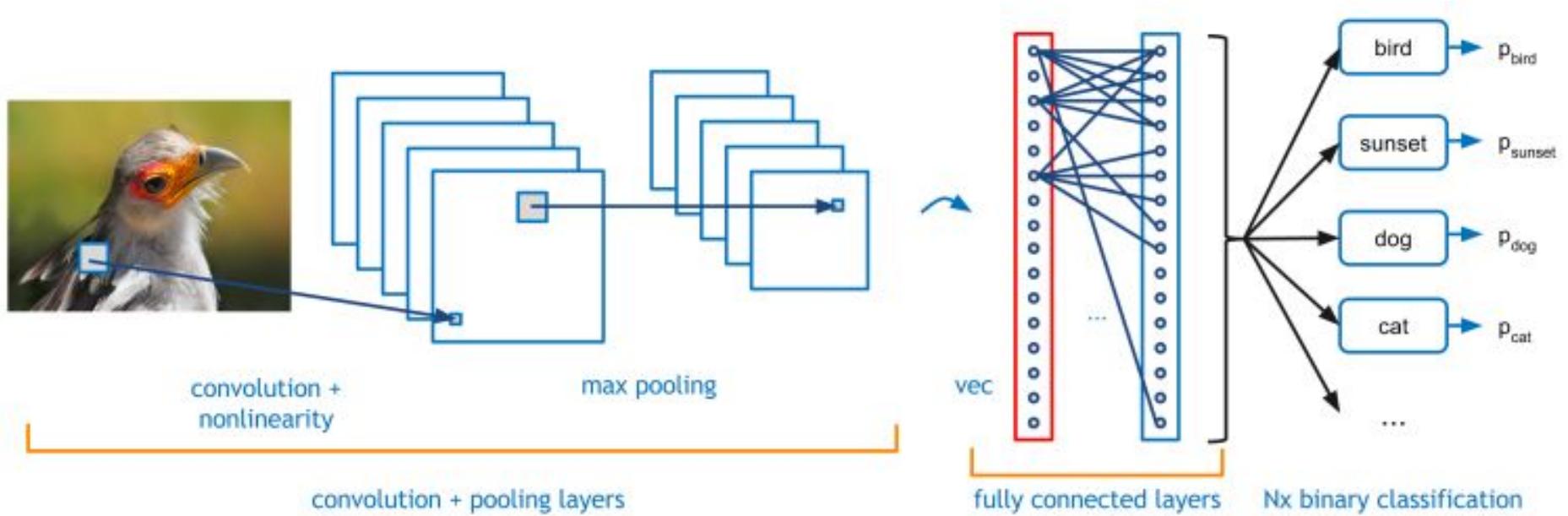
YES

Ah yes, [Everglades](#) is truly beautiful.

BIRD?

YES

Dude, that is such a bird.



All in a day's work with Caffe

What is Caffe?

Open framework, models, and worked examples
for deep learning

- 4 years old
- 6,000+ citations, 250+ contributors, 20,000+ 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 library 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

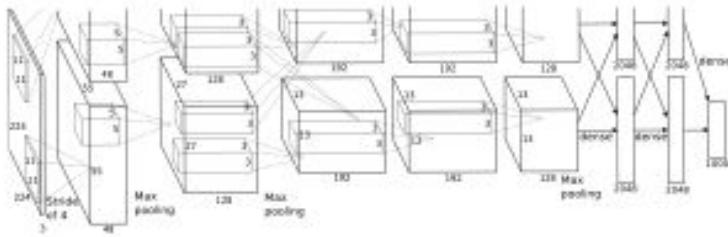
New Issues

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**.

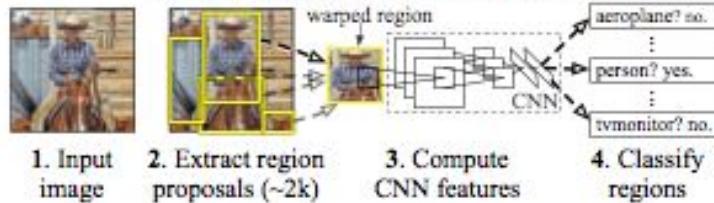


Reference Models

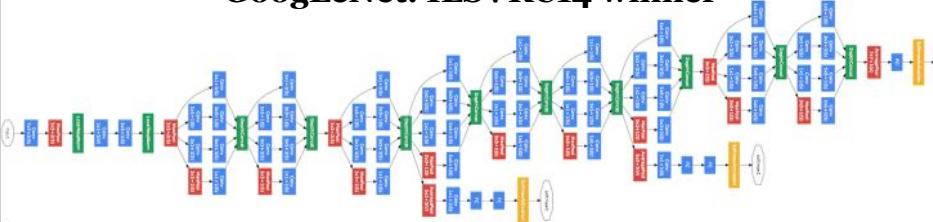
AlexNet: ImageNet Classification



R-CNN: *Regions with CNN features*



GoogLeNet: ILSVRC14 winner



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**

helps 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)

CAFFE EXAMPLES + APPLICATIONS

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

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).

Ethereal



HDR



Melancholy



Minimal



Other Styles:

[Vintage](#)

[Long Exposure](#)

[Noir](#)

[Pastel](#)

[Macro](#)

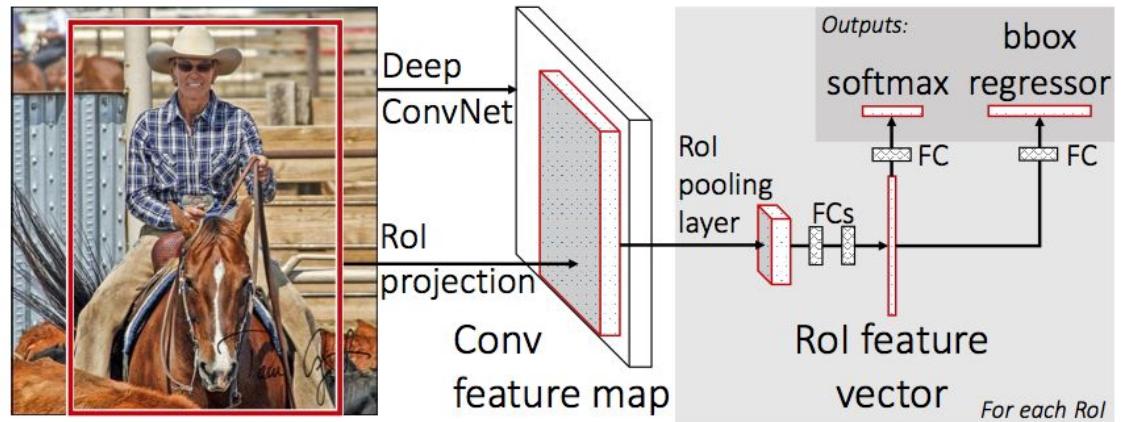
... and so on.

Object Detection

R-CNNs: Region-based Convolutional Networks

Fast R-CNN

- convolve once
- project + detect



Faster R-CNN

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

papers + code online

Ross Girshick, Shaoqing Ren,
Kaiming He, Jian Sun

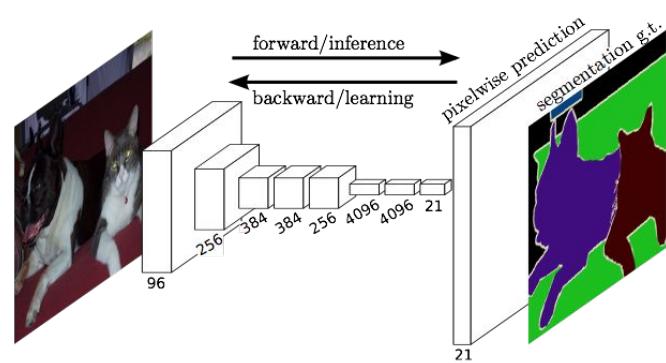
Pixelwise Prediction

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



Visual Sequence Tasks

Activity Recognition

Input:
Sequence
of Frames

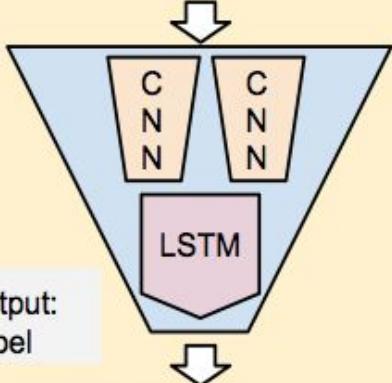
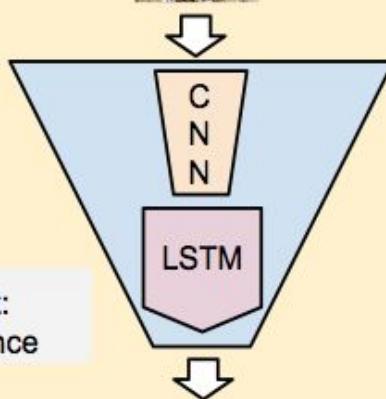


Image Description

Input:
Image

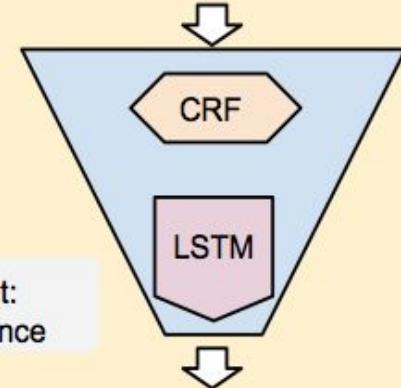


Output:
Sentence

A large building with a
clock on the front of it

Video Description

Input:
Video



Output:
Sentence

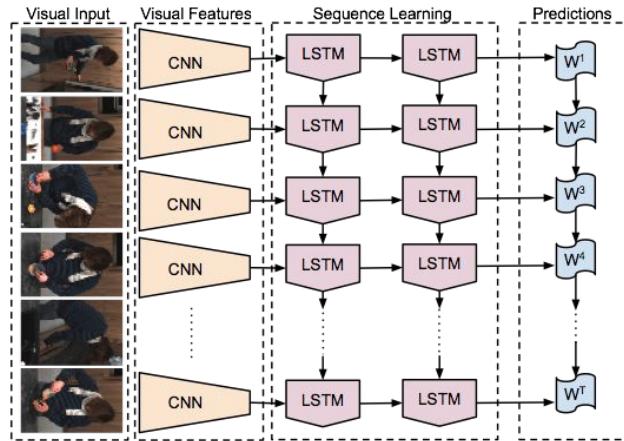
A man juiced the orange

Recurrent Networks for Sequences

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

- video
- language
- dynamics

learned by backpropagation through time

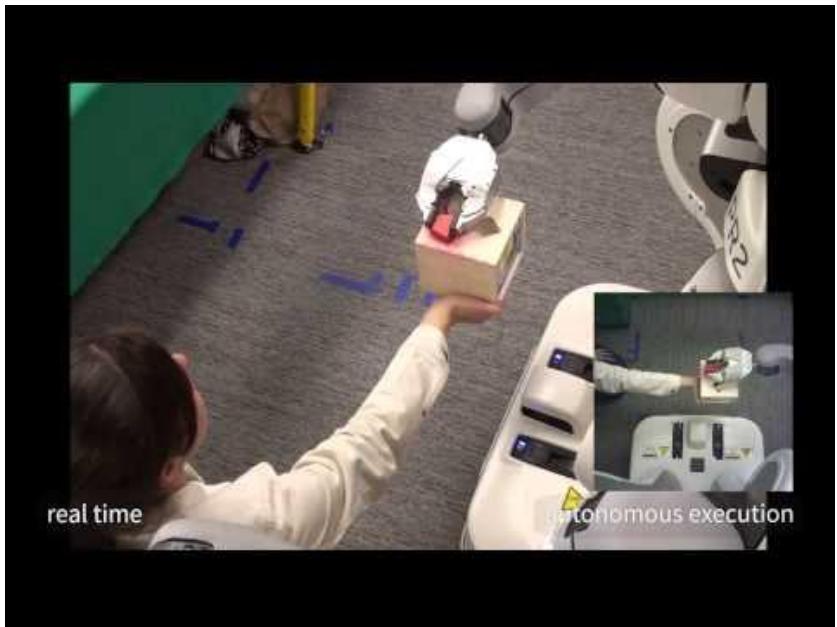


LRCN: Long-term Recurrent Convolutional Network

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

LRCN:
recurrent + convolutional
for visual sequences

Deep Visuomotor Control

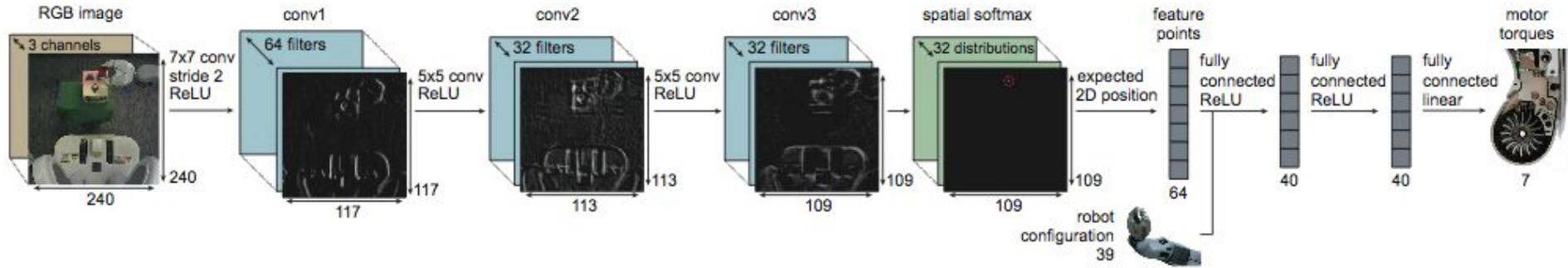


example experiments



feature visualization

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
- in-progress OpenCL port
thanks Fabian Tschopp!
+ AMD, Intel, and the community
- community Android port
thanks sh1r0!



CUDA [Jetson TX1](#), [TK1](#)

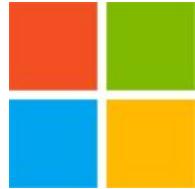


[OpenCL branch](#)



Android [lib](#), [demo](#)

Caffeinated Companies



SIEMENS



... 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

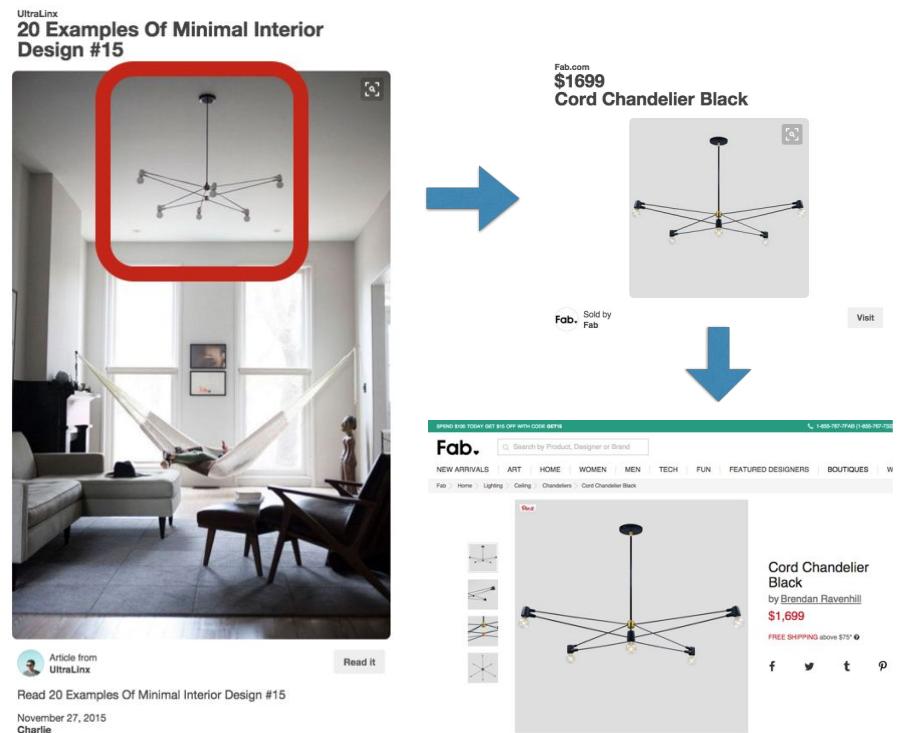


Automatic Alt Text
recognize photo content
for accessibility



Caffe at Pinterest

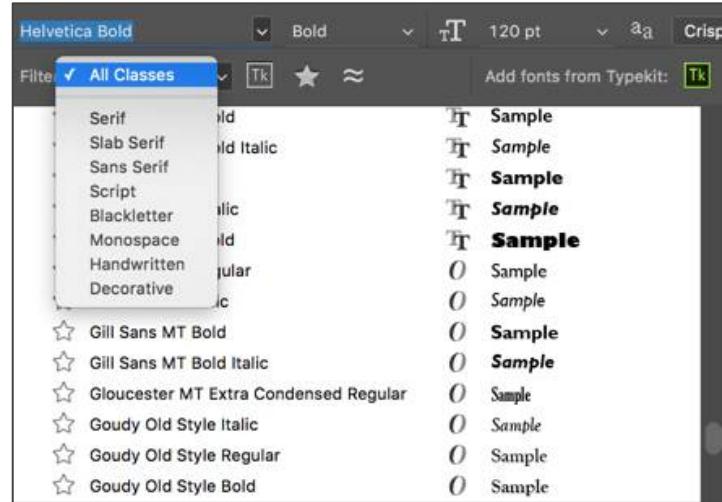
- in production for **vision at scale**: uploaded photos run through Caffe
- deep learning for visual search: **retrieval over billions of images** in <250 ms
- ~4 million requests/day
- built on an open platform of Caffe, FLANN, Thrift, ...



[example credit Andrew Zhai, Pinterest]

Caffe at Adobe

- training networks for research in vision and graphics
- custom inference in products, including Photoshop



Photoshop Type Similarity
catalogue typefaces automatically

Caffe at Yahoo! Japan

- curate news and restaurant photos for recommendation
- arrange user photo albums



News Image Recommendation
select and crop images for news

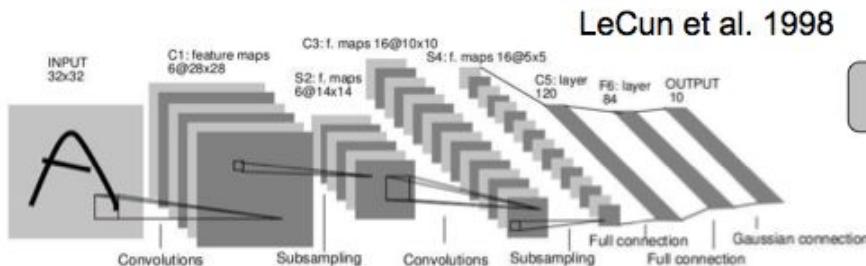
Classification

instant recognition the Caffe way

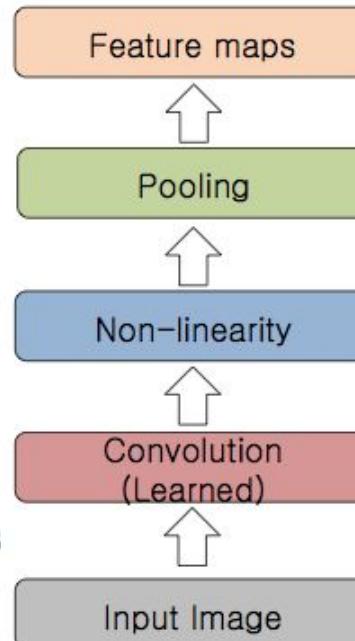
[see notebook](#)

Convolutional Network

- Feed-forward:
 - Convolve input
 - Non-linearity (rectified linear)
 - Pooling (local max)
- Supervised
- Train convolutional filters by back-propagating classification error

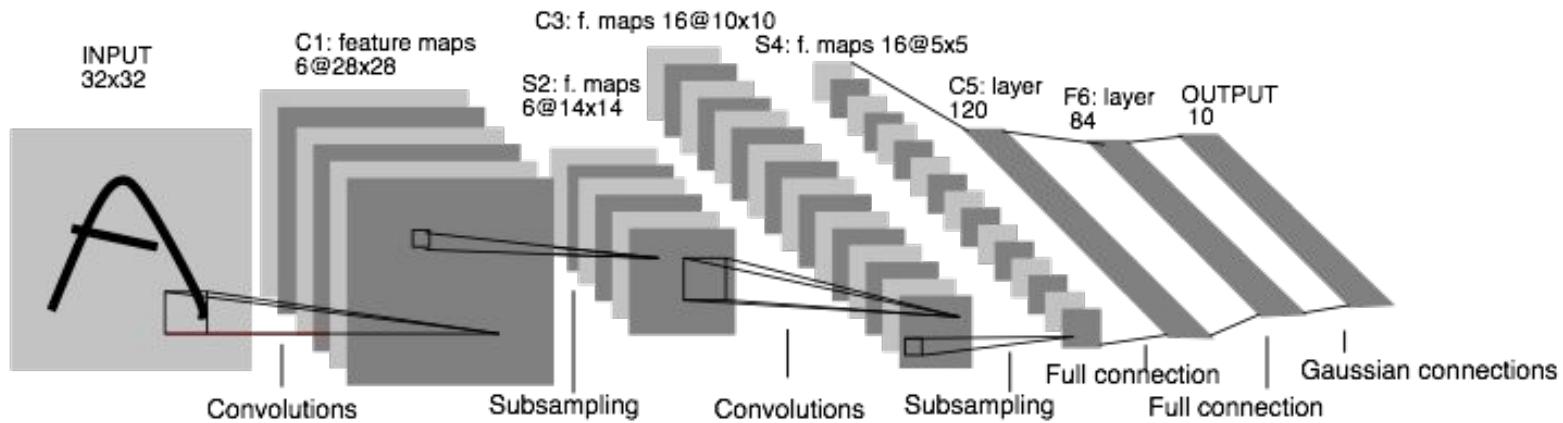


LeCun et al. 1998



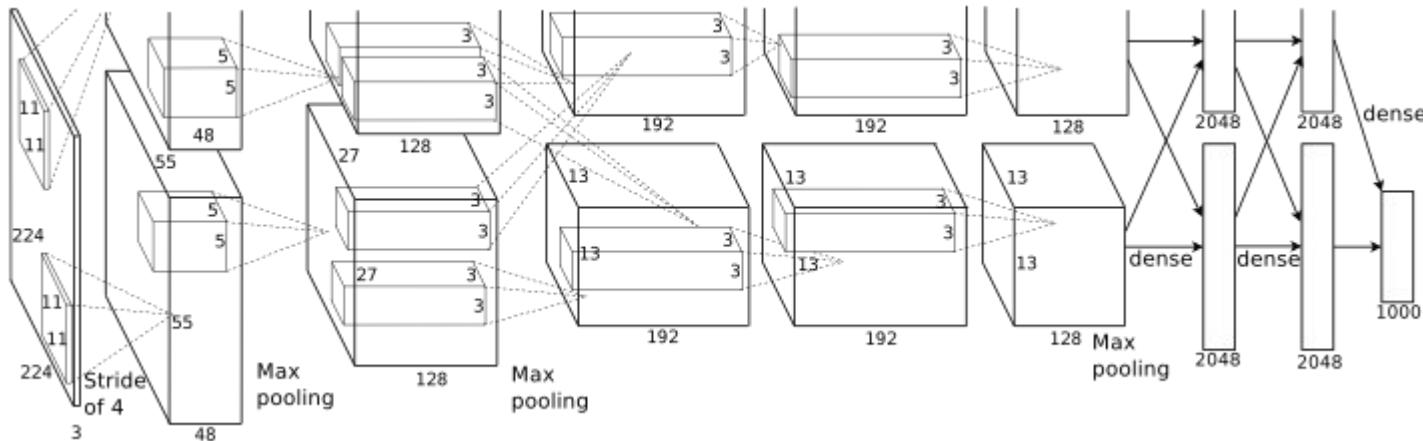
Slide: R. Fergus

Convolutional Networks: 1989



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

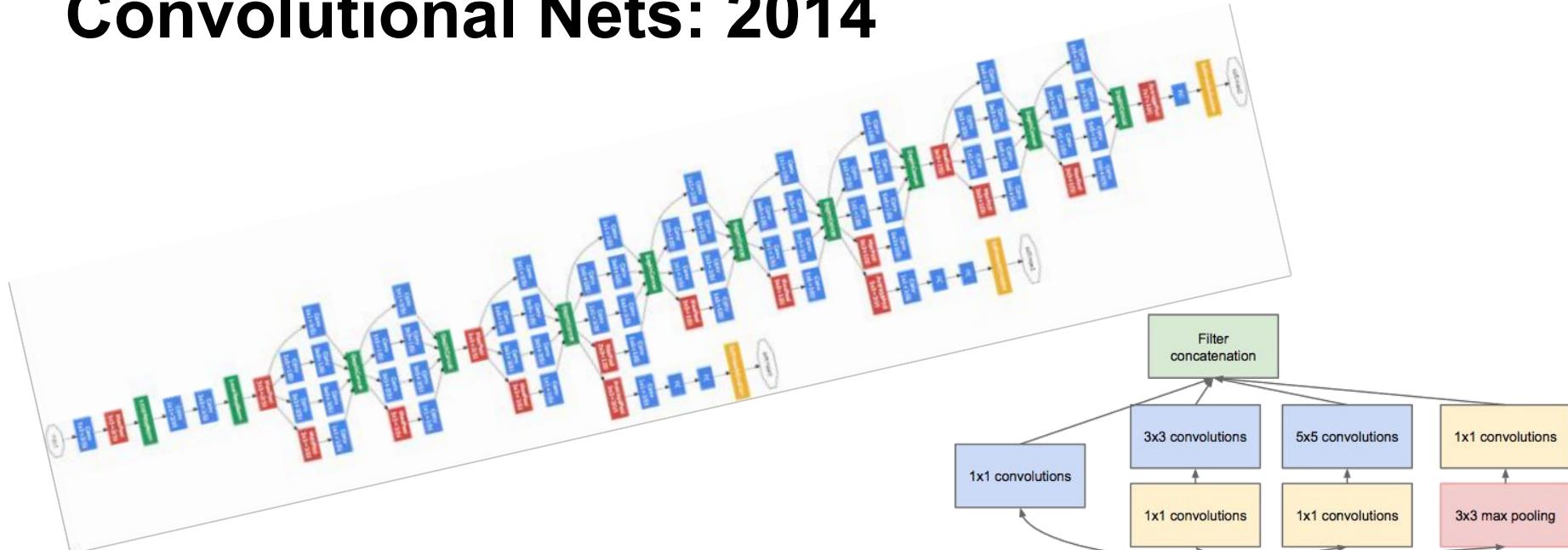
Convolutional Nets: 2012



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 nonlinearity
- + regularization

Convolutional Nets: 2014



ILSVRC14 Winners: **~6.6% Top-5 error**

- GoogLeNet: composition of multi-scale dimension-reduced modules (pictured)
- VGG: 16 layers of 3x3 convolution interleaved with max pooling + 3 fully-connected layers

+ depth
+ data
+ dimensionality reduction

Learning LeNet

back to the future of visual recognition

[see notebook](#)

Deep Learning, as it is executed...

What should a framework handle?

Compositional Models

Decompose the problem and code!

End-to-End Learning

Configure and solve!

Many Architectures and Tasks

Define, experiment, and extend!

Net

- A network is a set of layers and their connections:

```
name : "dummy-net"
```

```
layer { name: "data" ... }
```

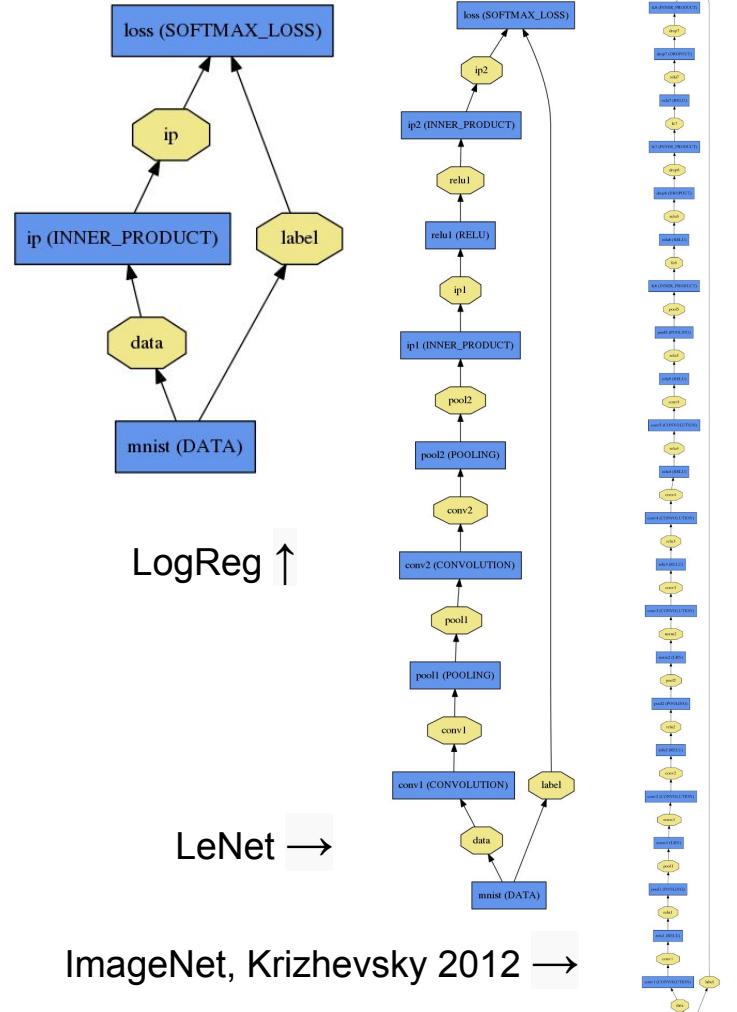
```
layer { name: "conv" ... }
```

```
layer { name: "pool" ... }
```

... more layers ...

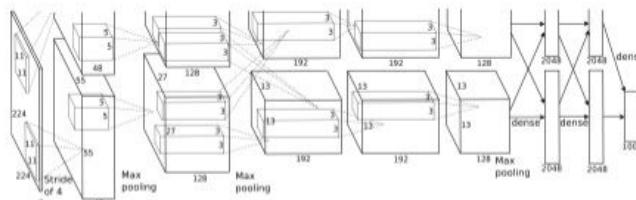
```
layer { name: "loss" ... }
```

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



Forward / Backward the essential Net computations

Forward:
inference $f_W(x)$



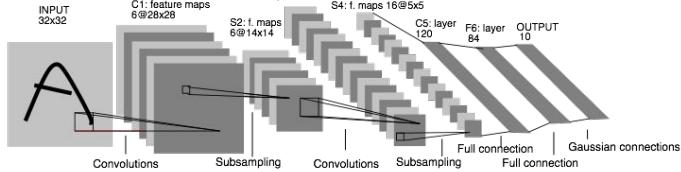
"espresso"
+ loss

$\nabla f_W(x)$ 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.

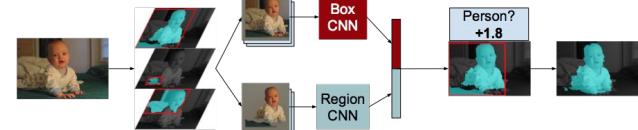
DAG 有向无环图

Many current deep models have linear structure

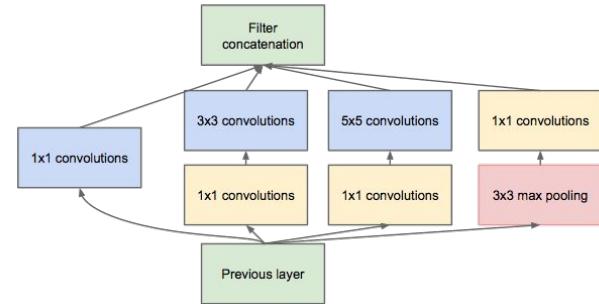


but Caffe nets can have any directed acyclic graph (DAG) structure.

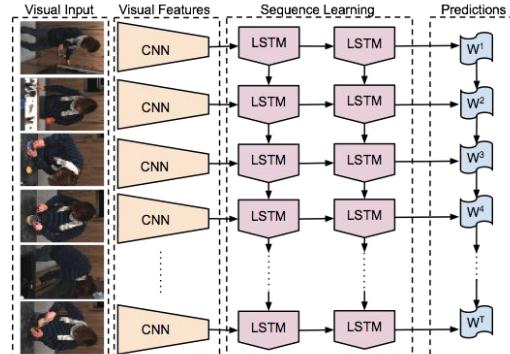
Define bottoms and tops and Caffe will connect the net.



SDS two-stream net



GoogLeNet Inception Module



LRCN joint vision-sequence model

Layer Protocol

Setup: run once for initialization.

Forward: make output given input.

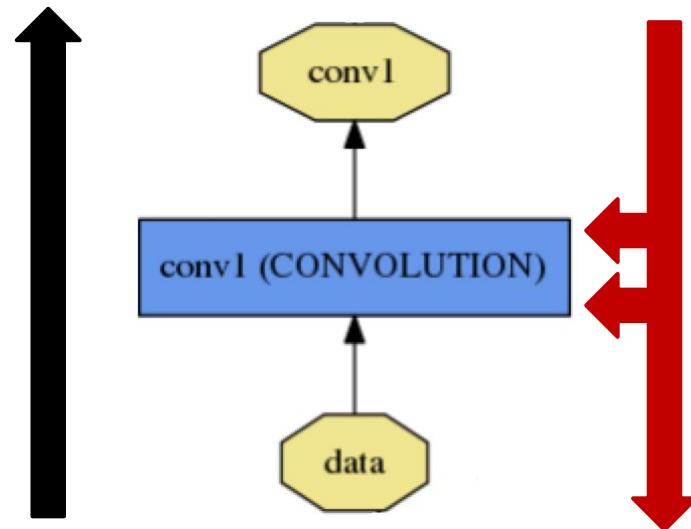
Backward: make gradient of output

- w.r.t. bottom
- w.r.t. parameters (if needed)

Reshape: set dimensions.

Compositional Modeling

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



[Layer Development Checklist](#)

```
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.

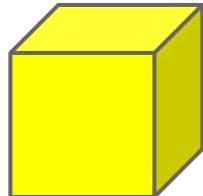
Include your new layer type in a network and keep brewing.

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

Blob

Blobs are N-D arrays for storing and communicating information.

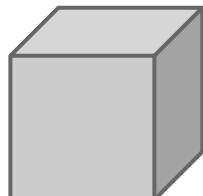
- hold data, derivatives, and parameters
- lazily allocate memory
- shuttle between CPU and GPU



Data

Number x K Channel x Height x Width

256 x 3 x 227 x 227 for ImageNet train input



Parameter: Convolution Weight

N Output x K Input x Height x Width

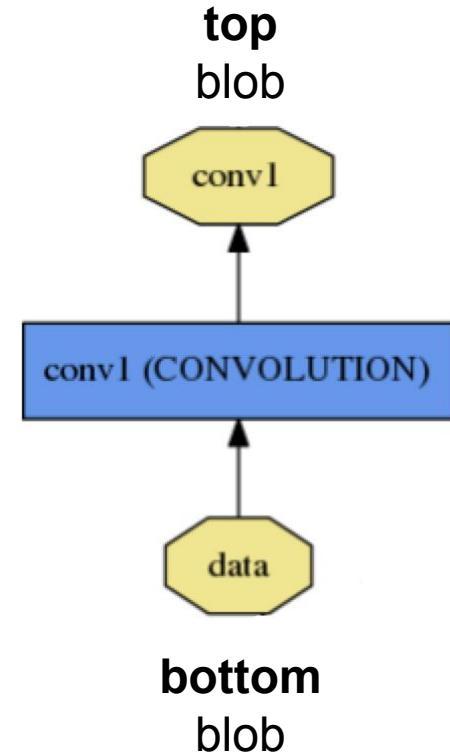
96 x 3 x 11 x 11 for CaffeNet conv1



Parameter: Convolution Bias

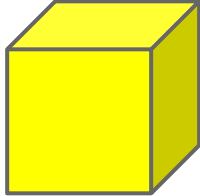
96 x 1 x 1 x 1 for CaffeNet conv1

```
name: "conv1"
type: CONVOLUTION
bottom: "data"
top: "conv1"
... definition ...
```



Blob

Blobs provide a unified memory interface.



Reshape(num, channel, height, width)

- declare dimensions
- make *SyncedMem* -- but only lazily allocate

cpu_data(), mutable_cpu_data()

- host memory for CPU mode

gpu_data(), mutable_gpu_data()

- device memory for GPU mode

{cpu,gpu}_diff(), mutable_{cpu,gpu}_diff()

- derivative counterparts to data methods
- easy access to data + diff in forward / backward

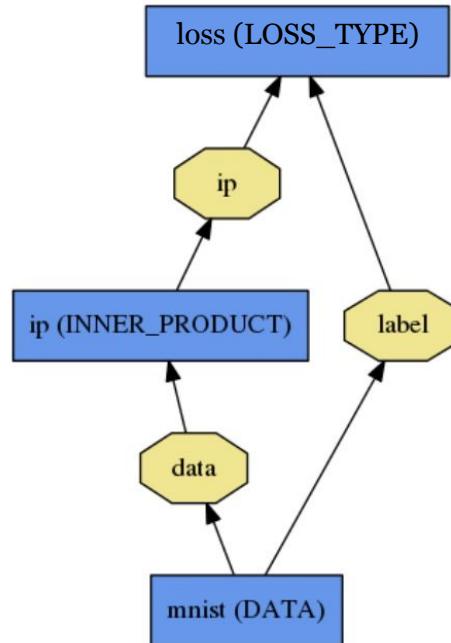
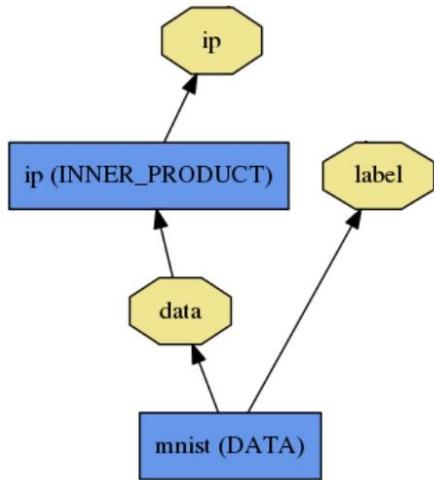


SyncedMem
allocation + communication



Loss

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**.

The models are defined in plaintext protocol buffer schema (prototxt) while the learned models are serialized as binary protocol buffer (binaryproto) .caffemodel files.

Protobuf Model Format

- Strongly typed format
- Auto-generates code
- Developed by Google
- Defines Net / Layer / Solver

schemas in `caffe.proto`

The model format is defined by the protobuf schema in `caffe.proto`.
can be found at `$CAFFE_ROOT/src/caffe/proto/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];  
}
```

```
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.

Solving: Training a Net

Optimization like model definition is configuration.

`train_net`: "lenet_train.prototxt"

`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`

Stochastic Gradient Descent (SGD) + momentum ·

Adaptive Gradient (ADAGRAD) · Nesterov's Accelerated Gradient (NAG)

Solver Showdown: MNIST Autoencoder

AdaGrad

```
I0901 13:36:30.007884 24952 solver.cpp:232] Iteration 65000, loss = 64.1627
I0901 13:36:30.007922 24952 solver.cpp:251] Iteration 65000, Testing net (#0) # train set
I0901 13:36:33.019305 24952 solver.cpp:289] Test loss: 63.217
I0901 13:36:33.019356 24952 solver.cpp:302]      Test net output #0: cross_entropy_loss = 63.217 (* 1 = 63.217 loss)
I0901 13:36:33.019773 24952 solver.cpp:302]      Test net output #1: l2_error = 2.40951
```

SGD

```
I0901 13:35:20.426187 20072 solver.cpp:232] Iteration 65000, loss = 61.5498
I0901 13:35:20.426218 20072 solver.cpp:251] Iteration 65000, Testing net (#0) # train set
I0901 13:35:22.780092 20072 solver.cpp:289] Test loss: 60.8301
I0901 13:35:22.780138 20072 solver.cpp:302]      Test net output #0: cross_entropy_loss = 60.8301 (* 1 = 60.8301 loss)
I0901 13:35:22.780146 20072 solver.cpp:302]      Test net output #1: l2_error = 2.02321
```

Nesterov

```
I0901 13:36:52.466069 22488 solver.cpp:232] Iteration 65000, loss = 59.9389
I0901 13:36:52.466099 22488 solver.cpp:251] Iteration 65000, Testing net (#0) # train set
I0901 13:36:55.068370 22488 solver.cpp:289] Test loss: 59.3663
I0901 13:36:55.068410 22488 solver.cpp:302]      Test net output #0: cross_entropy_loss = 59.3663 (* 1 = 59.3663 loss)
I0901 13:36:55.068418 22488 solver.cpp:302]      Test net output #1: l2_error = 1.79998
```

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

Recipe for Brewing

- Convert the data to Caffe-format
 - Imdb, 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/*`

Brewing Models

from logistic regression to non-linearity

[see notebook](#)

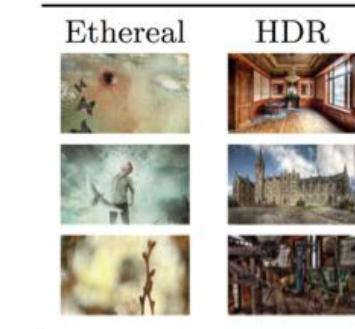
Take a pre-trained model and fine-tune to new tasks
[DeCAF] [Zeiler-Fergus] [OverFeat]

Lots of Data



image by Andrej Karpathy

Your Task



Style Recognition



© kaggle.com

Dogs vs. Cats top 10 in 10 minutes

From ImageNet to Style

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

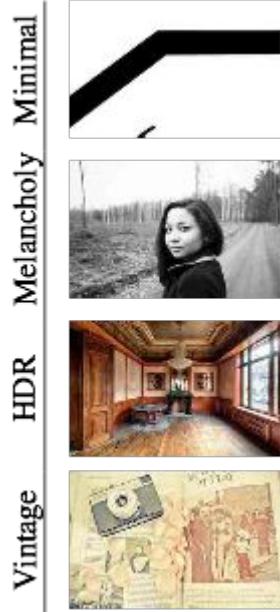
Last Layer:
A different classifier

From ImageNet to Style

```
> 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()
```



Fine-tuning

transferring features to style recognition

[see notebook](#)

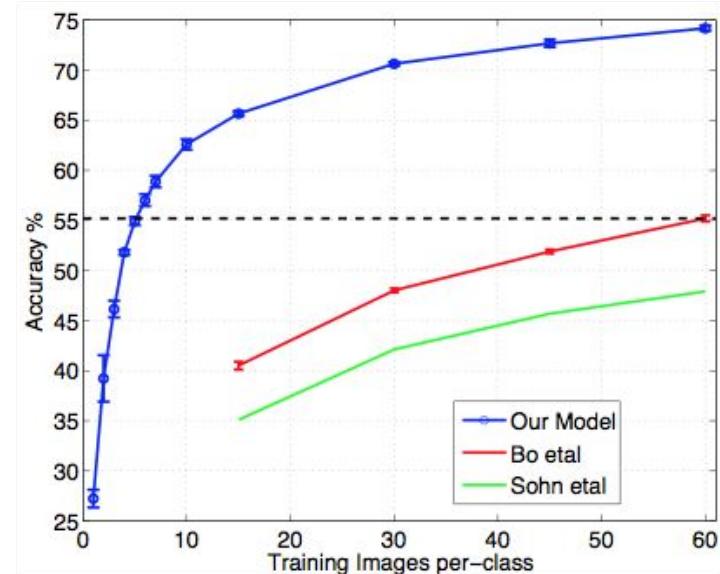
When to Fine-tune?

A good first step

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

State-of-the-art results in

- recognition
- detection
- segmentation



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 early divergence by setting `lr_mult: 0` to fix a parameter.
- Stop if good enough, or keep fine-tuning

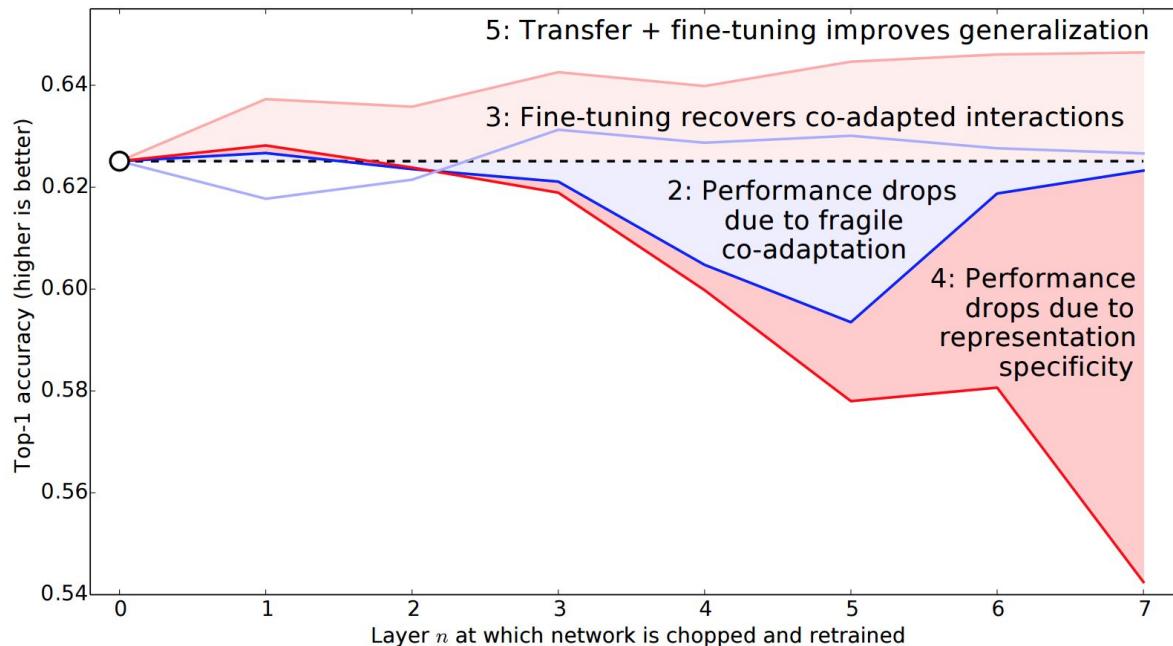
Reduce the learning rate

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

Do net surgery see notebook on [editing model parameters](#)

Transferability of Features

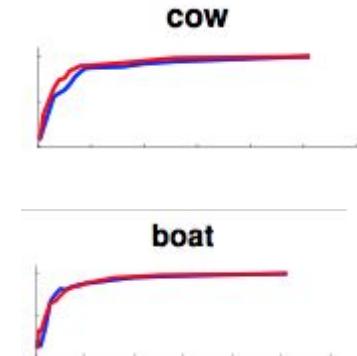
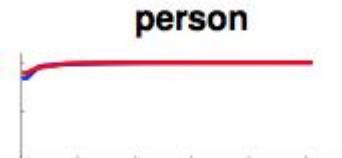
Yosinski et al. NIPS 2014



After fine-tuning

- Supervised pre-training does not overfit
- Representation is (mostly) distributed
- Sparsity comes “for free” in deep representation

	feature map	binarize	sp-shuffle	sp-max
Filter 1	[5 0 0 0 2 0 1 8 0]	[1 0 0 0 1 0 1 1 0]	[9 1 0 0 2 5 0 0 0]	[9]
	[0 1 11 3 0 0 0 2 8]	[0 0 1 1 0 0 0 1 1]	[2 0 11 0 0 0 3 1 8]	[11]
	[• • • • • • 0 2 3]	[• • • • • • 0 1 1]	[• • • • • • 3 0 3]	[• • • • • • 7]
Filter 2	[0 2 3 0 7 0 0 3 0]	[0 1 1 0 1 0 0 1 0]	[0 7 0 0 2 0 0 2 0]	
Filter N				



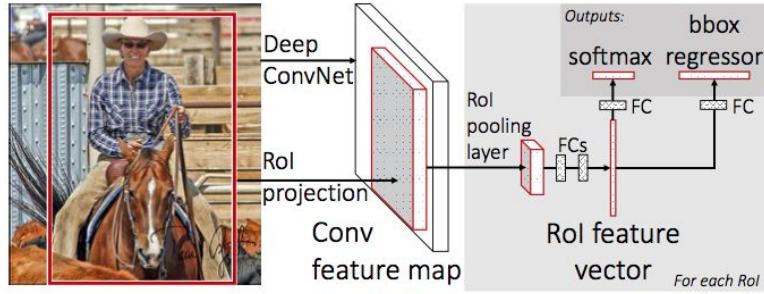
Editing model parameters

how to do net surgery to set custom weights

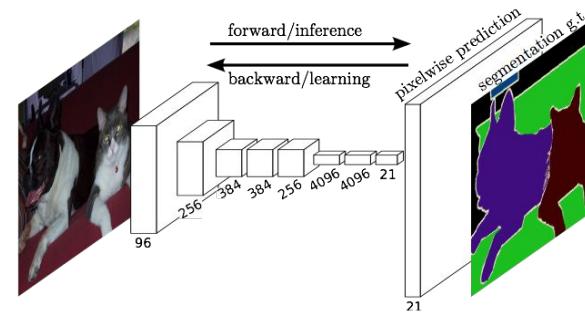
[see notebook](#)

Up Next The Latest Roast

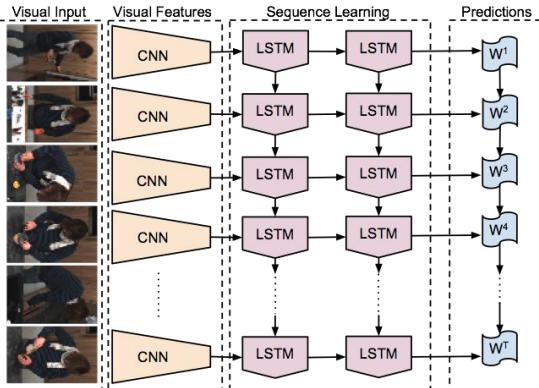
Detection



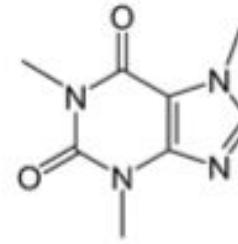
Pixelwise Prediction



Sequences



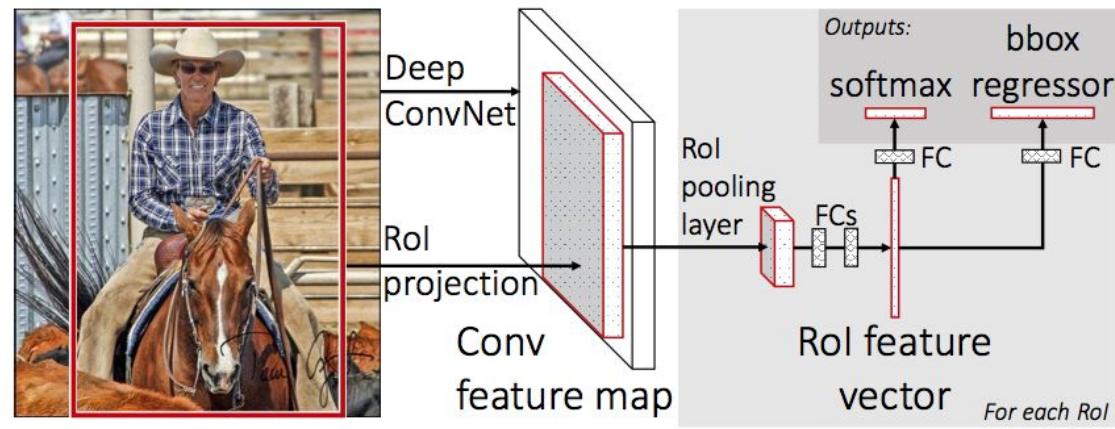
Framework Future



Detection

Fast R-CNN

- convolve once
- project + detect



Faster R-CNN

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

[arXiv](#) and [code](#) for Fast R-CNN

Ross Girshick, Shaoqing Ren,
Kaiming He, Jian Sun

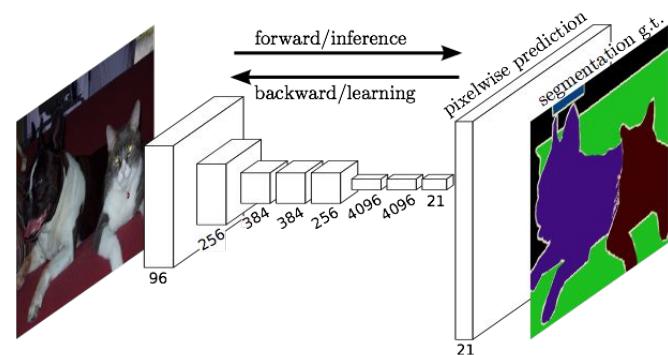
Pixelwise Prediction

Fully convolutional networks for pixel prediction applied to semantic segmentation

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

Further applications

- depth
- boundaries
- flow + more



CVPR15 [arXiv](#) and [reference models + code](#)

Jon Long* & Evan Shelhamer*,
Trevor Darrell

Sequences

Recurrent Net and Long Short Term Memory LSTM
are sequential models

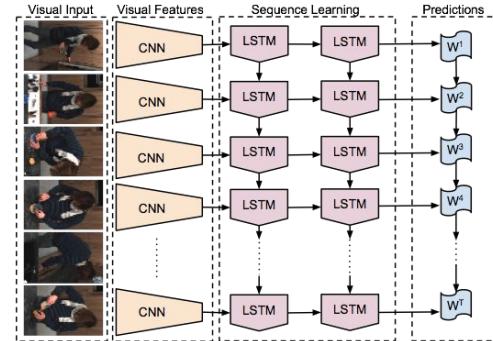
- video
- language
- dynamics

learned by backpropagation through time.

LRCN: Long-term Recurrent Convolutional Network

- activity recognition
- image captioning
- video captioning

CVPR15 [arXiv](#) and [project site](#)



A group of young men playing a game of soccer.

Jeff Donahue et al.

Framework Future

1.0 is coming stability, documentation, packaging

Performance Tuning for GPU (cuDNN v5) and CPU (nppack)

In-progress Ports for OpenCL and Windows

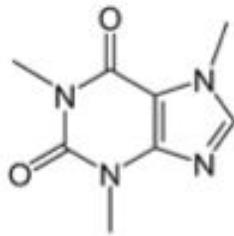
Halide interface for prototyping and experimenting

Widening the Circle continued and closer collaborative development

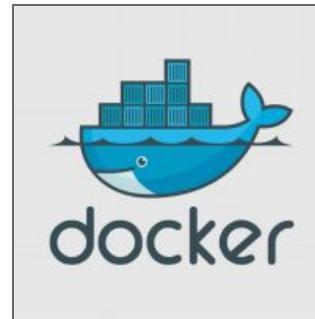
Next Steps

Now you've seen the progress made with
DIY deep learning and the democratization of models

Next Up:



caffe.berkeleyvision.org



 github.com/BVLC/caffe

Check out Caffe on github

[Run Caffe through Docker](#)
and NVIDIA Docker for GPU

Join the [caffe-users](#) mailing list

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

Thanks to the Caffe Crew



...plus the cold-brew

Yangqing Jia, Evan Shelhamer, Jeff Donahue, Jonathan Long,
Sergey Karayev, Ross Girshick, Sergio Guadarrama, Ronghang Hu, Trevor Darrell
and our [open source contributors!](#)

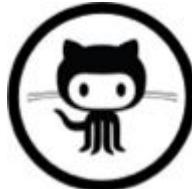
Acknowledgements



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 150+
open source contributors
and vibrant community!



Thank you to A9 and AWS
for a research grant for Caffe dev
and reproducible research

References

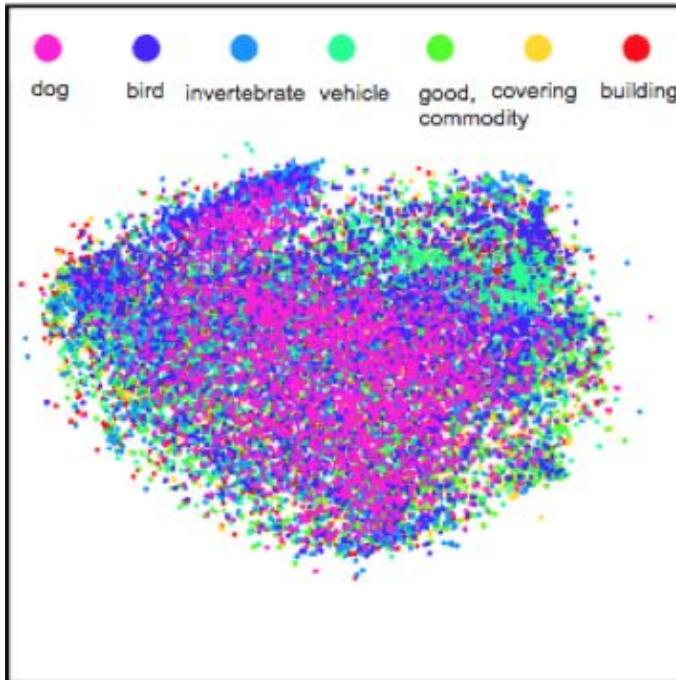
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END

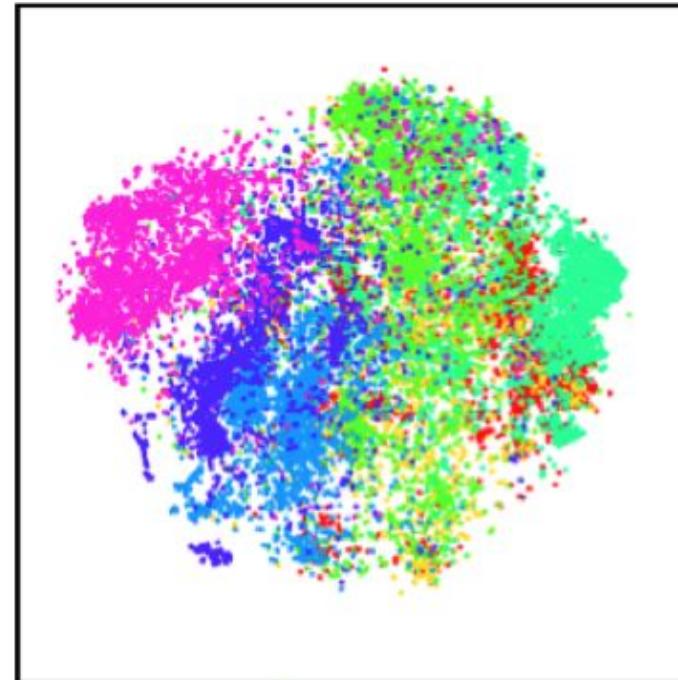
MORE DETAILS

Why Deep Learning?

The Unreasonable Effectiveness of Deep Features



Low-level: Pool₁

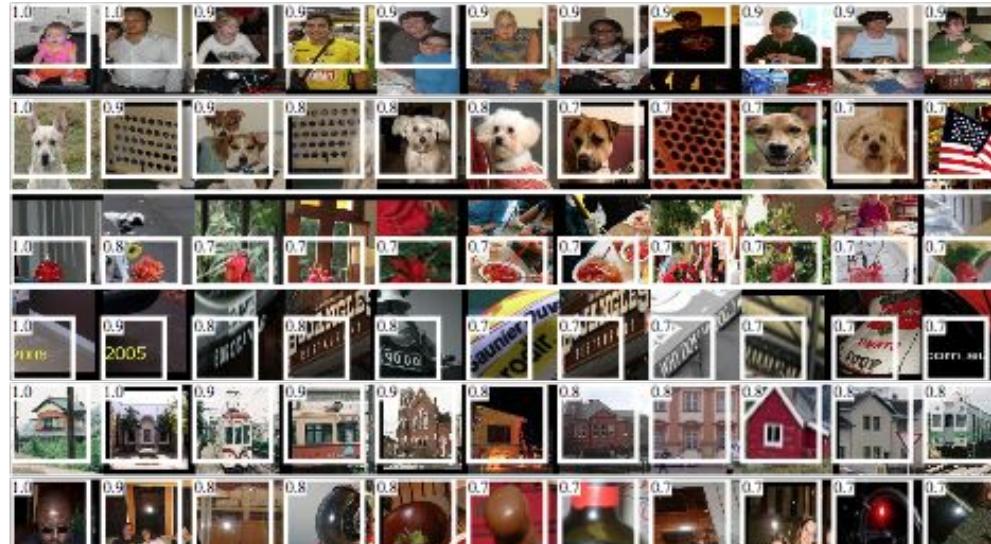


High-level: FC₆

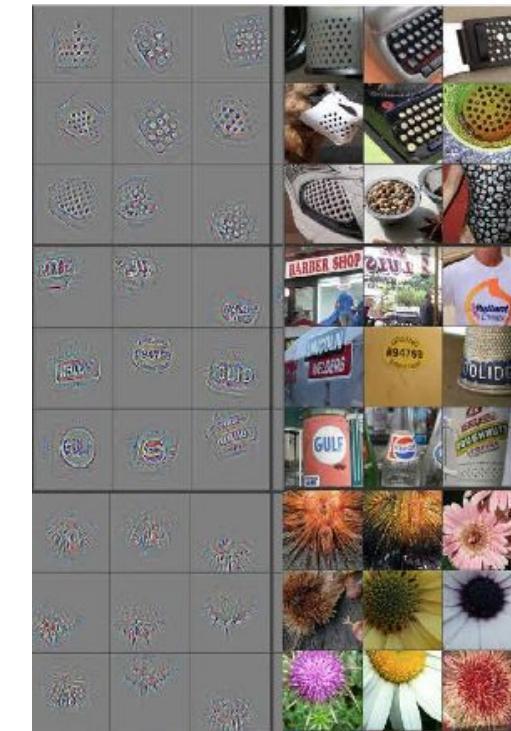
Classes separate in the deep representations and transfer to many tasks.
[DeCAF] [Zeiler-Fergus]

Why Deep Learning?

The Unreasonable Effectiveness of Deep Features



Maximal activations of pool₅ units



conv₅ DeConv visualization
[Zeiler-Fergus]

Rich visual structure of features deep in hierarchy.

Why Deep Learning?

The Unreasonable Effectiveness of Deep Features

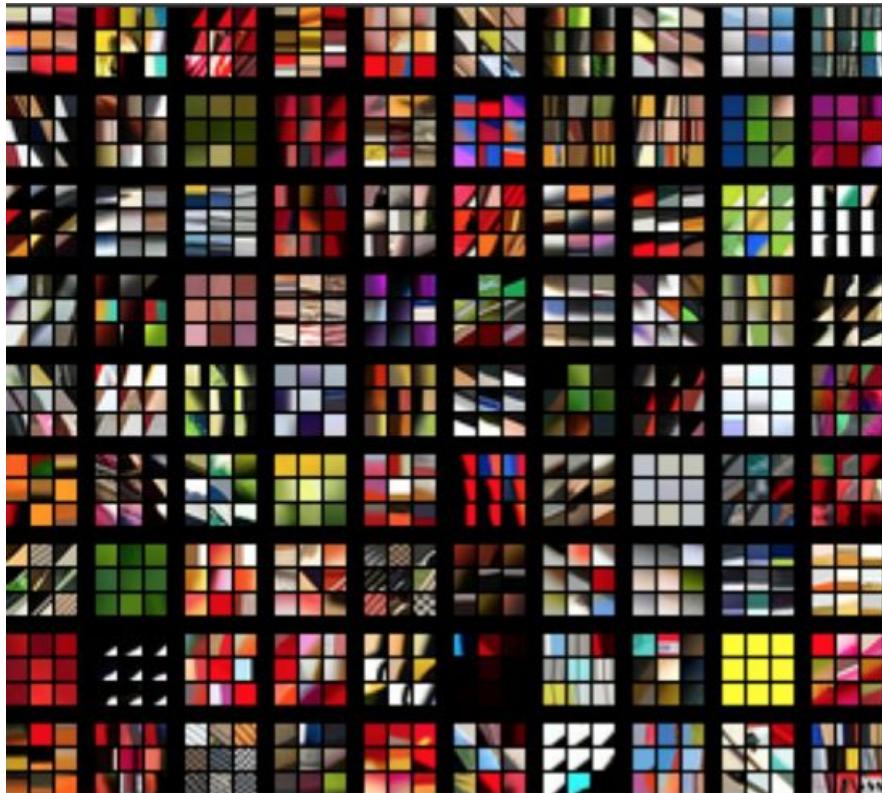
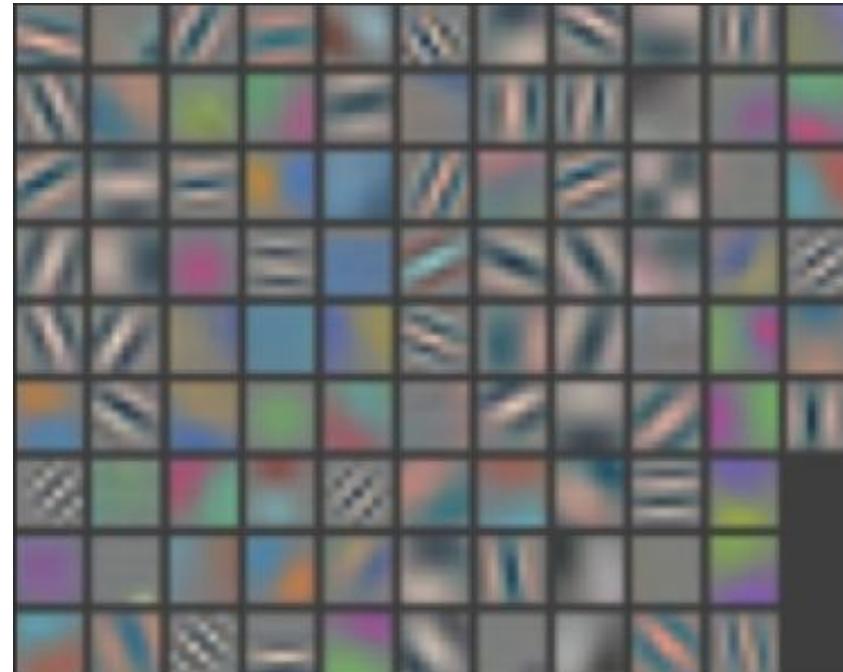


image patches that strongly activate 1st layer filters



1st layer filters

[Zeiler-Fergus]