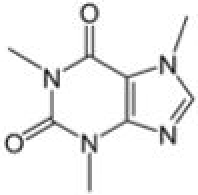
DIY Deep Learning for Vision: a Hands-On Tutorial with Caffe

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

Tutorial Schedule

Caffe tour and latest roast

Caffe Tour

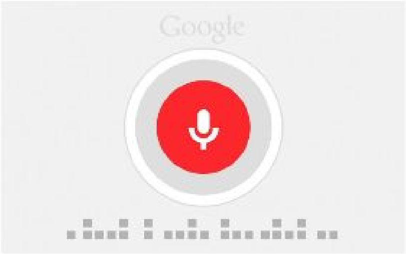
- the why and how of Caffe
- highlight reel of examples + applications
- do-it-yourself notebooks

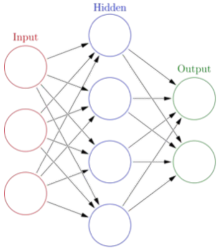
Latest Roast

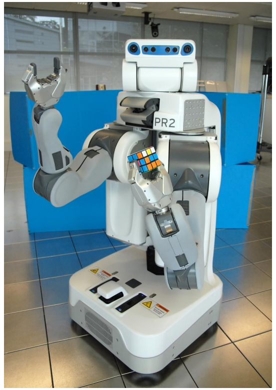
- detection *Ross Girshick*
- sequences and vision + language *Jeff Donahue*
- pixelwise prediction *Jon Long and Evan Shelhamer*
- framework future *Yangqing Jia*

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 → abstract
learning

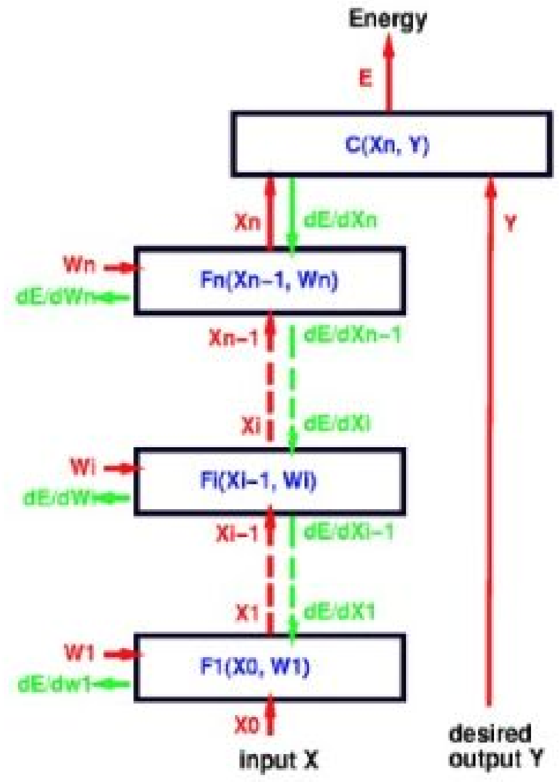


figure credit Yann LeCun, ICML '13 tutorial

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.

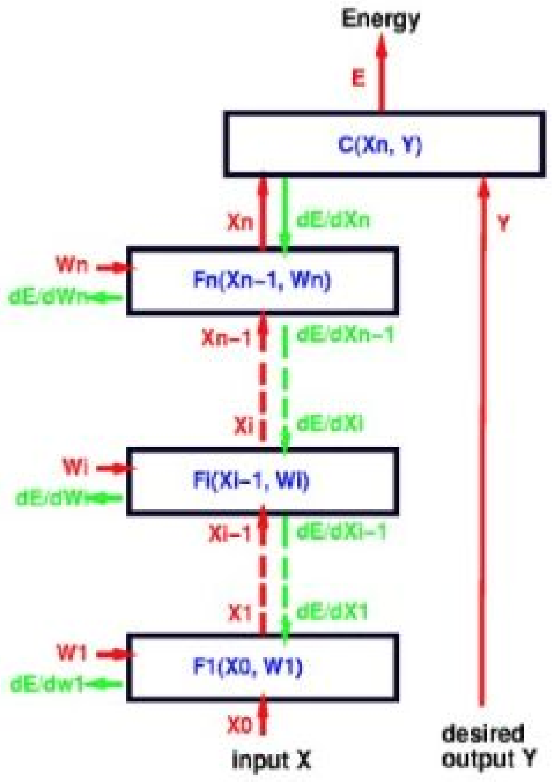
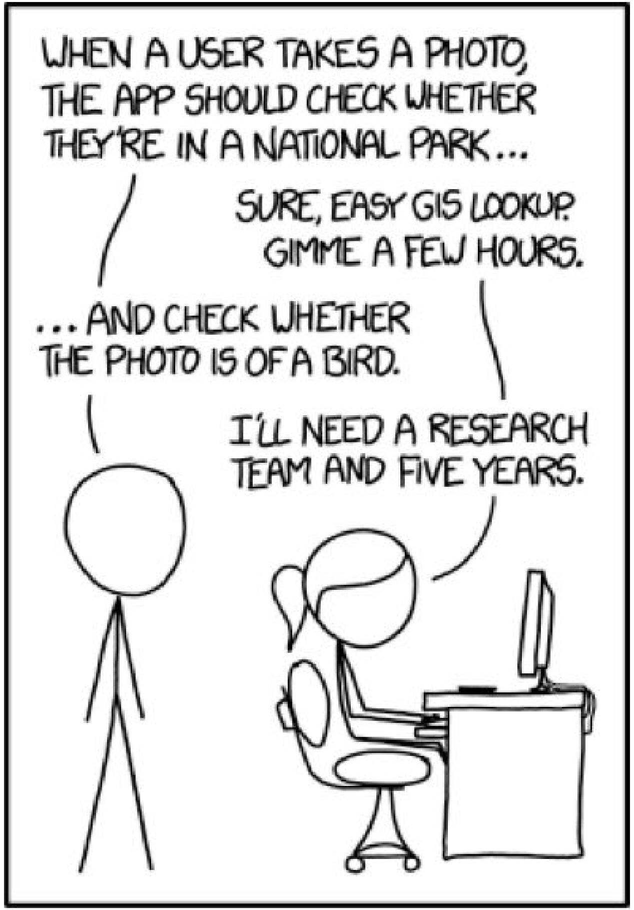


figure credit Yann LeCun, ICML '13 tutorial



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

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?

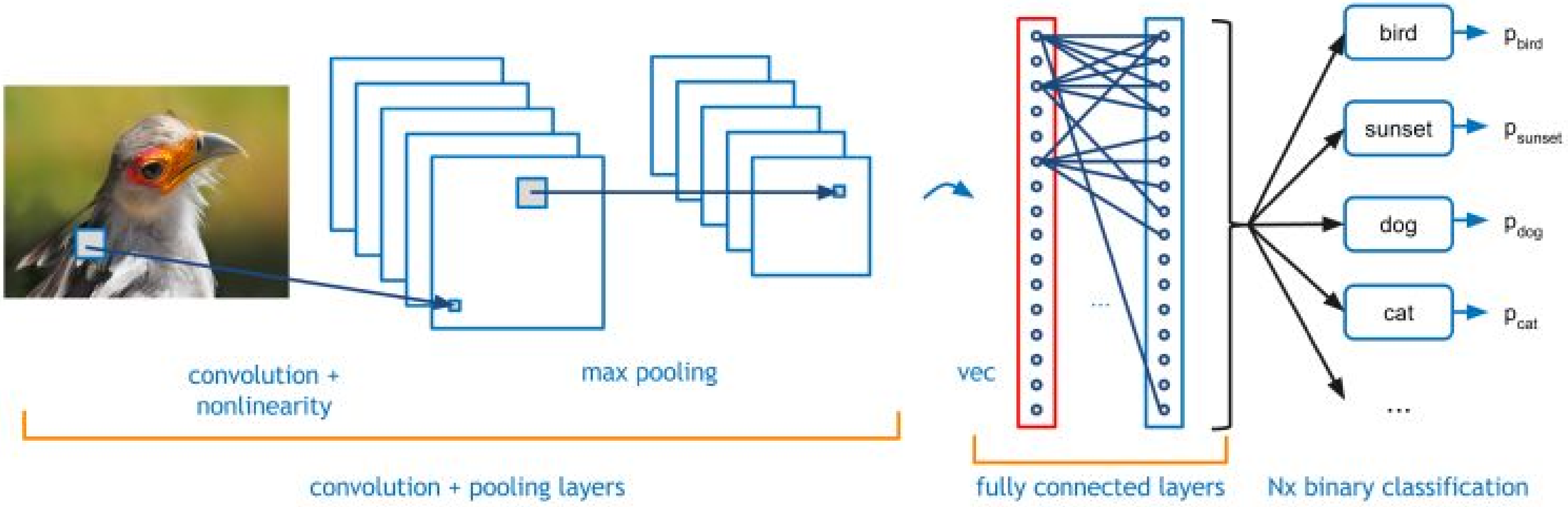
YES

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/

What is Caffe?

Open framework, models, and worked examples
for deep learning

- < 2 years
- 600+ citations, 100+ contributors, 6,000+ stars
- 3,400+ 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

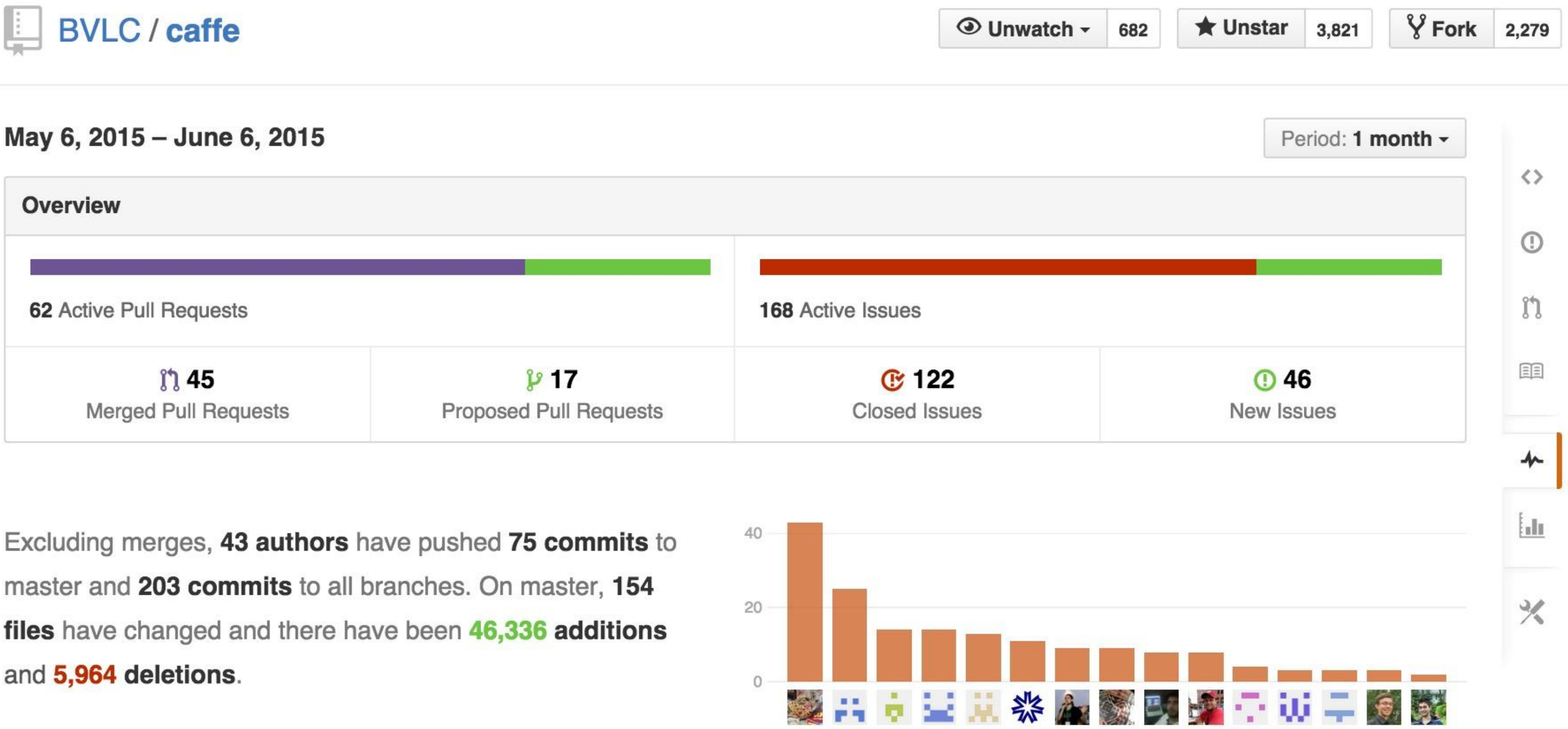
Prototype

Train

Deploy

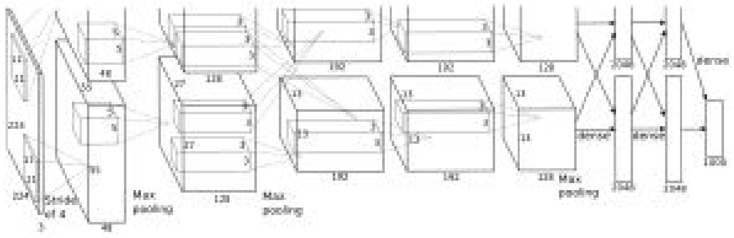
Caffe is a Community

[project pulse]

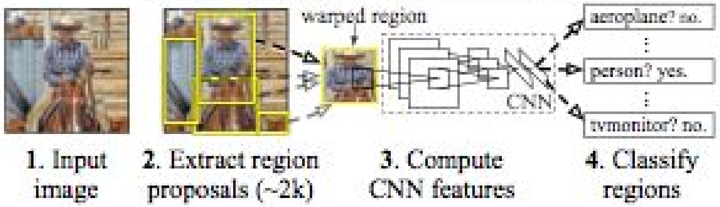


Reference Models

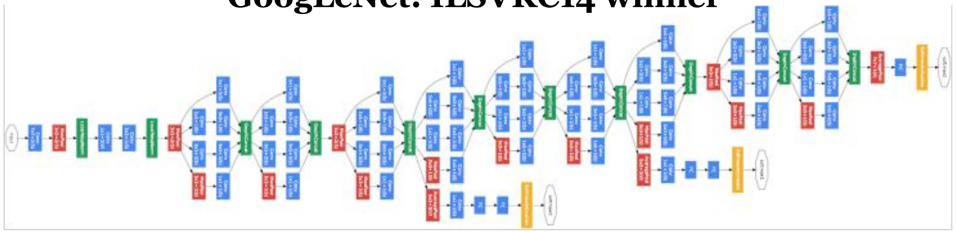
AlexNet: ImageNet Classification



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
    - VGG ILSVRC14 + Devil models in the zoo
    - Network-in-Network / CCCP model in the zoo
    - MIT Places scene recognition 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 v2 on Titan X
  - 72 million images / day with batched IO
  - 8-core CPU: ~20 ms/image
- 9k lines of C++ code (20k with tests)

C++ 84.2% Python 10.5% Cuda 3.9% Other 1.4%

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:

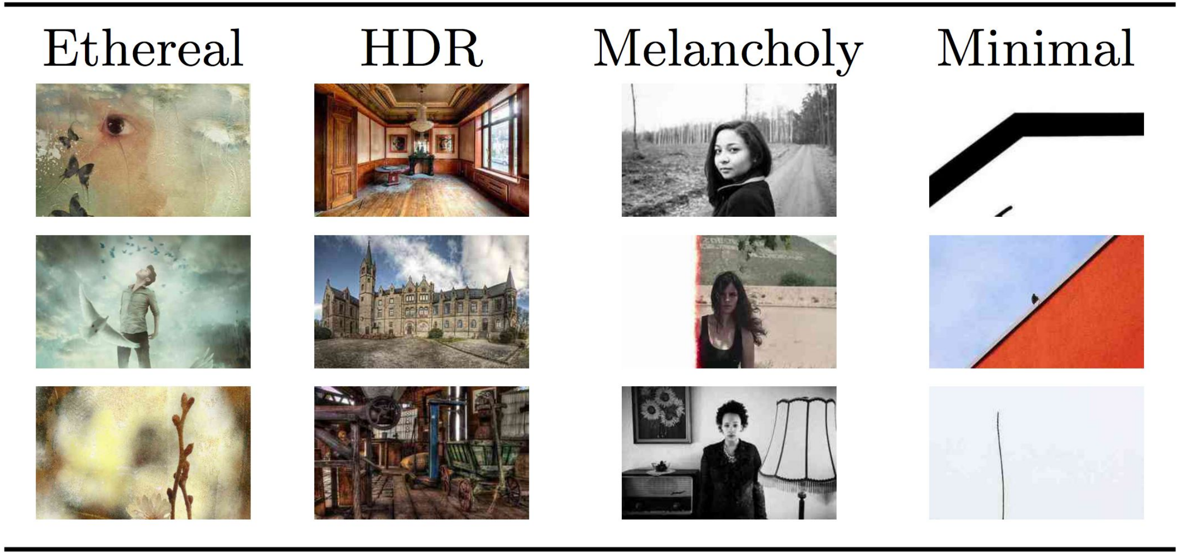
- **Type of environment:** outdoor
- **Semantic categories:** skyscraper:0.69, tower:0.16, office_building:0.11,
- **SUN scene attributes:** man-made, vertical components, natural light, open area, nohorizon, glossy, metal, wire, clouds, far-away horizon

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-CNN: Region-based Convolutional Networks

http://nbviewer.ipython.org/github/BVLC/caffe/blob/master/examples/detection.ipynb

Full R-CNN scripts available at

https://github.com/rbgirshick/rcnn

Ross Girshick et al.
Rich feature hierarchies for accurate object detection and semantic segmentation. CVPR14.

Fast R-CNN - Later today!

arXiv and code

Sequences

Recurrent Net RNN and Long Short Term Memory LSTM are sequential models

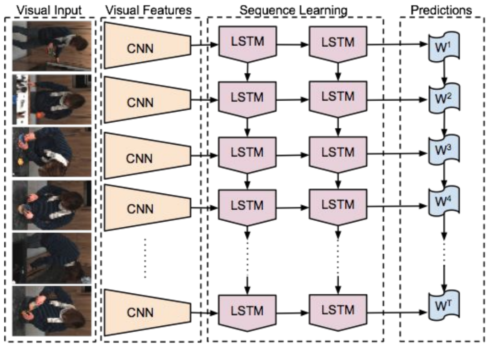
- video
- language
- dynamics

learned by back-propagation through time.

LRCN: Long-term Recurrent Convolutional Network

- activity recognition
- image captioning
- video captioning

arXiv and web page & PR



A group of young men playing a game of soccer.

Jeff Donahue et al.

Segmentation

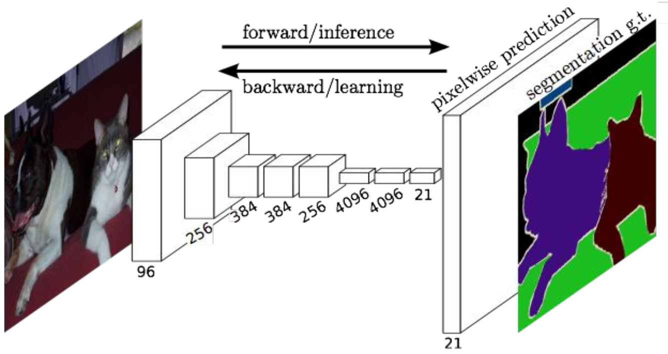
Fully convolutional networks for pixel prediction applied to semantic segmentation

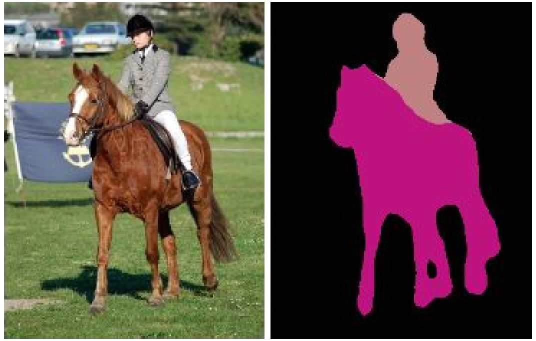
- end-to-end learning
- efficiency in inference and learning
  175 ms per-image prediction
- multi-modal, multi-task

Further applications

- depth estimation
- denoising

[arXiv]() and [pre-release]()

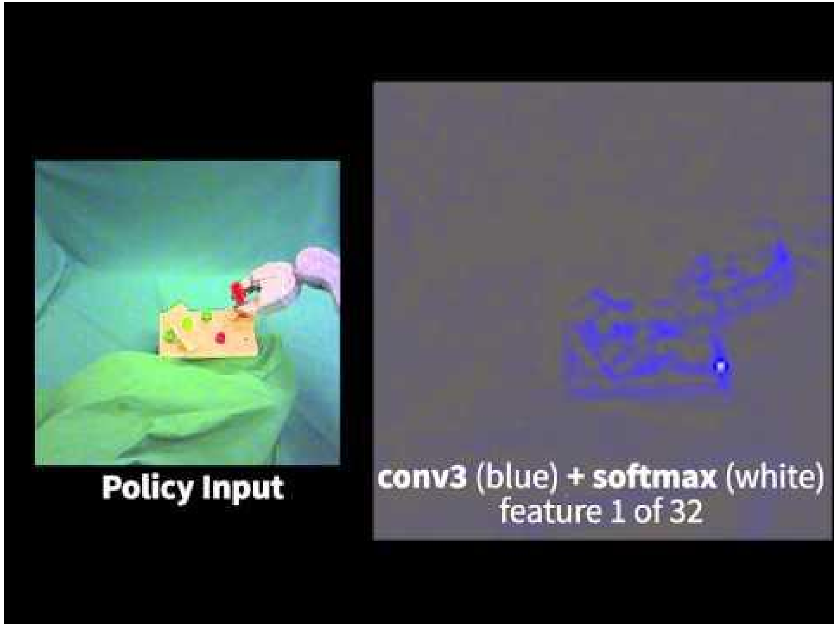




Jon Long* & Evan Shelhamer*, Trevor Darrell

Deep Visuomotor Control

example experiments

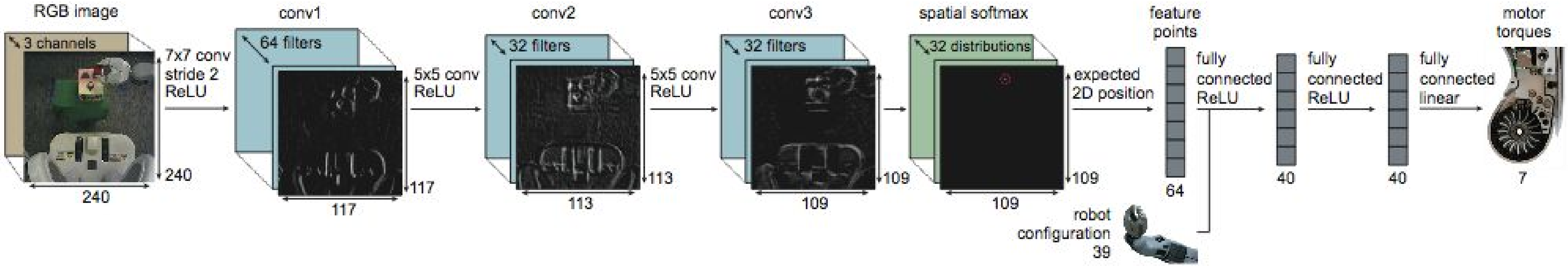


feature visualization

tech report http://tinyurl.com/visuomotor

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

Deep Visuomotor Control



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

tech report http://tinyurl.com/visuomotor

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

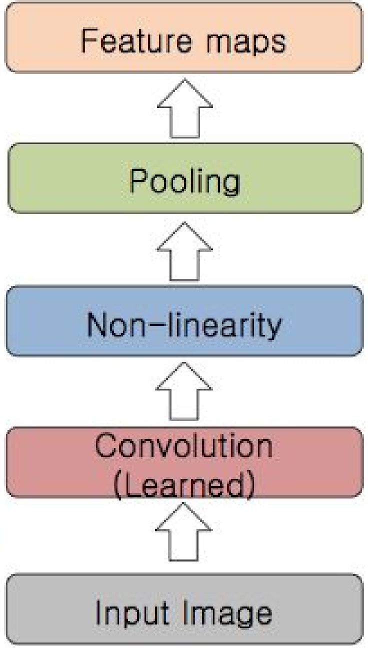
Embedded Caffe

[Caffe on the NVIDIA Jetson TK1 mobile board]

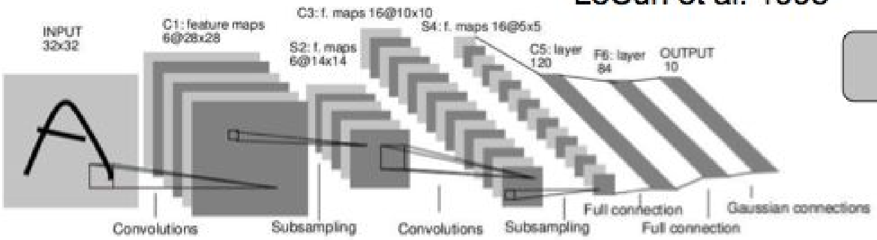
- 10 watts of power
- inference at 35 ms per image
- no need to change the code

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



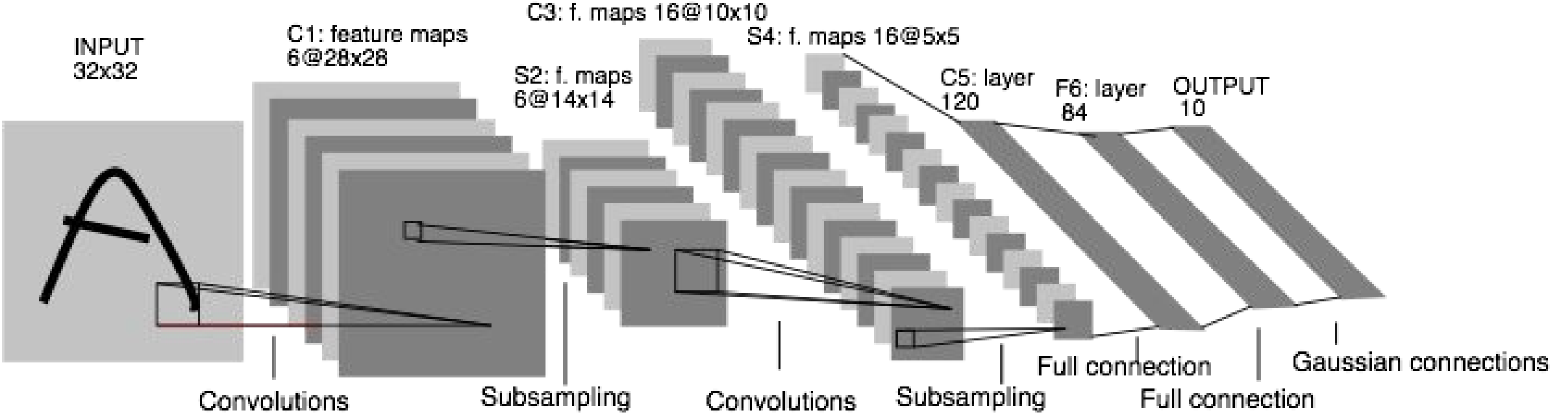
Slide: R. Fergus

Classification

instant recognition the Caffe way

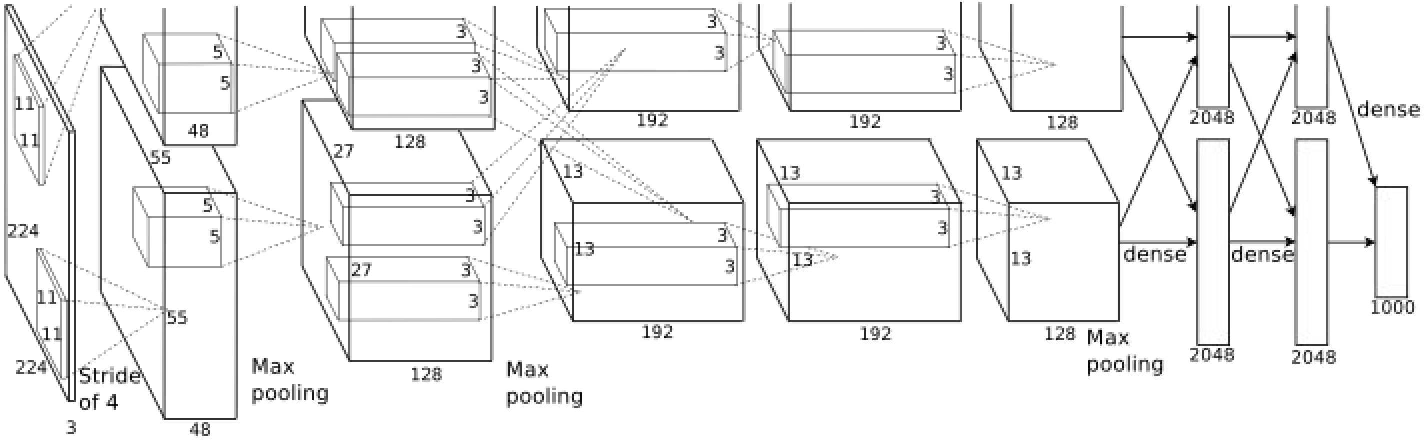
see notebook

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]

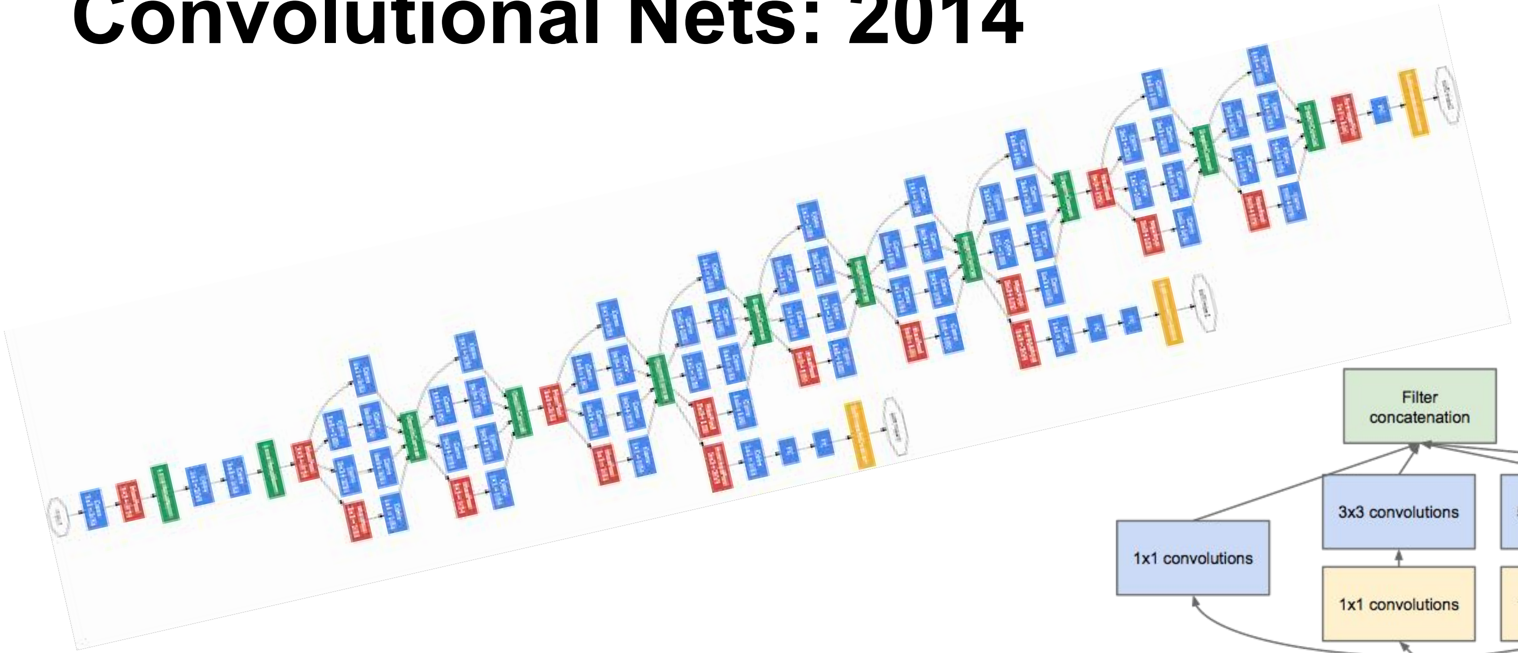
Convolutional Nets: 2012

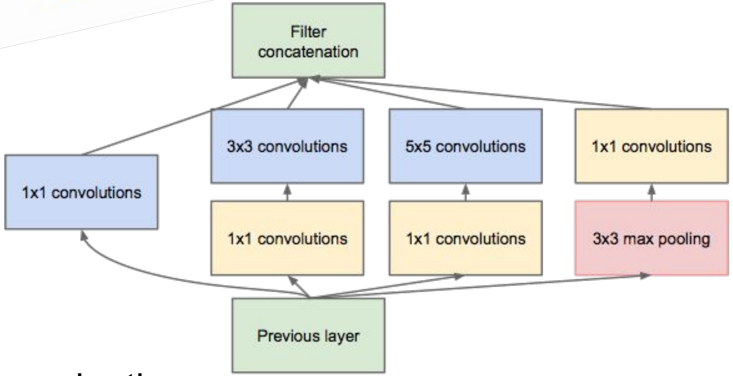


AlexNet: a layered model composed of convolution, subsampling, and further operations followed by a holistic representation and all-in-all a landmark classifier on ILSVRC12. [AlexNet]

+ 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

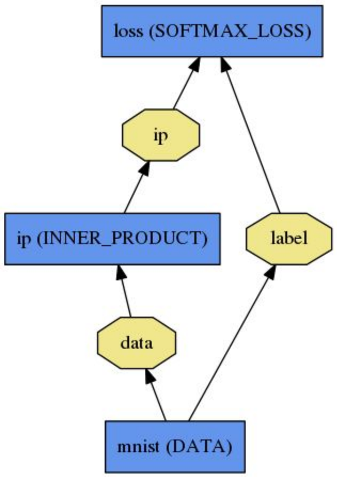
Define, experiment, and extend!

Net

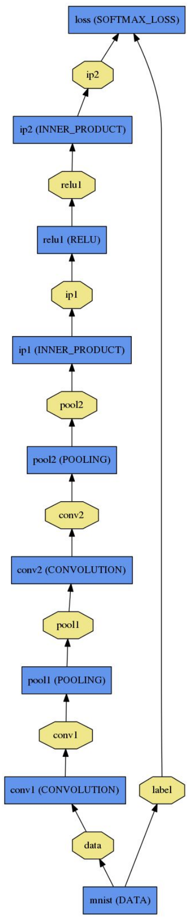
- A network is a set of layers and their connections:

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

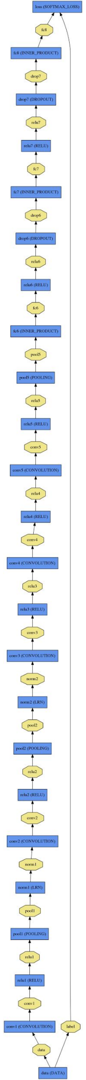
- Caffe creates and checks the net from the definition.
- Data and derivatives flow through the net as *blobs* – an array interface



LogReg ↑



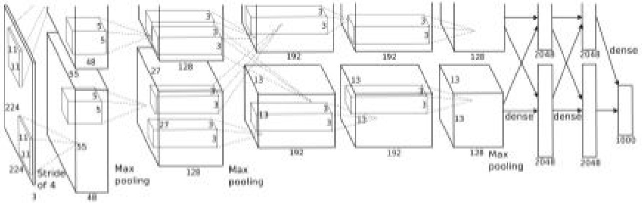
LeNet →



ImageNet, Krizhevsky 2012 →

Forward / Backward the essential Net computations

Forward:
inference $f_W(x)$



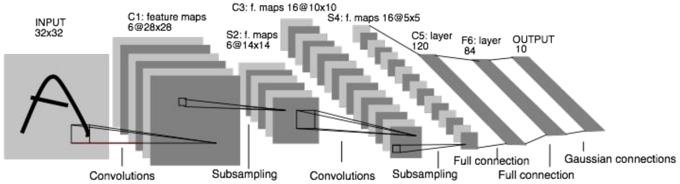
"espresso"
+ loss

$\nabla f_W(x)$ 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.

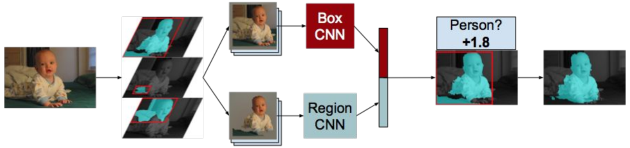
DAG

Many current deep models have linear structure

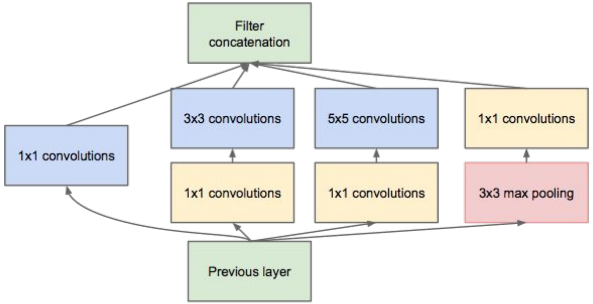


but Caffe nets can have any directed acyclic graph (DAG) structure.

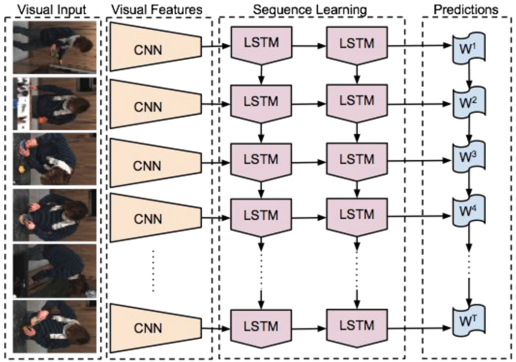
Define `bottoms` and `tops` and Caffe will connect the net.



SDS two-stream net



GoogLeNet Inception Module



LRCN joint vision-sequence model

Layer Protocol

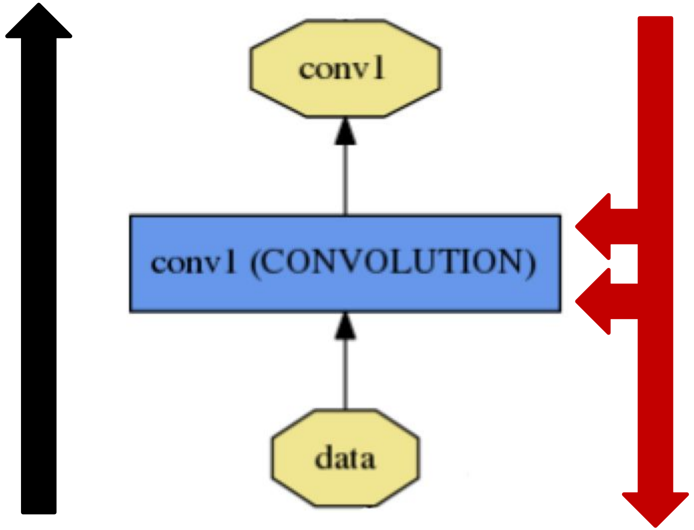
Setup: run once for initialization.

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]

```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.

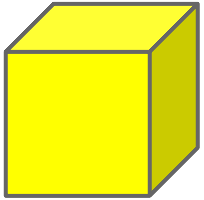
```
layer {
type: "Python"
python_param {
  module: "layers"
  layer: "EuclideanLoss"
} }
```

Blob

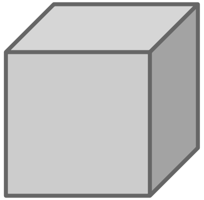
```
name: "conv1"
type: CONVOLUTION
bottom: "data"
top: "conv1"
… definition …
```

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

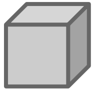
- hold data, derivatives, and parameters
- lazily allocate memory
- shuttle between CPU and GPU



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

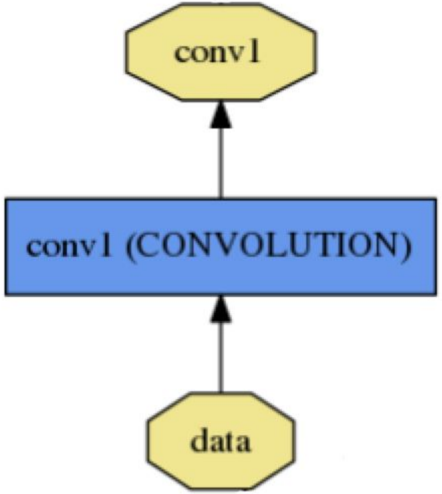


Parameter: Convolution Weight
N Output x *K* Input x *H*eight x *W*idth
96 x 3 x 11 x 11 for CaffeNet conv1



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

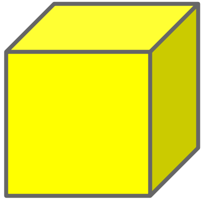
top
blob



bottom
blob

Blob

Blobs provide a unified memory interface.

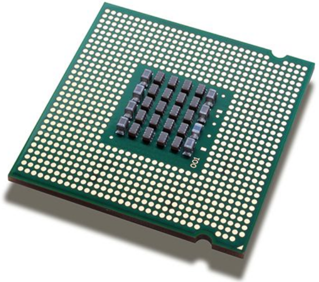


Reshape(num, channel, height, width)
- declare dimensions
- make *SyncedMem* -- but only lazily allocate

cpu_data(), mutable_cpu_data()
- host memory for CPU mode

gpu_data(), mutable_gpu_data()
- device memory for GPU mode

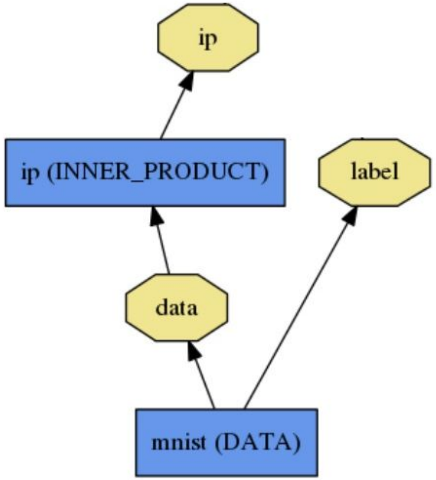
{cpu,gpu}_diff(), mutable_{cpu,gpu}_diff()
- derivative counterparts to data methods
- easy access to data + diff in forward / backward

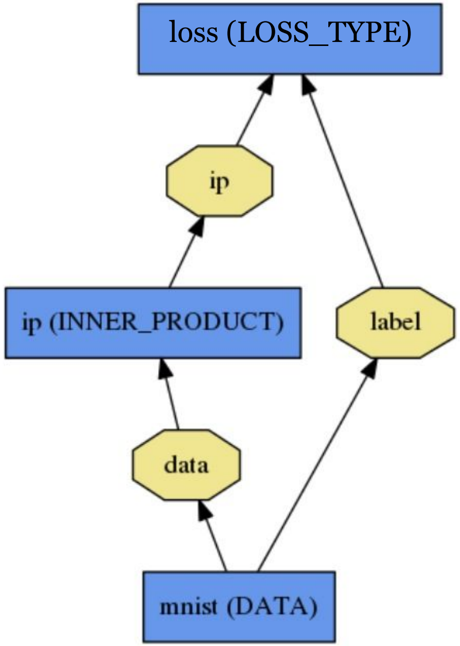


SyncedMem
allocation + communication

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**.

Protobuf Model Format

- 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];
}
```

```
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
  - 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/*`

Brewing Models

from logistic regression to non-linearity

[see notebook](#)

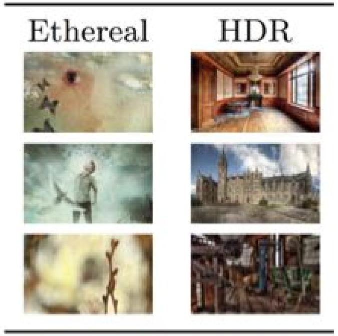
Take a pre-trained model and fine-tune to new tasks

[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

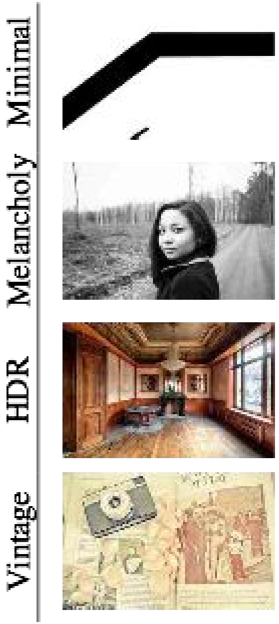
Last Layer:
    A different classifier

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

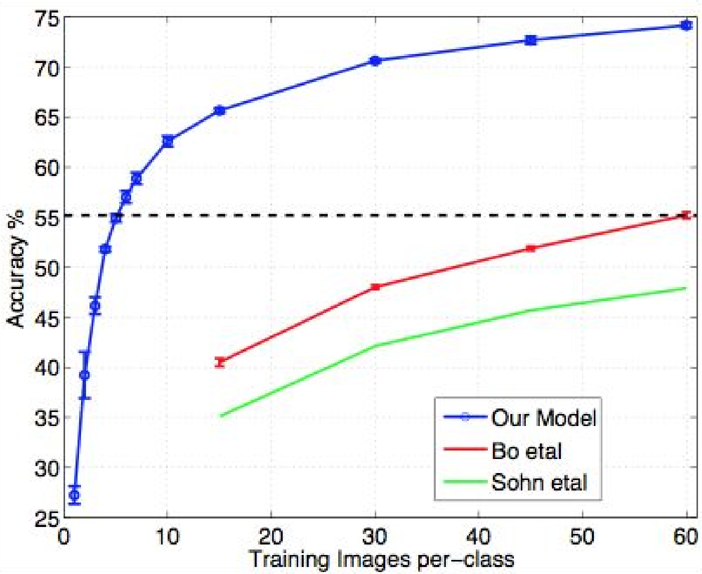
When to Fine-tune?

A good first step

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

State-of-the-art results in

- recognition
- detection
- segmentation



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

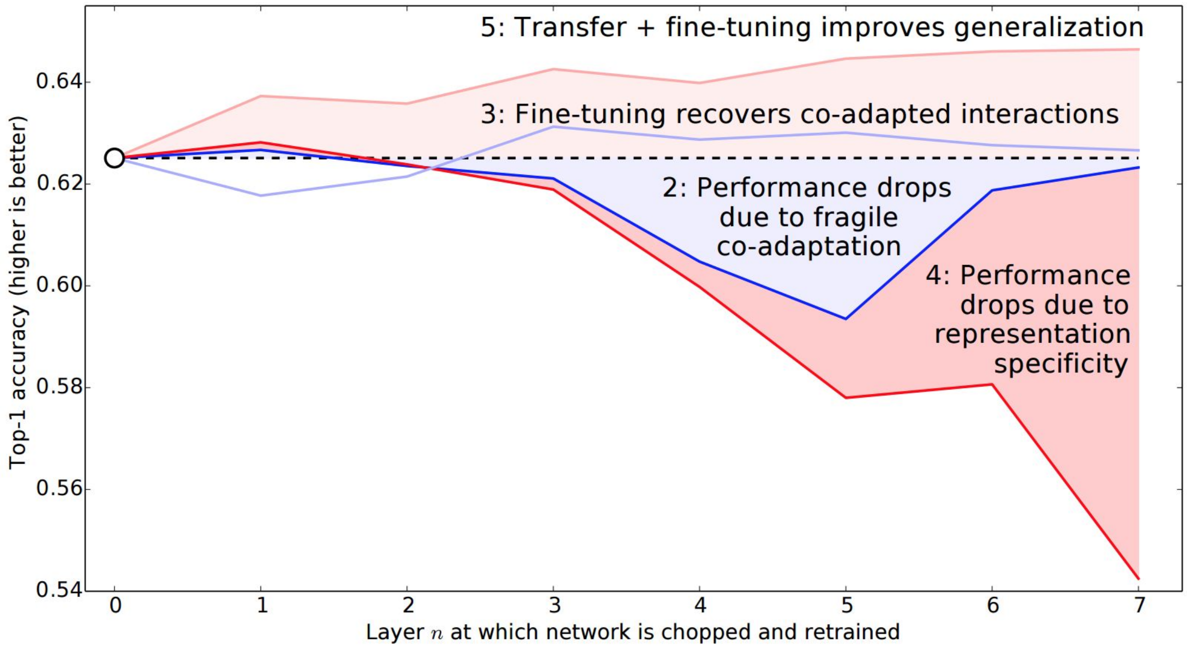
Reduce the learning rate

- 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

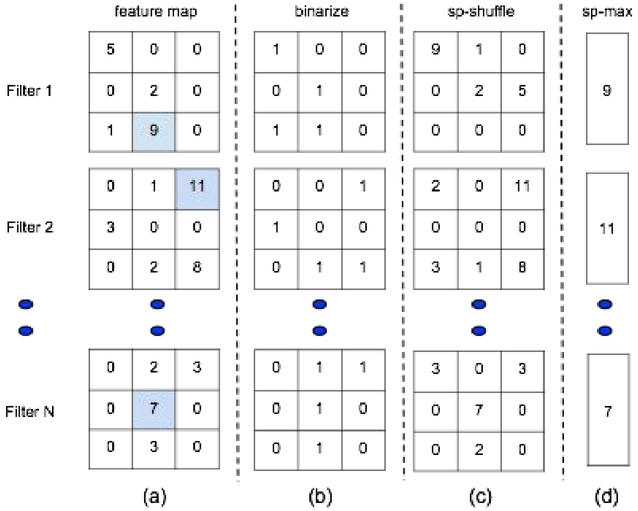
Transferability of Features

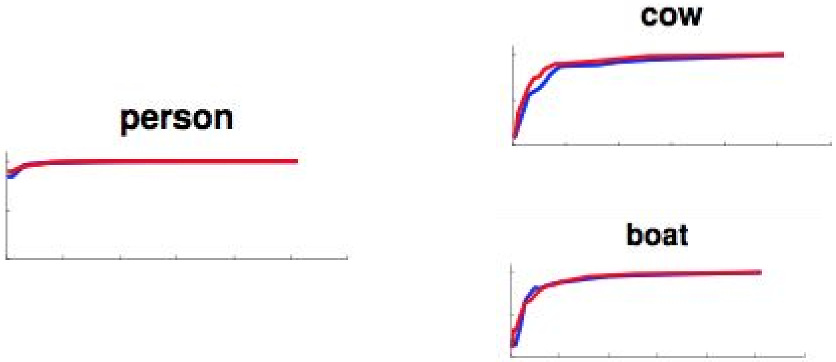
Yosinski et al. NIPS 2014



After fine-tuning

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





P. Agarwal et al. ECCV 14

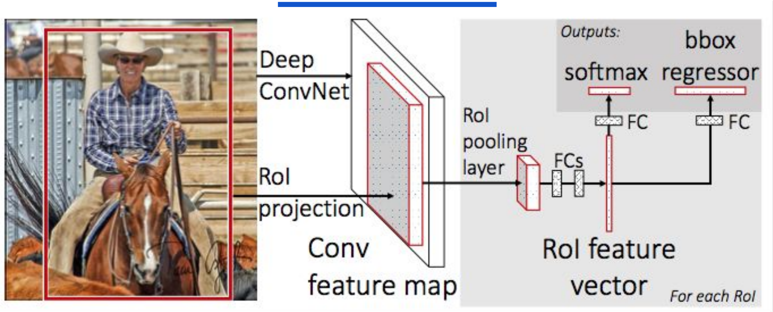
Editing model parameters

how to do net surgery to set custom weights

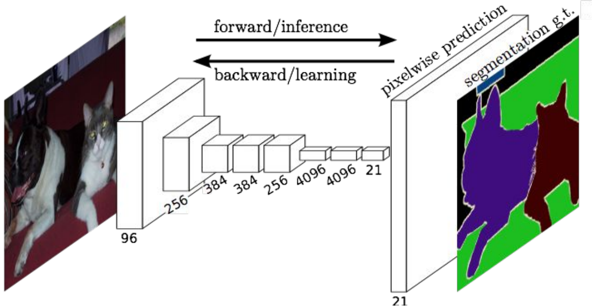
[see notebook]

Up Next The Latest Roast

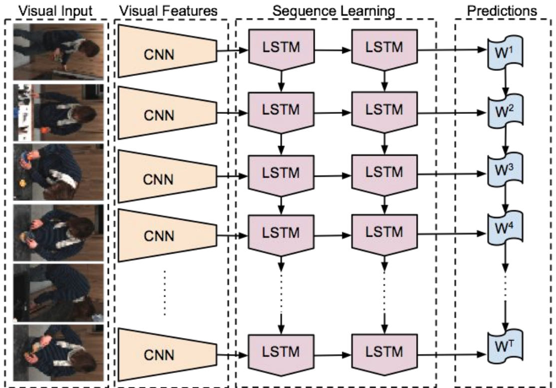
Detection



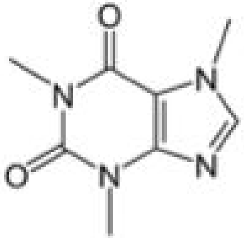
Pixelwise Prediction



Sequences



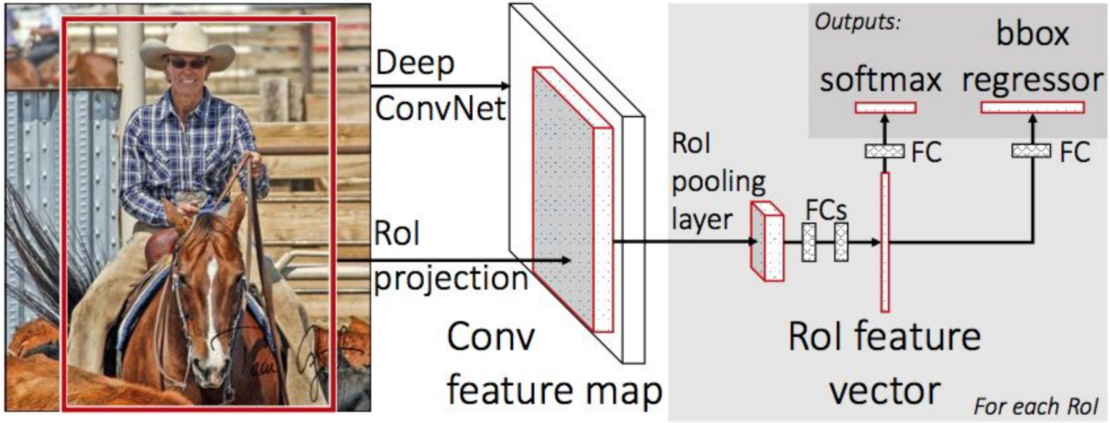
Framework Future



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

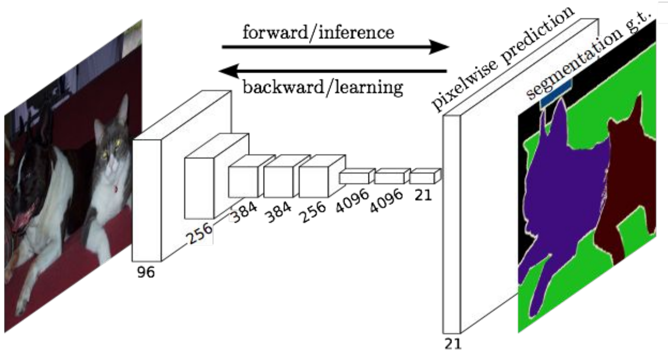
Fully convolutional networks for pixel prediction applied to semantic segmentation

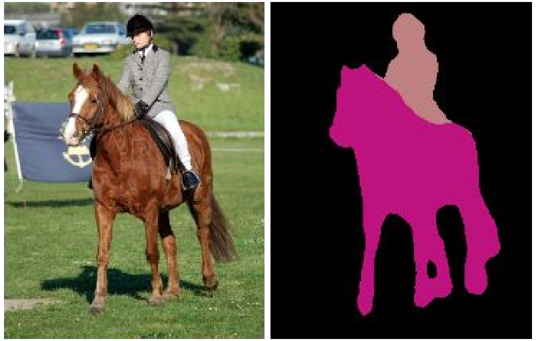
- end-to-end learning
- efficient inference and learning
  150 ms per-image prediction
- multi-modal, multi-task

Further applications

- depth
- boundaries
- flow + more

CVPR15 arXiv and pre-release





Jon Long* & Evan Shelhamer*, Trevor Darrell

Sequences

Recurrent Net and Long Short Term Memory LSTM are sequential models

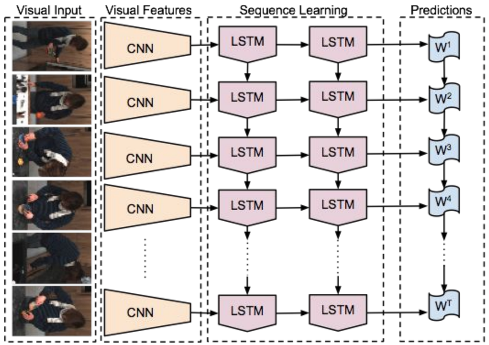
- video
- language
- dynamics

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.

Caffe Postdoc

BVLC is seeking a postdoc for Caffe brewing:

- help develop Caffe and build community

- one year renewable postdoc at UC Berkeley
  with Prof. Trevor Darrell

- send CV and Caffe portfolio to trevor@eecs.berkeley.edu
  with subject line containing [CAFFE-Postdoc]

Help Brewing

Documentation

- tutorial documentation
- worked examples

Modeling, Usage, and Installation

- caffe-users group
- gitter.im chat

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

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for a research grant for Caffe dev
and reproducible research.

Thank you to our 100+
open source contributors
and vibrant community!

References

[DeCAF] J. Donahue, Y. Jia, O. Vinyals, J. Hoffman, N. Zhang, E. Tzeng, and T. Darrell. Decaf: A deep convolutional activation feature for generic visual recognition. ICML, 2014.

[R-CNN] R. Girshick, J. Donahue, T. Darrell, and J. Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. CVPR, 2014.

[Zeiler-Fergus] M. Zeiler and R. Fergus. Visualizing and understanding convolutional networks. ECCV, 2014.

[LeNet] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. IEEE, 1998.

[AlexNet] A. Krizhevsky, I. Sutskever, and G. Hinton. Imagenet classification with deep convolutional neural networks. NIPS, 2012.

[OverFeat] P. Sermanet, D. Eigen, X. Zhang, M. Mathieu, R. Fergus, and Y. LeCun. Overfeat: Integrated recognition, localization and detection using convolutional networks. ICLR, 2014.

[Image-Style] S. Karayev, M. Trentacoste, H. Han, A. Agarwala, T. Darrell, A. Hertzmann, H. Winnemoeller. Recognizing Image Style. BMVC, 2014.

[Karpathy14] A. Karpathy, G. Toderici, S. Shetty, T. Leung, R. Sukthankar, and L. Fei-Fei. Large-scale video classification with convolutional neural networks. CVPR, 2014.

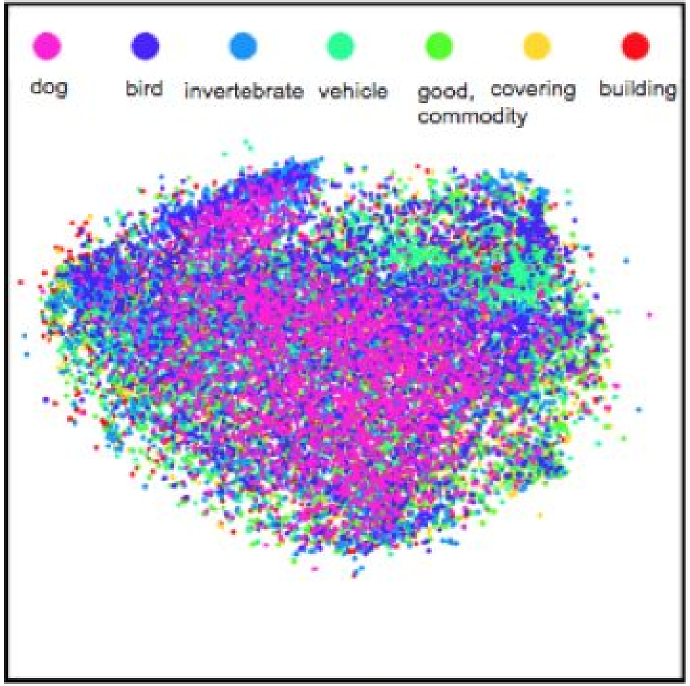
[Sutskever13] I. Sutskever. Training Recurrent Neural Networks.
PhD thesis, University of Toronto, 2013.

[Chopra05] S. Chopra, R. Hadsell, and Y. LeCun. Learning a similarity metric discriminatively, with application to face verification. CVPR, 2005.

END

MORE DETAILS

Why Deep Learning?
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]

Why Deep Learning?

The Unreasonable Effectiveness of Deep Features

Maximal activations of $pool_5$ units [R-CNN]

$conv_5$ DeConv visualization [Zeiler-Fergus]

Rich visual structure of features deep in hierarchy.

Why Deep Learning?

The Unreasonable Effectiveness of Deep Features

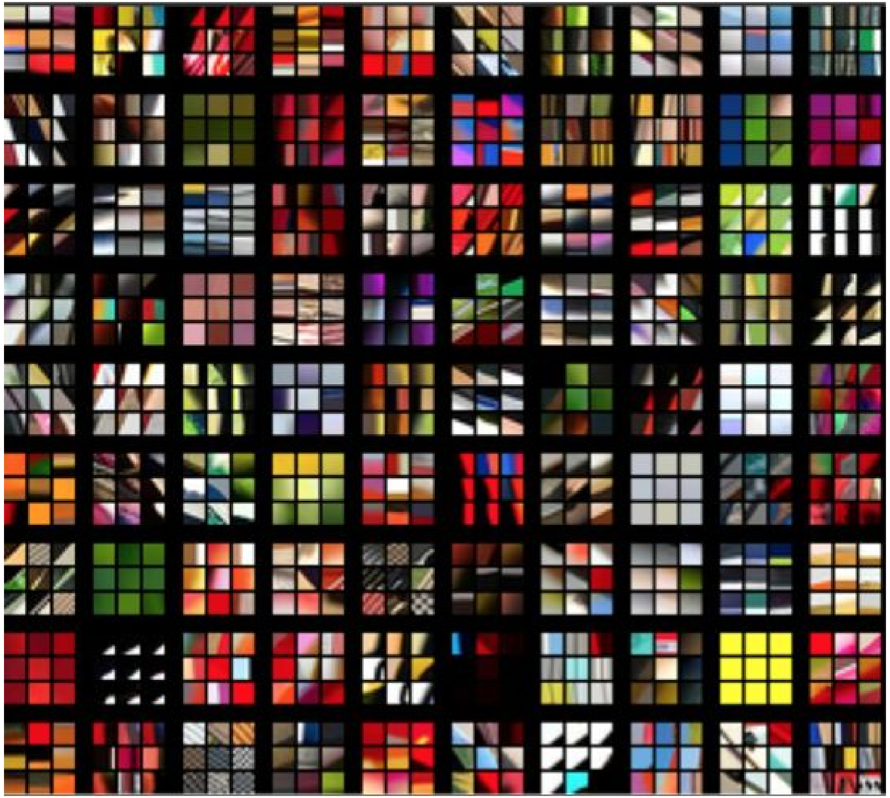
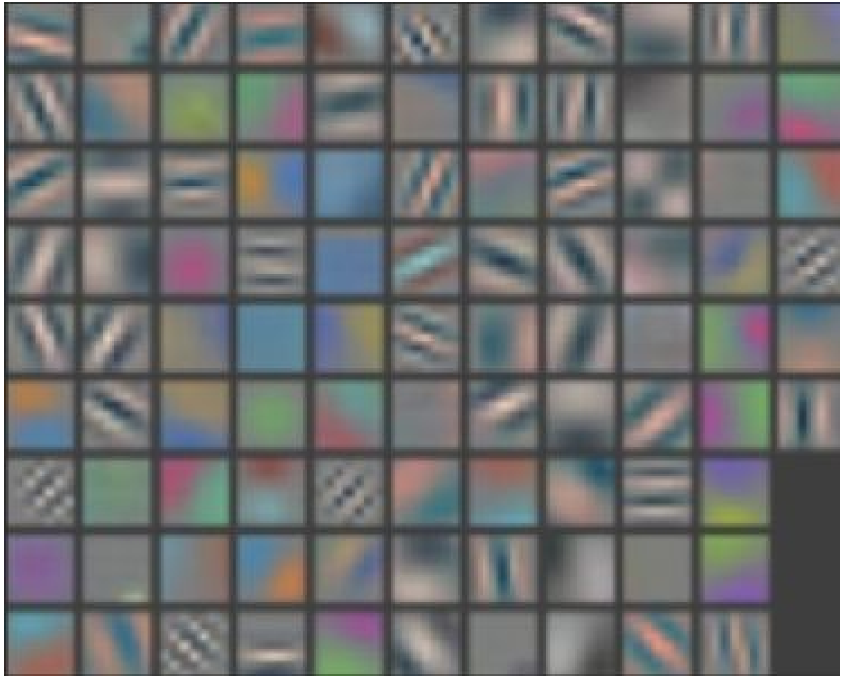


image patches that strongly activate 1st layer filters



1st layer filters

[Zeiler-Fergus]