CMPSCI 370: Intro. to Computer Vision
Deep learning

University of Massachusetts, Amherst
April 19/21, 2016

Instructor: Subhransu Maji

Administrivia

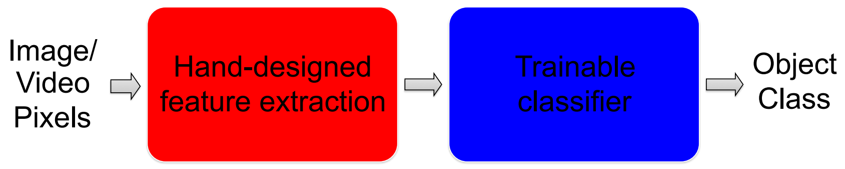
- Finals (everyone)
  - Thursday, May 5, 1-3pm, Hasbrouck 113 — Final exam
  - Tuesday, May 3, 4-5pm, Location: TBD **(Review?)**
  - Syllabus includes everything taught after and including SIFT features. Lectures March 03 onwards.
- Honors section
  - Tuesday, April 26, 4-5pm — 20 min presentation
  - Friday, May 6, midnight — writeup of 4-6 pages

Overview

- Shallow vs. deep architectures
- Background
  - Traditional neural networks
  - Inspiration from neuroscience
- Stages of CNN architecture
- Visualizing CNNs
- State-of-the-art results
- Packages

Many slides are by Rob Fergus and S. Lazebnik

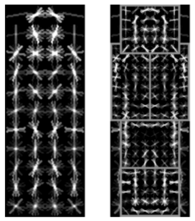
Traditional Recognition Approach

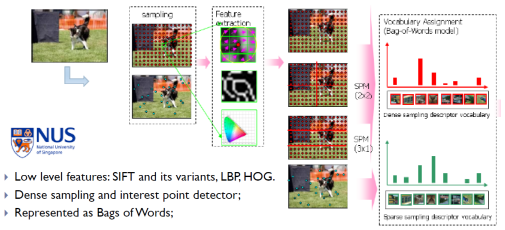


- Features are not learned
- Trainable classifier is often generic (e.g. SVM)

Traditional Recognition Approach

- Features are key to recent progress in recognition
- Multitude of hand-designed features currently in use
  - SIFT, HOG, ...
- Where next? Better classifiers? Or keep building more features?


Felzenszwalb, Girshick, McAllester and Ramanan, PAMI 2007

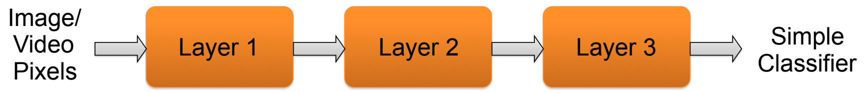

sampling
Feature extraction
SPM (2x2)
SPM (3x1)
Vocabulary Assignment (Bag-of-Words model)
Dense sampling descriptor vocabulary
Sparse sampling descriptor vocabulary
NUS National University of Singapore

- Low level features: SIFT and its variants, LBP, HOG.
- Dense sampling and interest point detector;
- Represented as Bags of Words;

Yan & Huang
(Winner of PASCAL 2010 classification competition)

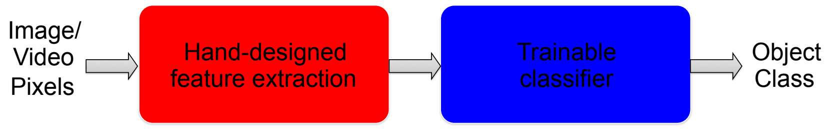
What about learning the features?

- Learn a ***feature hierarchy*** all the way from pixels to classifier
- Each layer extracts features from the output of previous layer
- Train all layers jointly

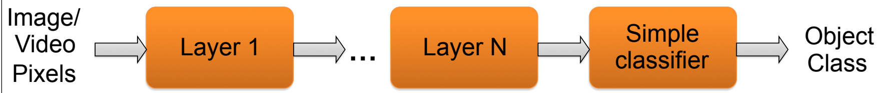


"Shallow" vs. "deep" architectures

Traditional recognition: "Shallow" architecture



Deep learning: "Deep" architecture



Artificial neural networks

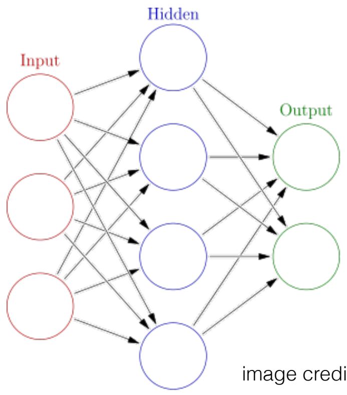
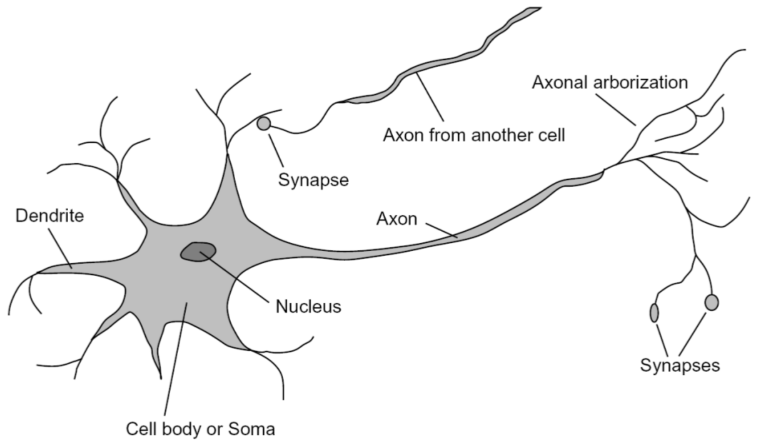


image credit wikipedia

- Artificial neural network is a group of interconnected nodes
- Circles here represent artificial "neurons"
- Note the directed arrows (denoting the flow of information)

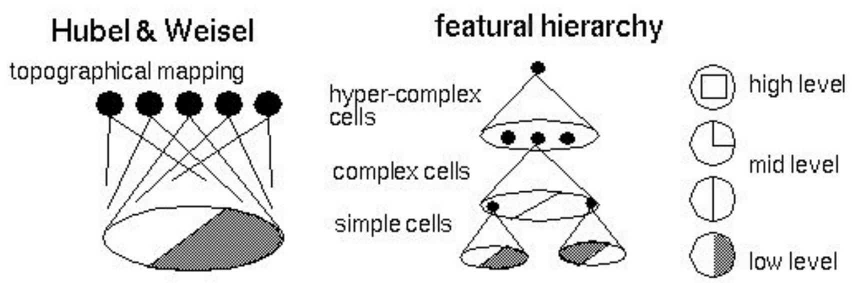
Inspiration: Neuron cells



http://en.wikipedia.org/wiki/Neuron

Hubel/Wiesel Architecture

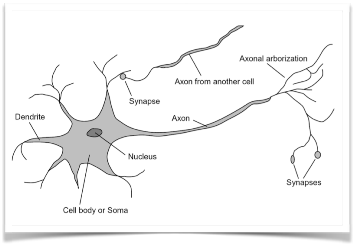
- D. Hubel and T. Wiesel (1959, 1962, Nobel Prize 1981)
- Visual cortex consists of a hierarchy of simple, complex, and hyper-complex cells



Source

Perceptron: a single neuron

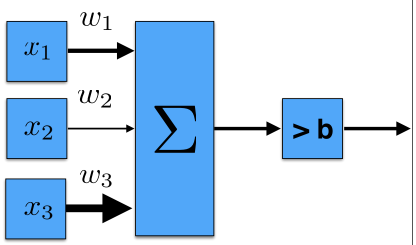
- Basic unit of computation
  - Input are feature values
  - Each feature has a weight
  - Sum in the activation



$$\text{activation}(\mathbf{w}, \mathbf{x}) = \sum_i w_i x_i = \mathbf{w}^T\mathbf{x}$$

- If the activation is:
  - > b, output *class 1*
  - otherwise, output *class 2*

$$\mathbf{x} \rightarrow (\mathbf{x}, 1)$$
$$\mathbf{w}^T\mathbf{x} + b \rightarrow (\mathbf{w}, b)^T(\mathbf{x}, 1)$$



Example: Spam

- Imagine 3 features (spam is "positive" class):
  - free (number of occurrences of "free")
  - money (number of occurrences of "money")
  - BIAS (intercept, always has value 1)

email	$\mathbf{x}$	$\mathbf{w}$	$\mathbf{w}^T\mathbf{x}$
"free money"	BIAS : 1 free : 1 money : 1 ...	BIAS : -3 free : 4 money : 2 ...	(1)(−3) + (1)(4) + (1)(2) + ... = 3

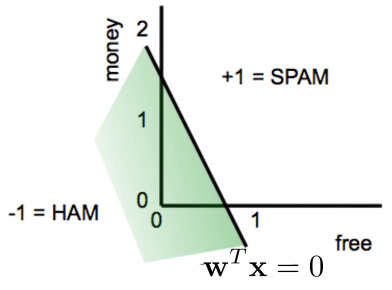
$$\mathbf{w}^T\mathbf{x} > 0 \rightarrow \text{SPAM!!}$$

Geometry of the perceptron

- In the space of feature vectors
  - examples are points (in D dimensions)
  - an weight vector is a hyperplane (a D-1 dimensional object)
  - One side corresponds to y=+1
  - Other side corresponds to y=-1
- Perceptrons are also called as linear classifiers

$\mathbf{w}$

```
BIAS  : -3
free  :  4
money :  2
...
```



$\mathbf{w}^T\mathbf{x} = 0$

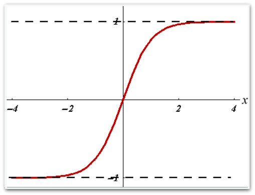
Two-layer network architecture

$$y = \mathbf{v}^T\mathbf{h}$$

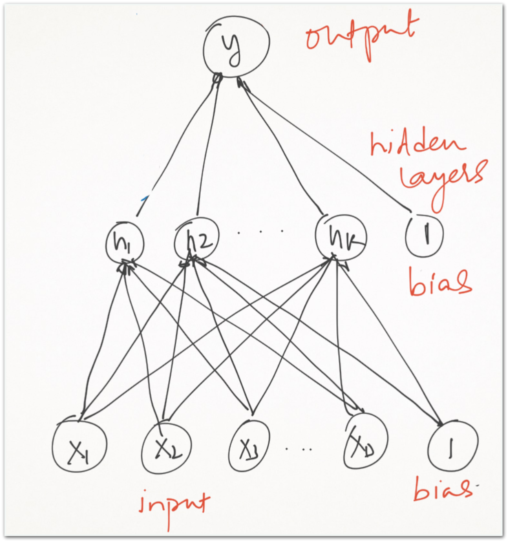
Non-linearity is important

link function

$$h_i = f(\mathbf{w}_i^T\mathbf{x})$$



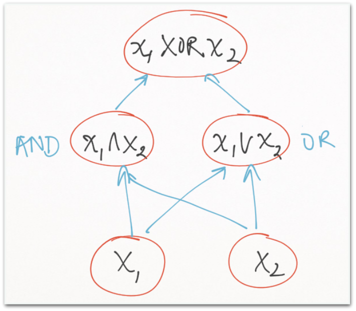
$$\tanh(x) = \frac{1-e^{-2x}}{1+e^{-2x}}$$



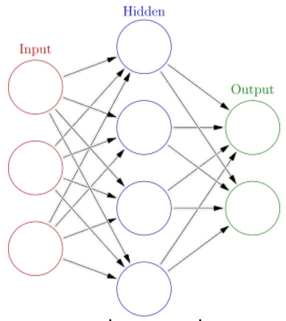
The XOR function

- Can a single neuron learn the XOR function?
- **Exercise:** come up with the parameters of a two layer network with two hidden units that computes the XOR function
  - Here is a table for the XOR function

y	x_1	x_2
+1	+1	+1
+1	-1	-1
-1	+1	-1
-1	-1	+1



Training ANNs



we know the desired output

"Chain rule" of gradient

d**f**(**g**(x))/dx = (d**f**/d**g**)(d**g**/dx)

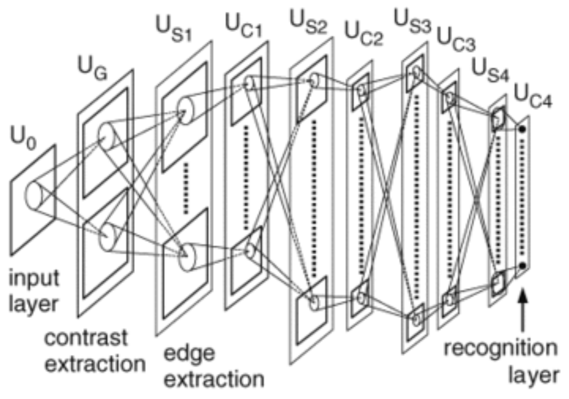
- **Back-propagate** the gradients to match the outputs
- Were too impractical till computers became faster

http://page.mi.fu-berlin.de/rojas/neural/chapter/K7.pdf

Issues with ANNs

- In the 1990s and early 2000s, simpler and faster learning methods such as linear classifiers, nearest neighbor classifiers, and decision trees were favored over ANNs.
- Why?
  - Need many layers to learn good features — many parameters need to be learned
  - Needs vast amounts of training data (related to the earlier point)
  - Training using gradient descent is slow, get stuck in local minima

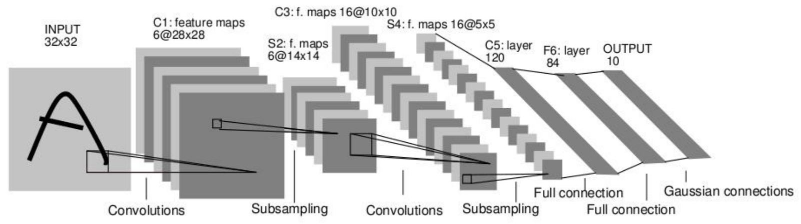
ANNs for vision



The **neocognitron**, by Fukushima (1980)
(But he didn't propose a way to learn these models)

Convolutional Neural Networks

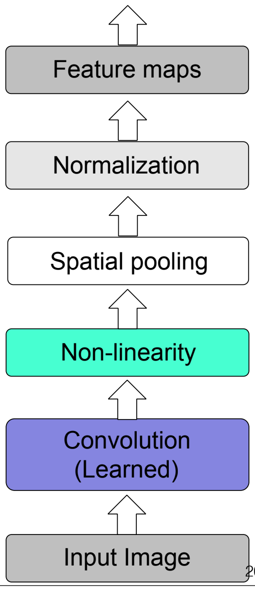
- Neural network with specialized connectivity structure
- Stack multiple stages of feature extractors
- Higher stages compute more global, more invariant features
- Classification layer at the end



Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86(11): 2278–2324, 1998.

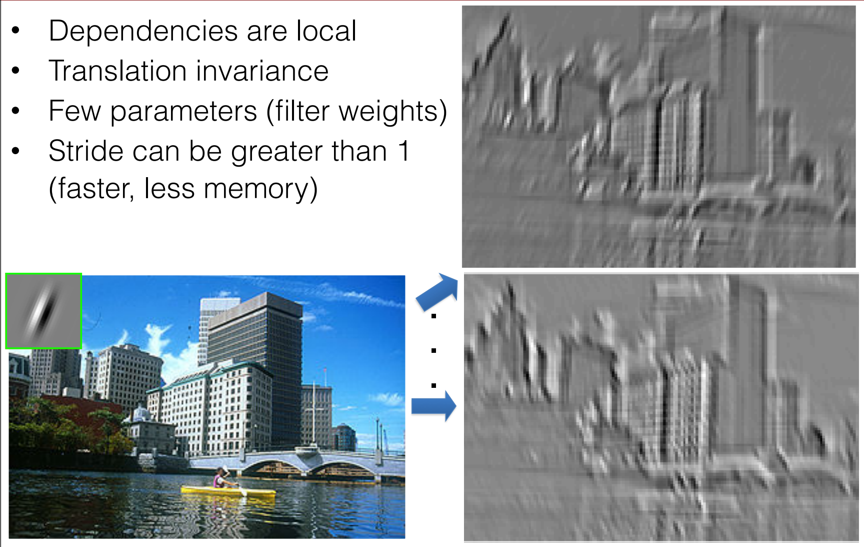
Convolutional Neural Networks

- Feed-forward feature extraction:
  1. Convolve input with learned filters
  2. Non-linearity
  3. Spatial pooling
  4. Normalization
- Supervised training of convolutional filters by back-propagating classification error



1. Convolution

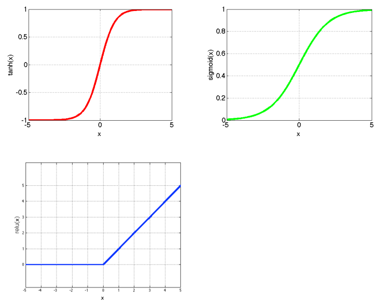
- Dependencies are local
- Translation invariance
- Few parameters (filter weights)
- Stride can be greater than 1 (faster, less memory)


Input
Feature Map

2. Non-Linearity

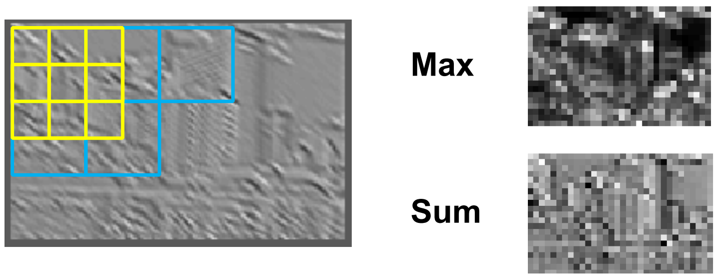
- Per-element (independent)
- Options:
  - Tanh
  - Sigmoid: 1/(1+exp(-x))
  - Rectified linear unit (ReLU)
    - Simplifies backpropagation
    - Makes learning faster
    - Avoids saturation issues

    → Preferred option



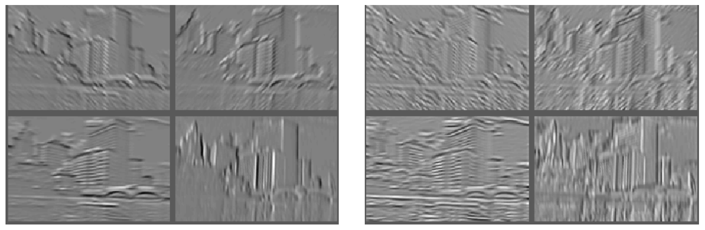
3. Spatial Pooling

- Sum or max
- Non-overlapping / overlapping regions
- Role of pooling:
  - Invariance to small transformations
  - Larger receptive fields (see more of input)



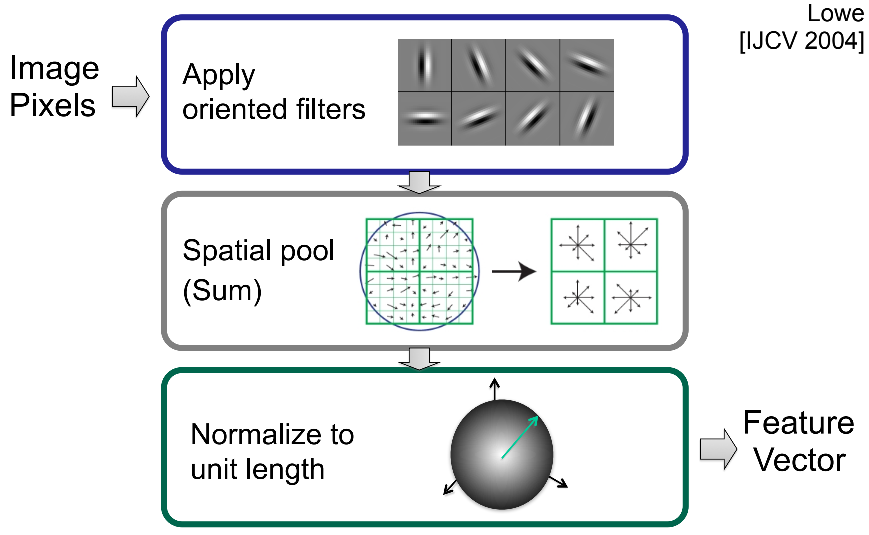
4. Normalization

- Within or across feature maps
- Before or after spatial pooling


Feature Maps
Feature Maps After Contrast Normalization

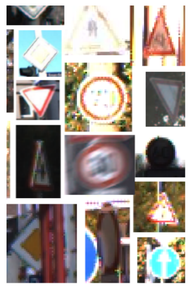
Compare: SIFT Descriptor

Lowe
[IJCV 2004]



CNN successes

- Handwritten text/digits
  - MNIST (0.17% error [Ciresan et al. 2011])
  - Arabic & Chinese [Ciresan et al. 2012]
- Simpler recognition benchmarks
  - CIFAR-10 (9.3% error [Wan et al. 2013])
  - Traffic sign recognition
    - 0.56% error vs 1.16% for humans [Ciresan et al. 2011]
- But until recently, less good at more complex datasets
  - Caltech-101/256 (few training examples)



ImageNet Challenge 2012

[Deng et al. CVPR 2009]

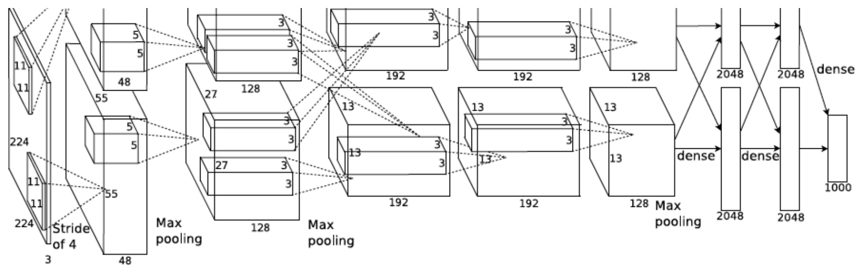
IMAGENET

- 14+ million labeled images, 20k classes
- Images gathered from Internet
- Human labels via Amazon Turk
- The challenge: 1.2 million training images, 1000 classes

A. Krizhevsky, I. Sutskever, and G. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012

ImageNet Challenge 2012

- Similar framework to LeCun'98 but:
  - Bigger model (7 hidden layers, 650,000 units, 60,000,000 params)
  - More data (10^6 vs. 10^3 images)
  - GPU implementation (50x speedup over CPU)
    - Trained on two GPUs for a week
  - Better regularization for training (DropOut)

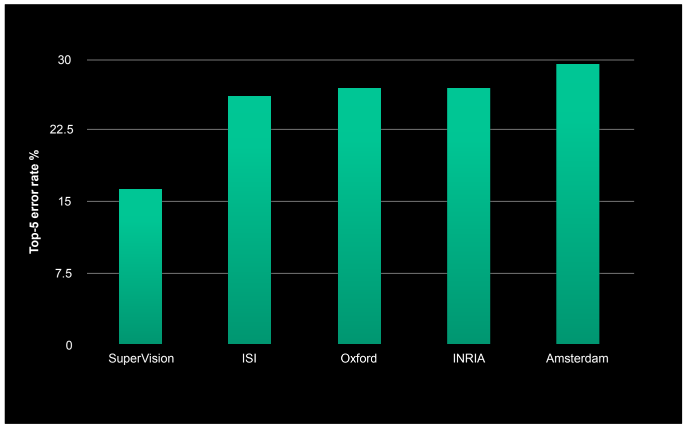


A. Krizhevsky, I. Sutskever, and G. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012

ImageNet Challenge 2012

Krizhevsky et al. -- **16.4% error** (top-5)

Next best (SIFT + Fisher vectors) – **26.2% error**



Visualizing CNNs

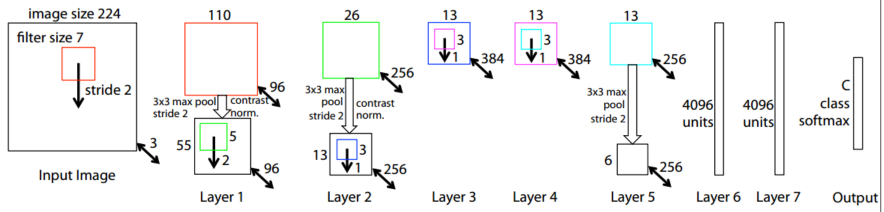
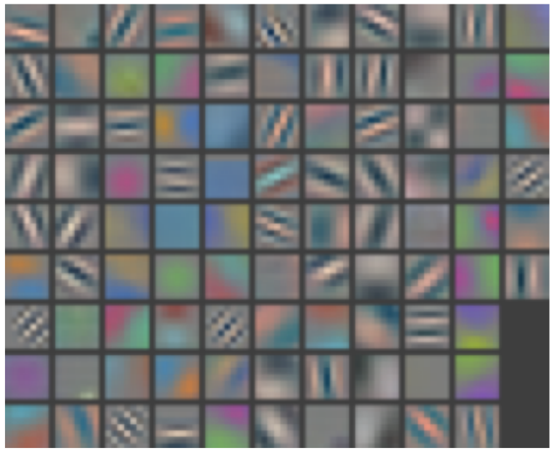


Figure 3. Architecture of our 8 layer convnet model. A 224 by 224 crop of an image (with 3 color planes) is presented as the input. This is convolved with 96 different 1st layer filters (red), each of size 7 by 7, using a stride of 2 in both x and y. The resulting feature maps are then: (i) passed through a rectified linear function (not shown), (ii) pooled (max within 3x3 regions, using stride 2) and (iii) contrast normalized across feature maps to give 96 different 55 by 55 element feature maps. Similar operations are repeated in layers 2,3,4,5. The last two layers are fully connected, taking features from the top convolutional layer as input in vector form ($6 \cdot 6 \cdot 256 = 9216$ dimensions). The final layer is a C-way softmax function, C being the number of classes. All filters and feature maps are square in shape.

M. Zeiler and R. Fergus, Visualizing and Understanding Convolutional Networks, arXiv preprint, 2013

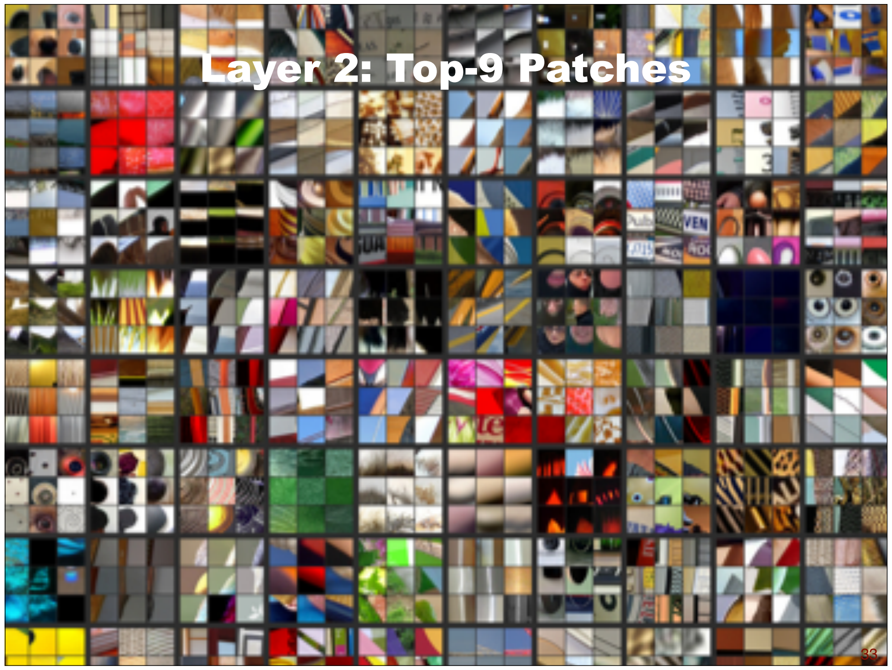
Layer 1 Filters

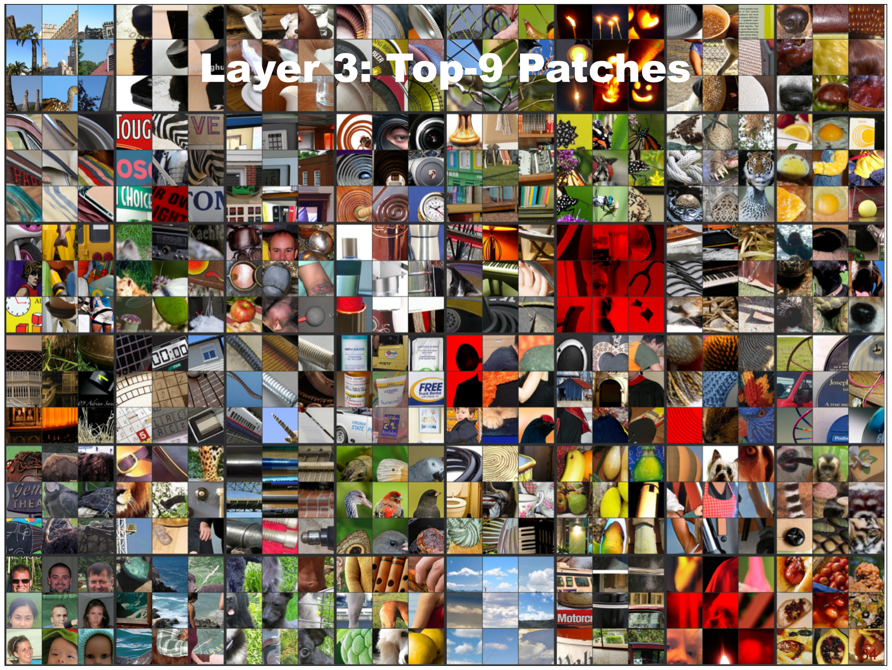


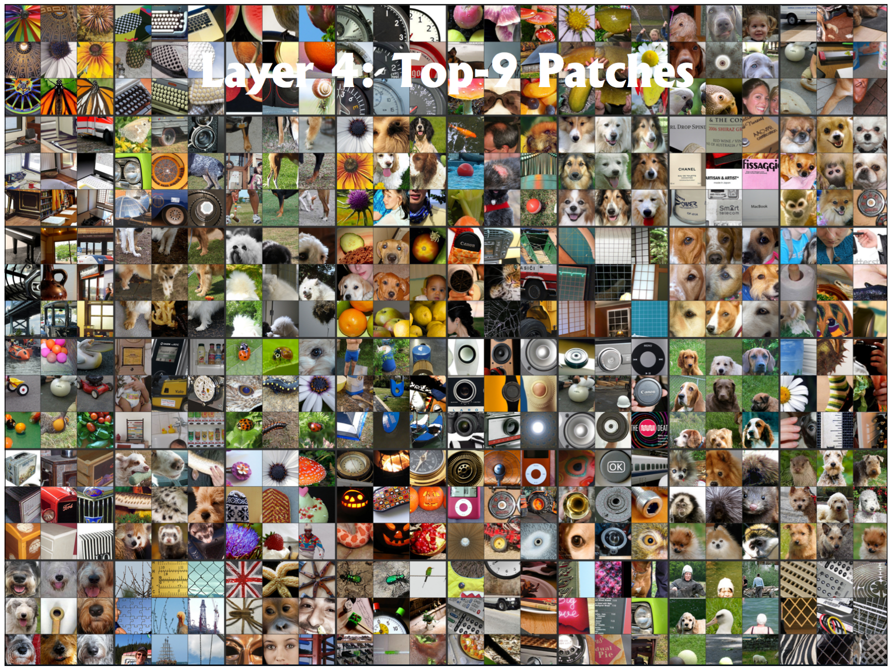
Similar to the filter banks used for texture recognition

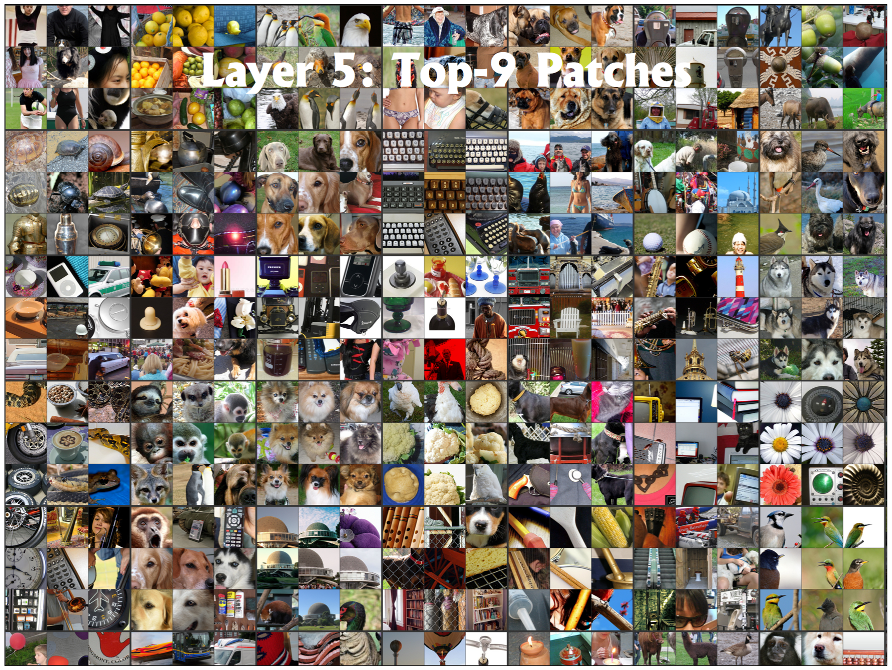
Layer 1: Top-9 Patches

• Patches from validation images that give maximal activation of a given feature map

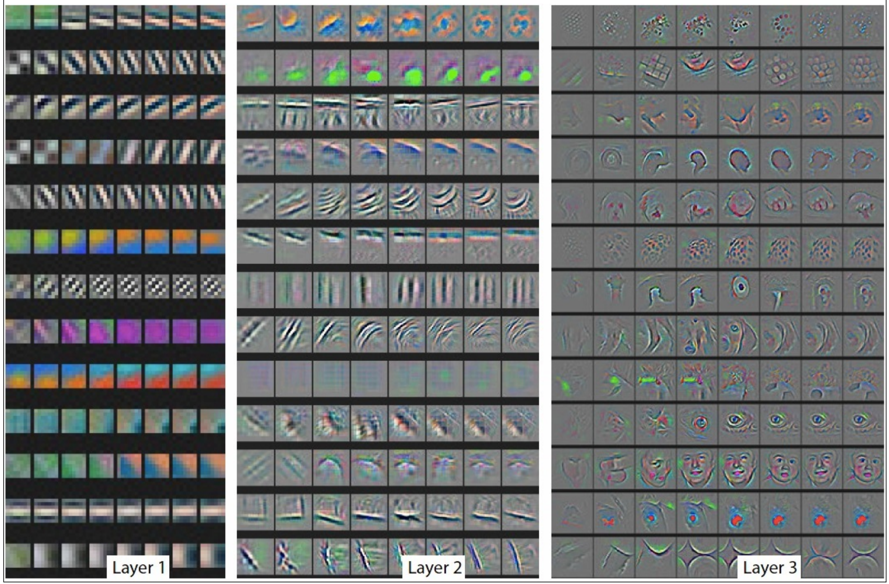

Layer 2: Top-9 Patches


Layer 3: Top-9 Patches

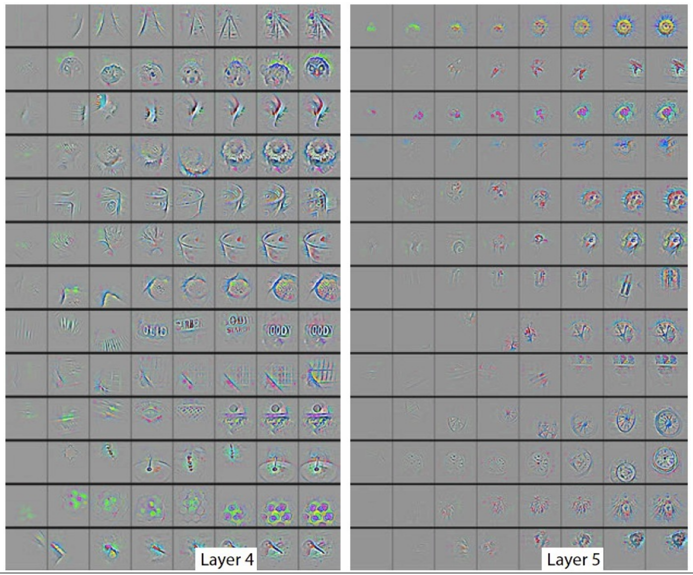

Layer 4: Top-9 Patches


Layer 5: Top-9 Patches

Evolution of Features During Training

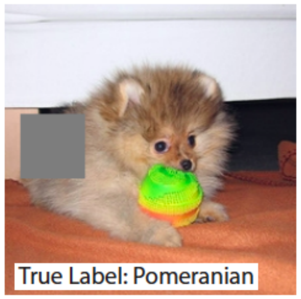


Evolution of Features During Training

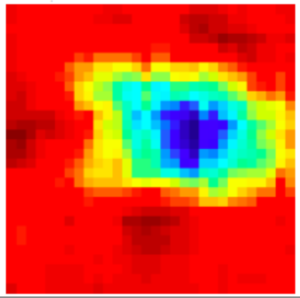


Occlusion Experiment

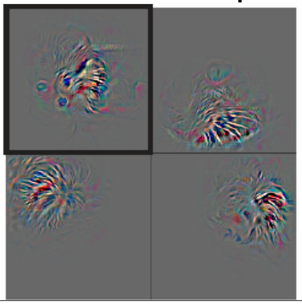
- Mask parts of input with occluding square
- Monitor output (class probability)

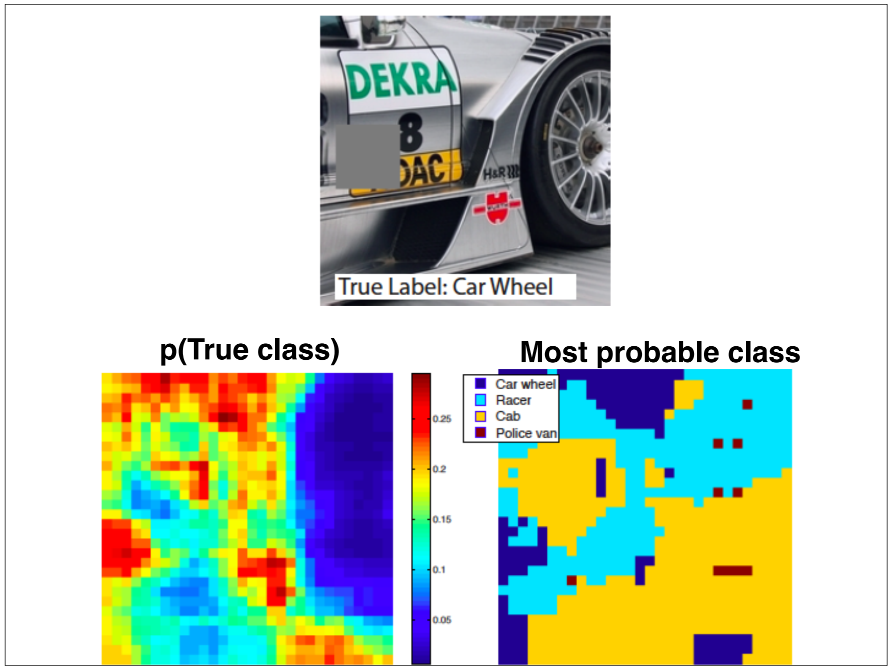


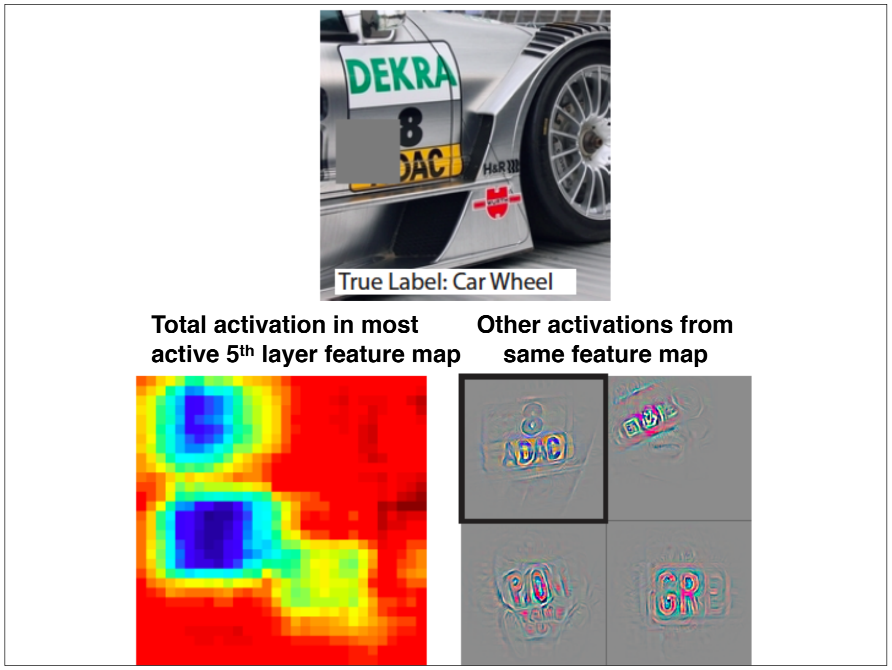
Total activation in most active 5th layer feature map

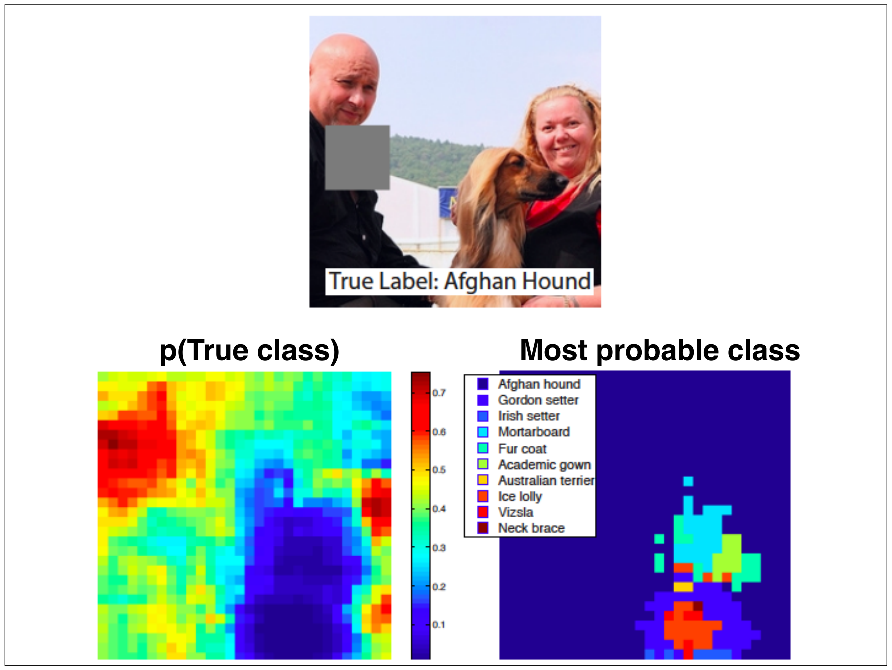


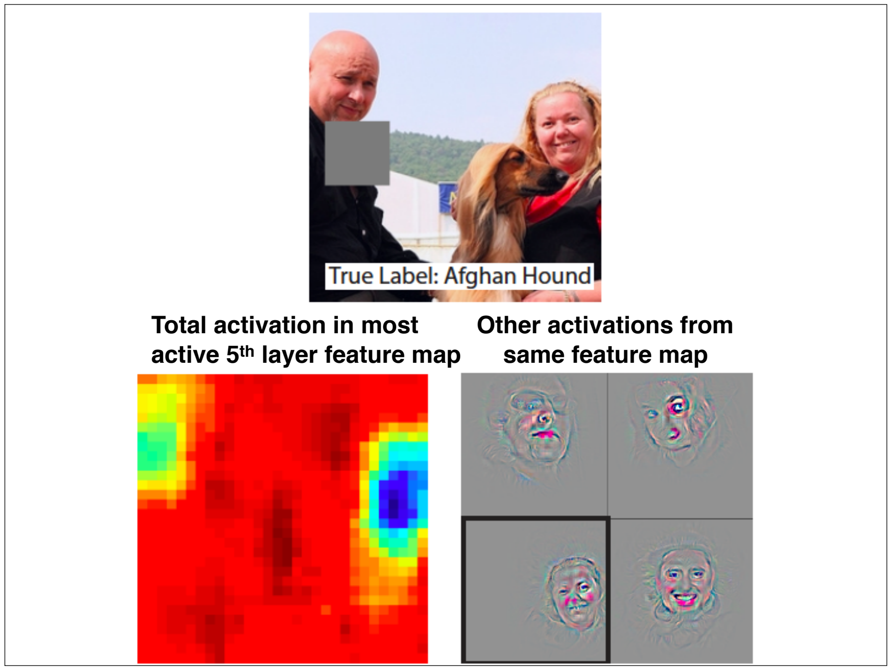
Other activations from same feature map




True Label: Car Wheel
p(True class)
Most probable class
0.25
0.2
0.15
0.1
0.05
Car wheel
Racer
Cab
Police van

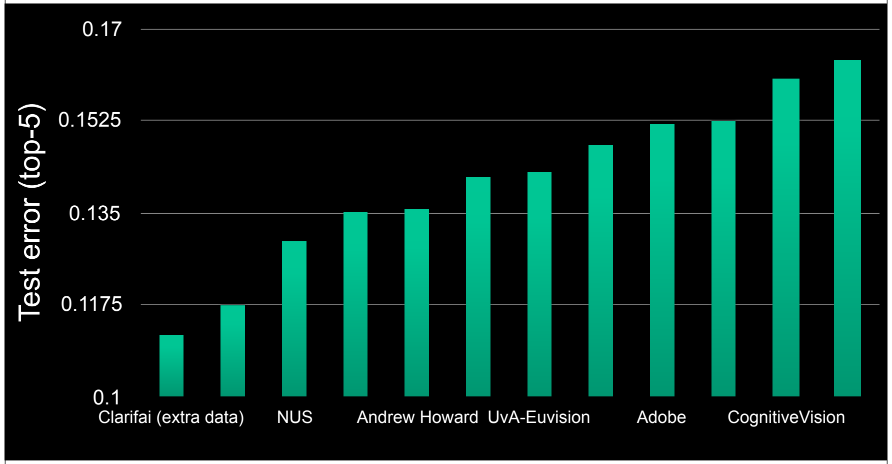

True Label: Car Wheel
Total activation in most active 5th layer feature map
Other activations from same feature map


True Label: Afghan Hound
p(True class)
Most probable class
0.7
0.6
0.5
0.4
0.3
0.2
0.1
Afghan hound
Gordon setter
Irish setter
Mortarboard
Fur coat
Academic gown
Australian terrier
Ice lolly
Vizsla
Neck brace


True Label: Afghan Hound
Total activation in most active 5th layer feature map
Other activations from same feature map

ImageNet Classification 2013 Results

http://www.image-net.org/challenges/LSVRC/2013/results.php



ImageNet 2014 - Test error at 0.07 (Google & Oxford groups)
http://image-net.org/challenges/LSVRC/2014/results

CNNs for small datasets

- Take model trained on ImageNet
- Take outputs of 6th or 7th layer before or after nonlinearity as features
- Train linear SVMs on these features (like retraining the last layer of the network)
- Optionally back-propagate: fine-tune features and/or classifier on new dataset

Tapping off features at each Layer

Plug features from each layer into linear SVM

	Cal-101 (30/class)	Cal-256 (60/class)
SVM (1)	44.8 ± 0.7	24.6 ± 0.4
SVM (2)	66.2 ± 0.5	39.6 ± 0.3
SVM (3)	72.3 ± 0.4	46.0 ± 0.3
SVM (4)	76.6 ± 0.4	51.3 ± 0.1
SVM (5)	$\mathbf{86.2 \pm 0.8}$	65.6 ± 0.3
SVM (7)	$\mathbf{85.5 \pm 0.4}$	$\mathbf{71.7 \pm 0.2}$

Higher layers are better

Results on benchmarks

[1] Caltech-101 (30 samples per class)

	DeCAF_5	DeCAF_6	DeCAF_7
LogReg	63.29 ± 6.6	84.30 ± 1.6	84.87 ± 0.6
LogReg with Dropout	-	86.08 ± 0.8	85.68 ± 0.6
SVM	77.12 ± 1.1	84.77 ± 1.2	83.24 ± 1.2
SVM with Dropout	-	$\mathbf{86.91 \pm 0.7}$	85.51 ± 0.9
Yang et al. (2009)		84.3	
Jarrett et al. (2009)		65.5	

[1] SUN 397 dataset (DeCAF)

	DeCAF_6	DeCAF_7
LogReg	$\mathbf{40.94 \pm 0.3}$	40.84 ± 0.3
SVM	39.36 ± 0.3	40.66 ± 0.3
Xiao et al. (2010)	38.0	

[1] Caltech-UCSD Birds (DeCAF)

Method	Accuracy
DeCAF_6	58.75
DPD + DeCAF_6	**64.96**
DPD (Zhang et al., 2013)	50.98
POOF (Berg & Belhumeur, 2013)	56.78

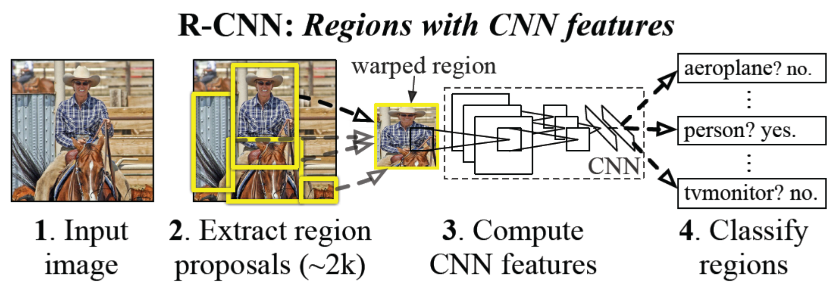
[2] MIT-67 Indoor Scenes dataset (OverFeat)

Method	mean Accuracy
ROI + Gist[36]	26.05
DPM[30]	30.40
Object Bank[25]	37.60
RBow[31]	37.93
BoP[22]	46.10
miSVM[26]	46.40
D-Parts[40]	51.40
IFV[22]	60.77
MLrep[11]	**64.03**
CNN-SVM	58.44

[1] 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**, arXiv preprint, 2014

[2] A. Razavian, H. Azizpour, J. Sullivan, and S. Carlsson, **CNN Features off-the-shelf: an Astounding Baseline for Recognition**, arXiv preprint, 2014

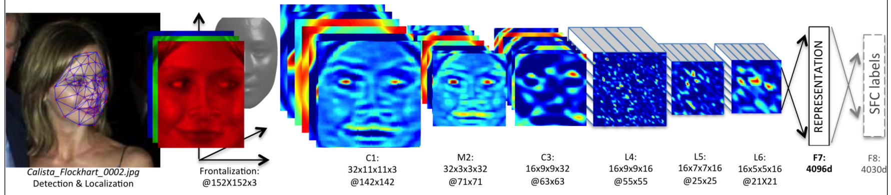
CNN features for detection

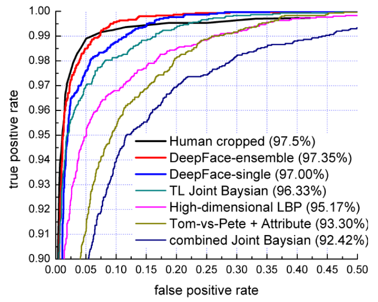


R-CNN achieves mAP of **53.7%** on PASCAL VOC 2010
For comparison, **Uijlings et al. (2013)** report **35.1%** mAP using the *same region proposals*, but with a spatial pyramid and bag-of-visual-words approach.
Part-based model with HOG (DPM, Poselets) ~ **33.5%**

R. Girshick, J. Donahue, T. Darrell, and J. Malik, **Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation**, CVPR 2014

CNN features for face verification





Y. Taigman, M. Yang, M. Ranzato, L. Wolf, DeepFace: Closing the Gap to Human-Level Performance in Face Verification, CVPR 2014, to appear.

Open-source CNN software

- **Cuda-convnet** (Alex Krizhevsky, Google)
  - High speed convolutions on the GPU
- **Caffe** (Y. Jia, Berkeley)
  - Replacement of deprecated **Decaf**
  - High performance CNNs
  - Flexible CPU/GPU computations
- **Overfeat** (NYU)
- **MatConvNet** (Andrea Vedaldi, Oxford)
  - An easy to use toolbox for CNNs from MATLAB
  - Comparable performance/features with Caffe