CVPR 2014 Tutorial

Deep Learning for Computer Vision

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https://sites.google.com/site/deeplearningcvpr2014

Tutorial Overview

https://sites.google.com/site/deeplearningcvpr2014

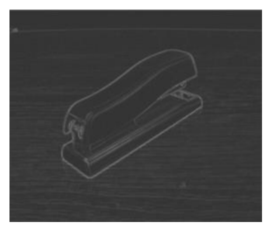
- Basics
  - Introduction - Honglak Lee
  - Supervised Learning - Marc'Aurelio Ranzato
  - Unsupervised Learning - Graham Taylor
- Libraries
  - Torch7 - Marc'Aurelio Ranzato
  - Theano/Pylearn2 - Ian Goodfellow
  - CAFFE - Yangqing Jia
- Advanced topics
  - Object detection - Pierre Sermanet
  - Regression methods for localization - Alex Toshev
  - Large scale classification and GPU parallelization - Alex Krizhevsky
  - Learning transformations from videos - Roland Memisevic
  - Multimodal and multi task learning - Honglak Lee
  - Structured prediction - Yann LeCun

Traditional Recognition Approach

Features are not learned

Input data (pixels) → feature representation (hand-crafted) → Learning Algorithm (e.g., SVM)

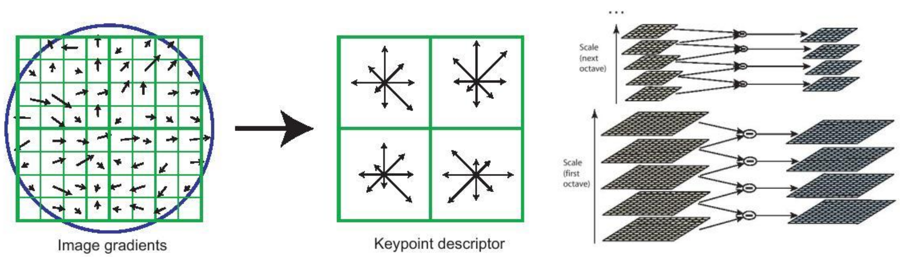
Image



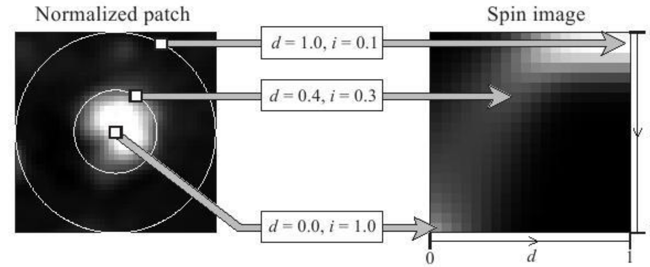
Low-level vision features (edges, SIFT, HOG, etc.)

Object detection / classification

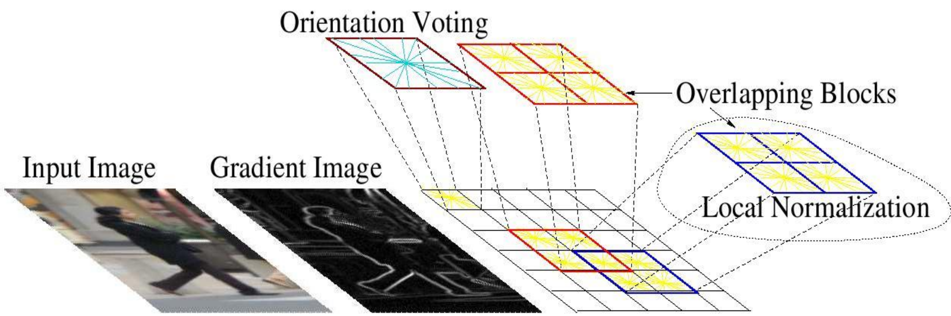
Computer vision features



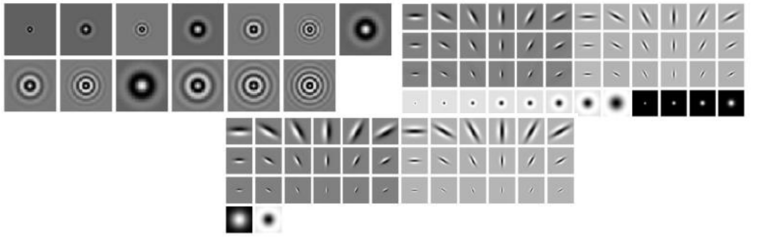
SIFT



Spin image



HoG



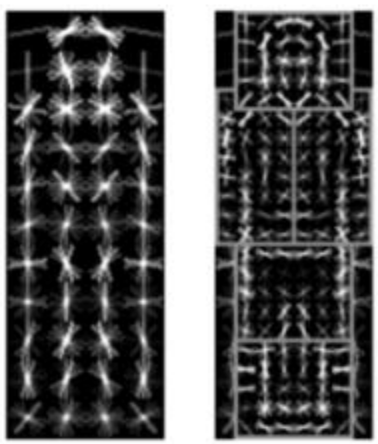
Textons

and many others:

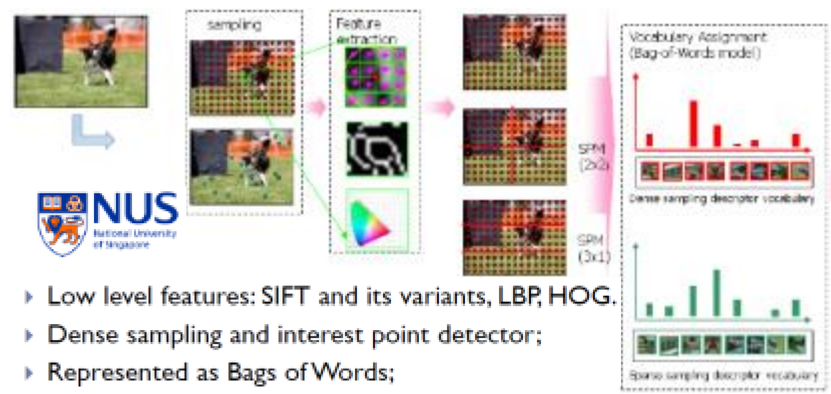
SURF, MSER, LBP, Color-SIFT, Color histogram, GLOH, …..

Motivation

- Features are key to recent progress in recognition
- Multitude of hand-designed features currently in use
- Where next? Better classifiers? building better features?



Felzenszwalb, Girshick,
McAllester and Ramanan, PAMI 2007



Yan & Huang
(Winner of PASCAL 2010 classification competition)

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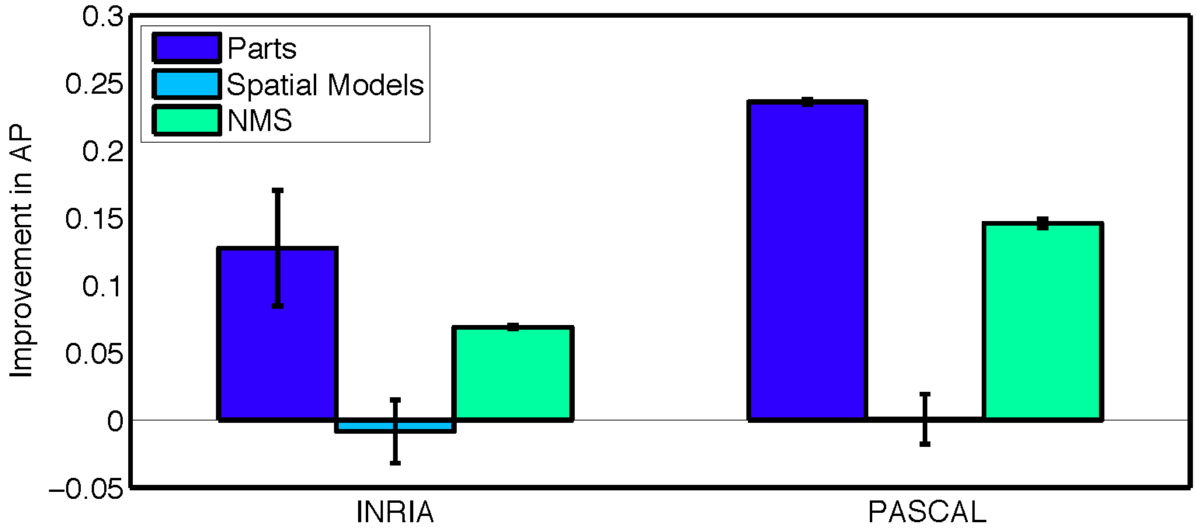
What Limits Current Performance?

- Ablation studies on Deformable Parts Model
  - Felzenszwalb, Girshick, McAllester, Ramanan, PAMI’10
- Replace each part with humans (Amazon Turk):



Parikh & Zitnick, CVPR’10

- Also removal of part deformations has small (<2%) effect.
  - Are “Deformable Parts” necessary in the Deformable Parts Model? Divvala, Hebert, Efros, ECCV 2012

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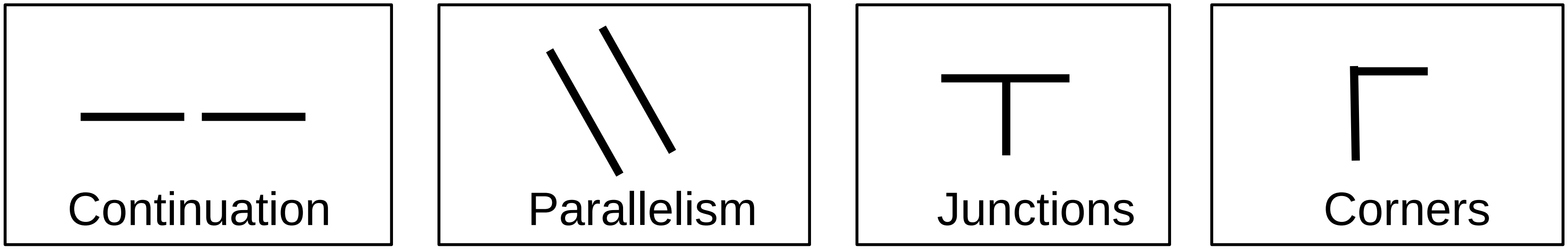
Mid-Level Representations

- Mid-level cues



"Tokens" from Vision by D.Marr:

- Object parts:

- Difficult to hand-engineer → What about learning them?

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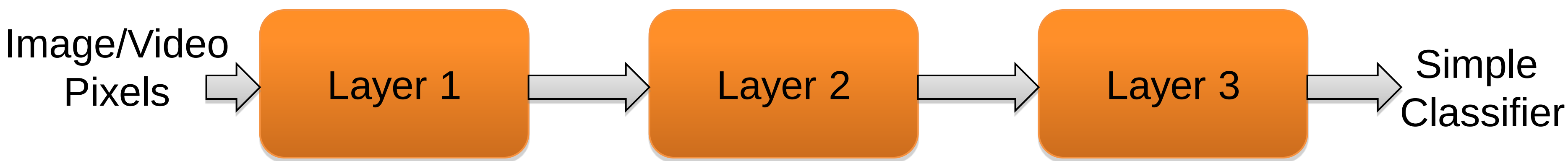
Learning Feature Hierarchy

- Learn hierarchy
- All the way from pixels → classifier
- One layer extracts features from output of previous layer



- Train all layers jointly

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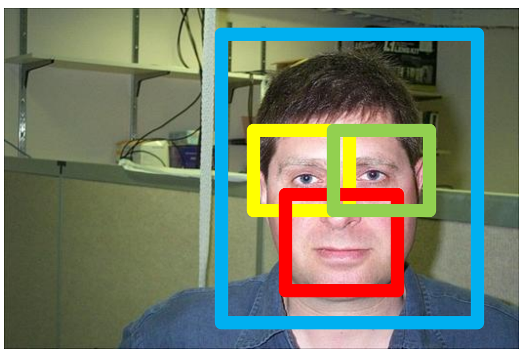
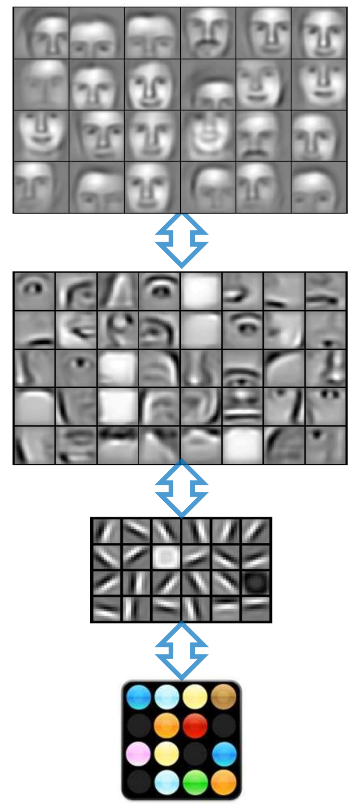
Learning Feature Hierarchy

1. Learn **useful higher-level features** from images

Input data



Feature representation



3rd layer
"Objects"

2nd layer
"Object parts"

1st layer
"Edges"

Pixels

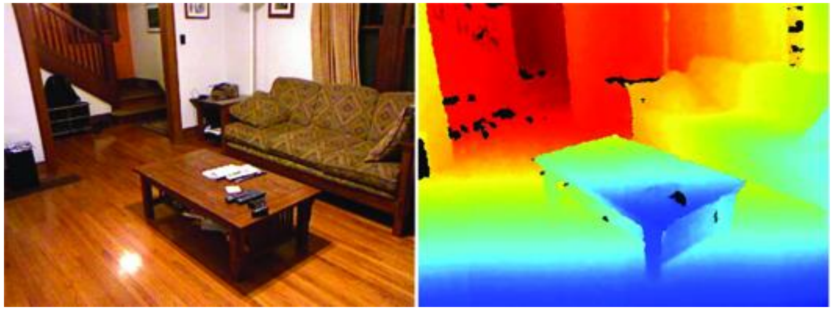
Lee et al., ICML 2009;
CACM 2011

2. **Fill in representation gap** in recognition

Learning Feature Hierarchy

- Better performance

- Other domains (unclear how to hand engineer):
  - Kinect
  - Video
  - Multi spectral



- Feature computation time
  - Dozens of features now regularly used [e.g., MKL]
  - Getting prohibitive for large datasets (10’s sec /image)

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Approaches to learning features

- Supervised Learning
  - End-to-end learning of deep architectures (e.g., deep neural networks) with back-propagation
  - Works well when the amounts of labels is large
  - Structure of the model is important (e.g. convolutional structure)

- Unsupervised Learning
  - Learn statistical structure or dependencies of the data from unlabeled data
  - Layer-wise training
  - Useful when the amount of labels is not large

Taxonomy of feature learning methods

Supervised

- Support Vector Machine
- Logistic Regression
- Perceptron

- Deep Neural Net
- Convolutional Neural Net
- Recurrent Neural Net

Shallow **Deep**

- Denoising Autoencoder
- Restricted Boltzmann machines*
- Sparse coding*

- Deep (stacked) Denoising Autoencoder*
- Deep Belief Nets*
- Deep Boltzmann machines*
- Hierarchical Sparse Coding*

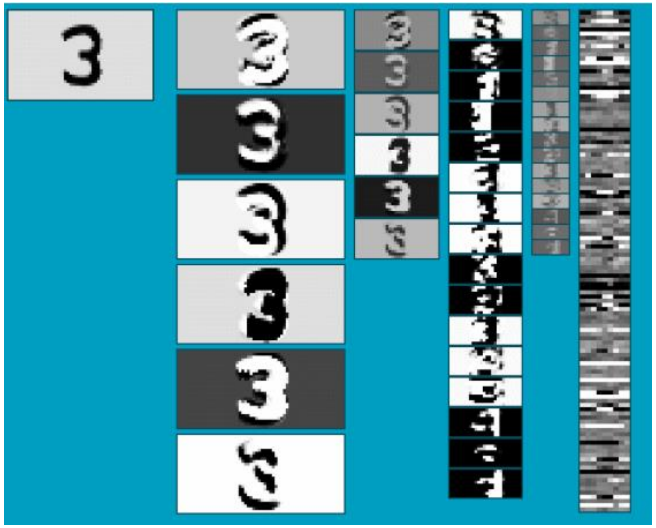
Unsupervised

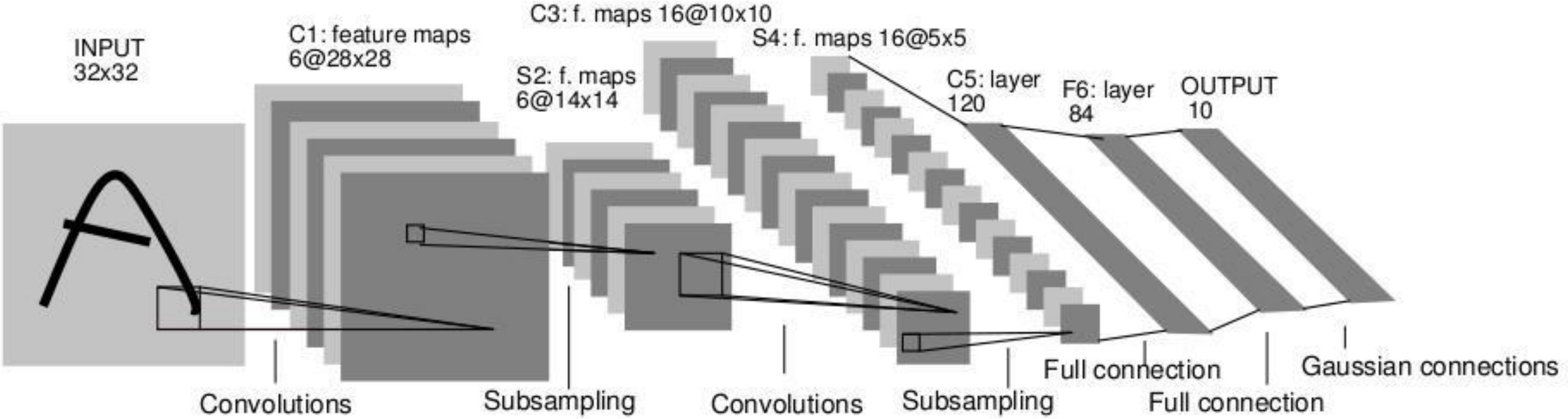
* supervised version exists

Supervised Learning

Example: Convolutional Neural Networks

- LeCun et al. 1989
- Neural network with specialized connectivity structure





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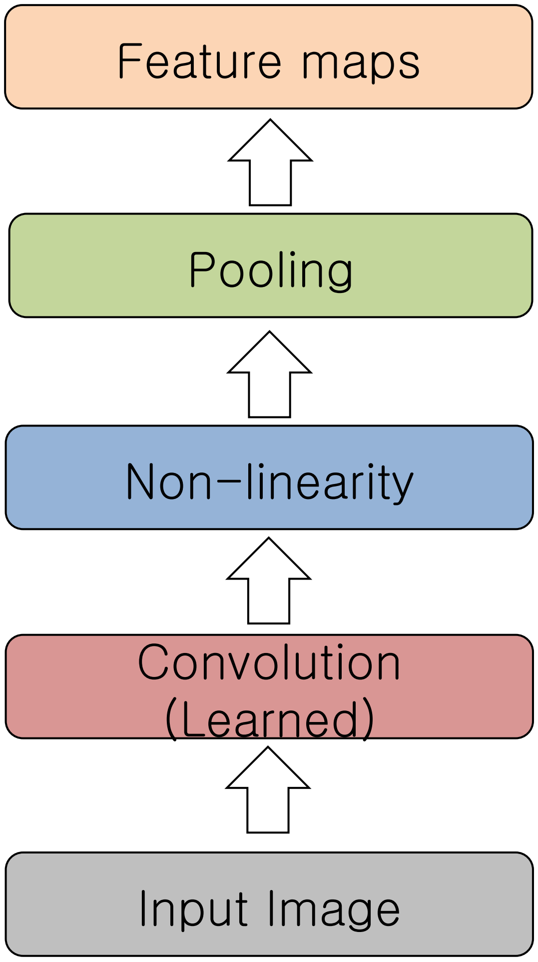
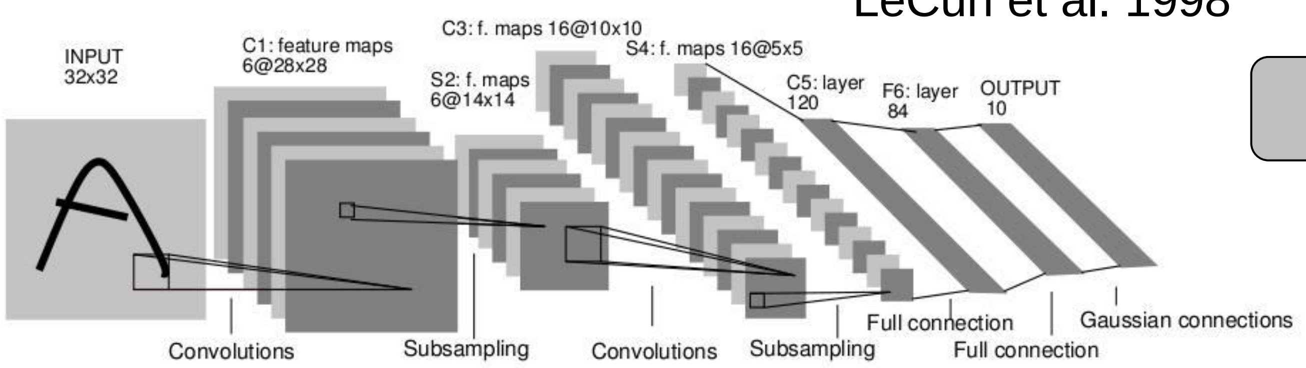
Convolutional Neural Networks

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



LeCun et al. 1998



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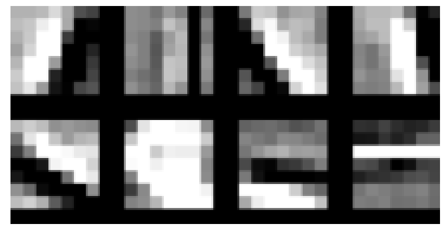
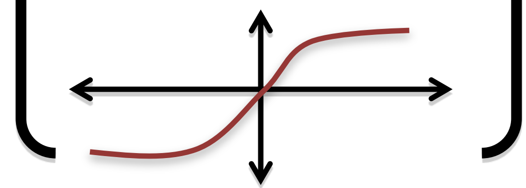
Components of Each Layer

Pixels /
Features

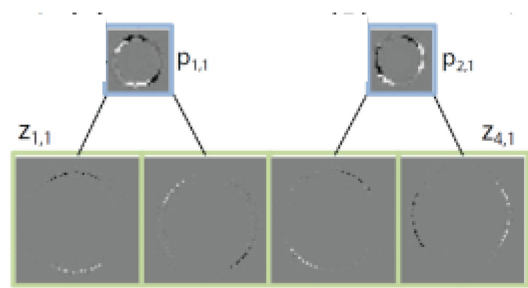
Filter with
Dictionary
(convolutional
or tiled)



+ Non-linearity



Spatial/Feature
(Sum or Max)



[Optional]

Normalization
between
feature
responses

Output
Features

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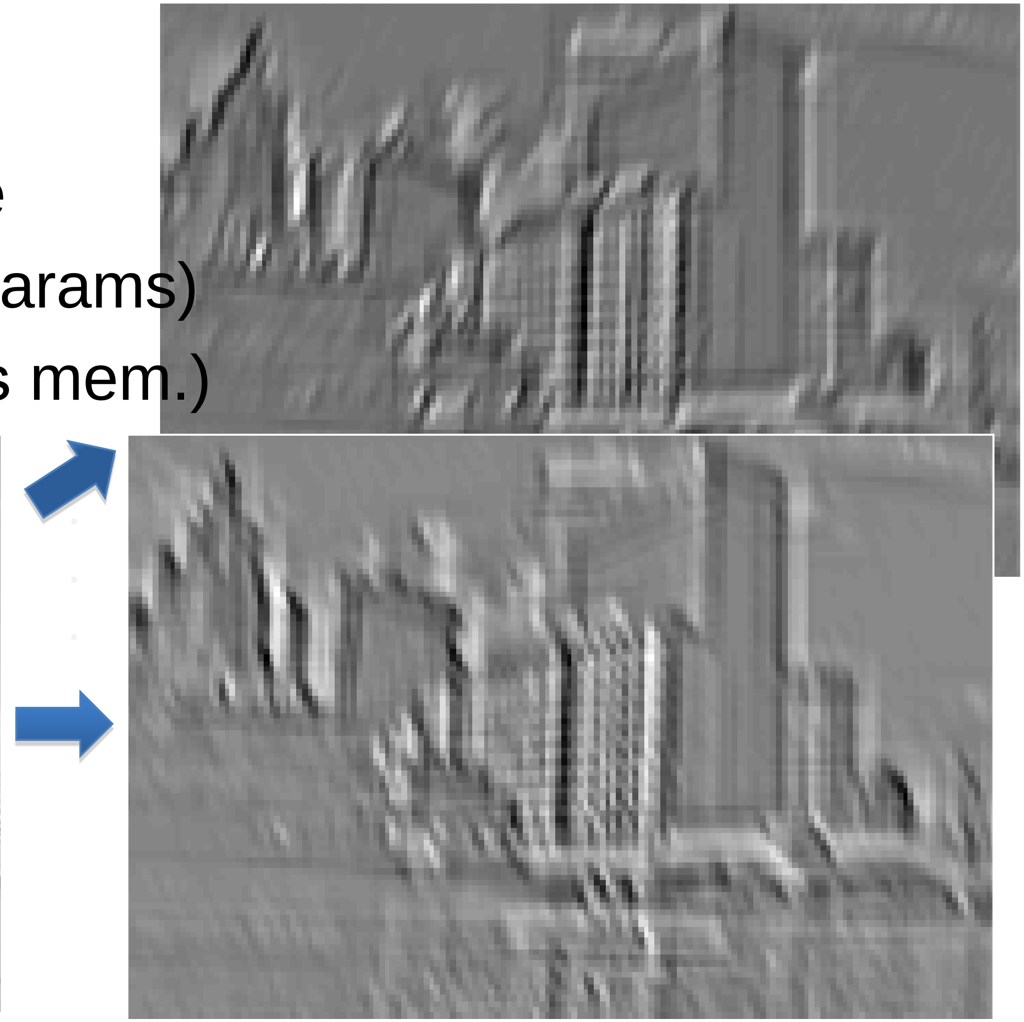
Filtering

- Convolutional
  - Dependencies are local
  - Translation equivariance
  - Tied filter weights (few params)
  - Stride 1,2,… (faster, less mem.)

Input



Feature Map

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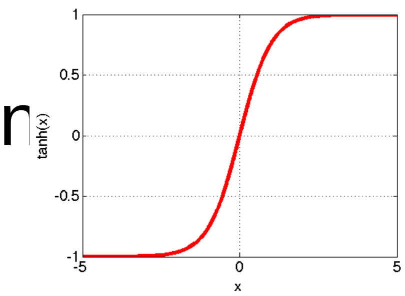
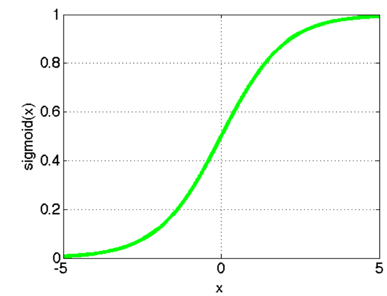
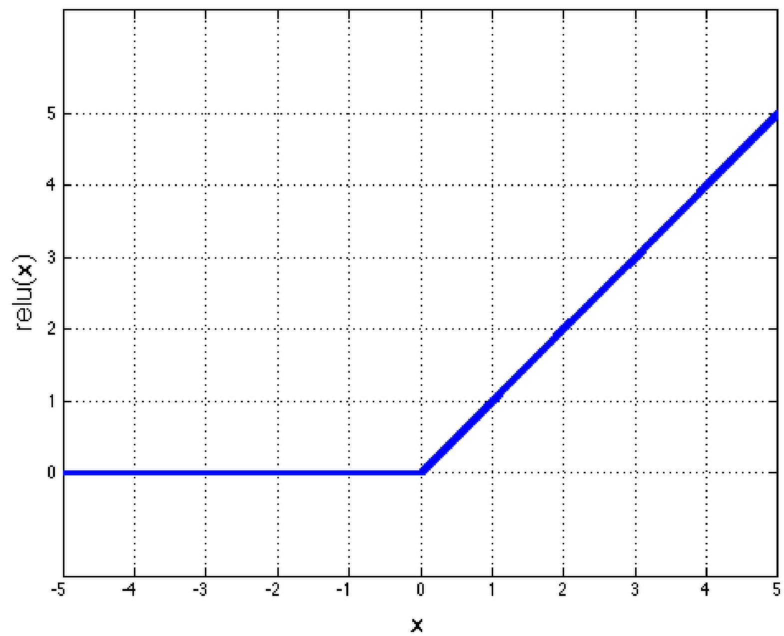
Non-Linearity

- Non-linearity
  - – Per-element (independen
  - – Tanh
  - – Sigmoid: 1/(1+exp(-x))
  - – Rectified linear
    - Simplifies backprop
    - Makes learning faster
    - Avoids saturation issues

    → Preferred option







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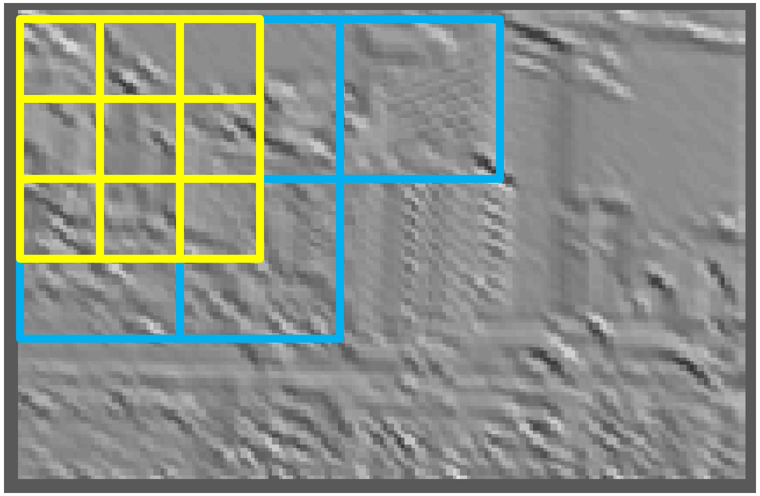
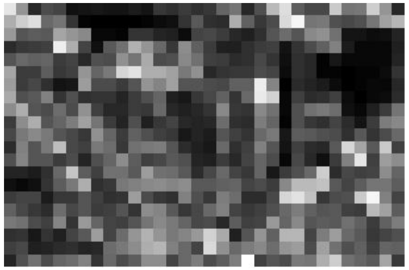
Pooling

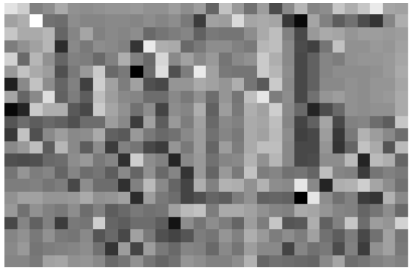
- Spatial Pooling
  - Non-overlapping / overlapping regions
  - Sum or max
  - Boureau et al. ICML'10 for theoretical analysis



Max



Sum



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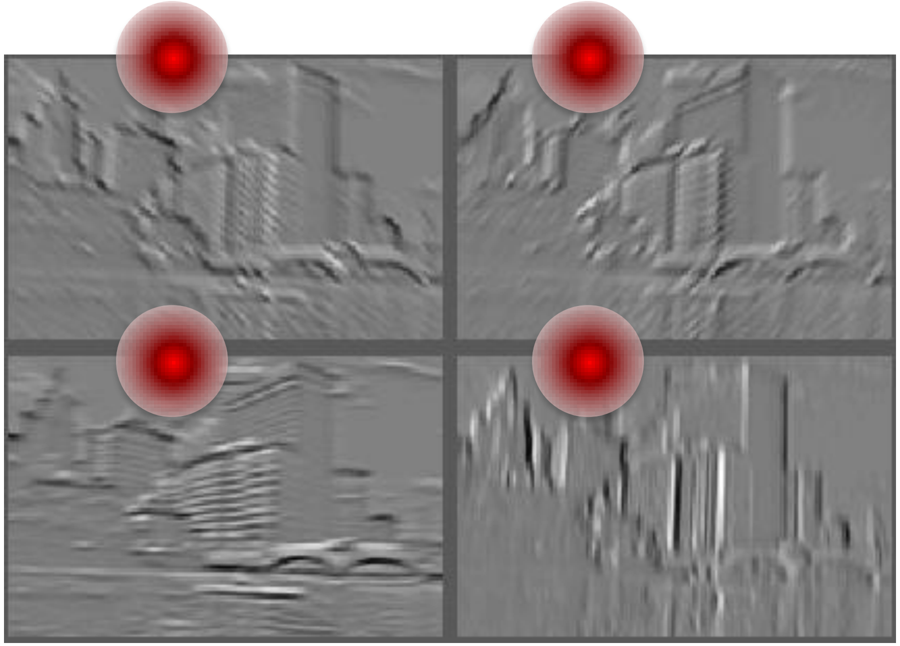
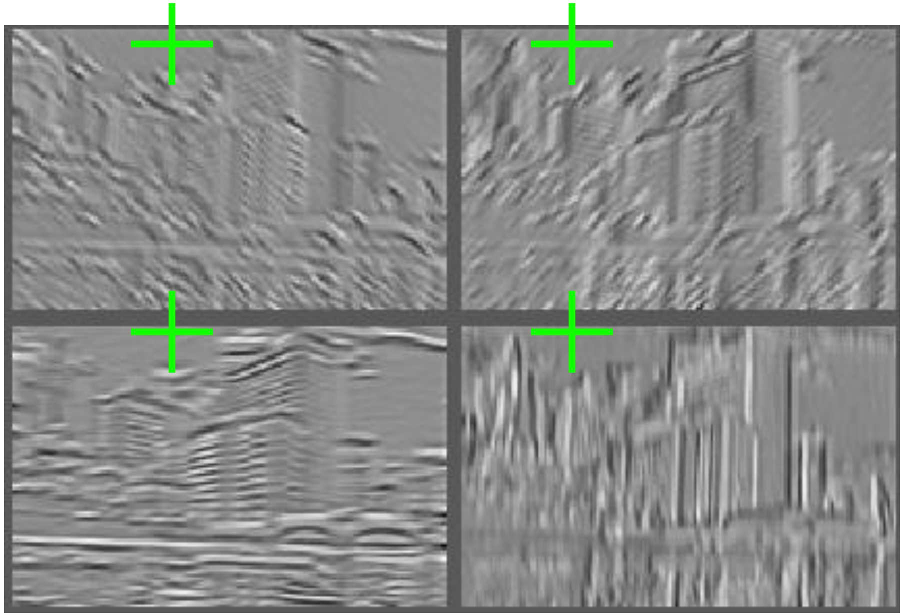
Normalization

- Contrast normalization (across feature maps)
  - Local mean = 0, local std. = 1, “Local” → 7x7 Gaussian
  - Equalizes the features maps

Feature Maps



Feature Maps
After Contrast Normalization



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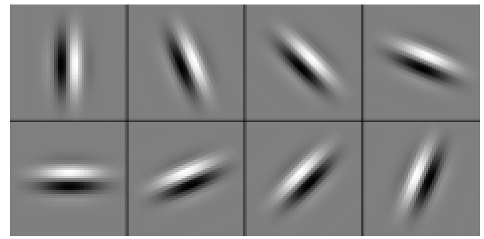
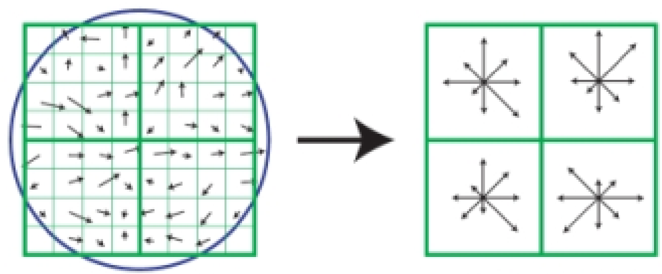
Compare: SIFT Descriptor

Image Pixels

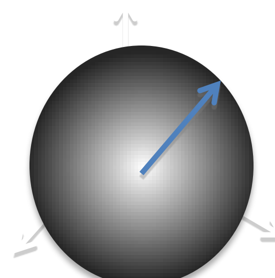
Apply
Gabor filters



Spatial pool
(Sum)



Normalize to
unit length



Feature Vector

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Applications

- 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]

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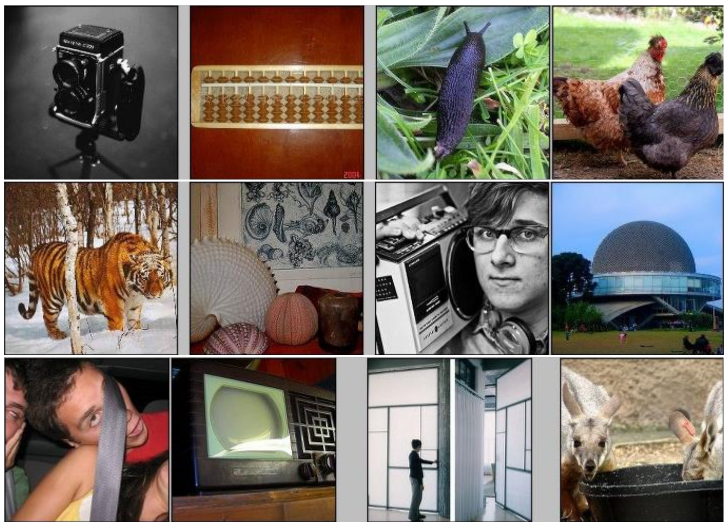
Application: ImageNet

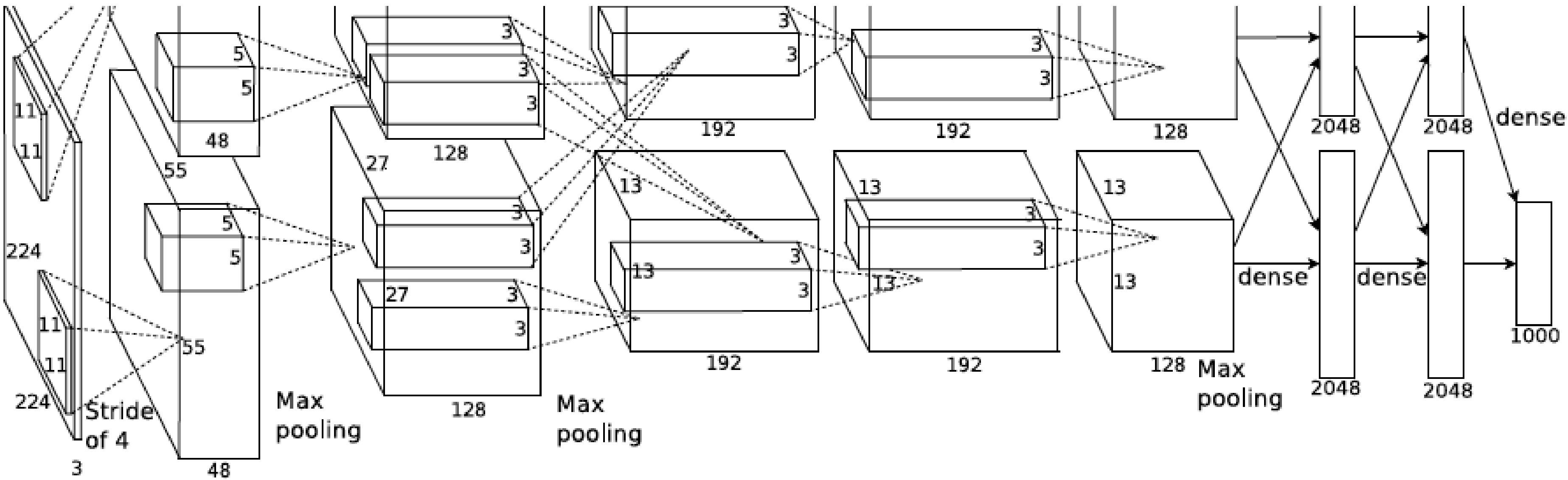


[Deng et al. CVPR 2009]

- ~14 million labeled images, 20k classes
- Images gathered from Internet
- Human labels via Amazon Turk

Krizhevsky et al. [NIPS 2012]

- Same model as LeCun'98 but:
  - Bigger model (8 layers)
  - More data (10^6 vs 10^3 images)
  - GPU implementation (50x speedup over CPU)
  - Better regularization (DropOut)



- 7 hidden layers, 650,000 neurons, 60,000,000 parameters
- Trained on 2 GPUs for a week

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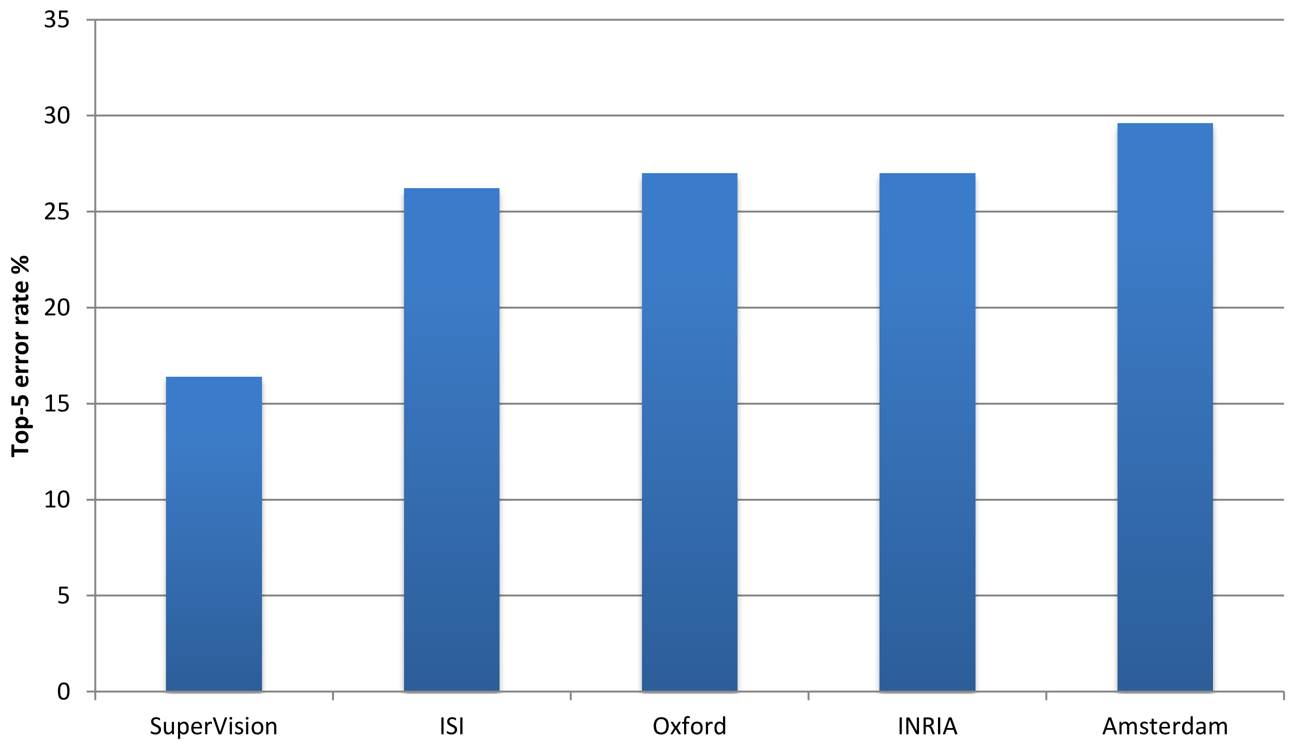
ImageNet Classification 2012

- Krizhevsky et al. -- 16.4% error (top-5)
- Next best (non-convnet) – 26.2% error



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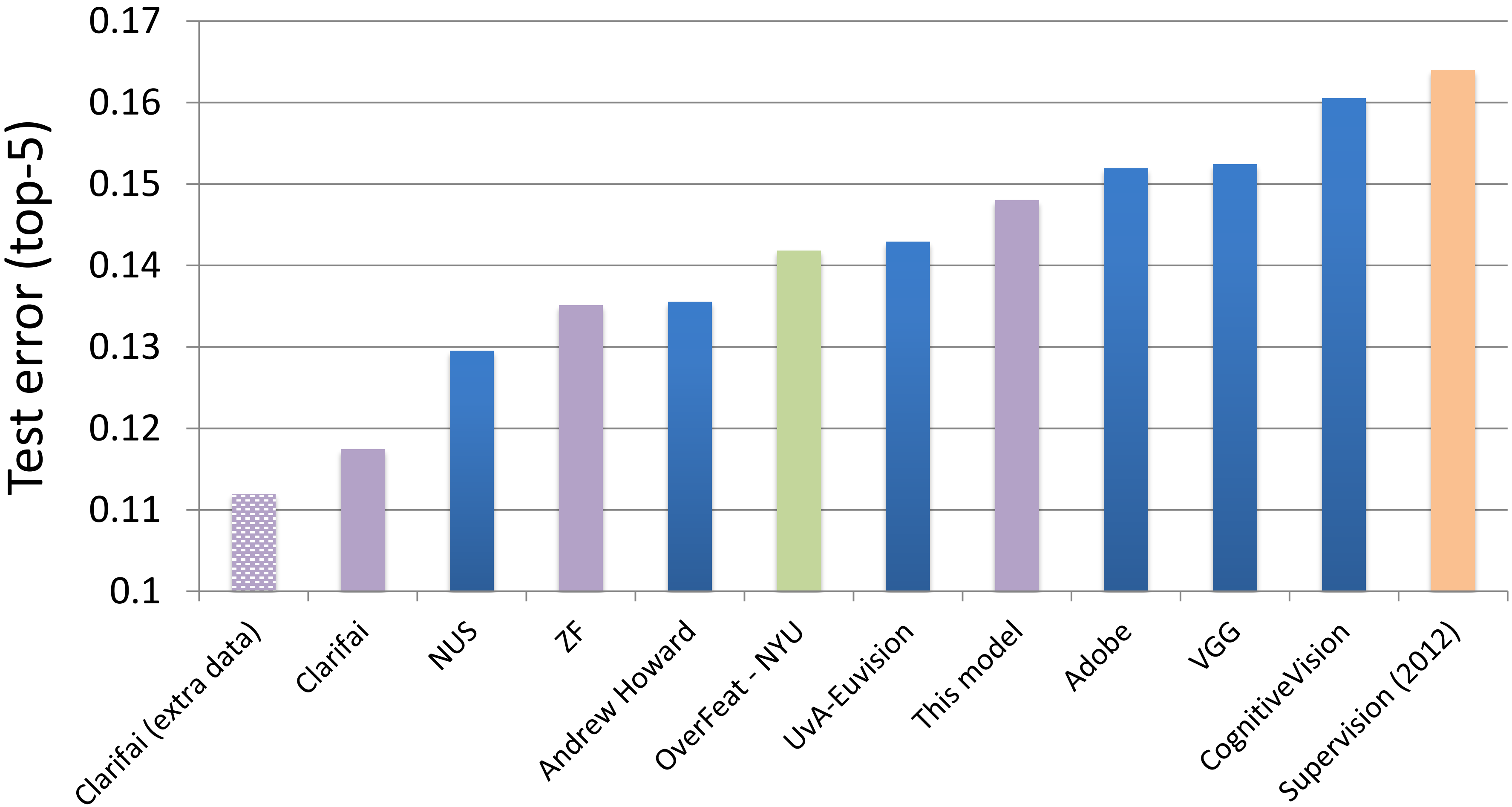
ImageNet Classification 2013 Results

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



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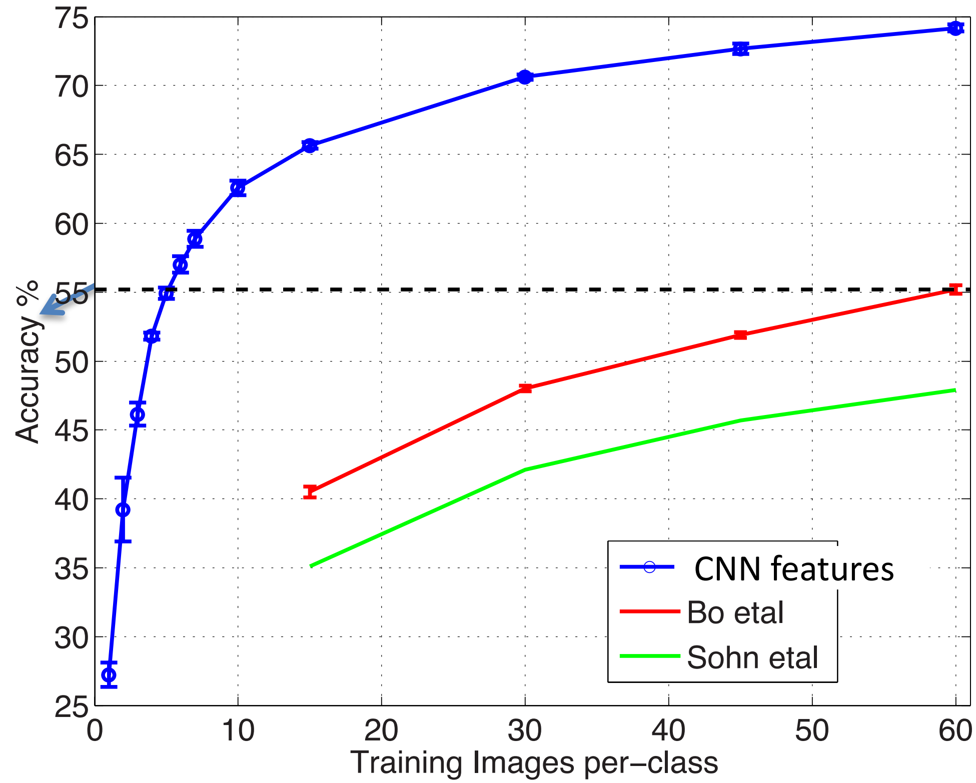
Feature Generalization

- Zeiler & Fergus, arXiv 1311.2901, 2013 (Caltech-101,256)
- Girshick et al. CVPR'14 (Caltech-101, SunS)
- Oquab et al. CVPR'14 (VOC 2012)
- Razavian et al. arXiv 1403.6382, 2014 (lots of datasets)

- Pre-train on Imagnet

  Retrain classifier on Caltech256



From Zeiler & Fergus, *Visualizing and Understanding Convolutional Networks*, arXiv 1311.2901, 2013

Bo, Ren, Fox, CVPR 2013
Sohn, Jung, Lee, Hero, ICCV 2011

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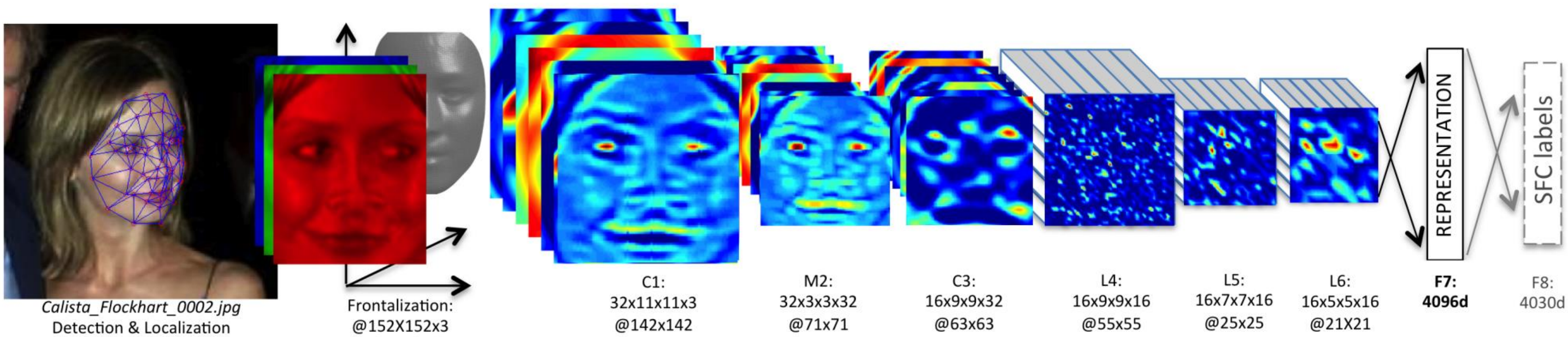
Industry Deployment

- Used in Facebook, Google, Microsoft
- Image Recognition, Speech Recognition, ...
- Fast at test time



Taigman et al. DeepFace: Closing the Gap to Human-Level Performance in Face Verification, CVPR'14

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Unsupervised Learning

Unsupervised Learning

- <u>Model distribution of input data</u>

- Can use unlabeled data (unlimited)

- Can be refined with standard supervised techniques (e.g. backprop)

- Useful when the amount of labels is small

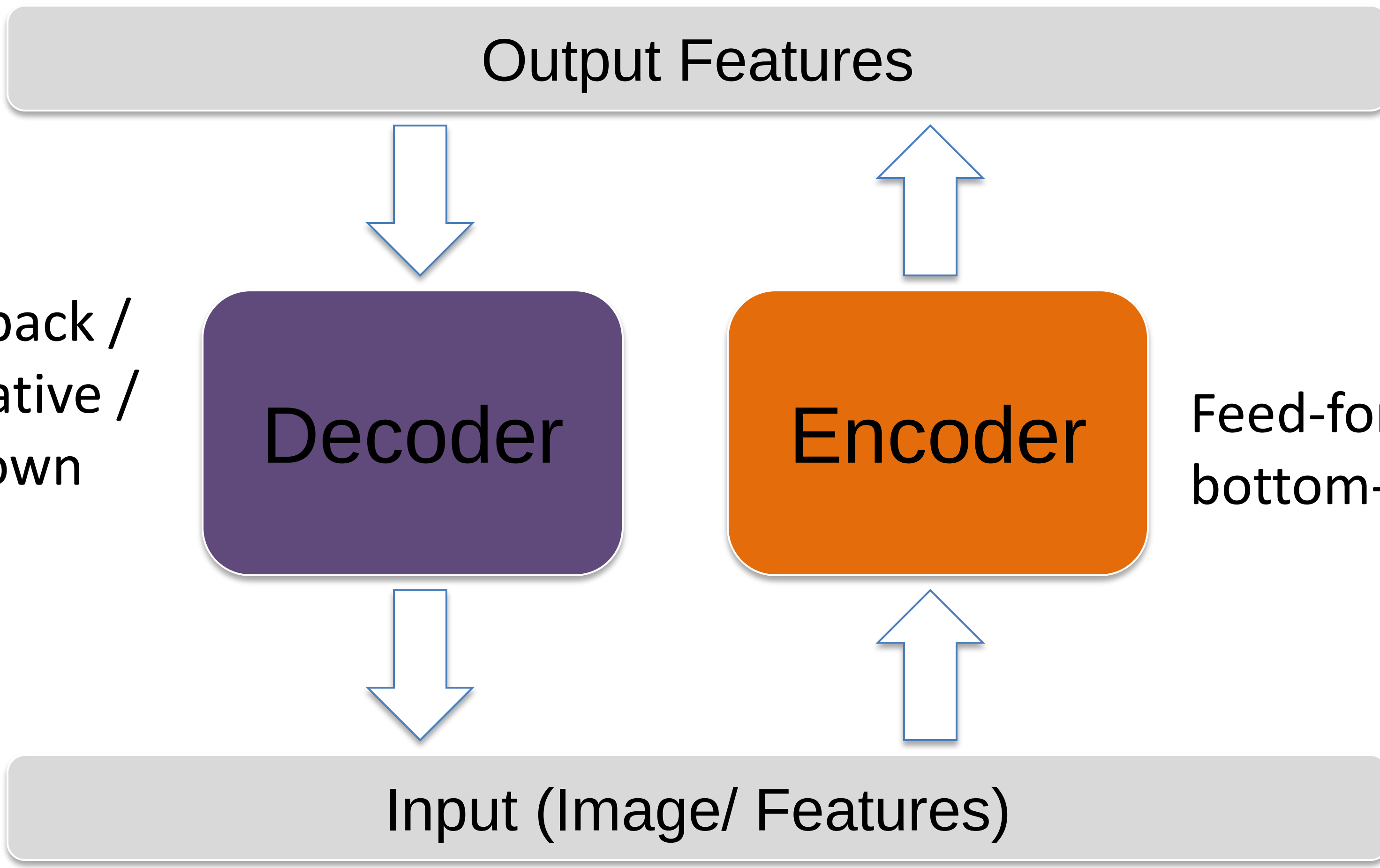
Unsupervised Learning

- Main idea: model distribution of input data
  - Reconstruction error + regularizer (sparsity, denoising, etc.)
  - Log-likelihood of data

- Models
  - Basic: PCA, KMeans
  - Denoising autoencoders
  - Sparse autoencoders
  - Restricted Boltzmann machines
  - Sparse coding
  - Independent Component Analysis
  - …

Example: Auto-Encoder

Feed-back / generative / top-down path



Feed-forward / bottom-up path

Bengio et al., NIPS’07; Vincent et al., ICML’08

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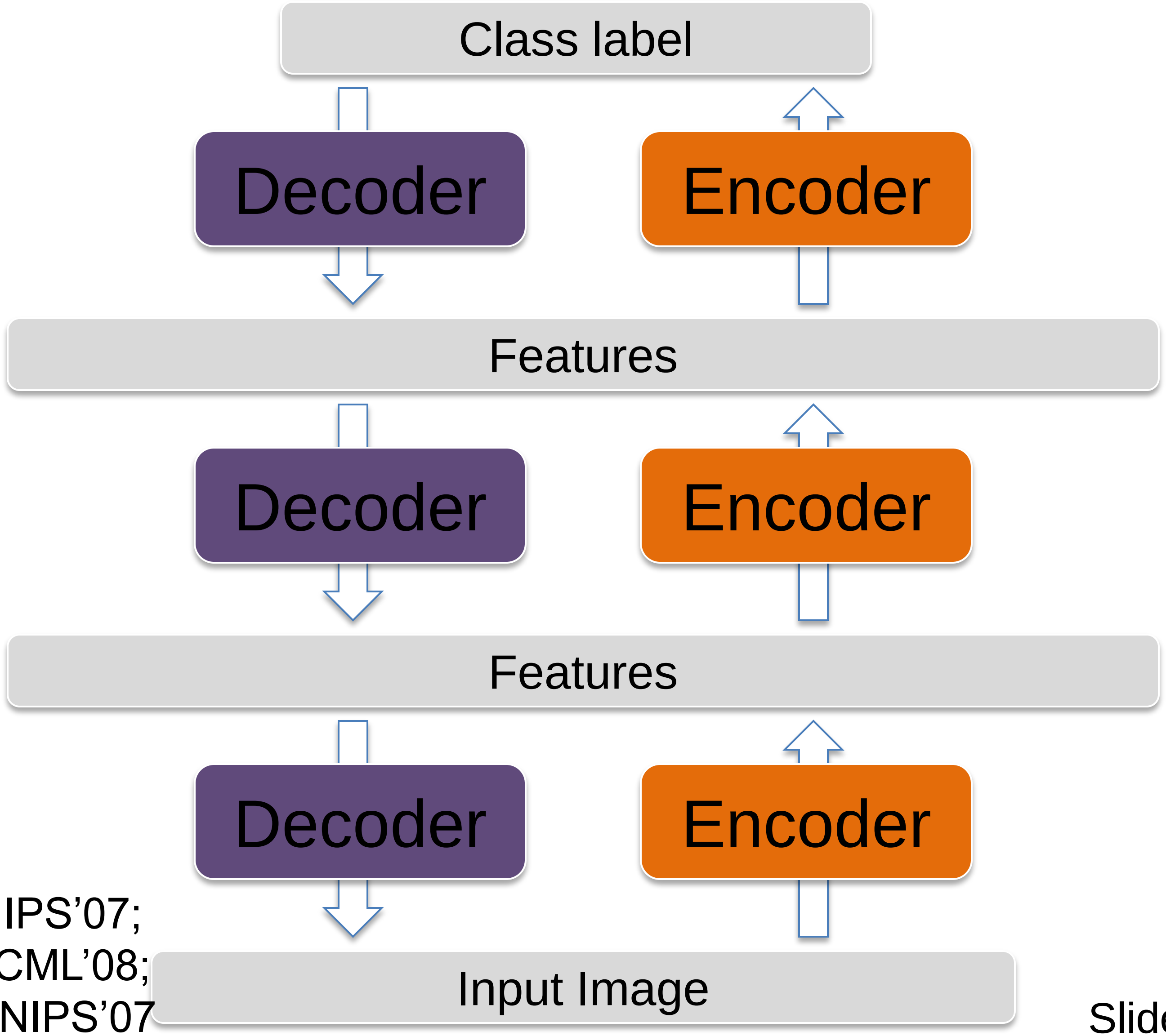
Stacked Auto-Encoders



Bengio et al., NIPS'07;
Vincent et al., ICML'08;
Ranzato et al., NIPS'07

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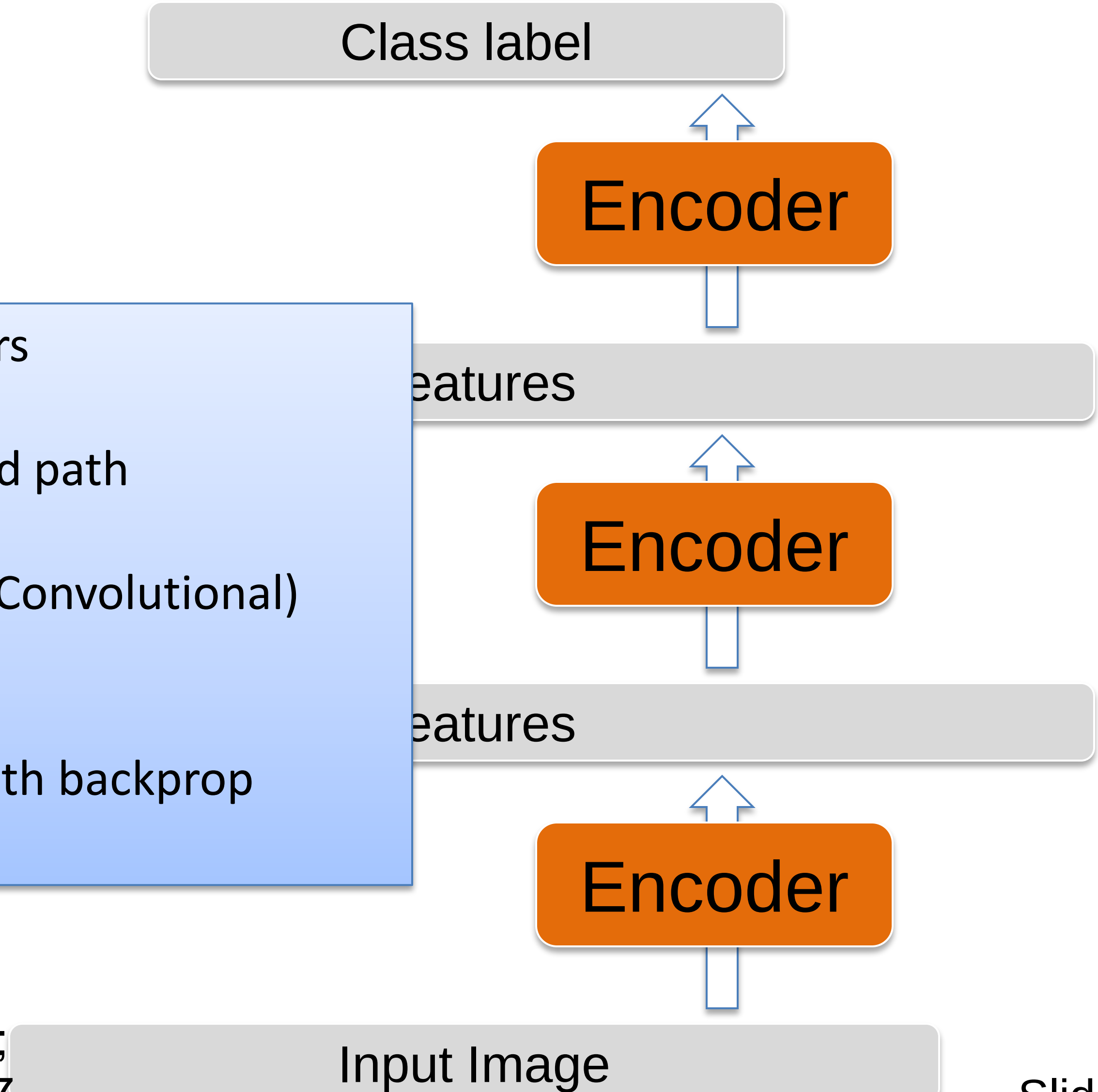
At Test Time

- Remove decoders
- Use feed-forward path
- Gives standard (Convolutional) Neural Network
- Can fine-tune with backprop



Bengio et al., NIPS'07;
Vincent et al., ICML'08;
Ranzato et al., NIPS'07

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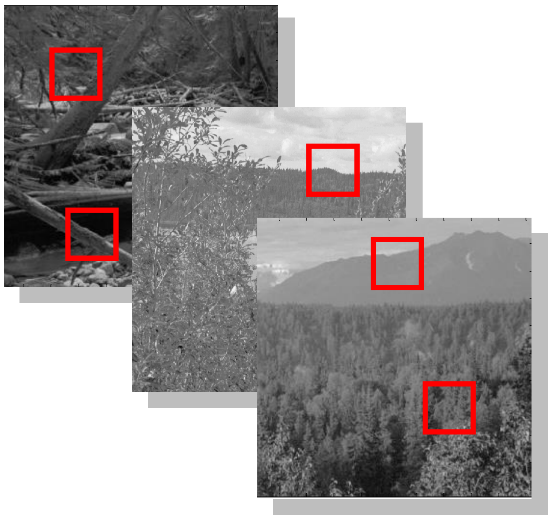
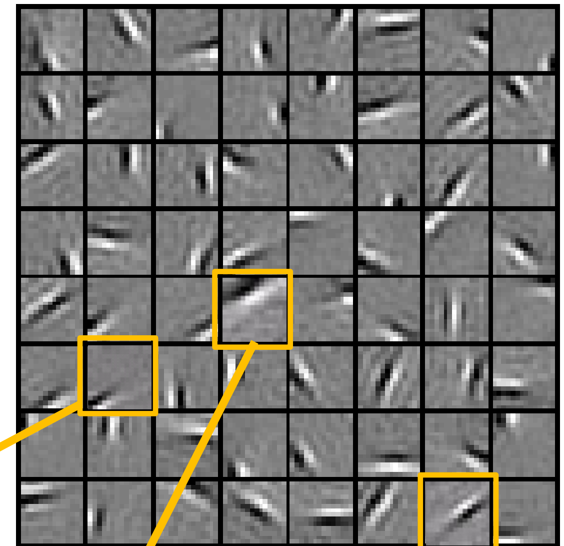
Learning basis vectors for images

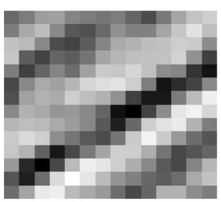
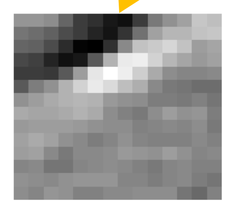
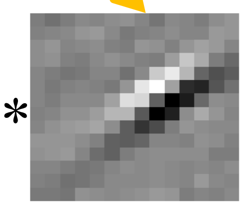
Natural Images



Learned bases: “Edges”



Test example

 ~ 0.8 *  + 0.3 *  + 0.5 * 

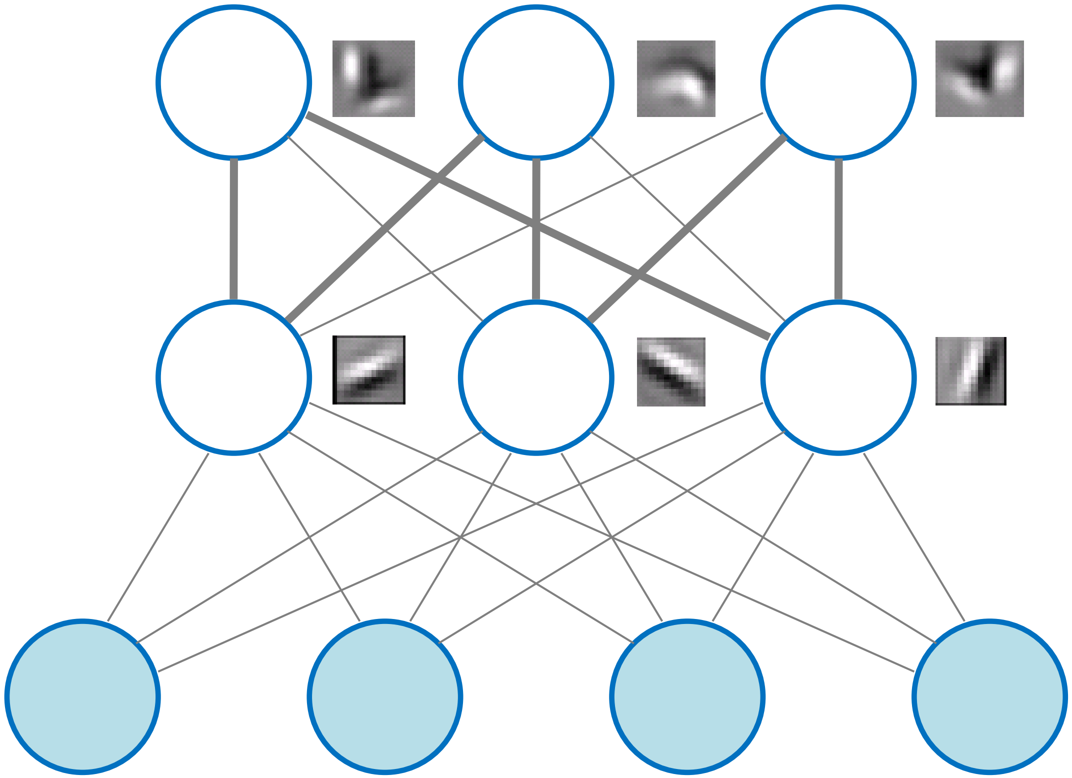
$$x \sim 0.8 * w_{36} + 0.3 * w_{42} + 0.5 * w_{65}$$

[0, 0, …, 0, **0.8**, 0, …, 0, **0.3**, 0, …, 0, **0.5**, …]
= coefficients (feature representation)

Compact & easily interpretable

[Olshausen & Field, Nature 1996, Ranzato et al., NIPS 2007; Lee et al., NIPS 2007; Lee et al., NIPS 2008; Jarret et al., CVPR 2009; etc.]

Learning Feature Hierarchy



Higher layer (Combinations of edges)

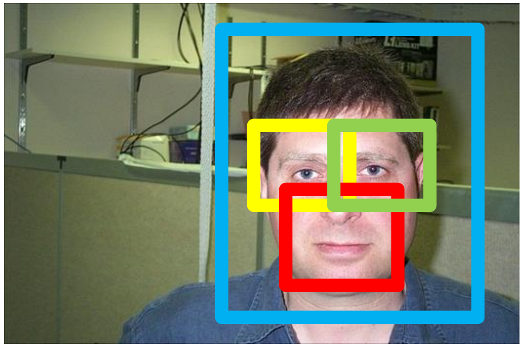
First layer (edges)

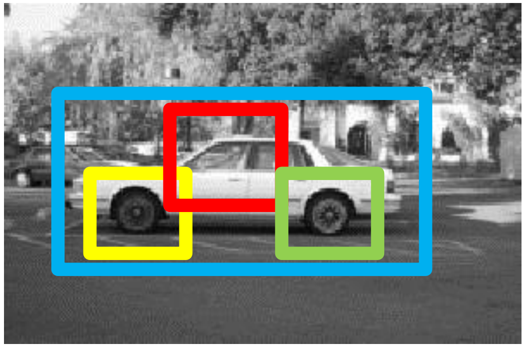
Input image (pixels)

[Olshausen & Field, Nature 1996, Ranzato et al., NIPS 2007; Lee et al., NIPS 2007; Lee et al., NIPS 2008; Jarret et al., CVPR 2009; etc.]

Learning object representations

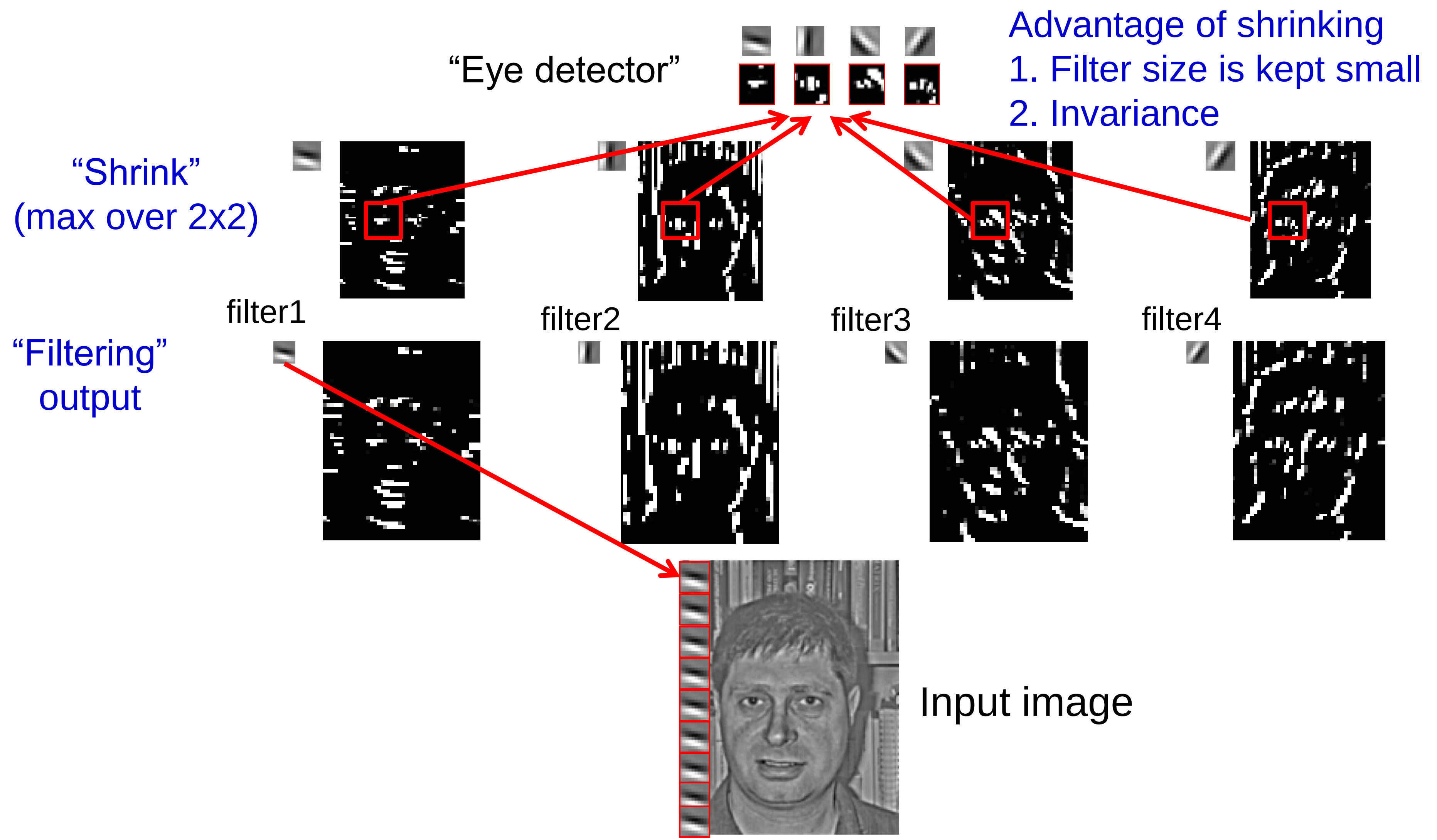
- Learning objects and parts in images





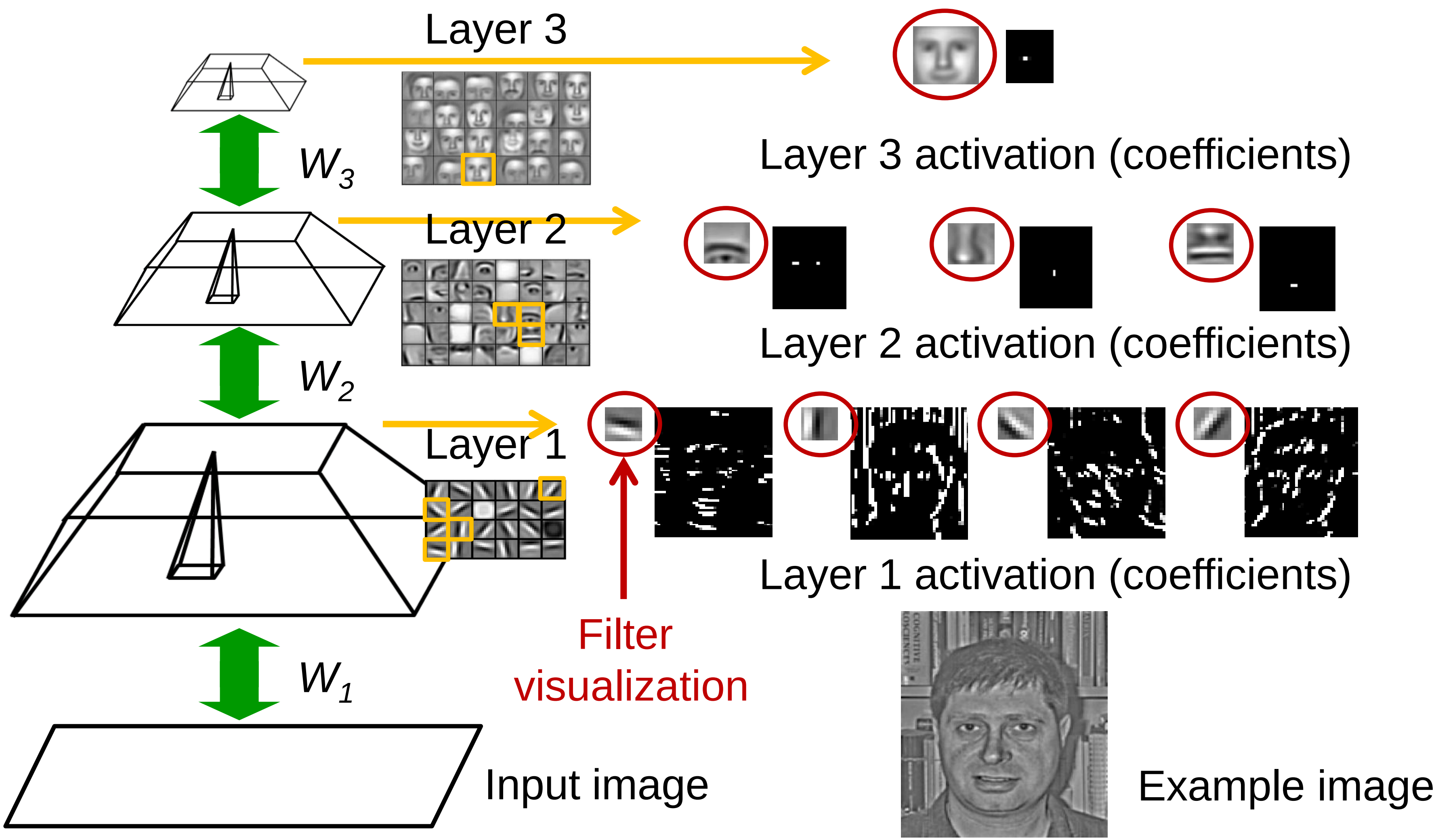
- Large image patches contain interesting higher-level structures.
  - E.g., object parts and full objects

Unsupervised learning of feature hierarchy



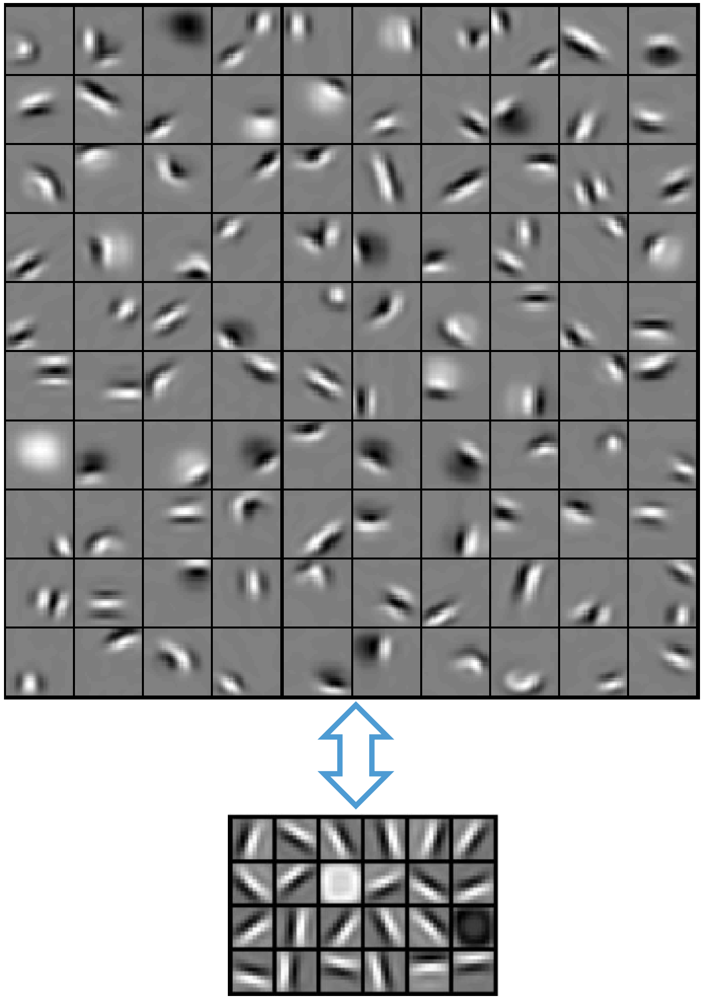
H. Lee, R. Grosse, R. Ranganath, A. Ng, ICML 2009; Comm. ACM 2011

Unsupervised learning of feature hierarchy



H. Lee, R. Grosse, R. Ranganath, A. Ng, ICML 2009; Comm. ACM 2011

Unsupervised learning from natural images



Second layer bases

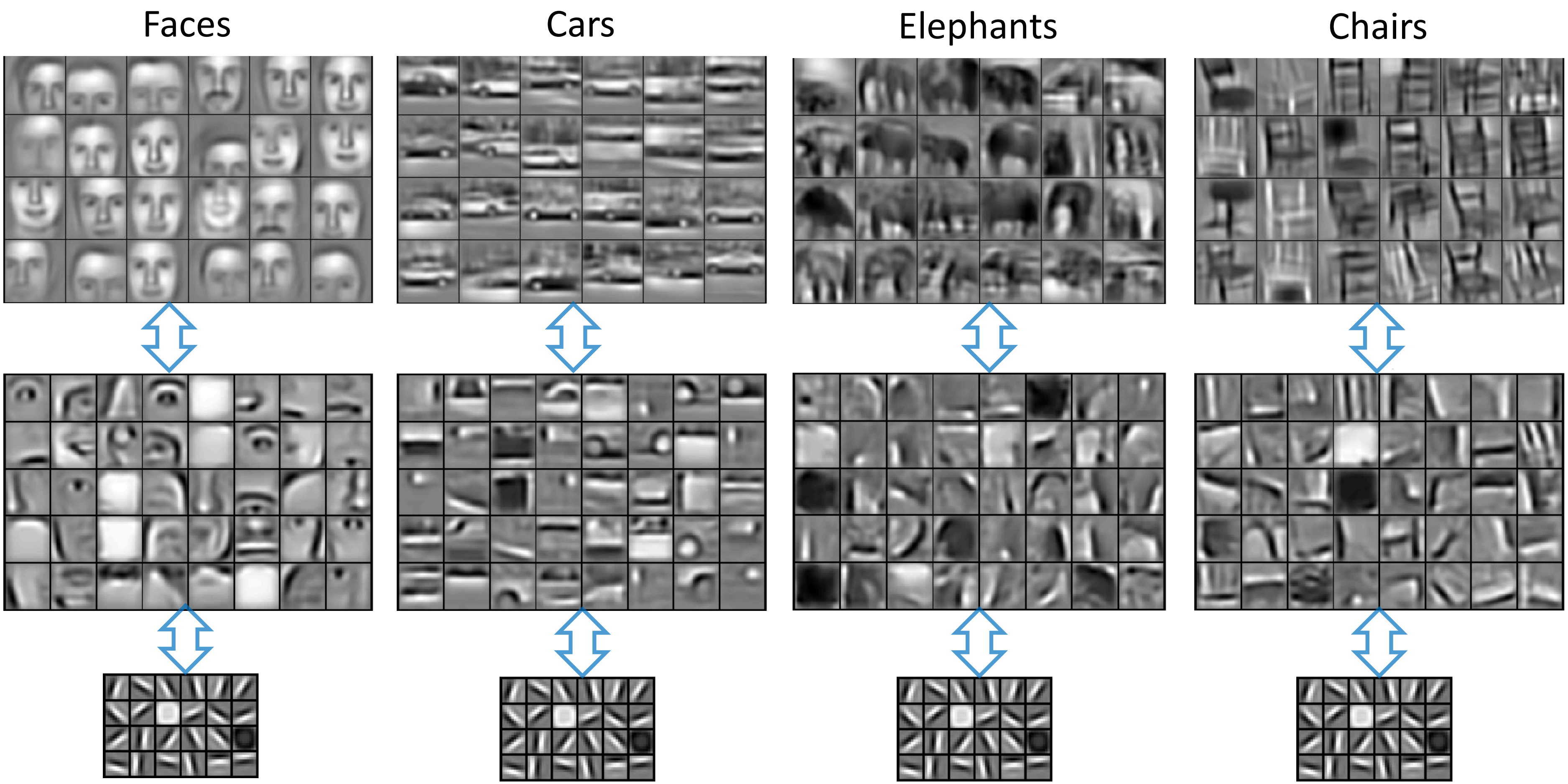
contours, corners, arcs, surface boundaries

First layer bases

localized, oriented edges

Related work: Zeiler et al., CVPR'10, ICCV'11; Kavuckuglou et al., NIPS'09

Learning object-part decomposition



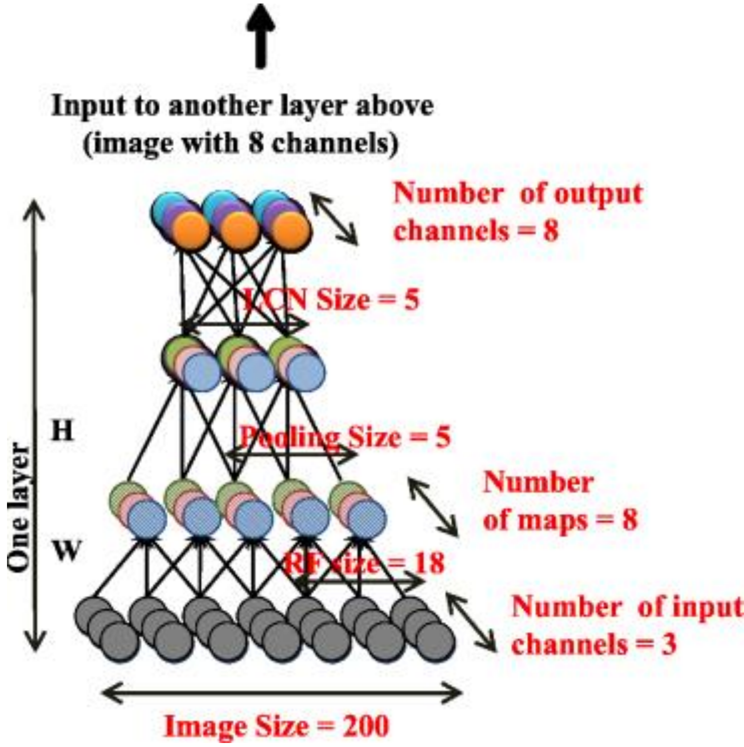
Applications:

- Object recognition (Lee et al., ICML'09, Sohn et al., ICCV'11; Sohn et al., ICML'13)
- Verification (Huang et al., CVPR'12)
- Image alignment (Huang et al., NIPS'12)

Cf. Convnet [Krizhevsky et al., 2012];
Deconvnet [Zeiler et al., CVPR 2010]

Large-scale unsupervised learning

- Large-scale deep autoencoder (three layers)
- Each stage consists of
  - local filtering
  - L2 pooling
  - local contrast normalization
- Training jointly the three layers by:
  - <u>reconstructing the input of each layer</u>
  - <u>sparsity on the code</u>



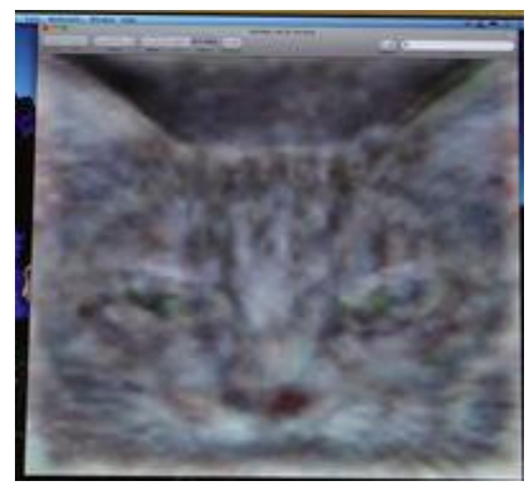
Le et al. “Building high-level features using large-scale unsupervised learning, 2011

Slide: M. Ranzato

Large-scale unsupervised learning

- Large-scale deep autoencoder
- Discovers high-level features from large amounts of unlabeled data

- Achieved state-of-the-art performance on Imagenet classification 10k categories



Le et al. “Building high-level features using large-scale unsupervised learning, 2011

Supervised vs. Unsupervised

- Supervised models
  - Work very well with large amounts of labels (e.g., imagenet)
  - Convolutional structure is important

- Unsupervised models
  - Work well given limited amounts of labels.
  - Promise of exploiting virtually unlimited amount of data without need of labeling

Summary

- Deep Learning of Feature Hierarchies
  - showing great promises for computer vision problems

- More details will be presented later:
  - Basics: Supervised and Unsupervised
  - Libraries: Torch7, Theano/Pylearn2, CAFFE
  - Advanced topics:
    - Object detection, localization, structured output prediction, learning from videos, multimodal/multitask learning, structured output prediction

Tutorial Overview

https://sites.google.com/site/deeplearningcvpr2014

- Basics
  - Introduction - Honglak Lee
  - Supervised Learning - Marc'Aurelio Ranzato
  - Unsupervised Learning - Graham Taylor
- Libraries
  - Torch7 - Marc'Aurelio Ranzato
  - Theano/Pylearn2 - Ian Goodfellow
  - CAFFE - Yangqing Jia
- Advanced topics
  - Object detection - Pierre Sermanet
  - Regression methods for localization - Alex Toshev
  - Large scale classification and GPU parallelization - Alex Krizhevsky
  - Learning transformations from videos - Roland Memisevic
  - Multimodal and multi task learning - Honglak Lee
  - Structured prediction - Yann LeCun