The Influence of Neuroscience in Machine Learning and Computer Perception

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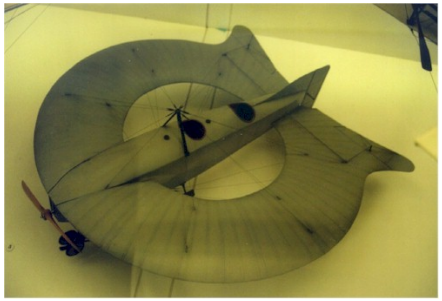
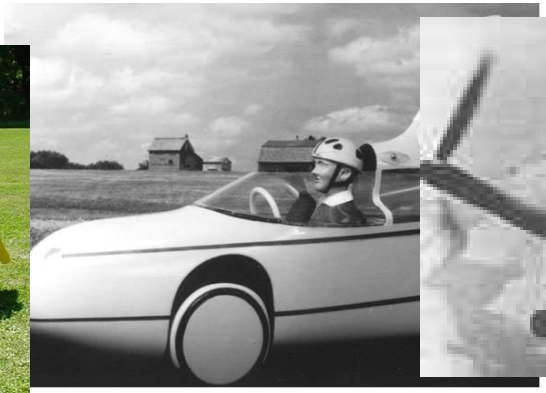
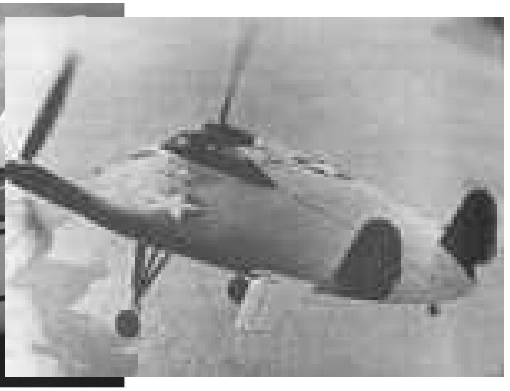
Challenges for Machine Learning, Vision, Signal Processing, AI, Neuroscience

- How can learning build a perceptual system?
- How do we learn representations of the perceptual world?
- In ML/CV/ASR/MIR: How do we learn features (not just classifiers)?
- With good representations, we can learn categories from just a few examples.
- ML has neglected the question of learning representations, relying instead on domain expertise to engineer features and kernels.
- Deep Learning addresses the problem of learning representations
- Goal 1: biologically-plausible methods for deep learning
- Goal 2: representation learning for computer perception

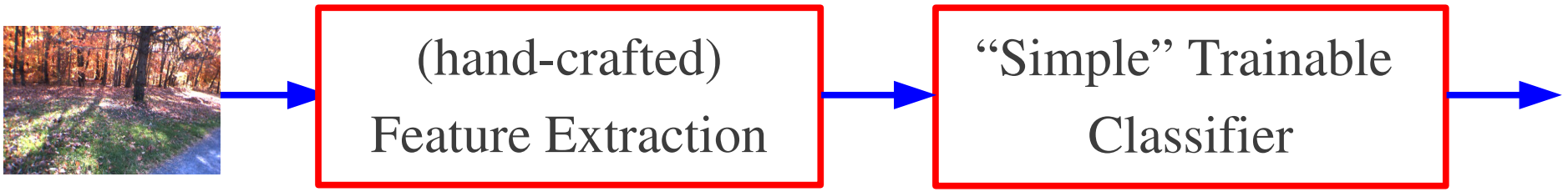




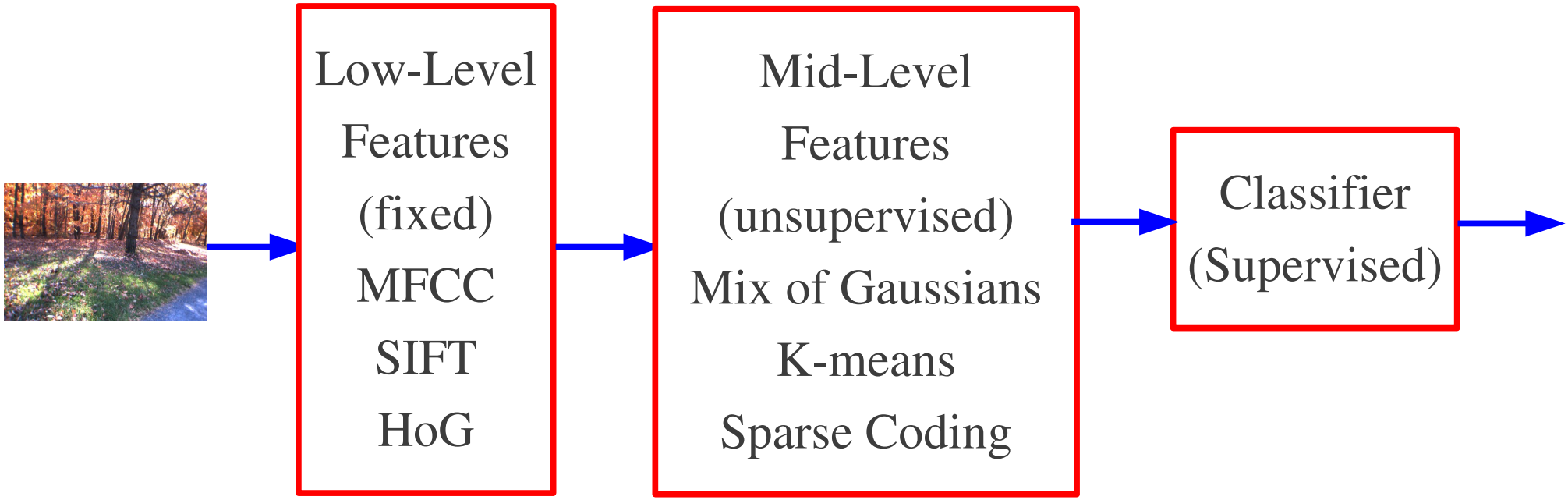


Architecture of "Mainstream" Systems

- Traditional way: handcrafted features + classifier

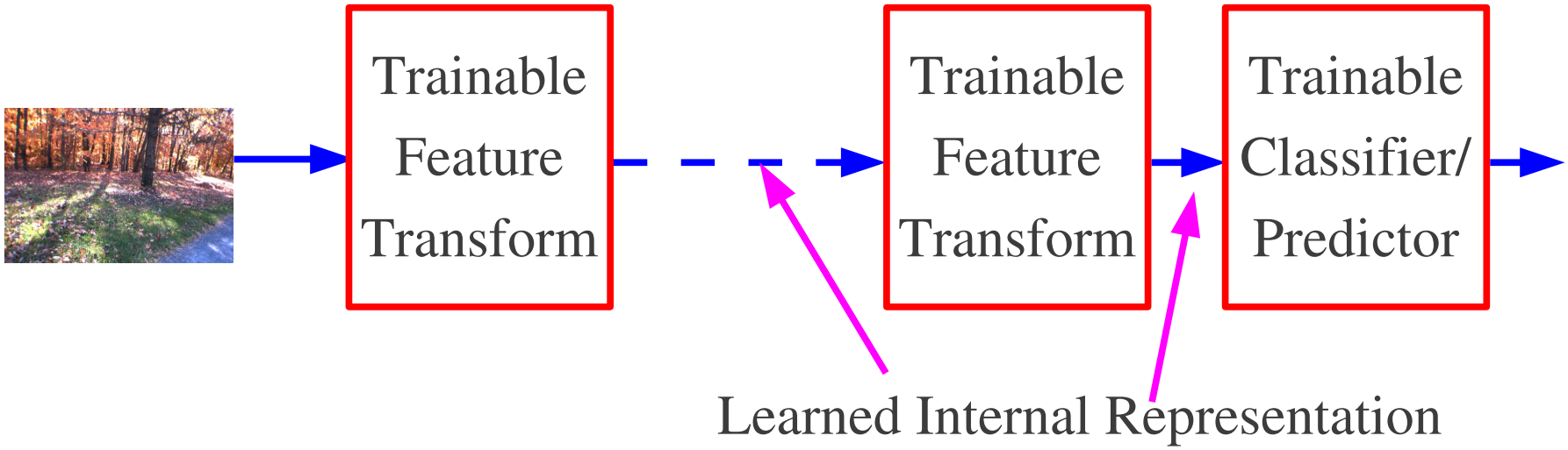


- Mainstream Approaches to Image and Speech Recognition



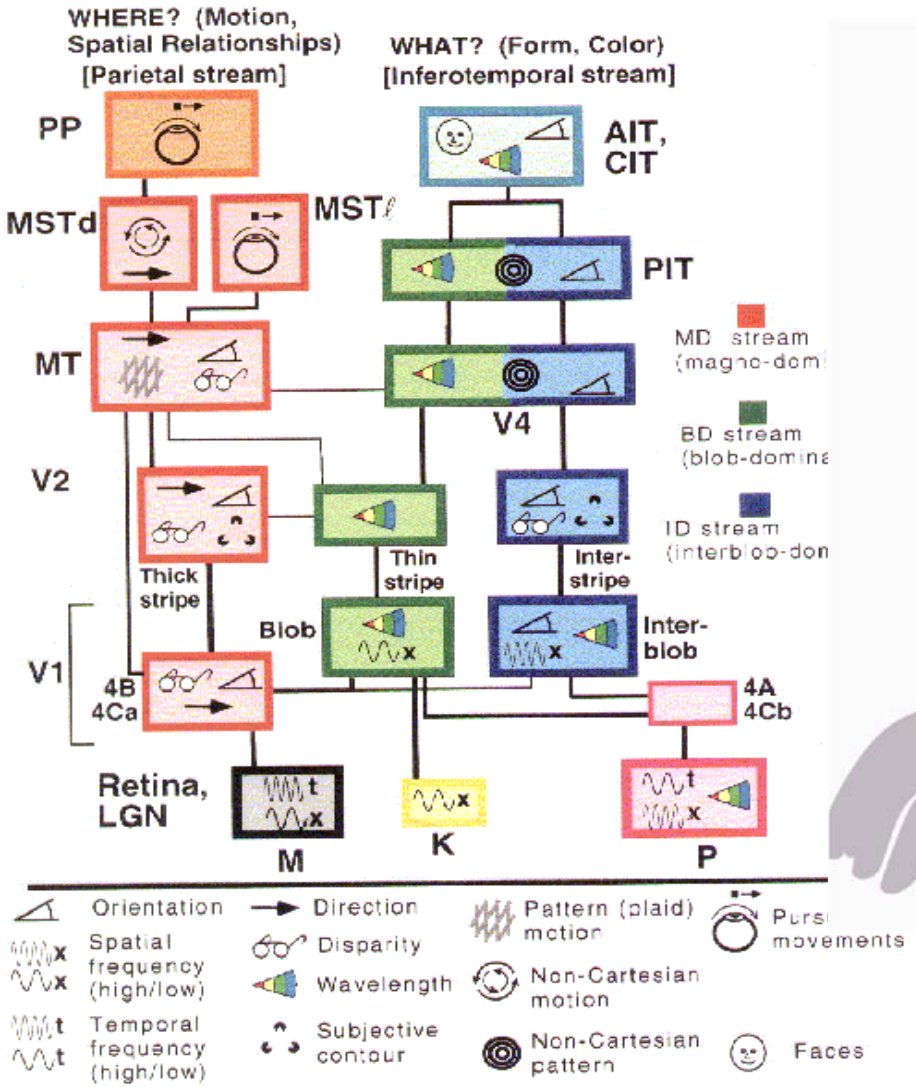
Trainable Feature Hierarchies

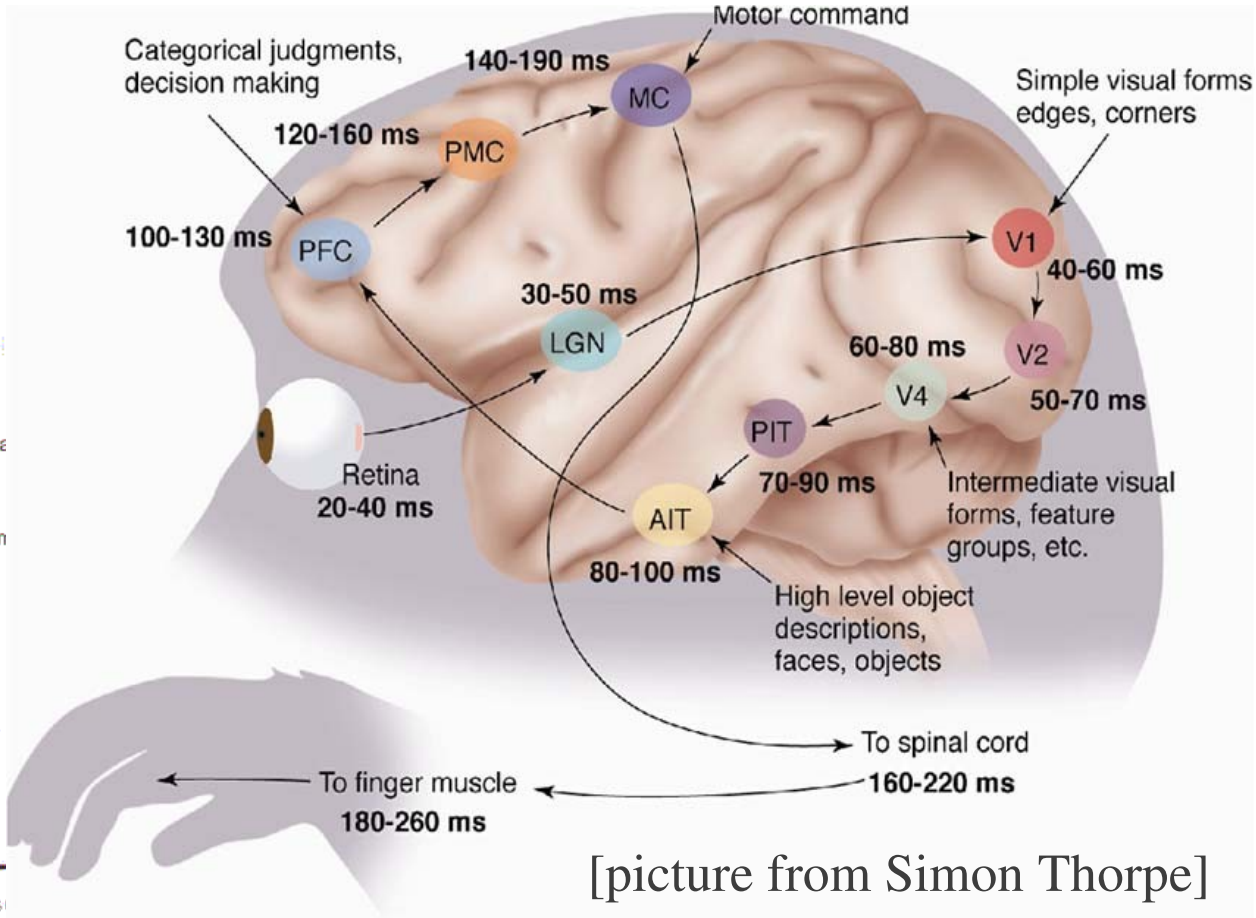
- Why can't we make all the modules trainable?
- Proposed way: hierarchy of trained features



The Mammalian Visual Cortex is Hierarchical

- The ventral (recognition) pathway in the visual cortex has multiple stages
- Retina - LGN - V1 - V2 - V4 - PIT - AIT ....

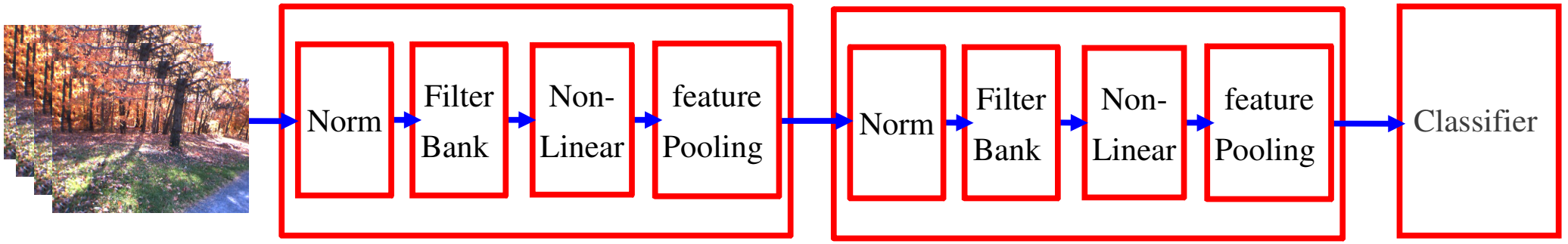




[picture from Simon Thorpe]

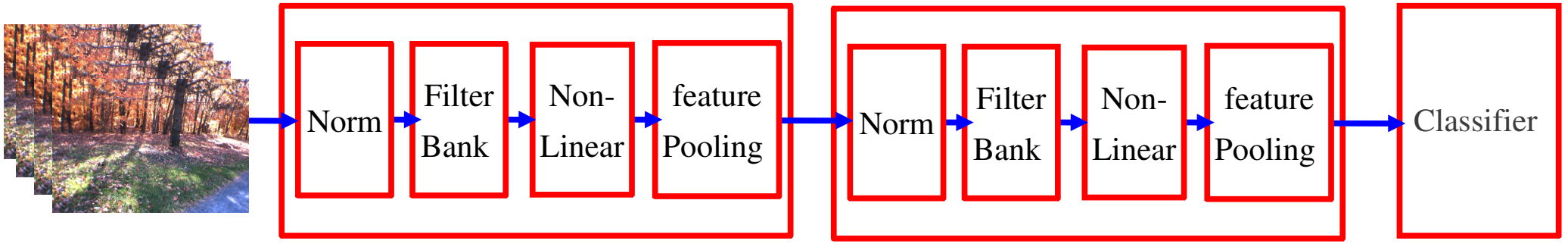
[Gallant & Van Essen]

Feature Transform = Normalization → Filter Bank → Non-Linearity → Pooling



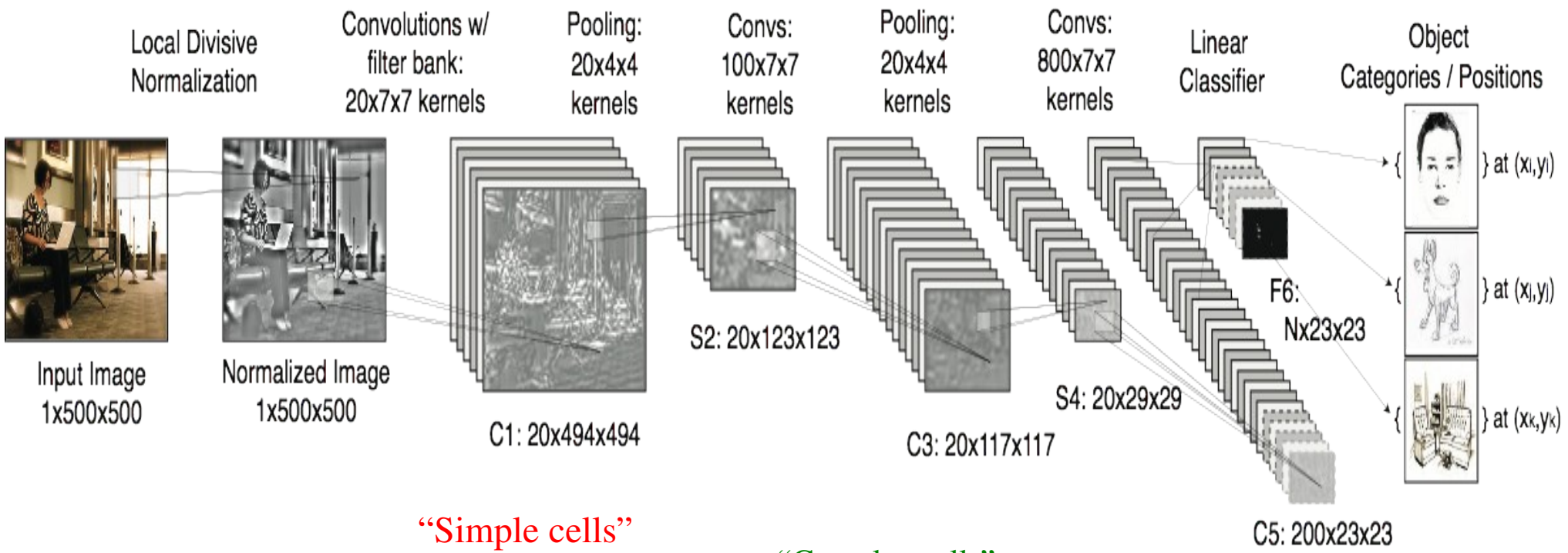
- Stacking multiple stages of
  - [Normalization → Filter Bank → Non-Linearity → Pooling].
- Normalization: variations on whitening
  - Subtractive: average removal, high pass filtering
  - Divisive: local contrast normalization, variance normalization
- Filter Bank: dimension expansion, projection on overcomplete basis
- Non-Linearity: sparsification, saturation, lateral inhibition....
  - Component-wise shrinkage or tanh, winner-takes-all
- Pooling: aggregation over space or feature type, subsampling
  - $AVERAGE: \frac{1}{K}\sum_i X_i; \quad MAX: \underset{i}{Max}\, X_i; \quad L_p: \sqrt[p]{X_i^p}; \quad PROB: \frac{1}{b}\log\left(\sum_i e^{b X_i}\right)$

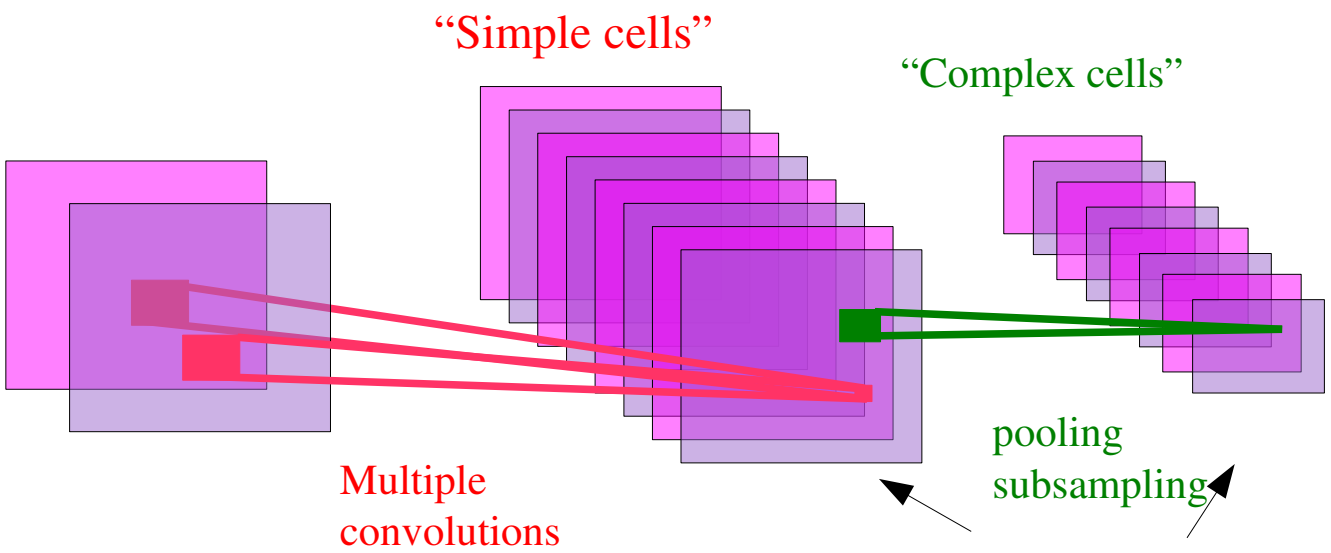
Feature Transform = Normalization → Filter Bank → Non-Linearity → Pooling



- Filter Bank → Non-Linearity = Non-linear embedding in high dimension
- Feature Pooling = contraction, dimensionality reduction, smoothing
- Learning the filter banks at every stage
- Creating a hierarchy of features
- Basic elements are inspired by models of the visual (and auditory) cortex
  - Simple Cell + Complex Cell model of [Hubel and Wiesel 1962]
  - Many "traditional" feature extraction methods are based on this
  - SIFT, GIST, HoG, Convolutional networks.....
- [Fukushima 1974-1982], [LeCun 1988-now], [Poggio 2005-now], [Ng 2006-now], many others....

Basic Convolutional Network Architecture

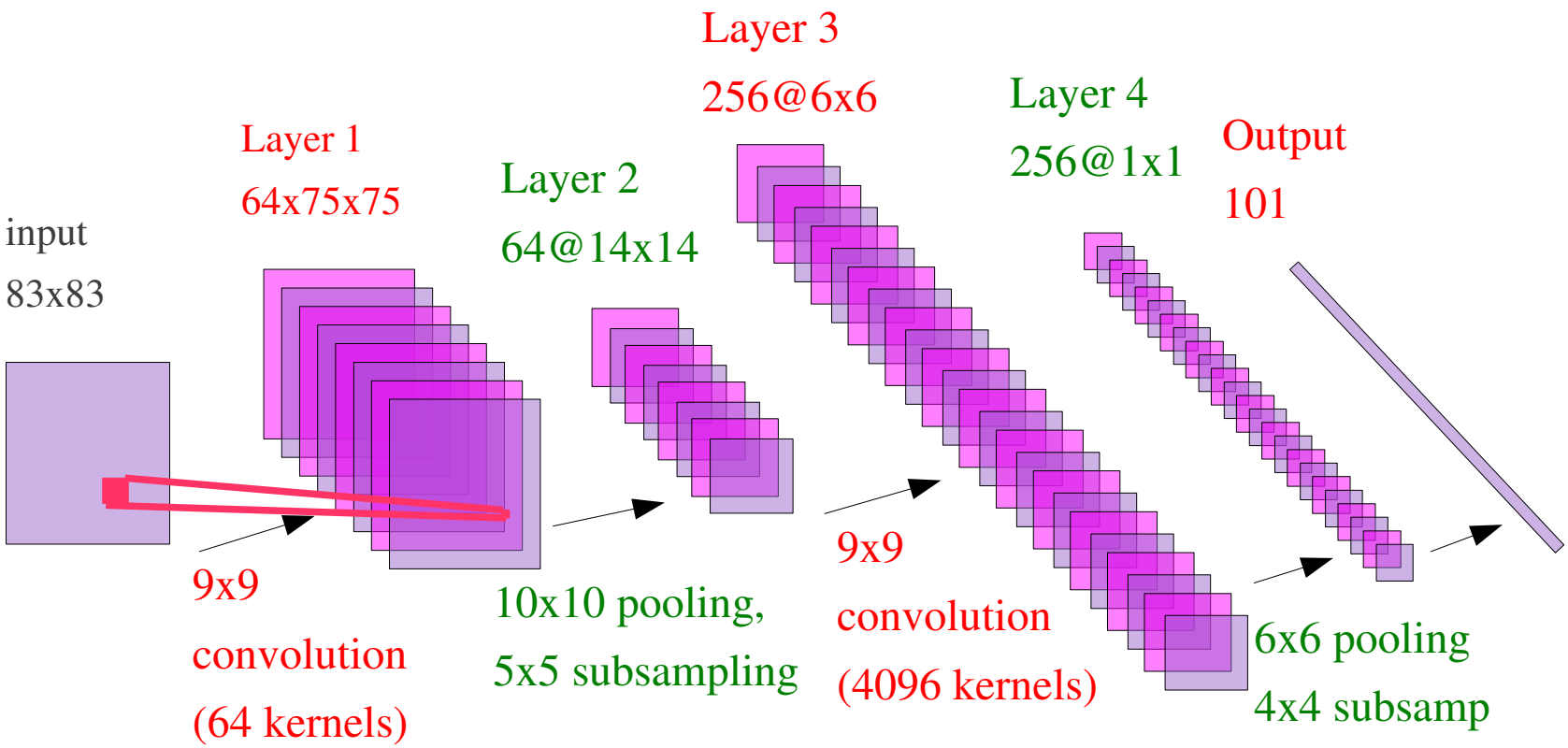




[LeCun et al. 89]

[LeCun et al. 98]

Convolutional Network (ConvNet)

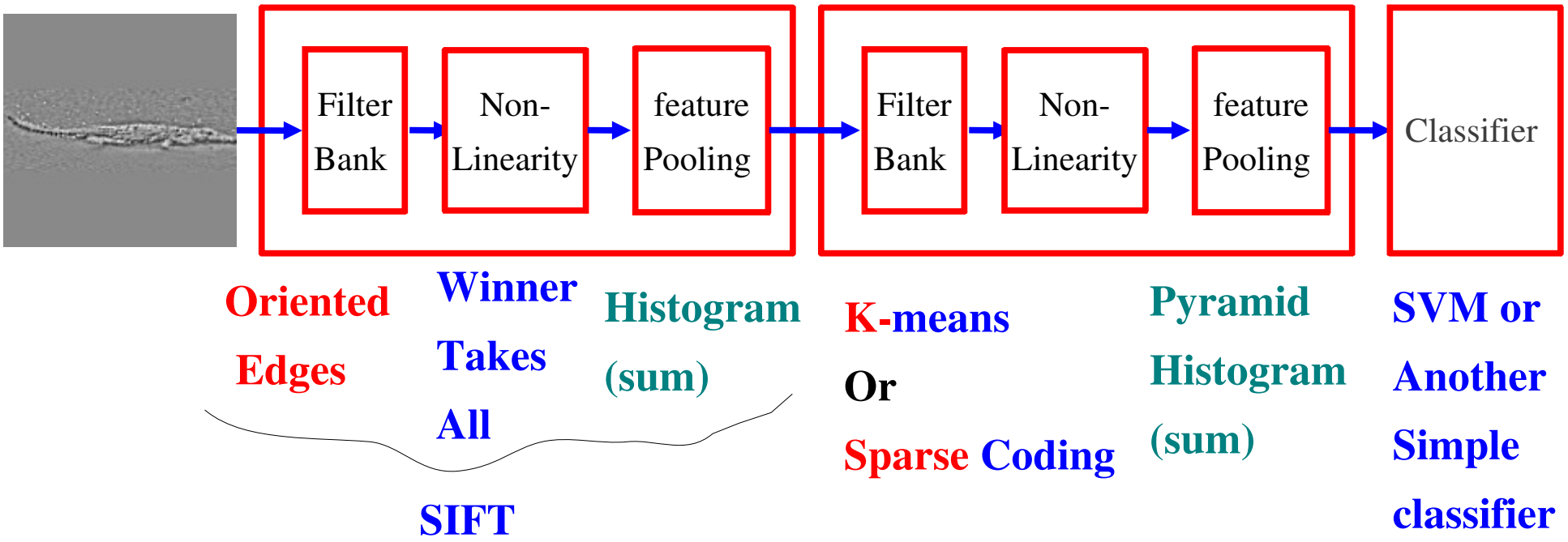


- Non-Linearity: shrinkage function, tanh
- Pooling: L2, average, max, average→tanh
- Training: Supervised (1988-2006), Unsupervised+Supervised (2006-now)

Convolutional Network (vintage 1990)

- filters → tanh → average-tanh → filters → tanh → average-tanh → filters → tanh

"Mainstream" object recognition pipeline 2006-2010: similar to ConvNets



- Fixed low-level Features + unsupervised mid-level features + simple classifier
- Example (on Caltech 101 dataset):
  - SIFT + Vector Quantization + Pyramid pooling + SVM: **>65%**
    - [Lazebnik et al. CVPR 2006]
  - SIFT + Local Sparse Coding Macrofeat. + Pyr/ pooling + SVM: **>77%**
    - [Boureau et al. ICCV 2011]

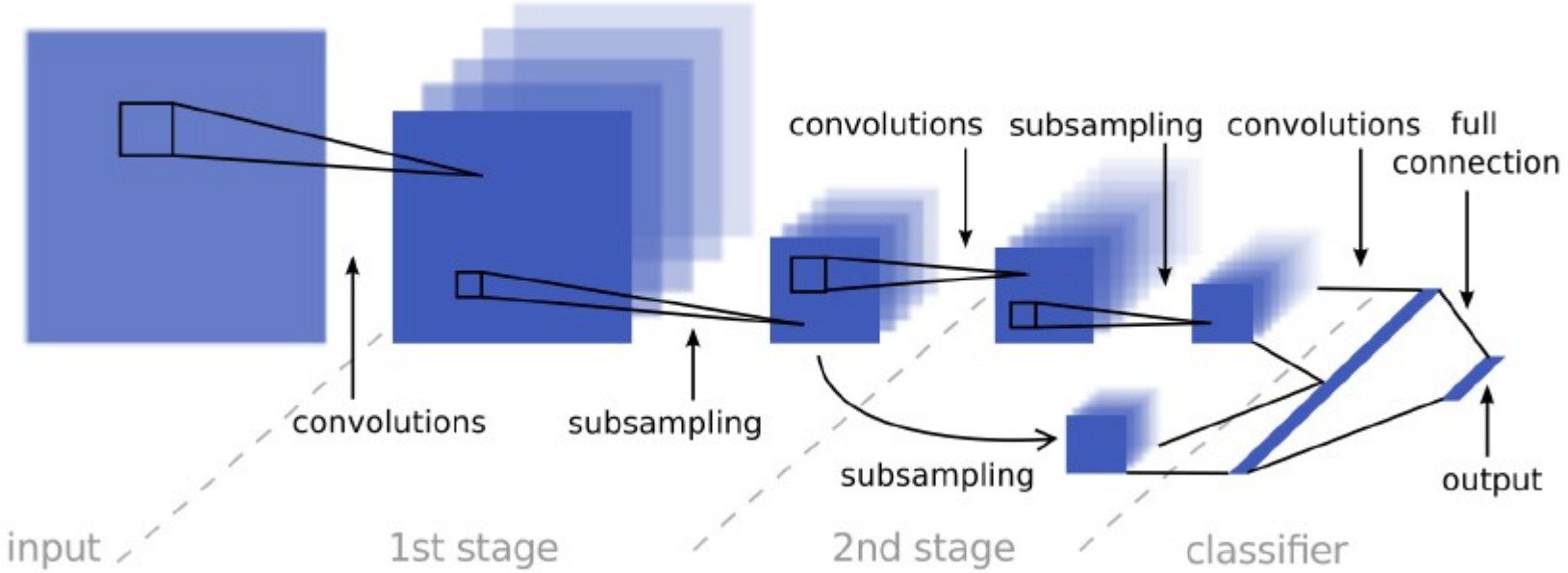
Other Applications with State-of-the-Art Performance

- **Traffic Sign Recognition (GTSRB)**
  - German Traffic Sign Reco Bench
  - 97.2% accuracy

- **House Number Recognition (Google)**
  - Street View House Numbers
  - 94.8% accuracy

ConvNet Architecture with Multi-Stage Features

- **Feature maps from all stages are pooled/subsampled and sent to the final classification layers**
  - Pooled low-level features: good for textures and local motifs
  - High-level features: good for "gestalt" and global shape



Task	Single-Stage features	Multi-Stage features	Improvement %
Pedestrians detection (INRIA) [9]	14.26%	9.85%	31%
Traffic Signs classification (GTSRB) [11]	1.80%	0.83%	54%
House Numbers classification (SVHN)	5.72%	5.67%	0.9%

[Sermanet, Chintala, LeCun ArXiv:1204.3968, 2012]

Industrial Applications of ConvNets

- AT&T/Lucent/NCR
  - Check reading, OCR, handwriting recognition (deployed 1996)
- NEC
  - Intelligent vending machines and advertizing posters, cancer cell detection, automotive applications
- Google
  - Face and license plate removal from StreetView images
- Microsoft
  - Handwriting recognition, speech detection
- Orange
  - Face detection, HCI, cell phone-based applications
- Startups, other companies...

Deep Learning and Feature Learning Today

- **Deep Learning is the hottest topic in speech recognition today**
  - A few long-standing performance records were broken with deep learning methods
  - Microsoft and Google have both deployed DL-based speech recognition system in their products
  - Microsoft, Google, IBM, AT&T, and all the major players in speech recognition have projects on deep learning
- **Deep Learning is about to become the hottest topic in Computer Vision**
  - Feature engineering is the bread-and-butter of a large portion of the CV community, which creates some resistance to feature learning
  - The record holder on the ImageNet dataset is a convolutional net
  - The record holder on semantic segmentation is a convolutional net
- **Deep Learning is becoming hot in Natural Language Processing**
  - The DL tutorial at ACL 2012 was the most popular of all tutorials
- **Deep Learning/Feature Learning in Applied Mathematics**
  - IPAM Graduate summer school on DL/FL attracted 160 people
  - The connection with Applied Math is through sparse coding, non-convex optimization, stochastic gradient algorithms, etc...

Deep Learning: A Theoretician's Paradise?

- **Deep Learning is about representing high-dimensional data**
  - There has to be interesting theoretical questions there
  - What is the geometry of natural signals?
  - Is there an equivalent of statistical learning theory for unsupervised learning?
  - What are good criteria on which to base unsupervised learning?
- **Deep Learning is a form of latent variable factor graphs**
  - Internal representations can be viewed as latent variables to be inferred, and deep belief networks are a particular type of latent variable models.
  - The most interesting deep belief nets have intractable loss functions: how do we get around that problem?
- **Theory from harmonic analysis and sparse coding**
  - Mallat's "scattering transform", Osher's "split Bregman" methods for sparse modeling, Morton's "algebraic geometry of DBN",

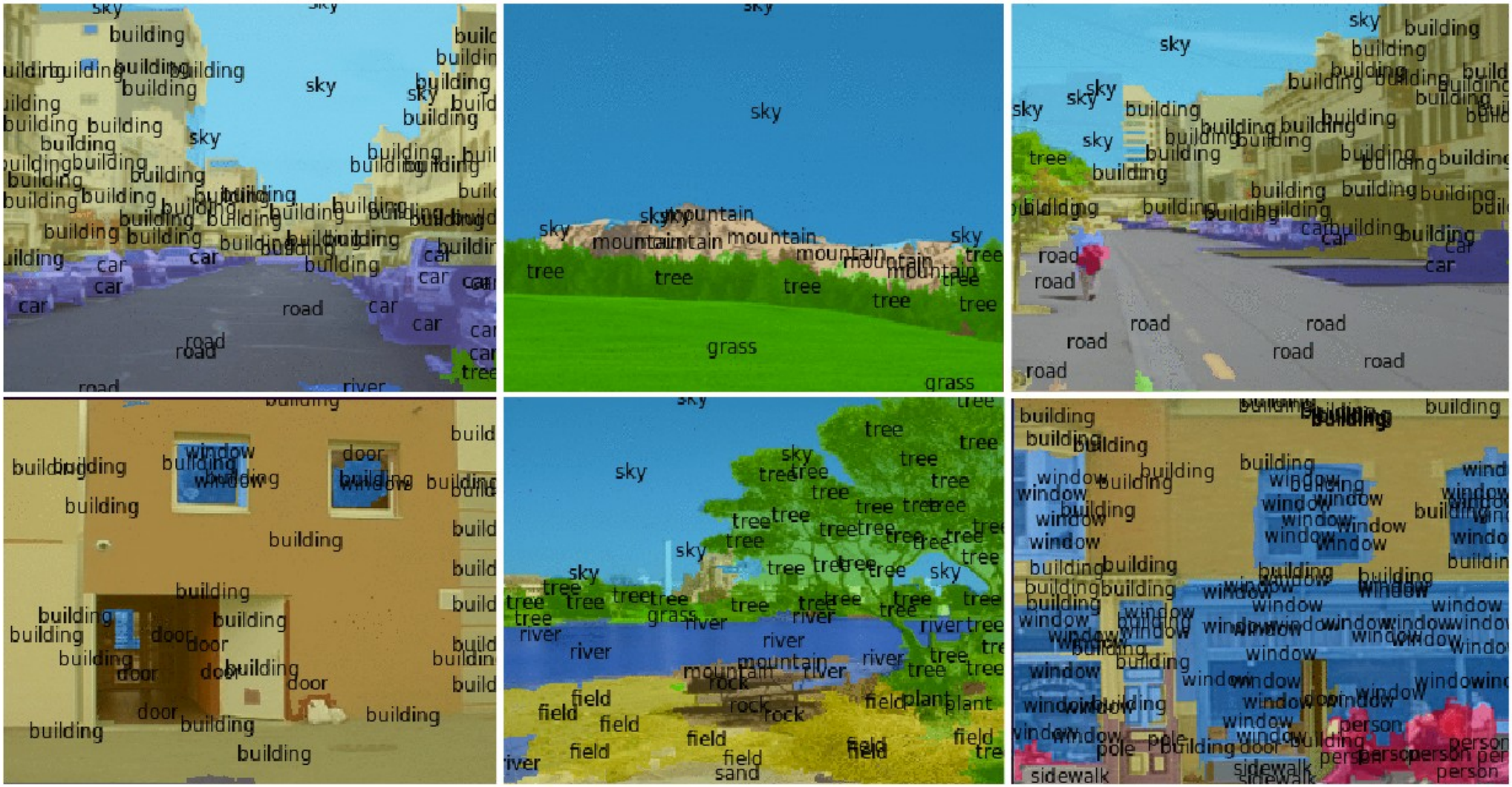
Fast Scene Parsing with Multiscale ConvNet

[Farabet, Couprie, Najman, LeCun, ICML 2012]

[Farabet, Couprie, Najman, LeCun, IEEE T.PAMI 2013]

Labeling every pixel with the object it belongs to

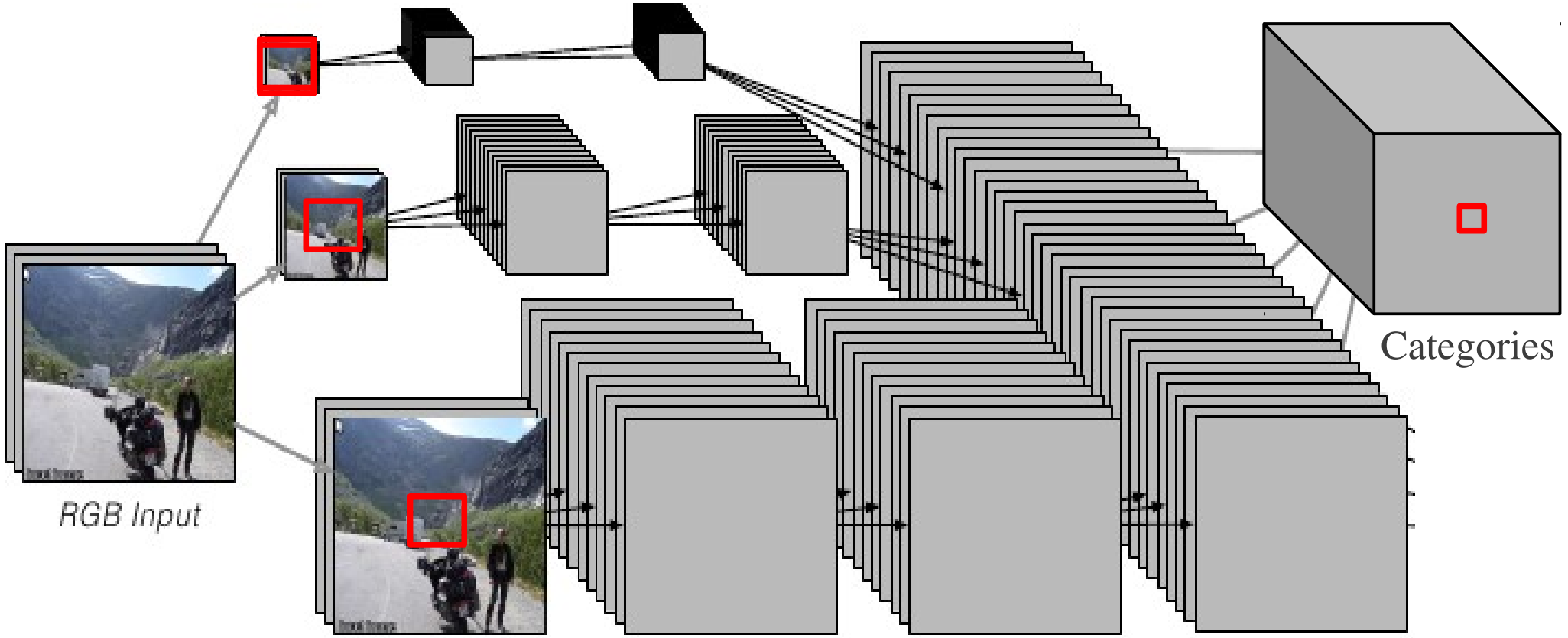
- Would help identify obstacles, targets, landing sites, dangerous areas
- Would help line up depth map with edge maps



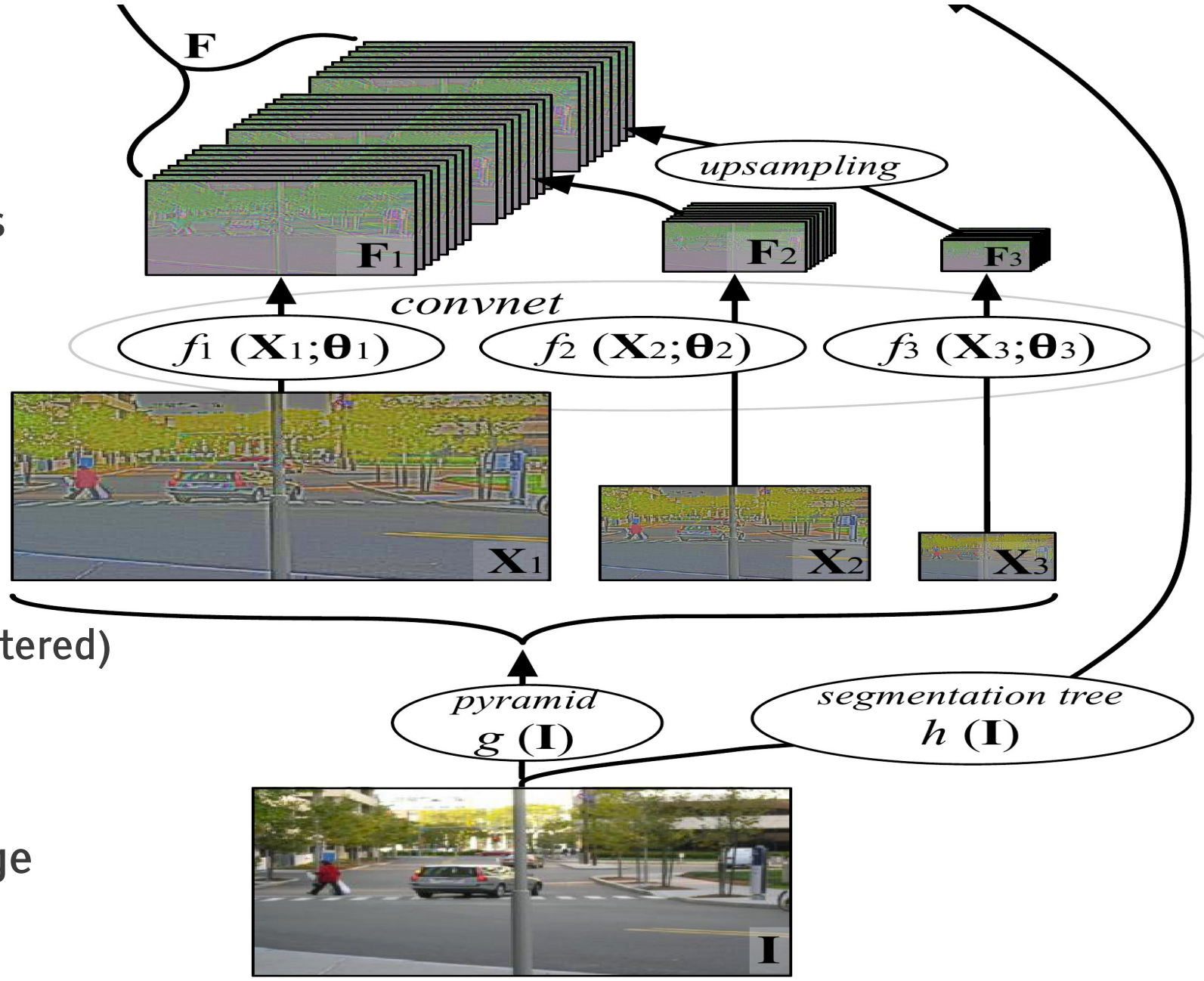
[Farabet et al. ICML 2012]

Scene Parsing/Labeling: ConvNet Architecture

- Each output sees a large input context:
  - **46x46** window at full rez; **92x92** at ½ rez; **184x184** at ¼ rez
  - [7x7conv]->[2x2pool]->[7x7conv]->[2x2pool]->[7x7conv]->
  - Trained supervised on fully-labeled images



Scene Parsing/Labeling: System Architecture



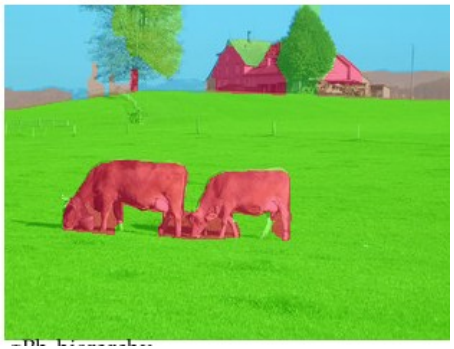
Method 1: majority over super-pixel regions

Input image

Super-pixel boundary hypetheses

Superpixel boundaries

Majority Vote Over Superpixels



Categories aligned With region boundaries

Multi-scale ConvNet

Features from Convolutional net (d=768 per pixel)

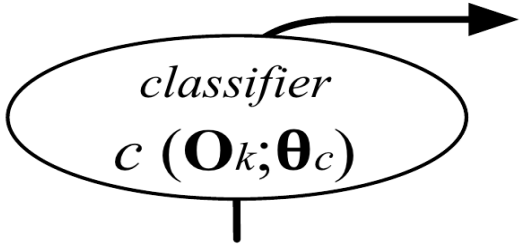
Convolutional classifier

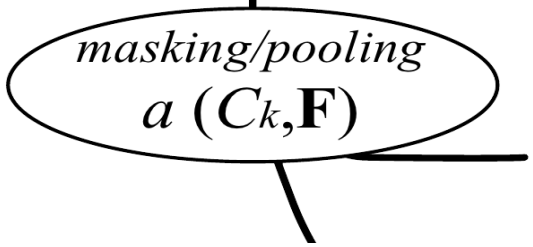
"soft" categories scores

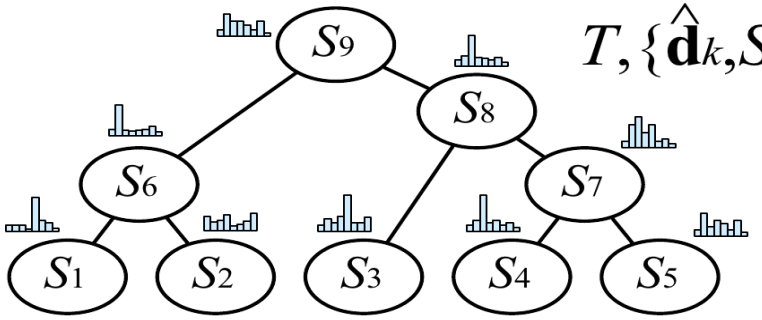
[Farabet et al. IEEE T. PAMI 2012]

Method 2: optimal cover of purity tree

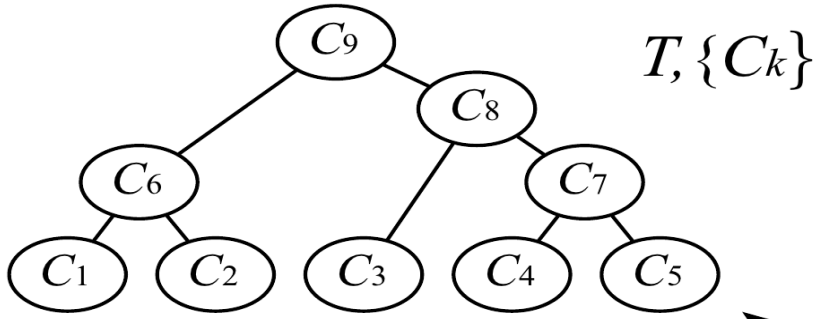
2-layer Neural net



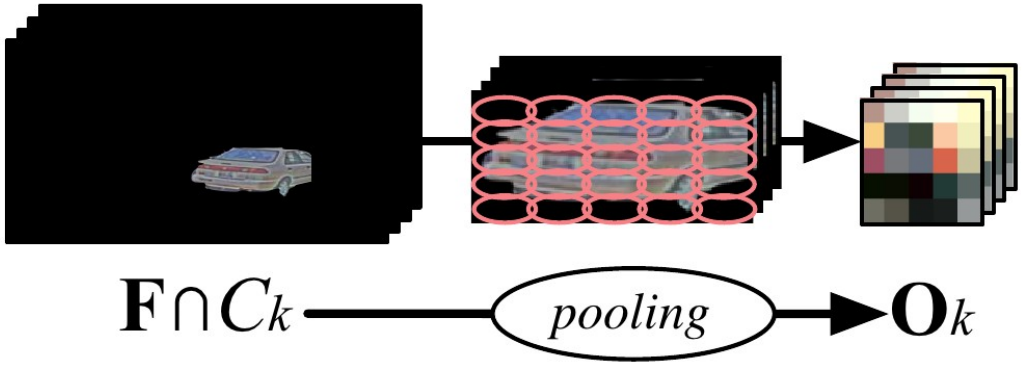




Distribution of Categories within Each Segment



Spanning Tree From pixel Similarity graph



[Farabet et al. ICML 2012]

Scene Parsing/Labeling: Performance

- Stanford Background Dataset [Gould 1009]: 8 categories

	Pixel Acc.	Class Acc.	CT (sec.)
Gould *et al.* 2009 [14]	76.4%	-	10 to 600s
Munoz *et al.* 2010 [32]	76.9%	66.2%	12s
Tighe *et al.* 2010 [46]	77.5%	-	10 to 300s
Socher *et al.* 2011 [45]	78.1%	-	?
Kumar *et al.* 2010 [22]	79.4%	-	$< 600s$
Lempitzky *et al.* 2011 [28]	**81.9%**	72.4%	$> 60s$
singlescale convnet	66.0 %	56.5 %	0.35s
multiscale convnet	78.8 %	72.4%	0.6s
multiscale net + superpixels	80.4%	74.56%	**0.7s**
multiscale net + gPb + cover	80.4%	75.24%	61s
multiscale net + CRF on gPb	81.4%	**76.0%**	60.5s

[Farabet et al. IEEE T. PAMI 2012]

Scene Parsing/Labeling: Performance

	Pixel Acc.	Class Acc.
Liu *et al.* 2009 [31]	74.75%	-
Tighe *et al.* 2010 [44]	76.9%	29.4%
raw multiscale net[1]	67.9%	45.9%
multiscale net + superpixels[1]	71.9%	**50.8%**
multiscale net + cover[1]	72.3%	**50.8%**
multiscale net + cover[2]	**78.5%**	29.6%

- SIFT Flow Dataset
- [Liu 2009]:
- 33 categories

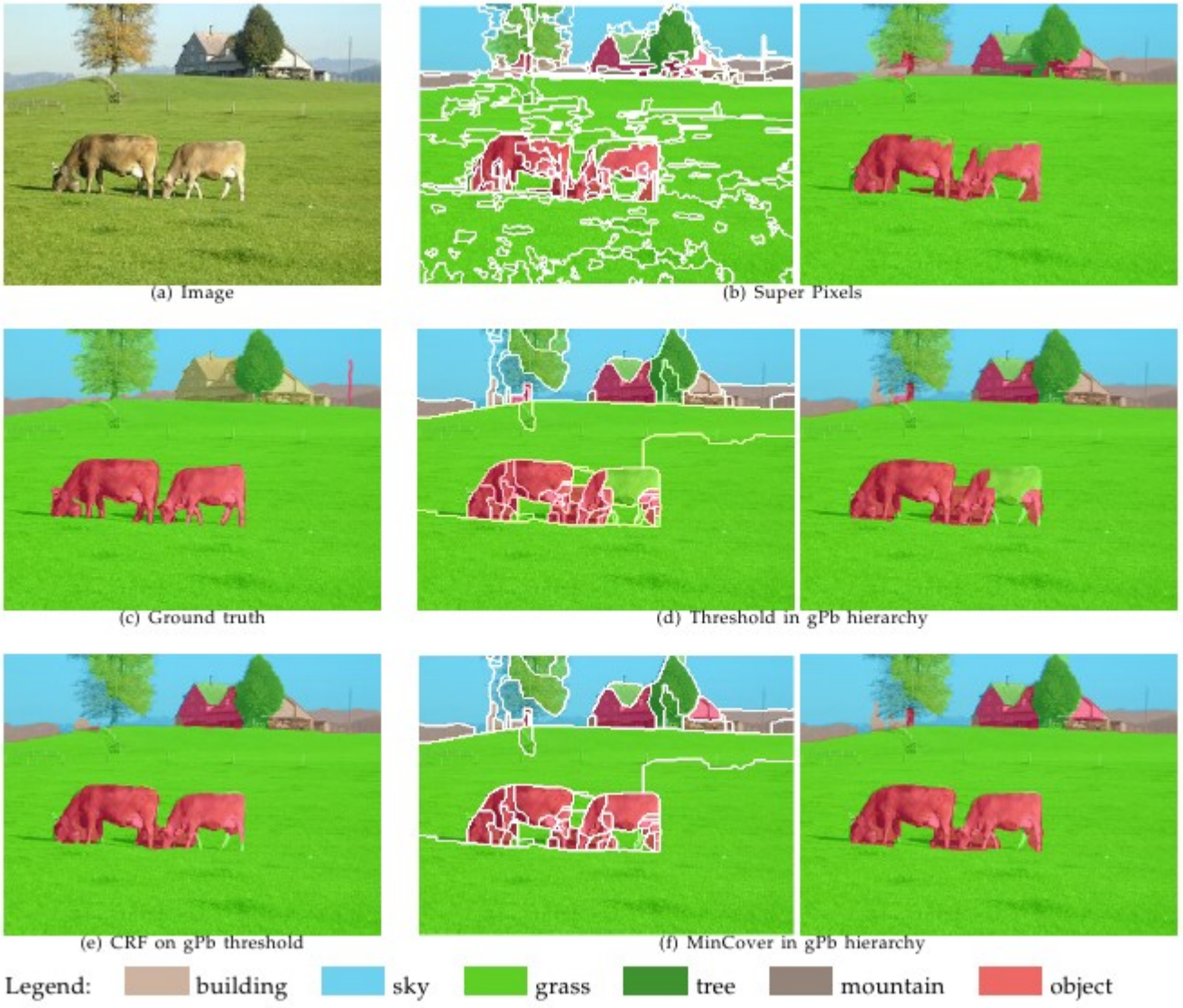
- Barcelona dataset
- [Tighe 2010]:
- 170 categories.

	Pixel Acc.	Class Acc.
Tighe *et al.* 2010 [44]	66.9%	7.6%
raw multiscale net[1]	37.8%	**12.1%**
multiscale net + superpixels[1]	44.1%	**12.4%**
multiscale net + cover[1]	46.4%	**12.5%**
multiscale net + cover[2]	**67.8%**	**9.5%**

[Farabet et al. IEEE T. PAMI 2012]

Scene Parsing/Labeling: Results

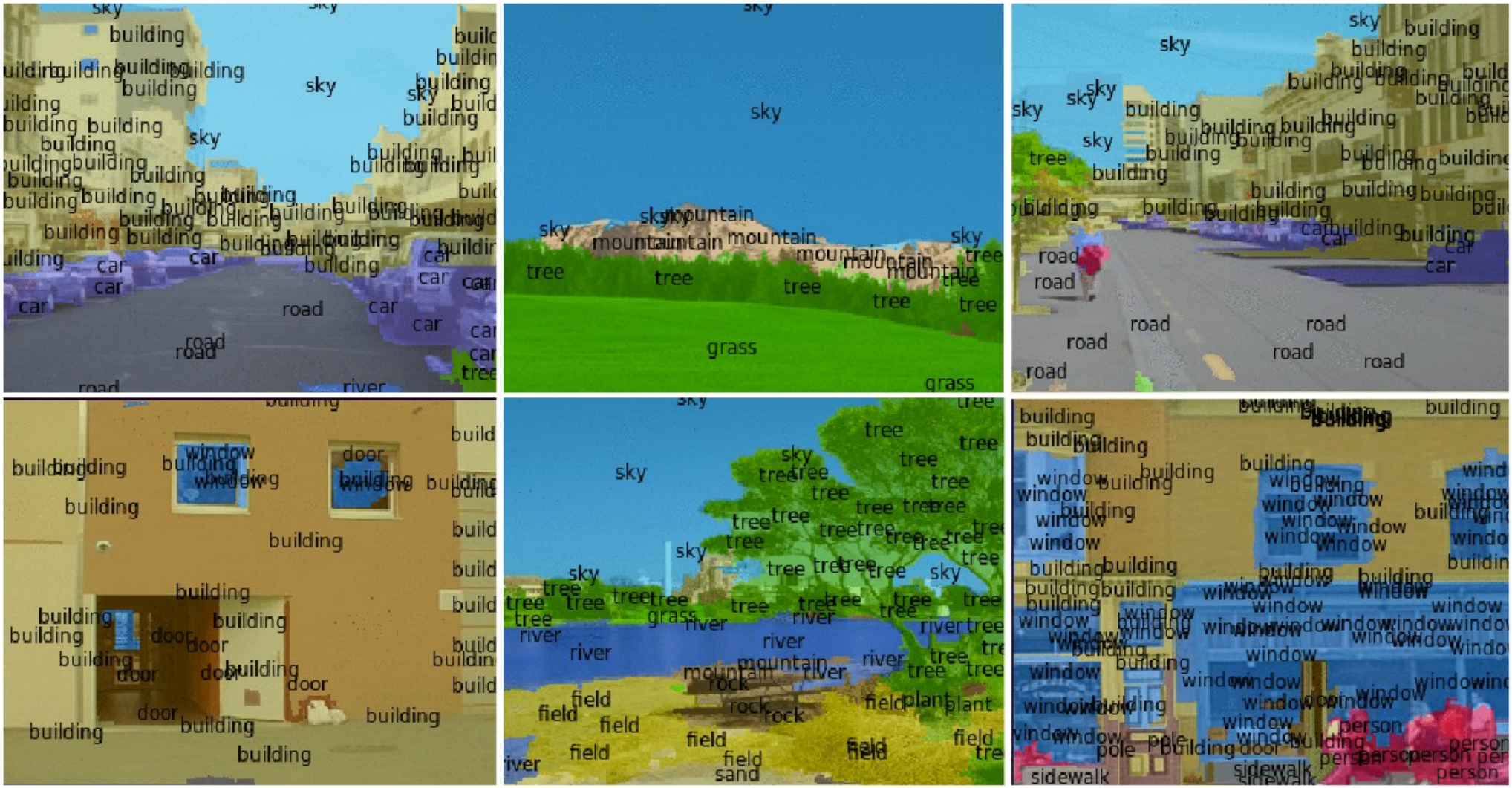
- Samples from the SIFT-Flow dataset (Liu)



[Farabet et al. 2012]

Scene Parsing/Labeling: SIFT Flow dataset (33 categories)

- Samples from the SIFT-Flow dataset (Liu)



[Farabet et al. ICML 2012]

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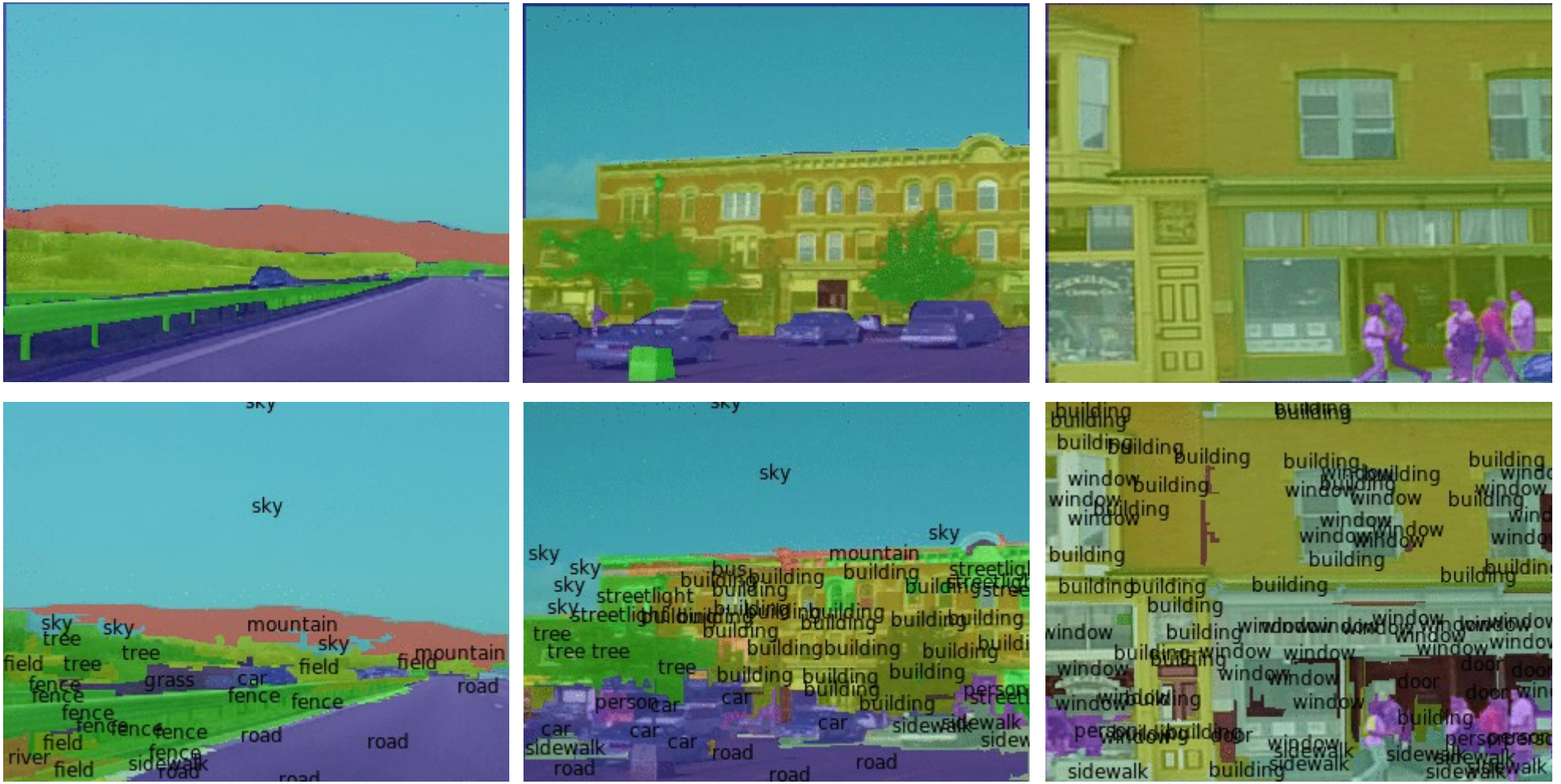

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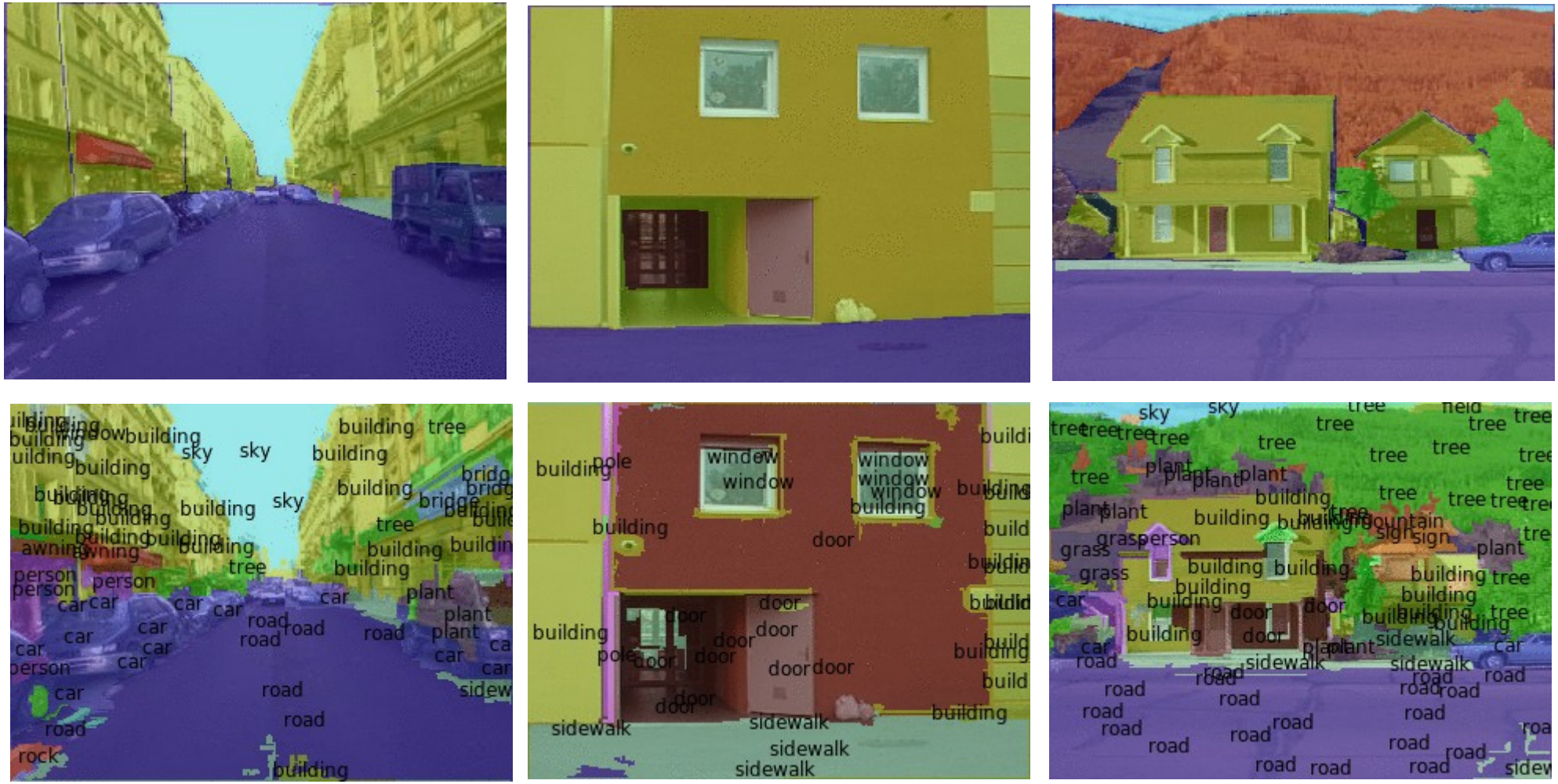
Scene Parsing/Labeling



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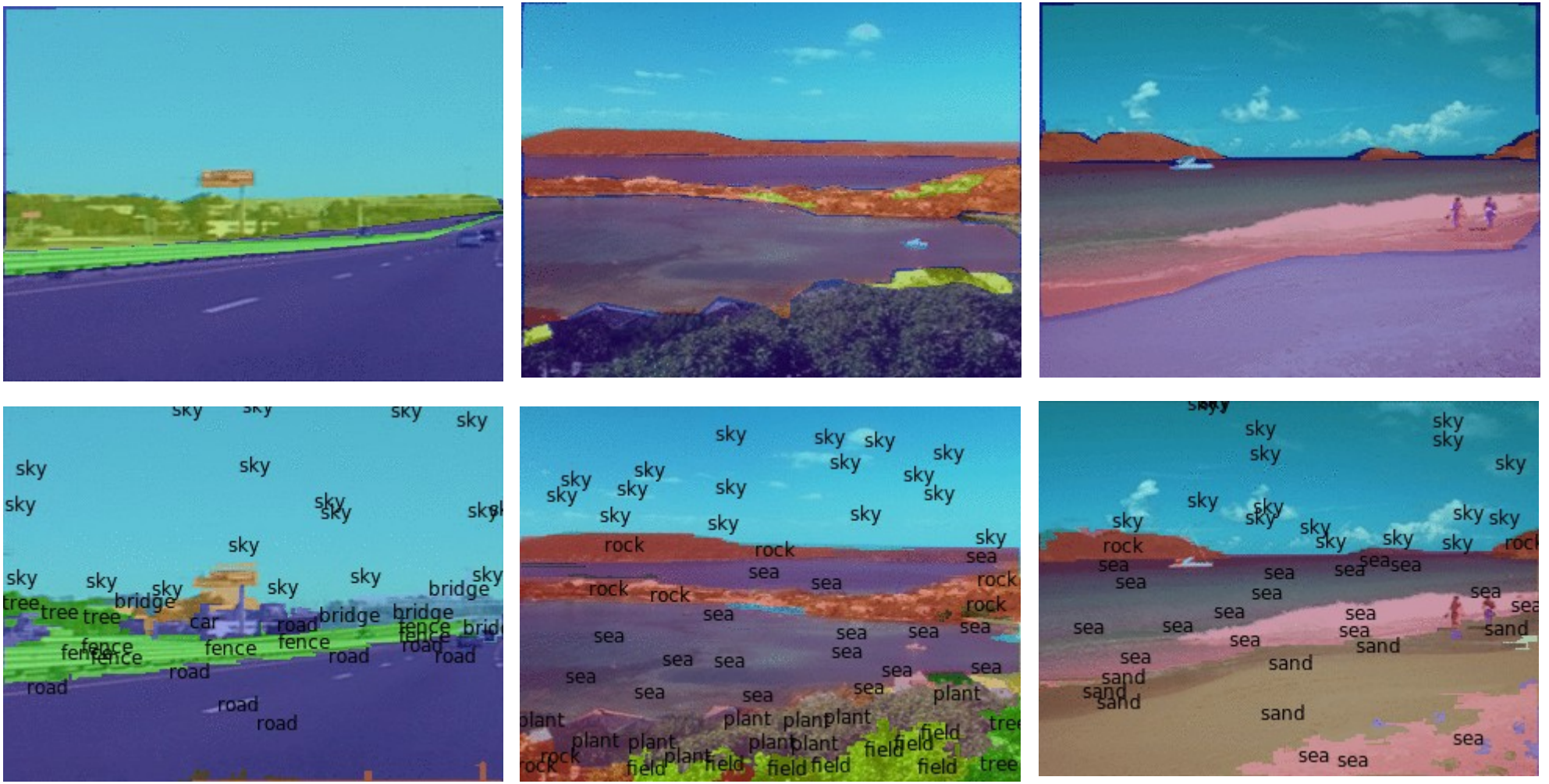

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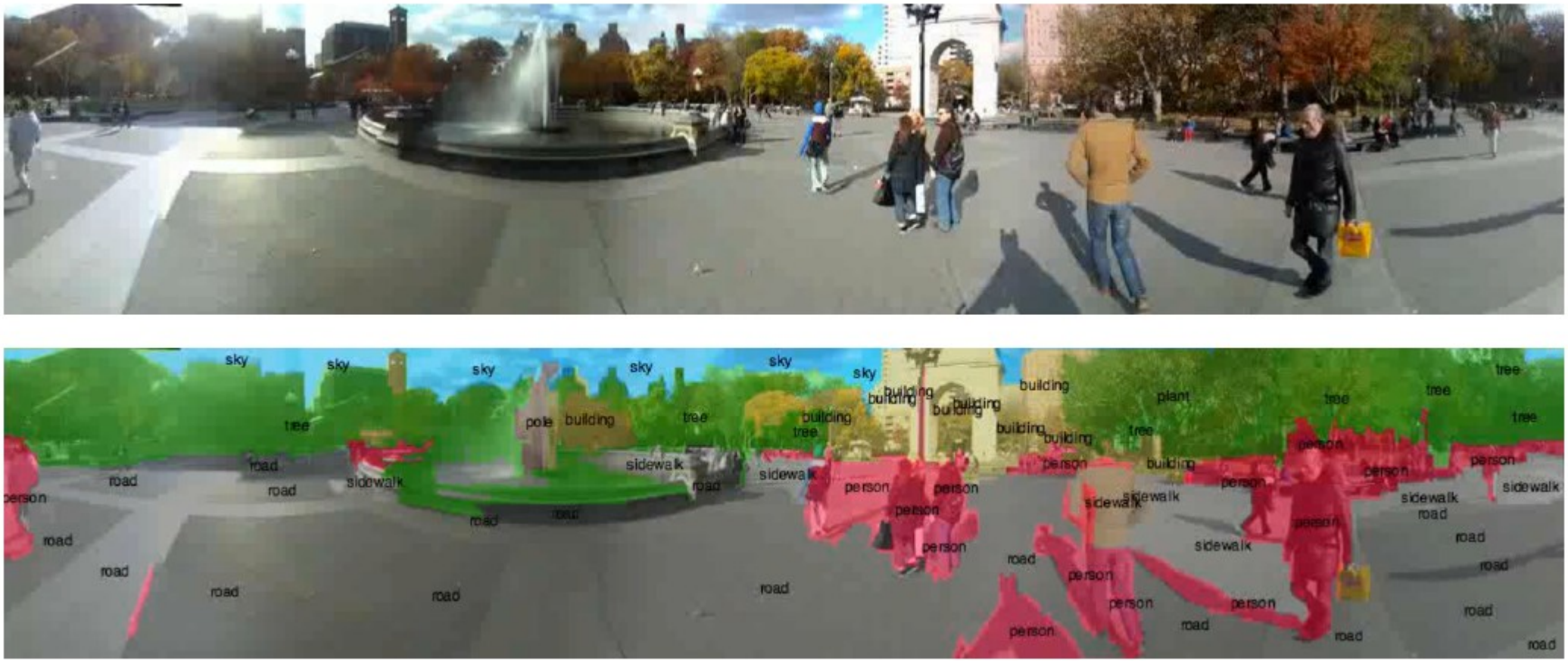

[Farabet et al. 2012]

Scene Parsing/Labeling

[Farabet et al. 2012]

Scene Parsing/Labeling

- No post-processing
- Frame-by-frame
- ConvNet runs at 50ms/frame on Virtex-6 FPGA hardware
  - But communicating the features over ethernet limits system perf.

Scene Parsing/Labeling: Temporal Consistency

- Majority Vote on Spatio-Temporal Super-Pixels
- Reset every second

Scene Parsing/Labeling: Temporal Consistency

- Majority Vote on Spatio-Temporal Super-Pixels
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Unsupervised Feature Learning

variations on the sparse auto-encoder theme

Learning Features with Unsupervised Pre-Training

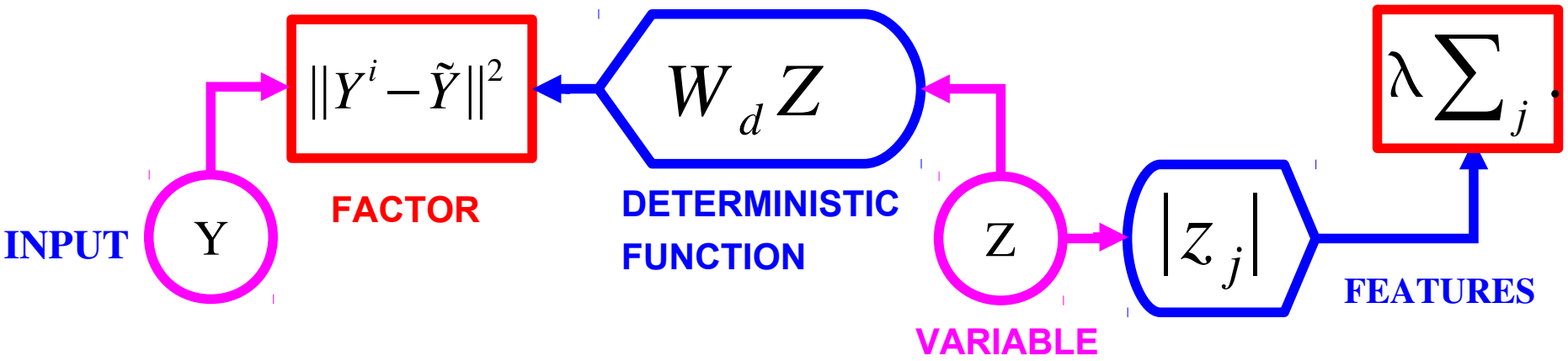
- Supervised learning requires lots of labeled samples
- Most available data is unlabeled
- Models need to be large to "understand" the task
- But large models have many parameters and require many labeled samples
- Unsupervised learning can be used to pre-train the system before supervised refinement
- Unsupervised pre-training "consumes" degrees of freedom while placing the system in a favorable region of parameter space.
- Supervised refinement merely find the closest local minimum within the attractor found by unsupervised pre-training.
- Unsupervised feature learning through sparse/overcomplete auto-encoders
- With high-dimensional and sparse representations, the data manifold is "flattened" (any collection of points is flatter in higher dimension)

Sparse Coding & Sparse Modeling

[Olshausen & Field 1997]

- Sparse linear reconstruction
- Energy = reconstruction_error + code_prediction_error + code_sparsity

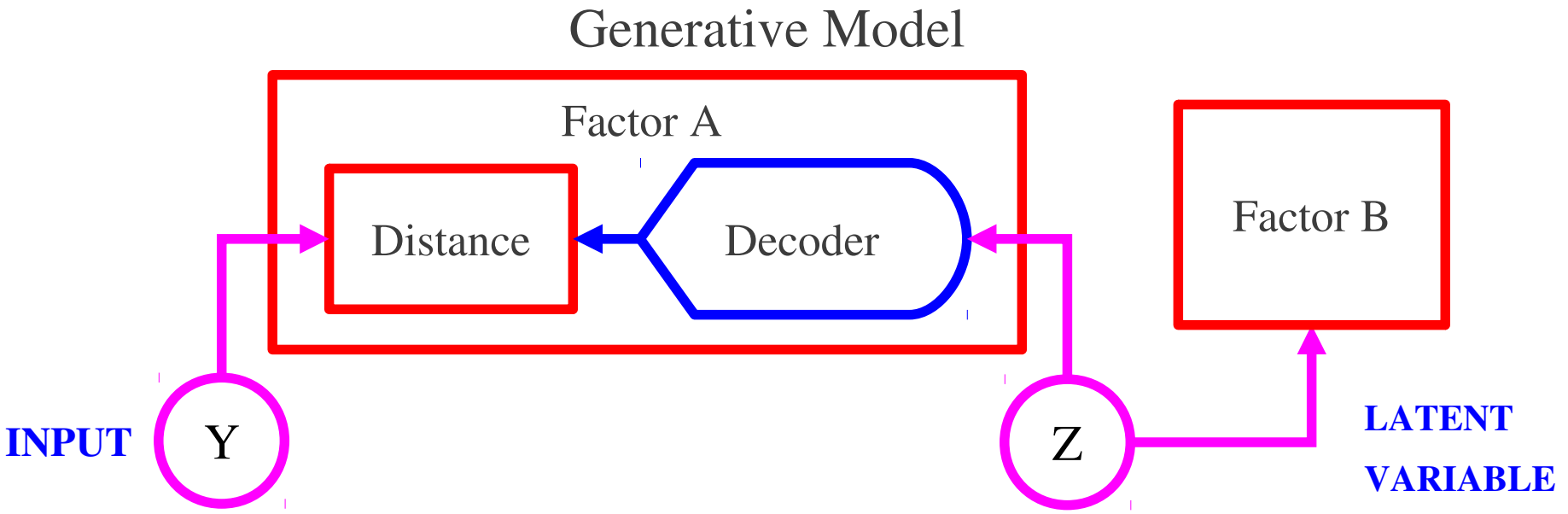
$$E(Y^i, Z) = \|Y^i - W_d Z\|^2 + \lambda \sum_j |z_j|$$



- Inference is slow $Y \rightarrow \hat{Z} = argmin_Z E(Y, Z)$

How to Speed Up Inference in a Generative Model?

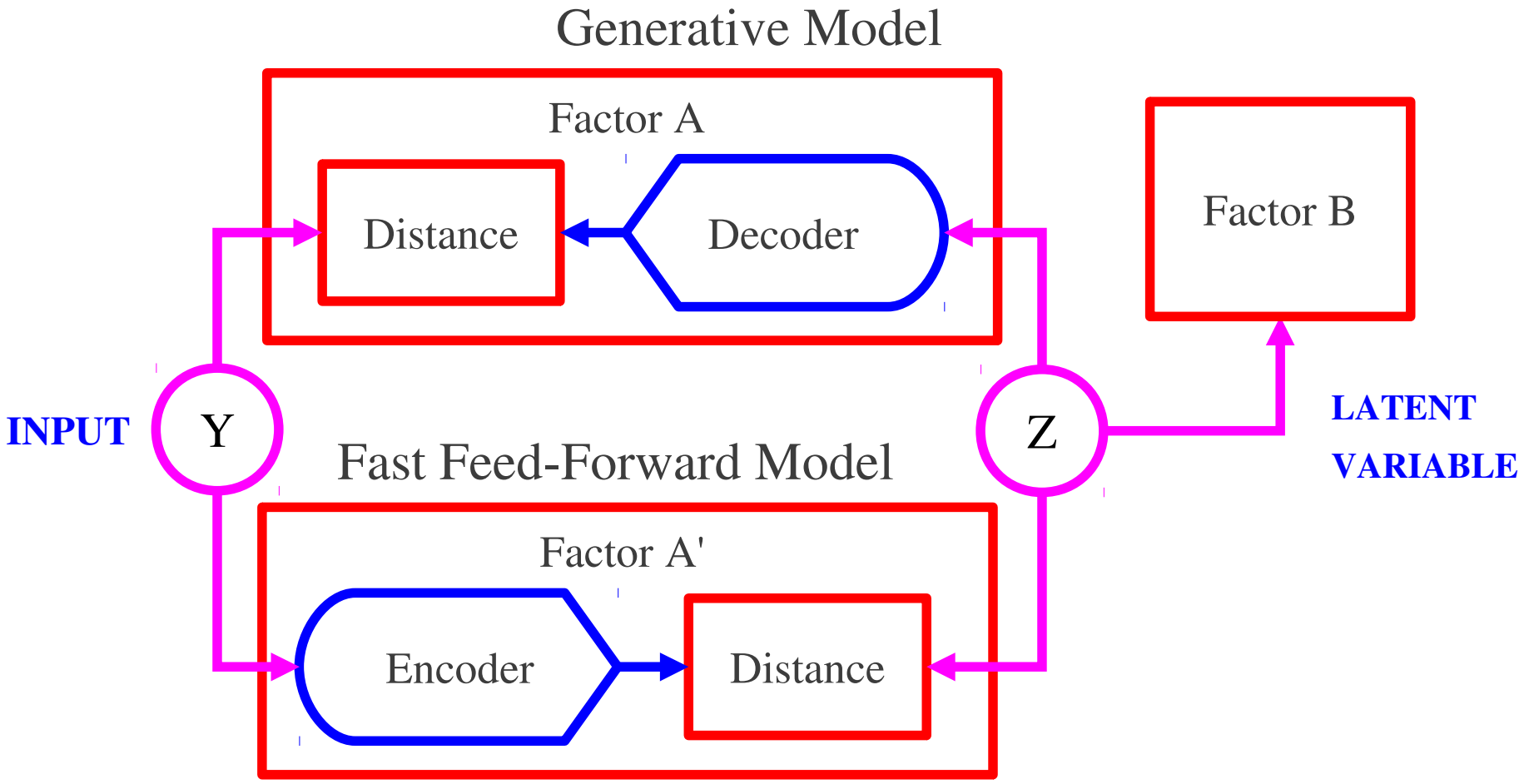
- Factor Graph with an asymmetric factor
- Inference Z → Y is easy
  - Run Z through deterministic decoder, and sample Y
- Inference Y → Z is hard, particularly if Decoder function is many-to-one
  - MAP: minimize sum of two factors with respect to Z
  - Z* = argmin_z Distance[Decoder(Z), Y] + FactorB(Z)



Idea: Train a "simple" function to approximate the solution

[Kavukcuoglu, Ranzato, LeCun, rejected by every conference, 2008-2009]

- Train a "simple" feed-forward function to predict the result of a complex optimization on the data points of interest



- 1. Find optimal Zi for all Yi; 2. Train Encoder to predict Zi from Yi

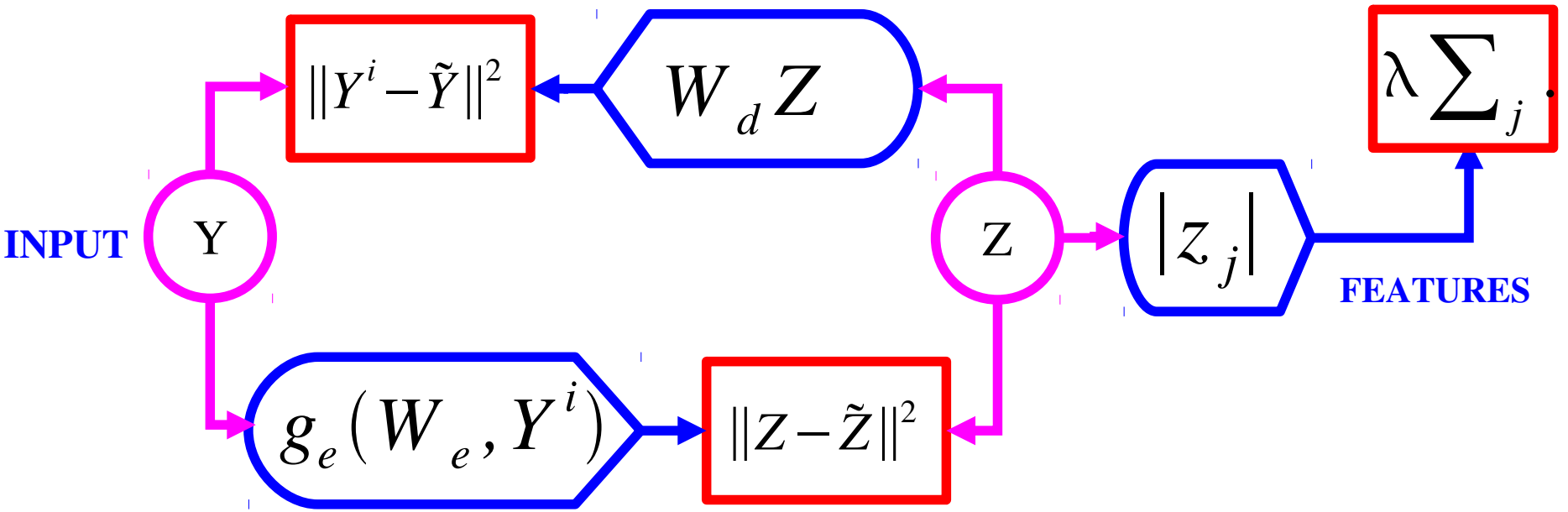
Predictive Sparse Decomposition (PSD): sparse auto-encoder

[Kavukcuoglu, Ranzato, LeCun, 2008 → arXiv:1010.3467],

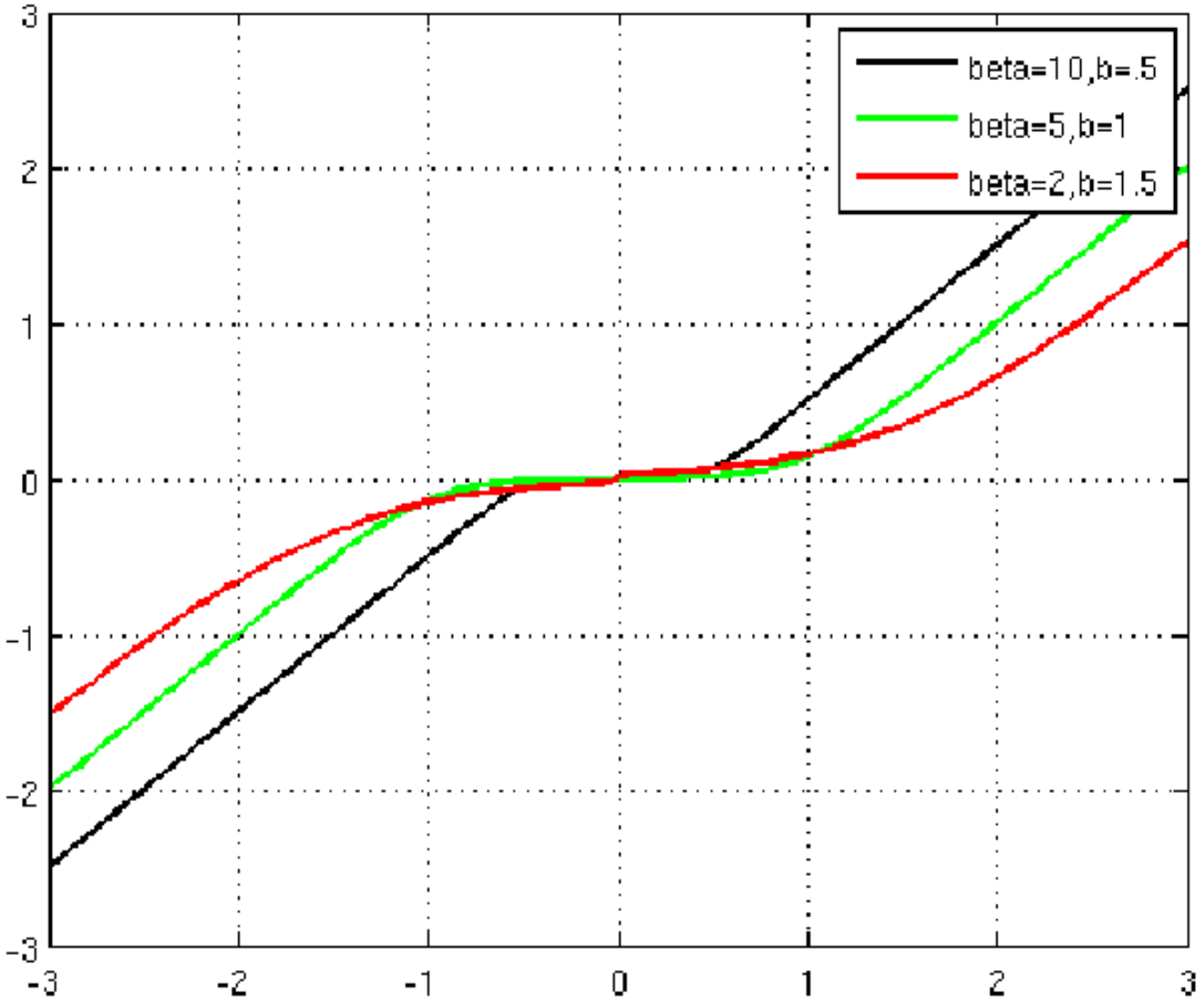
- Prediction the optimal code with a trained encoder
- Energy = reconstruction_error + code_prediction_error + code_sparsity

$$E(Y^i, Z) = \|Y^i - W_d Z\|^2 + \|Z - g_e(W_e, Y^i)\|^2 + \lambda \sum_j |z_j|$$

$$g_e(W_e, Y^i) = shrinkage(W_e Y^i)$$

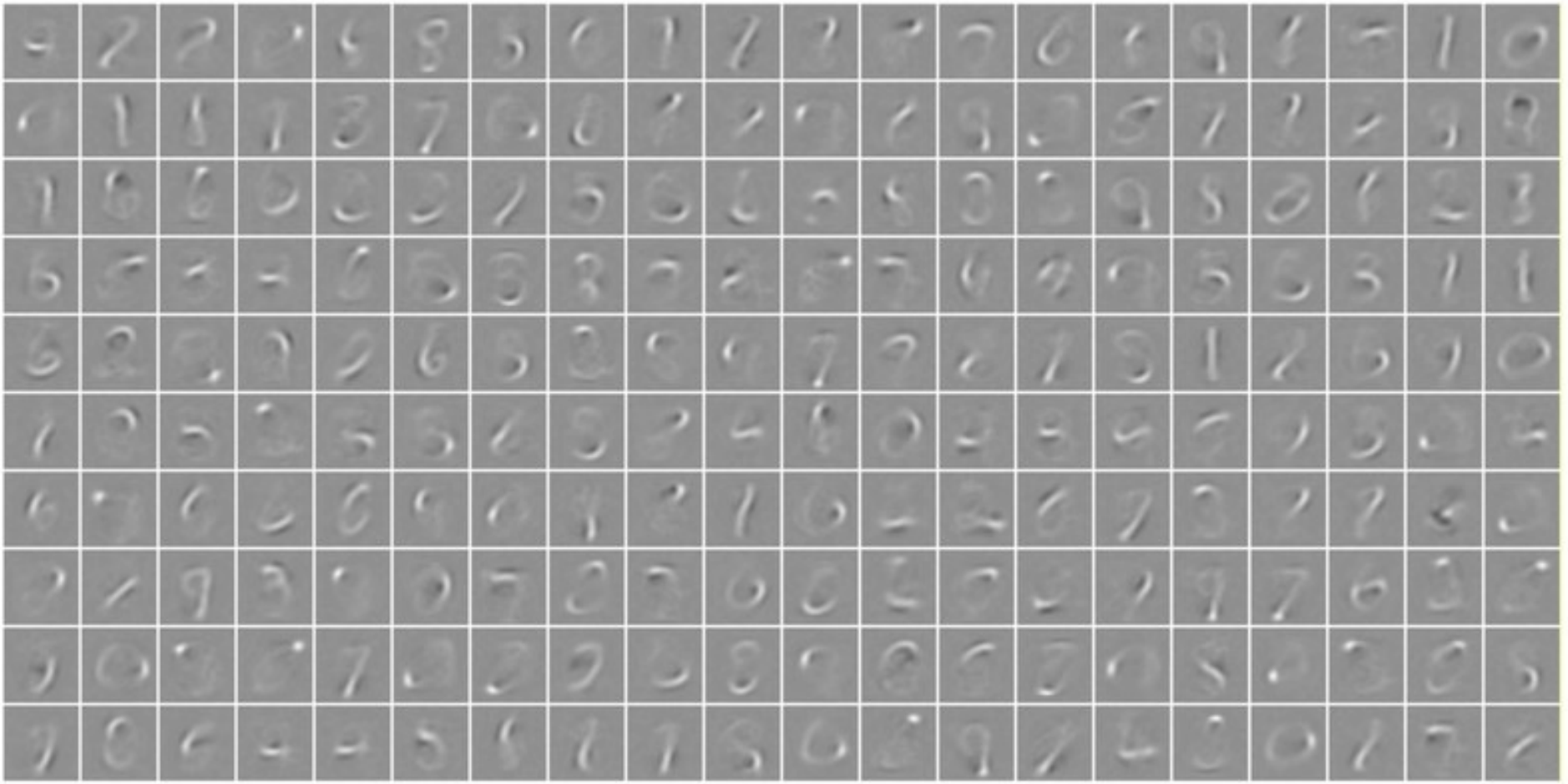


Soft Shrinkage Non-Linearity



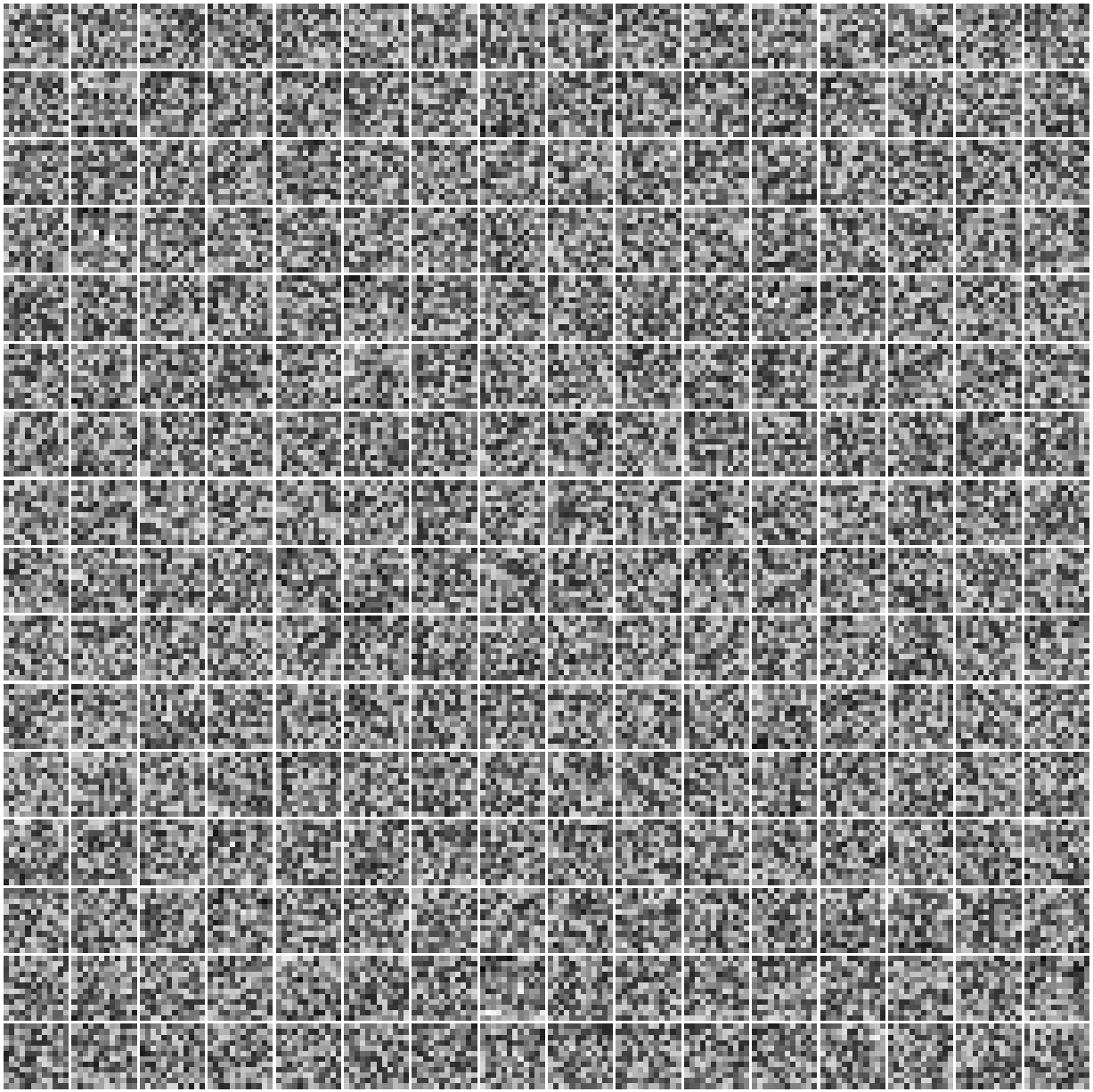
PSD: Basis Functions on MNIST

- Basis functions (and encoder matrix) are digit parts

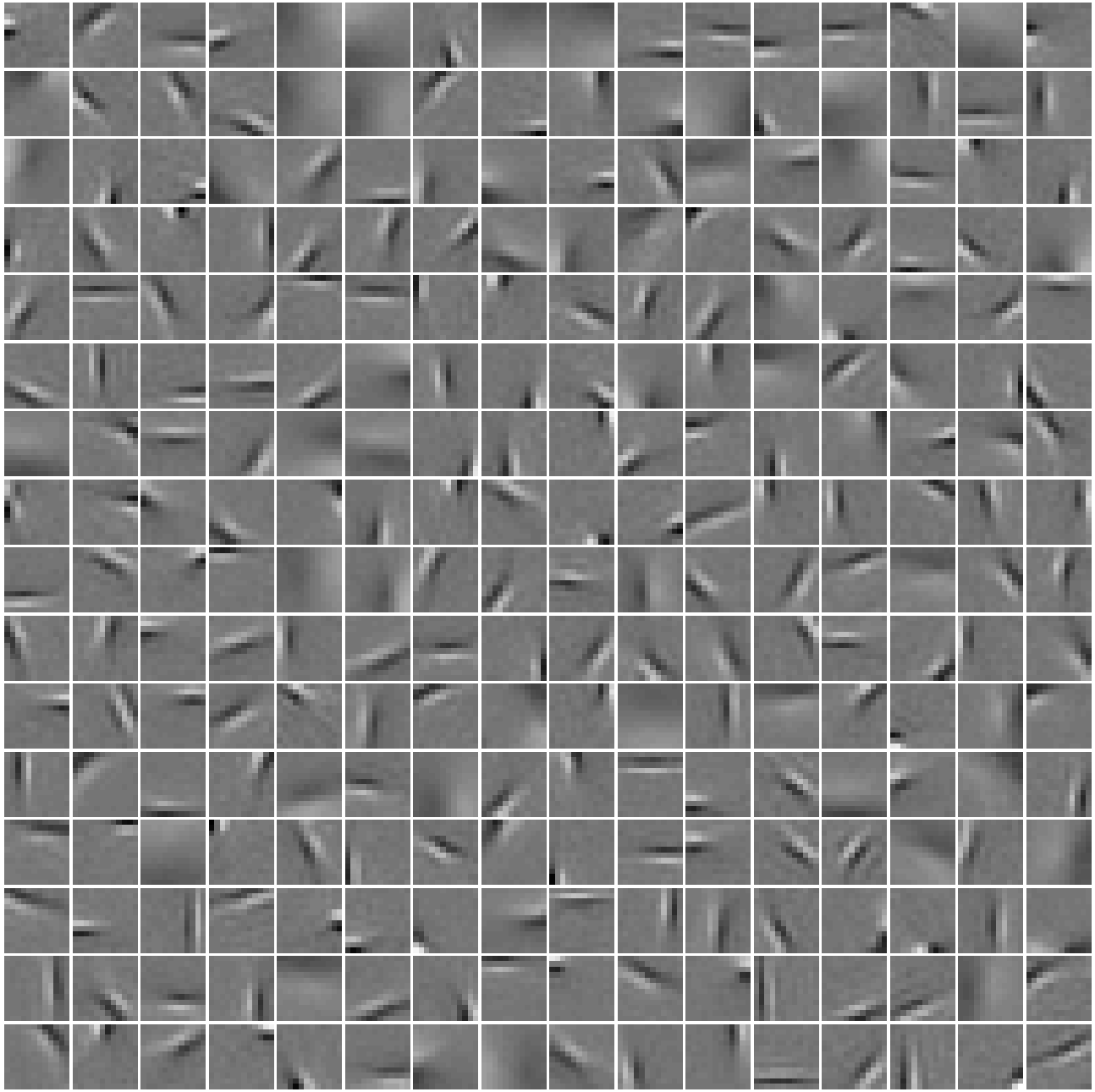


Predictive Sparse Decomposition (PSD): Training

- Training on natural images patches.
  - 12X12
  - 256 basis functions



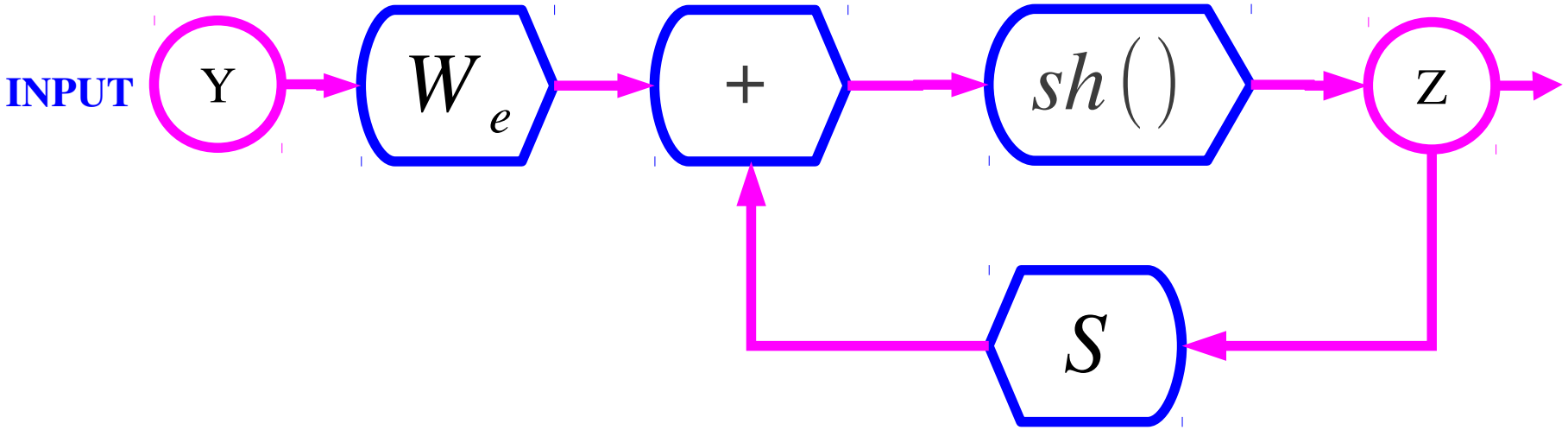
Learned Features on natural patches: V1-like receptive fields



Better Idea: Give the "right" structure to the encoder

[Gregor & LeCun, ICML 2010], [Bronstein et al. ICML 2012]

- ISTA/FISTA: iterative algorithm that converges to optimal sparse code

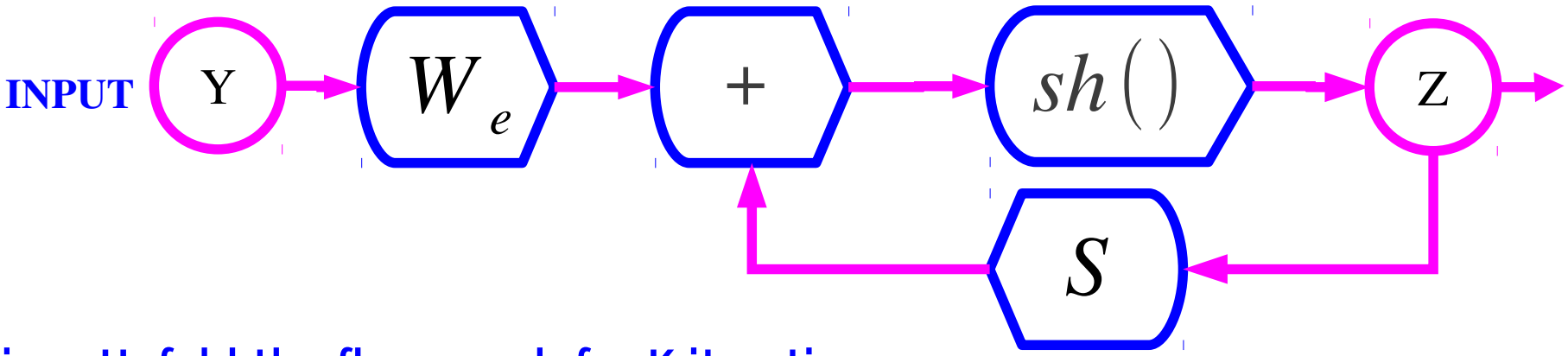


$$Z(t+1) = \text{Shrinkage}_{\lambda/L}\left[Z(t) - \frac{1}{L}W_d^T(W_d Z(t) - Y)\right]$$

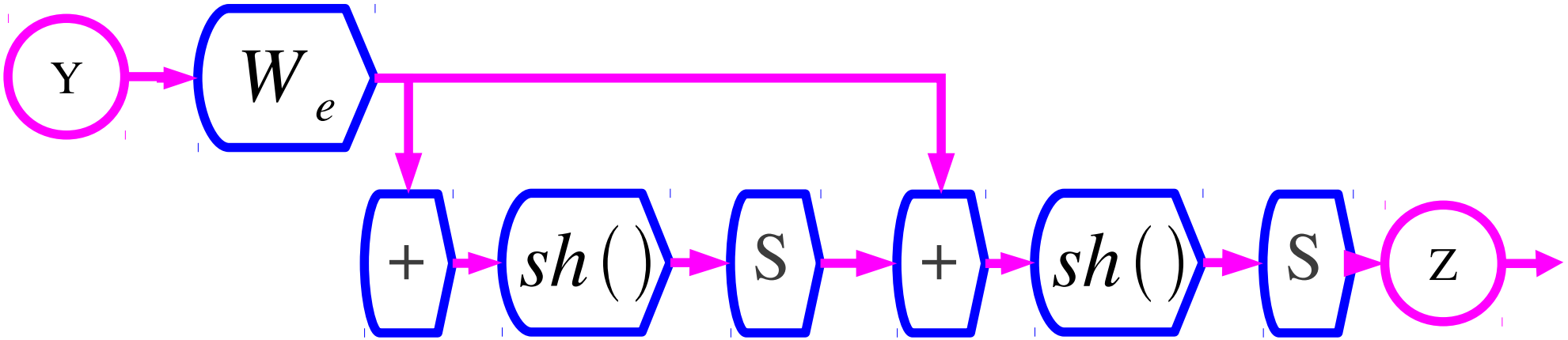
$$Z(t+1) = \text{Shrinkage}_{\lambda/L}\left[W_e^T Y + SZ(t)\right]; \quad W_e = \frac{1}{L}W_d; \quad S = I - \frac{1}{L}W_d^T W_d$$

LISTA: Train We and S matrices to give a good approximation quickly

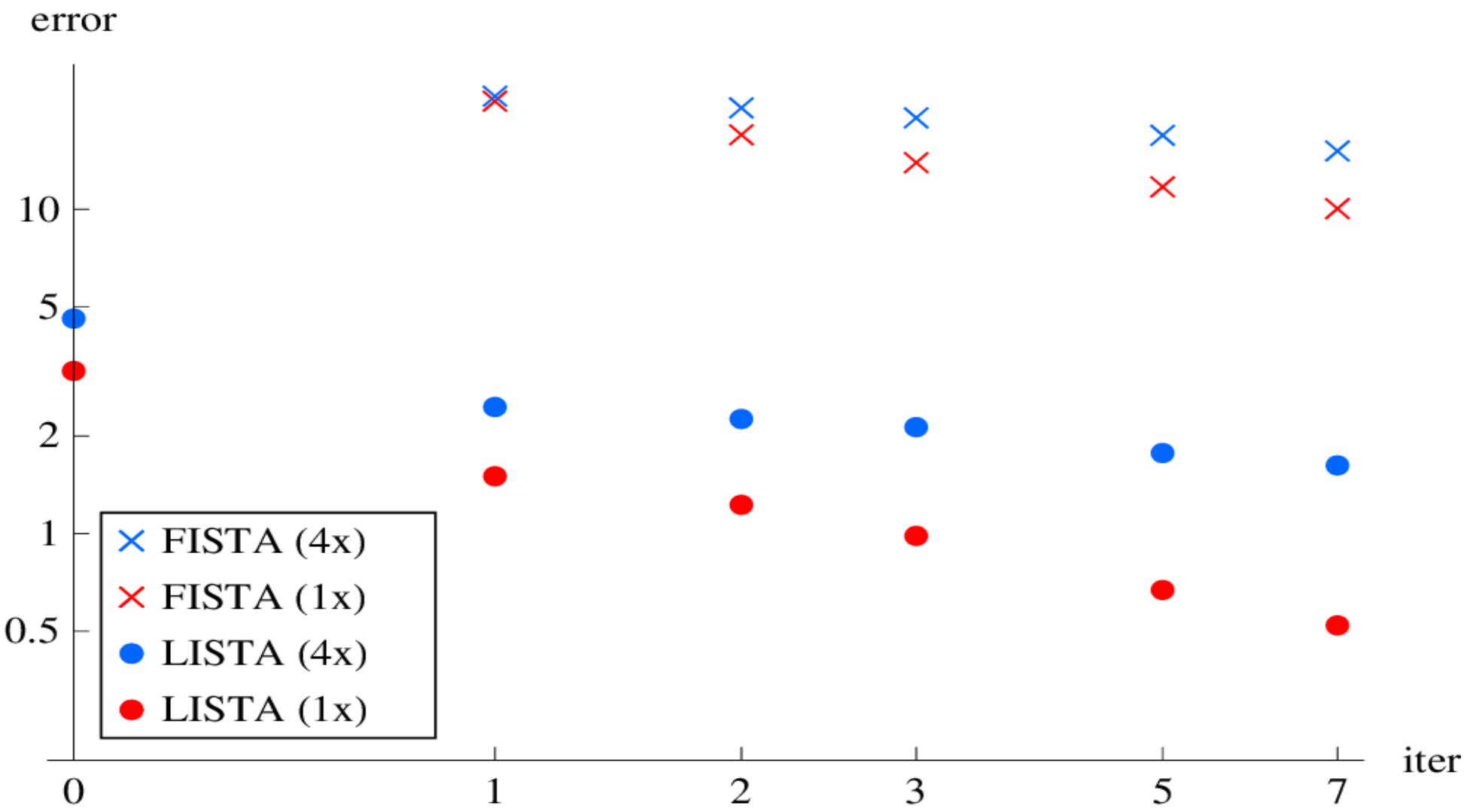
- Think of the FISTA flow graph as a recurrent neural net where We and S are trainable parameters



- Time-Unfold the flow graph for K iterations
- Learn the We and S matrices with "backprop-through-time"
- Get the best approximate solution within K iterations



Learning ISTA (LISTA) vs ISTA/FISTA



One Stage: filter → Shrinkage → L2 Pooling → Contrast Norm

subtractive+divisive contrast normalization

Convolutions

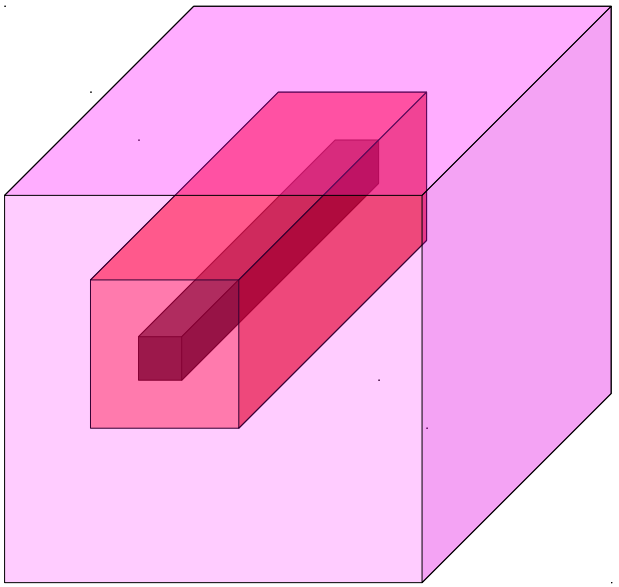
Shrinkage

L2 Pooling & sub-sampling

THIS IS ONE STAGE OF THE CONVNET

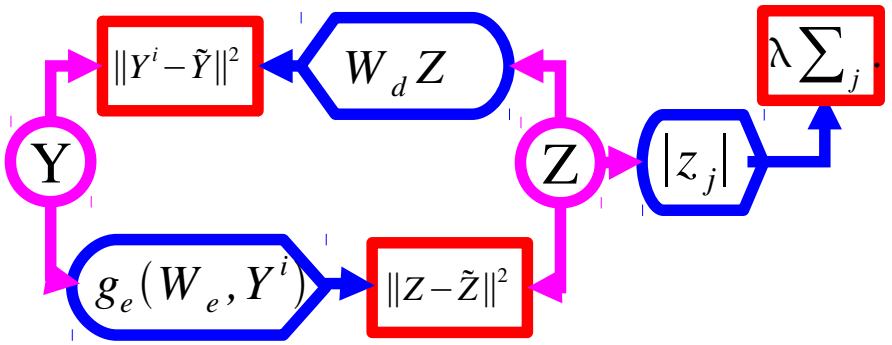
Local Contrast Normalization

- Performed on the state of every layer, including the input
- Subtractive Local Contrast Normalization
  - Subtracts from every value in a feature a Gaussian-weighted average of its neighbors (high-pass filter)
- Divisive Local Contrast Normalization
  - Divides every value in a layer by the standard deviation of its neighbors over space and over all feature maps
- Subtractive + Divisive LCN performs a kind of approximate whitening.



Using PSD to Train a Hierarchy of Features

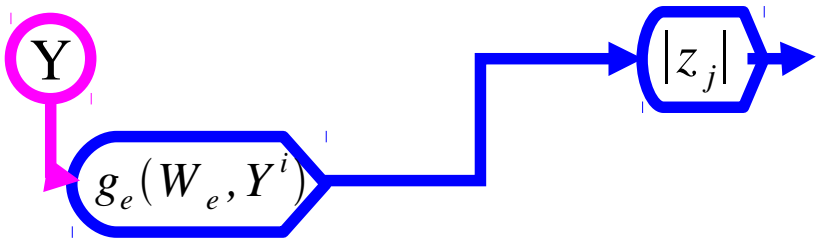
- Phase 1: train first layer using PSD



FEATURES

Using PSD to Train a Hierarchy of Features

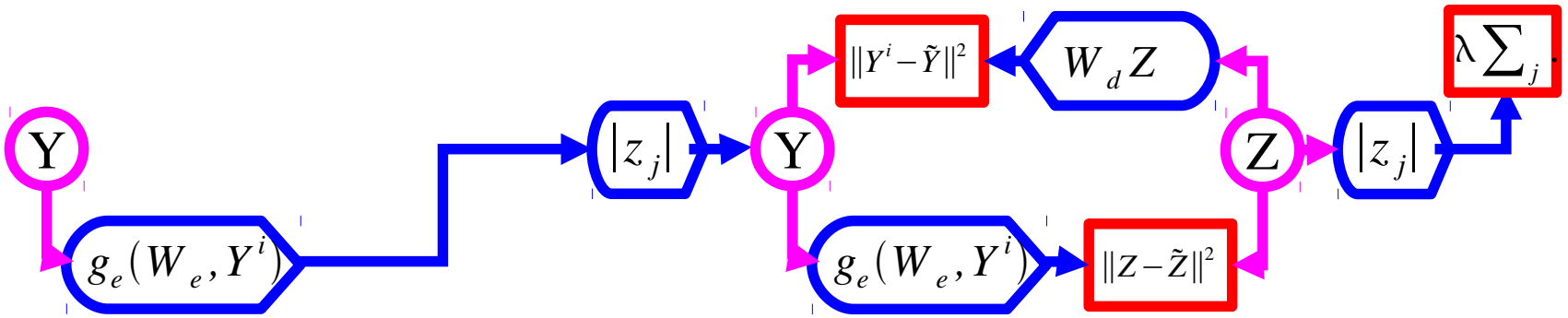
- Phase 1: train first layer using PSD
- Phase 2: use encoder + absolute value as feature extractor



FEATURES

Using PSD to Train a Hierarchy of Features

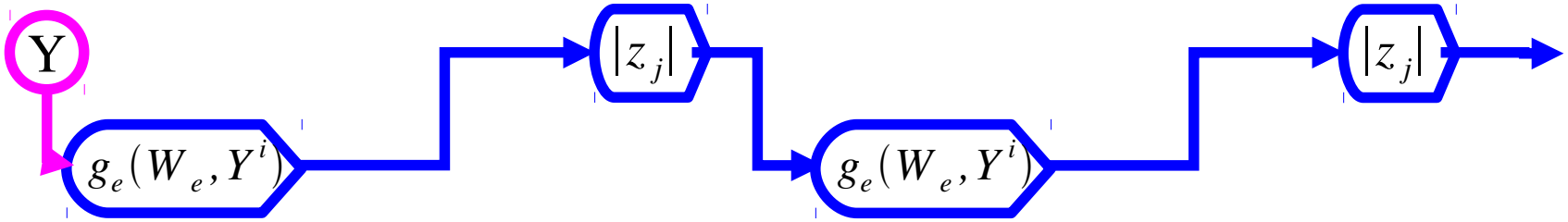
- Phase 1: train first layer using PSD
- Phase 2: use encoder + absolute value as feature extractor
- Phase 3: train the second layer using PSD



FEATURES

Using PSD to Train a Hierarchy of Features

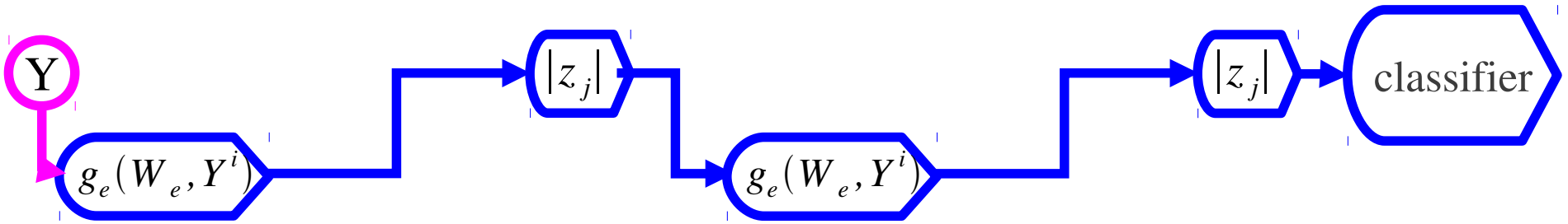
- Phase 1: train first layer using PSD
- Phase 2: use encoder + absolute value as feature extractor
- Phase 3: train the second layer using PSD
- Phase 4: use encoder + absolute value as 2nd feature extractor



FEATURES

Using PSD to Train a Hierarchy of Features

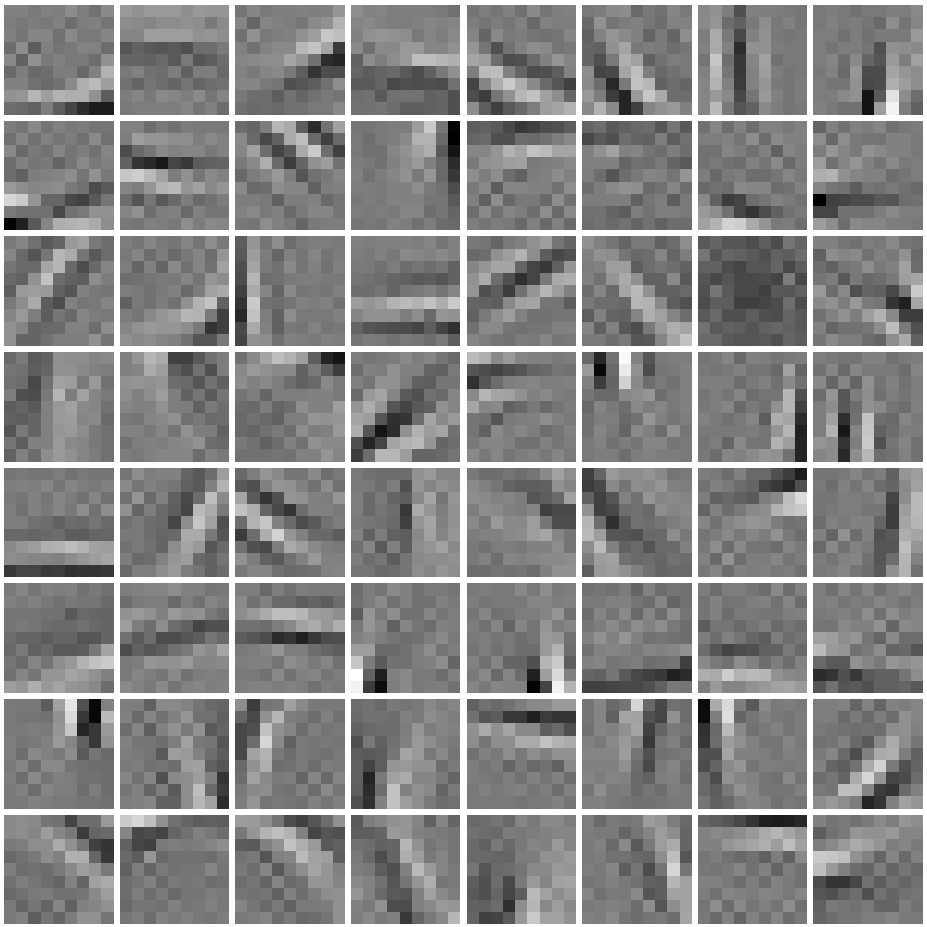
- Phase 1: train first layer using PSD
- Phase 2: use encoder + absolute value as feature extractor
- Phase 3: train the second layer using PSD
- Phase 4: use encoder + absolute value as 2nd feature extractor
- Phase 5: train a supervised classifier on top
- Phase 6 (optional): train the entire system with supervised back-propagation



FEATURES

Using PSD Features for Object Recognition

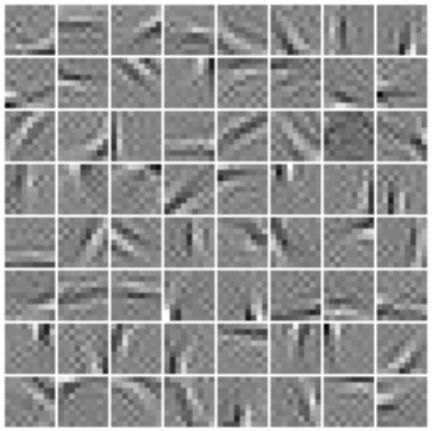
- 64 filters on 9x9 patches trained with PSD
  - with Linear-Sigmoid-Diagonal Encoder

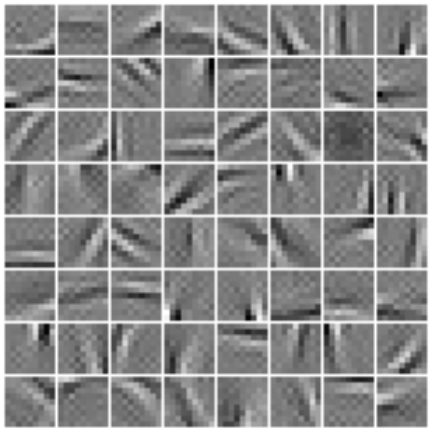


Multistage Hubel-Wiesel Architecture: Filters

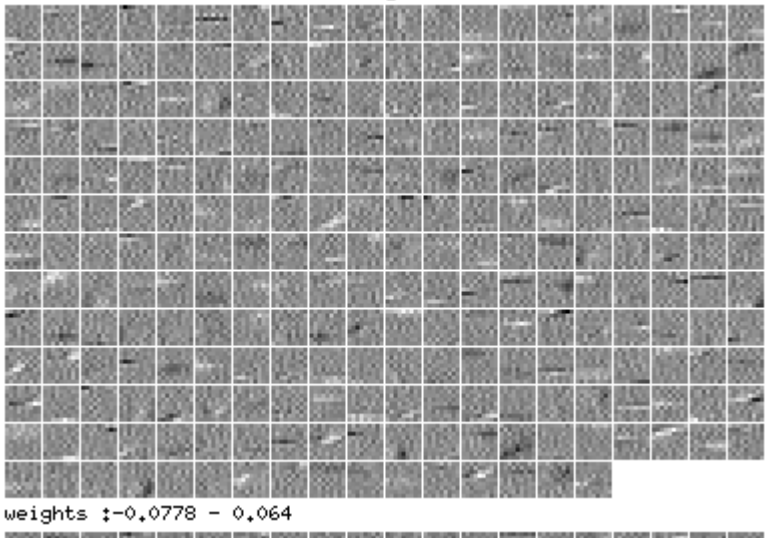
- After PSD
- After supervised refinement

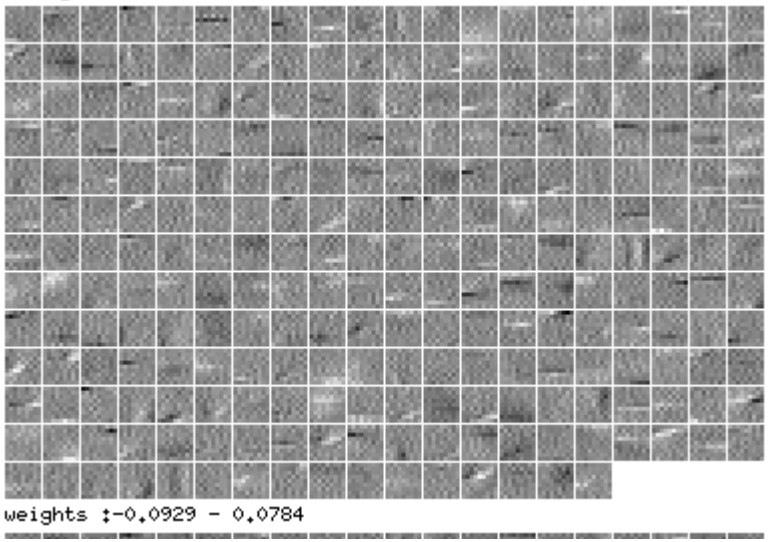
- Stage 1





- Stage2



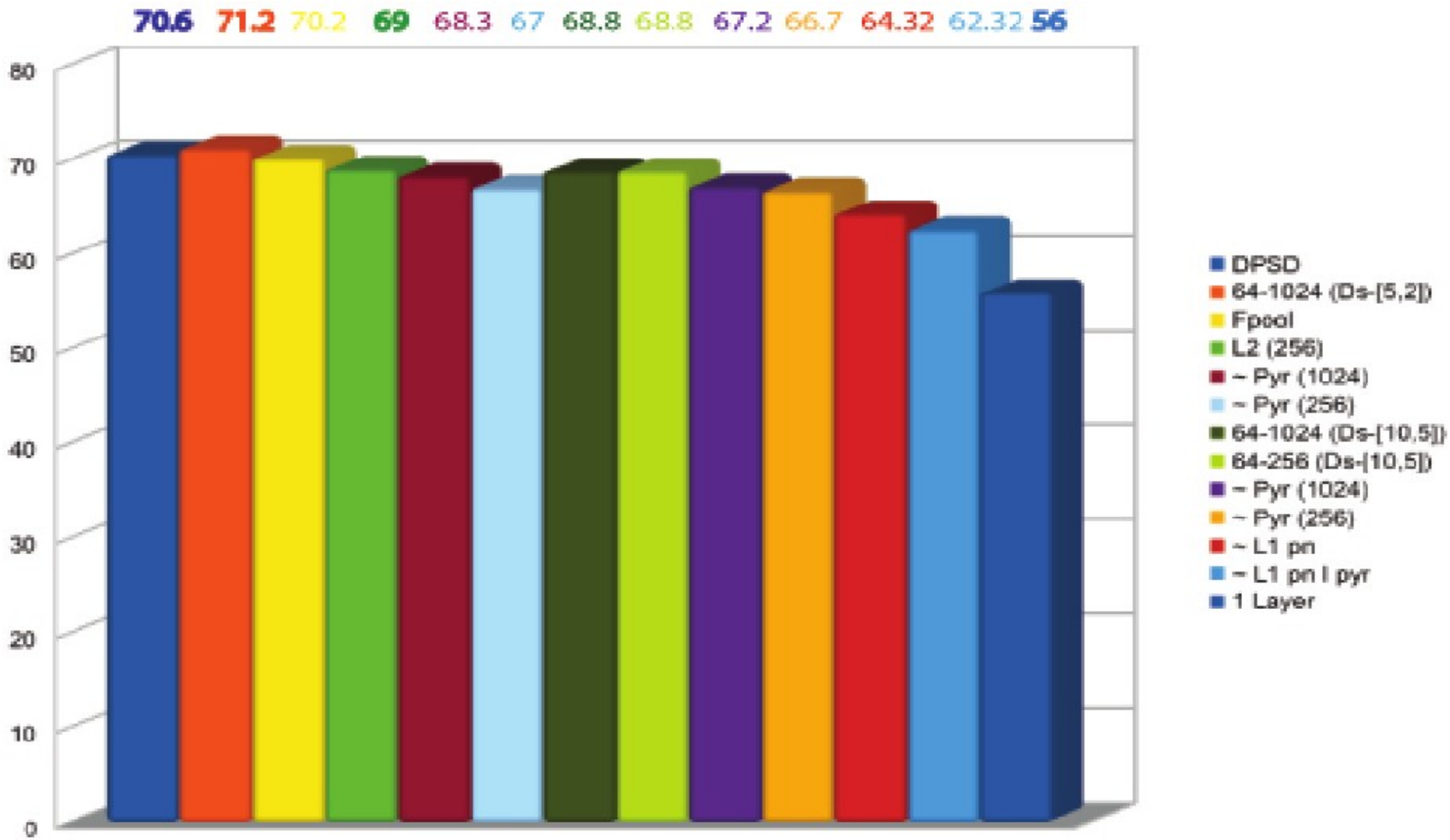


Results on Caltech101 with sigmoid non-linearity

Single Stage System: $[64.F_{CSG}^{9\times9} - R/N/P^{5\times5}]$ **- log_reg**					
R/N/P	$R_{abs} - N - P_A$	$R_{abs} - P_A$	$N - P_M$	$N - P_A$	P_A
U^+	54.2%	50.0%	44.3%	18.5%	14.5%
R^+	54.8%	47.0%	38.0%	16.3%	14.3%
U	52.2%	43.3%($\pm$1.6)	44.0%	17.2%	13.4%
R	53.3%	31.7%	32.1%	15.3%	12.1%($\pm$2.2)
G	52.3%				
Two Stage System: $[64.F_{CSG}^{9\times9} - R/N/P^{5\times5}] - [256.F_{CSG}^{9\times9} - R/N/P^{4\times4}]$ **- log_reg**					
R/N/P	$R_{abs} - N - P_A$	$R_{abs} - P_A$	$N - P_M$	$N - P_A$	P_A
U^+U^+	65.5%	60.5%	61.0%	34.0%	32.0%
R^+R^+	64.7%	59.5%	60.0%	31.0%	29.7%
UU	63.7%	46.7%	56.0%	23.1%	9.1%
RR	62.9%	33.7%($\pm$1.5)	37.6%($\pm$1.9)	19.6%	8.8%
GT	55.8%	← like HMAX model			
Single Stage: $[64.F_{CSG}^{9\times9} - R/N/P^{5\times5}]$ **- PMK-SVM**					
U	64.0%				
Two Stages: $[64.F_{CSG}^{9\times9} - R/N/P^{5\times5}] - [256.F_{CSG}^{9\times9} - R/N]$ **- PMK-SVM**					
UU	52.8%				

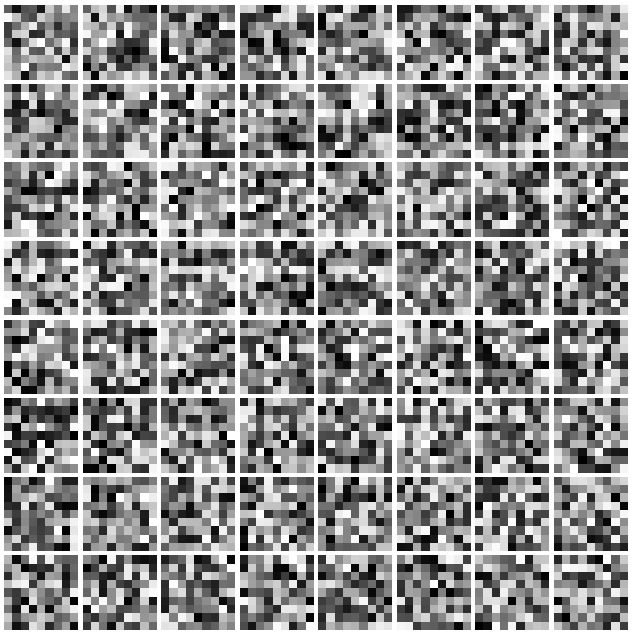
Results on Caltech101: purely supervised with soft-shrink, L2 pooling, contrast normalization

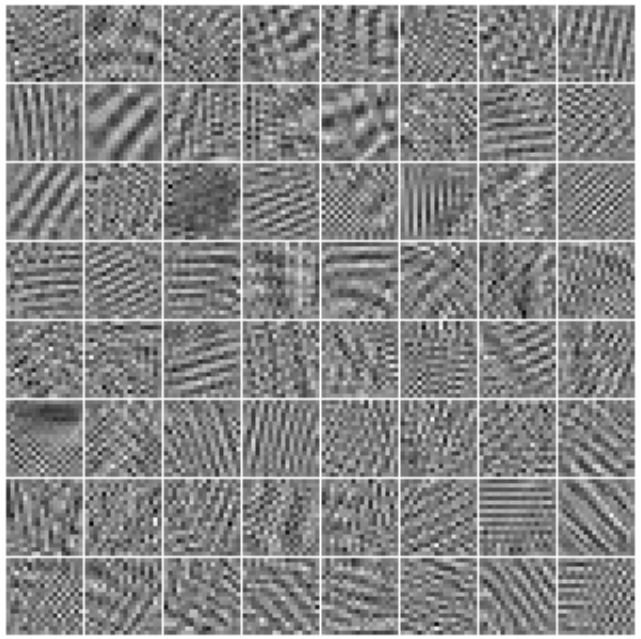
- Supervised learning with soft-shrinkage non-linearity, L2 complex cells, and sparsity penalty on the complex cell outputs: 71%



Why Do Random Filters Work?

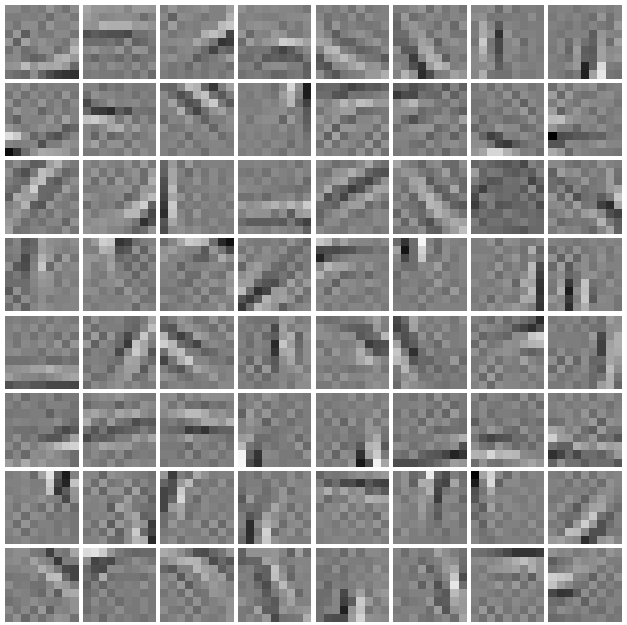
Random Filters For Simple Cells

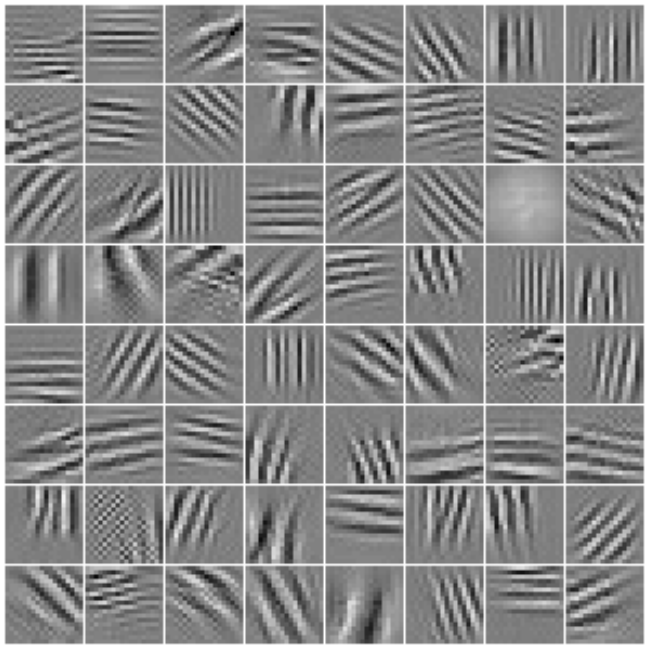




Optimal Stimuli for each Complex Cell

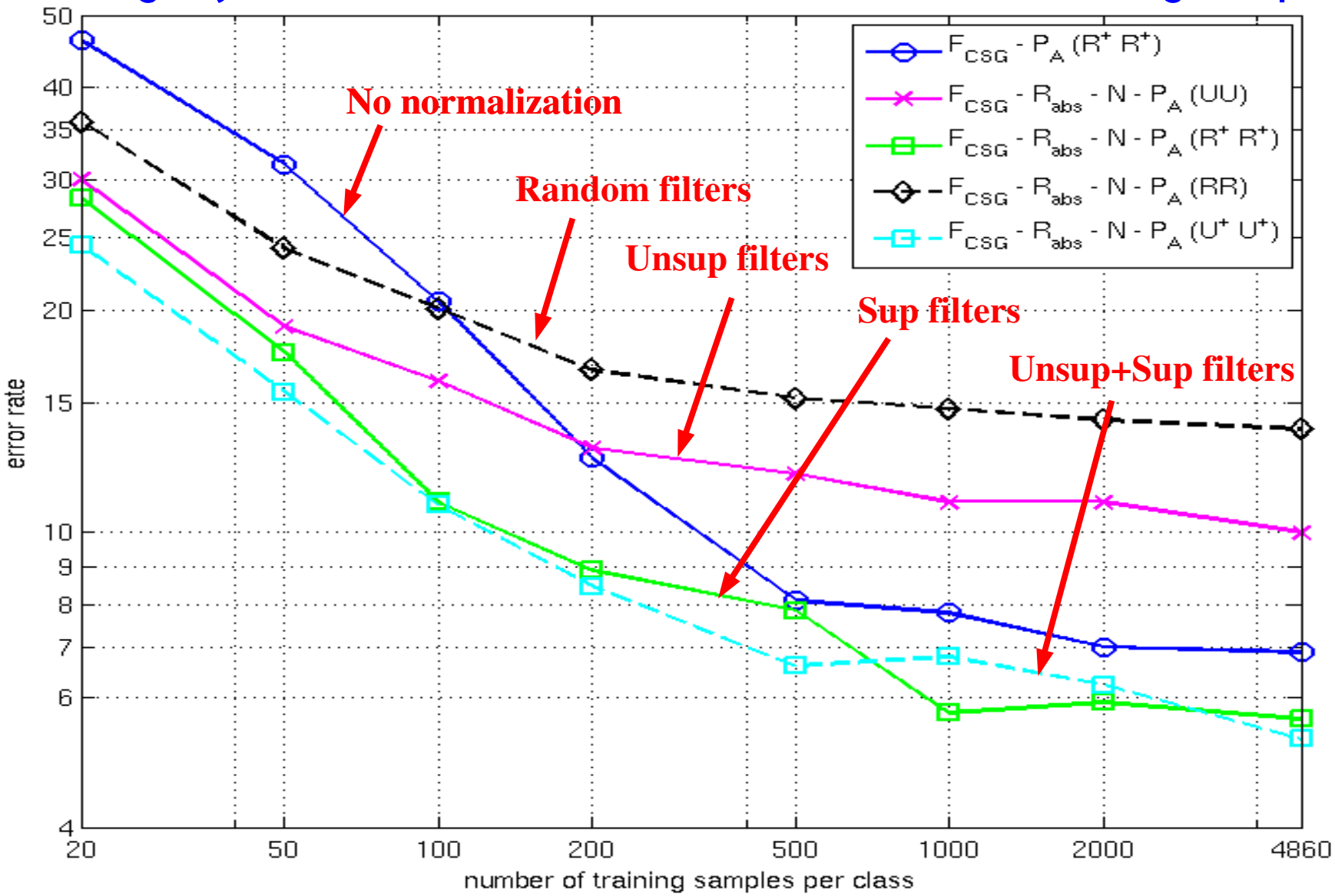
Trained Filters For Simple Cells





Small NORB dataset

- Two-stage system: error rate versus number of labeled training samples



Convolutional Sparse Coding
Convolutional PSD

[Kavukcuoglu, Sermanet, Boureau, Mathieu, LeCun. NIPS 2010]: convolutional PSD

[Zeiler, Krishnan, Taylor, Fergus, CVPR 2010]: Deconvolutional Network

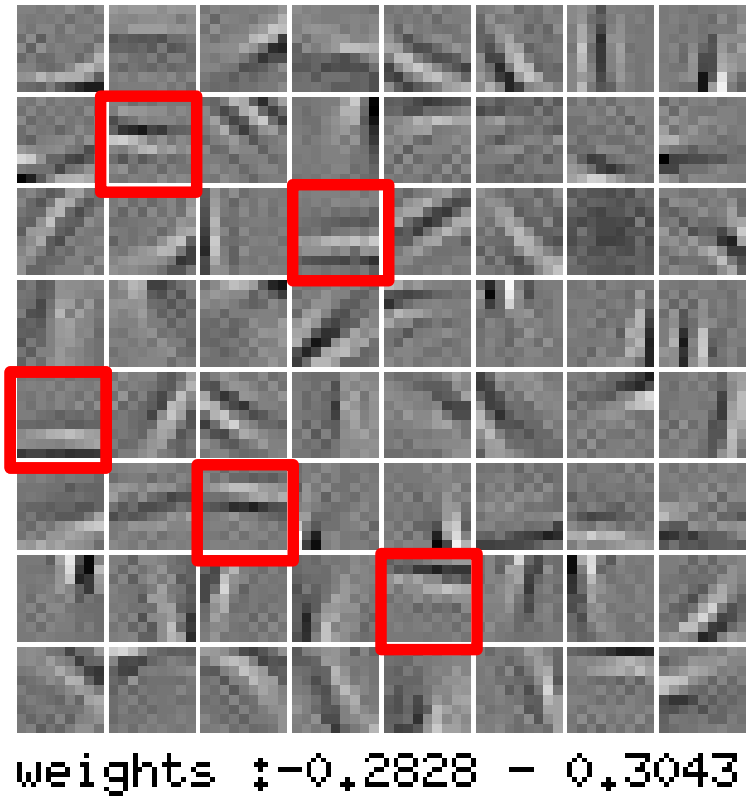
[Lee, Gross, Ranganath, Ng, ICML 2009]: Convolutional Boltzmann Machine

[Norouzi, Ranjbar, Mori, CVPR 2009]: Convolutional Boltzmann Machine

[Chen, Sapiro, Dunson, Carin, Preprint 2010]: Deconvolutional Network with automatic adjustment of code dimension.

Convolutional Training

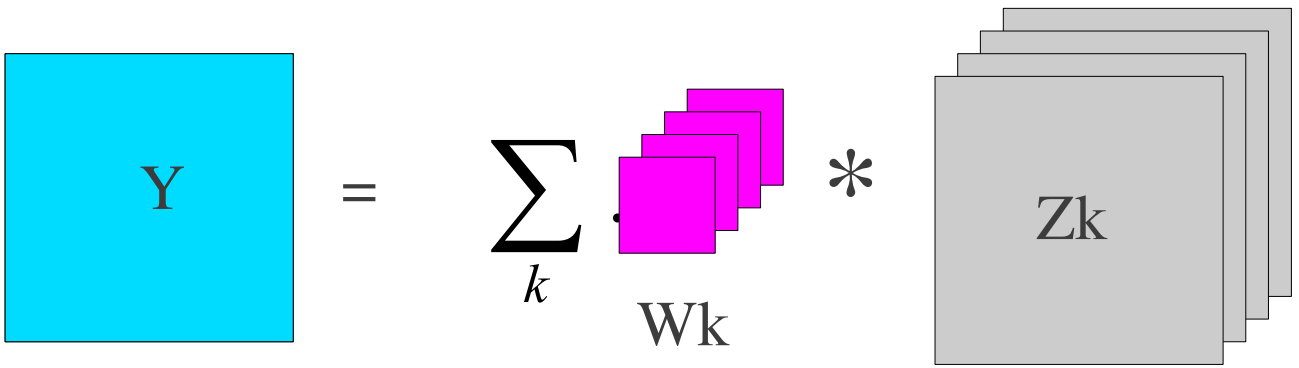
- **Problem:**
  - With patch-level training, the learning algorithm must reconstruct the entire patch with a single feature vector
  - But when the filters are used convolutionally, neighboring feature vectors will be highly redundant



Patch-level training produces lots of filters that are shifted versions of each other.

Convolutional Sparse Coding

- **Replace the dot products with dictionary element by convolutions.**
  - Input Y is a full image
  - Each code component Zk is a feature map (an image)
  - Each dictionary element is a convolution kernel
- **Regular sparse coding** $E(Y,Z) = ||Y - \sum_k W_k Z_k||^2 + \alpha \sum_k |Z_k|$
- **Convolutional S.C.** $E(Y,Z) = ||Y - \sum_k W_k * Z_k||^2 + \alpha \sum_k |Z_k|$



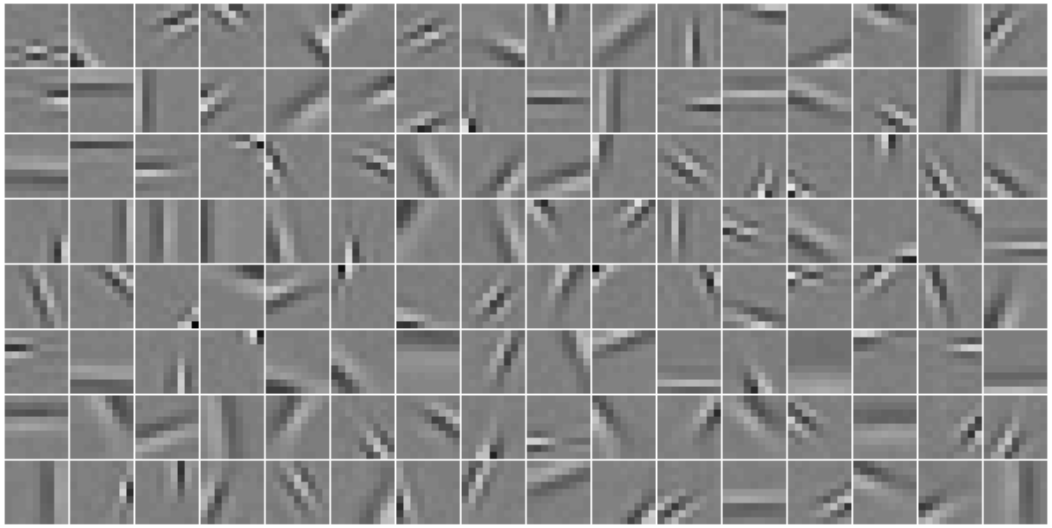
"deconvolutional networks" [Zeiler, Taylor, Fergus CVPR 2010]

Convolutional PSD: Encoder with a soft sh() Function

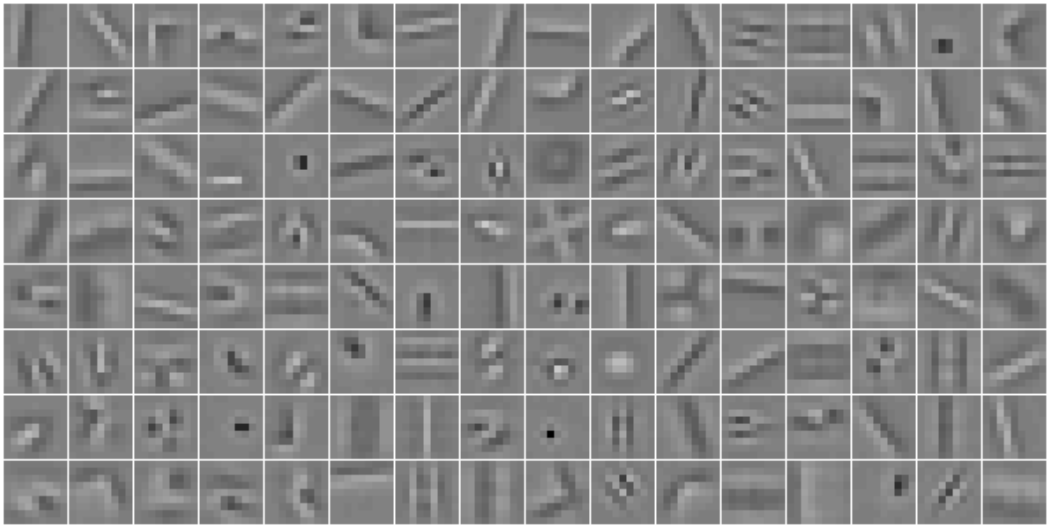
Convolutional Formulation

- Extend sparse coding from ***PATCH*** to ***IMAGE***

$$\mathcal{L}(x, z, \mathcal{D}) = \frac{1}{2}||x - \sum_{k=1}^{K} \mathcal{D}_k * z_k||_2^2 + \sum_{k=1}^{K} ||z_k - f(W^k * x)||_2^2 + |z|_1$$

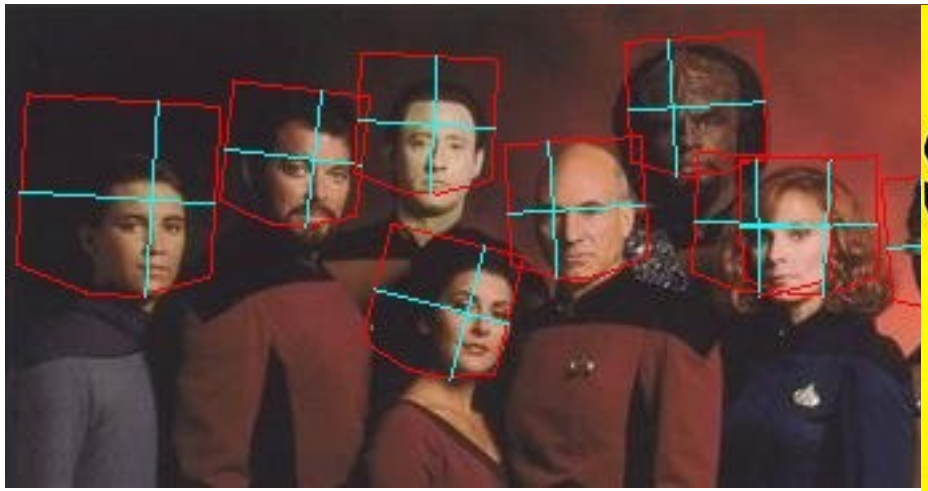


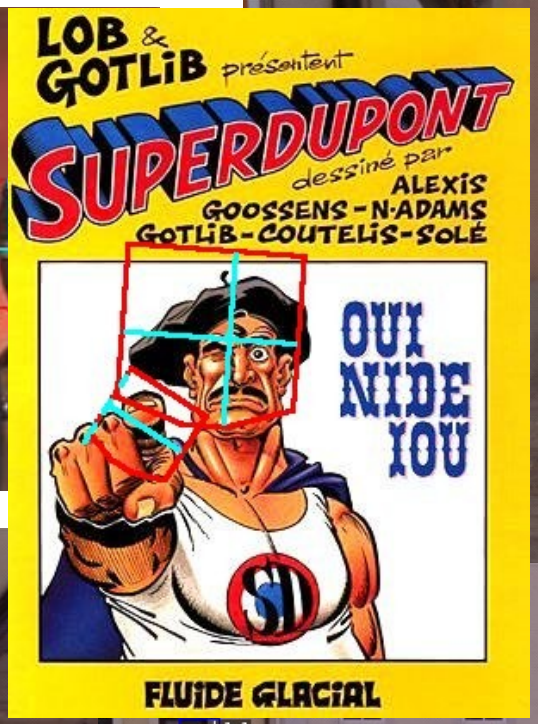
- ***PATCH*** based learning

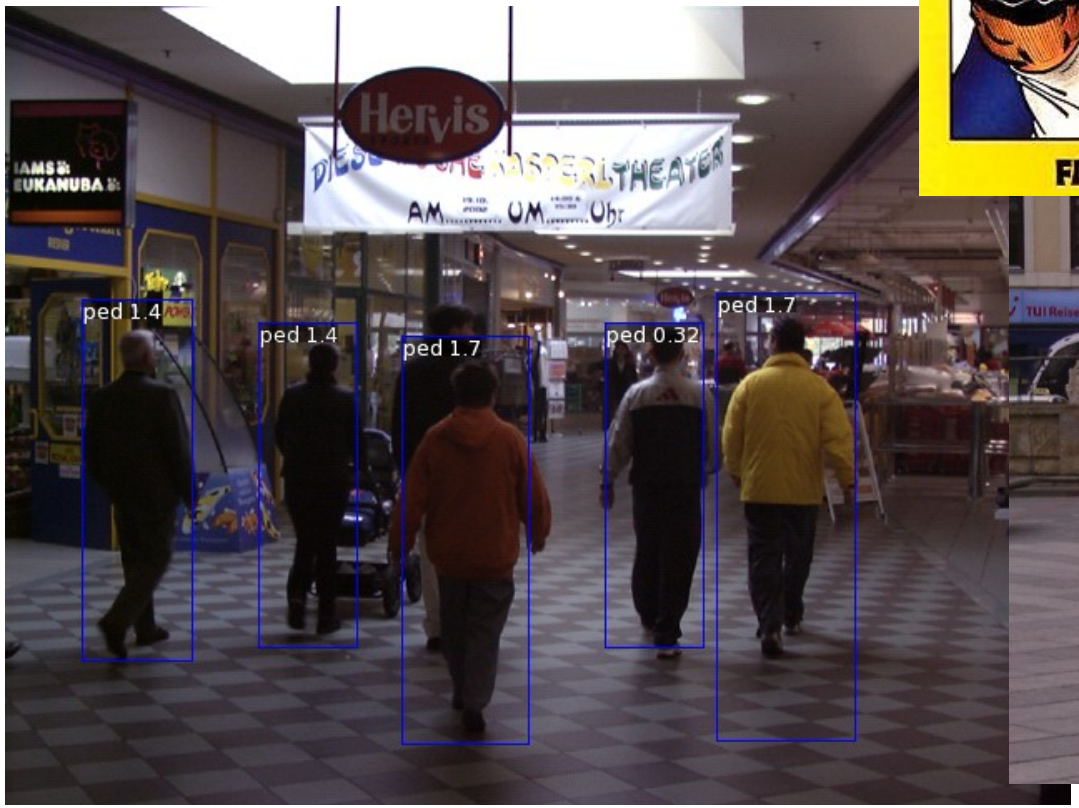


- ***CONVOLUTIONAL*** learning

Pedestrian Detection, Face Detection



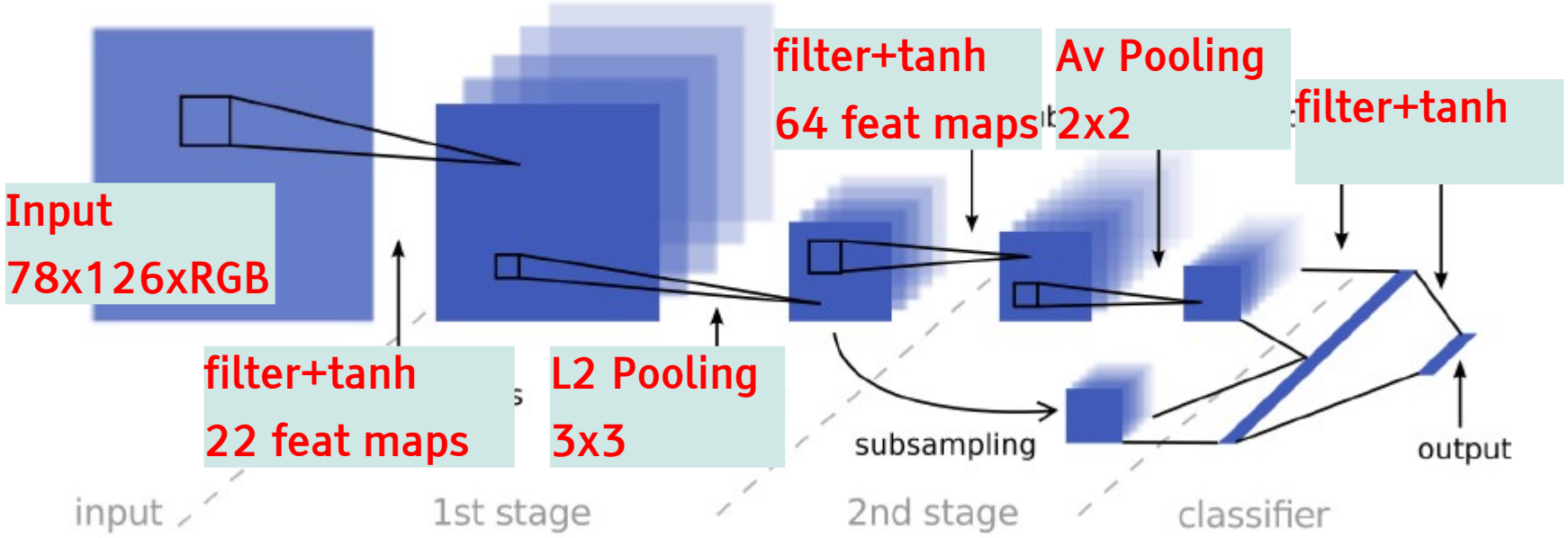




[Osadchy,Miller LeCun JMLR 2007],[Kavukcuoglu et al. NIPS 2010]

ConvNet Architecture with Multi-Stage Features

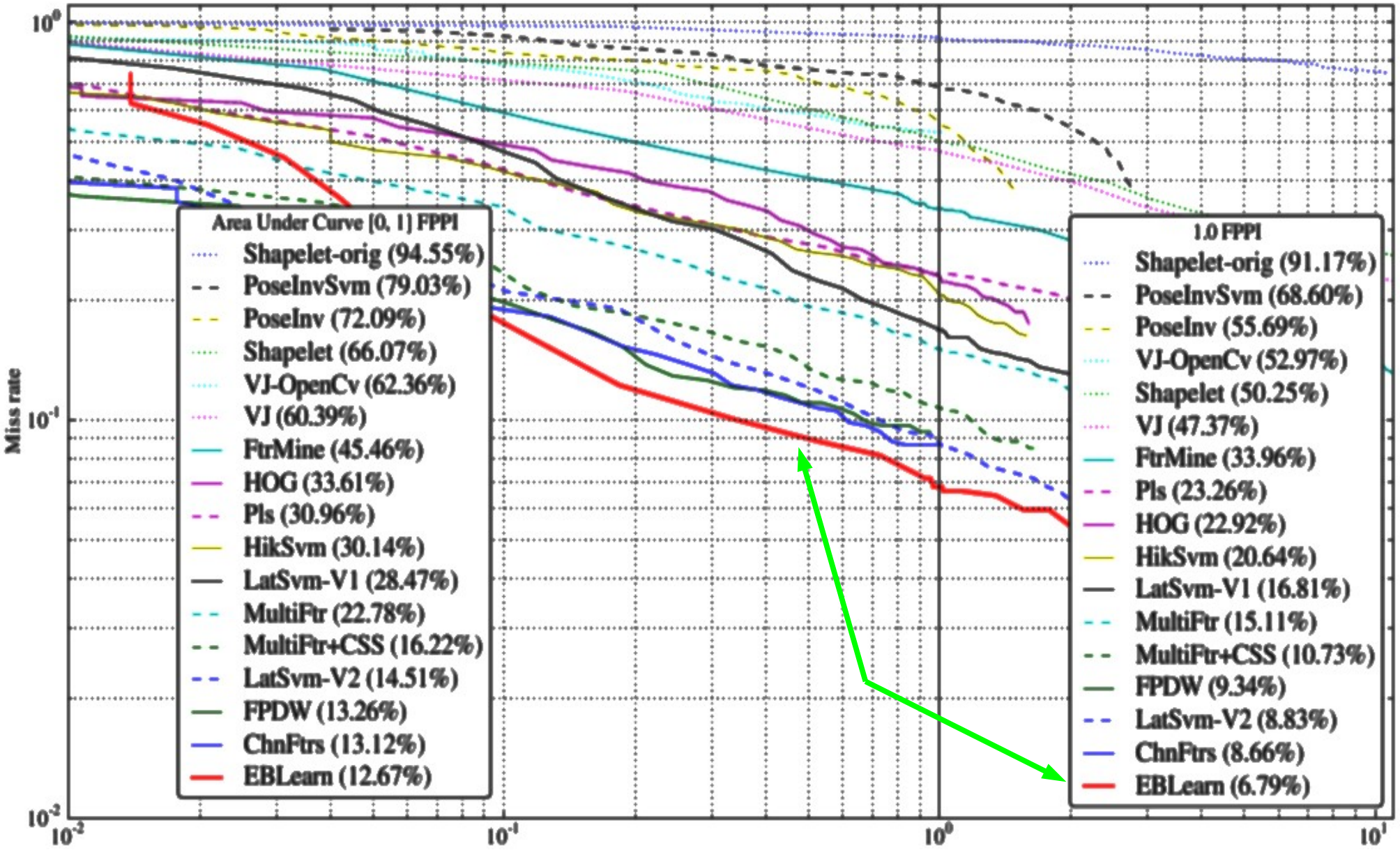
- Feature maps from all stages are pooled/subsampled and sent to the final classification layers
  - Pooled low-level features: good for textures and local motifs
  - High-level features: good for "gestalt" and global shape



Task	Single-Stage features	Multi-Stage features	Improvement %
Pedestrians detection (INRIA) [9]	14.26%	9.85%	31%
Traffic Signs classification (GTSRB) [11]	1.80%	0.83%	54%
House Numbers classification (SVHN)	5.72%	5.67%	0.9%

[Sermanet, Chintala, LeCun ArXiv:1204.3968, 2012]

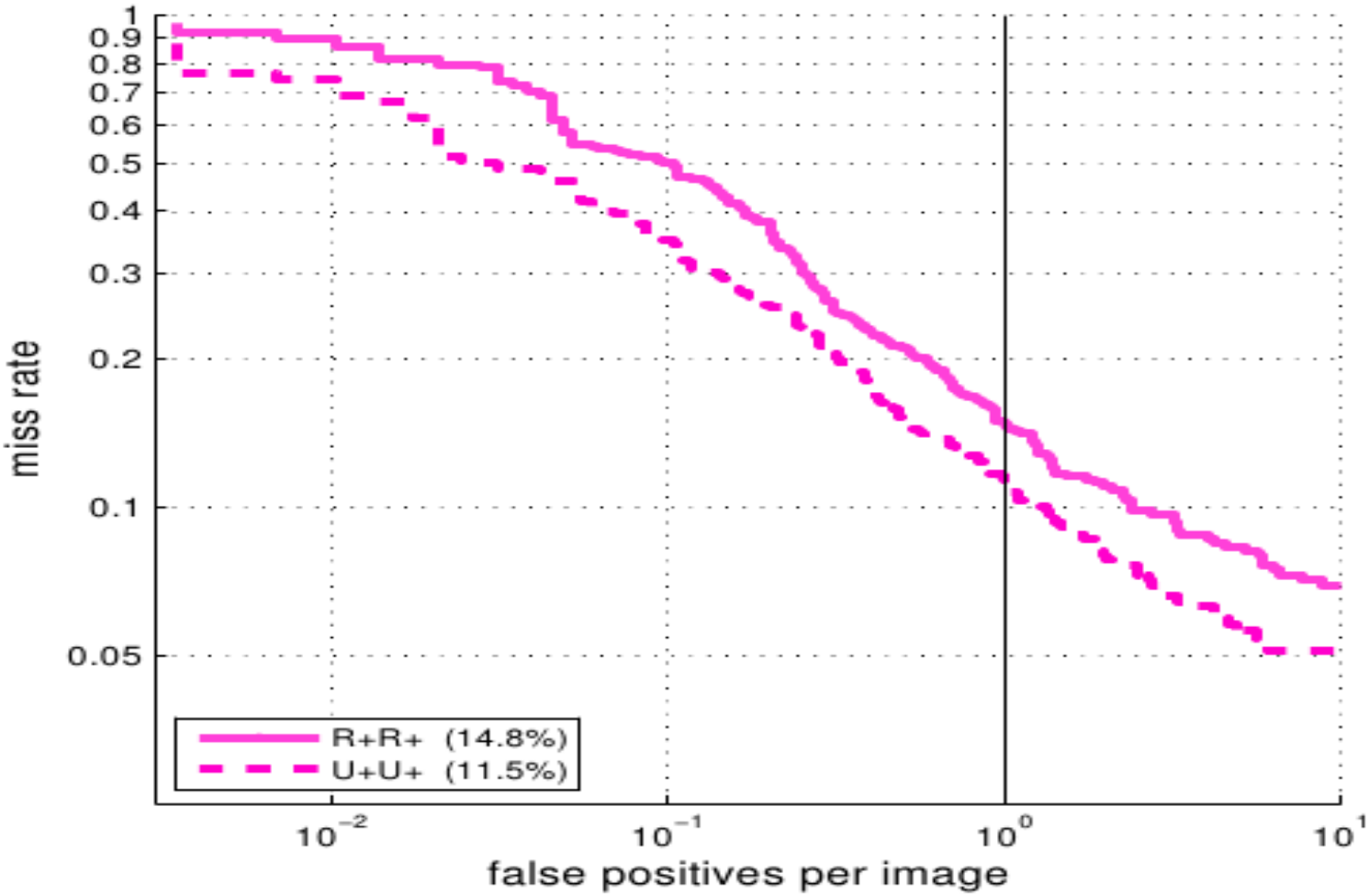
Pedestrian Detection (INRIA Dataset)



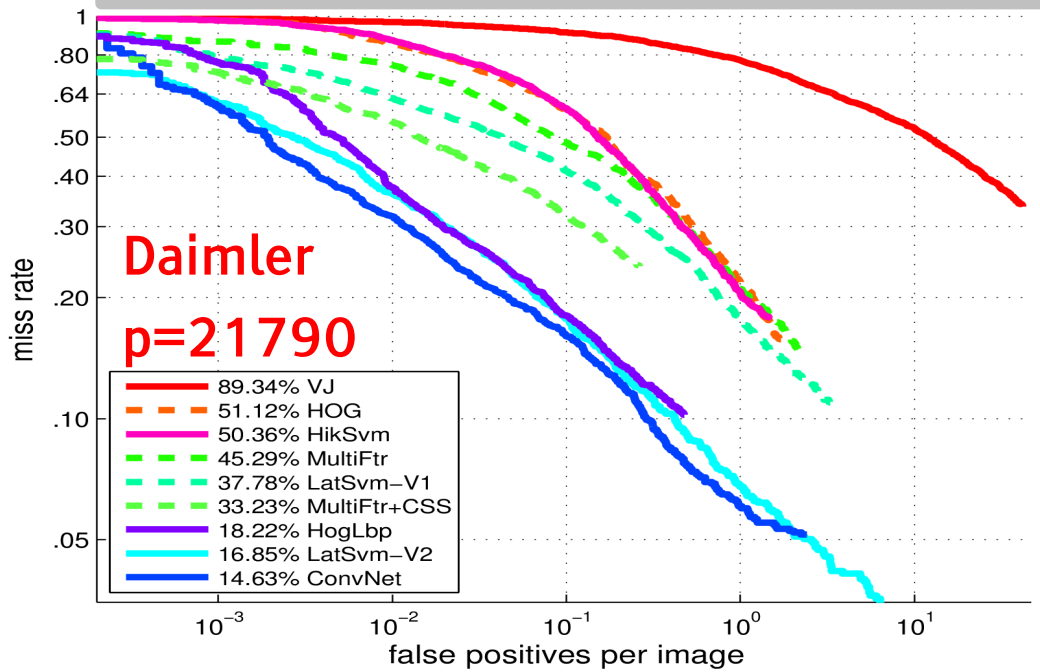
[Kavukcuoglu et al. NIPS 2010]

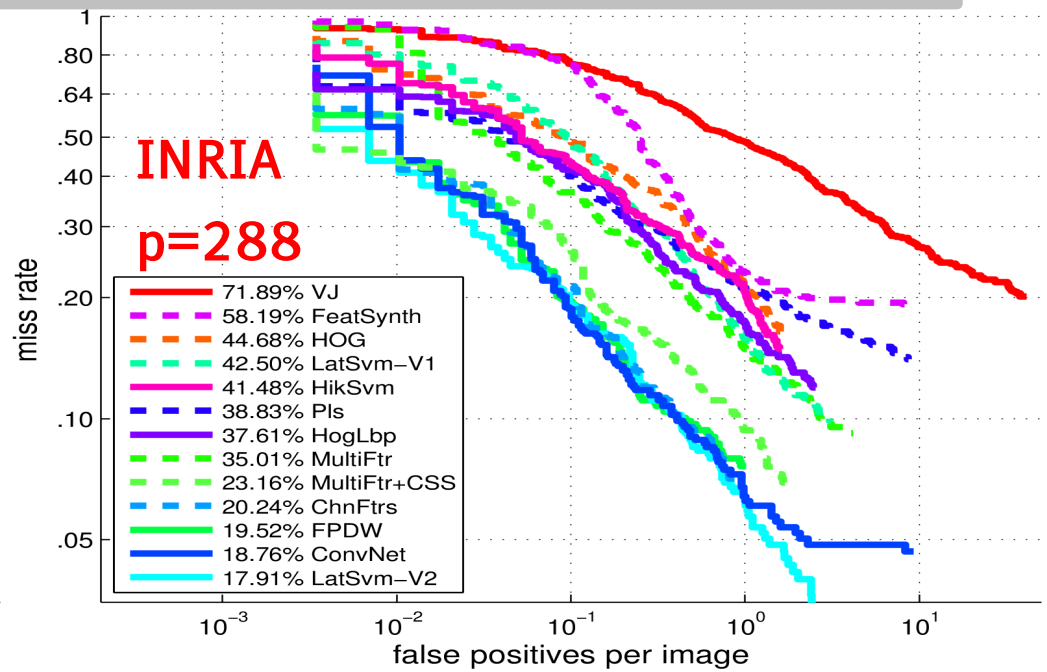
Convolutional PSD pre-training for pedestrian detection

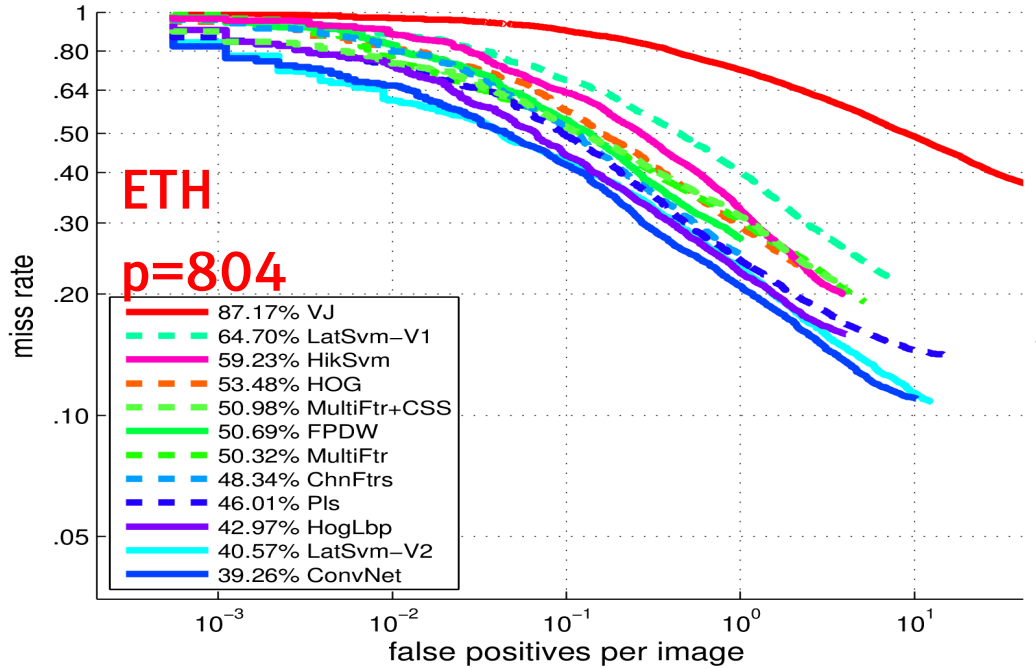
- ConvPSD pre-training improves the accuracy of pedestrian detection over purely supervised training from random initial conditions.

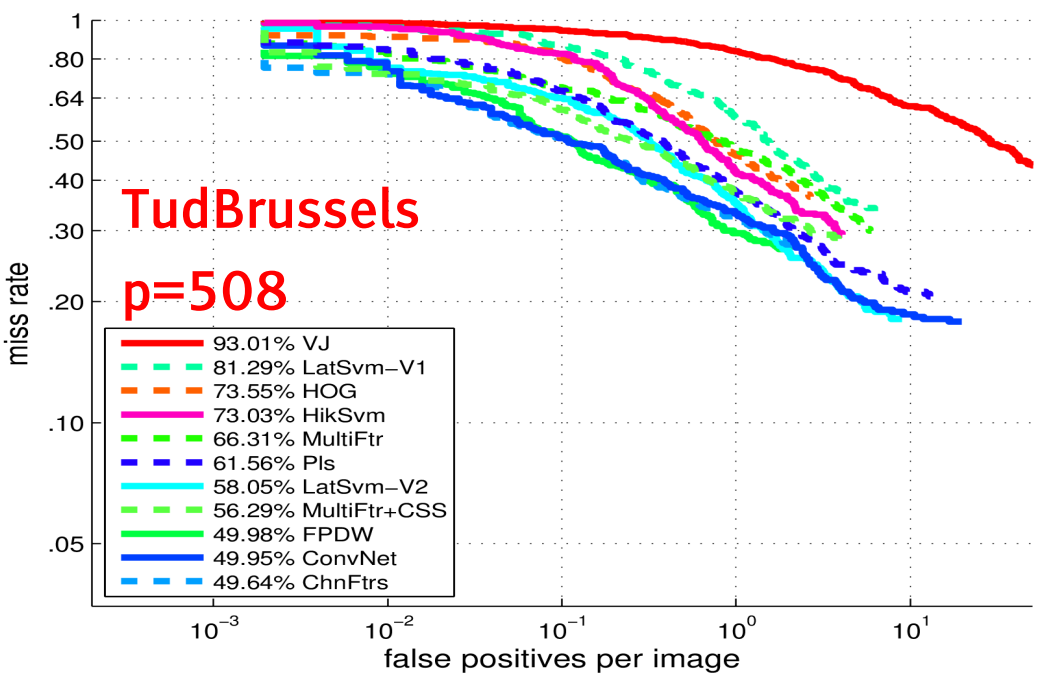


Results on "Near Scale" Images (>80 pixels tall, no occlusions)

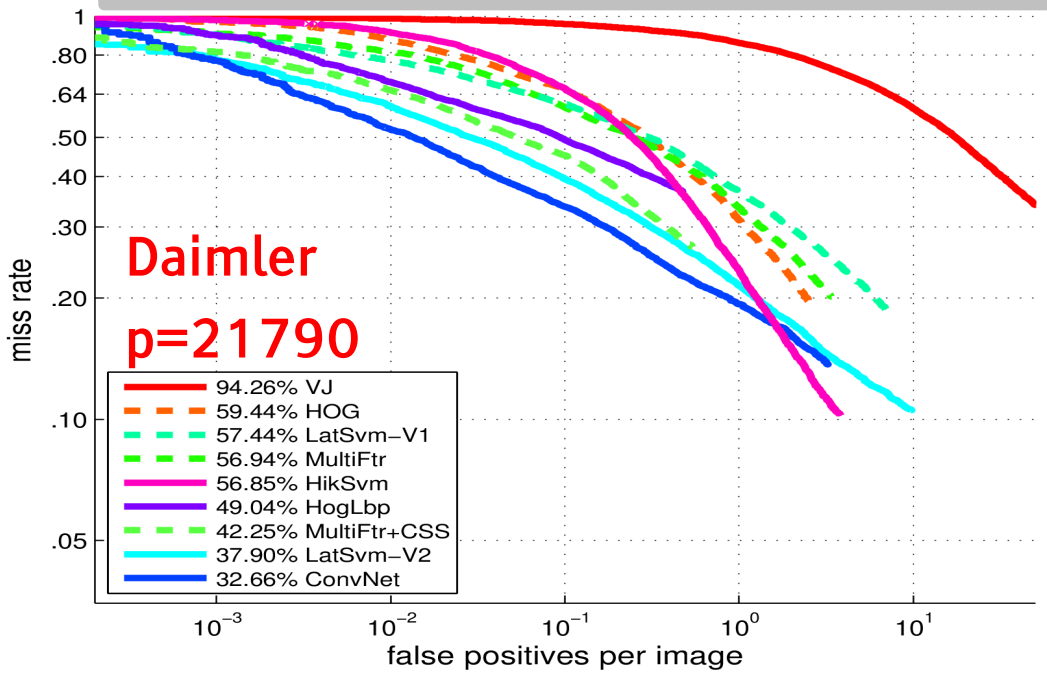


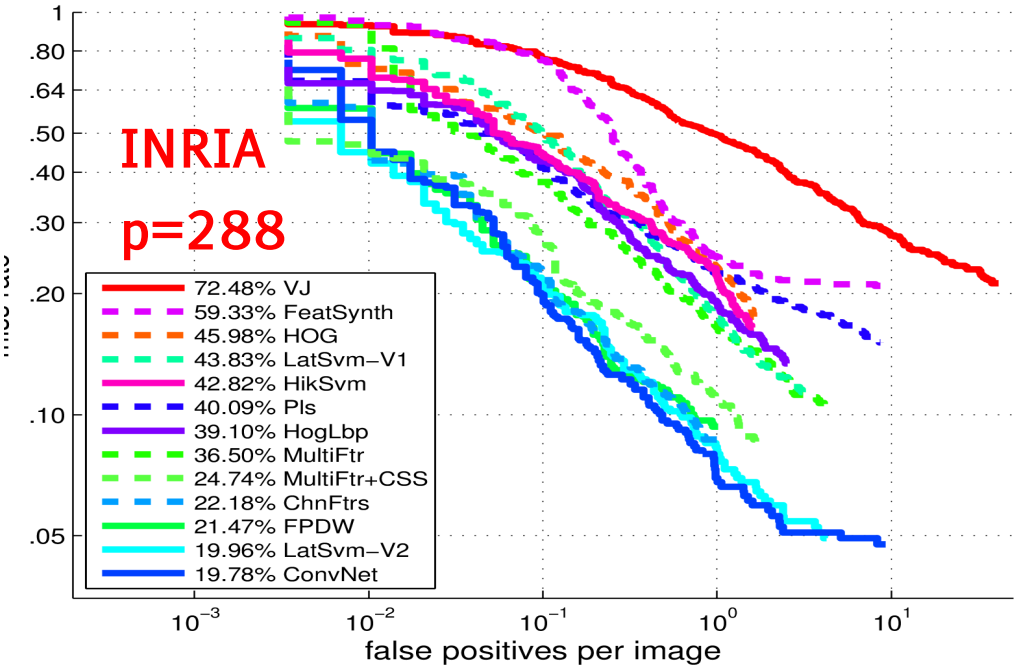


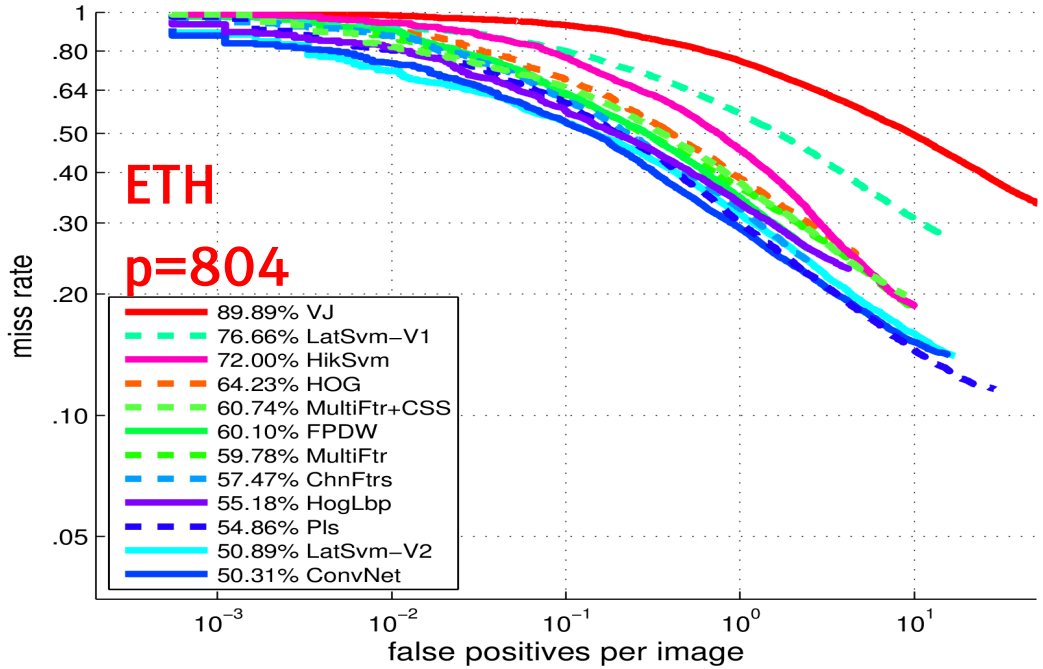


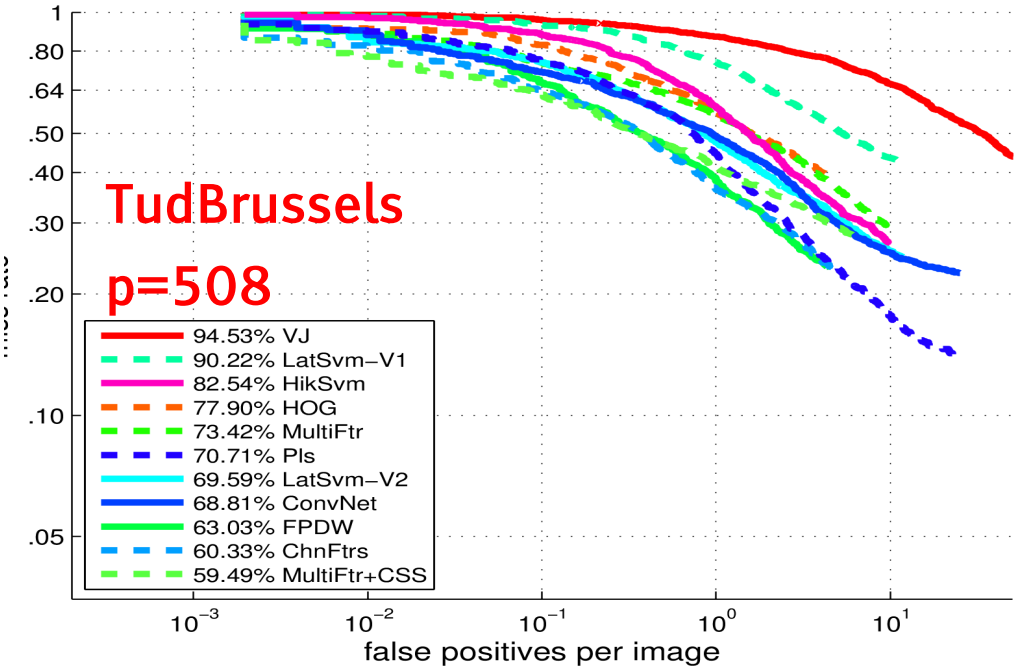


Results on "Reasonable" Images (>50 pixels tall, few occlusions)









Musical Genre Recognition

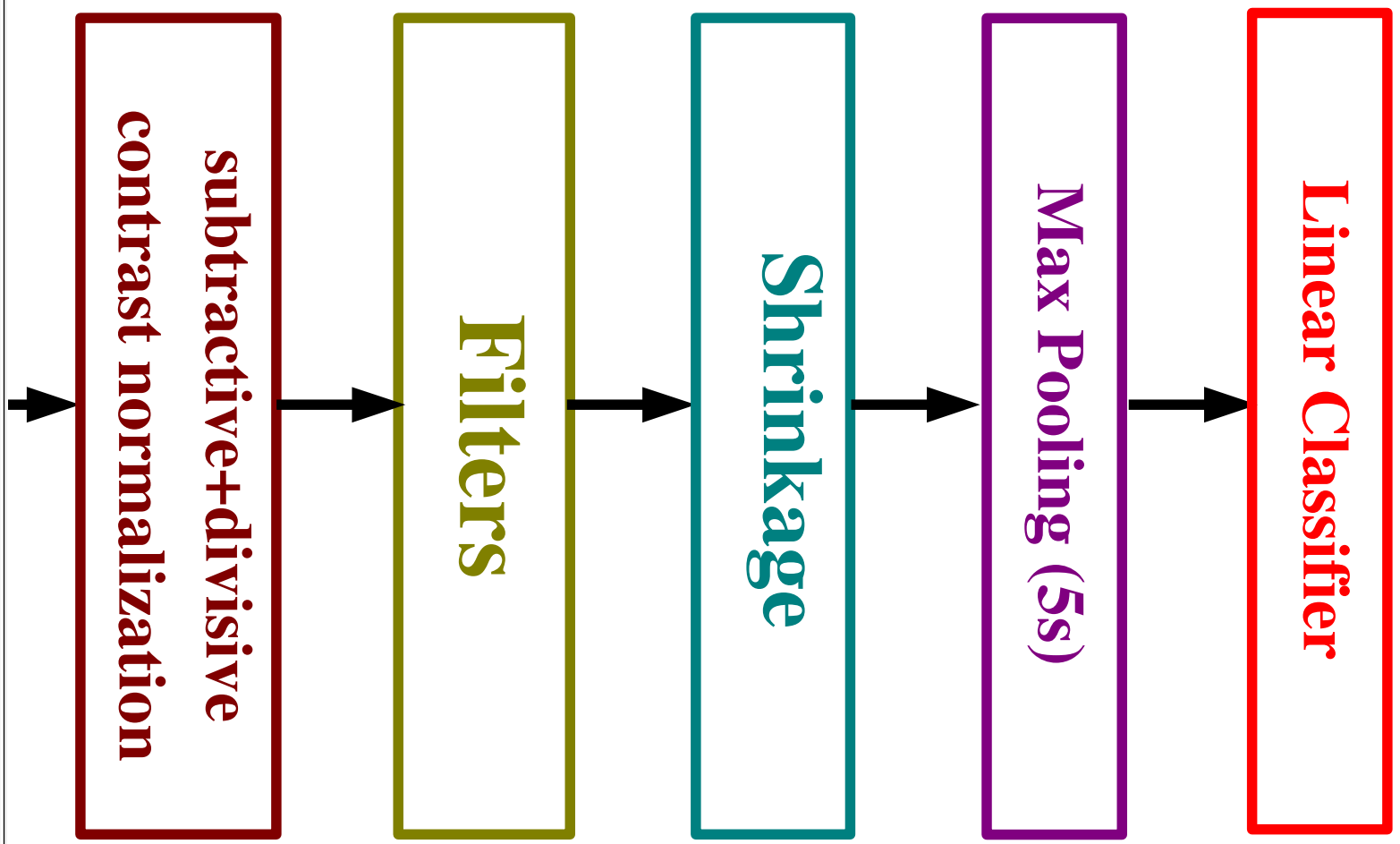
Same Architecture, Different Data

[Henaff et al. ISMIR 2011]

Convolutional PSD Features on Time-Frequency Signals

- **Input: "Constant Q Transform" over 46.4ms windows (1024 samples)**
  - 96 filters, with frequencies spaced every quarter tone (4 octaves)
- **Architecture:**
  - Input: sequence of contrast-normalized CQT vectors
  - 1: PSD features, 512 trained filters
  - 2: shrinkage function → rectification
  - 3: pooling over 5 seconds
  - 4: linear SVM classifier
  - 5: pooling of SVM categories over 30 seconds
- **GTZAN Dataset**
  - 1000 clips, 30 second each
  - 10 genres: blues, classical, country, disco, hiphop, jazz, metal, pop, reggae and rock.
- **Results**
  - 84% correct classification
  - (state of the art is at 92% with many features)

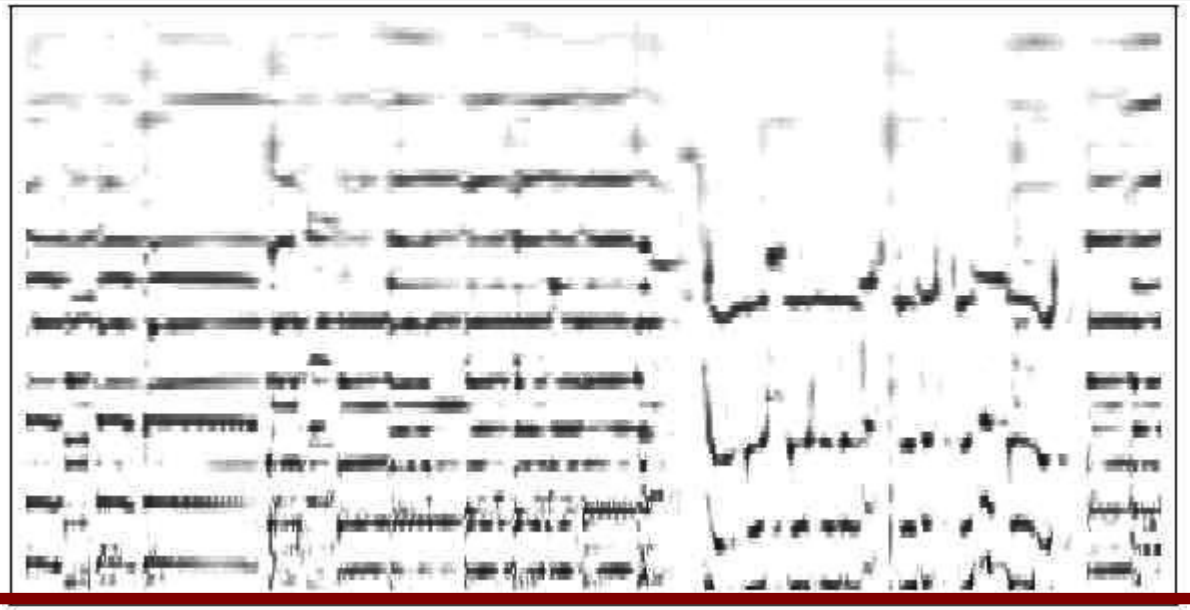
Architecture: contrast norm → filters → shrink → max pooling



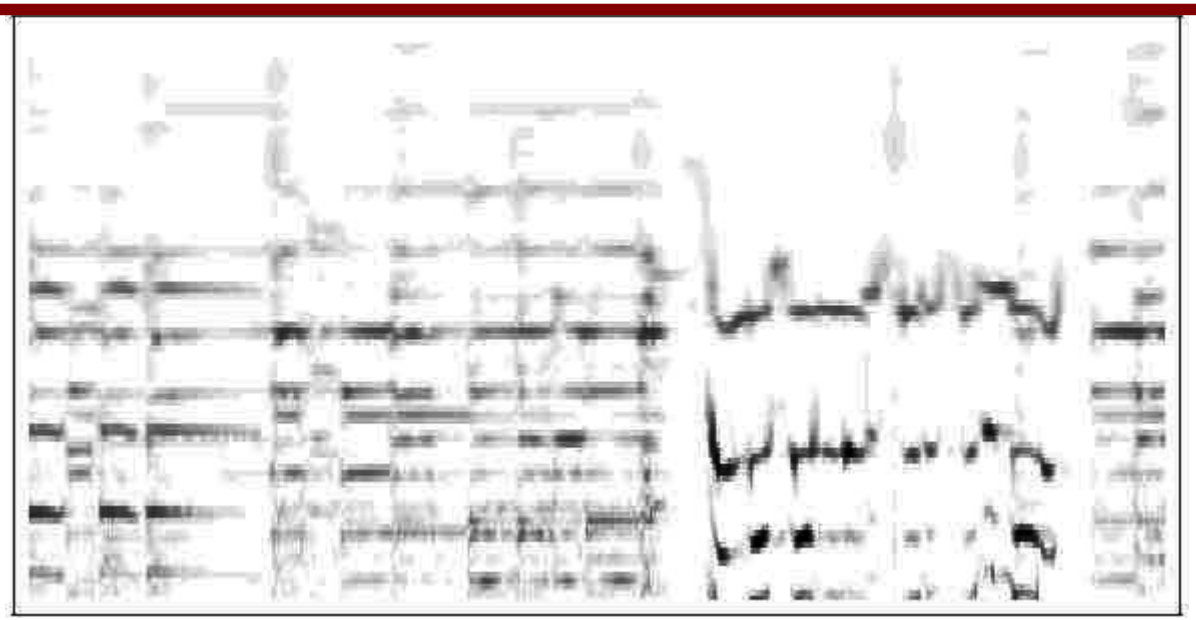
Single-Stage Convolutional Network

Training of filters: PSD (unsupervised)

Constant Q Transform over 46.4 ms → Contrast Normalization

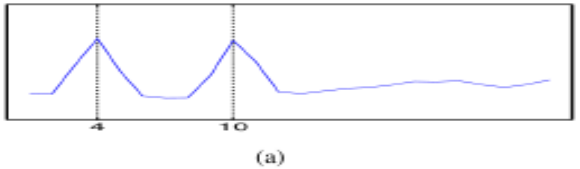


subtractive+divisive contrast normalization



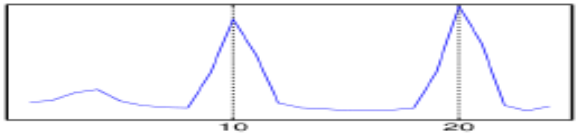
Convolutional PSD Features on Time-Frequency Signals

- Octave-wide features



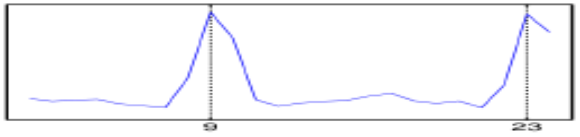
(a)

- Minor 3rd



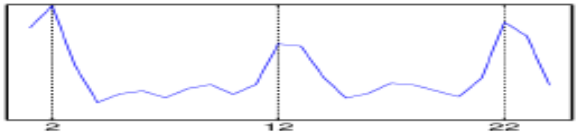
(b)

- Perfect 4th



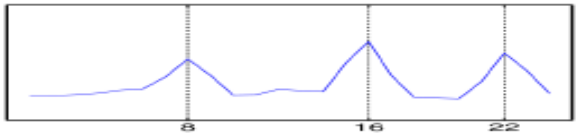
(c)

- Perfect 5th



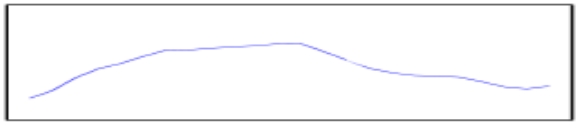
(d)

- Quartal chord



(e)

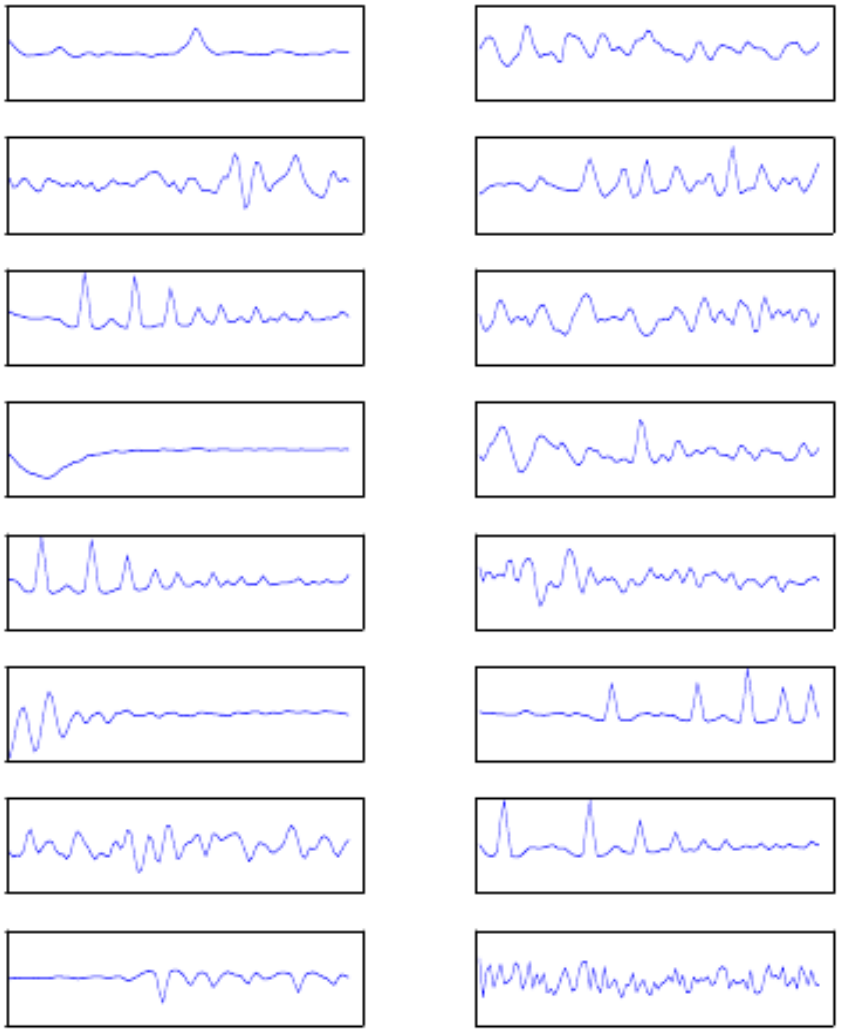
- Major triad



(f)

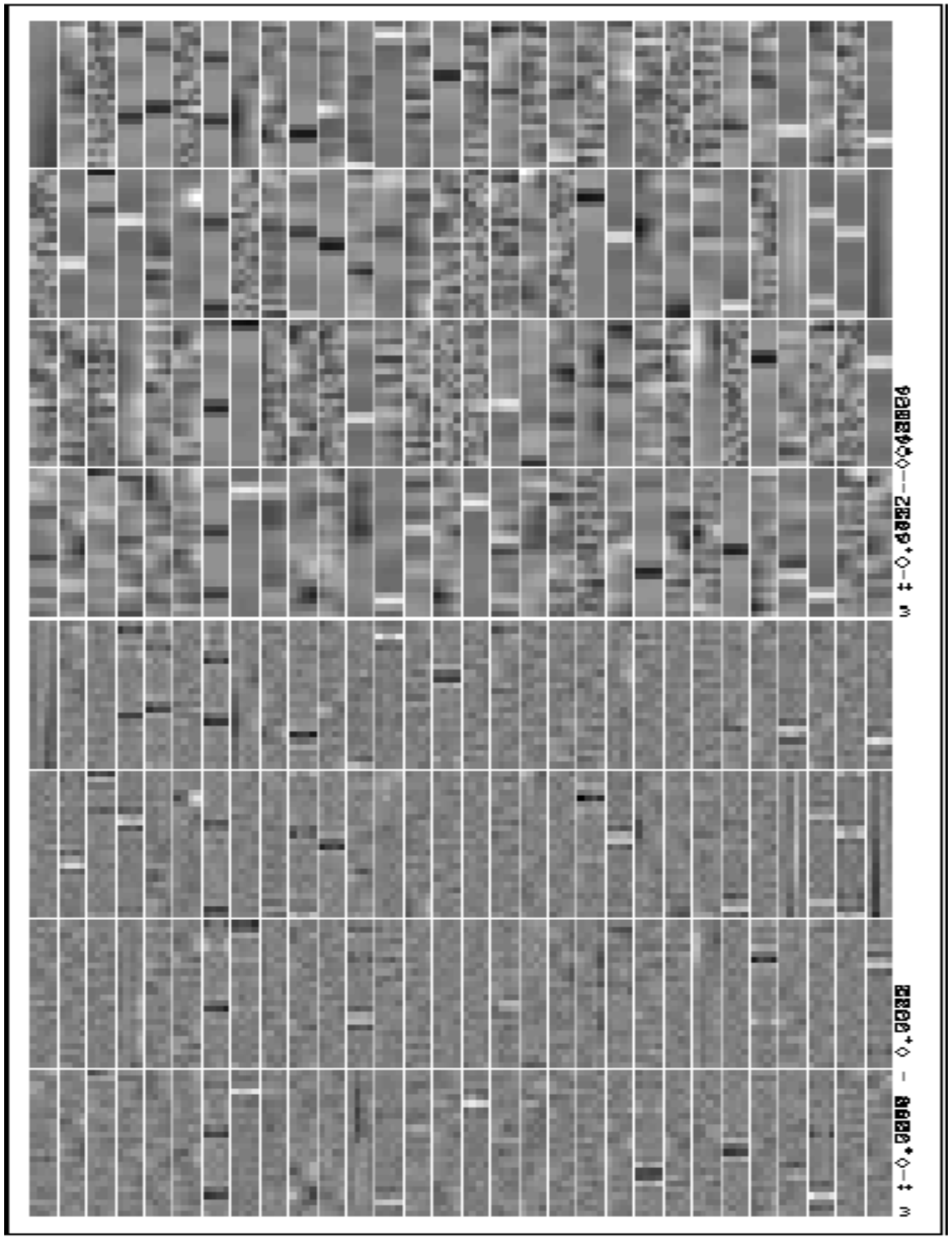
- transient

full 4-octave features



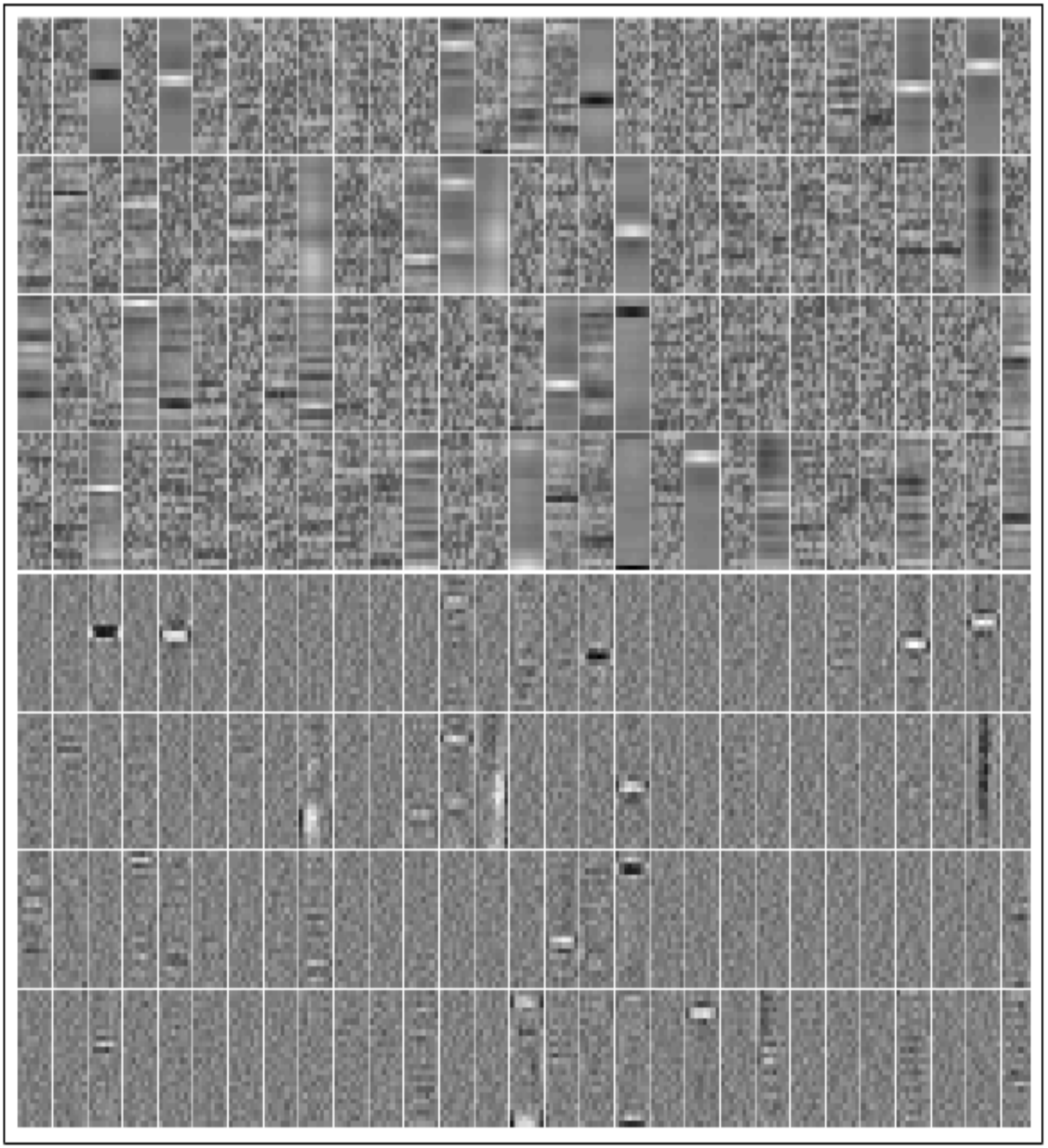
PSD Features on Constant-Q Transform

- Octave-wide features
  - Encoder basis functions
  - Decoder basis functions



Time-Frequency Features

- Octave-wide features on 8 successive acoustic vectors
  - Almost no temporal structure in the filters!



Accuracy on GTZAN dataset (small, old, etc...)

- Accuracy: 83.4%. State of the Art: 84.3%
- Very fast

Classifier	Features	Acc. (%)
CSC	Many features [6]	92.7
SRC	Auditory cortical feat. [25]	92
RBF-SVM	Learned using DBN [12]	84.3
Linear SVM	Learned using PSD on octaves	**83.4 ± 3.1**
AdaBoost	Many features [2]	83
Linear SVM	Learned using PSD on frames	**79.4 ± 2.8**
SVM	Daubechies Wavelets [19]	78.5
Log. Reg.	Spectral Covariance [3]	77
LDA	MFCC + other [18]	71
Linear SVM	Auditory cortical feat. [25]	70
GMM	MFCC + other [29]	61

Learning Invariant Features (learning complex cells)

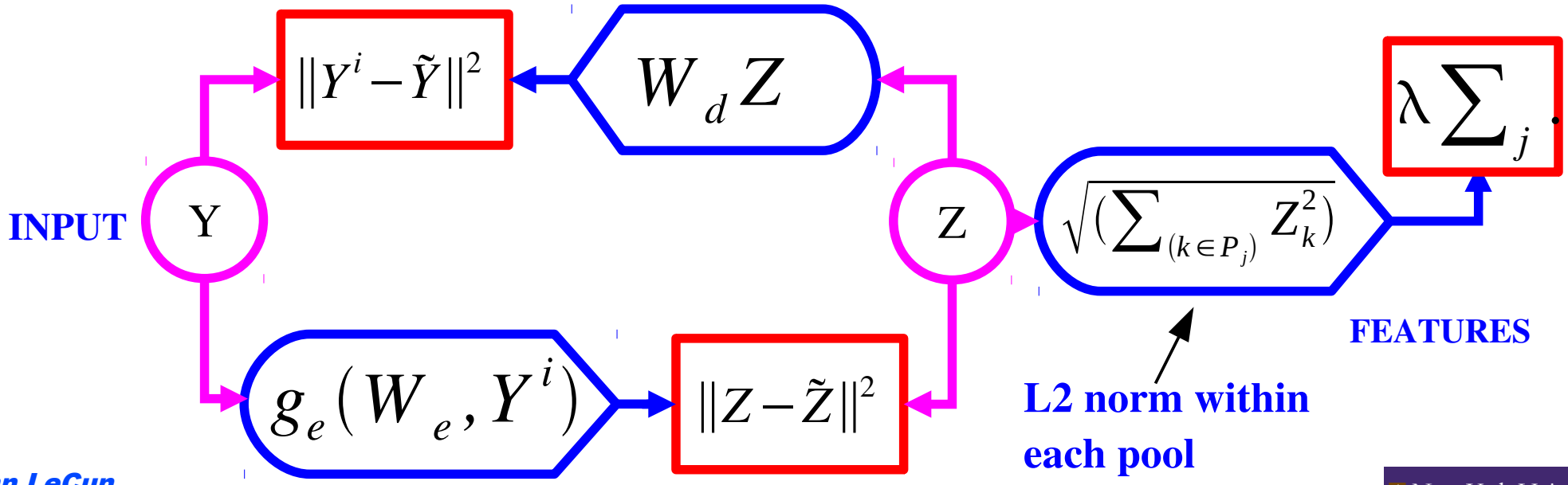
[Kavukcuoglu, Ranzato, Fergus, LeCun, CVPR 2009]

[Gregor & LeCun 2010]

Learning Invariant Features with L2 Group Sparsity

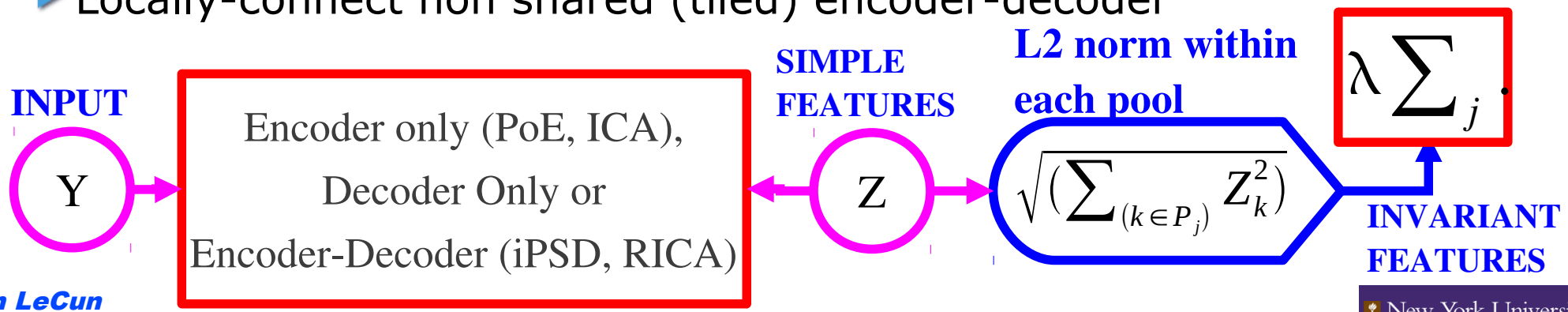
- Unsupervised PSD ignores the spatial pooling step.
- Could we devise a similar method that learns the pooling layer as well?
- Idea [Hyvarinen & Hoyer 2001]: group sparsity on pools of features
  - Minimum number of pools must be non-zero
  - Number of features that are on within a pool doesn't matter
  - Pools tend to regroup similar features

$$E(Y,Z) = \|Y - W_d Z\|^2 + \|Z - g_e(W_e, Y)\|^2 + \sum_j \sqrt{\sum_{k \in P_j} Z_k^2}$$



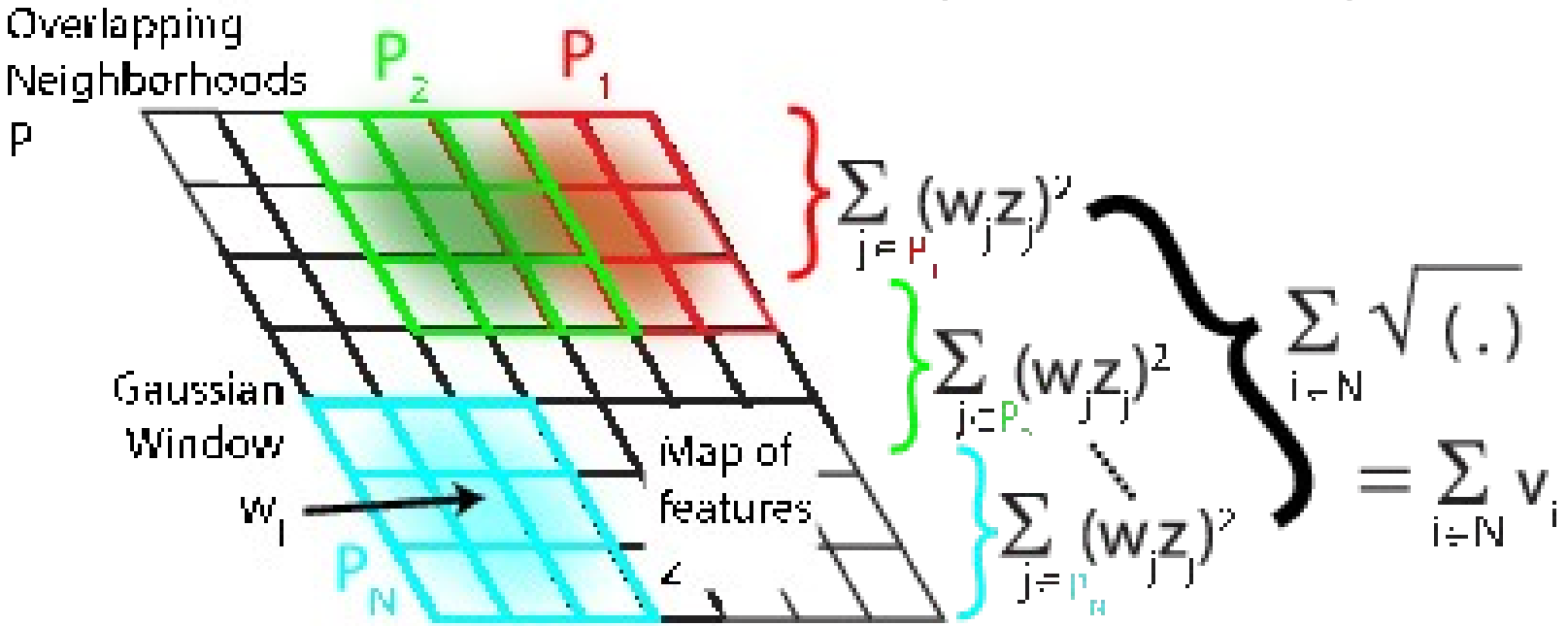
Learning Invariant Features with L2 Group Sparsity

- Idea: features are pooled in group.
  - Sparsity: sum over groups of L2 norm of activity in group.
- [Hyvärinen Hoyer 2001]: "subspace ICA"
  - decoder only, square
- [Welling, Hinton, Osindero NIPS 2002]: pooled product of experts
  - encoder only, overcomplete, log student-T penalty on L2 pooling
- [Kavukcuoglu, Ranzato, Fergus LeCun, CVPR 2010]: Invariant PSD
  - encoder-decoder (like PSD), overcomplete, L2 pooling
- [Le et al. NIPS 2011]: Reconstruction ICA
  - Same as [Kavukcuoglu 2010] with linear encoder and tied decoder
- [Gregor & LeCun arXiv:1006:0448, 2010] [Le et al. ICML 2012]
  - Locally-connect non shared (tiled) encoder-decoder



Pooling Similar Features using Group Sparsity

- A sparse-overcomplete version of Hyvarinen's subspace ICA
- Decoder ensures reconstruction (unlike ICA which requires orthonogonal matrix)
  1. Apply filters on a patch (with suitable non-linearity)
  2. Arrange filter outputs on a 2D plane
  3. square filter outputs
  4. minimize sqrt of sum of blocks of squared filter outputs



[Kavukcuoglu, Ranzato, Fergu, LeCun, CVPR 2009]
[Jenatton, Obozinski, Bach AISTATS 2010] [Le et al. NIPS2011]

Groups are local in a 2D Topographic Map

- The filters arrange themselves spontaneously so that similar filters enter the same pool.
- The pooling units can be seen as complex cells
- Outputs of pooling units are invariant to local transformations of the input
  - For some it's translations, for others rotations, or other transformations.

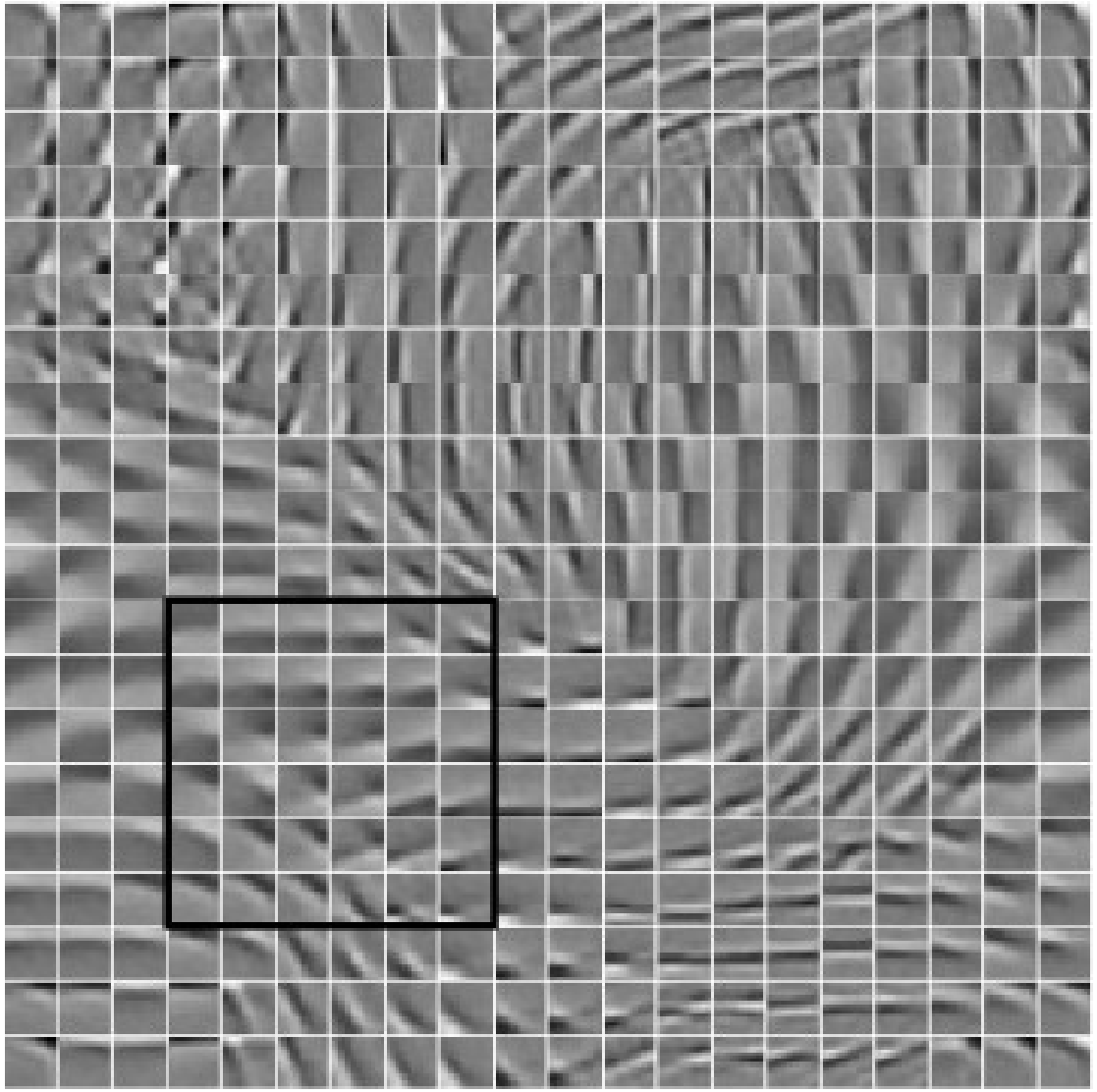


Image-level training, local filters but no weight sharing

- Training on 115x115 images. Kernels are 15x15 (not shared across space!)
  - [Gregor & LeCun 2010]
  - Local receptive fields
  - No shared weights
  - 4x overcomplete
  - L2 pooling
  - Group sparsity over pools

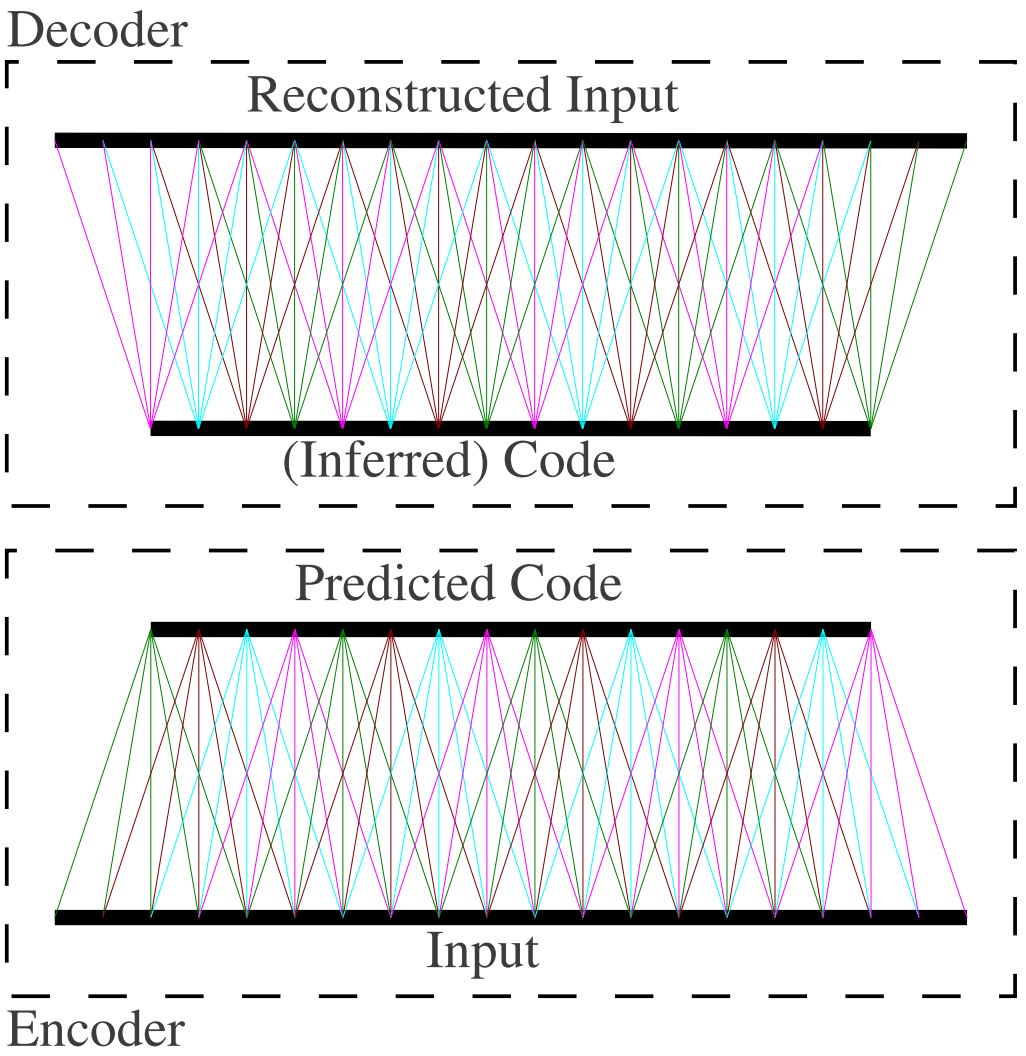


Image-level training, local filters but no weight sharing

- Topographic maps of continuously-varying features
- Local overlapping pools are invariant complex cells
  - [Gregor & LeCun arXiv:1006.0448] (double tanh encoder)
  - [Le et al. ICML'12] (linear encoder)

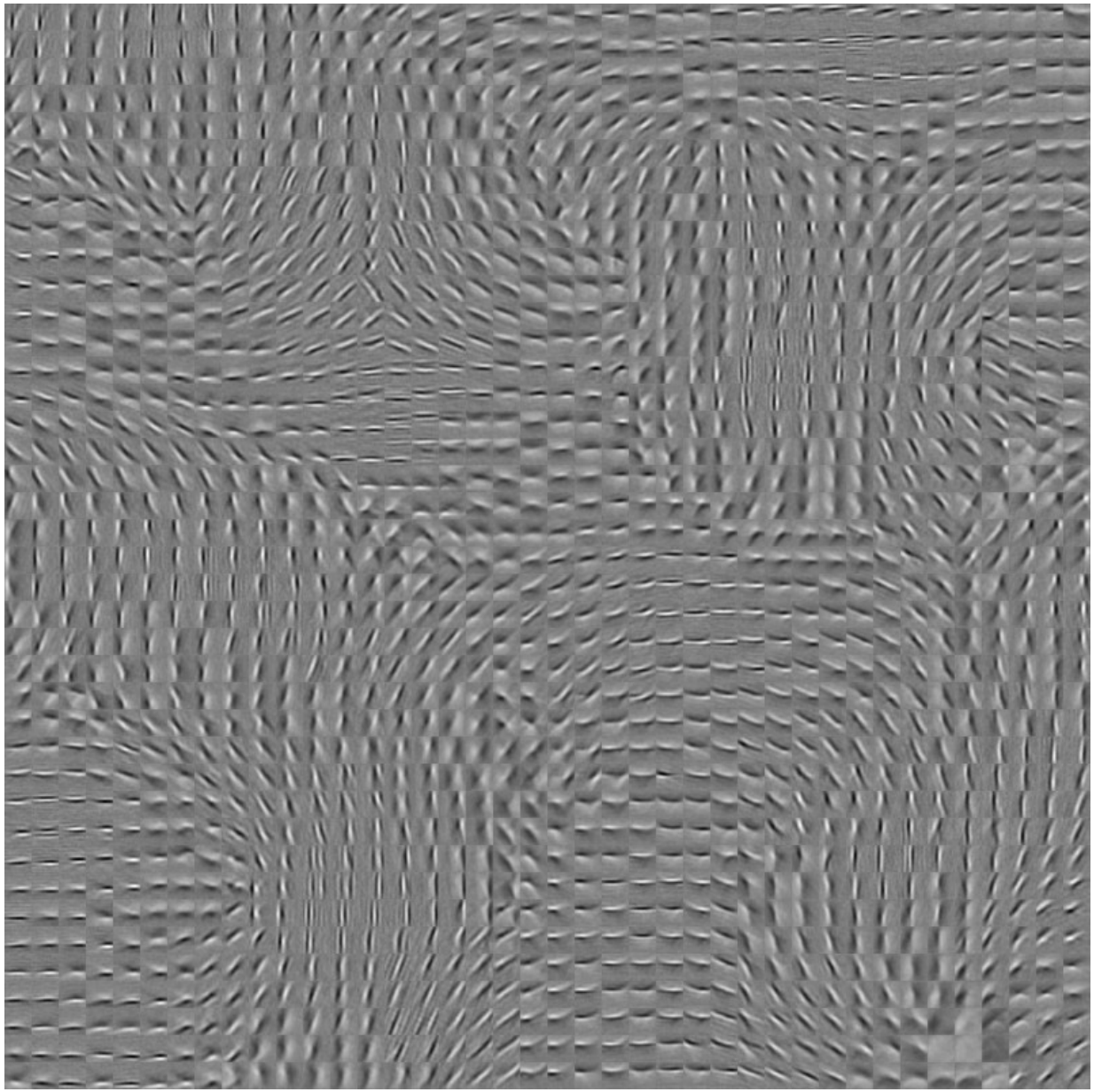
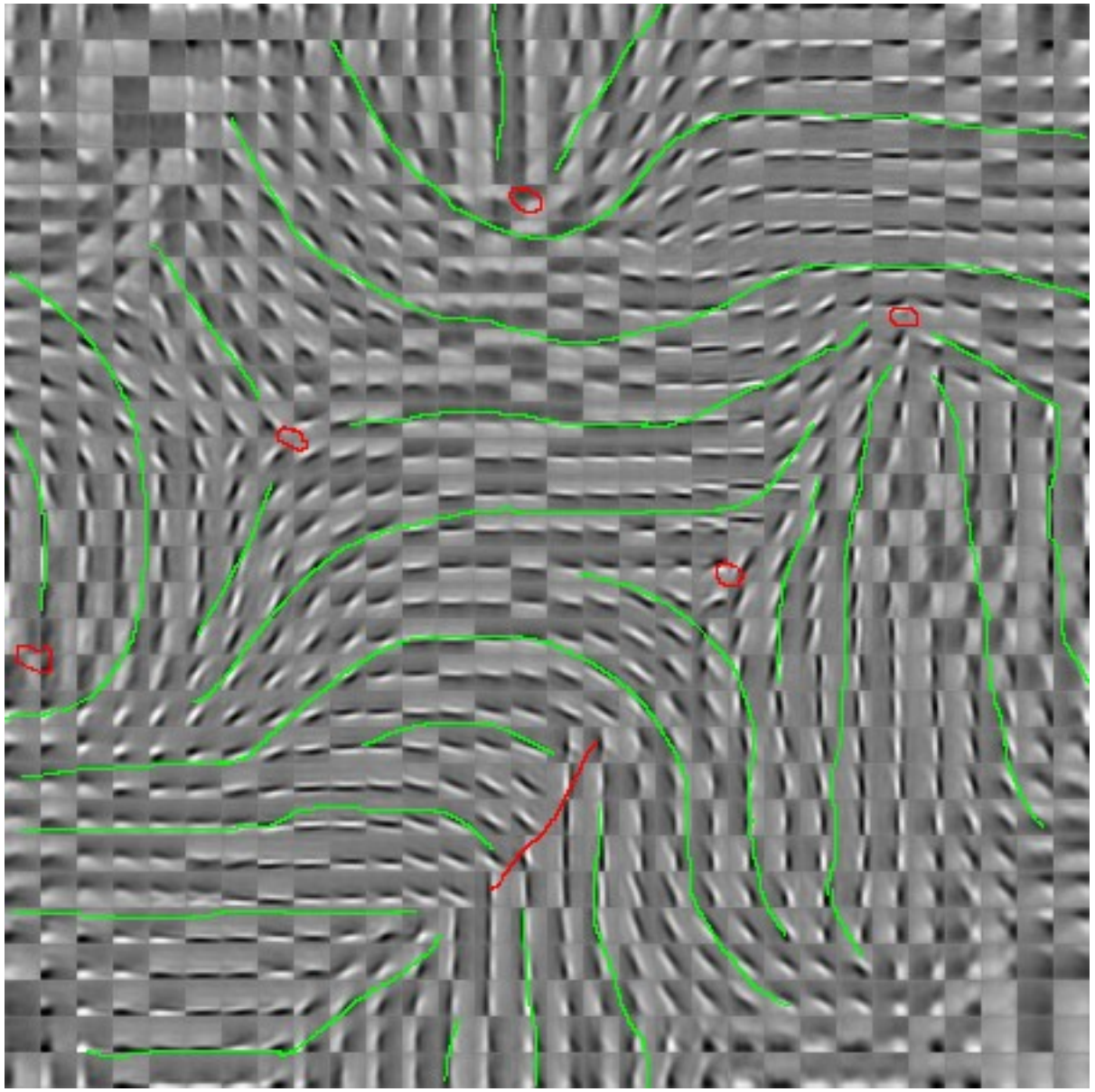
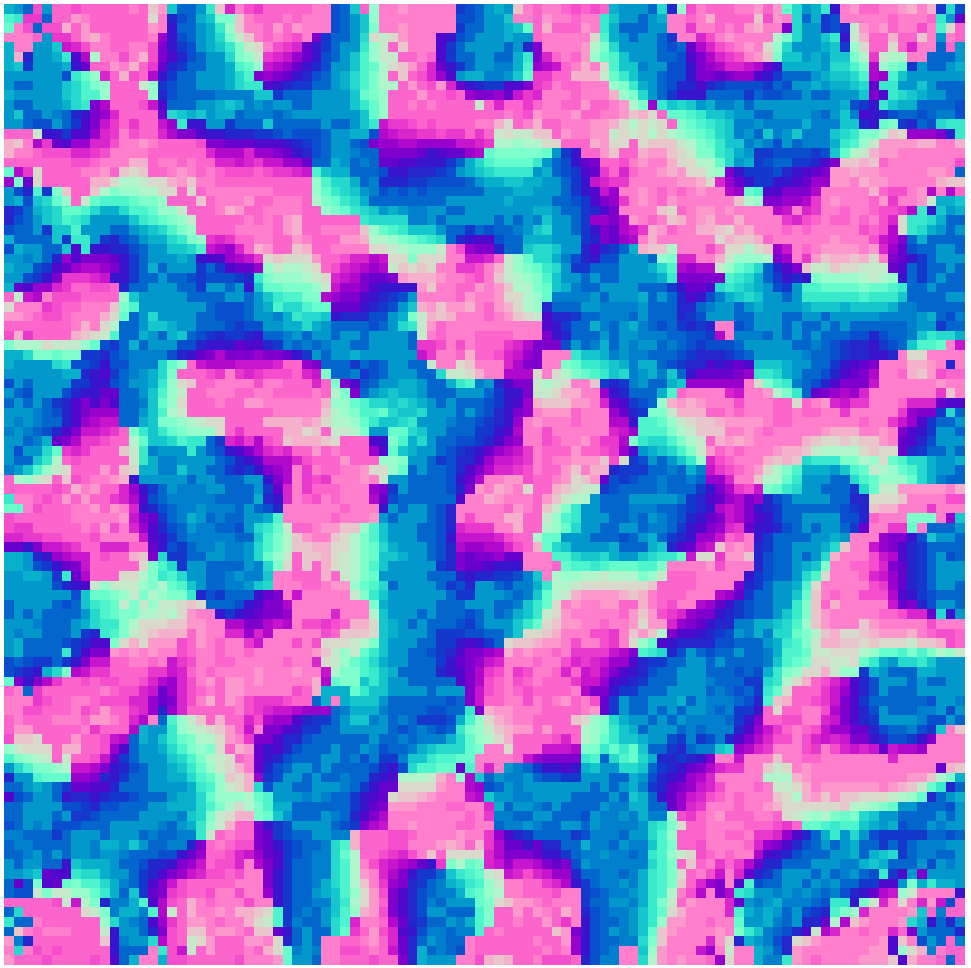


Image-level training, local filters but no weight sharing

- Training on 115x115 images. Kernels are 15x15 (not shared across space!)





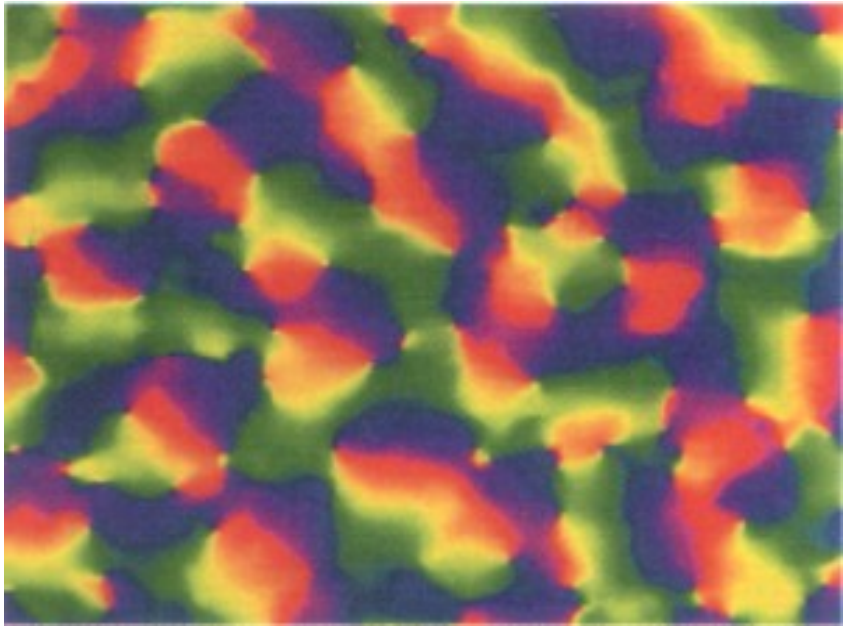
119x119 Image Input

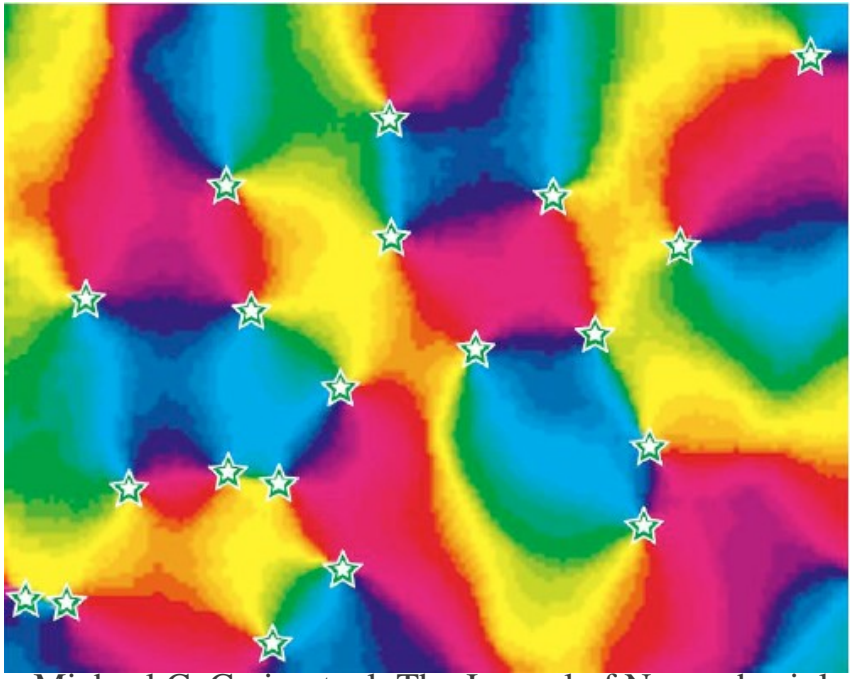
100x100 Code

20x20 Receptive field size

sigma=5

K Obermayer and GG Blasdel, Journal of Neuroscience, Vol 13, 4114-4129 (**Monkey**)

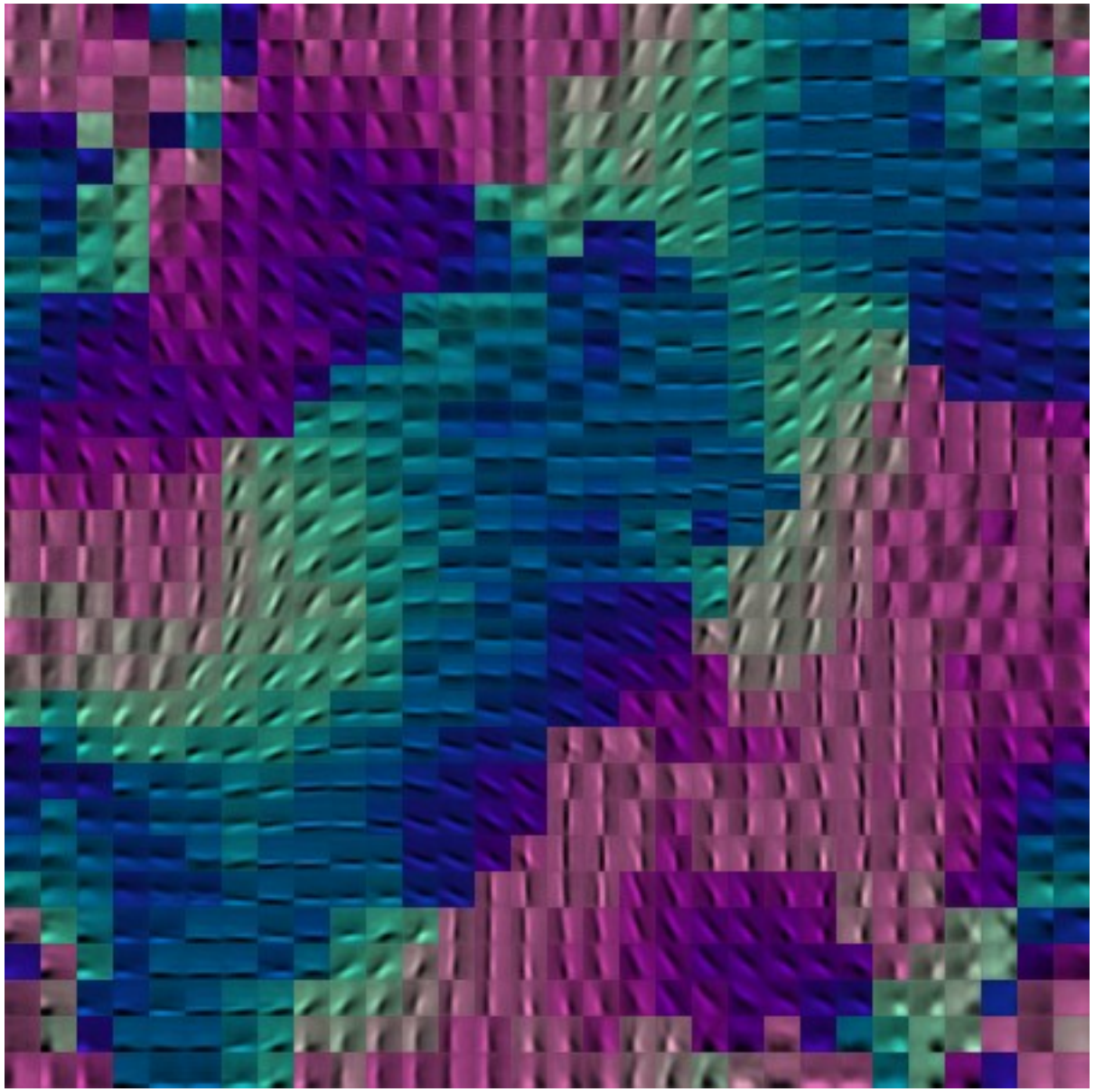




Michael C. Crair, et. al. The Journal of Neurophysiology Vol. 77 No. 6 June 1997, pp. 3381-3385 (**Cat**)

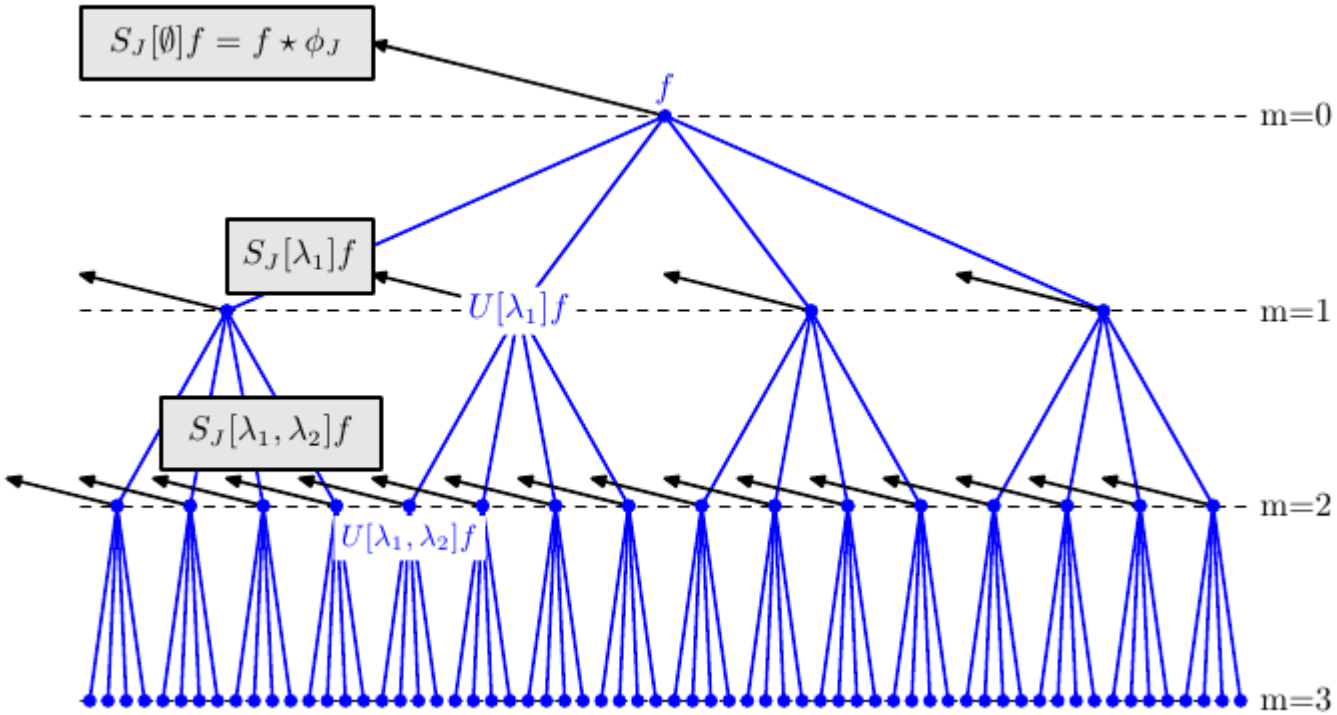
Image-level training, local filters but no weight sharing

- Color indicates orientation (by fitting Gabors)



Theory of Repeated [Filter Bank → L2 Pooling → Average Pooling]

- Stéphane Mallat's "Scattering Transform": Theory of ConvNet-like architectures
- [Mallat & Bruna CVPR 2011] Classification with Scattering Operators
- [Mallat & Bruna, arXiv:1203.1513 2012] Invariant Scattering Convolution Networks
- [Mallat CPAM 2012] Group Invariant Scattering



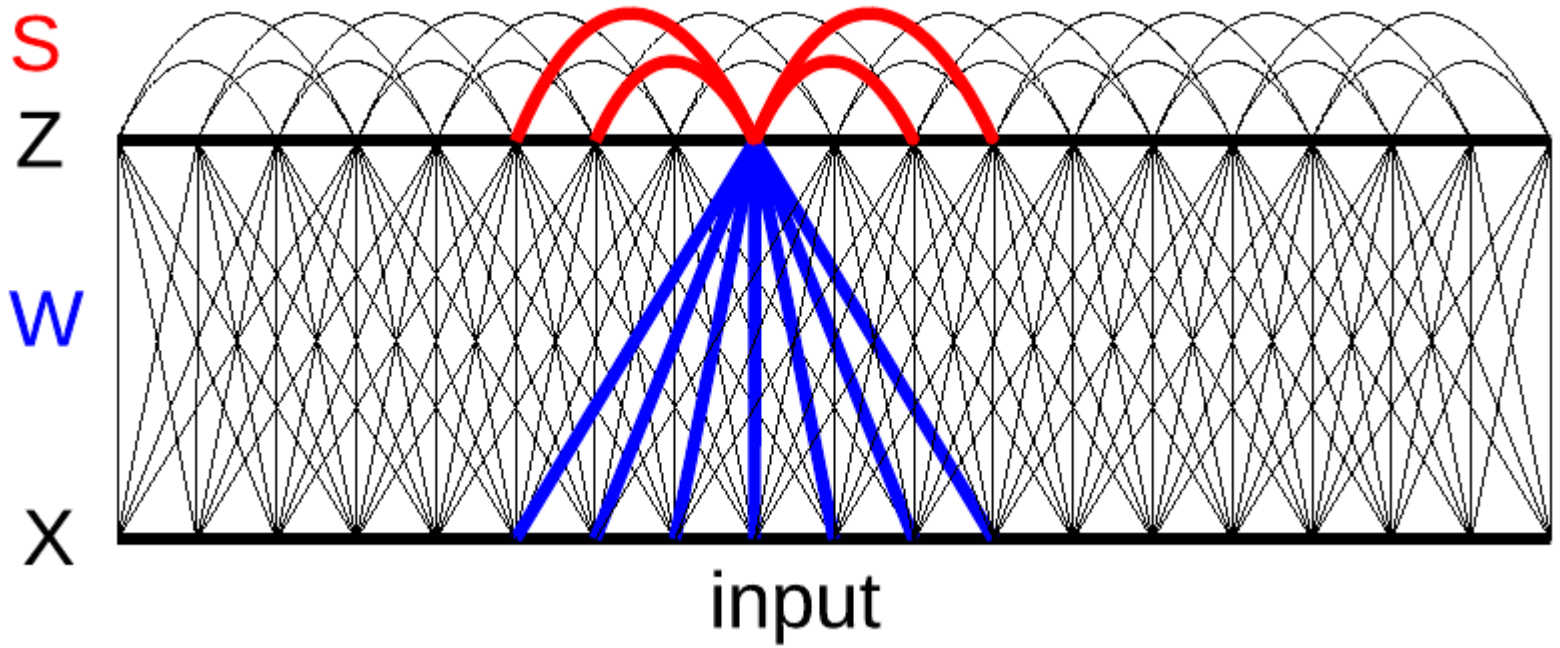
Sparse Coding Using Lateral Inhibition

[Gregor, Szlam, LeCun, NIPS 2011]

Invariant Features Lateral Inhibition

- Replace the L1 sparsity term by a lateral inhibition matrix
- Easy way to impose some structure on the sparsity

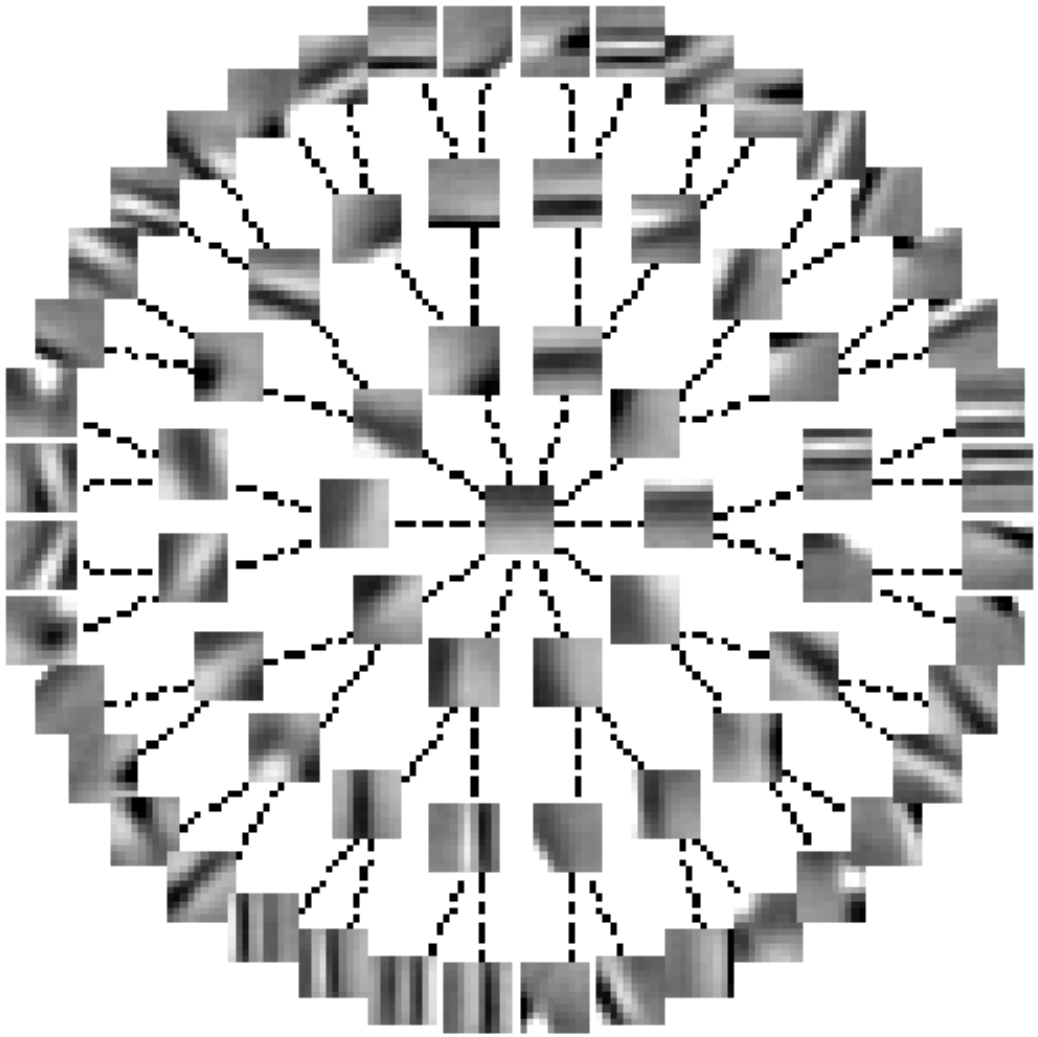
$$\min_{W,Z} \sum_{x \in X} ||Wz - x||^2 + |z|^T S|z|$$

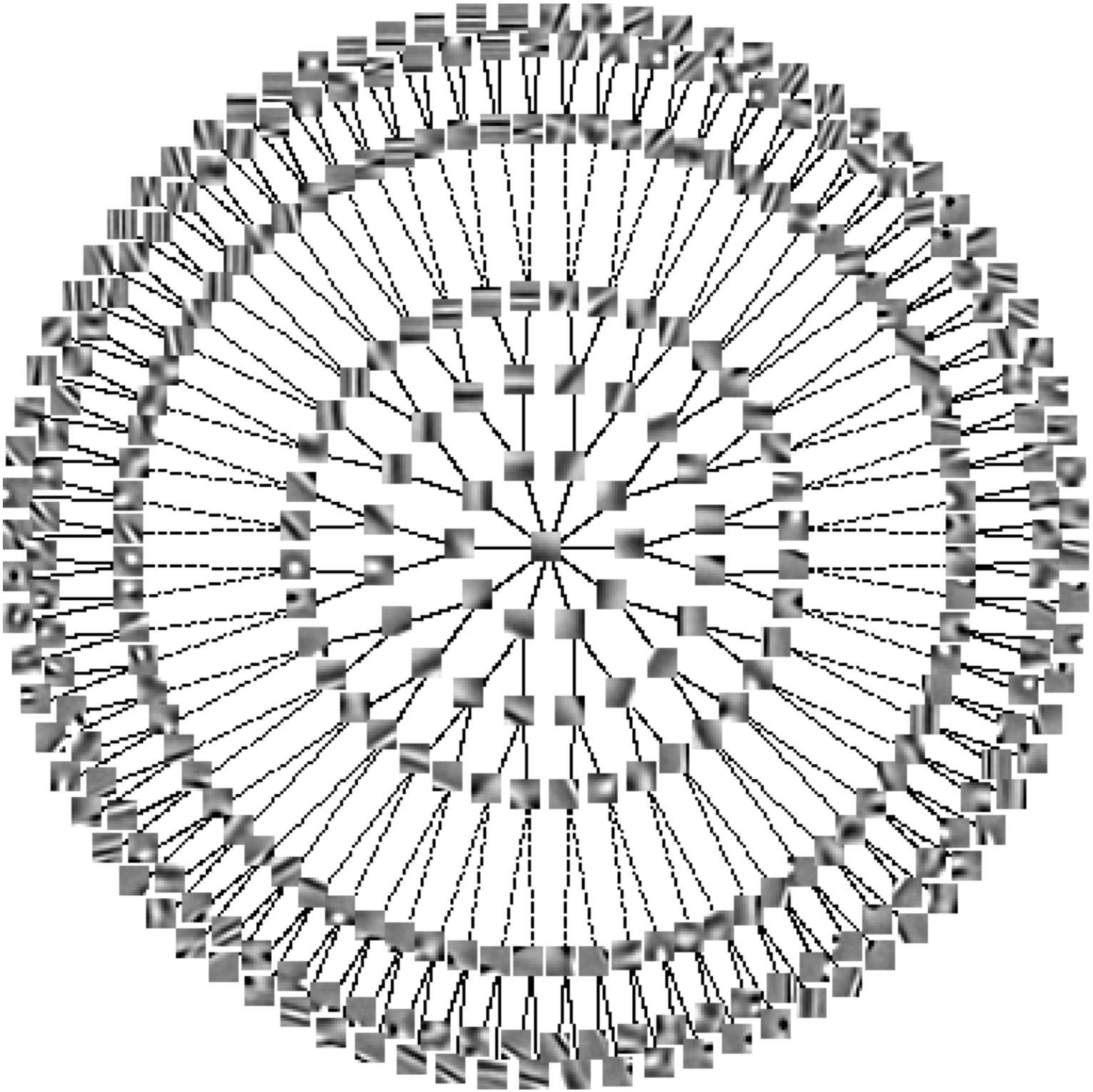


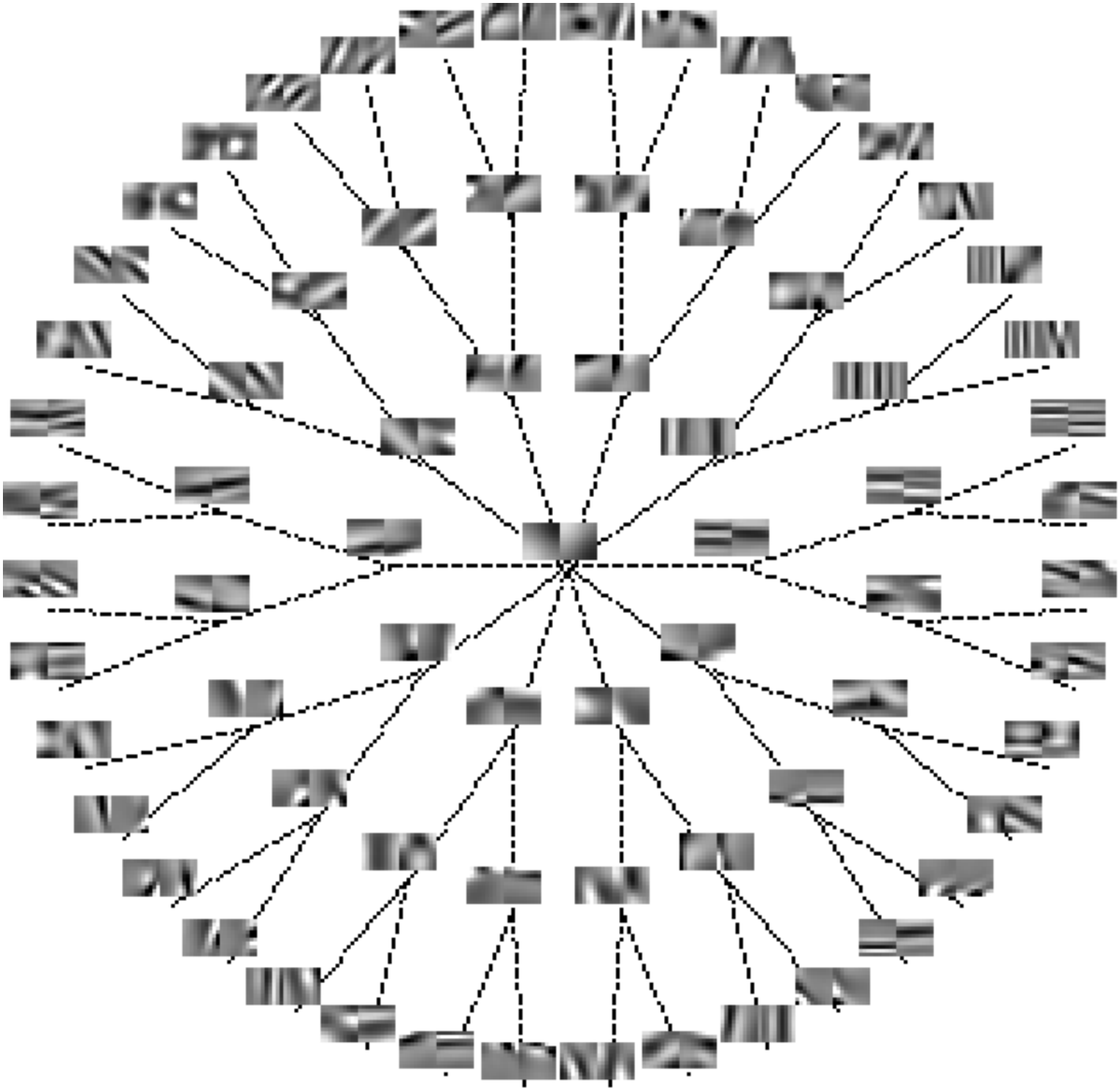
[Gregor, Szlam, LeCun NIPS 2011]

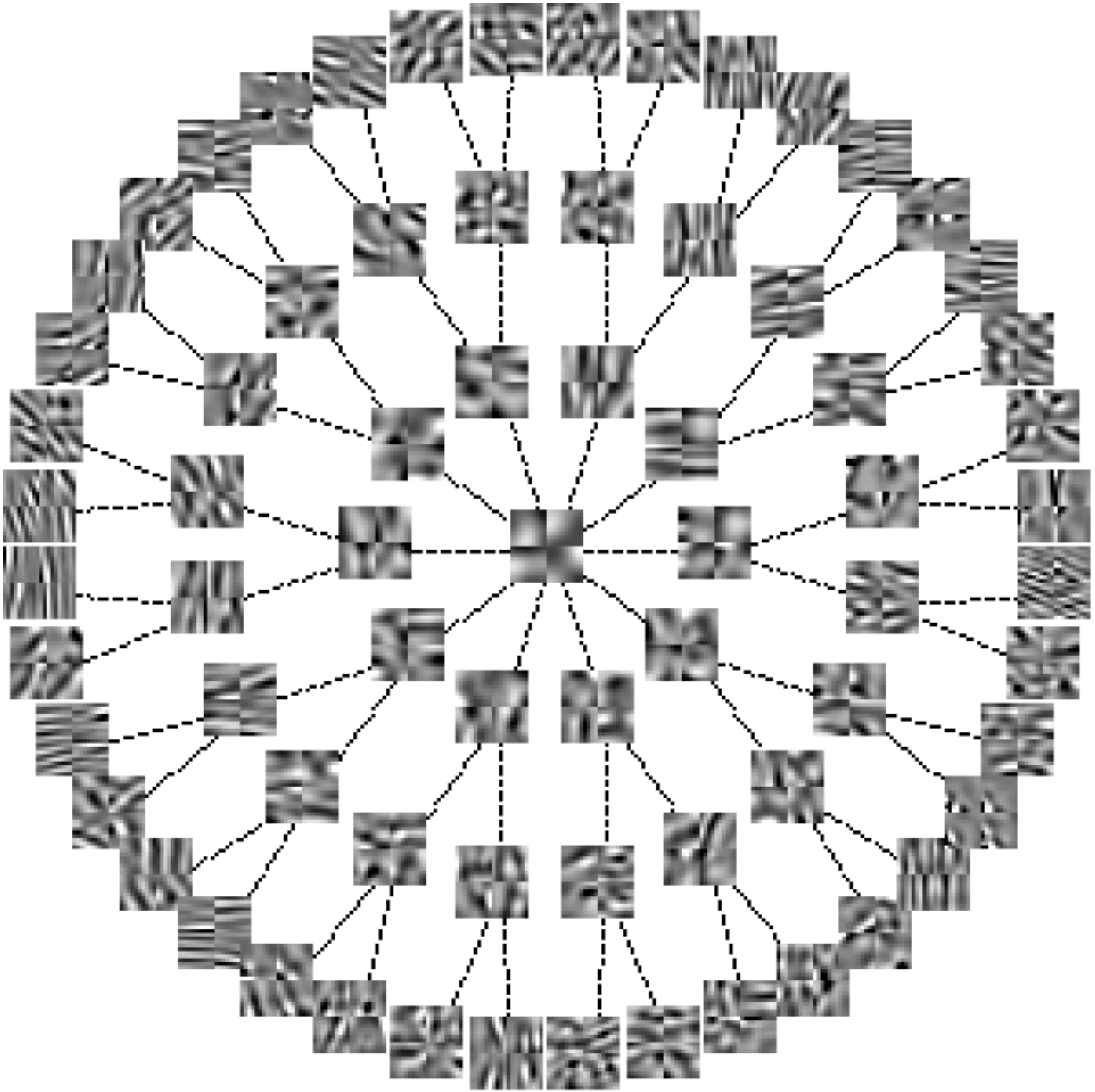
Invariant Features via Lateral Inhibition: Structured Sparsity

- Each edge in the tree indicates a zero in the S matrix (no mutual inhibition)
- Sij is larger if two neurons are far away in the tree



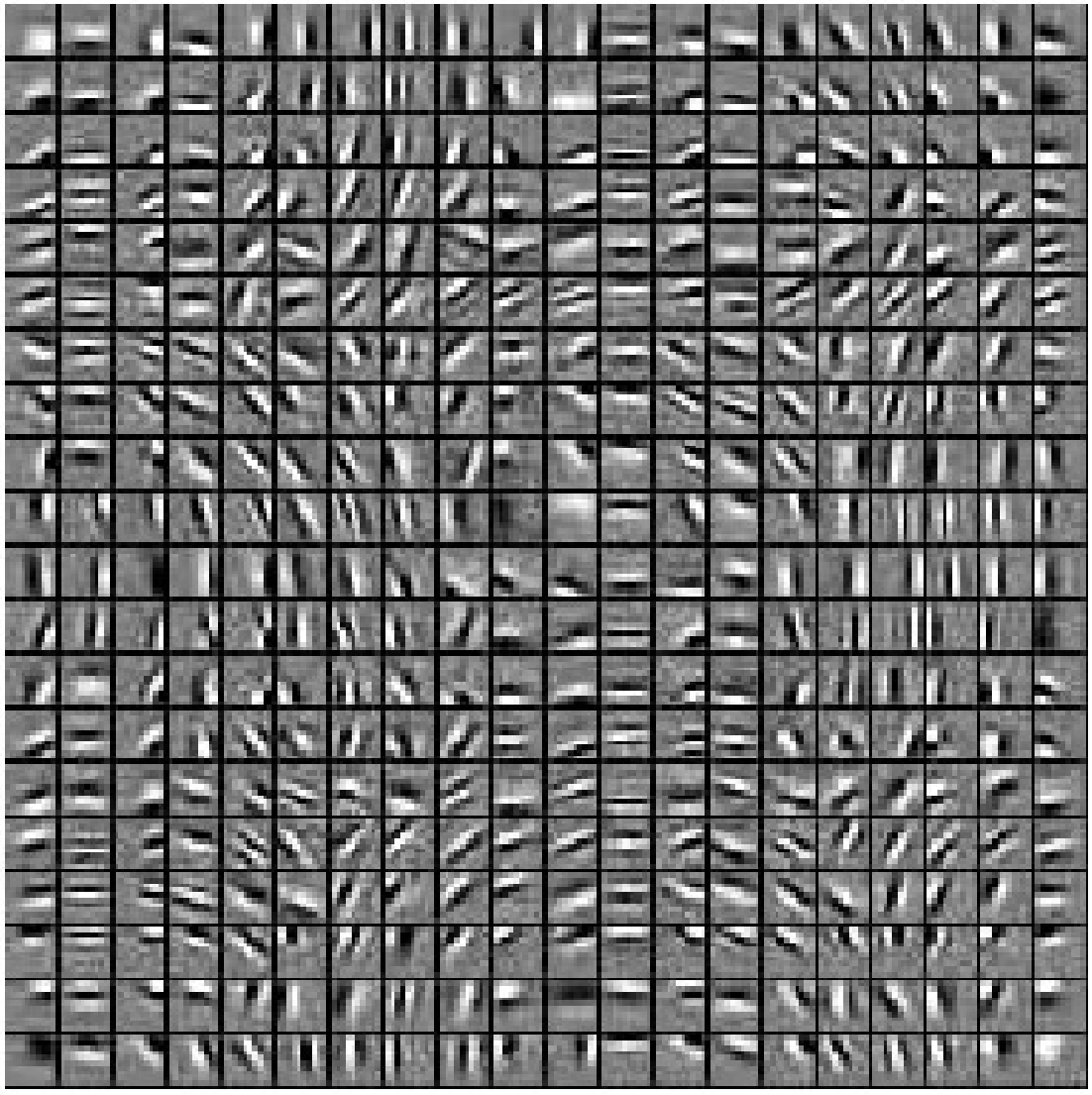






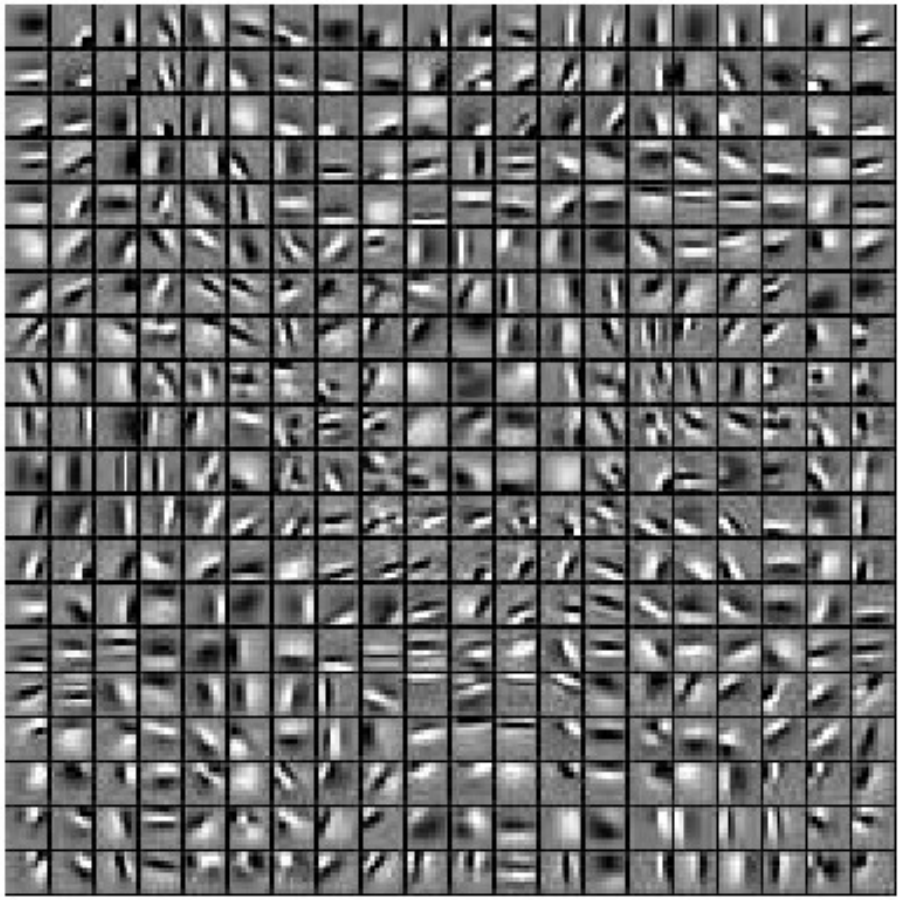
Invariant Features via Lateral Inhibition: Topographic Maps

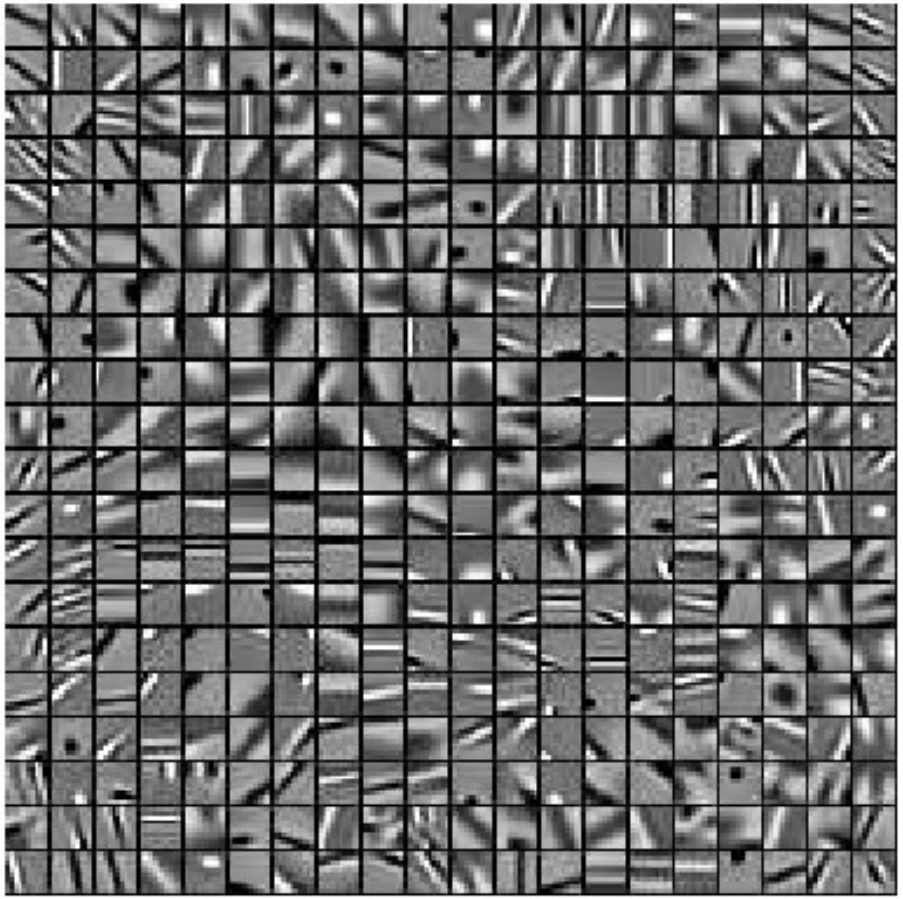
- Non-zero values in S form a ring in a 2D topology
  - Input patches are high-pass filtered



Invariant Features via Lateral Inhibition: Topographic Maps

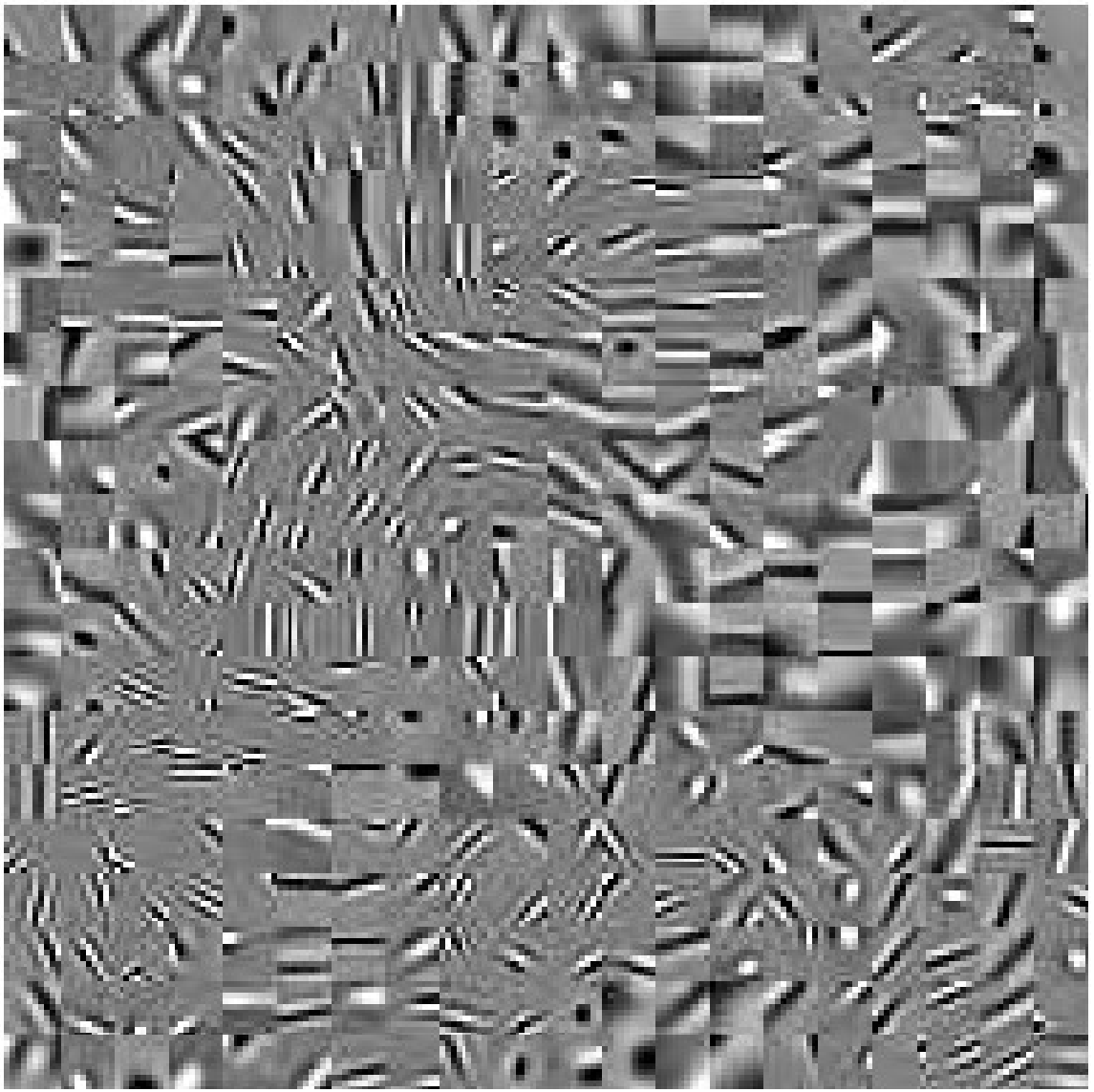
- Non-zero values in S form a ring in a 2D topology
  - Left: no high-pass filtering of input
  - Right: patch-level mean removal





Invariant Features via Lateral Excitation: Topographic Maps

- Short-range lateral excitation + L1 sparsity

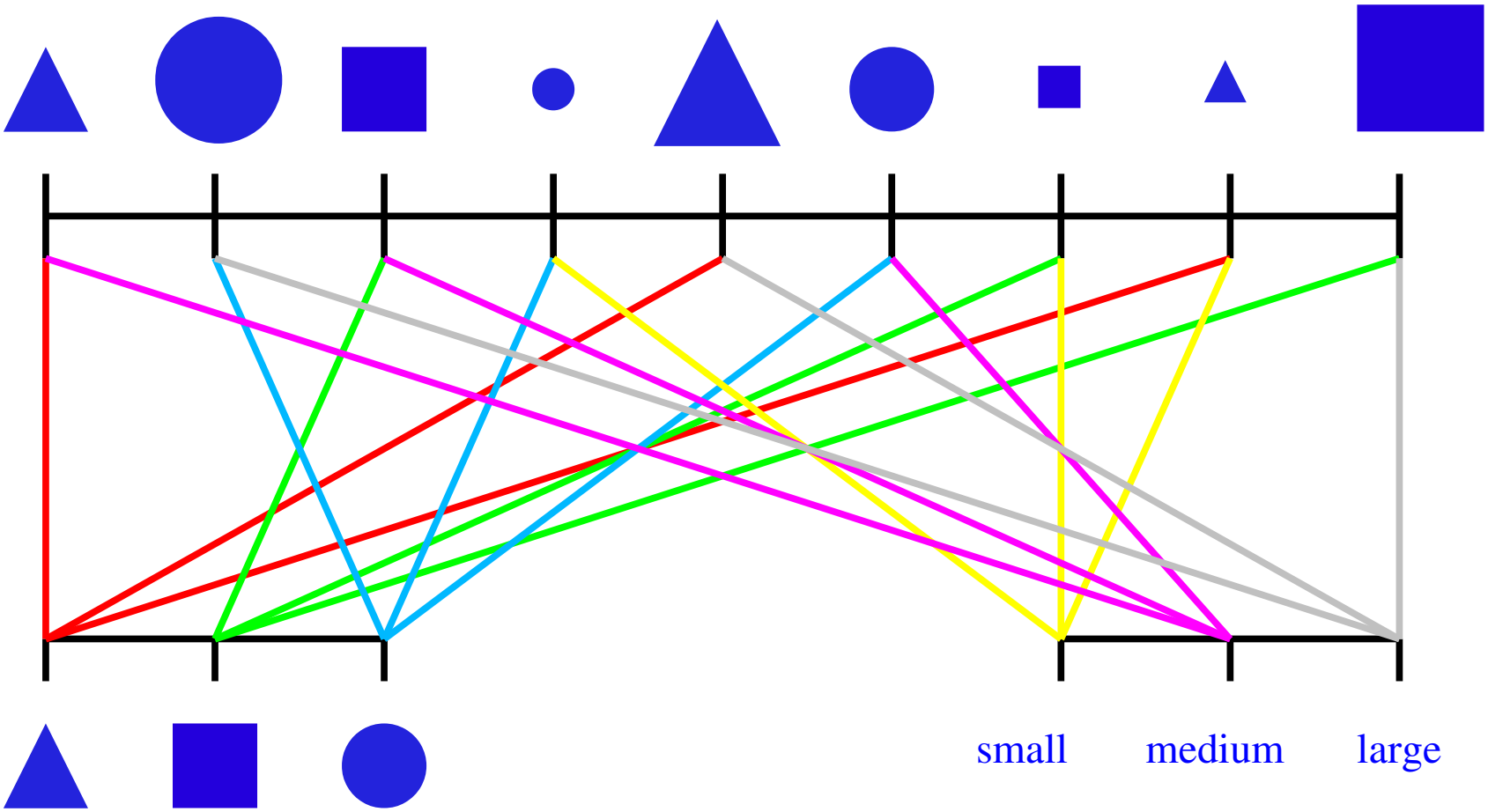


Learning What/Where Features with Temporal Constancy

[Gregor & LeCun arXiv:1006.0448, 2010]

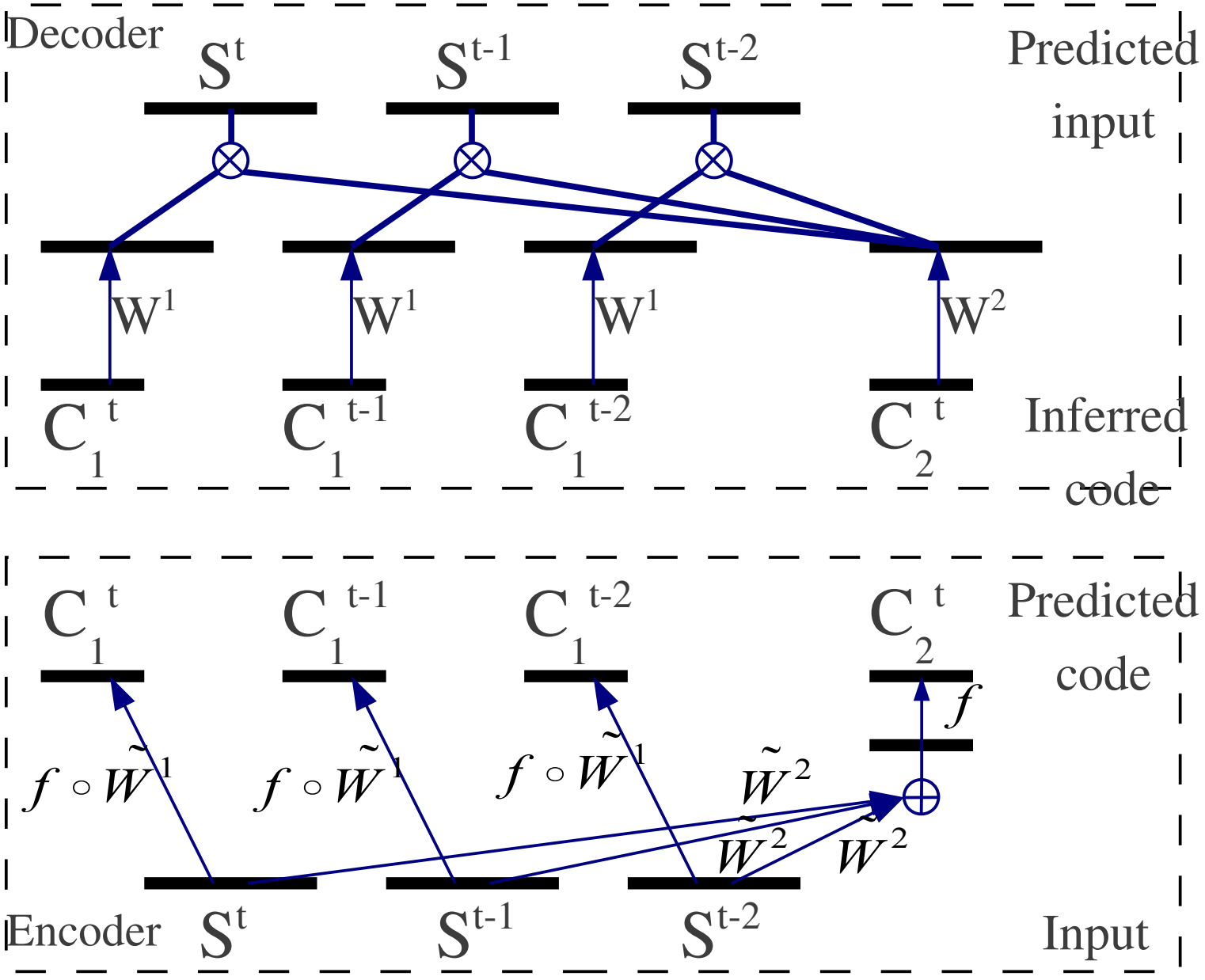
Invariant Features through Temporal Constancy

- Object is cross-product of object type and instantiation parameters
  - Mapping units [Hinton 1981], capsules [Hinton 2011]



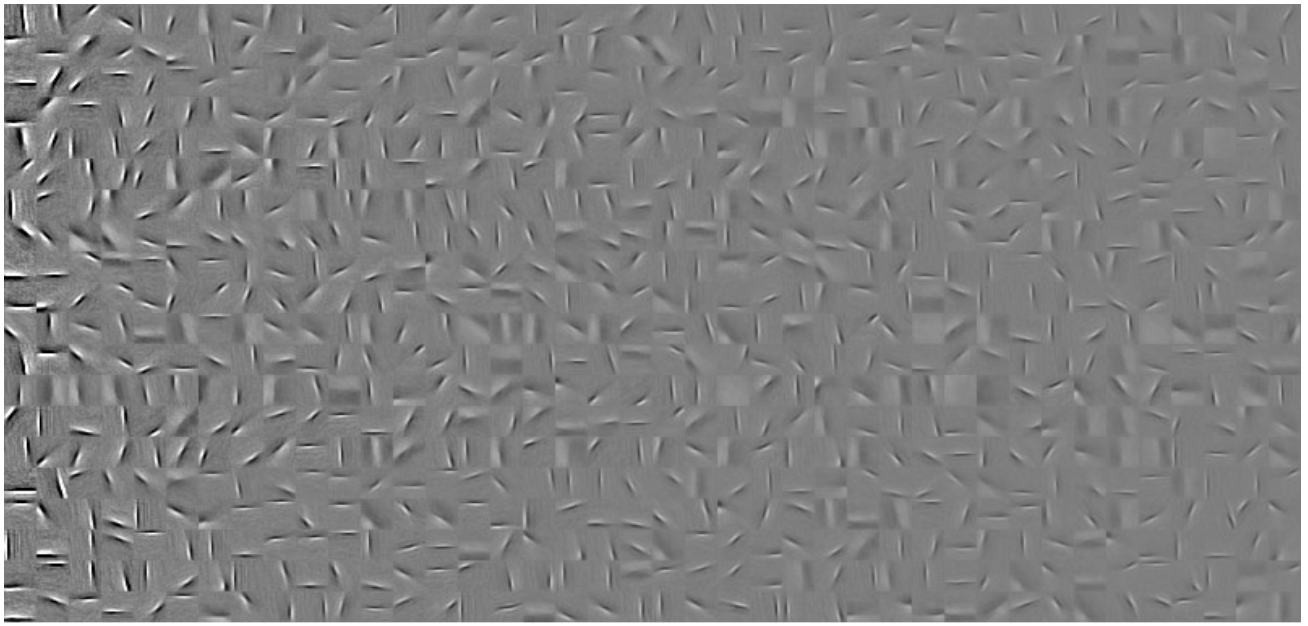
[Karol Gregor et al.]

What-Where Auto-Encoder Architecture

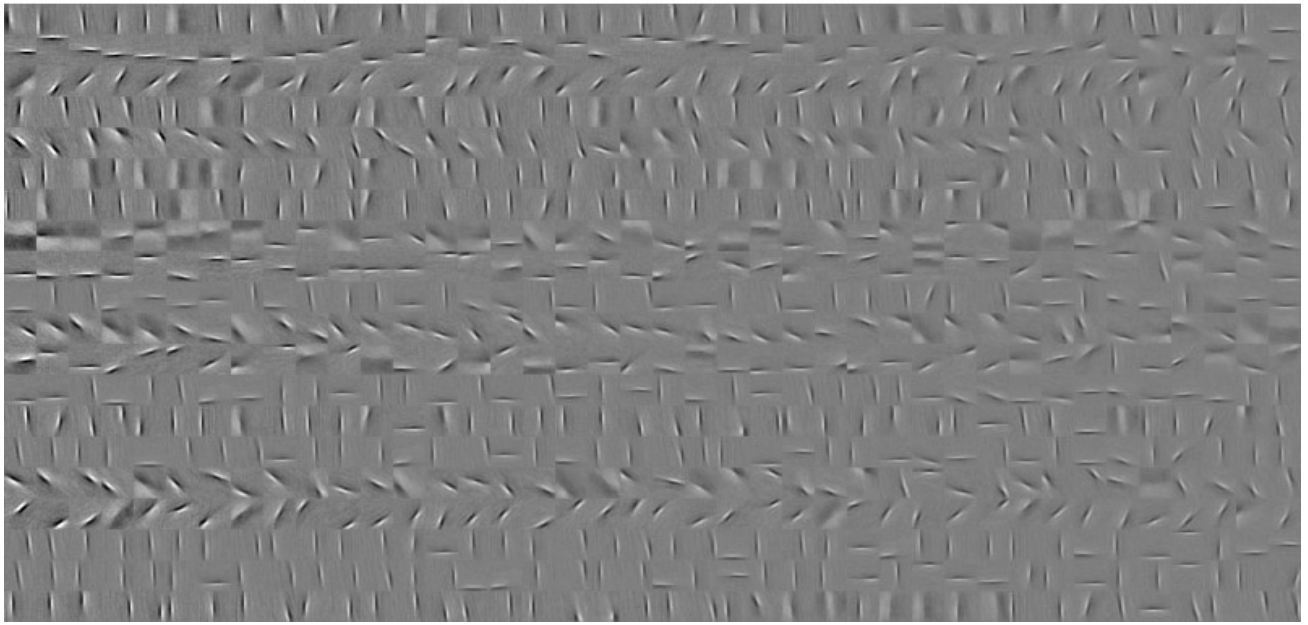


Low-Level Filters Connected to Each Complex Cell

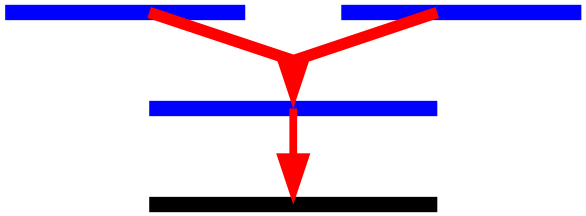
C1
(where)

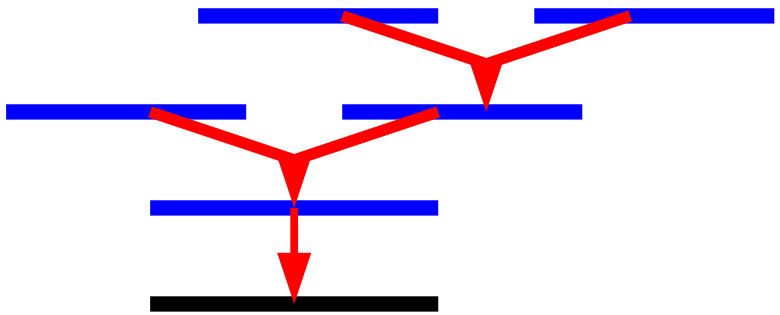


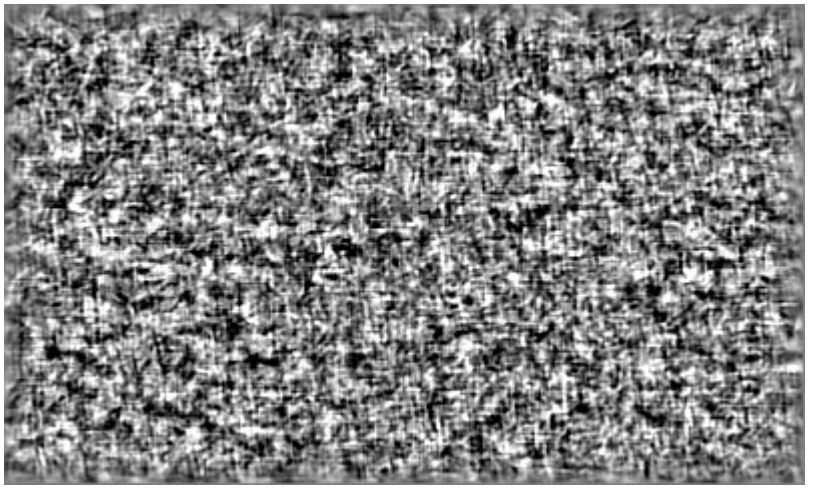
C2
(what)

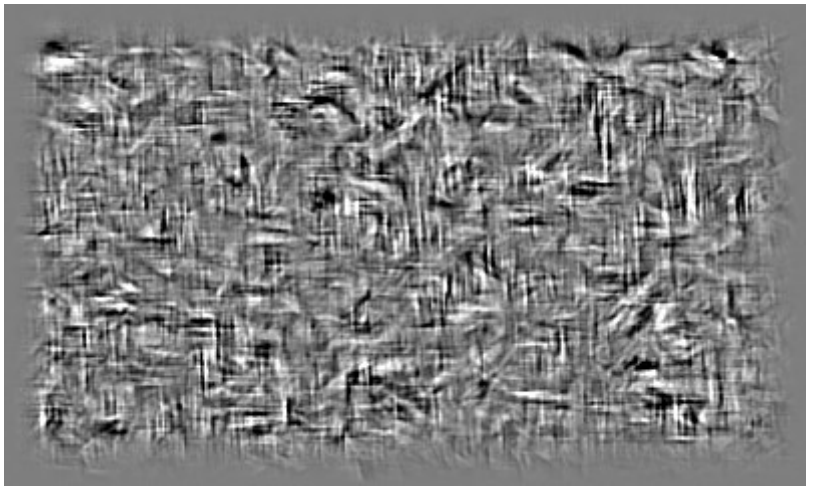


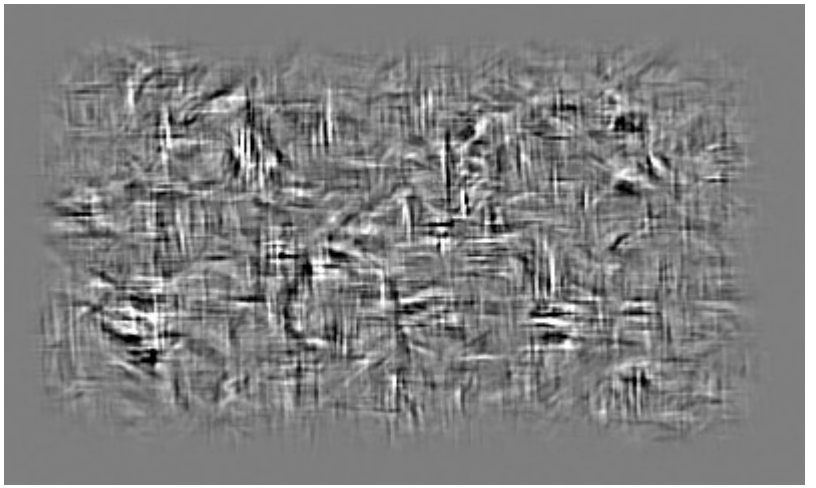
Generating from the Network







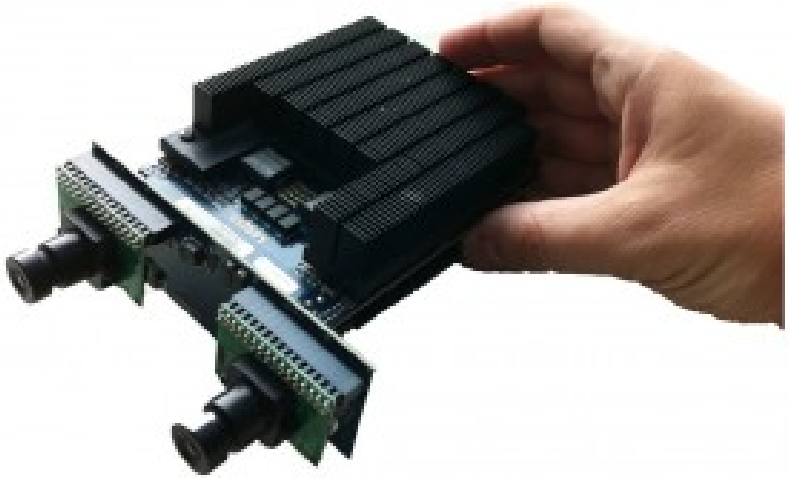




Hardware Implementations

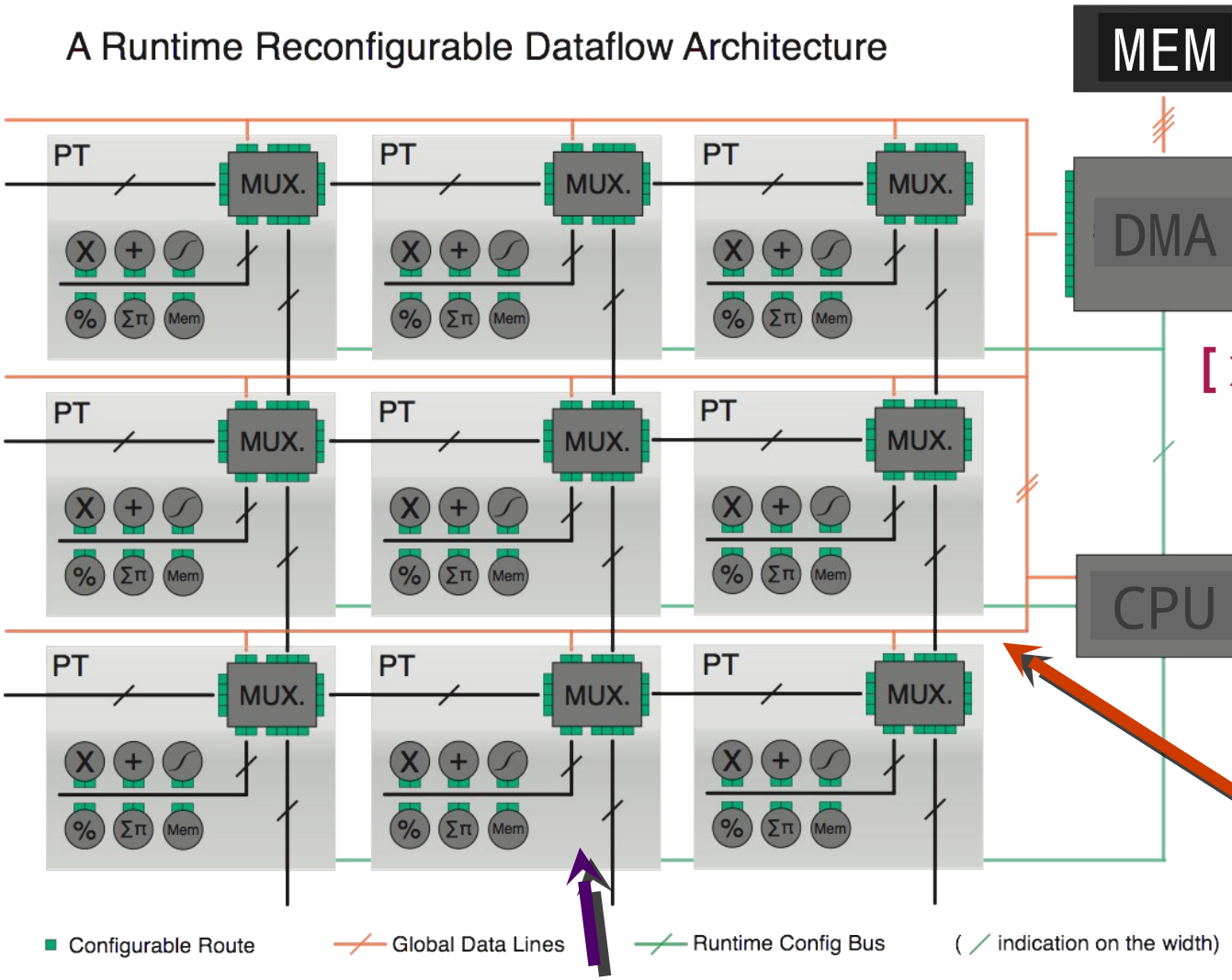
Higher End: FPGA with NeuFlow architecture

- Now Running on Picocomputing 8x10cm high-performance FPGA board
  - Virtex 6 LX240T: 680 MAC units, 20 neuflow tiles
- Full scene labeling at 20 frames/sec (50ms/frame) at 320x240



New board with Virtex-6

NewFlow: Architecture



Multi-port memory controller (DMA)

[x12 on a V6 LX240T]

RISC CPU, to reconfigure tiles and data paths, at runtime

global network-on-chip to allow fast reconfiguration

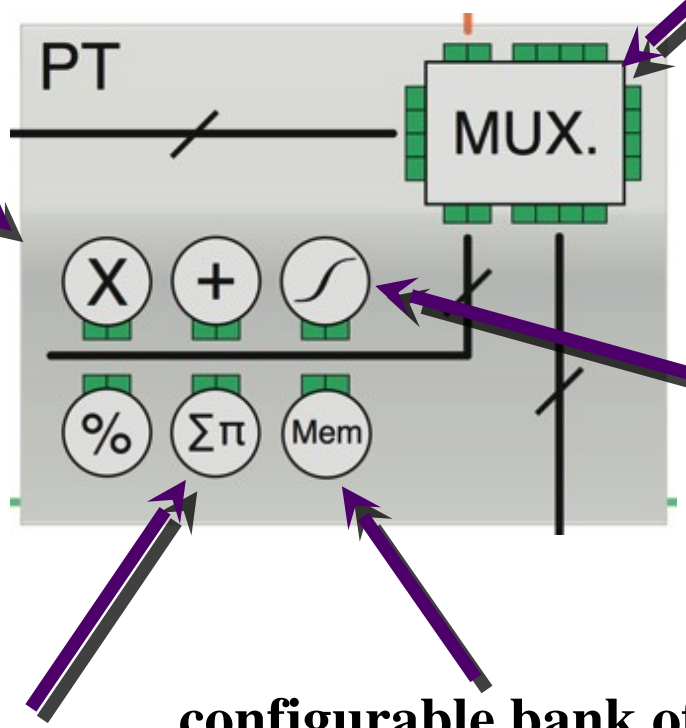
grid of passive processing tiles (PTs)

[x20 on a Virtex6 LX240T]

NewFlow: Processing Tile Architecture

Term-by:-term streaming operators (MUL,DIV,ADD,SUB,MAX)

[x8,2 per tile]



configurable router, to stream data in and out of the tile, to neighbors or DMA ports

[x20]

configurable piece-wise linear or quadratic mapper

[x4]

full 1/2D parallel convolver with 100 MAC units

[x4]

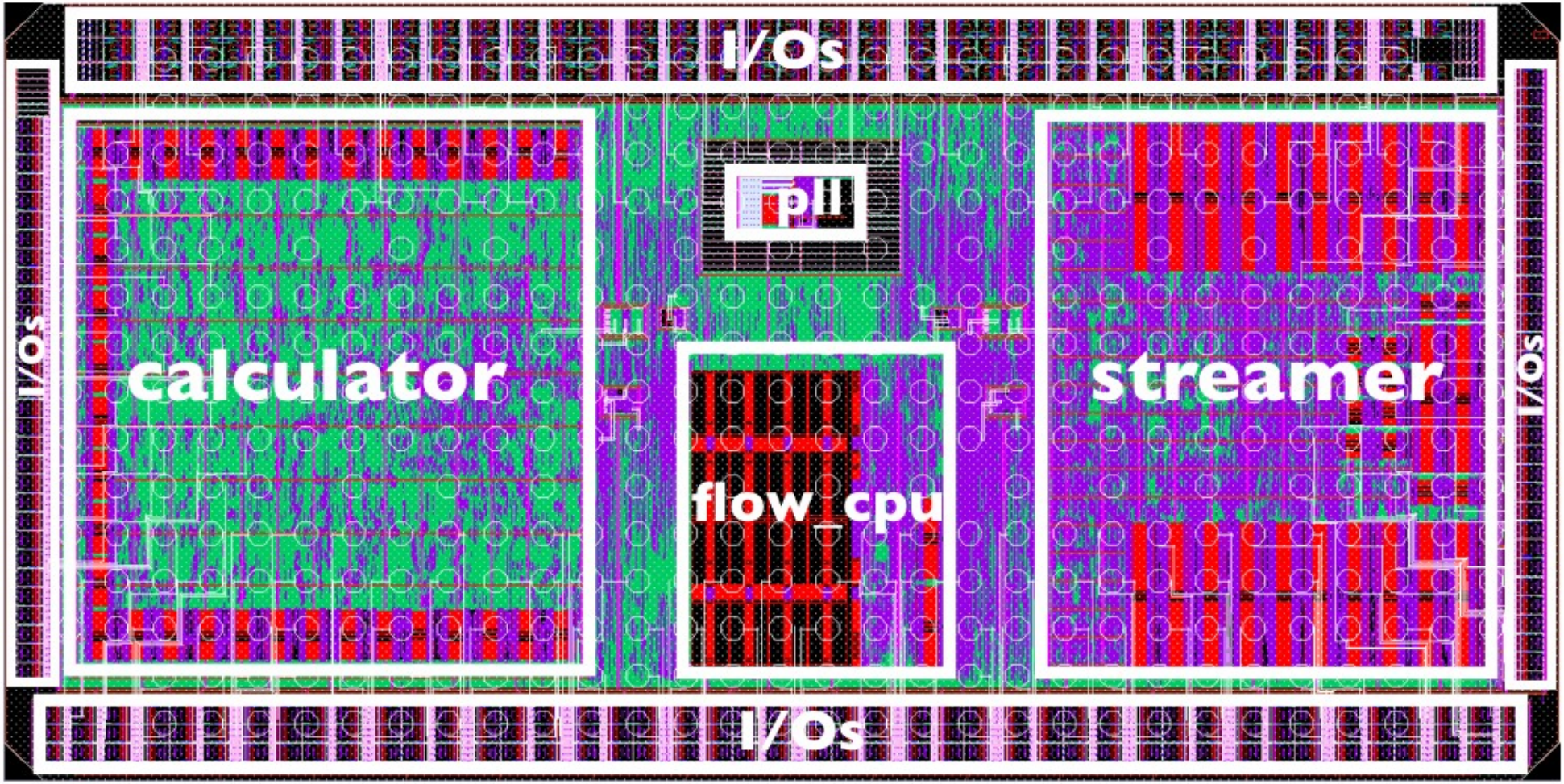
configurable bank of FIFOs , for stream buffering, up to 10kB per PT

[x8]

[Virtex6 LX240T]

NewFlow ASIC: 2.5x5 mm, 45nm, 0.6Watts, 160GOPS

- Collaboration NYU-Purdue (Eugenio Culurciello's group)
- Suitable for vision-enabled embedded and mobile devices
- Status: samples have been received and are being packaged and tested.



Pham, Jelaca, Farabet, Martini, LeCun, Culurciello 2012]

NewFlow: Performance

	Intel I7 4 cores	neuFlow Virtex4	neuFlow Virtex 6	nVidia GT335m	neuFlow IBM 45nm	nVidia GTX480
Peak GOP/sec	40	40	160	182	160	1350
Actual GOP/sec	12	37	147	54	147	294
FPS	14	46	182	67	182	374
Power (W)	50	10	10	30	0.6	220
Embed? (GOP/s/W)	0.24	3.7	14.7	1.8	245	1.34

The History of Deep Learning: fast technology transfer

- 1986: popularization of the back-propagation learning algorithm
- 1989: first Convolutional Nets at Bell Labs (LeCun)
- 1992: invention of Support Vector Machines at Bell Labs (V. Vapnik)
- 1996: convolutional net + CRF deployed for check reading by Bell Labs
- 1996-2005: neural network winter.
- 2006: first "modern" deep learning paper by Geoff Hinton (Toronto)
- 2006-2010: Hinton (Toronto), Bengio (Montreal), Ng (Stanford), and LeCun (NYU) develop several deep learning algorithms. Deep Learning gets support from CifAR, NSF, ONR, and DARPA.
- 2011: several records are broken in speech recognition, action recognition, musical genre classification, and natural language processing.
- 2012: Google and Microsoft deploy speech recognition systems based on deep learning (and more are coming....)
- 2012: Convolutional Nets hold records in ImageNet classification and three semantic segmentation benchmarks.

But Biological Inspiration has its Limits

- It's nice to imitate Nature,
- But we also need to understand
- How do we know which details are important?
- Which details are simply the result of evolution, and which are due to biochemistry?
- For airplanes, we developed aerodynamics and compressible fluid dynamics.
- We figured that feathers and wing flapping weren't crucial
- What is the equivalent of aerodynamics for understanding intelligence?

L'Avion III de Clément Ader, 1897
(Musée du CNAM, Paris)

Acknowledgements

- Y-Lan Boureau 
- Kevin Jarrett 
- Koray Kavukcuoglu 
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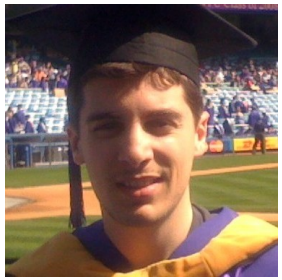
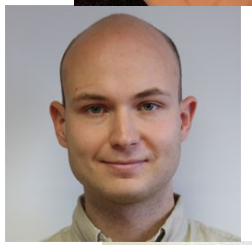
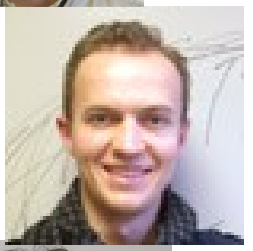
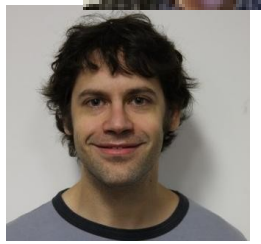
- Pierre Sermanet 
- Camille Couprie 
- Karol Gregor 
- Clément Farabet 
- Arthur Szlam 
- Rob Fergus 
- Laurent Najman (ESIEE) 
- Eugenio Culurciello (Purdue) 

The End