Can Robots Learn to See?

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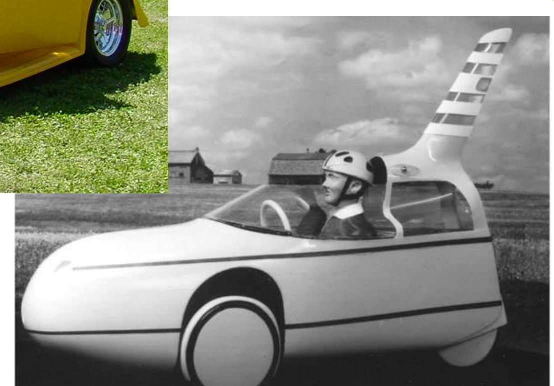
The Next Challenge for AI, Robotics, and Neuroscience

How do we learn vision and perception?

- From the image of an airplane, how do we extract a representation that is invariant to pose, illumination, background, clutter, object instance....
- How can a human (or a machine) learn those representations by just looking at the world?

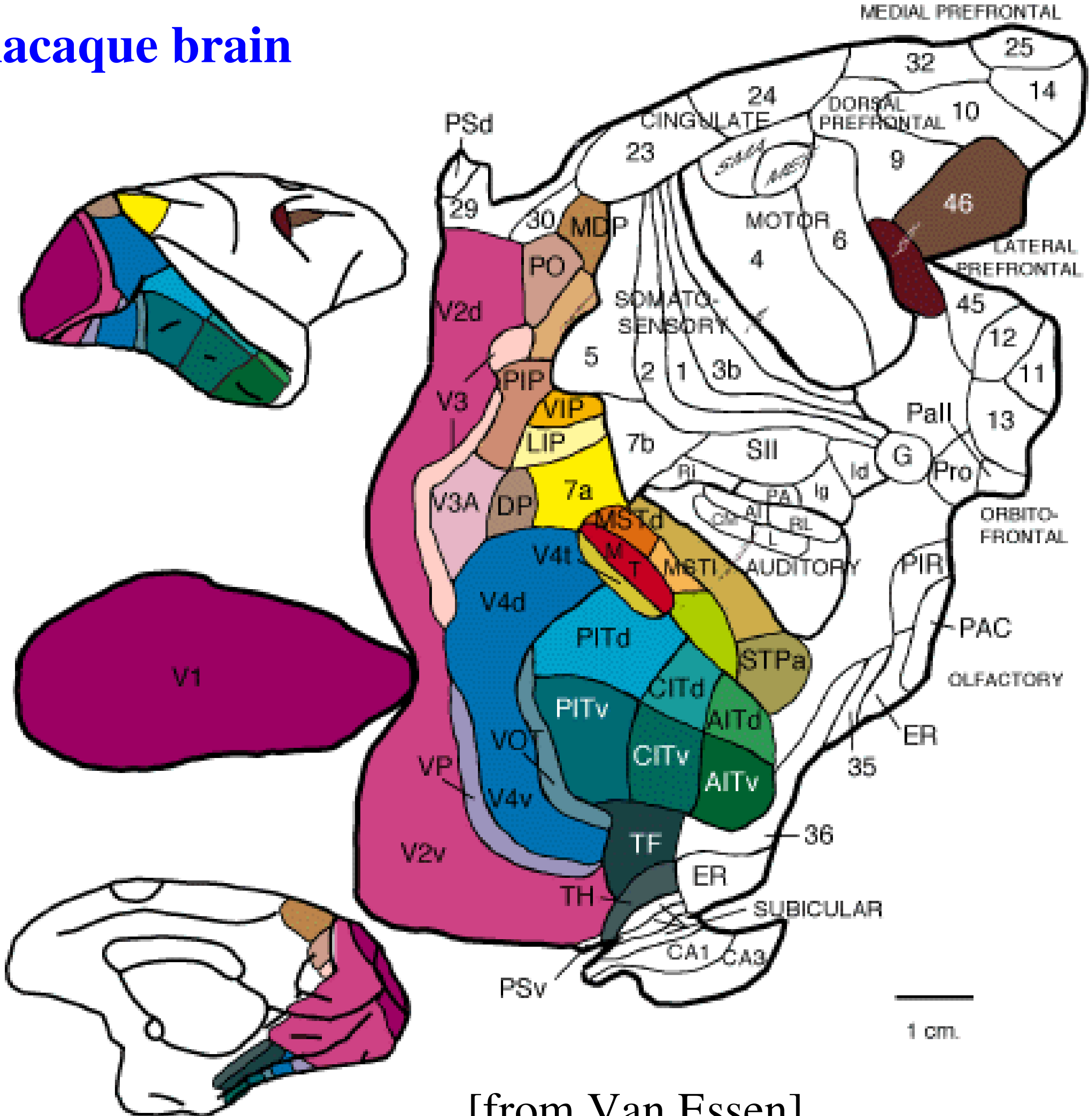
How can we learn visual categories from just a few examples?

- I don't need to see many airplanes before I can recognize every airplane (even really weird ones)



Vision occupies a big chunk of our brains

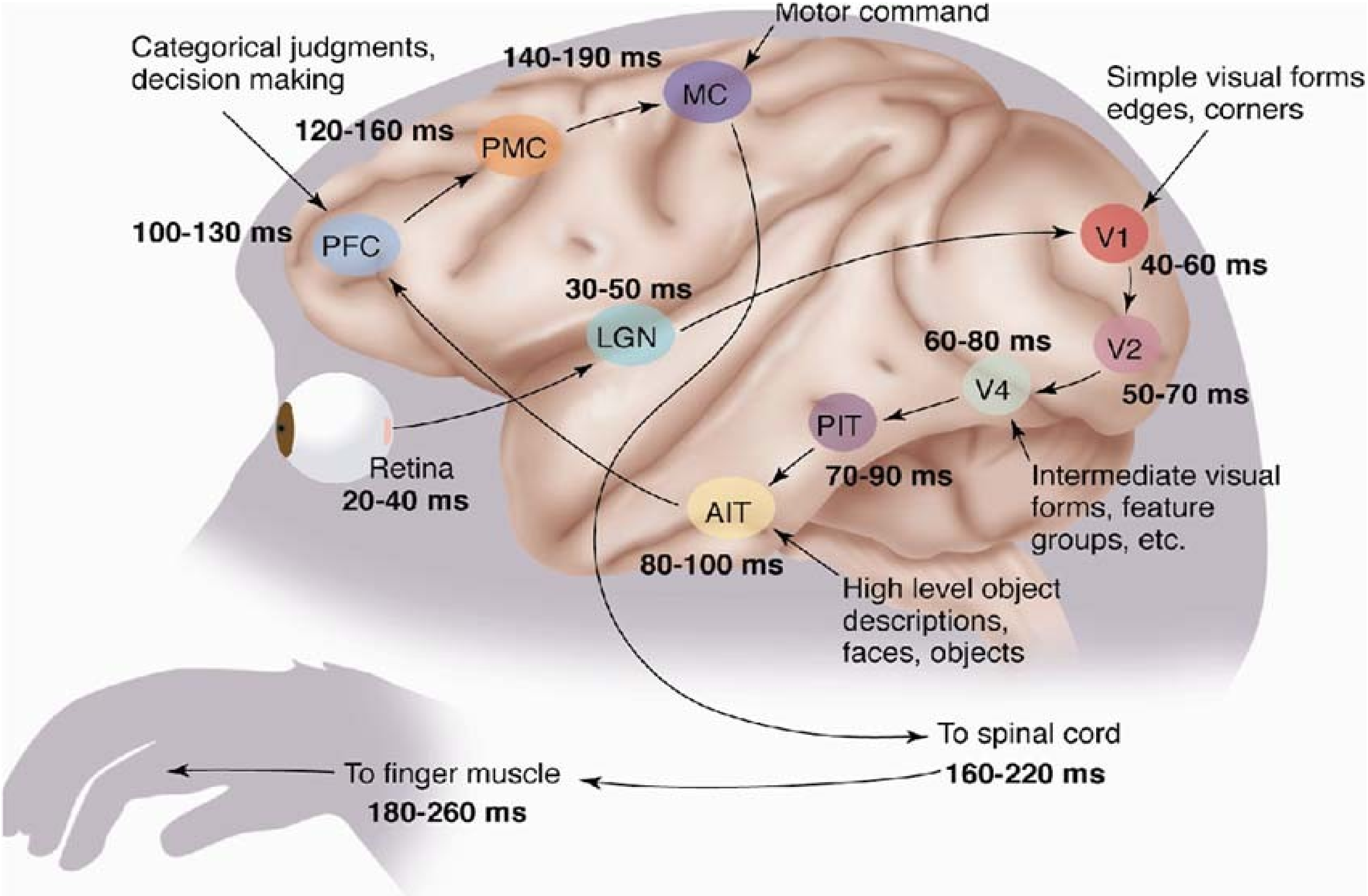
- 1/3 of the macaque brain



[from Van Essen]

Vision is very fast and the visual cortex is hierarchical

- **The ventral (recognition) pathway in the visual cortex**



[picture from Simon Thorpe]

The Primate's Visual System is Deep (LGN->V1->V2->V4->IT)

- **The recognition of everyday objects is a very fast process.**
  - The recognition of common objects is essentially "feed forward."
  - But not all of vision is feed forward.
- **Much of the visual system (all of it?) is the result of learning**
  - How much prior structure is there?
- **If the visual system is deep (around 10 layers) and learned**
- **what is the learning algorithm of the visual cortex?**
  - What learning algorithm can train neural nets as "deep" as the visual system (10 layers?).
  - Unsupervised vs Supervised learning
  - What is the loss function?
  - What is the organizing principle?
  - Broader question (Hinton): what is the learning algorithm of the neo-cortex?

The Broader Challenge of Machine Learning and AI

- **Can we devise learning algorithms to train a “deep” artificial visual system, and other artificial perception systems.**
- **How can we learn the structure of the world?**
  - How can we build/learn internal representations of the world that allow us to discover its hidden structure?
  - How can we learn internal representations that capture the relevant information and eliminates irrelevant variabilities?
- **How can a human or a machine learn internal representations by just looking at the world?**
- **Can we find learning methods that solve really complex problems end-to-end, such as vision, natural language, speech....?**

The Traditional "Shallow" Architecture for Recognition

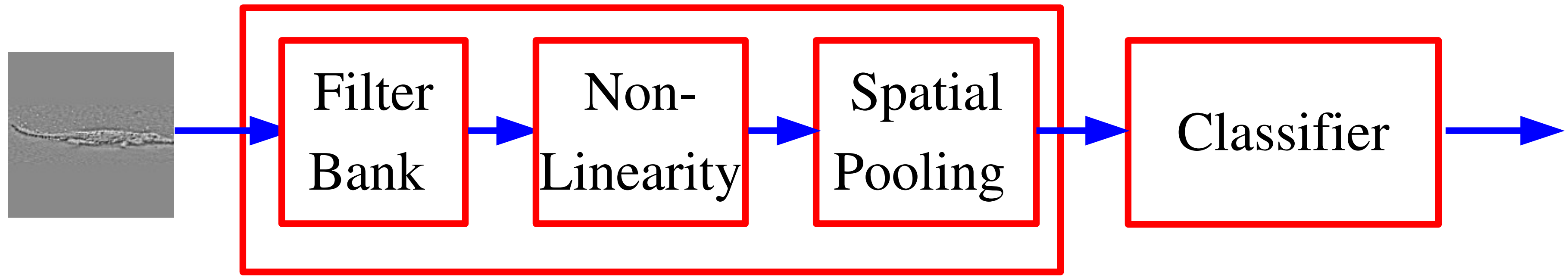
Pre-processing / Feature Extraction → "Simple" Trainable Classifier →

this part is mostly hand-crafted

Internal Representation

- **The raw input is pre-processed through a hand-crafted feature extractor**
- **The features are not learned**
- **The trainable classifier is often generic (task independent), and "simple" (linear classifier, kernel machine, nearest neighbor,.....)**
- **The most common Machine Learning architecture: the Kernel Machine**

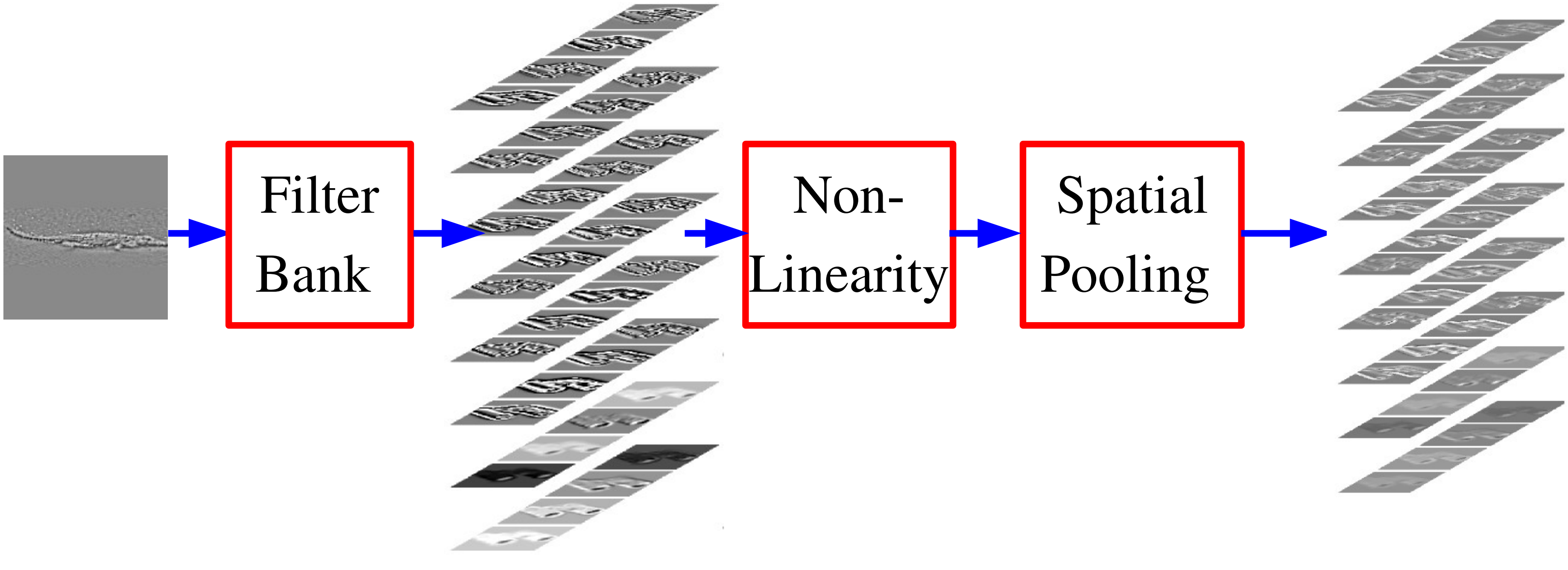
"Modern" Object Recognition Architecture in Computer Vision



Oriented Edges	Sigmoid	Averaging
Gabor Wavelets	Rectification	Max pooling
Other Filters...	Vector Quant.	VQ+Histogram
	Contrast Norm.	Geometric Blurr

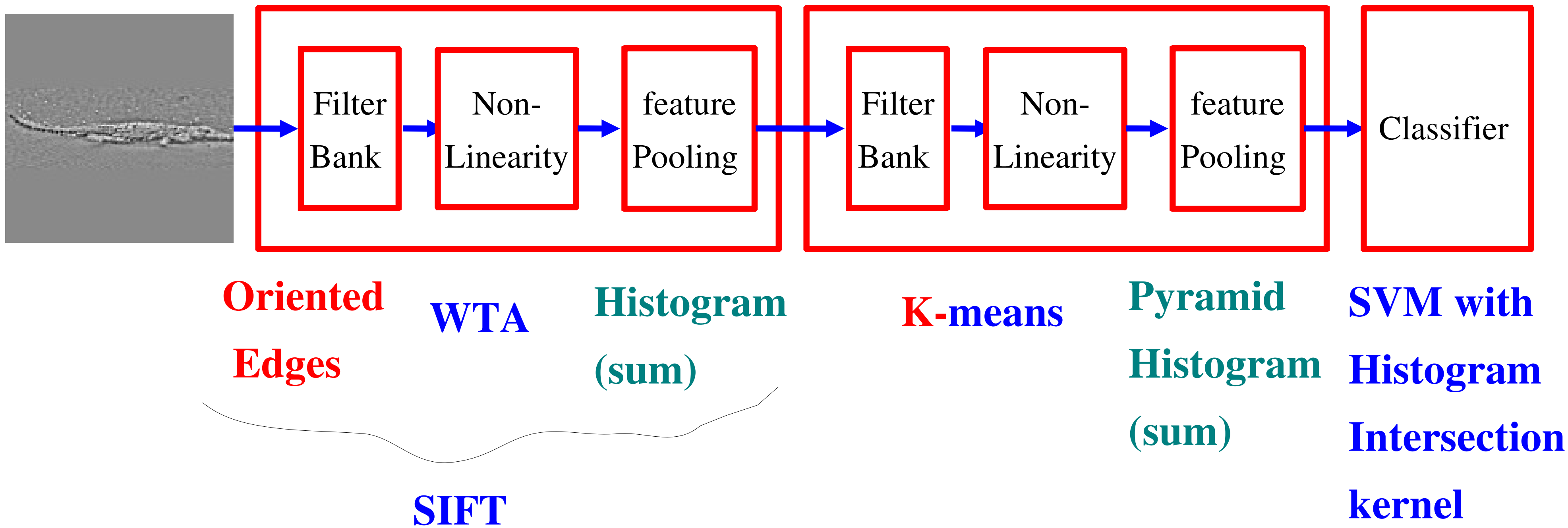
- **Example:**
  - Edges + Rectification + Histograms + SVM [Dalal & Triggs 2005]
  - SIFT + classification
- **Fixed Features + "shallow" classifier**

Feature Extraction by Filtering and Pooling



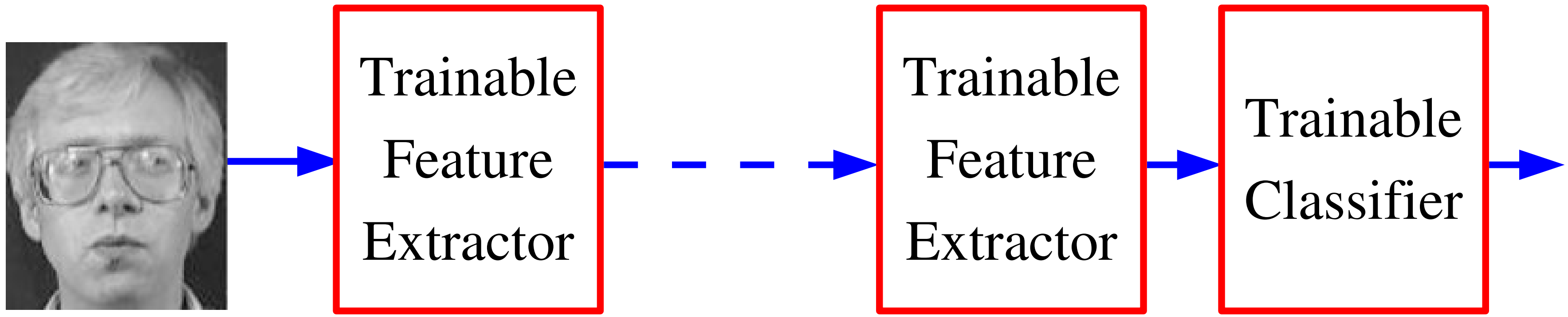
- **Biologically-inspired models of low-level feature extraction**
  - Inspired by [Hubel and Wiesel 1962]

“State of the Art” architecture for object recognition



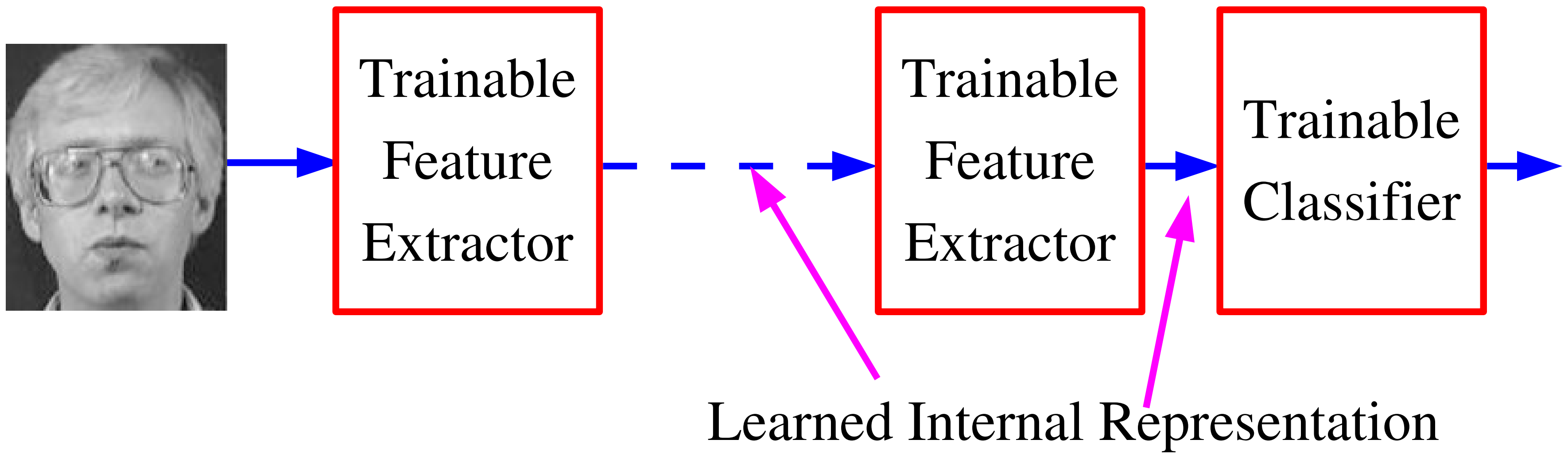
- **Example:**
  - SIFT features with Spatial Pyramid Match Kernel SVM [Lazebnik et al. 2006]
- **Fixed Features + unsupervised features + “shallow” classifier**

Good Representations are Hierarchical



- **In Language: hierarchy in syntax and semantics**
  - Words->Parts of Speech->Sentences->Text
  - Objects,Actions,Attributes...-> Phrases -> Statements -> Stories
- **In Vision: part-whole hierarchy**
  - Pixels->Edges->Textons->Parts->Objects->Scenes

"Deep" Learning: Learning Hierarchical Representations



- **Deep Learning: learning a hierarchy of internal representations**
- **From low-level features to mid-level invariant representations, to object identities**
- **Representations are increasingly invariant as we go up the layers**
- **using multiple stages gets around the specificity/invariance dilemma**

Do we really need deep architectures?

- **We can approximate any function as close as we want with shallow architecture (e.g. a kernel machine). Why would we need deep ones?**

$$y = \sum_{i=1}^{P} \alpha_i K(X, X^i) \qquad\qquad y = F(W^1.F(W^0.X))$$

  - kernel machines and 2-layer neural net are "universal".

- **Deep learning machines**

$$y = F(W^K.F(W^{K-1}.F(....F(W^0.X)...)))$$

- **Deep machines are more efficient for representing certain classes of functions, particularly those involved in visual recognition**
  - they can represent more complex functions with less "hardware"

- **We need an efficient parameterization of the class of functions that are useful for "AI" tasks.**

Why are Deep Architectures More Efficient?

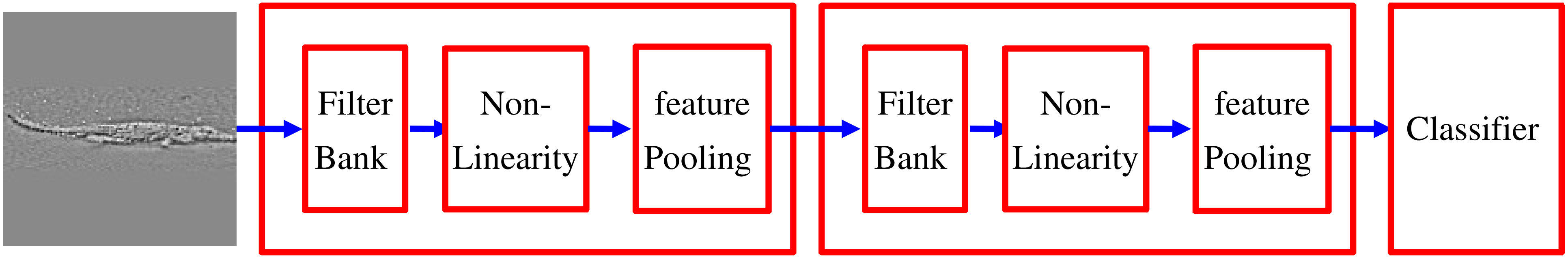
[Bengio & LeCun 2007 "Scaling Learning Algorithms Towards AI"]

- **A deep architecture trades space for time (or breadth for depth)**
  - more layers (more sequential computation),
  - but less hardware (less parallel computation).
  - Depth-Breadth tradoff
- **Example1: N-bit parity**
  - requires N-1 XOR gates in a tree of depth log(N).
  - requires an exponential number of gates of we restrict ourselves to 2 layers (DNF formula with exponential number of minterms).
- **Example2: circuit for addition of 2 N-bit binary numbers**
  - Requires O(N) gates, and O(N) layers using N one-bit adders with ripple carry propagation.
  - Requires lots of gates (some polynomial in N) if we restrict ourselves to two layers (e.g. Disjunctive Normal Form).
  - Bad news: almost all boolean functions have a DNF formula with an exponential number of minterms O(2^N).....

Deep Supervised Learning is Hard

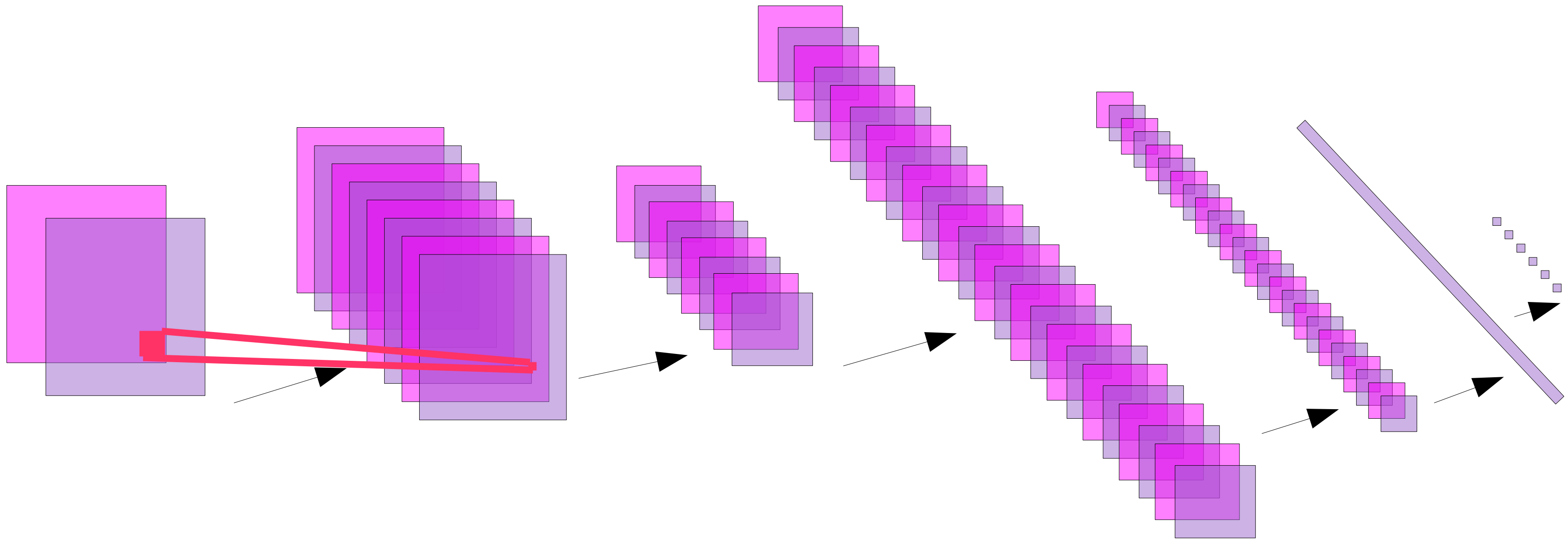
- The loss surface is non-convex, ill-conditioned, has saddle points, has flat spots.....
- For large networks, it will be horrible! (not really, actually)
- Back-prop doesn't work well with networks that are tall and skinny.
  - Lots of layers with few hidden units.
- Back-prop works fine with short and fat networks
  - But over-parameterization becomes a problem without regularization
  - Short and fat nets with fixed first layers aren't very different from SVMs.
- For reasons that are not well understood theoretically, back-prop works well when they are highly structured
  - e.g. convolutional networks.

Can't we train multi-stage vision architectures?



- **Stacking multiple stages of feature extraction/pooling.**
- **Creates a hierarchy of features**

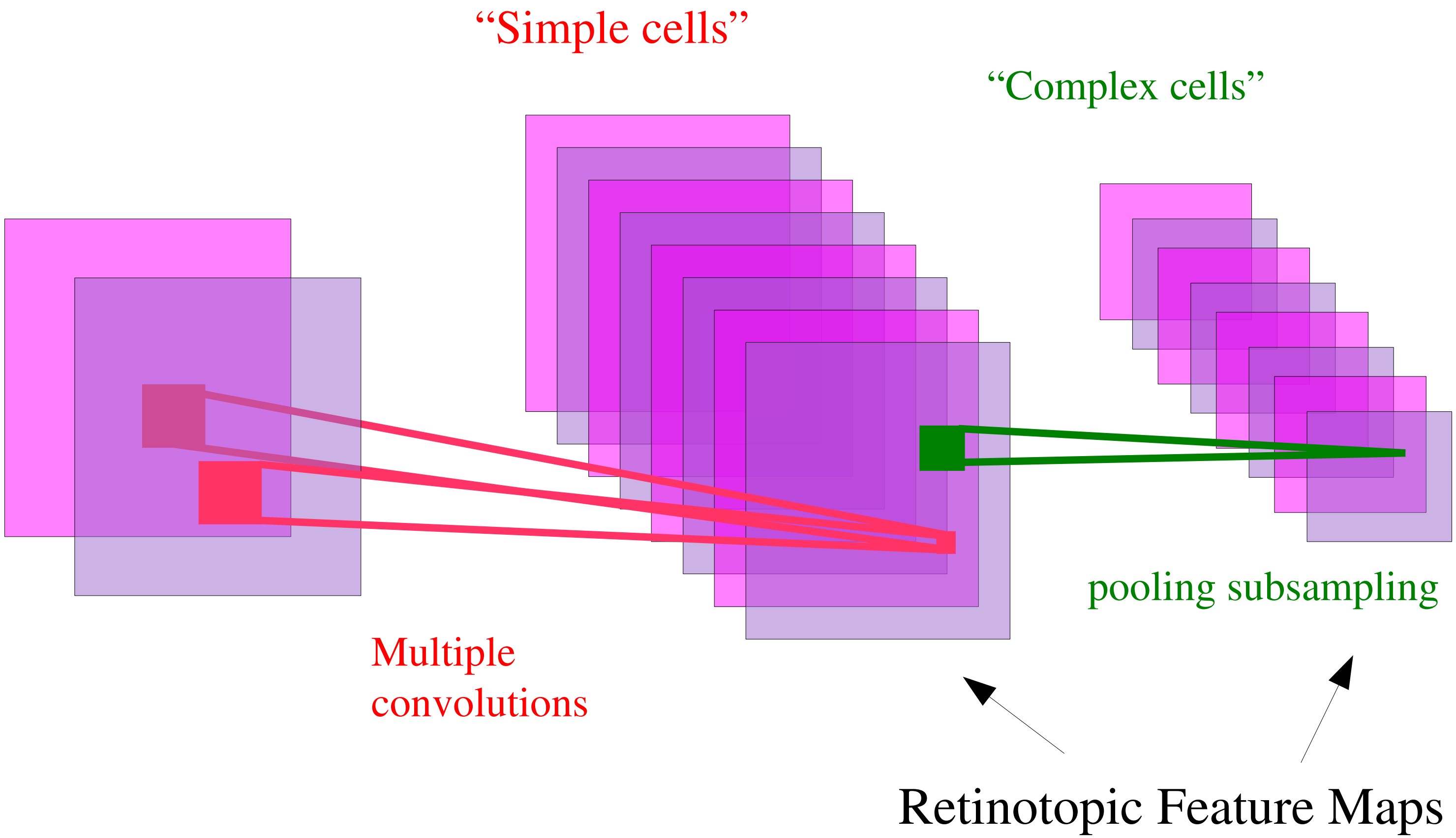
Convolutional Network



- **Hierarchical/multilayer:** features get progressively more global, invariant, and numerous
- **dense features:** features detectors applied everywhere (no interest point)
- **broadly tuned (possibly invariant) features:** sigmoid units are on half the time.
- **Global discriminative training:** The whole system is trained "end-to-end" with a gradient-based method to minimize a global loss function
- **Integrates segmentation, feature extraction, and invariant classification in one fell swoop.**

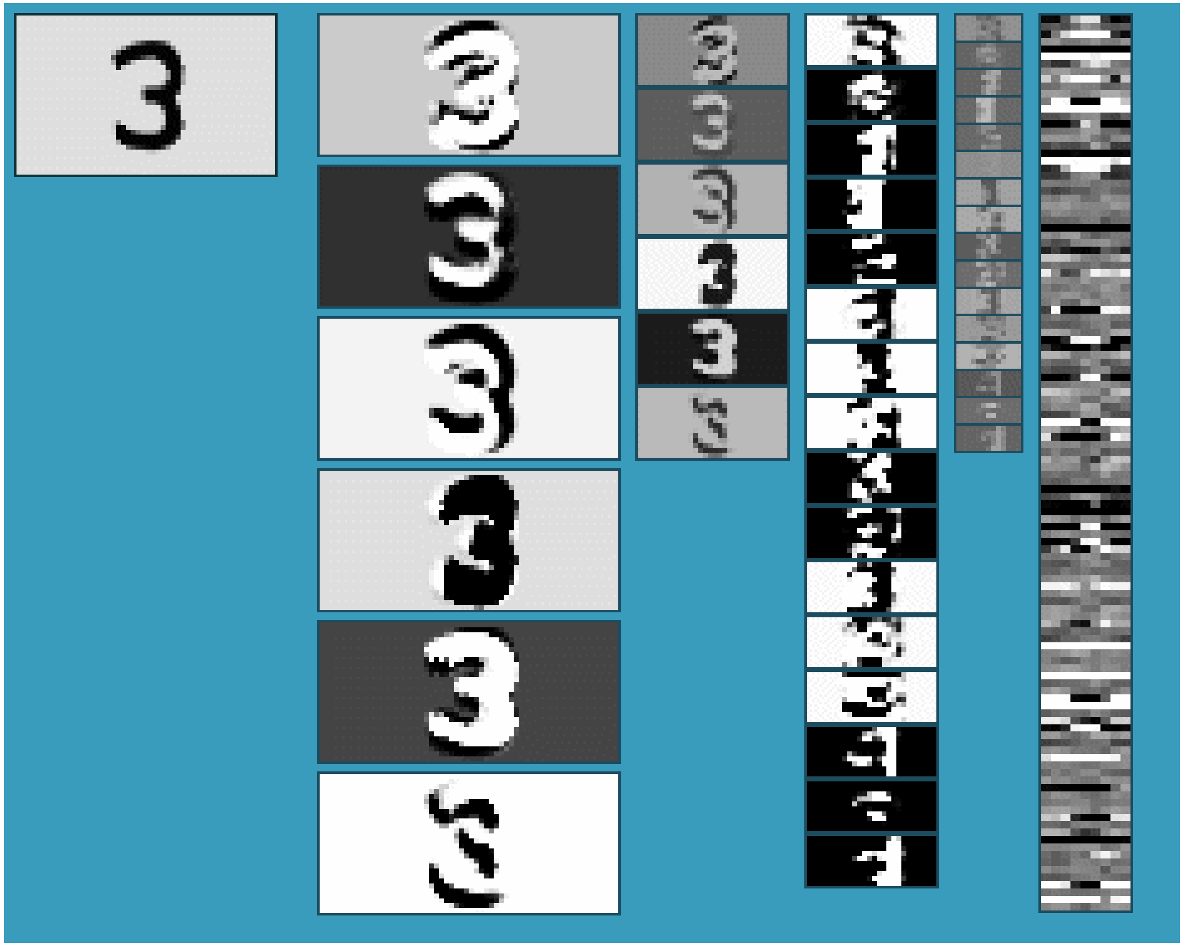
An Old Idea for Local Shift Invariance

- **[Hubel & Wiesel 1962]:**
  - simple cells detect local features
  - complex cells "pool" the outputs of simple cells within a retinotopic neighborhood.



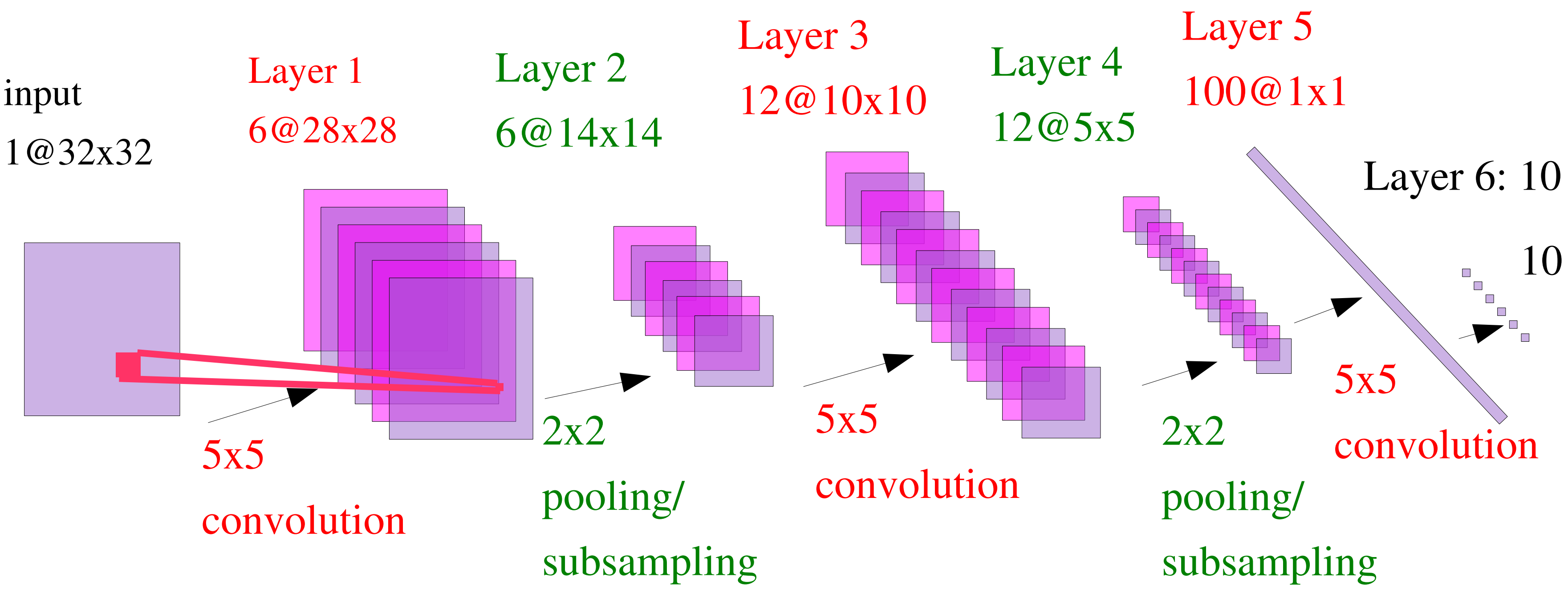
The Multistage Hubel-Wiesel Architecture

- **Building a complete artificial vision system:**
  - Stack multiple stages of simple cells / complex cells layers
  - Higher stages compute more global, more invariant features
  - Stick a classification layer on top
  - [Fukushima 1971-1982]
    - neocognitron
  - [LeCun 1988-2007]
    - convolutional net
  - [Poggio 2002-2006]
    - HMAX
  - [Ullman 2002-2006]
    - fragment hierarchy
  - [Lowe 2006]
    - HMAX



- **QUESTION: How do we find (or learn) the filters?**

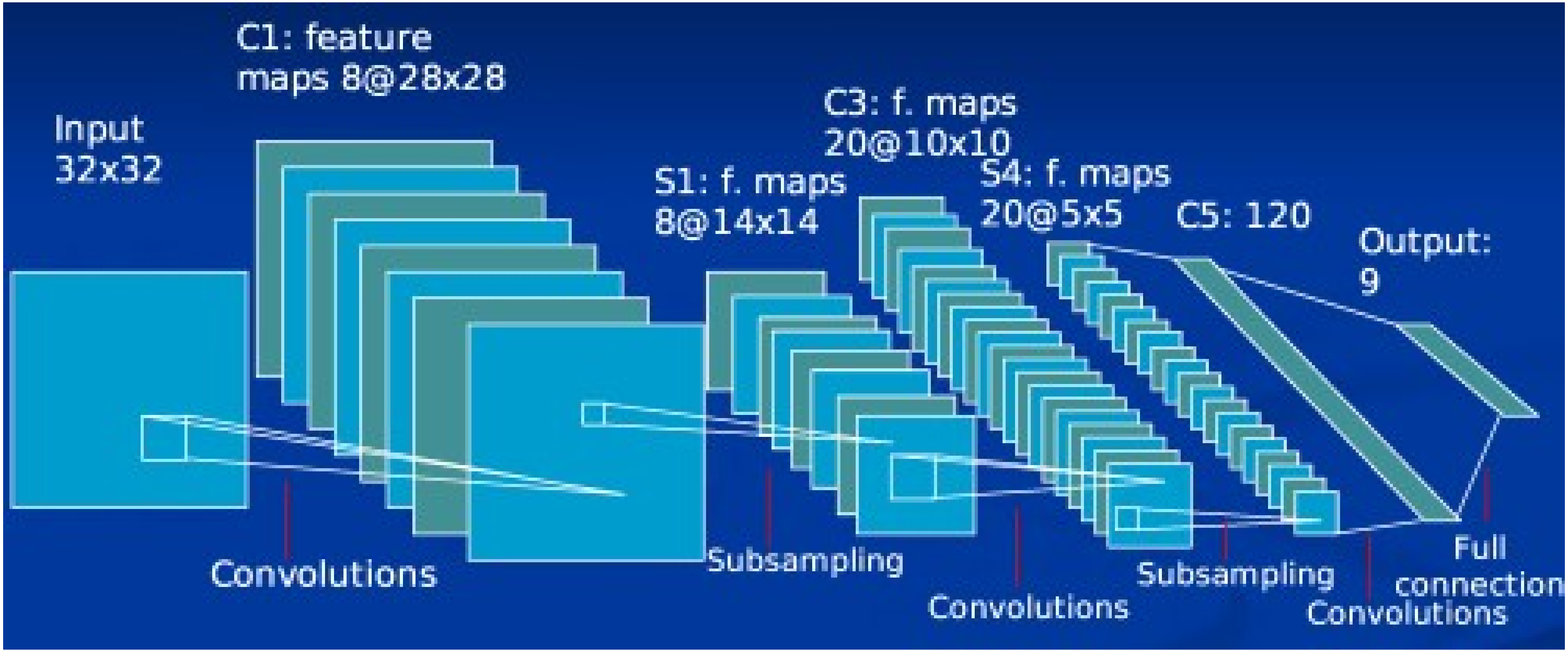
Convolutional Net Architecture



- **Convolutional net for handwriting recognition** (400,000 synapses)
- Convolutional layers (simple cells): all units in a feature plane share the same weights
- Pooling/subsampling layers (complex cells): for invariance to small distortions.
- **Supervised gradient-descent learning using back-propagation**
- **The entire network is trained end-to-end. All the layers are trained simultaneously**.

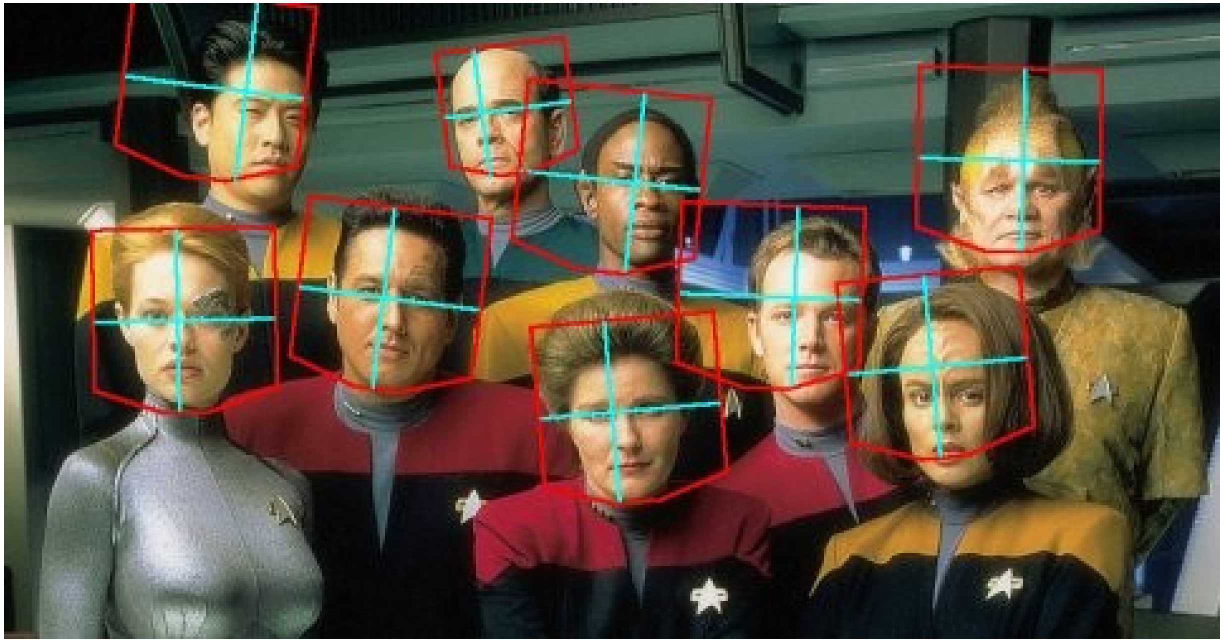
Face Detection and Pose Estimation with Convolutional Nets

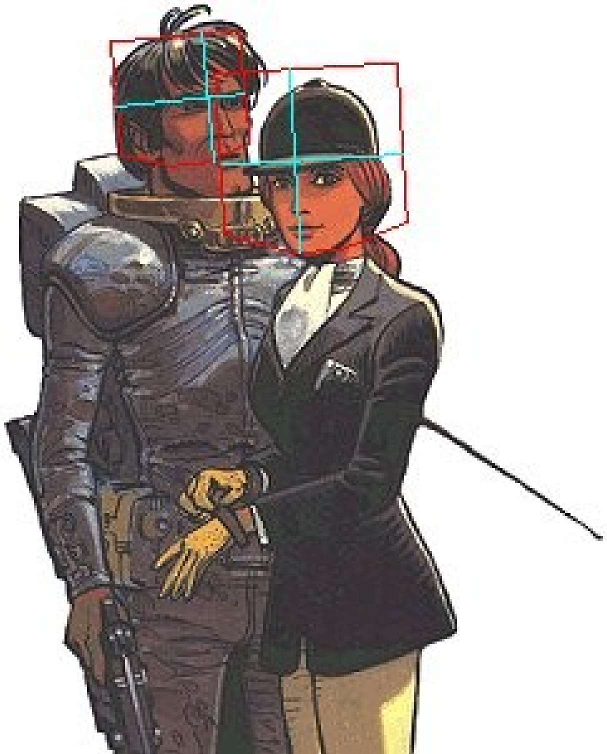
- **Training:** 52,850, 32x32 grey-level images of faces, 52,850 non-faces.
- **Each sample:** used 5 times with random variation in scale, in-plane rotation, brightness and contrast.
- **2nd phase:** half of the initial negative set was replaced by false positives of the initial version of the detector .



Face Detection: Results

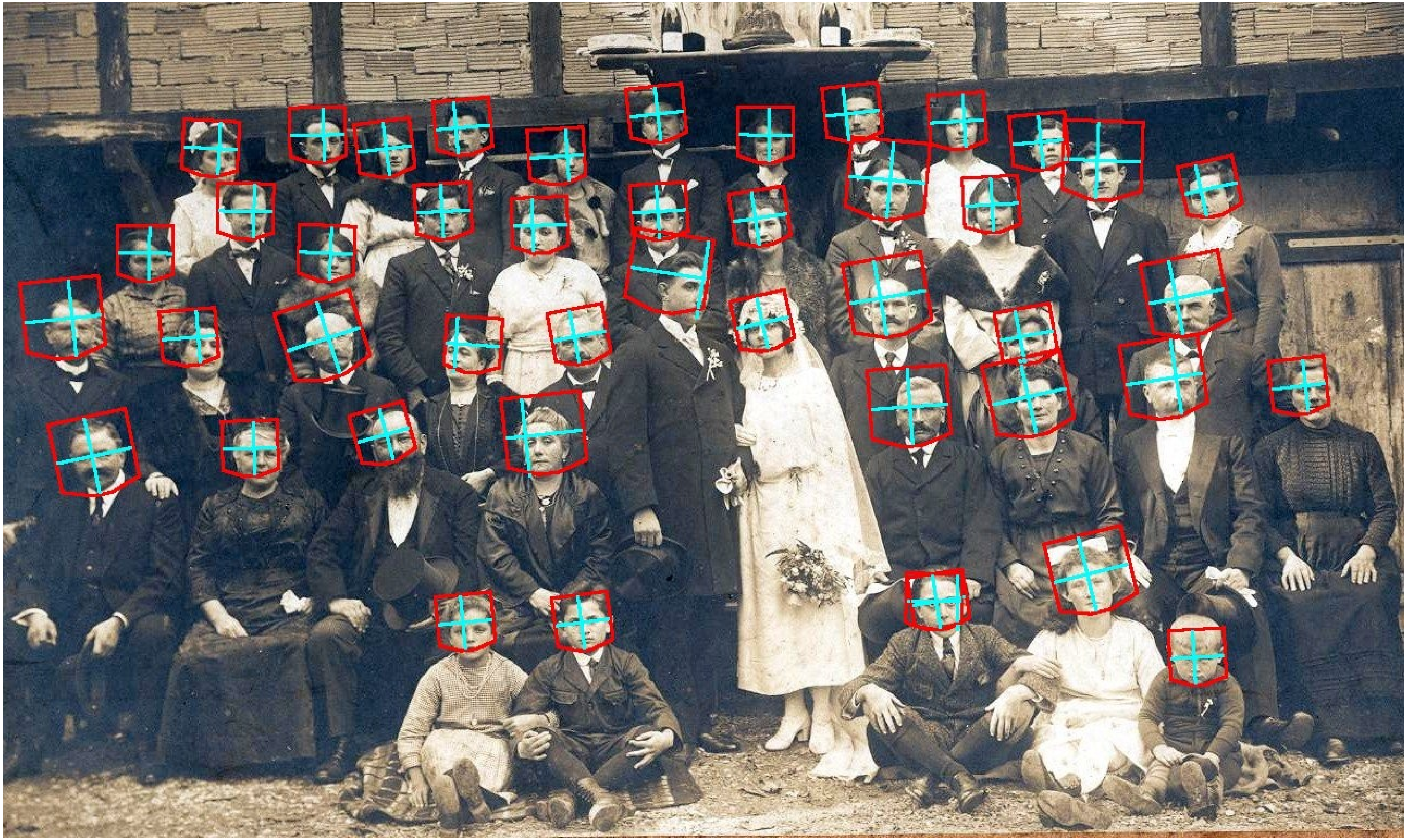
Data Set-> *False positives per image->*	TILTED		PROFILE		MIT+CMU	
	4.42	26.9	0.47	3.36	0.5	1.28
Our Detector	90%	97%	67%	83%	83%	88%
Jones & Viola (tilted)	90%	95%	x		x	
Jones & Viola (profile)	x		70%	83%	x	



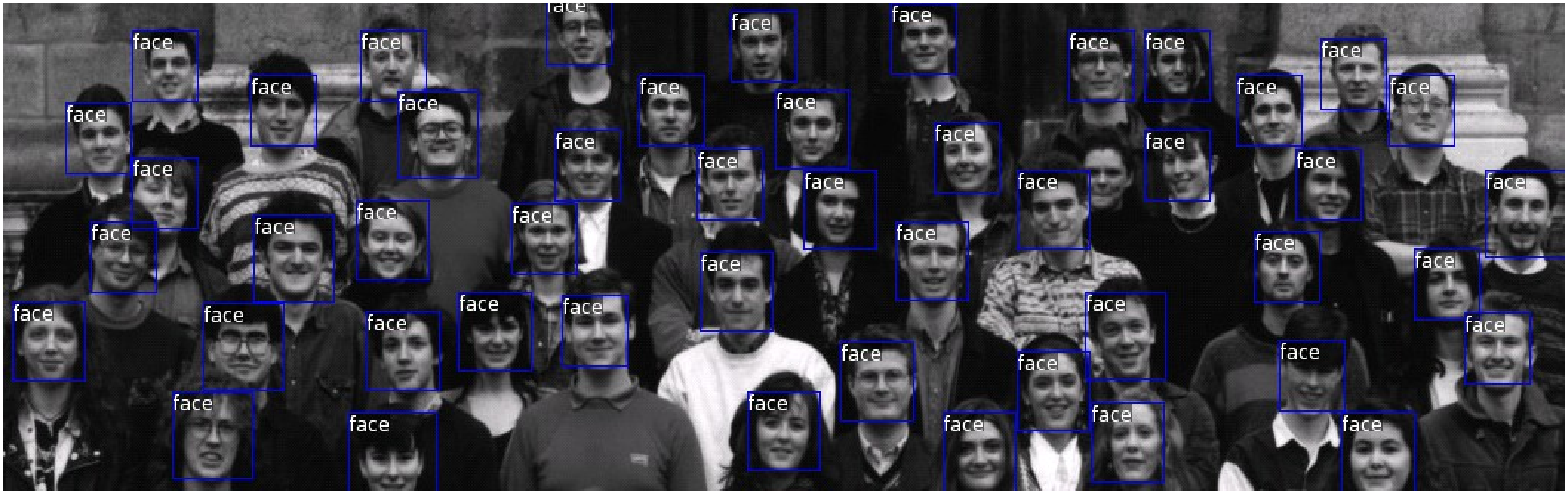


Face Detection and Pose Estimation: Results

Face Detection with a Convolutional Net



Face Detection with a ConvNet

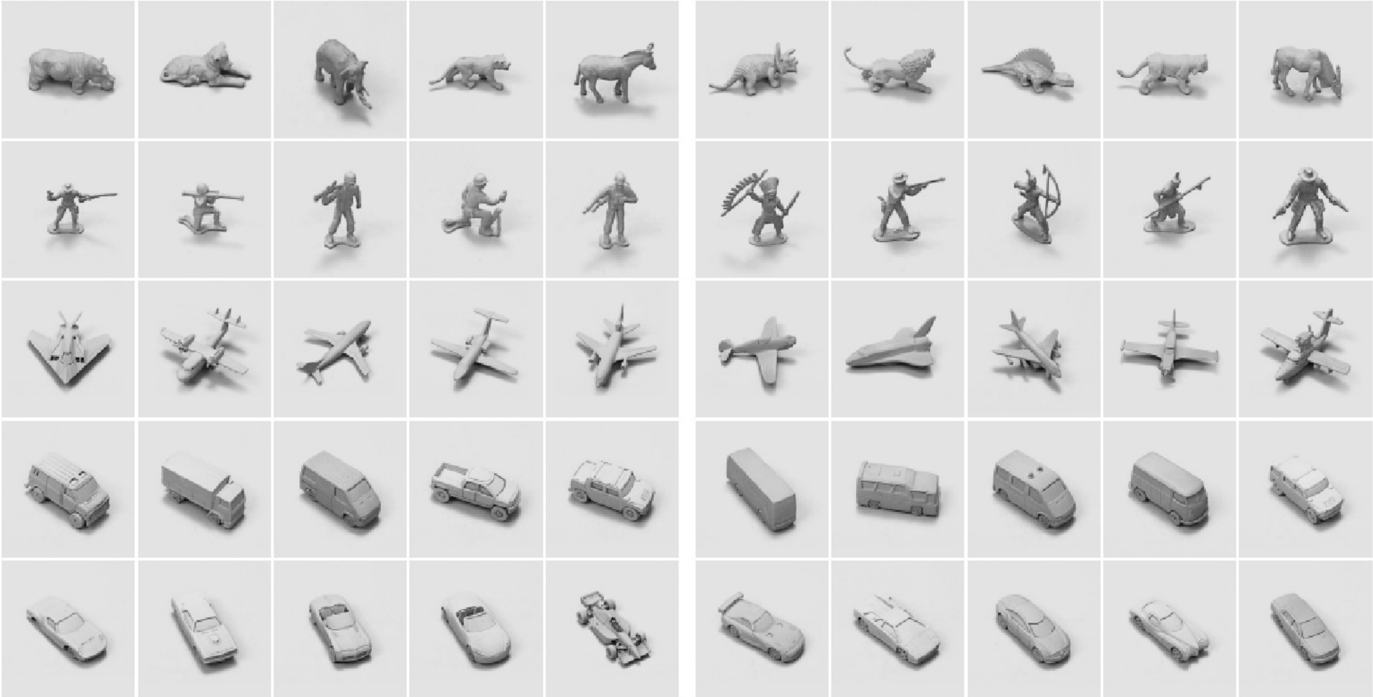


- Demo produced with EBLearn open source package
- http://eblearn.sf.net

Generic Object Detection and Recognition with Invariance to Pose and Illumination

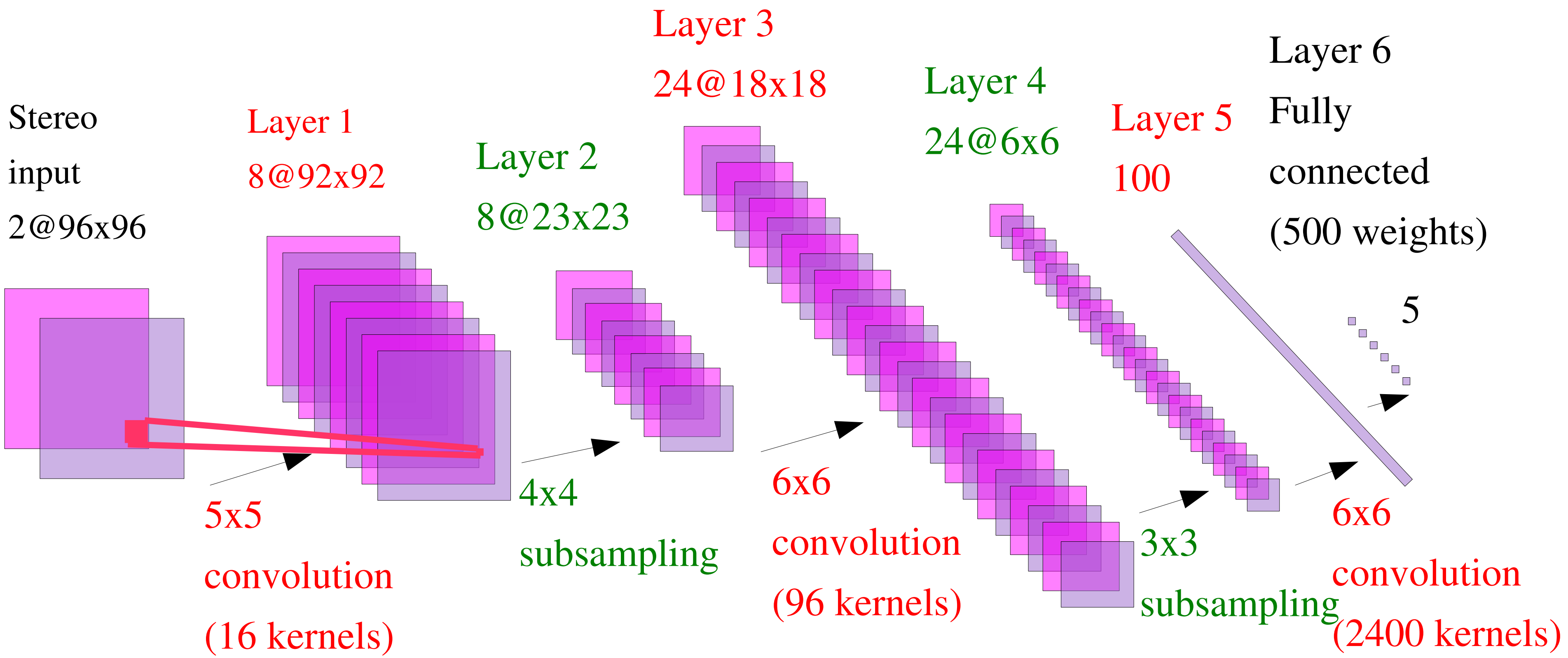
- **50** toys belonging to 5 categories: **animal, human figure, airplane, truck, car**
- **10** instance per category: 5 instances used for training, 5 instances for testing
- **Raw dataset:** **972** stereo pair of each object instance. **48,600** image pairs total.

- **For each instance:**
- **18 azimuths**
  - 0 to 350 degrees every 20 degrees
- **9 elevations**
  - 30 to 70 degrees from horizontal every 5 degrees
- **6 illuminations**
  - on/off combinations of 4 lights
- **2 cameras (stereo)**
  - 7.5 cm apart
  - 40 cm from the object



Training instances **Test instances**

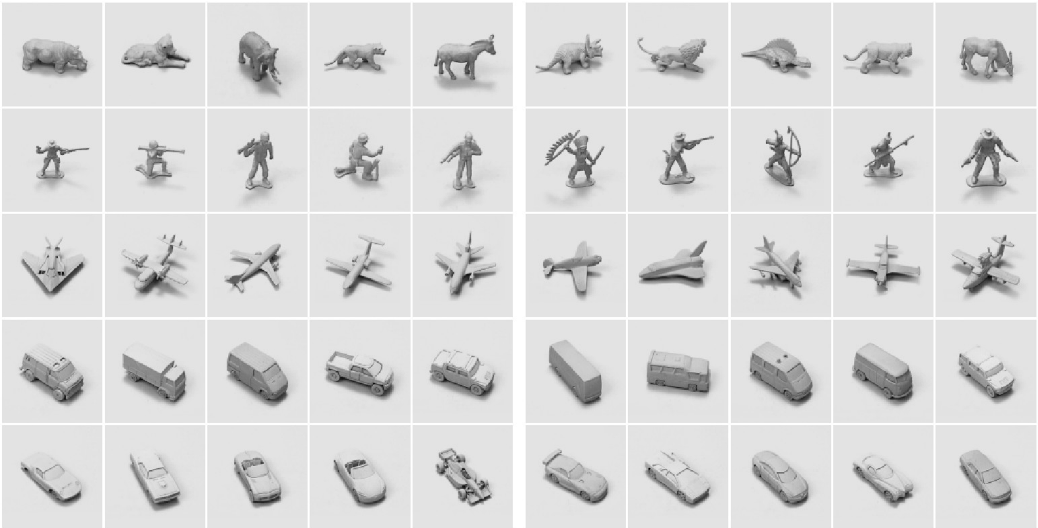
Convolutional Network



- **90,857 free parameters, 3,901,162 connections.**
- The architecture alternates convolutional layers (feature detectors) and subsampling layers (local feature pooling for invariance to small distortions).
- **The entire network is trained end-to-end** (all the layers are trained simultaneously).
- A gradient-based algorithm is used to minimize a supervised loss function.

Normalized-Uniform Set: Error Rates

- Linear Classifier on raw stereo images: 30.2% error.
- K-Nearest-Neighbors on raw stereo images: 18.4% error.
- K-Nearest-Neighbors on PCA-95: 16.6% error.
- Pairwise SVM on 96x96 stereo images: 11.6% error
- Pairwise SVM on 95 Principal Components: 13.3% error.
- Convolutional Net on 96x96 stereo images: 5.8% error.



Training instances Test instances

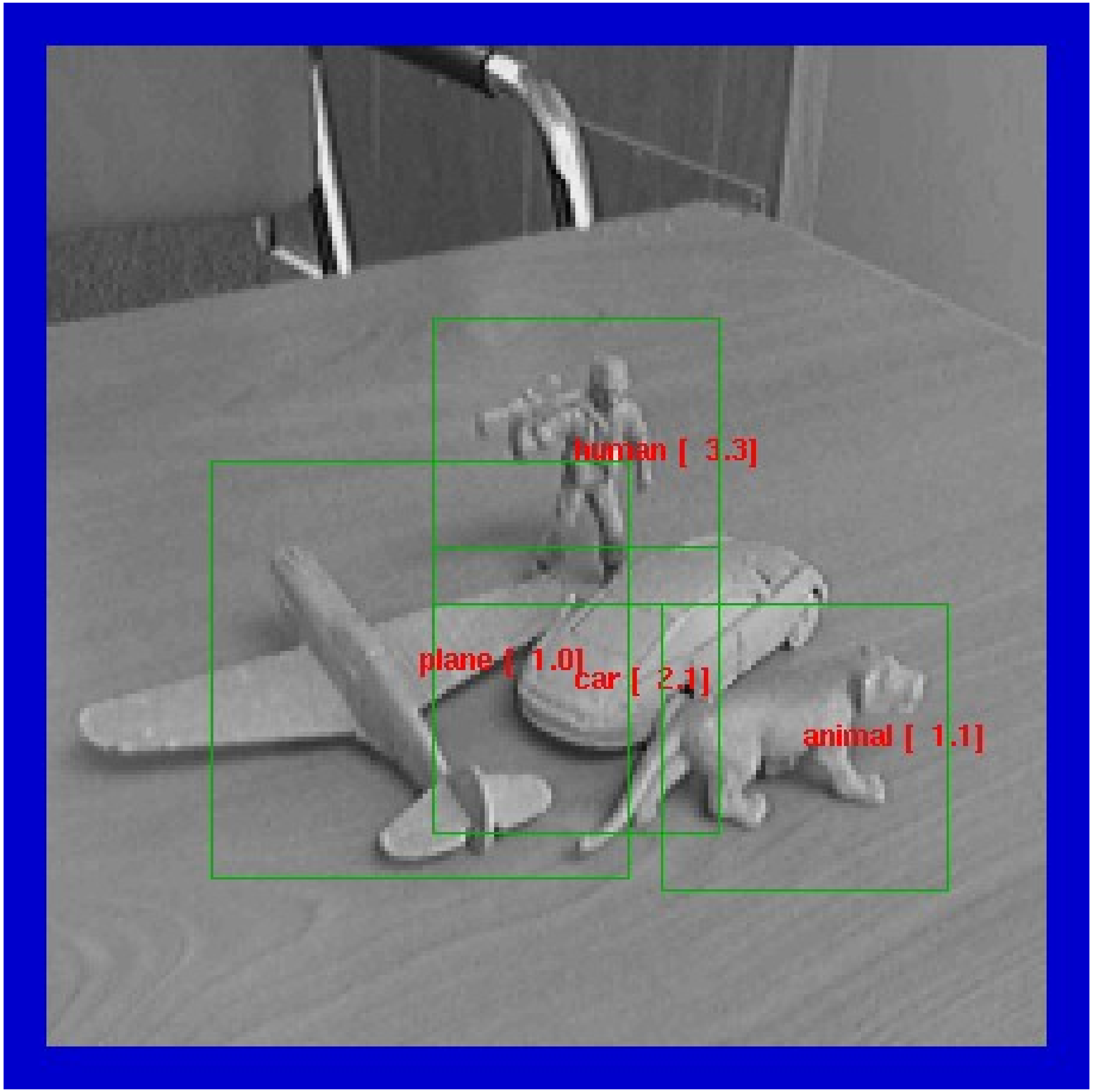
Jittered-Cluttered Dataset

- **Jittered-Cluttered Dataset:**
- **291,600** tereo pairs for training, **58,320** for testing
- Objects are jittered: position, scale, in-plane rotation, contrast, brightness, backgrounds, distractor objects,...
- Input dimension: 98x98x2 (approx 18,000)

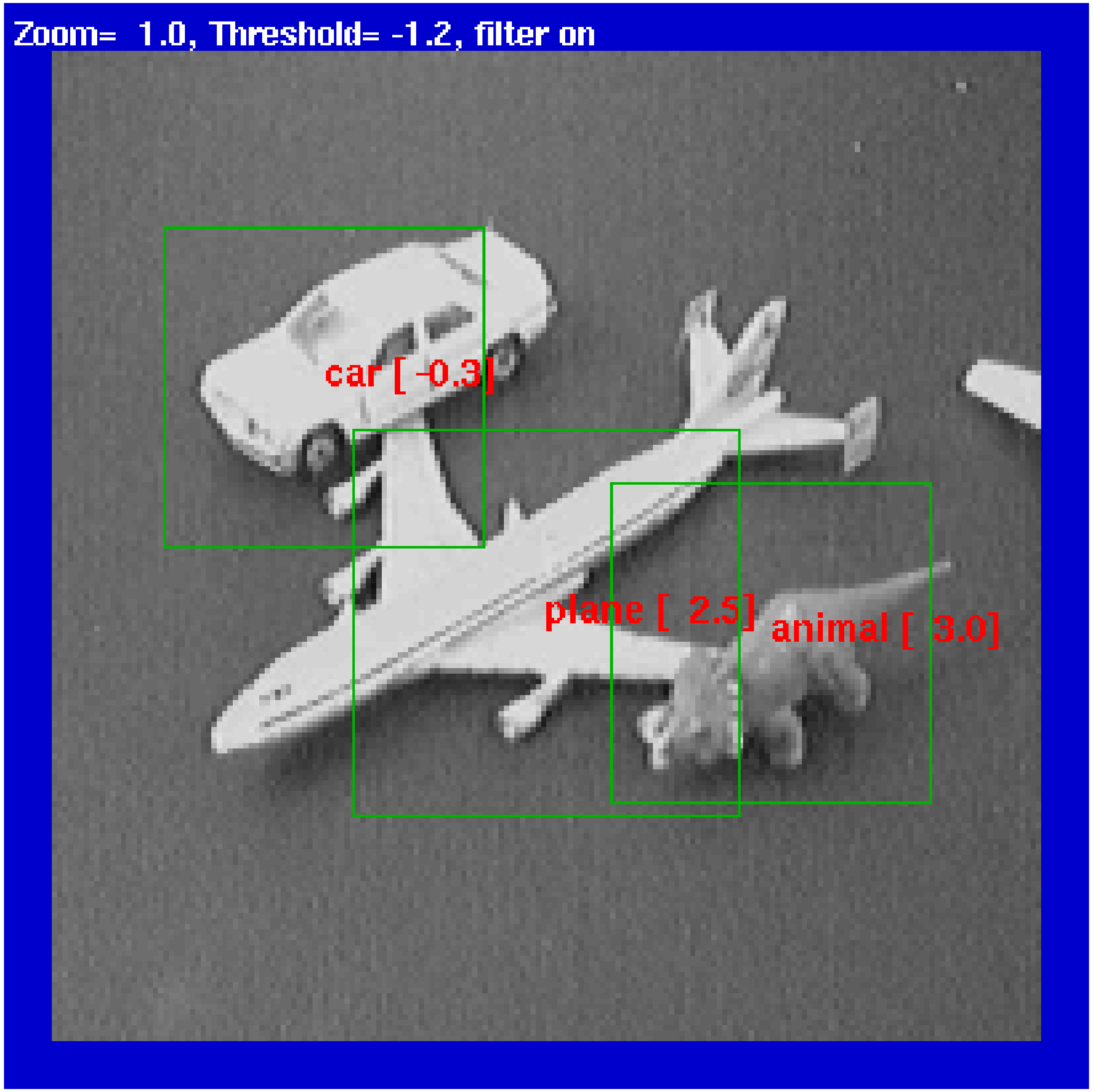
Experiment 2: Jittered-Cluttered Dataset

- **291,600** training samples, **58,320** test samples
- **SVM with Gaussian kernel** — **43.3% error**
- **Convolutional Net with binocular input:** — **7.8% error**
- **Convolutional Net + SVM on top:** — **5.9% error**
- **Convolutional Net with monocular input:** — **20.8% error**
- **Smaller mono net (DEMO):** — **26.0% error**
- **Dataset available from http://www.cs.nyu.edu/~yann**

Examples (Monocular Mode)

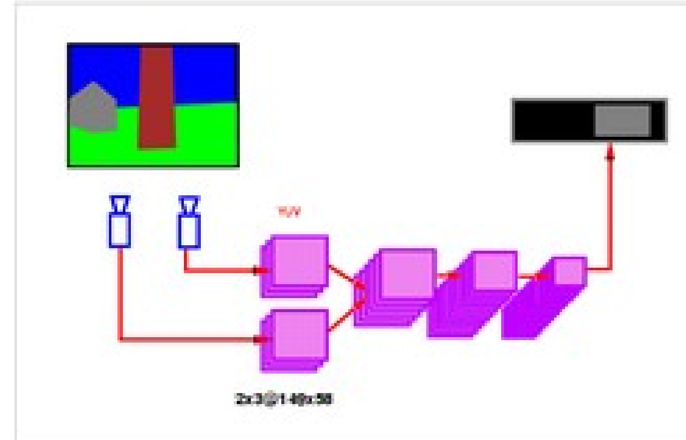


Examples (Monocular Mode)

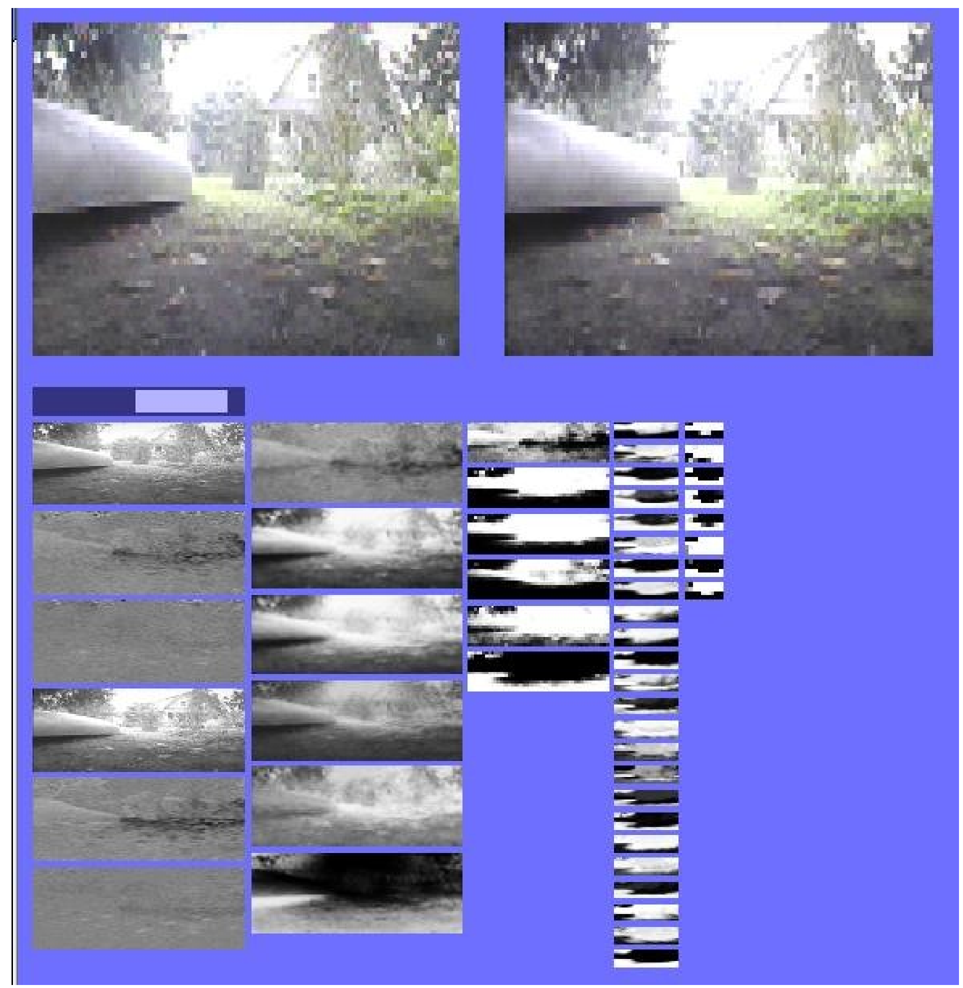


Visual Navigation for a Mobile Robot

[LeCun et al. NIPS 2005]

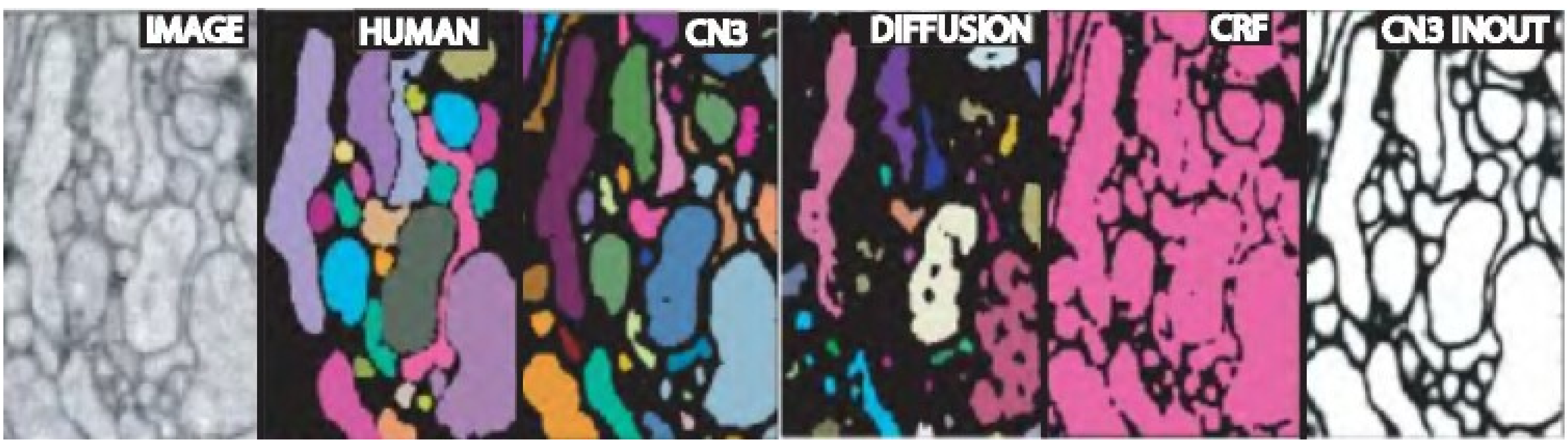


- Mobile robot with two cameras
- The convolutional net is trained to emulate a human driver from recorded sequences of video + human-provided steering angles.
- The network maps stereo images to steering angles for obstacle avoidance



Convolutional Nets For Brain Imaging and Biology

- **Brain tissue reconstruction from slice images [Jain,....,Denk, Seung 2007]**
  - Sebastian Seung's lab at MIT.
  - 3D convolutional net for image segmentation
  - ConvNets Outperform MRF, Conditional Random Fields, Mean Shift, Diffusion,...[ICCV'07]

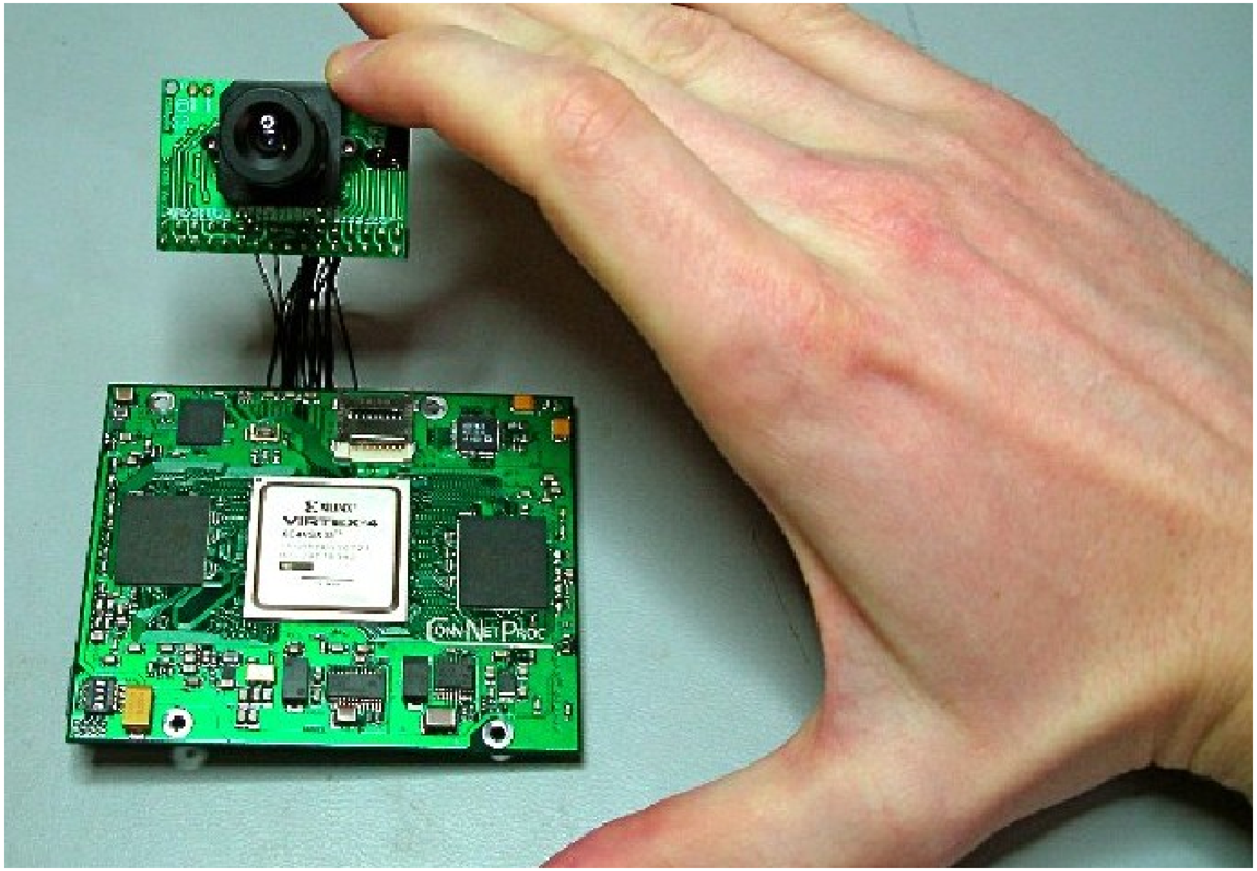


Industrial Applications of ConvNets

- **AT&T/Lucent/NCR**
  - Check reading, OCR, handwriting recognition (deployed 1996)
- **Vident Inc**
  - Vident Inc's “SmartCatch” system deployed in several airports and facilities around the US for detecting intrusions, tailgating, and abandoned objects (Vident is a spin-off of NEC)
- **NEC Labs**
  - Cancer cell detection, automotive applications, kiosks
- **Google**
  - OCR, face and license plate removal from StreetView
- **Microsoft**
  - OCR, handwriting recognition, speech detection
- **France Telecom**
  - Face detection, HCI, cell phone-based applications
- **Other projects: HRL (3D vision)....**

FPGA Custom Board: NYU ConvNet Processor

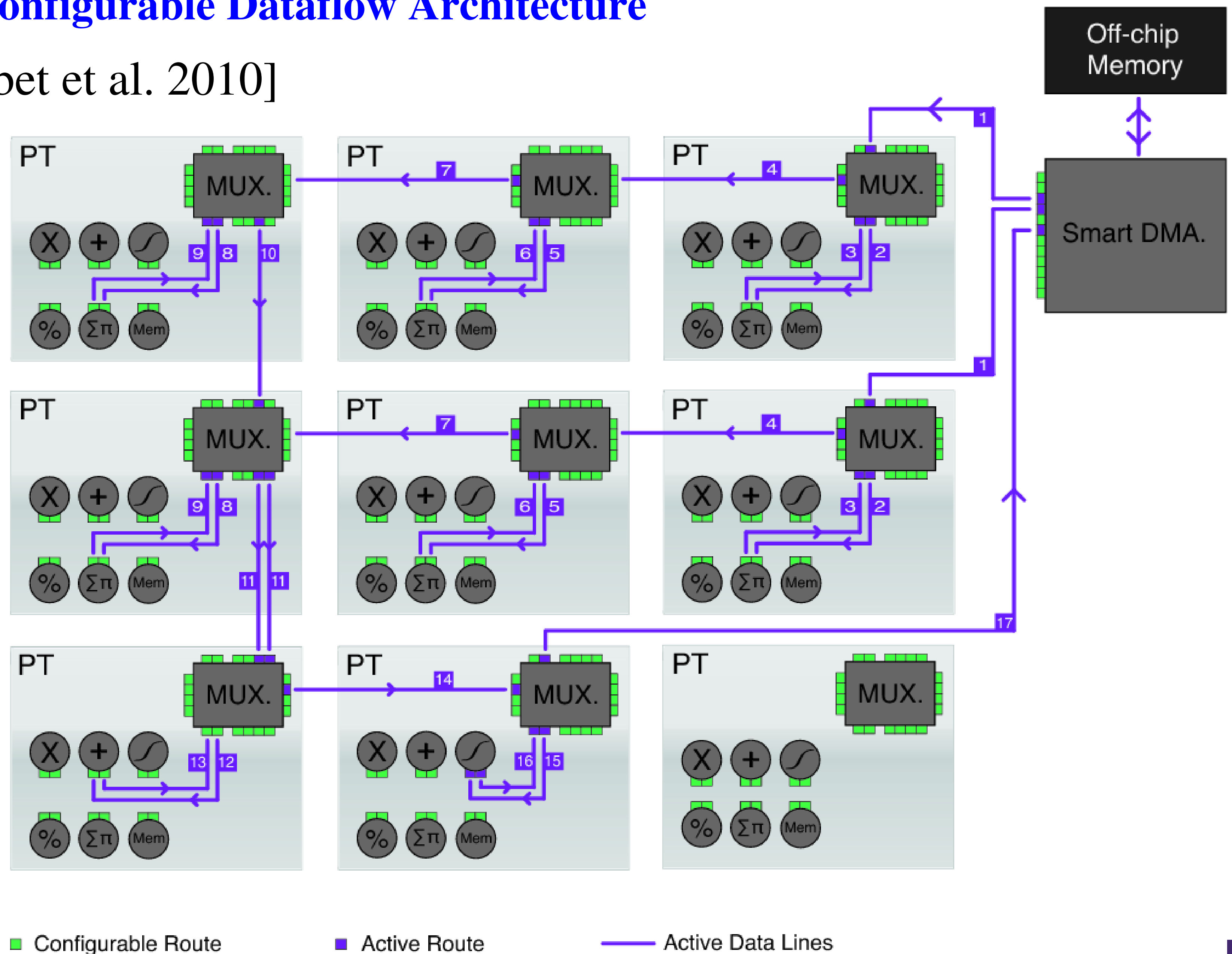
- **Xilinx Virtex 4 FPGA, 8x5 cm board** [Farabet et al. 2009]
  - Dual camera port, Fast dual QDR RAM,
- **New version being developed with Eugenio Culurciello (Yale EE)**
  - Full custom chip
  - Version for Virtex 6 FPGA



ConvNet/Vision Processor (FPGA and ASIC)

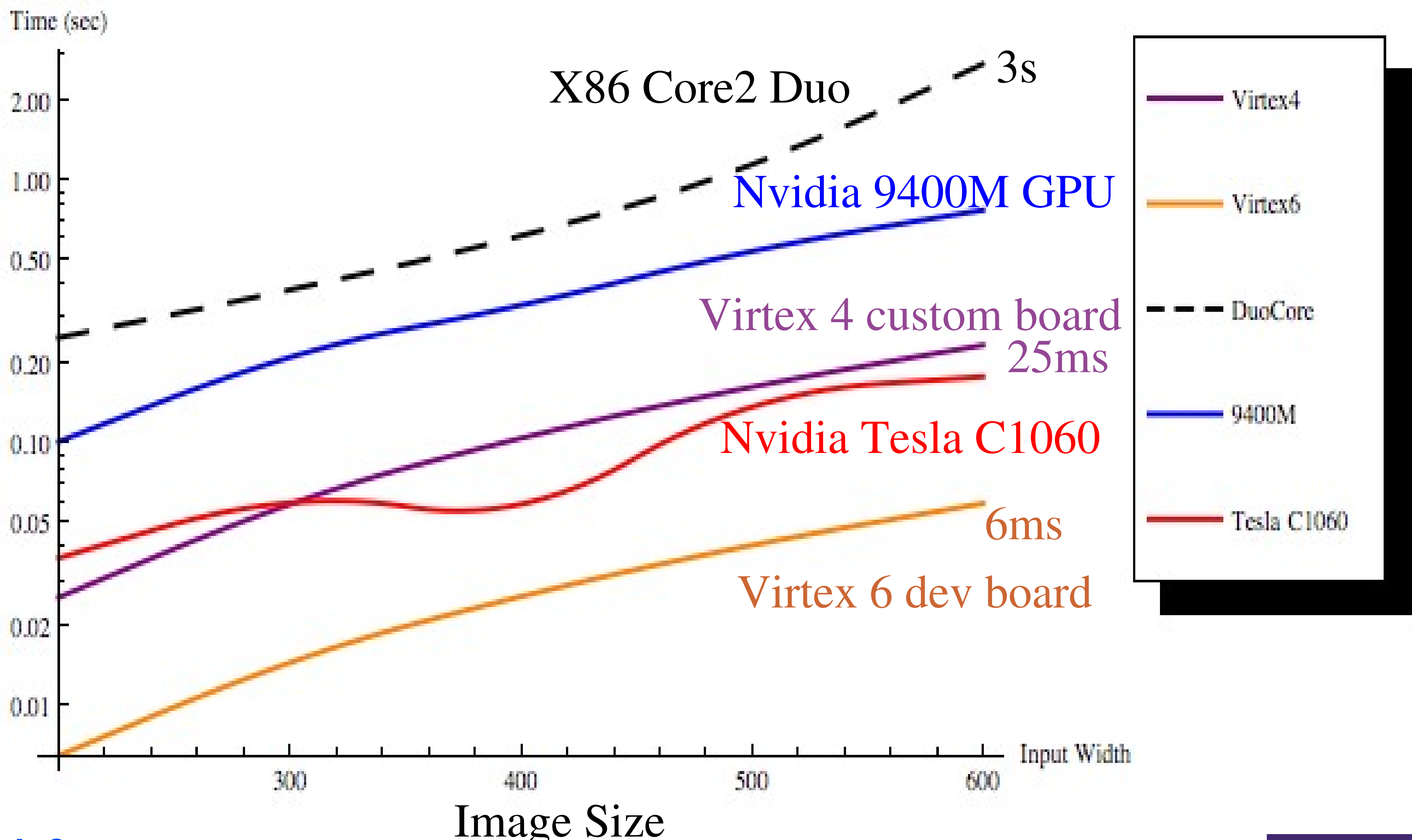
Reconfigurable Dataflow Architecture

[Farabet et al. 2010]



FPGA Performance

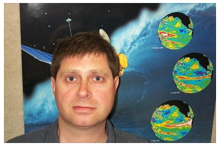
- **Seconds per frame for a robot vision task (log scale)** [Farabet et al. 2010]



Problem: supervised ConvNets don't work with few labeled samples

- **On recognition tasks with few labeled samples, deep supervised architectures don't do so well**
- **Example: Caltech-101 Object Recognition Dataset**
  - 101 categories of objects (gathered from the web)
  - Only 30 training samples per category!
- **Recognition rates (OUCH!):**
  - Supervised ConvNet: **29.0%**
  - SIFT features + Pyramid Match Kernel SVM: **64.6%**
    - [Lazebnik et al. 2006]
- **When learning the features, there are simply too many parameters to learn in purely supervised mode (or so we thought).**

face



beaver

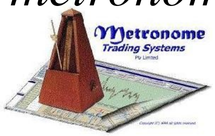
wild cat

lotus

ant

dollar

metronome



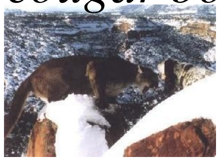
w. chair

minaret

cellphone

joshua t.

cougar body



background

Unsupervised Deep Learning: Leveraging Unlabeled Data

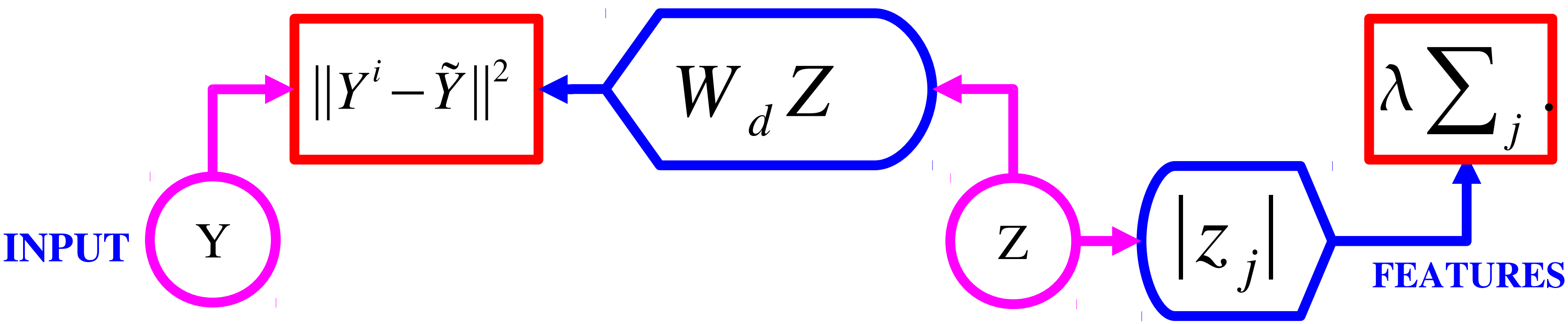
[Hinton 05, Bengio 06, LeCun 06, Ng 07]

- **Unlabeled data is usually available in large quantity**
- **A lot can be learned about the world by just looking at it**
- **Unsupervised learning captures underlying regularities about the data**
- **The best way to capture underlying regularities is to learn good representations of the data**
- **The main idea of Unsupervised Deep Learning**
  - Learn each layer one at a time in unsupervised mode
  - Stick a supervised classifier on top
  - Optionally: refine the entire system in supervised mode
- **Unsupervised Learning view as Energy-Based Learning**

Unsupervised Feature Learning with Sparse Coding

[Olshausen & field 1997]

- **Find a dictionary of basis functions such that any input can be reconstructed of a sparse linear combination of them.**



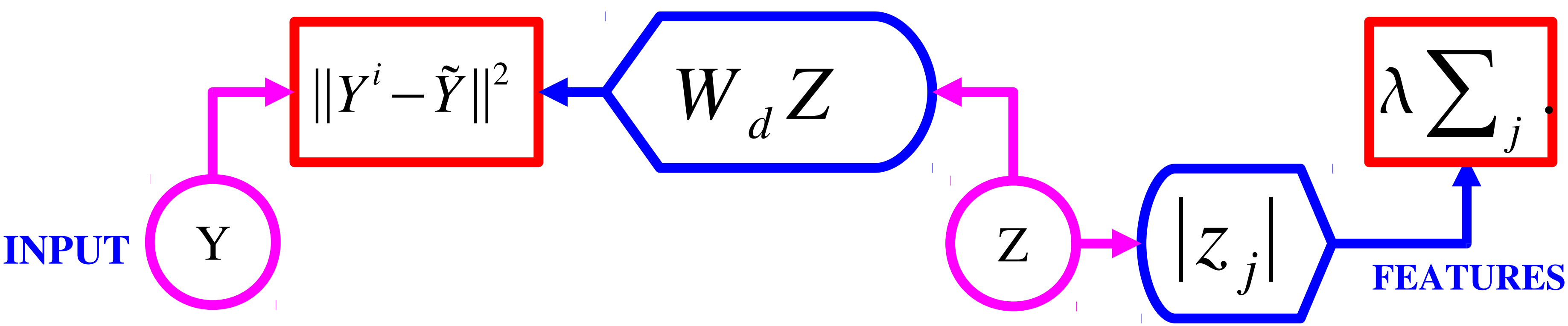
- **Energy:** $$E(Y^i, Z; W_d) = \|Y^i - W_d Z\|^2 + \lambda \sum_j |z_j|$$
- **Optimal Code** $$Z^i = argmin_z E(Y^i, z; W_d)$$
- **Free Energy:** $$F(Y^i; W_d) = F(Z^i) = min_z E(Y^i, z; W_d)$$

Unsupervised Feature Learning with Sparse Coding

- **The learning algorithm minimizes the loss function:**

$$L(W_d) = \sum_i F(Y^i; W_d) = \sum_i (min_Z E(Y^i, Z; W_d))$$

- **The columns of Wd are normalized**



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

- **Free Energy:** $$F(Y^i; W_d) = F(Z^i) = min_z E(Y^i, z; W_d)$$

Problem with Sparse Coding: Inference is slow

- **Inference: find Z that minimizes the energy for a given Y**

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

$$Z^i = argmin_z E(Y^i, z; W_d)$$

- **For each new Y, an optimization algorithm must be run to find the corresponding optimal Z**
- **This would be very slow for large scale vision tasks**
- **Also, the optimal Z are very unstable:**
  - A small change in Y can cause a large change in the optimal Z

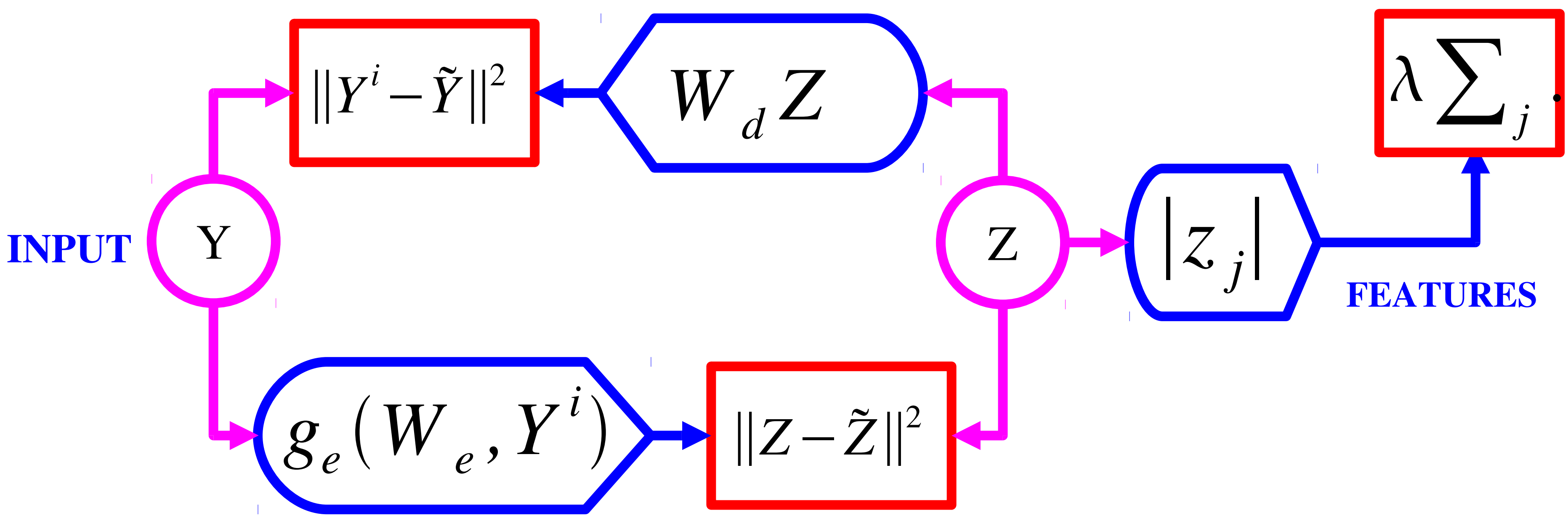
Solution: Predictive Sparse Decomposition (PSD)

[Kavukcuoglu, Ranzato, LeCun, 2009]

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

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

$$g_e(W_e, Y^i) = D \tanh(W_e Y)$$

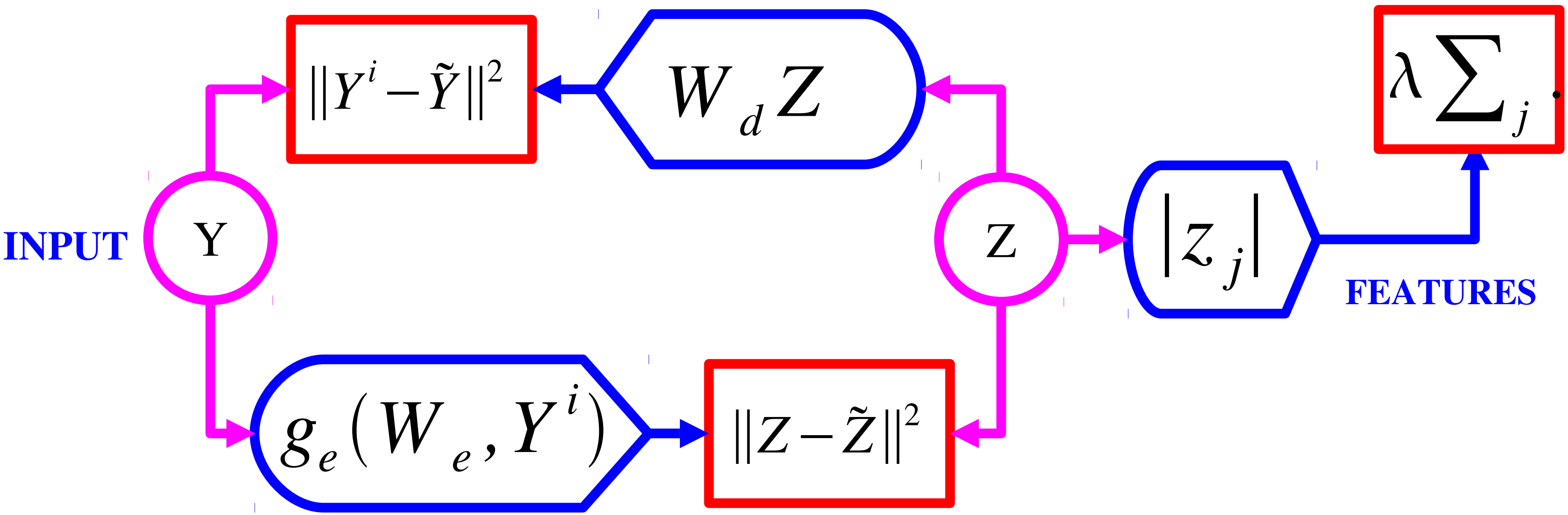


PSD: Inference

- **Inference by gradient descent starting from the encoder output**

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

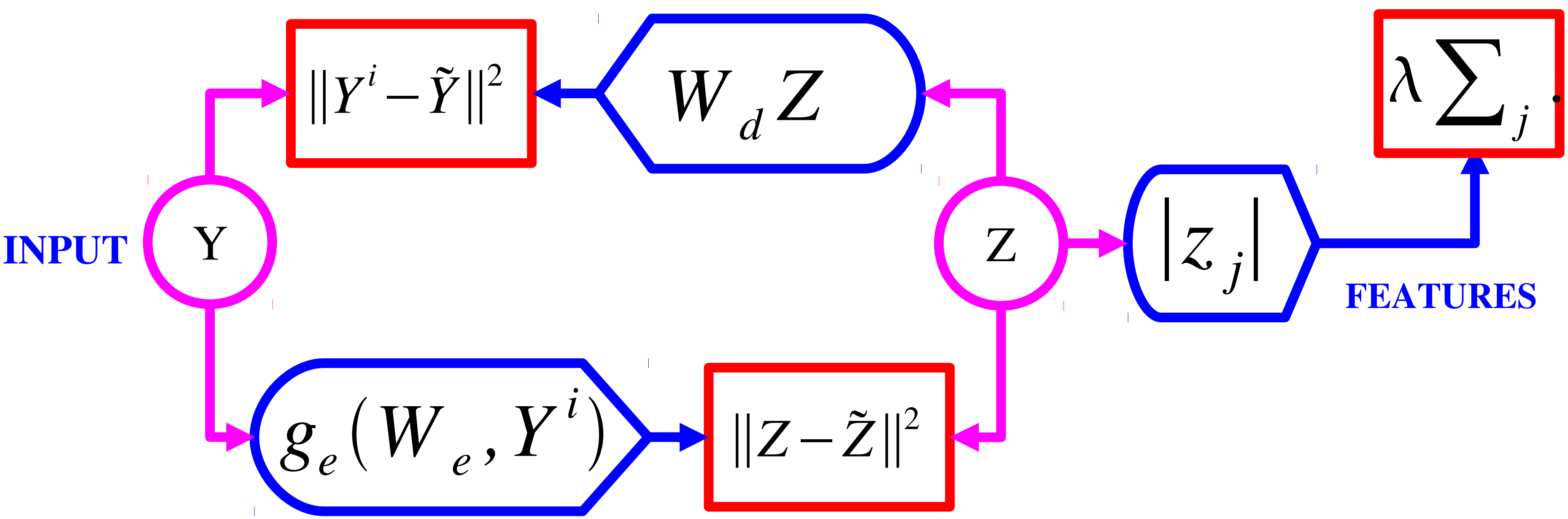
$$Z^i = argmin_z E(Y^i, z; W)$$



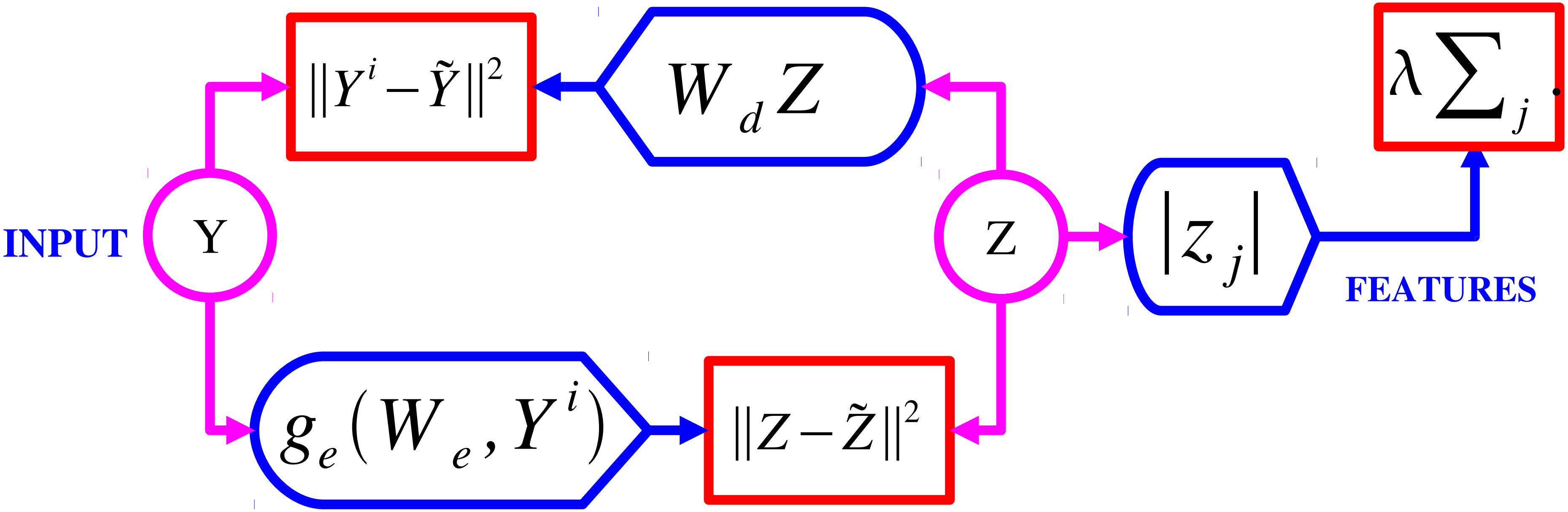
PSD: Learning [Kavukcuoglu et al. 2009]

- Learning by minimizing the average energy of the training data with respect to Wd and We.
- Loss function: $L(W_d, W_e) = \sum_i F(Y^i; W_d, W_e)$

$$F(Y^i; W_d, W_e) = min_z E(Y^i, z; W_d, W_e)$$



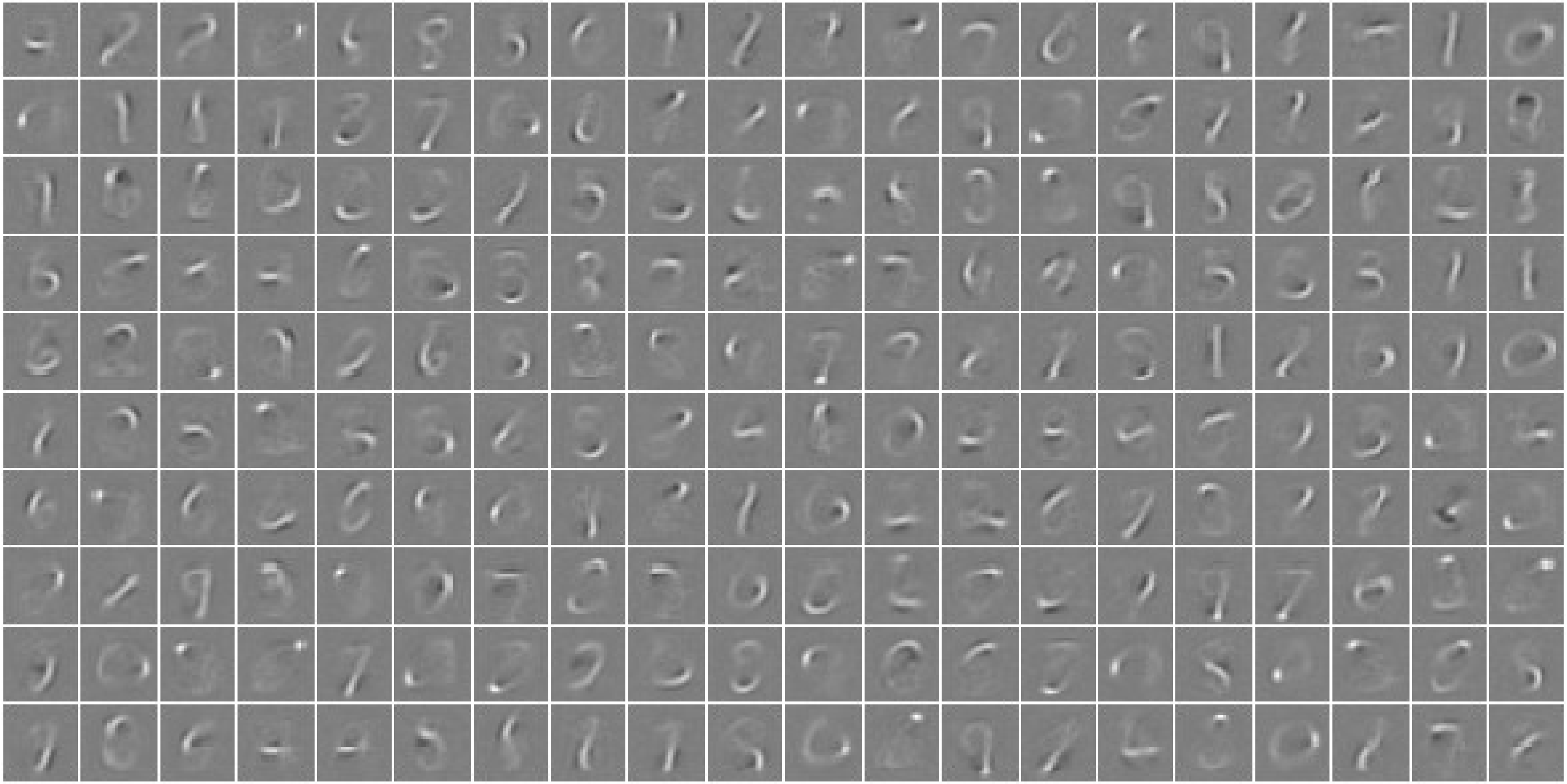
PSD: Learning Algorithm



- 1. Initialize Z = Encoder(Y)
- 2. Find Z that minimizes the energy function
- 3. Update the Decoder basis functions to reduce reconstruction error
- 4. Update Encoder parameters to reduce prediction error
- Repeat with next training sample

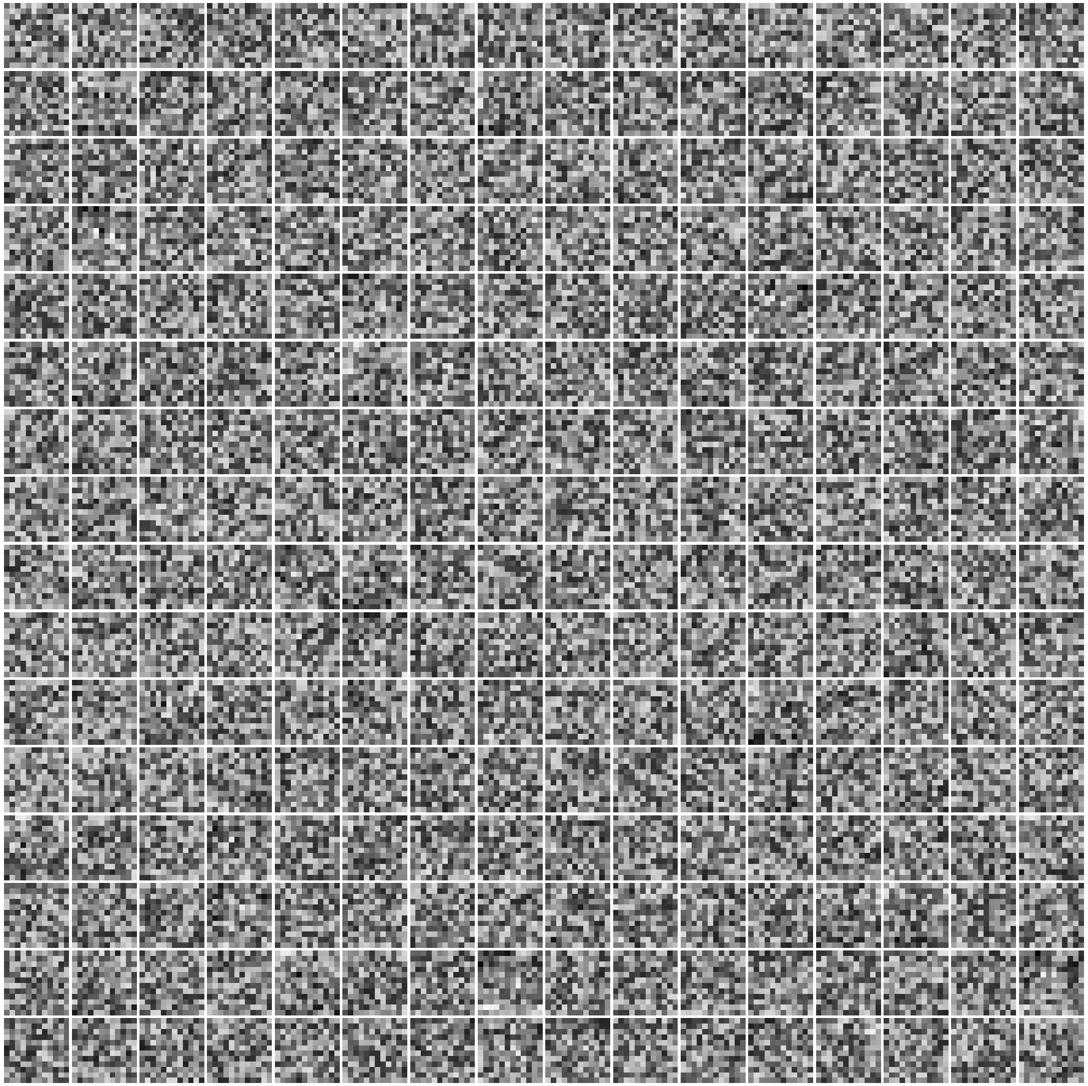
Decoder Basis Functions on MNIST

- **PSD trained on handwritten digits: decoder filters are "parts" (strokes).**
  - Any digit can be reconstructed as a linear combination of a small number of these "parts".

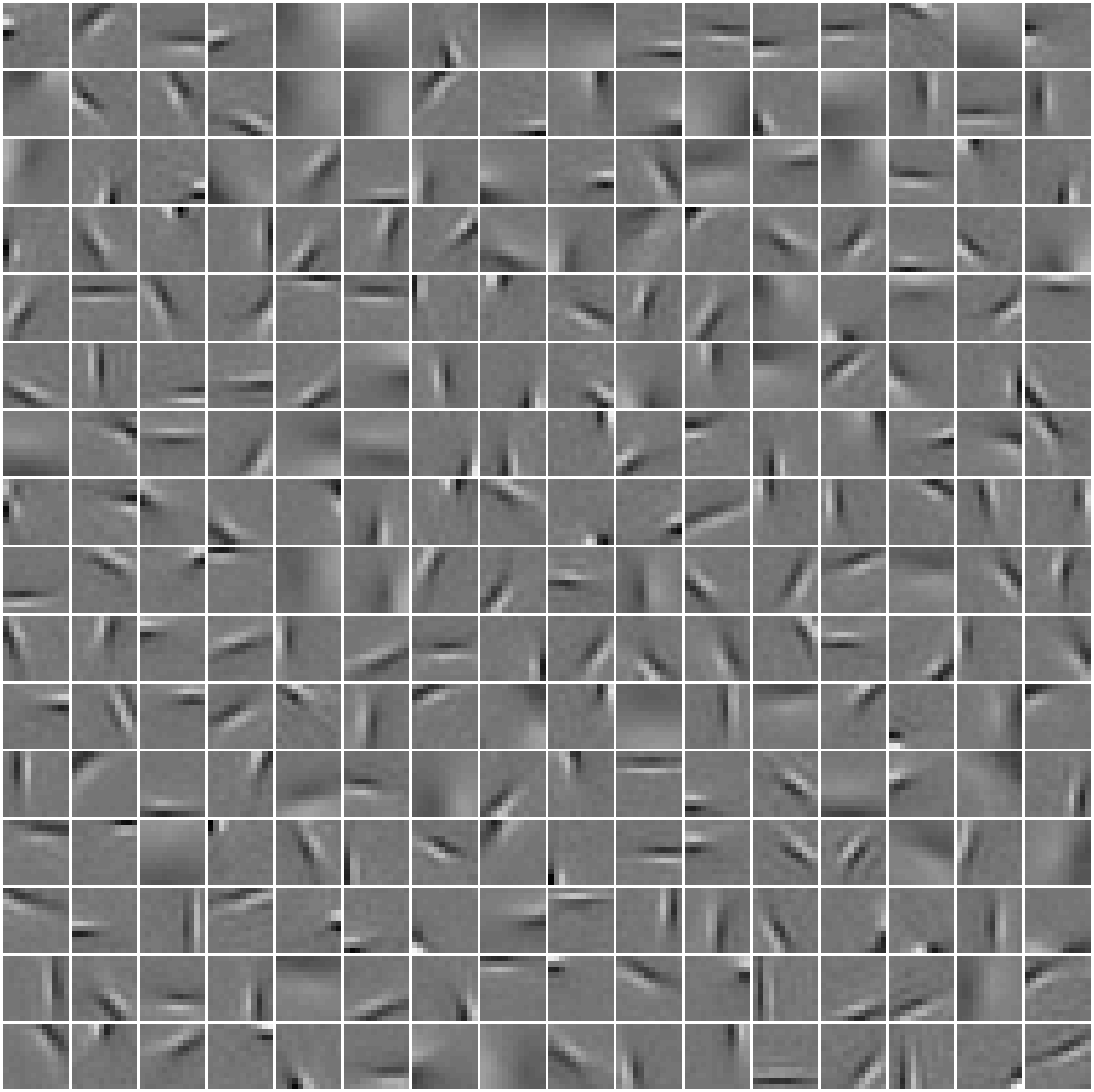


PSD Training on Natural Image Patches

- Basis functions are like Gabor filters (like receptive fields in V1 neurons)
- 256 filters of size 12x12
- Trained on natural image patches from the Berkeley dataset
- Encoder is linear-tanh-diagonal

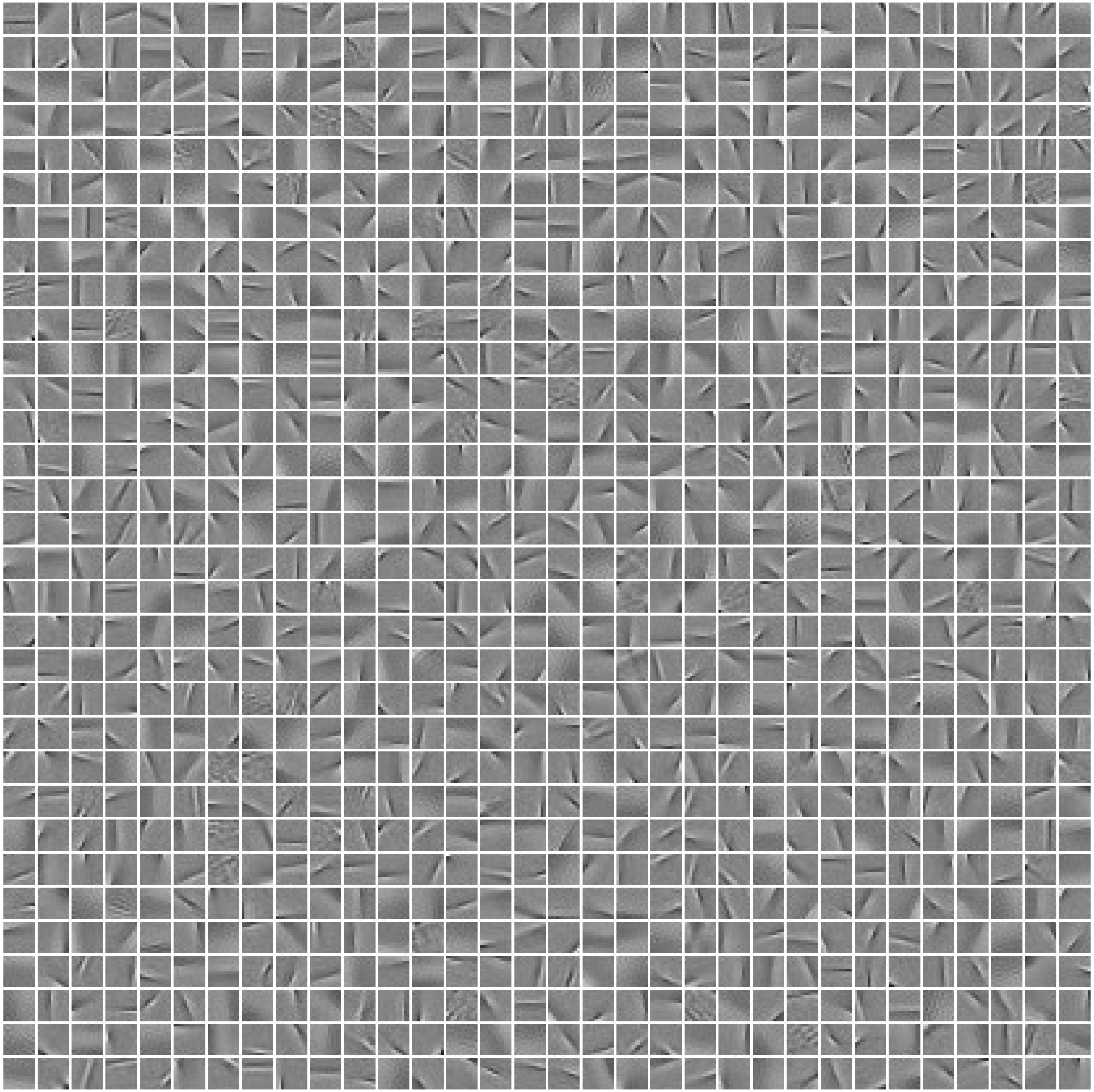


Learned Features on natural patches: V1-like receptive fields



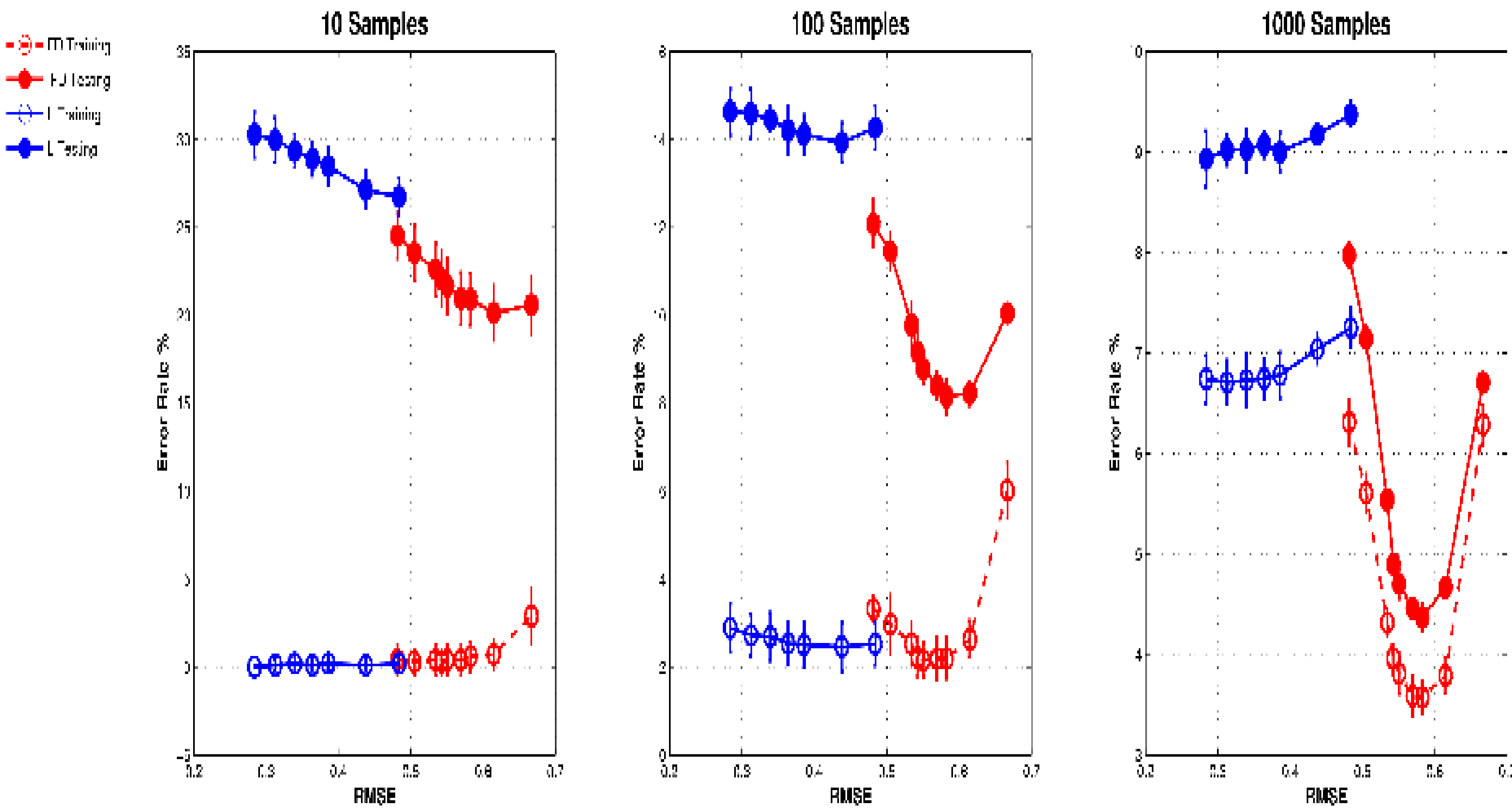
Learned Features: V1-like receptive fields

- 12x12 filters
- 1024 filters



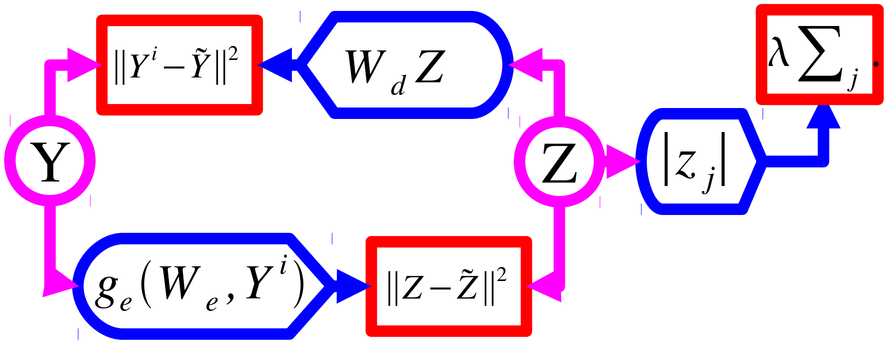
Classification Error Rate on MNIST

- **Supervised Linear Classifier trained on 200 trained sparse features**
  - Red: linear-tanh-diagonal encoder; Blue: linear encoder



Using PSD to Train a Hierarchy of Features

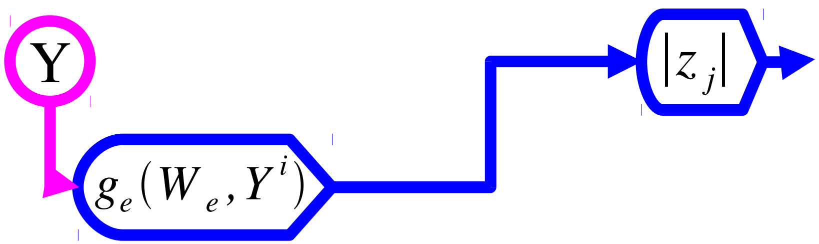
- **Phase 1: train first layer using PSD**



FEATURES

Using PSD to Train a Hierarchy of Features

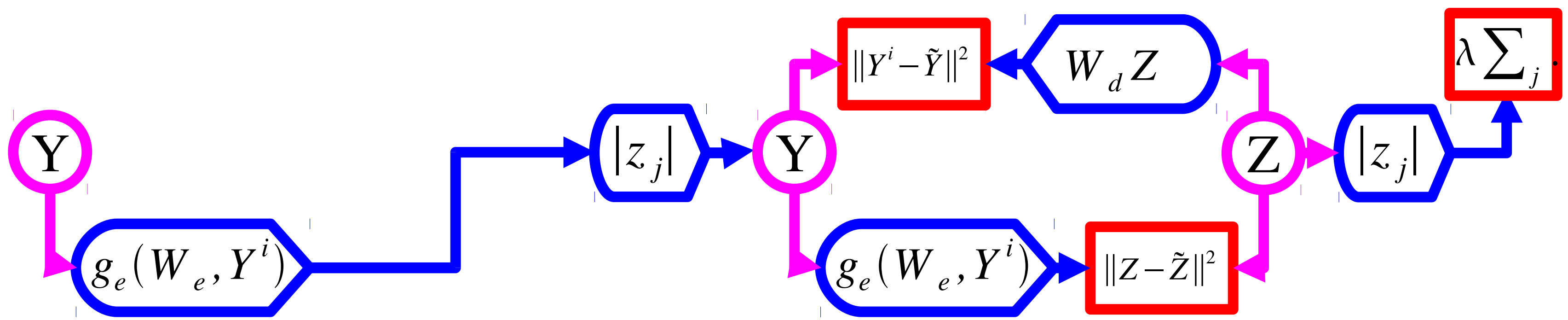
- Phase 1: train first layer using PSD
- Phase 2: use encoder + absolute value as feature extractor



FEATURES

Using PSD to Train a Hierarchy of Features

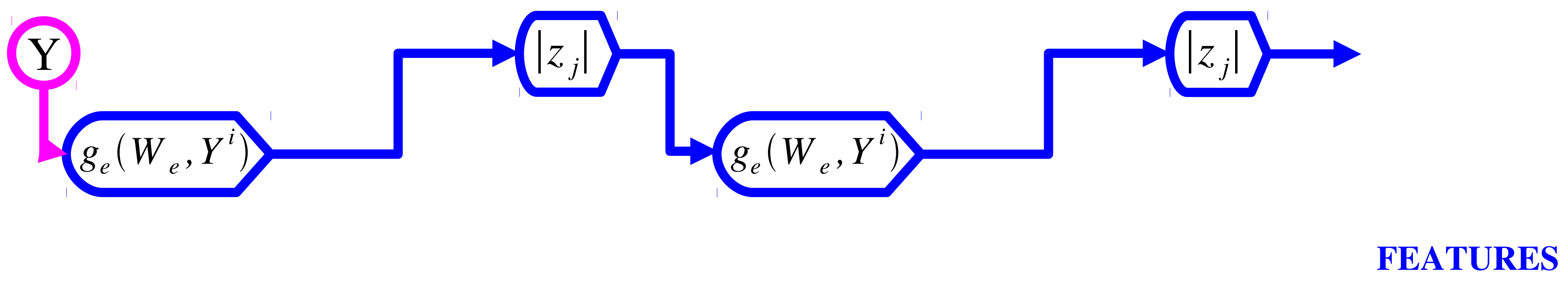
- Phase 1: train first layer using PSD
- Phase 2: use encoder + absolute value as feature extractor
- Phase 3: train the second layer using PSD



FEATURES

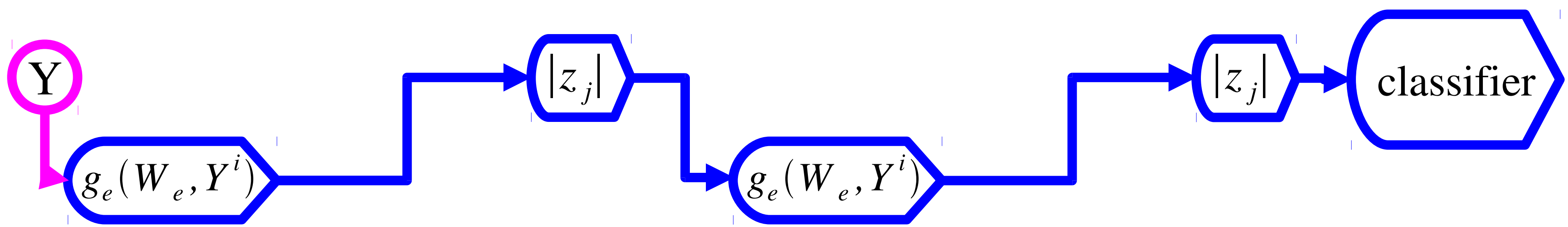
Using PSD to Train a Hierarchy of Features

- 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



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

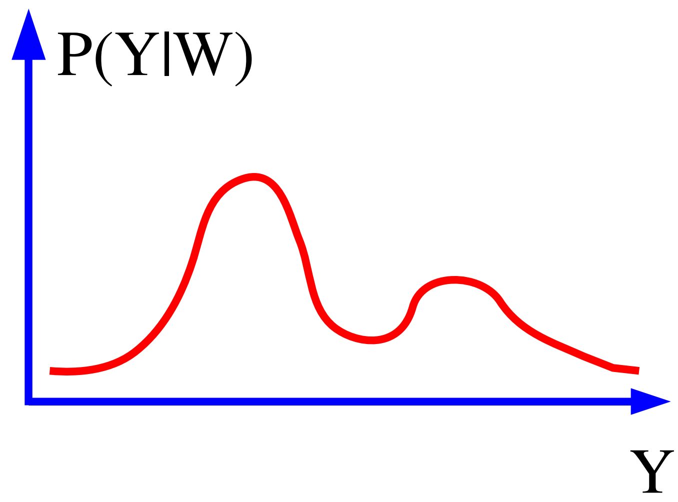
"Deep Learning"

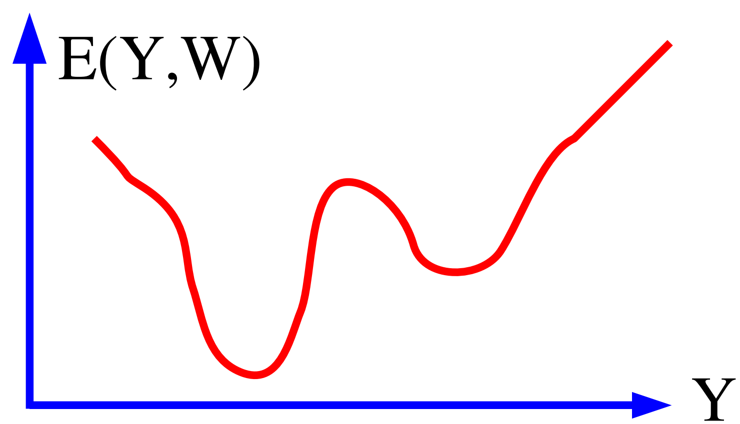
[Hinton 05, Bengio 06, LeCun 06, Ng 07]

- **The "deep learning" method was popularized by Hinton for training "deep belief networks".**
  - DBN use a special kind of encoder-decoder architecture called Restricted Boltzmann Machines (RBM)
- **1. Train each layer in an unsupervised fashion, layer by layer**
- **2. Stick a supervised classifier on top, and refine the entire system with gradient descent (back-prop) on a supervised criterion.**

Unsupervised Learning: Capturing Dependencies Between Variables

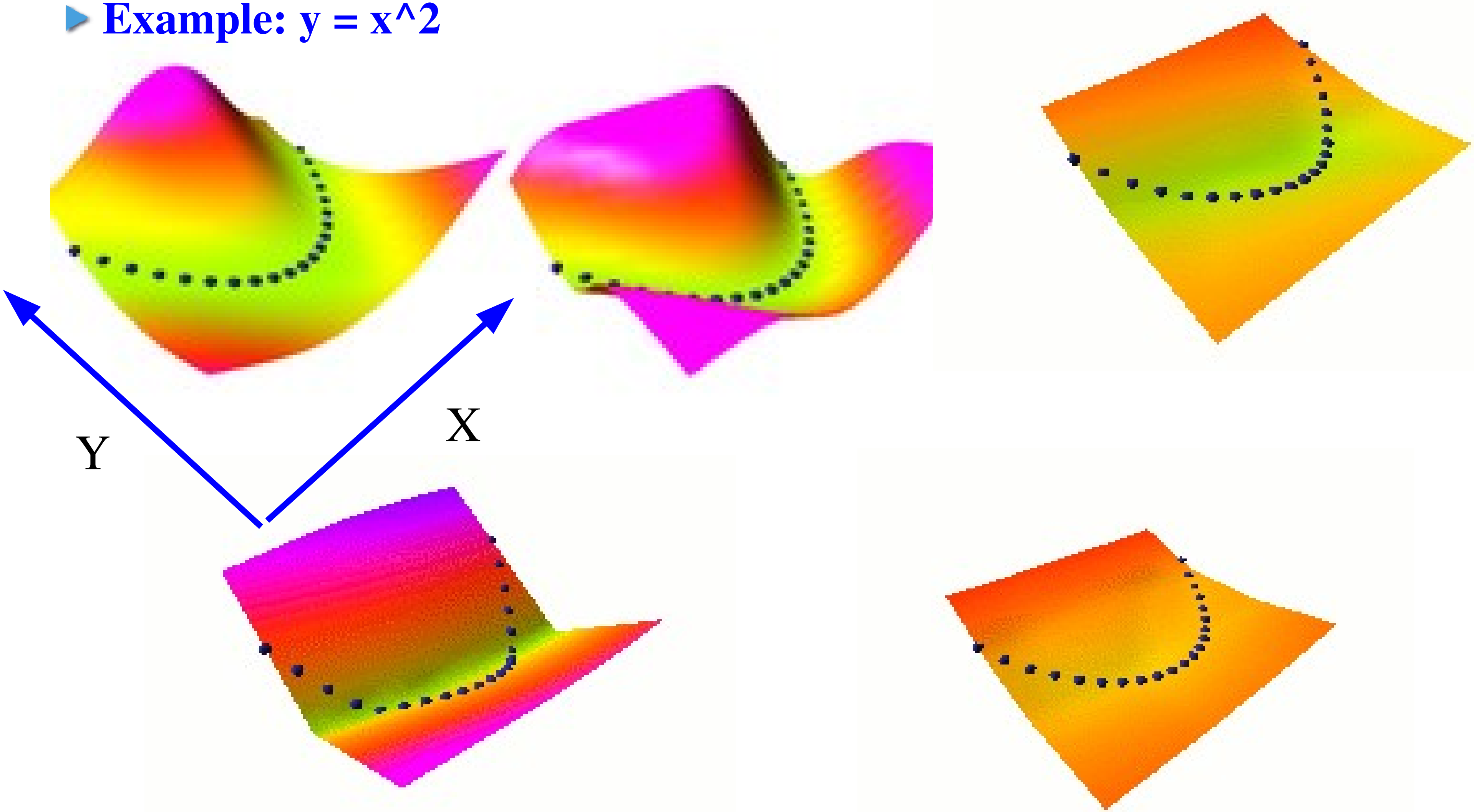
- **Energy function: viewed as a negative log probability density**
- **Probabilistic View:**
  - Produce a probability density function that:
  - has high value in regions of high sample density
  - has low value everywhere else (integral = 1).
- **Energy-Based View:**
  - produce an energy function E(Y,W) that:
  - has low value in regions of high sample density
  - has high(er) value everywhere else





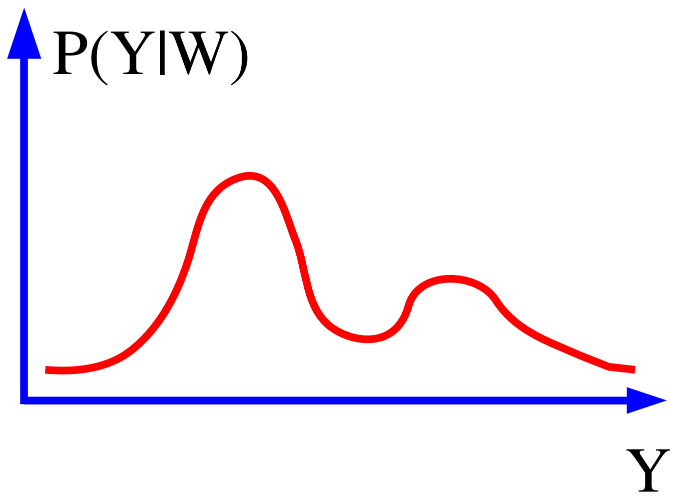
Unsupervised Learning: Capturing Dependencies Between Variables

- Energy function viewed as a negative log density
  - Example: $y = x^2$

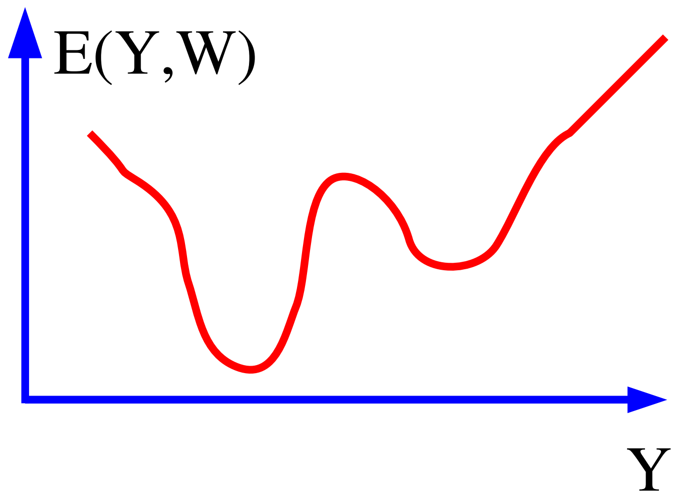


Energy <-> Probability

$$P(Y|W) = \frac{e^{-\beta E(Y,W)}}{\int_y e^{-\beta E(y,W)}}$$

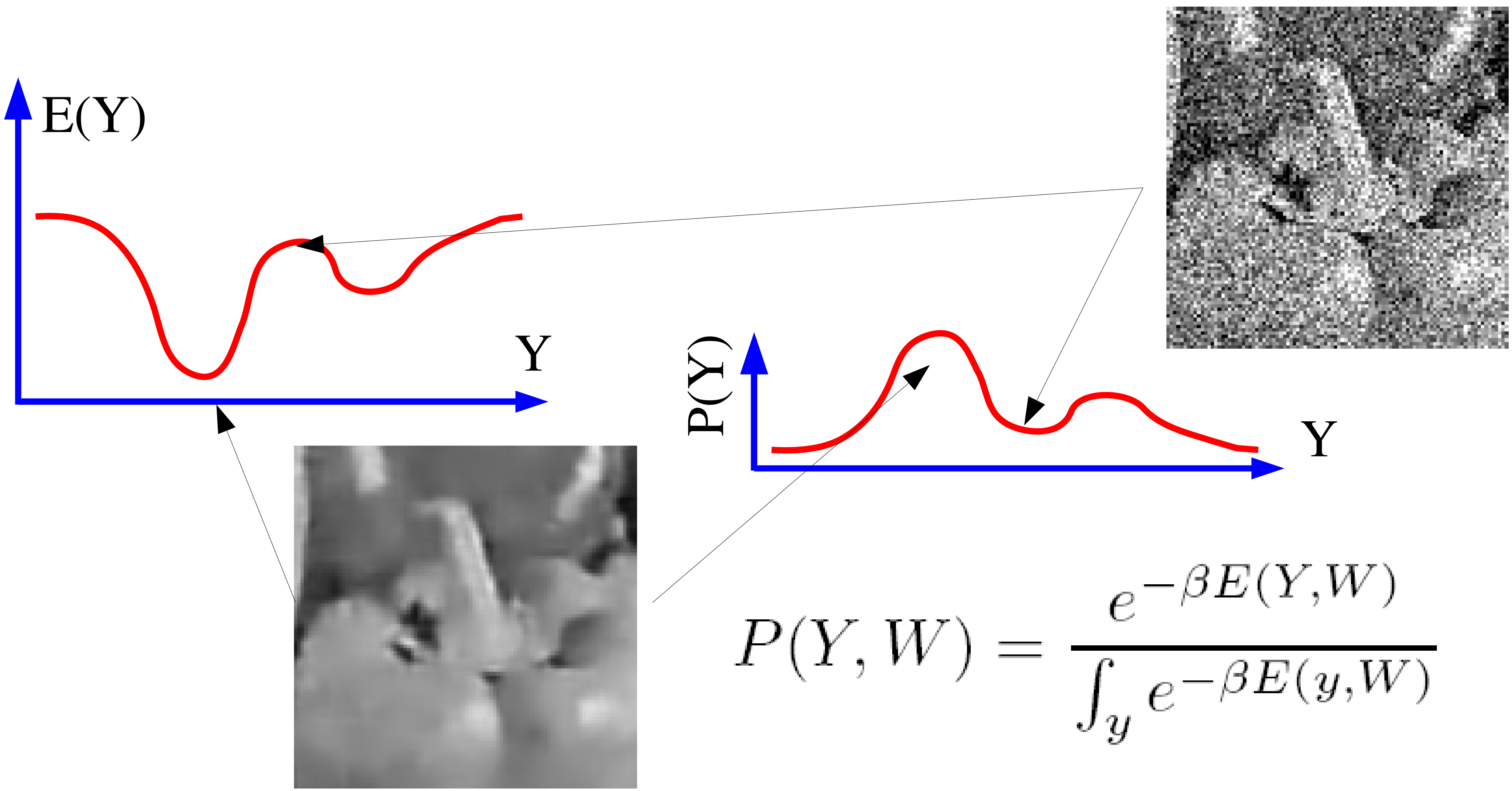


$$E(Y,W) \propto -\log P(Y|W)$$



Training an Energy-Based Model

- **Make the energy around training samples low**
- **Make the energy everywhere else higher**



$$P(Y, W) = \frac{e^{-\beta E(Y,W)}}{\int_y e^{-\beta E(y,W)}}$$

Training an Energy-Based Model to Approximate a Density

Maximizing P(Y|W) on training samples

make this big

$$P(Y|W) = \frac{e^{-\beta E(Y,W)}}{\int_y e^{-\beta E(y,W)}}$$

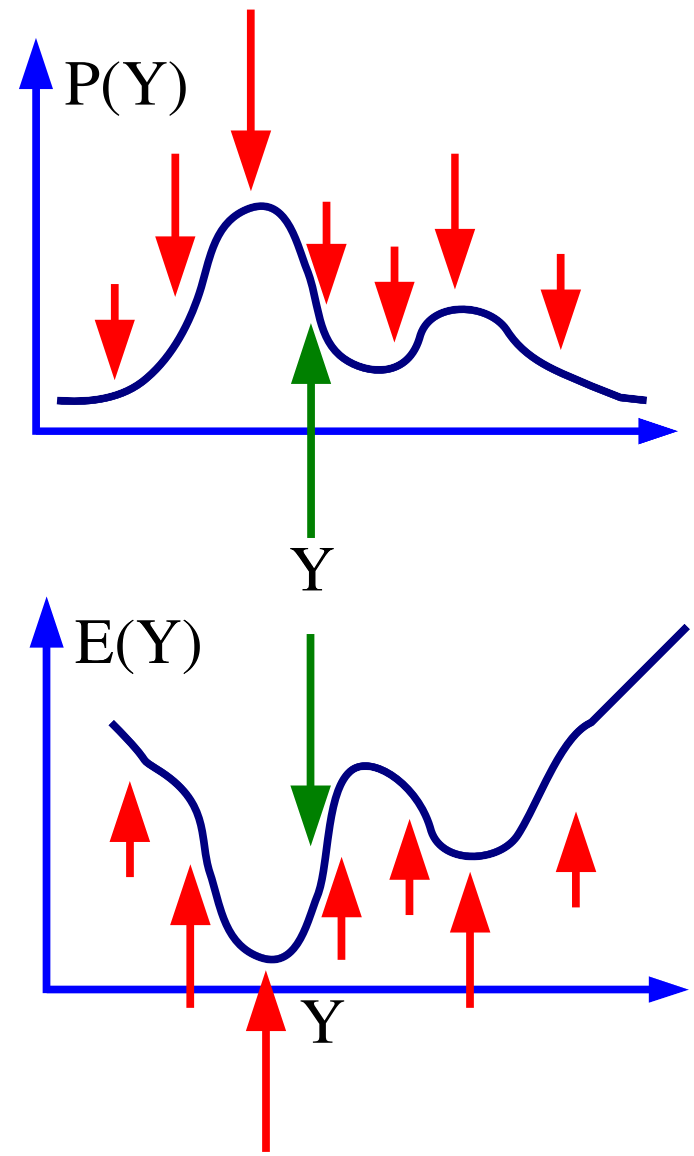
make this small

Minimizing -log P(Y,W) on training samples

$$L(Y,W) = E(Y,W) + \frac{1}{\beta} \log \int_y e^{-\beta E(y,W)}$$

make this small

make this big



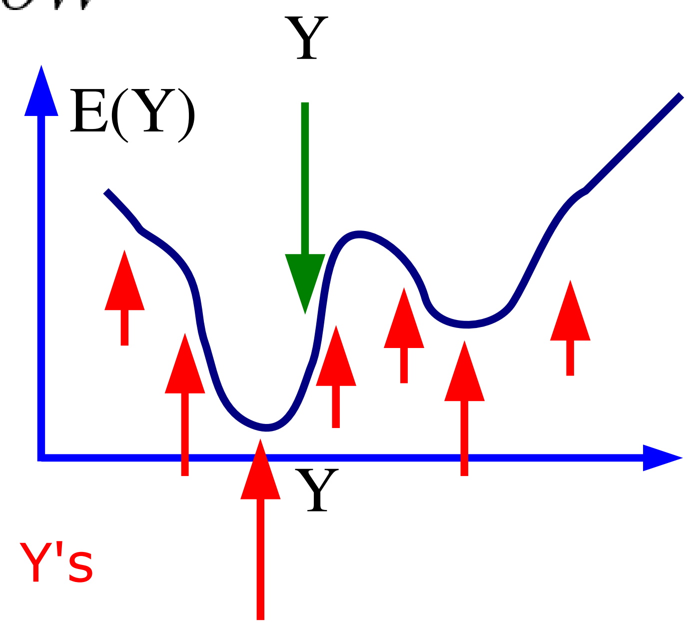
Training an Energy-Based Model with Gradient Descent

- **Gradient of the negative log-likelihood loss for one sample Y:**

$$\frac{\partial L(Y,W)}{\partial W} = \frac{\partial E(Y,W)}{\partial W} - \int_y P(y|W)\frac{\partial E(y,W)}{\partial W}$$

- **Gradient descent:**

$$W \leftarrow W - \eta\frac{\partial L(Y,W)}{\partial W}$$



Pushes down on the energy of the samples

Pulls up on the energy of low-energy Y's

$$W \leftarrow W - \eta\frac{\partial E(Y,W)}{\partial W} + \eta\int_y P(y|W)\frac{\partial E(y,W)}{\partial W}$$

How do we push up on the energy of everything else?

- **Solution 1: contrastive divergence [Hinton 2000]**
  - Move away from a training sample a bit
  - Push up on that
- **Solution 2: score matching**
  - On the training samples: minimize the gradient of the energy, and maximize the trace of its Hessian.
- **Solution 3: denoising auto-encoder (not really energy-based)**
  - Train the inference dynamics to map noisy samples to clean samples
- **Solution 4: MAIN INSIGHT! [Ranzato, ..., LeCun AI-Stat 2007]**
  - **Restrict the information content of the code (features) Z**
  - If the code Z can only take a few different configurations, only a correspondingly small number of Ys can be perfectly reconstructed
  - Idea: impose a sparsity prior on Z
  - This is reminiscent of sparse coding [Olshausen & Field 1997]

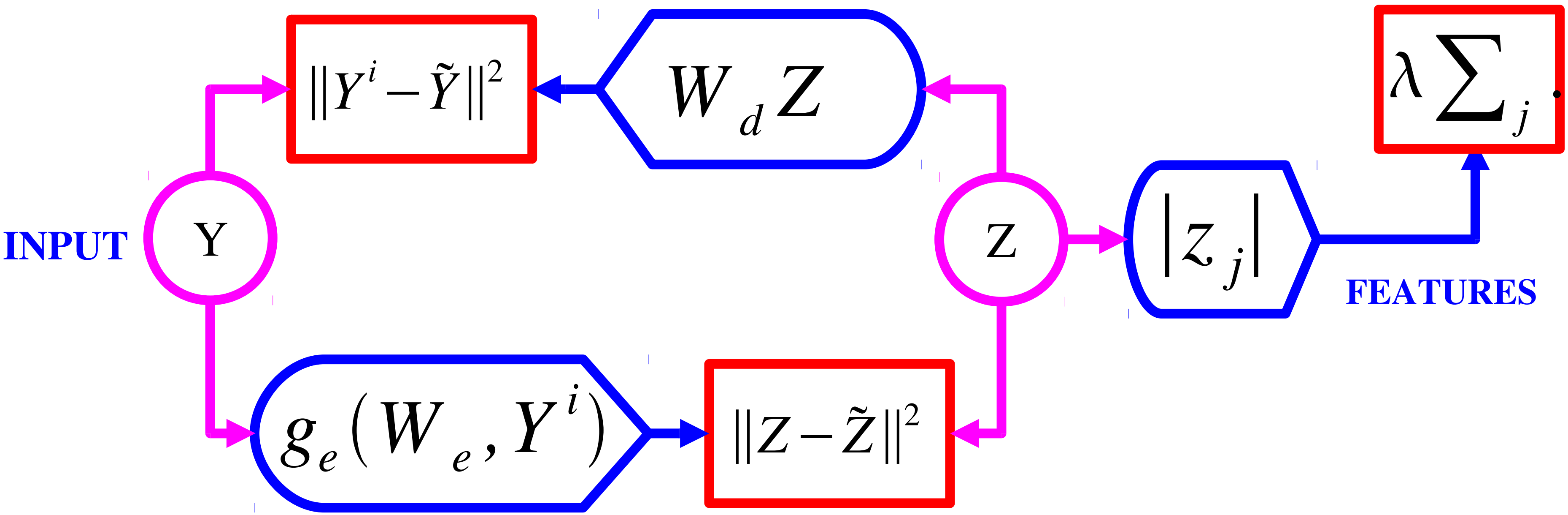
Encoder-Decoder with Sparsity (PSD)

[Kavukcuoglu, Ranzato, LeCun, 2009]

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

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

$$g_e(W_e, Y^i) = D \tanh(W_e Y)$$

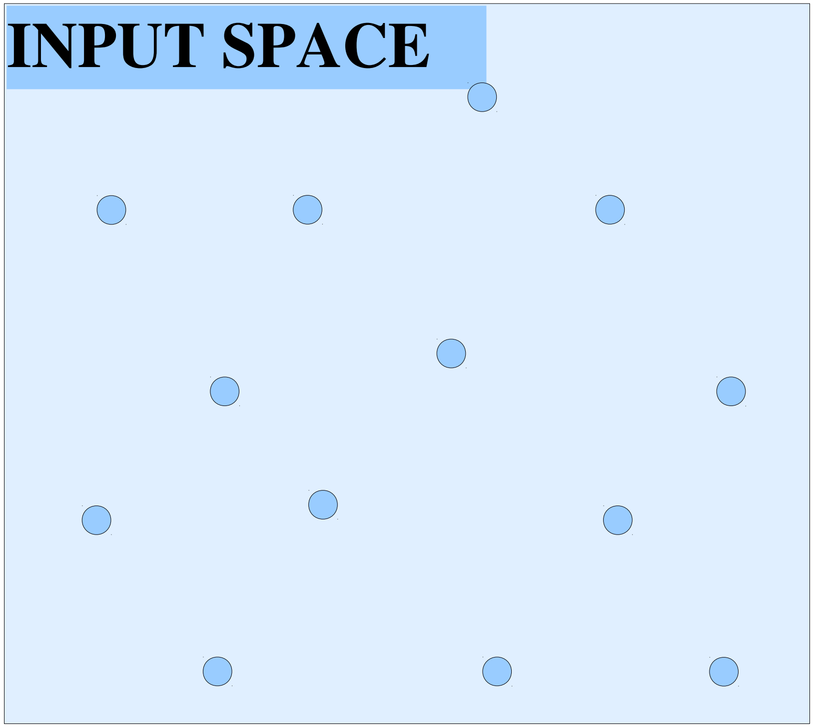


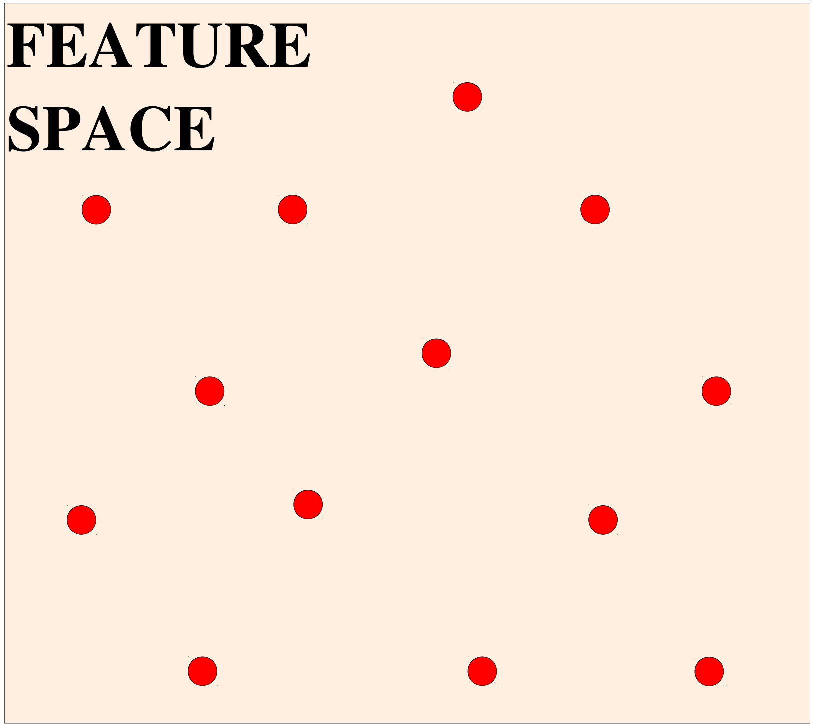
The Main Insight [Ranzato et al. AISTATS 2007]

- **If the information content of the feature vector is limited (e.g. by imposing sparsity constraints), the energy MUST be large in most of the space.**
  - pulling down on the energy of the training samples will necessarily make a groove
- **The volume of the space over which the energy is low is limited by the entropy of the feature vector**
  - Input vectors are reconstructed from feature vectors.
  - If few feature configurations are possible, few input vectors can be reconstructed properly

Why Limit the Information Content of the Code?

- Training sample
- Input vector which is NOT a training sample
- Feature vector

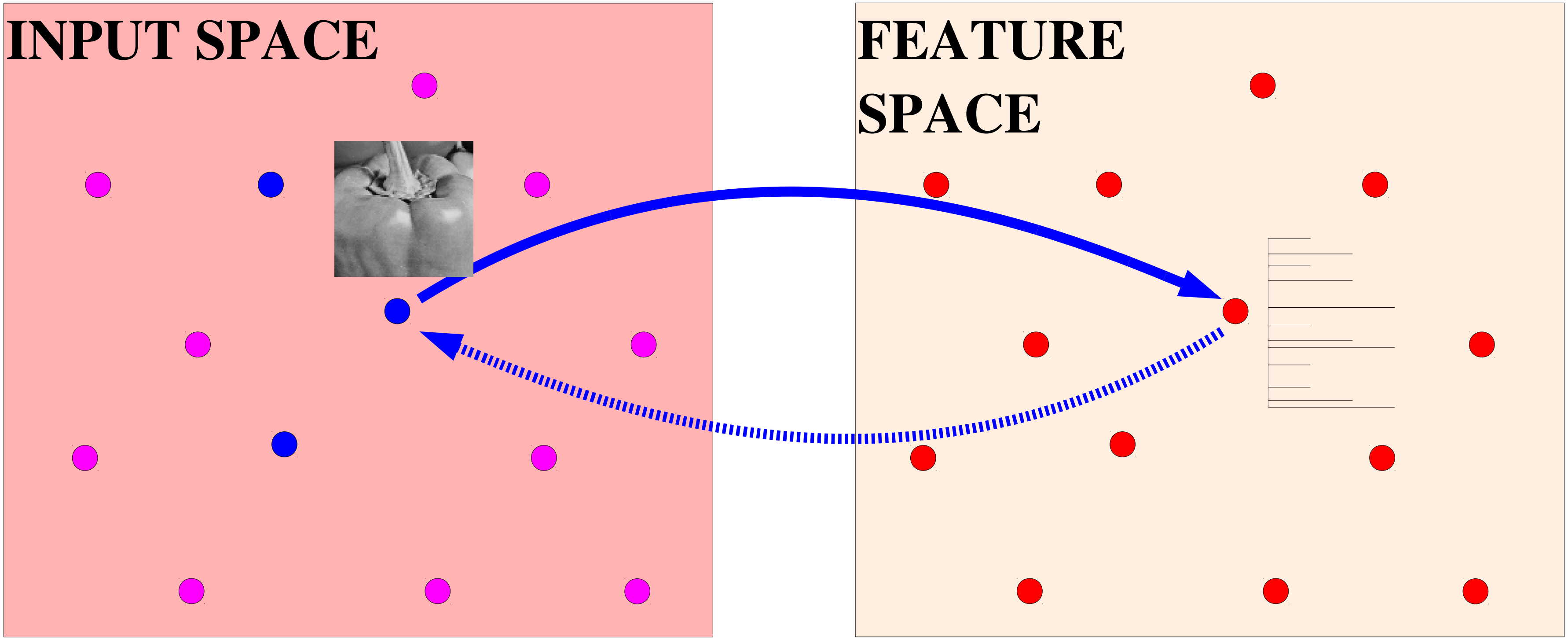




Why Limit the Information Content of the Code?

- Training sample
- Input vector which is NOT a training sample
- Feature vector

Training based on minimizing the reconstruction error over the training set

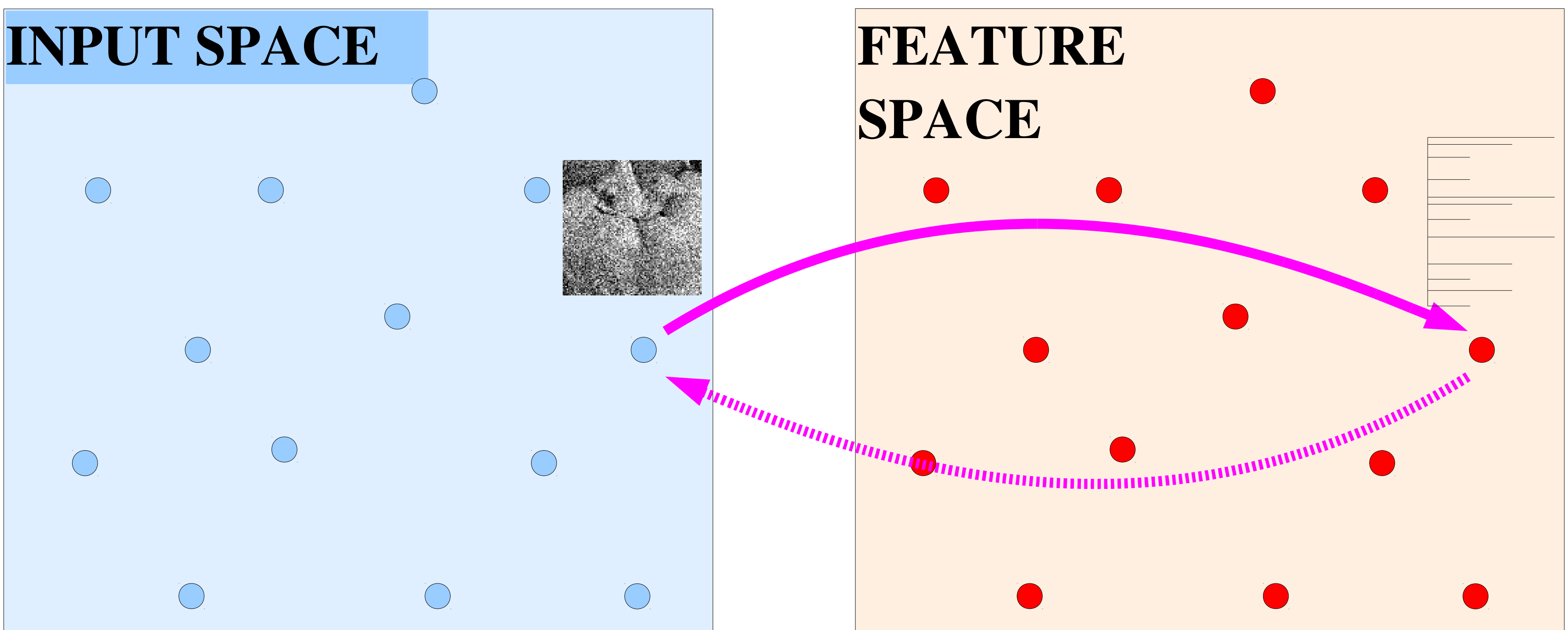


Why Limit the Information Content of the Code?

- Training sample
- Input vector which is NOT a training sample
- Feature vector

BAD: machine does not learn structure from training data!!

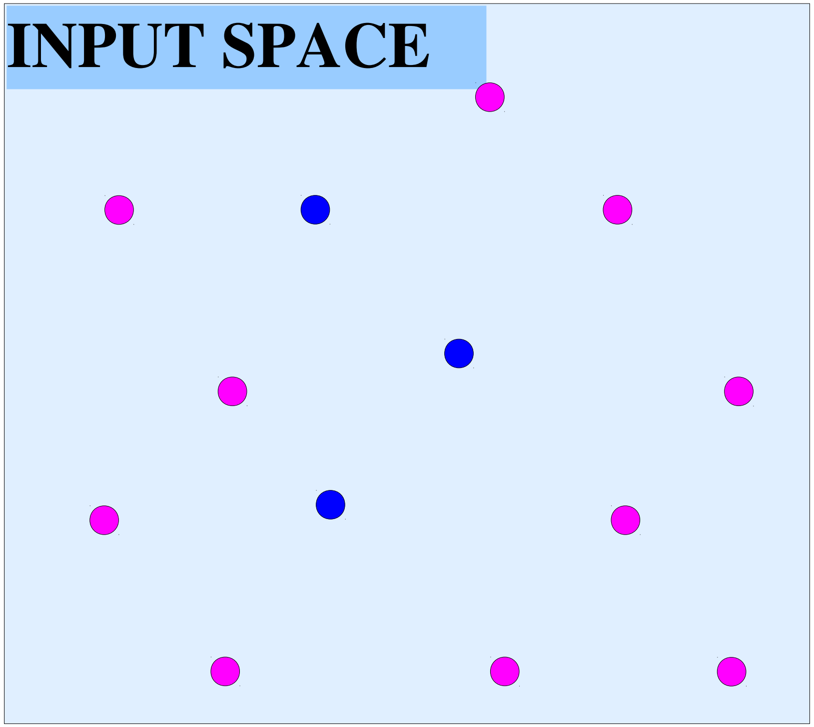
It just copies the data.

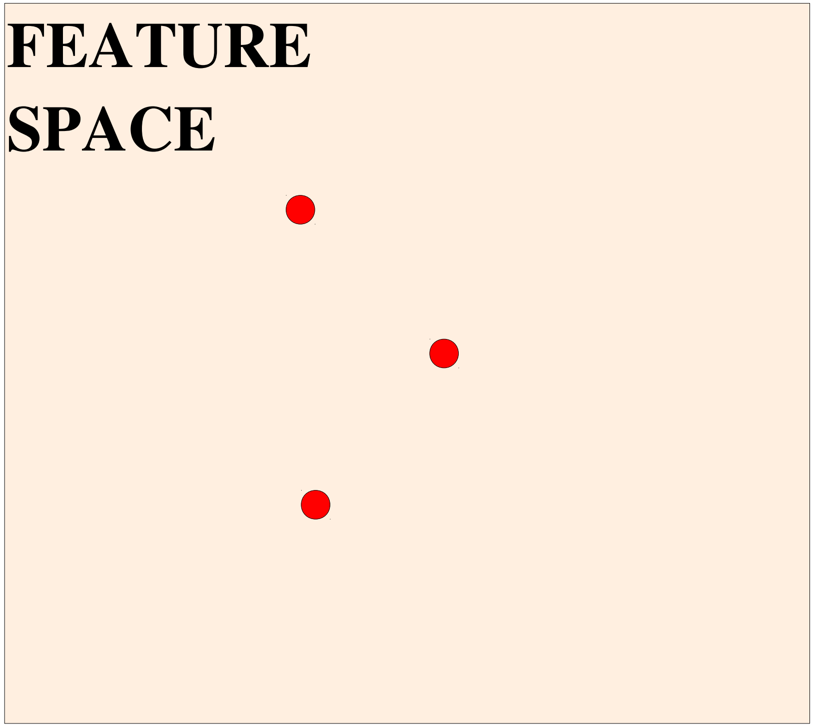


Why Limit the Information Content of the Code?

- Training sample
- Input vector which is NOT a training sample
- Feature vector

IDEA: reduce number of available codes.

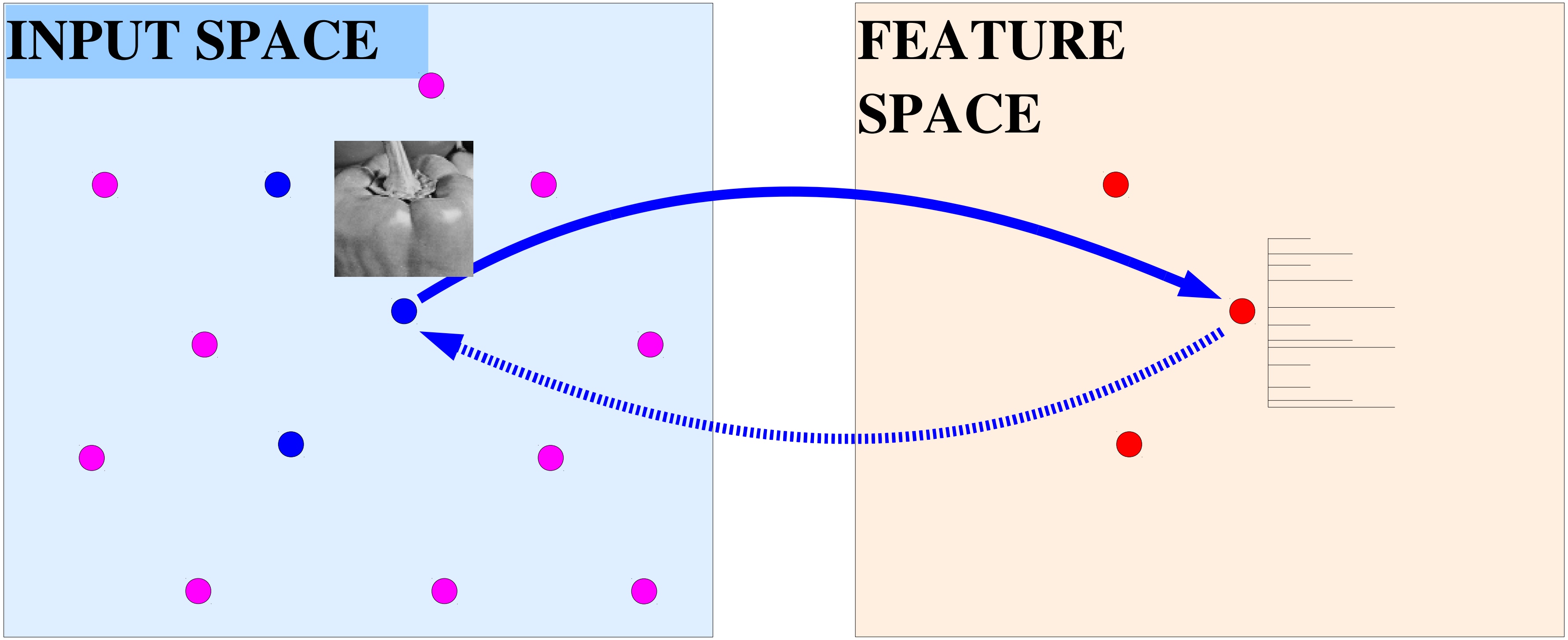




Why Limit the Information Content of the Code?

- **Training sample**
- **Input vector which is NOT a training sample**
- **Feature vector**

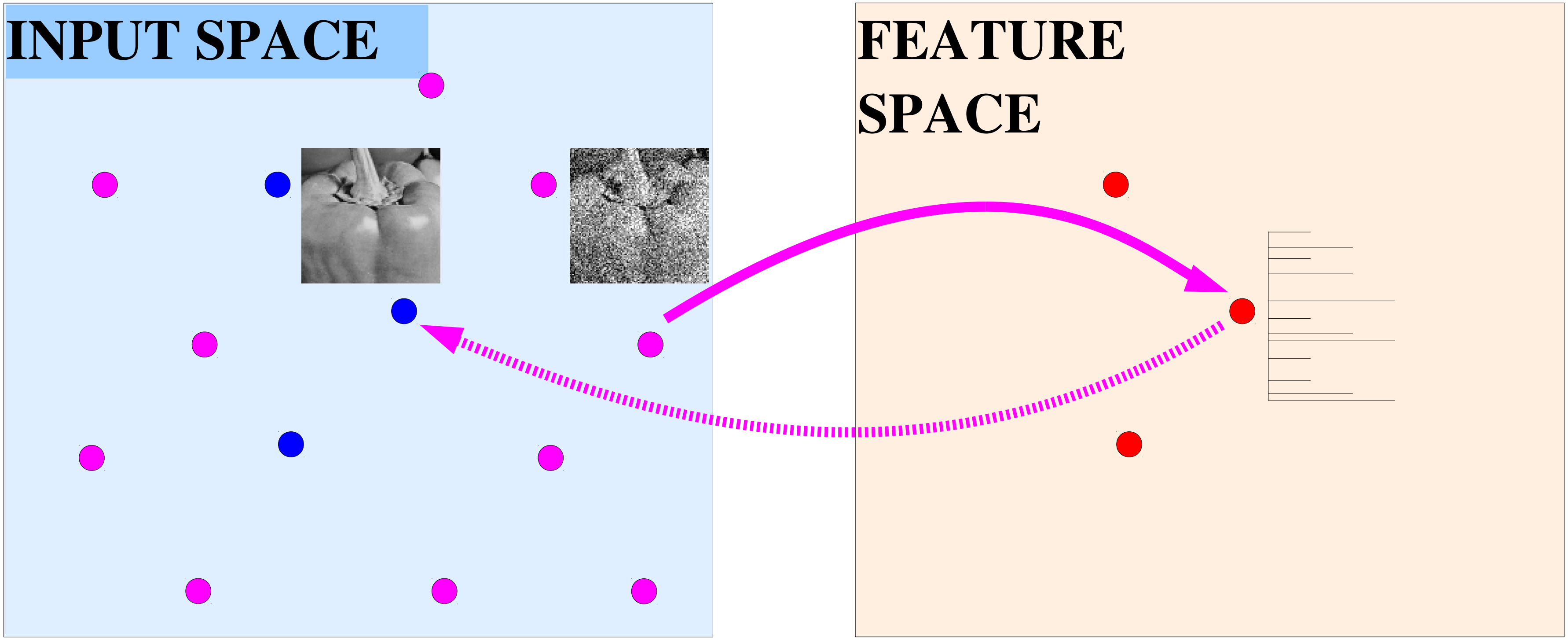
IDEA: reduce number of available codes.



Why Limit the Information Content of the Code?

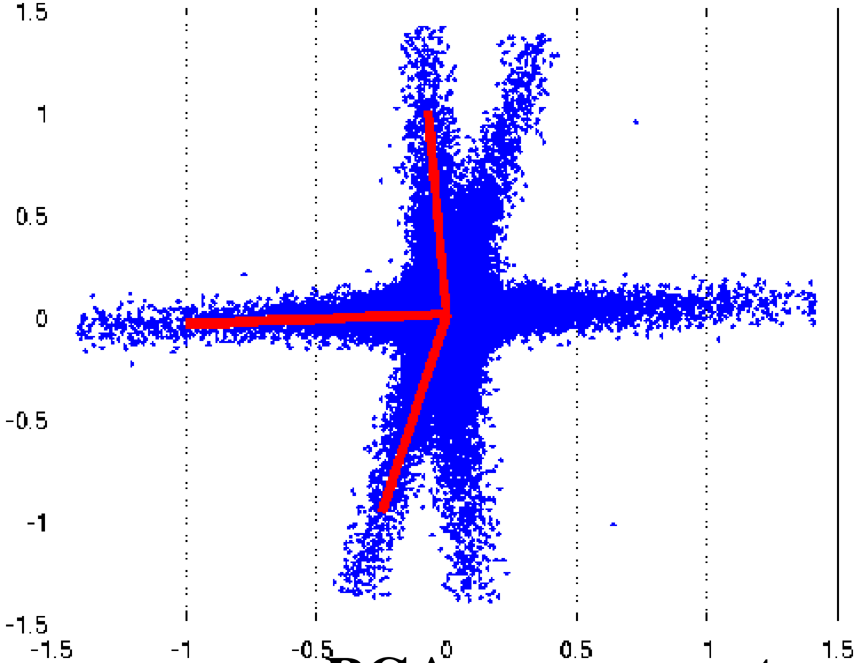
- Training sample
- Input vector which is NOT a training sample
- Feature vector

IDEA: reduce number of available codes.



Sparsity Penalty to Restrict the Code

- **We are going to impose a sparsity penalty on the code to restrict its information content.**
- **We will allow the code to have higher dimension than the input**
- **Categories are more easily separable in high-dim sparse feature spaces**
  - This is a trick that SVM use: they have one dimension per sample
- **Sparse features are optimal when an active feature costs more than an inactive one (zero).**
  - e.g. neurons that spike consume more energy
  - The brain is about 2% active on average.

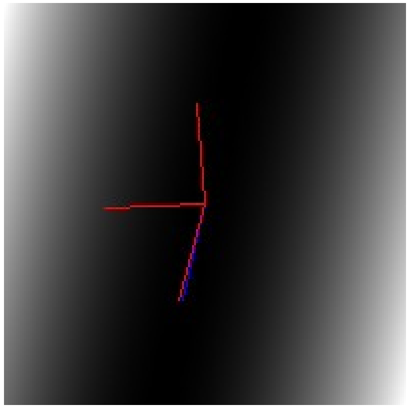
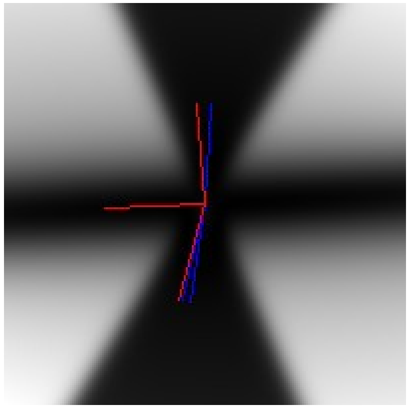
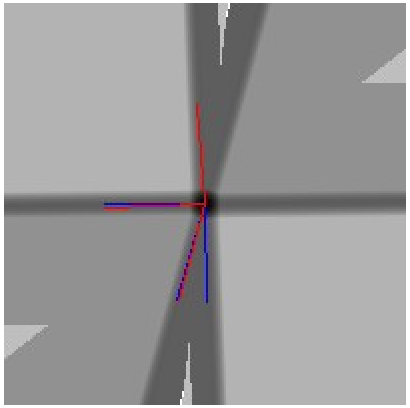
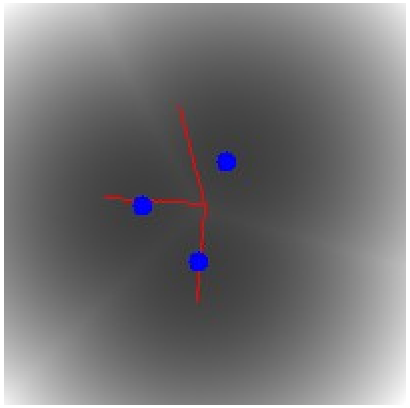


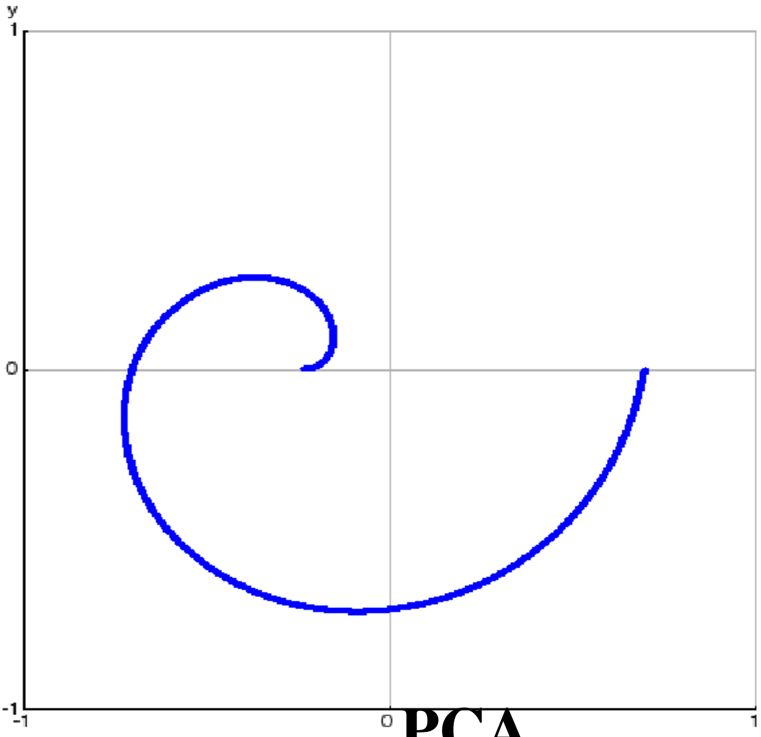
- 2 dimensional toy dataset
  - Mixture of 3 Cauchy distrib.
- Visualizing energy surface

(black = low, white = high)

[Ranzato 's PhD thesis 2009]

	PCA (1 code unit)	**autoencoder (3 code units)**	**sparse coding (3 code units)**	**K-Means (3 code units)**
encoder	$W^T Y$	$\sigma(W_e Y)$	—	—
decoder	WZ	$W_d Z$	WZ	WZ
energy	$\|\|Y-WZ\|\|^2$	$\|\|Y-WZ\|\|^2$	$\|\|Y-WZ\|\|^2+\lambda\|Z\|$	$\|\|Y-WZ\|\|^2$
loss	$F(Y)$	$F(Y)+\log\Gamma$	$F(Y)$	$F(Y)$
pull-up	dimens.	part. func.	sparsity	1-of-N code

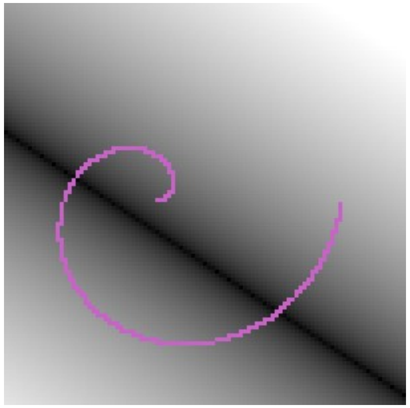
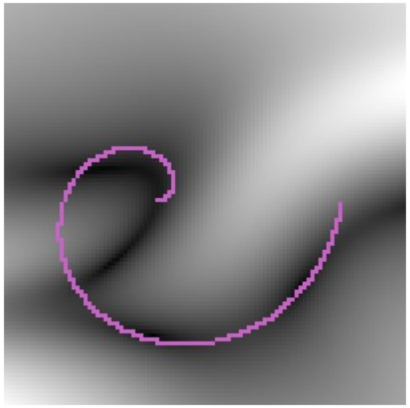
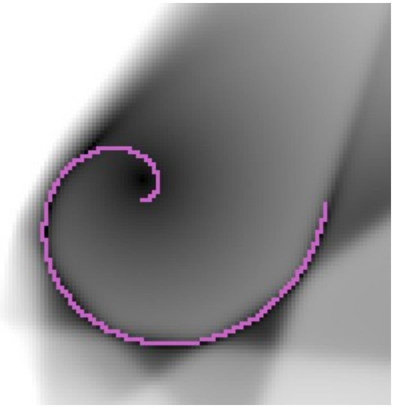
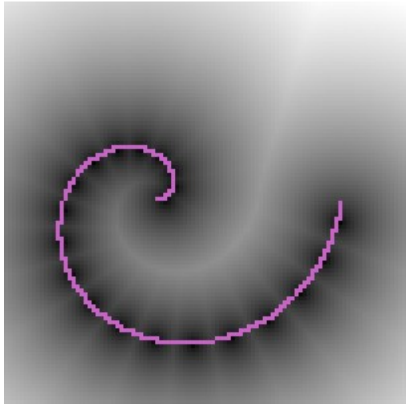







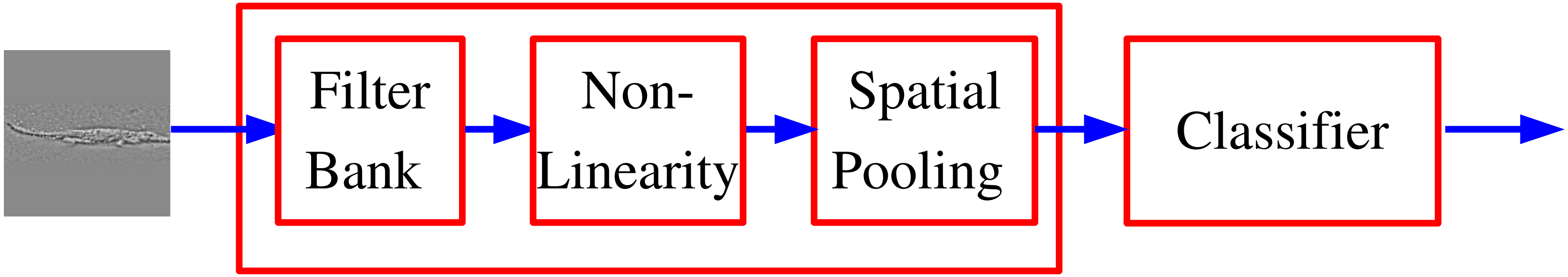
- 2 dimensional toy dataset
  - spiral
- Visualizing energy surface

(black = low, white = high)

	PCA (1 code unit)	**autoencoder (1 code unit)**	**sparse coding (20 code units)**	**K-Means (20 code units)**
encoder	$W^T Y$	$\sigma(W_e Y)$	$\sigma(W_e Z)$	$-$
decoder	WZ	$W_d Z$	$W_d Z$	WZ
energy	$\|Y - WZ\|^2$	$\|Y - WZ\|^2$	$\|Y - WZ\|^2$	$\|Y - WZ\|^2$
loss	$F(Y)$	$F(Y)$	$F(Y)$	$F(Y)$
pull-up	dimens.	dimens.	sparsity	1-of-N code

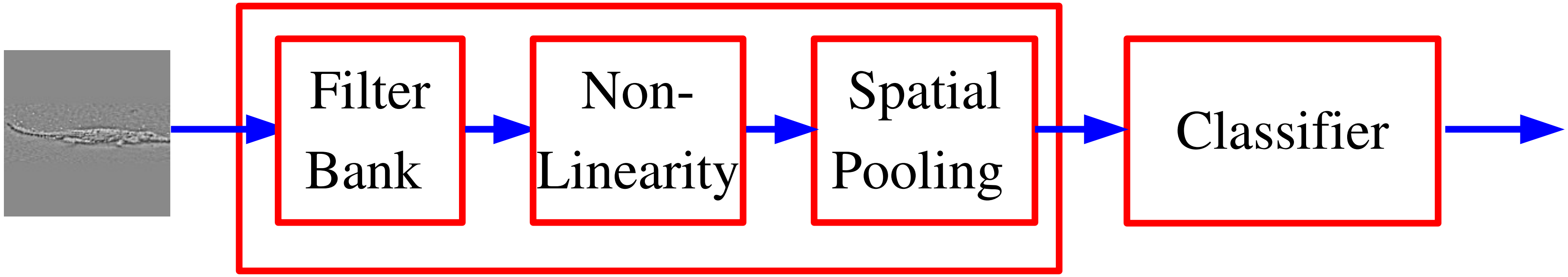





Using PSD to learn the features of an object recognition system



- **Learning the filters of a ConvNet-like architecture with PSD**
- **1. Train filters on images patches with PSD**
- **2. Plug the filters into a ConvNet architecture**
- **3. Train a supervised classifier on top**

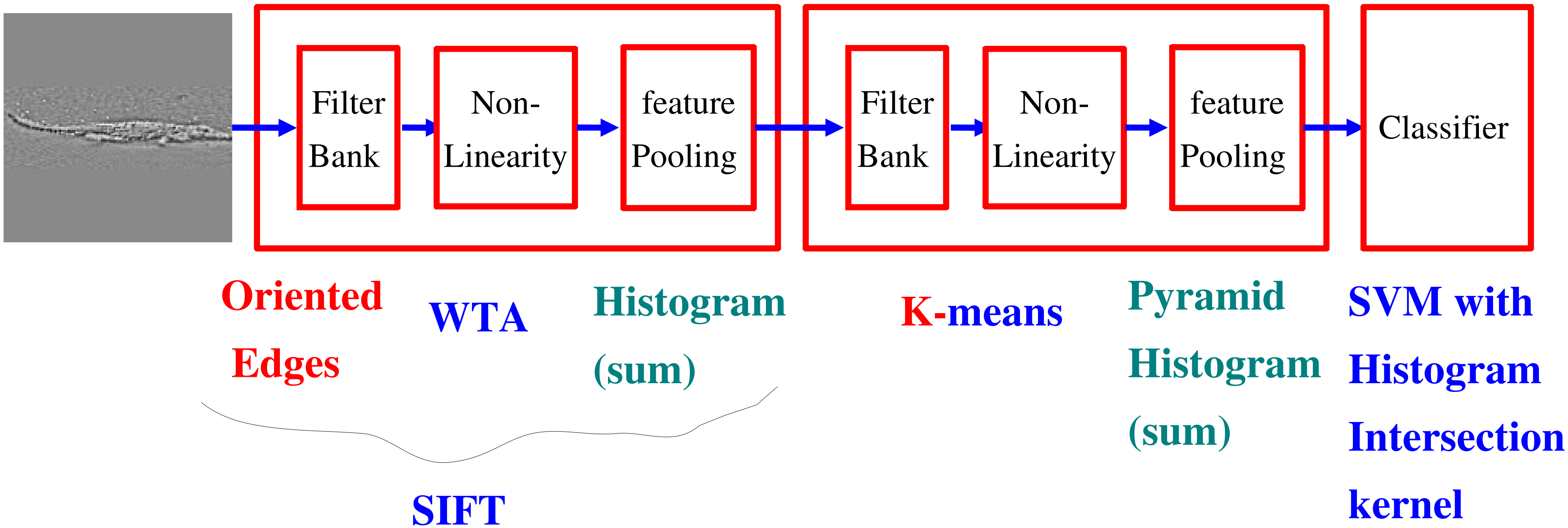
"Modern" Object Recognition Architecture in Computer Vision



Oriented Edges	Sigmoid	Averaging
Gabor Wavelets	Rectification	Max pooling
Other Filters...	Vector Quant.	VQ+Histogram
	Contrast Norm.	Geometric Blurr

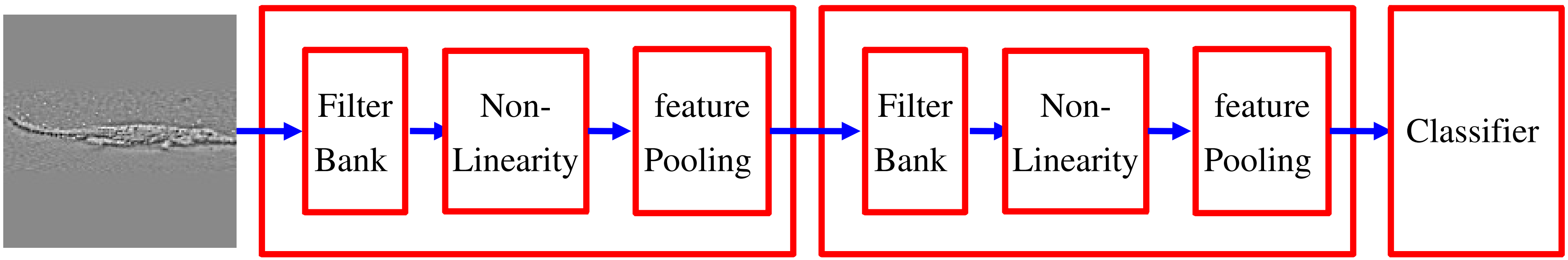
- **Example:**
  - Edges + Rectification + Histograms + SVM [Dalal & Triggs 2005]
  - SIFT + classification
- **Fixed Features + "shallow" classifier**

"State of the Art" architecture for object recognition



- **Example:**
  - SIFT features with Spatial Pyramid Match Kernel SVM [Lazebnik et al. 2006]
- **Fixed Features + unsupervised features + "shallow" classifier**

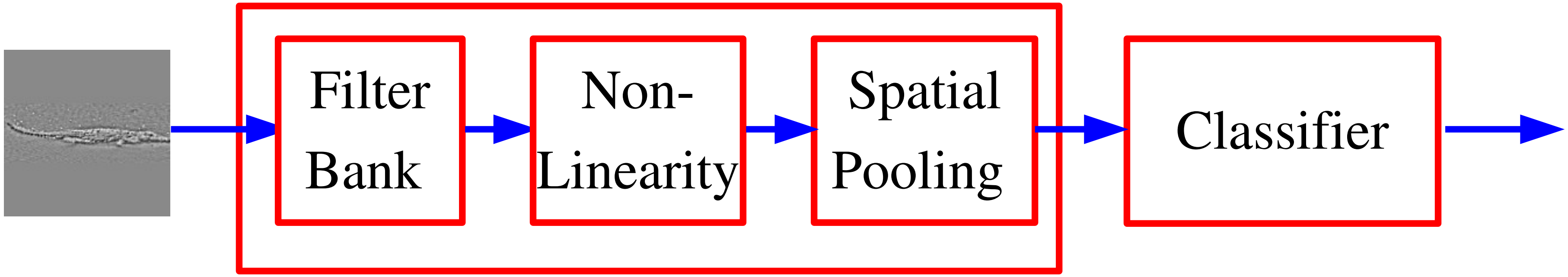
Can't we get the same results with (deep) learning?

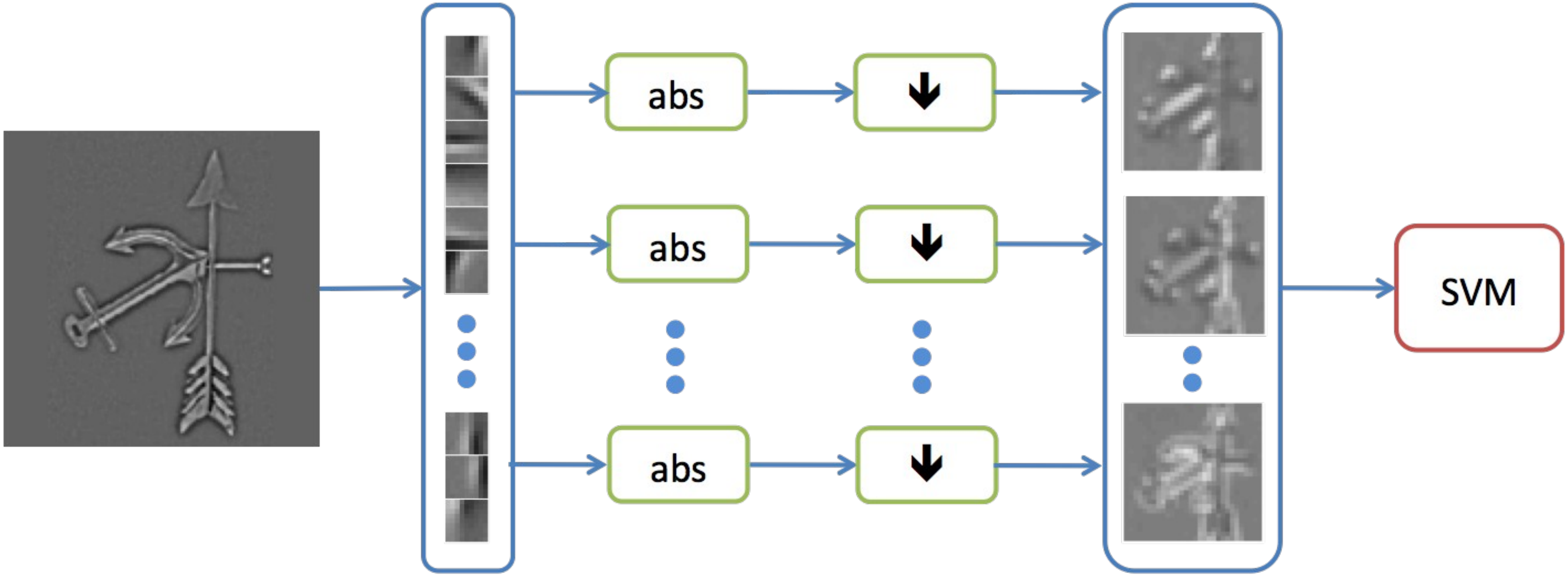


- **Stacking multiple stages of feature extraction/pooling.**
- **Creates a hierarchy of features**
- **ConvNets and SIFT+PMK-SVM architectures are conceptually similar**
- **Can deep learning make a ConvNet match the performance of SIFT+PNK-SVM?**

How well do PSD features work on Caltech-101?

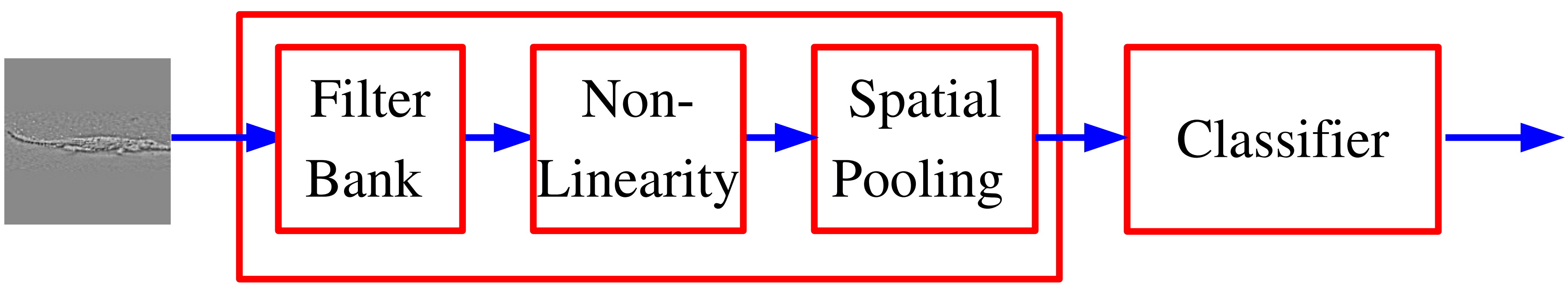
- **Recognition Architecture**





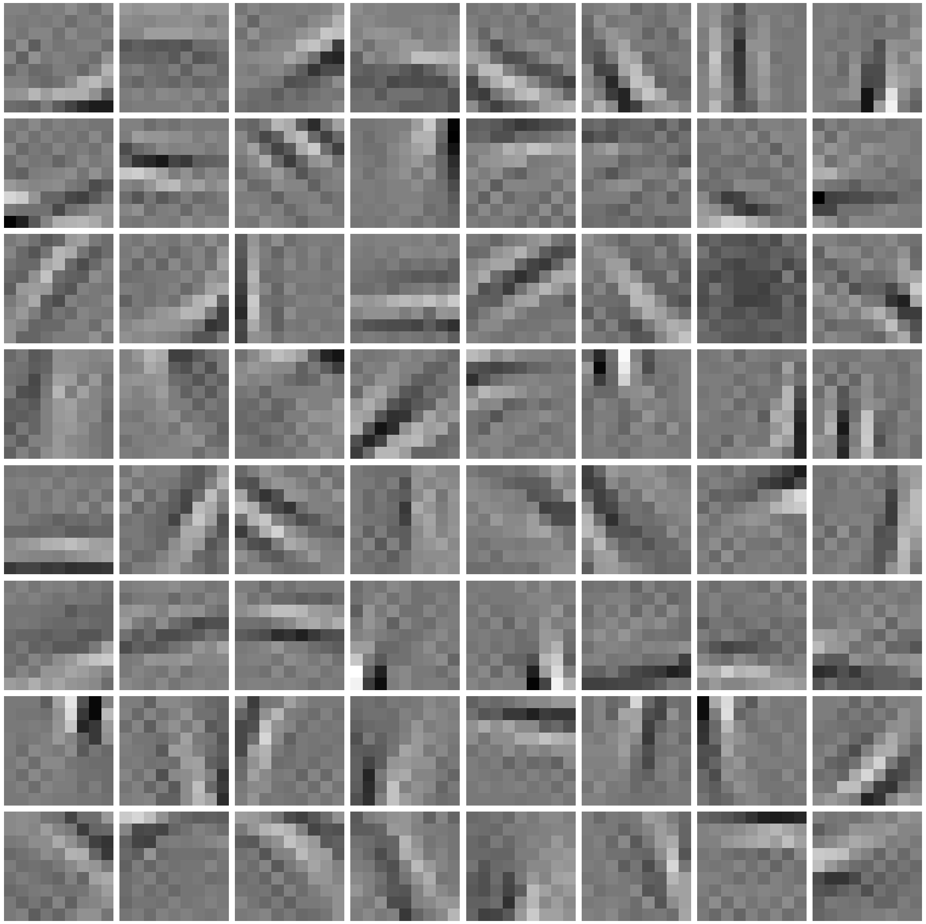
Procedure for a single-stage system

- **1. Pre-process images**
  - remove mean, high-pass filter, normalize contrast
- **2. Train encoder-decoder on 9x9 image patches**
- **3. use the filters in a recognition architecture**
  - Apply the filters to the whole image
  - Apply the tanh and D scaling
  - Add more non-linearities (rectification, normalization)
  - Add a spatial pooling layer
- **4. Train a supervised classifier on top**
  - Multinomial Logistic Regression or Pyramid Match Kernel SVM



Using PSD Features for Recognition

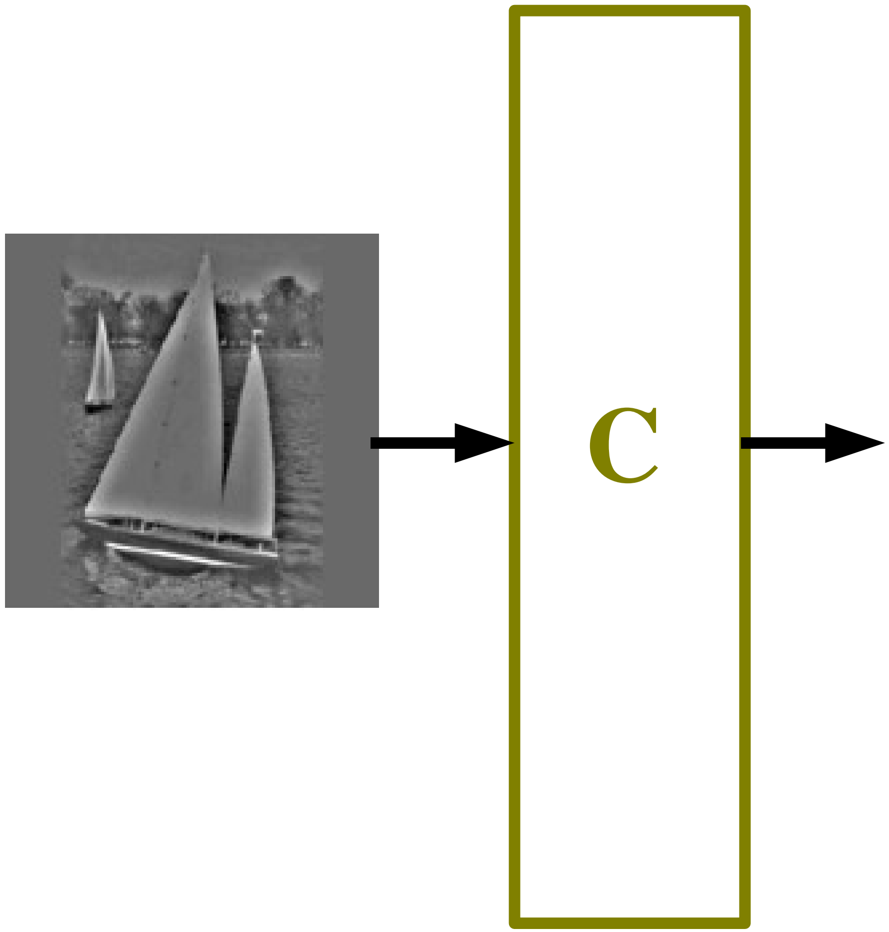
- **64 filters on 9x9 patches trained with PSD**
  - with Linear-Sigmoid-Diagonal Encoder



weights :-0.2828 - 0.3043

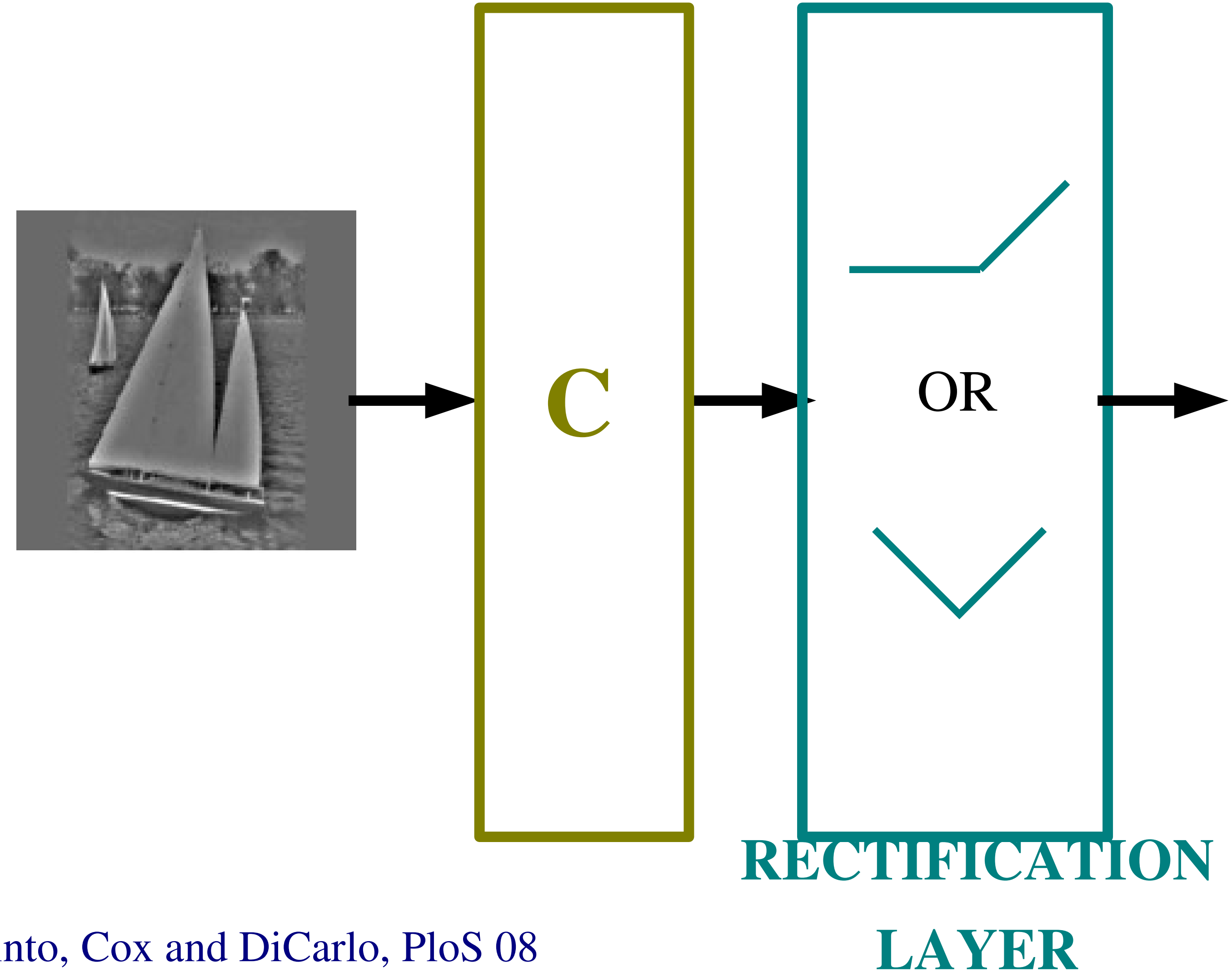
Feature Extraction

- **C** Convolution/sigmoid layer: filter bank? Learning, fixed Gabors?



Feature Extraction

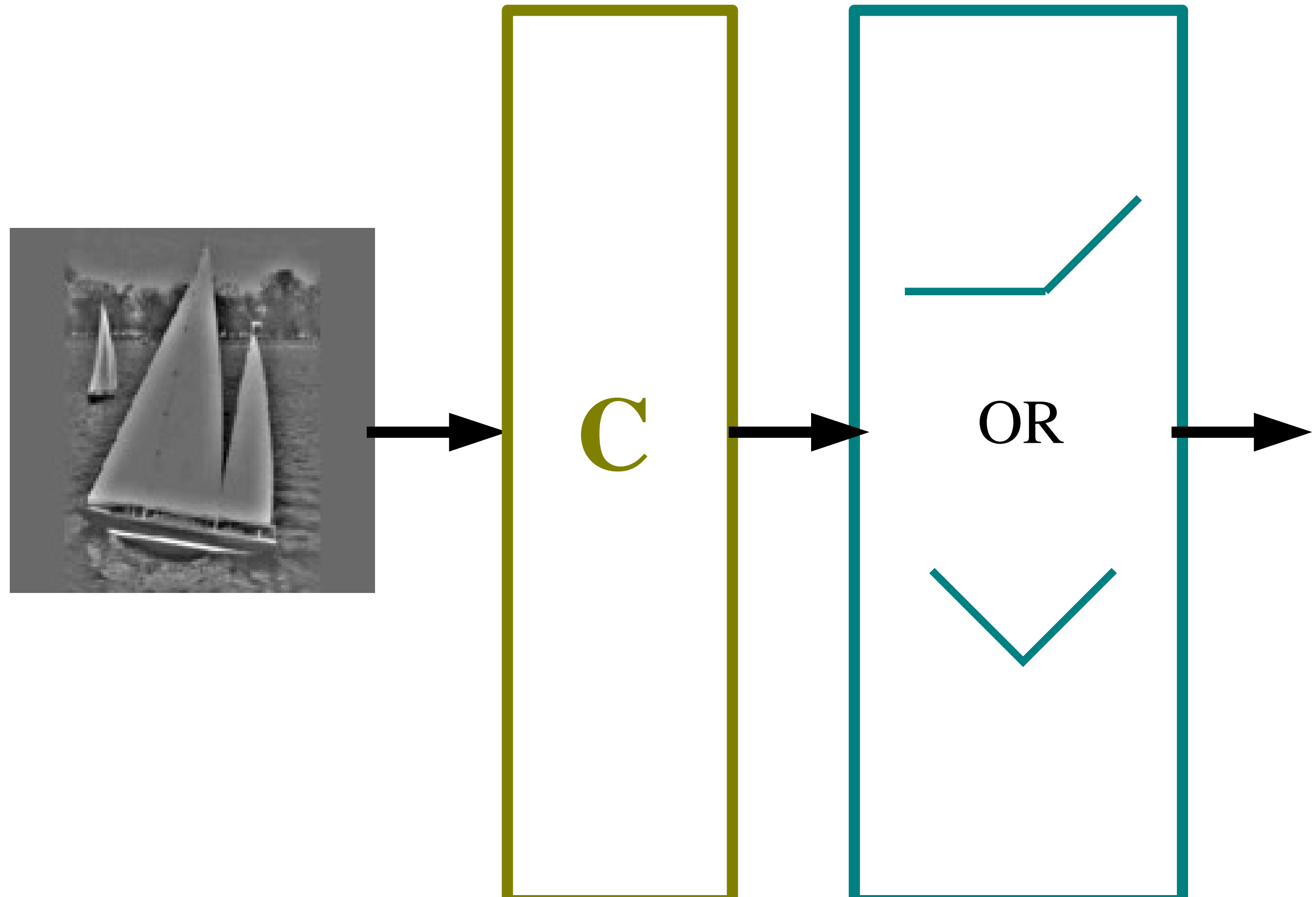
- C   Convolution/sigmoid layer: filter bank? Learning, fixed Gabors?



Pinto, Cox and DiCarlo, PloS 08

Feature Extraction

- C Convolution/sigmoid layer: filter bank? Learning, fixed Gabors?
- Abs Rectification layer: needed?

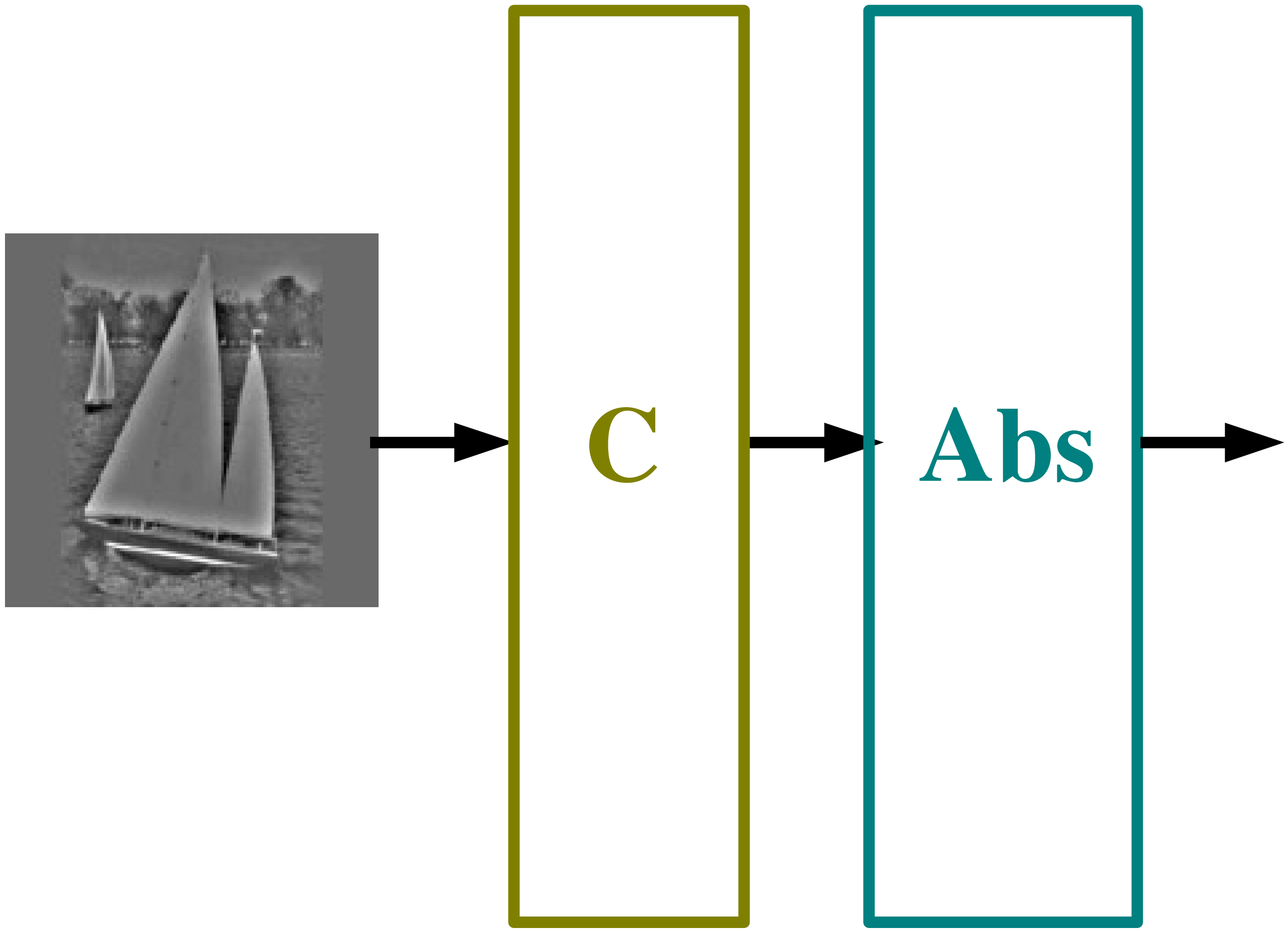


RECTIFICATION LAYER

Pinto, Cox and DiCarlo, PloS 08

Feature Extraction

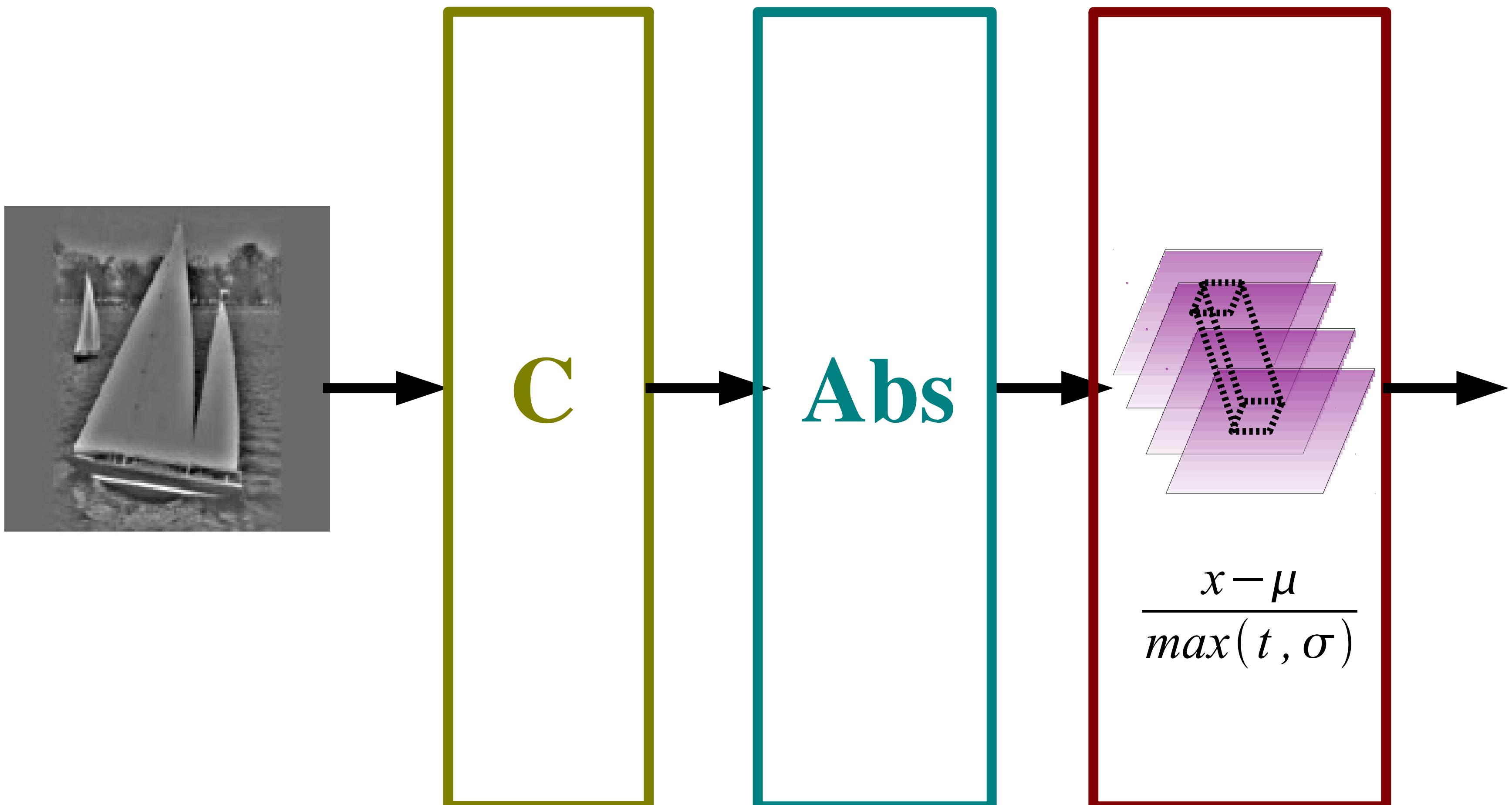
- C Convolution/sigmoid layer: filter bank? Learning, fixed Gabors?
- Abs Rectification layer: needed?



Pinto, Cox and DiCarlo, PloS 08

Feature Extraction

- C Convolution/sigmoid layer: filter bank? Learning, fixed Gabors?
- Abs Rectification layer: needed?

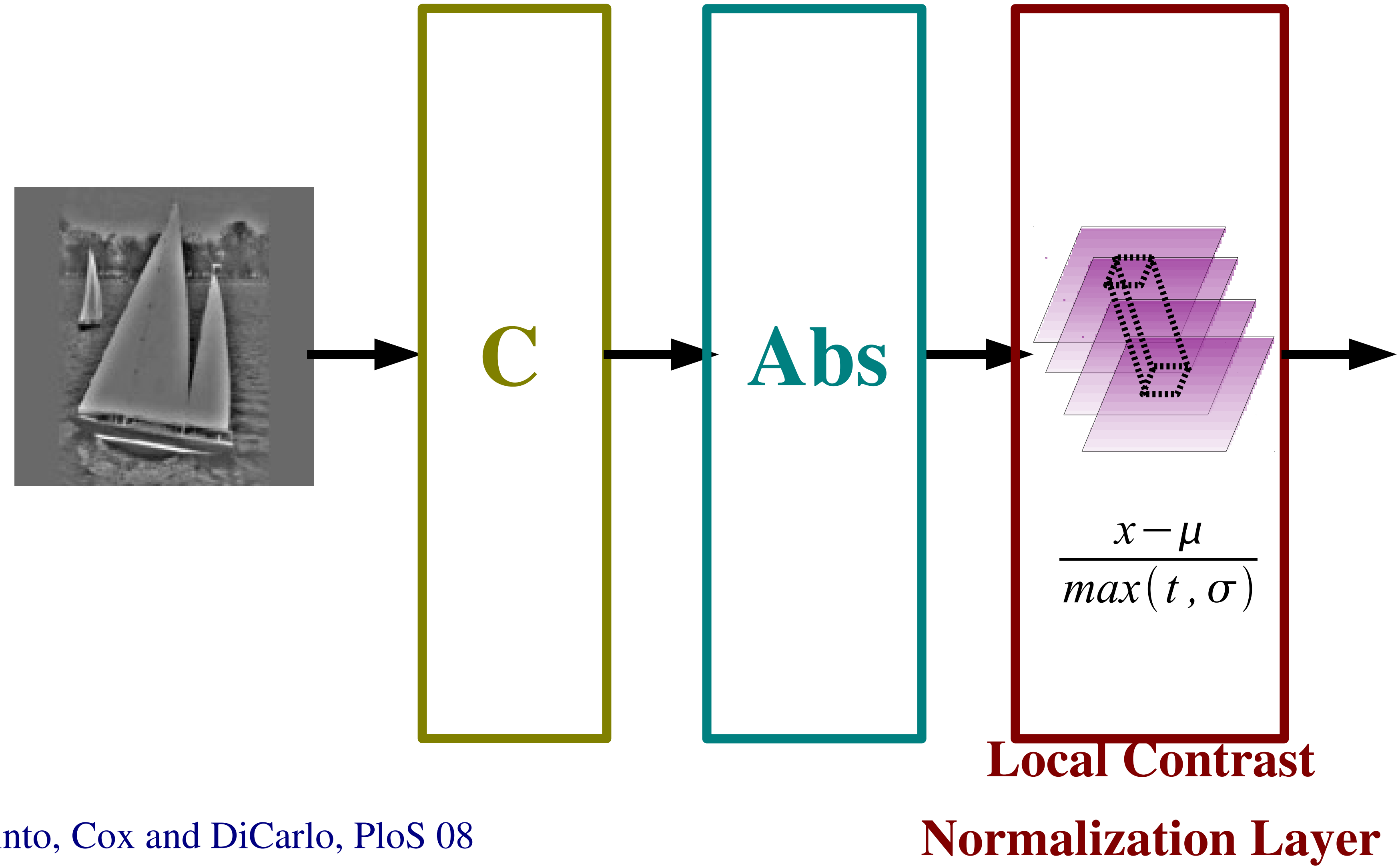


Local Contrast Normalization Layer

Pinto, Cox and DiCarlo, PloS 08

Feature Extraction

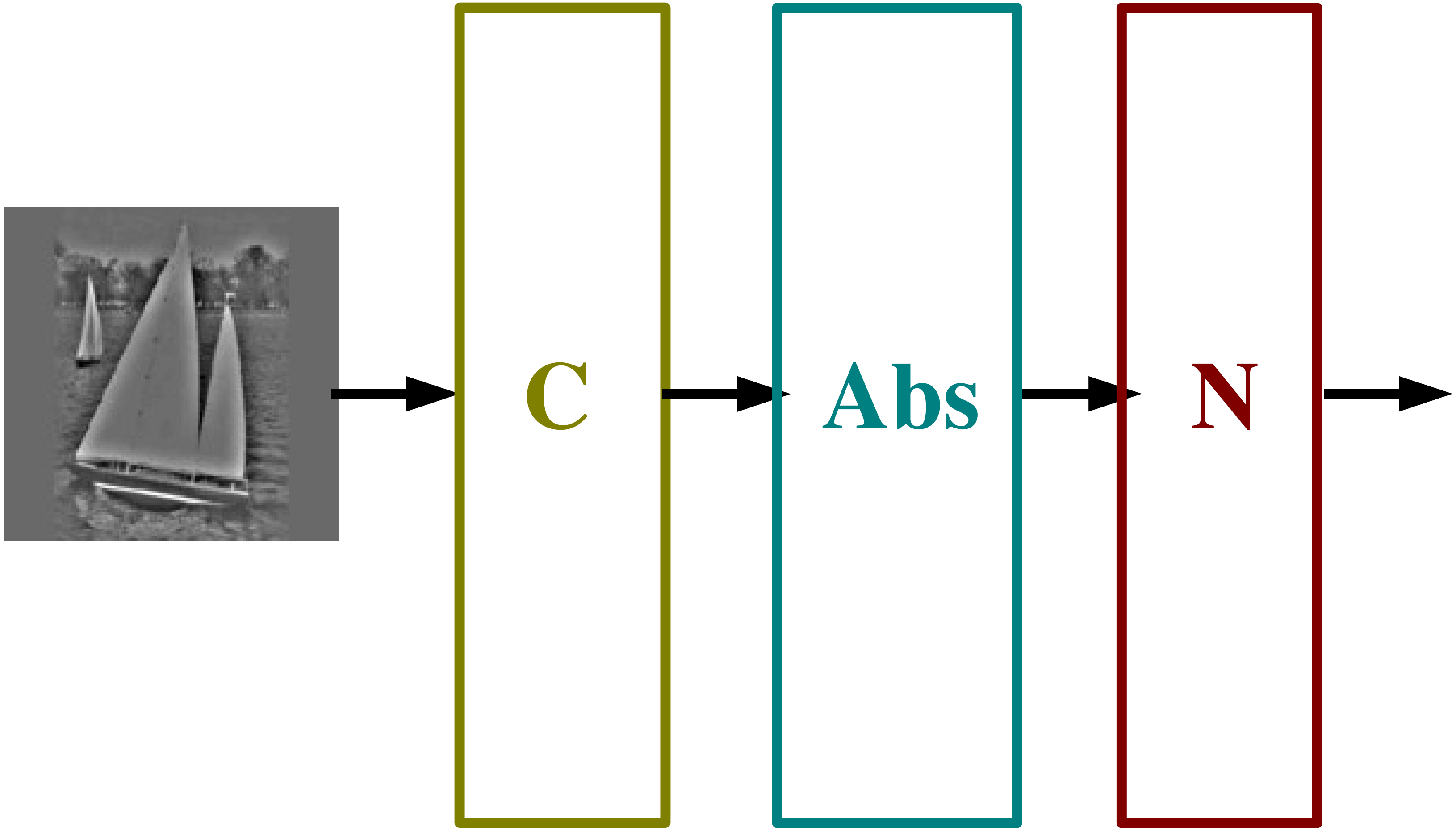
- **C** Convolution/sigmoid layer: filter bank? Learning, fixed Gabors?
- **Abs** Rectification layer: needed?
- **N** Normalization layer: needed?



Pinto, Cox and DiCarlo, PloS 08

Feature Extraction

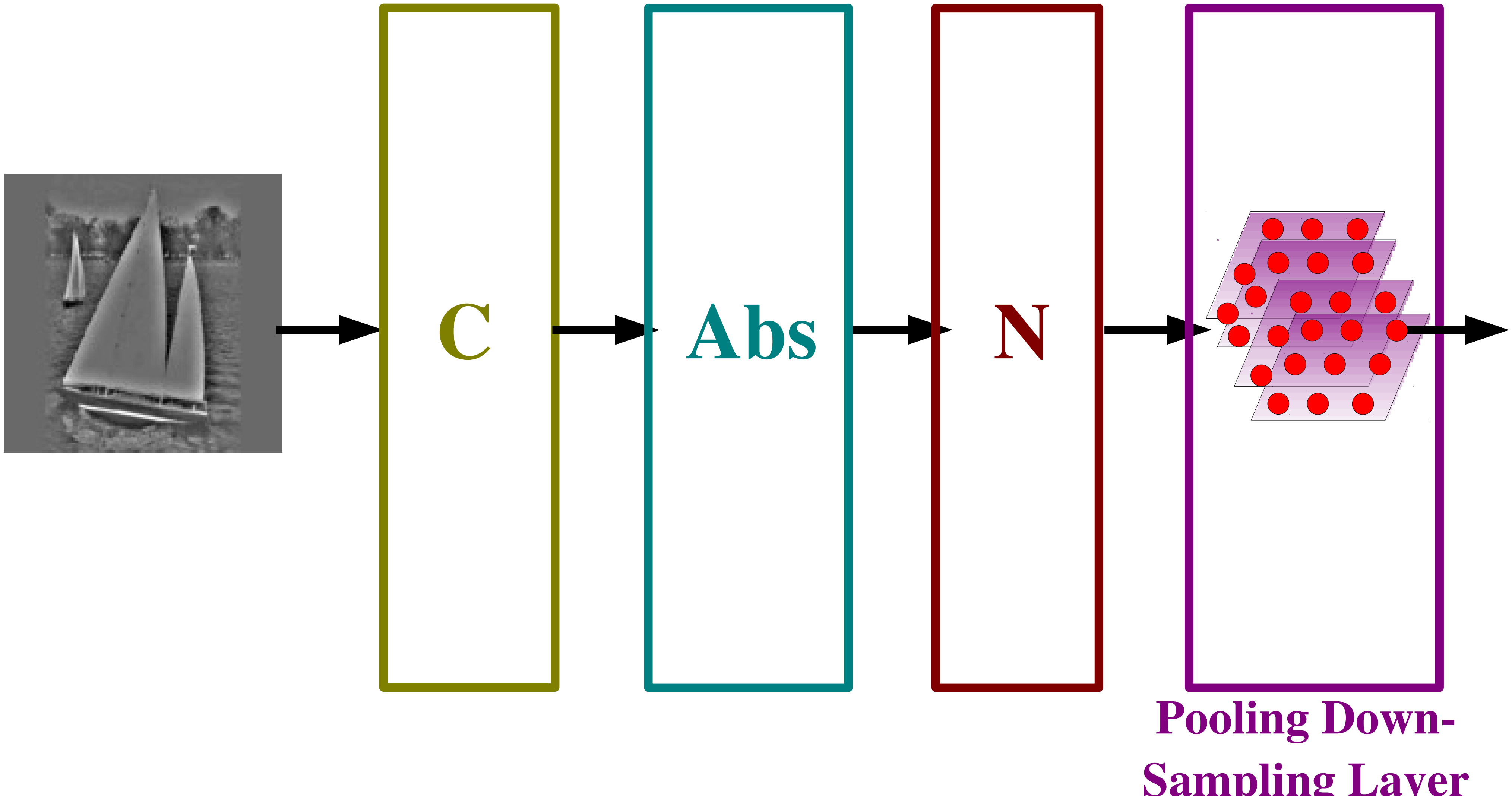
- C Convolution/sigmoid layer: filter bank? Learning, fixed Gabors?
- Abs Rectification layer: needed?
- N Normalization layer: needed?



Pinto, Cox and DiCarlo, PloS 08

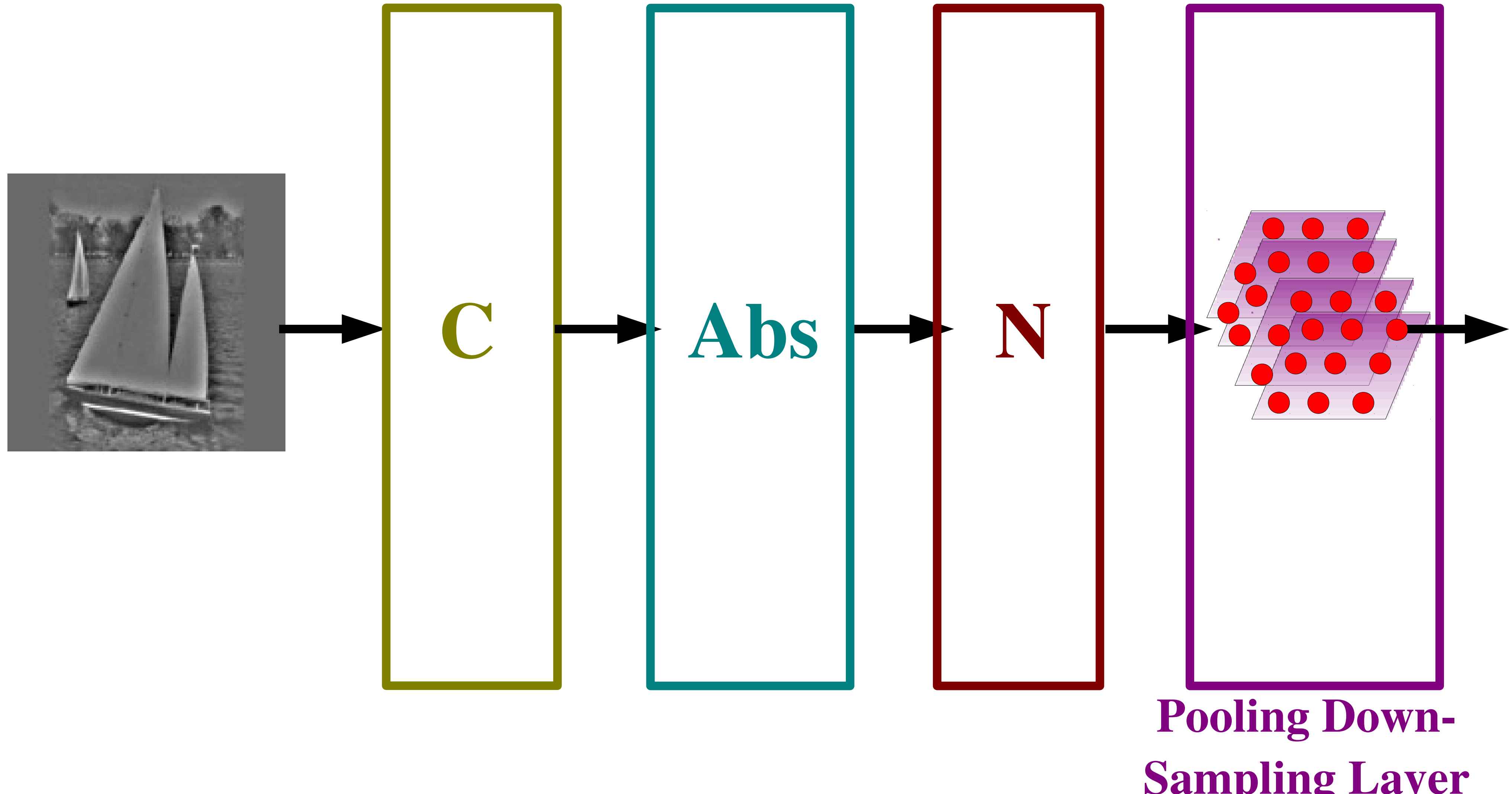
Feature Extraction

- C Convolution/sigmoid layer: filter bank? Learning, fixed Gabors?
- Abs Rectification layer: needed?
- N Normalization layer: needed?



Feature Extraction

- **C** Convolution/sigmoid layer: filter bank? Learning, fixed Gabors?
- **Abs** Rectification layer: needed?
- **N** Normalization layer: needed?
- **P** Pooling down-sampling layer: average or max?



Feature Extraction

- **C** Convolution/sigmoid layer: filter bank? Learning, fixed Gabors?
- **Abs** Rectification layer: needed?
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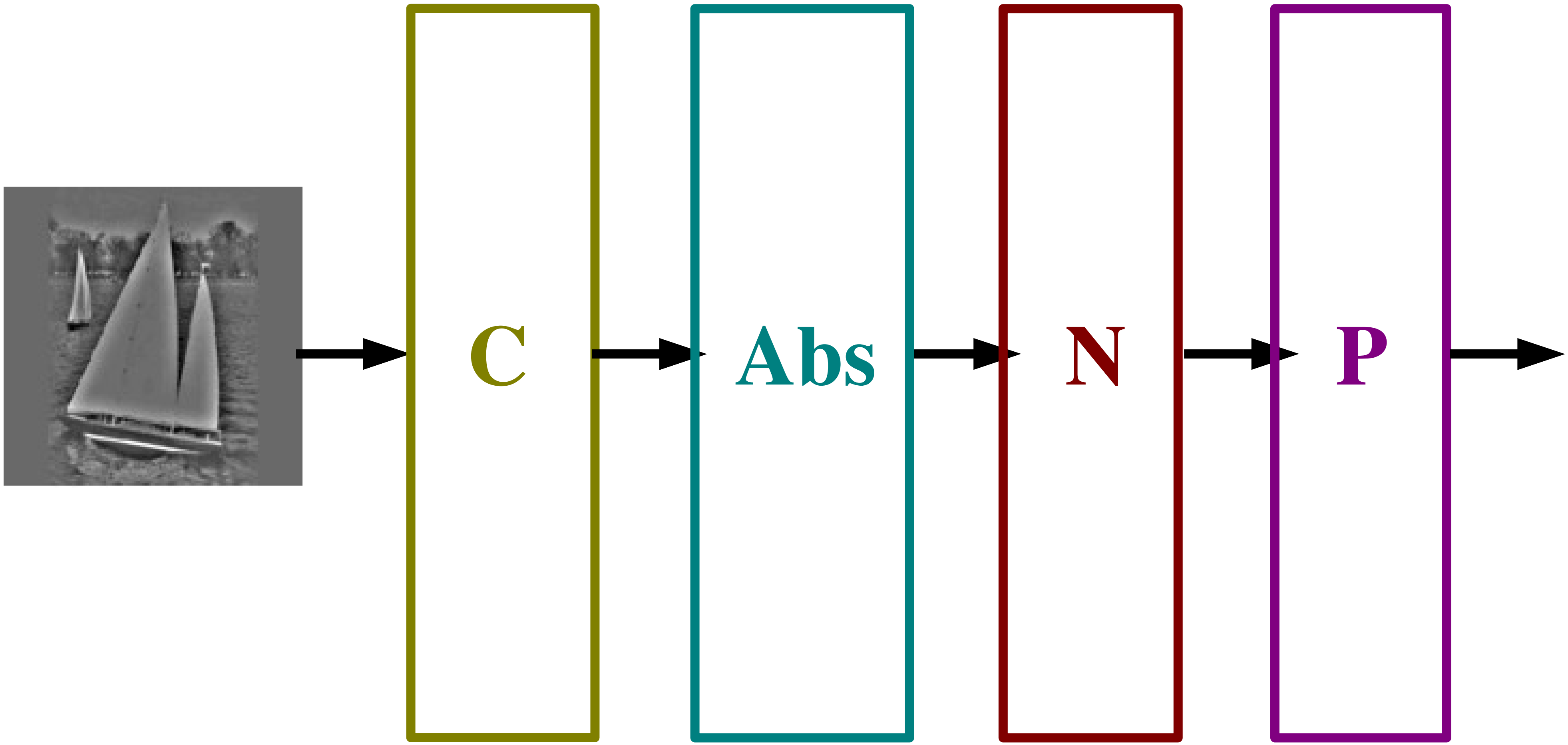

Feature Extraction

- C Convolution/sigmoid layer: filter bank? Learning, fixed Gabors?
- Abs Rectification layer: needed?
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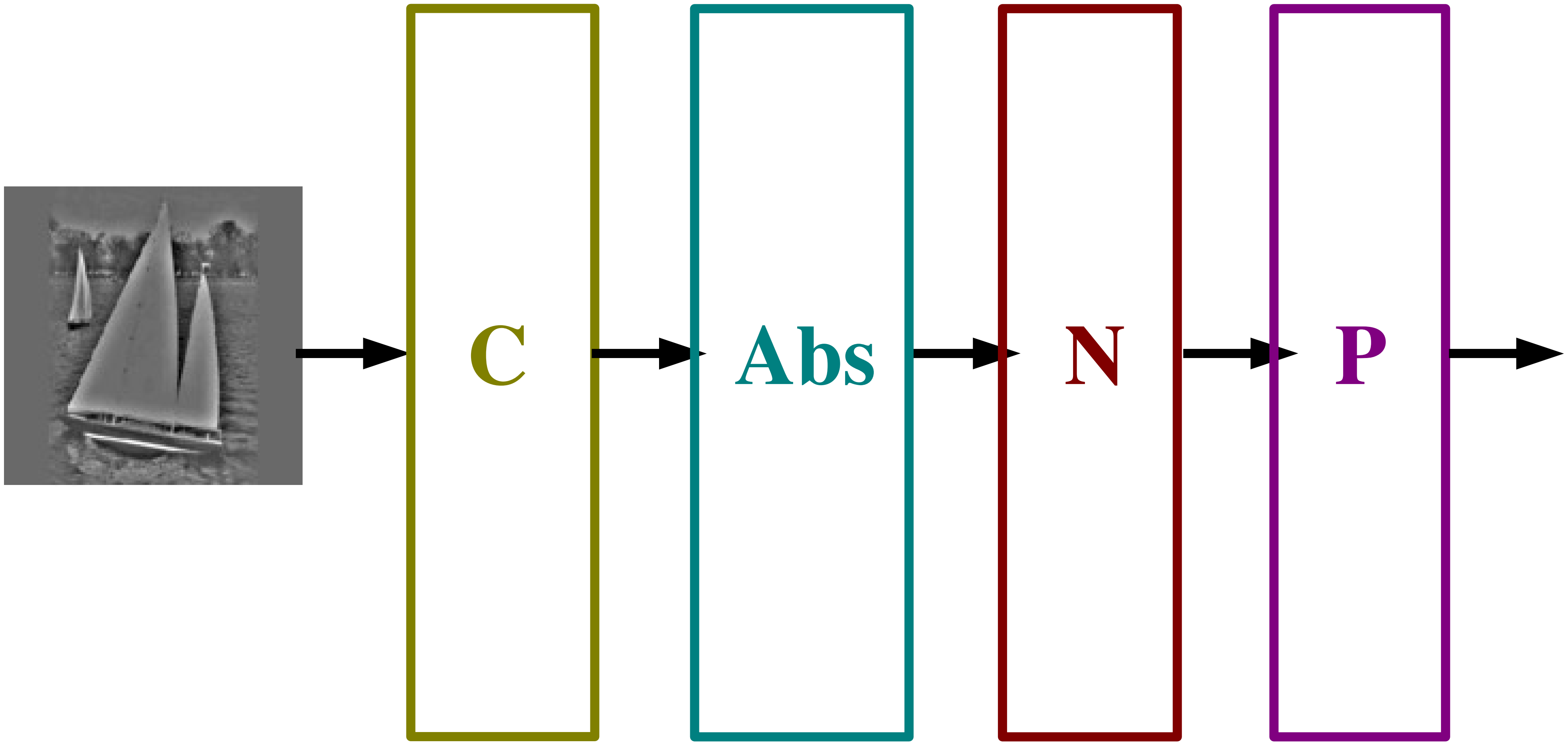
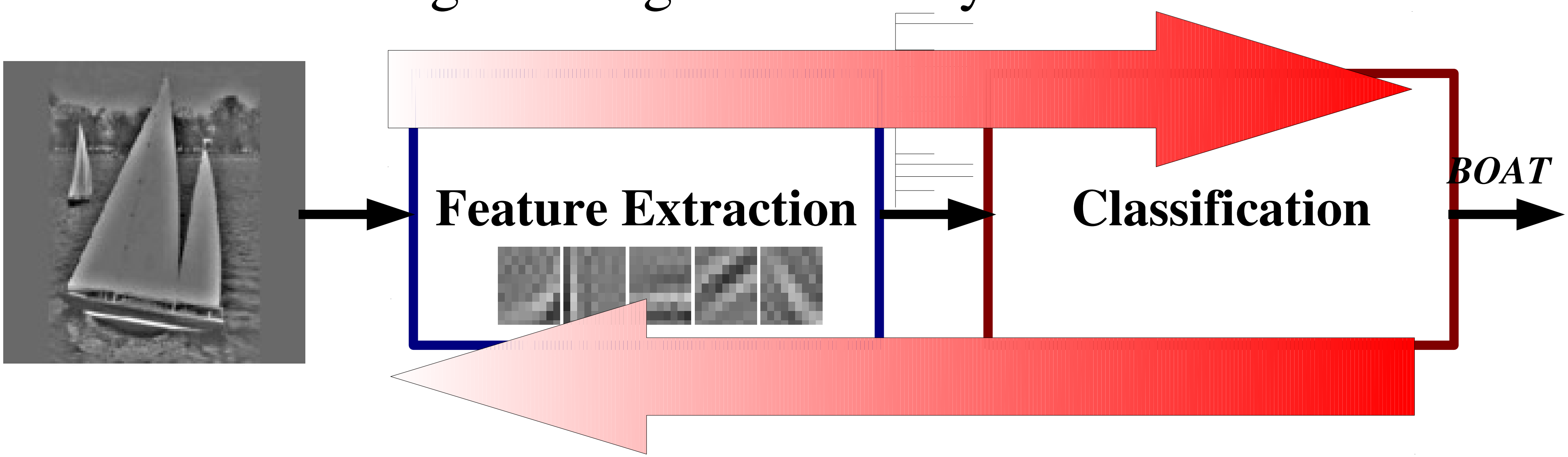


THIS IS ONE STAGE OF FEATURE EXTRACTION

Training Protocol

- **Training**
  - Logistic Regression on Random Features: R
  - Logistic Regression on PSD features: U
  - Refinement of whole net from random with backprop: R^+
  - Refinement of whole net starting from PSD filters: U^+
- **Classifier**
  - Multinomial Logistic Regression or Pyramid Match Kernel SVM



Using PSD Features for Recognition

$[64.F^{9\times9}_{CSG} - R/N/P^{5\times5}]$ - 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(±1.6)%	44.0%	17.2%	13.4%
R	53.3%	31.7%	32.1%	15.3%	12.1(±2.2)%
$[64.F^{9\times9}_{CSG} - R/N/P^{5\times5}]$ - PMK					
U	65.0%				

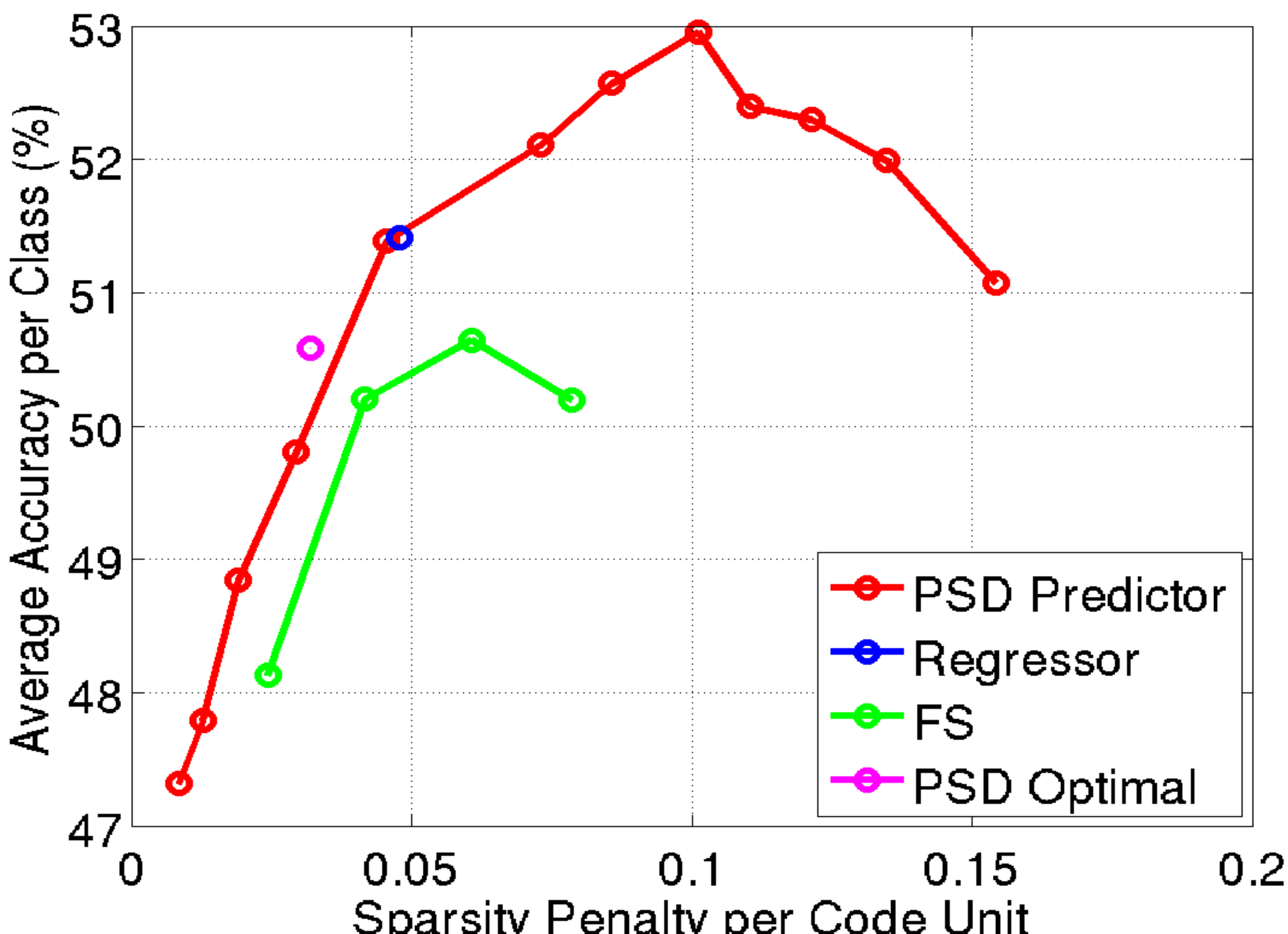
$[96.F^{9\times9}_{CSG} - R/N/P^{5\times5}]$ - PCA - lin_svm	
U	58.0%
96.Gabors - PCA - lin_svm (Pinto and DiCarlo 2006)	
Gabors	59.0%
SIFT - PMK (Lazebnik et al. CVPR 2006)	
Gabors	64.6%

Using PSD Features for Recognition

- **Rectification makes a huge difference:**
  - 14.5% -> 50.0%, without normalization
  - 44.3% -> 54.2% with normalization
- **Normalization makes a difference:**
  - 50.0 → 54.2
- **Unsupervised pretraining makes small difference**
- **PSD works just as well as SIFT**
- **Random filters work as well as anything!**
  - If rectification/normalization is present
- **PMK_SVM classifier works a lot better than multinomial log_reg on low-level features**
  - 52.2% → 65.0%

Comparing Optimal Codes Predicted Codes on Caltech 101

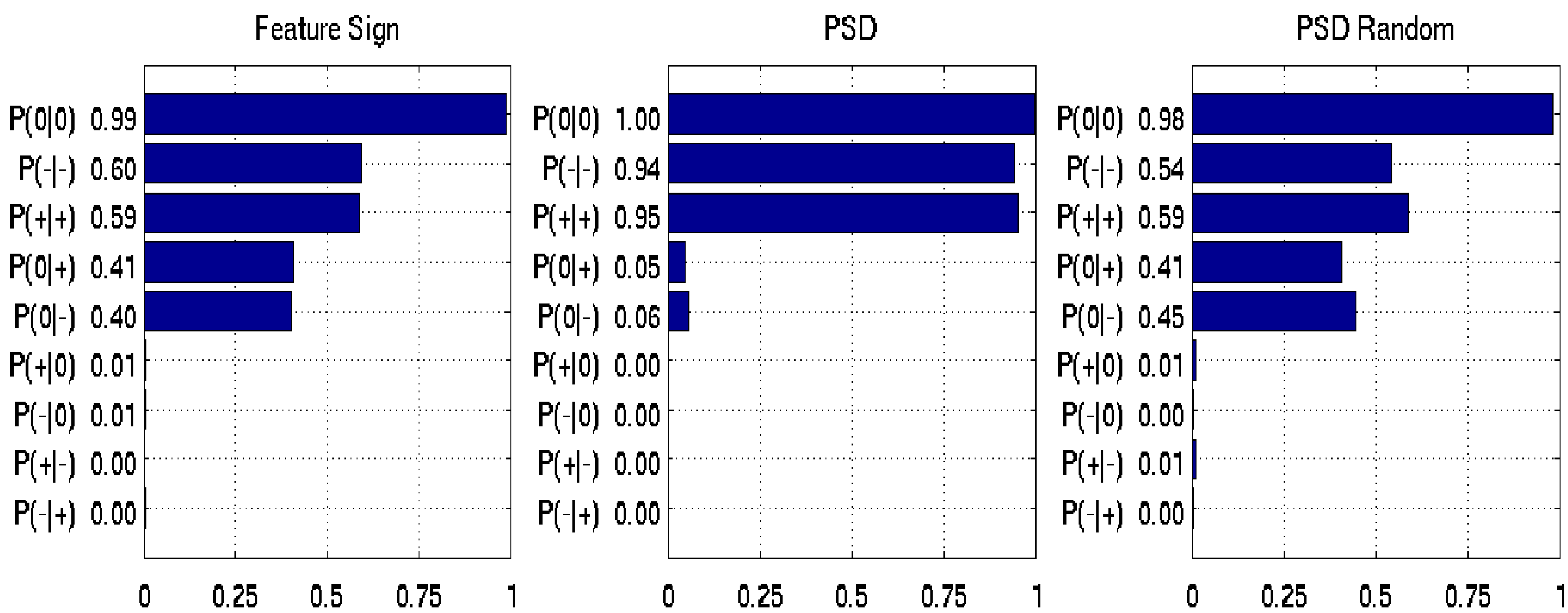
- **Approximated Sparse Features Predicted by PSD give better recognition results than Optimal Sparse Features computed with Feature Sign!**
  - PSD features are more stable.



Feature Sign (FS) is an optimization methods for computing sparse codes [Lee...Ng 2006]

PSD Features are more stable

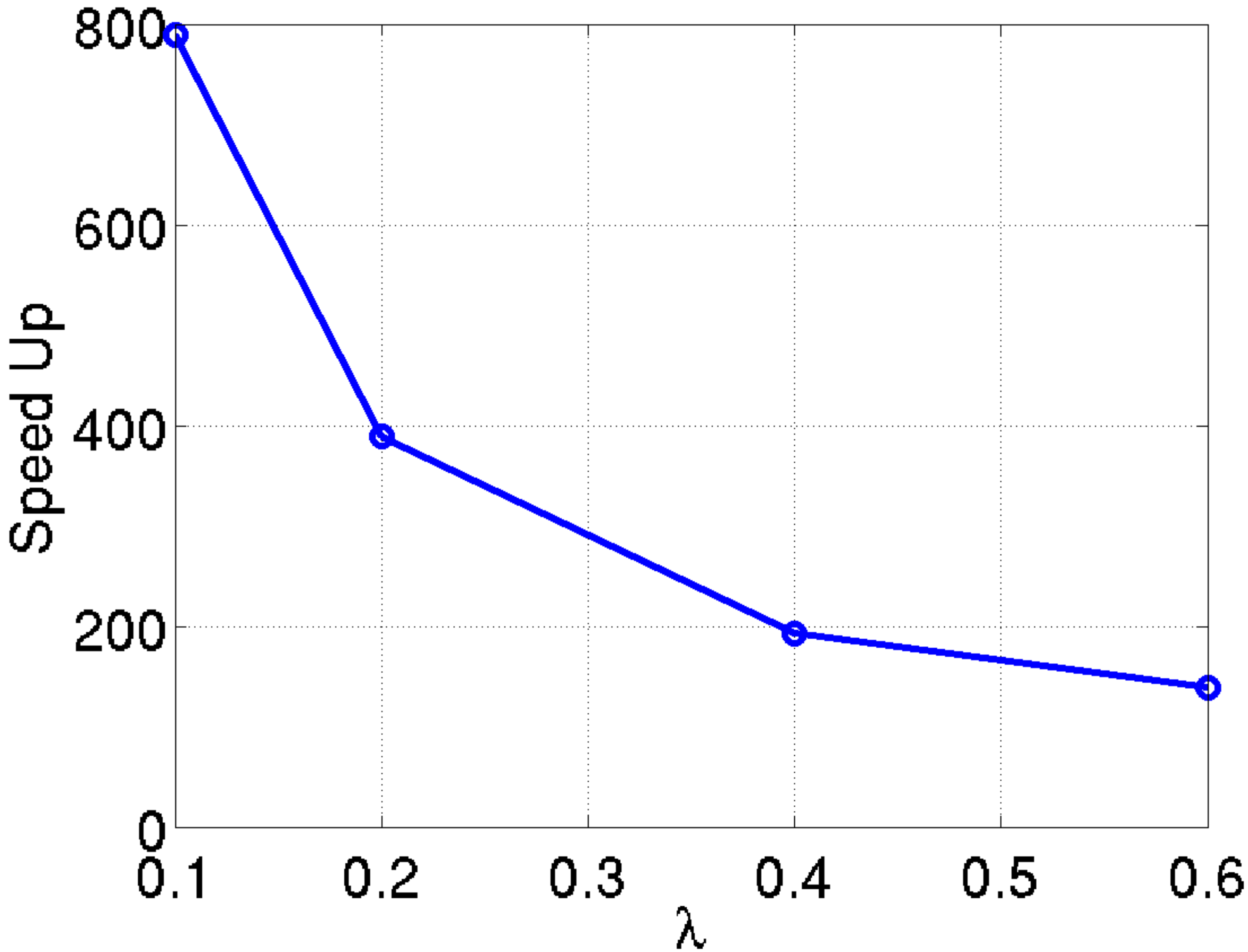
- **Approximated Sparse Features Predicted by PSD give better recognition results than Optimal Sparse Features computed with Feature Sign!**
- **Because PSD features are more stable. Feature obtained through sparse optimization can change a lot with small changes of the input.**



How many features change sign in patches from successive video frames (a,b), versus patches from random frame pairs (c)

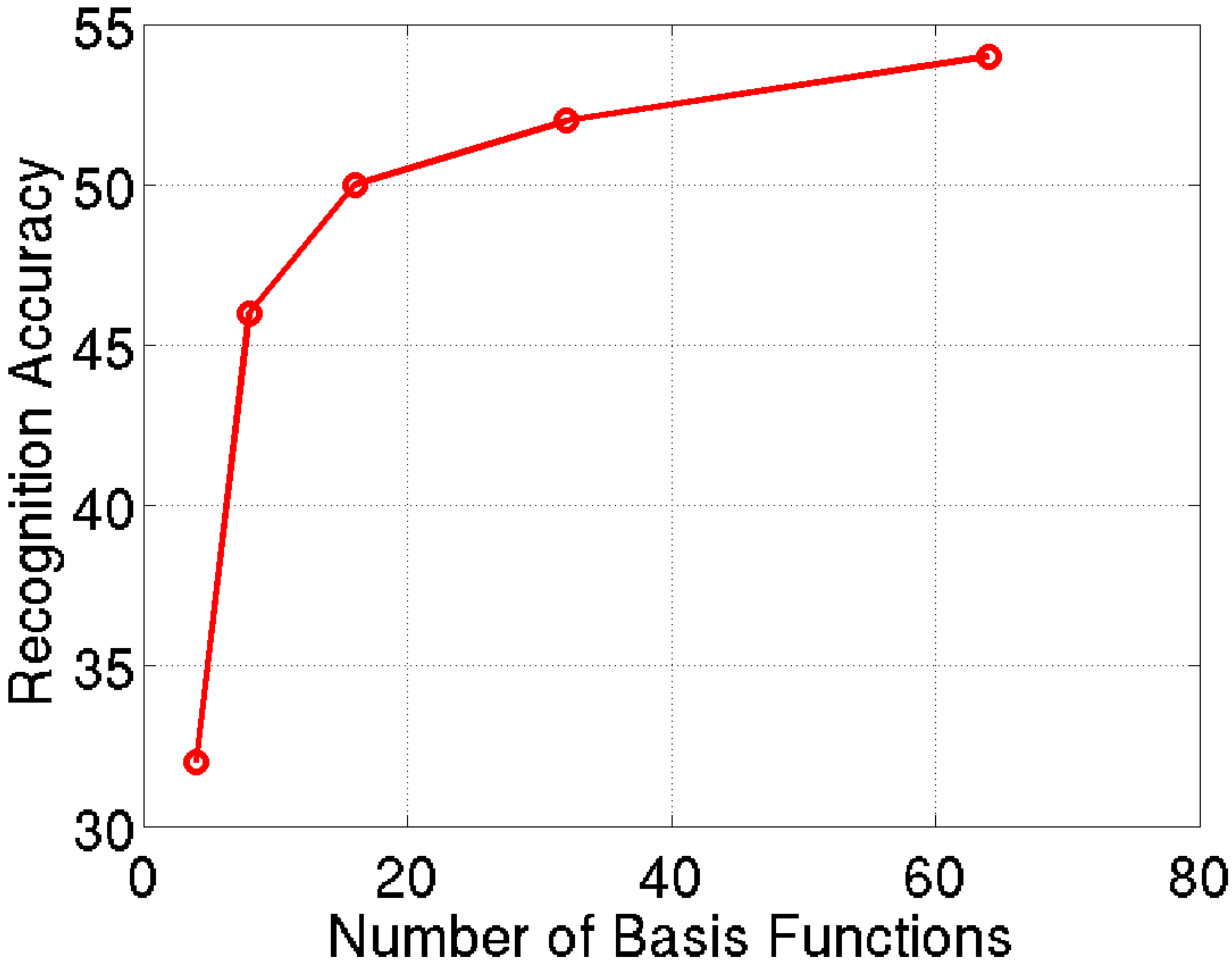
PSD features are much cheaper to compute

- **Computing PSD features is hundreds of times cheaper than Feature Sign.**

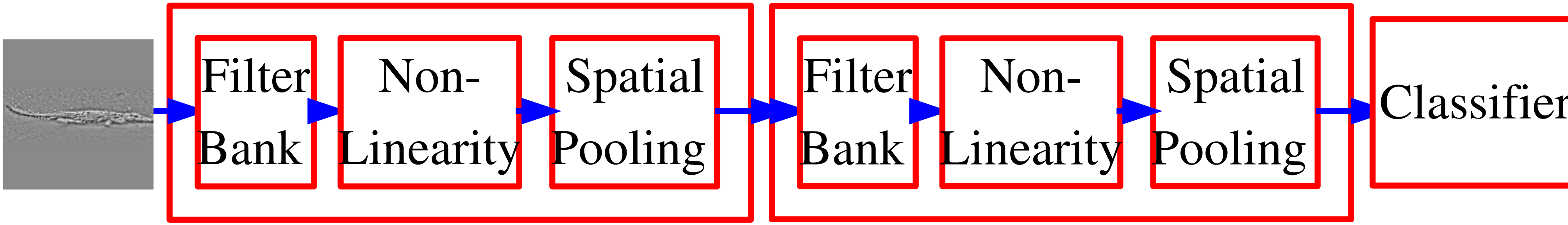


How Many 9x9 PSD features do we need?

- Accuracy increases slowly past 64 filters.

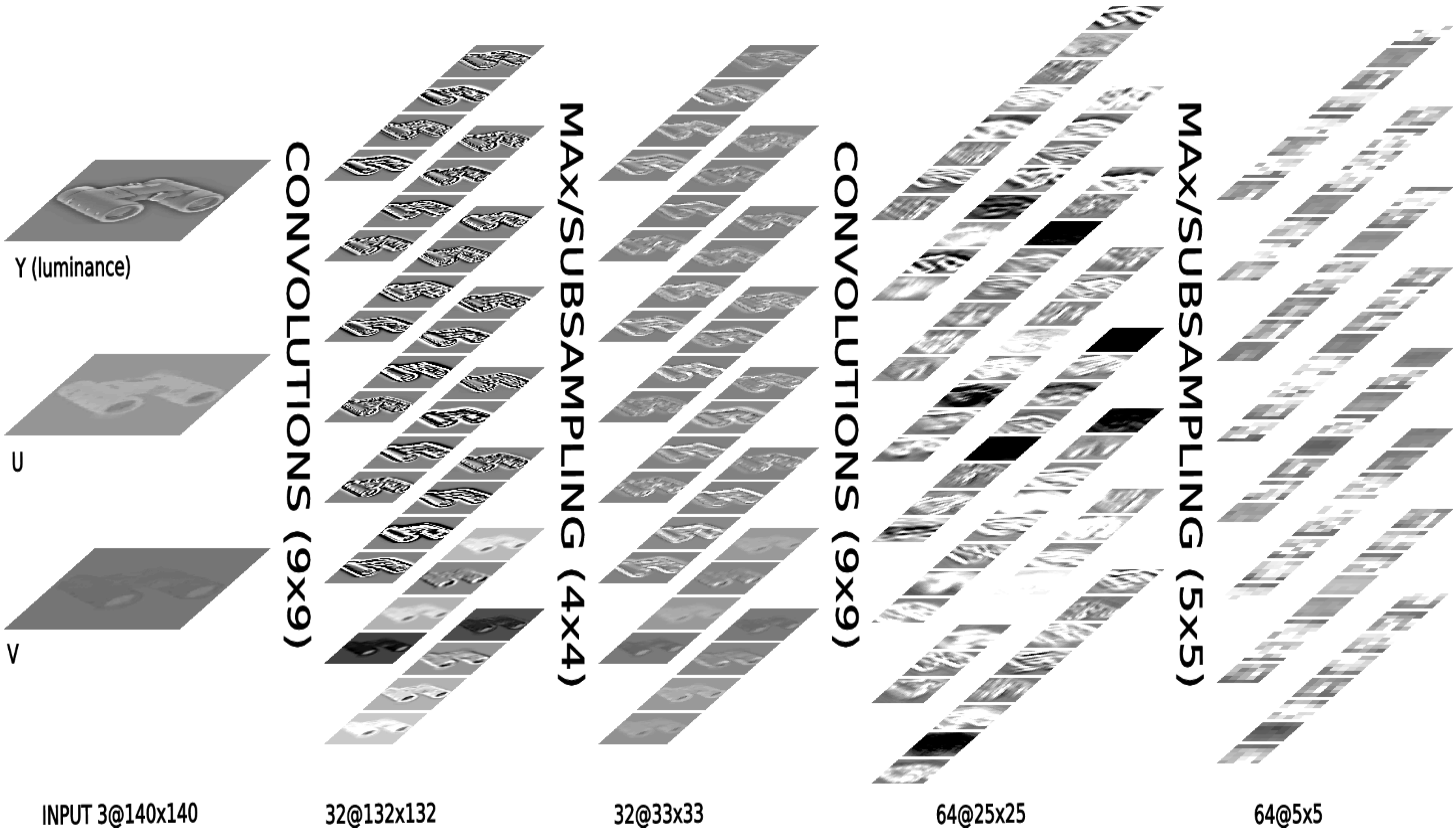


Training a Multi-Stage Hubel-Wiesel Architecture with PSD



- **1. Train stage-1 filters with PSD on patches from natural images**
- **2. Compute stage-1 features on training set**
- **3. Train state-2 filters with PSD on stage-1 feature patches**
- **4. Compute stage-2 features on training set**
- **5. Train linear classifier on stage-2 features**
- **6. Refine entire network with supervised gradient descent**
- **What are the effects of the non-linearities and unsupervised pretraining?**

Multistage Hubel-Wiesel Architecture on Caltech-101



Multistage Hubel-Wiesel Architecture

- **Image Preprocessing:**
  - High-pass filter, local contrast normalization (divisive)
- **First Stage:**
  - Filters: 64 9x9 kernels producing 64 feature maps
  - Pooling: 10x10 averaging with 5x5 subsampling
- **Second Stage:**
  - Filters: 4096 9x9 kernels producing 256 feature maps
  - Pooling: 6x6 averaging with 3x3 subsampling
  - Features: 256 feature maps of size 4x4 (4096 features)
- **Classifier Stage:**
  - Multinomial logistic regression
- **Number of parameters:**
  - Roughly 750,000

Multistage Hubel-Wiesel Architecture on Caltech-101

Single Stage System: $[64.F^{9\times9}_{CSG} - R/N/P^{5\times5}]$ - 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%(±1.6)	44.0%	17.2%	13.4%
R	53.3%	31.7%	32.1%	15.3%	12.1%(±2.2)
G	52.3%				
Two Stage System: $[64.F^{9\times9}_{CSG} - R/N/P^{5\times5}] - [256.F^{9\times9}_{CSG} - R/N/P^{4\times4}]$ **- 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%(±1.5)	37.6%(±1.9)	19.6%	8.8%
GT	55.8%	← like HMAX model			
Single Stage: $[64.F^{9\times9}_{CSG} - R/N/P^{5\times5}]$ **- PMK-SVM**					
U	64.0%				
Two Stages: $[64.F^{9\times9}_{CSG} - R/N/P^{5\times5}] - [256.F^{9\times9}_{CSG} - R/N]$ **- PMK-SVM**					
UU	52.8%				

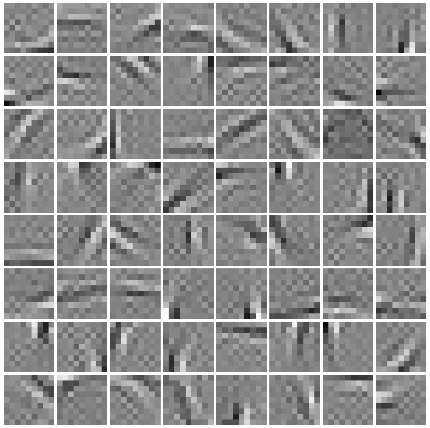
Two-Stage Result Analysis

- Second Stage + logistic regression = PMK_SVM
- Unsupervised pre-training doesn't help much :-(
- Random filters work amazingly well with normalization
- Supervised global refirnement helps a bit
- The best system is really cheap
- Either use rectification and average pooling or no rectification and max pooling.

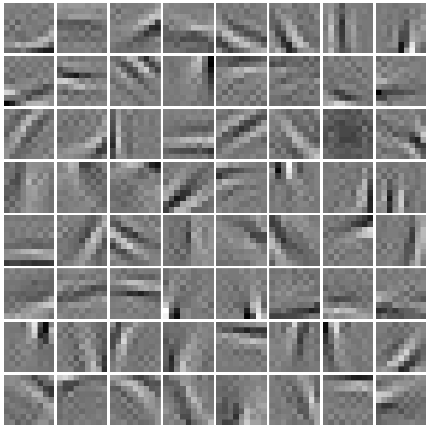
Multistage Hubel-Wiesel Architecture: Filters

- After PSD
- After supervised refinement

- Stage 1

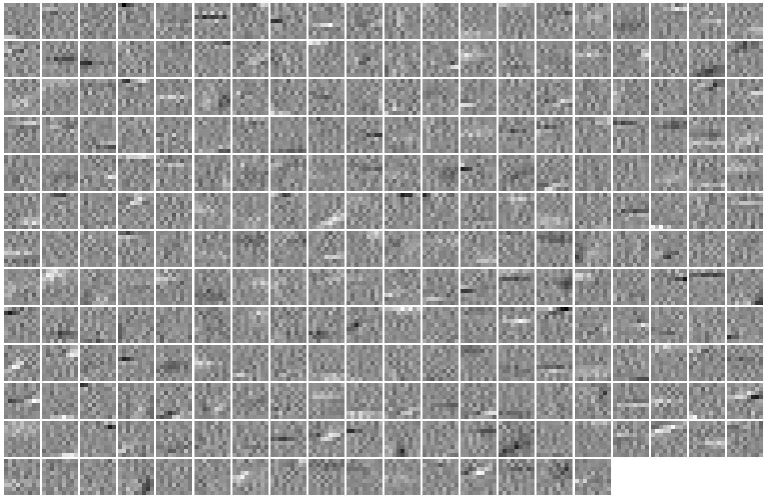


weights :-0.2232 - 0.2075

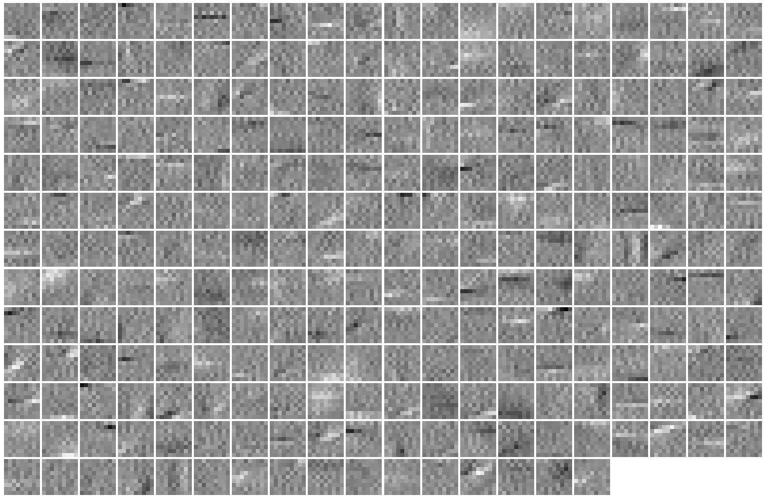


weights :-0.2828 - 0.3043

- Stage2

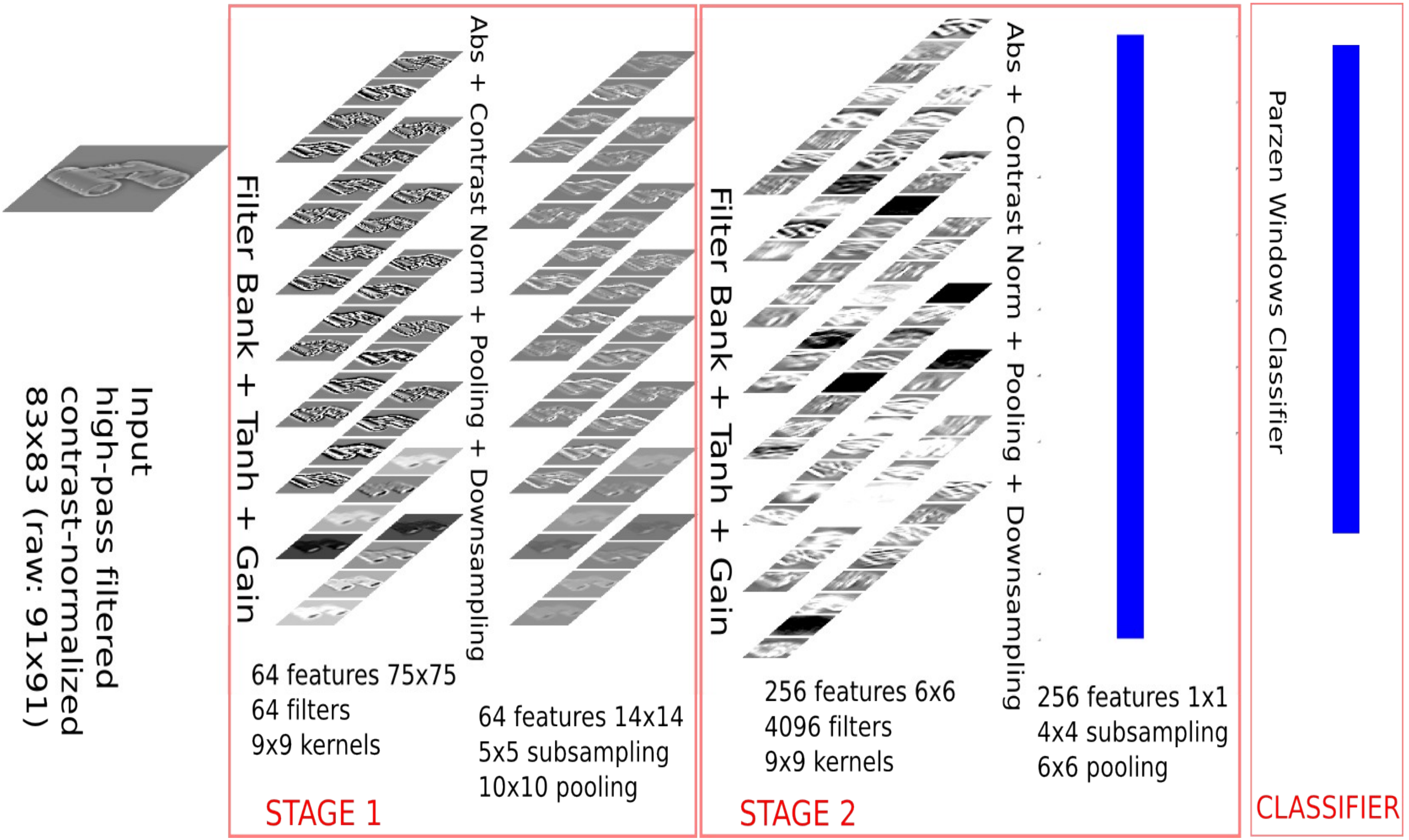


weights :-0.0778 - 0.064



weights :-0.0929 - 0.0784

Demo: real-time learning of visual categories

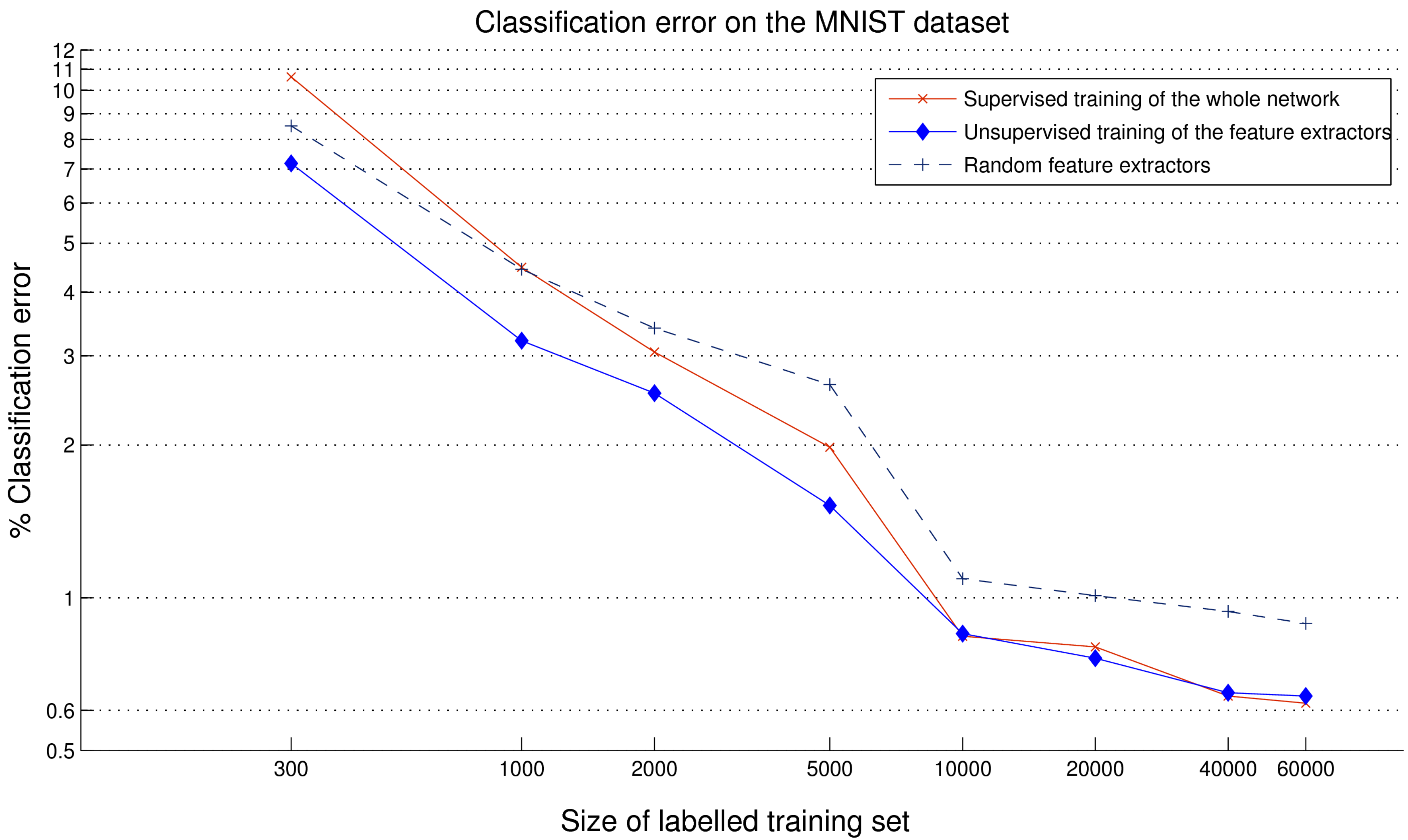


MNIST dataset

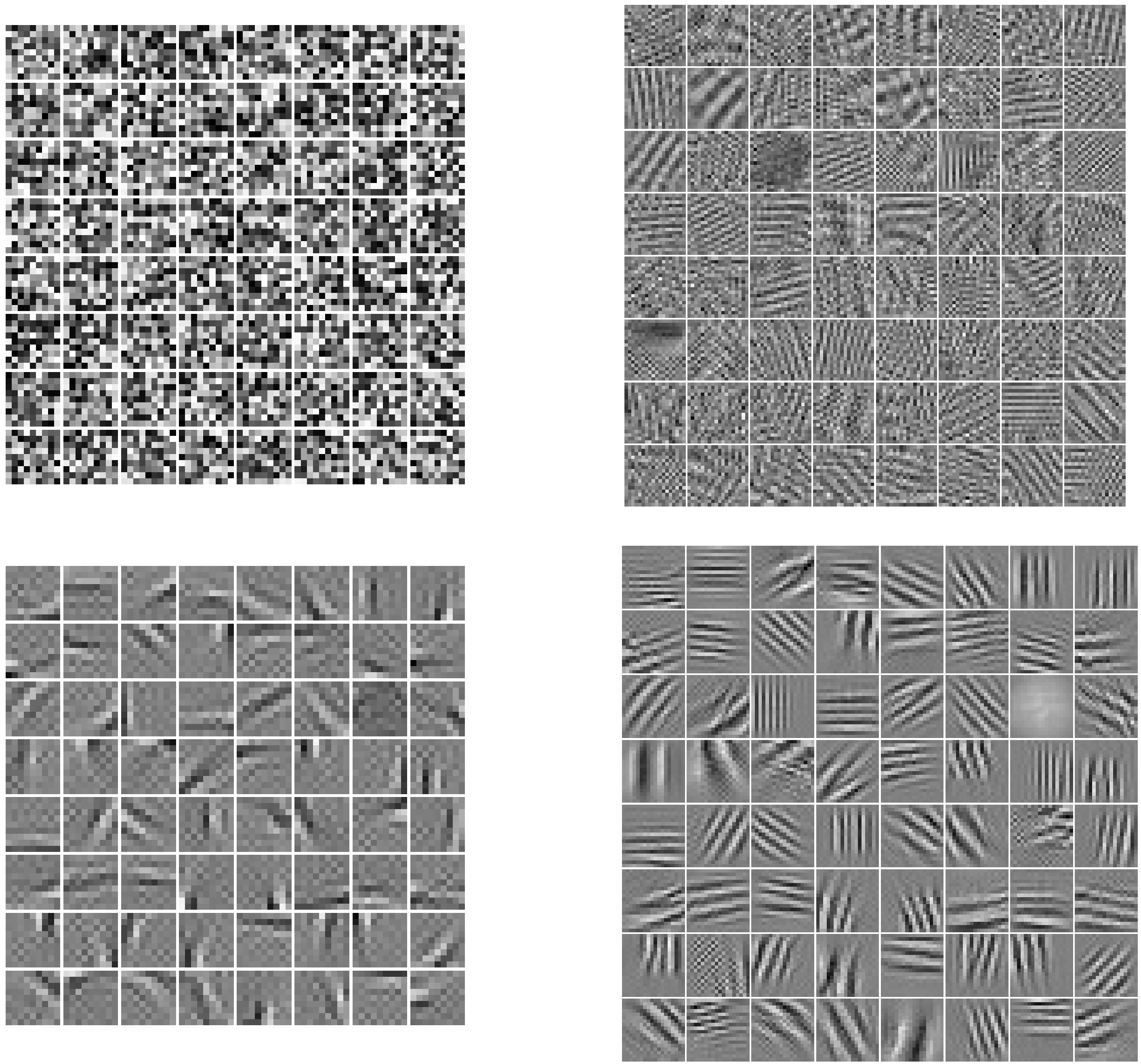
- 10 classes and up to 60,000 training samples per class

MNIST dataset

- **Architecture**
  - U^+U^+: 0.53% error (this is a record on the undistorted MNIST!)
  - Comparison: RR versus UU and R^+R^+



Why Random Filters Work?



The Competition: SIFT + Sparse-Coding + PMK-SVM

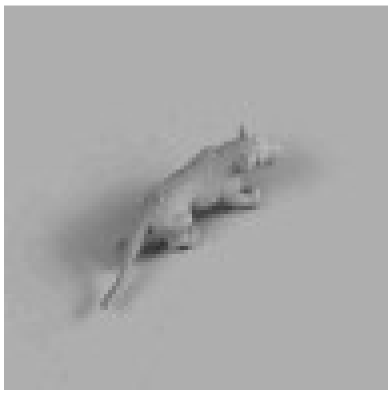
Replacing K-means with Sparse Coding

- [Yang 2008] [Boureau, Bach, Ponce, LeCun 2010]

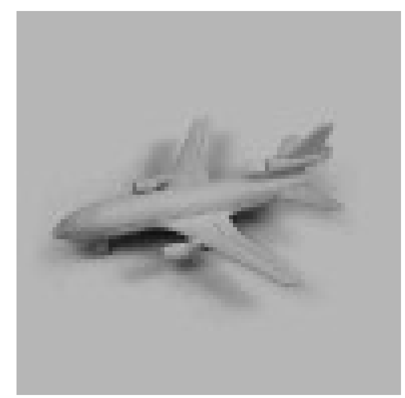
	Method	Caltech 15	Caltech 30	Scenes
Boiman et al. [1]	Nearest neighbor + spatial correspondence	65.00 ± 1.14	70.40	-
Jain et al. [8]	Fast image search for learned metrics	61.00	69.60	-
Lazebnik et al. [12]	Spatial Pyramid + hard quantization + kernel SVM	56.40	64.40 ± 0.80	81.40 ± 0.50
van Gemert et al. [24]	Spatial Pyramid + soft quantization + kernel SVM	–	64.14 ± 1.18	76.67 ± 0.39
Yang et al. [26]	SP + sparse codes + max pooling + linear	**67.00±0.45**	**73.2±0.54**	80.28 ± 0.93
Zhang et al. [27]	kNN-SVM	59.10 ± 0.60	66.20 ± 0.50	-
Zhou et al. [29]	SP + Gaussian mixture	–	–	**84.1 ± 0.5**
Baseline:	SP + hard quantization + avg pool + kernel SVM	56.74 ± 1.31	64.19 ± 0.94	80.89 ± 0.21
Unsupervised coding	SP + soft quantization + avg pool + kernel SVM	59.12 ± 1.51	66.42 ± 1.26	81.52 ± 0.54
1×1 features	SP + soft quantization + max pool + kernel SVM	63.61 ± 0.88	–	83.41 ± 0.57
8 pixel grid resolution	SP + sparse codes + avg pool + kernel SVM	62.85 ± 1.22	70.27 ± 1.29	83.15 ± 0.35
	SP + sparse codes + max pool + kernel SVM	64.62 ± 0.94	**71.81±0.96**	**84.25 ± 0.35**
	SP + sparse codes + max pool + linear	**64.71 ± 1.05**	71.52 ± 1.13	83.78 ± 0.53
Macrofeatures +	SP + sparse codes + max pool + kernel SVM	**69.03±1.17**	**75.72±1.06**	**84.60 ± 0.38**
Finer grid resolution	SP + sparse codes + max pool + linear	68.78 ± 1.09	75.14 ± 0.86	84.41 ± 0.26

Small NORB dataset

- 5 classes and up to 24,300 training samples per class



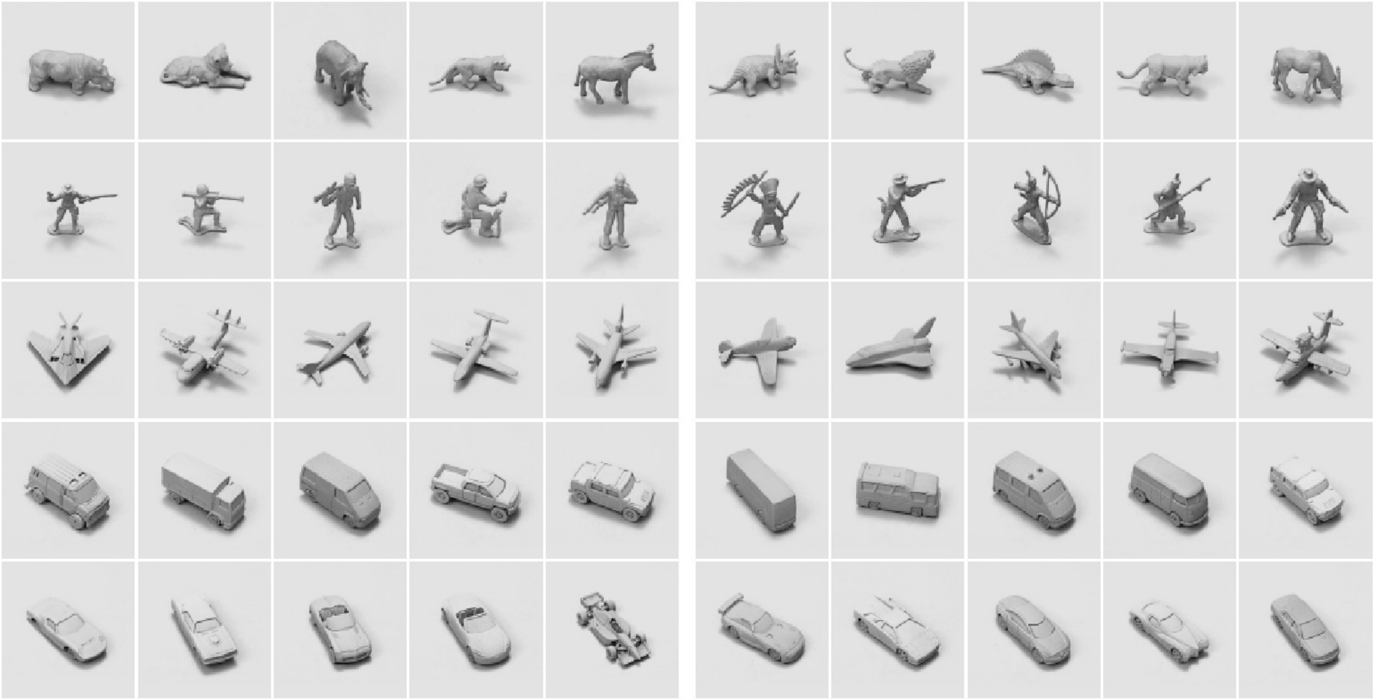


NORB Generic Object Recognition Dataset

- **50** toys belonging to 5 categories: **animal, human figure, airplane, truck, car**
- **10** instance per category: 5 instances used for training, 5 instances for testing
- **Raw dataset: 972** stereo pair of each object instance. **48,600** image pairs total.

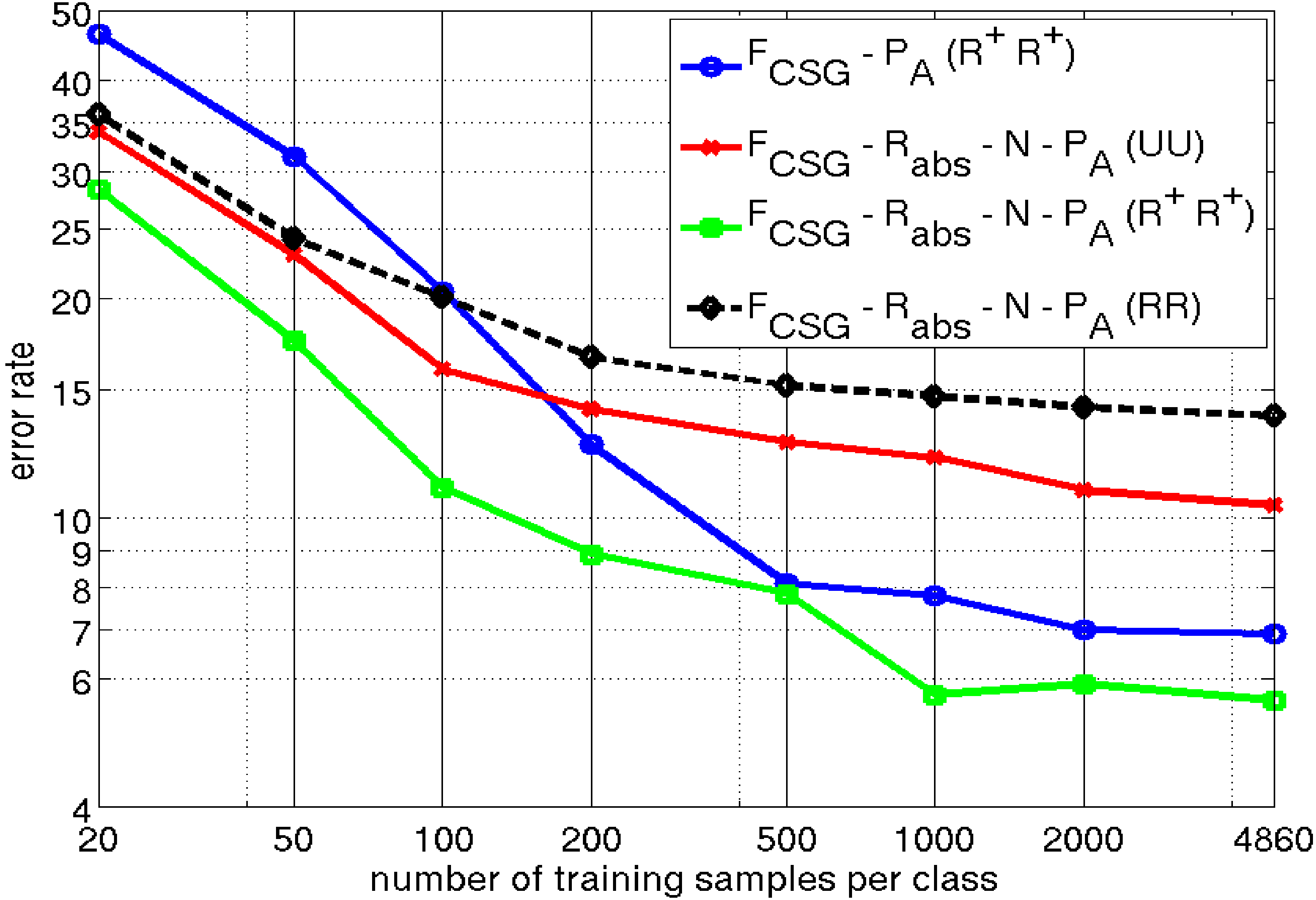
- **For each instance:**
- **18 azimuths**
  - 0 to 350 degrees every 20 degrees
- **9 elevations**
  - 30 to 70 degrees from horizontal every 5 degrees
- **6 illuminations**
  - on/off combinations of 4 lights
- **2 cameras (stereo)**
  - 7.5 cm apart
  - 40 cm from the object



Training instances **Test instances**

Small NORB dataset

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

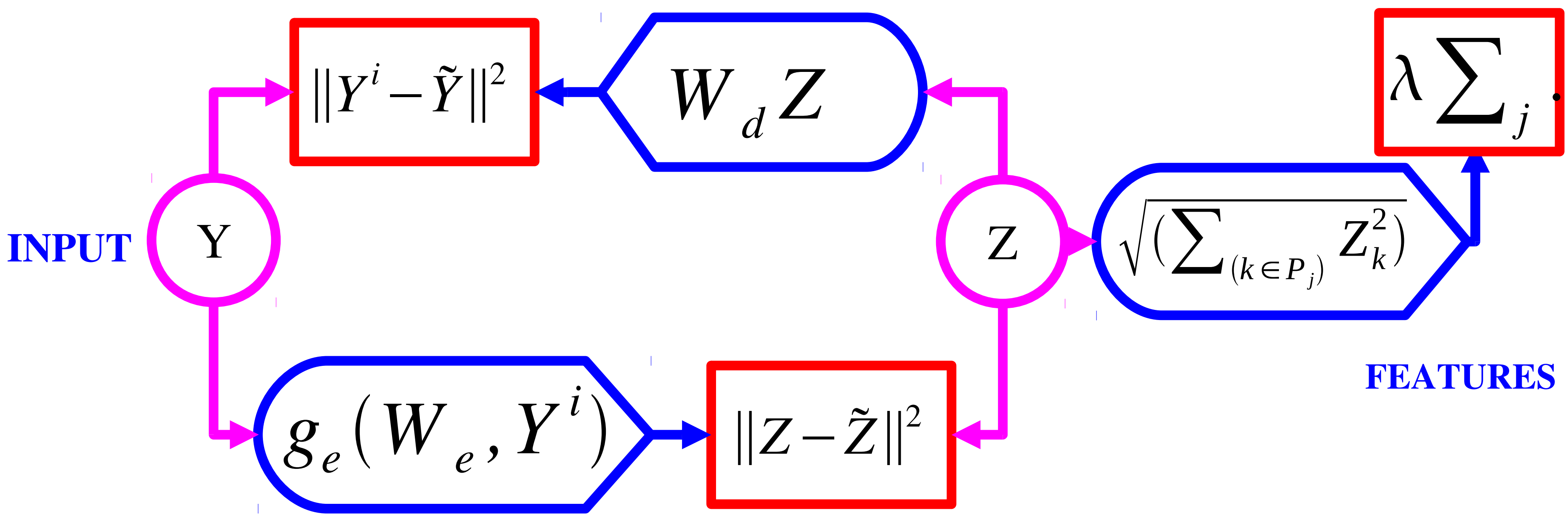


Learning Complex Cells with Invariance Properties

[Kavukcuoglu et al. CVPR 2008]

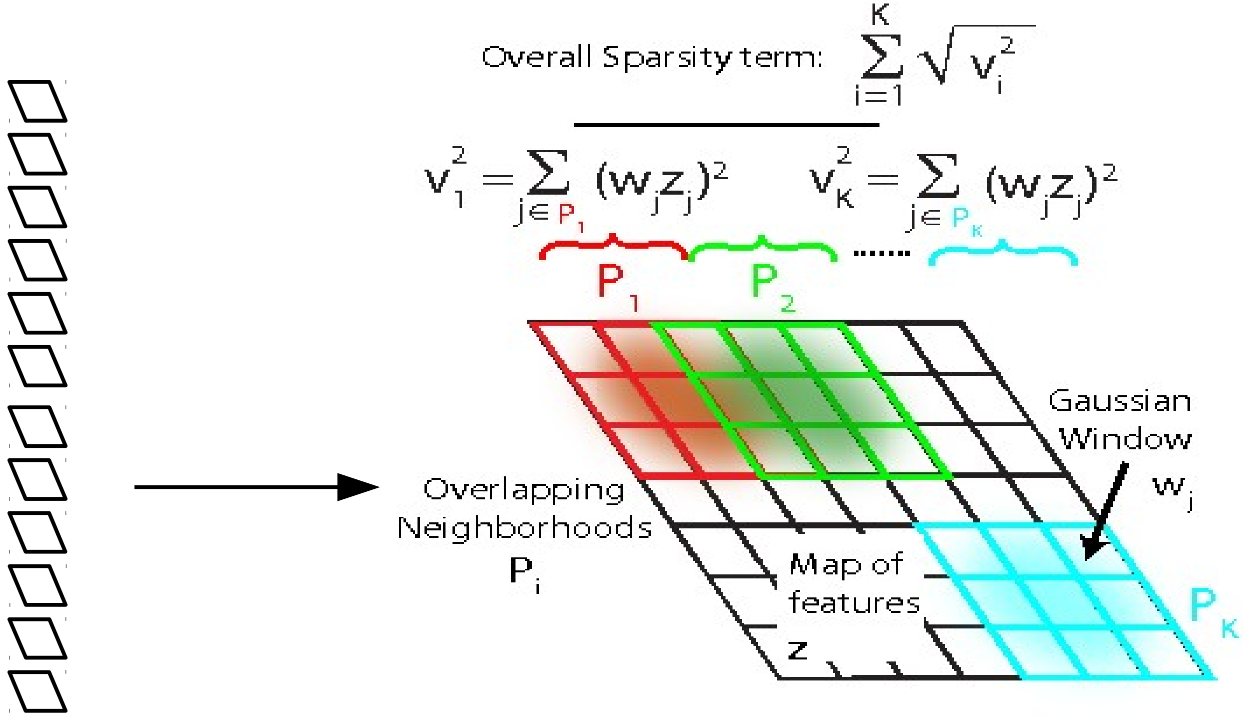
Learning Invariant Features [Kavukcuoglu et al. CVPR 2009]

- **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
  - Polls tend to regroup similar features



Learning the filters and the pools

- **Using an idea from Hyvarinen: topographic square pooling (subspace ICA)**
  - 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

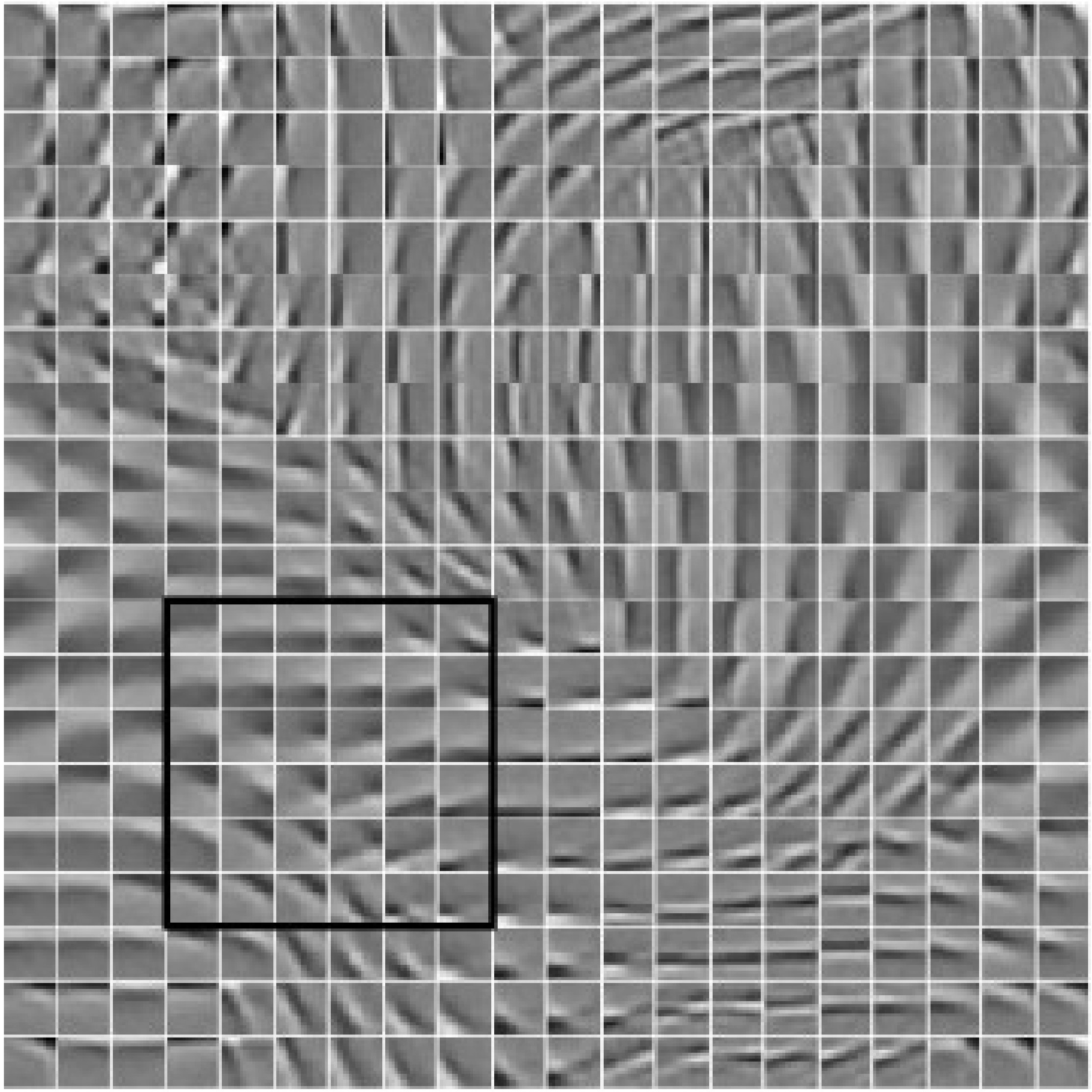


Units in the code Z

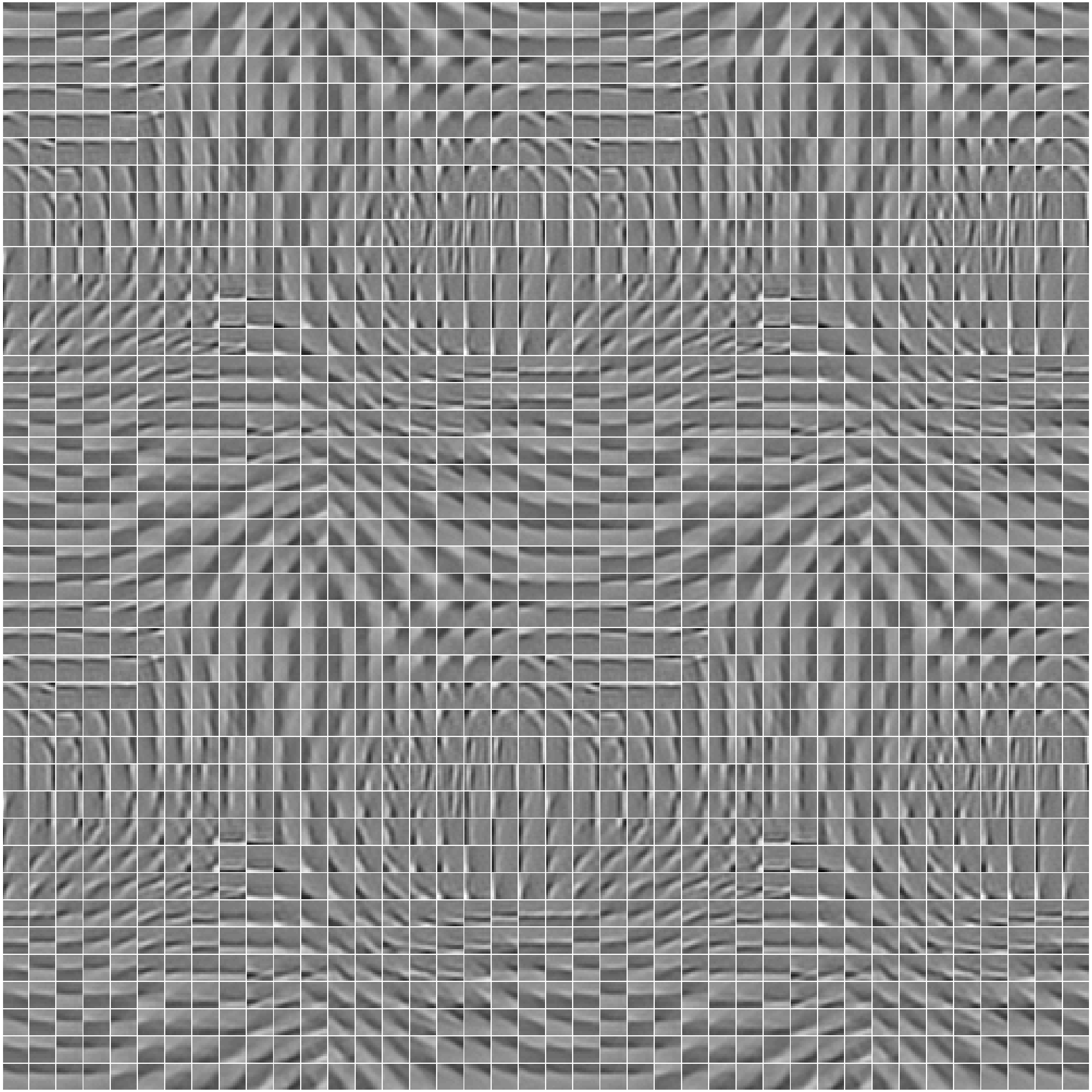
Define pools and enforce sparsity across pools

Learning the filters and the pools

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

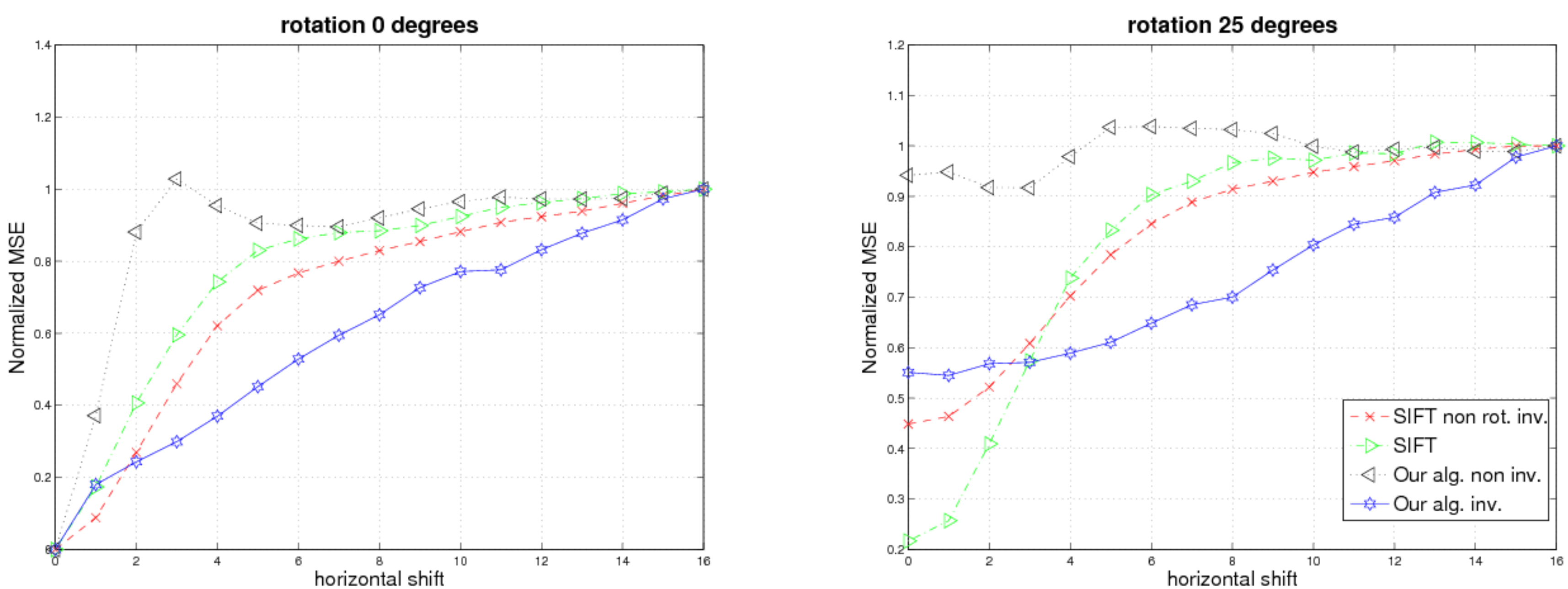


Pinwheels?



Invariance Properties Compared to SIFT

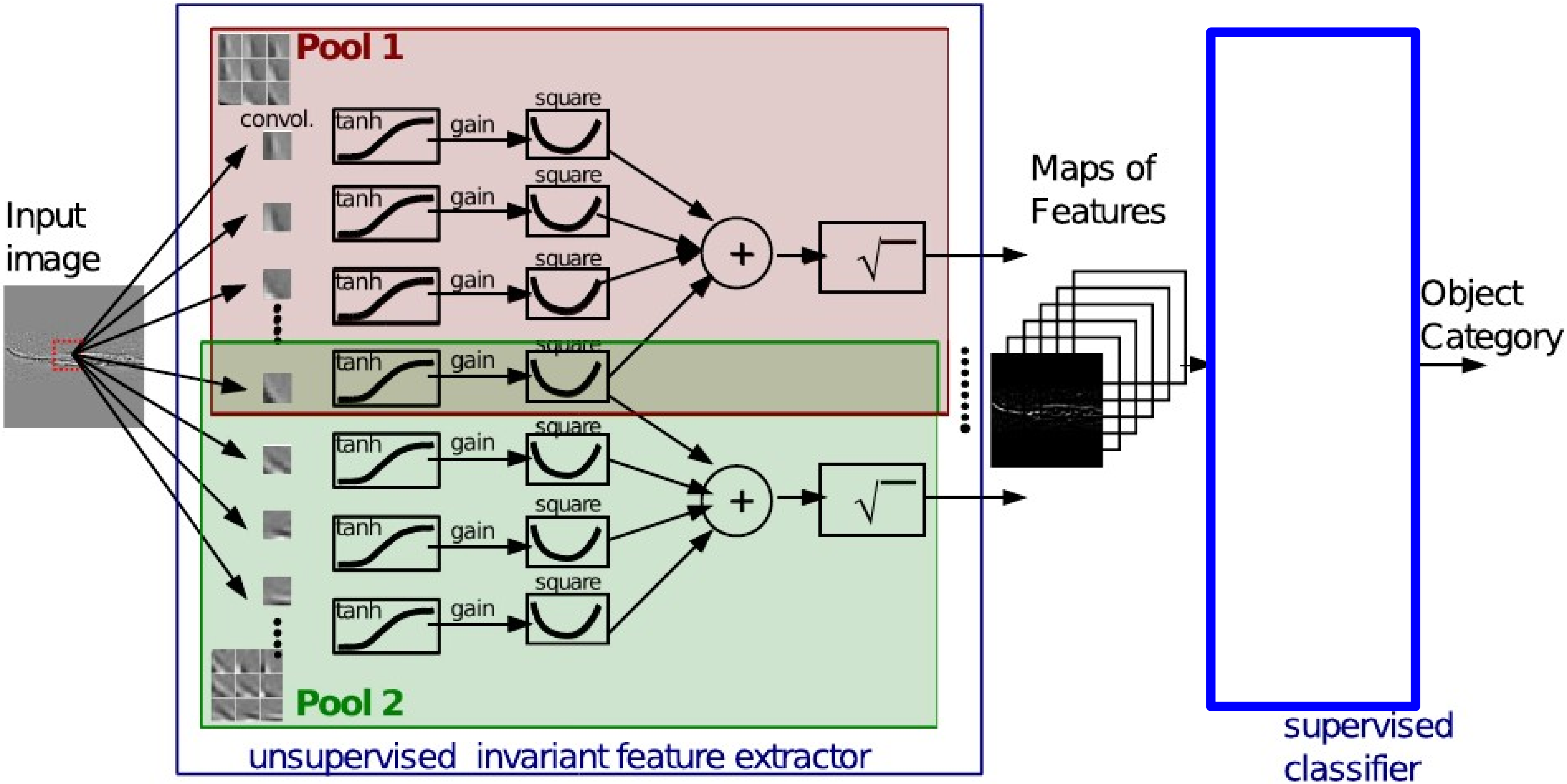
- **Measure distance between feature vectors (128 dimensions) of 16x16 patches from natural images**
  - Left: normalized distance as a function of translation
  - Right: normalized distance as a function of translation when one patch is rotated 25 degrees.
- **Topographic PSD features are more invariant than SIFT**



Learning Invariant Features

Recognition Architecture

- ->HPF/LCN->filters->tanh->sqr->pooling->sqrt->Classifier
- Block pooling plays the same role as rectification



Recognition Accuracy on Caltech 101

- A/B Comparison with SIFT (128x34x34 descriptors)
- 32x16 topographic map with 16x16 filters
- Pooling performed over 6x6 with 2x2 subsampling
- 128 dimensional feature vector per 16x16 patch
- Feature vector computed every 4x4 pixels (128x34x34 feature maps)
- Resulting feature maps are spatially smoothed

Method	Av. Accuracy/Class (%)
local norm$_{5\times5}$ + boxcar$_{5\times5}$ + PCA$_{3060}$ + linear SVM	
IPSD (24x24)	**50.9**
SIFT (24x24) (non rot. inv.)	**51.2**
SIFT (24x24) (rot. inv.)	**45.2**
Serre et al. features [25]	**47.1**
local norm$_{9\times9}$ + Spatial Pyramid Match Kernel SVM	
SIFT [11]	**64.6**
IPSD (34x34)	**59.6**
IPSD (56x56)	**62.6**
IPSD (120x120)	**65.5**

Recognition Accuracy on Tiny Images & MNIST

- A/B Comparison with SIFT (128x5x5 descriptors)
- 32x16 topographic map with 16x16 filters.

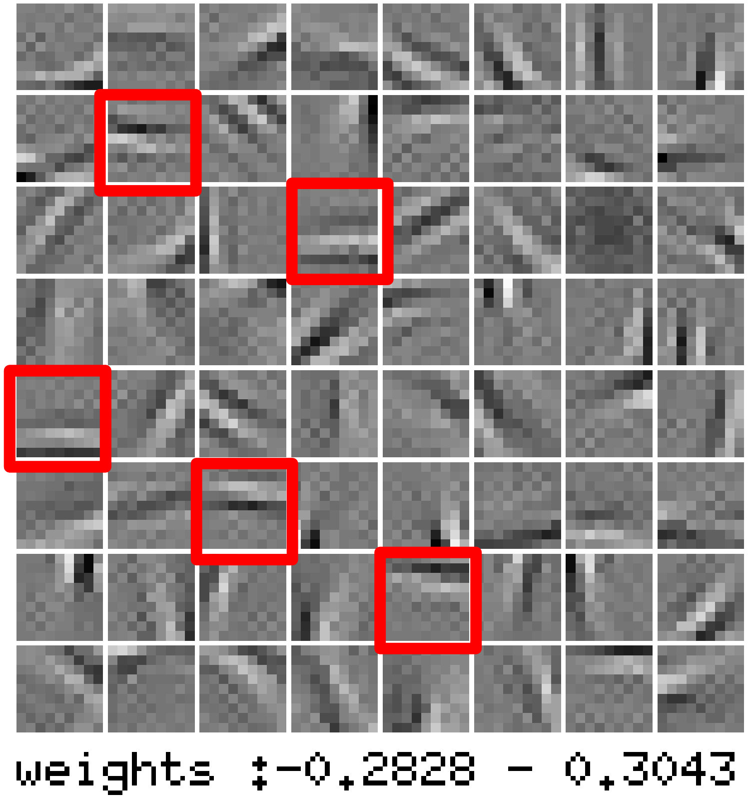
Performance on Tiny Images Dataset	
Method	**Accuracy** (%)
IPSD (5x5)	**54**
SIFT (5x5) (non rot. inv.)	**53**

Performance on MNIST Dataset	
Method	**Error Rate** (%)
IPSD (5x5)	**1.0**
SIFT (5x5) (non rot. inv.)	**1.5**

Learning fields of Convolutional Filters

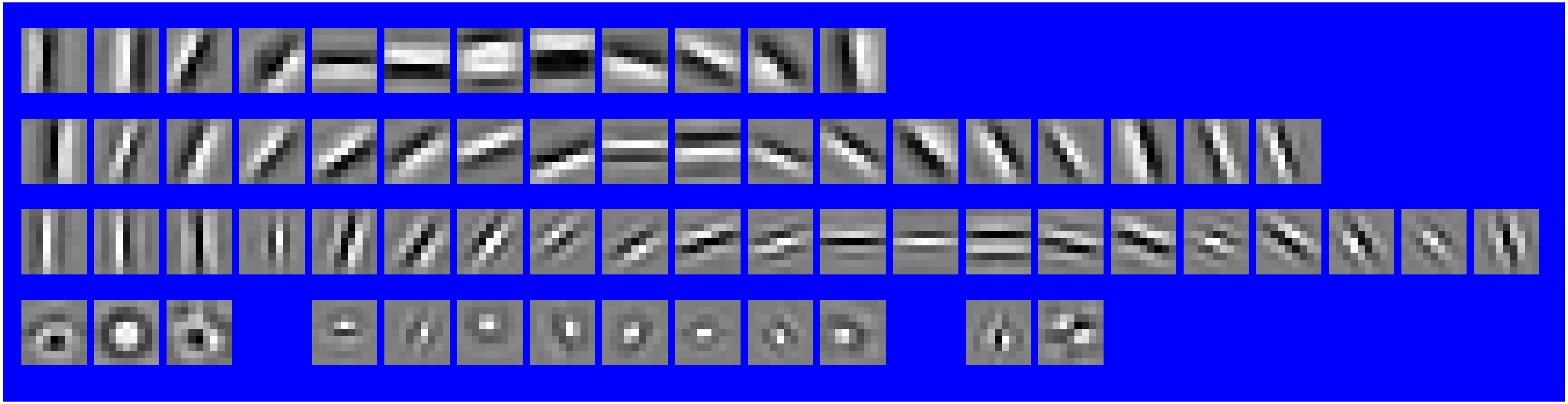
Convolutional Training

- **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



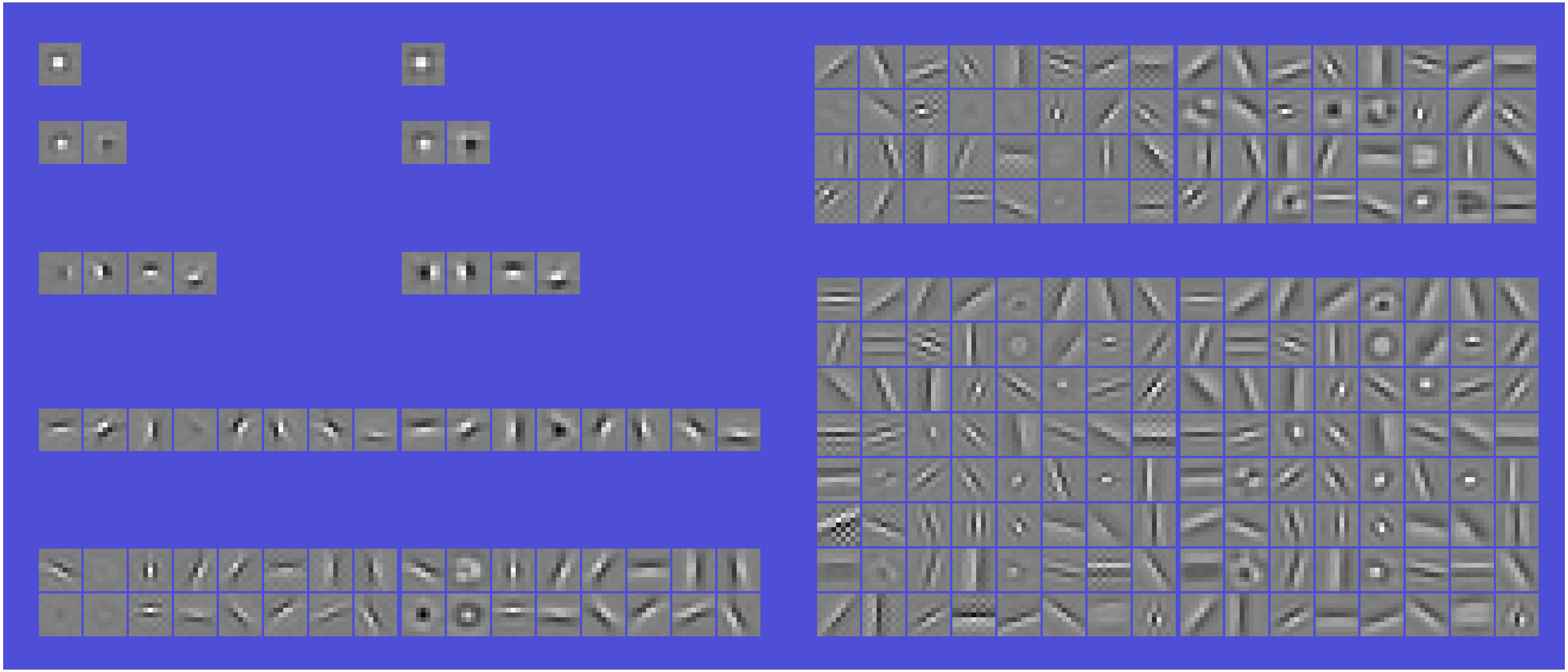
Convolutional Training

- **Problem with patch-based training: high correlation between outputs of filters from overlapping receptive fields.**



Convolutional Training

- **Filters and Basis Functions obtained with 1, 2, 4, 8, 16, 32, and 64 filters.**

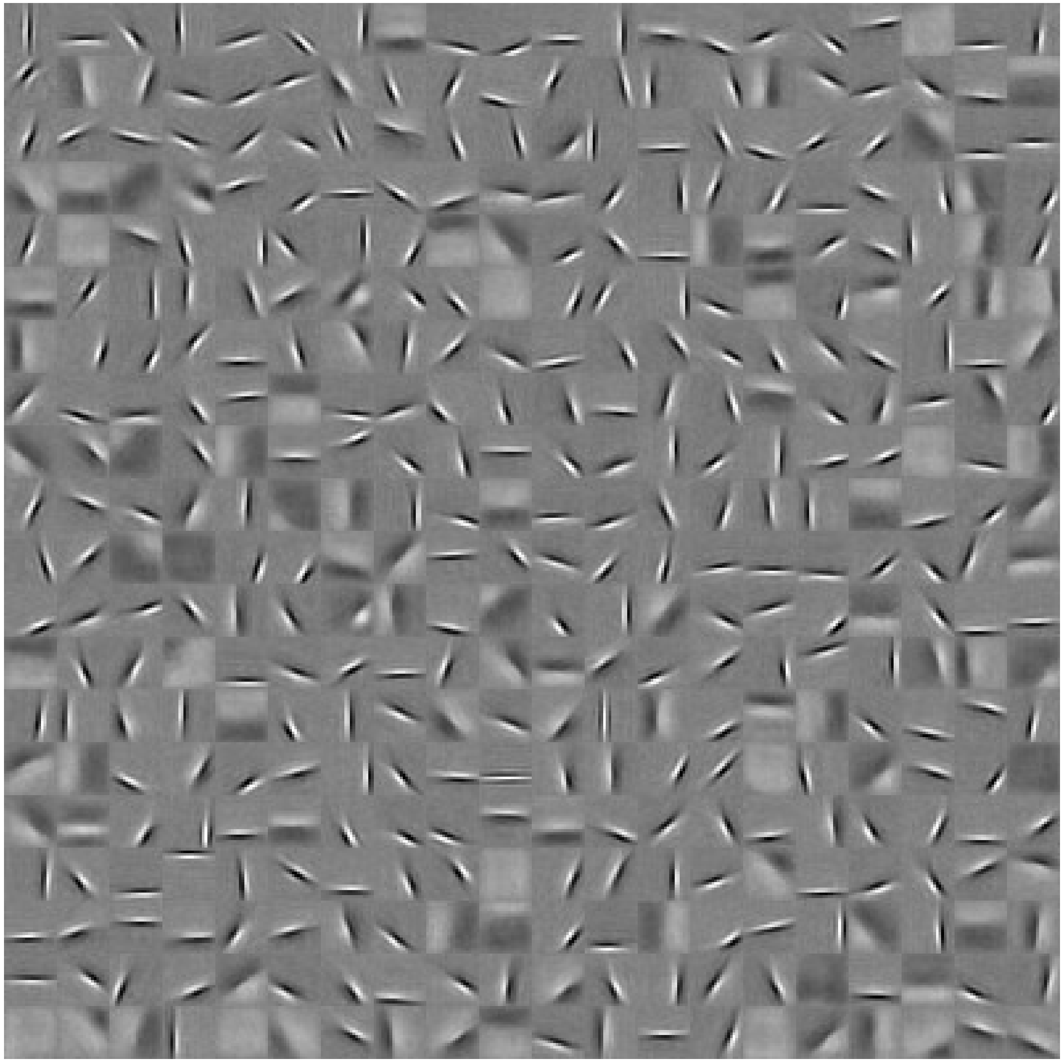


Learning fields of Simple Cells and Complex Cells

[Gregor and LeCun, 2010]

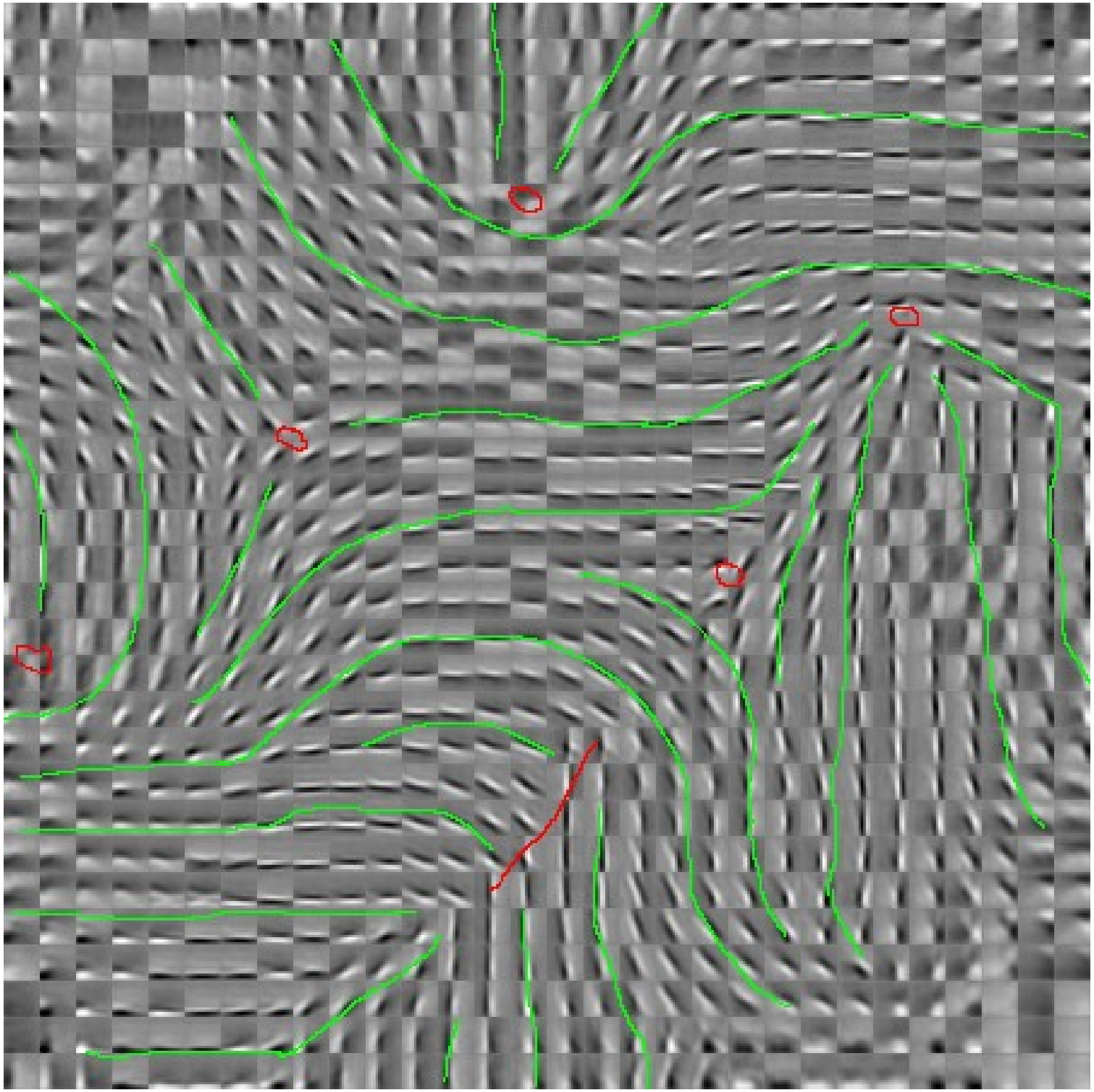
Training Simple Cells with Local Receptive Fields over Large Input Images

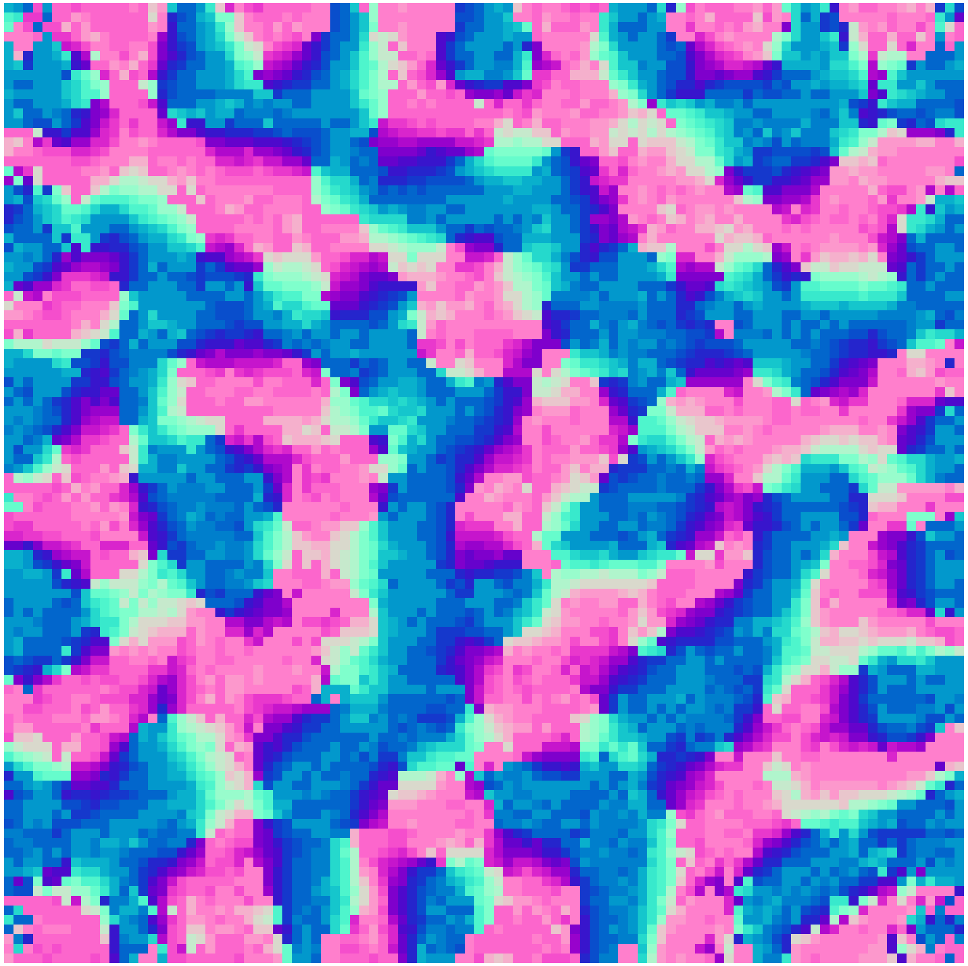
- Training on 115x115 images. Kernels are 15x15



Simple Cells + Complex Cells with Sparsity Penalty: Pinwheels

- **Training on 115x115 images. Kernels are 15x15**





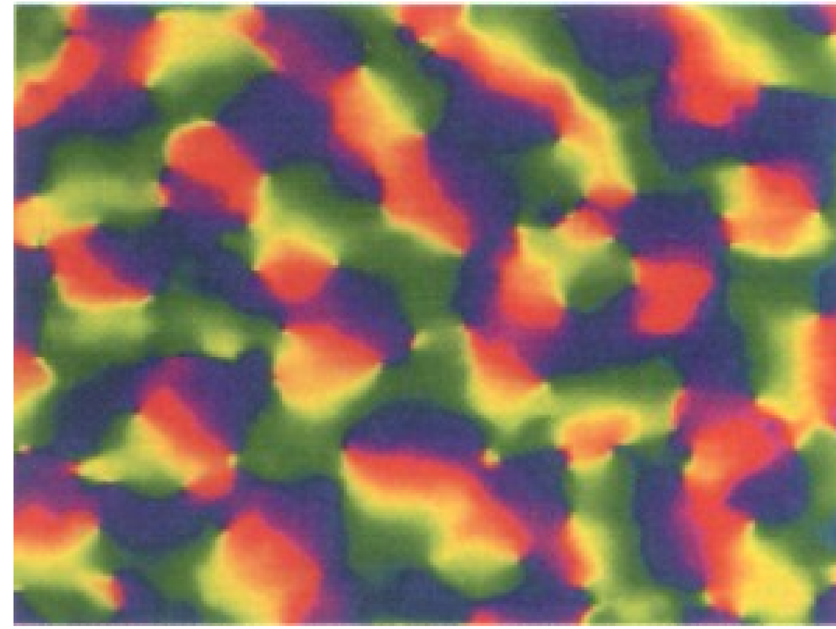
119x119 Image Input

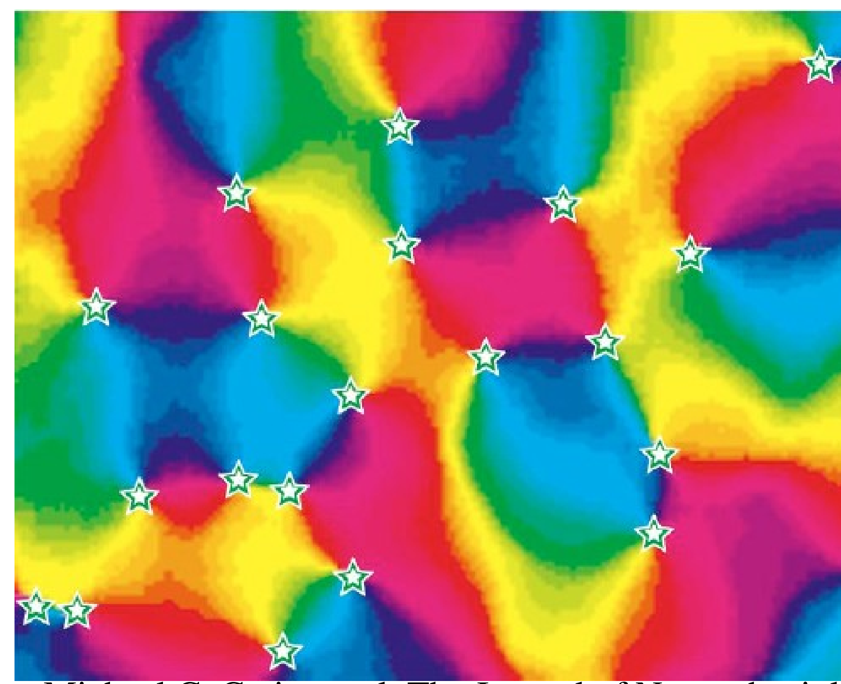
100x100 Code

20x20 Receptive field size

sigma=5

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

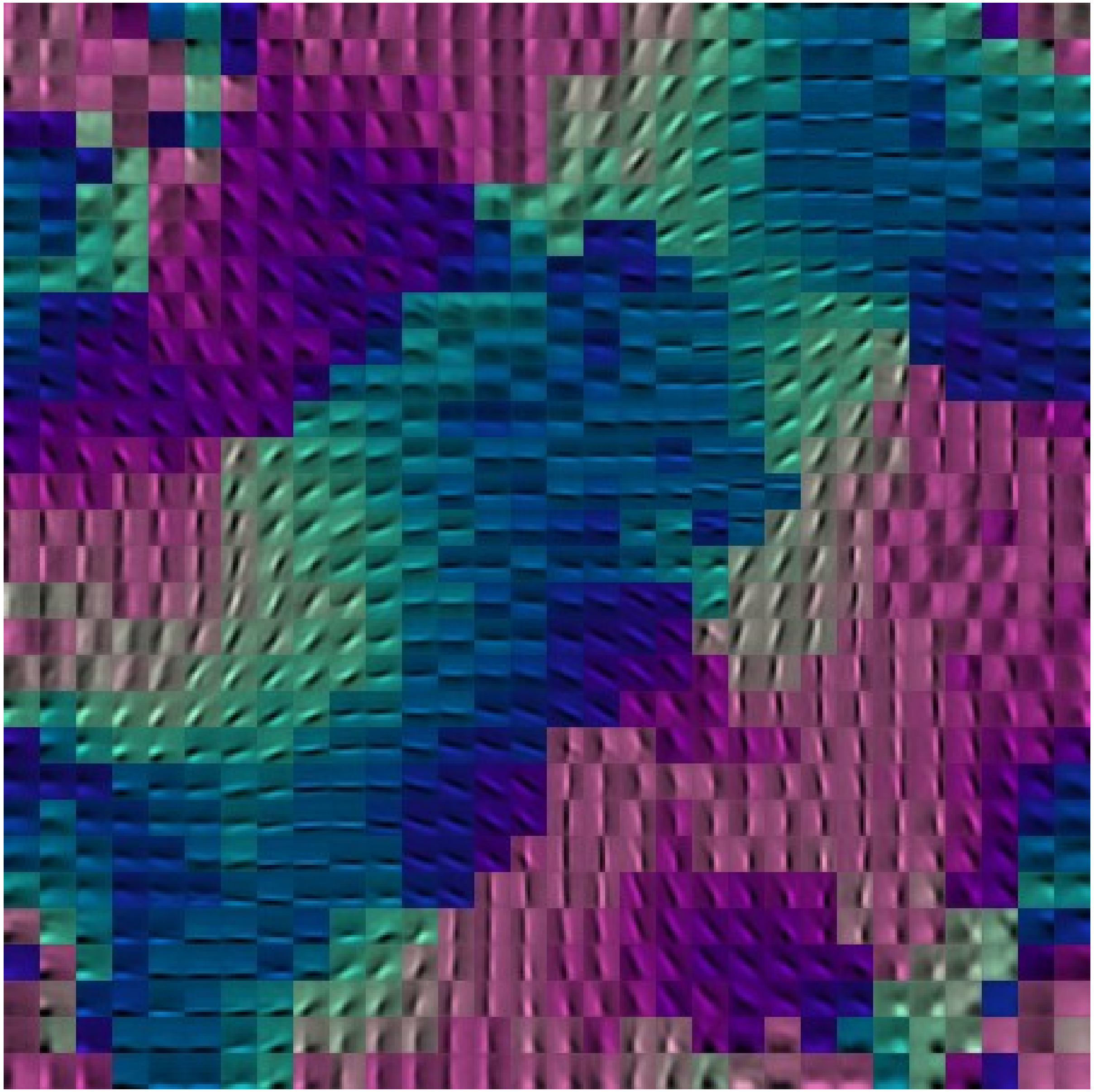




Michael C. Crair, et. al. The Journal of Neurophysiology Vol. 77 No. 6 June 1997, pp. 3381-3385 (**Cat**)

Same Method, withTraining at the Image Level (vs patch)

- Color indicates orientation (by fitting Gabors)



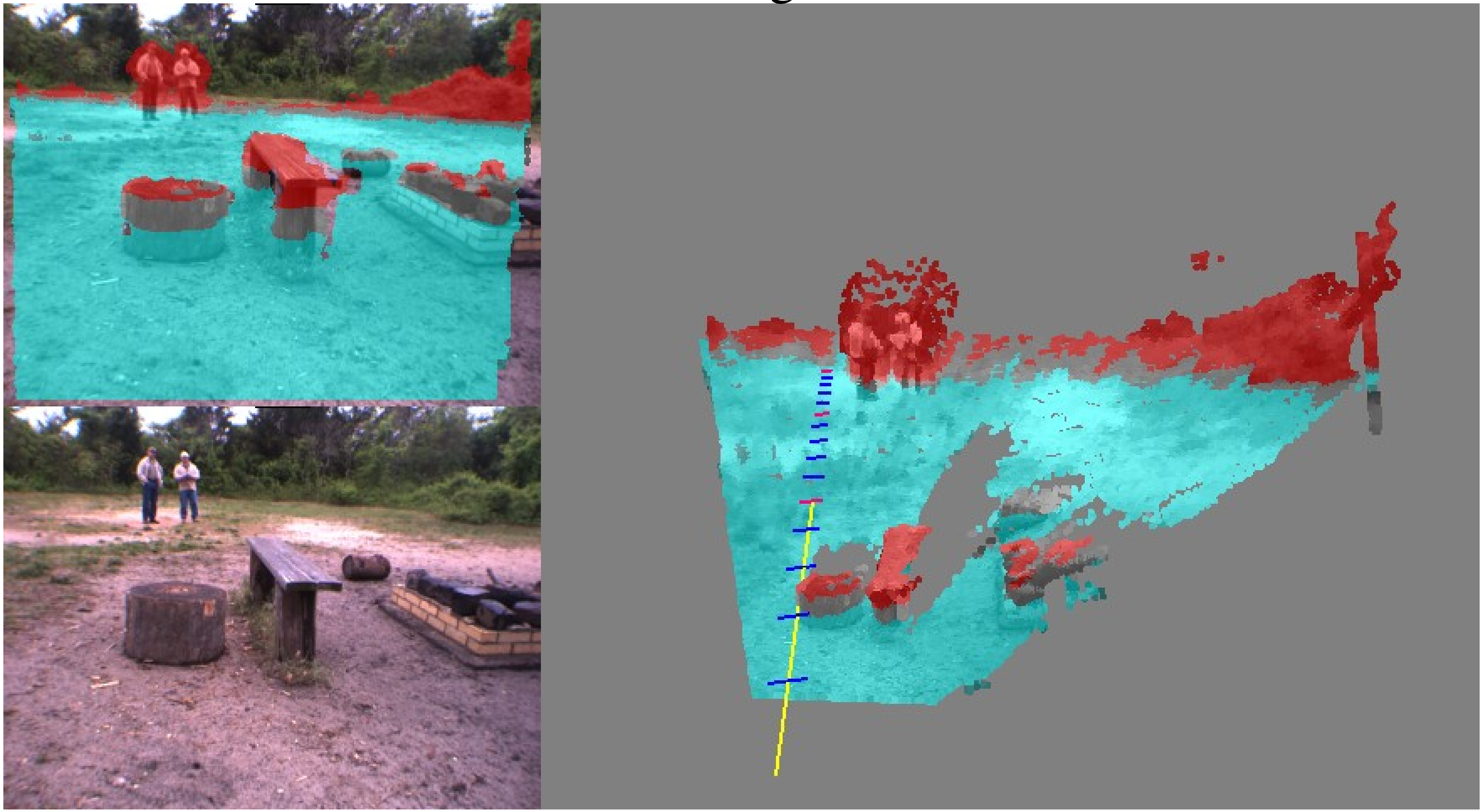
Deep Learning for Mobile Robot Vision

DARPA/LAGR: Learning Applied to Ground Robotics

- Getting a robot to drive autonomously in unknown terrain solely from vision (camera input).
- Our team (NYU/Net-Scale Technologies Inc.) was one of 8 participants funded by DARPA
- All teams received identical robots and can only modify the software (not the hardware)
- The robot is given the GPS coordinates of a goal, and must drive to the goal as fast as possible. The terrain is unknown in advance. The robot is run 3 times through the same course.
- Long-Range Obstacle Detection with on-line, self-trained ConvNet
- Uses temporal consistency!

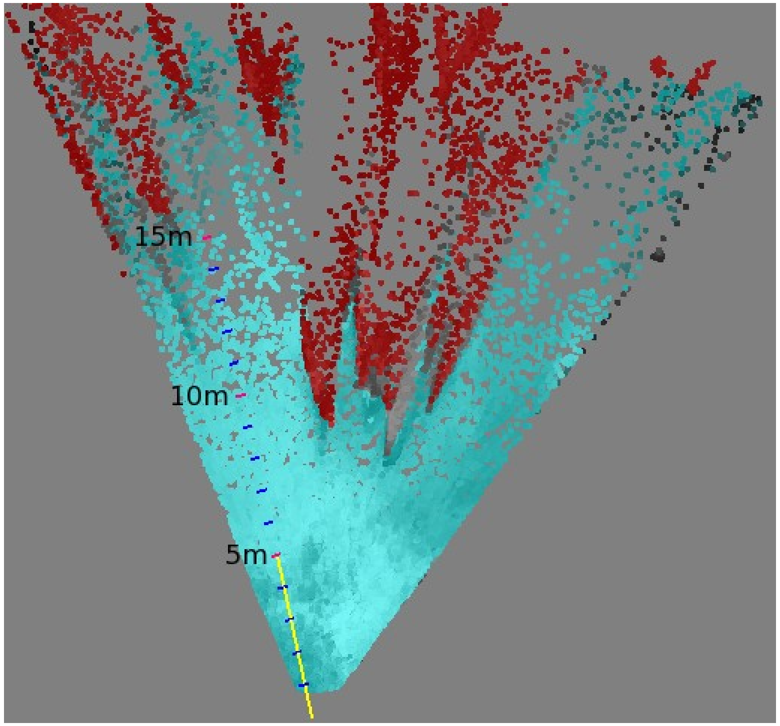
Obstacle Detection

Obstacles overlaid with camera image



Camera image | Detected obstacles (red)

Navigating to a goal is hard...



stereo perspective

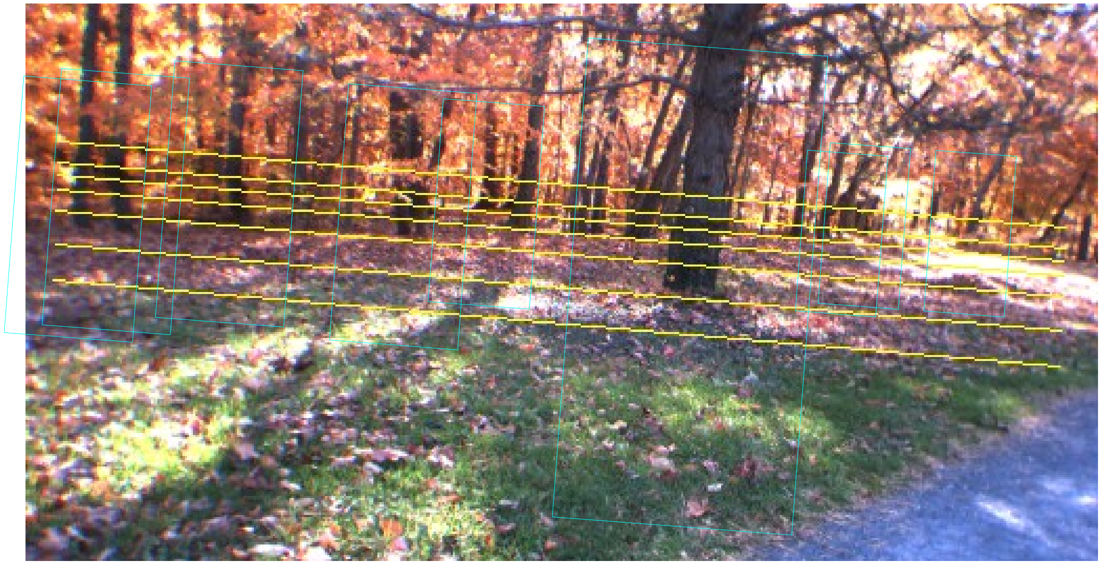
human perspective

especially in a snowstorm.

Self-Supervised Learning

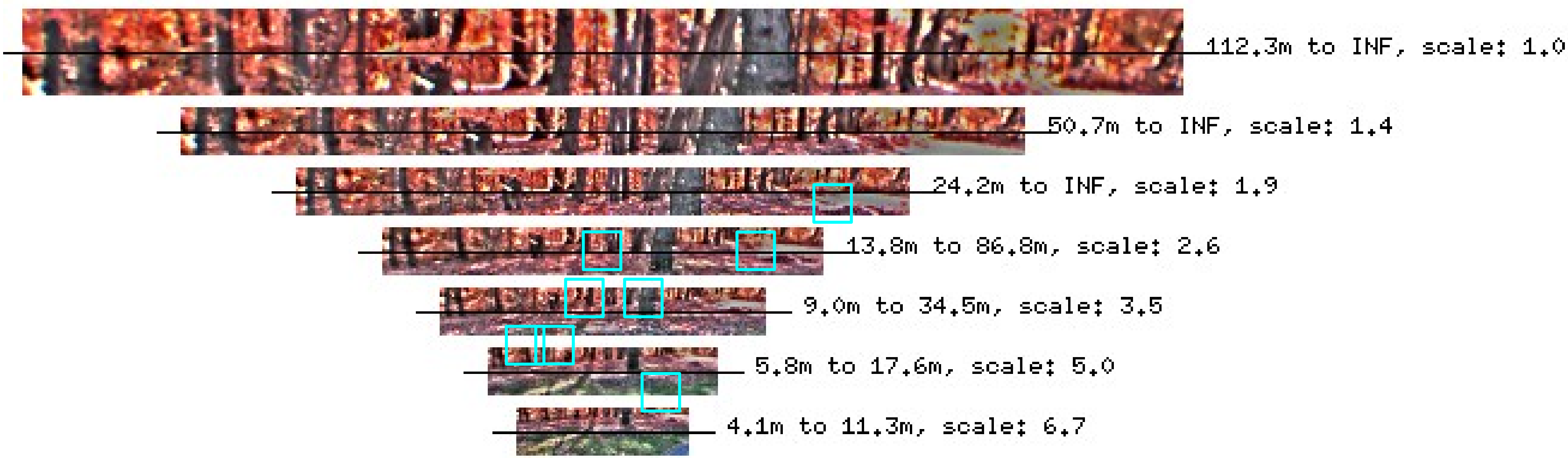
- Stereo vision tells us what nearby obstacles look like
- Use the labels (obstacle/traversible) produced by stereo vision to train a monocular neural network
- Self-supervised “near to far” learning

Long Range Vision: Distance Normalization



Pre-processing (125 ms)

- Ground plane estimation
- Horizon leveling
- Conversion to YUV + local contrast normalization
- Scale invariant pyramid of distance-normalized image “bands”

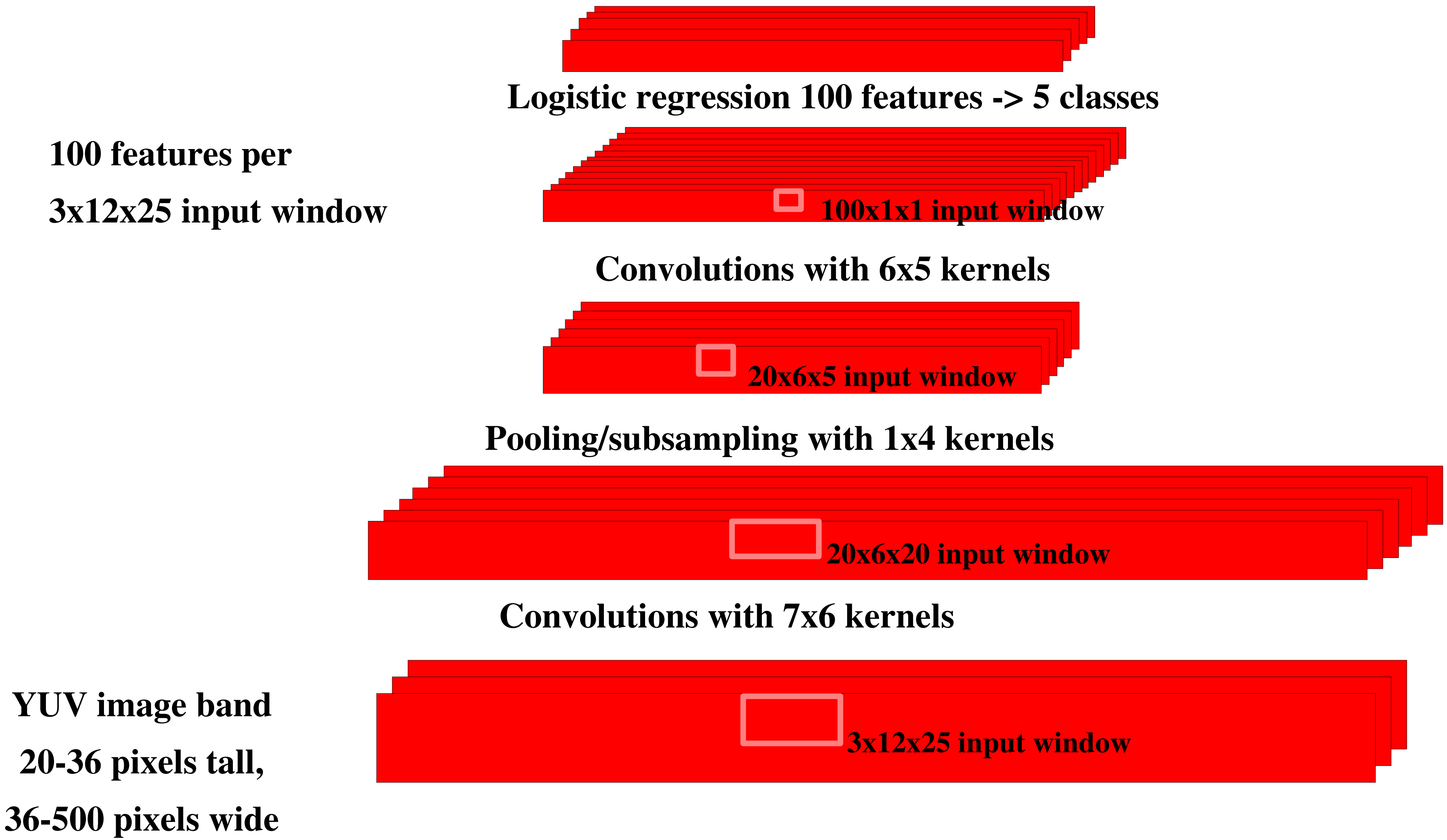


netSCALE Technologies, Inc.

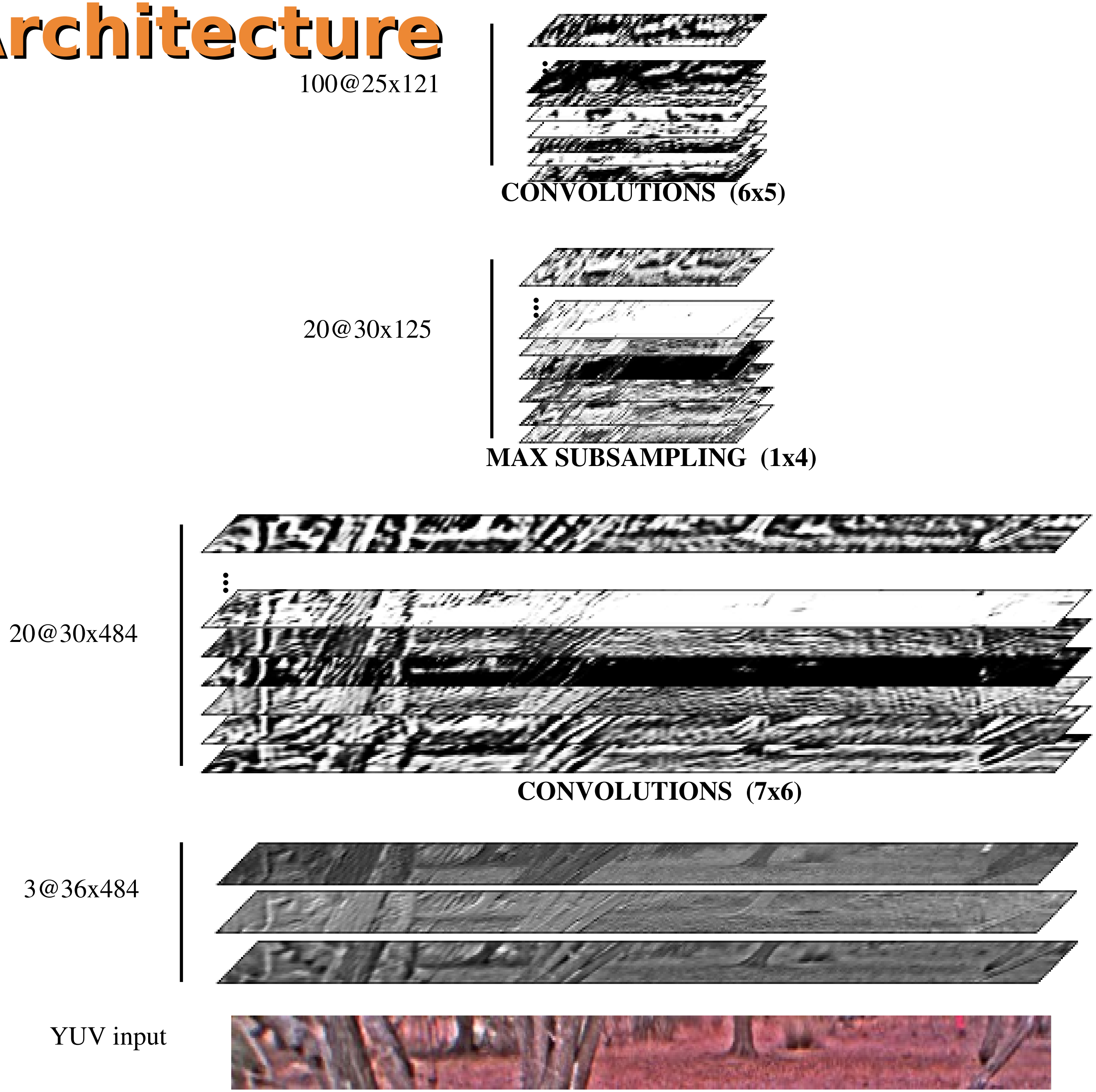
NEW YORK UNIVERSITY

Convolutional Net Architecture

- Operates on 12x25 YUV windows from the pyramid



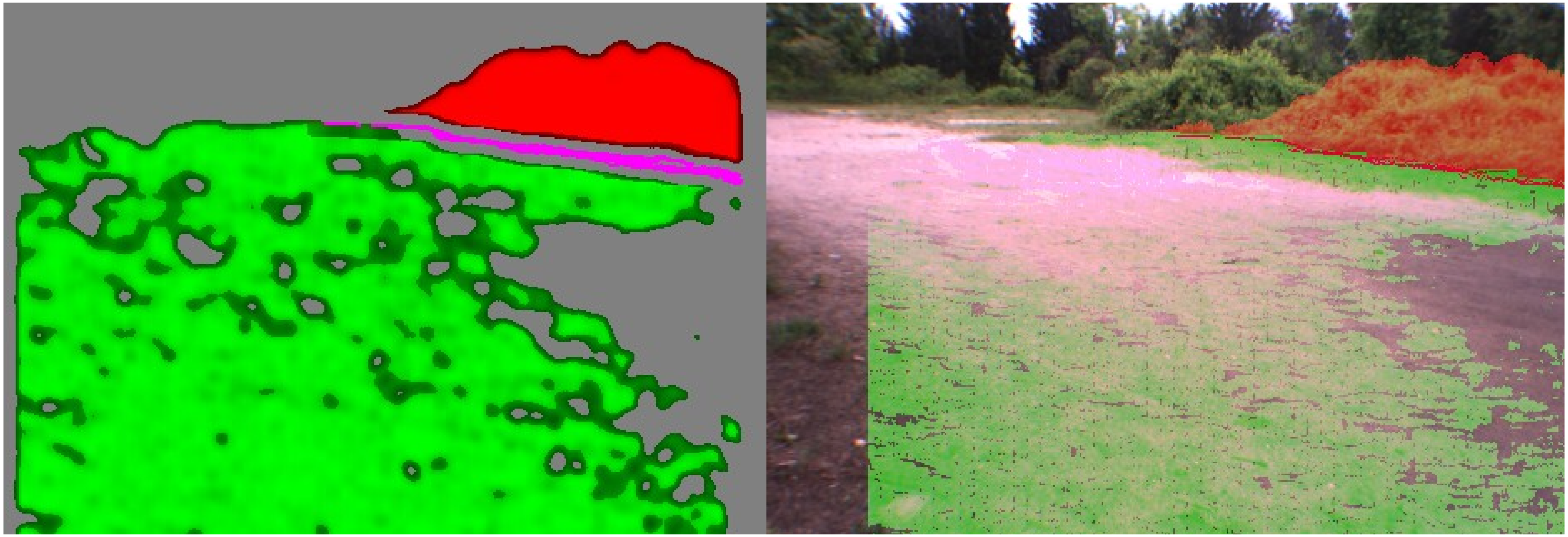
Convolutional Net Architecture



Long Range Vision: 5 categories

Online Learning (52 ms)

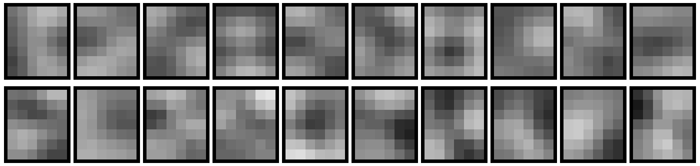
- Label windows using stereo information – 5 classes

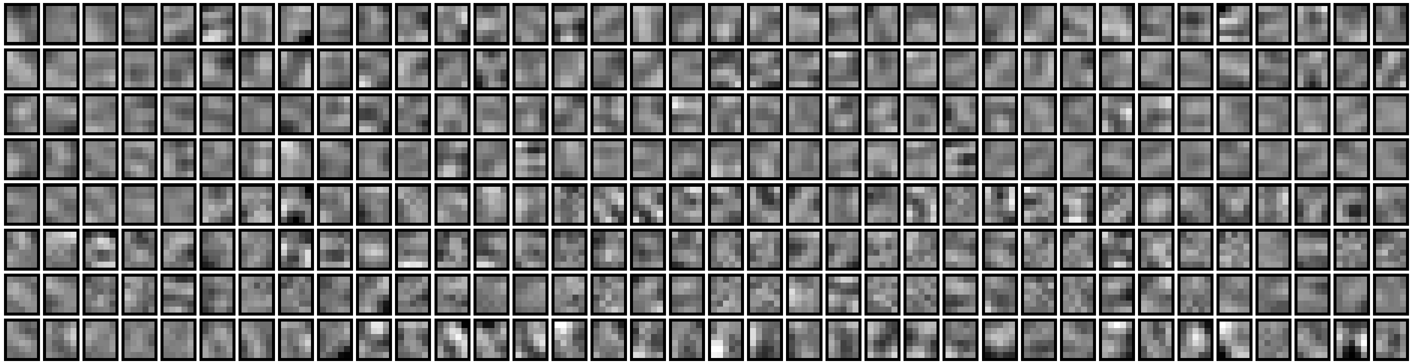


super-ground **ground** **footline** **obstacle** **super-obstacle**

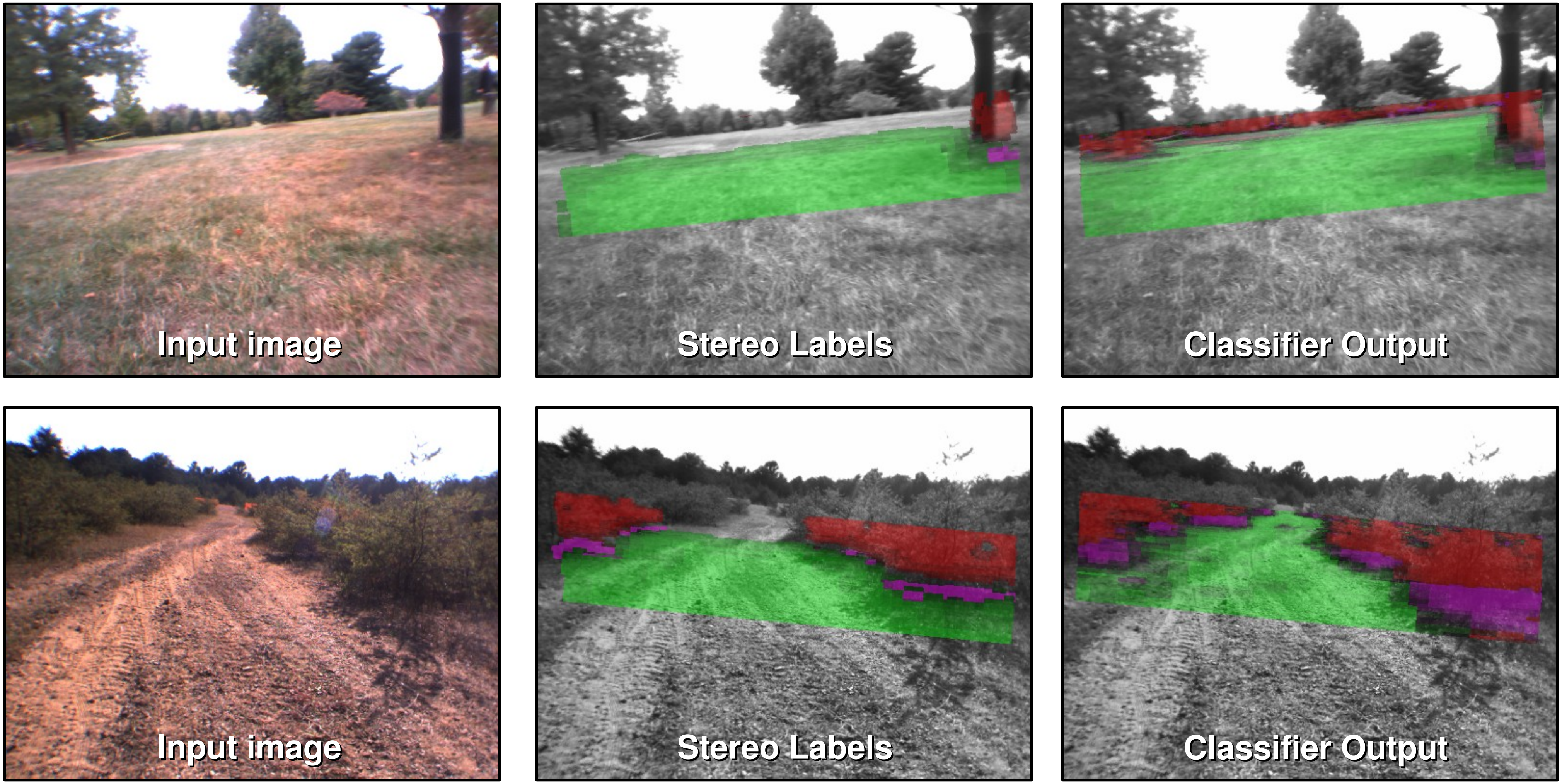
Trainable Feature Extraction

- "Deep belief net" approach to unsupervised feature learning
- Two stages are trained in sequence
  - each stage has a layer of convolutional filters and a layer of horizontal feature pooling.
  - Naturally shift invariant in the horizontal direction
- Filters of the convolutional net are trained so that the input can be reconstructed from the features
  - 20 filters at the first stage (layers 1 and 2)
  - 300 filters at the second stage (layers 3 and 4)
- Scale invariance comes from pyramid.
  - for near-to-far generalization





Long Range Vision Results



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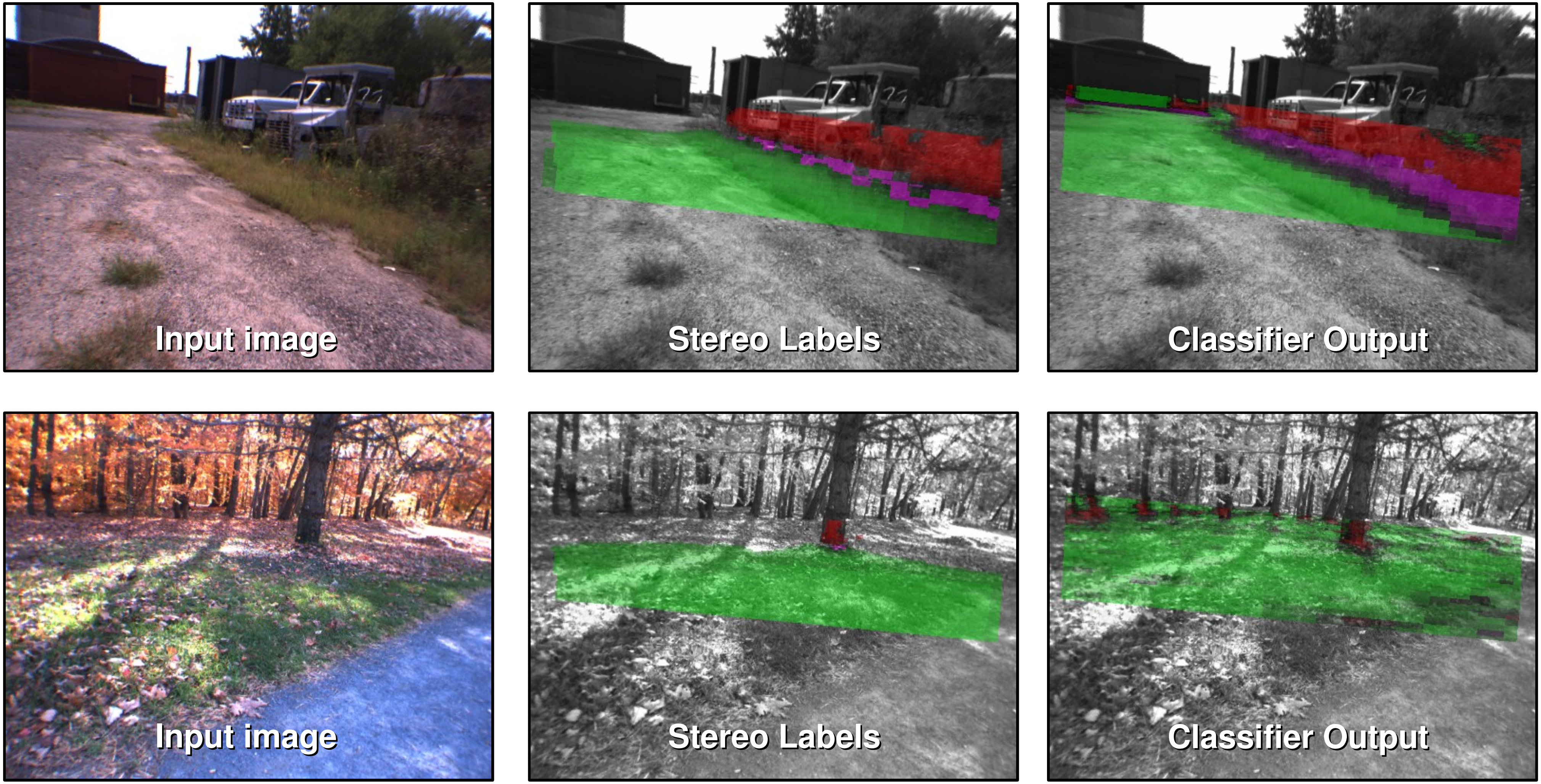

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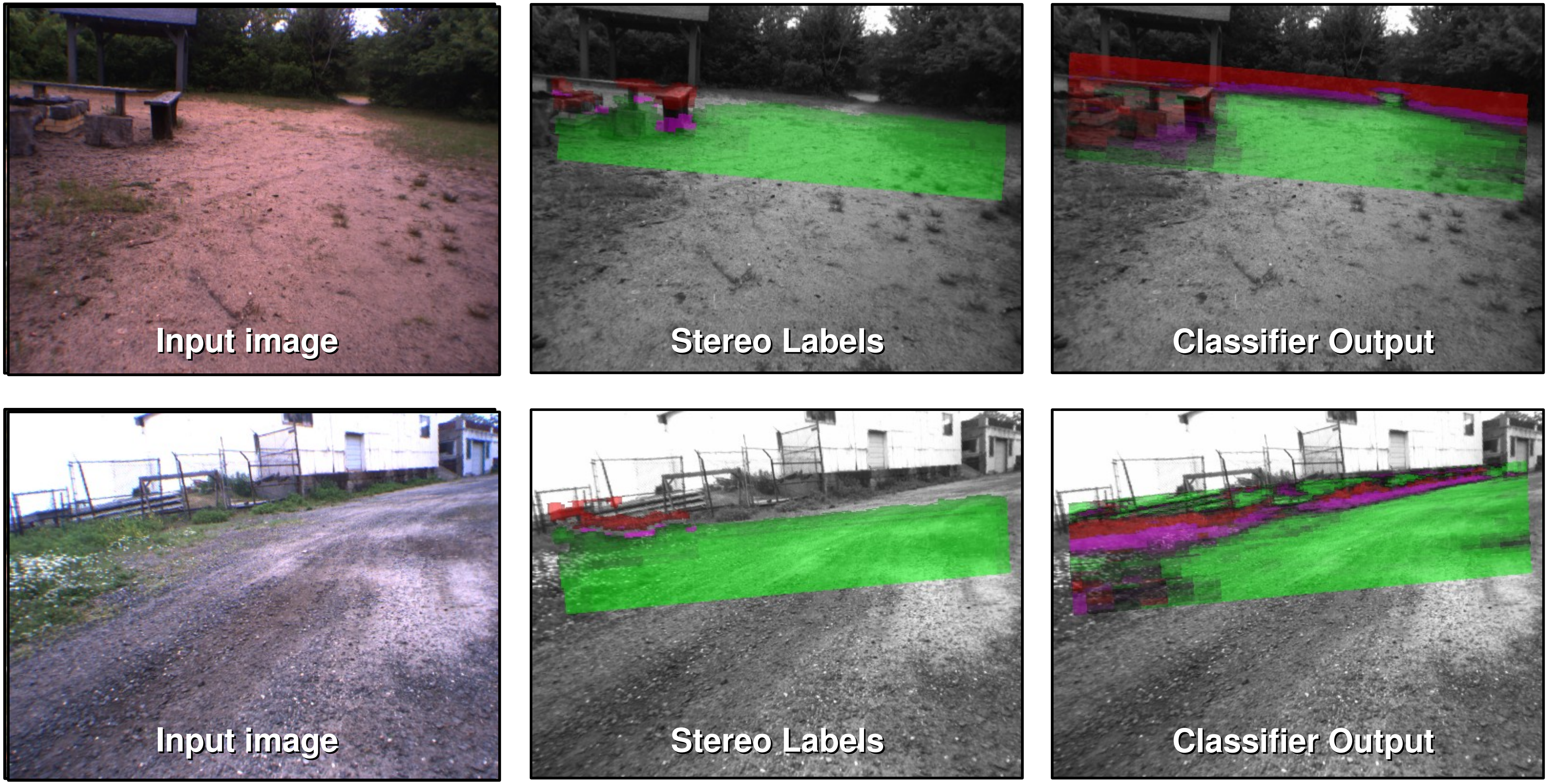

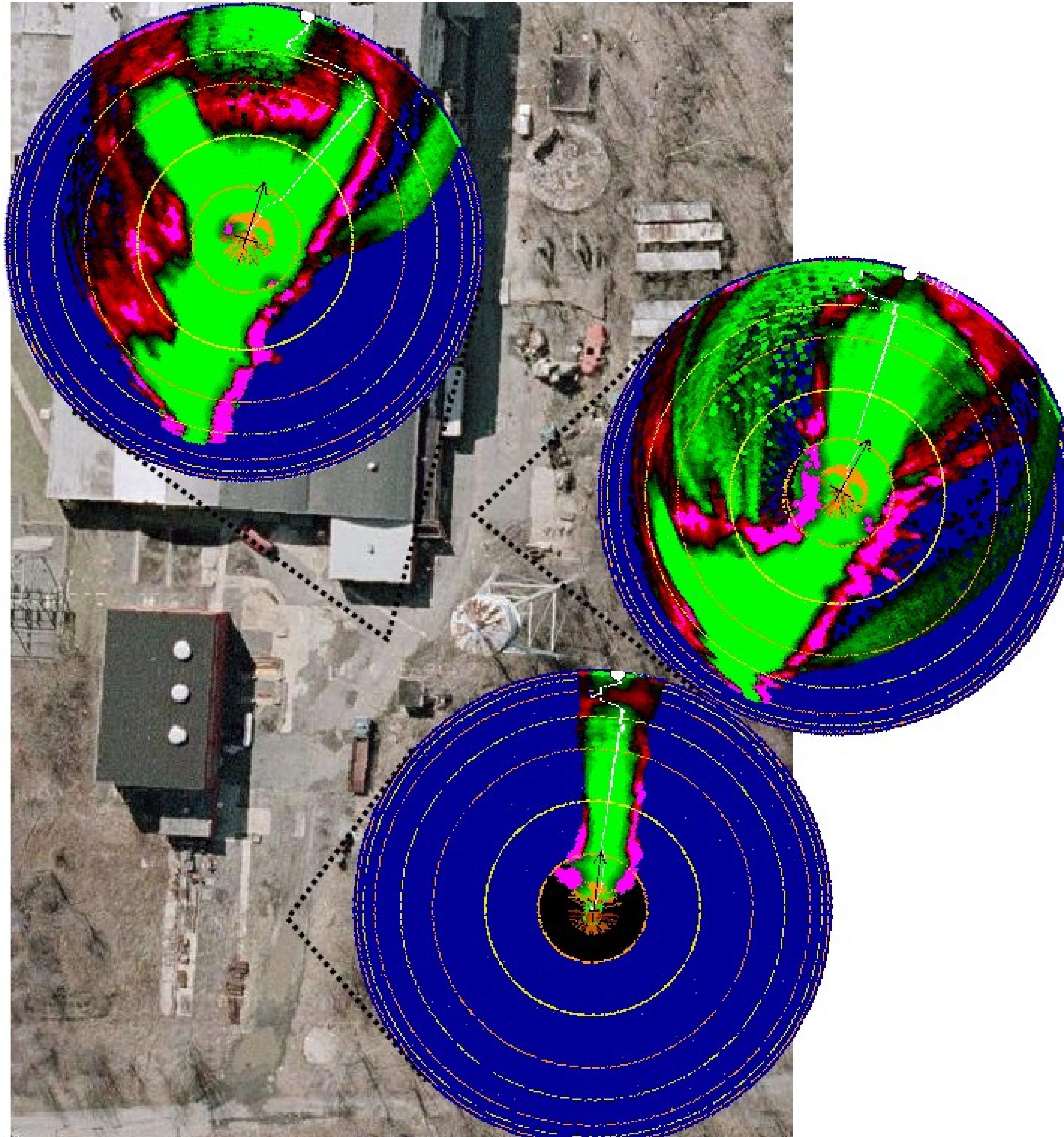

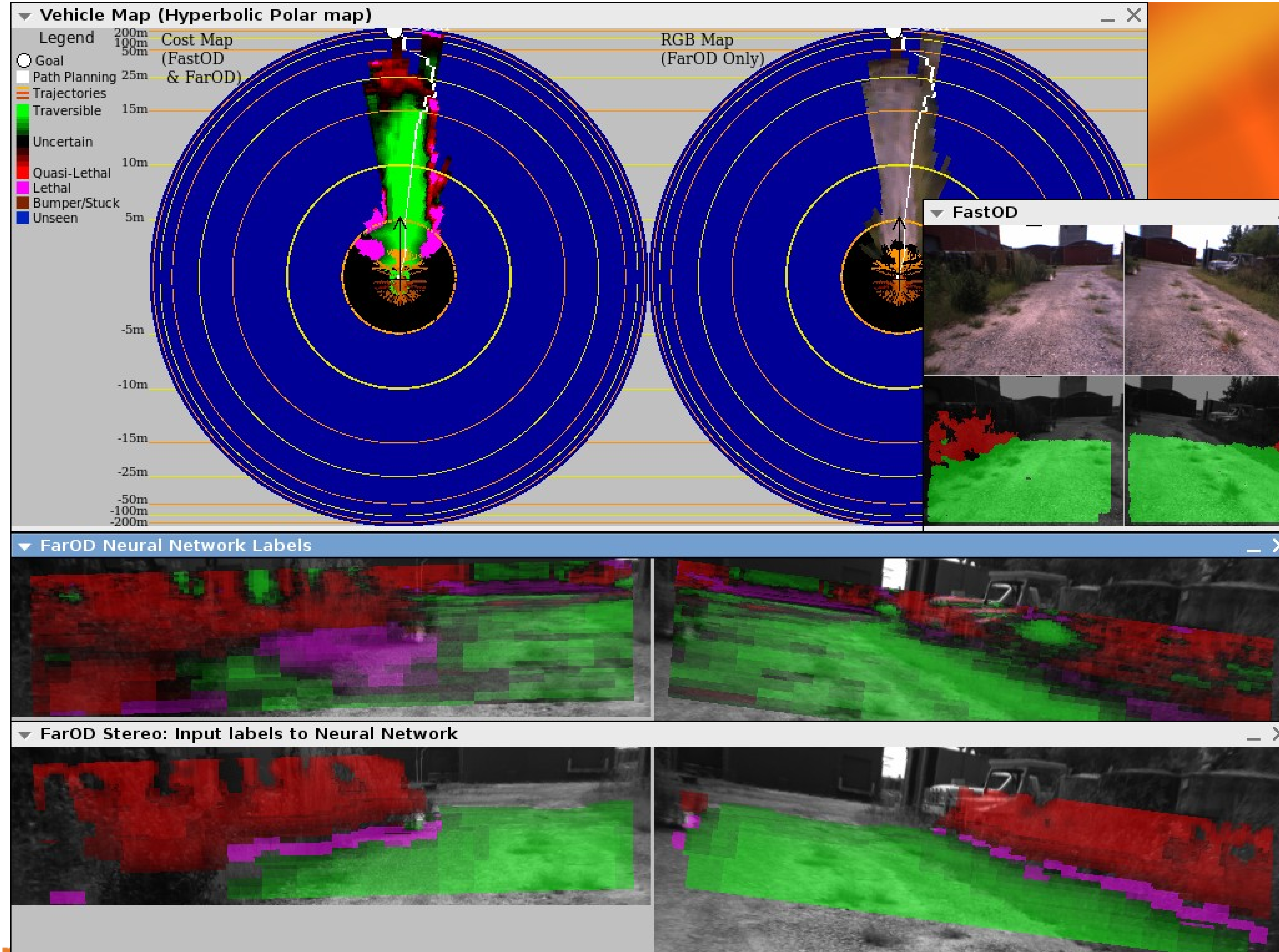
Vehicle Map (Hyperbolic Polar map)
Legend
Goal
Path Planning
Trajectories
Traversible
Uncertain
Quasi-Lethal
Lethal
Bumper/Stuck
Unseen
200m
100m
50m
25m
15m
10m
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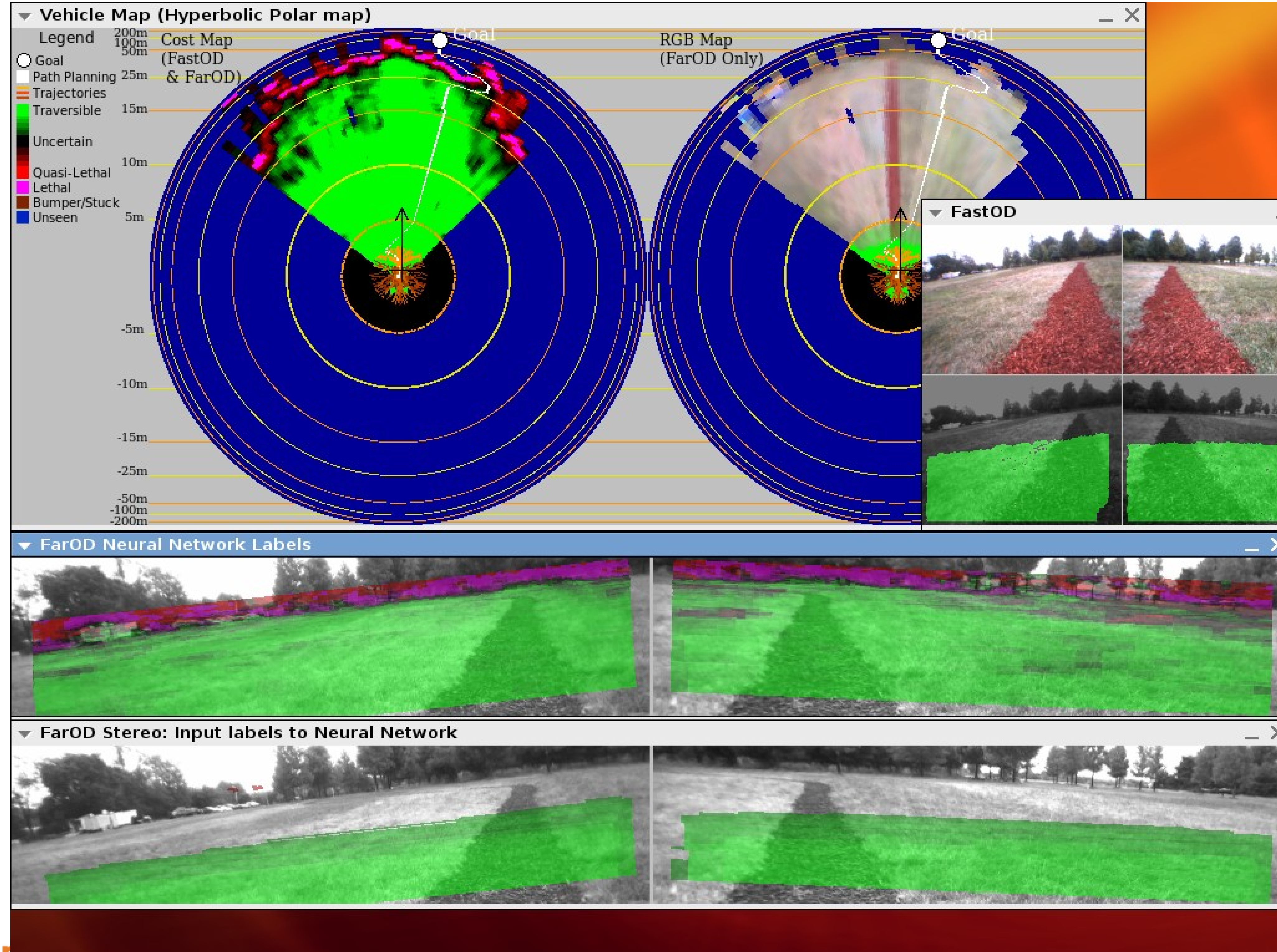
-200m
Cost Map
(FastOD
& FarOD)
RGB Map
(FarOD Only)
FastOD
FarOD Neural Network Labels
FarOD Stereo: Input labels to Neural Network



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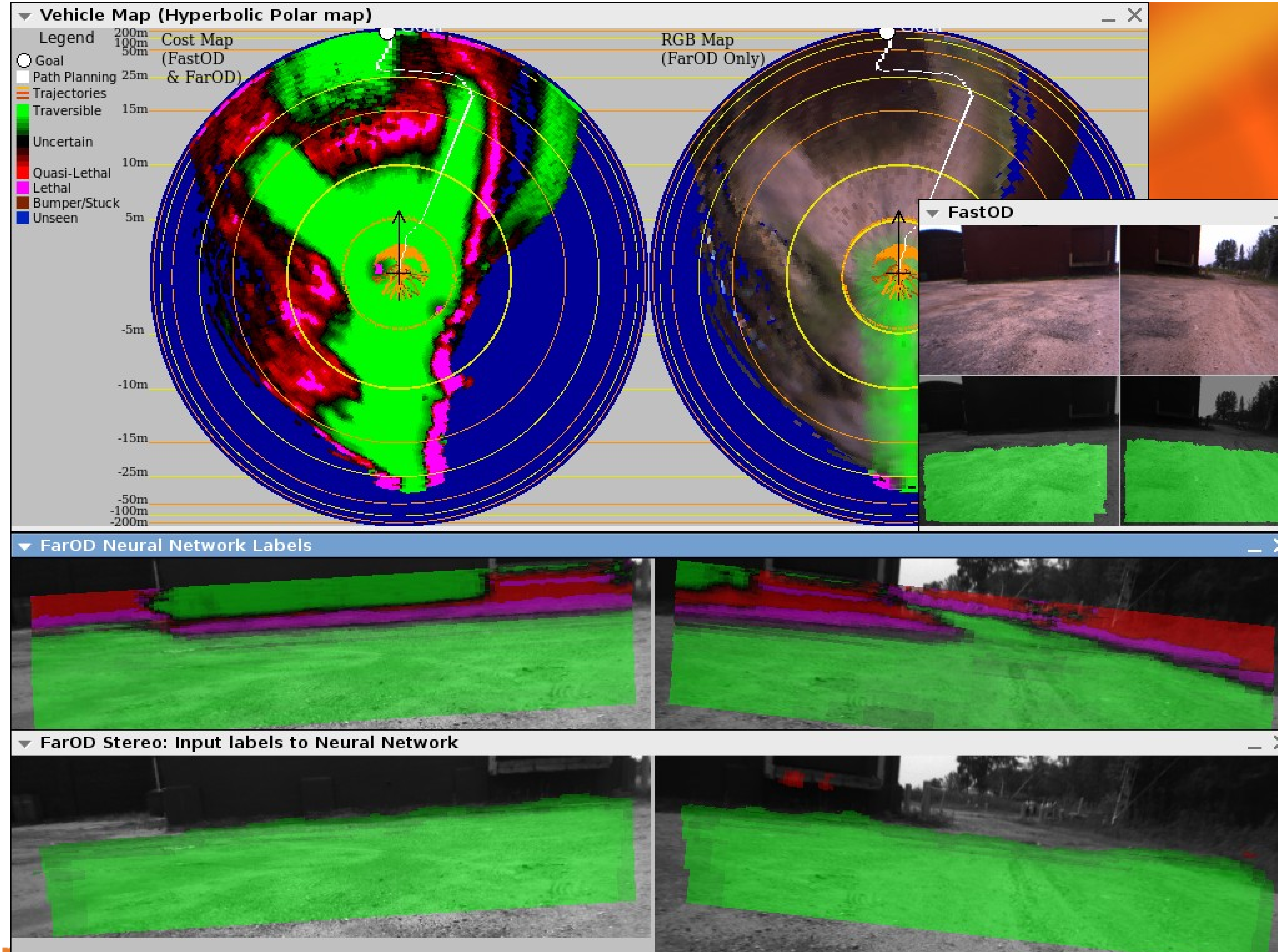
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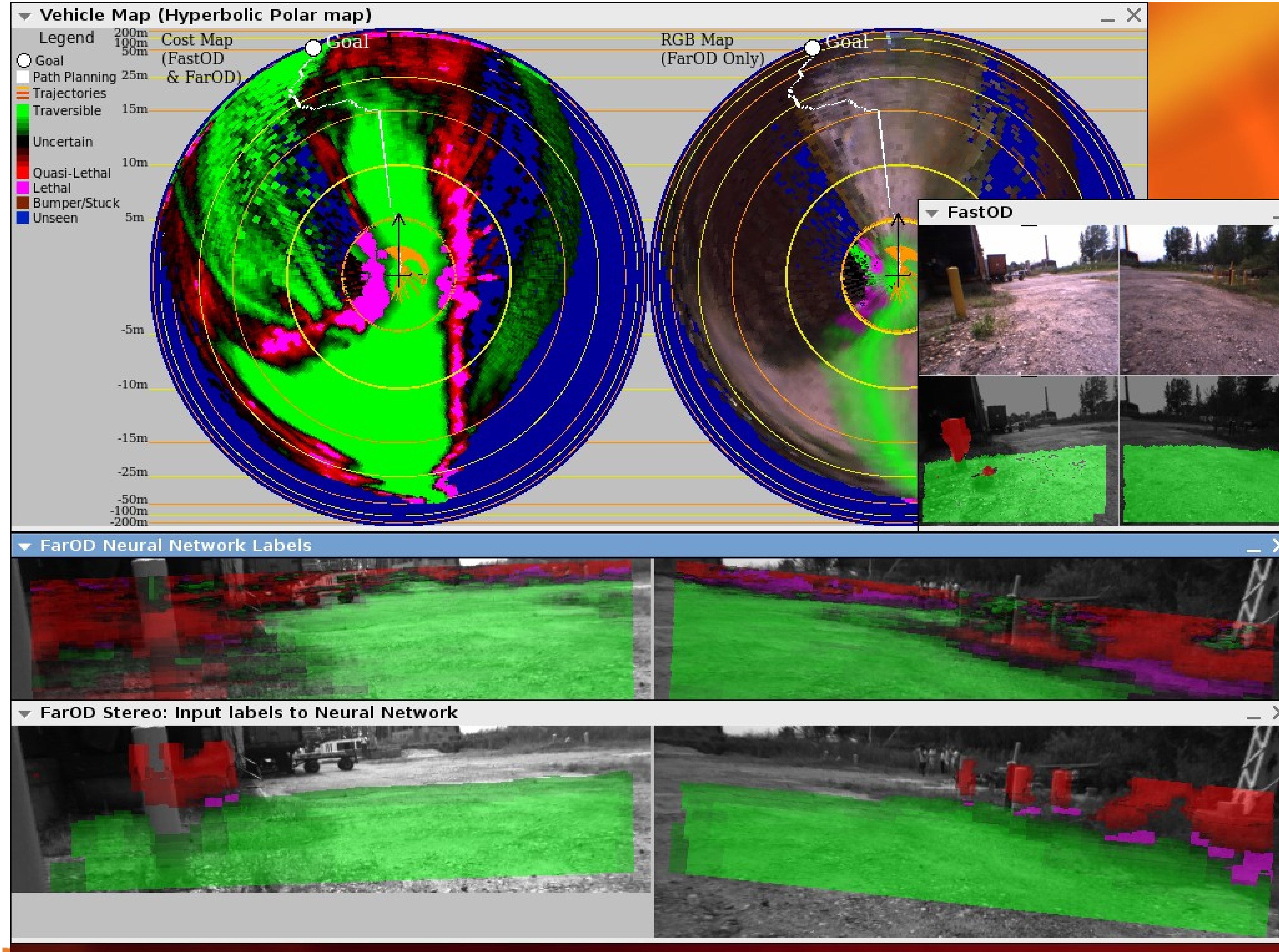
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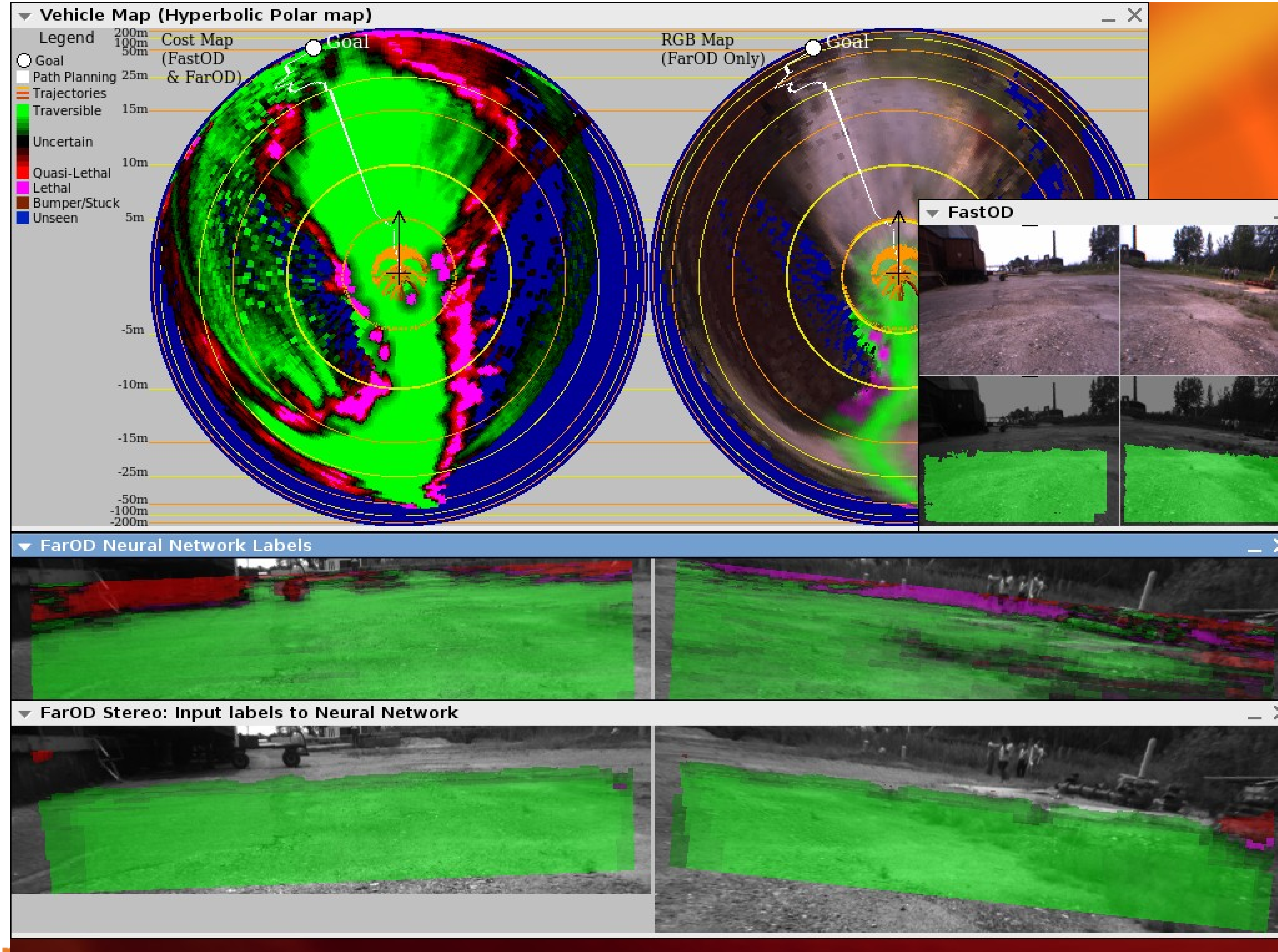

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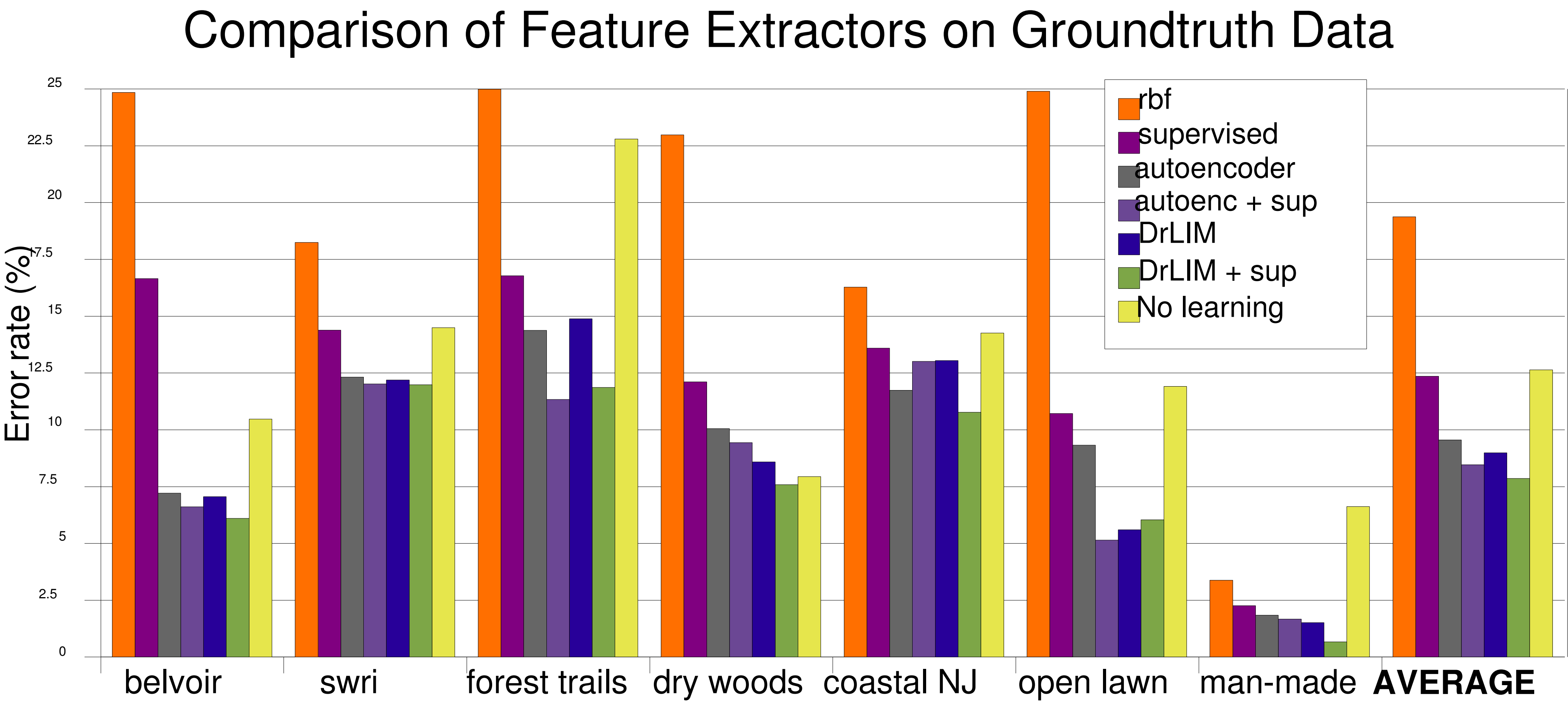
Feature Learning for traversability prediction (LAGR)

Comparing

- purely supervised
- stacked, invariant auto-encoders
- DrLIM invariant learning

Testing on hand-labeled groundtruth frames – binary labels



Collaborators

- **Current PhD students:**
  - Y-Lan Boureau, Koray Kavukcuoglu, Pierre Sermanet
- **Former PhD students:**
  - Raia Hadsell, Fu-Jie Huang, Marc'Aurelio Ranzato
- **Postdocs and Research Scientists**
  - Clément Farabet, Karol Gregor, Marco Scoffier
- **Senior Collaborators**
  - Rob Fergus (NYU): invariant feature learning
  - Eugenio Culurciello (Yale): FPGA/ASIC design
  - Yoshua Bengio (U. Montreal): deep learning
  - Leon Bottou (NEC Labs): handwriting recognition
  - Jean Ponce (ENS/INRIA), Francis Bach (ENS/INRIA): sparse coding.

The End