Learning Deep Hierarchies of Visual Features

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The Challenge of Computer Vision and Machine Learning

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

- **Given features, we know how to train good classifiers**
- **Our next challenge is to learn the features.**

Trainable Feature Extractor → - - → Trainable Feature Extractor → Trainable Classifier →

- **How do we learn internal representations of the visual world?**
- **How do we leverage unlabeled data?**

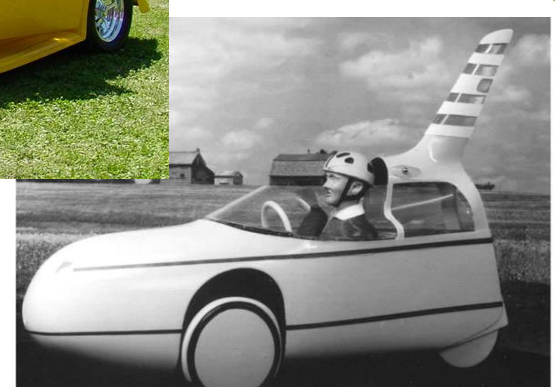
The Next Challenge of ML, Vision (and Neuroscience)

How do we learn invariant representations?

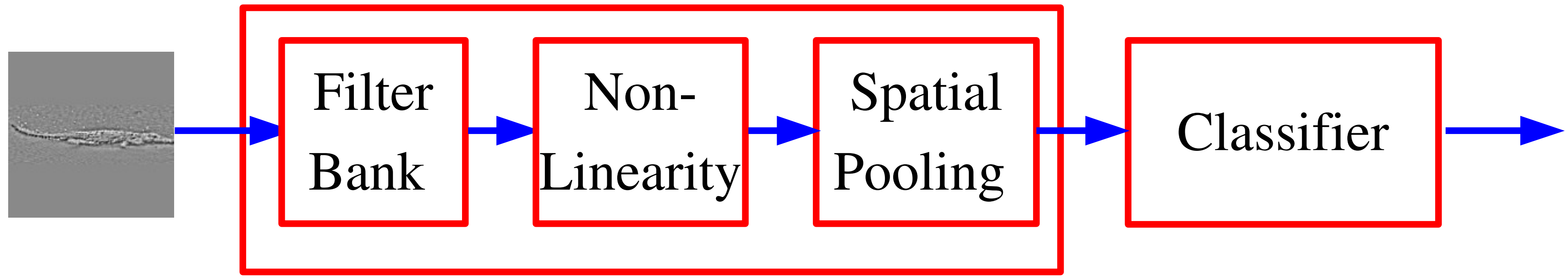
- From the image of an airplane, how do we extract a representation that is invariant to pose, illumination, background, clutter, object instance....
- How can a human (or a machine) learn those representations by just looking at the world?

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)



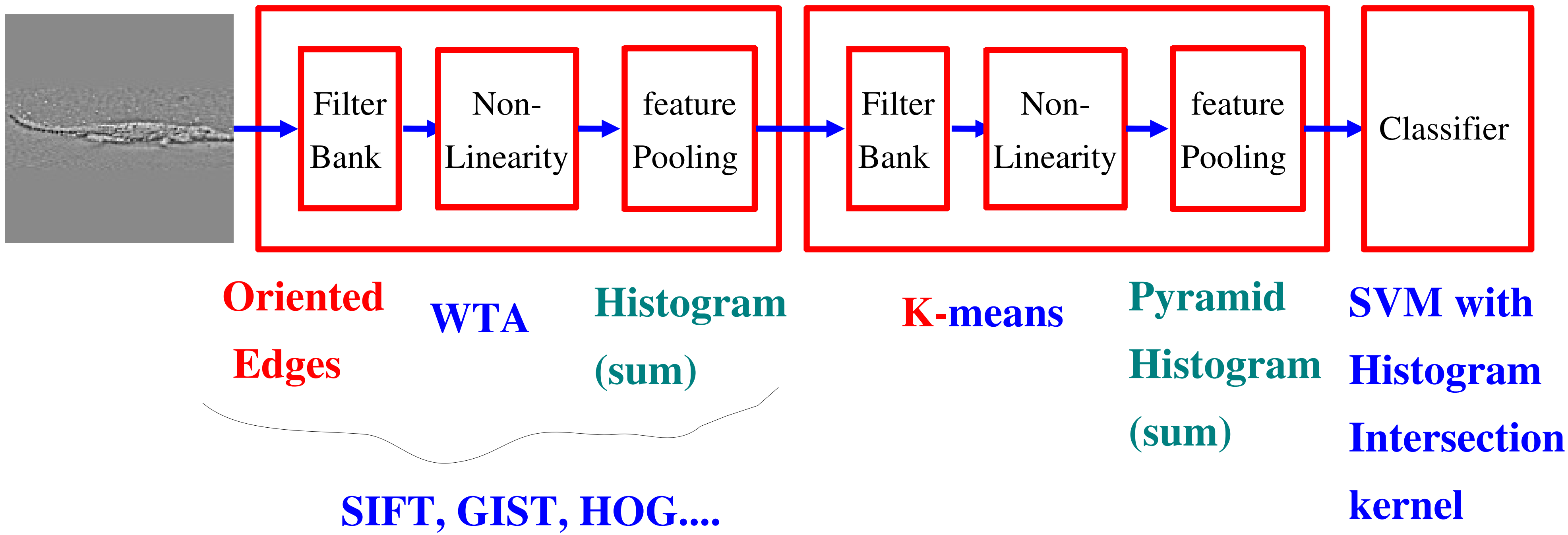
"Modern" Object Recognition Architecture in Computer Vision



Filter Bank	Non-Linearity	Spatial Pooling
Oriented Edges	Sigmoid	Averaging
Gabor Wavelets	Rectification	Max pooling
Other Filters...	Vector Quant.	VQ+Histogram
	Contrast Norm.	Geometric Blurr

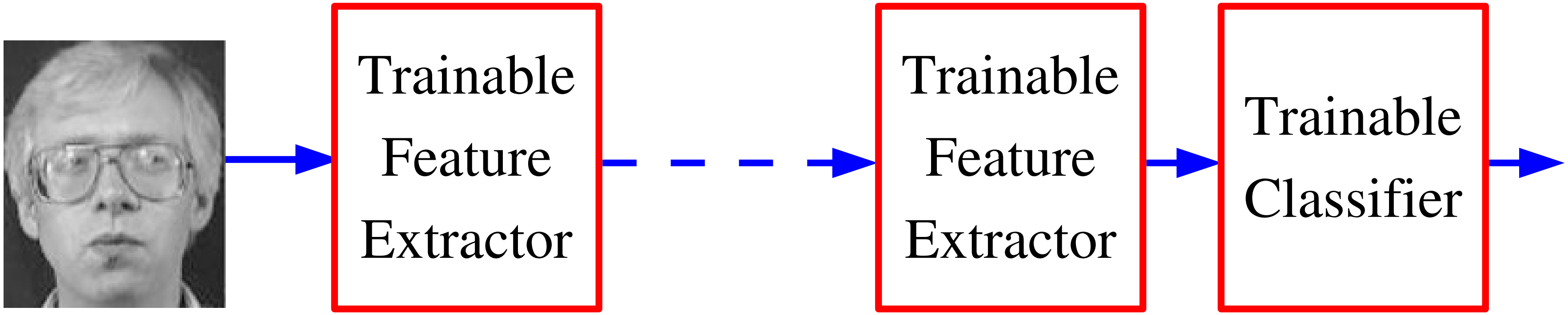
- **Example:**
  - Edges + Rectification + Histograms + SVM [Dalal & Triggs 2005]
  - SIFT + classification
- **Fixed Features + "shallow" classifier**

"State of the Art" architecture for object recognition



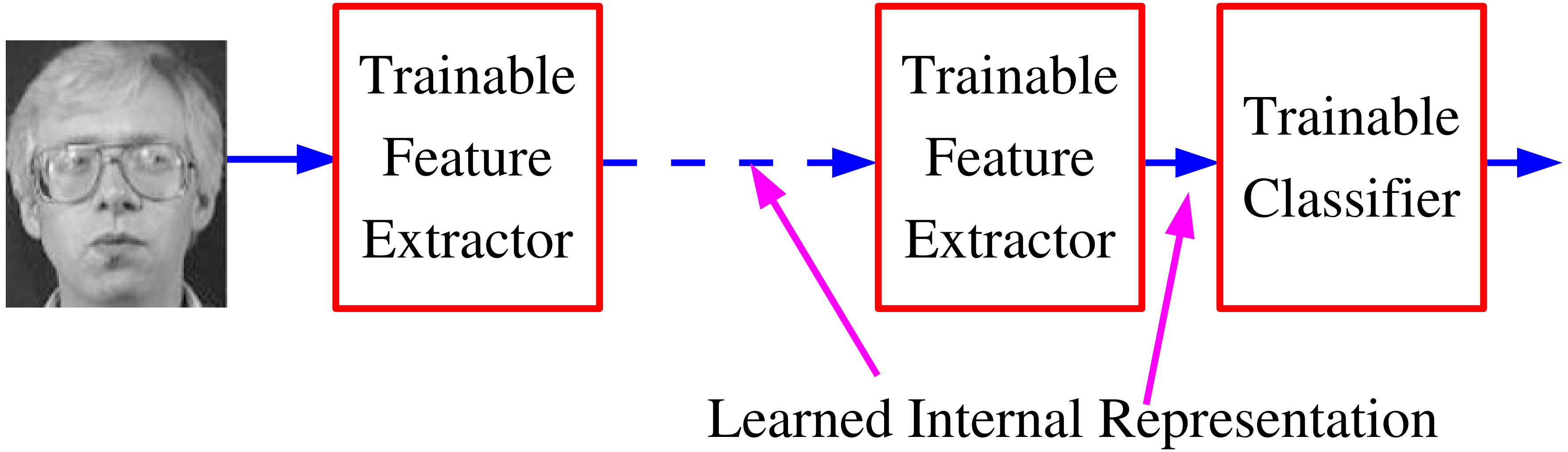
- **Example:**
  - SIFT features with Spatial Pyramid Match Kernel SVM [Lazebnik et al. 2006]
- **Fixed Features + unsupervised features + "shallow" classifier**

Good Representations are Hierarchical



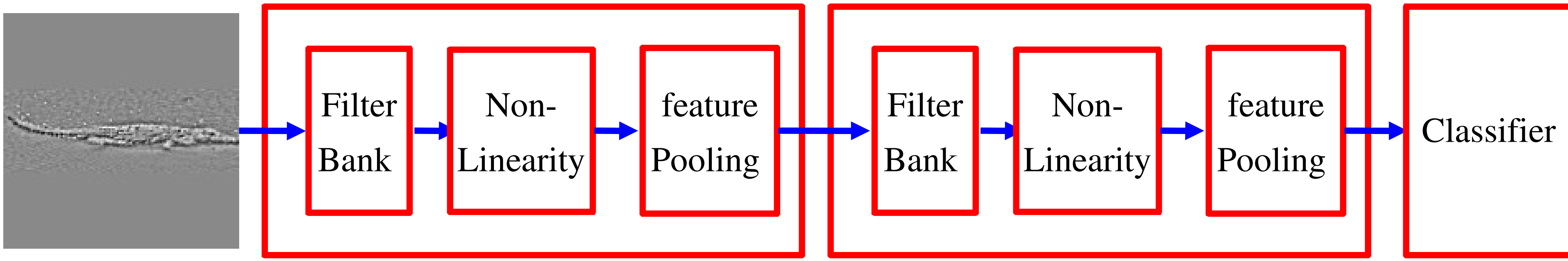
- **In Language: hierarchy in syntax and semantics**
  - Words->Parts of Speech->Sentences->Text
  - Objects,Actions,Attributes...-> Phrases -> Statements -> Stories
- **In Vision: part-whole hierarchy**
  - Pixels->Edges->Textons->Parts->Objects->Scenes

"Deep" Learning: Learning Hierarchical Representations



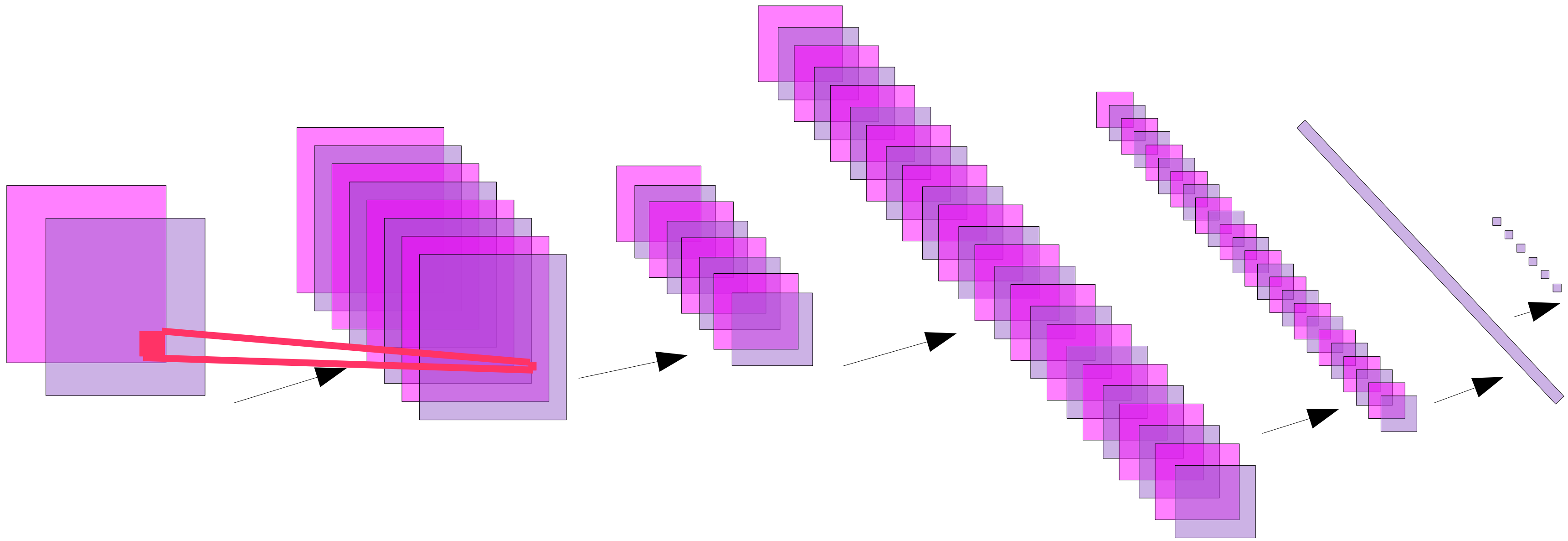
- **Deep Learning: learning a hierarchy of internal representations**
- **From low-level features to mid-level invariant representations, to object identities**
- **Representations are increasingly invariant as we go up the layers**
- **using multiple stages gets around the specificity/invariance dilemma**

Can't we train multi-stage vision architectures?



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

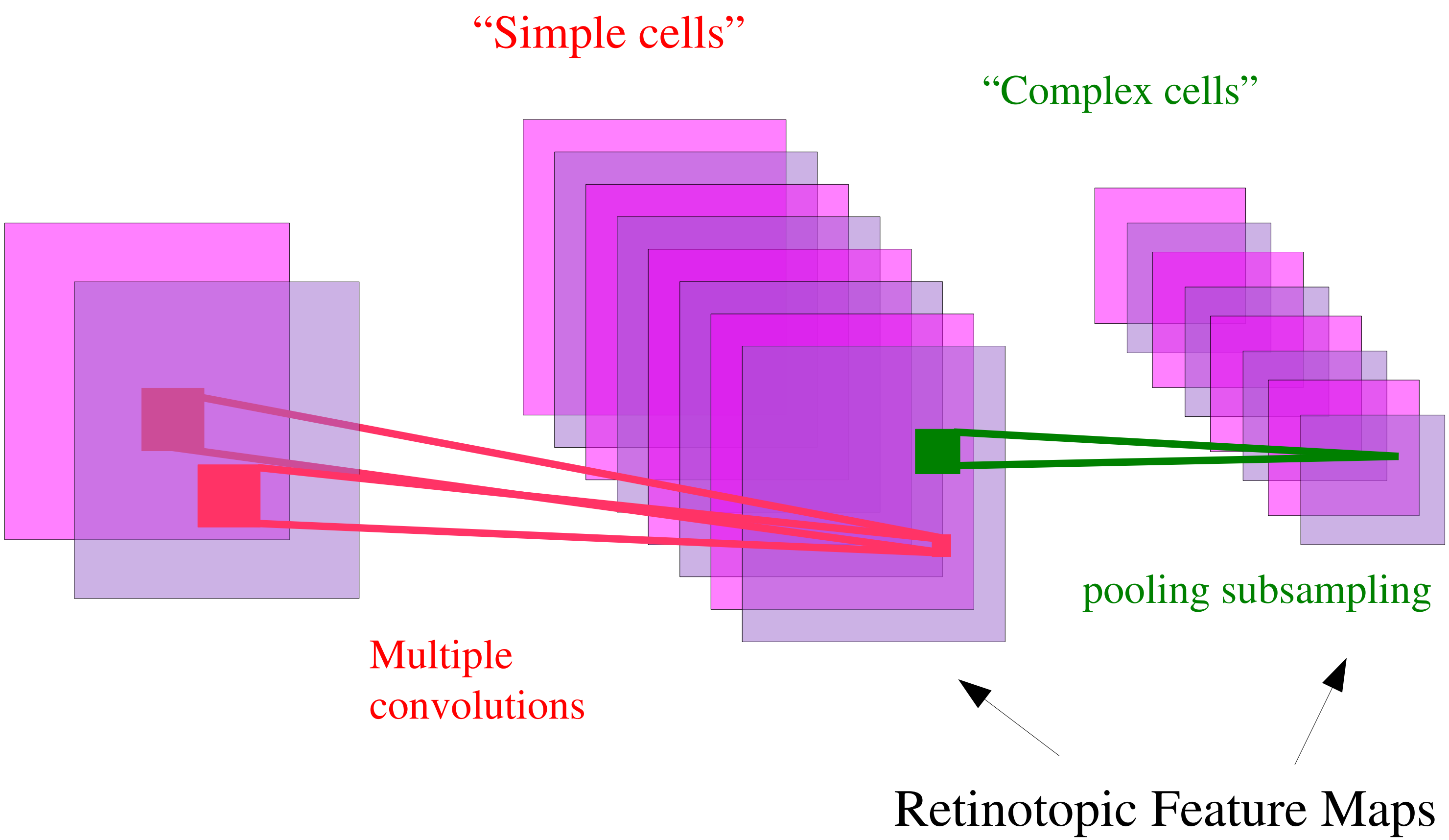
Supervised Convolutional Networks



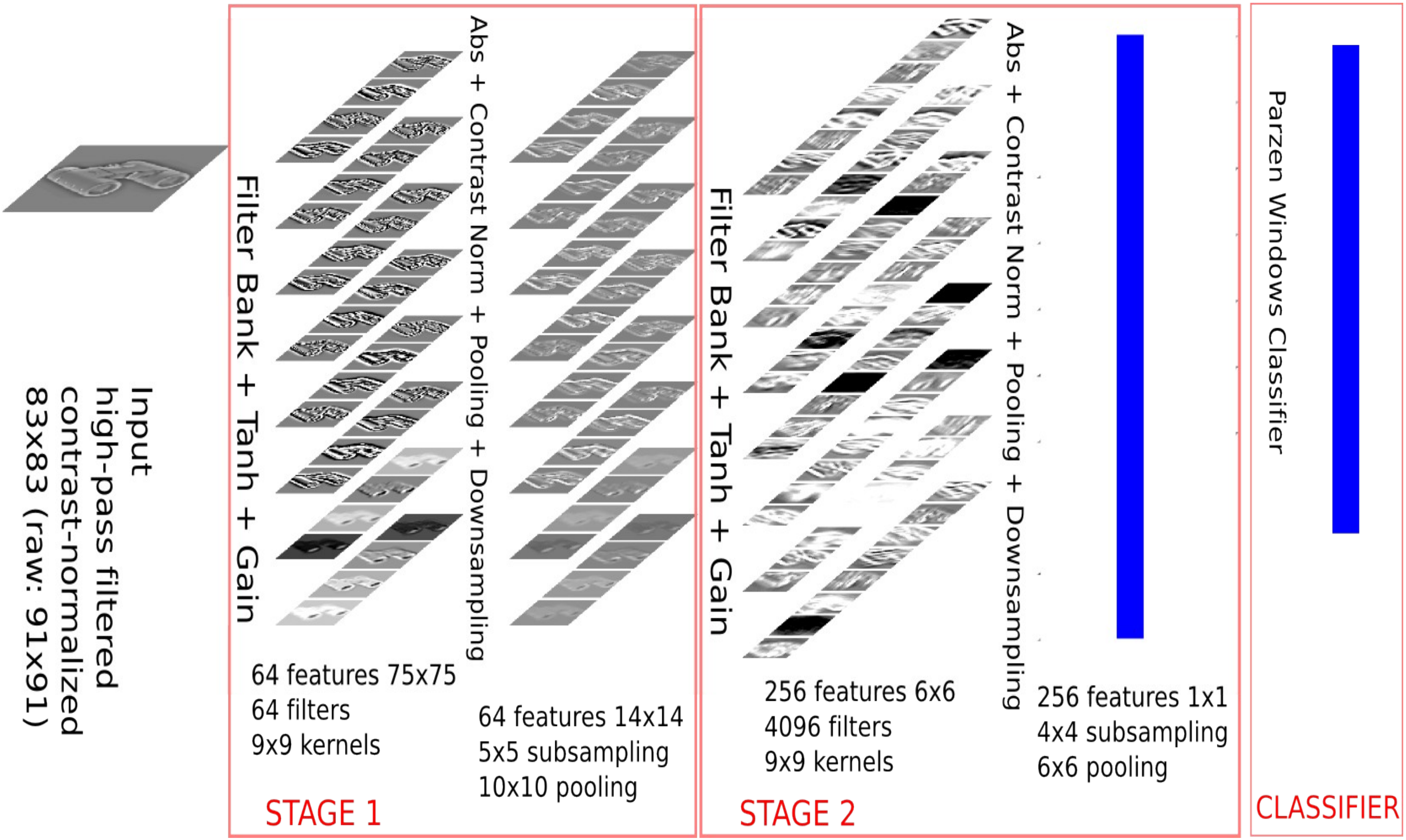
- **Hierarchical/multilayer:** features get progressively more global, invariant, and numerous
- **dense features:** features detectors applied everywhere (no interest point)
- **broadly tuned (possibly invariant) features:** sigmoid units are on half the time.
- **Global discriminative training:** The 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.



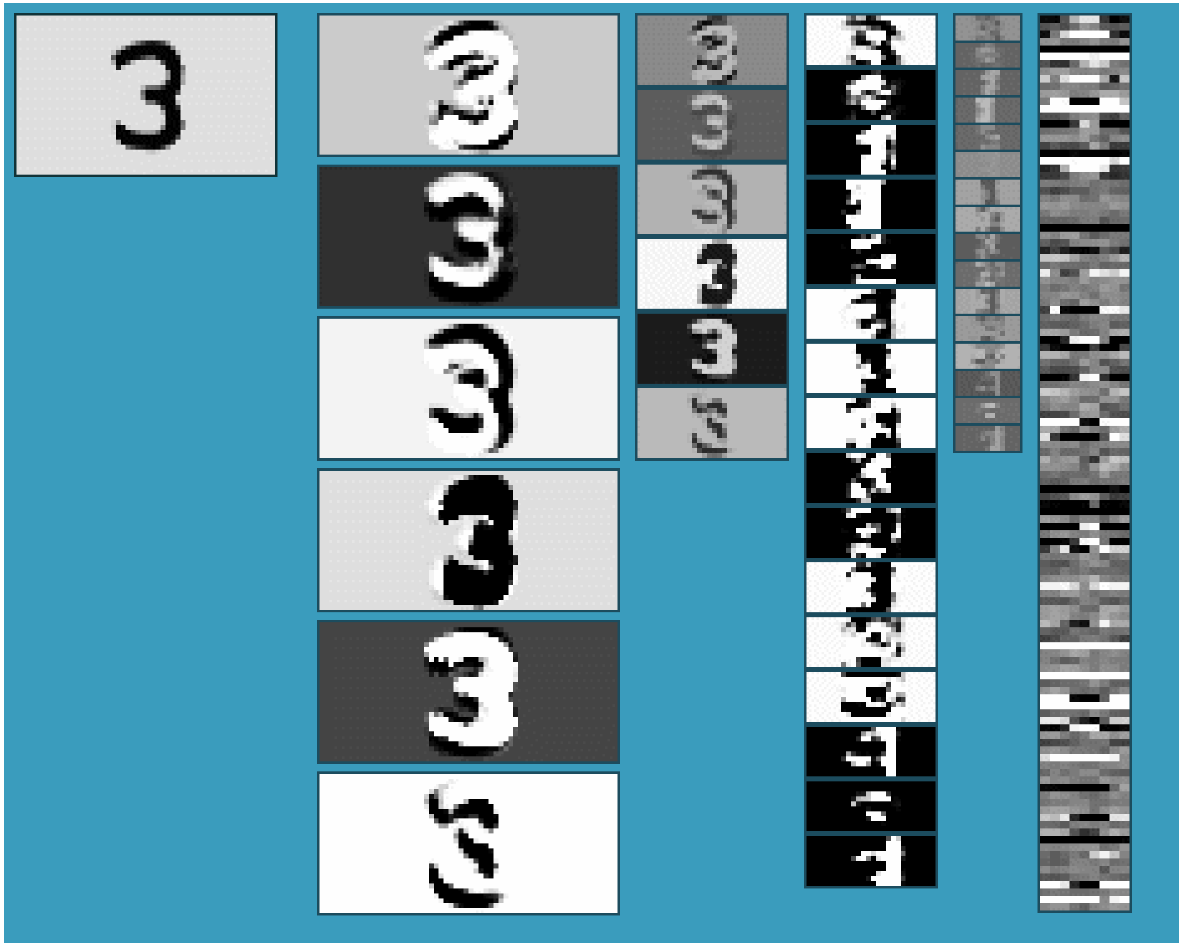
Convolutional Network Architecture



The Multistage Hubel-Wiesel Architecture

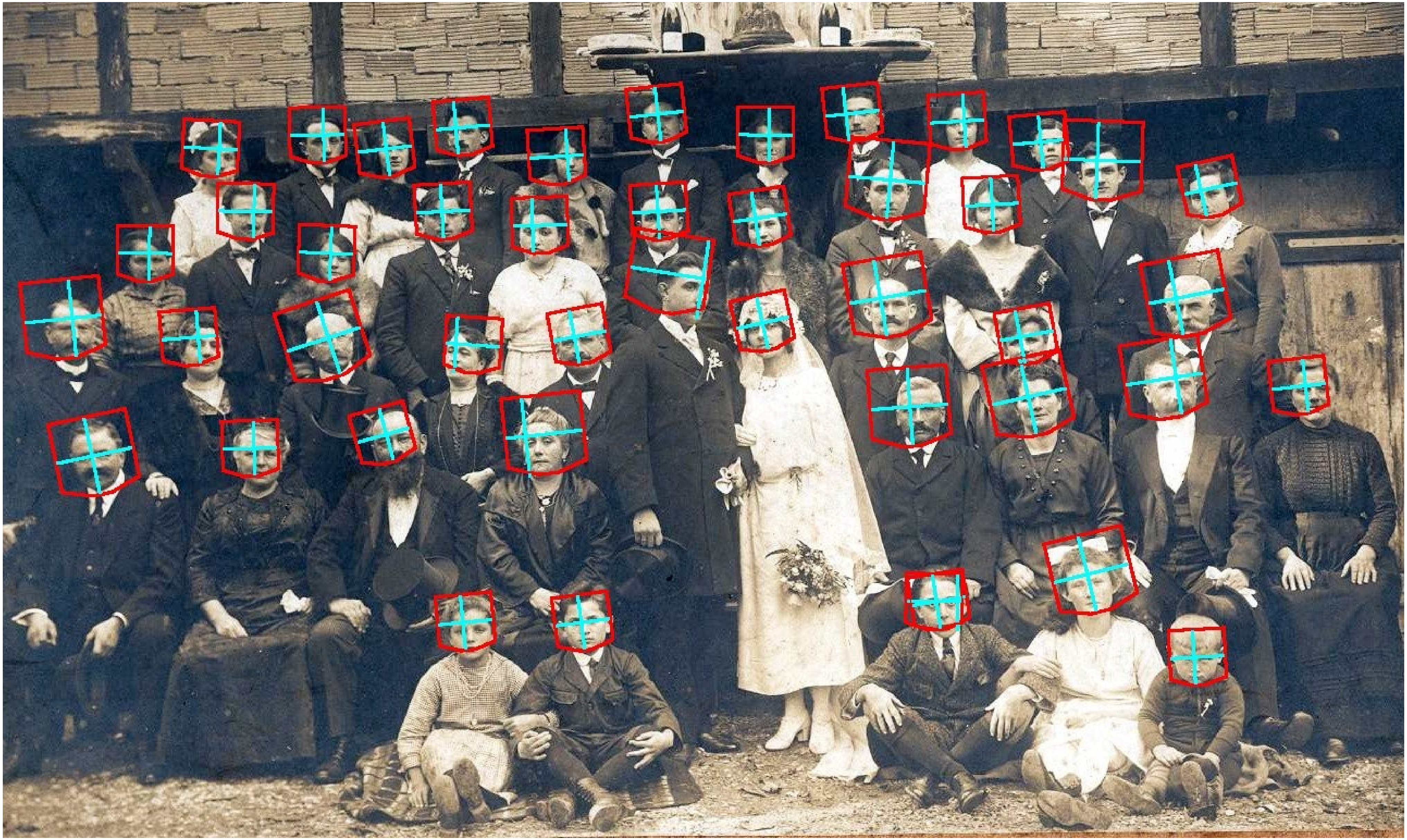
Building a complete artificial vision system:

- 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-now]
  - convolutional net
- [Poggio, Serre 2002-now]
  - HMAX
- [Ullman 2002-now]
  - fragment hierarchy
- [Lowe 2006]
  - HMAX

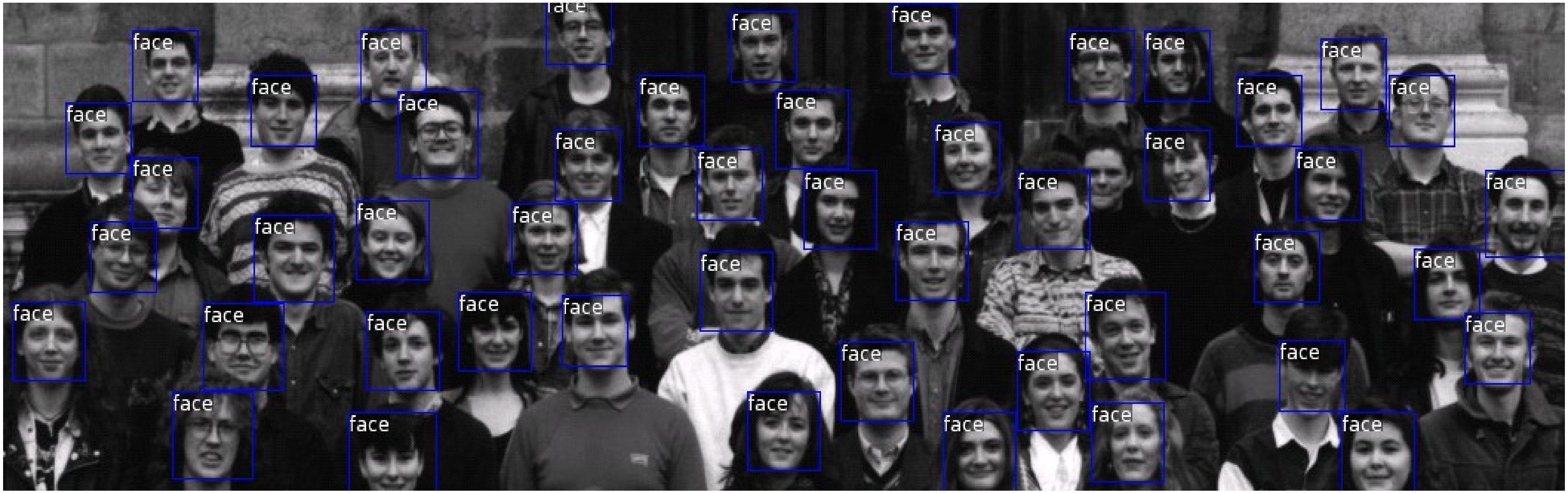


Face Detection and Pose Estimation with a ConvNet

Face Detection and Pose Estimation with a ConvNet



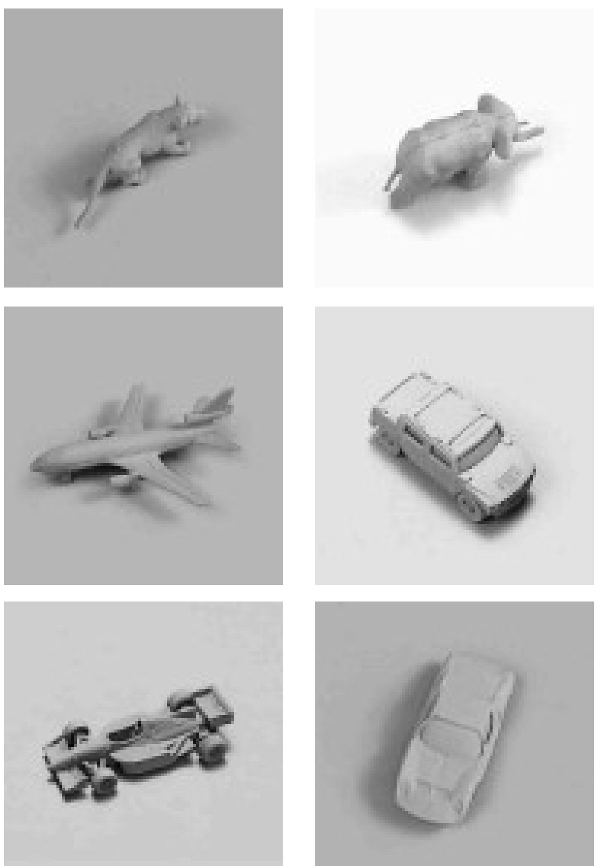
Face Detection with a ConvNet

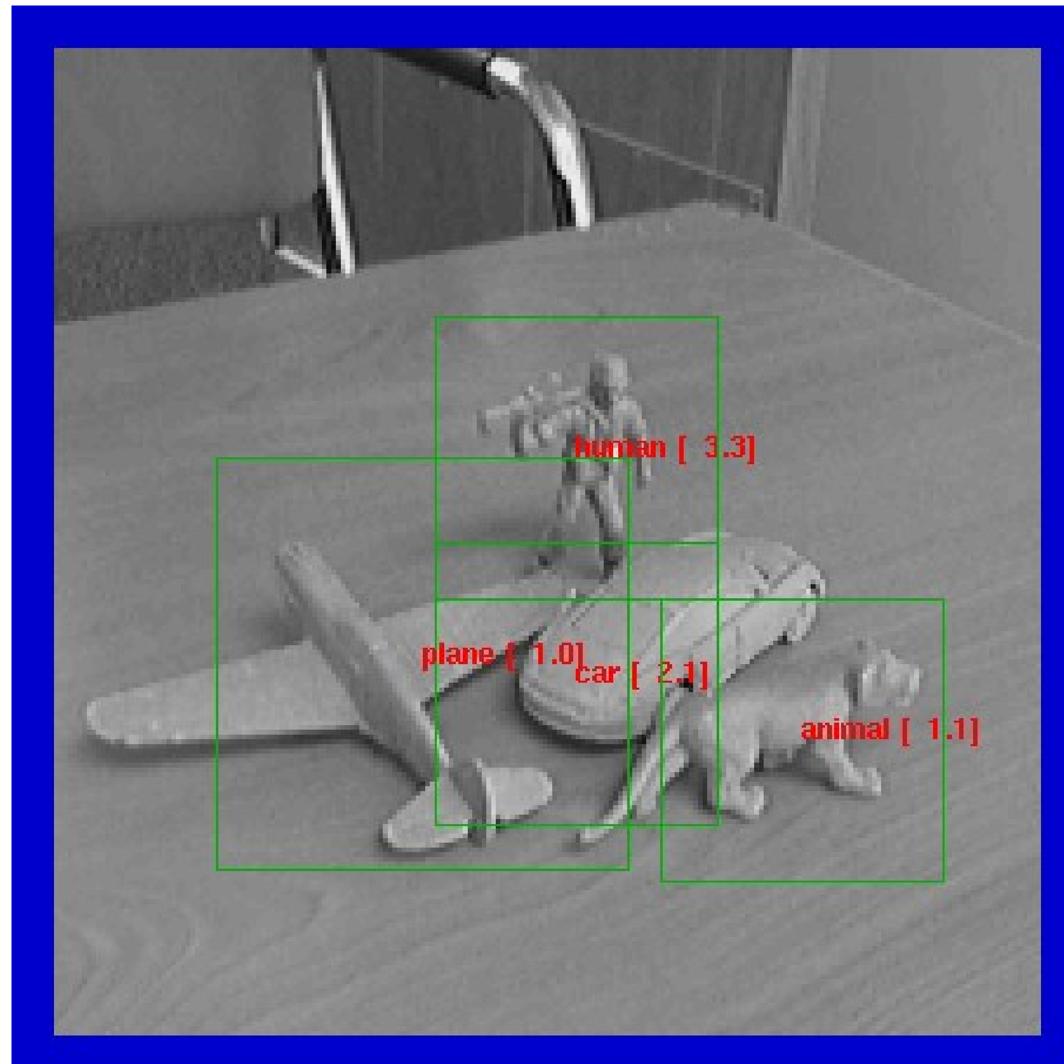


- Demo produced with EBLearn open source package
- http://eblearn.sf.net

Category-Level Object Recognition

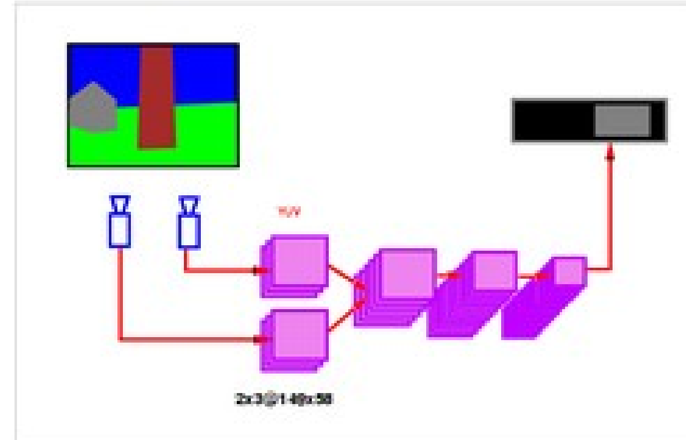
- 5 categories: humans, animals, airplanes, cars, trucks
- Only 5 training instances per class
- Lots of pose and lighting variations



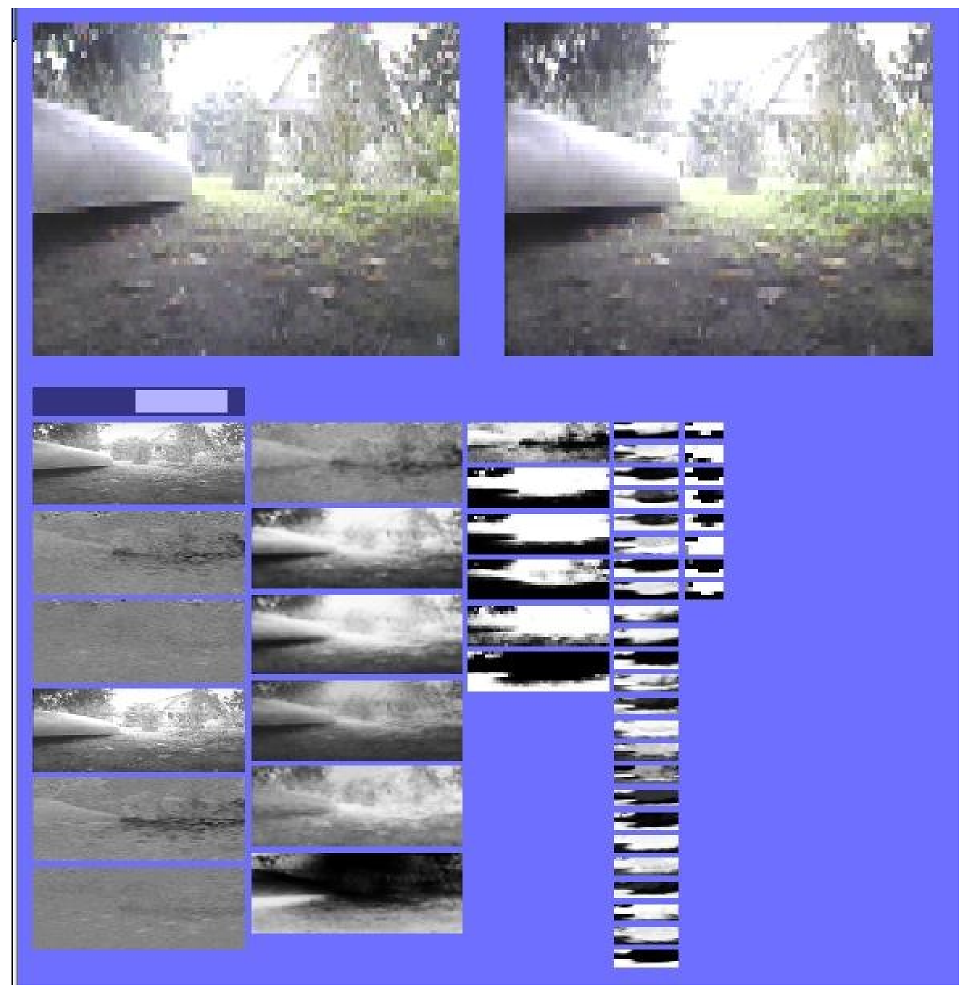


Visual Navigation for a Mobile Robot

[LeCun et al. NIPS 2005]

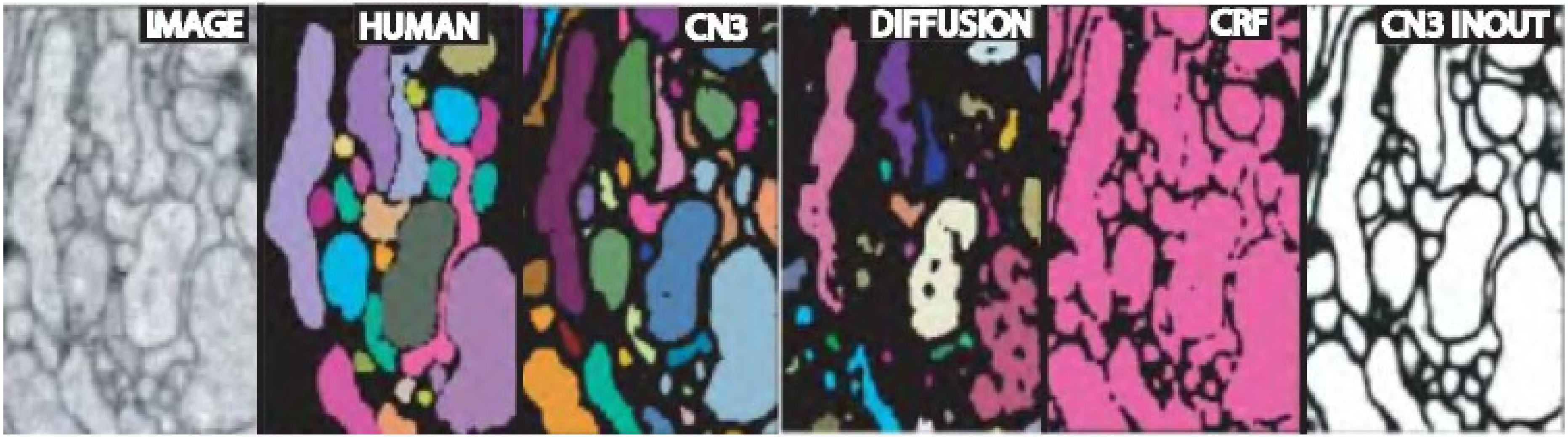


- Mobile robot with two cameras
- The convolutional net is trained to emulate a human driver from recorded sequences of video + human-provided steering angles.
- The network maps stereo images to steering angles for obstacle avoidance



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]

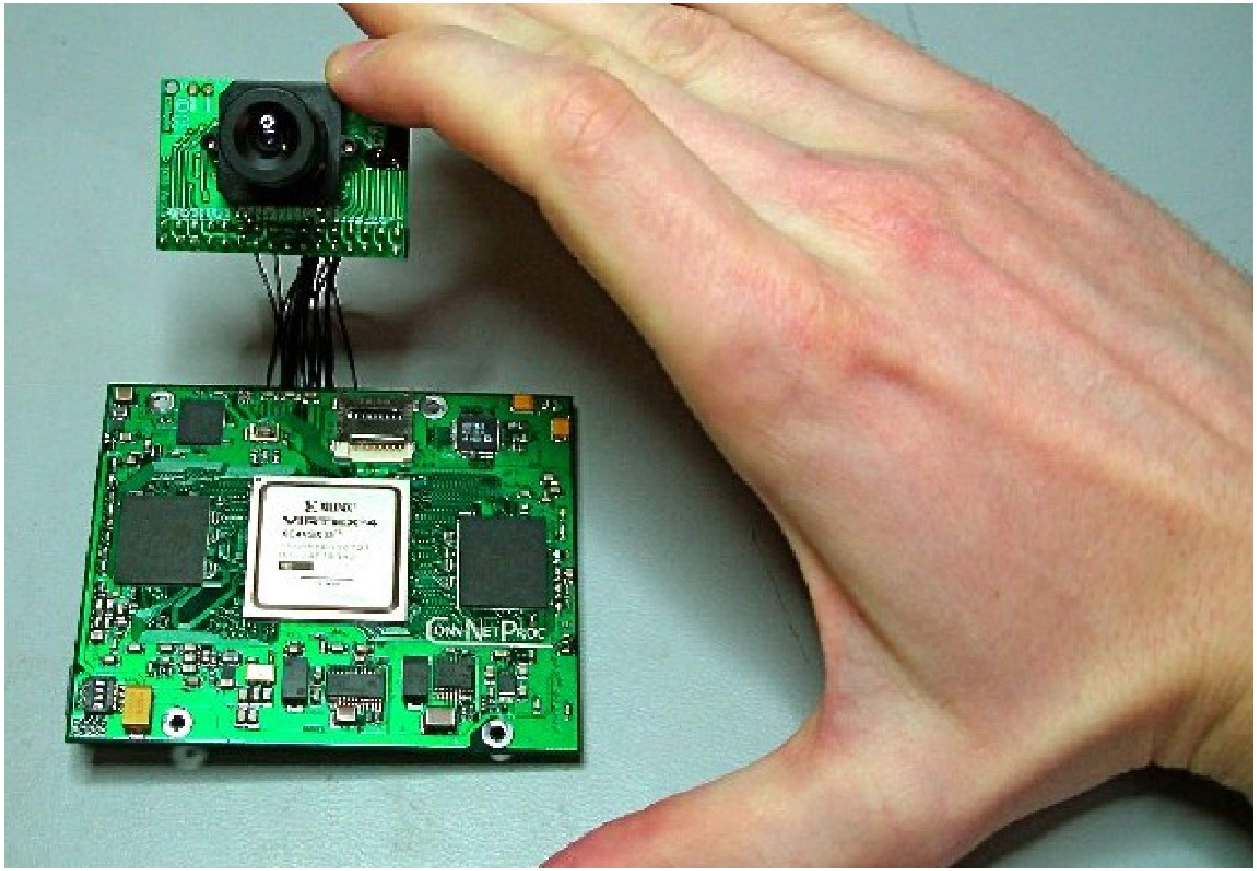


Industrial Applications of ConvNets

- **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)....**

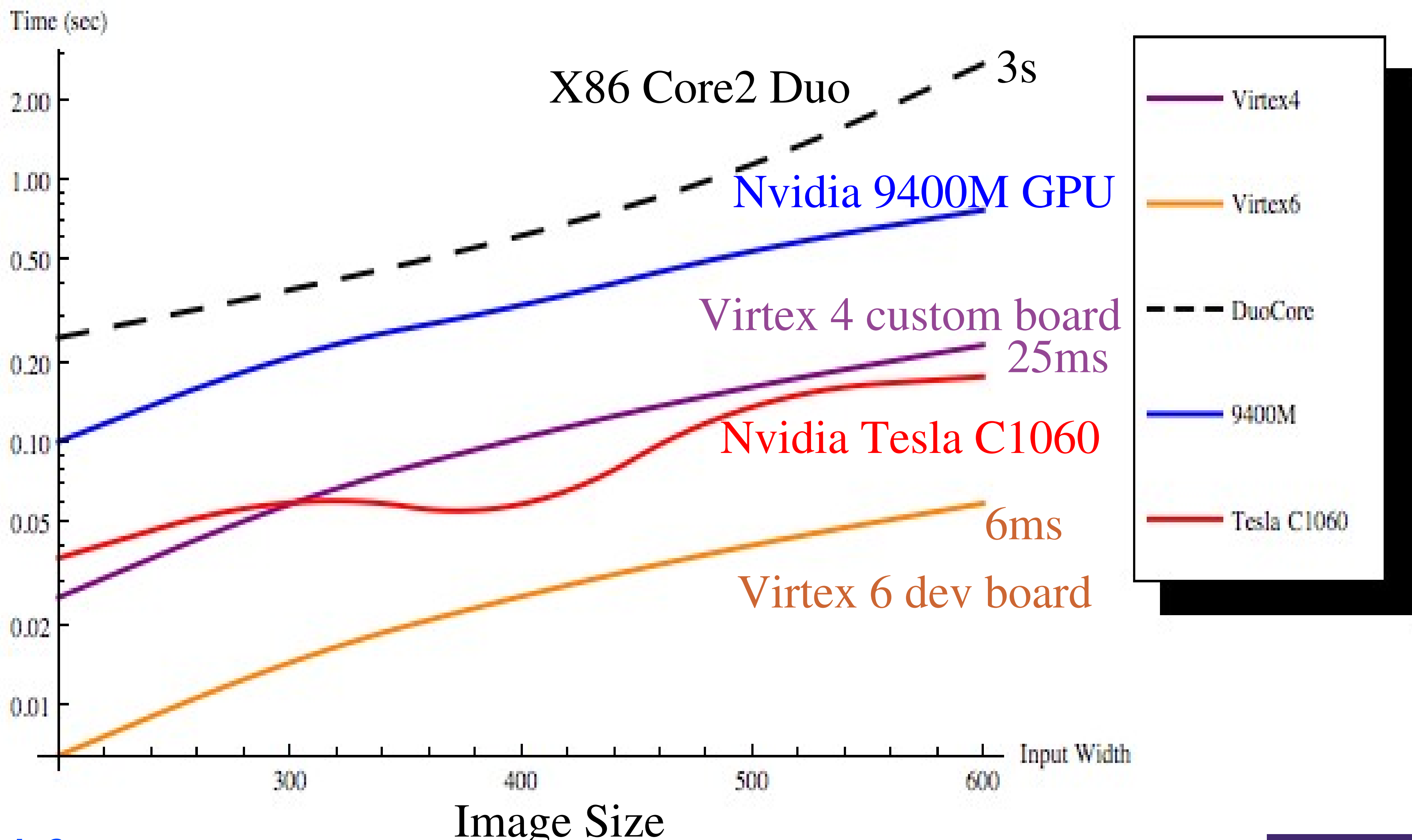
FPGA Custom Board: NYU ConvNet Processor

- **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 (ASIC)
  - Version for Virtex 6 FPGA



FPGA Performance

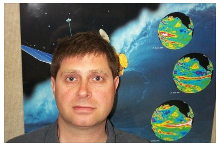
- **Seconds per frame for a robot vision task (log scale)** [Farabet et al. 2010]



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

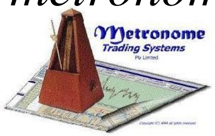
wild cat

lotus

ant

dollar

metronome



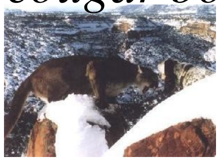
w. chair

minaret

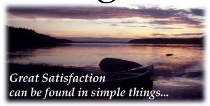
cellphone

joshua t.

cougar body



background



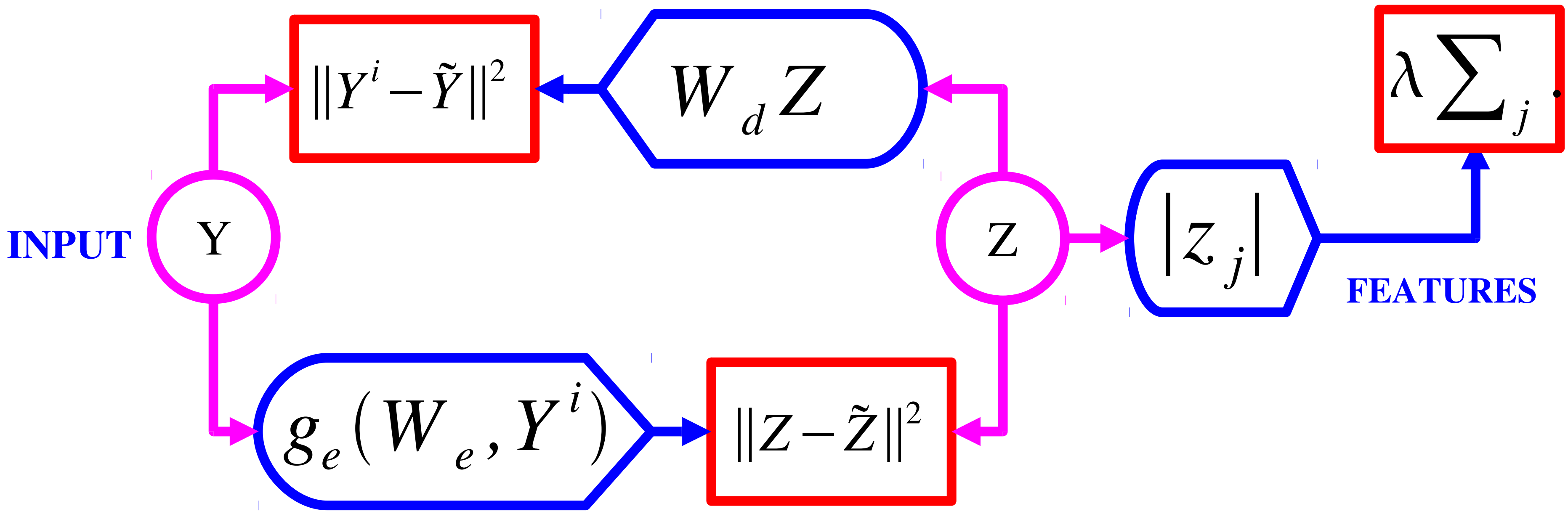
Fast Sparse Coding: Predictive Sparse Decomposition (PSD)

[Kavukcuoglu, Ranzato, LeCun, 2009]

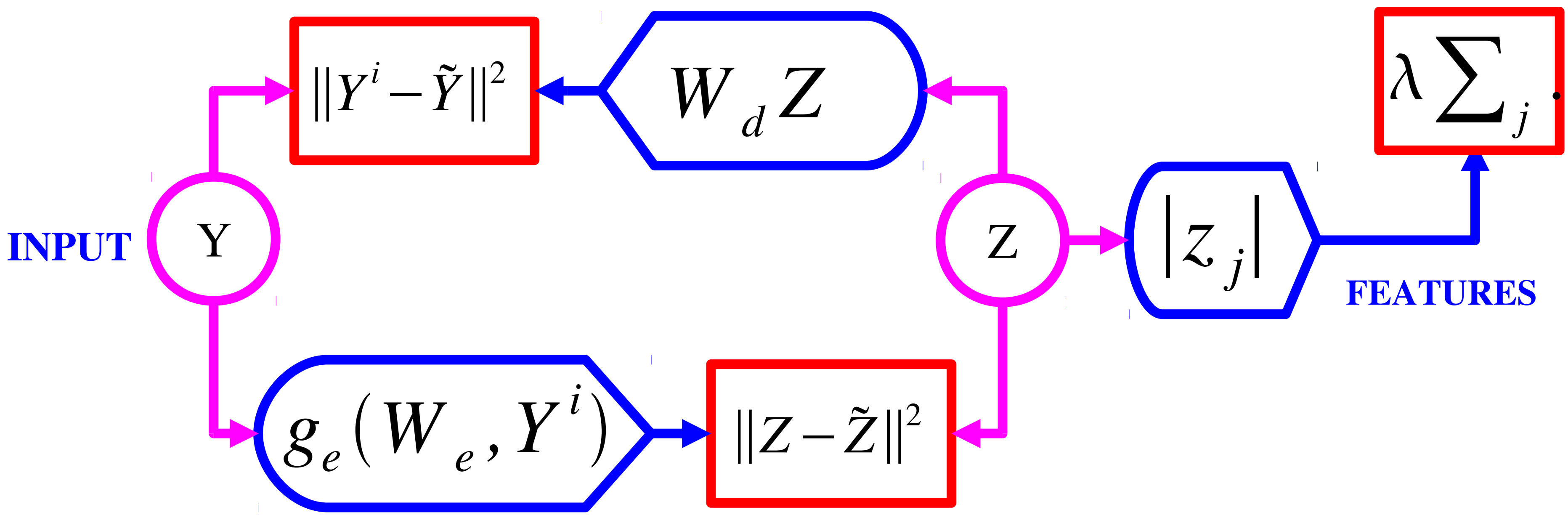
- **Prediction the optimal code with a trained encoder**
- **Energy = reconstruction_error + code_prediction_error + code_sparsity**

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

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



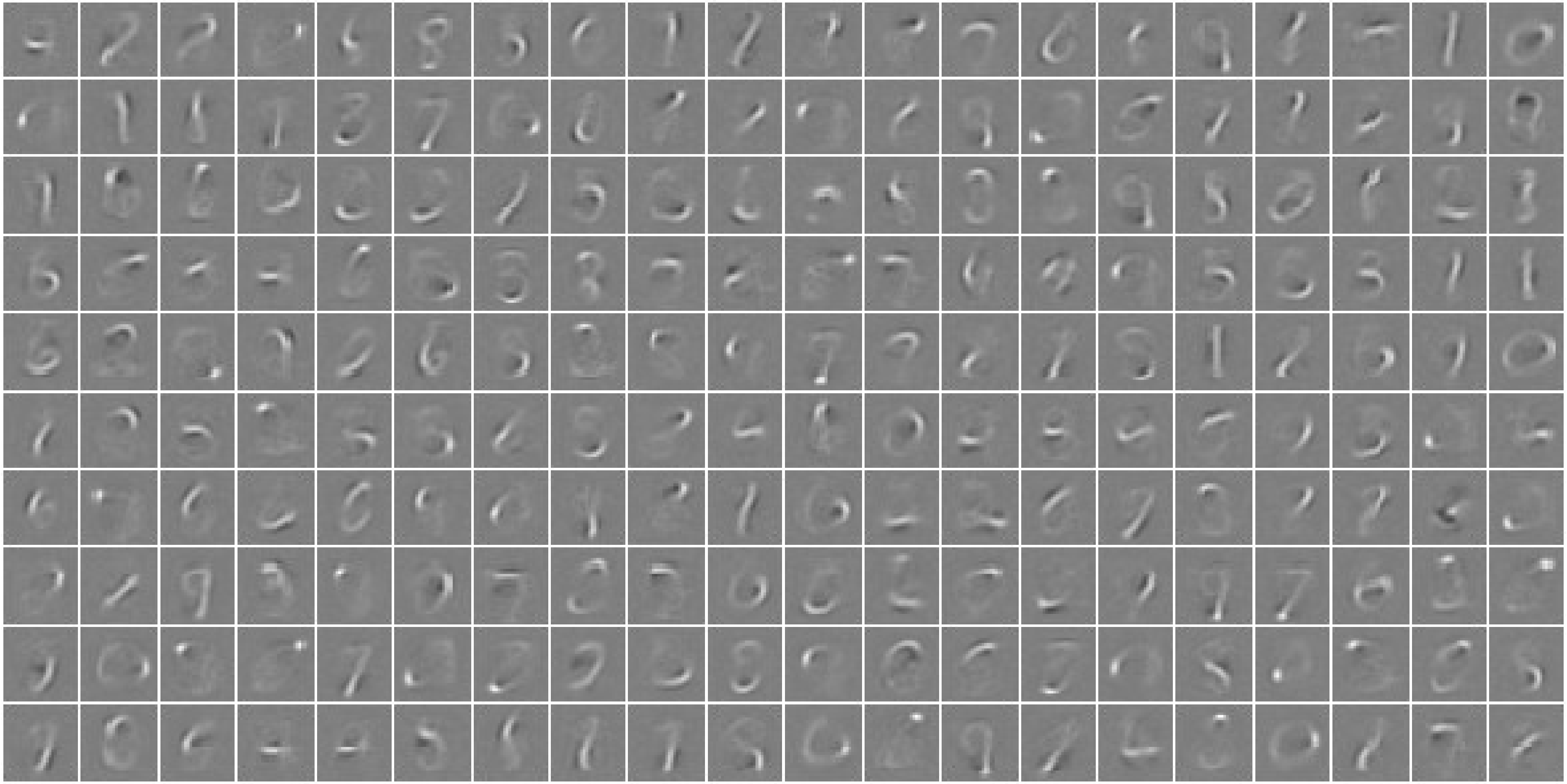
PSD: Learning Algorithm



- 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

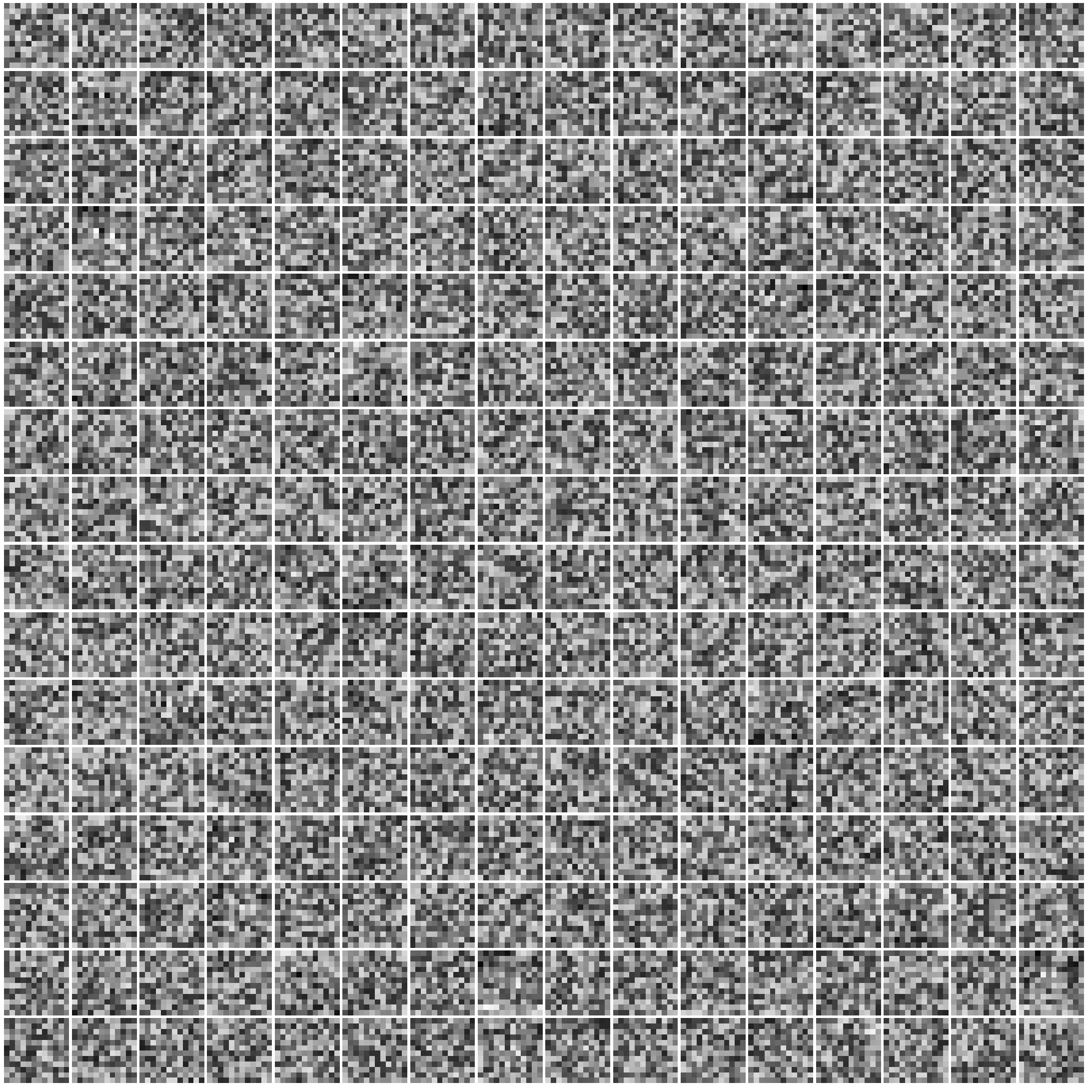
Decoder Basis Functions on MNIST

- **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".

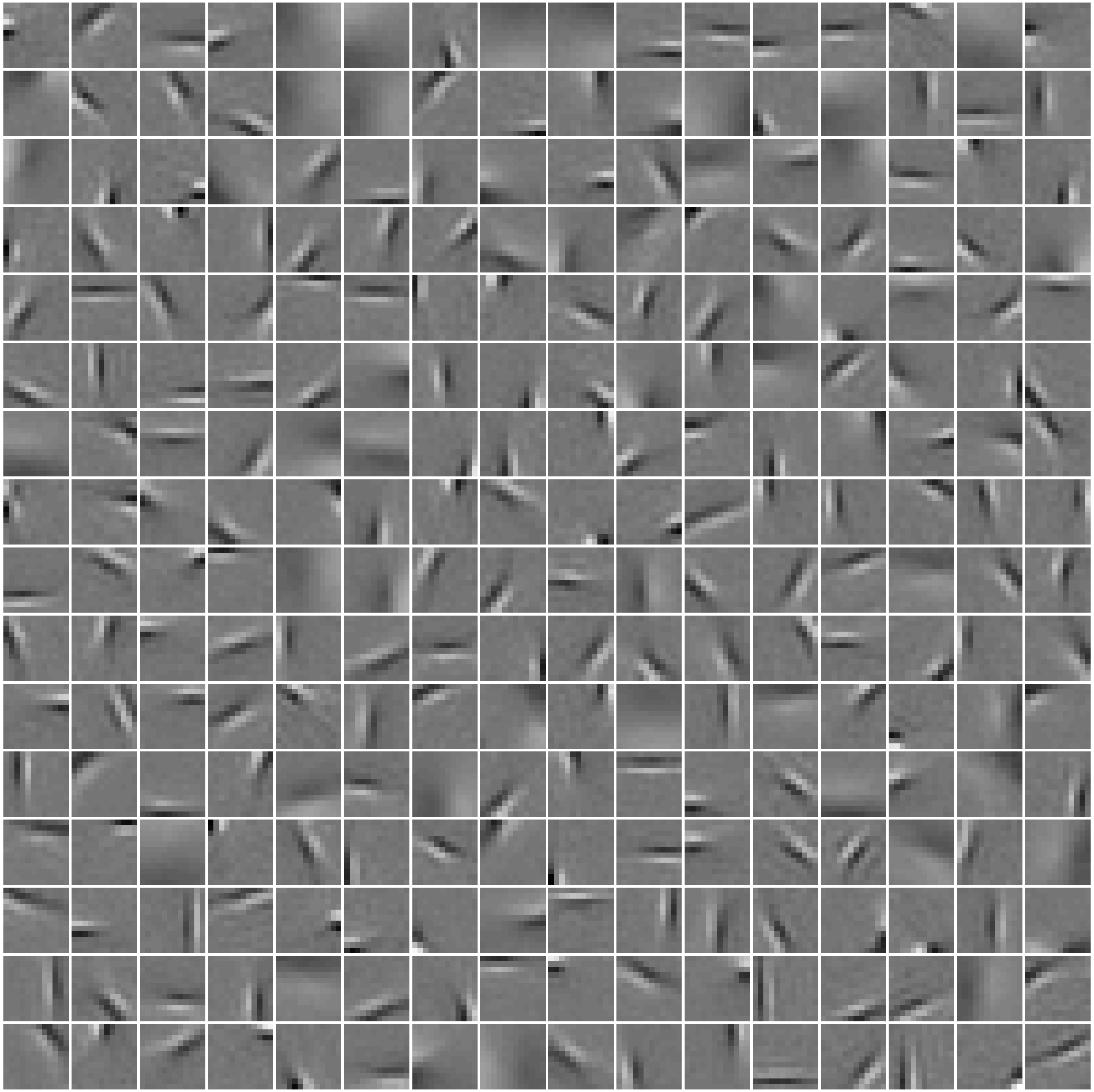


PSD Training on Natural Image Patches

- 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

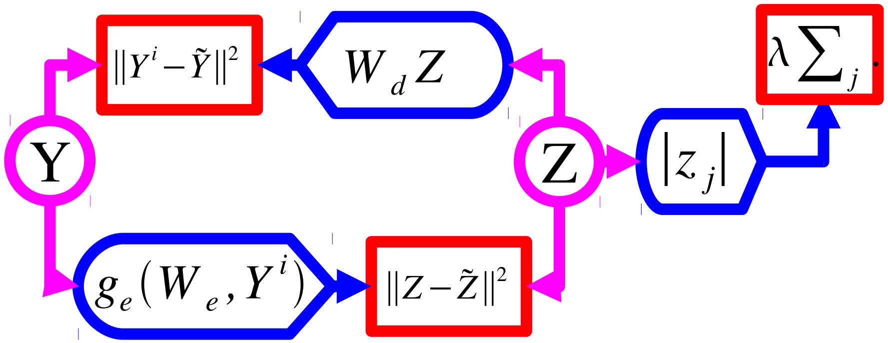


Learned Features on natural patches: V1-like receptive fields



Using PSD to Train a Hierarchy of Features

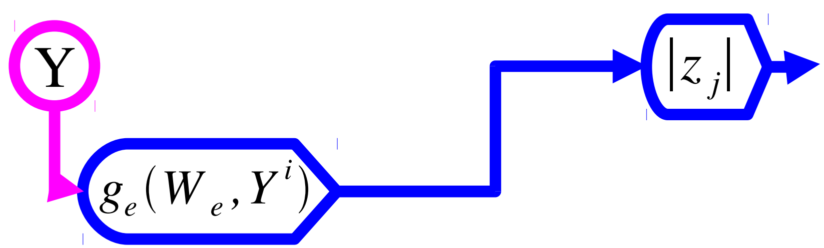
- **Phase 1: train first layer using PSD**



FEATURES

Using PSD to Train a Hierarchy of Features

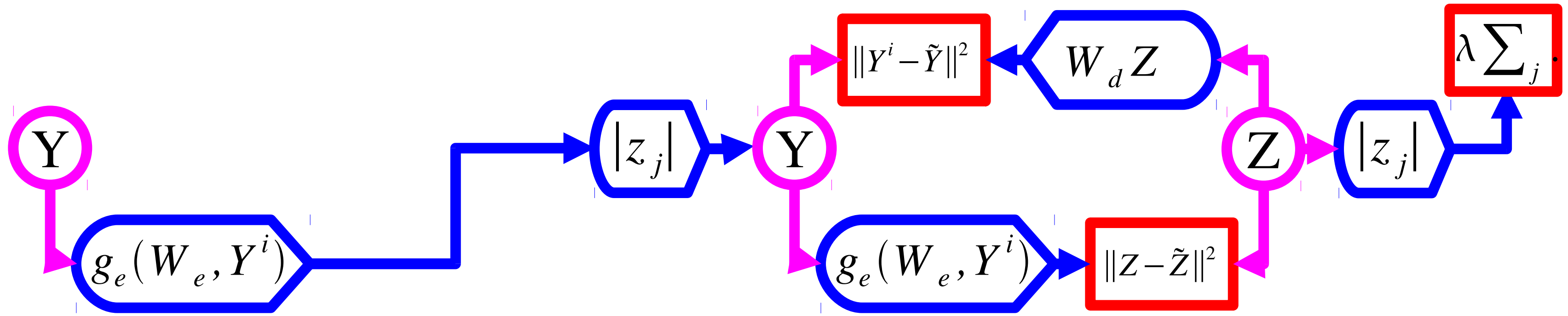
- **Phase 1: train first layer using PSD**
- **Phase 2: use encoder + absolute value as feature extractor**



FEATURES

Using PSD to Train a Hierarchy of Features

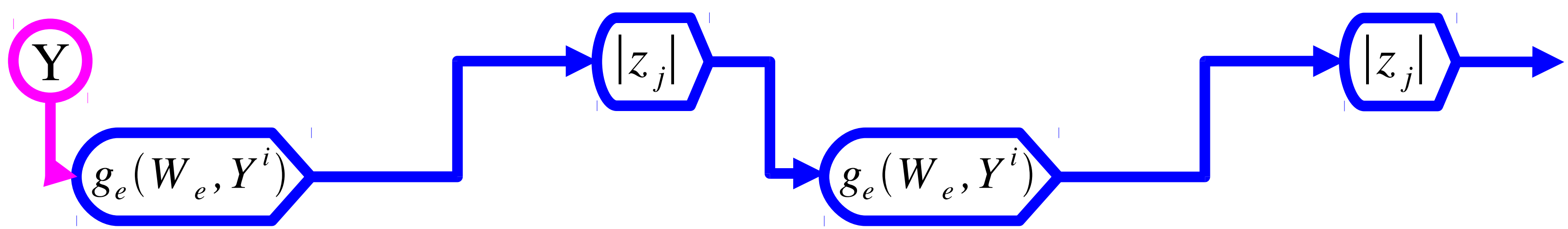
- Phase 1: train first layer using PSD
- Phase 2: use encoder + absolute value as feature extractor
- Phase 3: train the second layer using PSD



FEATURES

Using PSD to Train a Hierarchy of Features

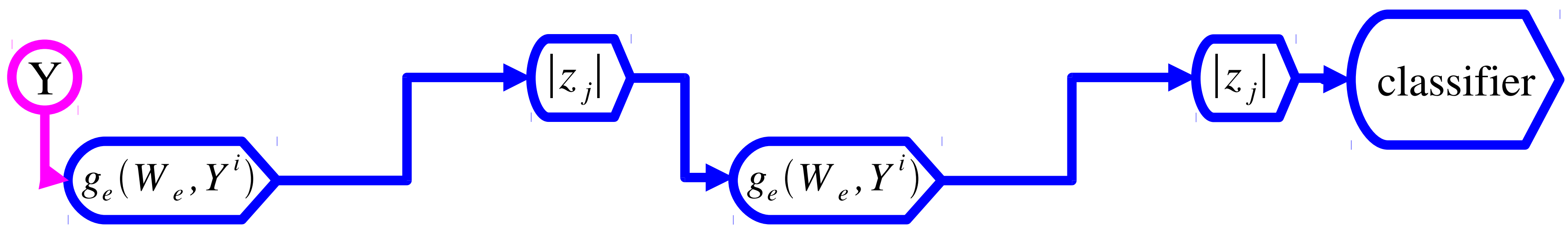
- Phase 1: train first layer using PSD
- Phase 2: use encoder + absolute value as feature extractor
- Phase 3: train the second layer using PSD
- Phase 4: use encoder + absolute value as 2nd feature extractor



FEATURES

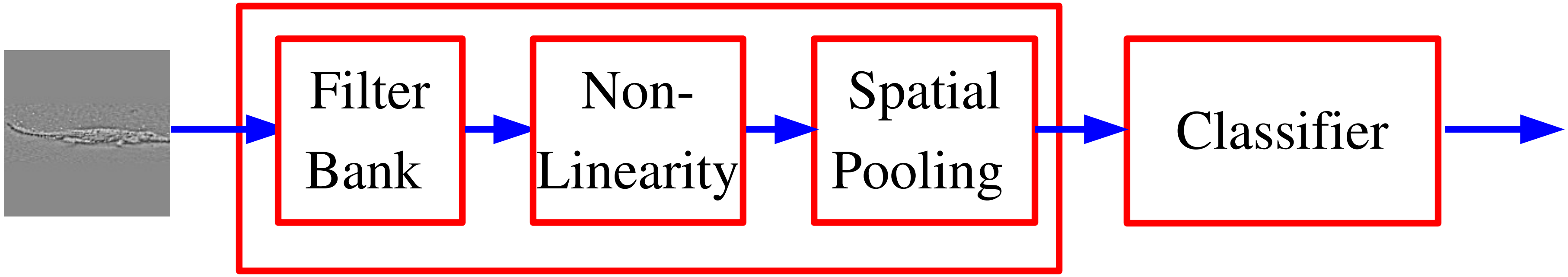
Using PSD to Train a Hierarchy of Features

- 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



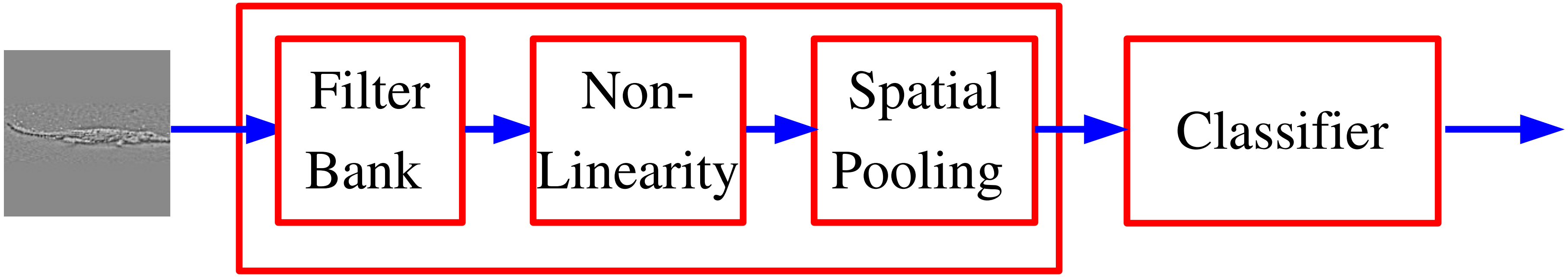
FEATURES

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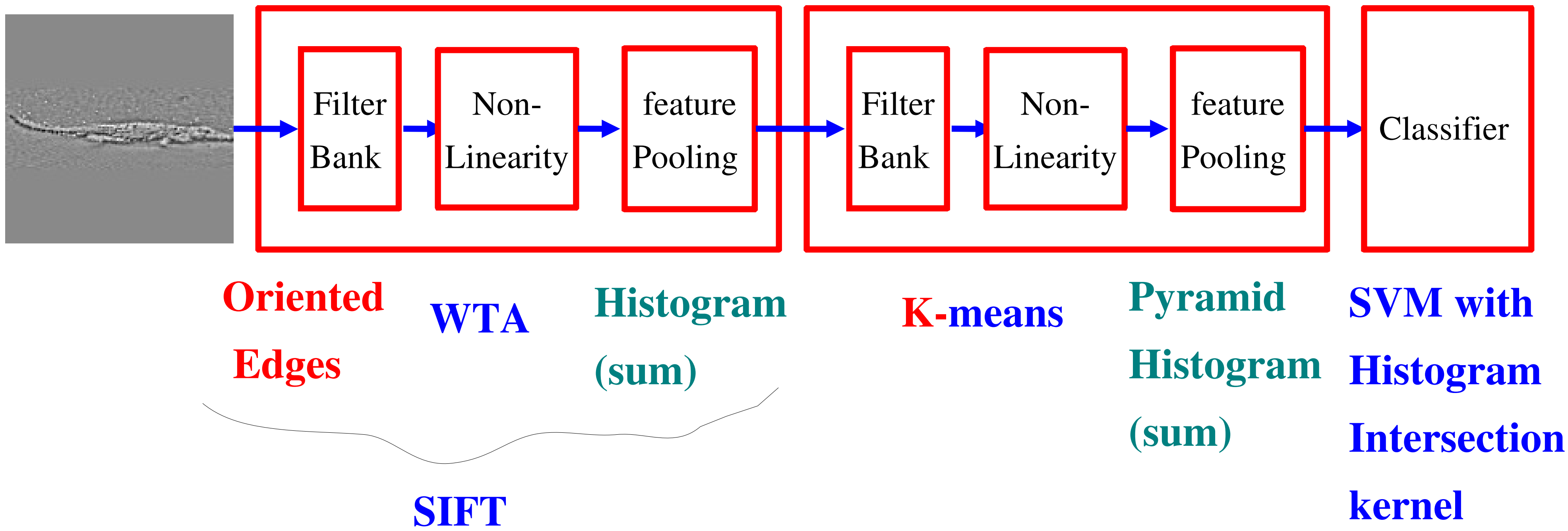
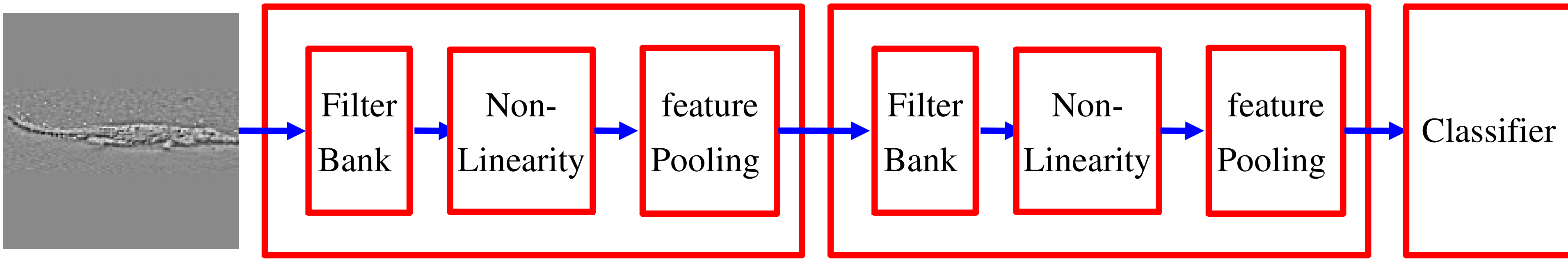
- **Example:**
  - Edges + Rectification + Histograms + SVM [Dalal & Triggs 2005]
  - SIFT + classification
- **Fixed Features + “shallow” classifier**

"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**

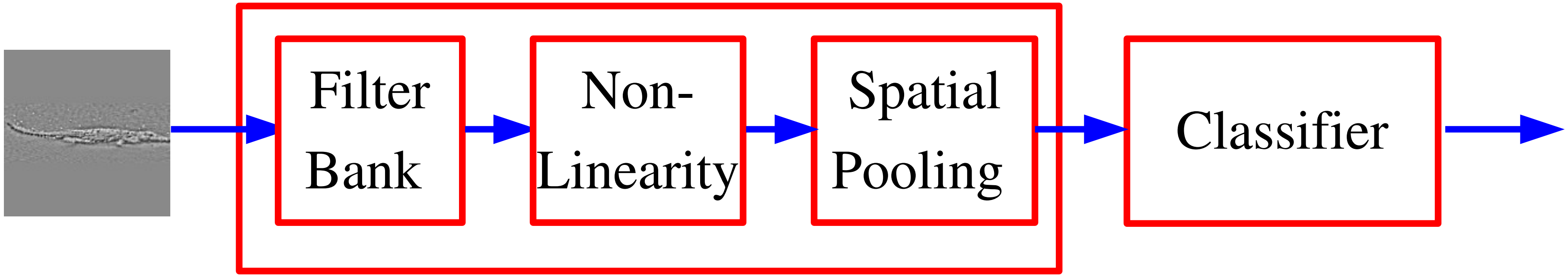
Can't we get the same results with (deep) learning?

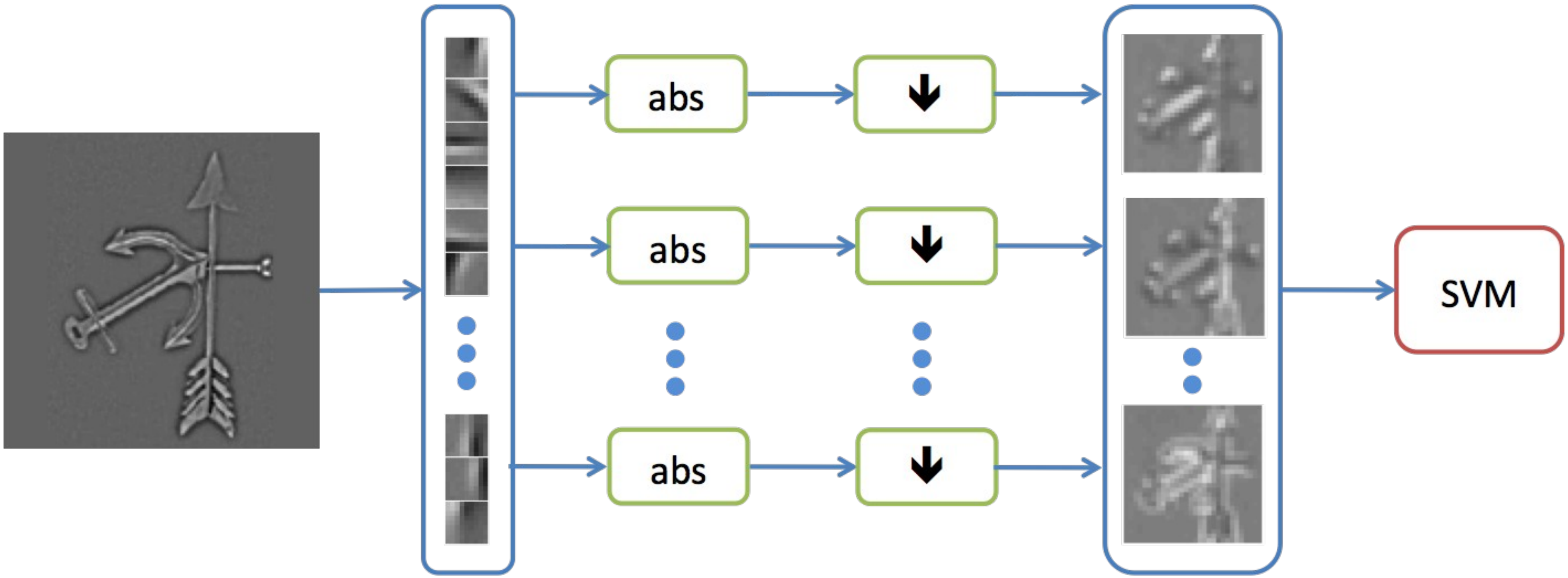


- **Stacking multiple stages of feature extraction/pooling.**
- **Creates a hierarchy of features**
- **ConvNets and SIFT+PMK-SVM architectures are conceptually similar**
- **Can deep learning make a ConvNet match the performance of SIFT+PNK-SVM?**

How well do PSD feature learning work on Caltech-101?

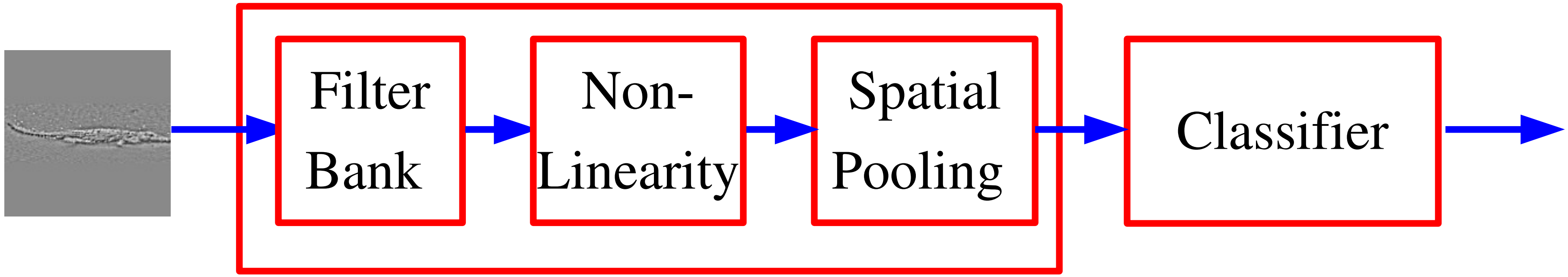
- **Recognition Architecture**





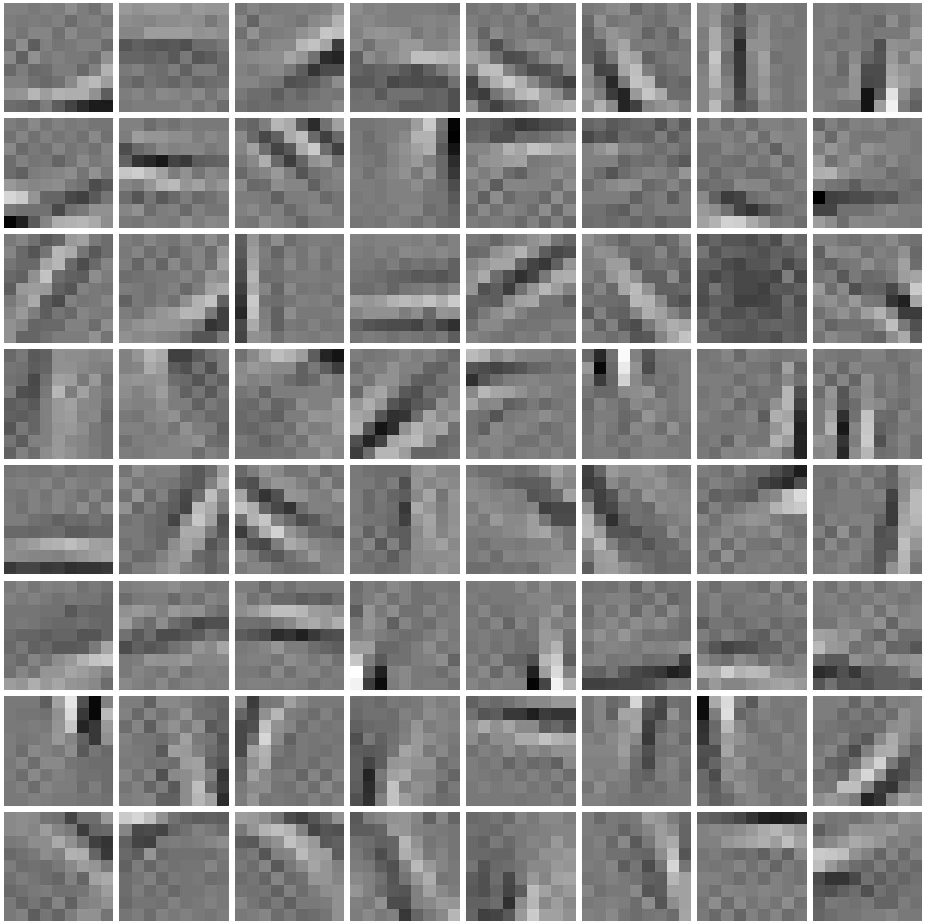
Procedure for a single-stage system

- **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

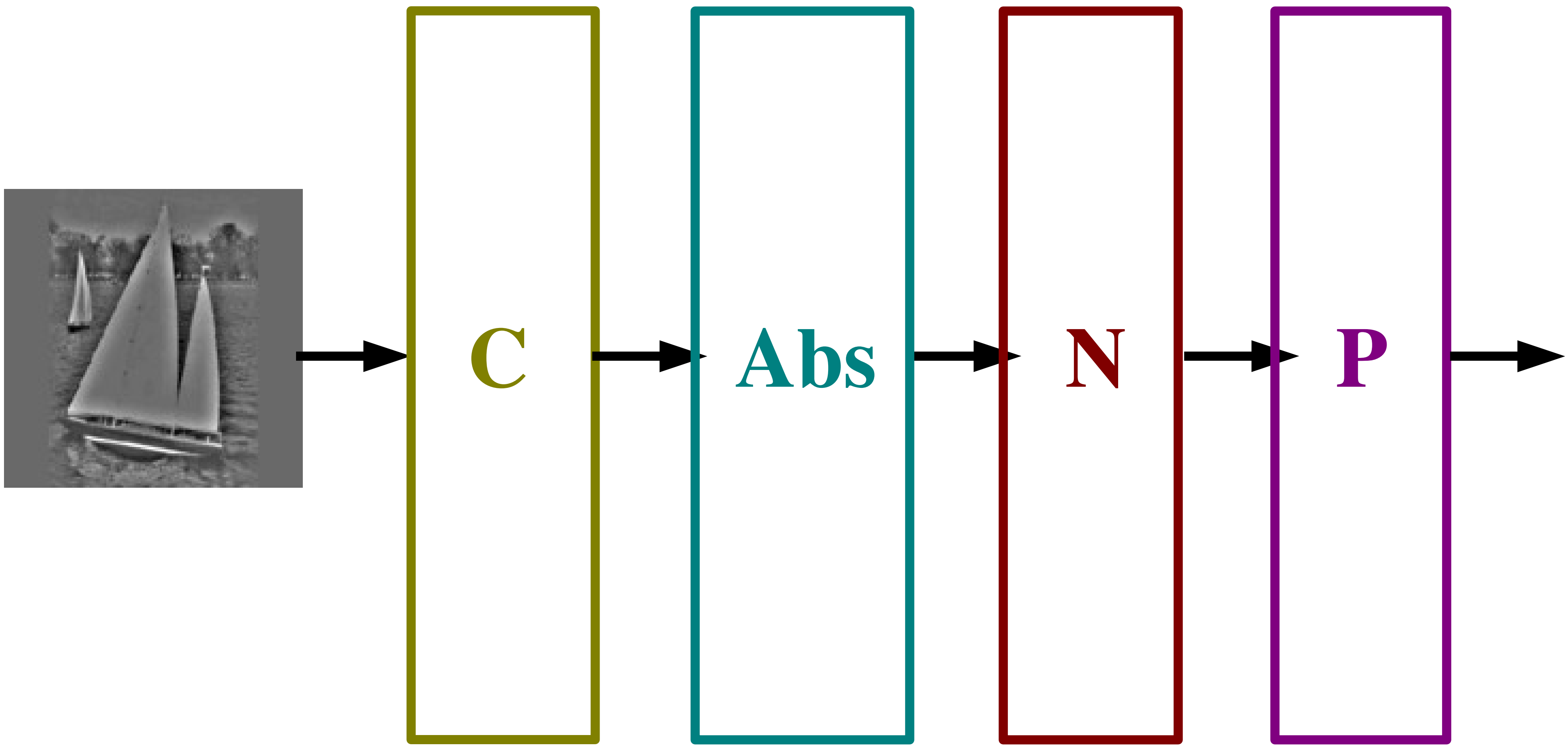
- **64 filters on 9x9 patches trained with PSD**
  - with Linear-Sigmoid-Diagonal Encoder



weights :-0.2828 - 0.3043

Feature Extraction

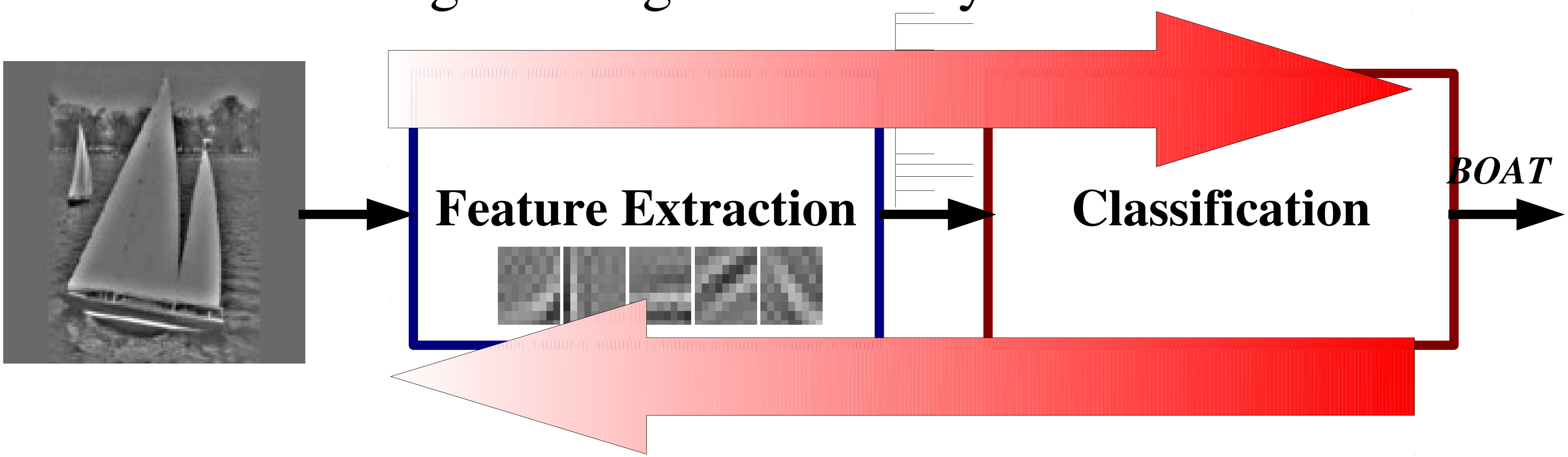
- **C** Convolution/sigmoid layer: filter bank? Learning, fixed Gabors?
- **Abs** Rectification layer: needed?
- **N** Normalization layer: needed?
- **P** Pooling down-sampling layer: average or max?



THIS IS ONE STAGE OF FEATURE EXTRACTION

Training Protocol

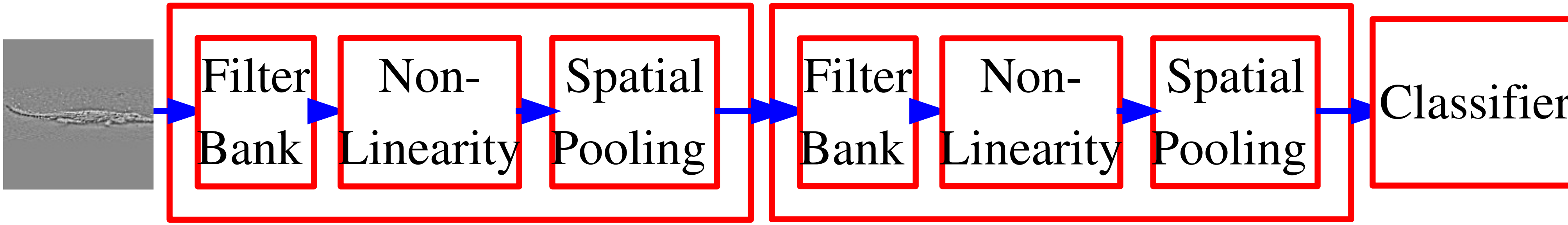
- **Training**
  - Logistic Regression on Random Features: R
  - Logistic Regression on PSD features: U
  - Refinement of whole net from random with backprop: R^+
  - Refinement of whole net starting from PSD filters: U^+
- **Classifier**
  - Multinomial Logistic Regression or Pyramid Match Kernel SVM



Using PSD Features for Recognition

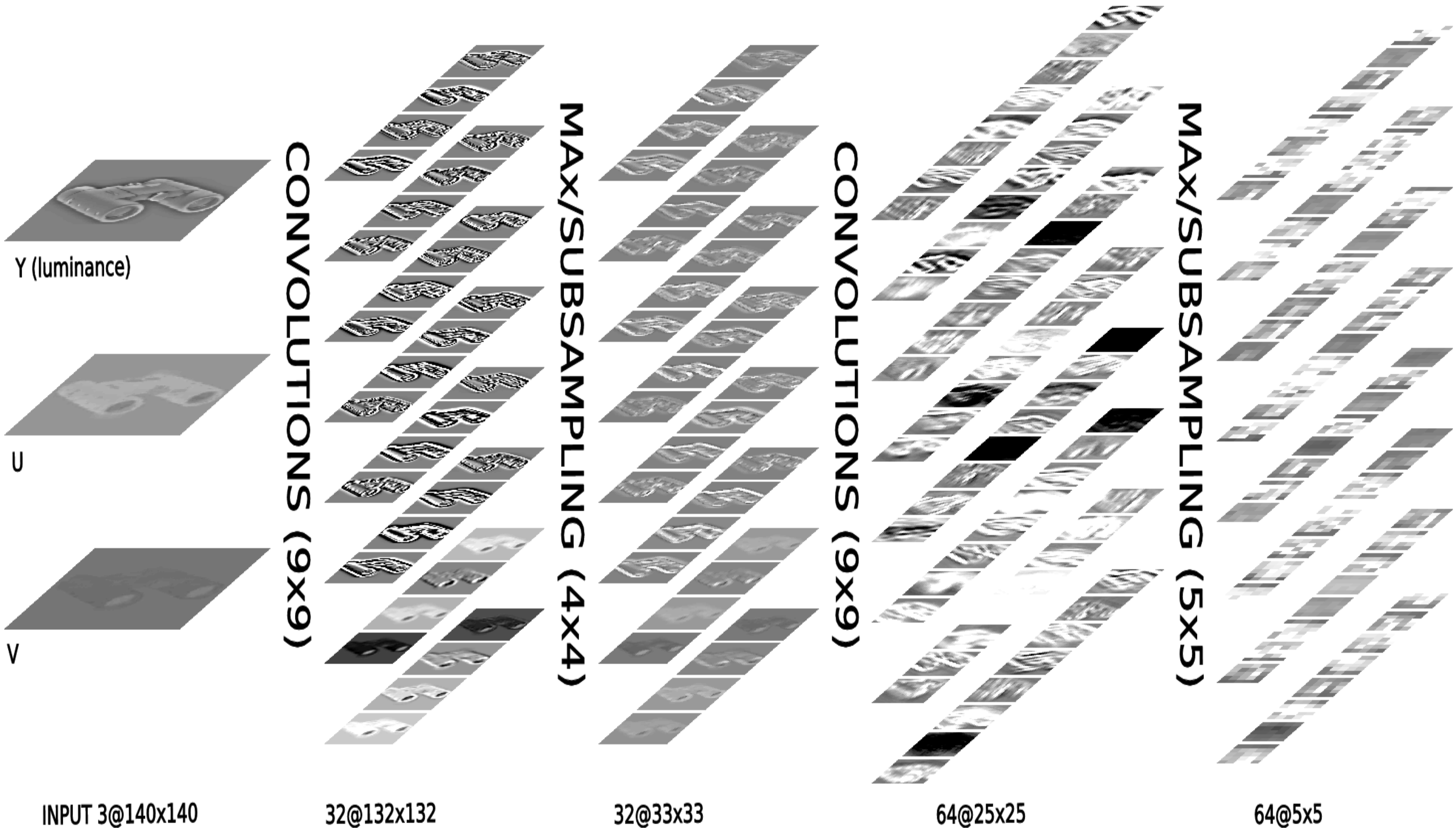
$[64.\mathrm{F}_{\mathrm{CSG}}^{9\times9} - \mathrm{R/N/P}^{5\times5}]$ - log_reg					
R/N/P	$\mathrm{R_{abs} - N - P_A}$	$\mathrm{R_{abs} - P_A}$	$\mathrm{N - P_M}$	$\mathrm{N - P_A}$	$\mathrm{P_A}$
U^+	54.2%	50.0%	44.3%	18.5%	14.5%
R^+	54.8%	47.0%	38.0%	16.3%	14.3%
U	52.2%	43.3(±1.6)%	44.0%	17.2%	13.4%
R	53.3%	31.7%	32.1%	15.3%	12.1(±2.2)%
$[64.\mathrm{F}_{\mathrm{CSG}}^{9\times9} - \mathrm{R/N/P}^{5\times5}]$ - PMK					
U	65.0%				
$[96.\mathrm{F}_{\mathrm{CSG}}^{9\times9} - \mathrm{R/N/P}^{5\times5}]$ - 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%				

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 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%				

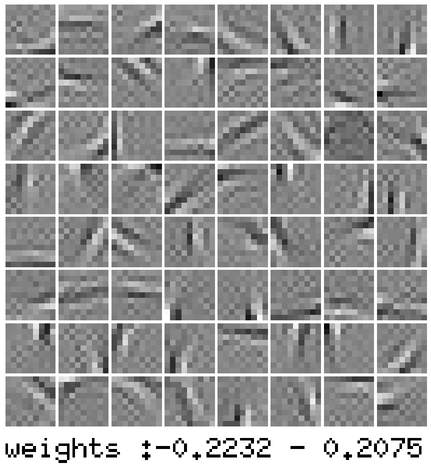
Two-Stage Result Analysis

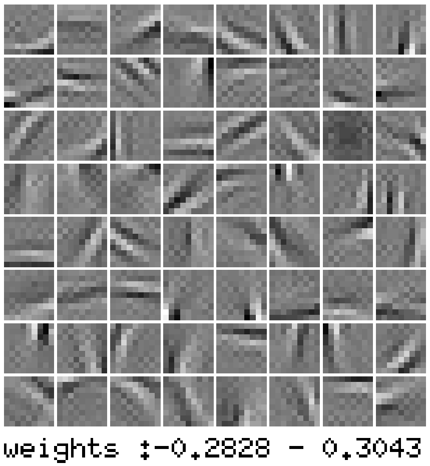
- Second Stage + logistic regression = PMK_SVM
- Unsupervised pre-training doesn't help much :-(
- Random filters work amazingly well with normalization
- Supervised global refirnement helps a bit
- The best system is really cheap
- Either use rectification and average pooling or no rectification and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

Multistage Hubel-Wiesel Architecture: Filters

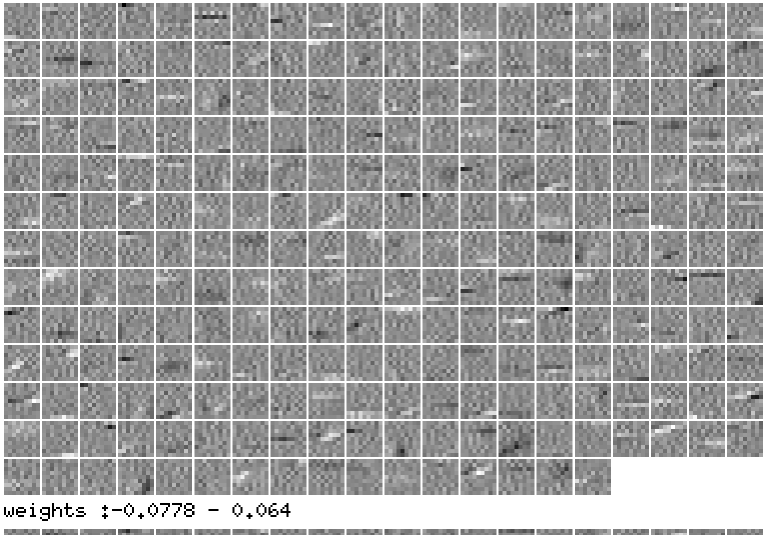
- After PSD
- After supervised refinement

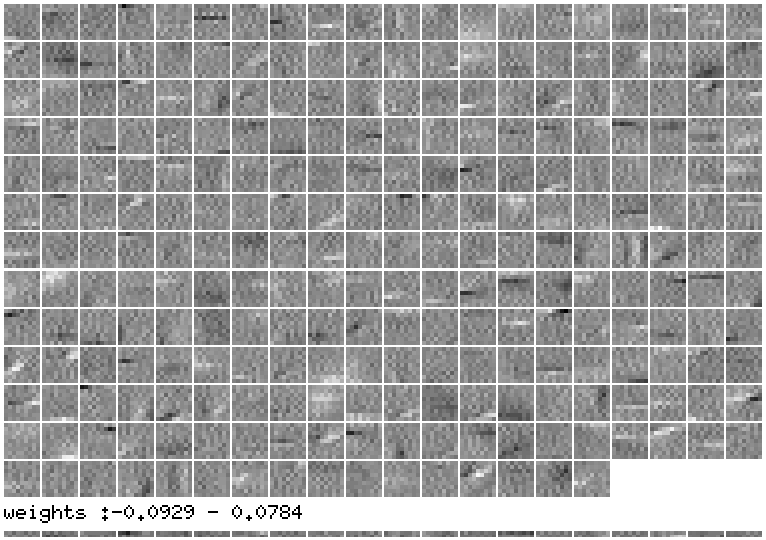
- Stage 1



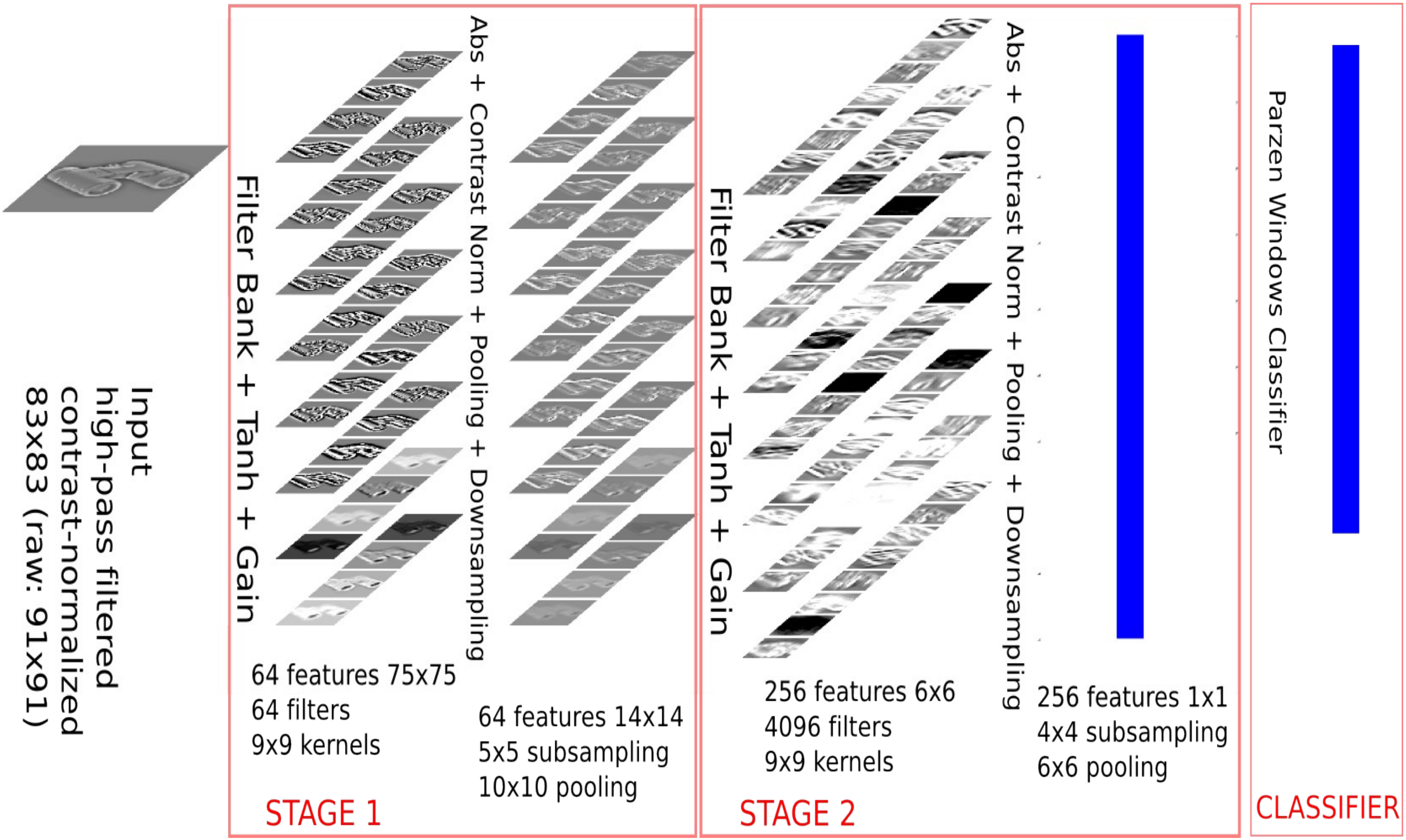


- Stage2

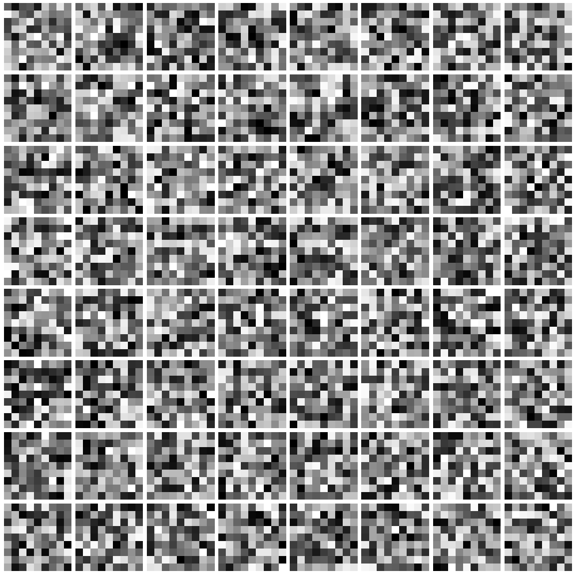


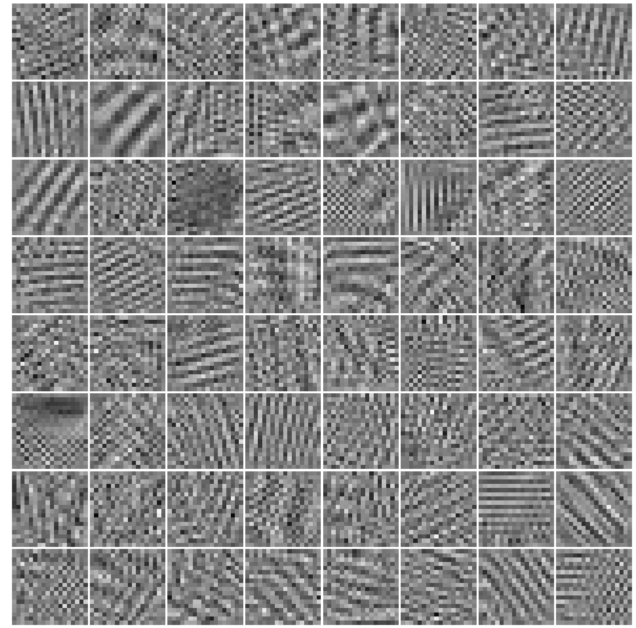


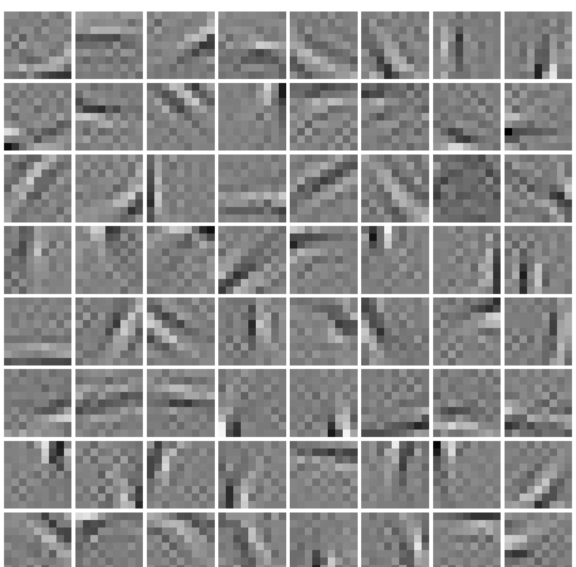
Demo: real-time learning of visual categories

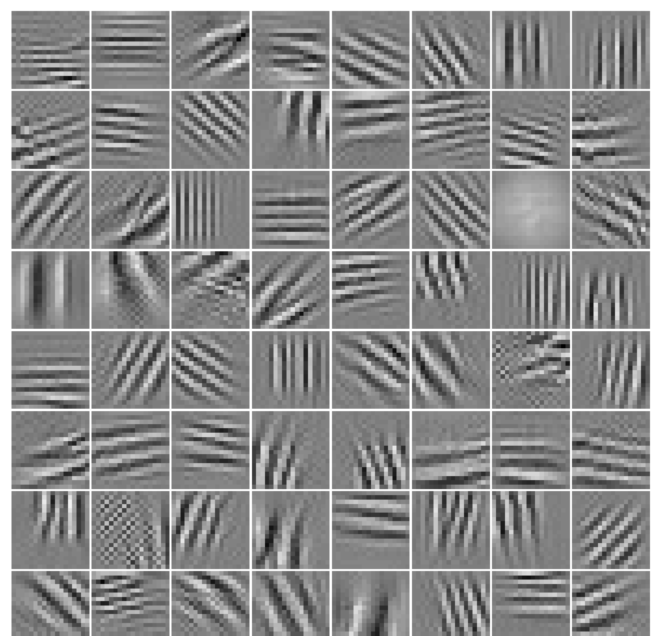


Why Random Filters Work?









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

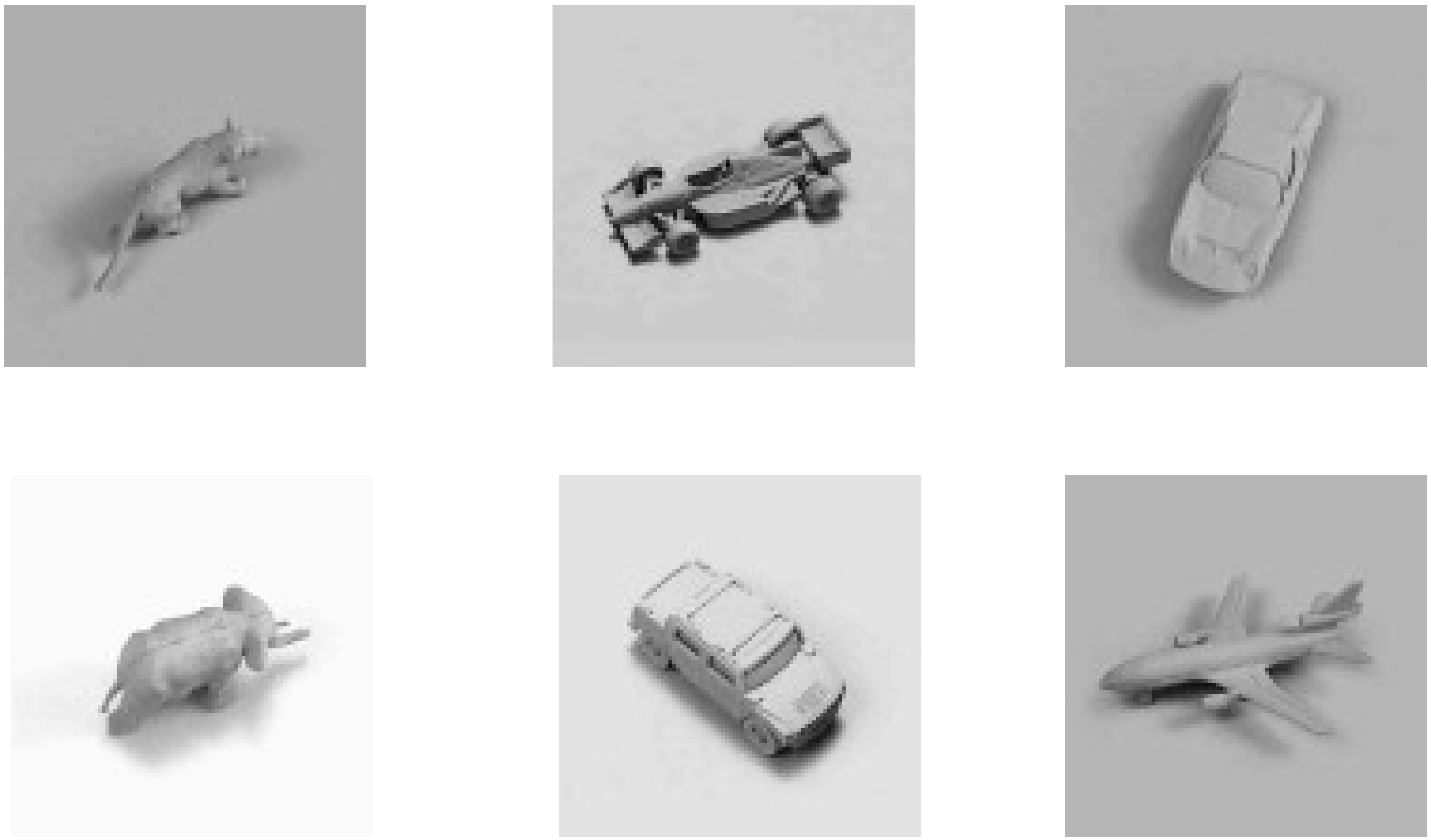
Replacing K-means with Sparse Coding

- [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

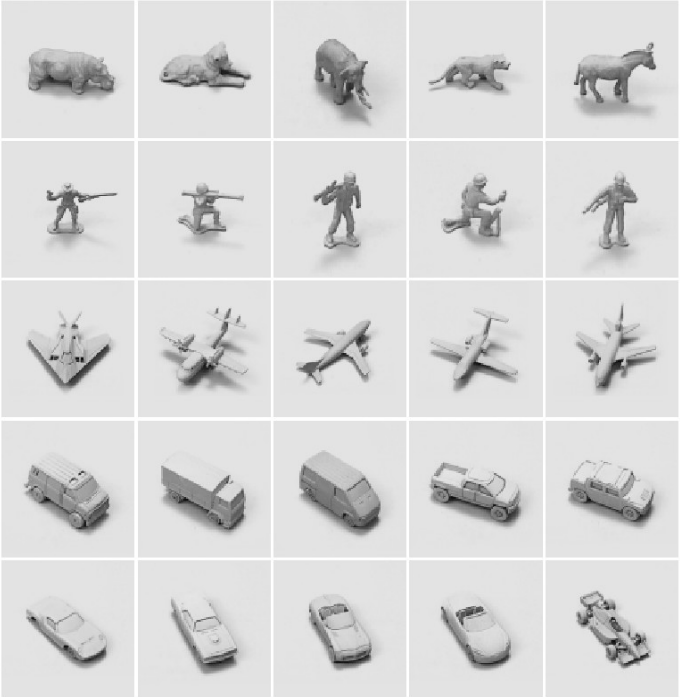
- 5 classes and up to 24,300 training samples per class

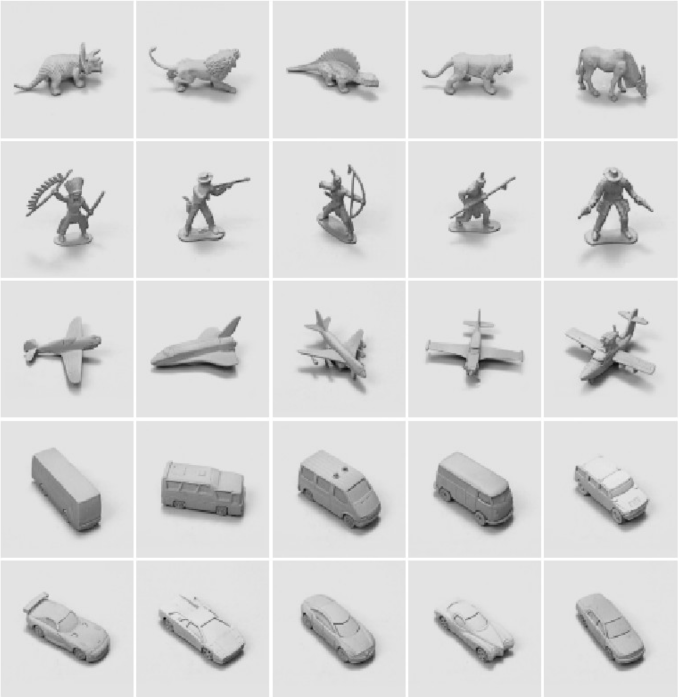


NORB Generic Object Recognition Dataset

- **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





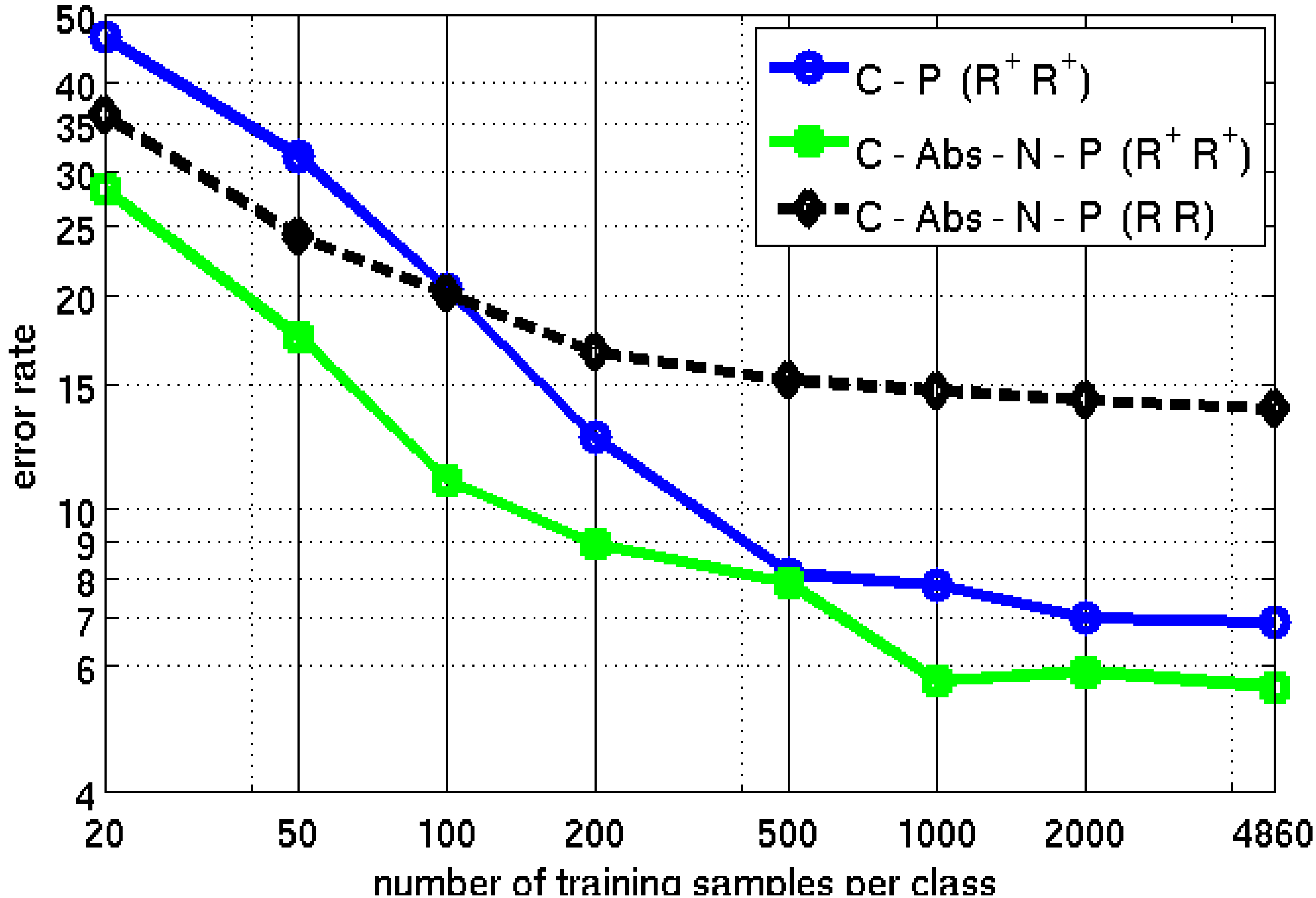
Training instances **Test instances**

Small NORB dataset

- **Architecture**

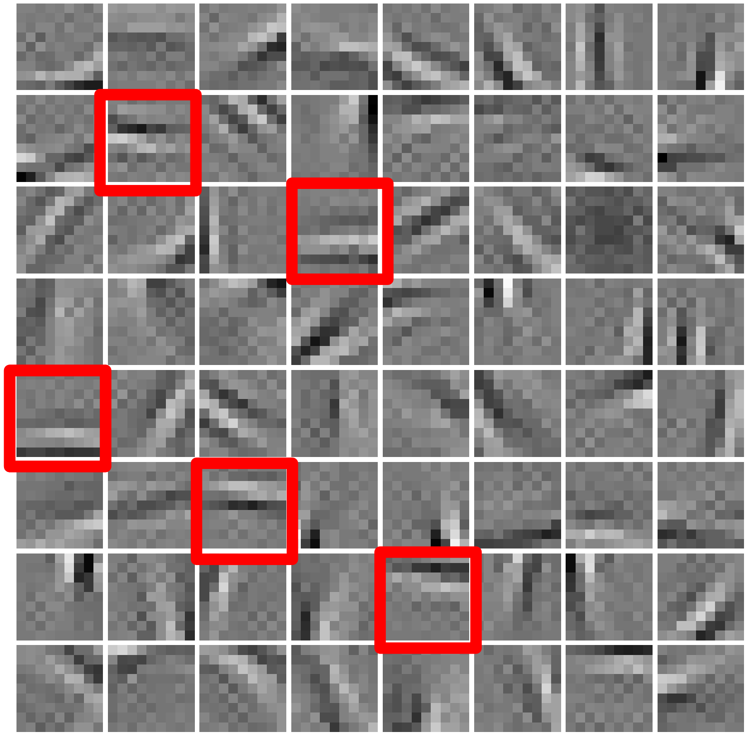
  - Two Stages

Error Rate (log scale) VS. **Number Training Samples** (log scale)



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

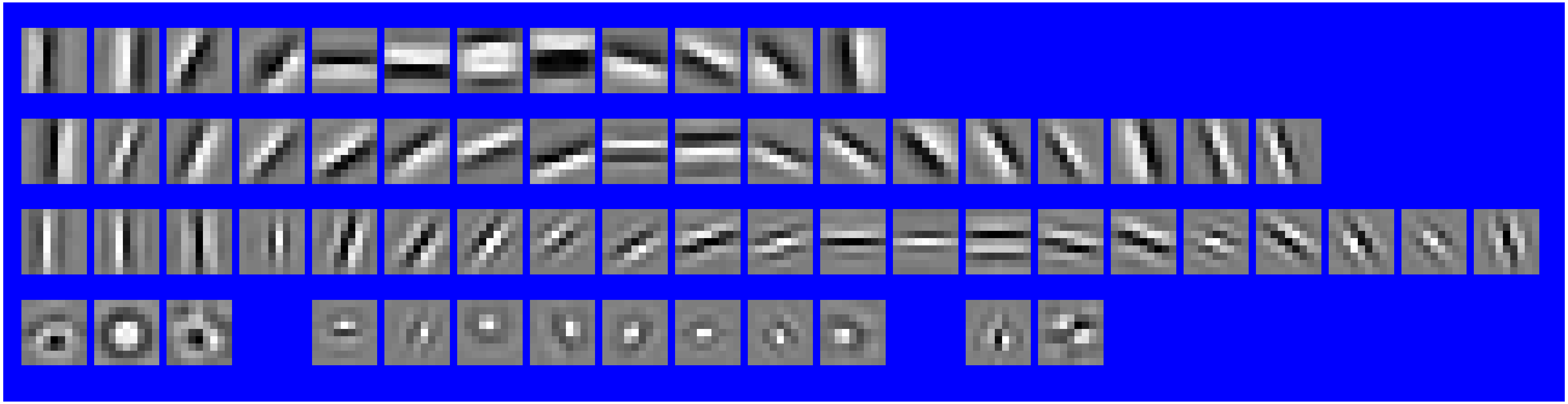


weights :-0.2828 - 0.3043

Yann LeCun

Convolutional Training

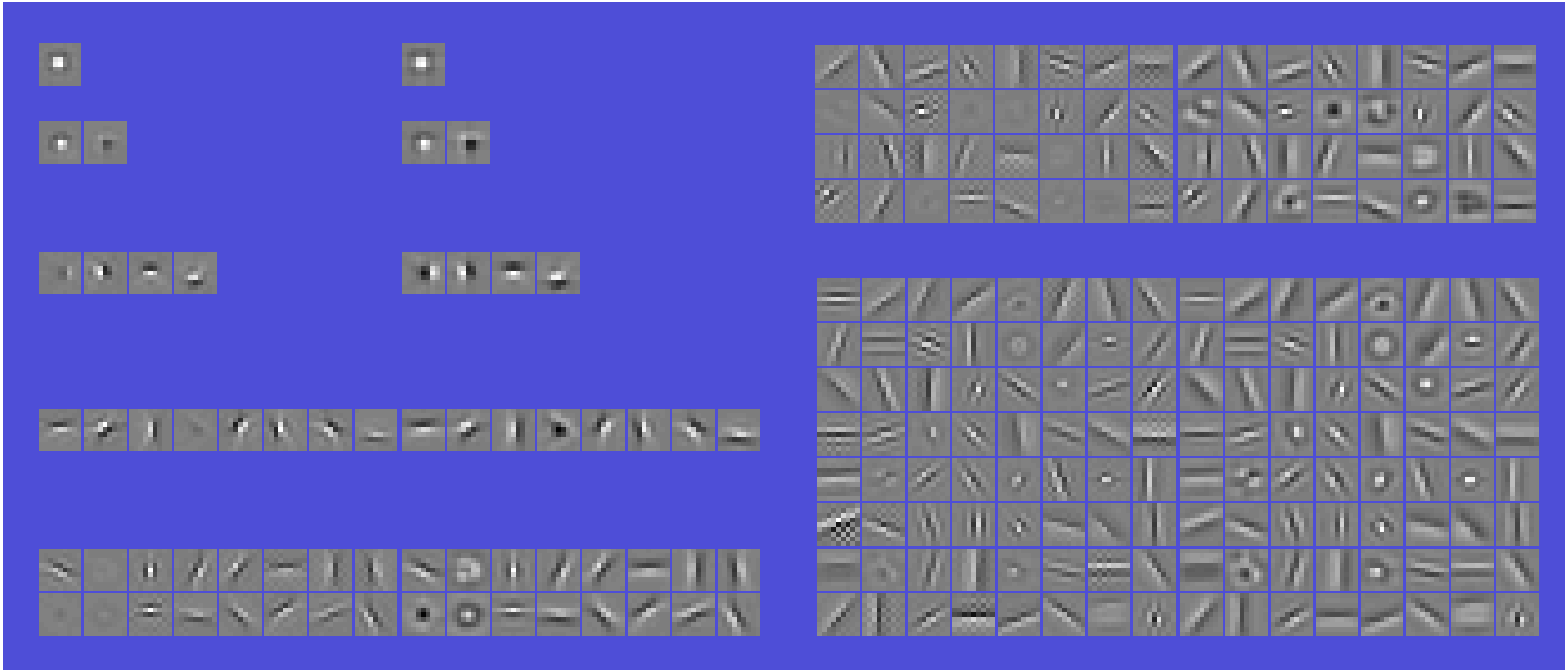
- **Problem with patch-based training: high correlation between outputs of filters from overlapping receptive fields.**



Learning Complex Cells with Invariance Properties

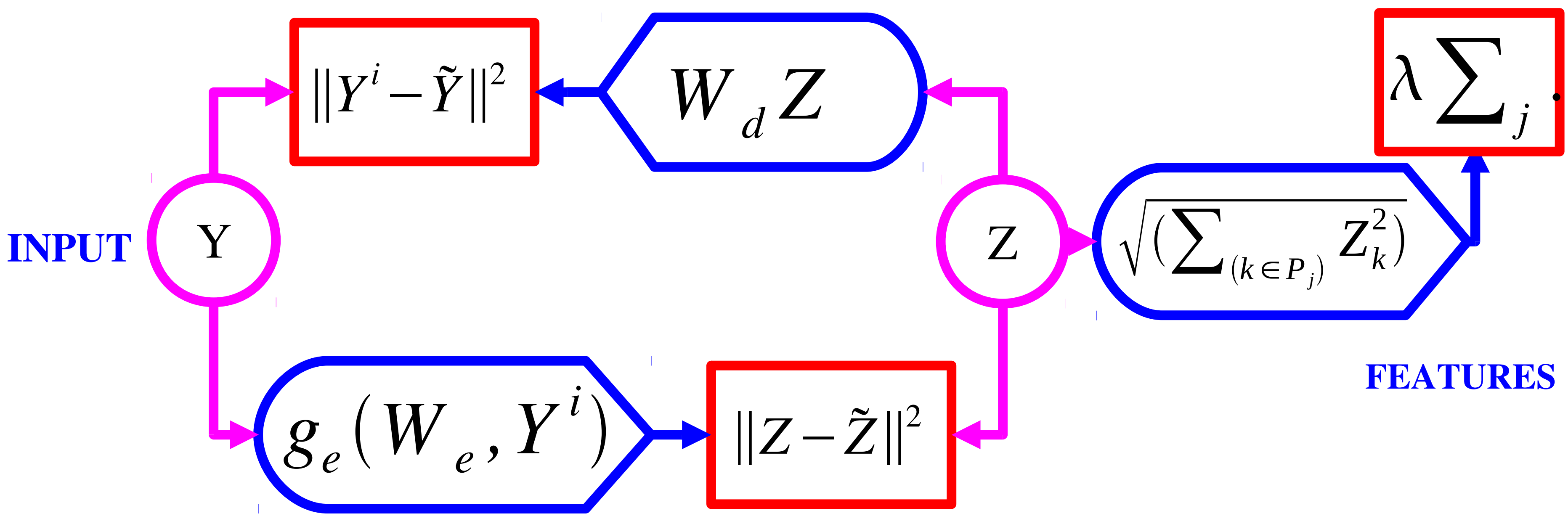
Convolutional Training

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



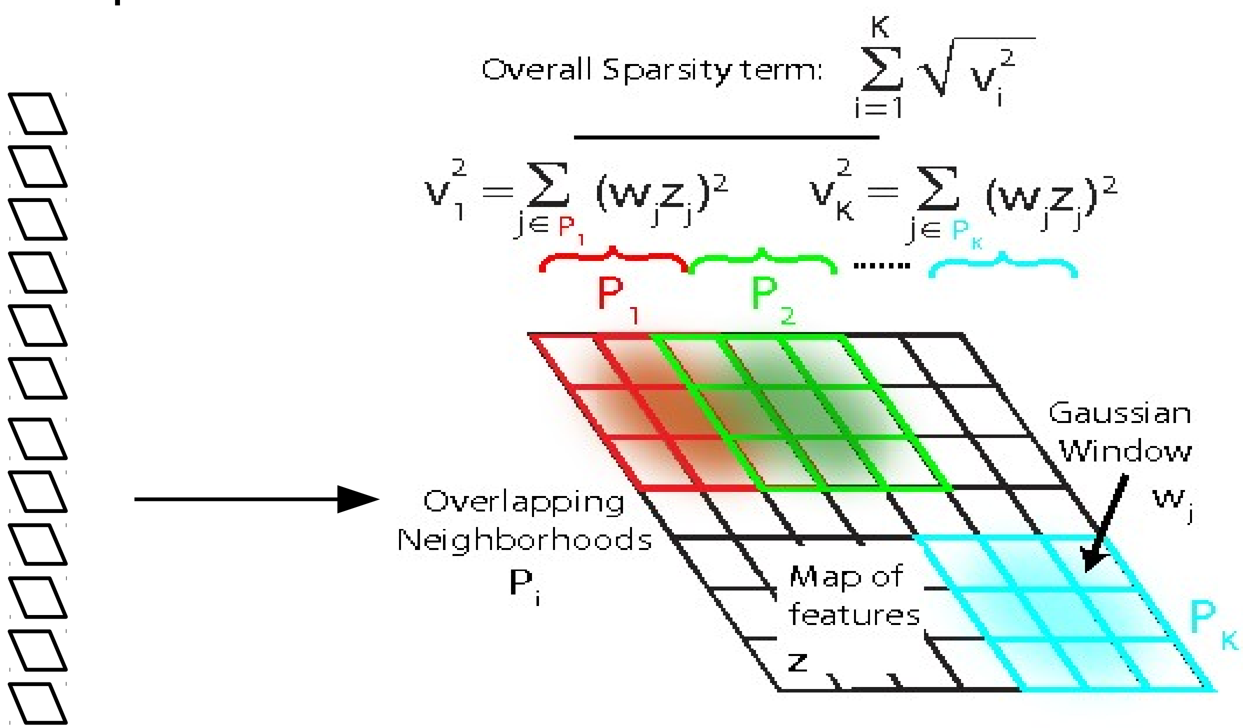
Learning Invariant Features [Kavukcuoglu et al. CVPR 2009]

- **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

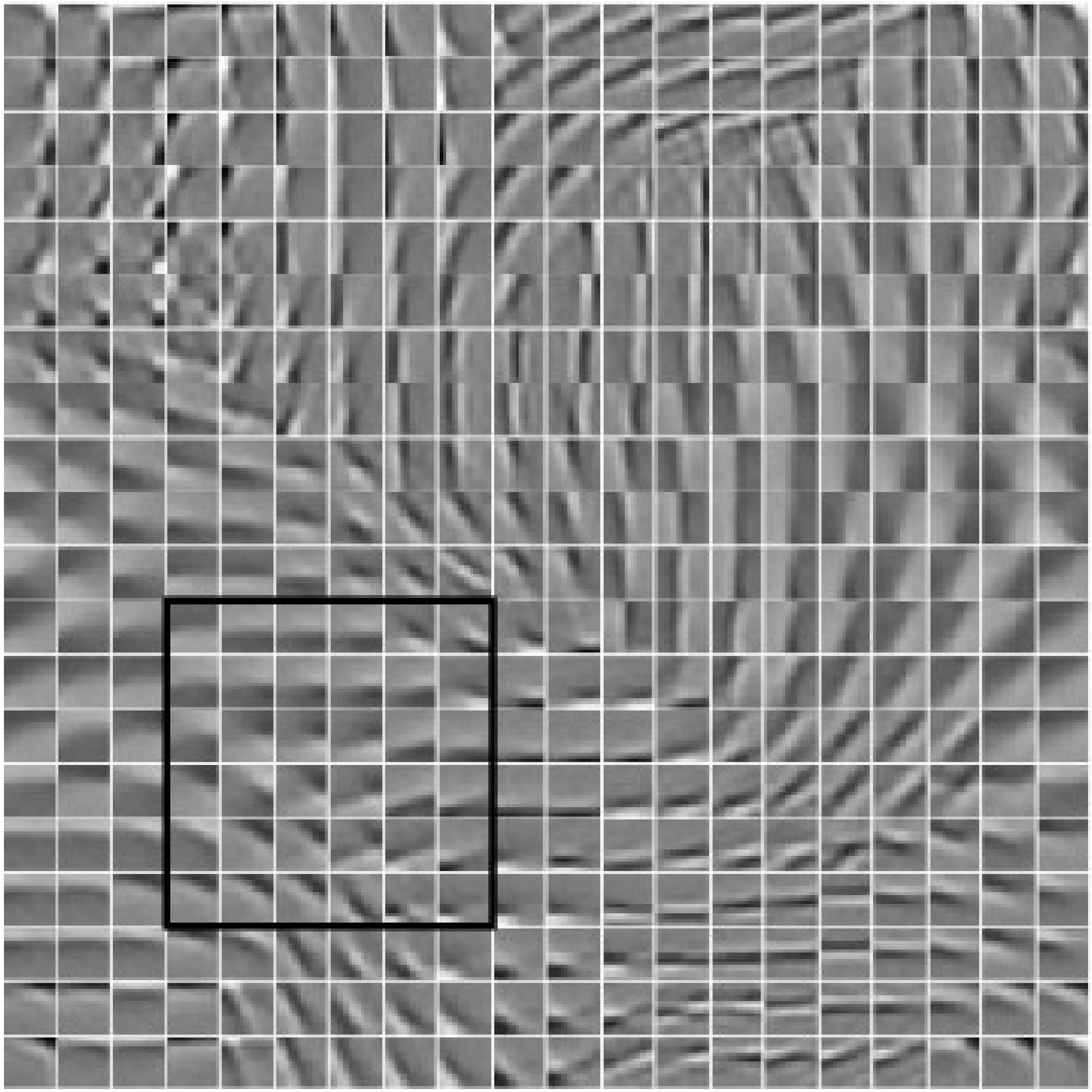


Units in the code Z

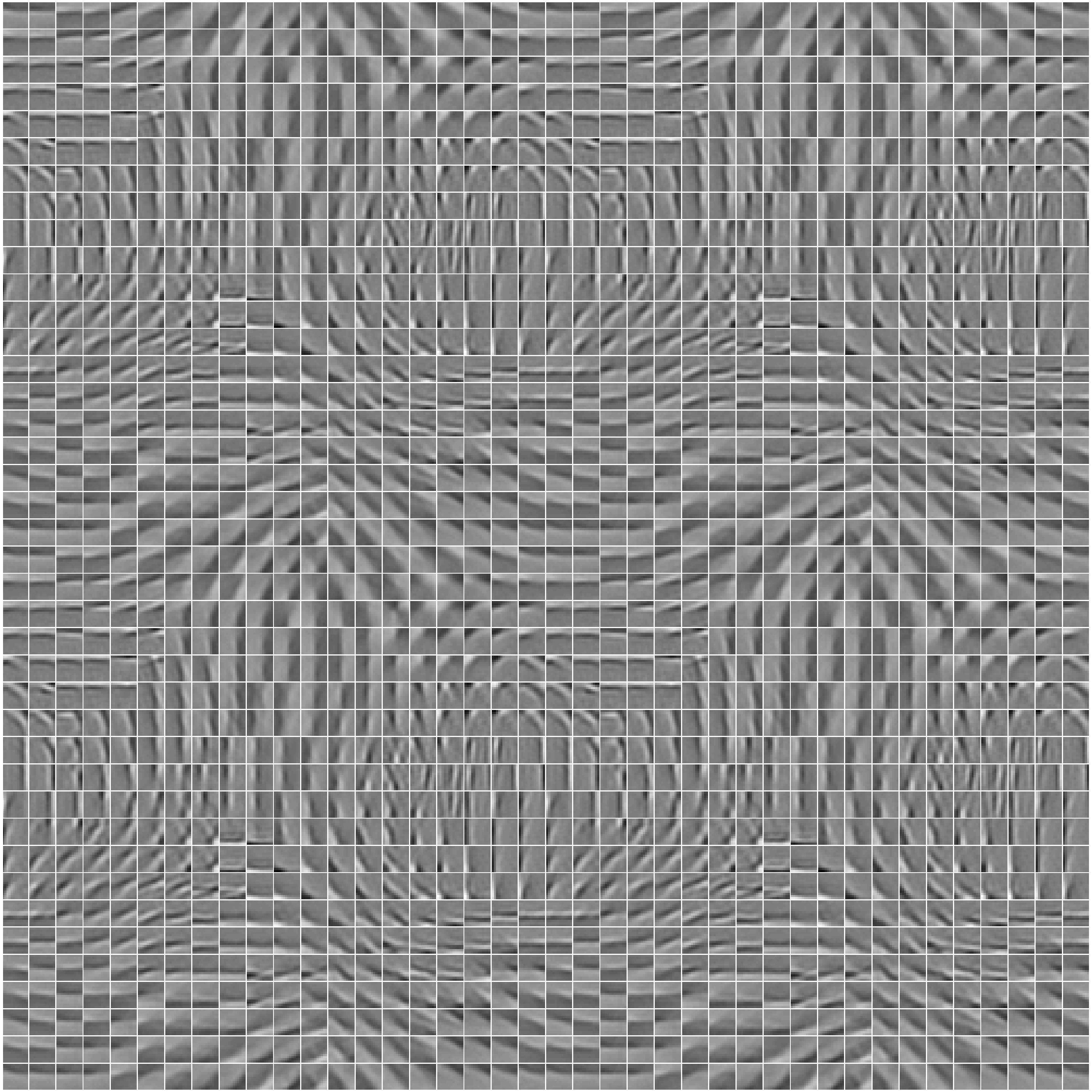
Define pools and enforce sparsity across pools

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.

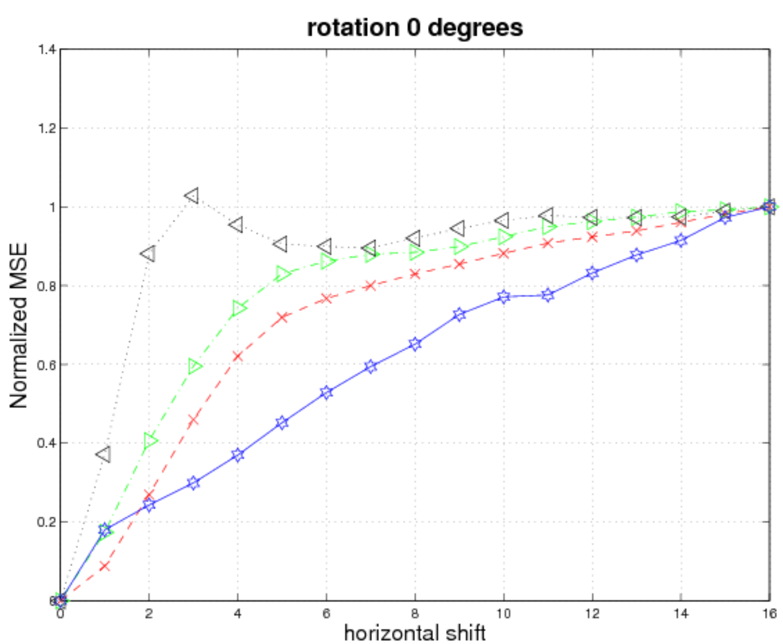


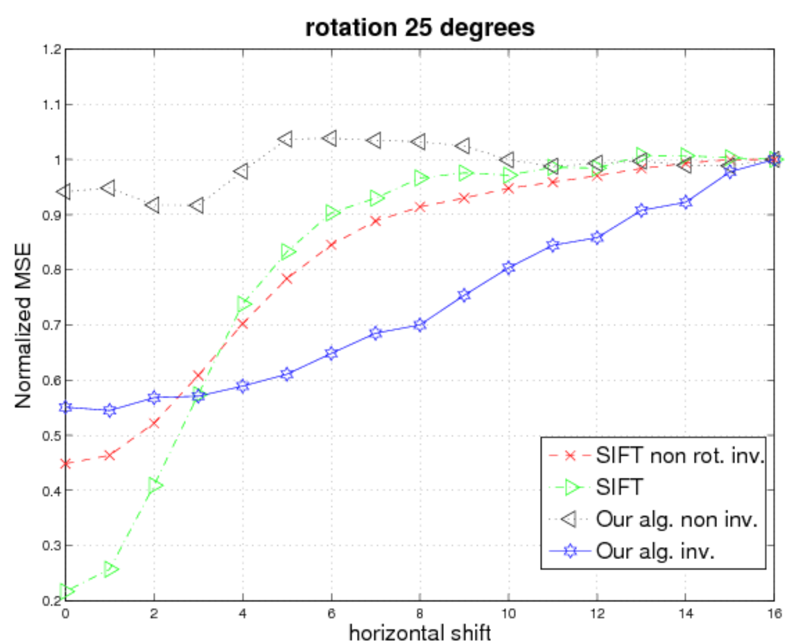
Pinwheels?



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**

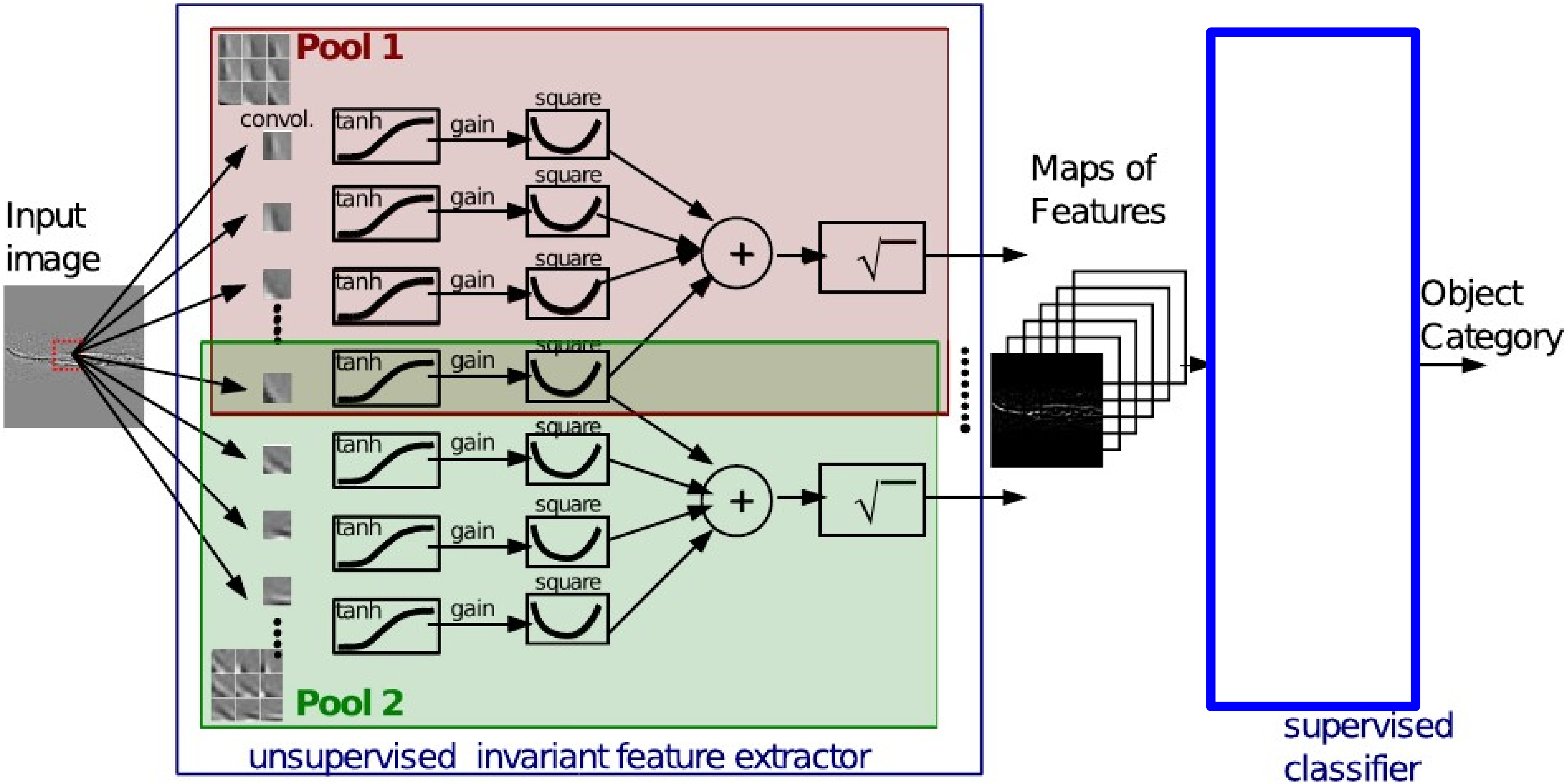




Learning Invariant Features

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**

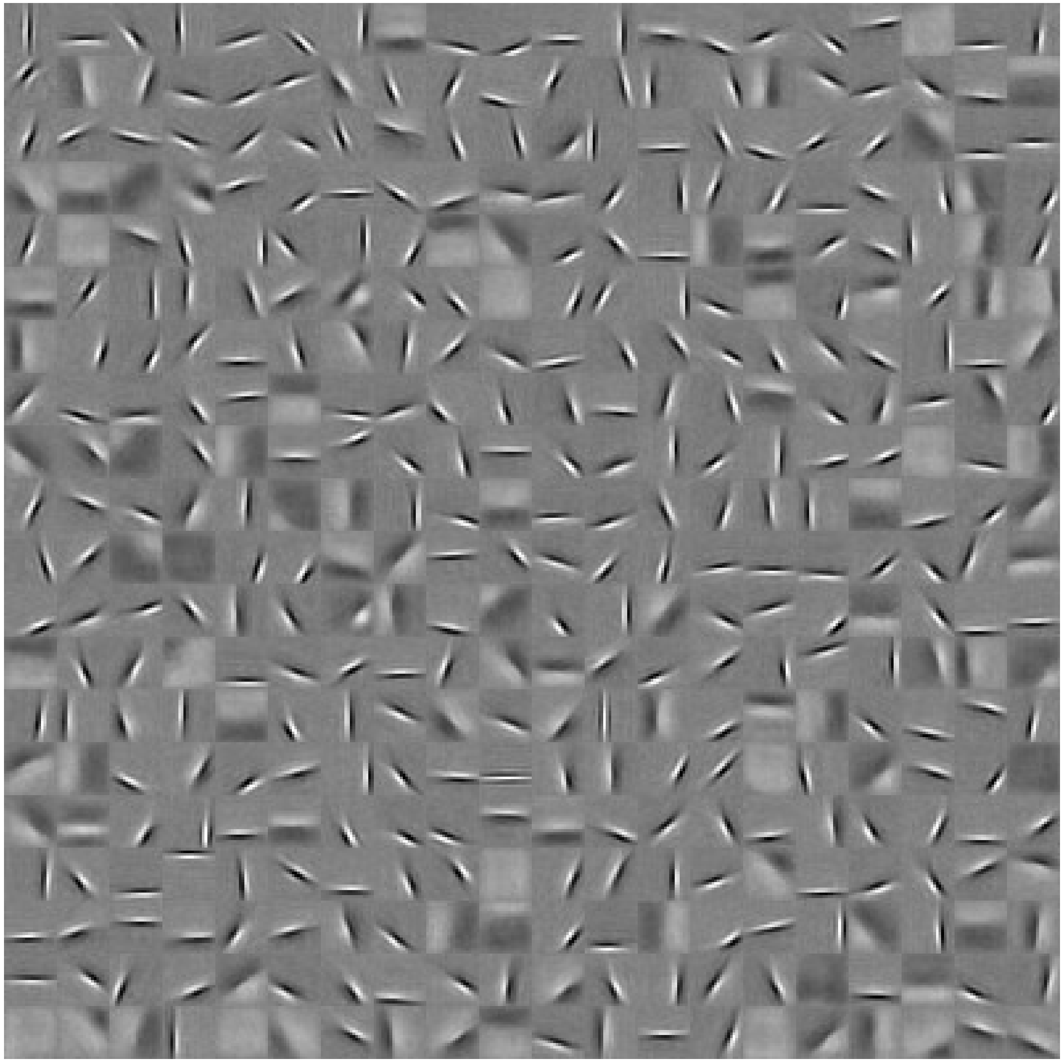
Performance on MNIST Dataset	
Method	**Error Rate (%)**
IPSD (5x5)	**1.0**
SIFT (5x5) (non rot. inv.)	**1.5**

Learning fields of Simple Cells and Complex Cells

[Gregor and LeCun, 2010]

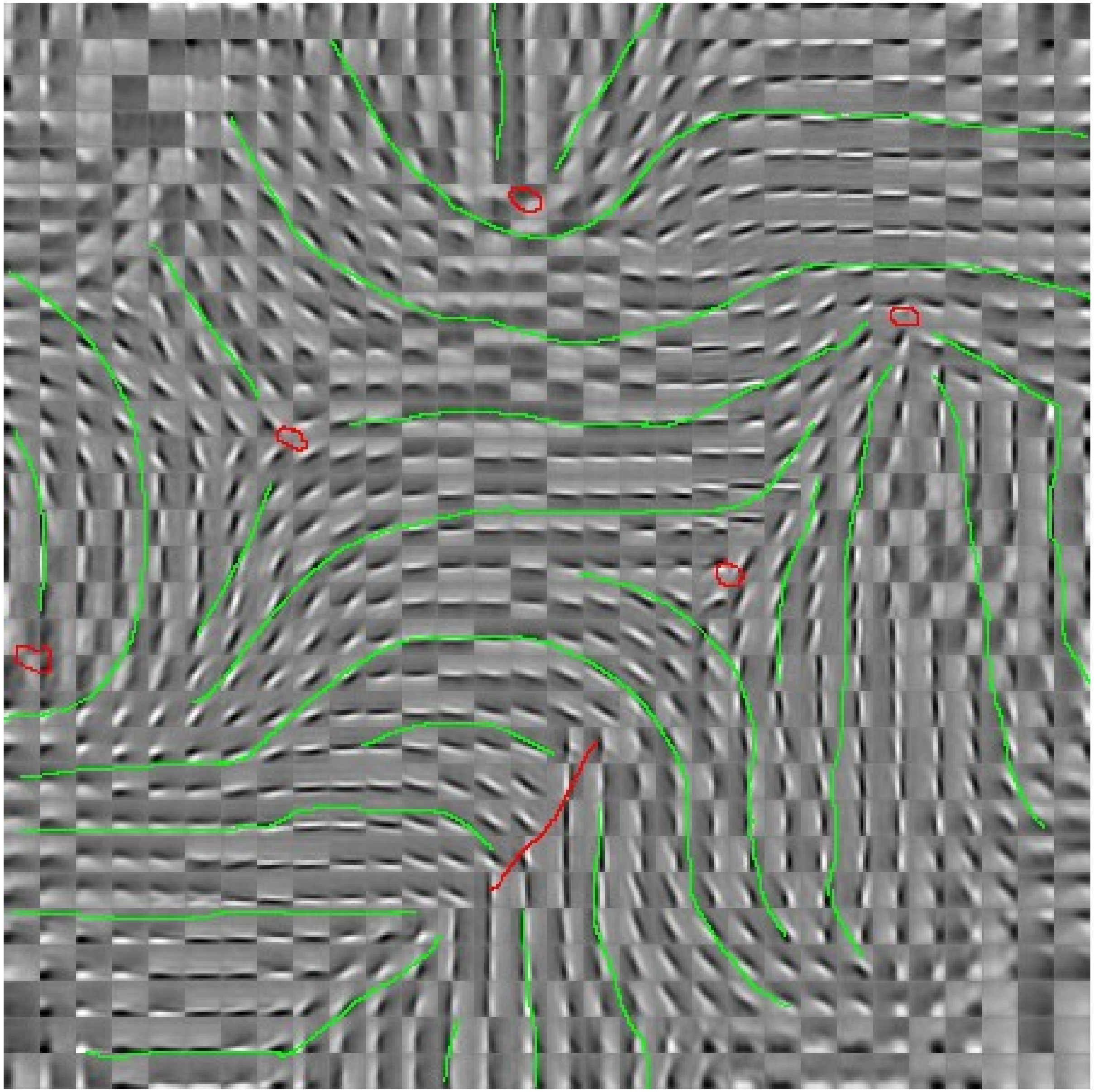
Training Simple Cells with Local Receptive Fields over Large Input Images

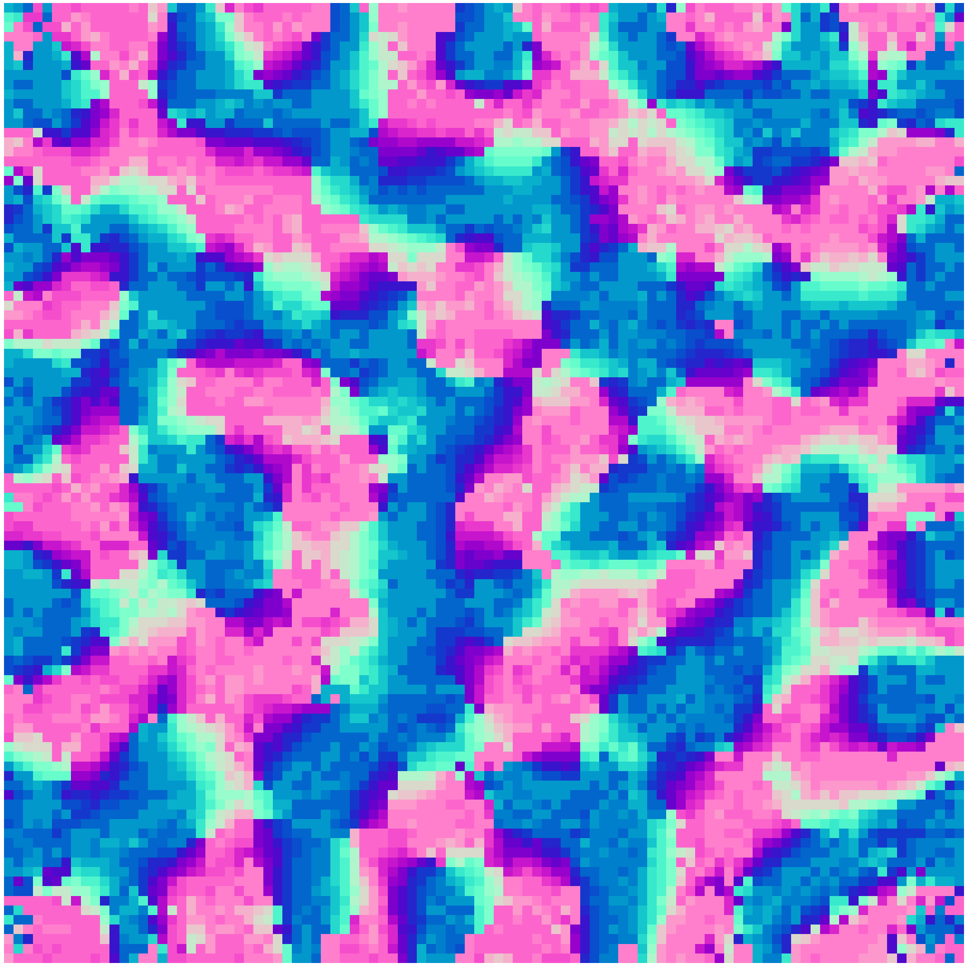
- Training on 115x115 images. Kernels are 15x15



Simple Cells + Complex Cells with Sparsity Penalty: Pinwheels

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





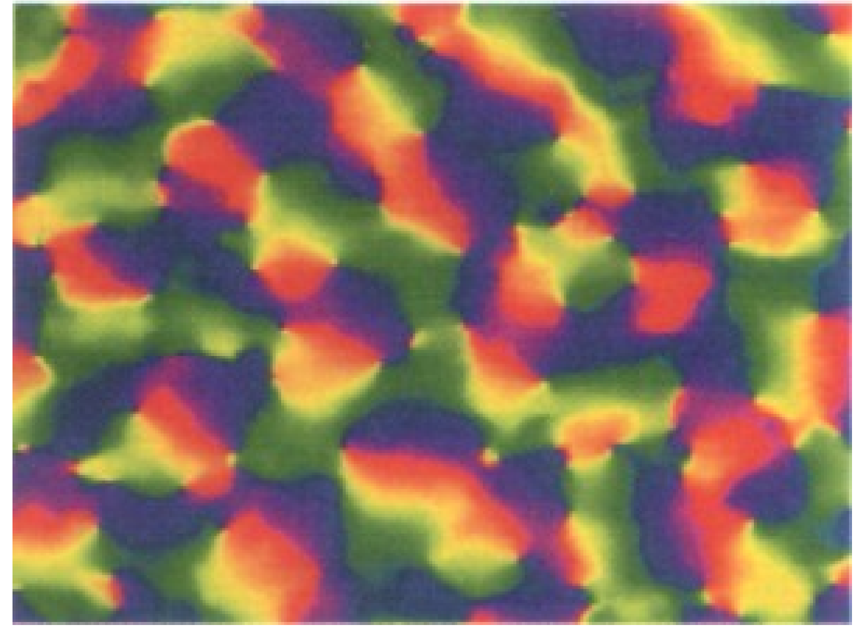
119x119 Image Input

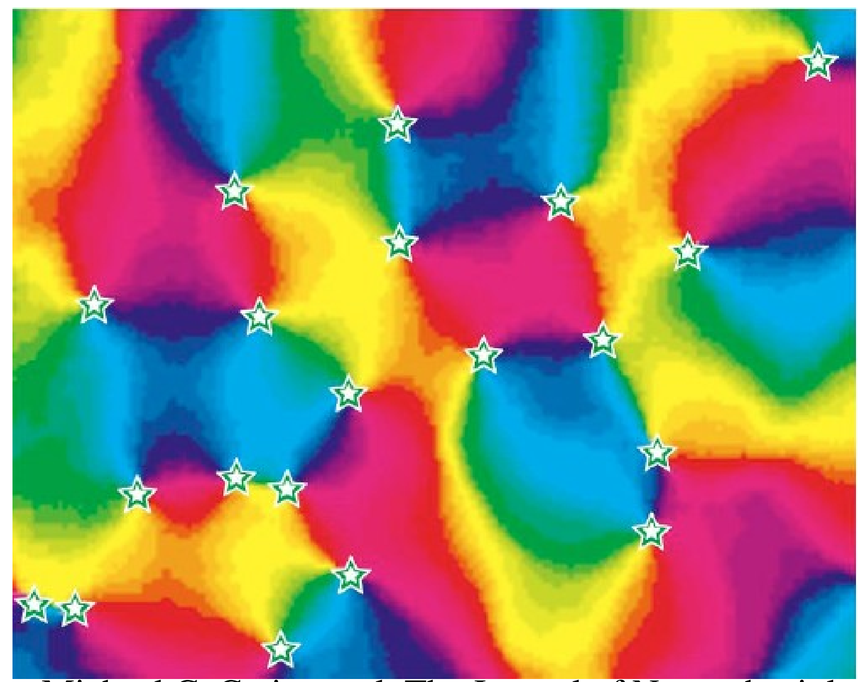
100x100 Code

20x20 Receptive field size

sigma=5

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

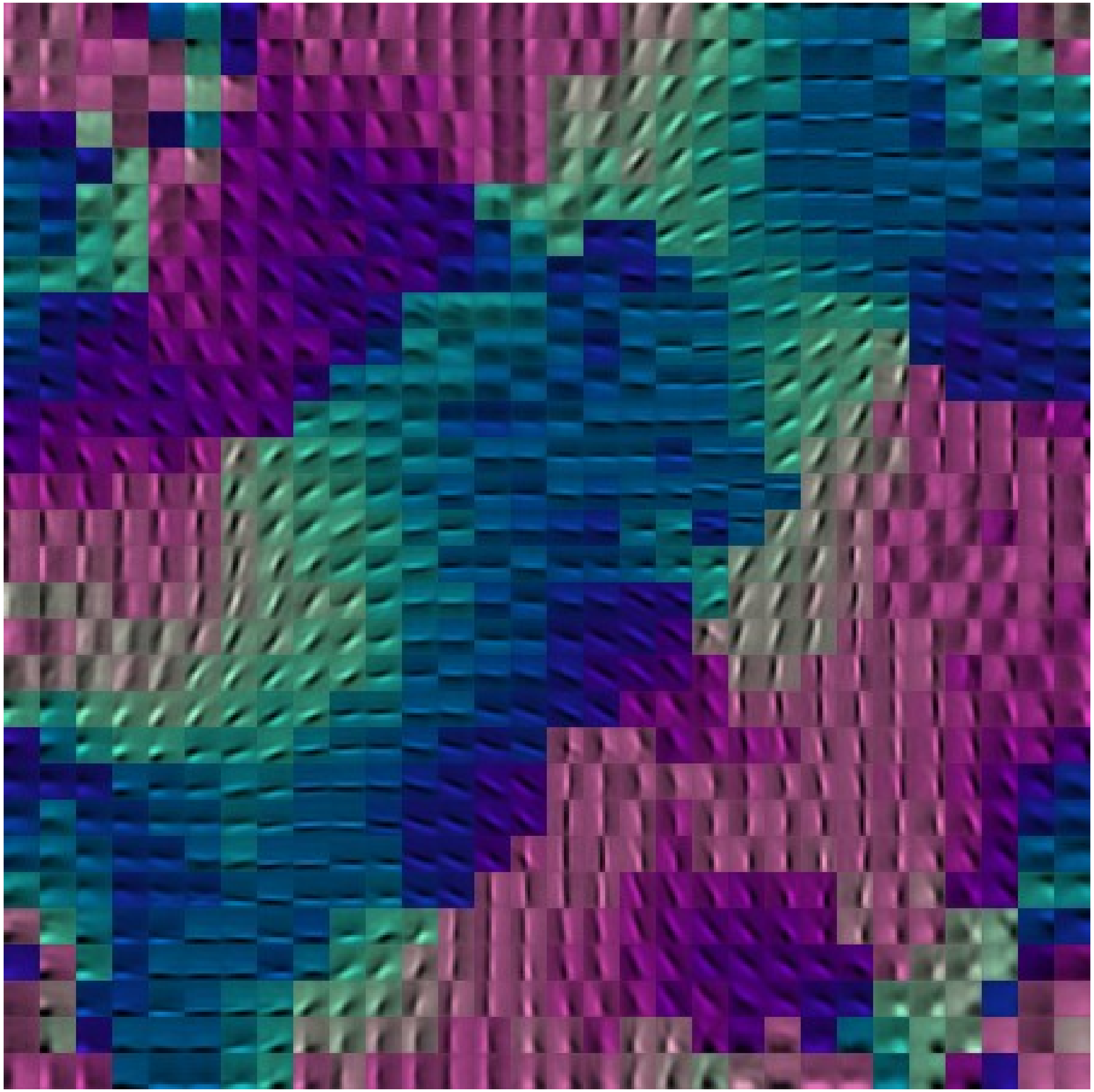




Michael C. Crair, et. al. The Journal of Neurophysiology Vol. 77 No. 6 June 1997, pp. 3381-3385 (**Cat**)

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

- **Color indicates orientation (by fitting Gabors)**



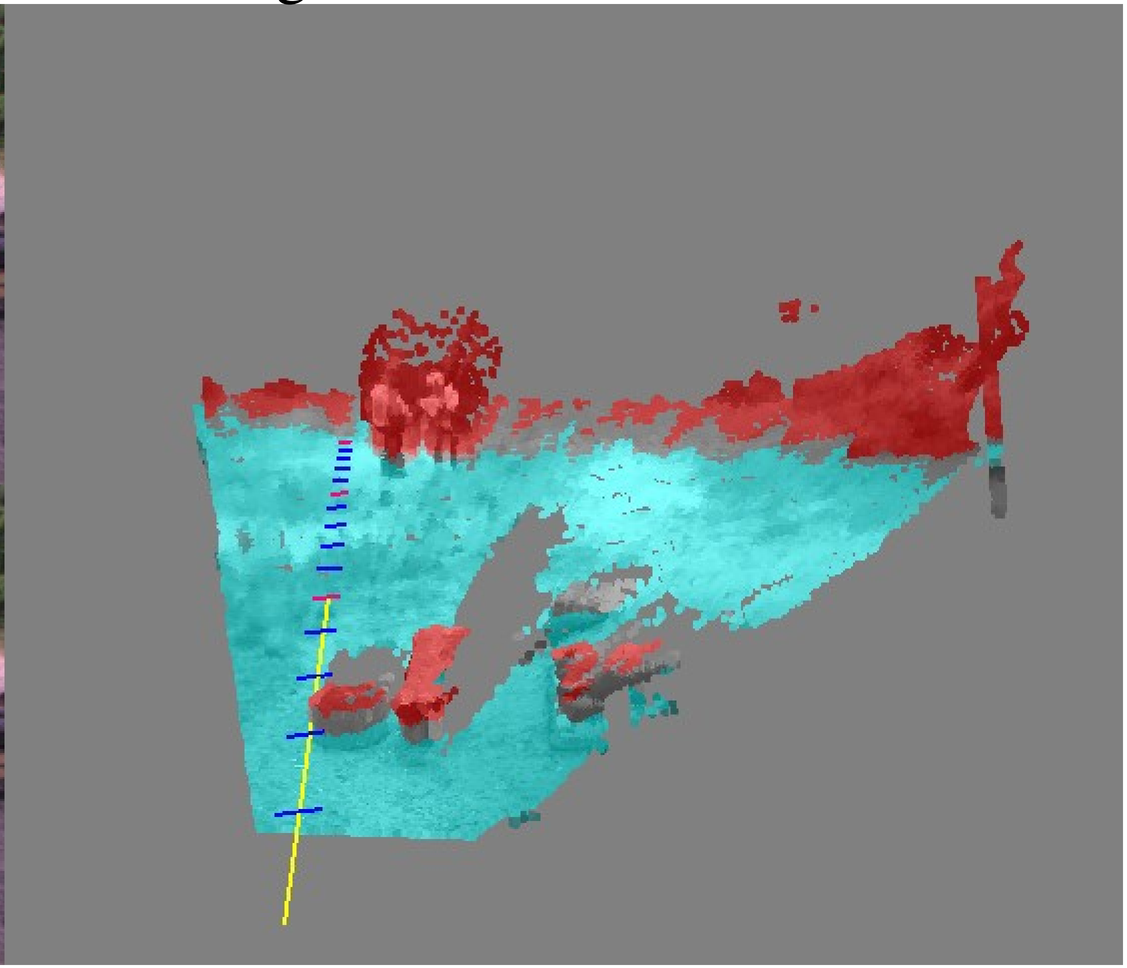
Deep Learning for Mobile Robot Vision

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

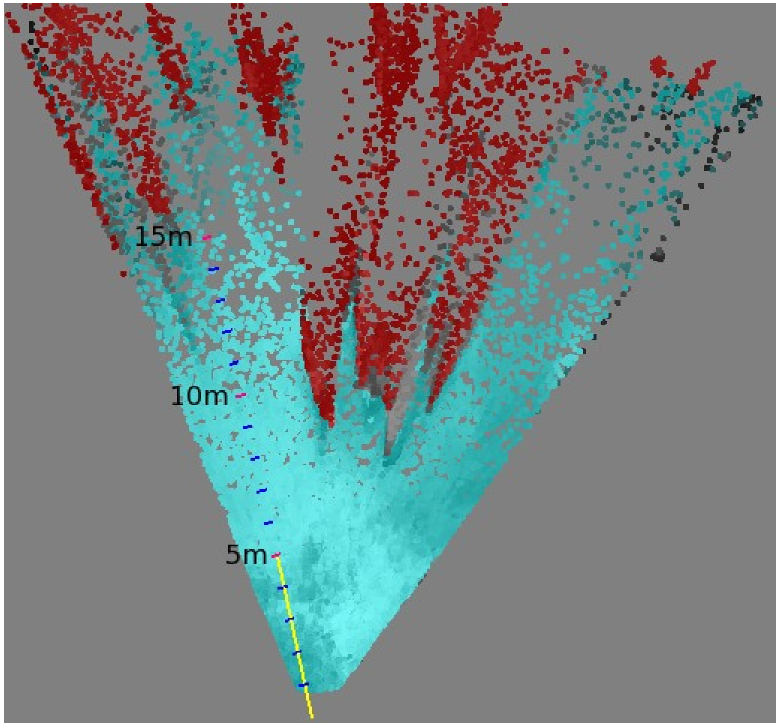
Obstacles overlaid with camera image



Camera image

Detected obstacles (red)

Navigating to a goal is hard...



stereo perspective

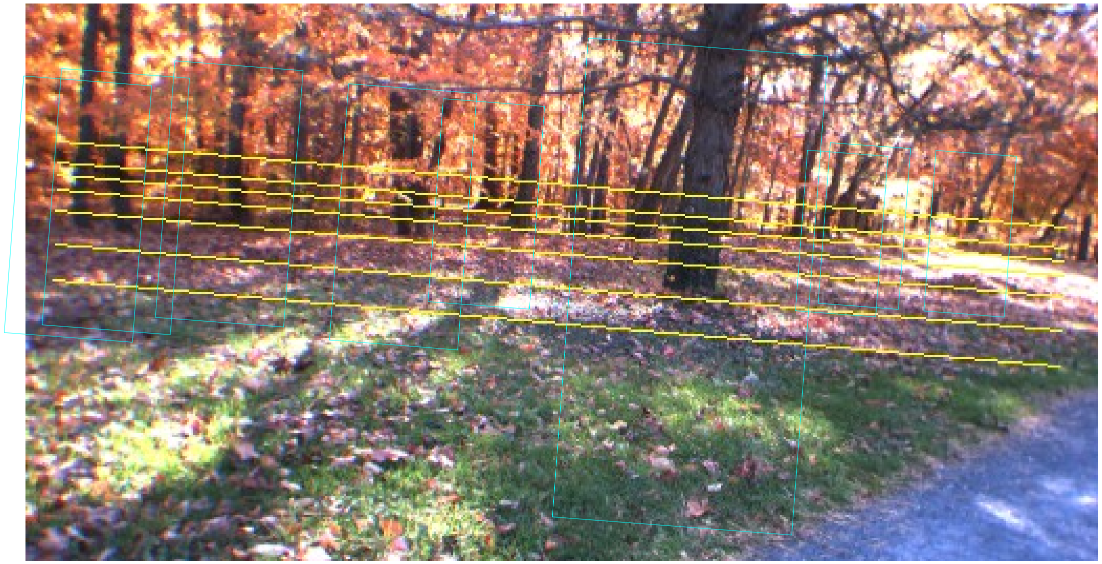
human perspective

especially in a snowstorm.

Self-Supervised Learning

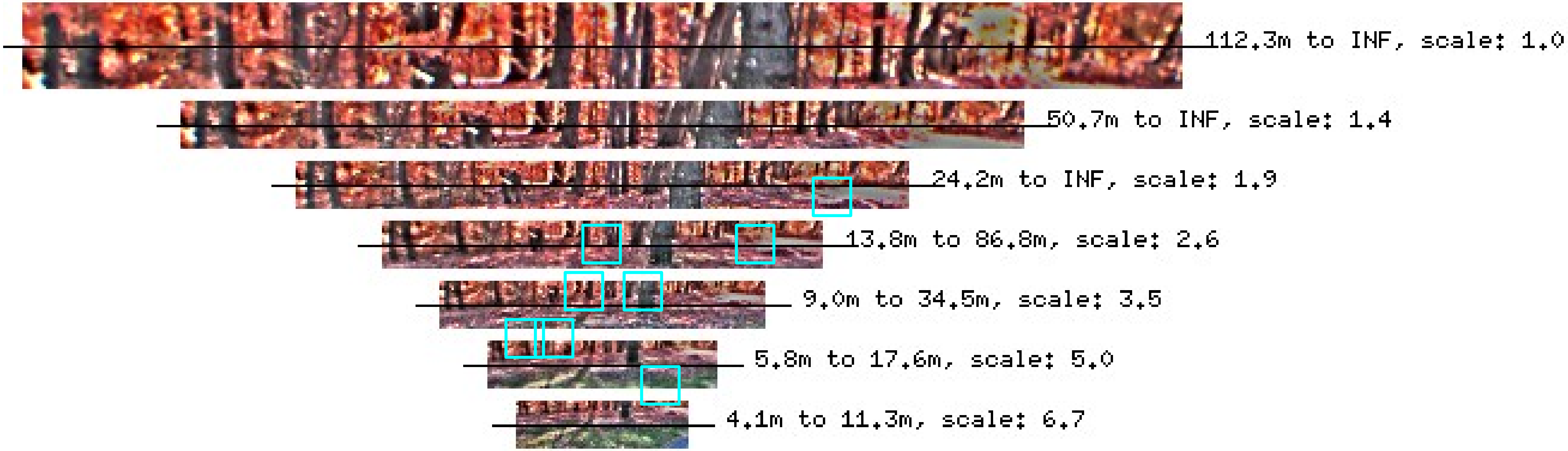
- **Stereo vision tells us what nearby obstacles look like**
- **Use the labels (obstacle/traversible) produced by stereo vision to train a monocular neural network**
- **Self-supervised "near to far" learning**

Long Range Vision: Distance Normalization



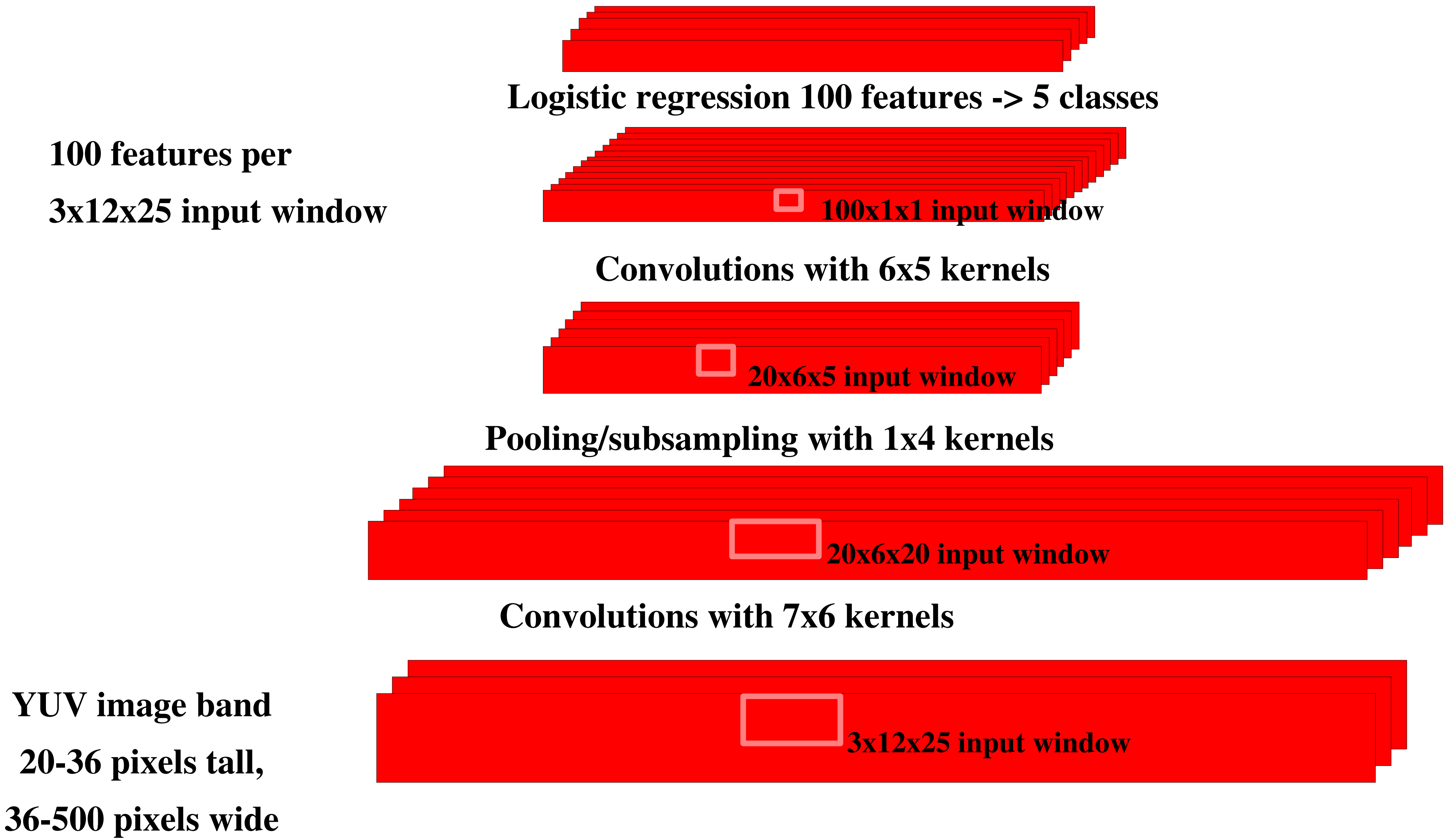
Pre-processing (125 ms)

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

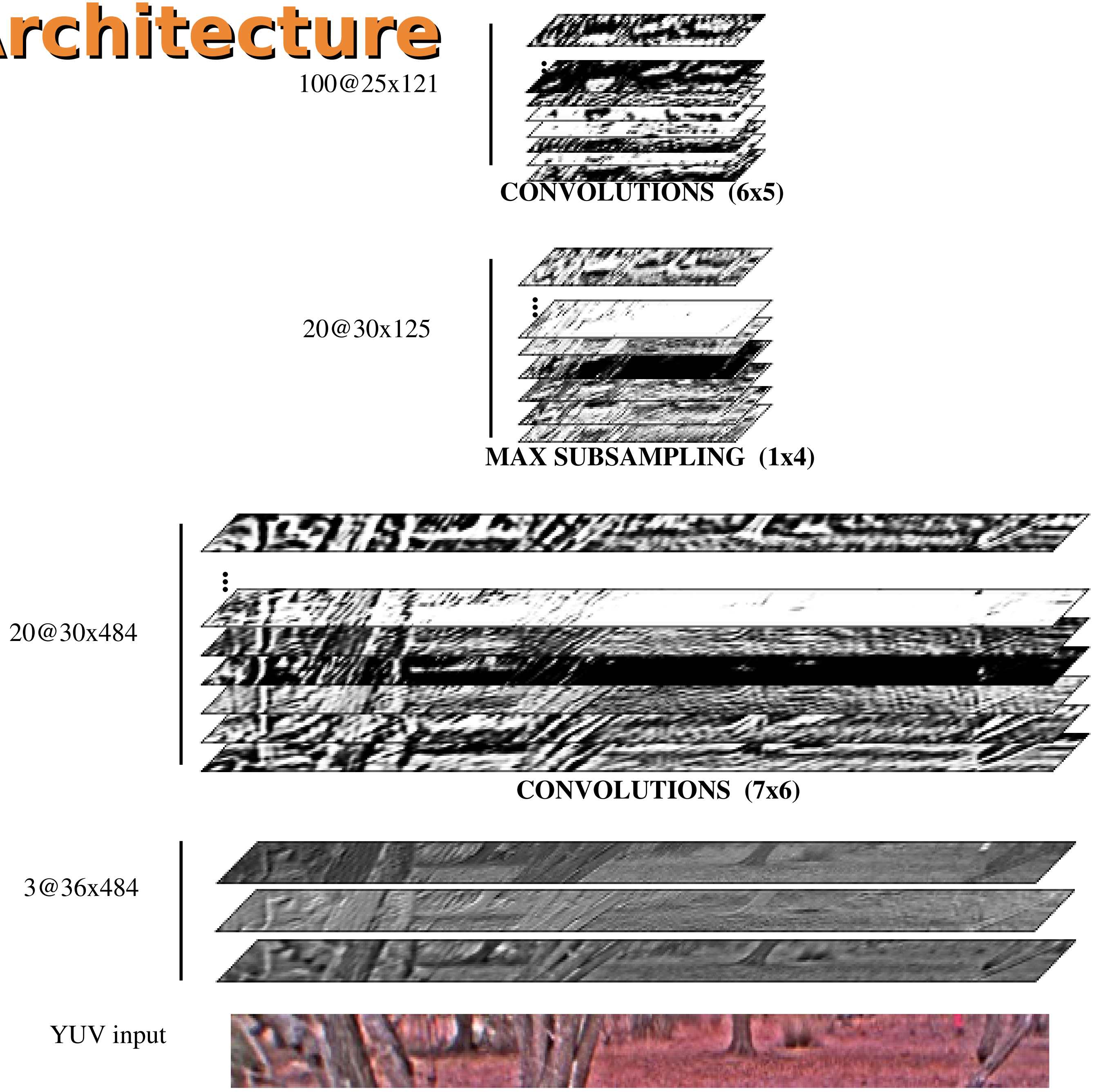


Convolutional Net Architecture

- Operates on 12x25 YUV windows from the pyramid



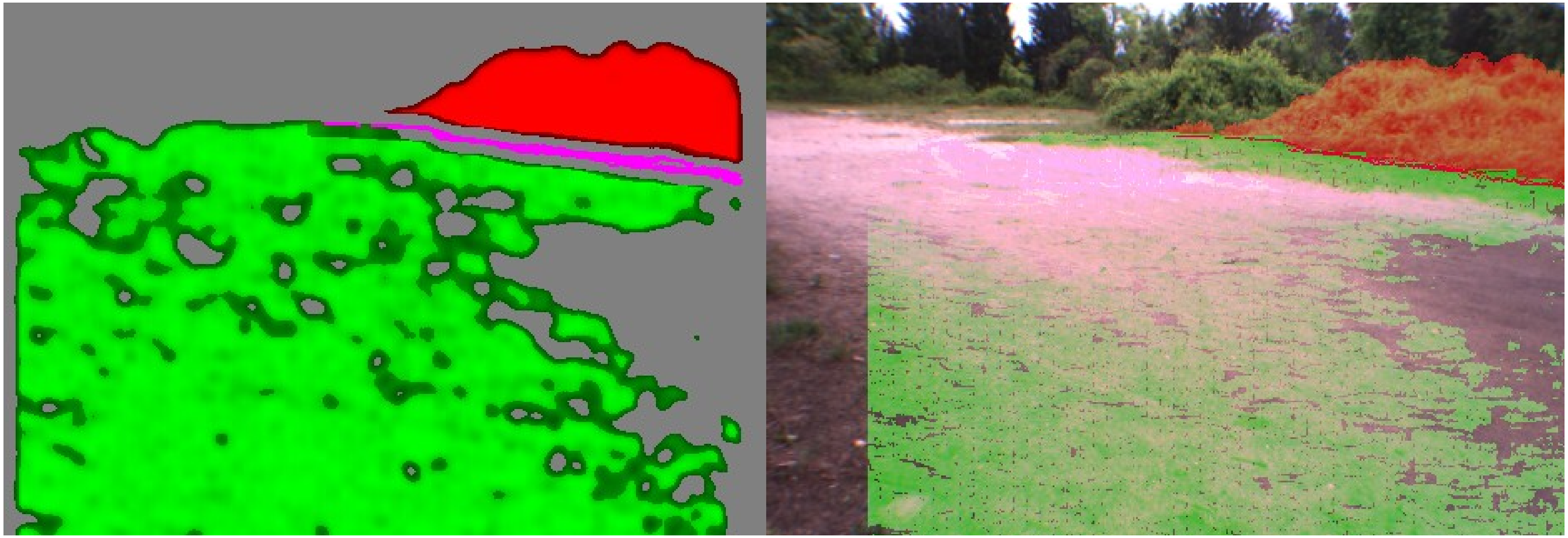
Convolutional Net Architecture



Long Range Vision: 5 categories

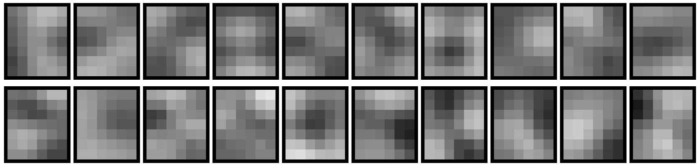
Online Learning (52 ms)

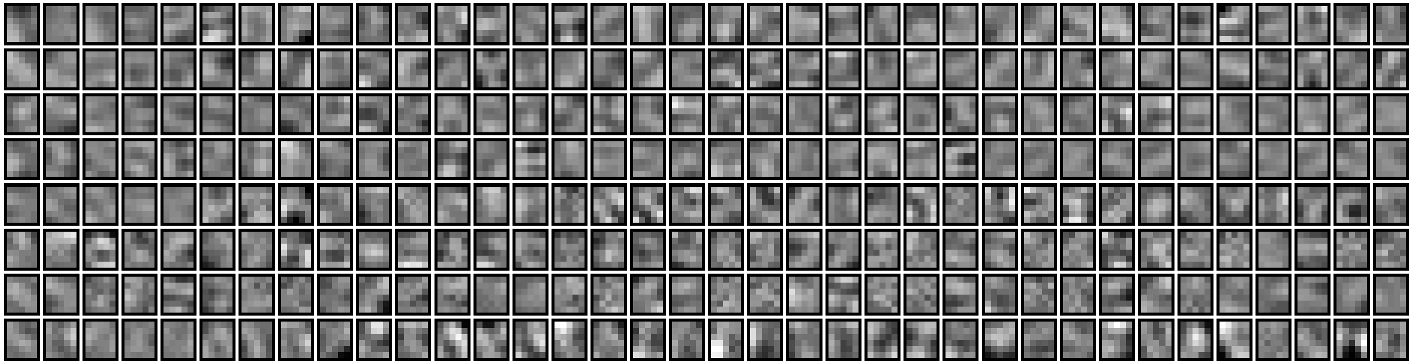
- Label windows using stereo information – 5 classes



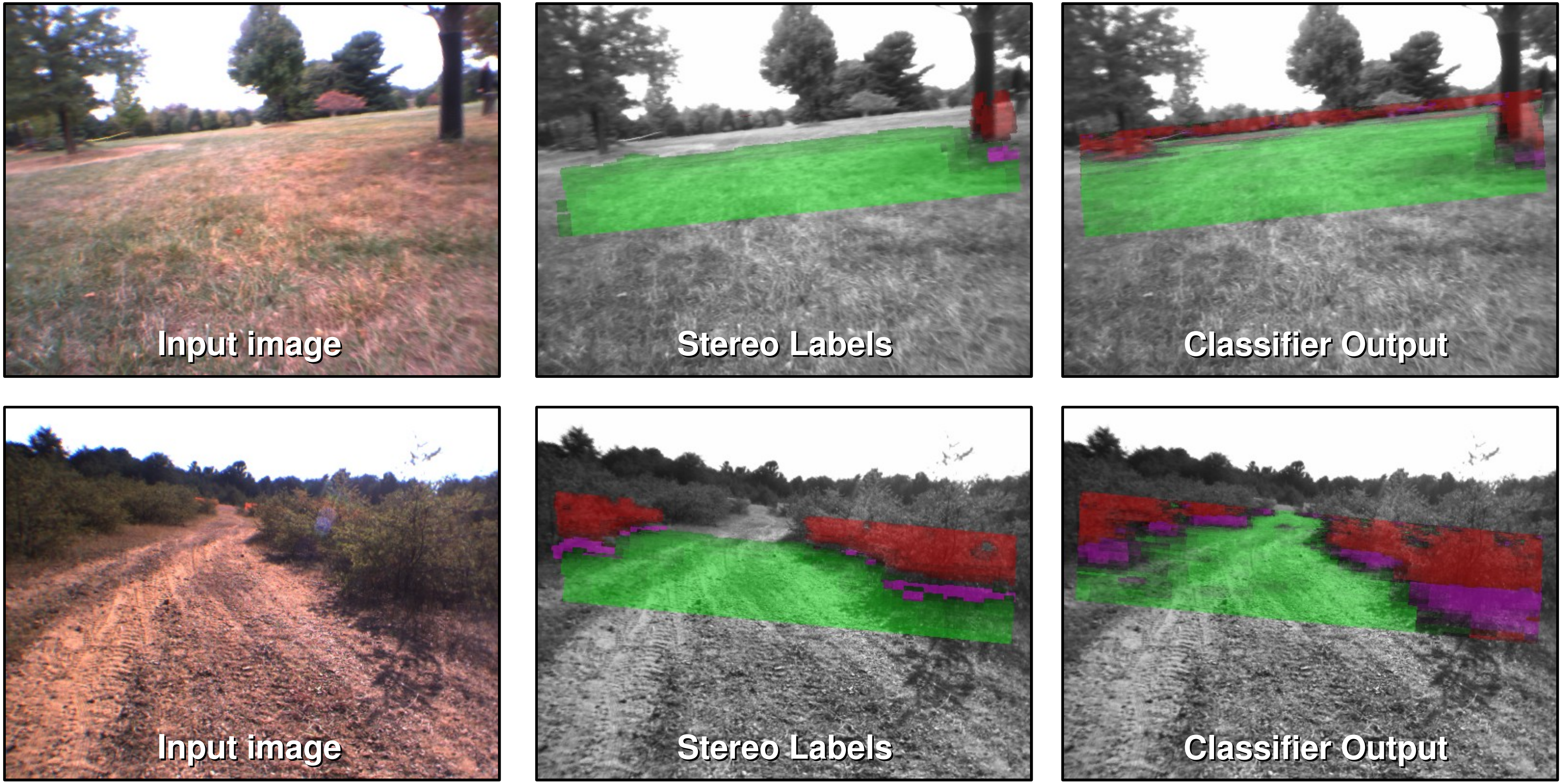
Trainable Feature Extraction

- "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

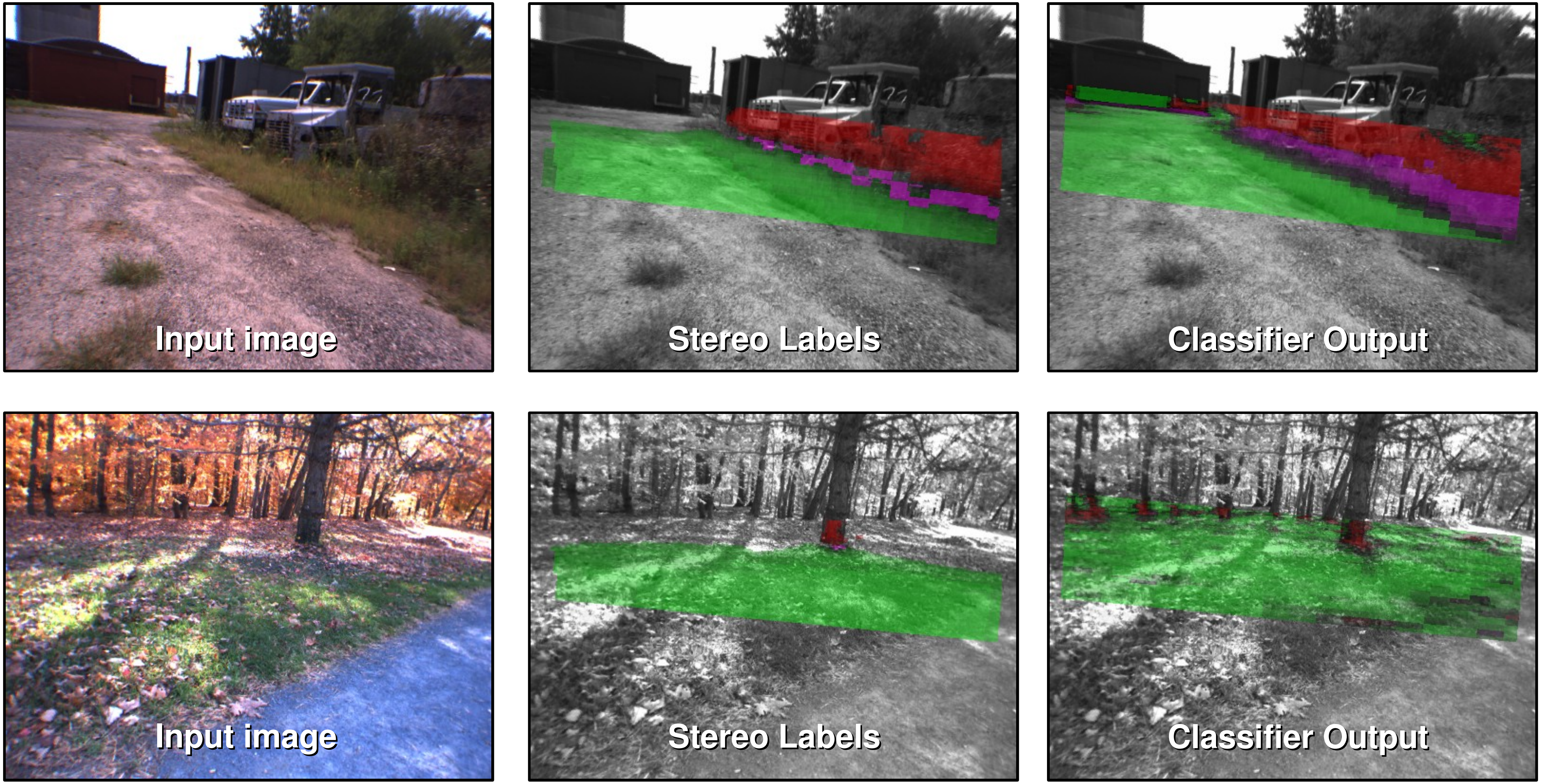




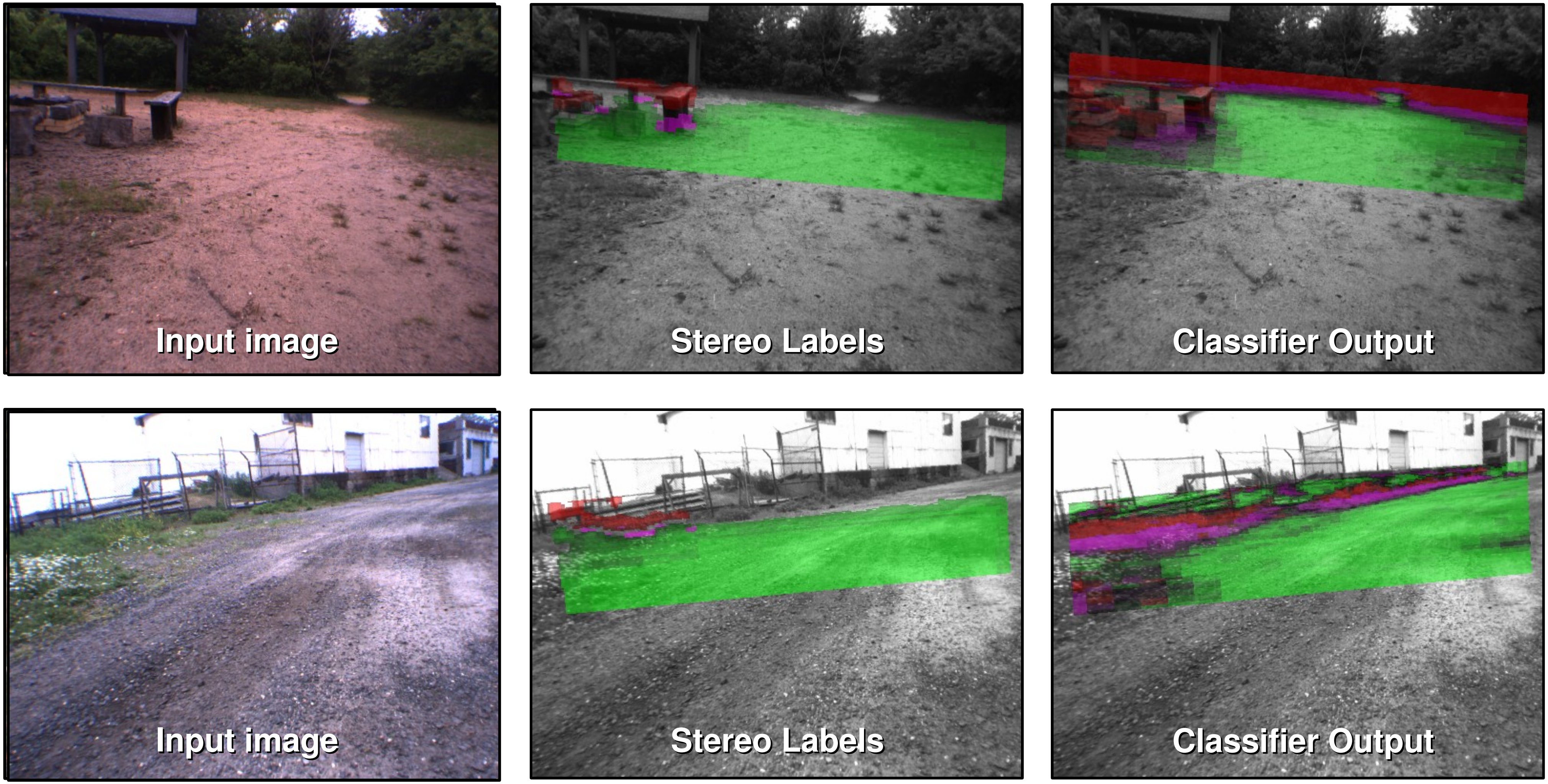
Long Range Vision Results

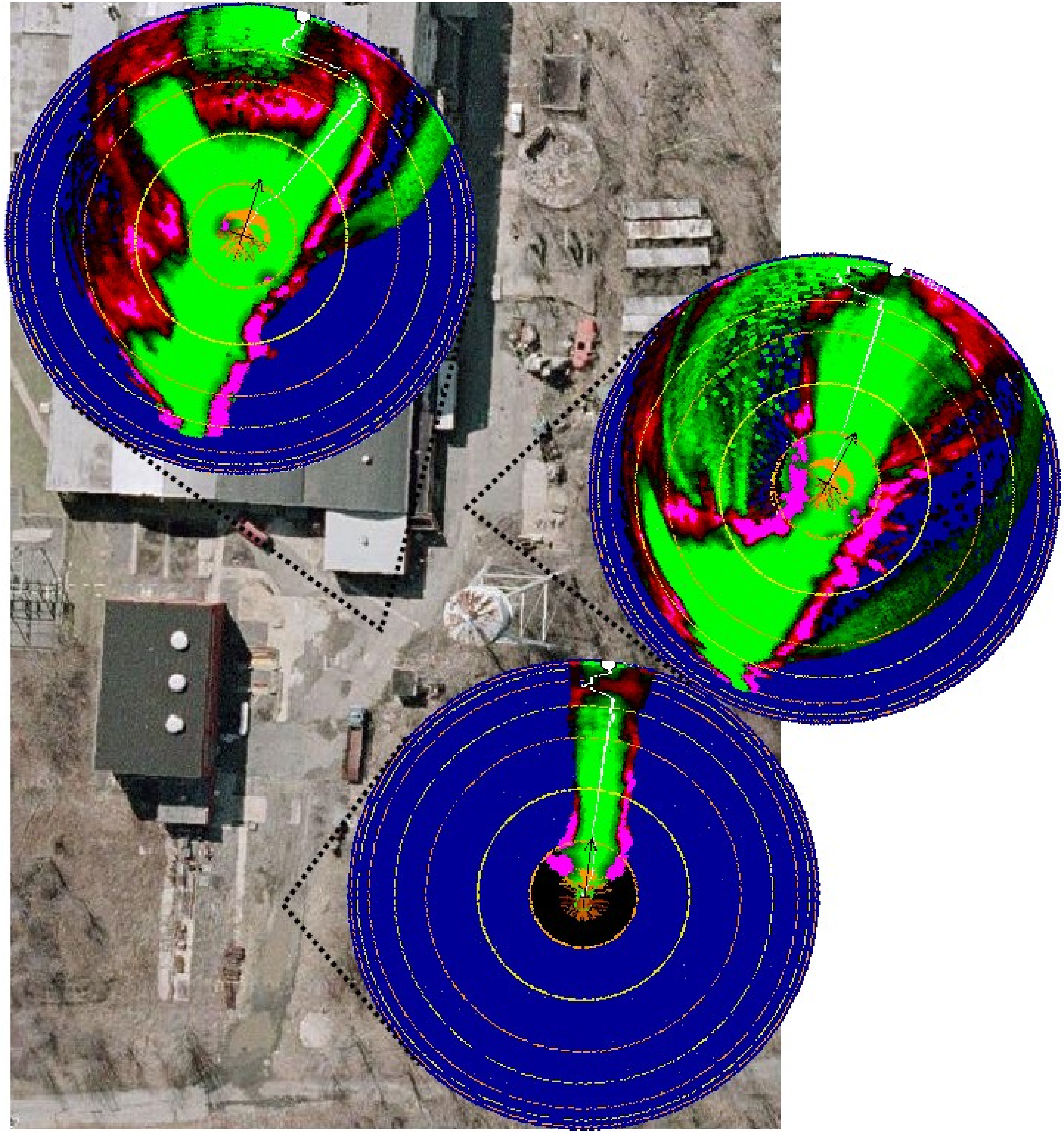


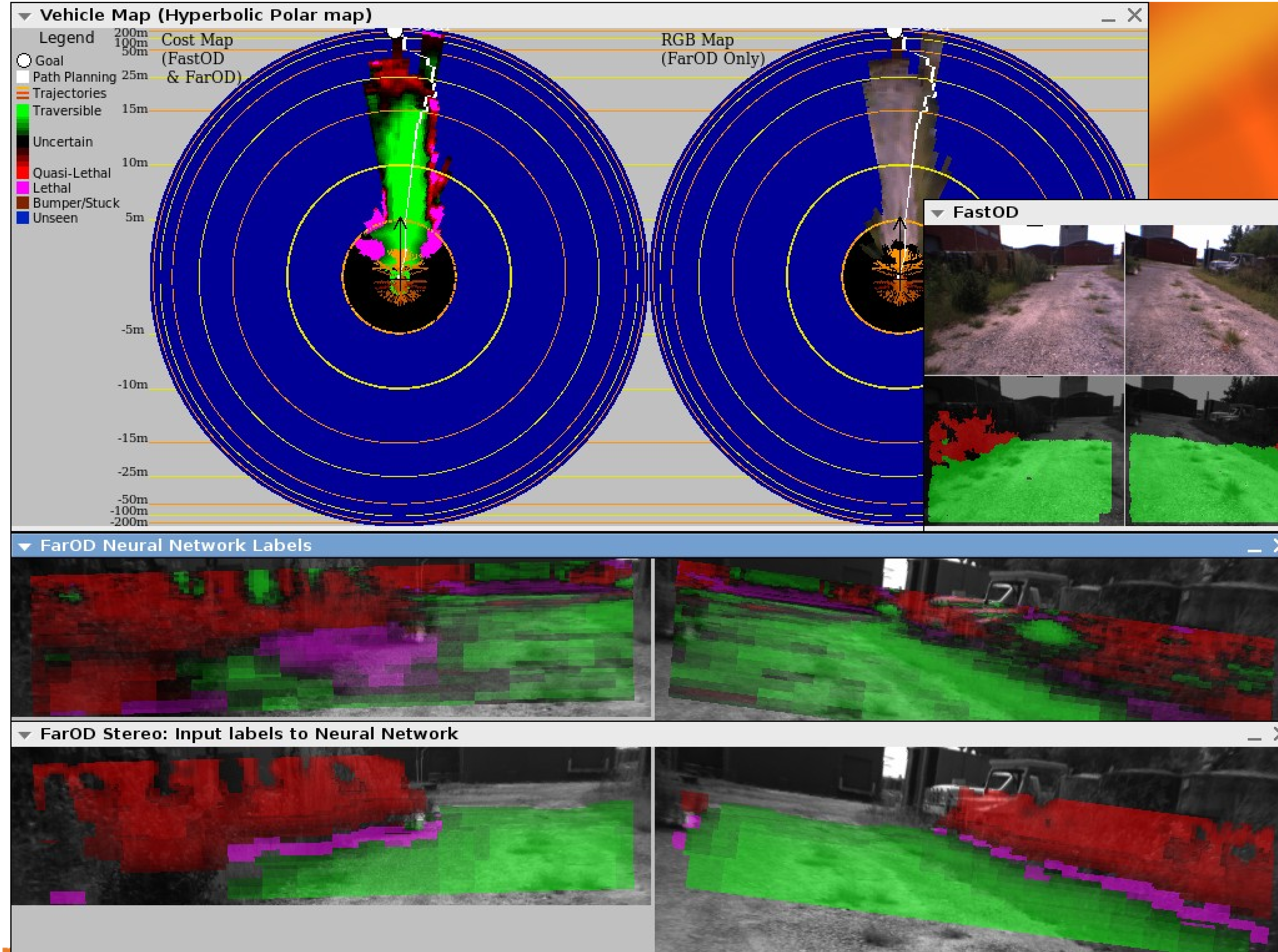
Long Range Vision Results



Long Range Vision Results






Vehicle Map (Hyperbolic Polar map)
Legend
Goal
Path Planning
Trajectories
Traversible
Uncertain
Quasi-Lethal
Lethal
Bumper/Stuck
Unseen
200m
100m
50m
25m
15m
10m
5m
-5m
-10m
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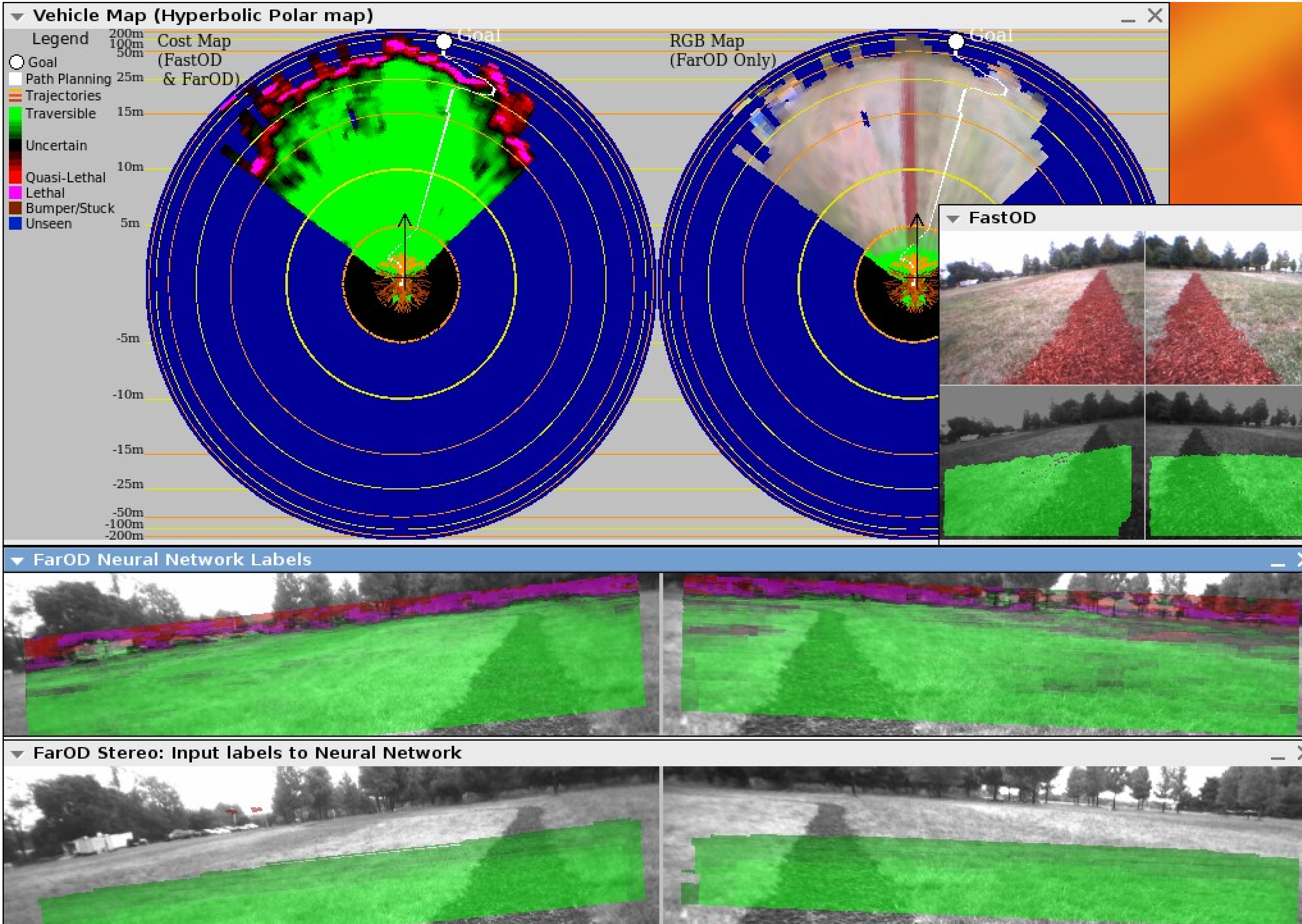
-25m
-50m
-100m
-200m
Cost Map
(FastOD
& FarOD)
RGB Map
(FarOD Only)
FastOD
FarOD Neural Network Labels
FarOD Stereo: Input labels to Neural Network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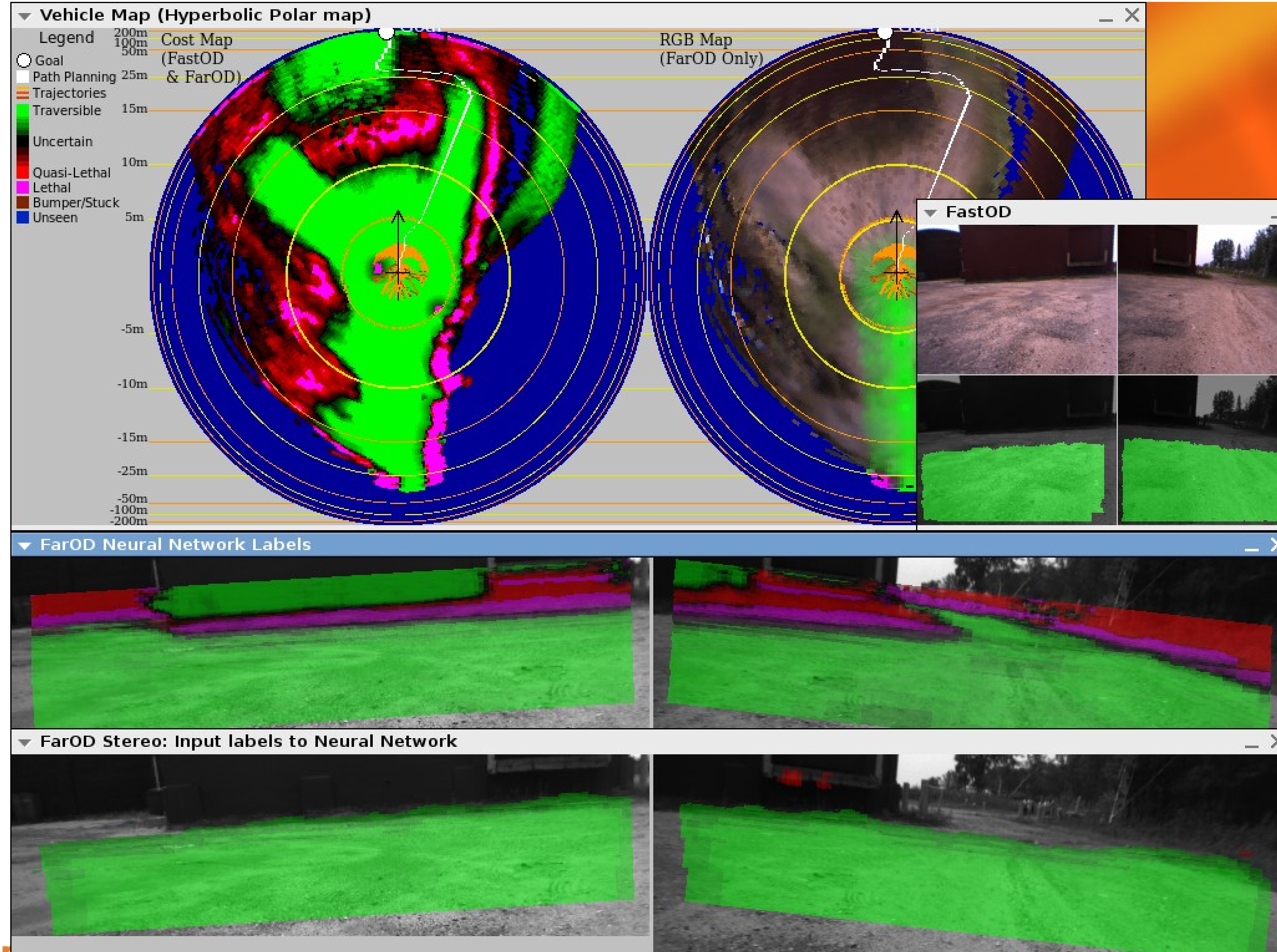
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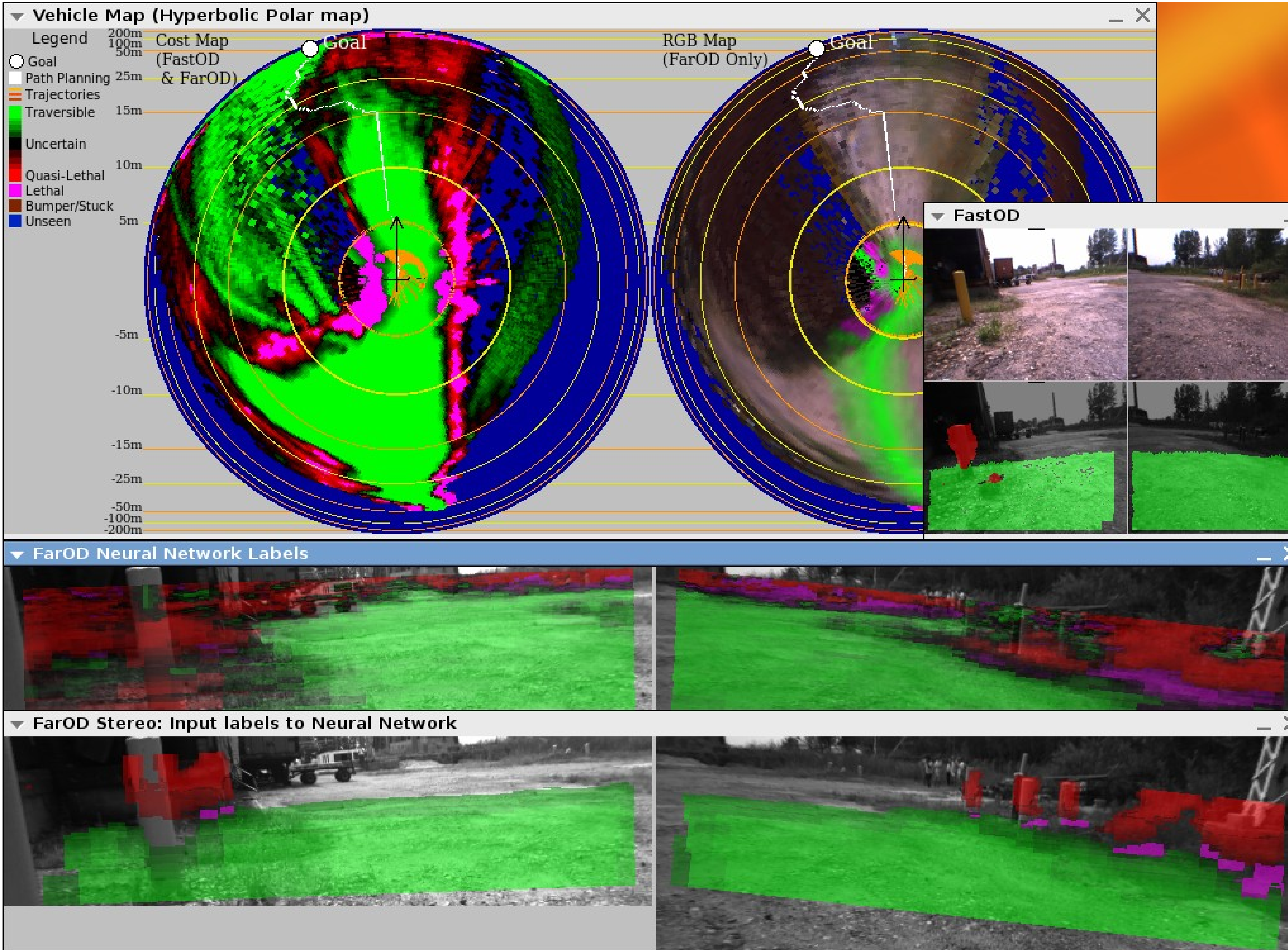

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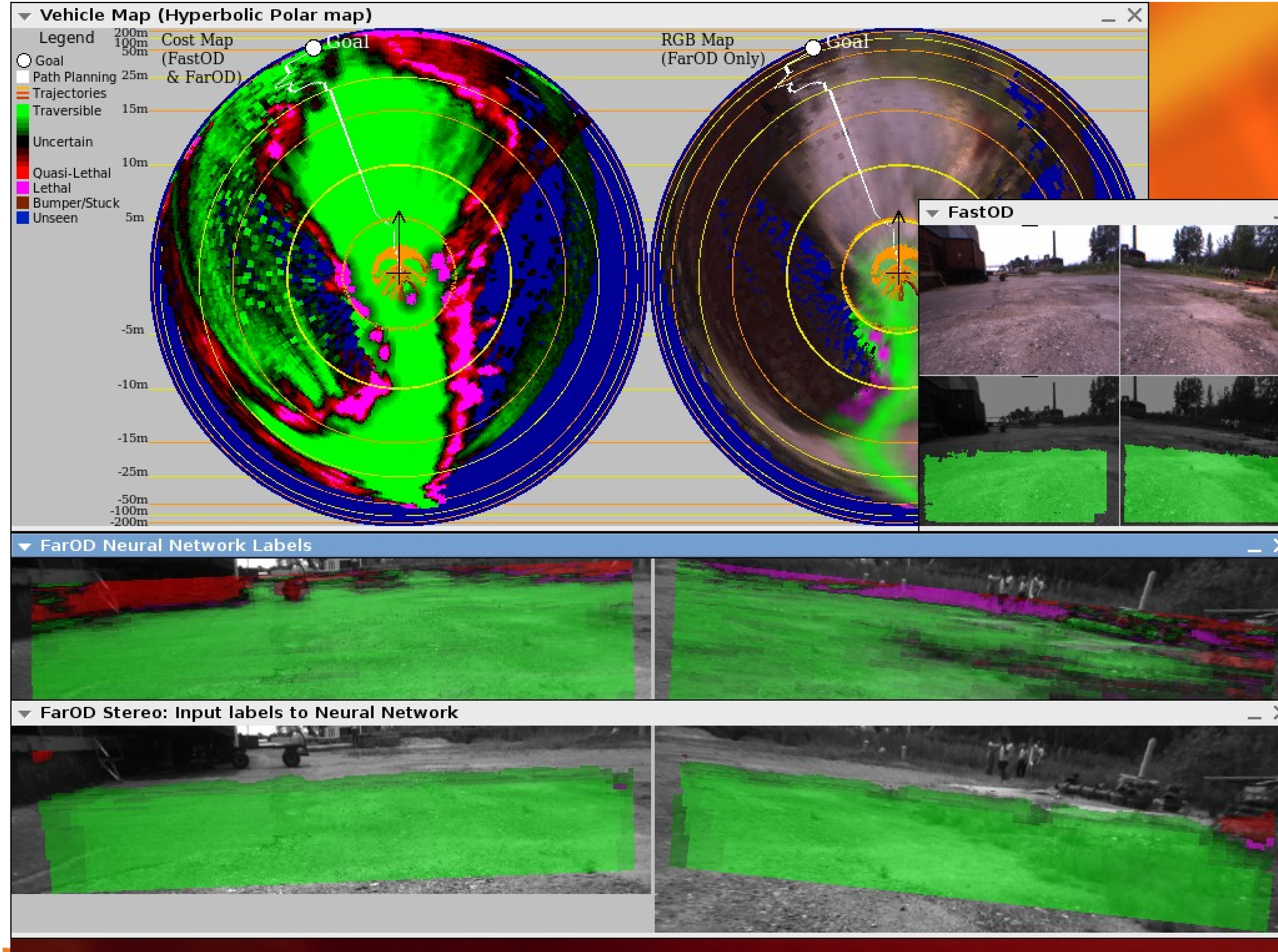
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Feature Learning for traversability prediction (LAGR)

Comparing

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

Testing on hand-labeled groundtruth frames – binary labels