Learning Hierarchies of Invariant Visual Features

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The Next Frontier in Machine Learning: Learning Representations

- **The big success of ML has been to learn classifiers from labeled data**
  - The representation of the input, and the metric to compare them are assumed to be “intelligently designed.”
  - Example: Support Vector Machines require a good input representation, and a good kernel function.
- **The next frontier is to “learn the features”**
  - The question: how can a machine learn good internal representations
  - In language, good representations are paramount.
    - What makes the words “cat” and “dog” semantically similar?
    - How can different sentences with the same meaning be mapped to the same internal representation?
- **How can we leverage unlabeled data (which is plentiful)?**

The Traditional "Shallow" Architecture for Recognition

Pre-processing / Feature Extraction

Trainable Classifier

this part is mostly hand-crafted

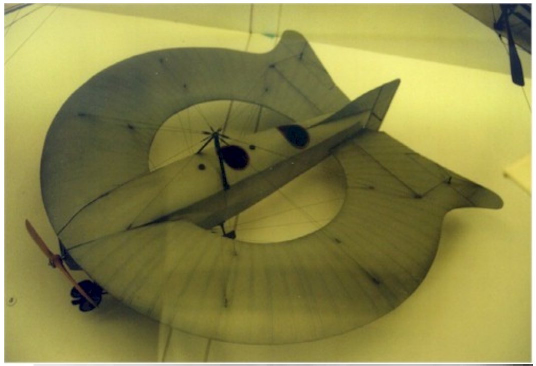
Internal Representation

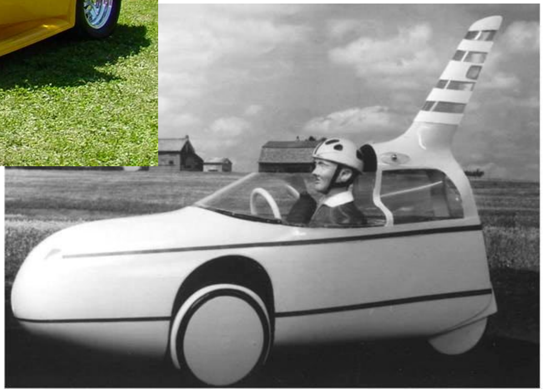
- **The raw input is pre-processed through a hand-crafted feature extractor**
- **The features are not learned**
- **The trainable classifier is often generic (task independent)**
- **The most common Machine Learning architecture: the Kernel Machine**

The Next Challenge of ML, Vision (and Neuroscience)

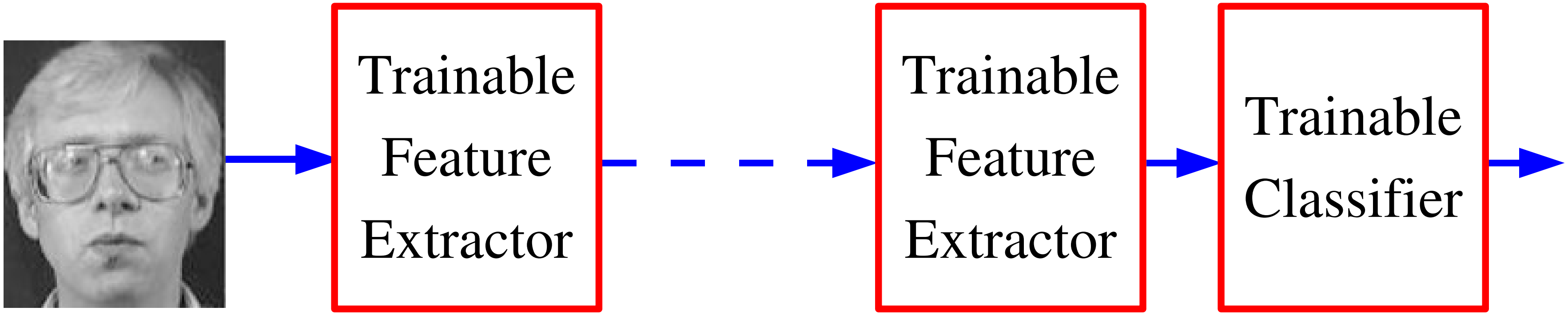
- **How do we learn invariant representations?**
  - From the image of an airplane, how do we extract a representation that is invariant to pose, illumination, background, clutter, object instance....
  - How can a human (or a machine) learn those representations by just looking at the world?

- **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)



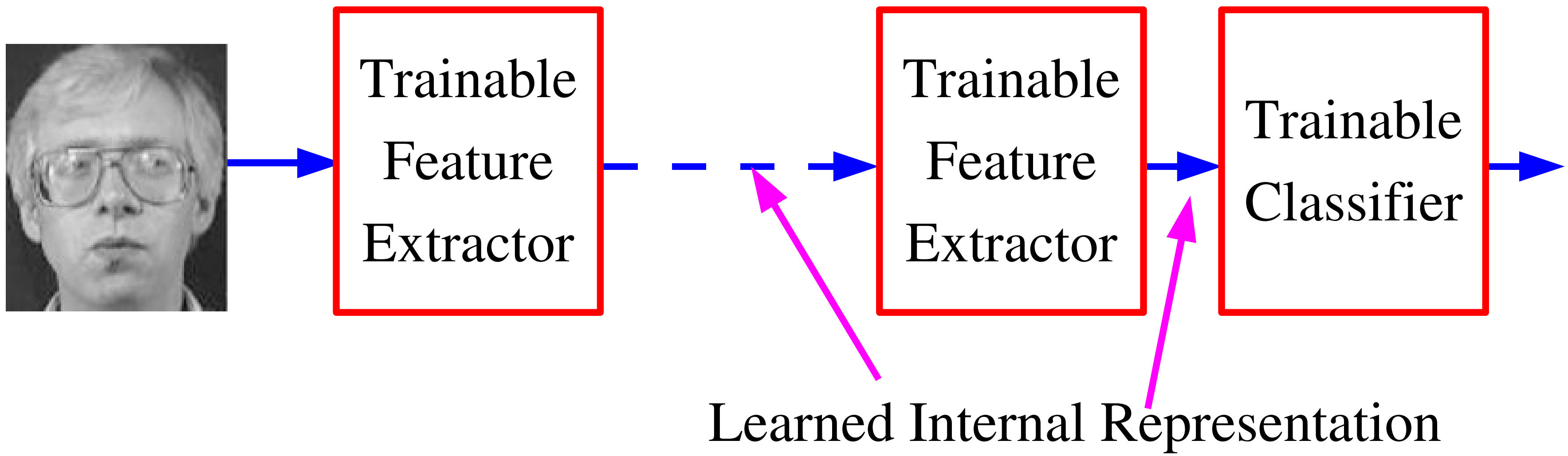


Good Representations are Hierarchical



- **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**

The Primate's Visual System is Deep

- **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 and learned, what is the learning algorithm?**
  - 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?

Do we really need deep architectures?

- **We can approximate any function as close as we want with shallow architecture. 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"

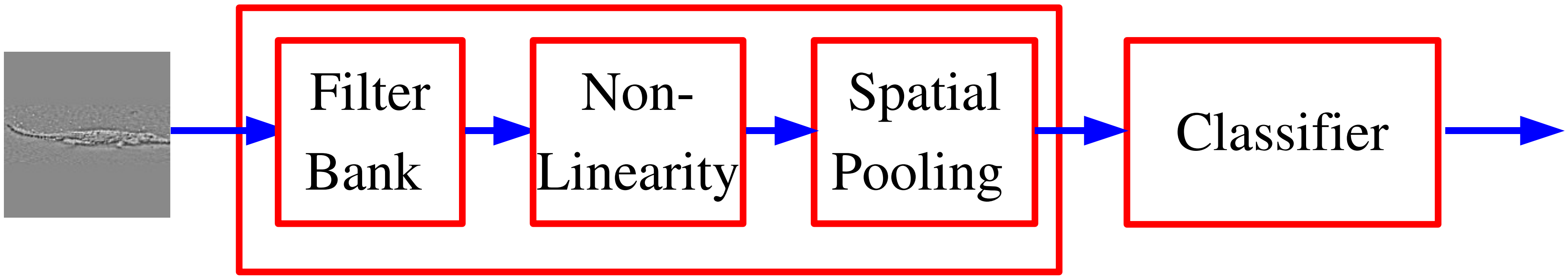
- **We need an efficient parameterization of the class of functions that are useful for "AI" tasks.**

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).....

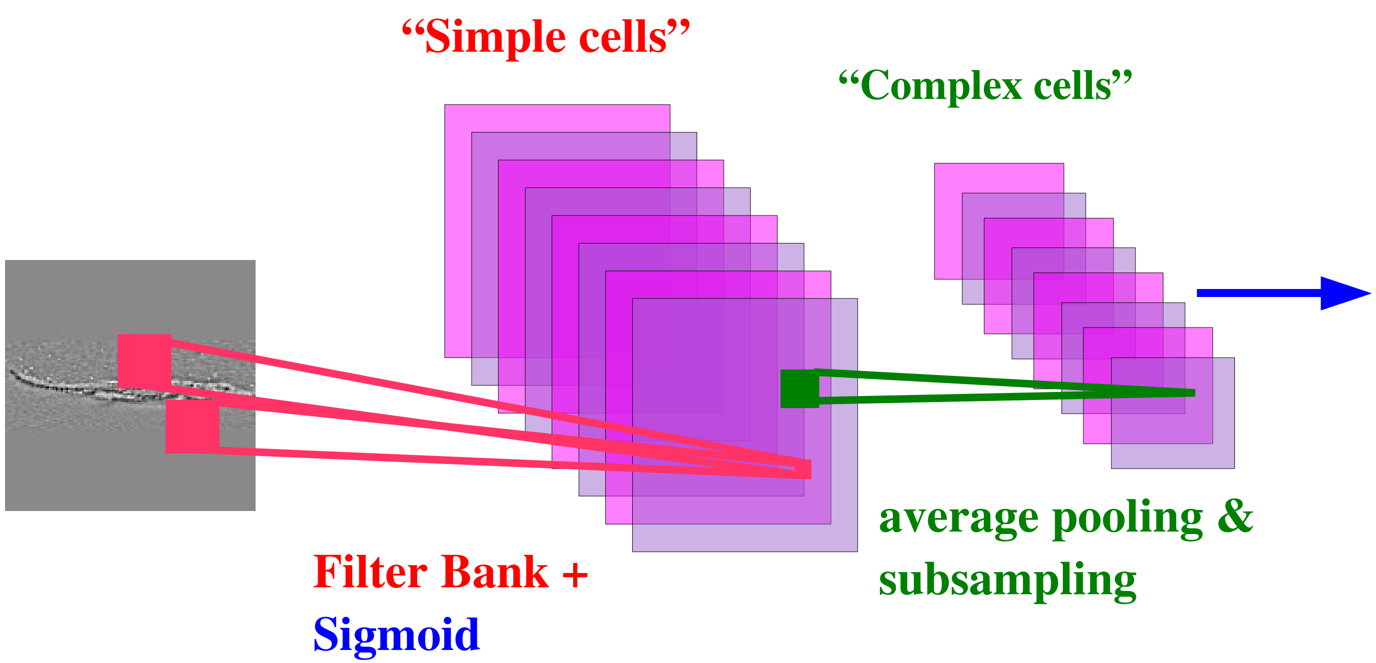
Feature Extraction in Computer Vision



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

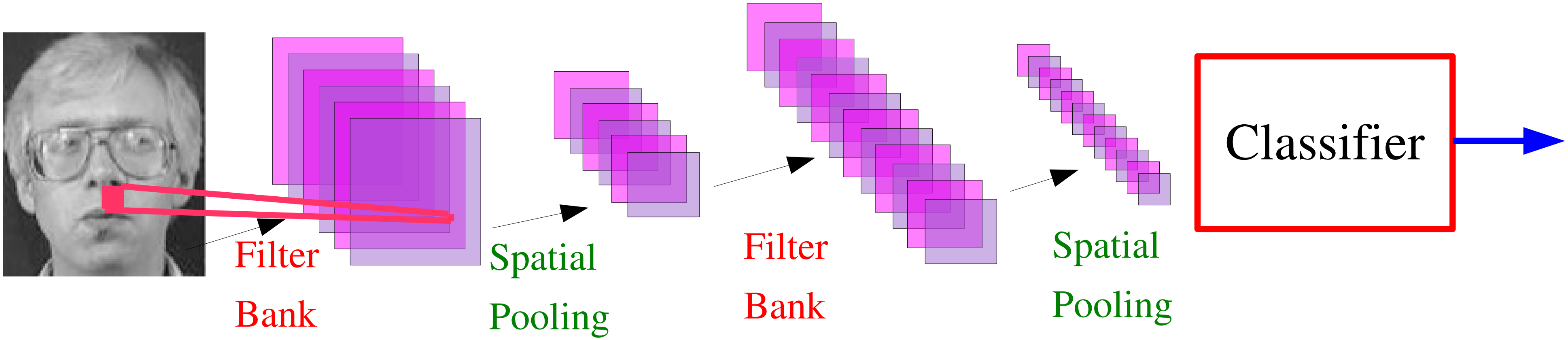
- **Examples:**
  - SIFT features with Spatial Pyramid Matching Kernel SVM [Lazebnik et al. 2006]
  - Edges + Rectification + Histograms + SVM [Dalal & Triggs 2005]
- **Fixed Features + "shallow" classifier**

Trainable Feature Extraction: Hubel-Wiesel Stage



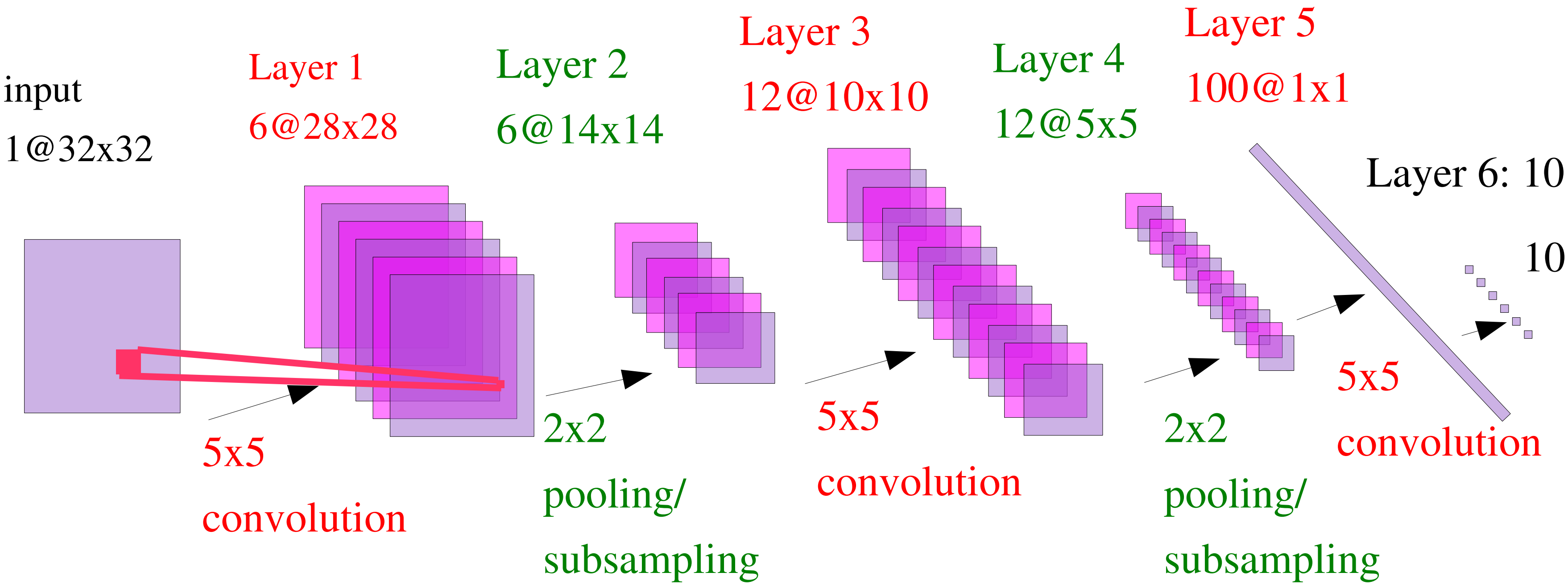
- Filter Bank -> Sigmoid -> Average Pooling & Subsampling
- Filter Bank + Sigmoid similar to "simple cells" in the visual cortex
- Pooling & Subsampling similar to "complex cells" in the visual cortex
  - [Hubel & Wiesel 1962]

Deep Architecture: The Multi-stage Hubel-Wiesel Architecture



- **Stacking multiple stages of simple cell / complex cell layer pairs**
- **We can't build the second layer features by hand!**
- **Neocognitron [Fukushima 1971-1982]**
  - simple unsupervised/competitive feature learning
- **Convolutional Nets [LeCun 1988-2007]**
  - fully supervised feature learning
  - A rare example of successful supervised deep learning
- **HMAX & friends [Poggio's group 2002-2006, Lowe 2006]**
  - simple feature learning (fixed Gabor filters + stored templates)

Convolutional Net: Supervised Multi-Stage Hubel-Wiesel Arch.

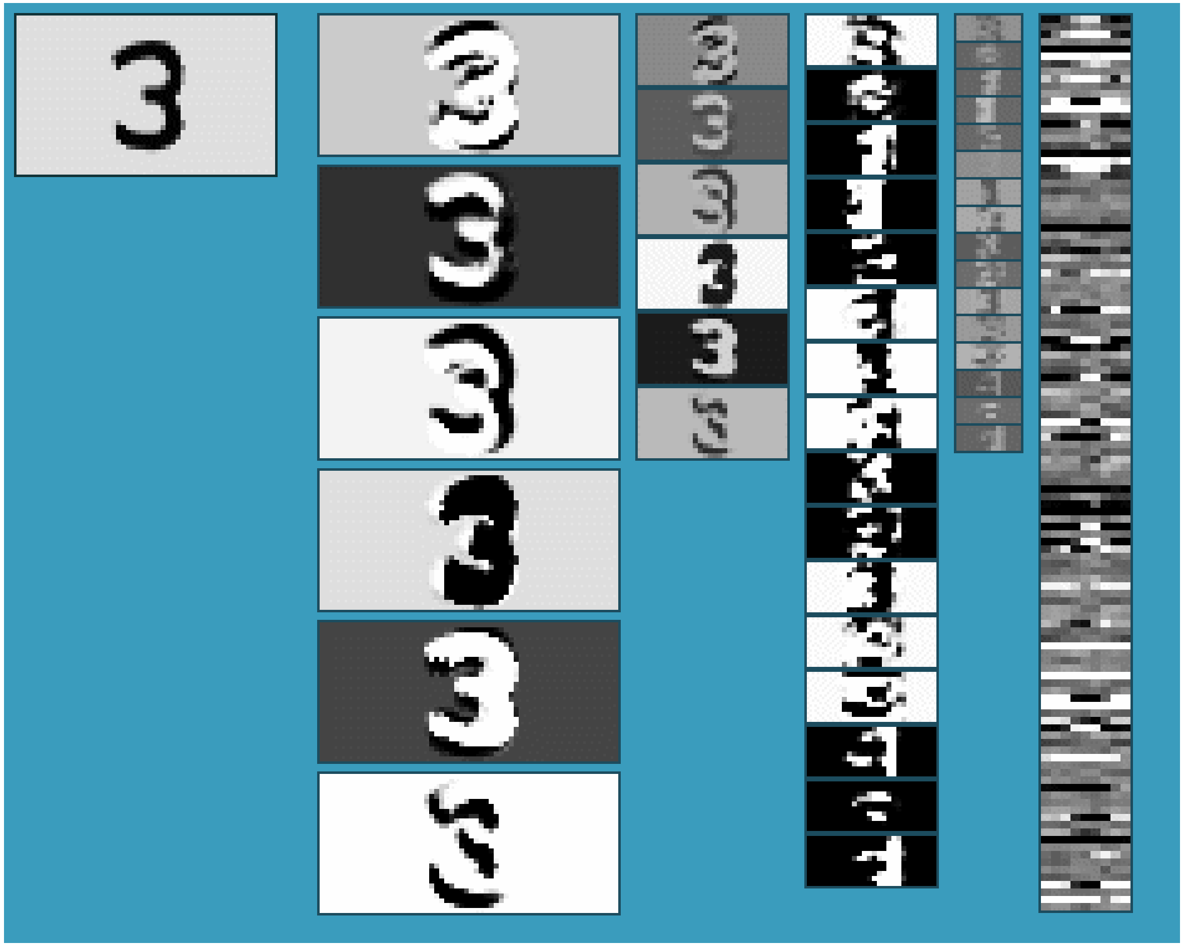


- **Convolutional Net: supervised multi-stage Hubel-Wiesel Architecture**
  - Convolutional Layers: detect local motifs
  - Pooling/Subsampling: builds local invariance to distortions
- **Training by supervised gradient descent (using back-propagation)**
  - Every coefficient of every filter is learned simultaneously
  - “end-to-end learning”
- **The architecture is biologically inspired, but not the learning algorithm.**

Supervised Training of Convolutional Network

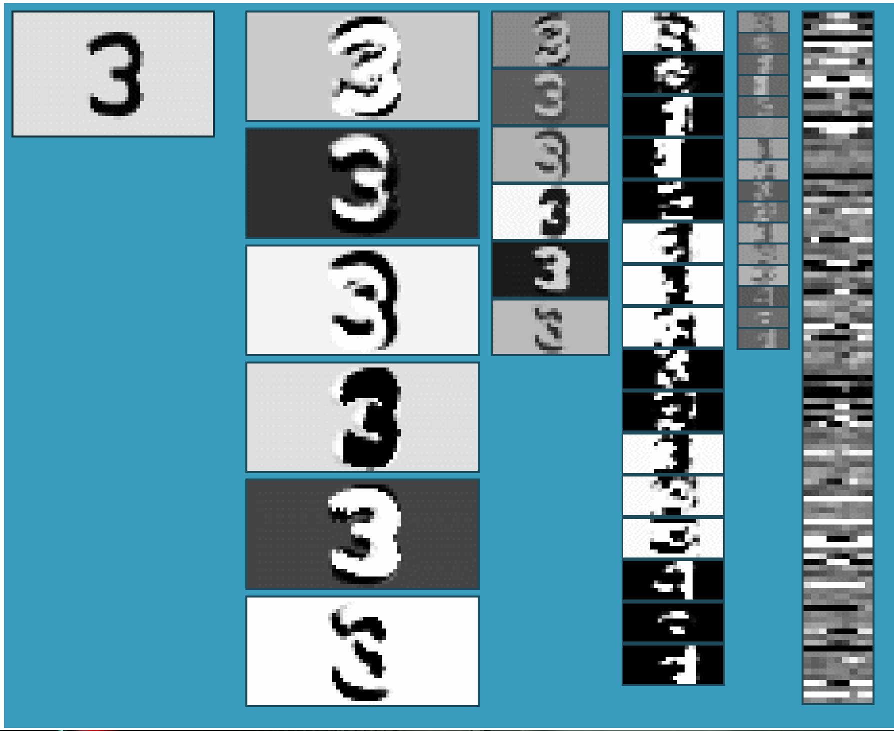
- **End-to-End Supervised Training of Convolutional Nets:**
  - Gradient-based learning algorithm (similar to back-propagation)
  - Every filter at every layer is learned.

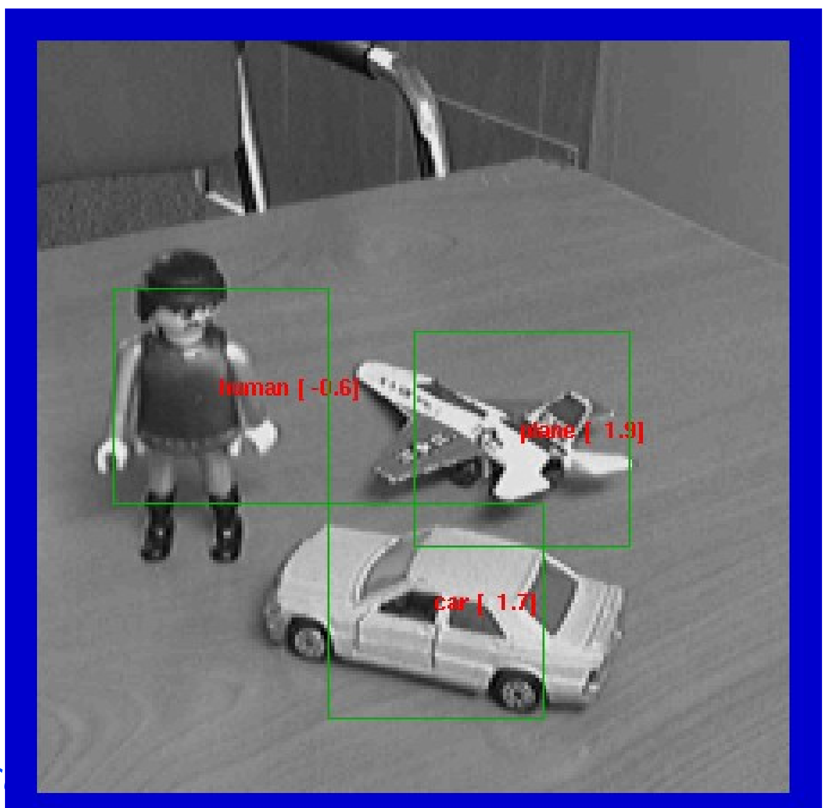
- **This training method works very well but it requires many labeled training samples.**
- **It is the record-holding method for hand-writing recognition**
- **It is used commercially by NCR for check reading machines, and Microsoft for OCR.**

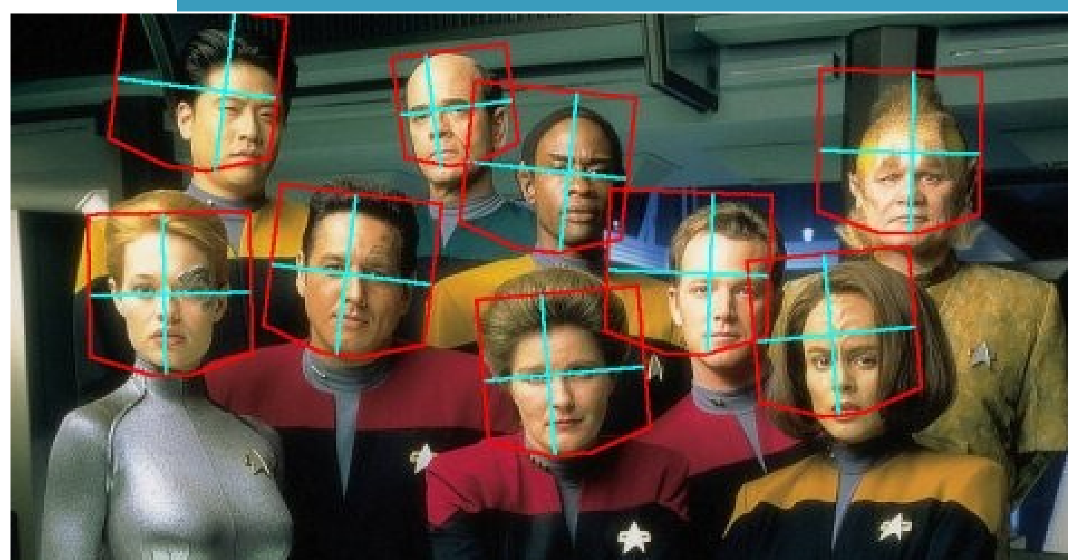


Supervised Convolutional Nets learn well with lots of data

- **Supervised Convolutional nets work very well for:**
  - handwriting recognition
    - Holds the record on MNIST!
  - face detection
  - object recognition with few classes and lots of training samples







Deep Supervised ConvNets Work (with lots of labeled data)

- **On recognition tasks with lots of training samples, deep supervised architecture outperform shallow architectures in speed and accuracy**

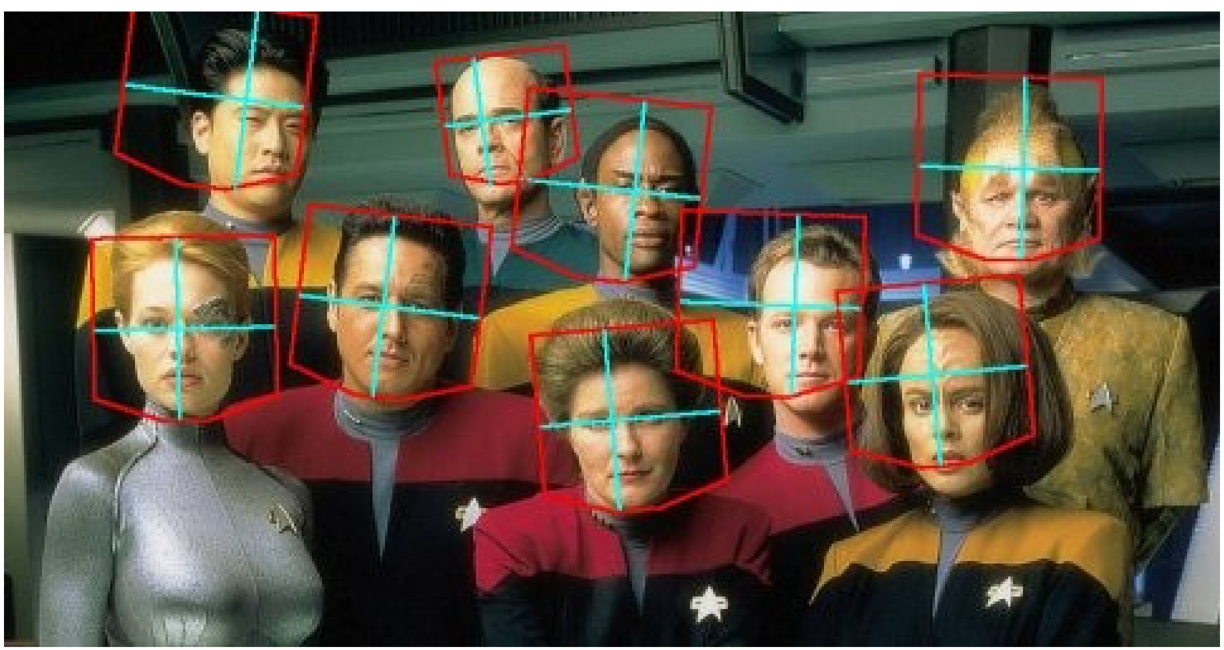
- **Handwriting Recognition: ConvNets hold the record**
  - raw MNIST: 0.62% for convolutional nets [Ranzato 07]
  - raw MNIST: 1.40% for SVMs [Cortes 92]
  - distorted MNIST: 0.40% for conv nets [Simard 03, Ranzato 06]
  - distorted MNIST: 0.67% for SVMs [Bordes 07]

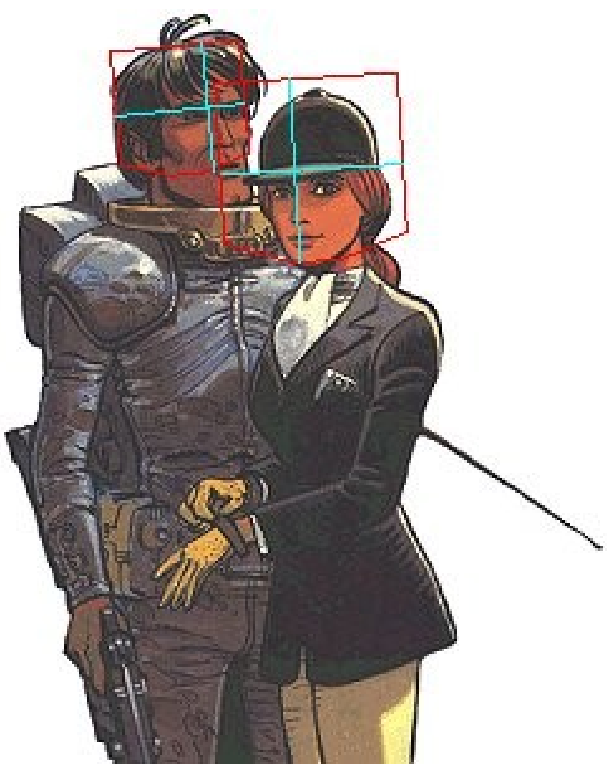
- **Object Recognition: beats SVMs**
  - small NORB: 6.0% for conv nets [Huang 05]
  - small NORB: 11.6% for SVM [Huang 05]
  - big NORB: 7.8% for conv nets [Huang 06]
  - big NORB: 43.3% for SVM [Huang 06]

- **Face Detection: ConvNets beat Viola-Jones**
  - [Vaillant 93,94][Garcia & Delakis PAMI 05][Osadchy JMLR 07]

Face Detection: Results

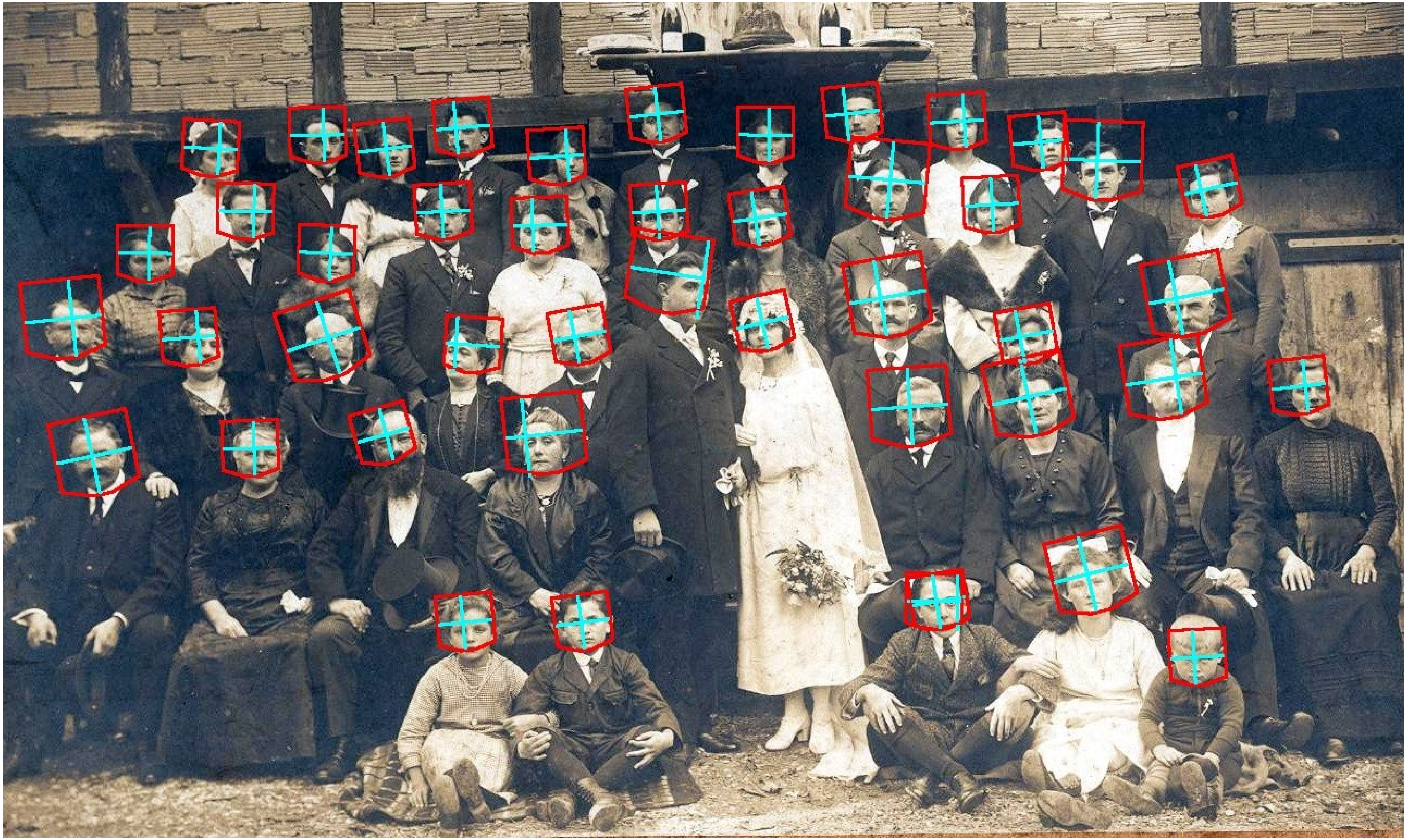
Data Set-> *False positives per image->*	TILTED		PROFILE		MIT+CMU	
	4.42	26.9	0.47	3.36	0.5	1.28
Our Detector	90%	97%	67%	83%	83%	88%
Jones & Viola (tilted)	90%	95%	x		x	
Jones & Viola (profile)	x		70%	83%	x	





Face Detection and Pose Estimation: Results

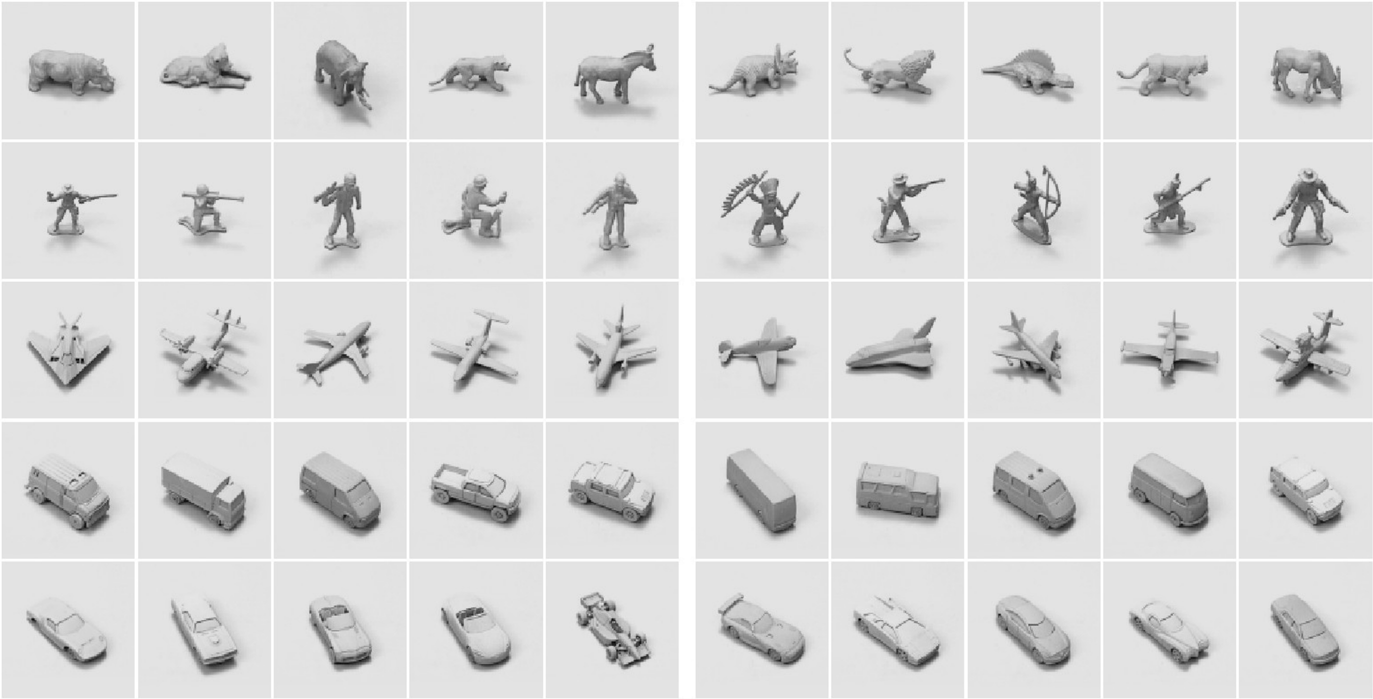
Face Detection with a Convolutional Net



Generic Object Detection and Recognition with Invariance to Pose and Illumination

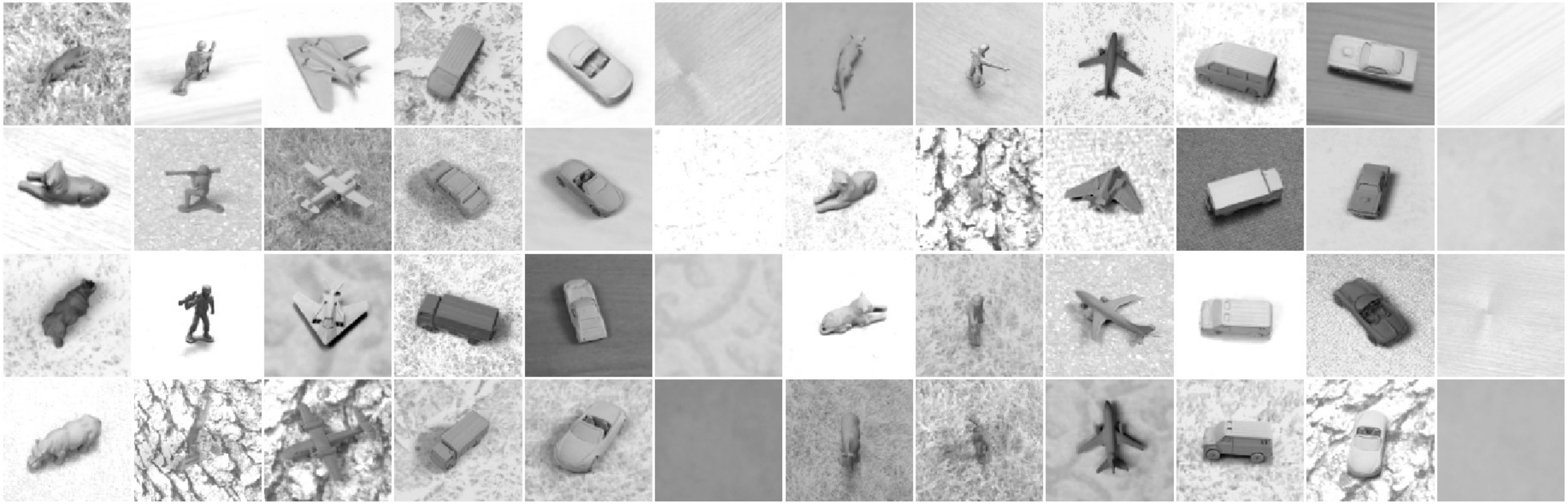
- **50** toys belonging to 5 categories: **animal, human figure, airplane, truck, car**
- **10** instance per category: 5 instances used for training, 5 instances for testing
- **Raw dataset: 972** stereo pair of each object instance. **48,600** image pairs total.

- **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

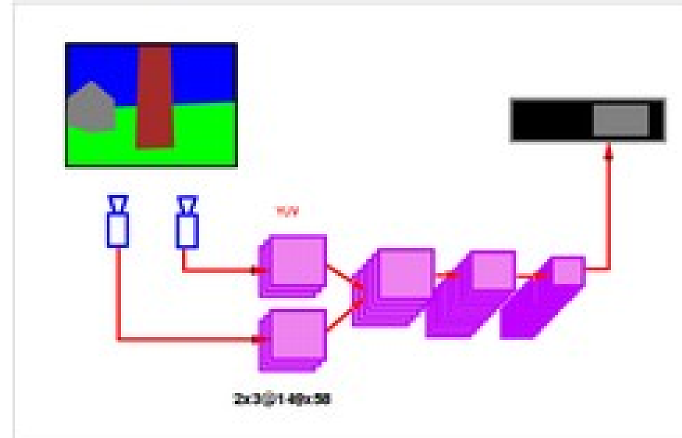


Training instances **Test instances**

Textured and Cluttered Datasets

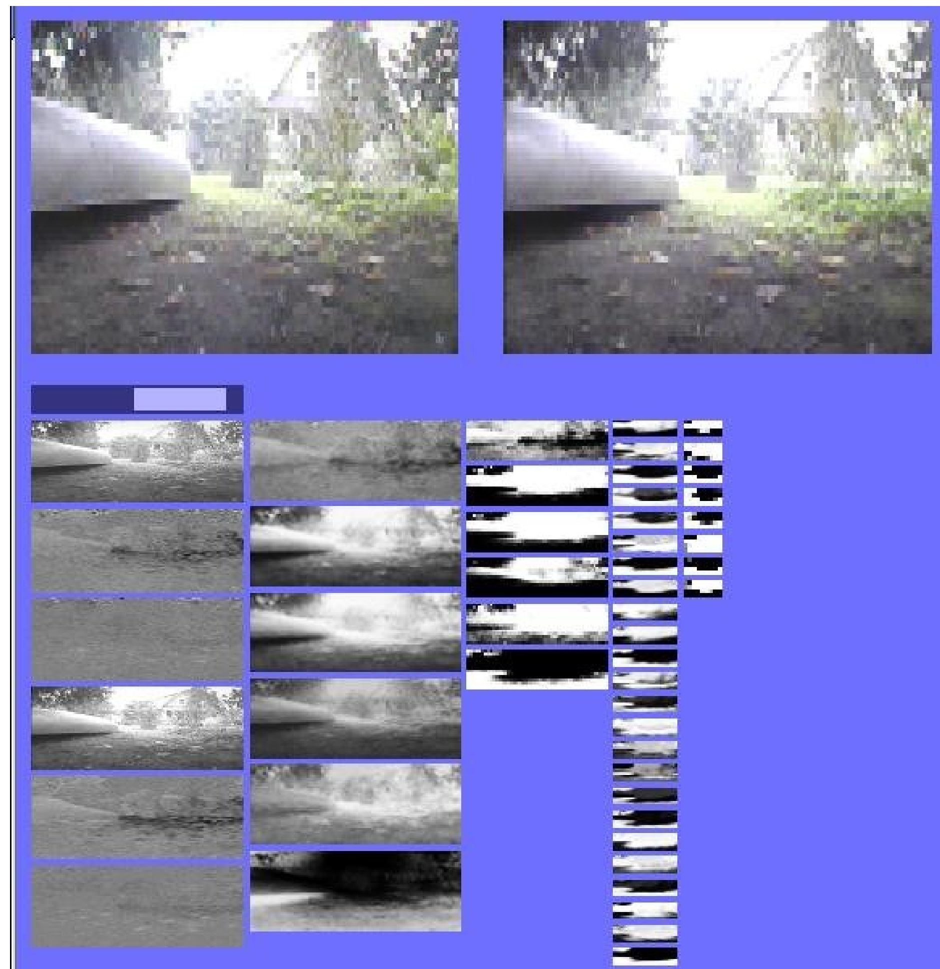


Visual Navigation for a Mobile Robot



[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



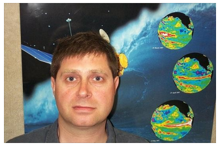
Industrial Applications of ConvNets

- **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, ???
- **Microsoft**
  - OCR, handwriting recognition, speech detection
- **France Telecom**
  - Face detection, HCI, cell phone-based applications
- **Other projects: HRL (3D vision)....**

Problem: ConvNets don't work when labeled samples are scarse

- **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: 26.0%
  - SIFT features + spatial pyramid kernel SVM: 66.2%
    - [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

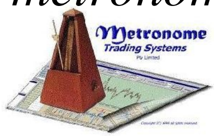
wild cat

lotus

ant

dollar

metronome



w. chair

minaret

cellphone

joshua t.

cougar body

background

How Can We Use Unlabeled Data to Learn Features?

- **We need unsupervised learning methods that can learn invariant feature hierarchies**
- **"Deep Belief Networks" strategy [Hinton 2005]**
  - train each stage unsupervised one after the other.
  - Hinton uses Restricted Boltzmann Machines for each stage.

[Hinton et al. "A fast learning algorithm for DBNs" 06]

[Hinton et al. "Reducing the dimensionality of data with neural nets" 06]

[Bengio et al. "Greedy layer-wise training of deep nets" 07]

[Ranzato et al. "Efficient learning of sparse representations with energy-based models" 07]

[Lee et al. 07]

The Deep Encoder/Decoder Architecture

- **Each stage is composed of** [Bengio 06, LeCun 06]
  - an encoder that produces a feature vector from the input
  - a decoder that reconstruct the input from the feature vector
    - Hinton's Restricted Boltzmann Machines are a special case
- **Each stage is trained one after the other in a greedy fashion**
  - the input to stage k+1 is the feature vector of stage k.

The Deep Encoder/Decoder Architecture

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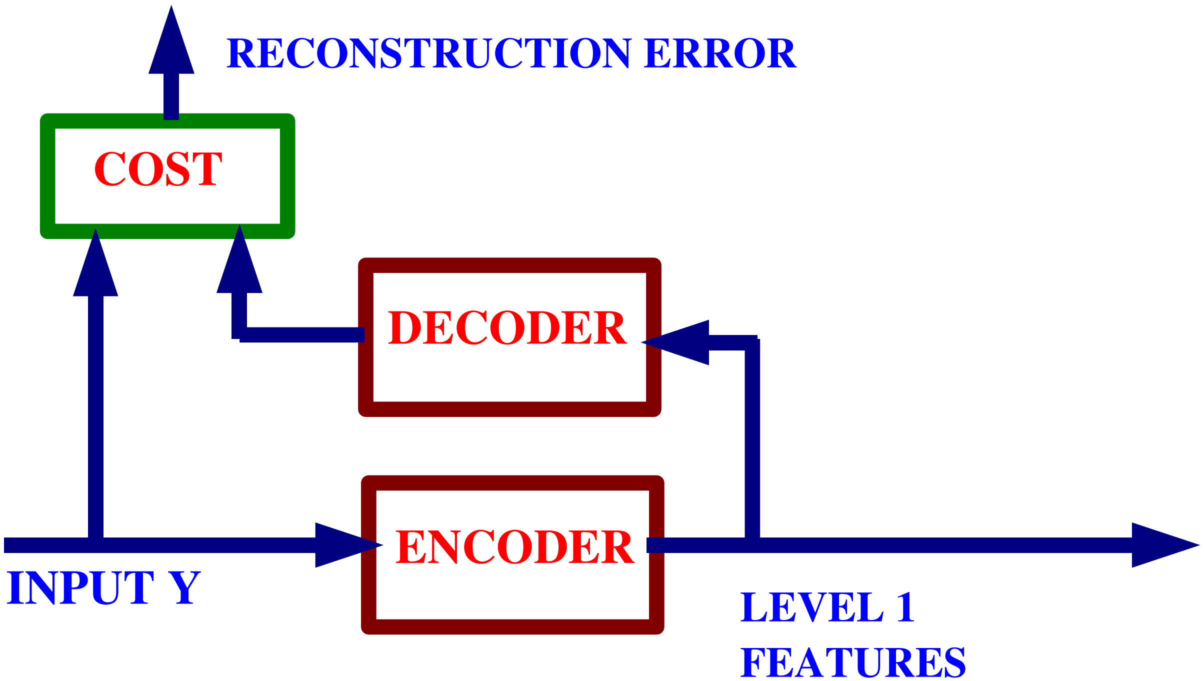
- **Each stage is trained one after the other**
  - Training stage 1



The Deep Encoder/Decoder Architecture

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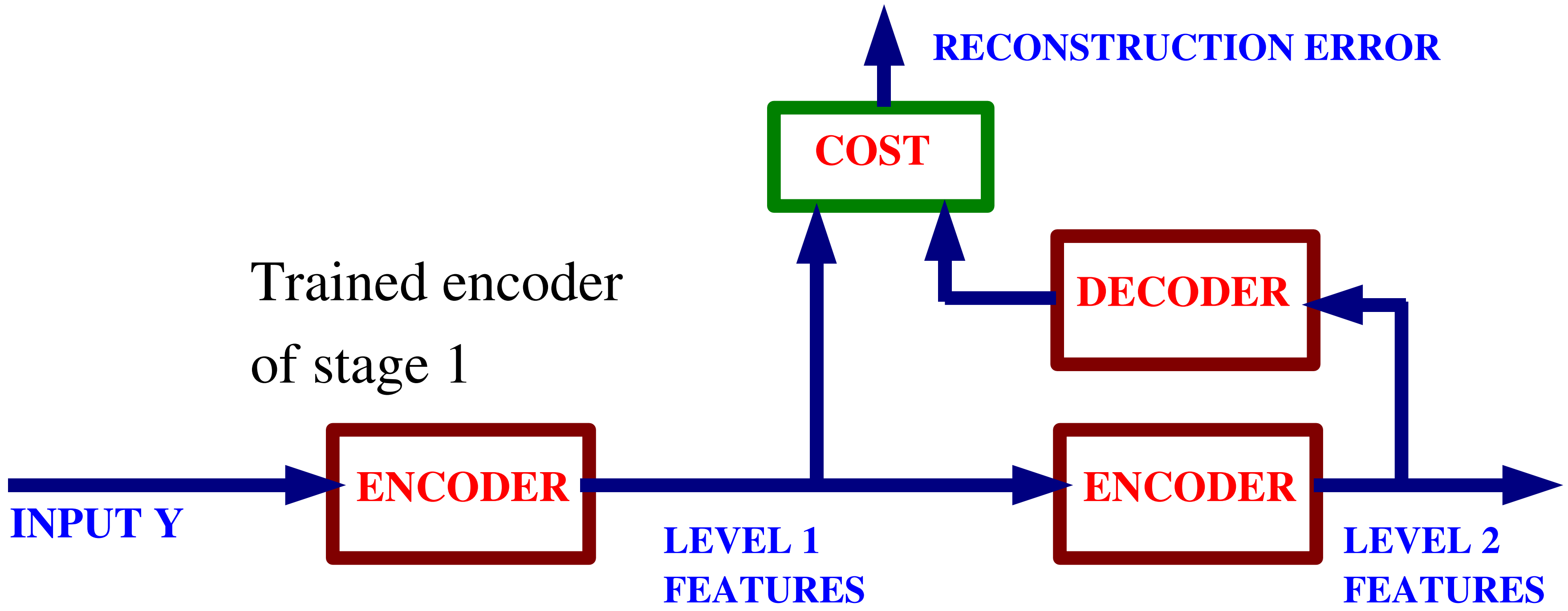
  - an encoder that produces a feature vector from the input
  - a decoder that reconstruct the input from the feature vector
    - Hinton's Restricted Boltzmann Machines are a special case
- **Each stage is trained one after the other**
  - Training stage 2

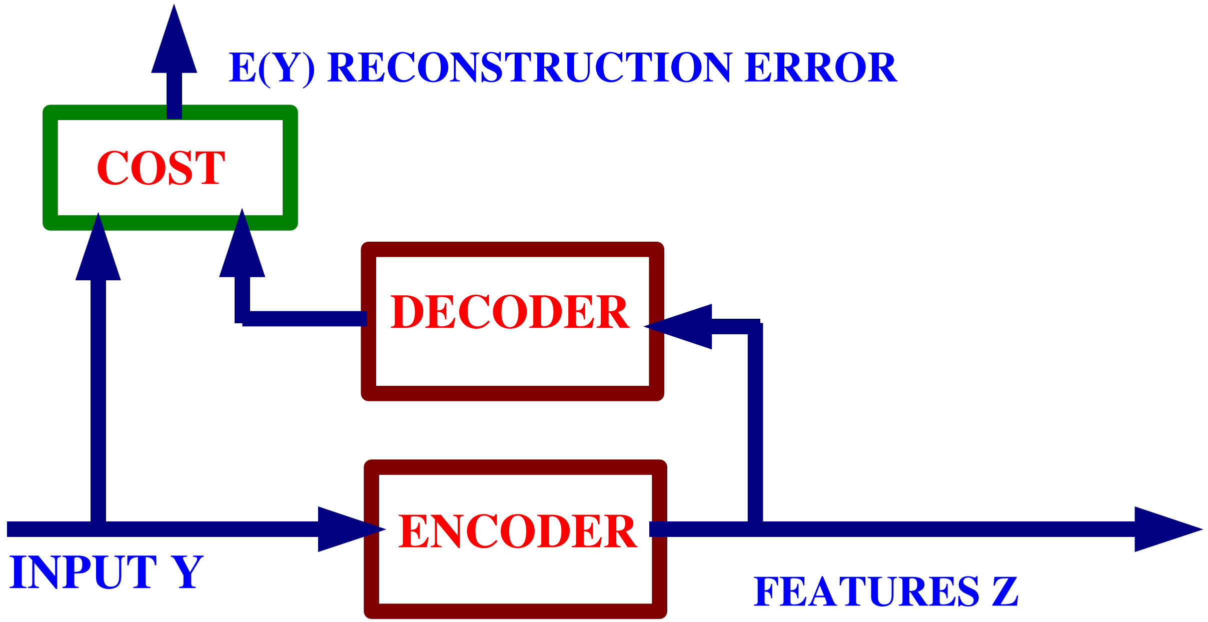
Trained encoder

of stage 1



Training an Encoder/Decoder Module

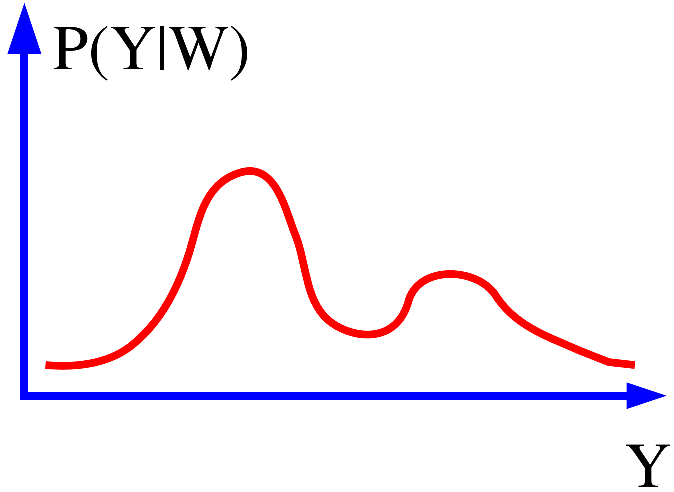
- **Define the Energy E(Y) as the reconstruction error**
  - Example: $E(Y) = || Y - Decoder(Encoder(Y)) ||^2$
- **Probabilistic Training, given a training set (Y1, Y2.......)**
  - Interpret the energy E(Y) as a -log P(Y) (unnormalized)
  - Train the encoder/decoder to maximize the prob of the data
- **Train the encoder/decoder so that:**
  - E(Y) is small in regions of high data density (good reconstruction)
  - E(Y) is large in regions of low data density (bad reconstruction)



Each Stage is Trained as an Estimator of the Input Density

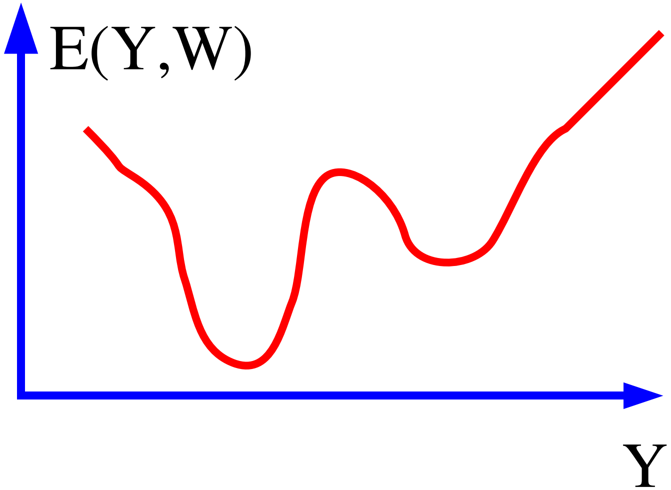
Probabilistic View:

- Produce a probability density function that:
- has high value in regions of high sample density
- has low value everywhere else (integral = 1).



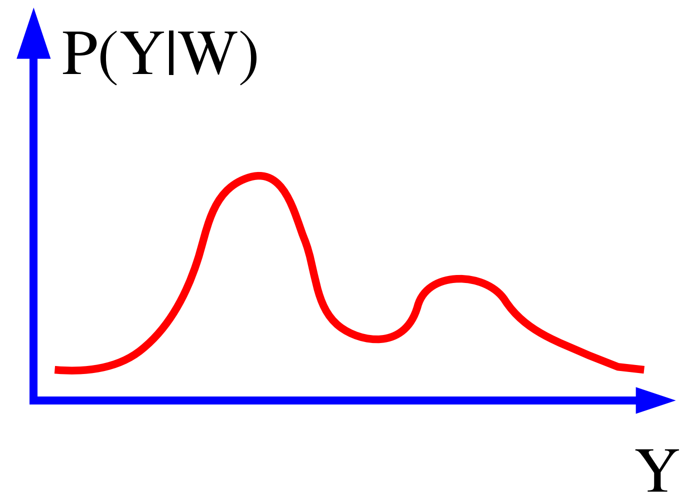
Energy-Based View:

- produce an energy function E(Y,W) that:
- has low value in regions of high sample density
- has high(er) value everywhere else

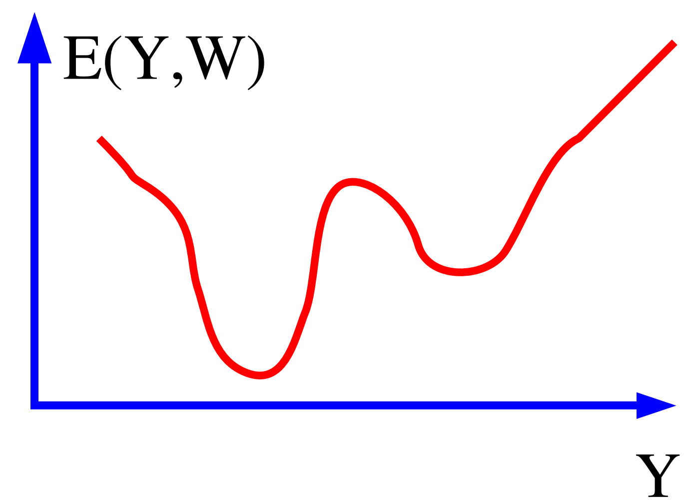


Energy <-> Probability

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

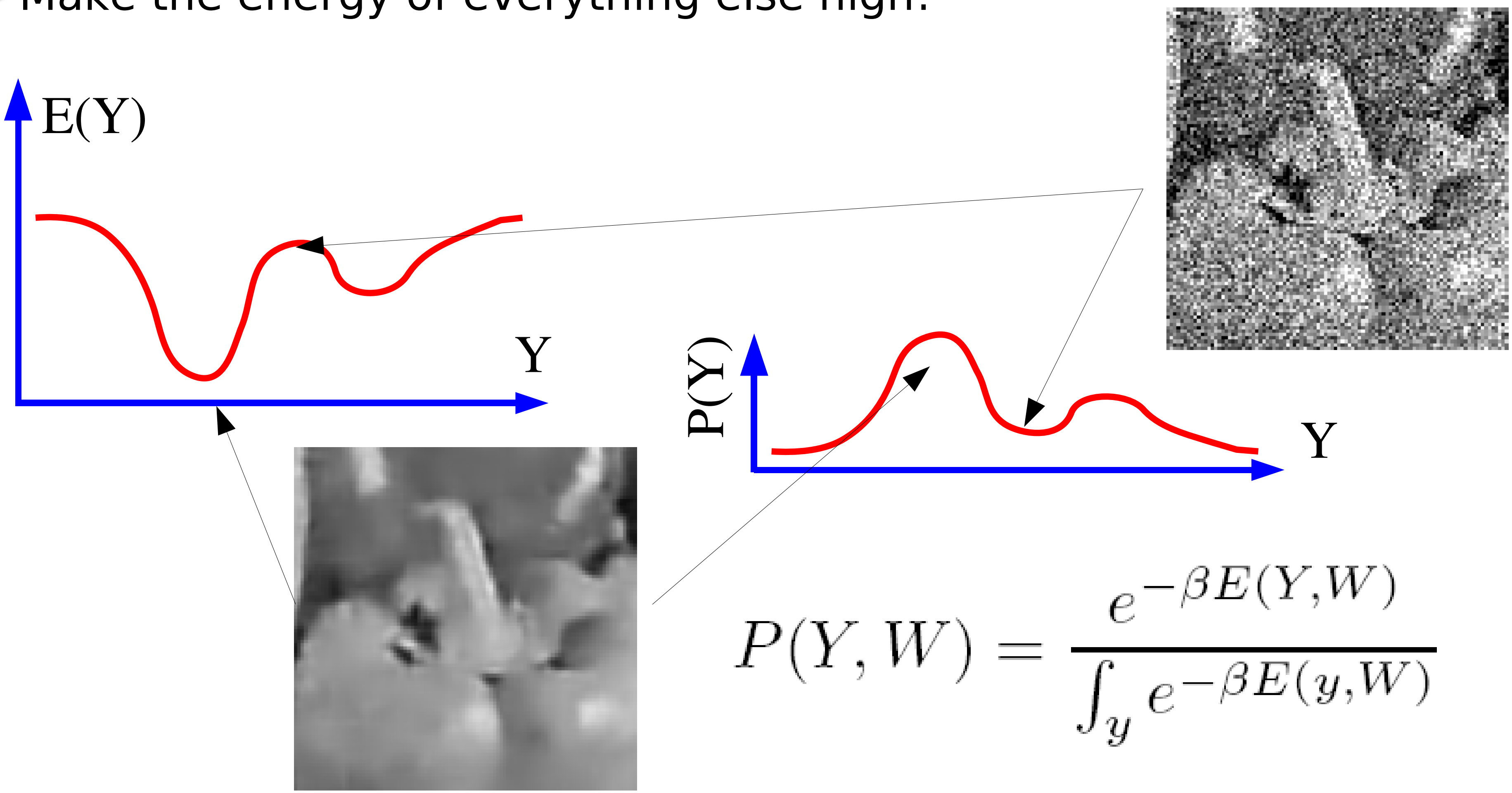


$$E(Y,W) \propto -\log P(Y|W)$$



The Intractable Normalization Problem

- **Example: Image Patches**
- **Learning:**
  - Make the energy of every “natural image” patch low
  - Make the energy of everything else high!



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

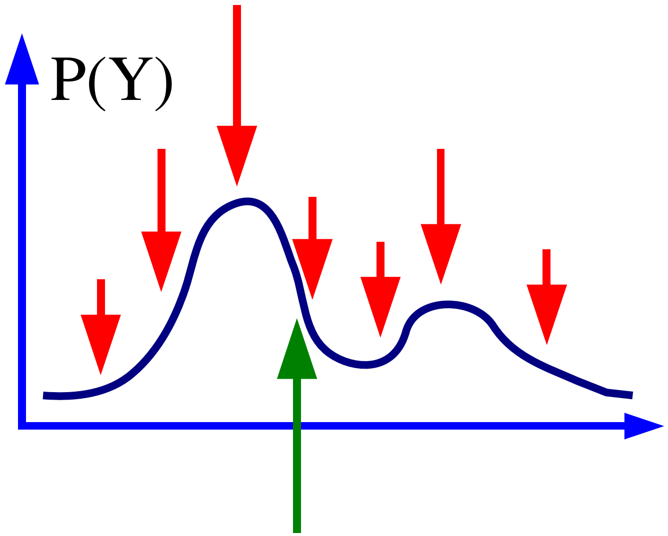
Training an Energy-Based Model to Approximate a Density

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

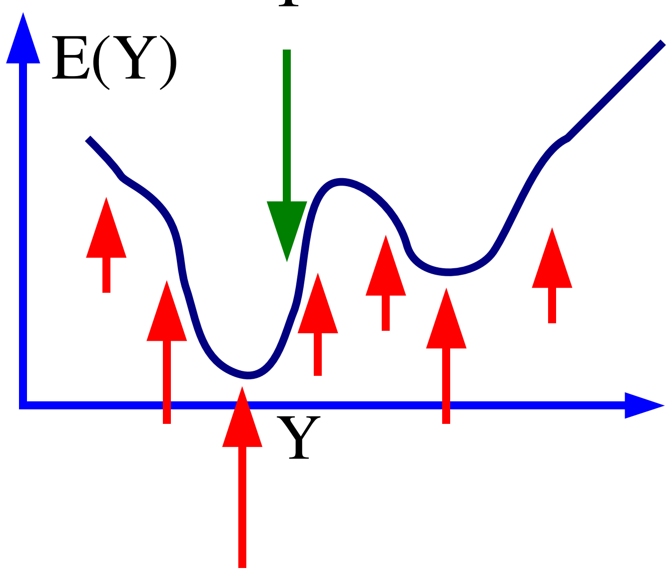


Minimizing -log P(Y,W) on training samples

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

make this small

make this big



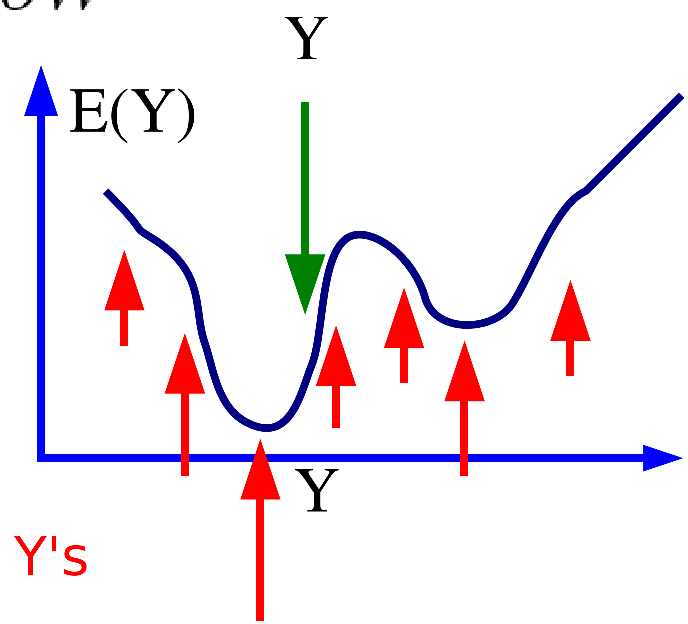
Training an Energy-Based Model with Gradient Descent

- **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

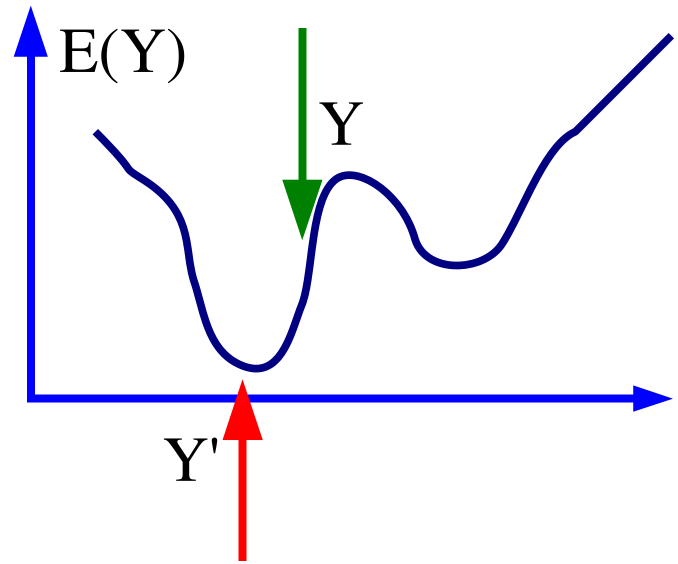
$$W \leftarrow W - \eta \frac{\partial E(Y,W)}{\partial W} + \eta \int_y P(y|W) \frac{\partial E(y,W)}{\partial W}$$

Solving The Intractable Normalization problem

- **Probabilistic unsupervised learning is hard**
  - Pushing up on the energy of every points in regions of low data density is often impractical.
- **Solution 1: contrastive divergence [Hinton 2000]**
  - Only push up on points that are not to far from the training samples, and only on those points that have low energy. These points are obtained from the training samples through MCMC.
  - This makes a “groove” in the energy surface around the data manifold.
- **Solution 2: 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]

Contrastive Divergence Trick [Hinton 2000]

- **push down on the energy of the training sample Y**
- **Pick a sample of low energy Y' near the training sample, and pull up its energy**
  - this digs a trench in the energy surface around the training samples



$$W \leftarrow W - \eta \frac{\partial E(Y,W)}{\partial W} + \eta \frac{\partial E(Y',W)}{\partial W}$$

Pushes down on the energy of the training sample Y

Pulls up on the energy Y'

Contrastive Divergence Trick [Hinton 2000]

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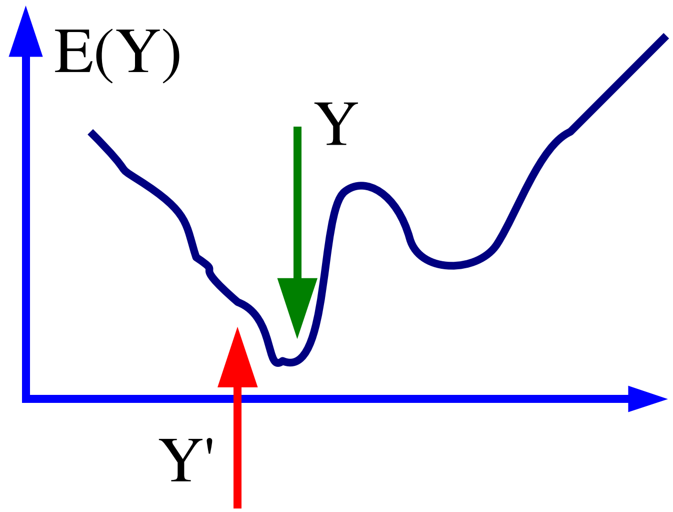
- **Pick a sample of low energy Y' near the training sample, and pull up its energy**
  - this digs a trench in the energy surface around the training samples



$$W \leftarrow W - \eta \frac{\partial E(Y,W)}{\partial W} + \eta \frac{\partial E(Y',W)}{\partial W}$$

Pushes down on the energy of the training sample Y

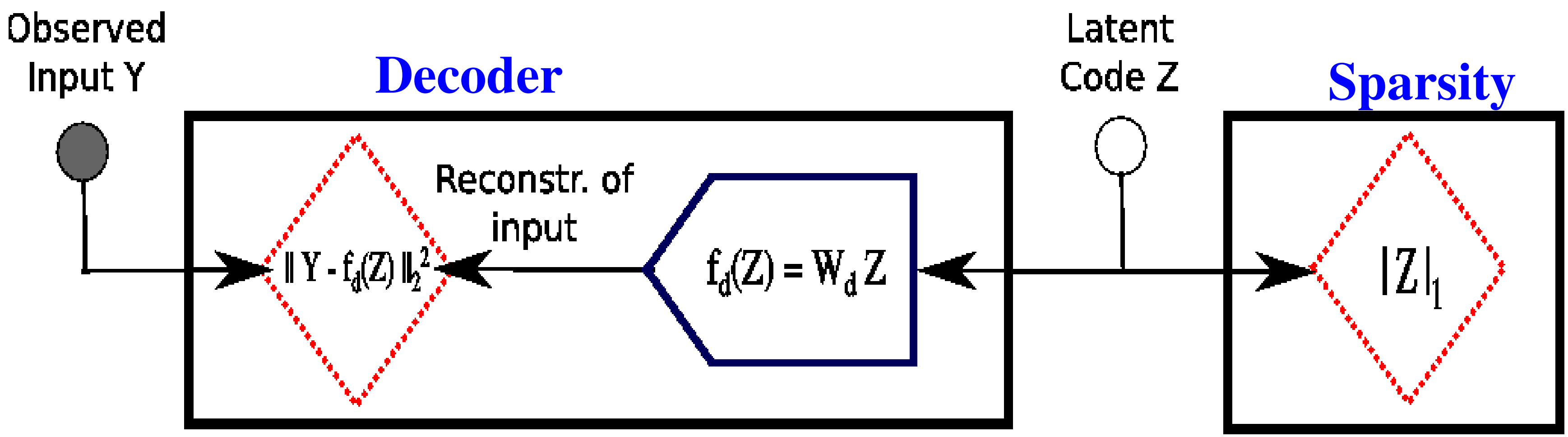
Pulls up on the energy Y'

The Main Insight [Ranzato et al. 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

Sparse Decomposition with Linear Reconstruction

- Energy(Input,Code) = || Input – Decoder(Code) $||^2$ + Sparsity(Code)
- Energy(Input) = Min_over_Code[Energy(Input,Code)]



- Energy: minimize to infer Z

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

- Loss: minimize to learn W (the columns of W are constrained to have norm

$$L(W) = \sum_i F(Y^i; W) = \sum_i (min_{Z^i} E(Y^i, Z^i; W))$$

Problem with Sparse Decomposition: It's slow

- **Inference: Optimal_Code = Arg_Min_over_Code[Energy(Input,Code)]**

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

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

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

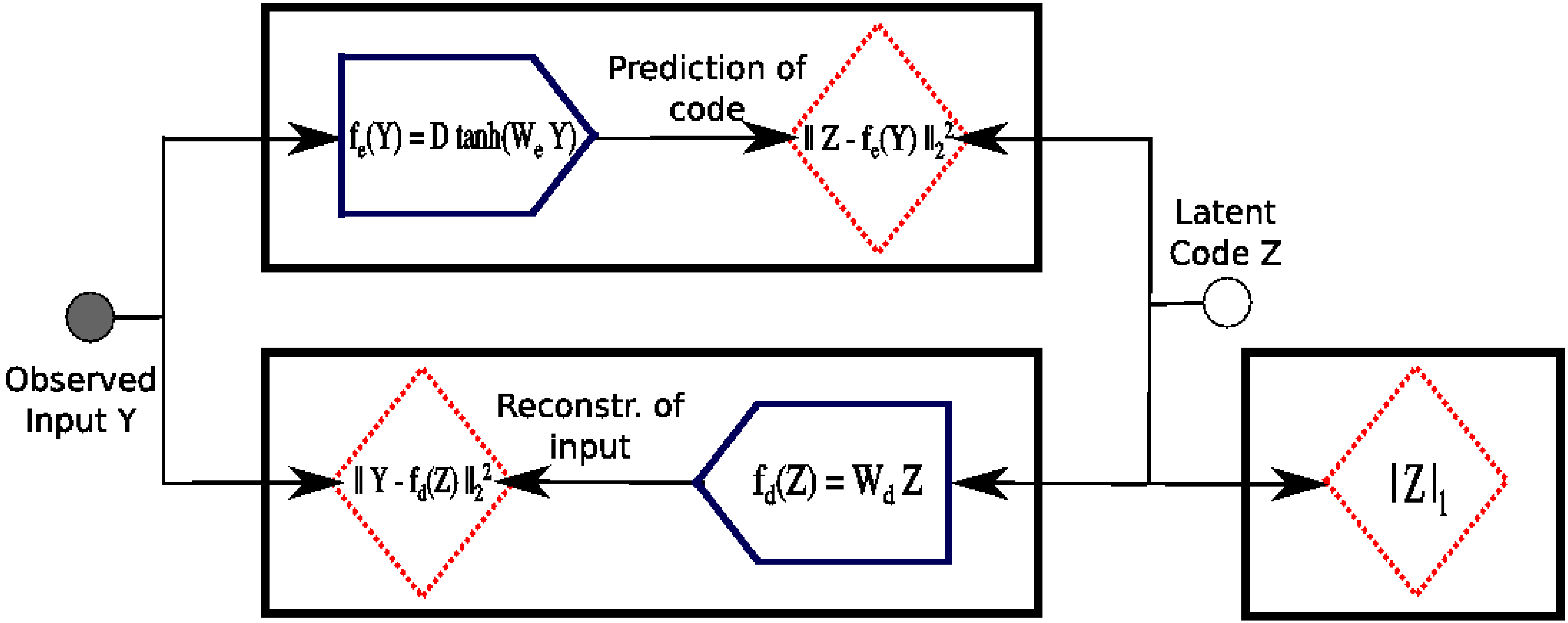
- **For each new Y, an optimization algorithm must be run to find the corresponding optimal Z**
- **This would be very slow for large scale vision tasks**
- **Also, the optimal Z are very unstable:**
  - A small change in Y can cause a large change in the optimal Z

Solution: Predictive Sparse Decomposition (PSD)

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

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

$$f_e(Y^i) = D \tanh(W_e Y)$$

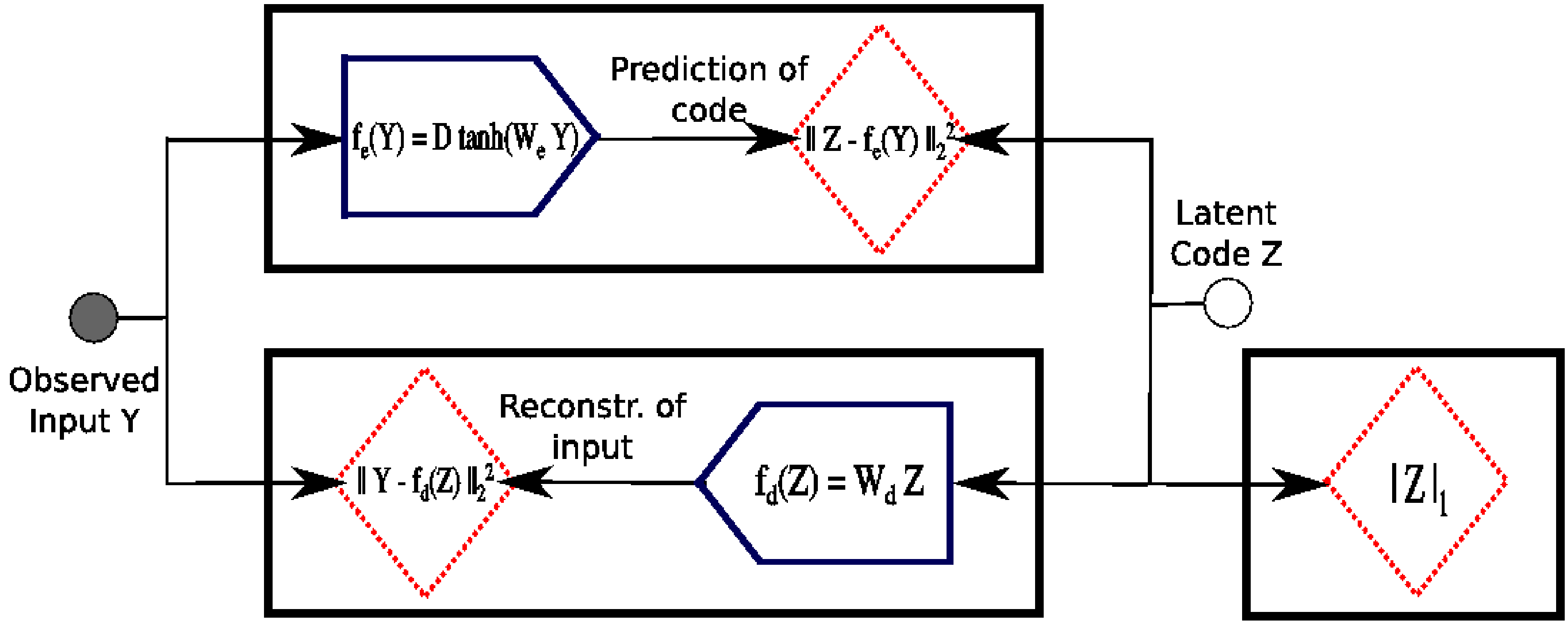


PSD: Inference

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

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

$$Z^i = \operatorname{argmin}_z E(Y^i, z; W)$$

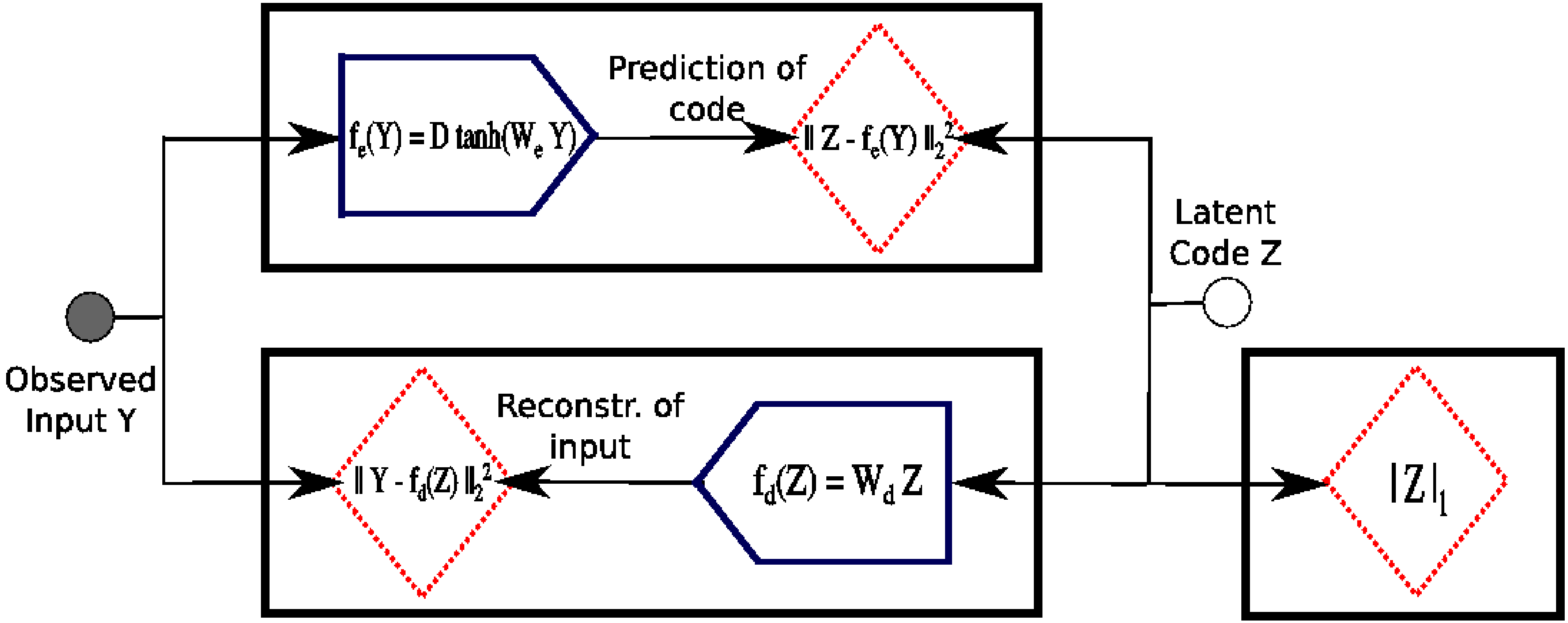


PSD: Learning [Kavukcuoglu et al. 2009]

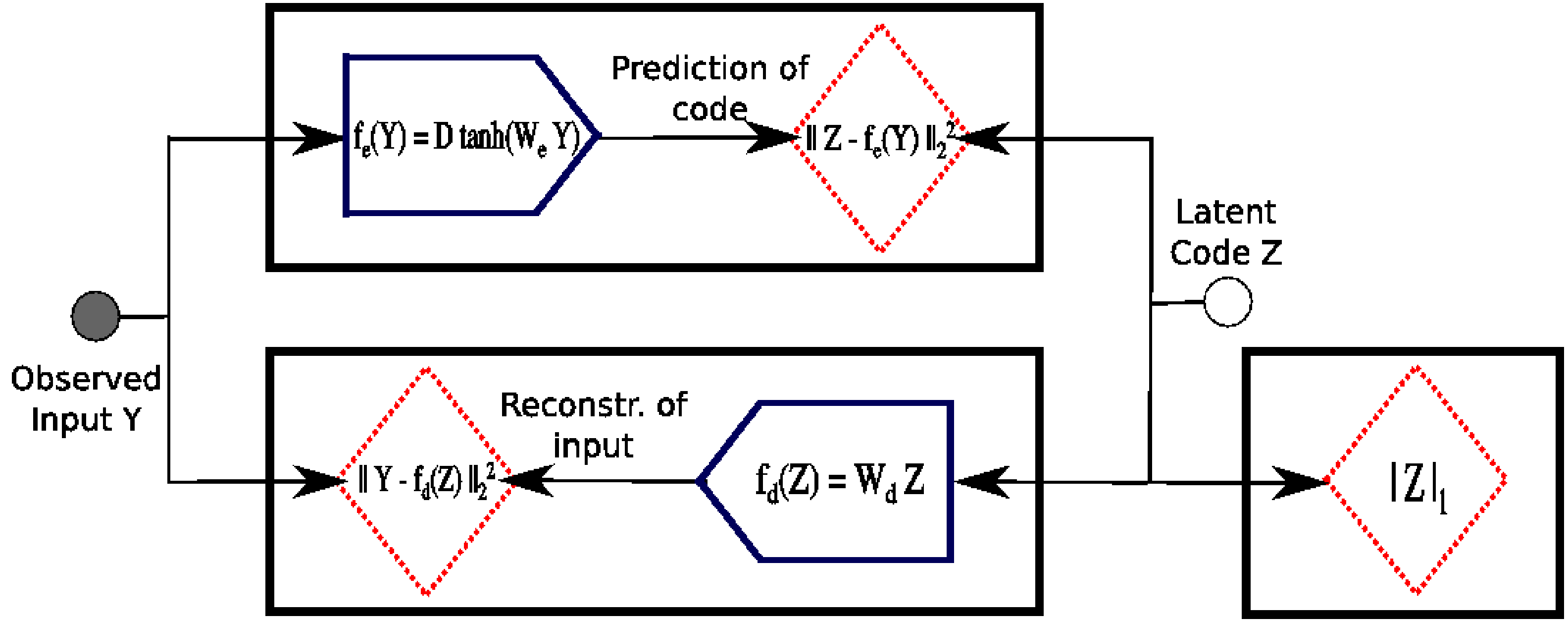
- **Learning by minimizing the average energy of the training data with respect to Wd and We.**
- **Loss function:**

$$L(W) = \sum_i F(Y^i; W)$$

$$F(Y^i; W) = \min_z E(Y^i, z; W)$$



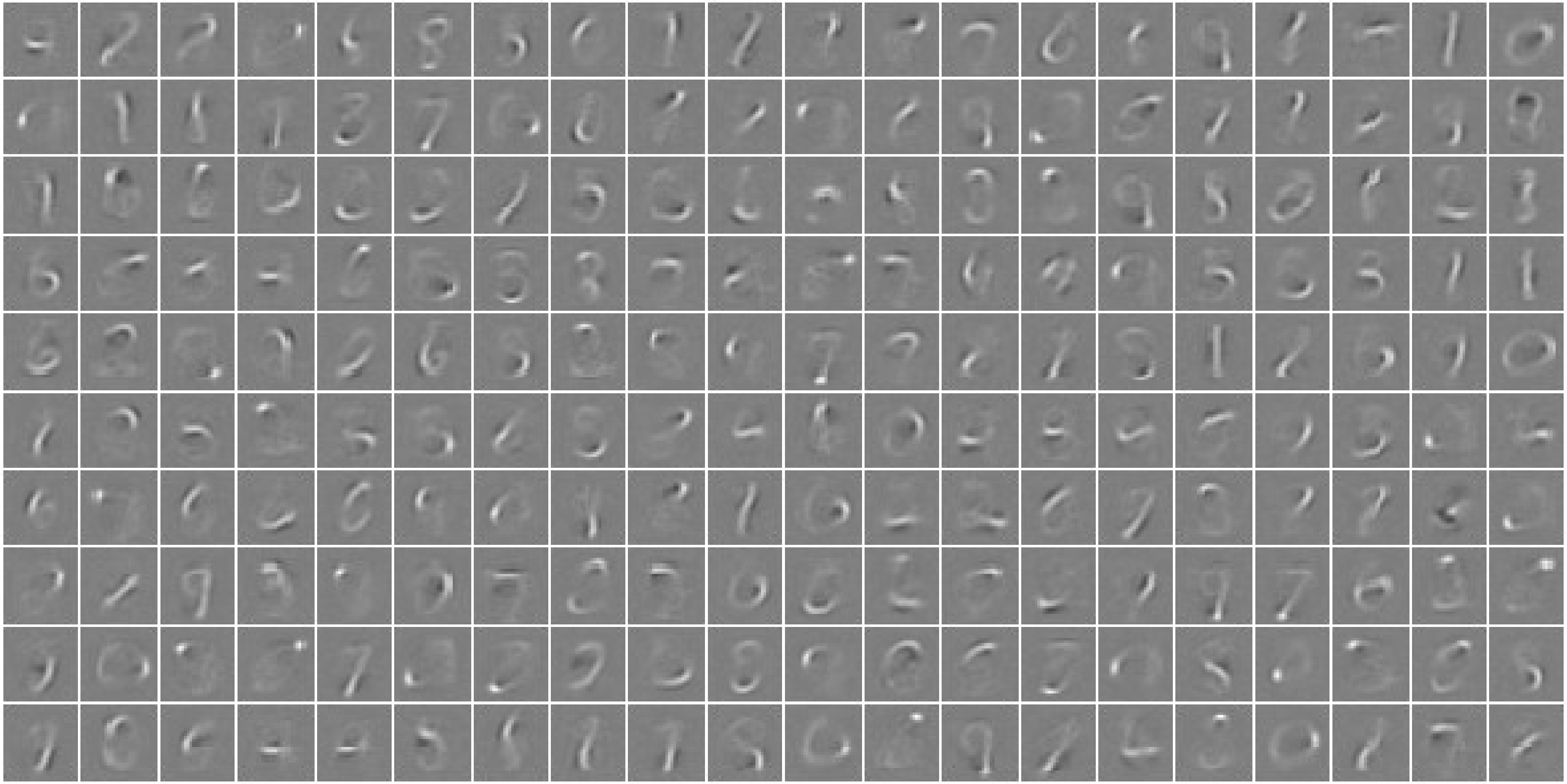
PSD: Learning Algorithm



- **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**

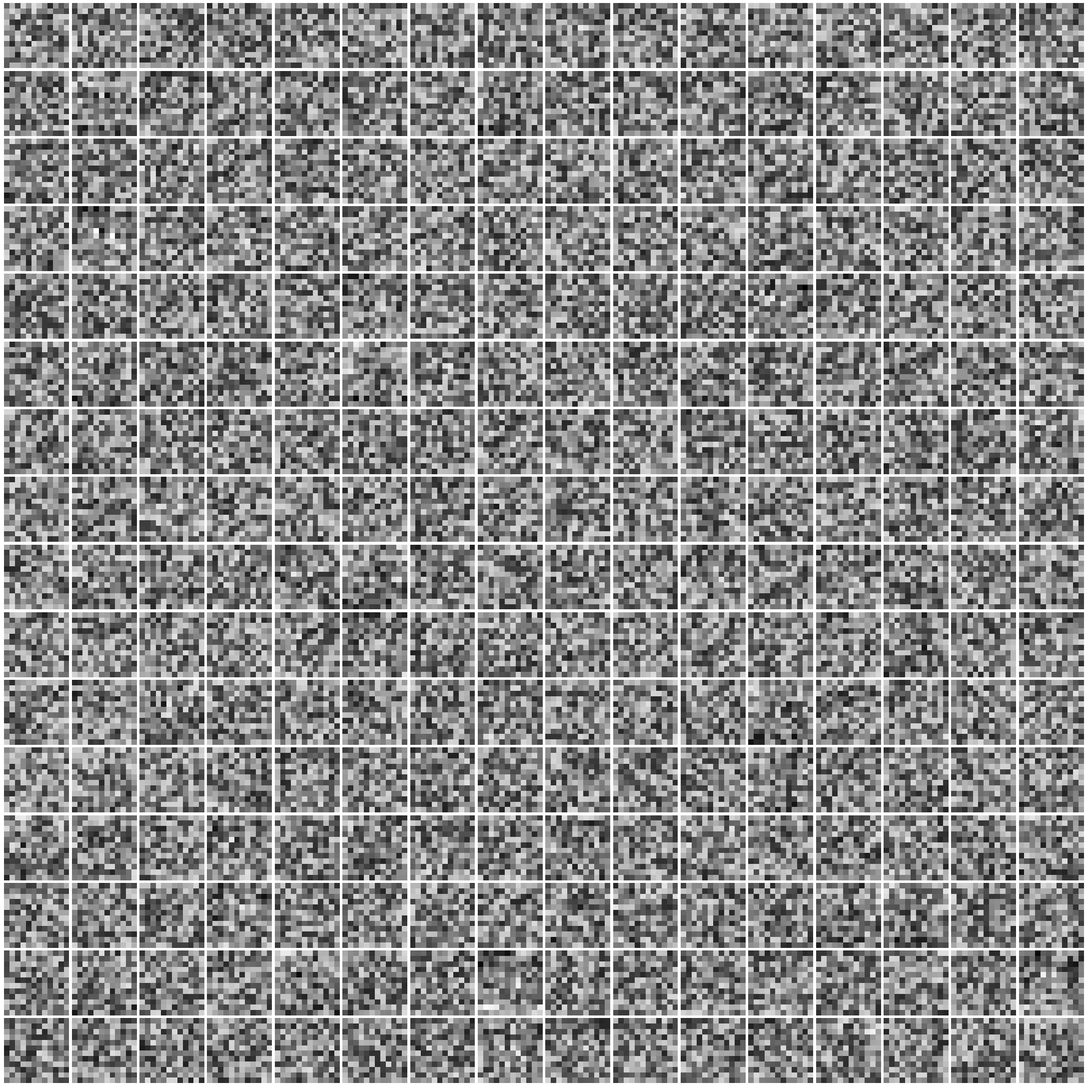
Decoder Basis Functions on MNIST

- **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

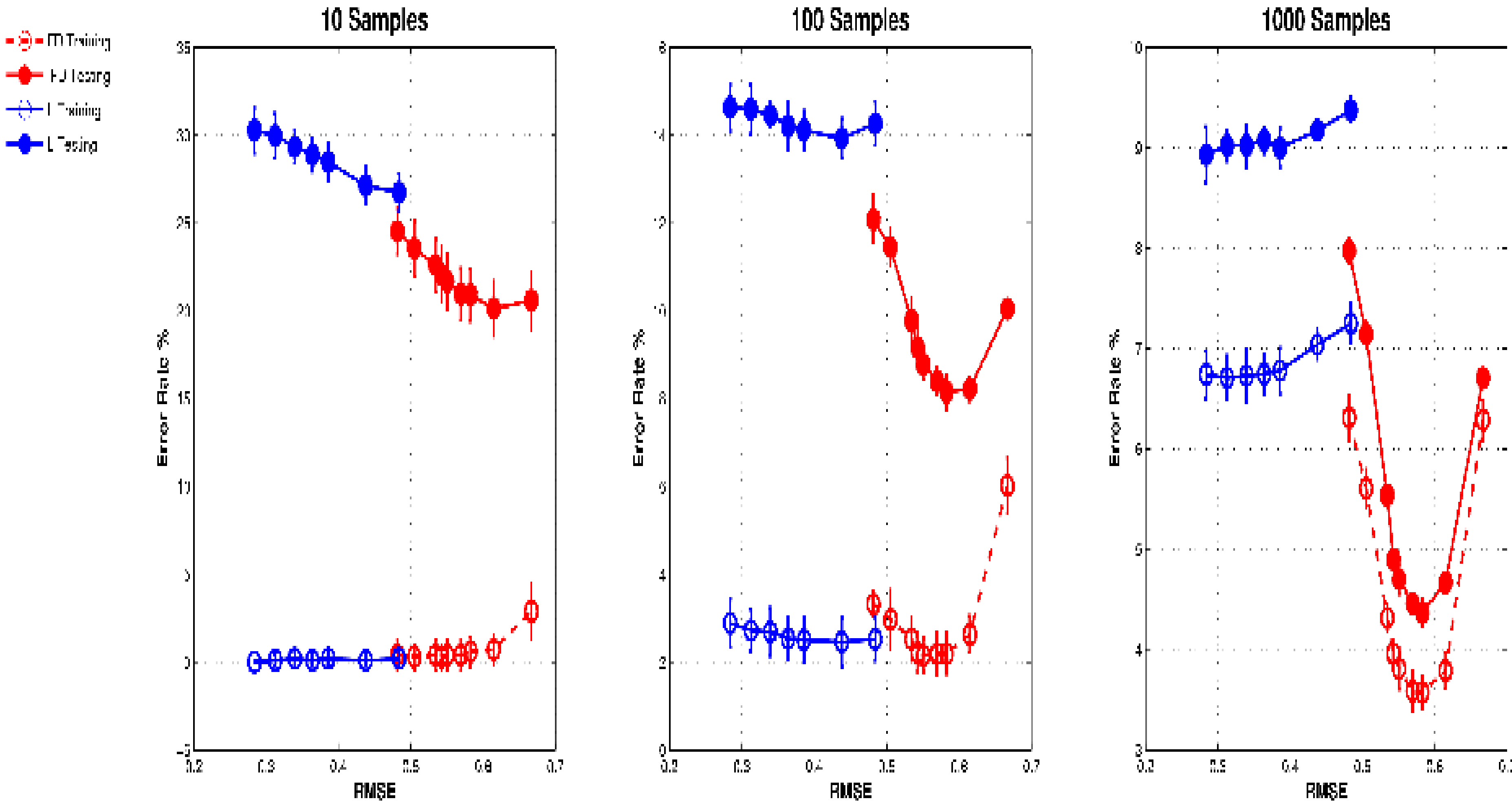
- Basis functions are like Gabor filters (like receptive fields in V1 neurons)
- 256 filters of size 12x12
- Trained on natural image patches from the Berkeley dataset
- Encoder is linear-tanh-diagonal



iteration no 0

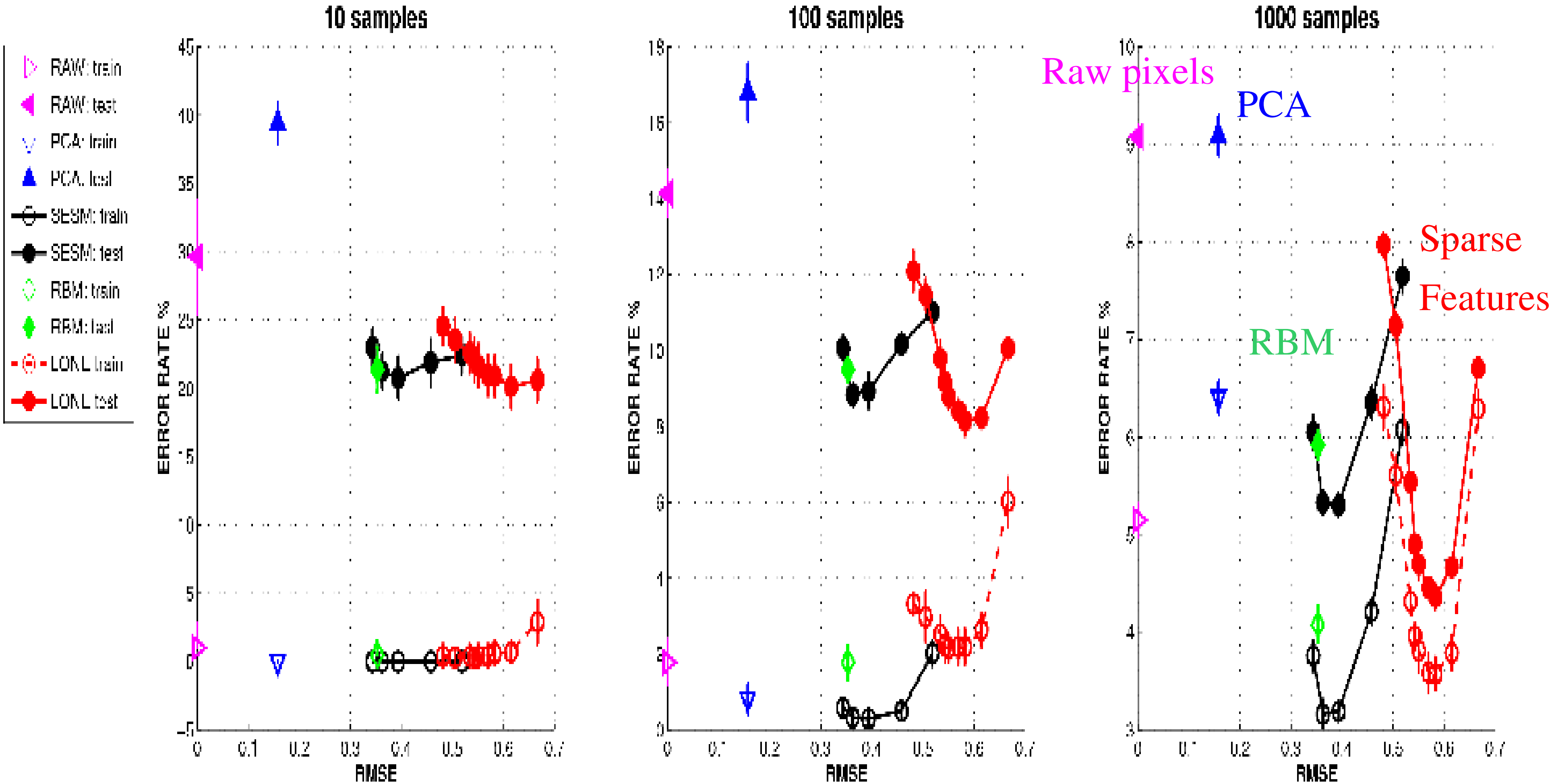
Classification Error Rate on MNIST

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

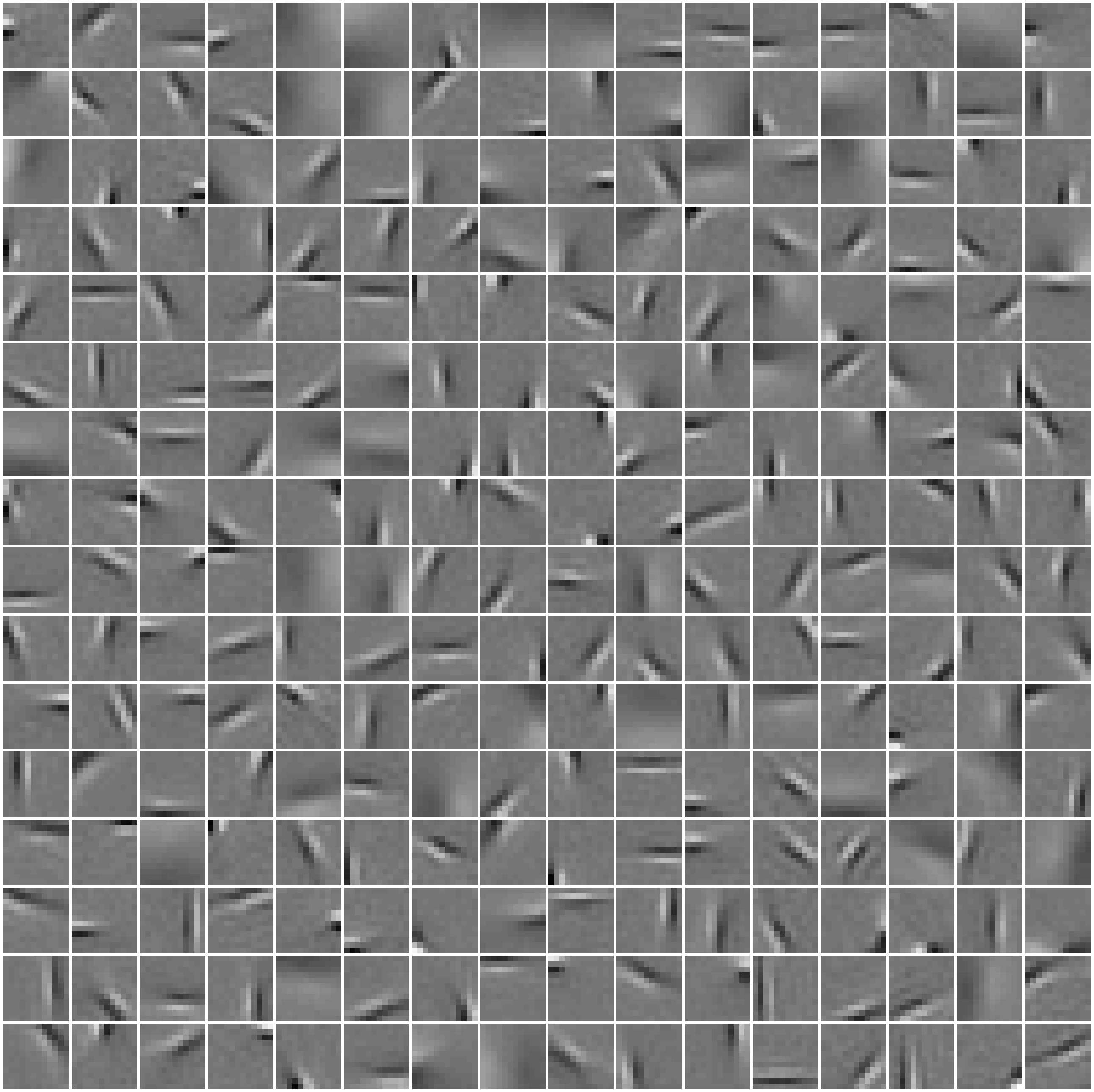


Classification Error Rate on MNIST

- **Supervised Linear Classifier trained on 200 trained sparse features**

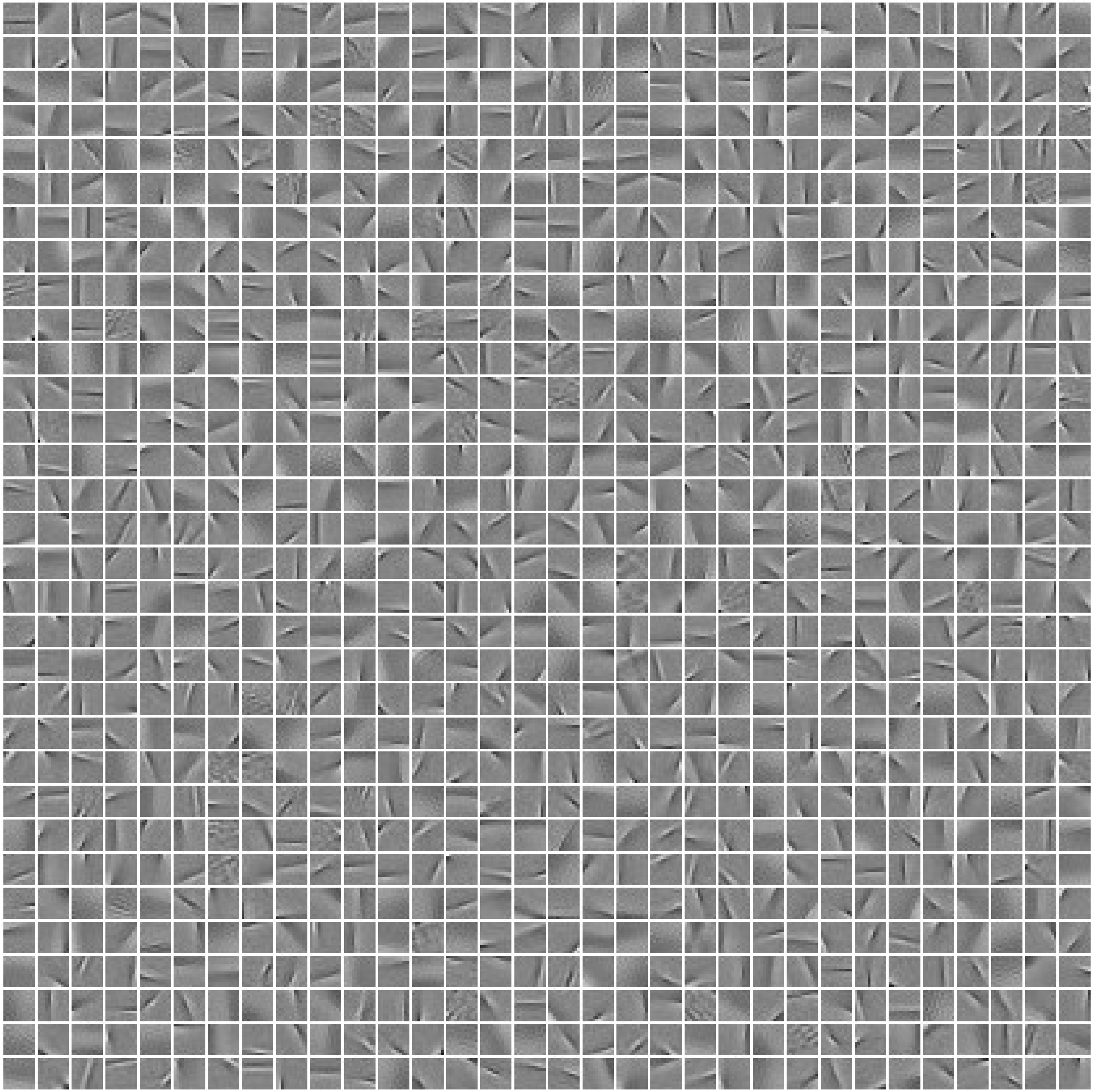


Learned Features on natural patches: V1-like receptive fields



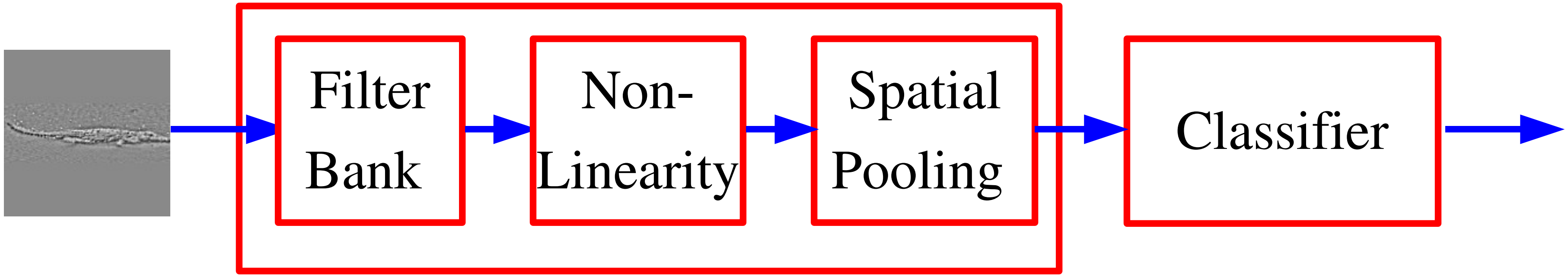
Learned Features: V1-like receptive fields

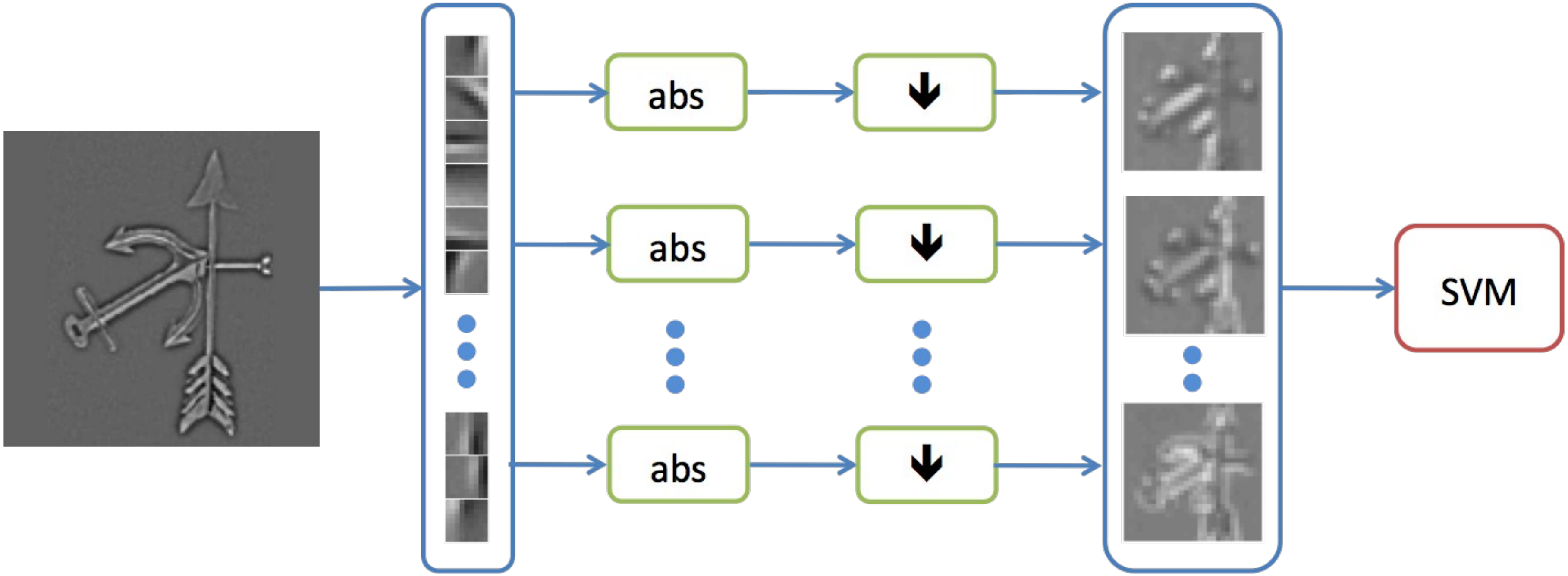
- **12x12 filters**
- **1024 filters**



How well do PSD features work on Caltech-101?

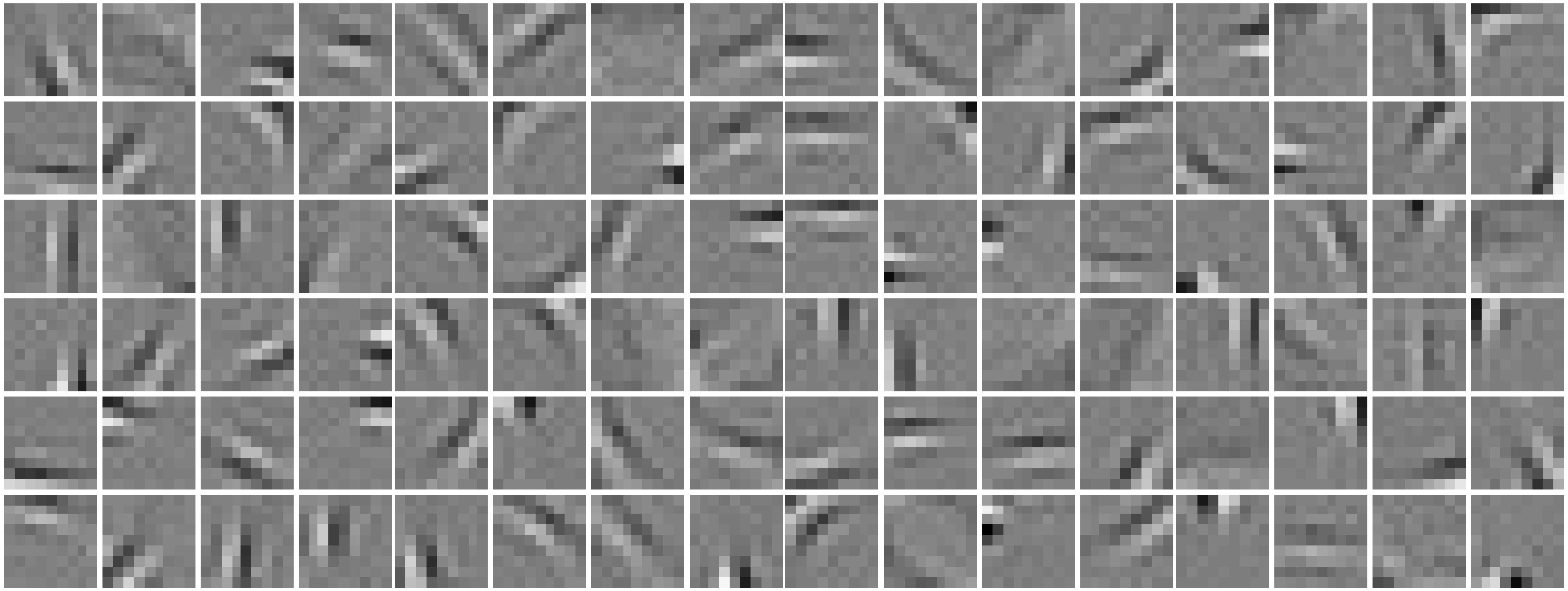
- **Recognition Architecture**





Using PSD Features for Recognition

- **96 filters on 9x9 patches trained with PSD**
  - with Linear-Sigmoid-Diagonal Encoder
- **Recognition:**
  - Normalized_Image -> Learned_Filters -> Rectification -> Local_Normalization -> Spatial_Pooling -> PCA -> Linear_Classifier
  - What is the effect of rectification and normalization?



PSD: Caltech-101 Recognition Rate

- **Learning 96 Filters with PSD**
  - Filters->Sigmoid->AvPool->PCA->LinSVM 16%
  - Filters->Sigmoid+Abs->AvPool->PCA->LinSVM 51%
  - LCN->Filters->Sigmoid+Abs->AvPool->PCA->LinSVM 56%
  - LCN->Filters->Sigm+Abs->LCN->AvPool->PCA->LinSVM 58%

  LCN = Local Contrast Normalization (division by std dev of neighbors)
  AvPool = Average pooling using boxcar filter and subsampling
  PCA = PCA to 3000 components; LinSVM: Linear SVM classifier.

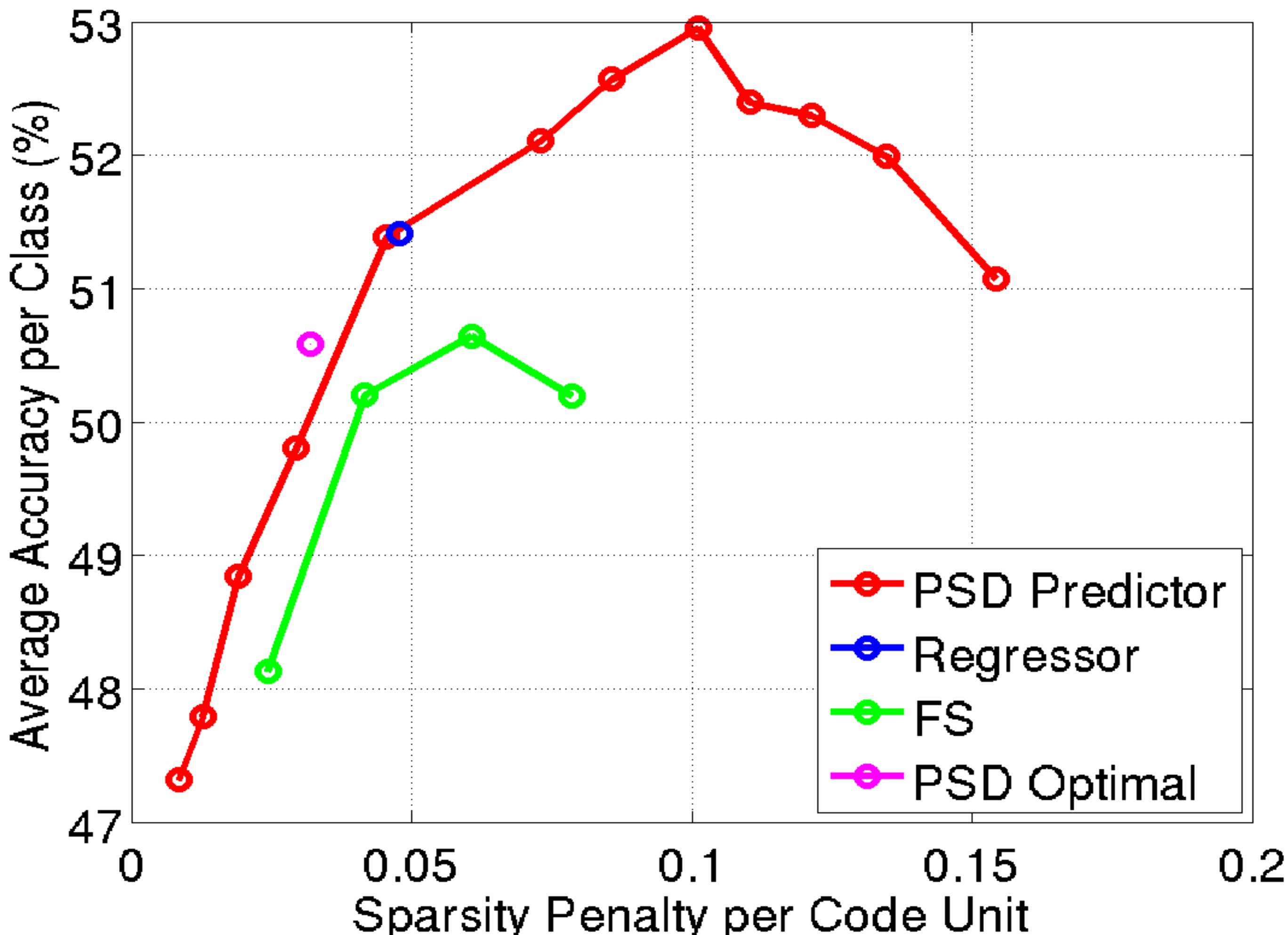
- **[Pinto&DiCarlo 2008] V1 model with 96 Gabor Filters (16 orientations, 4 scales) and half rectification**
  - LCN->G.Filters->Half-Rectif.->LCN->AvPool->PCA->LinSVM
  - Caltech-101 recognition rate 59%

- **Adding a rectification makes a huge difference: 16%->51%**
  - The right features are not the output of the encoder
  - The right features are the output of the sparsification function

- **Learning the filters with PSD gives the same results as multiscale Gabors**

Comparing Optimal Codes Predicted Codes on Caltech 101

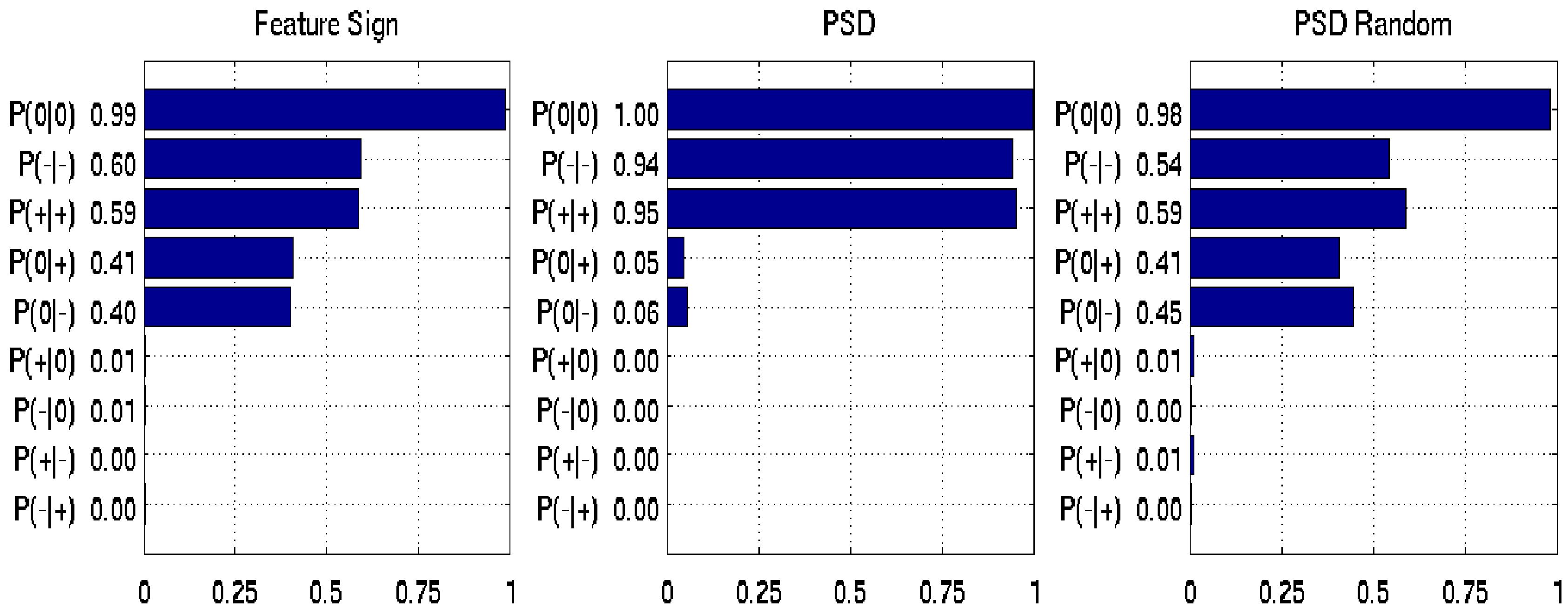
- **Approximated Sparse Features Predicted by PSD give better recognition results than Optimal Sparse Features computed with Feature Sign!**
  - PSD features are more stable.



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

PSD Features are more stable

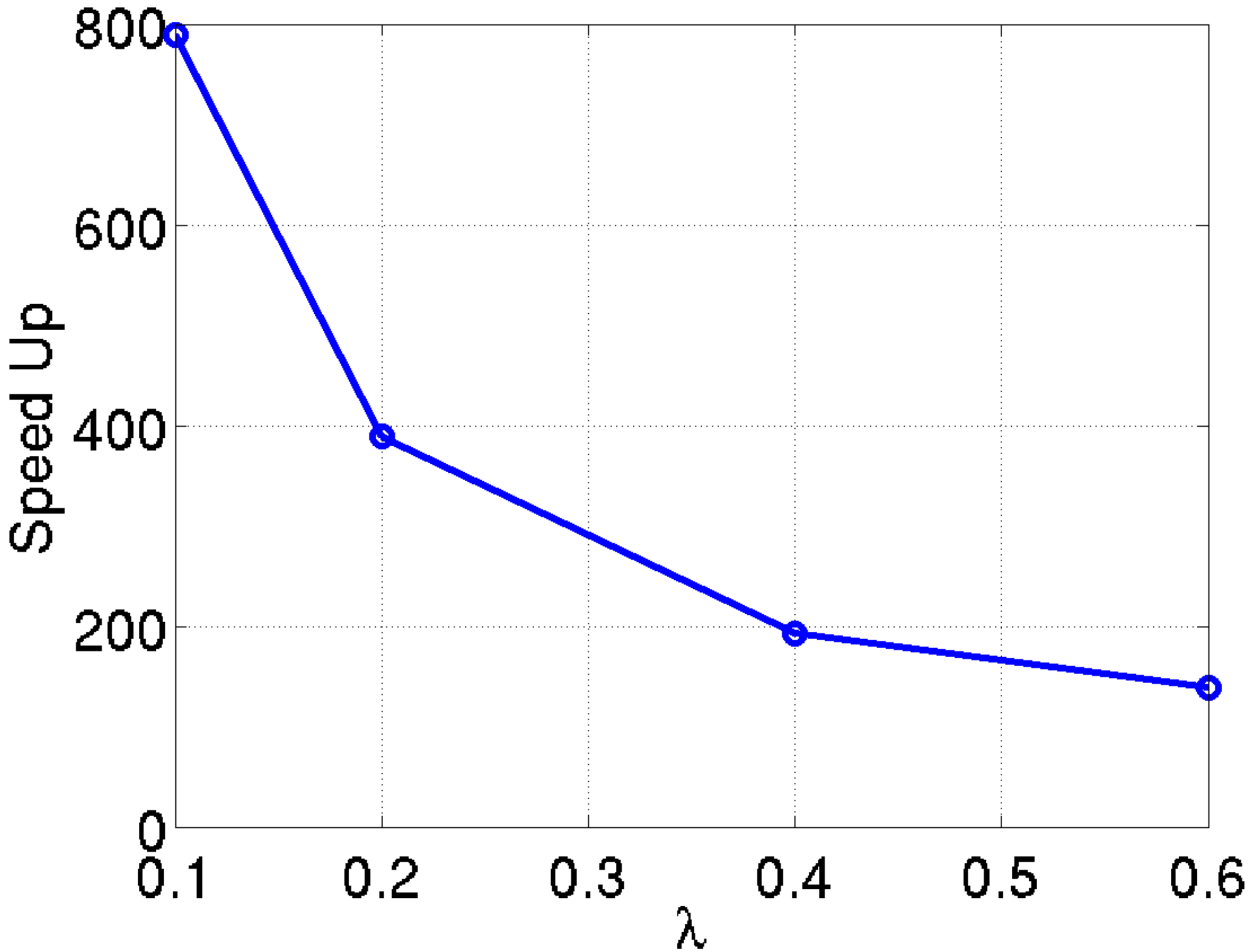
- **Approximated Sparse Features Predicted by PSD give better recognition results than Optimal Sparse Features computed with Feature Sign!**
- **Because PSD features are more stable. Feature obtained through sparse optimization can change a lot with small changes of the input.**



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

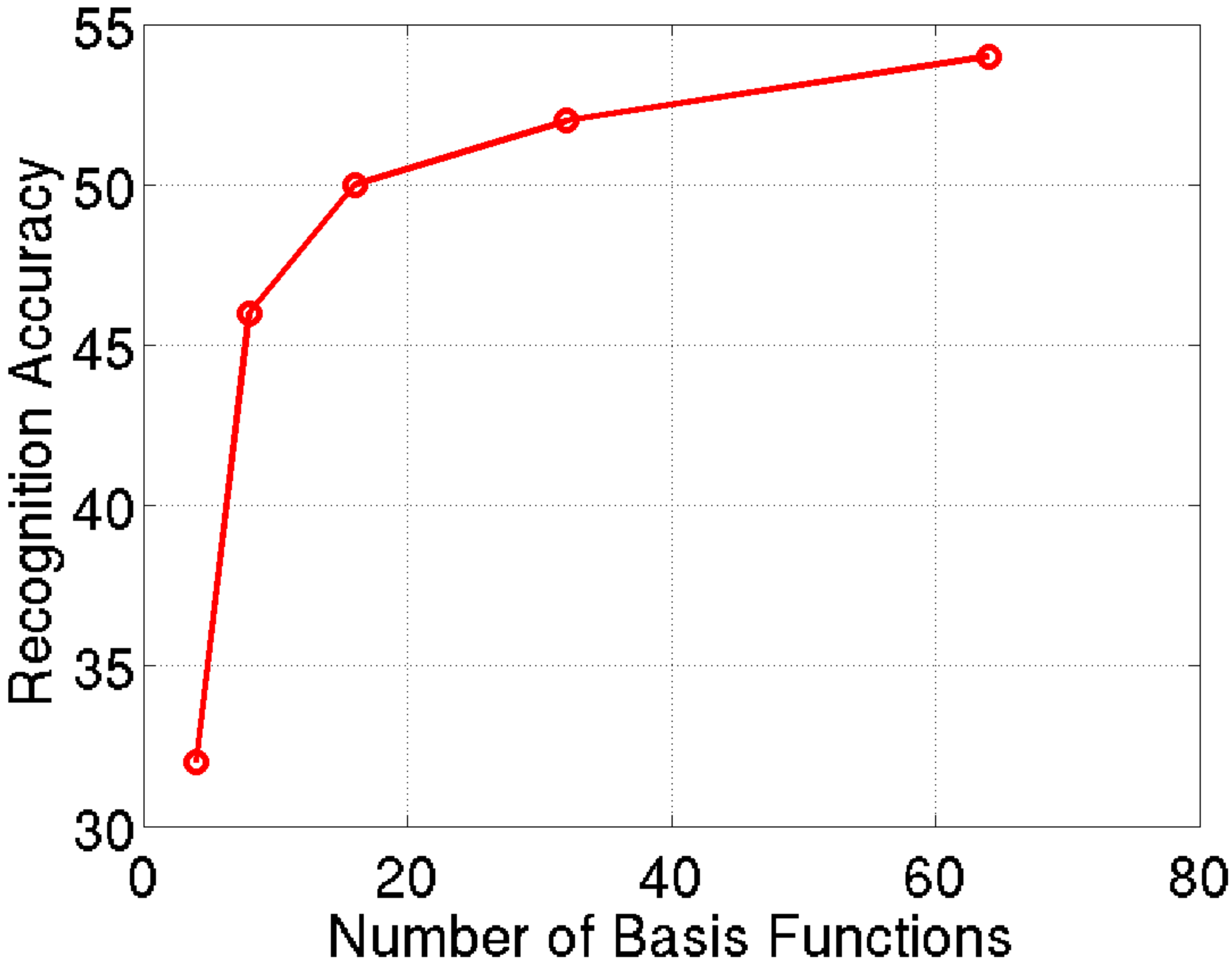
PSD features are much cheaper to compute

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

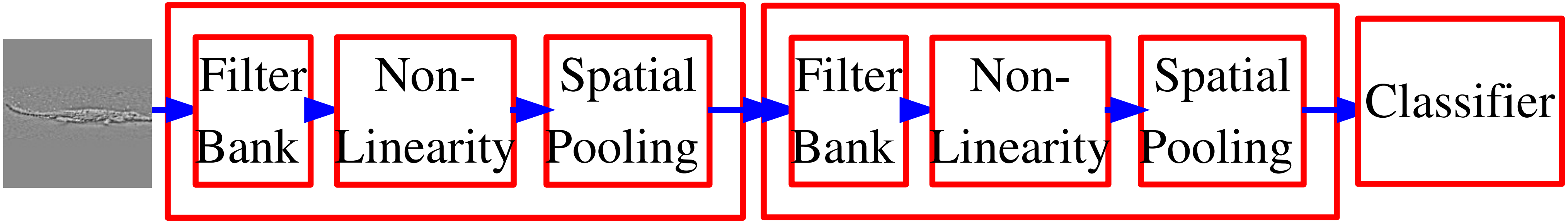


How Many 9x9 PSD features do we need?

- **Accuracy increases slowly past 64 filters.**

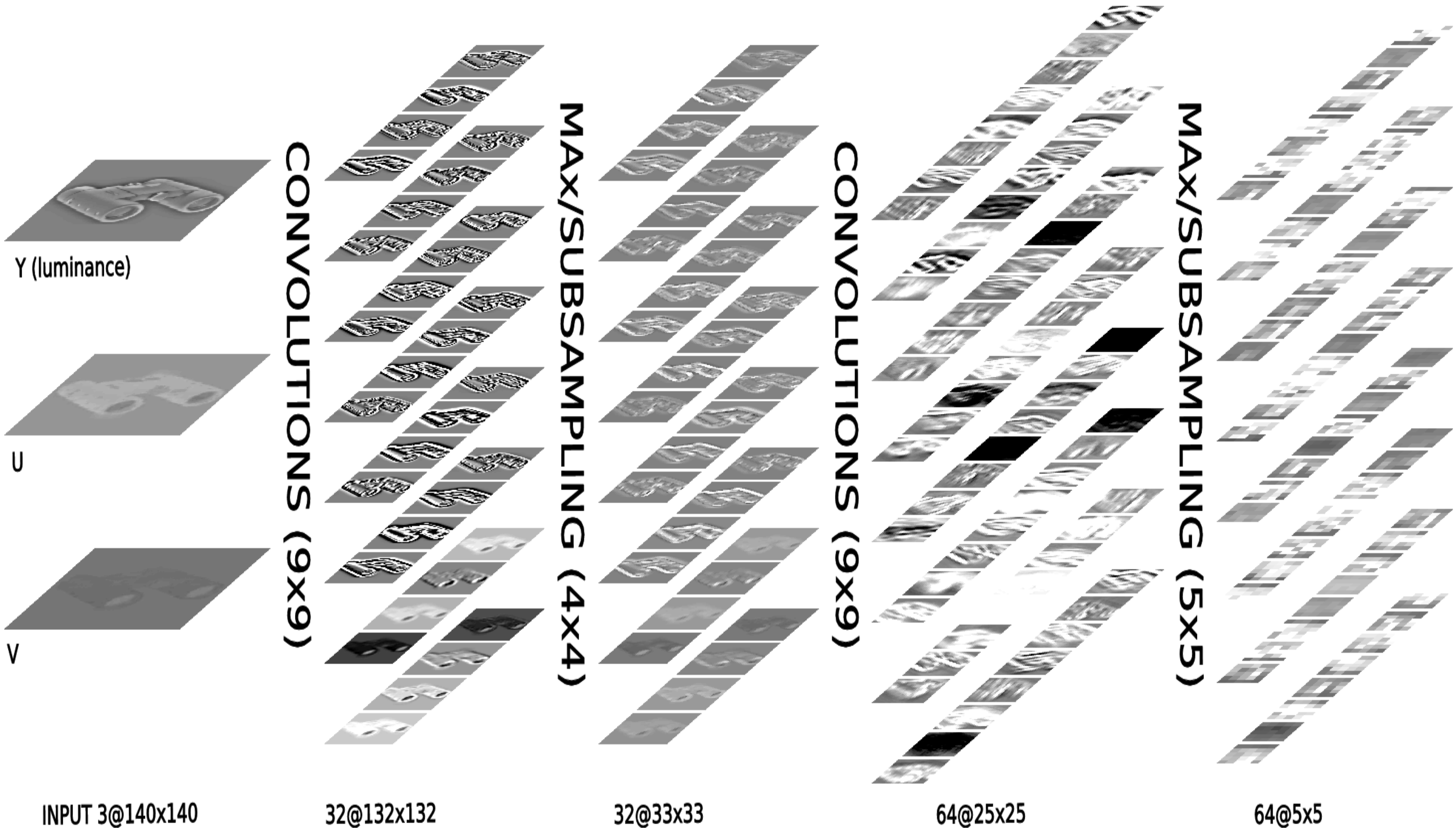


Training a Multi-Stage Hubel-Wiesel Architecture with PSD



- 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 on Caltech-101

- **Each architecture has two stages of feature extraction and pooling, plus a supervised linear classifier on top.**
- **Convolutional Net: purely supervised training**
  - Stage: Filters->Tanh->AveragePooling->Tanh
  - Architecture: Stage->Stage->LinClassifier 26%
- **Convolutional Net: unsupervised training of stages with SESM, and supervised training of top layer [Ranzato et al. CVPR 07]**
  - Stage: Filters->Tanh->MaxPooling
  - Architecture: Stage->Stage->LinClassifier 54%
- **HMAX [Serre 05] -> [Mutch&Lowe 06]**
  - Fixed Gabors at stage-1, simple learning algo for stage-2 (storing random templates)
  - Stage: MultiscaleFilters->Sigmoid->Scale/Space Pooling
  - Architecture: Stage->Stage->LinClassifier 56%

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

Various non-linearities and training protocols

- R: random initialization + supervised training
- P: PSD training (frozen)
- A: PSD training + supervised adjustment
- Tanh: sigmoid non-linearity
- Abs: sigmoid+absolute value non-linearity
- Cnorm: local contrast normalization

Id	Accuracy (%)	Protocol	Machine
Traditional ConvNet Architecture			
1	26.0%	RR	Tanh, 64 features
2	30.0%	AA	Tanh, CNorm, 64 features
With Absolute Value Non-Linearity			
3	58.0%	RR	Abs, 64 features
Abs and Contrast Normalization			
4	60.0%	RR	Abs, CNorm, 64 features
5	62.0%	AR	Abs, CNorm, 64 features
6	62.9%	PP	Abs, CNorm, 64 features
7	63.0%	PA	Abs, CNorm, 64 features
8	67.2%	AA	Abs, CNorm, 64 features
Smaller net with Abs and CNorm			
9	59.8%	PP	Abs, CNorm, 16 features
10	65.2%	AA	Abs, CNorm, 16 features

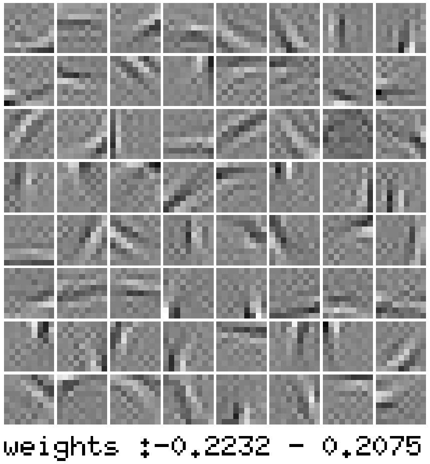
Multistage Hubel-Wiesel Architecture on Caltech-101

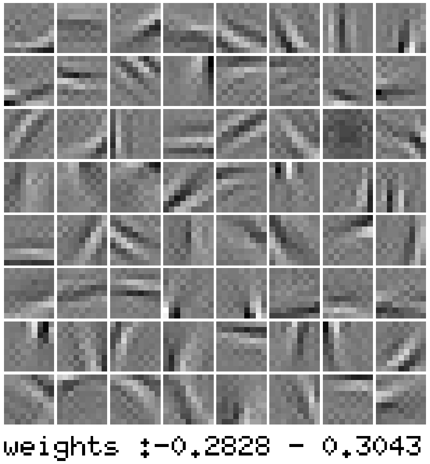
- **Our Best result is 67.2%**
  - comparable to the 66% of [Lazebnik 2006], which was obtained with SIFT features, Vector Quantization, and an SVM that uses the spatial pyramid matching kernel.
  - The result is below [Varma 2007] which uses a large number of hand-designed features and a learned linear combination of kernels
- **Our system is considerably cheaper/faster, and simpler**
  - Smaller net with only 16 features at stage-1 yield 65.2%.
- **The crucial ingredient seems to be the absolute value rectification**
  - A purely supervised system with rectification and contrast normalization yields 60%, despite the enormous number of parameters compared to the number of training samples!
- **Global supervised refinement is essential**
  - The 2nd stage features need supervised refinement.

Multistage Hubel-Wiesel Architecture: Filters

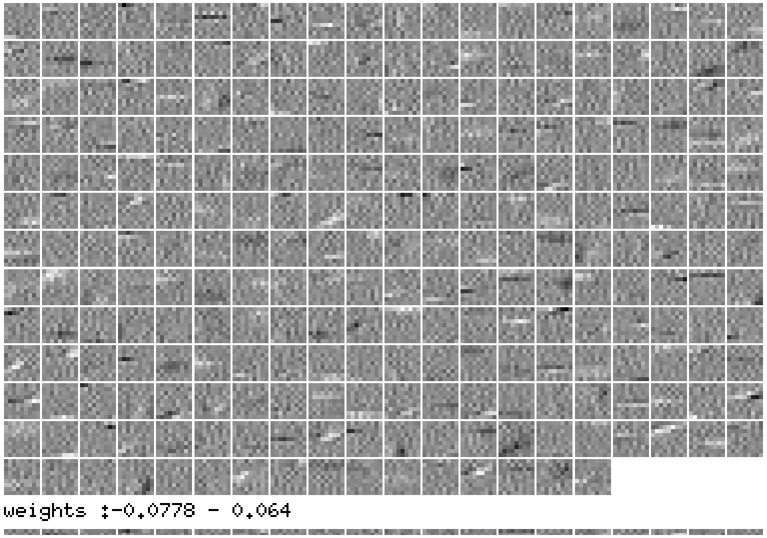
- **After PSD**
- **After supervised refinement**

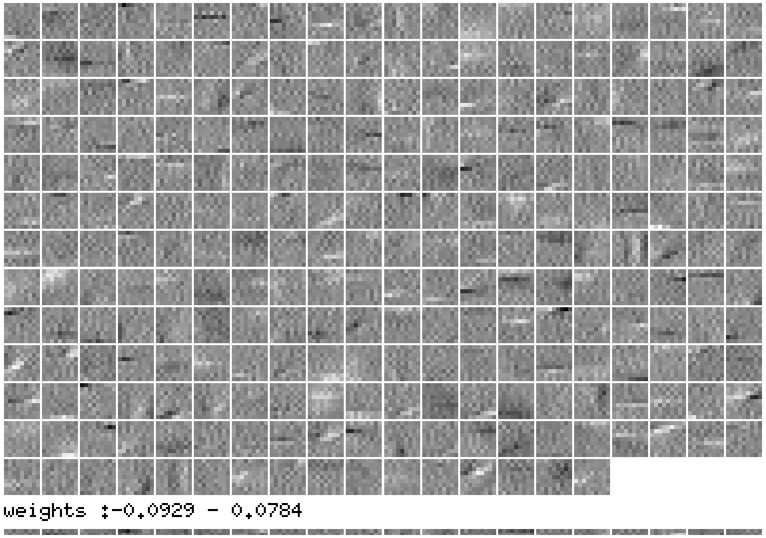
- **Stage 1**





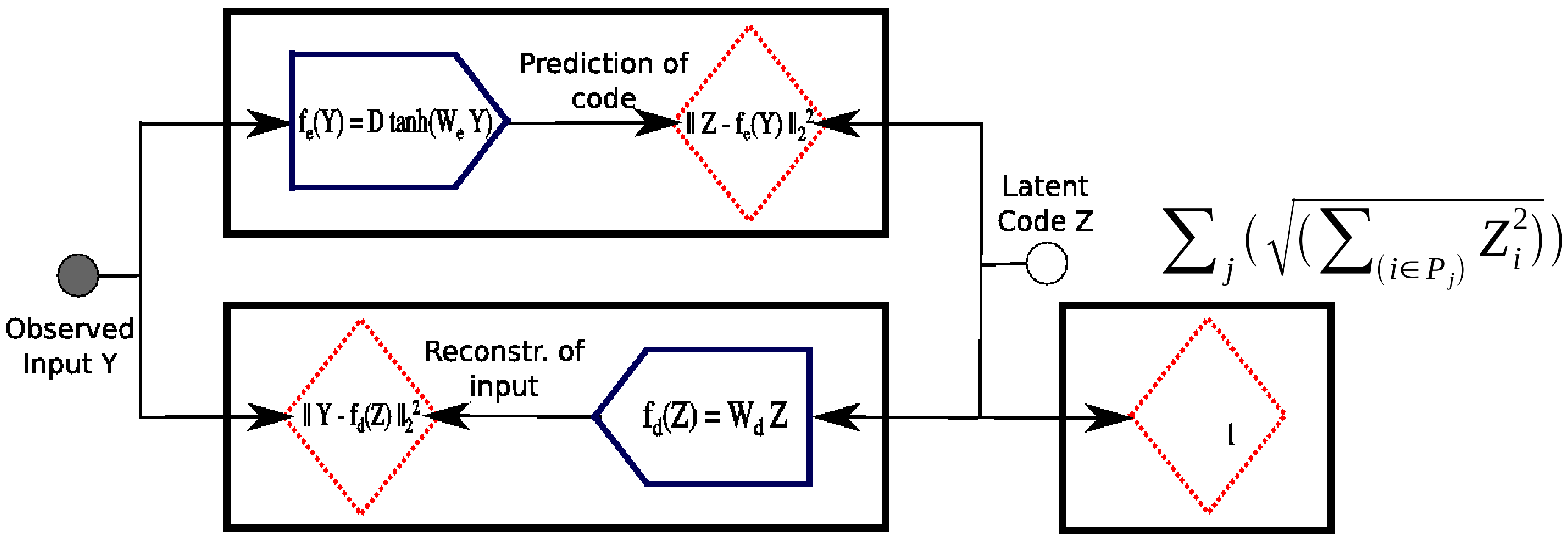
- **Stage2**





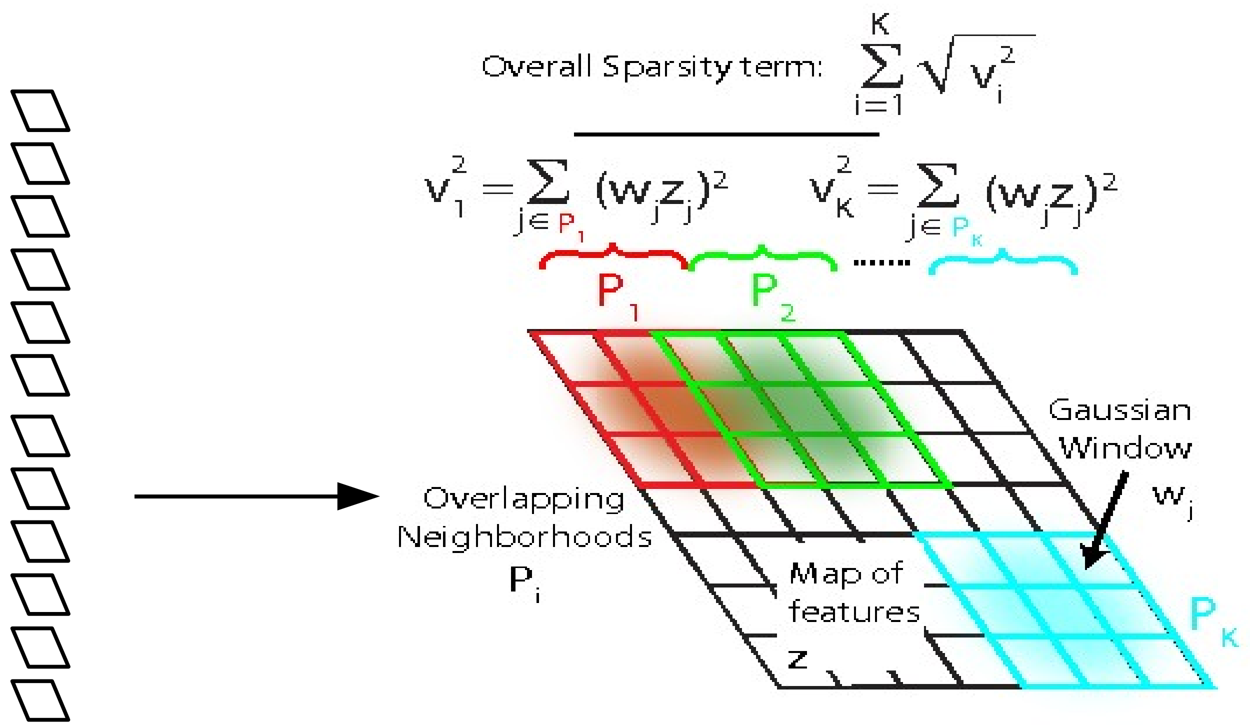
Learning Invariant Features [Kavukcuoglu et al. CVPR 2009]

- **Unsupervised PSD ignores the spatial pooling step.**
- **Could we devise a similar method that learns the pooling layer as well?**
- **Idea [Hyvarinen & Hoyer 2001]: 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

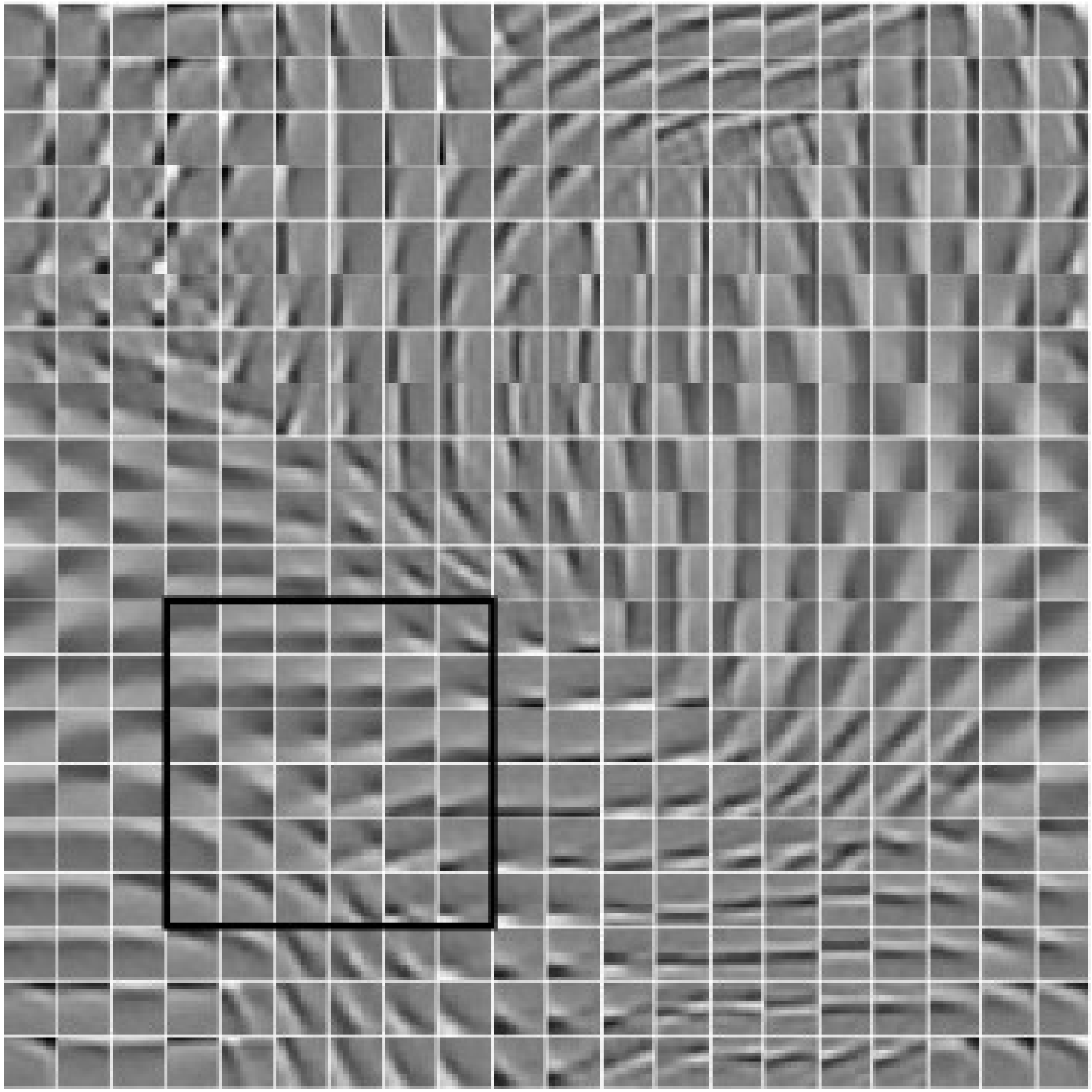


Units in the code Z

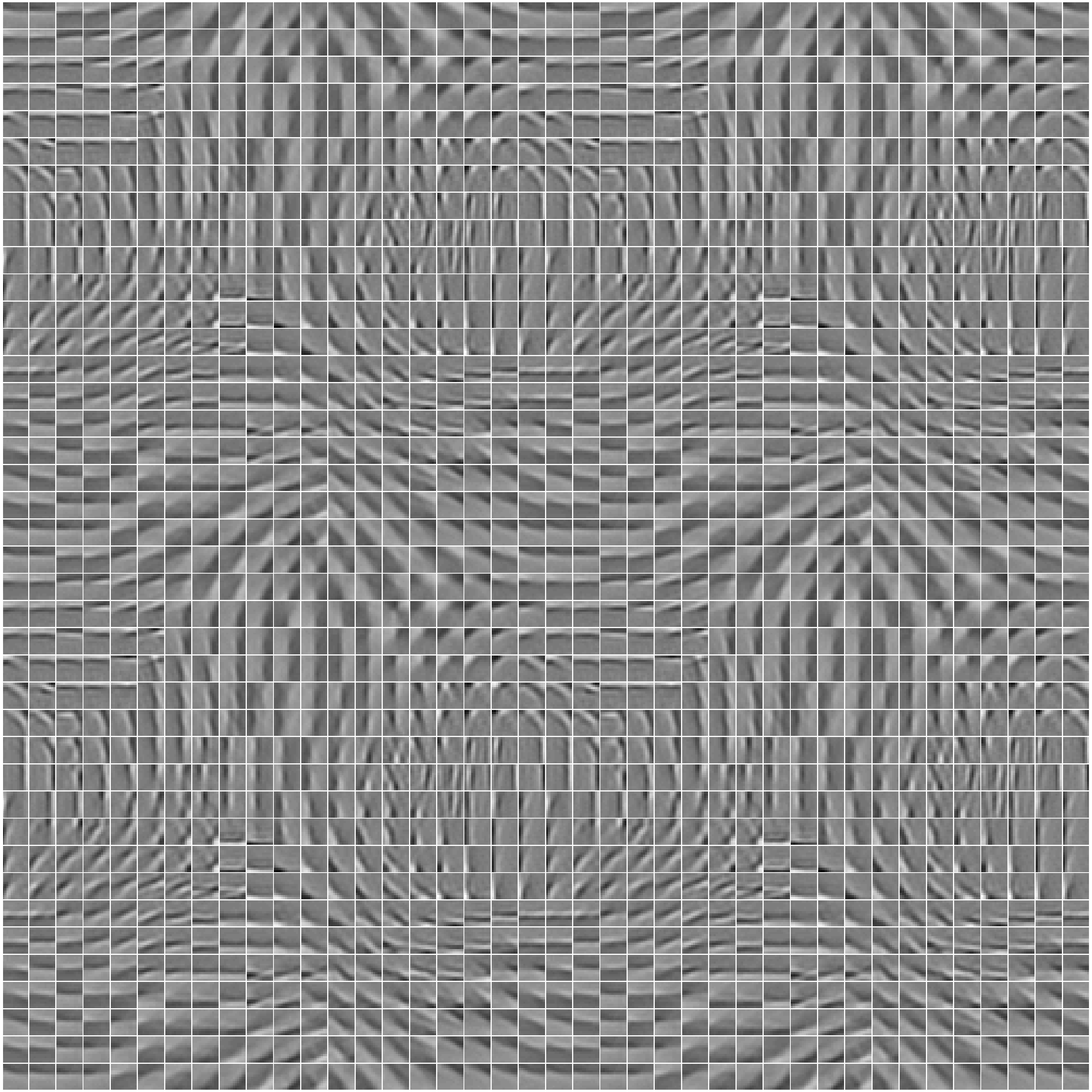
Define pools and enforce sparsity across pools

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.

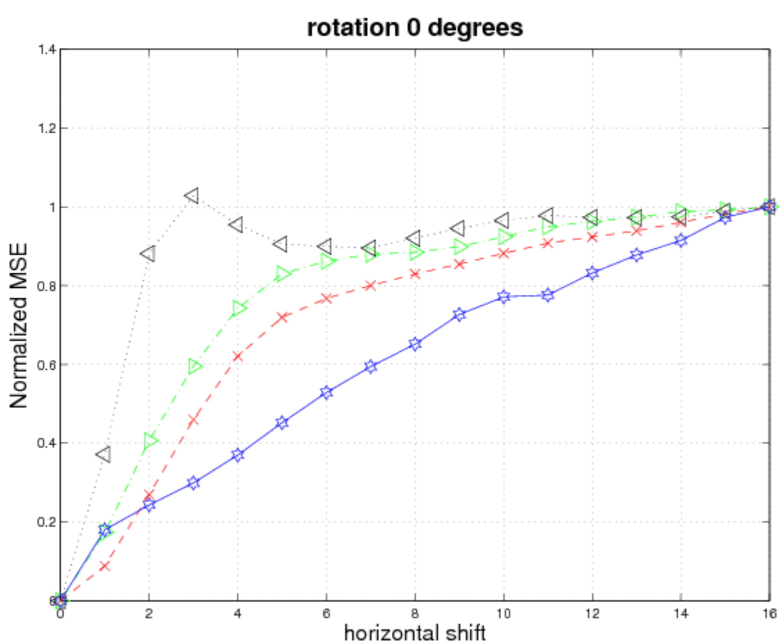


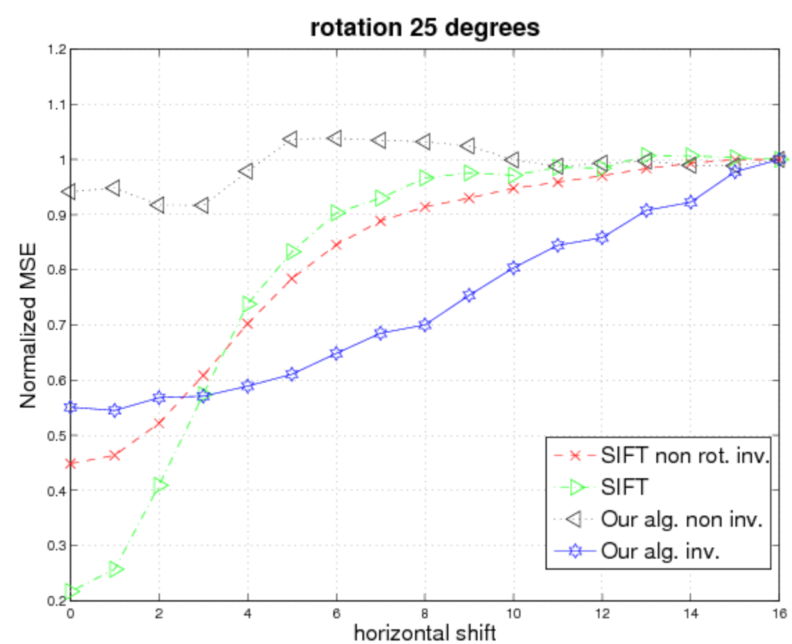
Pinwheels?



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**

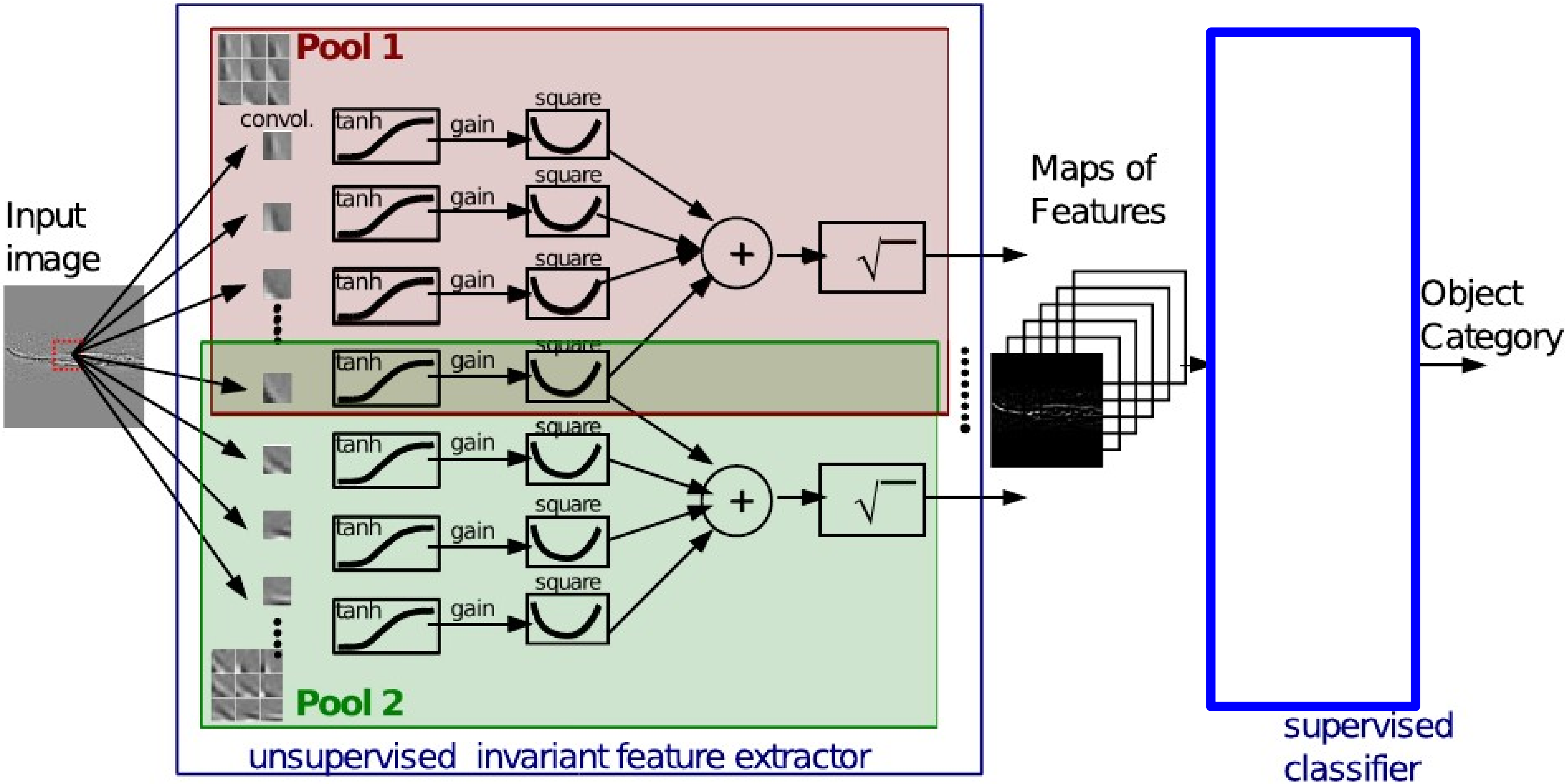




Learning Invariant Features

Recognition Architecture

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



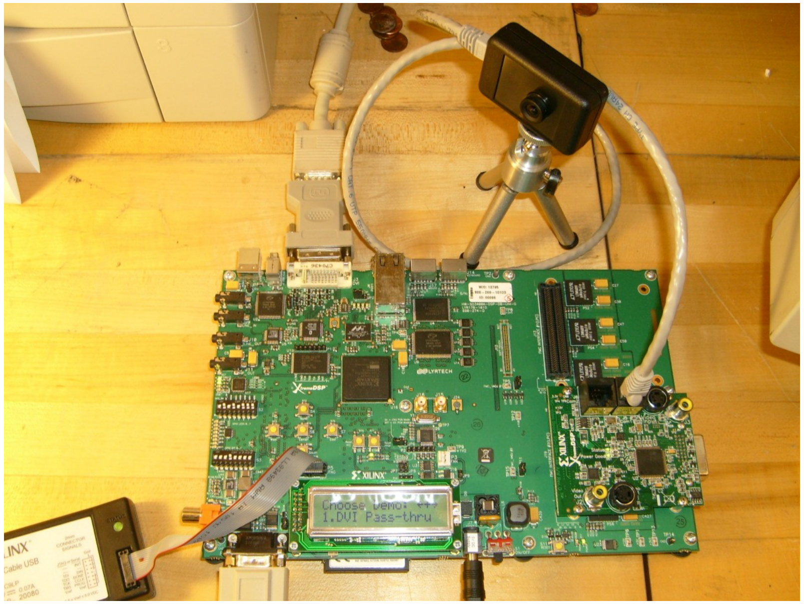
Recognition Accuracy on Caltech 101

- 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

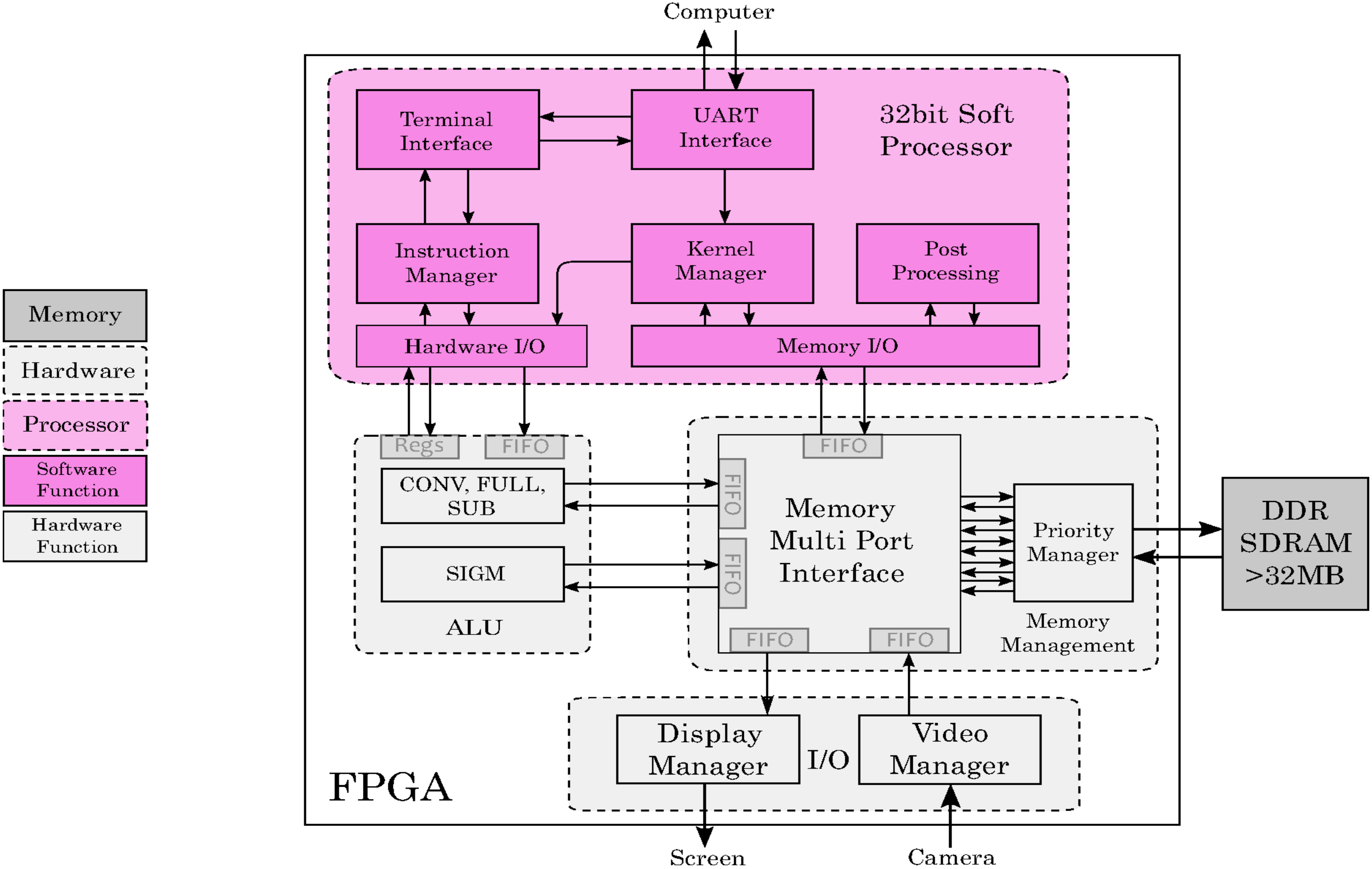
Method	**Avrge Accuracy/Class (%)**
classifier: PCA + linear SVM	
Proposed Method	50.9
SIFT (not rotation invariant)	51.2
SIFT (rotation invariant)	45.2
Serre et al. features [26]	47.1
classifier: Spatial Pyramid Matching Kernel SVM	
Proposed Method	**59.6**
SIFT	**65**

CNP: FPGA Implementation of ConvNets

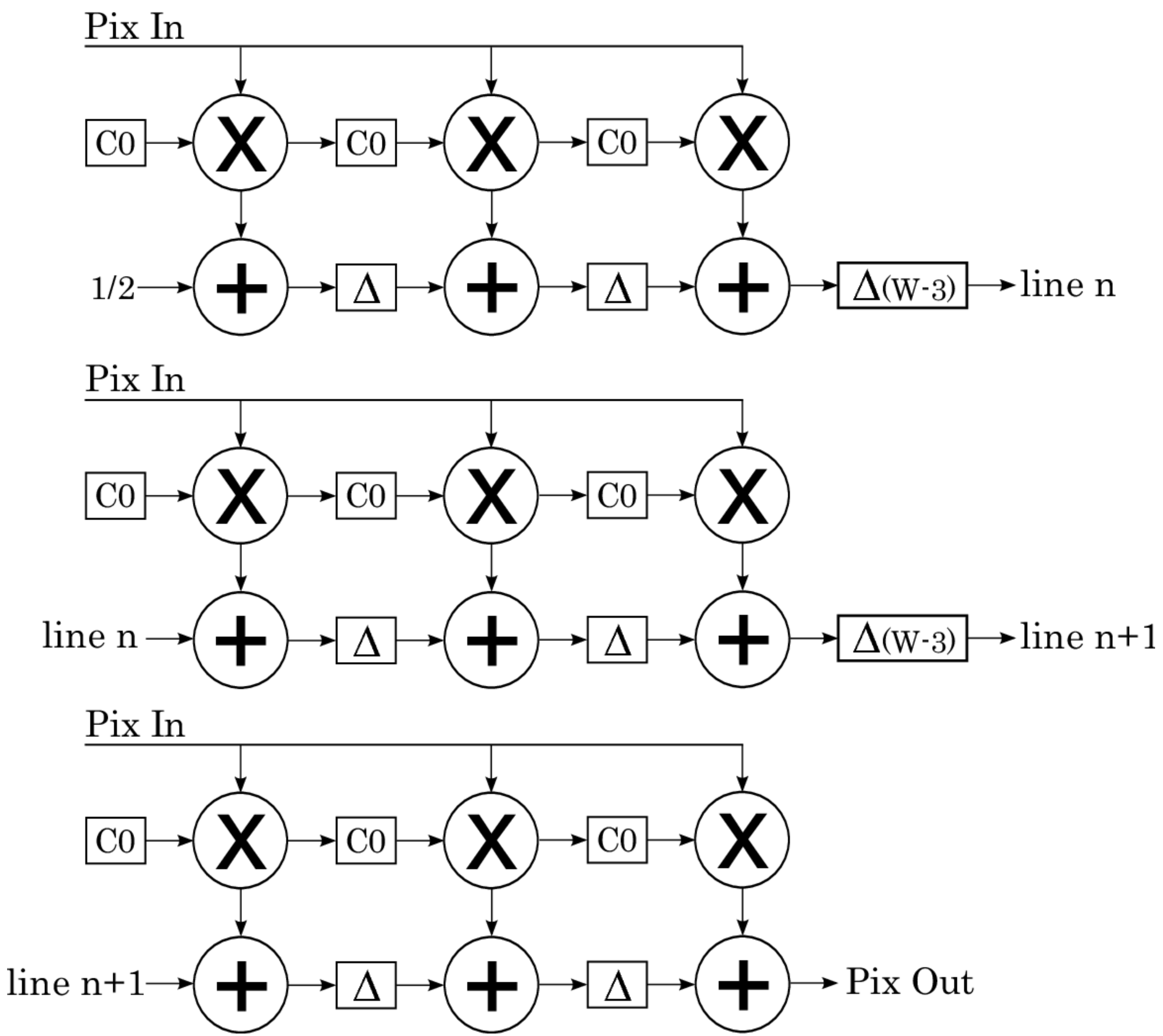
- **Implementation on low-end Xilinx FPGA**
  - Xilinx Spartan3A-DSP: 250MHz, 126 multipliers.
  - Face detector ConvNet at 640x480: 5e8 connections
  - 8fps with 200MHz clock: 4Gcps effective
    - Prototype runs at lower speed b/c of narrow memory bus on dev board
  - Very lightweight, very low power
    - Custom board the size of a matchbox (4 chips: FPGA + 3 RAM chips)
    - good for micro UAVs vision-based navigation.
  - High-End FPGA could deliver very high speed: 1024 multipliers at 500MHz: 500Gcps peak perf.



CNP Architecture



Systolic Convolver: 7x7 kernel in 1 clock cycle

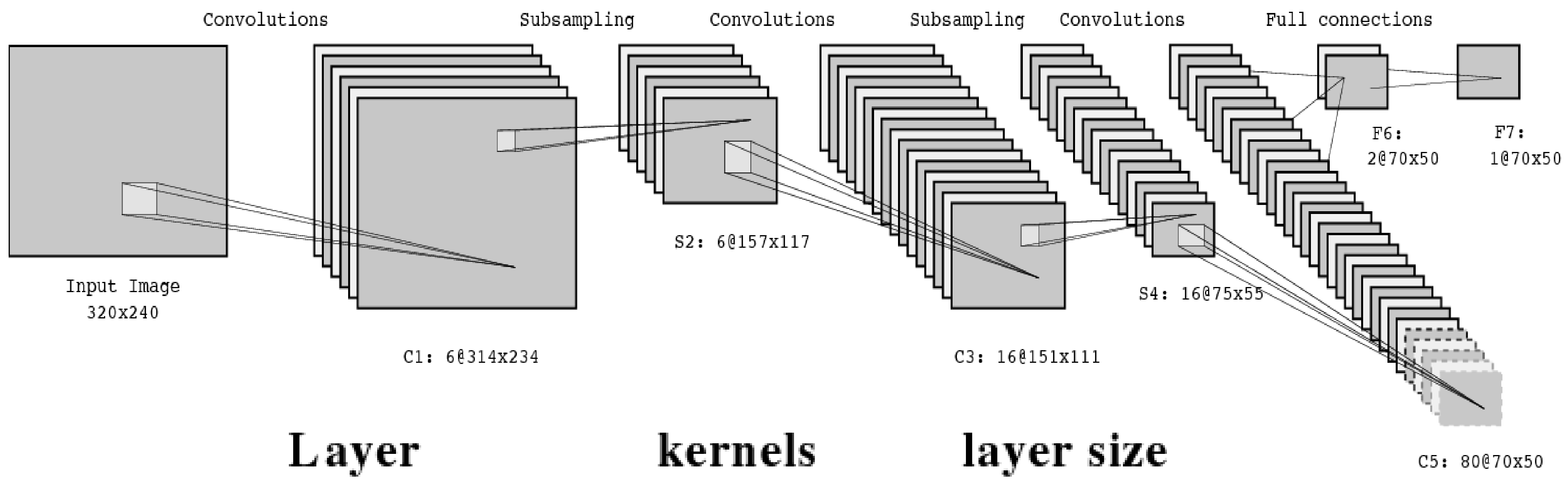


Design

- **Soft CPU used as micro-sequencer**
  - Micro-program is a C program on soft CPU
- **16x16 fixed-point multipliers**
  - Weights on 16 bits, neuron states on 8 bits.
- **Instruction set includes:**
  - Convolve X with kernel K result in Y, with sub-sampling ratio S
  - Sigmoid X to Y
  - Multiply/Divide X by Y (for contrast normalization)
- **Microcode generated automatically from network description in Lush**

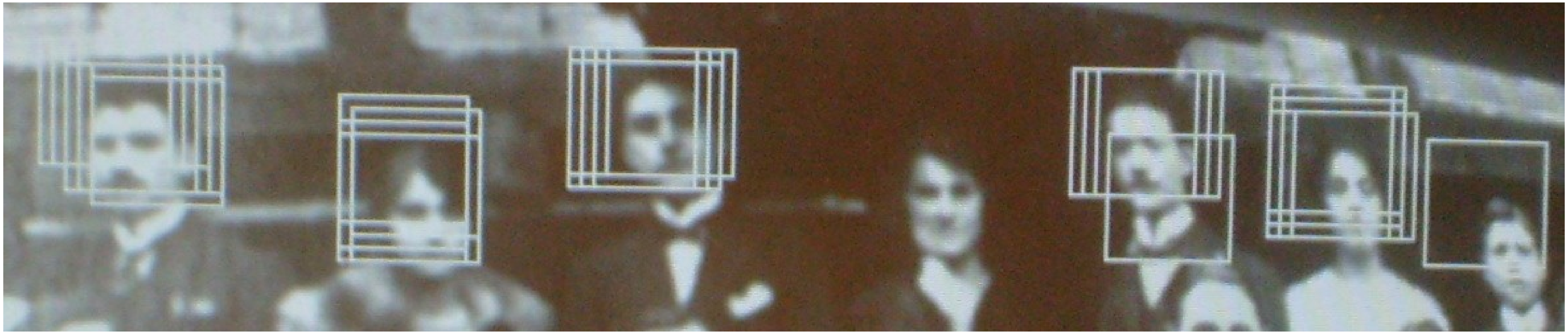
Entity	Occupancy	
I/Os	135 out of 469	28%
DCMs	2 out of 8	25%
Mult/Accs	56 out of 126	44%
Bloc Rams	100 out of 126	84%
Slices	16790 out of 23872	70%

Face detector on CNP



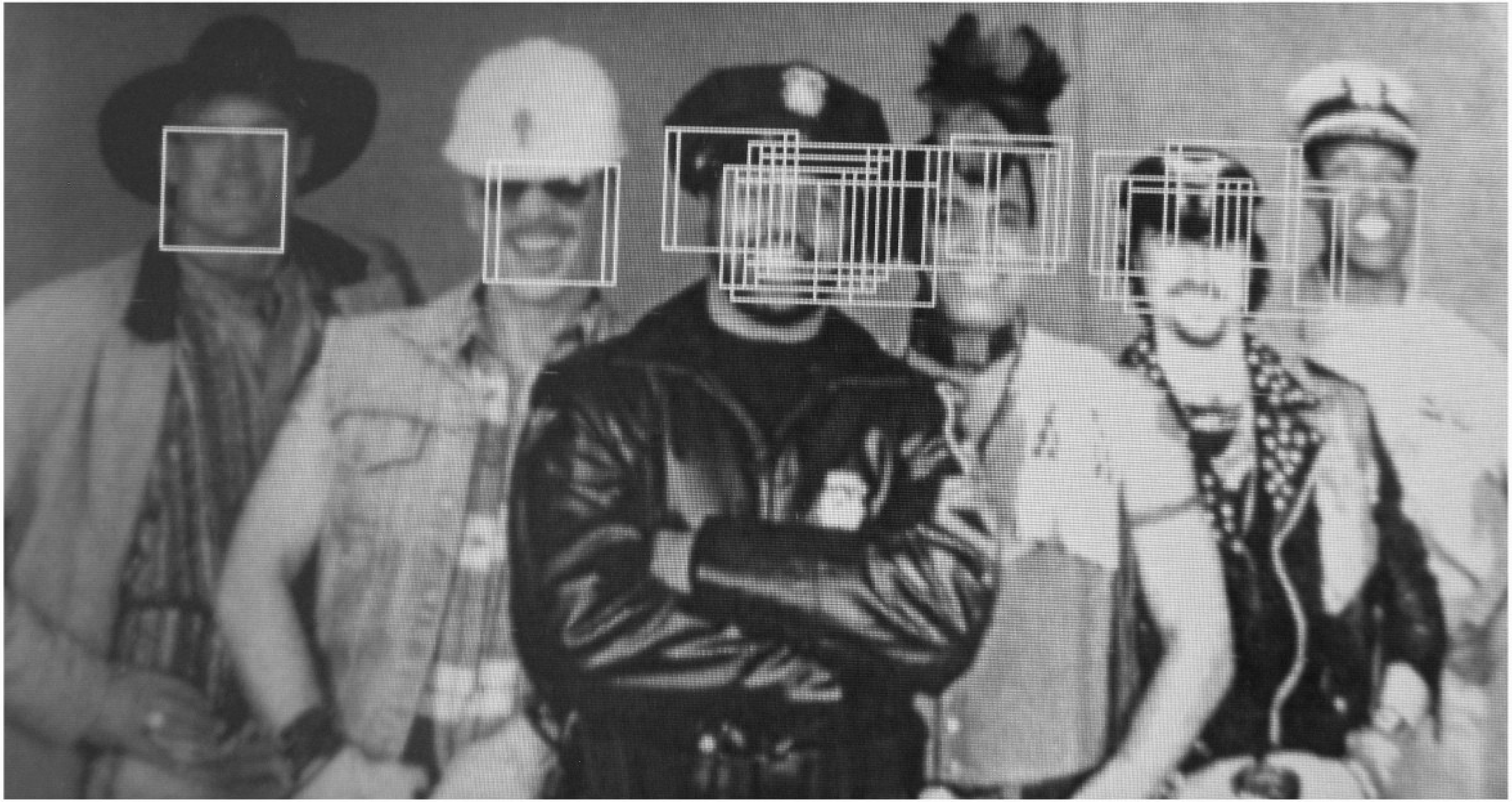
Layer	kernels	layer size
Input image		$1@42 \times 42$
C1 (Conv)	$[6@7 \times 7]$	$6@36 \times 36$
S2 (Pool)	$[6@2 \times 2]$	$6@18 \times 18$
C3 (Conv)	$[61@7 \times 7]$	$16@12 \times 12$
S4 (Pool)	$[16@2 \times 2]$	$16@6 \times 6$
C5 (Conv)	$[305@6 \times 6]$	$80@1 \times 1$
F6 (Dotp)	$[160@1 \times 1]$	$2@1 \times 1$

Results



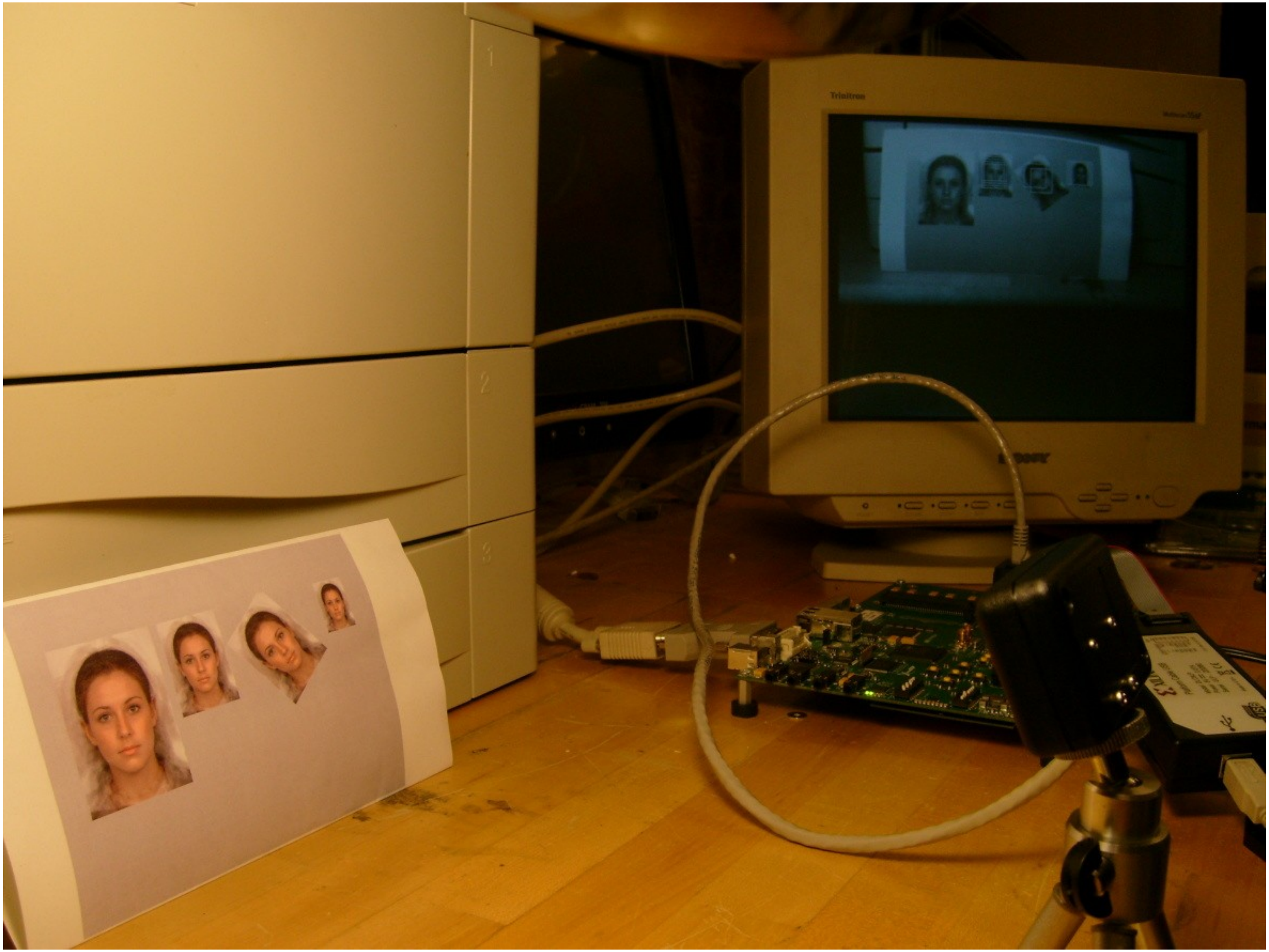
- **Clock speed limited by low memory bandwidth on the development board**
  - Dev board uses a single DDR with 32 bit bus
  - Custom board will use 128 bit memory bus
- **Currently uses a single 7x7 convolver**
  - We have space for 2, but the memory bandwidth limits us
- **Current Implementation: 5fps at 512x384**
- **Custom board will yield 30fps at 640x480**
  - 4e10 connections per second peak.

Results



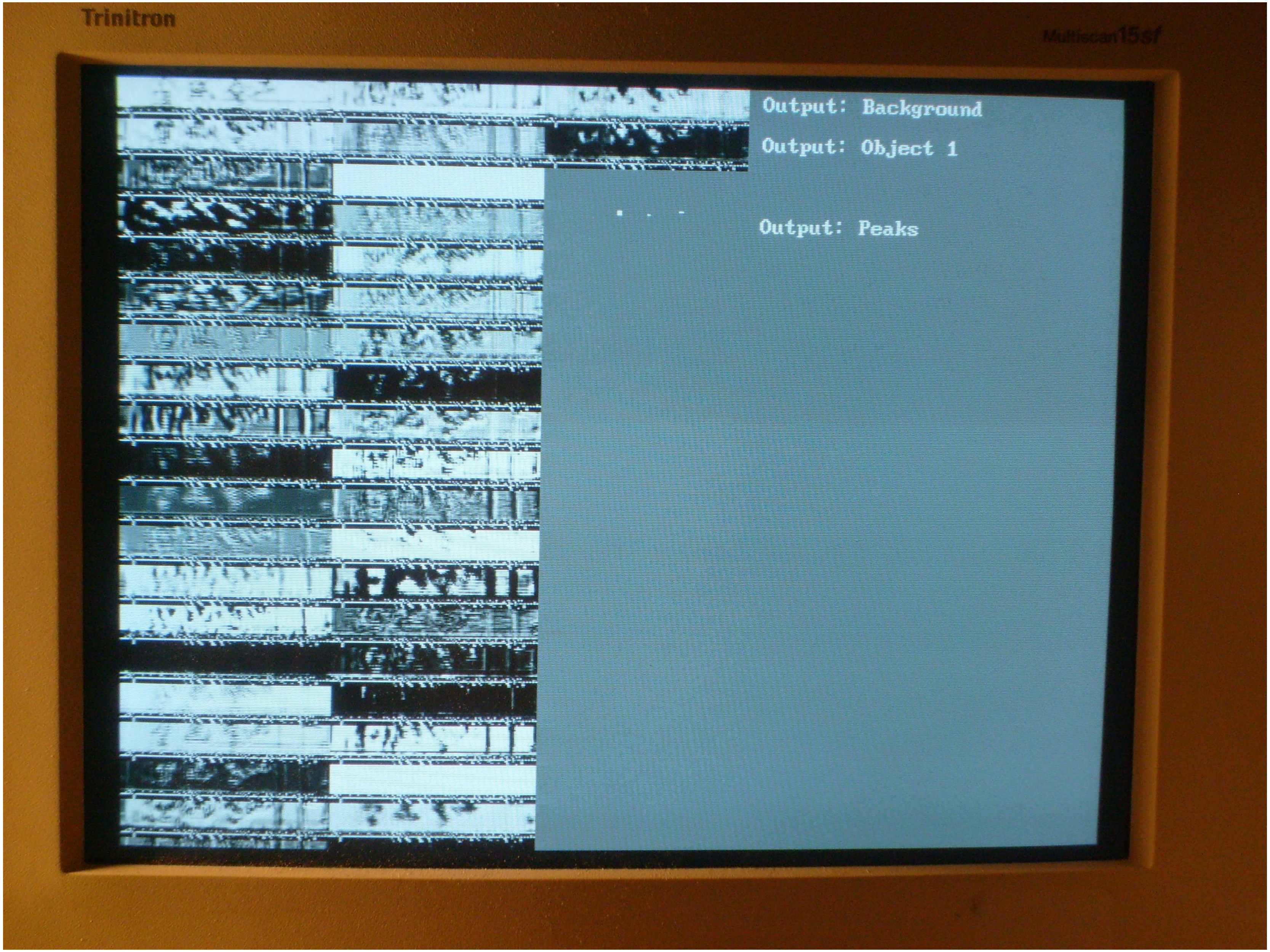
Results

Results



Results

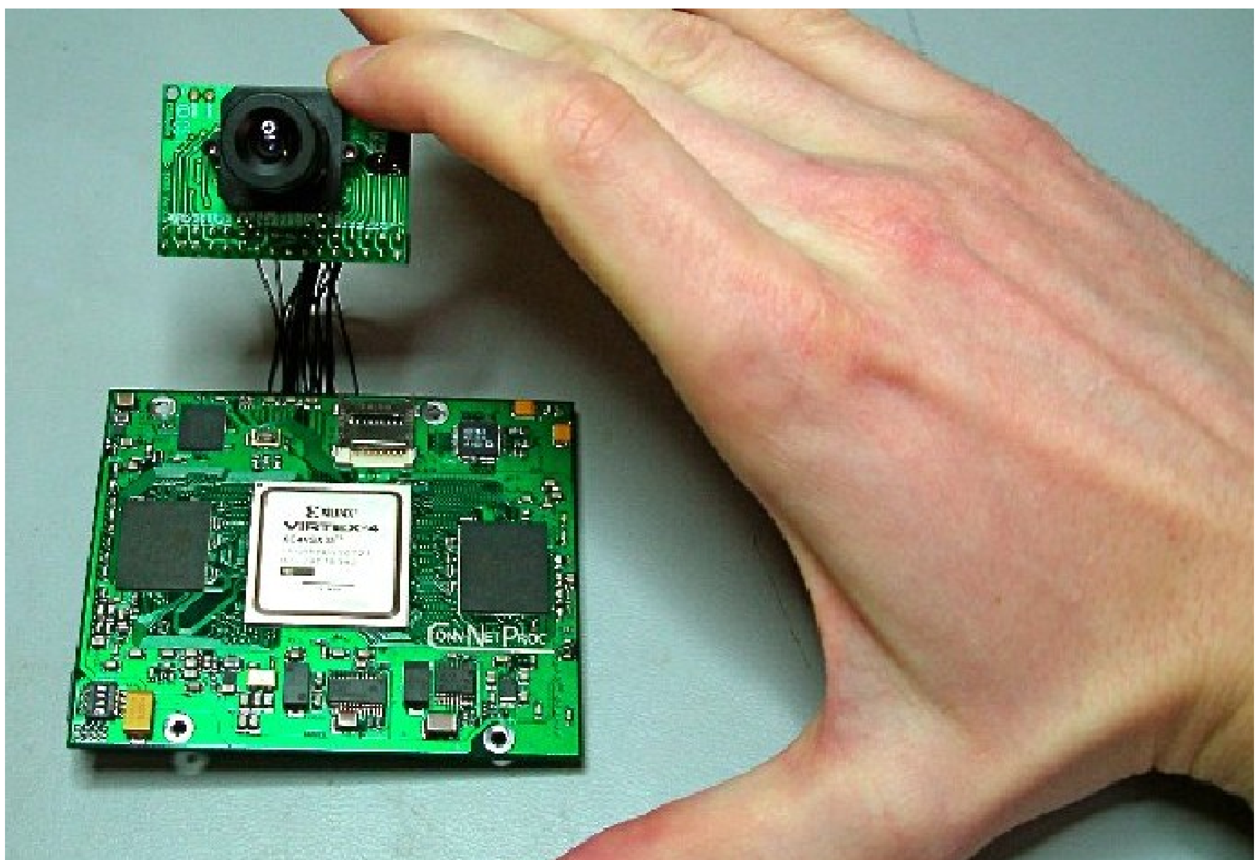
Results



FPGA Custom Board: NYU ConvNet Proc

Xilinx Virtex 4 FPGA, 8x5 cm board

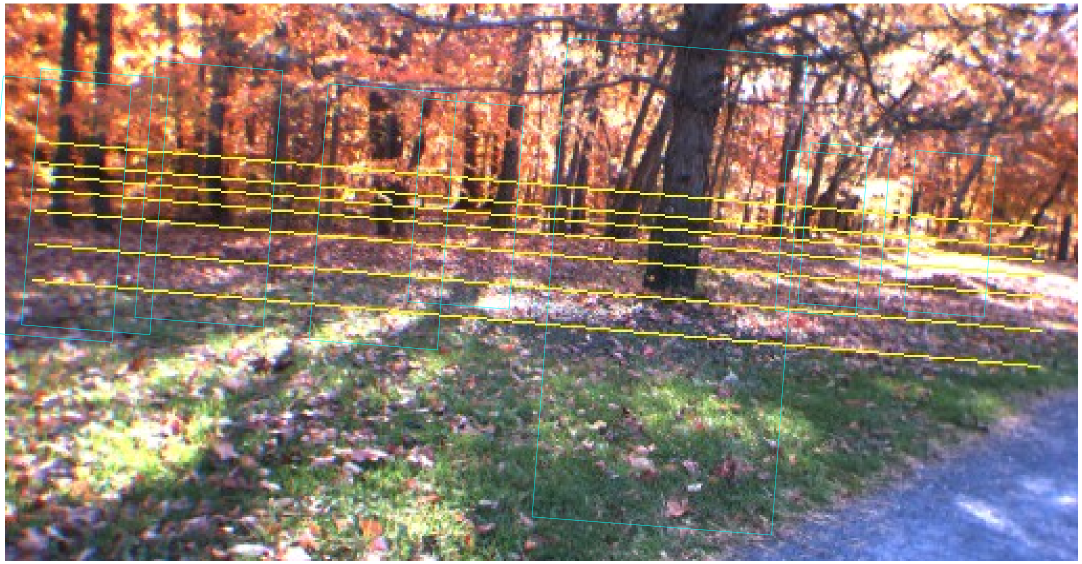
- Dual camera port, expansion and I/O port
- Dual QDR RAM for fast memory bandwidth
- MicroSD port for easy configuration
- DVI output
- Serial communication to optional host



DARPA/LAGR: Learning Applied to Ground Robotics

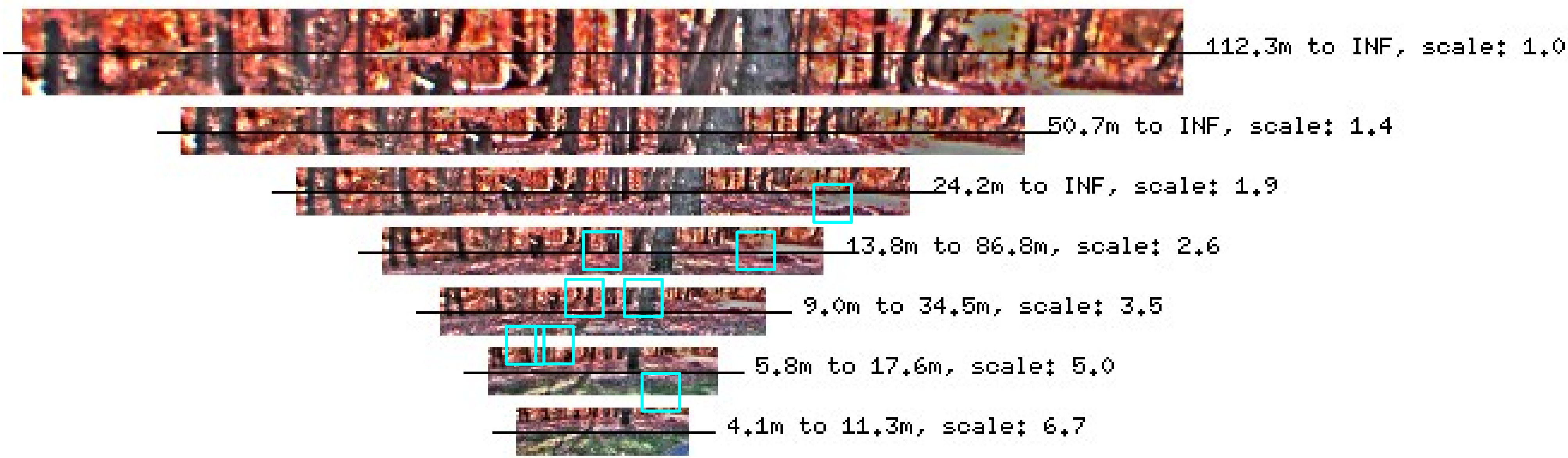
- Getting a robot to drive autonomously in unknown terrain solely from vision (camera input).
- Our team (NYU/Net-Scale Technologies Inc.) was one of 8 participants funded by DARPA
- All teams received identical robots and can only modify the software (not the hardware)
- The robot is given the GPS coordinates 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!

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”



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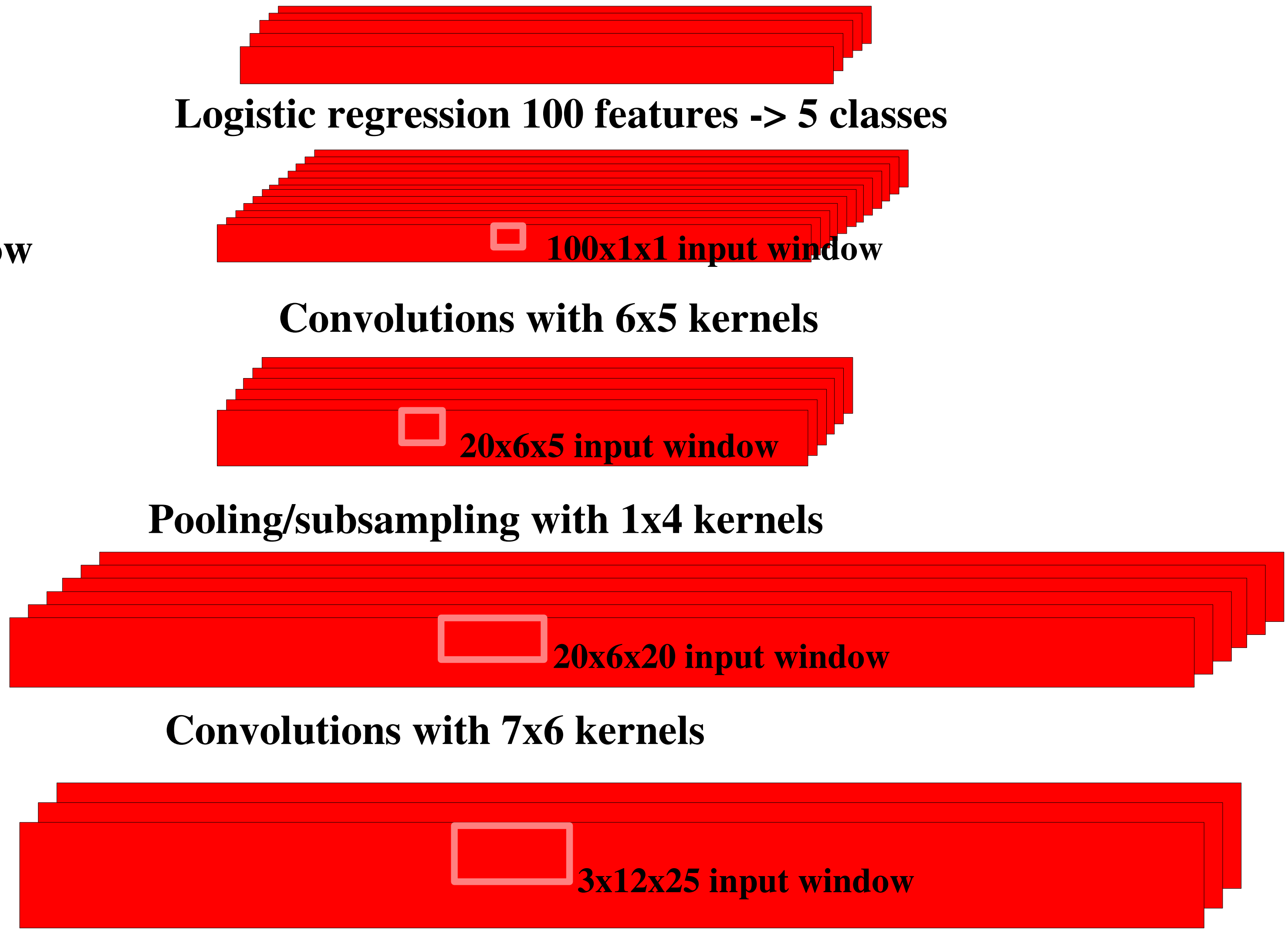
NEW YORK UNIVERSITY

Convolutional Net Architecture

- Operates on 12x25 YUV windows from the pyramid

100 features per

3x12x25 input window

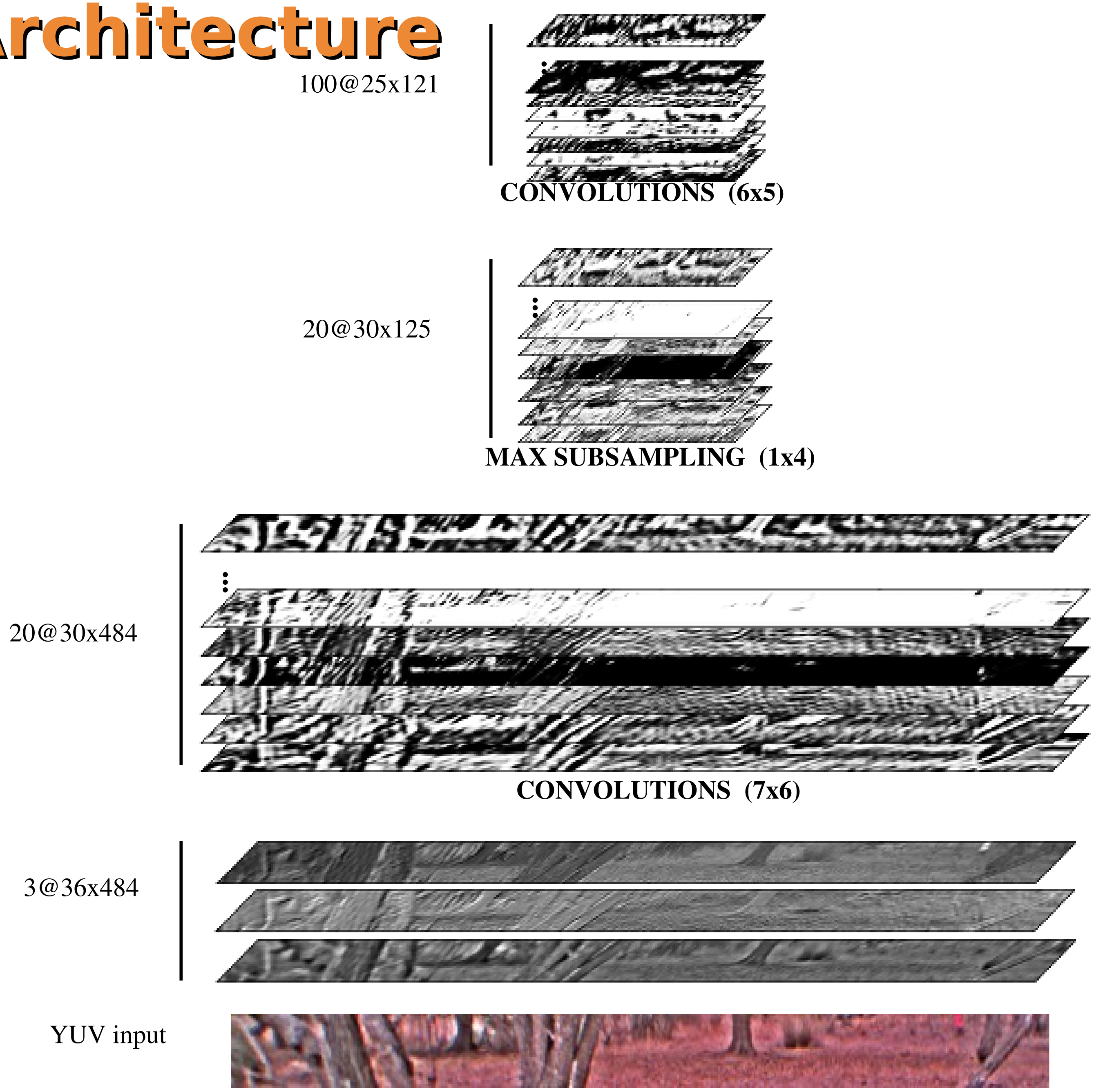


YUV image band

20-36 pixels tall,

36-500 pixels wide

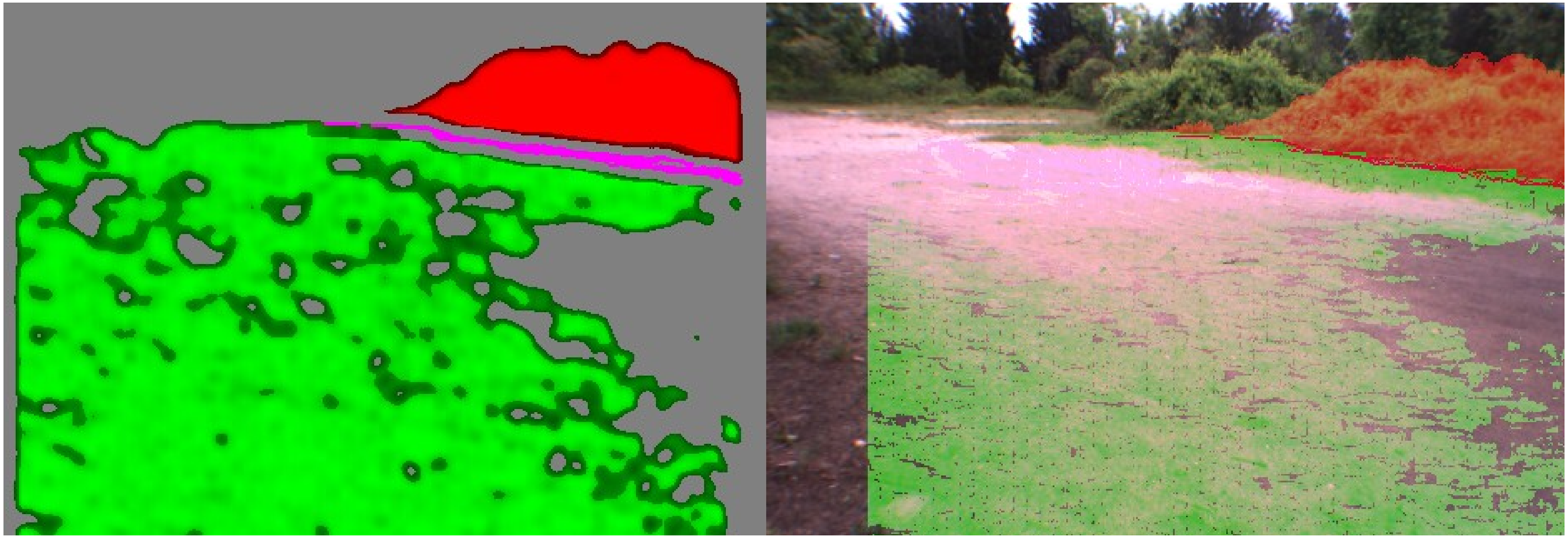
Convolutional Net Architecture



Long Range Vision: 5 categories

Online Learning (52 ms)

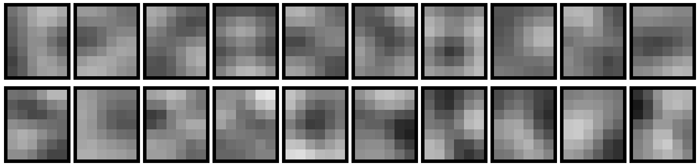
- Label windows using stereo information – 5 classes

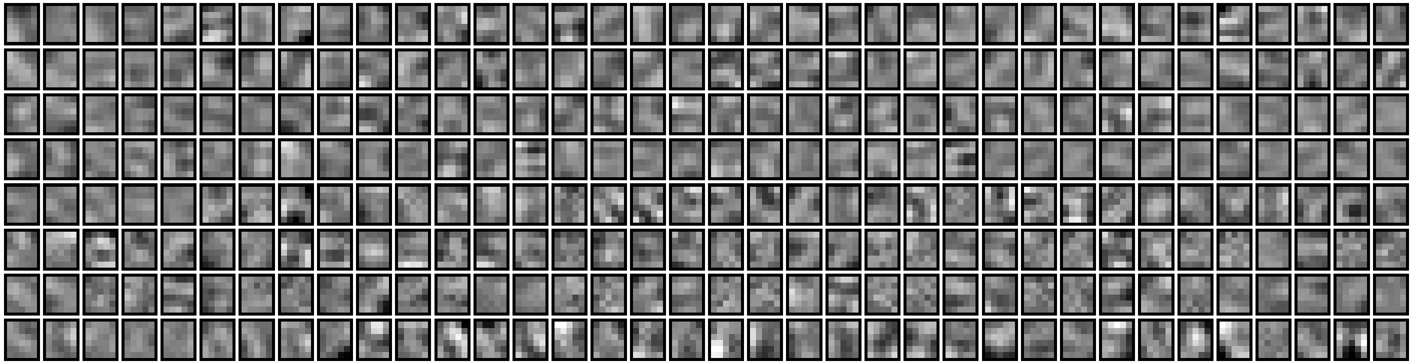


super-ground **ground** **footline** **obstacle** **super-obstacle**

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

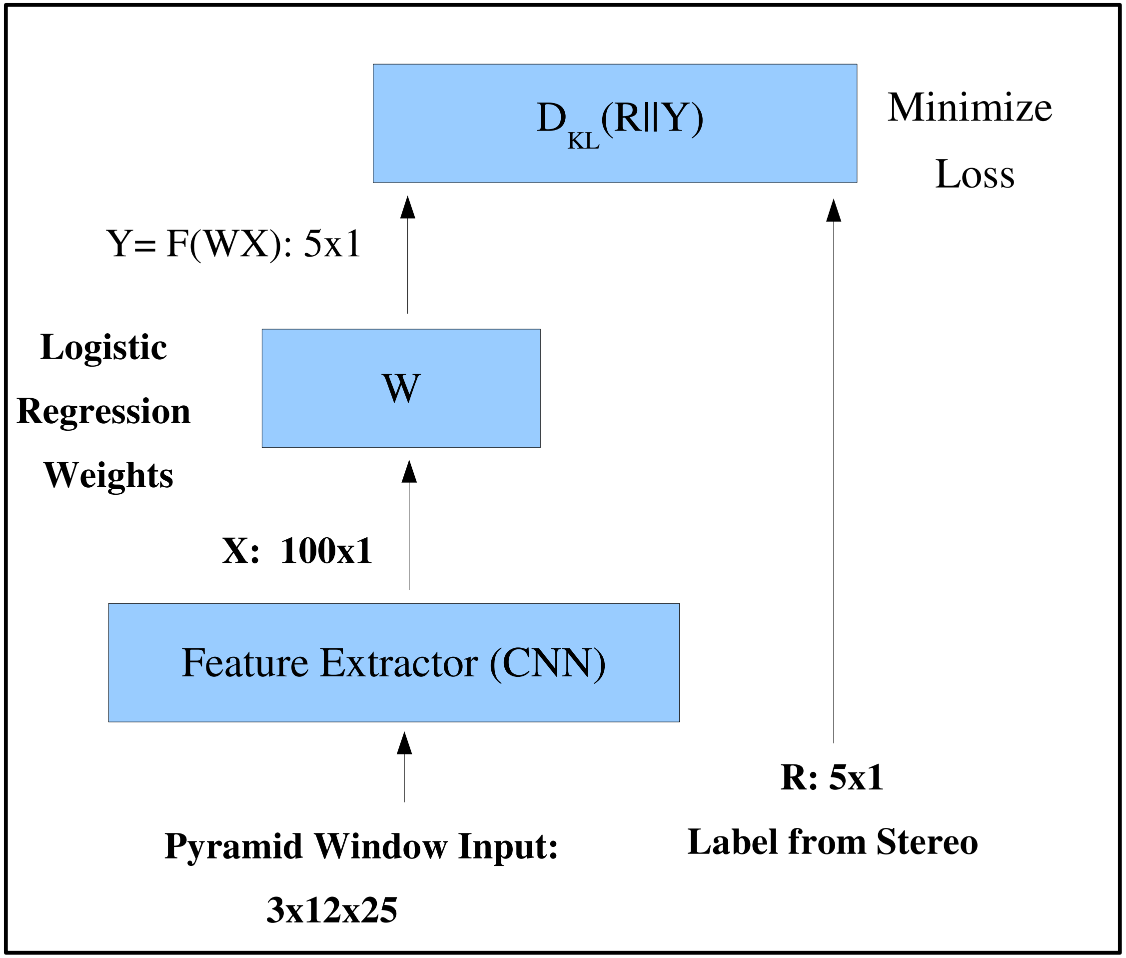




Long Range Vision: the Classifier

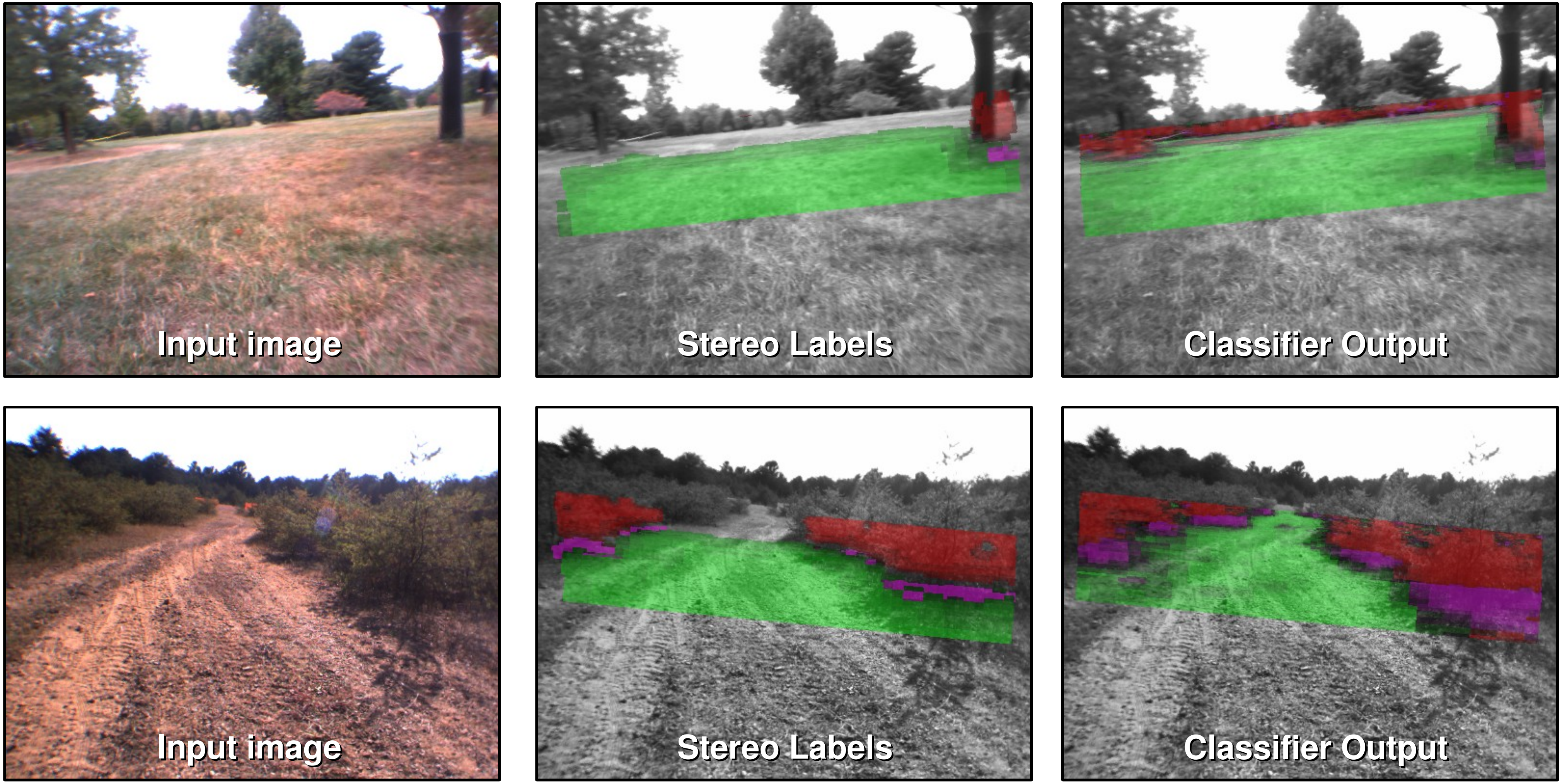
Online Learning (52 ms)

- Train a logistic regression on every frame, with cross entropy loss function

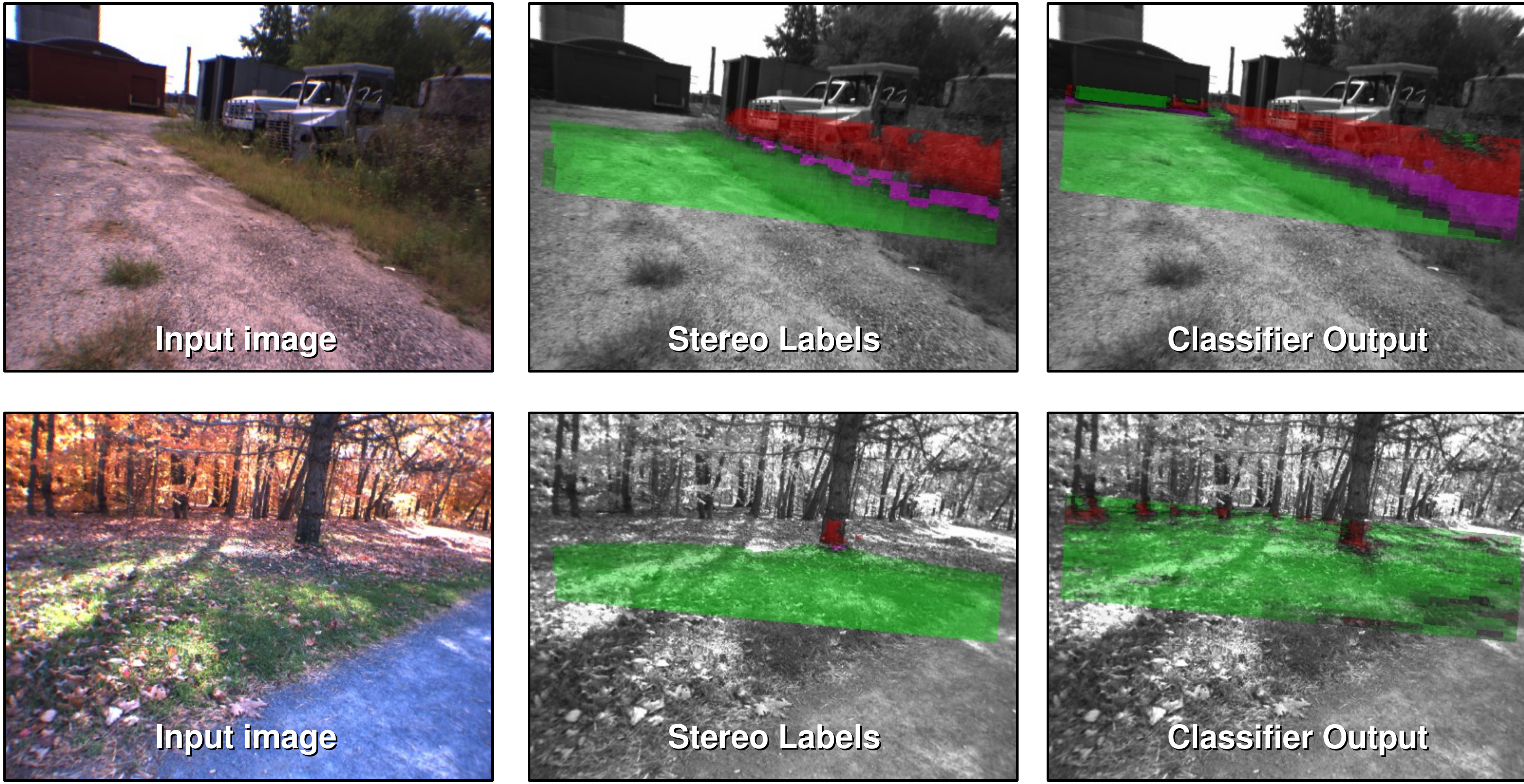


- 5 categories are learned
- 750 samples of each class are kept in a ring buffer: short term memory.
- Learning "snaps" to new environment in about 10 frames
- Weights are trained with stochastic gradient descent
- Regularization by decay to default weights

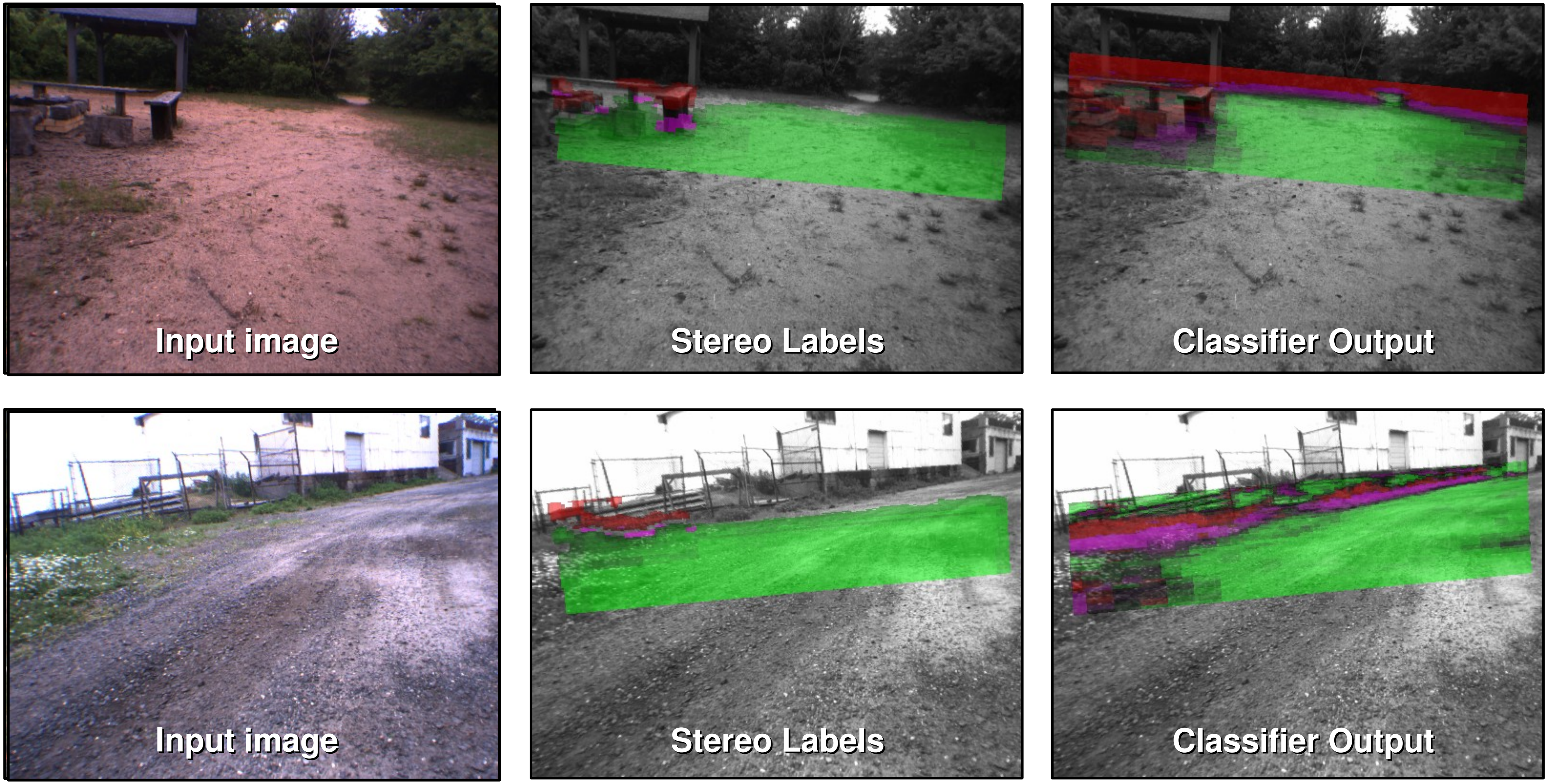
Long Range Vision Results

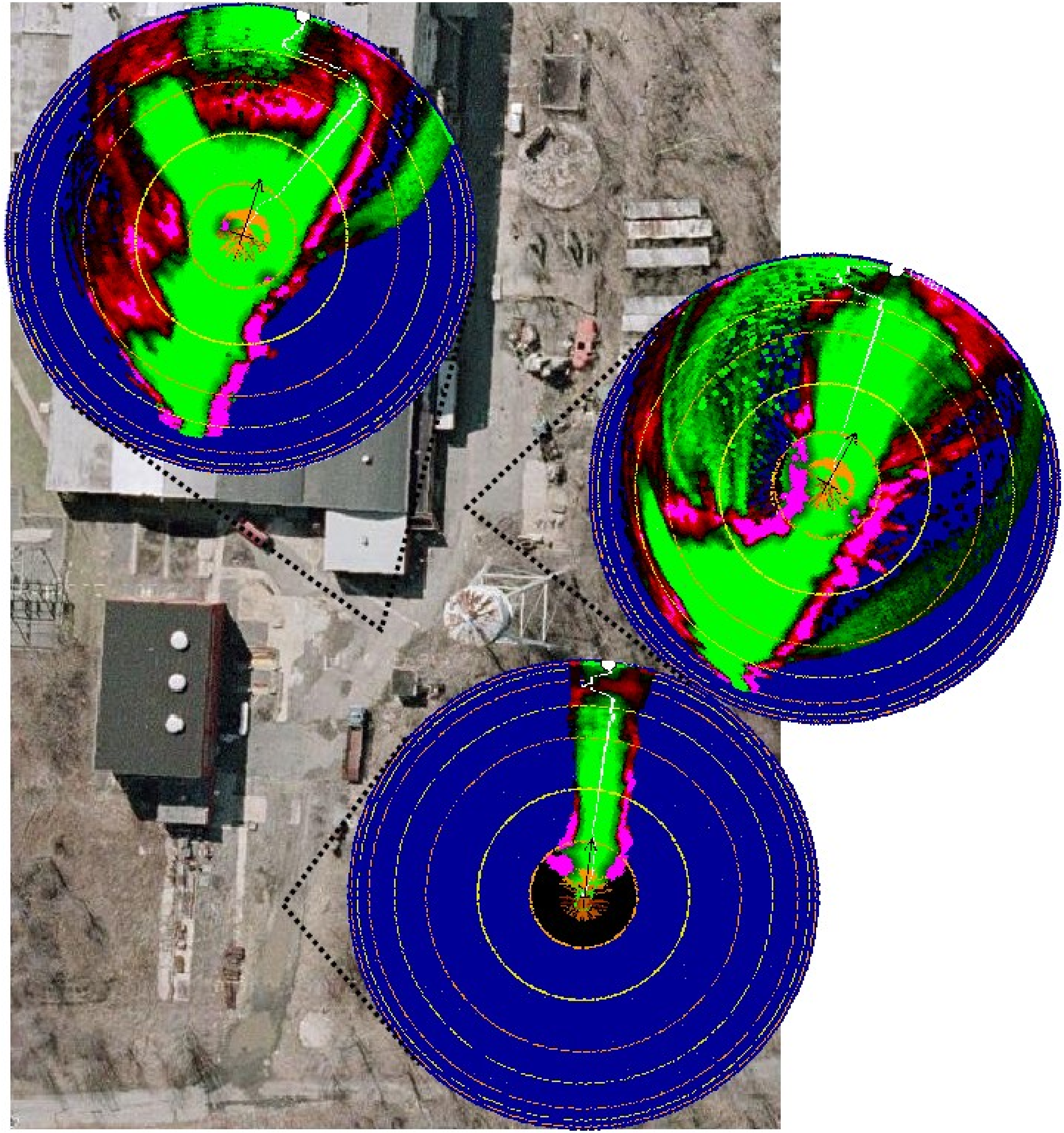


Long Range Vision Results



Long Range Vision Results





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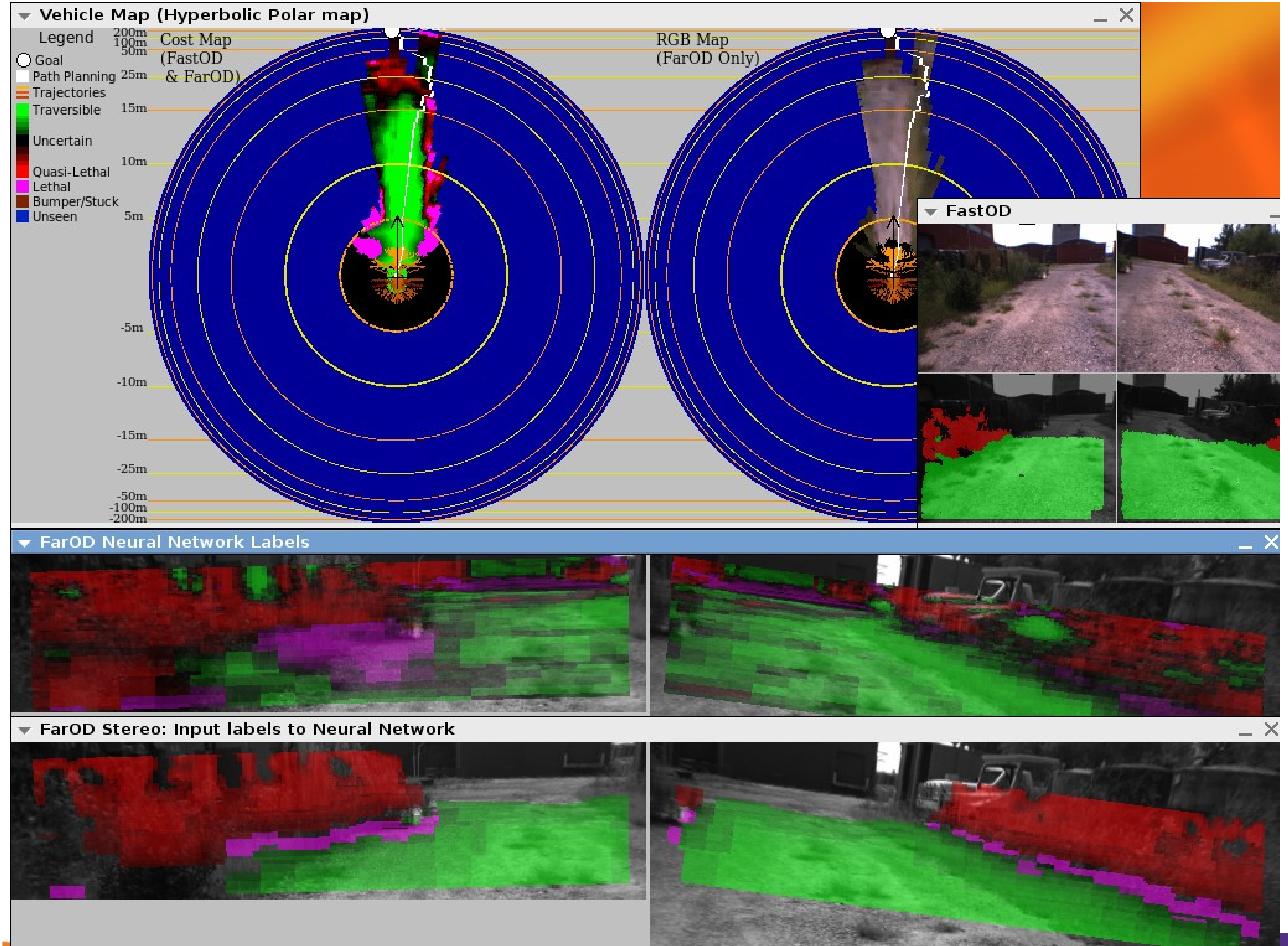
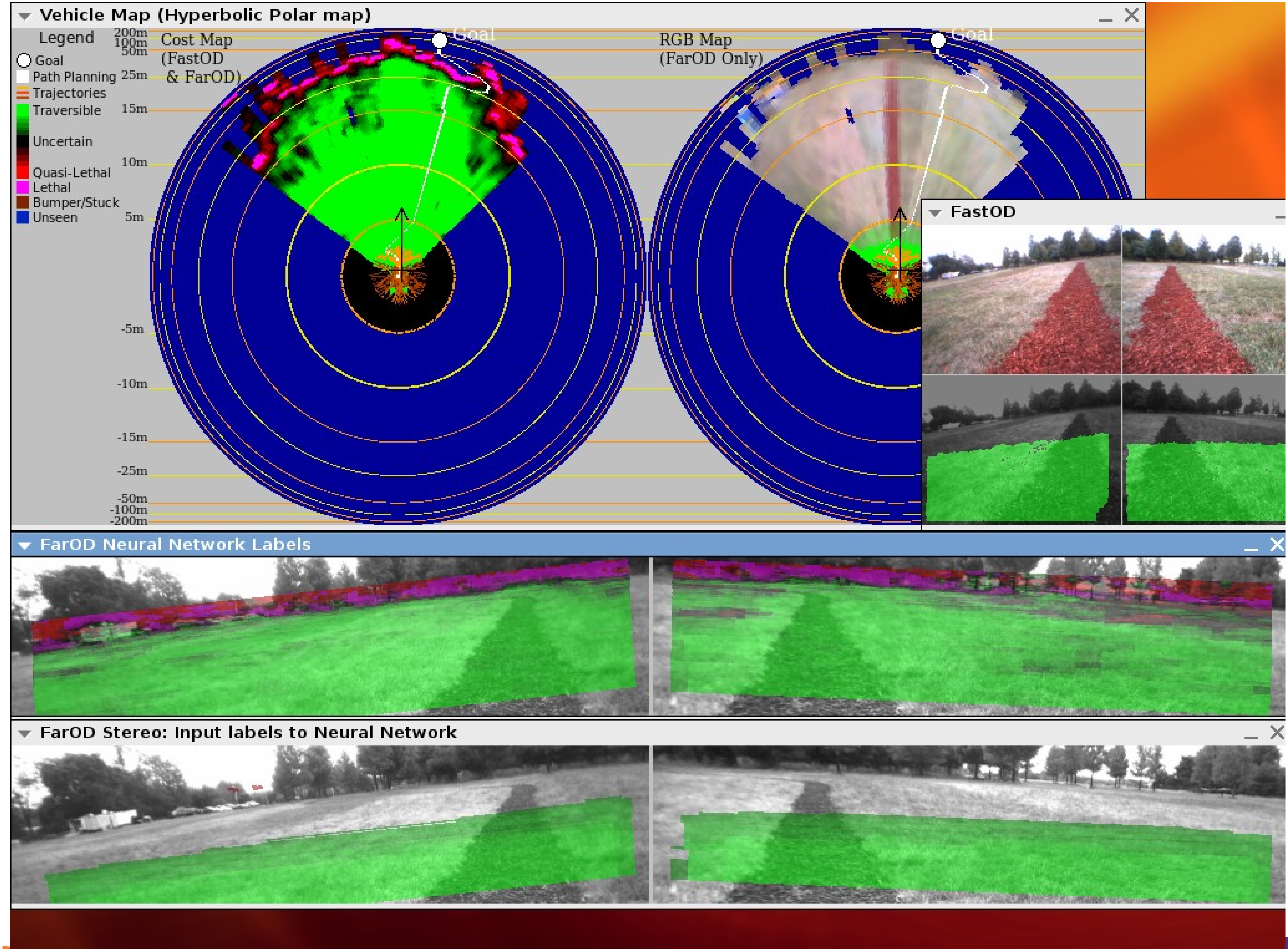

Vehicle Map (Hyperbolic Polar map)
Legend
Goal
Path Planning
Trajectories
Traversible
Uncertain
Quasi-Lethal
Lethal
Bumper/Stuck
Unseen
200m
100m
50m
25m
15m
10m
5m
-5m
-10m
-15m
-25m
-50m
-100m
-200m
Cost Map
(FastOD
& FarOD)
RGB Map
(FarOD Only)
FastOD
FarOD Neural Network Labels
FarOD Stereo: Input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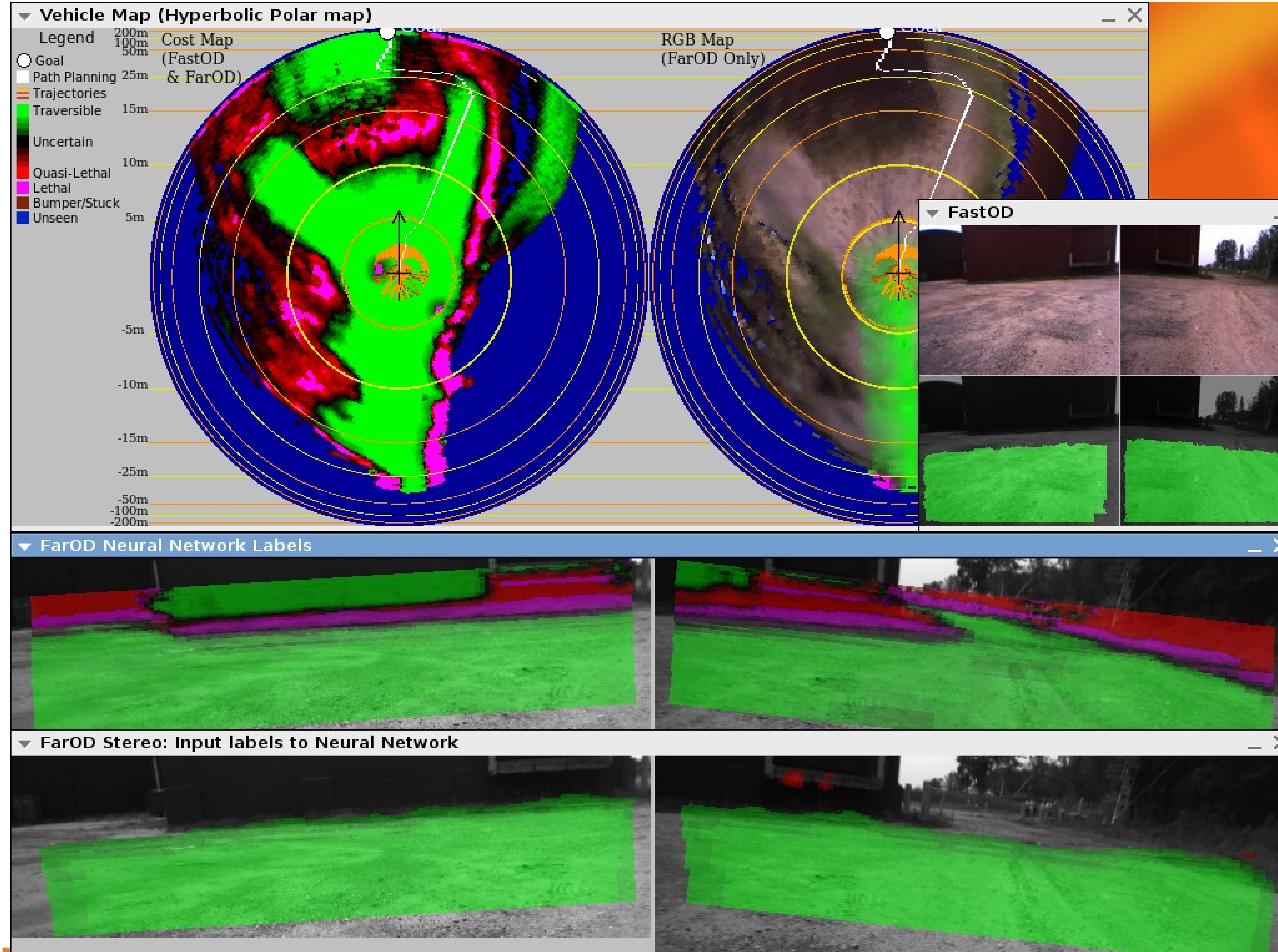

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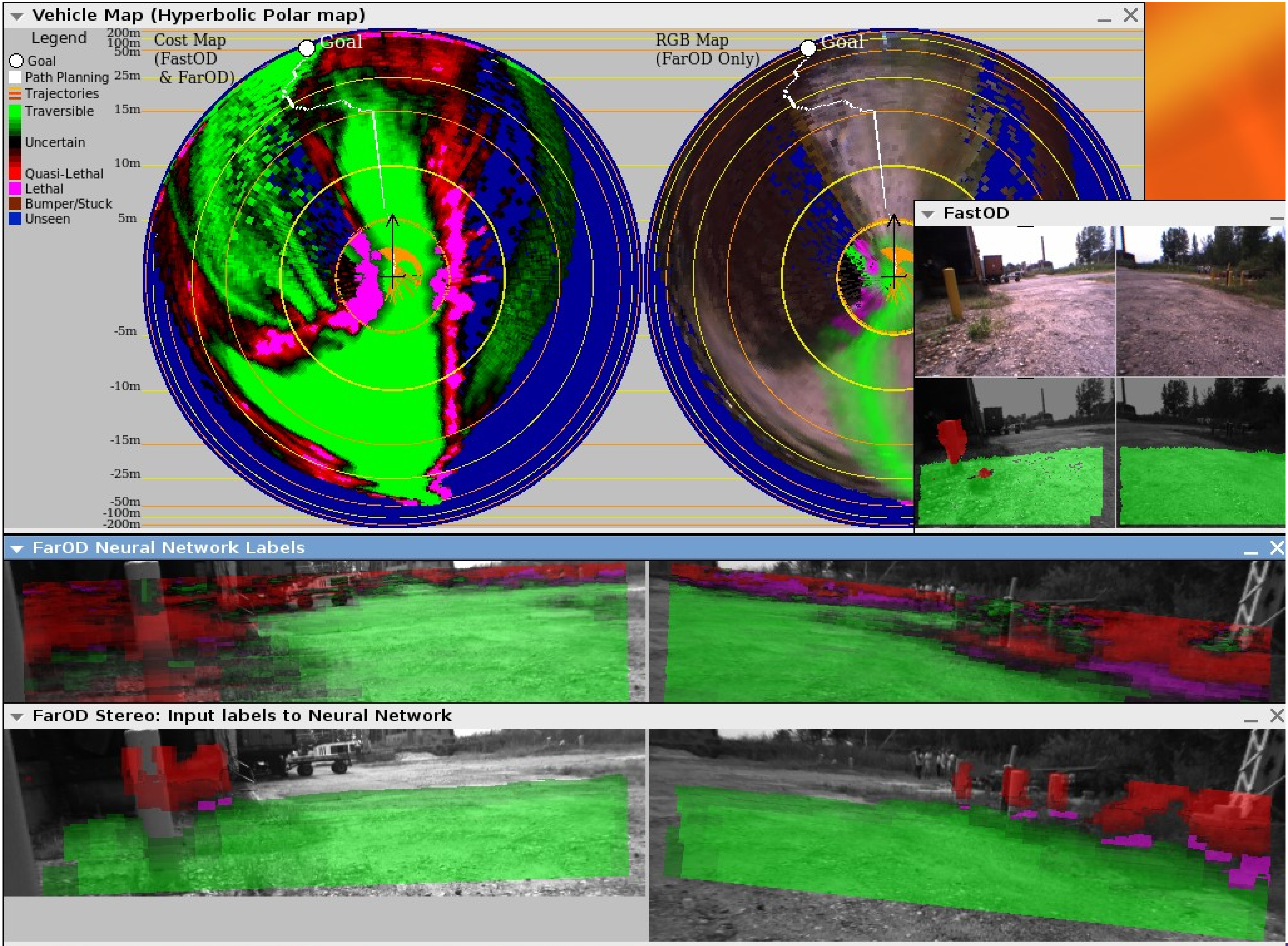
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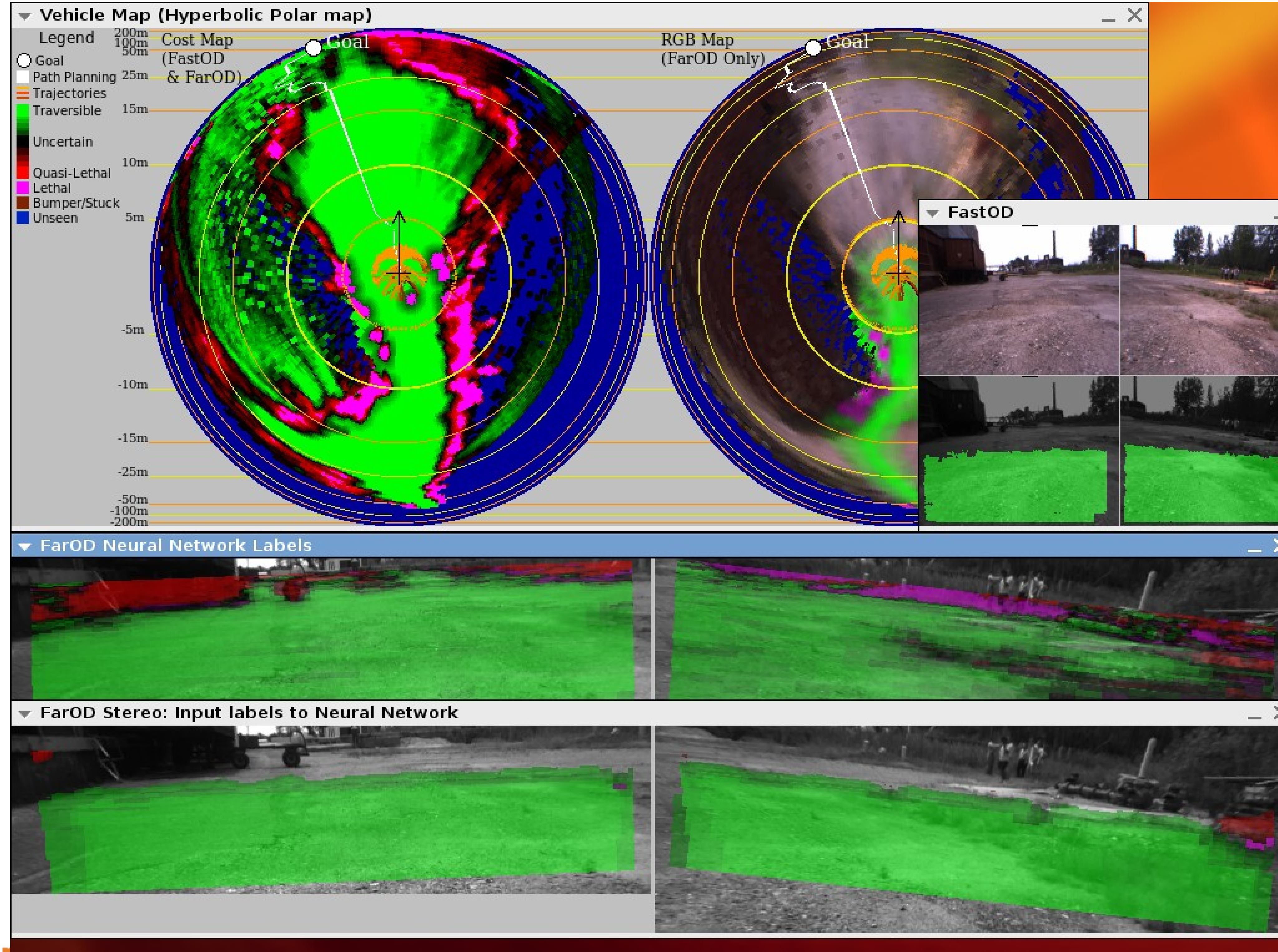

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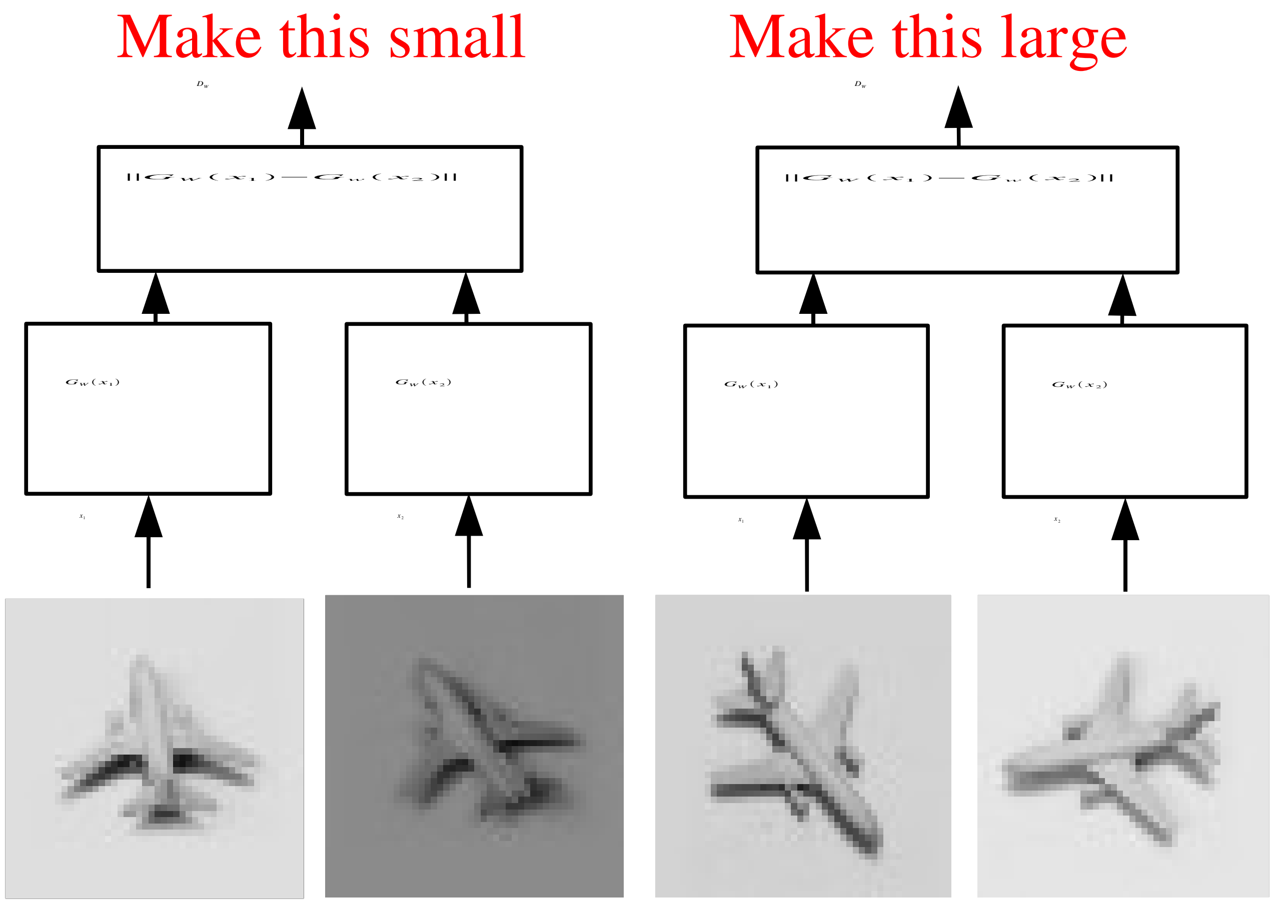
Another way to Learn Deep Invariant Features: DrLIM

Hadsell, Chopra, LeCun CVPR 06], also [Weston & Collobert ICML 08 for language models]

Loss function:

- Outputs corresponding to input samples that are neighbors in the neigborhood graph should be nearby
- Outputs for input samples that are not neighbors should be far away from each other



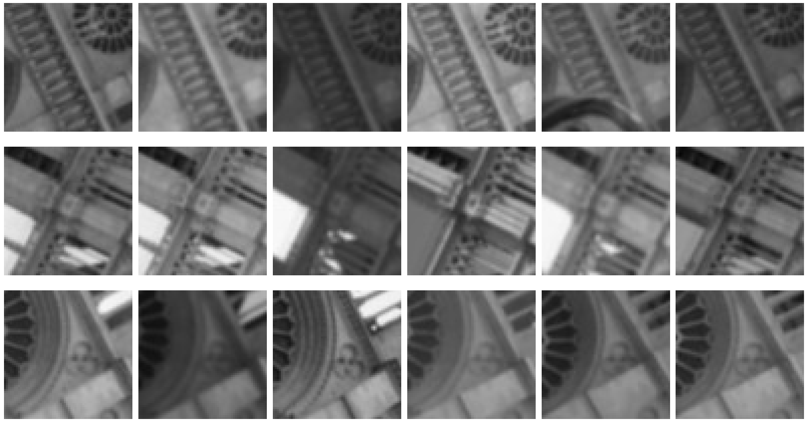
Similar images (neighbors in the neighborhood graph)

Dissimilar images (non-neighbors in the neighborhood graph)

Learning Deep Invariant Features with DrLIM

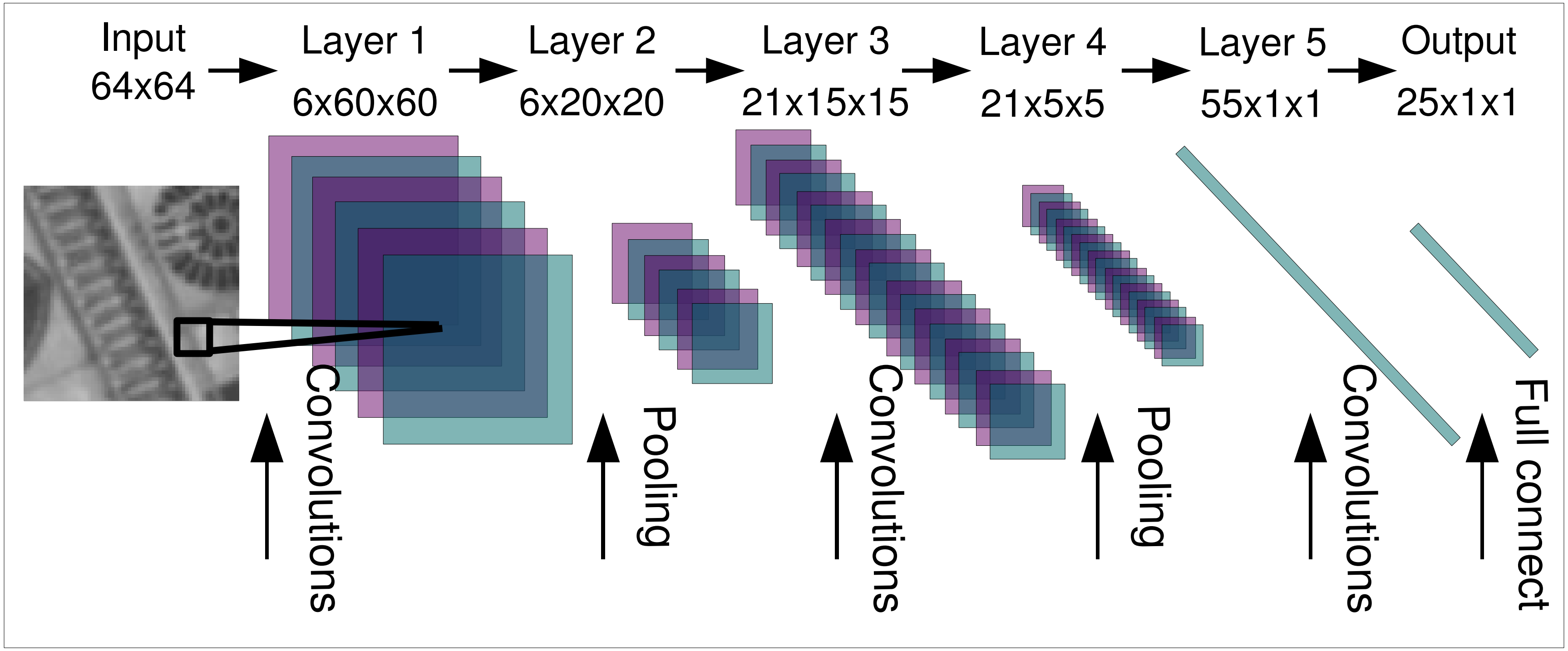
Co-location patch data

- multiple tourist photos
- 3d reconstruction
- groundtruth matches



Uses temporal consistency

- Pull together outputs for same patch
- Push away outputs for different patches



data from: Winder and Brown, CVPR 07

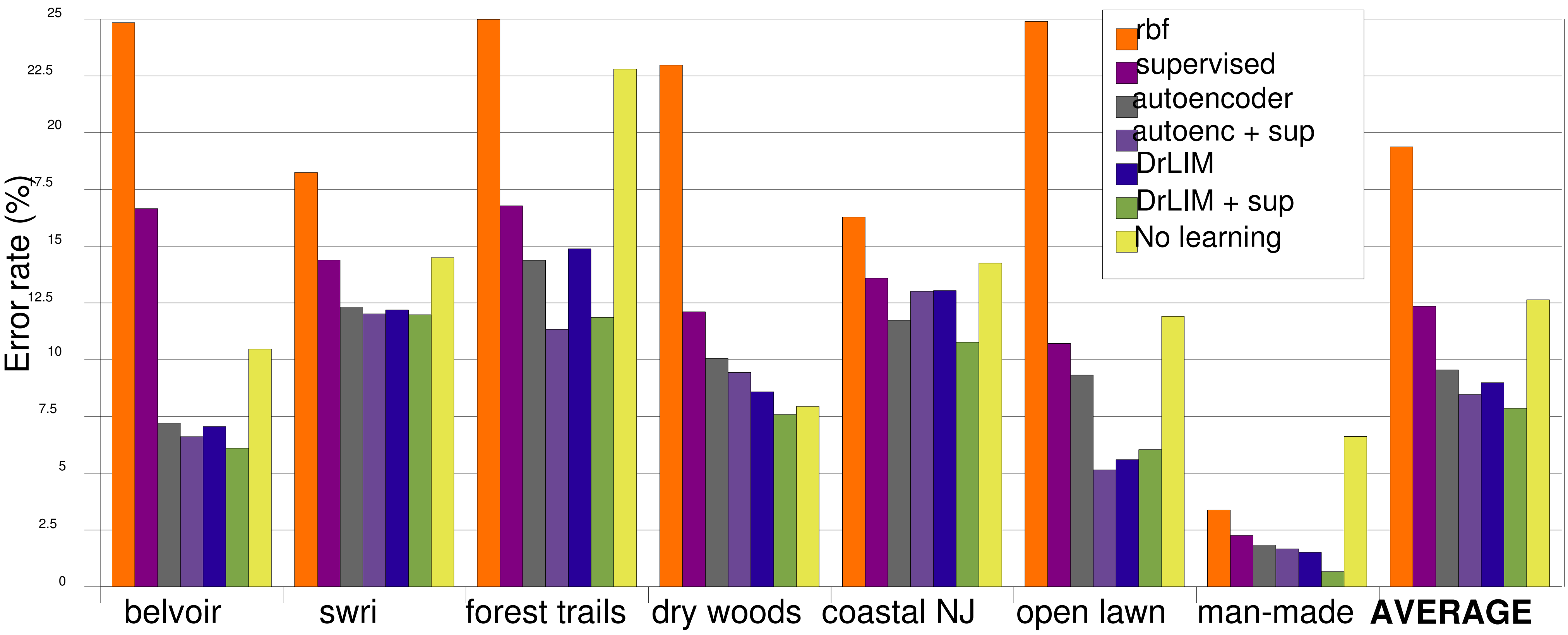
Feature Learning for traversability prediction (LAGR)

Comparing

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

Testing on hand-labeled groundtruth frames – binary labels

Comparison of Feature Extractors on Groundtruth Data



The End