Deep Learning

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The Challenges of Machine Learning

- **How can we use learning to progress towards AI?**
  - Can we find learning methods that scale?
  - Can we find learning methods that solve **really complex problems** end-to-end, such as vision, natural language, speech....?

- **How can we learn the structure of the world?**
  - How can we build/learn internal representations of the world that allow us to discover its hidden structure?
  - How can we learn internal representations that capture the relevant information and eliminates irrelevant variabilities?

- **How can a human or a machine learn internal representations by just looking at the world?**

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

"Simple" Trainable Classifier

this part is mostly hand-crafted

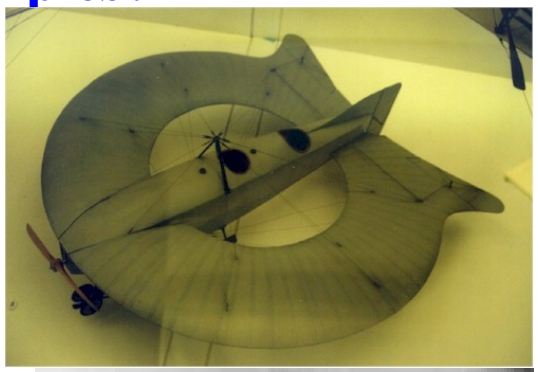
Internal Representation

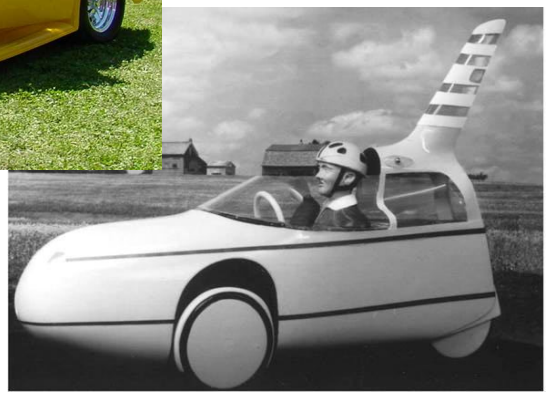
- **The raw input is pre-processed through a hand-crafted feature extractor**
- **The features are not learned**
- **The trainable classifier is often generic (task independent), and "simple" (linear classifier, kernel machine, nearest neighbor,.....)**
- **The most common Machine Learning architecture: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

The Next Challenge of ML, Vision (and Neuroscience)

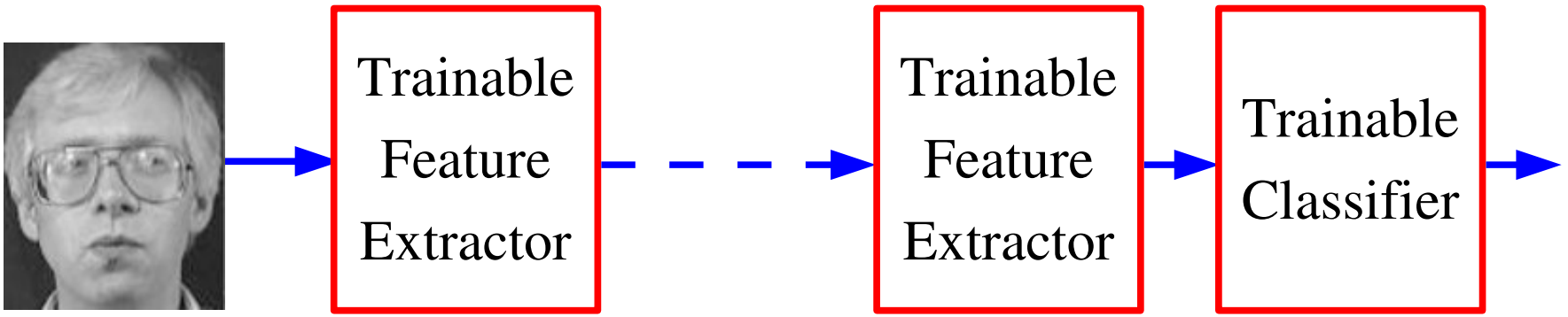
- **How do we learn invariant representations?**
  - From the image of an airplane, how do we extract a representation that is invariant to pose, illumination, background, clutter, object instance....
  - How can a human (or a machine) learn those representations by just looking at the world?

- **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)



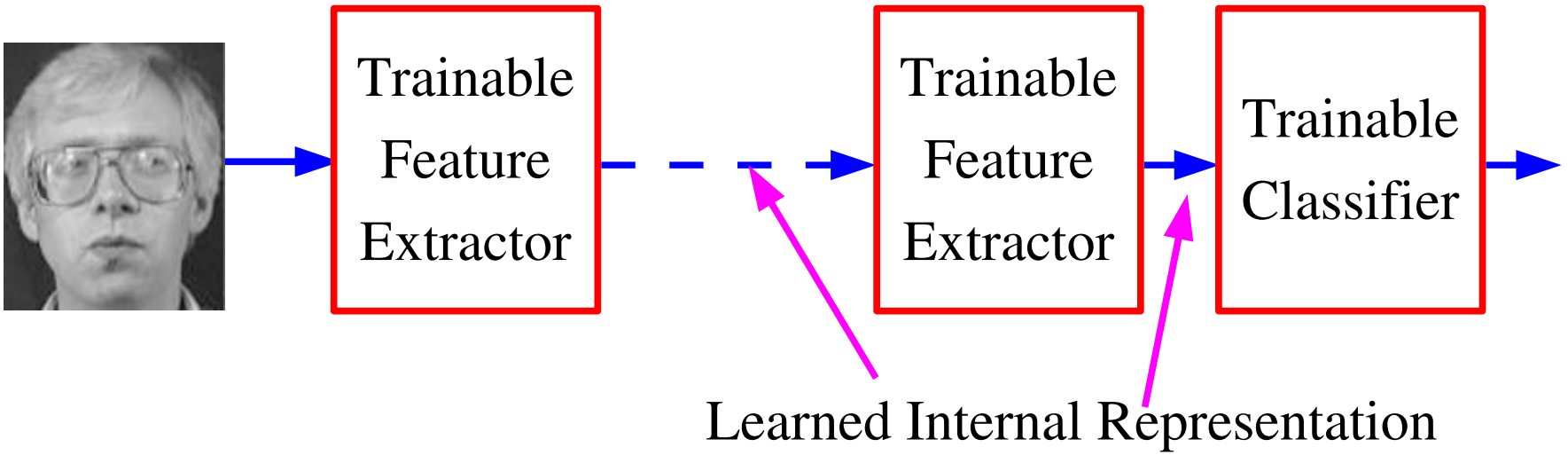


Good Representations are Hierarchical



- **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).....

Strategies (a parody of [Hinton 2007])

- **Defeatism: since no good parameterization of the "AI-set" is available, let's parameterize a much smaller set for each specific task through careful engineering (preprocessing, kernel....).**
- **Denial: kernel machines can approximate anything we want, and the VC-bounds guarantee generalization. Why would we need anything else?**
  - unfortunately, kernel machines with common kernels can only represent a tiny subset of functions efficiently
- **Optimism: Let's look for learning models that can be applied to the largest possible subset of the AI-set, while requiring the smallest amount of task-specific knowledge for each task.**
  - There is a parameterization of the AI-set with neurons.
  - Is there an efficient parameterization of the AI-set with computer technology?
- **Today, the ML community oscillates between defeatism and denial.**

Supervised Deep Learning,
The Convolutional Network Architecture

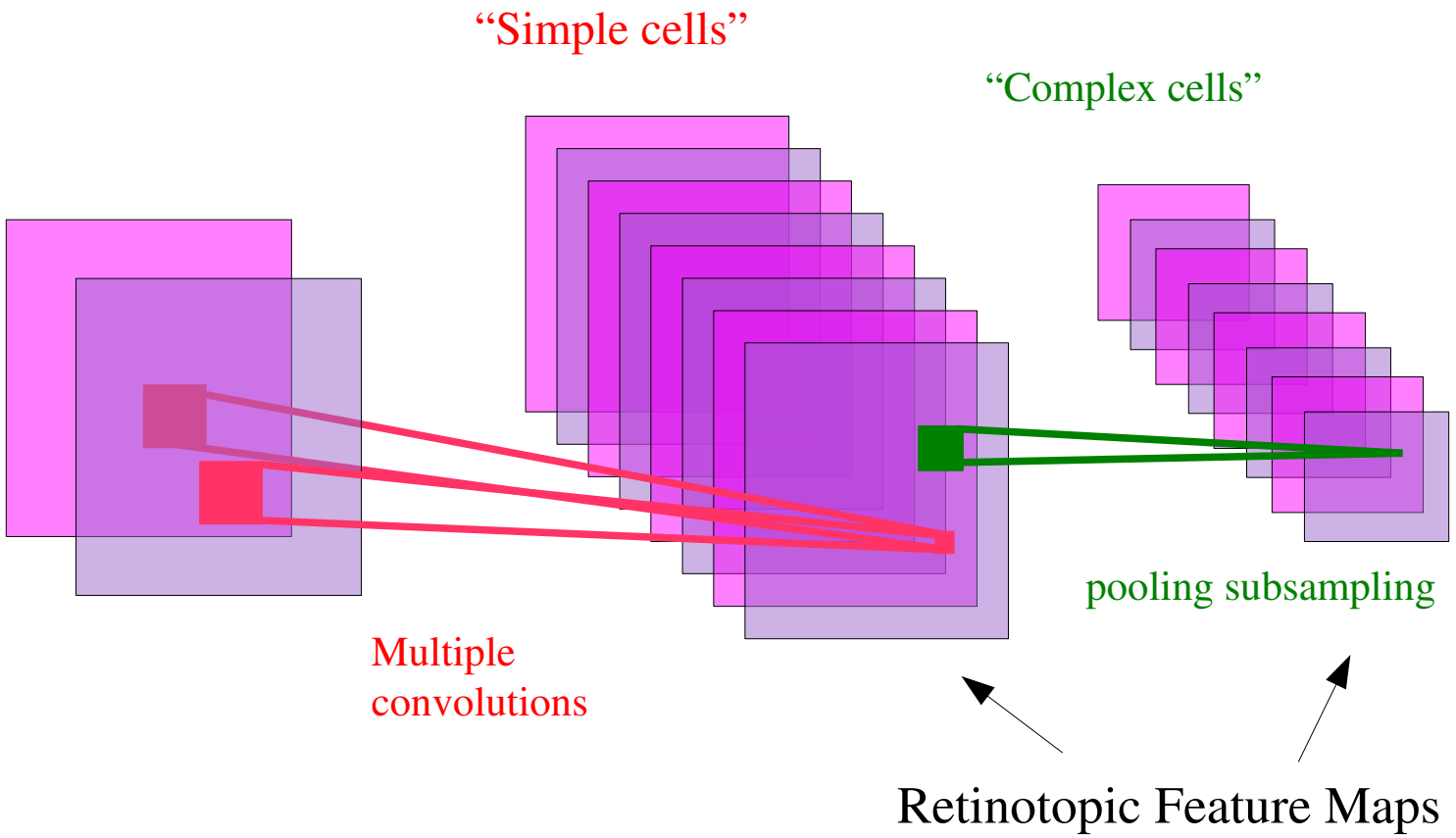
- **Convolutional Networks:**
  - [LeCun et al., Neural Computation, 1988]
  - [LeCun et al., Proc IEEE 1998] (handwriting recognition)
- **Face Detection and pose estimation with convolutional networks:**
  - [Vaillant, Monrocq, LeCun, IEE Proc Vision, Image and Signal Processing, 1994]
  - [Osadchy, Miller, LeCun, JMLR vol 8, May 2007]
- **Category-level object recognition with invariance to pose and lighting**
  - [LeCun, Huang, Bottou, CVPR 2004]
  - [Huang, LeCun, CVPR 2006]
- **autonomous robot driving**
  - [LeCun et al. NIPS 2005]

Deep Supervised Learning is Hard

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

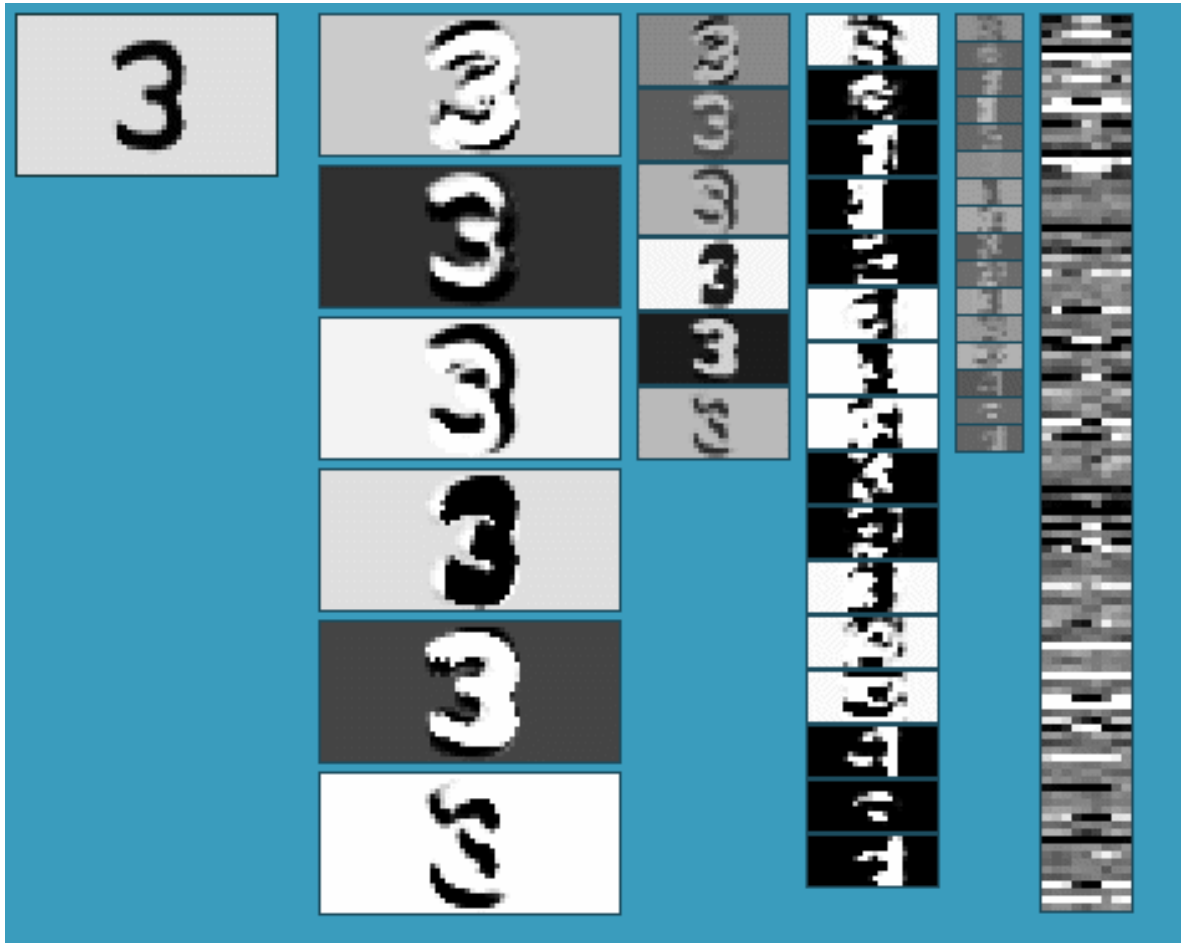
An Old Idea for Local Shift Invariance

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

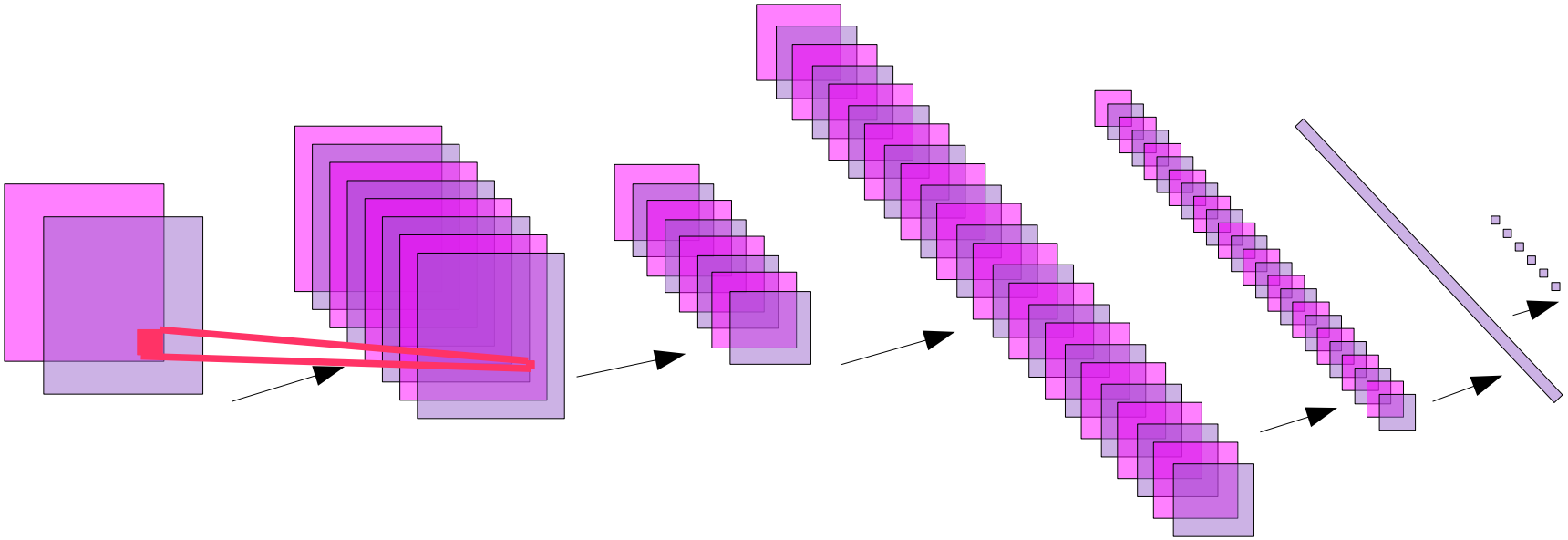


The Multistage Hubel-Wiesel Architecture

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

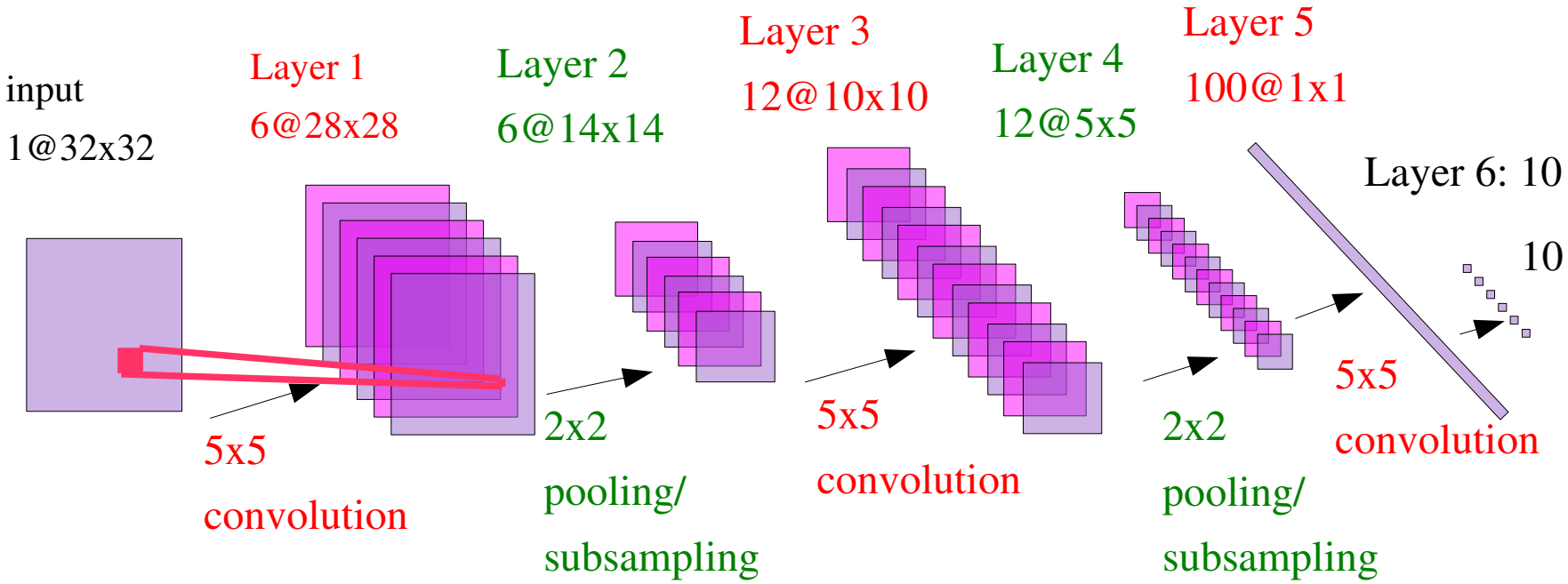


Getting Inspiration from Biology: Convolutional Network



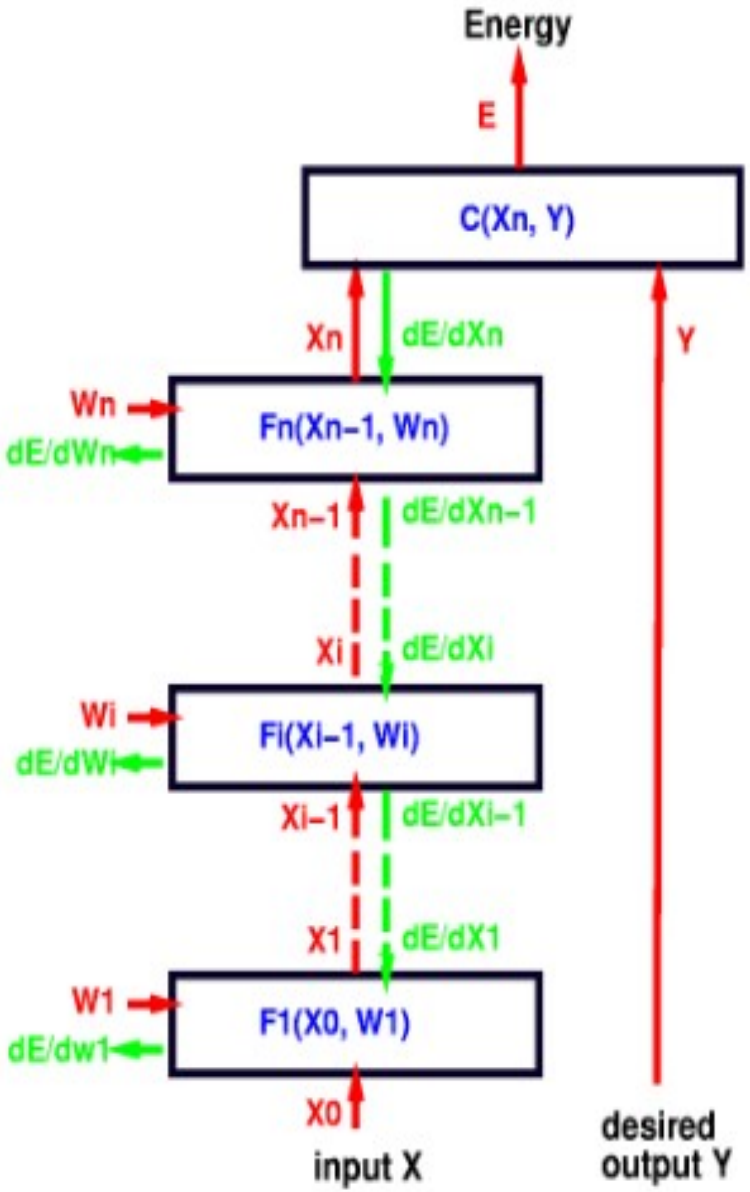
- **Hierarchical/multilayer:** features get progressively more global, invariant, and numerous
- **dense features:** features detectors applied everywhere (no interest point)
- **broadly tuned (possibly invariant) features:** sigmoid units are on half the time.
- **Global discriminative training:** The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

Convolutional Net Architecture



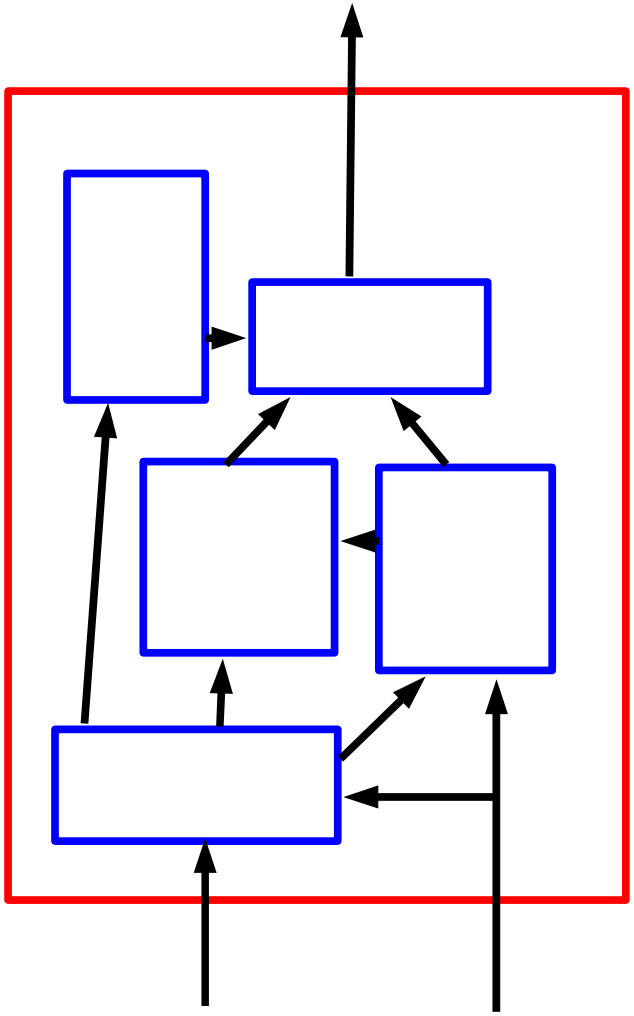
- **Convolutional net for handwriting recognition** (400,000 synapses)
- Convolutional layers (simple cells): all units in a feature plane share the same weights
- Pooling/subsampling layers (complex cells): for invariance to small distortions.
- **Supervised gradient-descent learning using back-propagation**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

Back-propagation: deep supervised gradient-based learning



- $\frac{\partial E}{\partial X_n} = \frac{\partial C(X_n, Y)}{\partial X_n}$
- $\frac{\partial E}{\partial X_{n-1}} = \frac{\partial E}{\partial X_n} \frac{\partial F_n(X_{n-1}, W_n)}{\partial X_{n-1}}$
- $\frac{\partial E}{\partial W_n} = \frac{\partial E}{\partial X_n} \frac{\partial F_n(X_{n-1}, W_n)}{\partial W_n}$
- $\frac{\partial E}{\partial X_{n-2}} = \frac{\partial E}{\partial X_{n-1}} \frac{\partial F_{n-1}(X_{n-2}, W_{n-1})}{\partial X_{n-2}}$
- $\frac{\partial E}{\partial W_{n-1}} = \frac{\partial E}{\partial X_{n-1}} \frac{\partial F_{n-1}(X_{n-2}, W_{n-1})}{\partial W_{n-1}}$
- ....etc, until we reach the first module.
- we now have all the $\frac{\partial E}{\partial W_i}$ for $i \in [1, n]$.

Any Architecture works

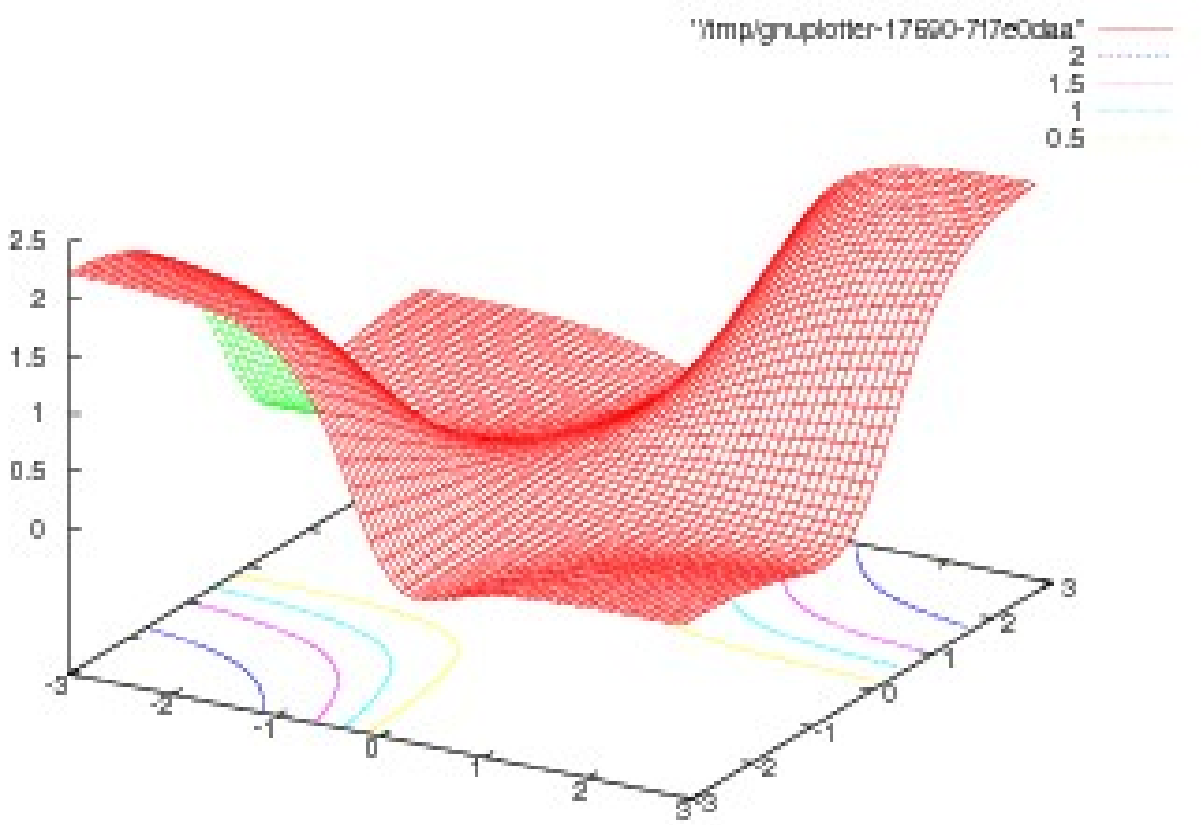


- **Any connection is permissible**
  - Networks with loops must be "unfolded in time".
- **Any module is permissible**
  - As long as it is continuous and differentiable almost everywhere with respect to the parameters, and with respect to non-terminal inputs.

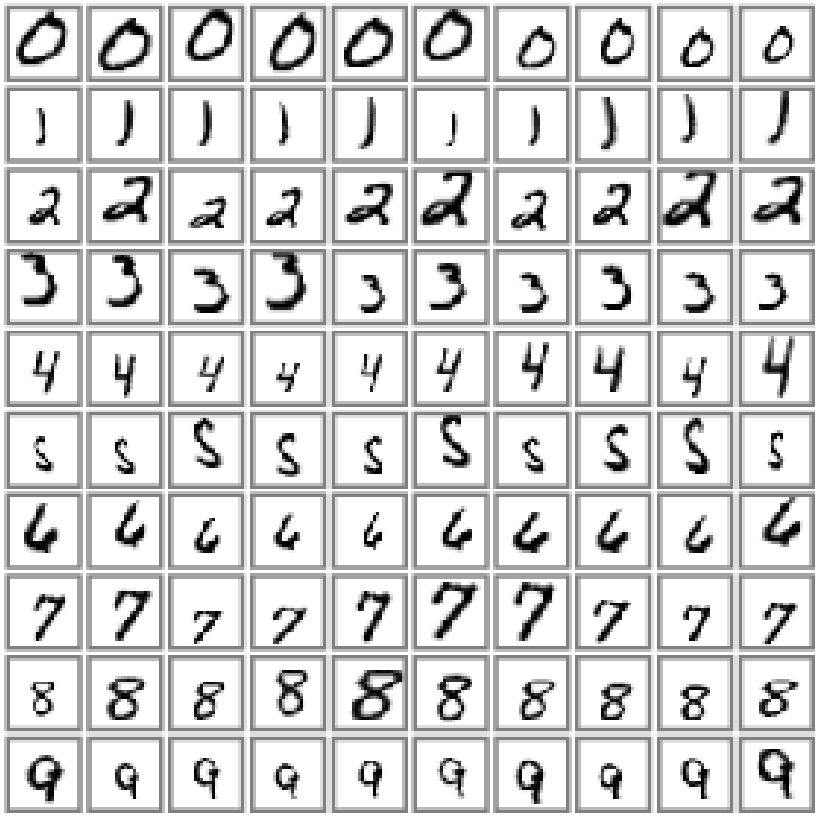
Deep Supervised Learning is Hard

- **Example: what is the loss function for the simplest 2-layer neural net ever**
  - Function: 1-1-1 neural net. Map 0.5 to 0.5 and -0.5 to -0.5 (identity function) with quadratic cost:

$$y = \tanh(W_1 \tanh(W_0.x)) \quad L = (0.5 - \tanh(W_1 \tanh(W_0 0.5)^2$$



MNIST Handwritten Digit Dataset



- Handwritten Digit Dataset MNIST: 60,000 training samples, 10,000 test samples

Results on MNIST Handwritten Digits

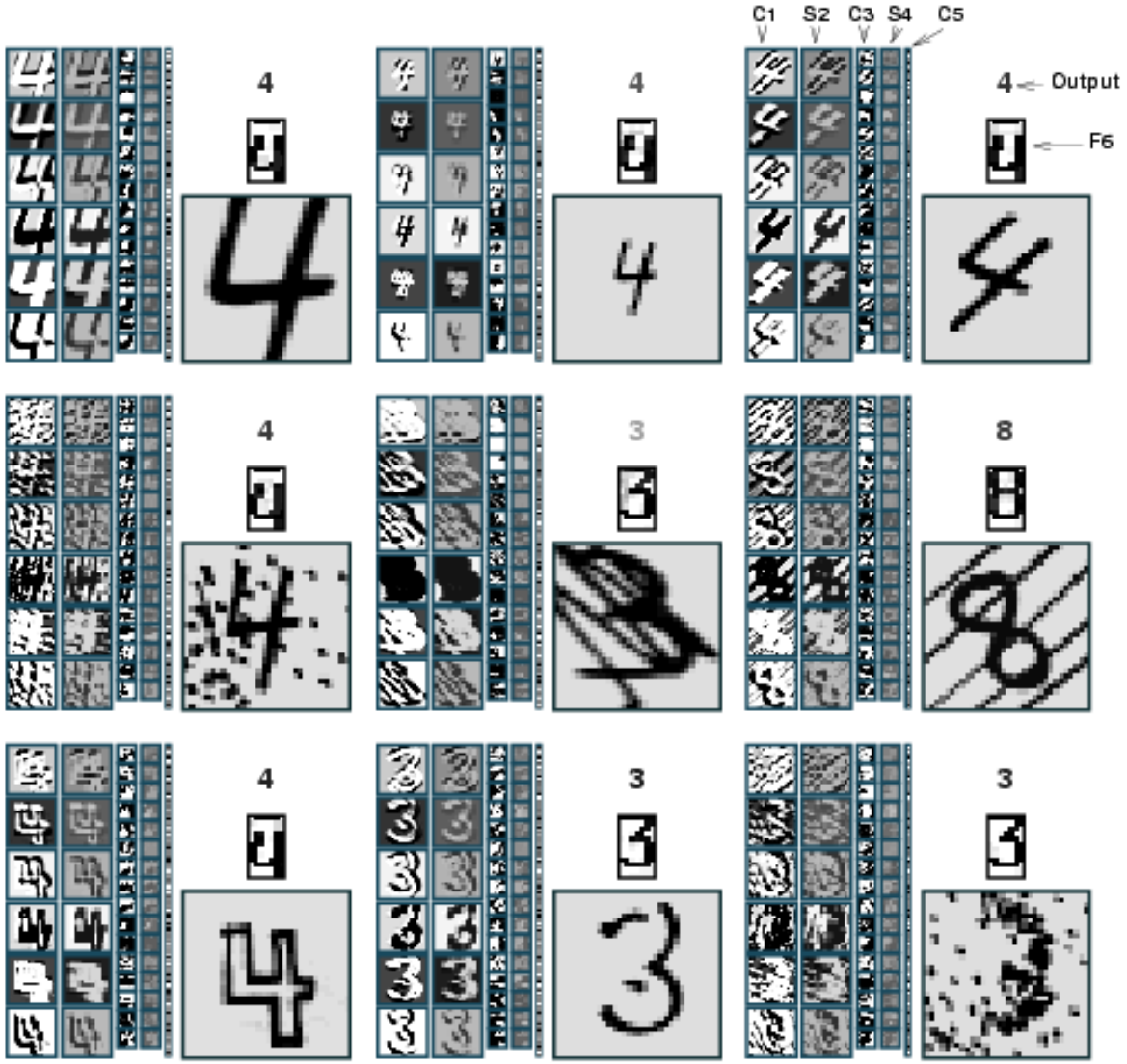
CLASSIFIER	DEFORMATION	PREPROCESSING	ERROR (%)	Reference
linear classifier (1-layer NN)		none	12.00	LeCun et al. 1998
linear classifier (1-layer NN)		deskewing	8.40	LeCun et al. 1998
pairwise linear classifier		deskewing	7.60	LeCun et al. 1998
K-nearest-neighbors, (L2)		none	3.09	Kenneth Wilder, U. Chicago
K-nearest-neighbors, (L2)		deskewing	2.40	LeCun et al. 1998
K-nearest-neighbors, (L2)		deskew, clean, blur	1.80	Kenneth Wilder, U. Chicago
K-NN L3, 2 pixel jitter		deskew, clean, blur	1.22	Kenneth Wilder, U. Chicago
K-NN, shape context matching		shape context feature	0.63	Belongie et al. IEEE PAMI 2002
40 PCA + quadratic classifier		none	3.30	LeCun et al. 1998
1000 RBF + linear classifier		none	3.60	LeCun et al. 1998
K-NN, Tangent Distance		subsamp 16x16 pixels	1.10	LeCun et al. 1998
SVM, Gaussian Kernel		none	1.40	
SVM deg 4 polynomial		deskewing	1.10	LeCun et al. 1998
Reduced Set SVM deg 5 poly		deskewing	1.00	LeCun et al. 1998
Virtual SVM deg-9 poly	Affine	none	0.80	LeCun et al. 1998
V-SVM, 2-pixel jittered		none	0.68	DeCoste and Scholkopf, MLJ 2002
V-SVM, 2-pixel jittered		deskewing	0.56	DeCoste and Scholkopf, MLJ 2002
2-layer NN, 300 HU, MSE		none	4.70	LeCun et al. 1998
2-layer NN, 300 HU, MSE,	Affine	none	3.60	LeCun et al. 1998
2-layer NN, 300 HU		deskewing	1.60	LeCun et al. 1998
3-layer NN, 500+150 HU		none	2.95	LeCun et al. 1998
3-layer NN, 500+150 HU	Affine	none	2.45	LeCun et al. 1998
3-layer NN, 500+300 HU, CE, reg		none	1.53	Hinton, unpublished, 2005
2-layer NN, 800 HU, CE		none	1.60	Simard et al., ICDAR 2003
2-layer NN, 800 HU, CE	Affine	none	1.10	Simard et al., ICDAR 2003
2-layer NN, 800 HU, MSE	Elastic	none	0.90	Simard et al., ICDAR 2003
2-layer NN, 800 HU, CE	Elastic	none	0.70	Simard et al., ICDAR 2003
Convolutional net LeNet-1		subsamp 16x16 pixels	1.70	LeCun et al. 1998
Convolutional net LeNet-4		none	1.10	LeCun et al. 1998
Convolutional net LeNet-5,		none	0.95	LeCun et al. 1998
Conv. net LeNet-5,	Affine	none	0.80	LeCun et al. 1998
Boosted LeNet-4	Affine	none	0.70	LeCun et al. 1998
Conv. net, CE	Affine	none	0.60	Simard et al., ICDAR 2003
Comv net, CE	Elastic	none	0.40	Simard et al., ICDAR 2003

Some Results on MNIST (from raw images: no preprocessing)

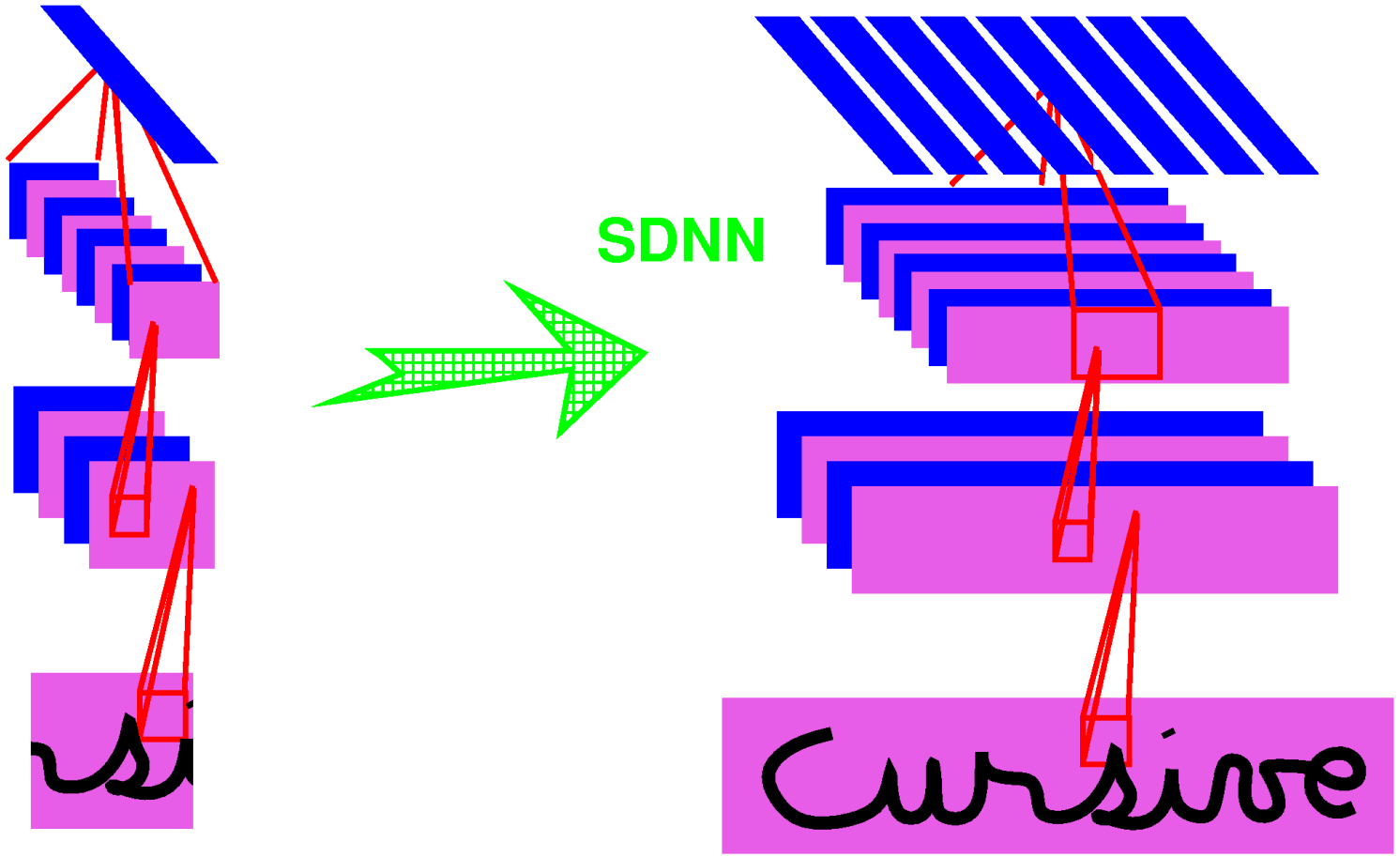
CLASSIFIER	DEFORMATION	ERROR	Reference
Knowledge-free methods (a fixed permutation of the pixels would make no difference)			
2-layer NN, 800 HU, CE		1.60	Simard et al., ICDAR 2003
3-layer NN, 500+300 HU, CE, reg		1.53	Hinton, in press, 2005
SVM, Gaussian Kernel		1.40	Cortes 92 + Many others
Convolutional nets			
Convolutional net LeNet-5,		0.80	Ranzato et al. NIPS 2006
Convolutional net LeNet-6,		0.70	Ranzato et al. NIPS 2006
Training set augmented with Affine Distortions			
2-layer NN, 800 HU, CE	Affine	1.10	Simard et al., ICDAR 2003
Virtual SVM deg-9 poly	Affine	0.80	Scholkopf
Convolutional net, CE	Affine	0.60	Simard et al., ICDAR 2003
Training et augmented with Elastic Distortions			
2-layer NN, 800 HU, CE	Elastic	0.70	Simard et al., ICDAR 2003
Convolutional net, CE	Elastic	0.40	Simard et al., ICDAR 2003

Note: some groups have obtained good results with various amounts of preprocessing such as deskewing (e.g. 0.56% using an SVM with smart kernels [deCoste and Schoelkopf]) hand-designed feature representations (e.g. 0.63% with "shape context" and nearest neighbor [Belongie]

Invariance and Robustness to Noise

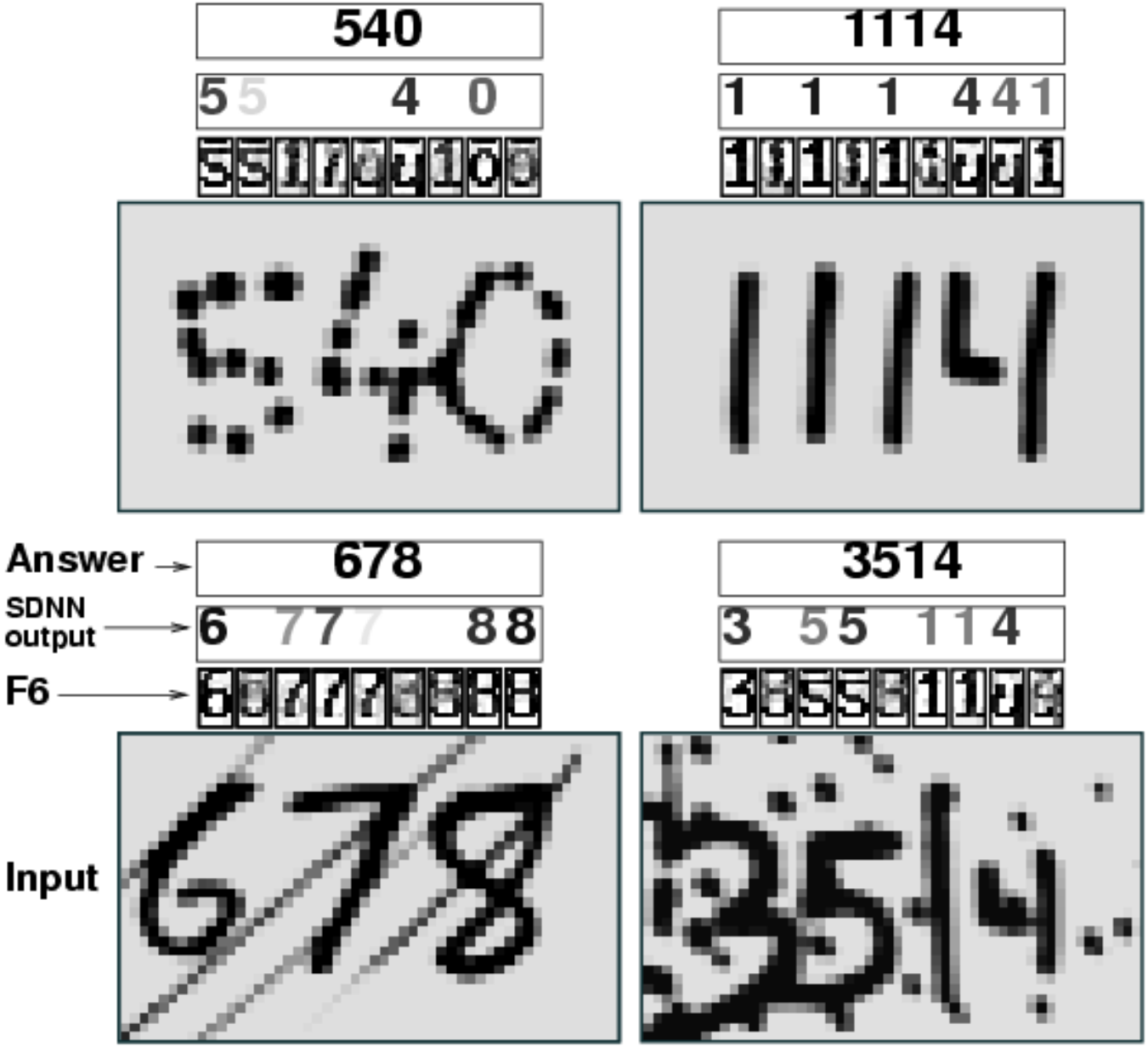


Recognizing Multiple Characters with Replicated Nets



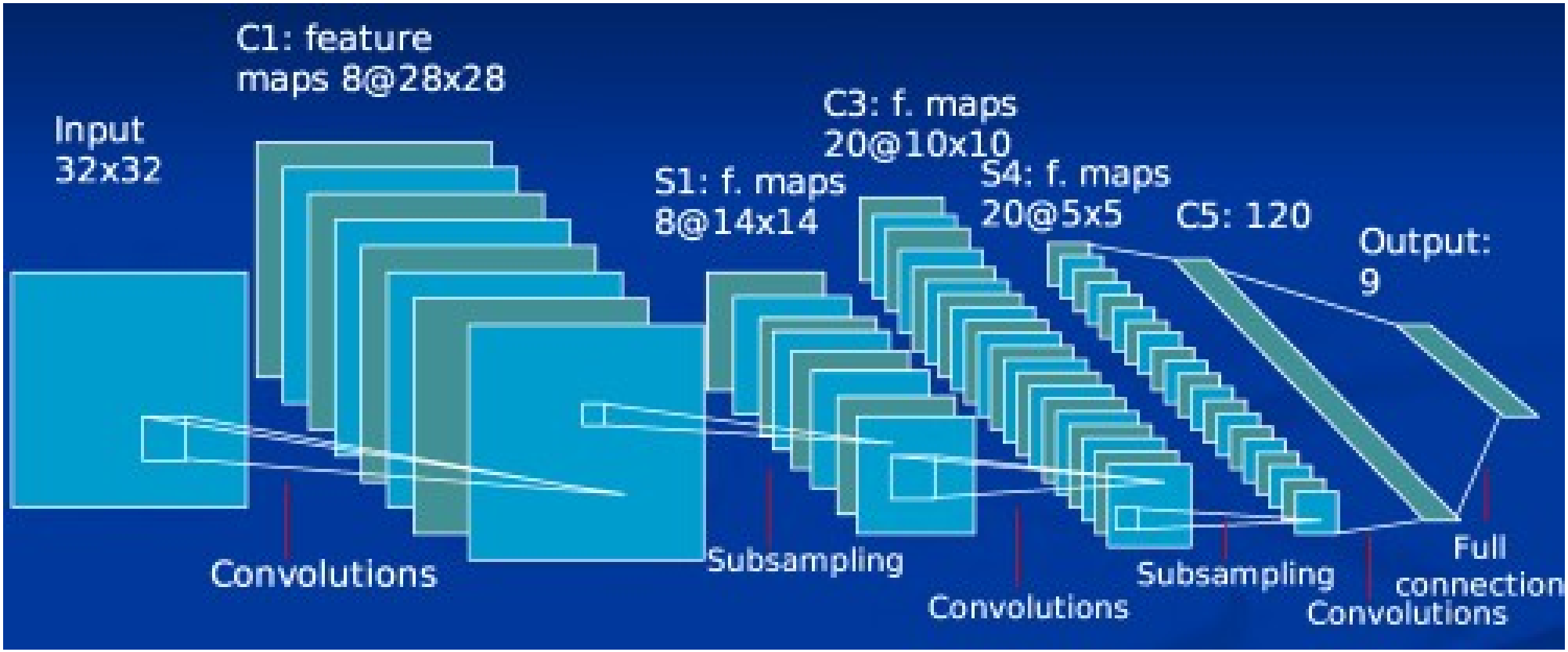
Recognizing Multiple Characters with Replicated Nets

Handwriting Recognition



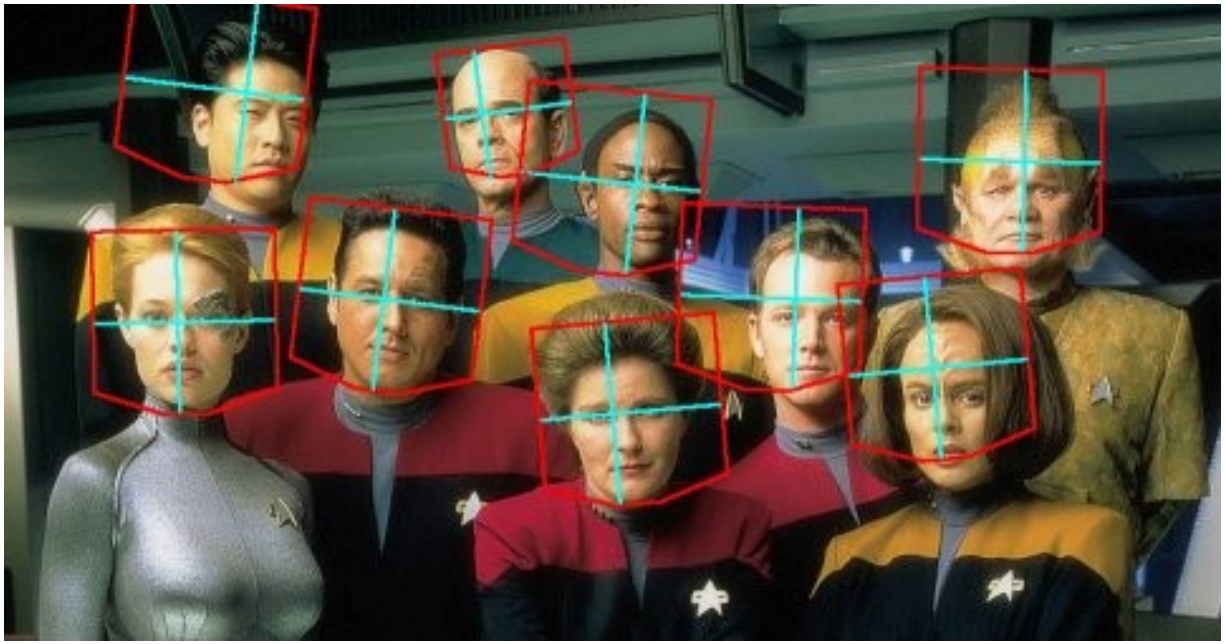
Face Detection and Pose Estimation with Convolutional Nets

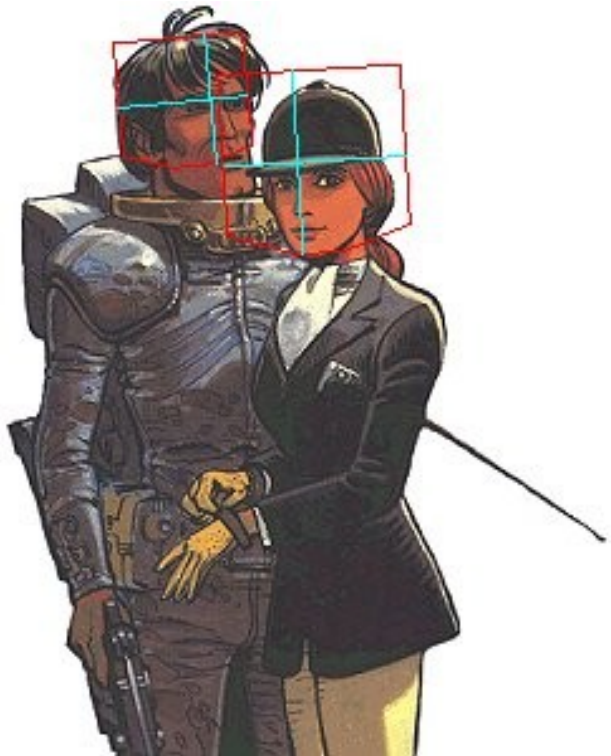
- **Training:** 52,850, 32x32 grey-level images of faces, 52,850 non-faces.
- **Each sample:** used 5 times with random variation in scale, in-plane rotation, brightness and contrast.
- **2nd phase:** half of the initial negative set was replaced by false positives of the initial version of the detector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



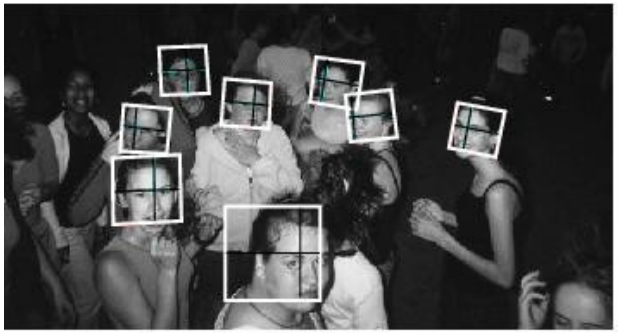
Face Detection: Results

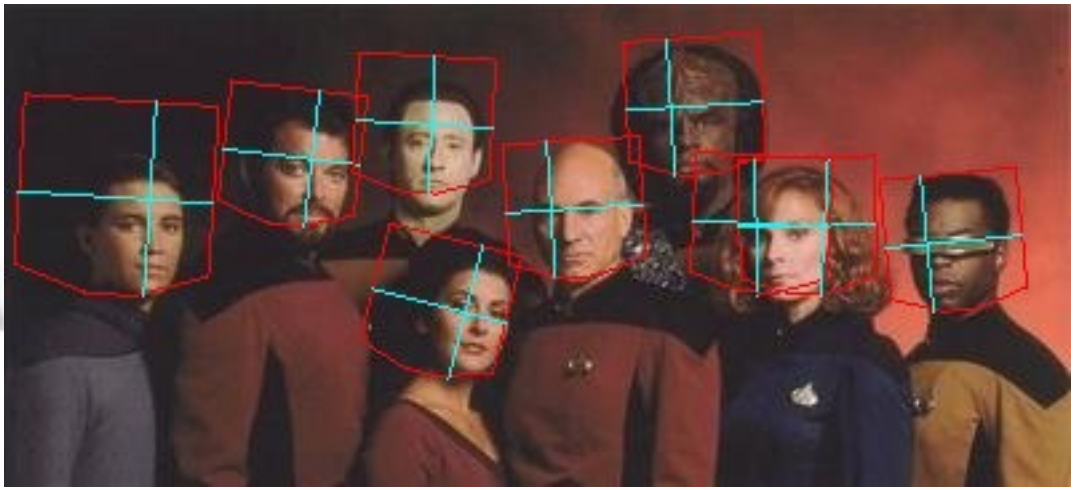
Data Set->	TILTED		PROFILE		MIT+CMU	
False positives per image->	4.42	26.9	0.47	3.36	0.5	1.28
Our Detector	90%	97%	67%	83%	83%	88%
Jones & Viola (tilted)	90%	95%	x		x	
Jones & Viola (profile)	x		70%	83%	x	

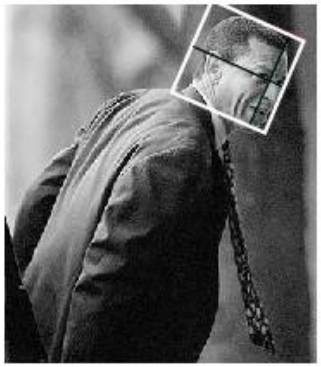


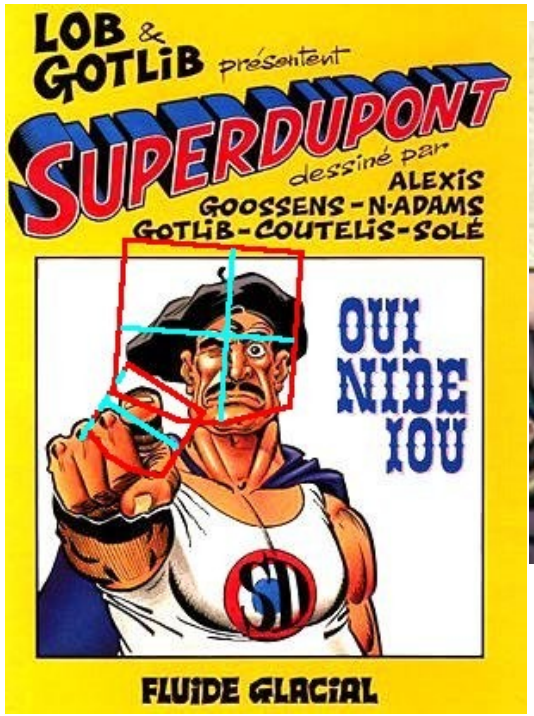


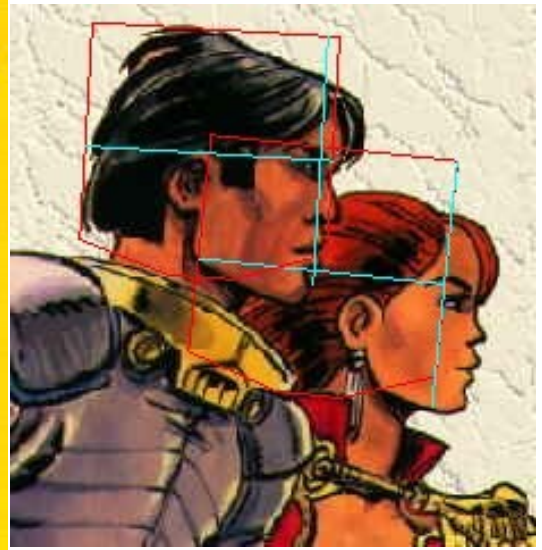
Face Detection and Pose Estimation: Results





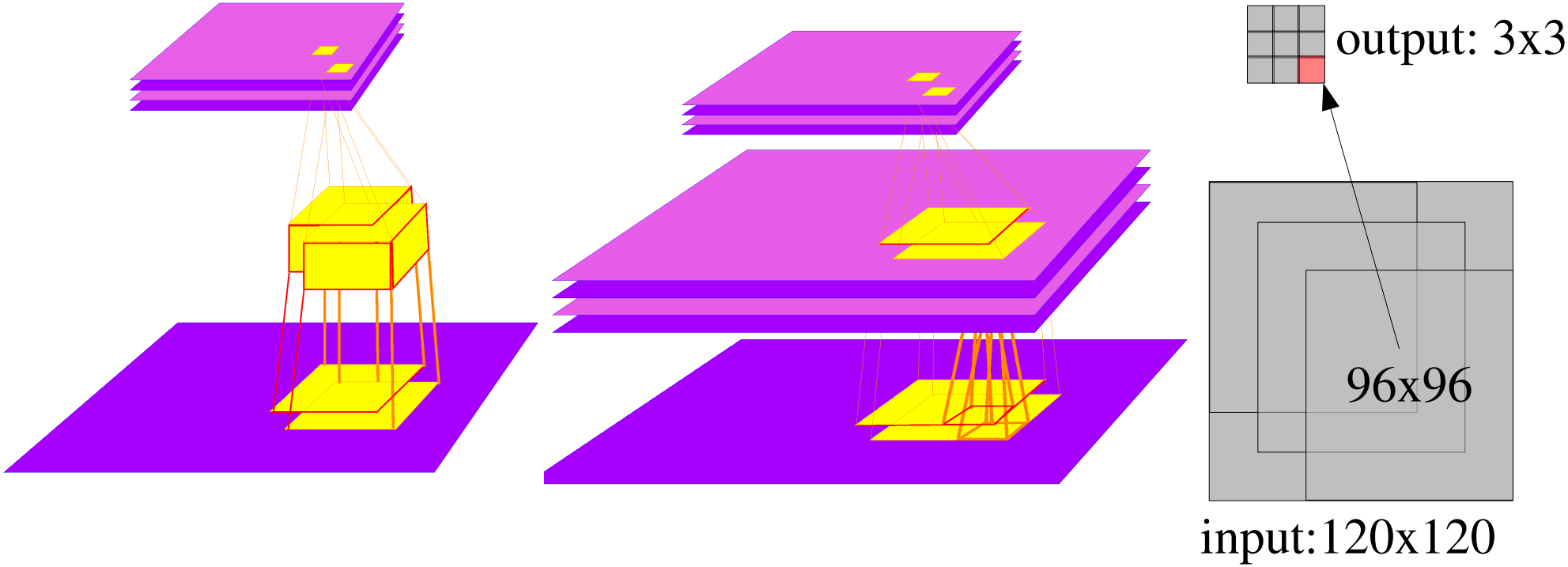






Face Detection with a Convolutional Net

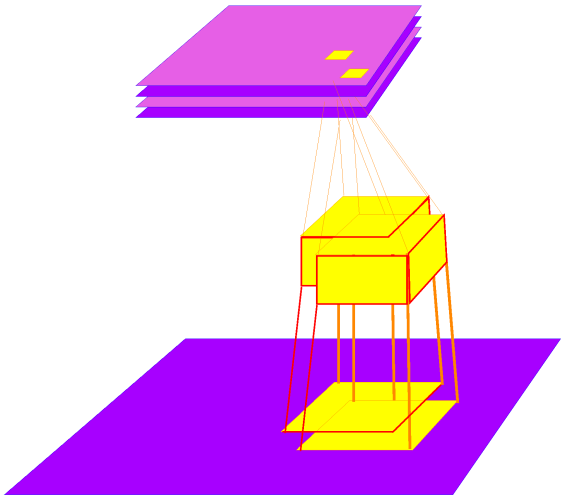
Applying a ConvNet on Sliding Windows is Very Cheap!

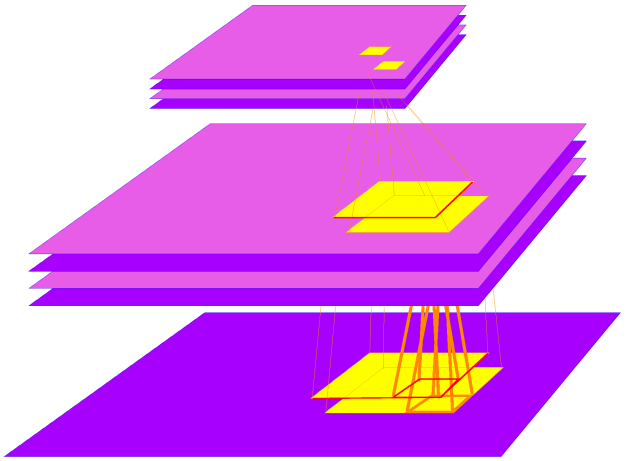


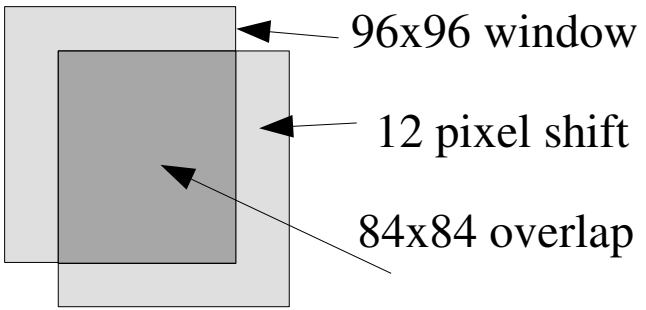
- Traditional Detectors/Classifiers must be applied to every location on a large input image, at multiple scales.
- Convolutional nets can replicated over large images very cheaply.
- The network is applied to multiple scales spaced by 1.5.

Building a Detector/Recognizer: Replicated Convolutional Nets

- Computational cost for replicated convolutional net:
  - 96x96 -> 4.6 million multiply-accumulate operations
  - 120x120 -> 8.3 million multiply-accumulate operations
  - 240x240 -> 47.5 million multiply-accumulate operations
  - 480x480 -> 232 million multiply-accumulate operations
- Computational cost for a non-convolutional detector of the same size, applied every 12 pixels:
  - 96x96 -> 4.6 million multiply-accumulate operations
  - 120x120 -> 42.0 million multiply-accumulate operations
  - 240x240 -> 788.0 million multiply-accumulate operations
  - 480x480 -> 5,083 million multiply-accumulate operations



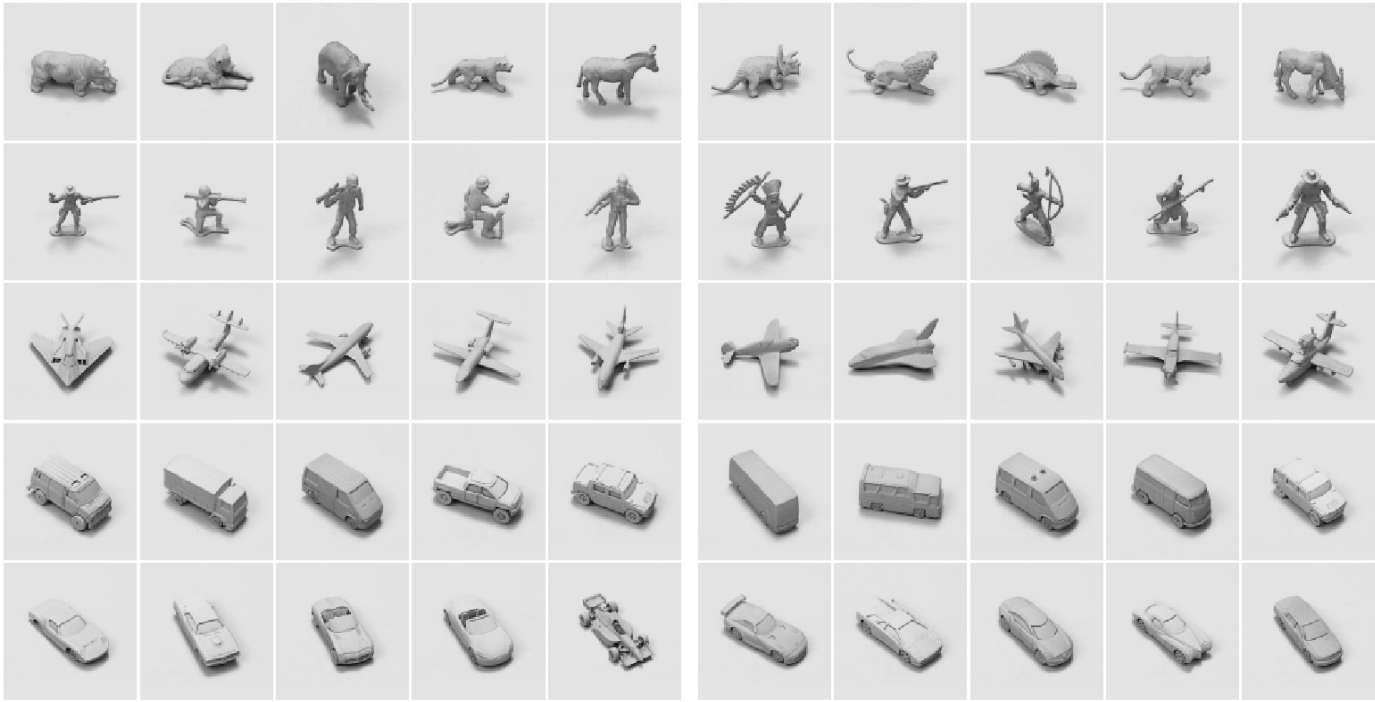




Generic Object Detection and Recognition with Invariance to Pose and Illumination

- **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.

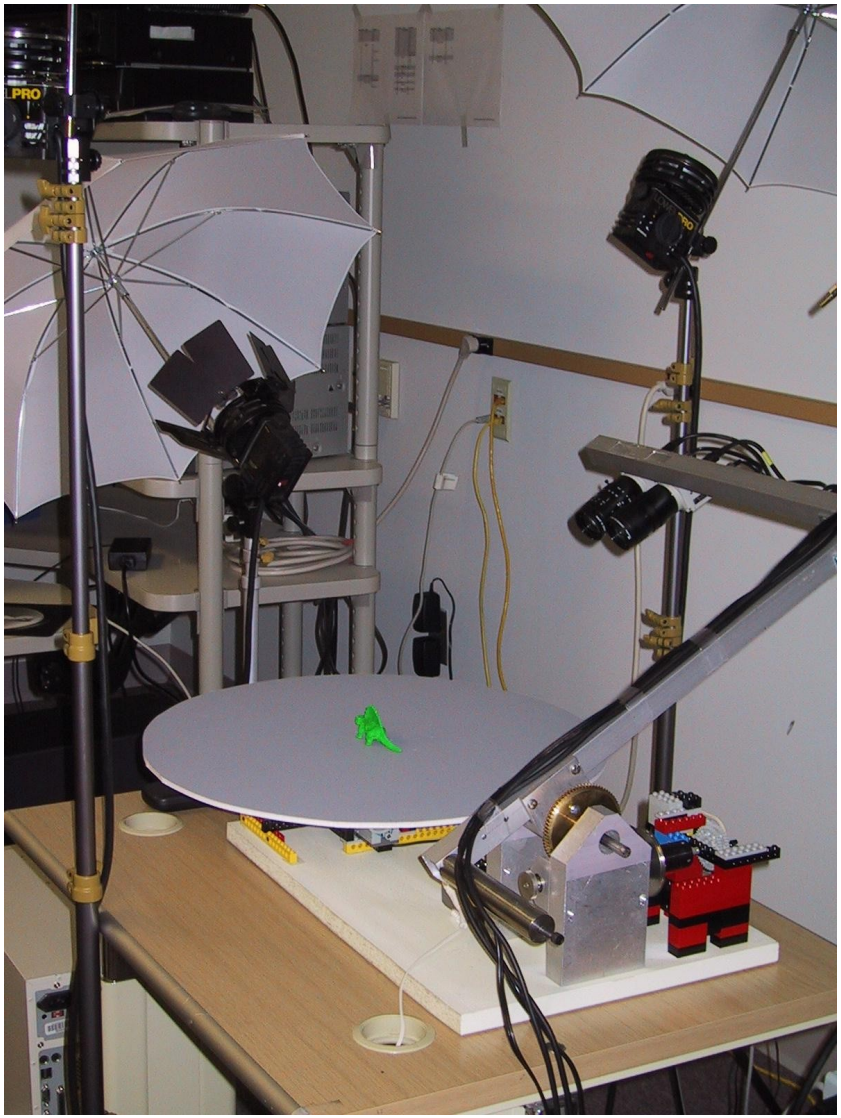
- **For each instance:**
- **18 azimuths**
  - 0 to 350 degrees every 20 degrees
- **9 elevations**
  - 30 to 70 degrees from horizontal every 5 degrees
- **6 illuminations**
  - on/off combinations of 4 lights
- **2 cameras (stereo)**
  - 7.5 cm apart
  - 40 cm from the object



Training instances **Test instances**

Data Collection, Sample Generation

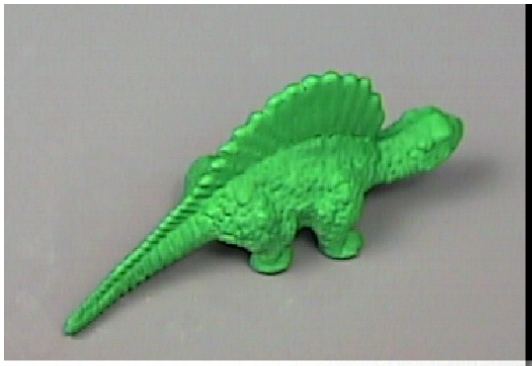
Image capture setup



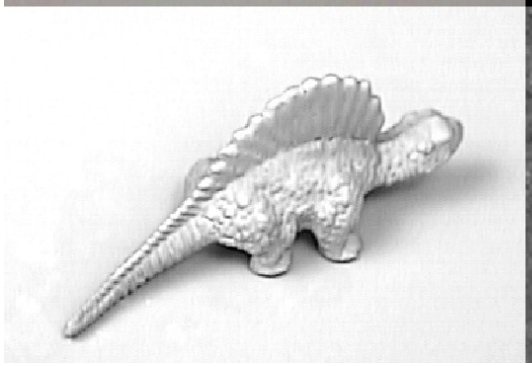
Objects are painted green so that:

- all features other than shape are removed
- objects can be segmented, transformed, and composited onto various backgrounds

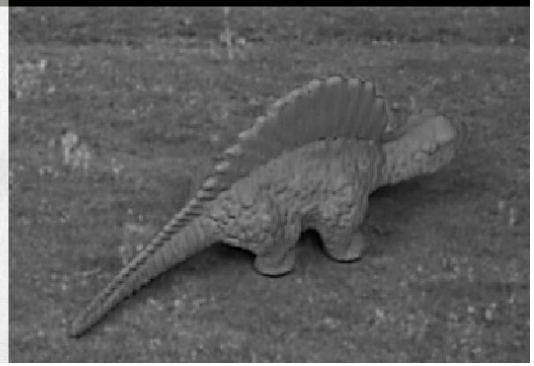
Original image



Object mask

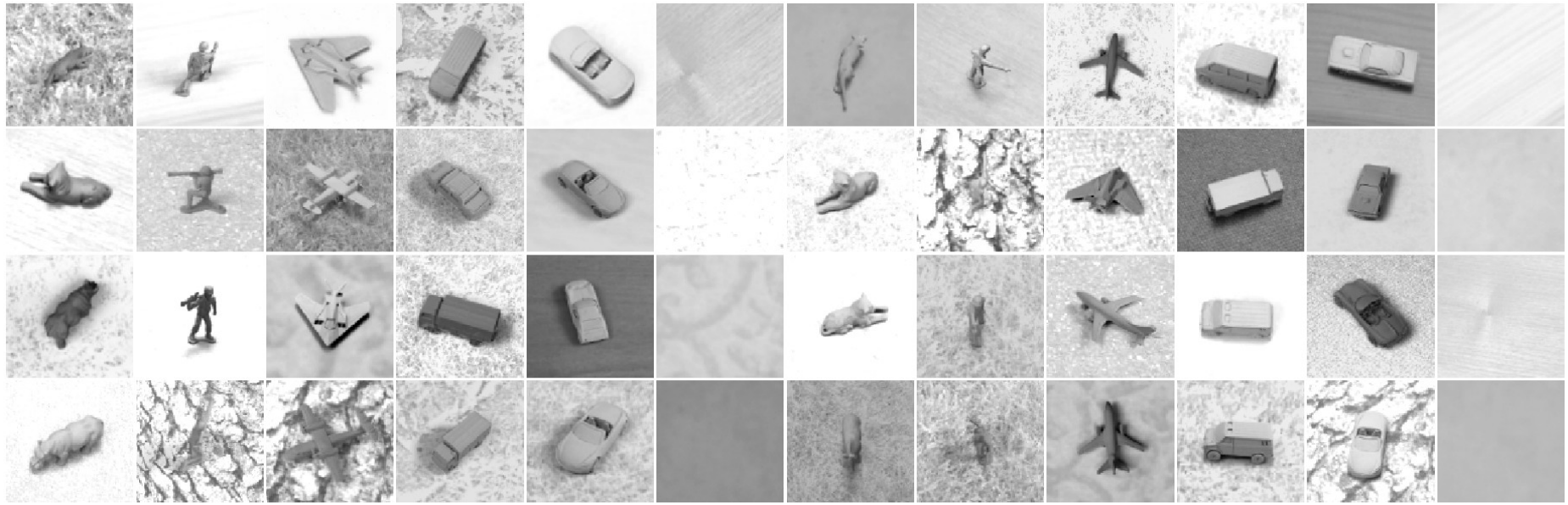


Shadow factor



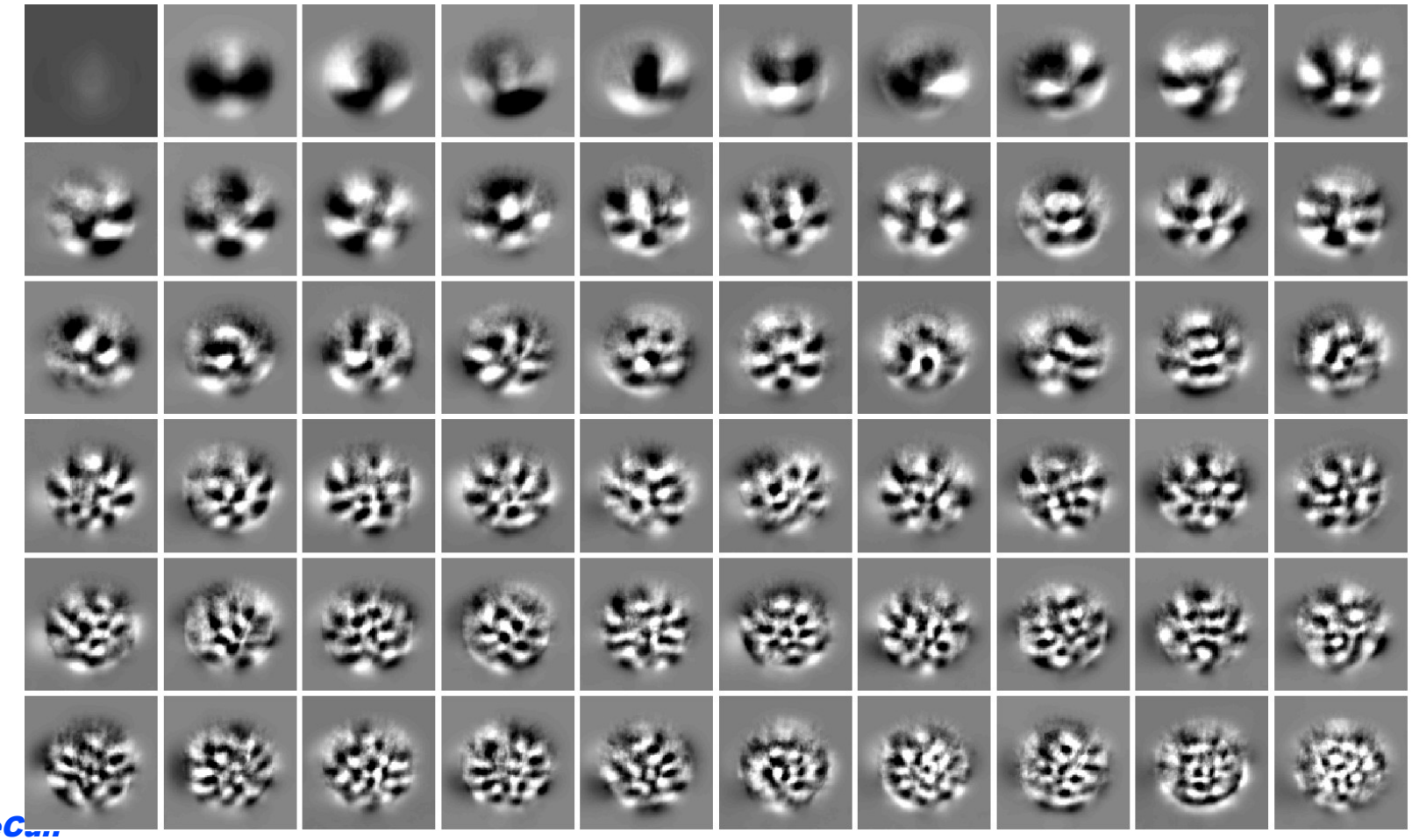
Composite image

Textured and Cluttered Datasets



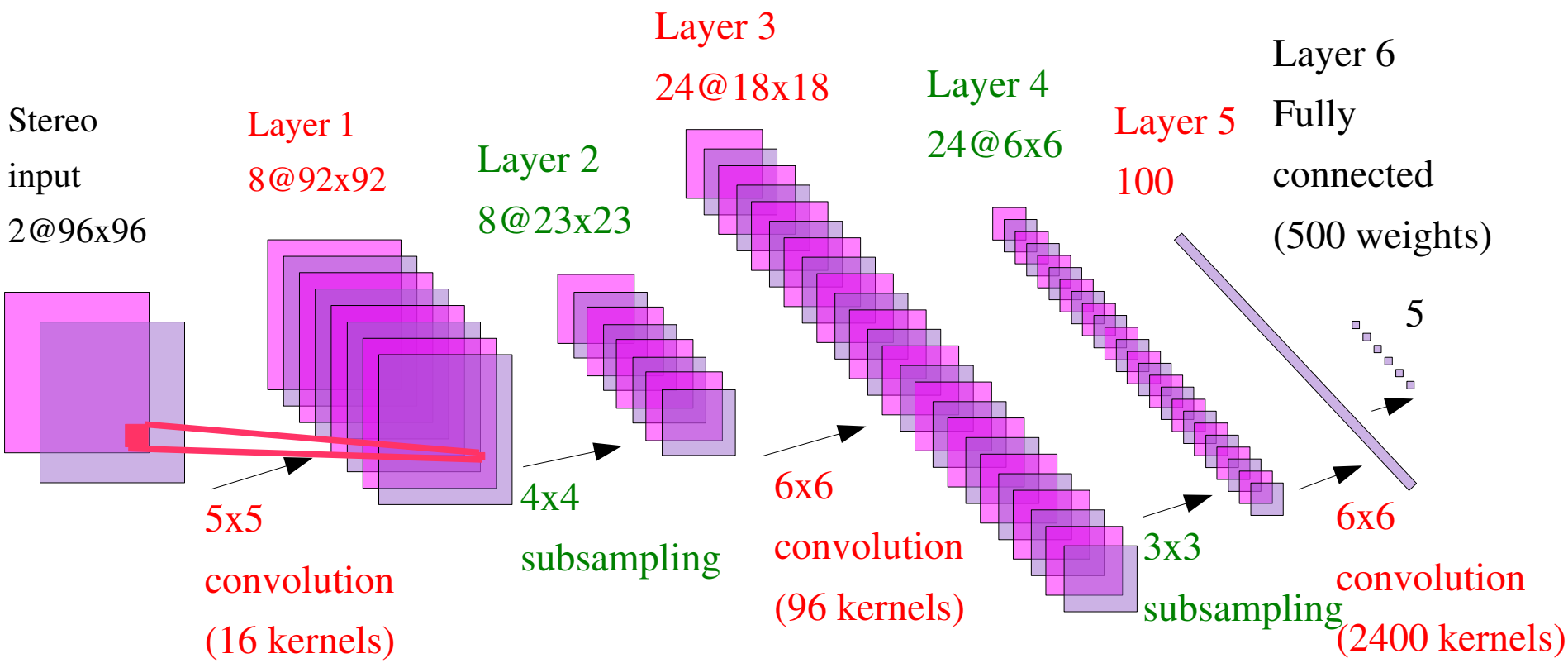
Experiment 1: Normalized-Uniform Set: Representations

- **1 - Raw Stereo Input:** 2 images 96x96 pixels **input dim. = 18432**
- **2 - Raw Monocular Input:**1 image, 96x96 pixels **input dim. = 9216**
- **3 – Subsampled Mono Input:** 1 image, 32x32 pixels **input dim = 1024**
- **4 – PCA-95 (EigenToys):** First 95 Principal Components **input dim. = 95**



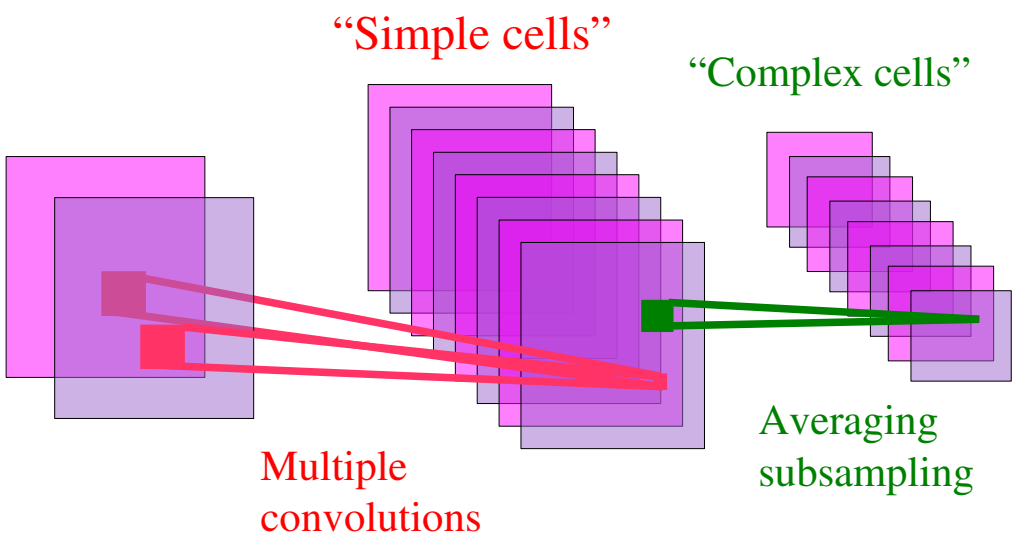
First 60 eigenvectors (EigenToys)

Convolutional Network

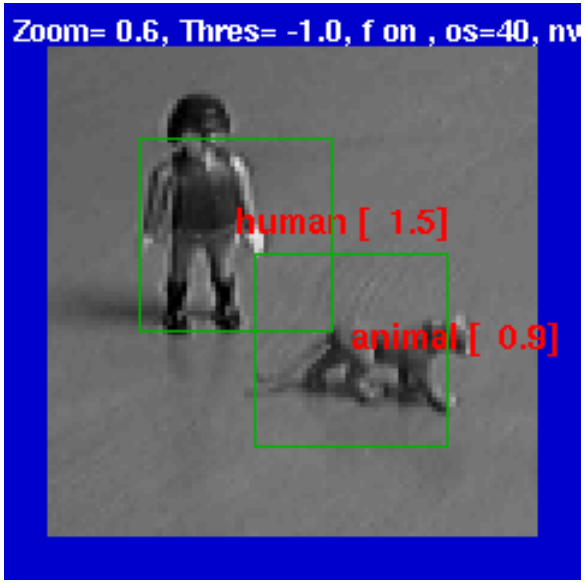


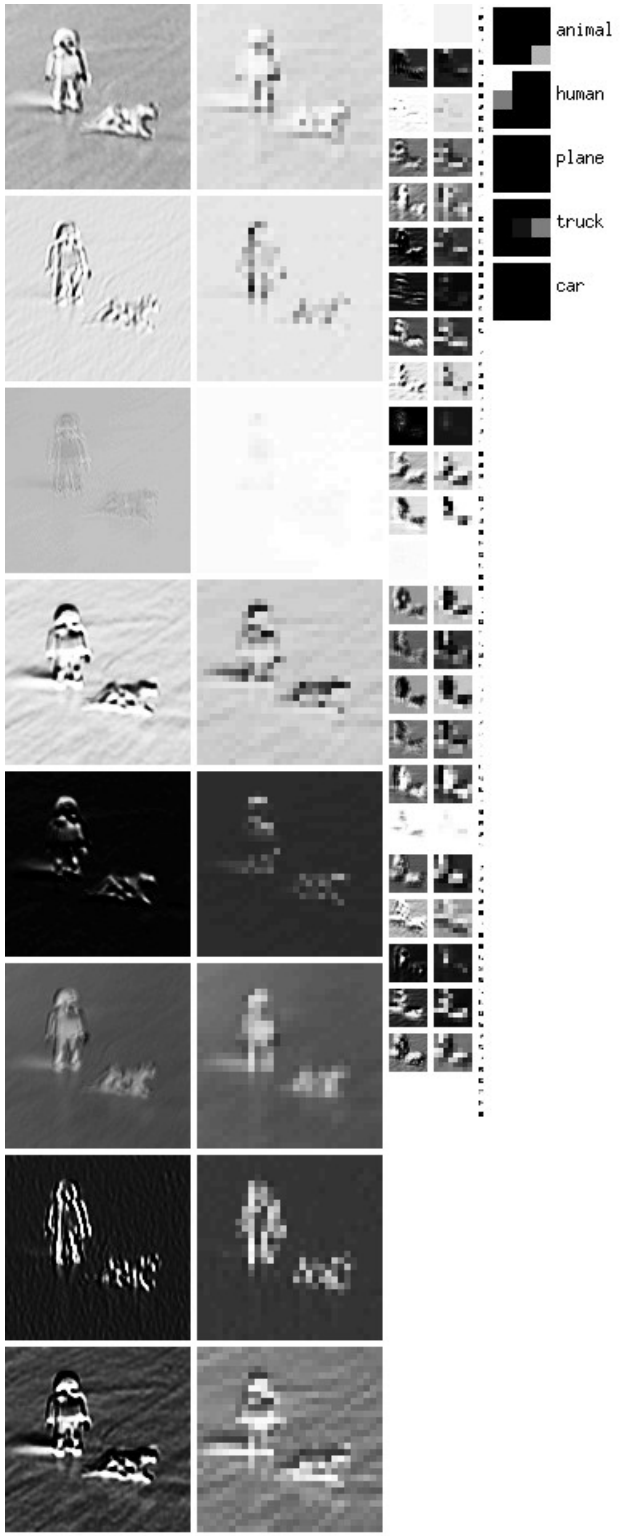
- **90,857 free parameters, 3,901,162 connections.**
- The architecture alternates convolutional layers (feature detectors) and subsampling layers (local feature pooling for invariance to small distortions).
- **The entire network is trained end-to-end** (all the layers are trained simultaneously).
-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

Alternated Convolutions and Subsampling



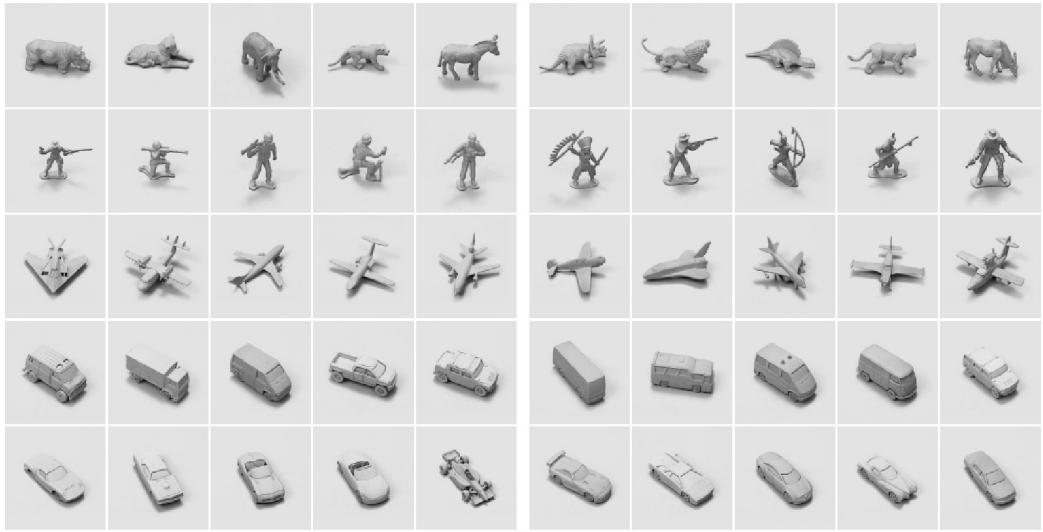
- Local features are extracted everywhere.
- averaging/subsampling layer builds robustness to variations in feature locations.
- Hubel/Wiesel'62, Fukushima'71, LeCun'89, Riesenhuber & Poggio'02, Ullman'02,....





Normalized-Uniform Set: Error Rates

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



Training instances Test instances

Normalized-Uniform Set: Learning Times

	SVM	Conv Net				SVM/Conv
test error	11.6%	10.4%	6.2%	5.8%	6.2%	5.9%
train time (min*GHz)	480	64	384	640	3,200	50+
test time per sample (sec*GHz)	0.95	0.03				0.04+
#SV	28%					28%
parameters	σ=2,000 C=40					dim=80 σ=5 C=0.01

SVM: using a parallel implementation by Graf, Durdanovic, and Cosatto (NEC Labs)

Chop off the last layer of the convolutional net and train an SVM on it

Jittered-Cluttered Dataset

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

Experiment 2: Jittered-Cluttered Dataset

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

Jittered-Cluttered Dataset

	SVM	Conv Net			SVM/Conv
test error	43.3%	16.38%	7.5%	7.2%	5.9%
train time (min*GHz)	10,944	420	2,100	5,880	330+
test time per sample (sec*GHz)	2.2	0.04			0.06+
#SV	5%				2%
parameters	σ=10^4 C=40				dim=100 σ=5 C=1

OUCH!

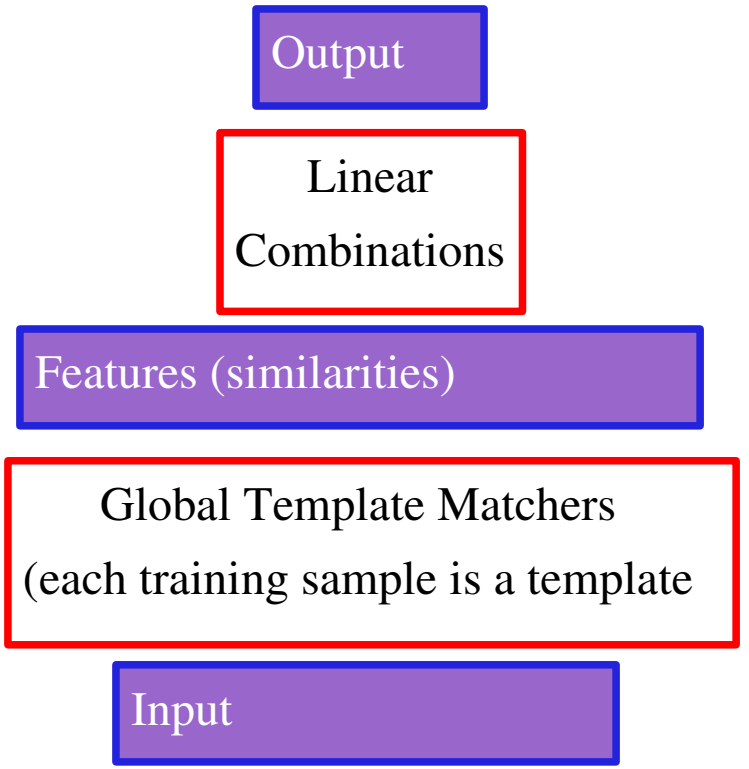
The convex loss, VC bounds and representers theorems don't seem to help

Chop off the last layer, and train an SVM on it it works!

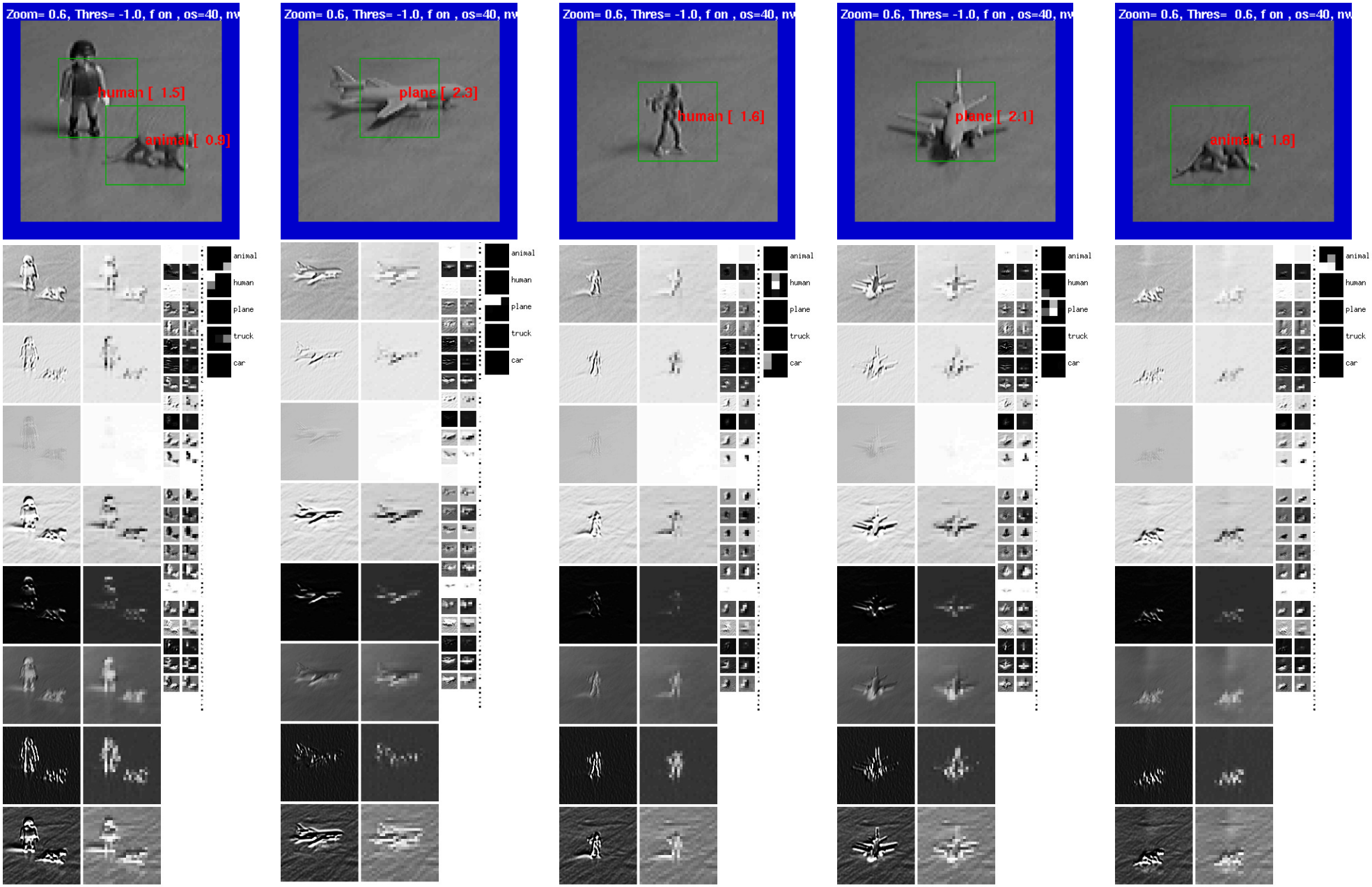
What's wrong with K-NN and SVMs?

- **K-NN and SVM with Gaussian kernels are based on matching global templates**
- **Both are "shallow" architectures**
- **There is now way to learn invariant recognition tasks with such naïve architectures (unless we use an impractically large number of templates).**

- **The number of necessary templates grows exponentially with the number of dimensions of variations.**
- **Global templates are in trouble when the variations include: category, instance shape, configuration (for articulated object), position, azimuth, elevation, scale, illumination, texture, albedo, in-plane rotation, background luminance, background texture, background clutter, ...**



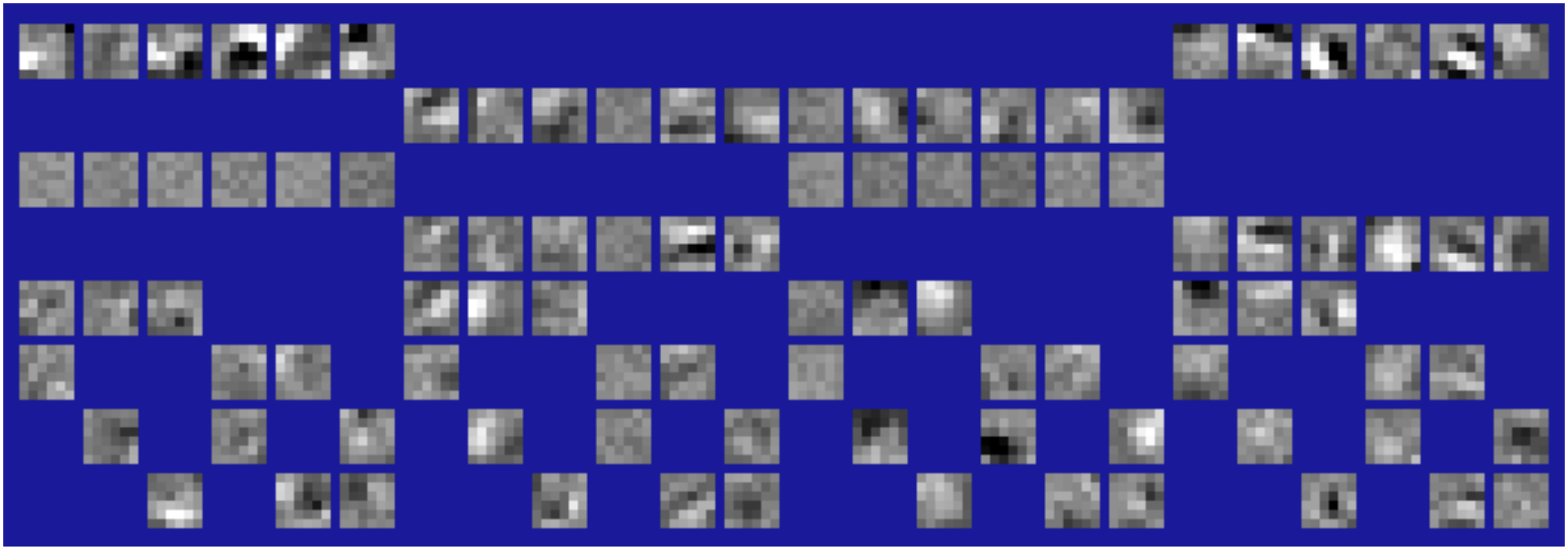
Examples (Monocular Mode)



Learned Features

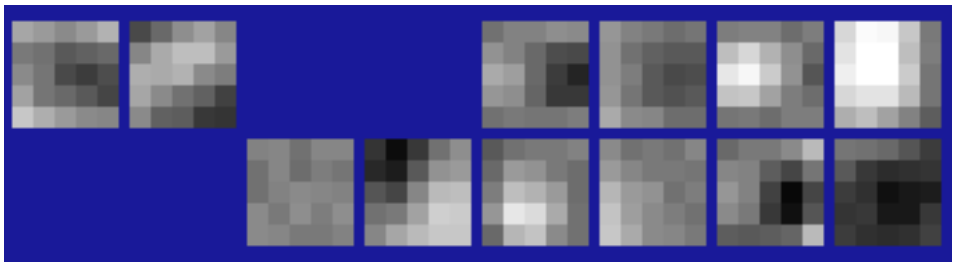
Layer 3

Layer 2

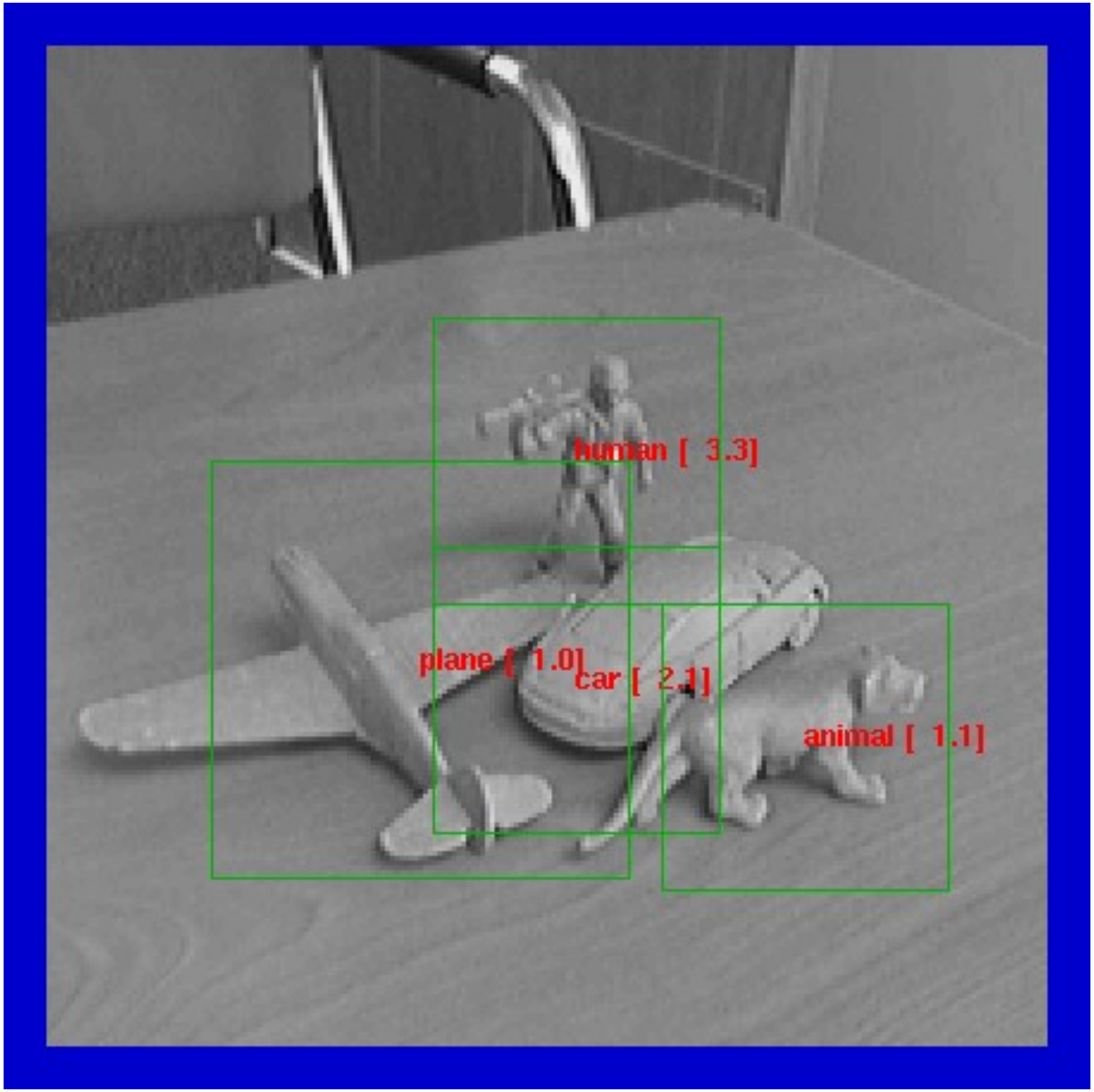


Layer 1

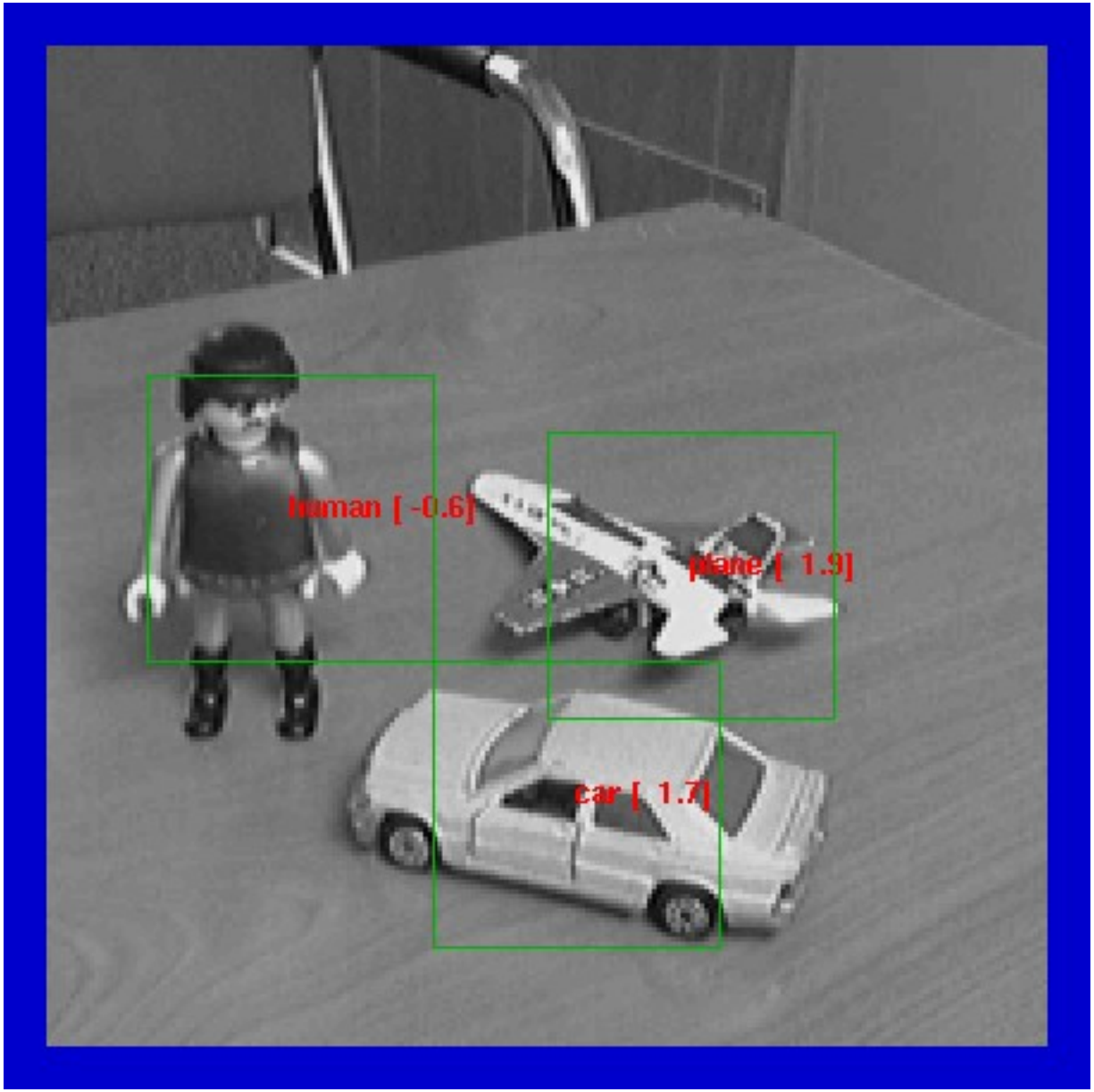
Input



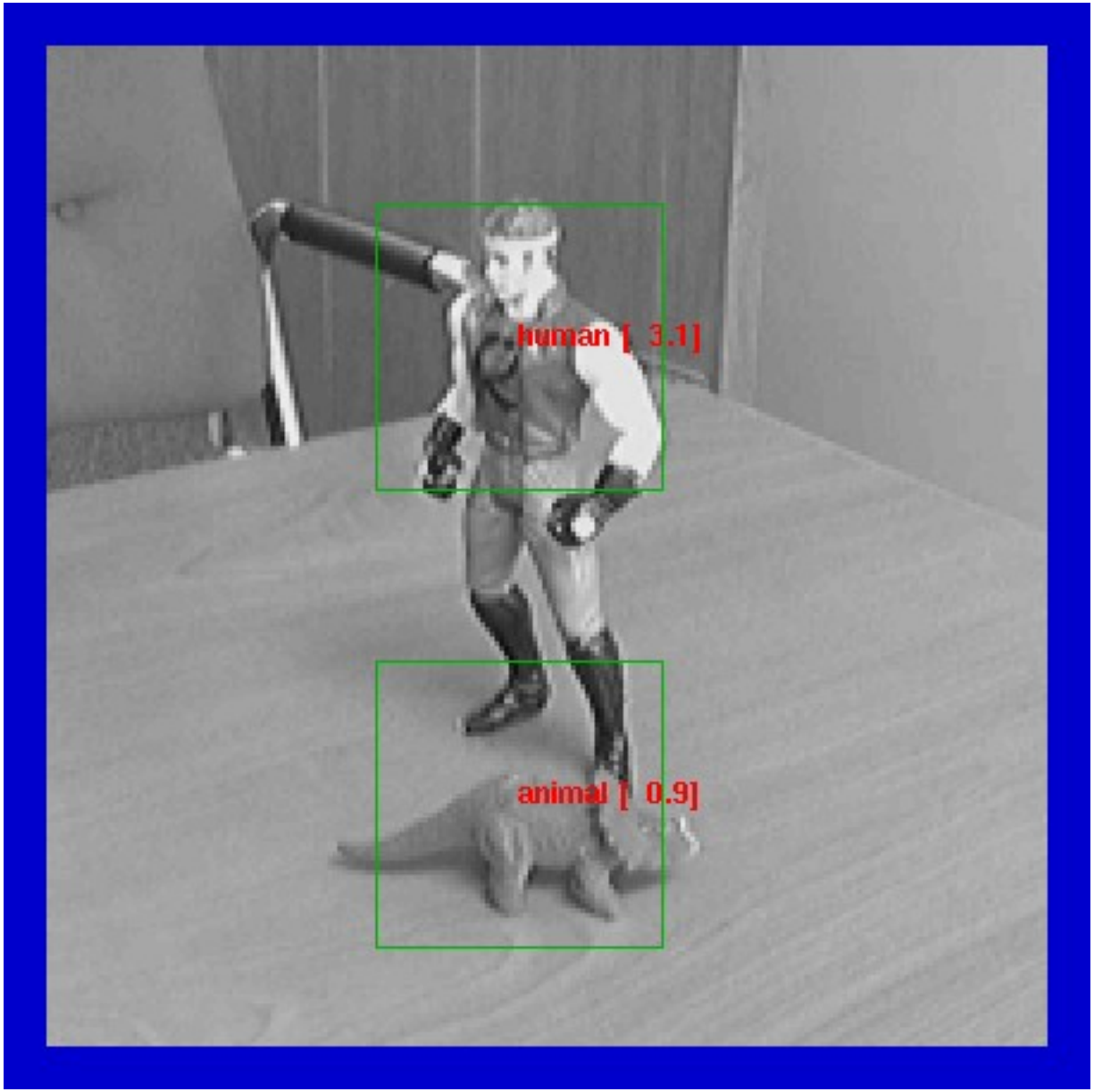
Examples (Monocular Mode)



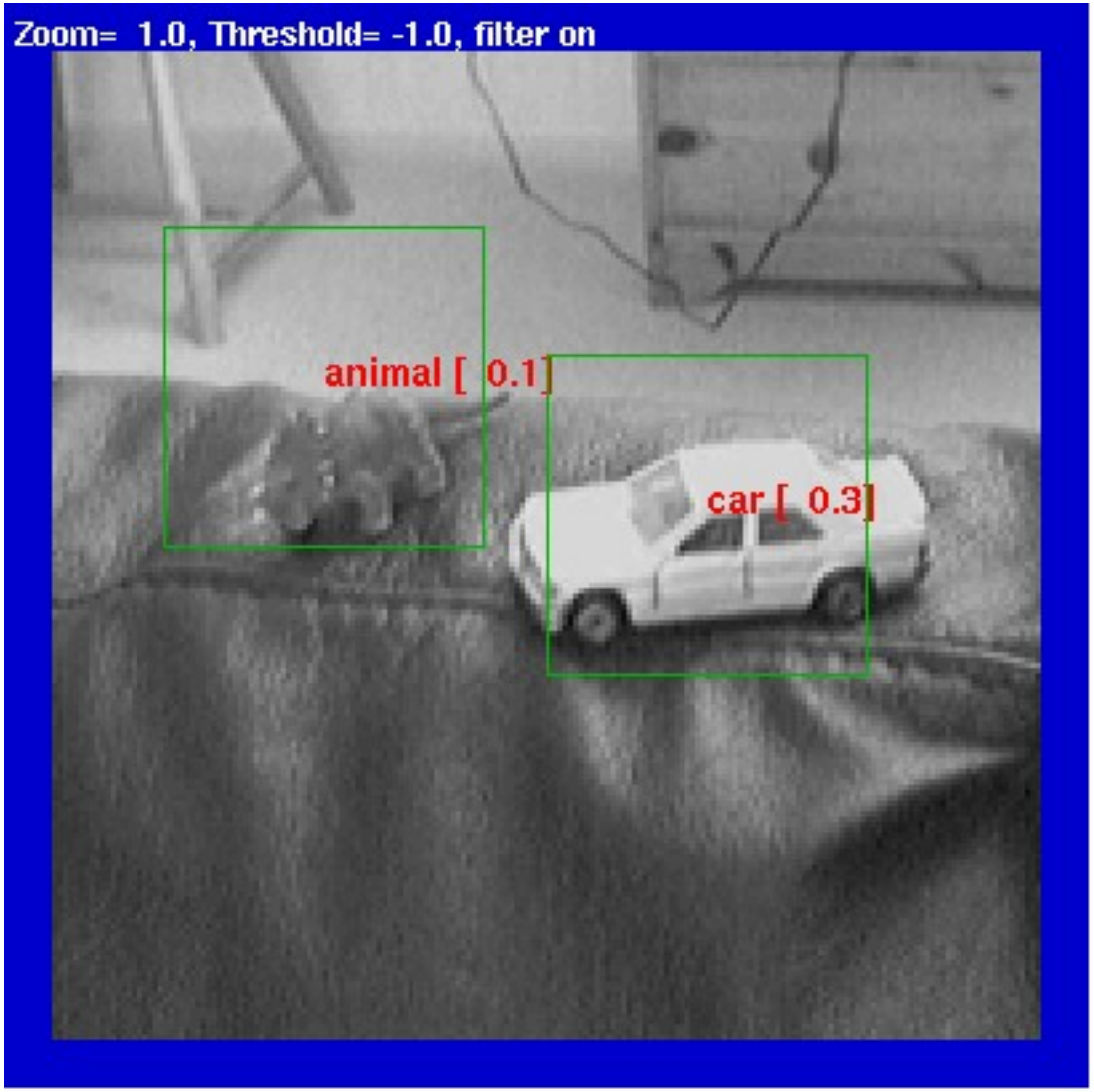
Examples (Monocular Mode)



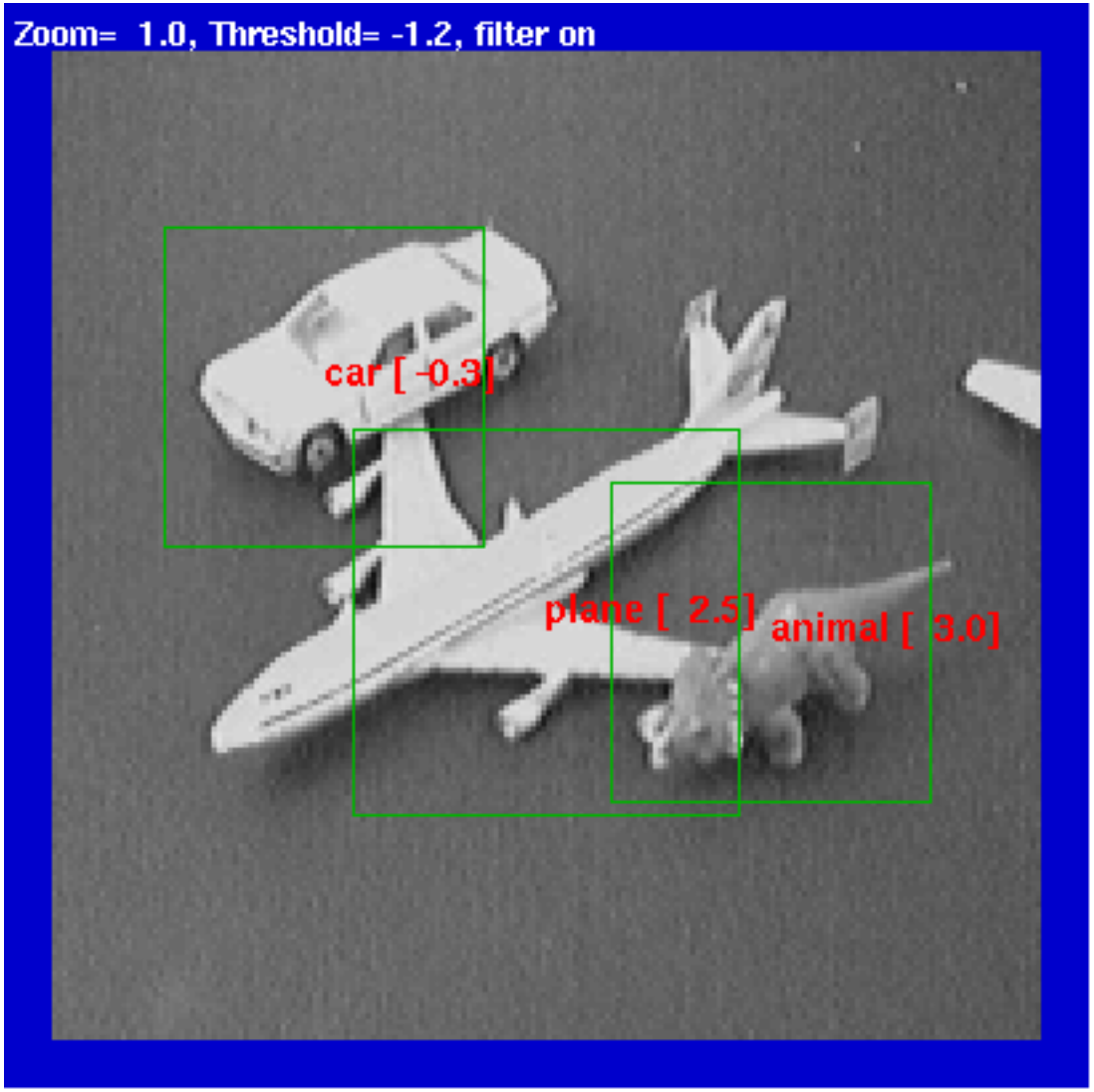
Examples (Monocular Mode)



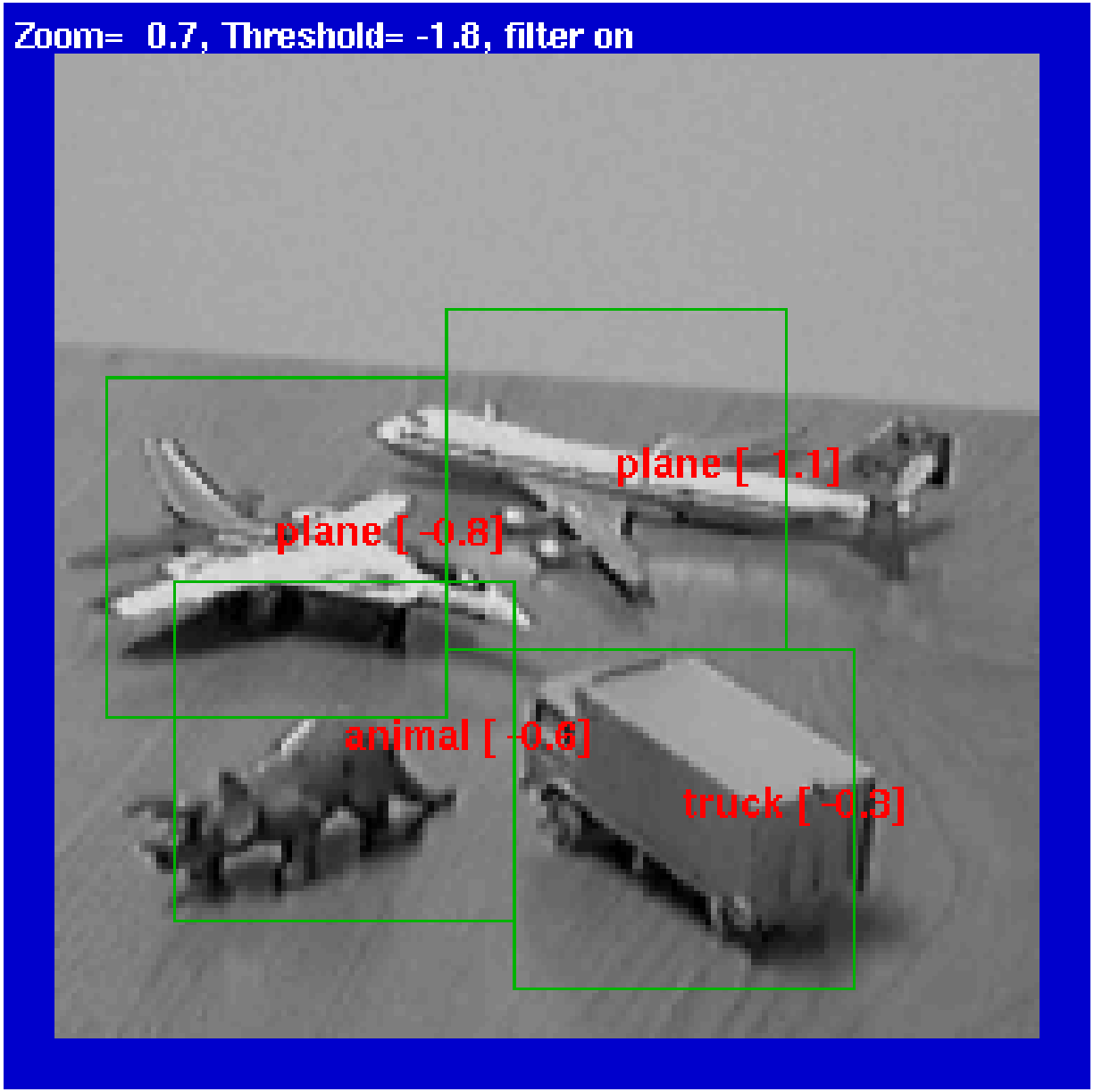
Examples (Monocular Mode)



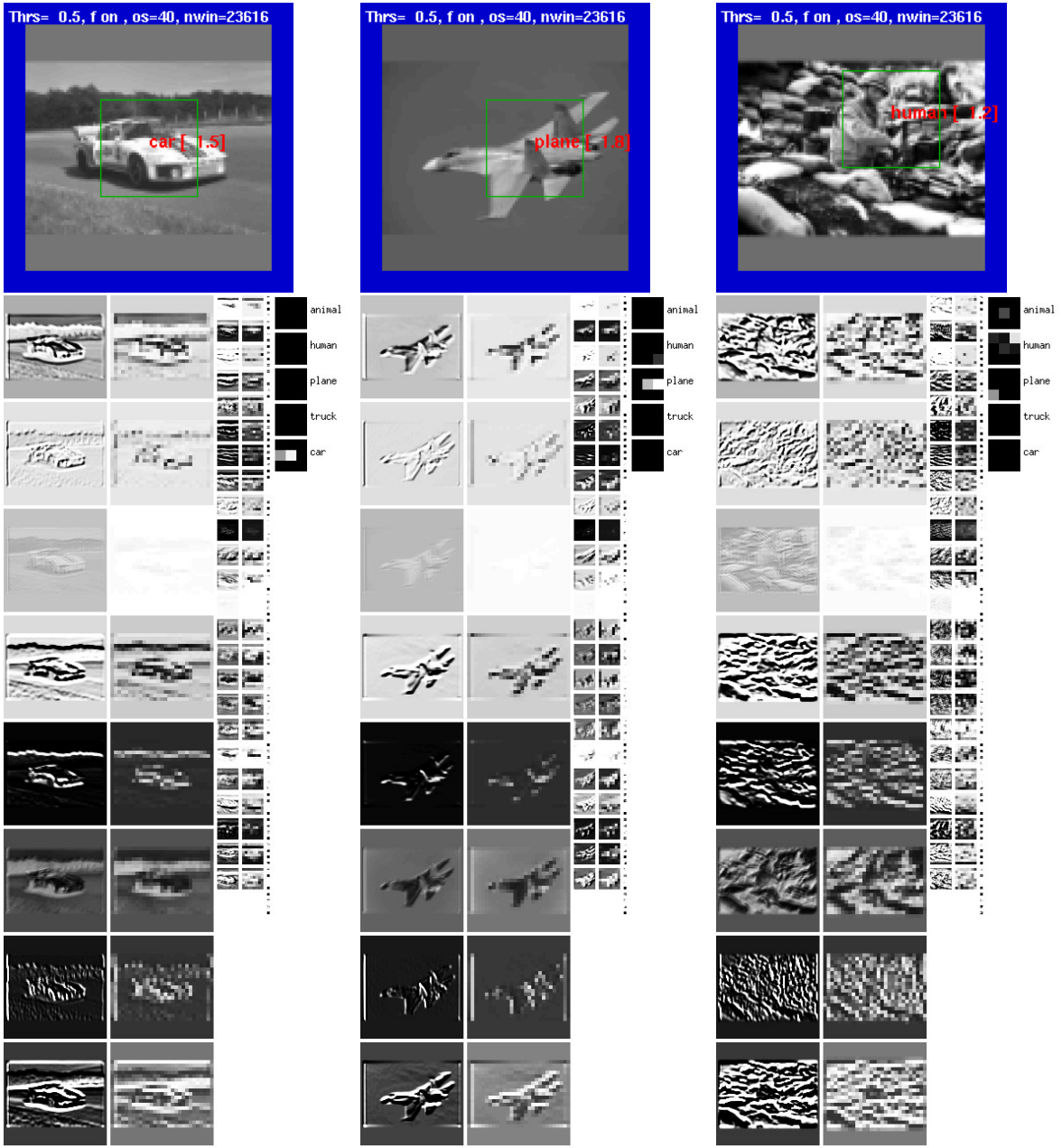
Examples (Monocular Mode)



Examples (Monocular Mode)

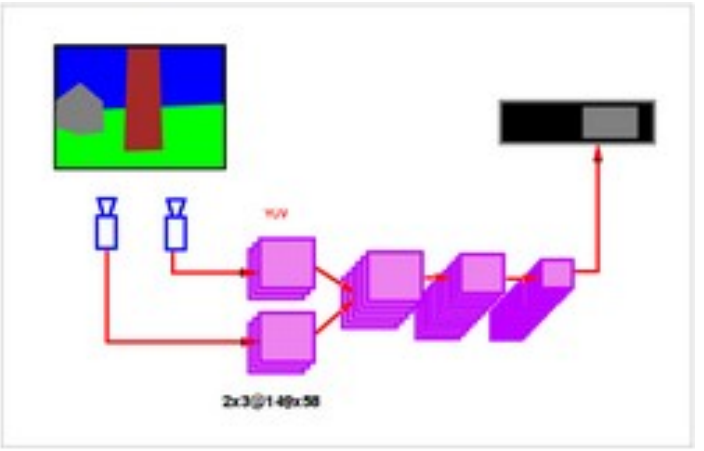


Natural Images (Monocular Mode)

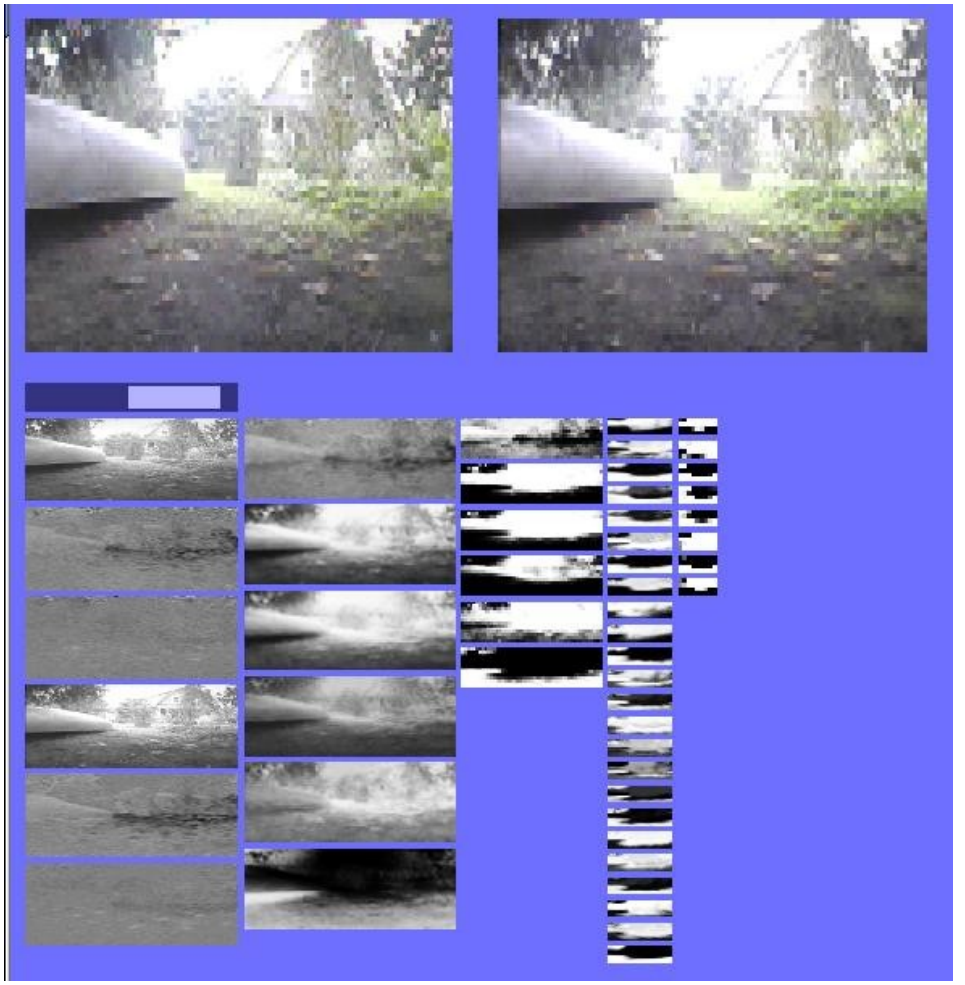


Visual Navigation for a Mobile Robot

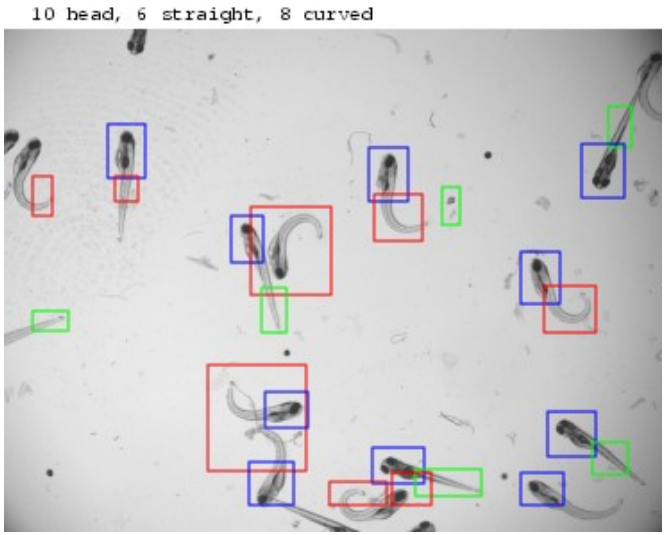
[LeCun et al. NIPS 2005]

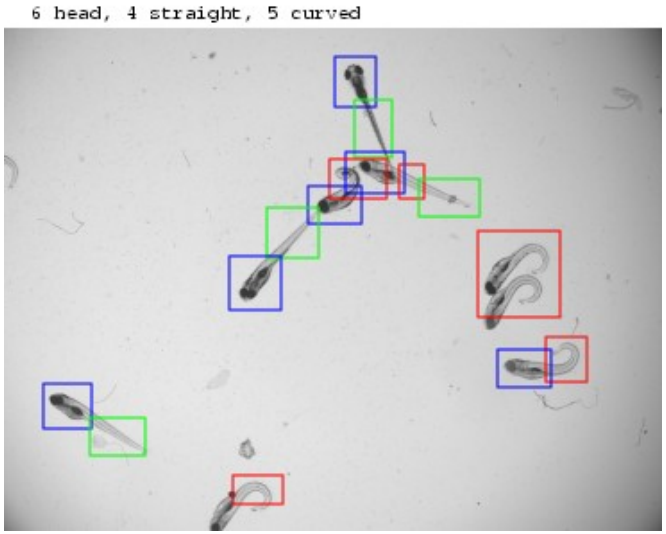


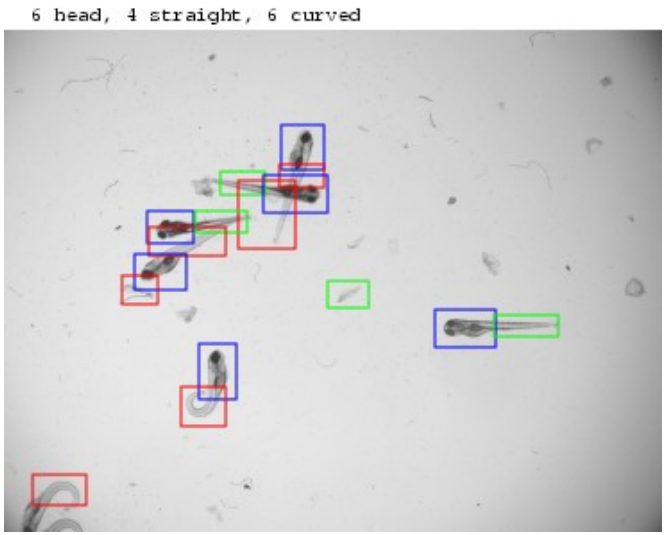
- Mobile robot with two cameras
- The convolutional net is trained to emulate a human driver from recorded sequences of video + human-provided steering angles.
- The network maps stereo images to steering angles for obstacle avoidance

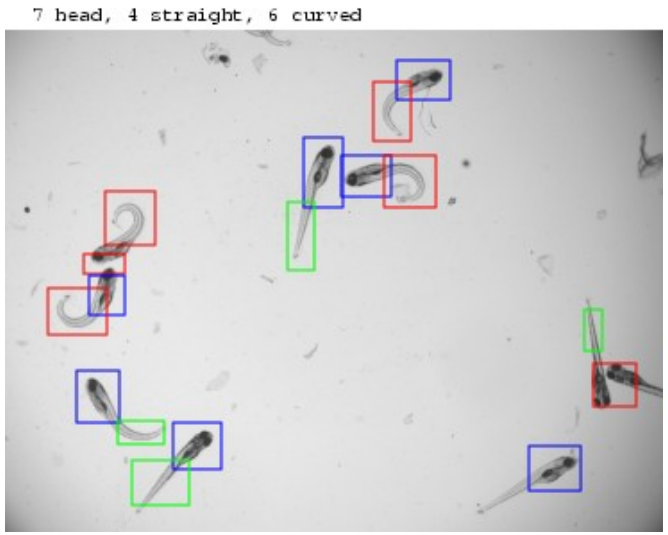


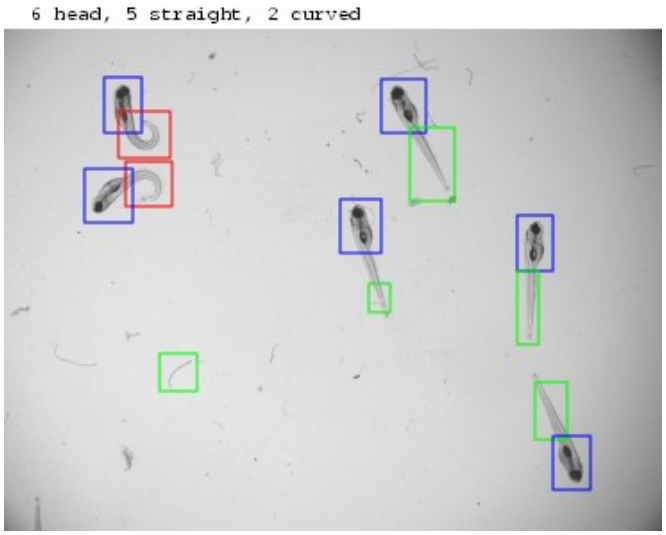
Convolutional Nets for Counting/Classifying Zebra Fish

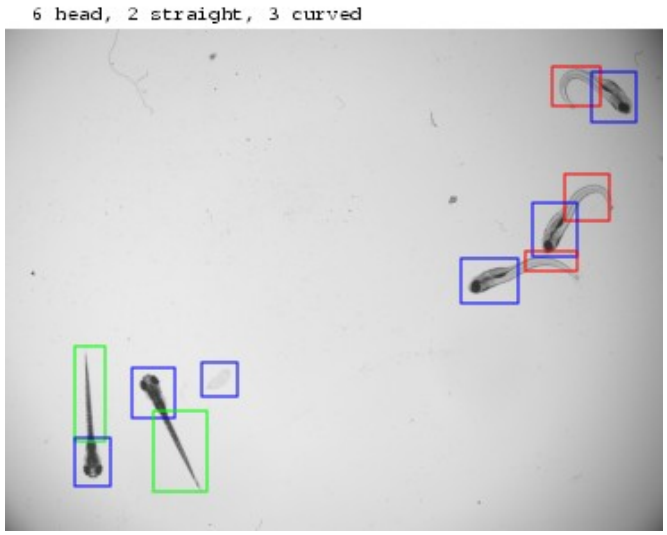








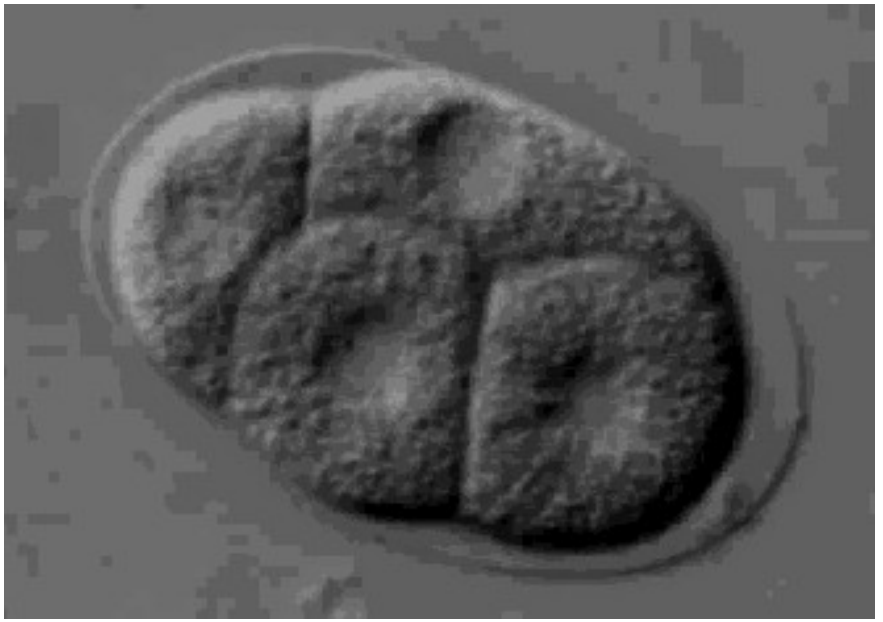


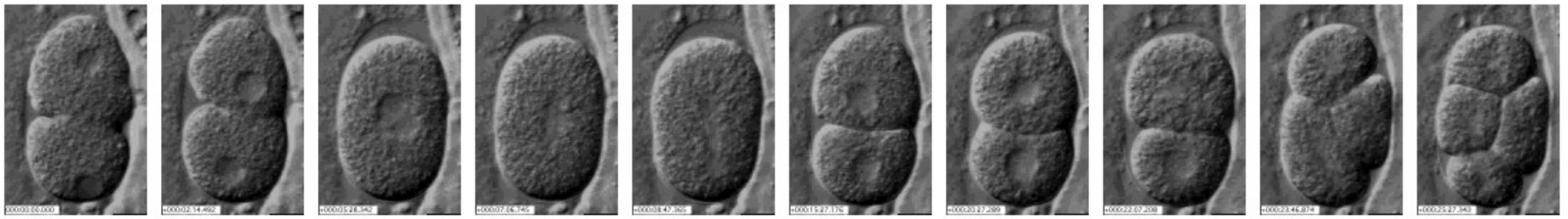


Head – Straight Tail – Curved Tail

C. Elegans Embryo Phenotyping

- Analyzing results for Gene Knock-Out Experiments





C. Elegans Embryo Phenotyping

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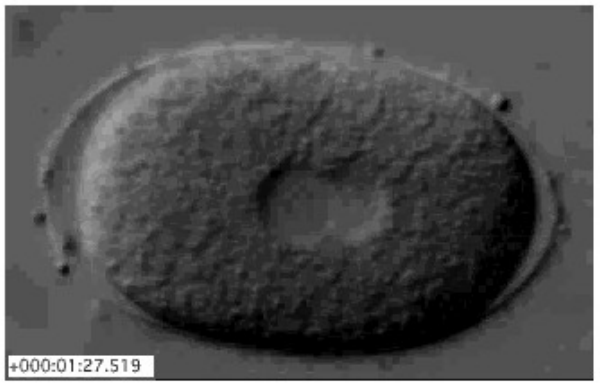
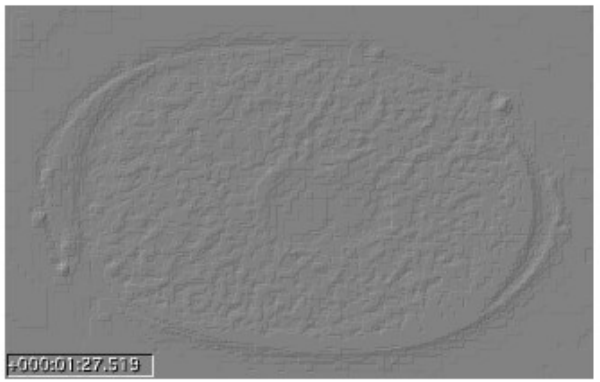
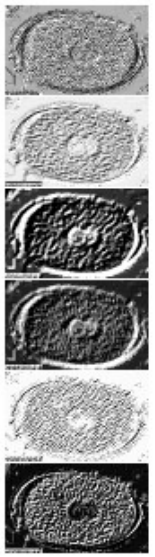
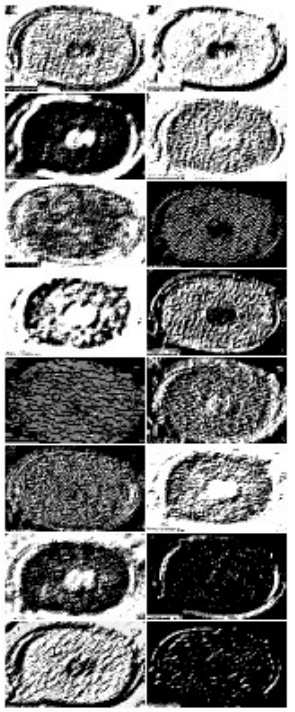
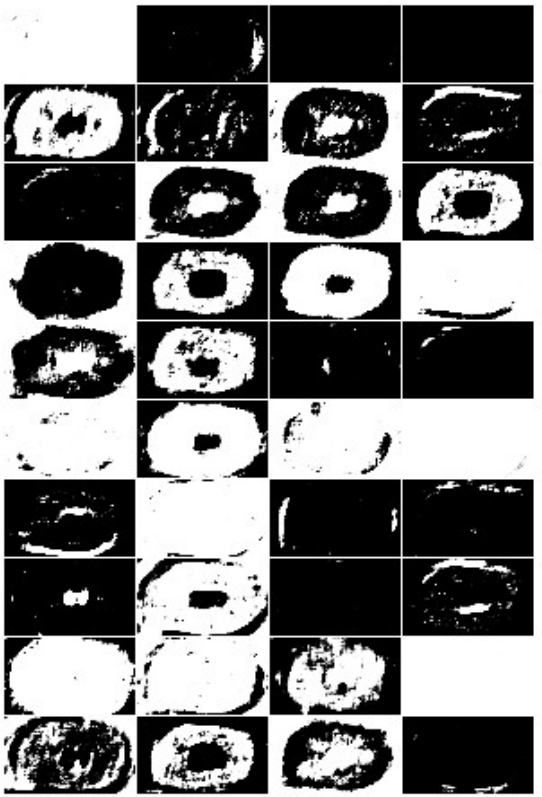
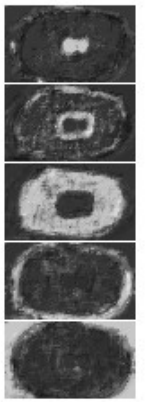






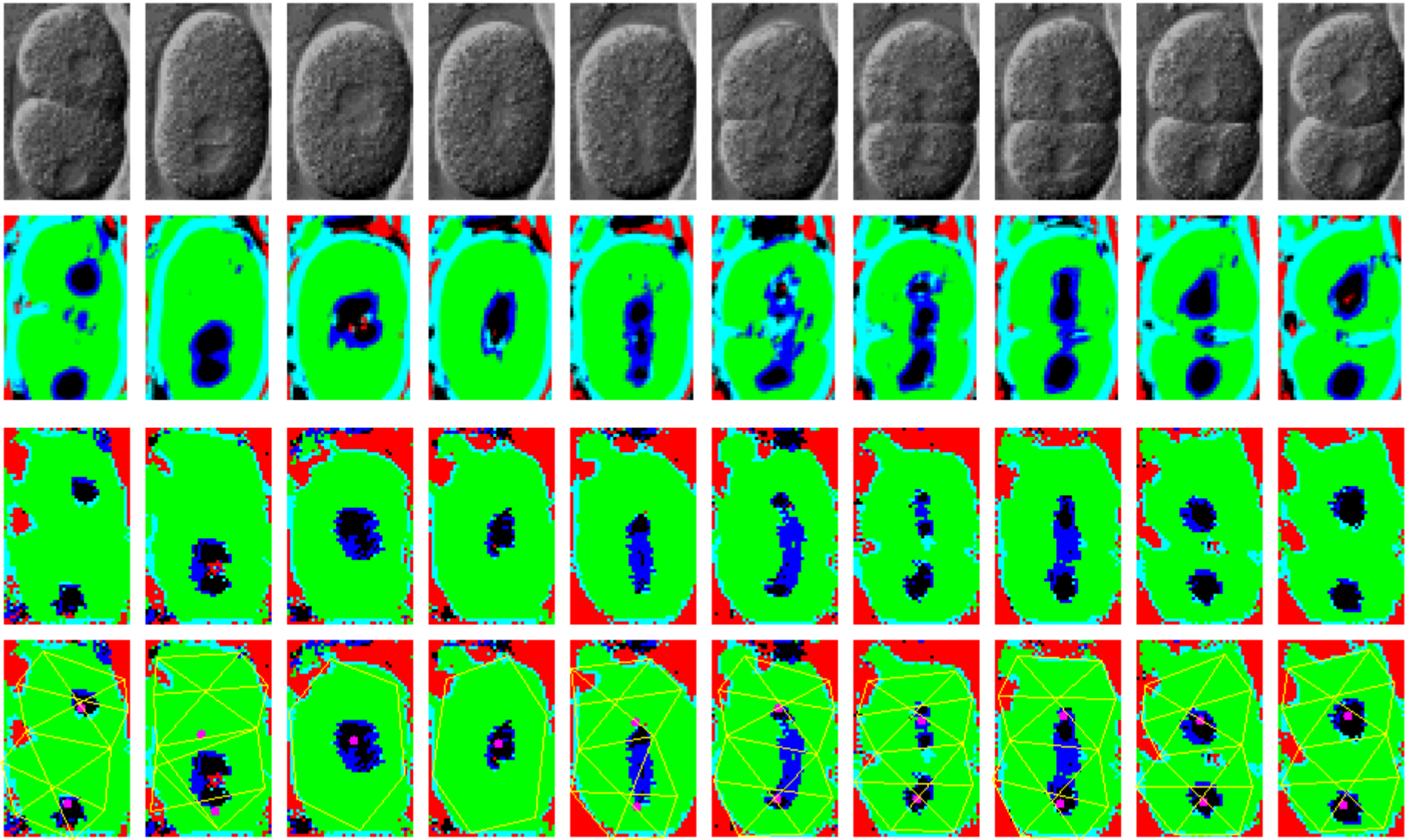






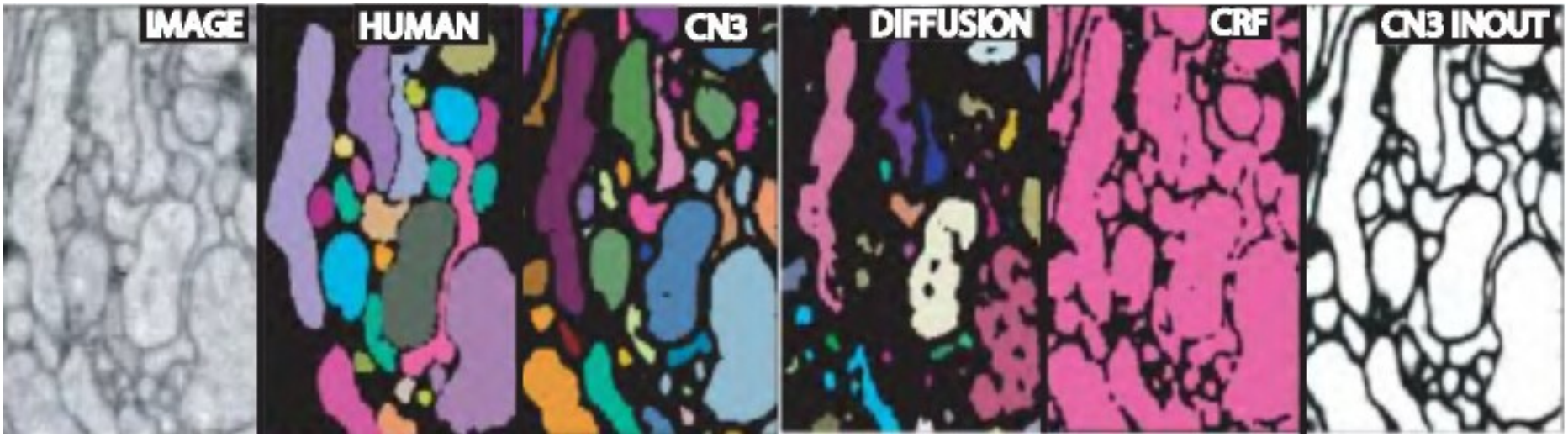
C. Elegans Embryo Phenotyping

- Analyzing results for Gene Knock-Out Experiments



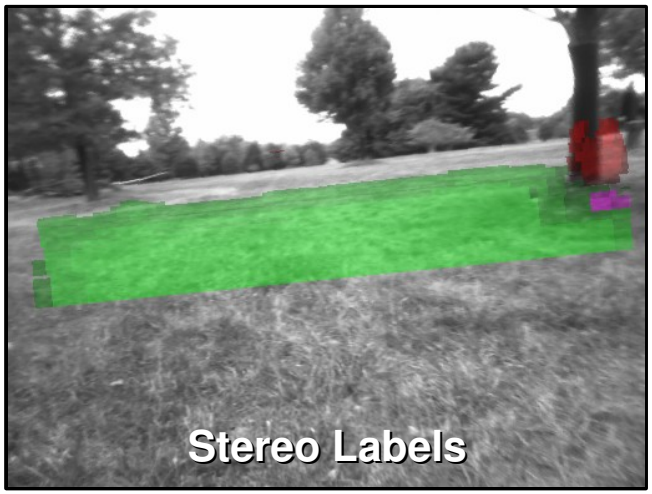
Convolutional Nets For Brain Imaging and Biology

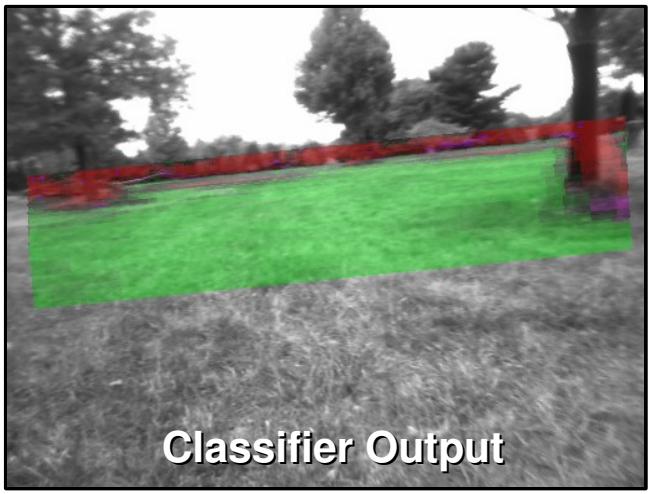
- **Brain tissue reconstruction from slice images [Jain,....,Denk, Seung 2007]**
  - Sebastian Seung's lab at MIT.
  - 3D convolutional net for image segmentation
  - ConvNets Outperform MRF, Conditional Random Fields, Mean Shift, Diffusion,...[ICCV'07]

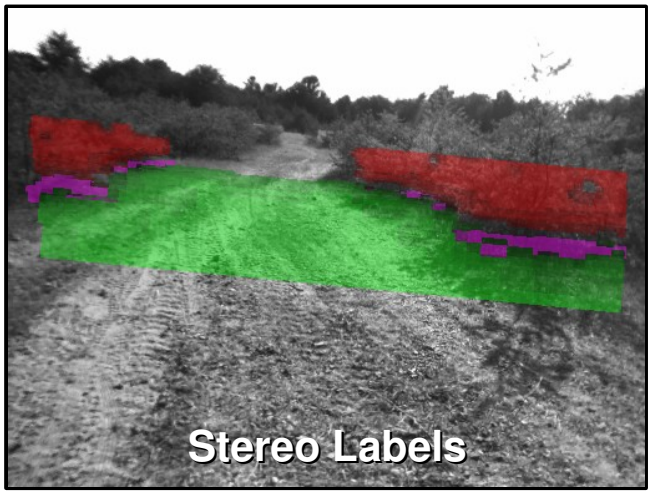


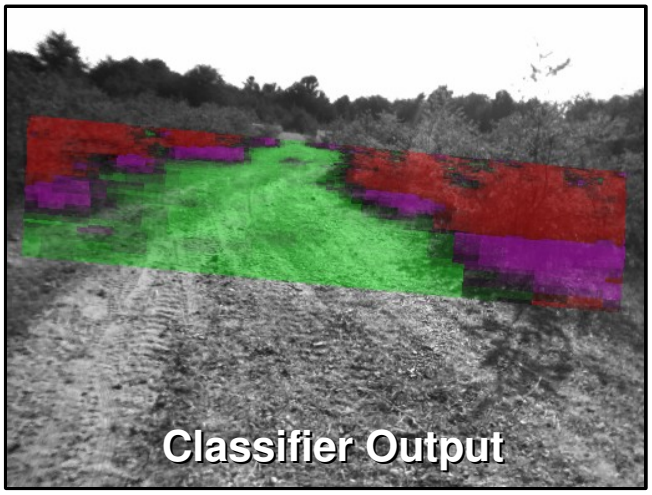
Convolutional Nets for Image Region Labeling

- **Long-range obstacle labeling for vision-based mobile robot navigation**
  - (more on this later....)

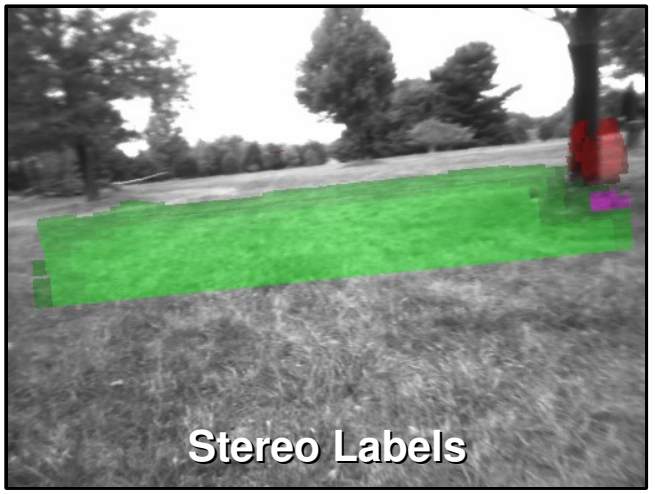


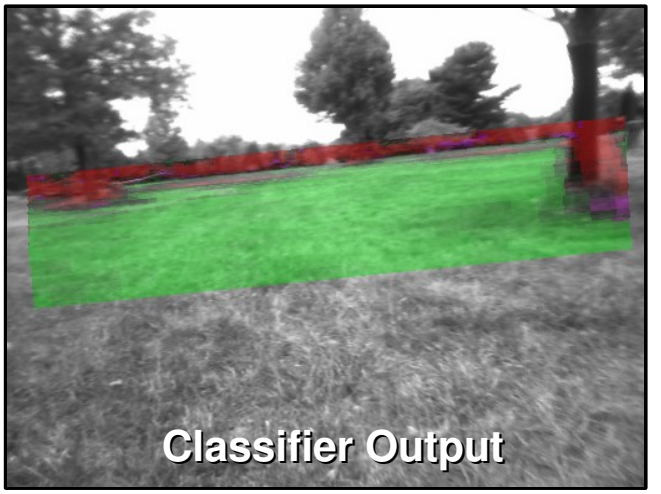




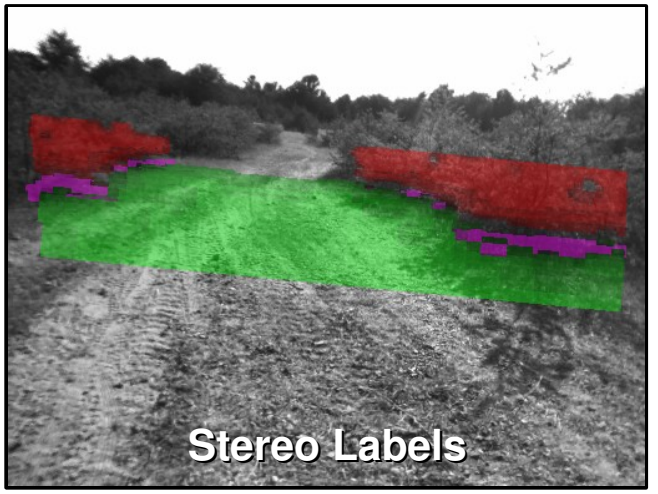


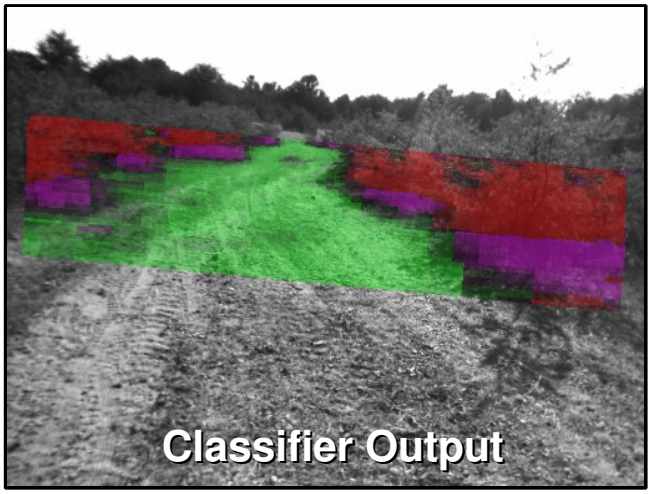

Input image


Stereo Labels


Classifier Output


Input image


Stereo Labels

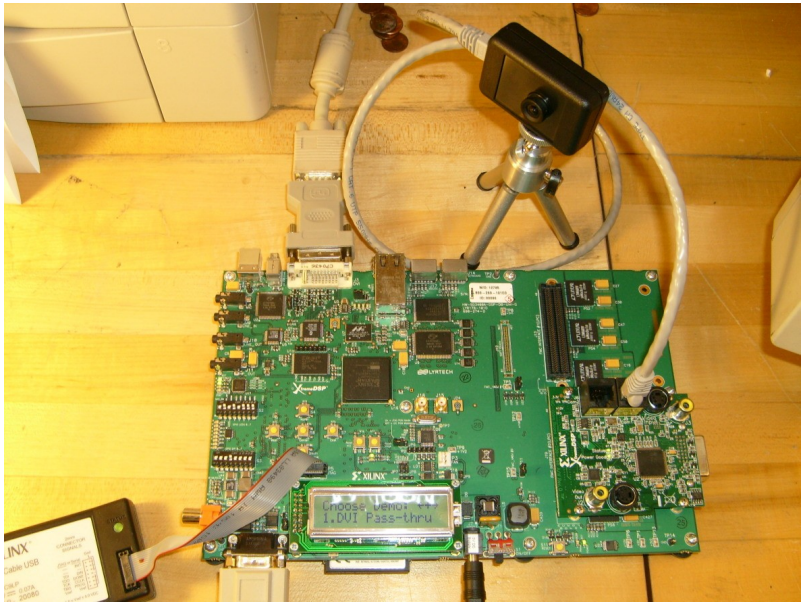

Classifier Output

Industrial Applications of ConvNets

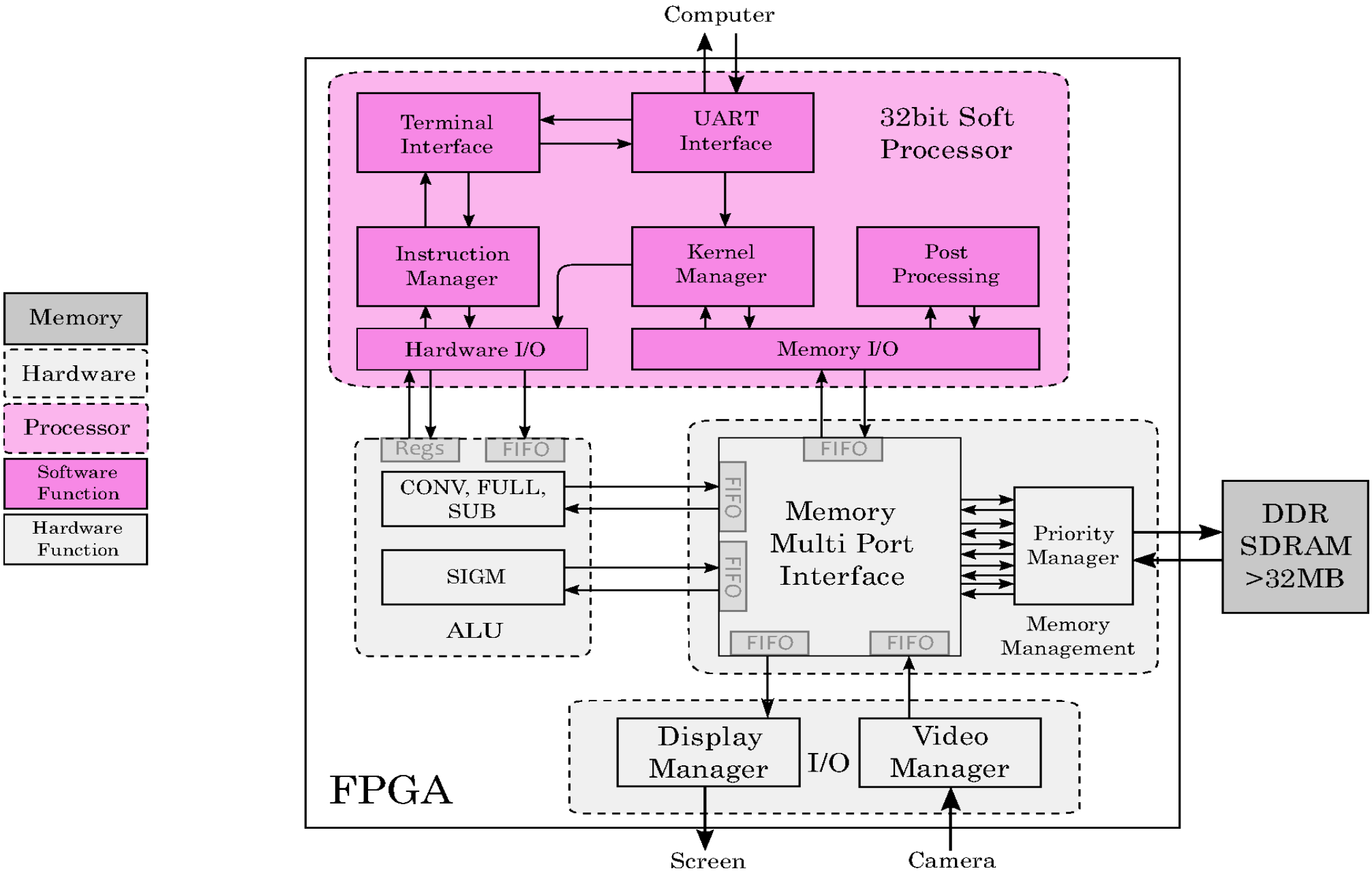
- **AT&T/Lucent/NCR**
  - Check reading, OCR, handwriting recognition (deployed 1996)
- **Vidient Inc**
  - Vidient Inc's "SmartCatch" system deployed in several airports and facilities around the US for detecting intrusions, tailgating, and abandoned objects (Vidient is a spin-off of NEC)
- **NEC Labs**
  - 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)....**

CNP: FPGA Implementation of ConvNets

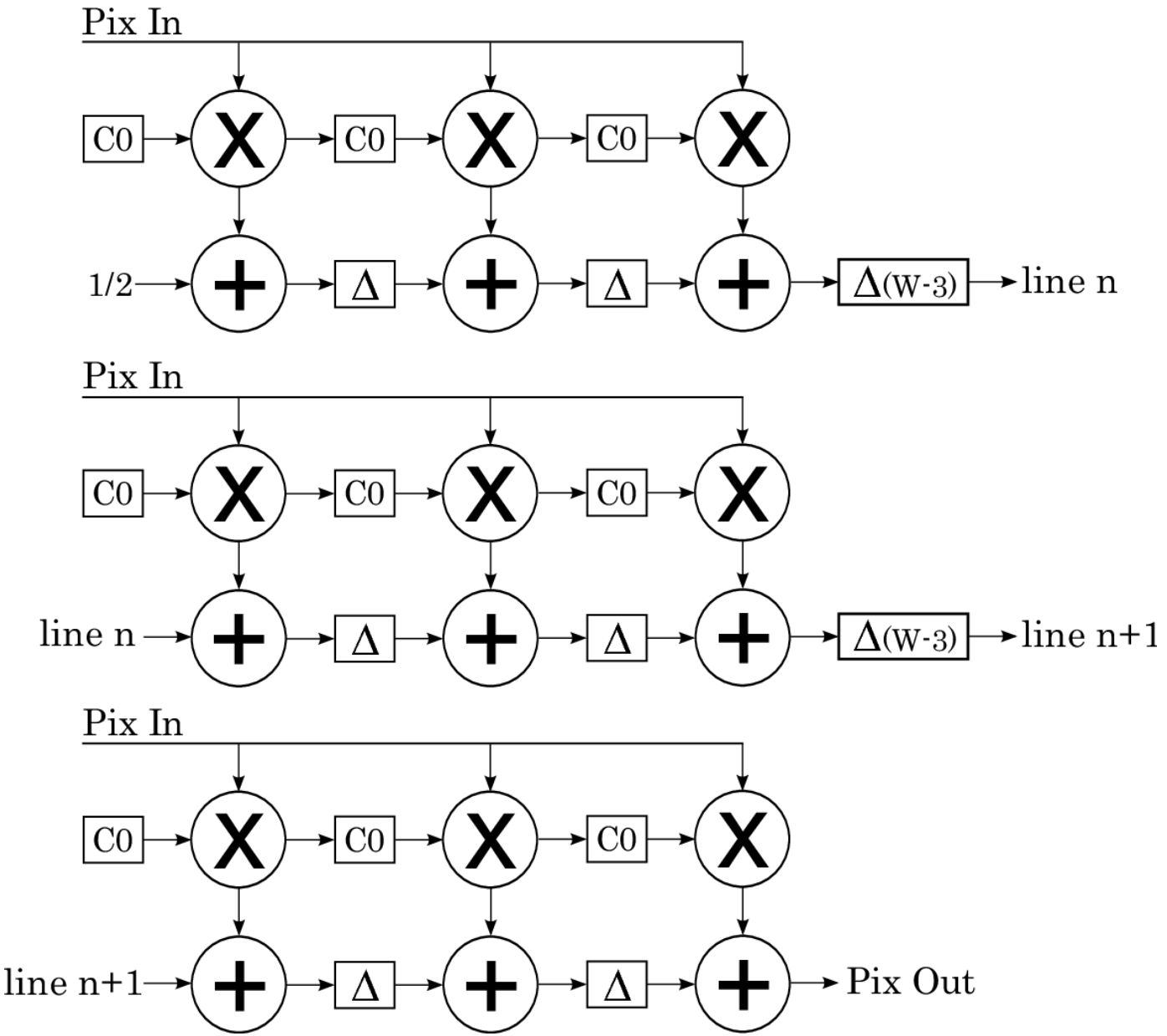
- **Implementation on low-end Xilinx FPGA**
  - Xilinx Spartan3A-DSP: 250MHz, 126 multipliers.
  - Face detector ConvNet at 640x480: 5e8 connections
  - 8fps with 200MHz clock: 4Gcps effective
    - Prototype runs at lower speed b/c of narrow memory bus on dev board
  - Very lightweight, very low power
    - 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

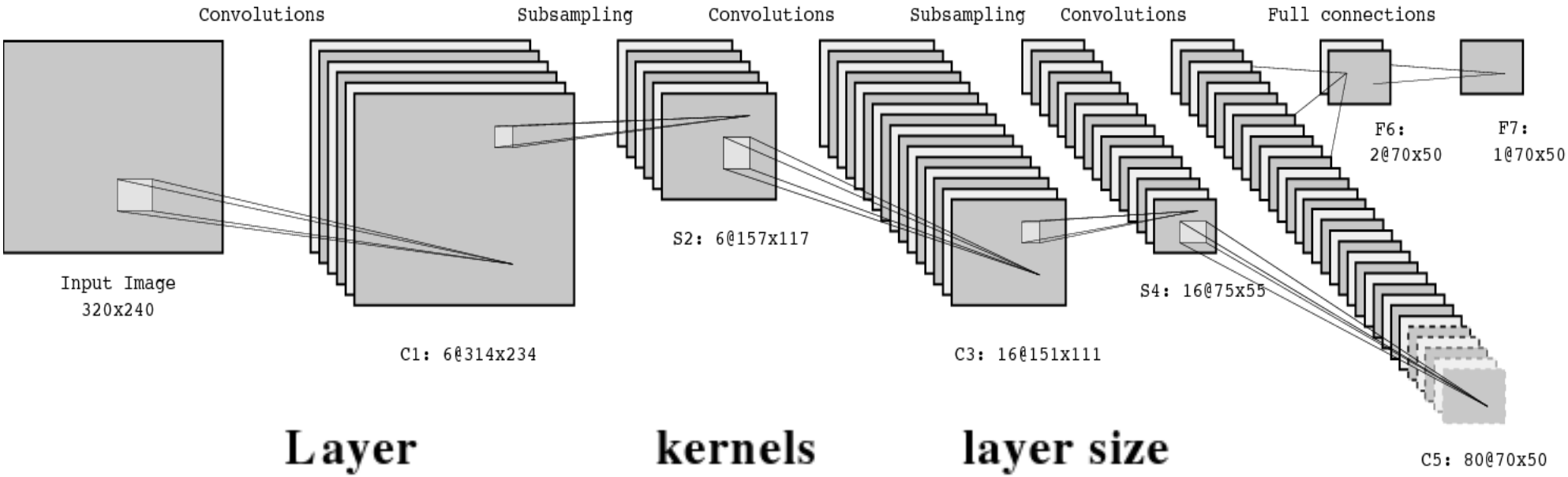


Design

- **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**

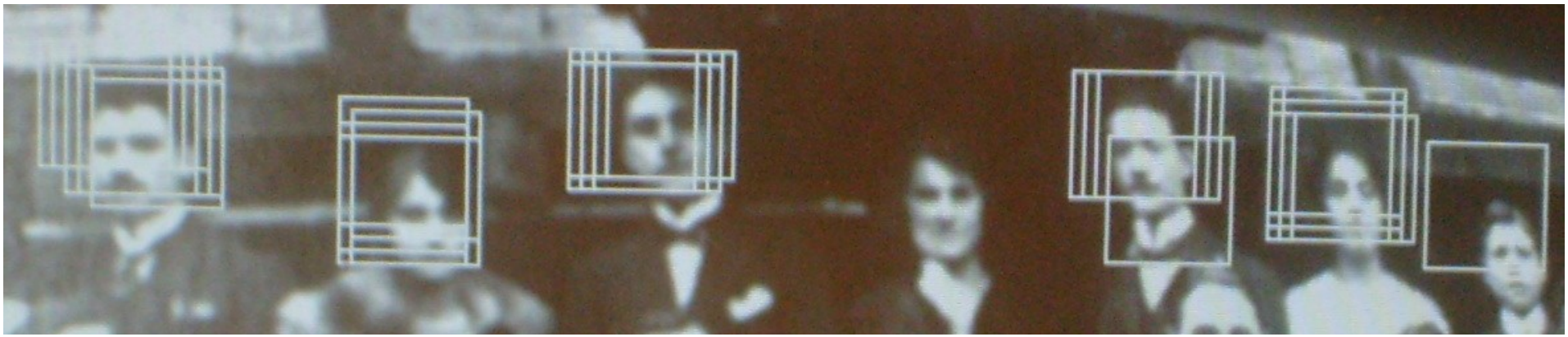
Entity	Occupancy	
I/Os	135 out of 469	28%
DCMs	2 out of 8	25%
Mult/Accs	56 out of 126	44%
Bloc Rams	100 out of 126	84%
Slices	16790 out of 23872	70%

Face detector on CNP



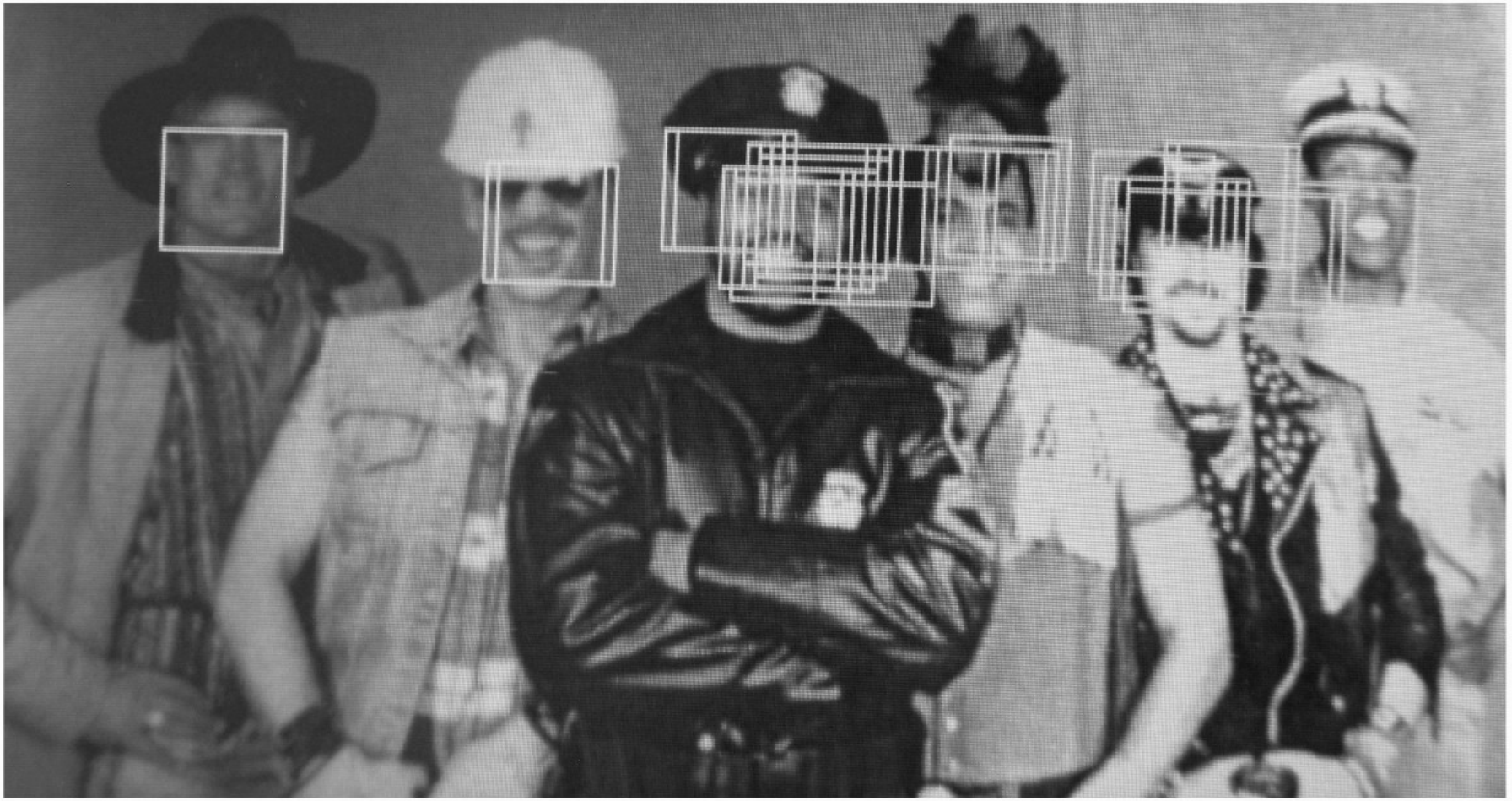
Layer	kernels	layer size
Input image		$1@42 \times 42$
C1 (Conv)	$[6@7 \times 7]$	$6@36 \times 36$
S2 (Pool)	$[6@2 \times 2]$	$6@18 \times 18$
C3 (Conv)	$[61@7 \times 7]$	$16@12 \times 12$
S4 (Pool)	$[16@2 \times 2]$	$16@6 \times 6$
C5 (Conv)	$[305@6 \times 6]$	$80@1 \times 1$
F6 (Dotp)	$[160@1 \times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

Results



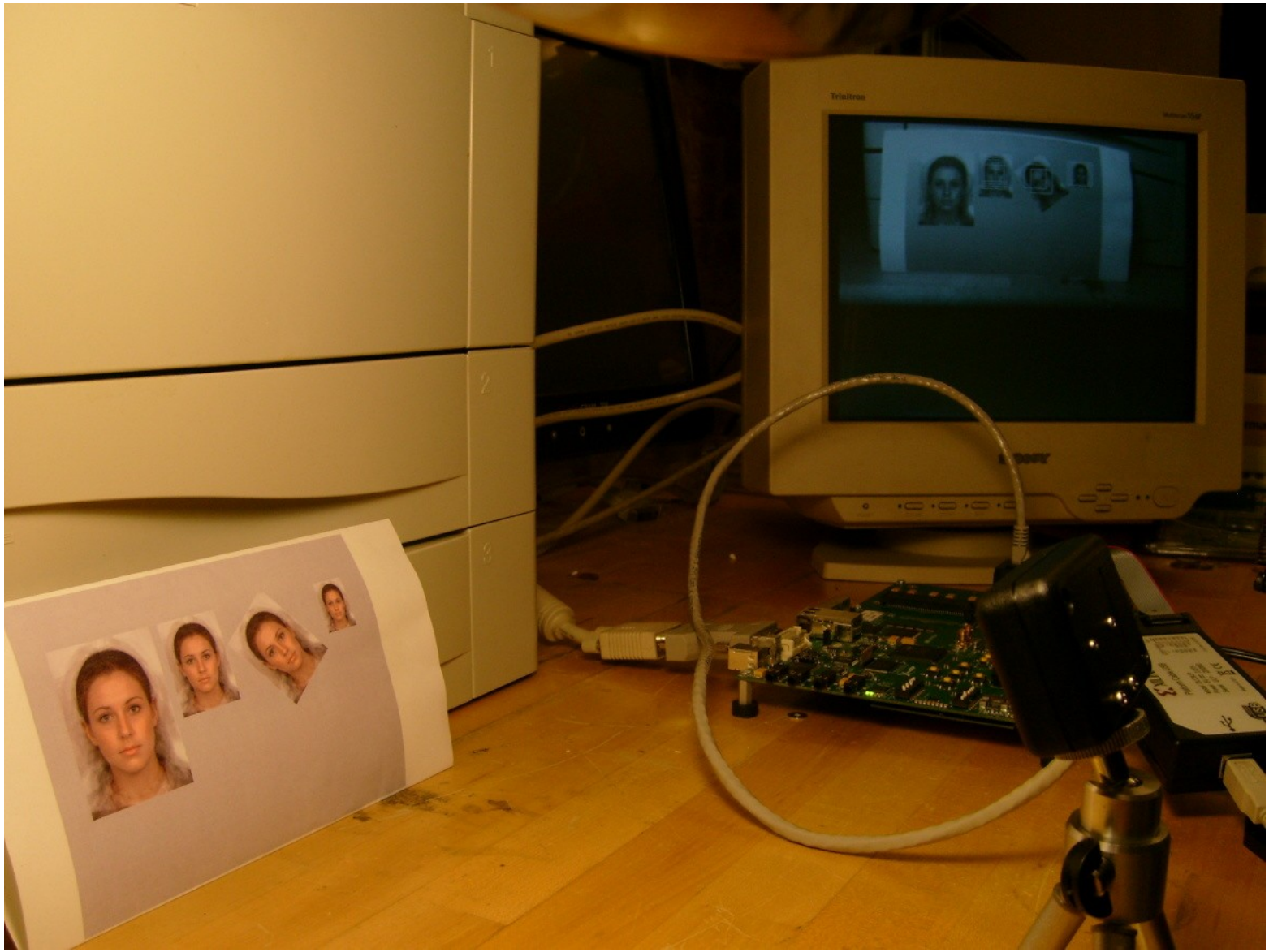
- **Clock speed limited by low memory bandwidth on the development board**
  - Dev board uses a single DDR with 32 bit bus
  - Custom board will use 128 bit memory bus
- **Currently uses a single 7x7 convolver**
  - We have space for 2, but the memory bandwidth limits us
- **Current Implementation: 5fps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

Results



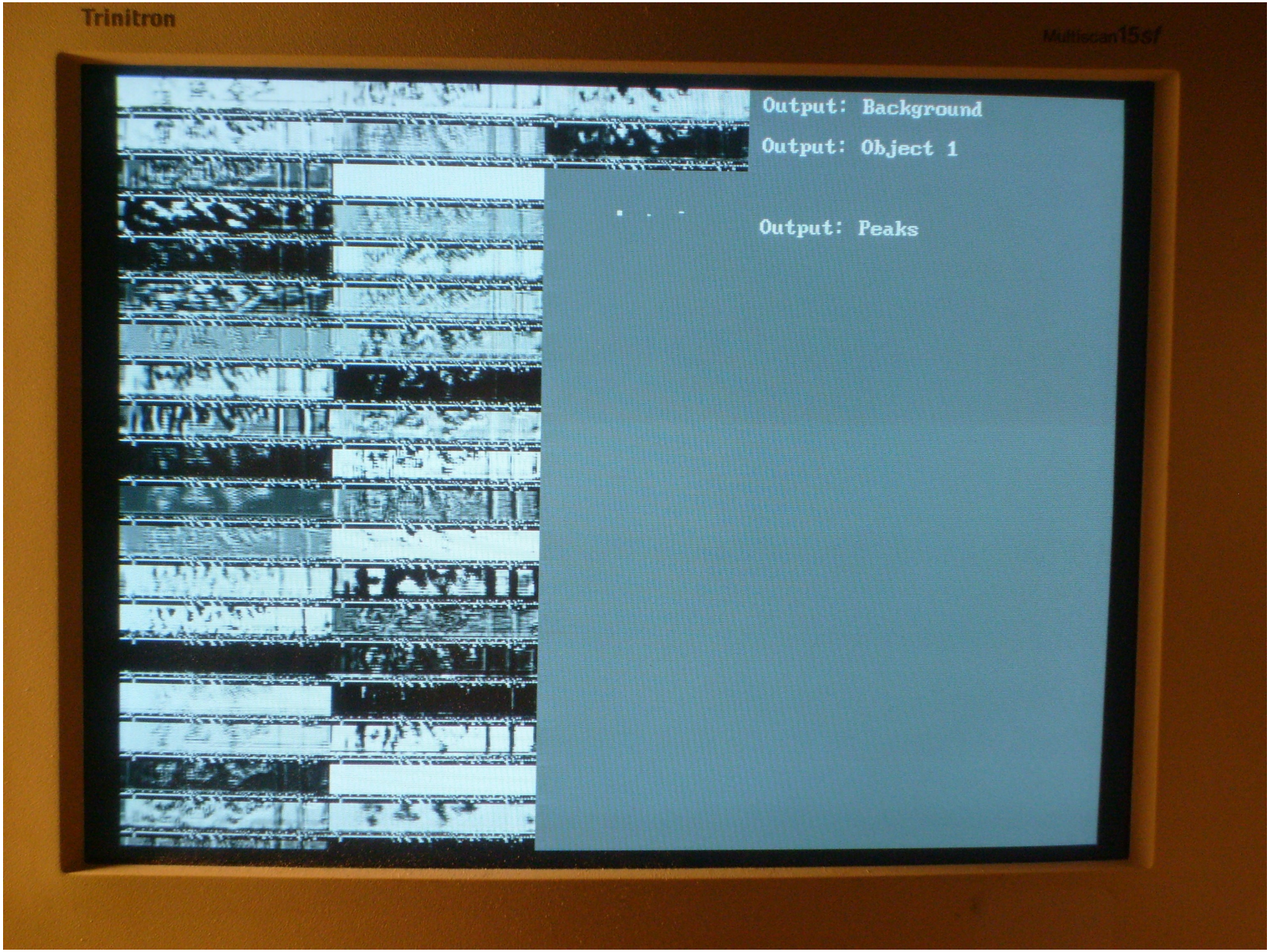
Results

Results



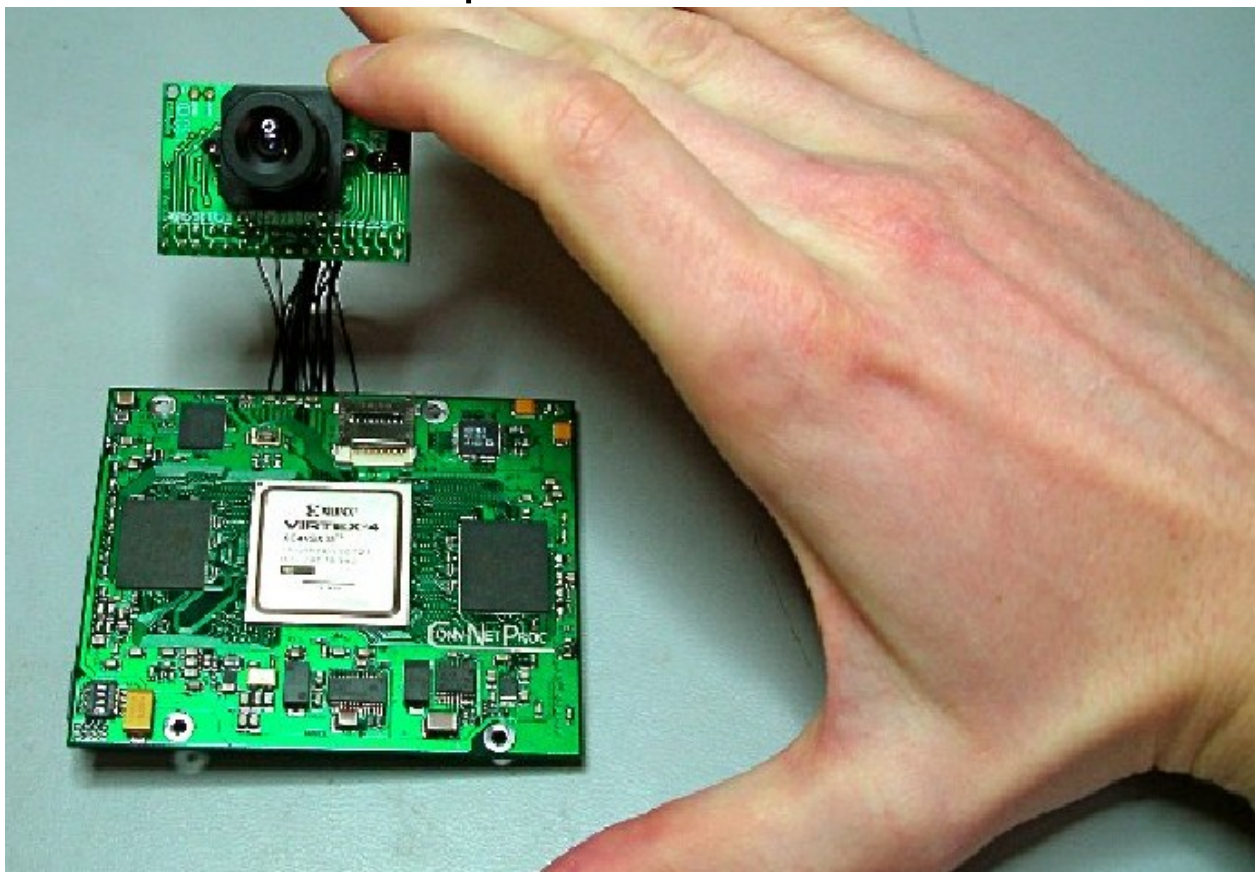
Results

Results


Trinitron
Multiscan15sf
Output: Background
Output: Object 1
Output: Peaks

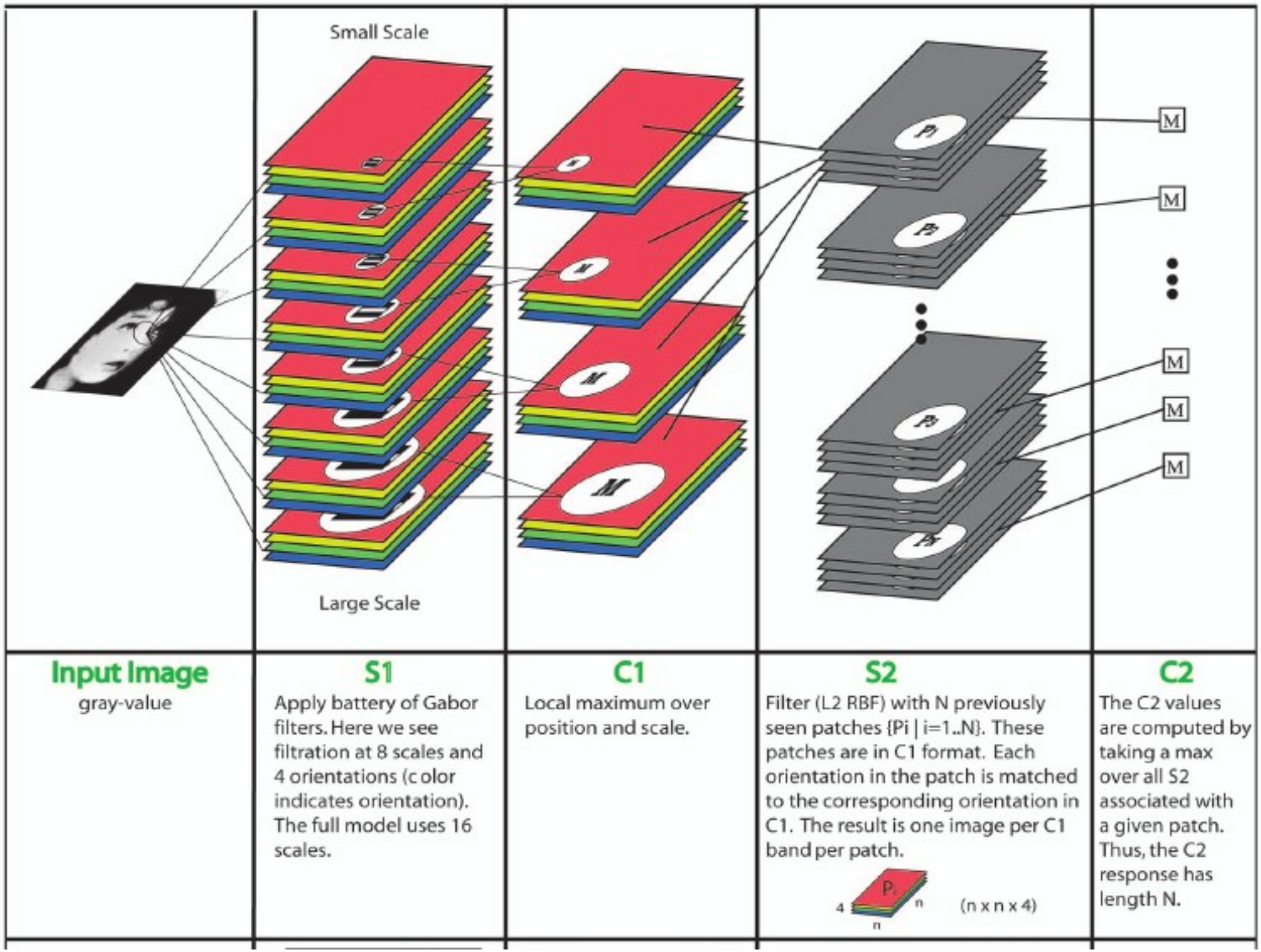
FPGA Custom Board: NYU ConvNet Proc

- **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



Models Similar to ConvNets

- **HMAX**
  - [Poggio & Riesenhuber 2003]
  - [Serre et al. 2007]
  - [Mutch and Low CVPR 2006]
- **Difference?**
  - the features are not learned
- **HMAX is very similar to Fukushima's Neocognitron**



[from Serre et al. 2007]