Towards Human-Level AI

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What is Intelligence?

- **Most wetware cycles in higher animals are devoted to perception, and most of the rest to motor control.**
  - 20% of our brain does vision
- **Intelligence includes the ability to derive complex behavior from massive amounts of sensory information.**
  - Intelligence requires making sense complex sensor input (including proprioception).
- **Intelligence is modeling, prediction, and evaluation**
  - The more intelligent the organism, the better it can predict the world, predict the consequences of its actions (including rewards), and pick the “best” action.
- **How can an intelligent agent learn to predict the world?**
  - Not the whole world, only the part of the world which is relevant to the purpose of its existence, including its own actions.

What is Intelligence?

- **In the past we thought that intelligence was what smart humans could do**
  - Speech, logical reasoning, playing chess, computing integrals.....
- **But those things turned out to be pretty simple computationally**
  - It turns out that the complicated things are perception, intuition and common sense
  - Things that even a mouse can do much better than any existing robot.
- **What about rat-level intelligence?**
  - We will achieve rat-level intelligence before we achieve human-level, so let's work on rat-leve intelligence
- **It is likely that intelligent agents cannot be "intelligently designed" ;-)**
  - They have to build themselves through learning
  - How much prior structure is required?
  - The more intelligent, the less prior structure.

Where are we now?

- **We are still quite far from rat-level intelligence**
  - We don't have robots that can run around without bumping into things or falling into ditches using vision only.
  - We know that the methods currently being developed are hacks.
- **Most NIPS papers do not take us any closer to rat-level intelligence**
  - In fact, some of them take us backward.
- **What problems should we work on, what type of new methods should we develop?**
- **Which methods currently being worked on the community, while being valuable, will not take us to rat-level intelligence?**
  - How do we avoid the trap of building ever so taller ladders when our goal is to reach the Moon?

Questions?

- **Is there a magic bullet?**
  - Is there a general principle, or just a bunch of tricks?
  - Is there a universal learning algorithm/architecture which, given a small amount of appropriate prior structure, can produce intelligent agents?
  - Or do we need to accumulate a large repertoire of "modules" to solve each specific problem an intelligent agent must solve. How would we assemble those modules?
- **Let's face it, our only working example uses neurons.**
  - Does that mean rat-level intelligence will be achieved with simulated neurons?
  - Airplanes don't flap their wings
  - Yes, but they exploit the same aerodynamical properties as birds (and they are not as efficient at it)
  - What is the analog of aerodymanics for intelligence?

Questions?

- **Every reasonable learning algorithm we know minimizes some sort of loss function?**
  - Does the brain minimize a loss function?
  - If yes, what is it, and how does it do it?
  - Is there any other way to build learning systems?
- **If we accept the loss function hypothesis:**
  - Can the loss function possibly be convex?
  - How is it parameterized?
    - What is the architecture?
  - How is it minimized
    - direct solution (like quadratic problems),
    - gradient-based iterative procedures
    - perturbation/trial and error
    - all of the above?

What Do We Need?

- **Learning**
  - Supervised, unsupervised, reinforcement
- **Efficient reasoning with large numbers of variables**
  - e.g. For image segmentation/labeling...
- **Very fast inference for high-dimensional complex tasks**
  - People and animal can recognize common visual categories in less than 100ms. There is no time for complex reasoning/relaxation/inference.
- **Emotions**
  - Emotion, in the restricted sense of reward prediction.

What Do We Need?

- **Learning algorithms that scale**
  - Sub-linearly with the number of training samples
  - Not much more than linearly with the size of the learning system
  - Non-exponentially with the size of the action space and state space
- **"Deep" Learning**
  - Intelligent inference requires lots of elementary decisions (non-linear steps):
    - pixels->low-level feature->high-level features->categories
    - Global goal->macro-action sequence->action sequence->motor commands
- **A framework with which to build large-scale "deep" learning machines with millions of parameters**
  - A framework that allows us to specify prior knowledge
- **How little prior knowledge can we get away with?**

What classes of methods should we develop/abandon?

Speculation Alert:

Opinions expressed in the following slides

are even more personal, heuristic, controversial,

and speculative than the previous ones.

What classes of methods will not take us there?

- **Template matching**
  - Fast nearest-neighbor methods and kernel methods are useful, but they won't take us there
- **"Shallow" learning**
  - Linear combinations of **fixed** basis functions won't take us there
  - Examples: SVM, generalized linear models, boosting with simple weak learners, Gaussian processes.....Those methods are useful, just not for our purpose
  - Shallow architectures are inefficient: most complex functions are more efficiently implemented with many layers of non-linear decisions
  - We need "hierarchical" models that learn high-level representations from low-level perceptions, features, macro features.....

What classes of methods will not take us there?

- **Convex Optimization with a practical number of variables**
  - If intelligence could be reduced to convex optimization, the order in which we learn things would not matter: we would go to the same minimum no matter what.
- **Purely generative methods, purely supervised methods, purely unsupervised methods.**
- **Fully probabilistic methods**
  - Because we can't normalize complicated distributions in high dimension
- **Purely discriminative methods**
  - Because not everything comes down to classification
  - We need to model the world

What problems should we solve?

- **Integrating reasoning with learning**
  - Graphical models (factor graphs in particular) are a good avenue, but we need to free ourselves from the "partition function problem"
  - How do we build non-probabilistic factor graphs that can be trained in supervised, unsupervised, and reinforcement mode.
- **Invariant Representations**
  - How do we learn complex invariances in vision?
  - We can pre-engineer some of it, but ultimately, we need a scheme to learn features and invariant representation automatically.
  - Optimization algorithms (learning) will become better at this than human engineer. It is already the case for handwriting recognition systems and speech recognition systems.

What problems should we solve?

Deep learning

- Ultimately, we need to think again about learning in deep structures with many layers on non-linear decisions.
- We have partial solutions that are not entirely satisfactory
- Pure back-prop can't handle more than a few layers and is very inefficient for unsupervised learning
- Probabilistic belief nets have some of the right ingredients (e.g. Boltzmann machines-like algorithms), but they are plagued by the "partition function problem": learning involves estimating intractable integrals.

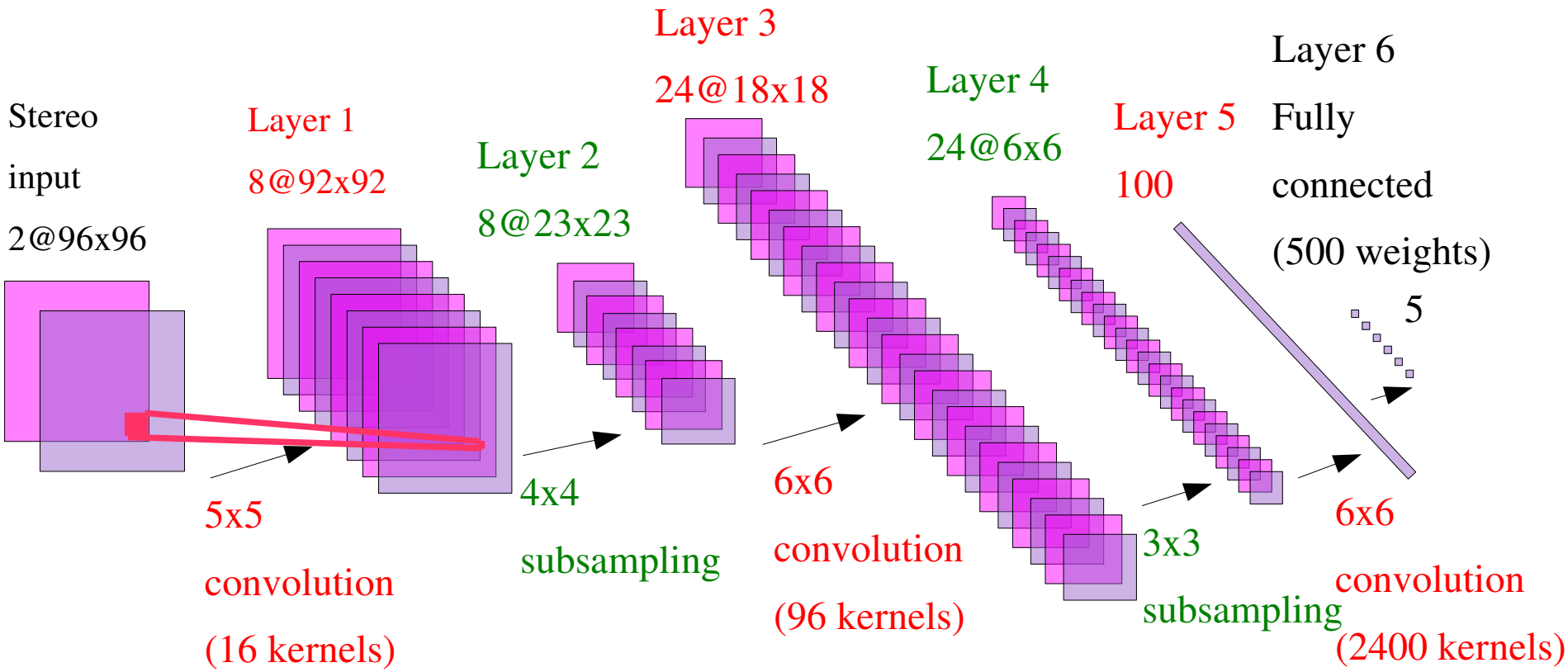
What Project should we work on?

- **Vision**
  - Generic object recognition, object detection, and such are some of the most challenging perceptual tasks for learning
  - We can make progress with clever as-hoc preprocessing combined with simple (linear) learning methods or generative models, but ultimately, good performance will be achieved when we come up with efficient "deep" learning algorithms that can learn the whole task **end-to-end** (with the minimum amount of prior knowledge)
- **Robotics**
  - The best way to integrate perception, action, and reinforcement.

Can we learn everything end-to-end?

- **There are simple situations where we have been able to demonstrate end-to-end learning in vision.**
  - Learning to recognize handwritten words from pixels to labels with no preprocessing and minimal prior knowledge (NIPS 1990-1998)
  - Learning to detect faces (NIPS 2004)
  - Learning to detect and recognize generic object categories from raw pixels to labels (CVPR 2003)
  - Training a robot to avoid obstacles from raw left/right image pairs to steering angles (NIPS 2005)

Convolutional Network

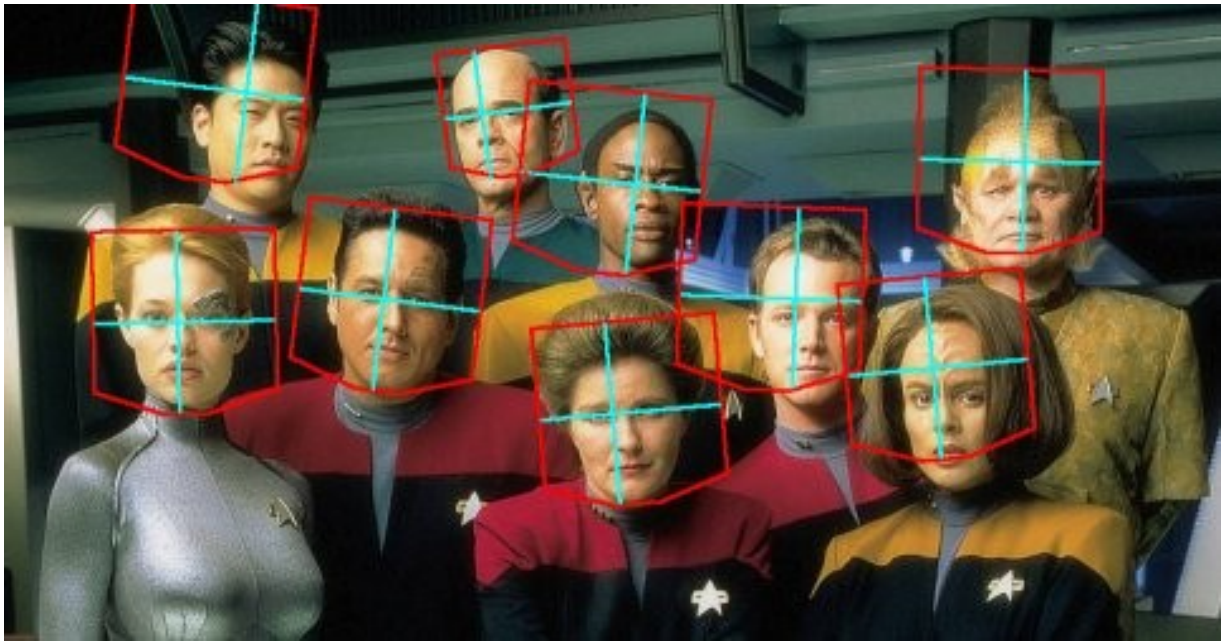


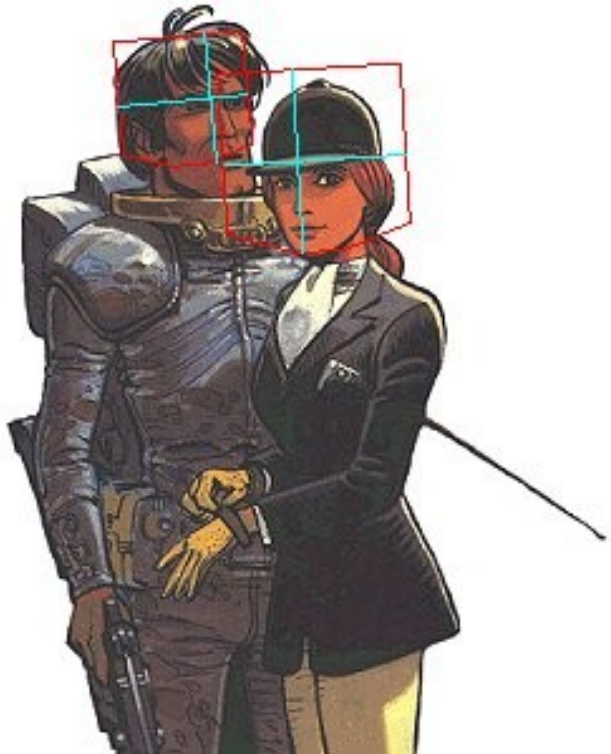
- **90,857 free parameters, 3,901,162 connections.**
- The architecture alternates convolutional layers (feature detectors) and subsampling layers (local feature pooling for invariance to small distortions).
- **The entire network is trained end-to-end** (all the layers are trained simultaneously).
-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

Recognizing Multiple Characters with Replicated Nets

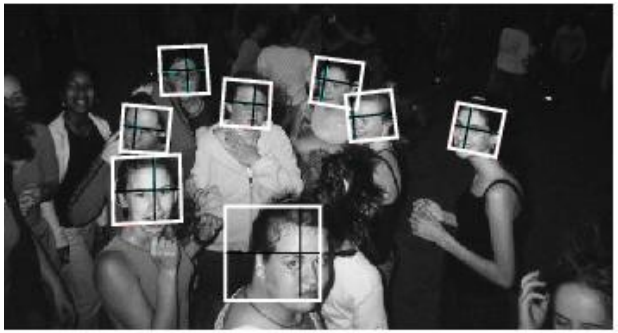
Face Detection: Results

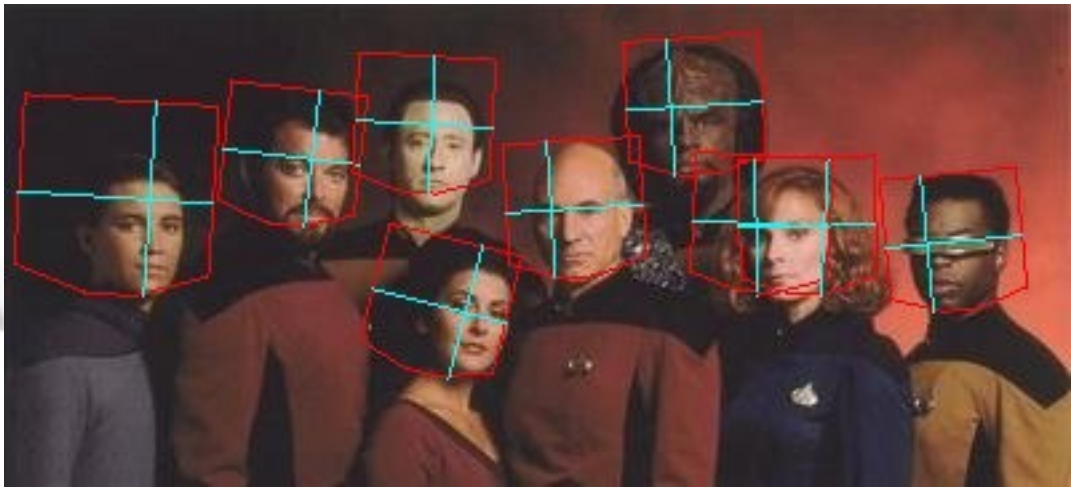
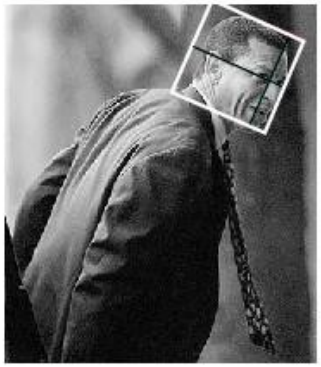
Data Set->	TILTED		PROFILE		MIT+CMU	
False positives per image->	4.42	26.9	0.47	3.36	0.5	1.28
Our Detector	90%	97%	67%	83%	83%	88%
Jones & Viola (tilted)	90%	95%	x		x	
Jones & Viola (profile)	x		70%	83%	x	



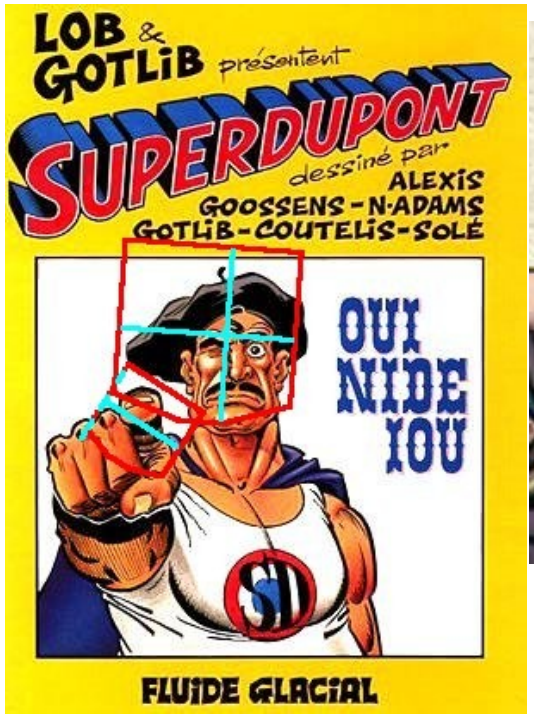


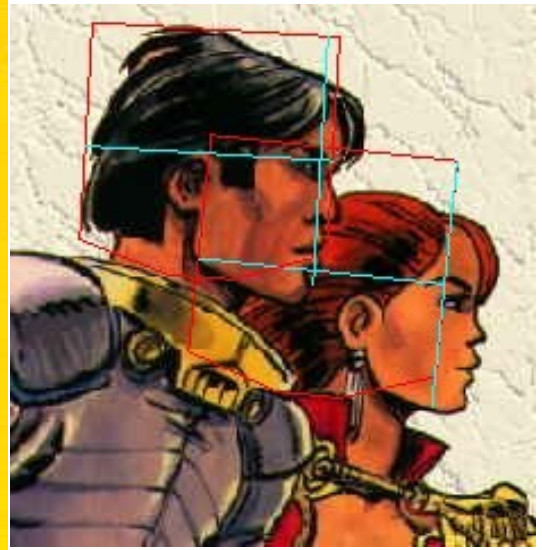
Face Detection: Results



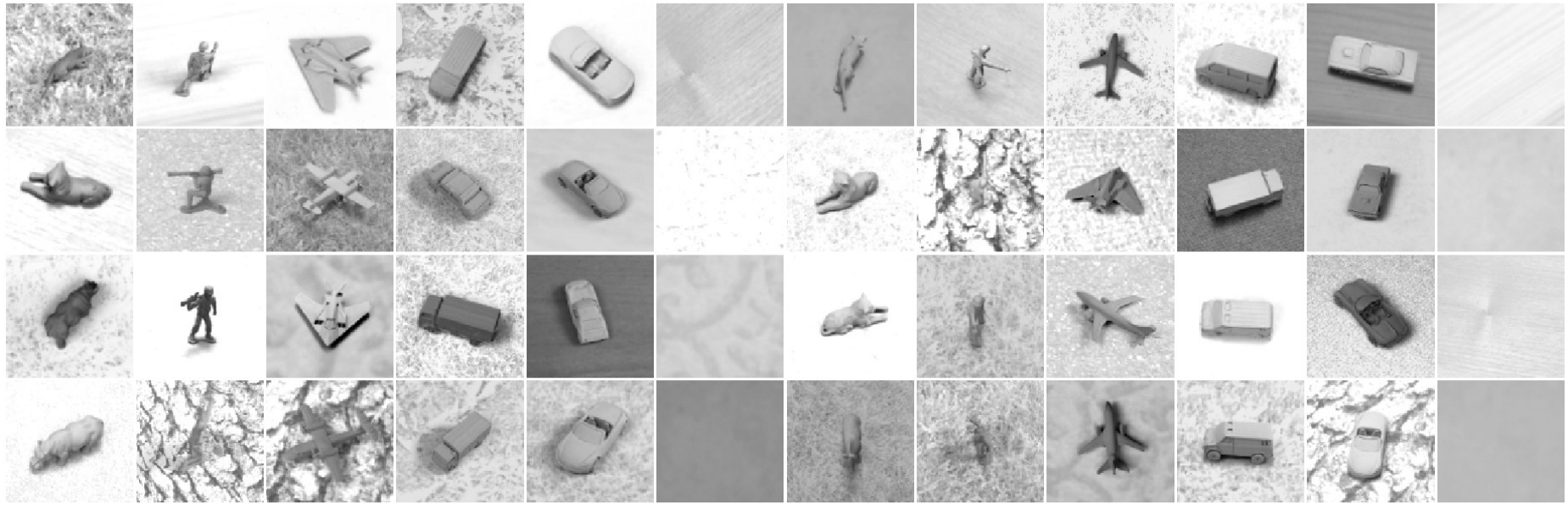




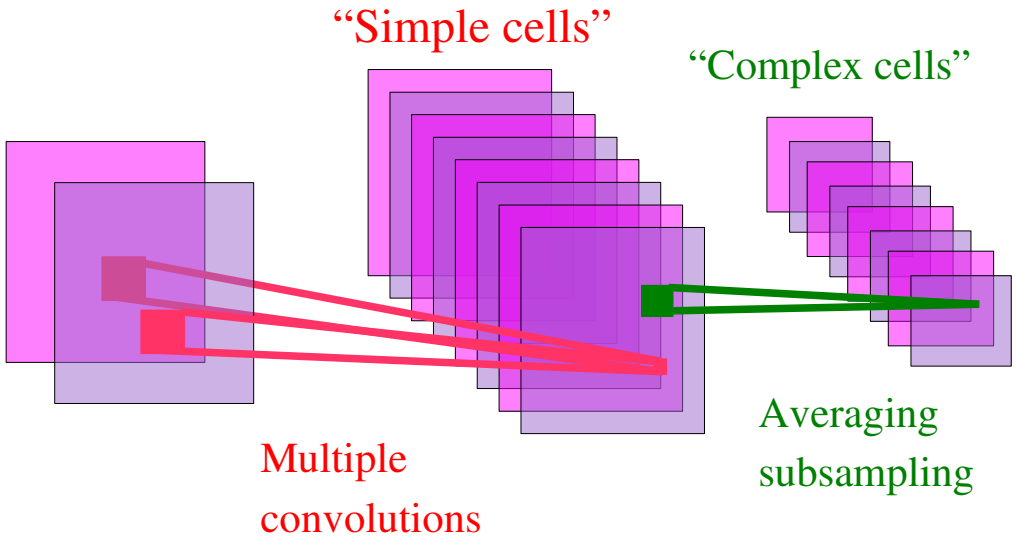


Face Detection with a Convolutional Net

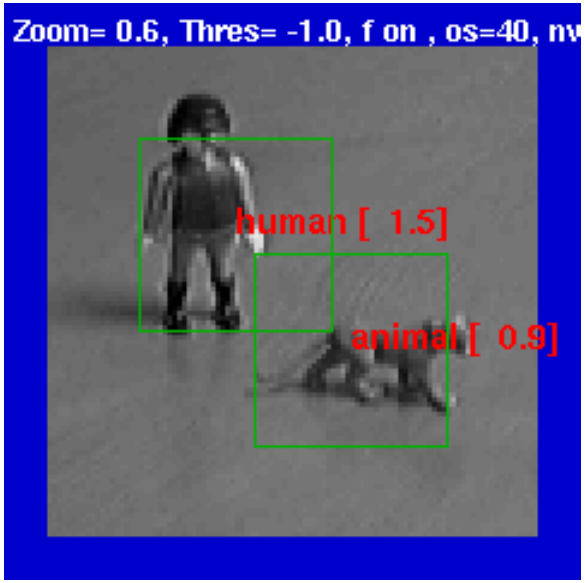
Textured and Cluttered Datasets

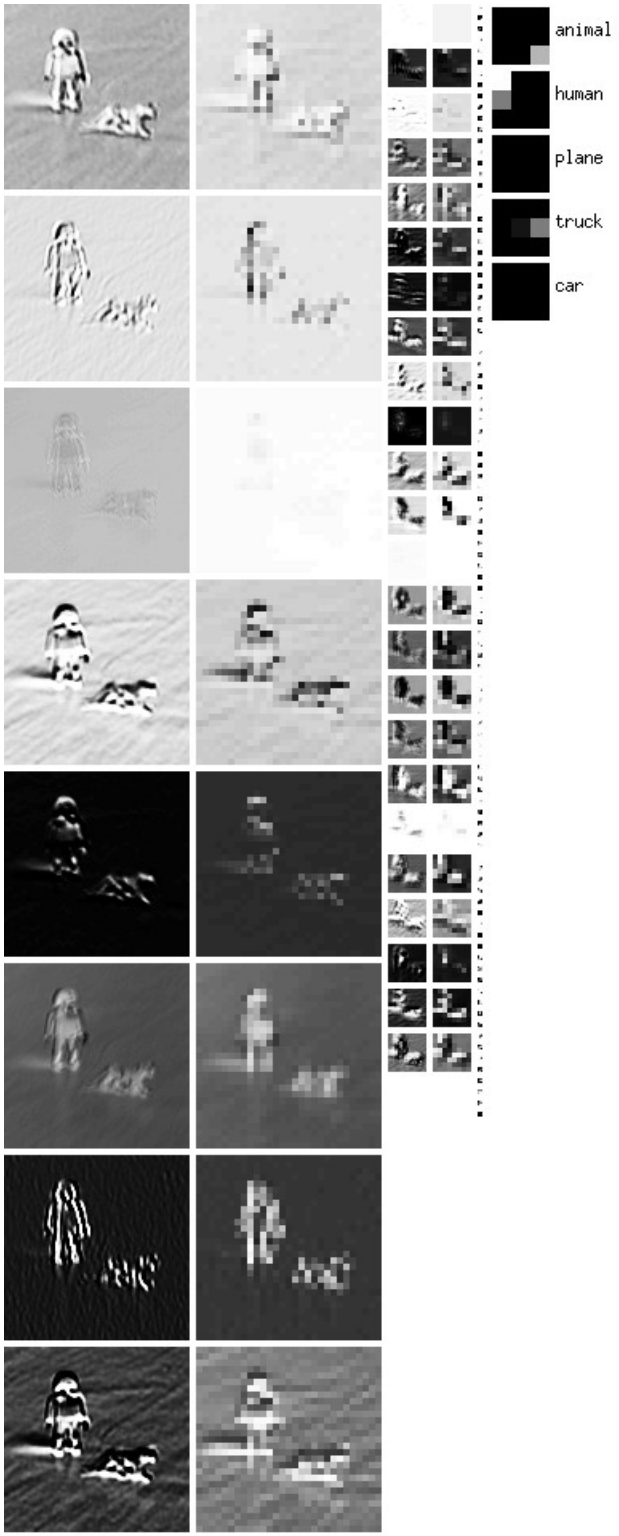


Alternated Convolutions and Subsampling

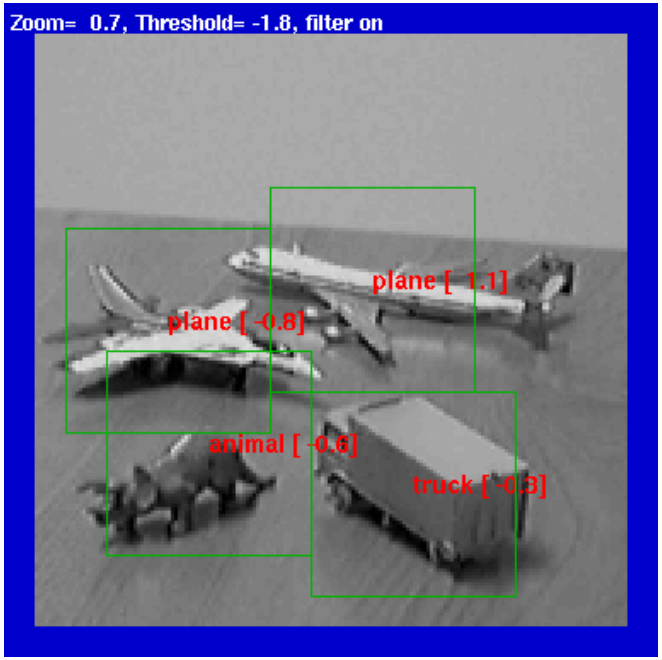


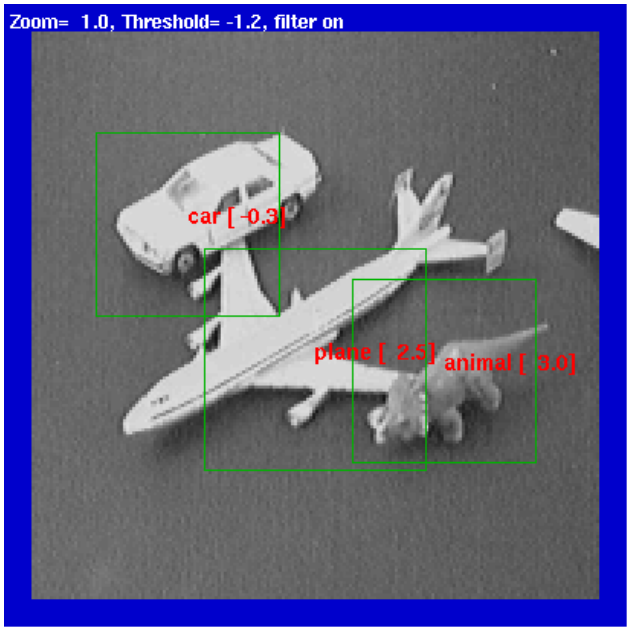
- **Local features are extracted everywhere.**
- **averaging/subsampling layer builds robustness to variations in feature locations.**
- **Hubel/Wiesel'62, Fukushima'71, LeCun'89, Riesenhuber & Poggio'02, Ullman'02,....**

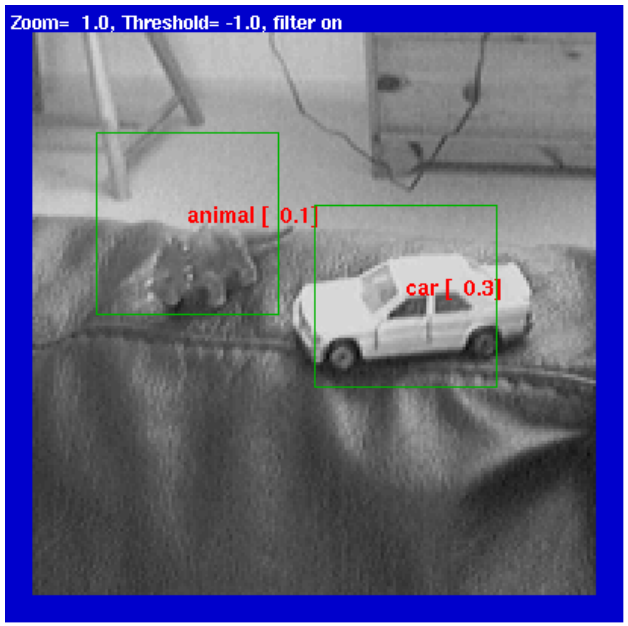


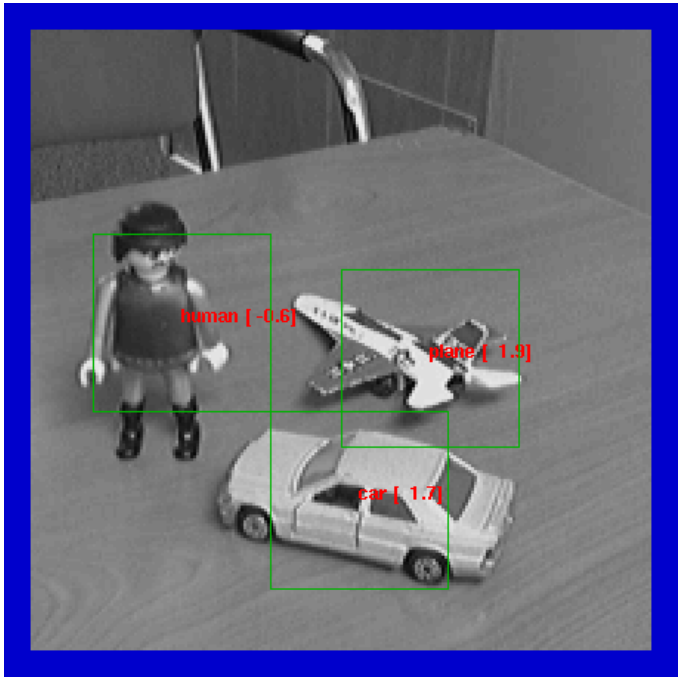


Examples (Monocular Mode)









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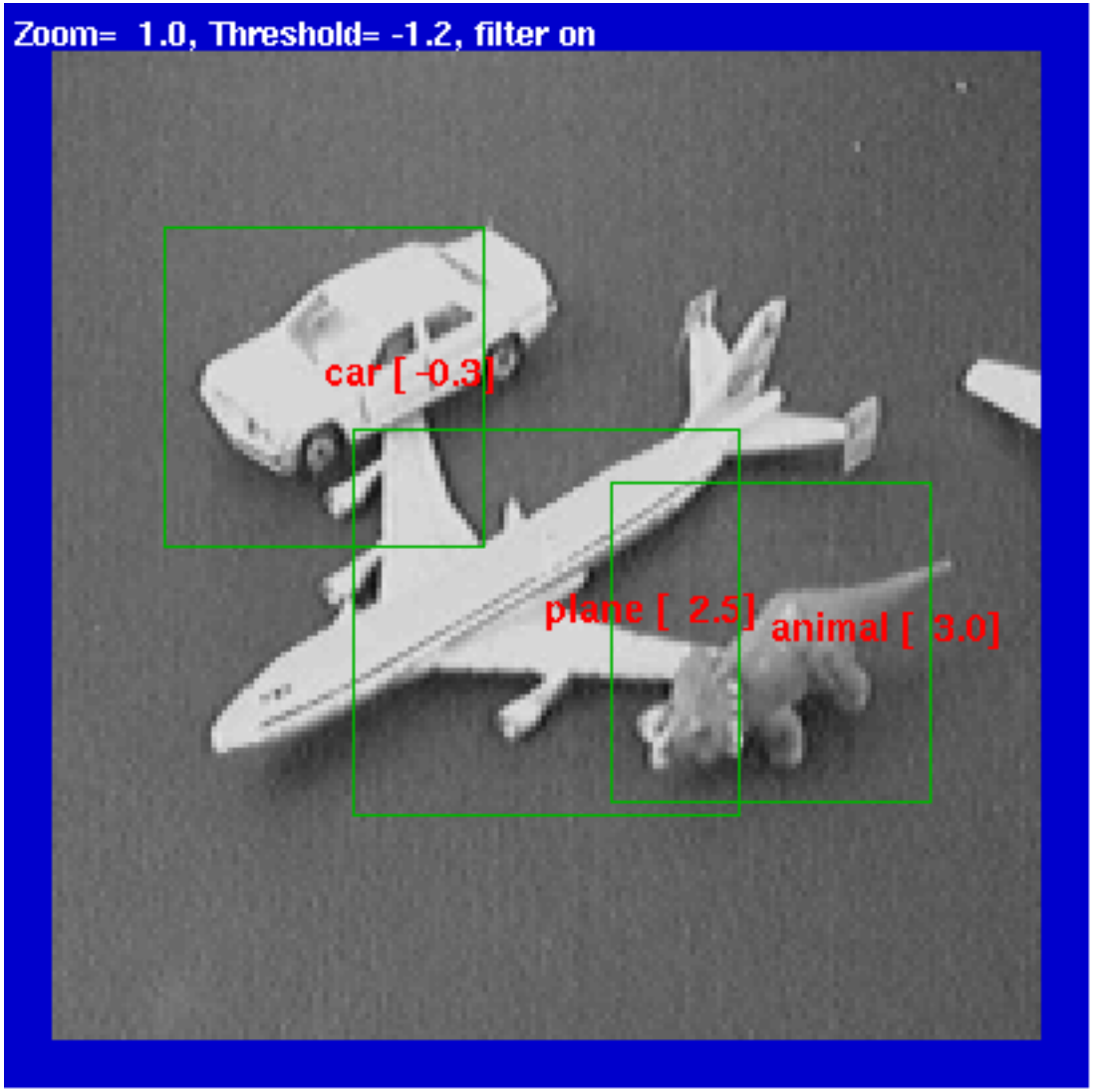
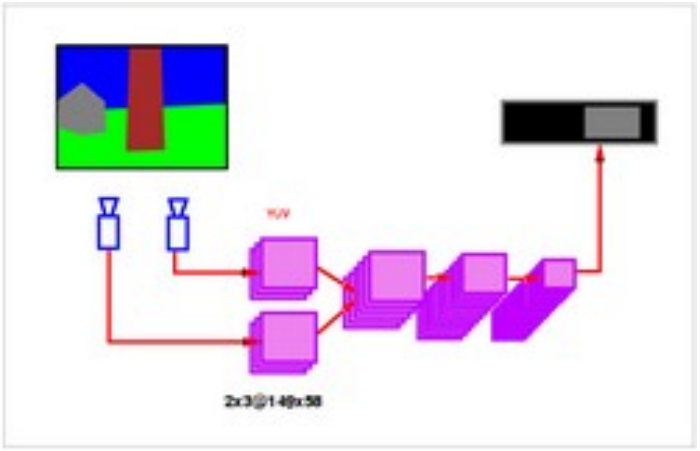
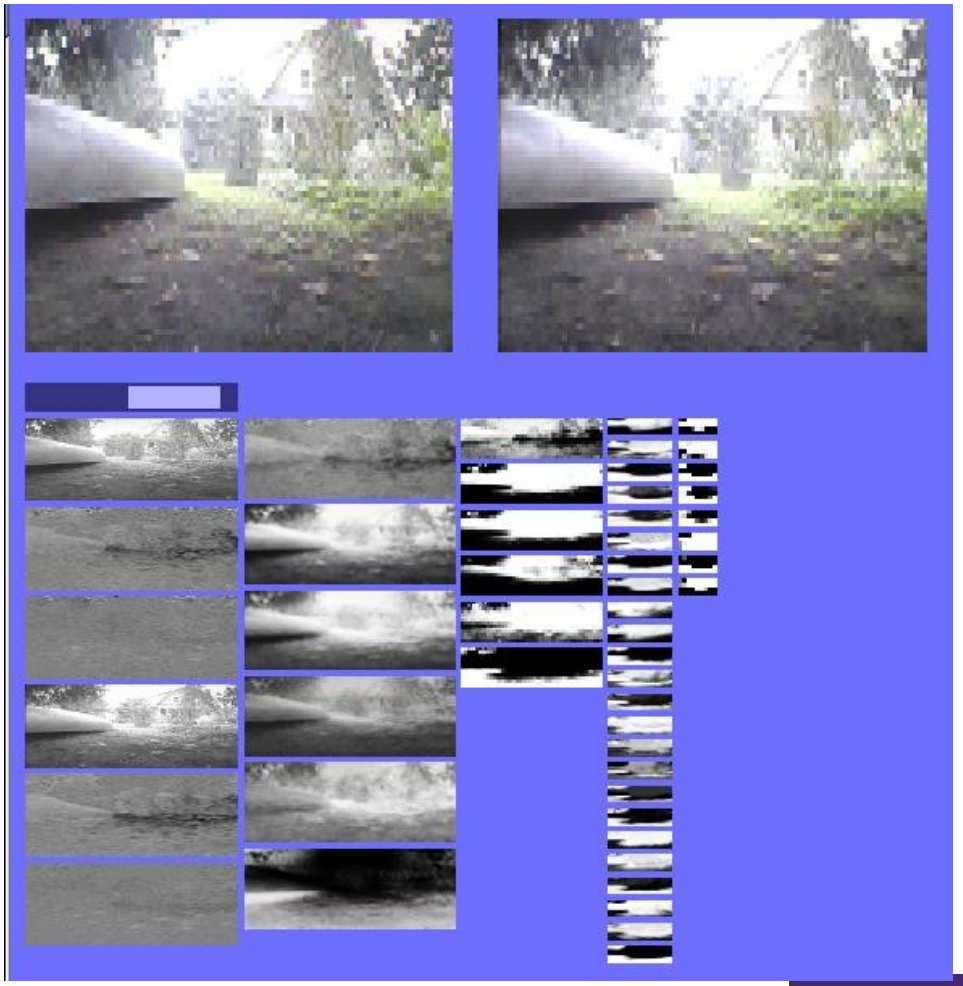


Visual Navigation for a Mobile Robot



- 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



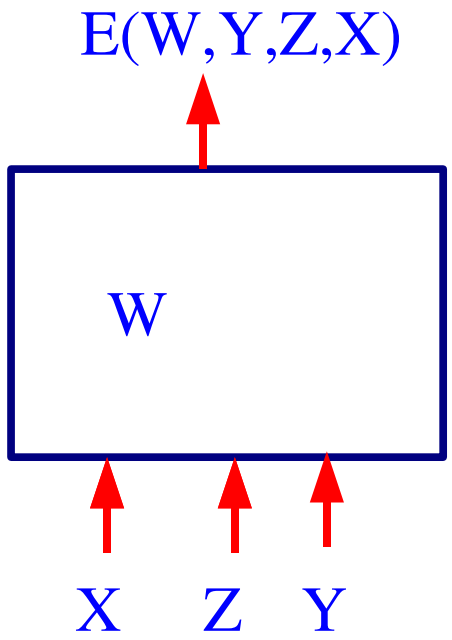
A philosophy: predict everything from everything else

- **This is an old idea that has been proposed and rediscovered by many people (Sutton, Hinton,.....)**
  - Predict one sensory modality from another
  - Predict a label (word) from an image
  - Predict the next state of the world
  - Train a fast module to predict the future output of a slower "reasoning" module
  - Train a module that processes unreliable/noisy inputs to predict the future output of a more reliable/accurate module

General Scheme: Energy-Based Models

- Non-probabilistic graphical models (factor graphs)

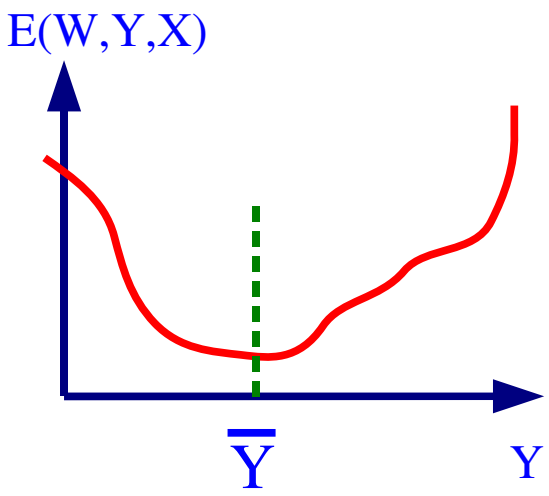
Energy-Based Models



- X: input (always observed)
- Y: output (observed occasionally)
- Z: latent variable (never observed)
- **MAP inference:** given an input X, find the value of Y that minimizes the energy:

$$\check{Y} = \text{argmin}_{y \in \{Y\}} \check{E}(W, y, X)$$

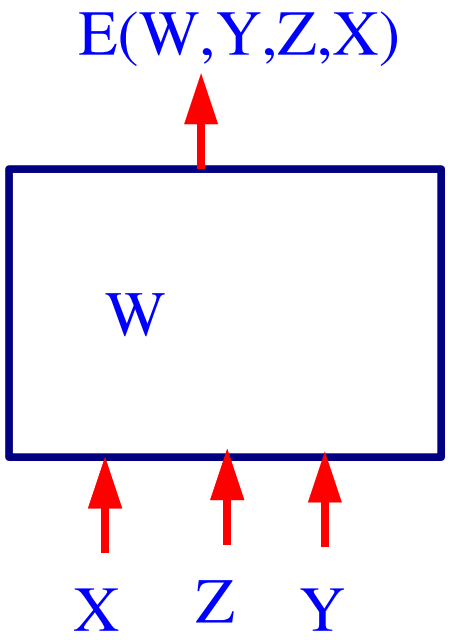
$$\check{E}(W, y, X) = \text{argmin}_{z \in \{Z\}} E(W, y, z, X)$$



- **Probabilistic Inference**: simply marginalize over Z.

$$P(Y|X) = \frac{\int_{z \in \{Z\}} \exp\left(-\beta E(W, Y, z, X)\right)}{\sum_{y \in \{Y\}} \int_{z \in \{Z\}} \exp\left(-\beta E(W, y, z, X)\right)}$$

Architecture + Inference Algo + Loss Function = Model



- **1. Design an architecture:** a particular form for E(W,Y,X).
- **2. Pick an inference algorithm for Y:** MAP or conditional distribution, belief prop, min cut, variational methods, gradient descent, MCMC, HMC.....
- **3. Pick a loss function:** in such a way that minimizing it with respect to W over a training set will make the inference algorithm find the correct Y for a given X.
- **4. Pick an optimization method.**