

Learning Image Features

Yann LeCun

The Courant Institute of Mathematical Sciences

And Center for Neural Science

New York University

The Next Challenge for AI, Robotics, and Neuroscience

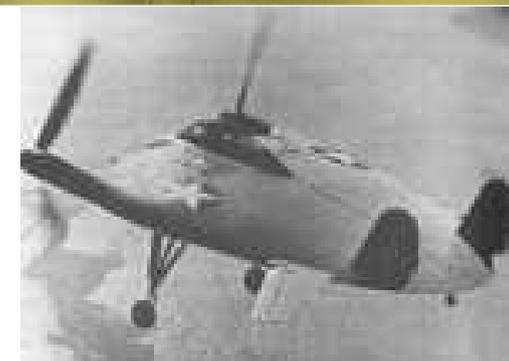
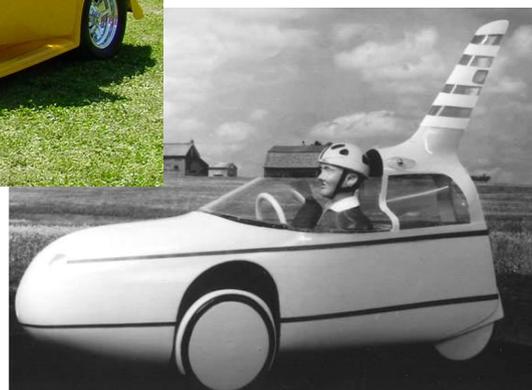
How do we learn vision and perception?

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



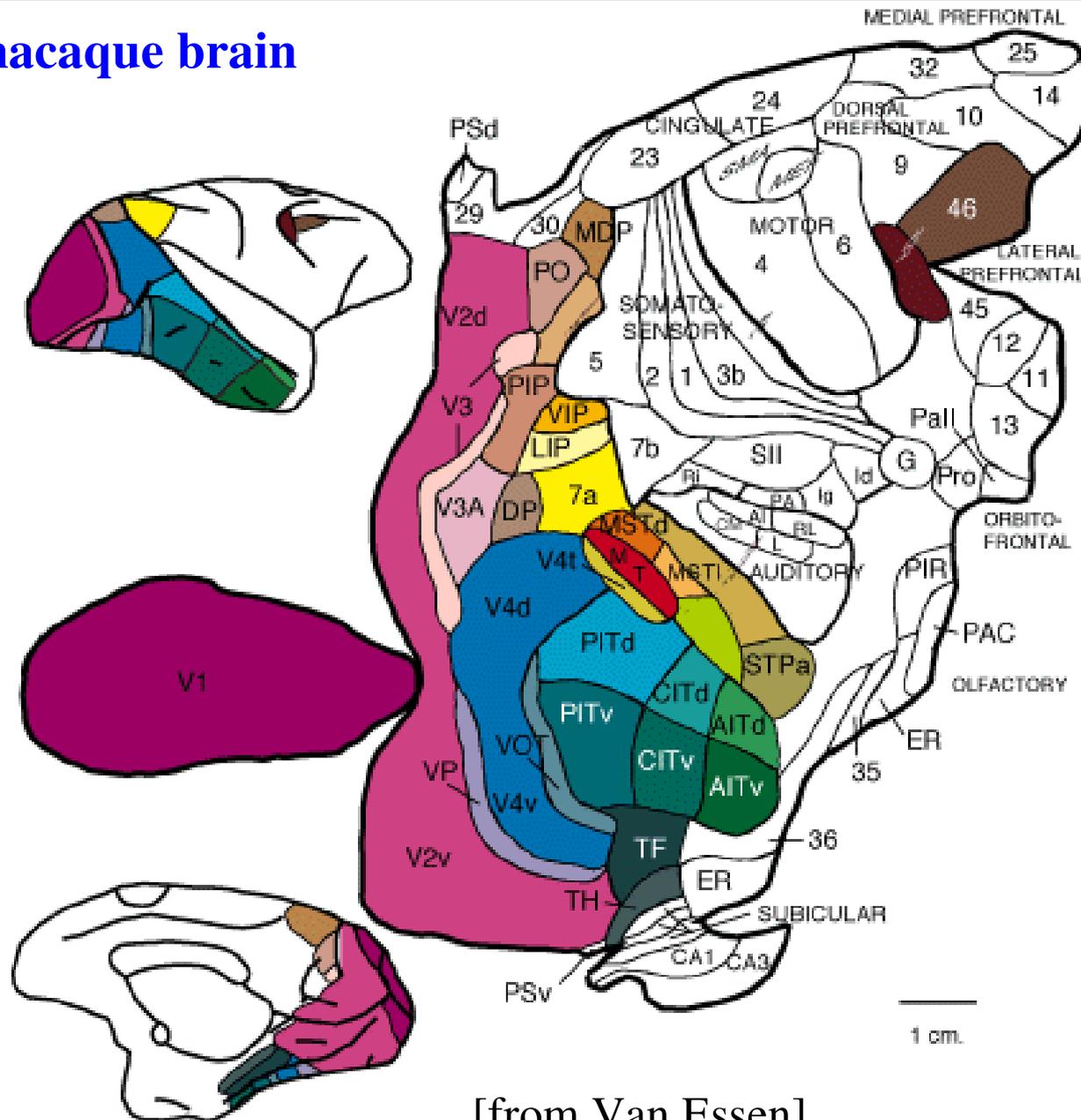
How can we learn visual categories from just a few examples?

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



Vision occupies a big chunk of our brains

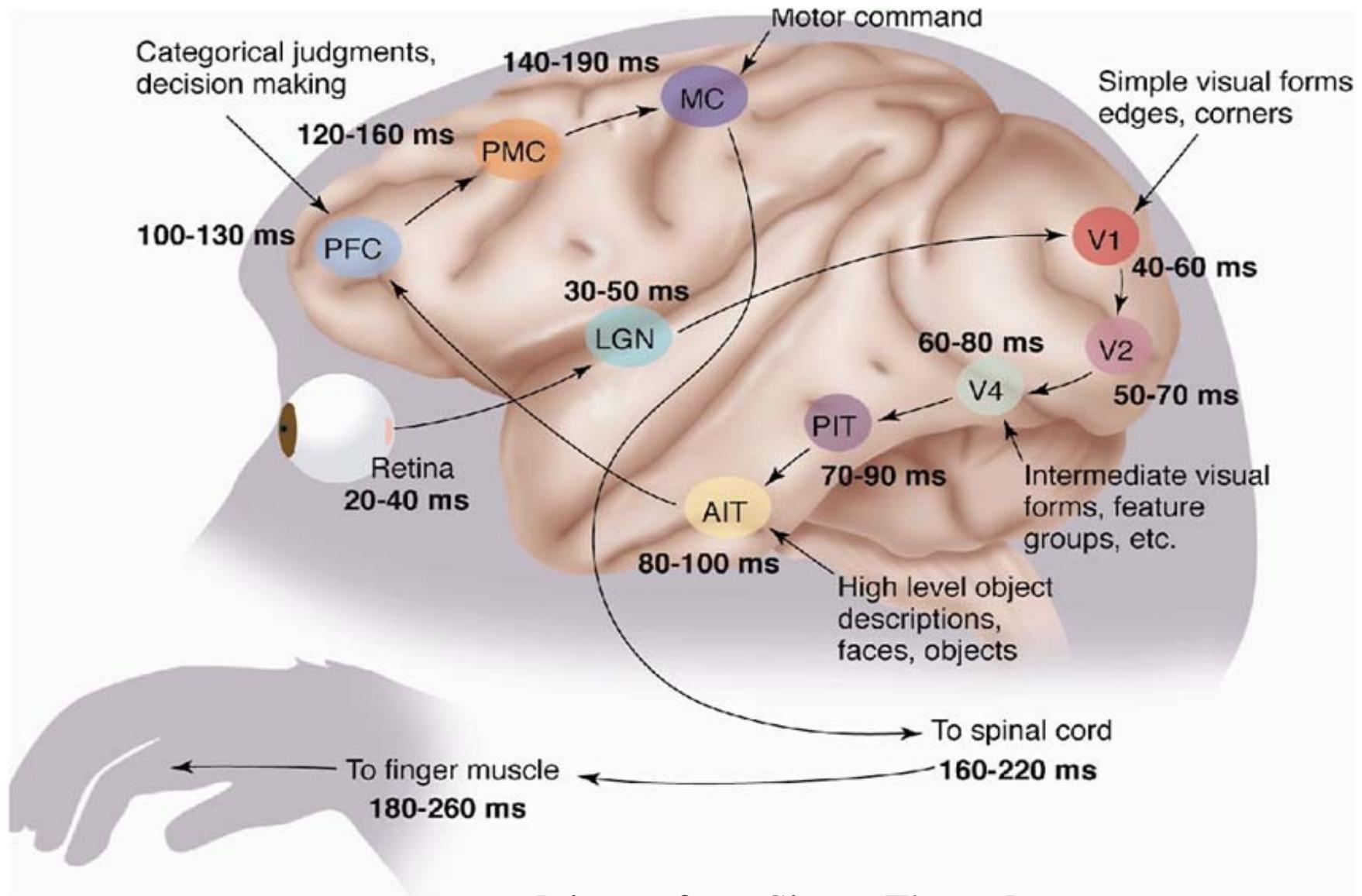
1/3 of the macaque brain



[from Van Essen]

Vision is very fast and the visual cortex is hierarchical

The ventral (recognition) pathway in the visual cortex



[picture from Simon Thorpe]

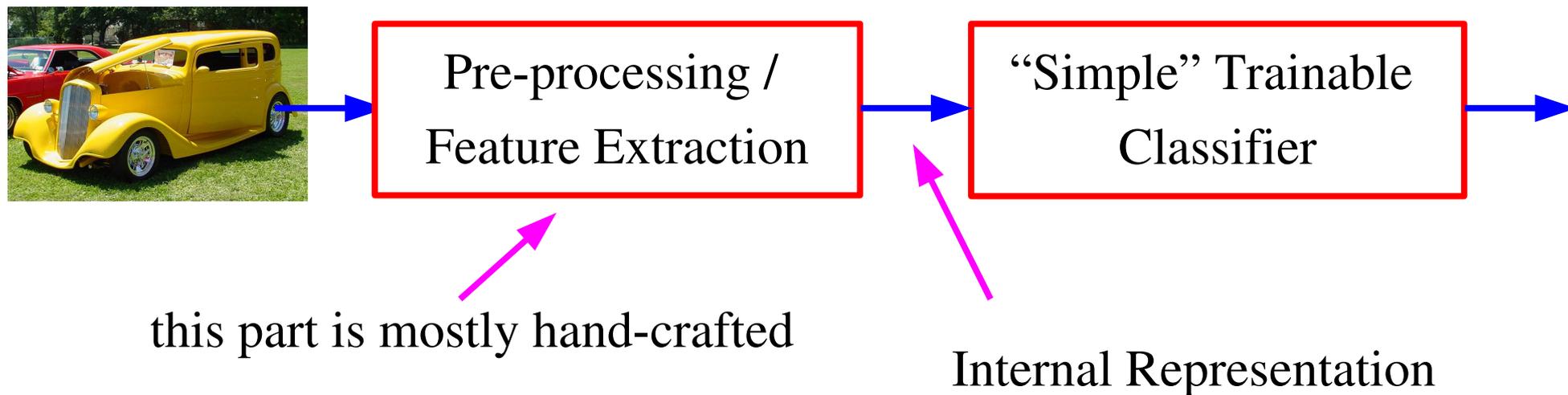
The Primate's Visual System is Deep (LGN->V1->V2->V4->IT)

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

The Broader Challenge of Machine Learning and AI

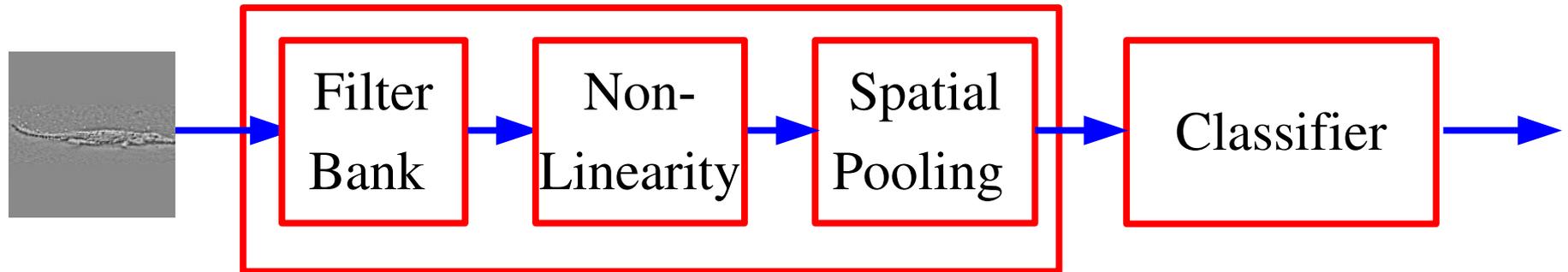
- **Can we devise learning algorithms to train a “deep” artificial visual system, and other artificial perception systems.**
- **How can we learn the structure of the world?**
 - ▶ How can we build/learn internal representations of the world that allow us to discover its hidden structure?
 - ▶ How can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

The Traditional “Shallow” Architecture for Recognition



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

“Modern” Object Recognition Architecture in Computer Vision



Oriented Edges

Gabor Wavelets

Other Filters...

Sigmoid

Rectification

Vector Quant.

Contrast Norm.

Averaging

Max pooling

VQ+Histogram

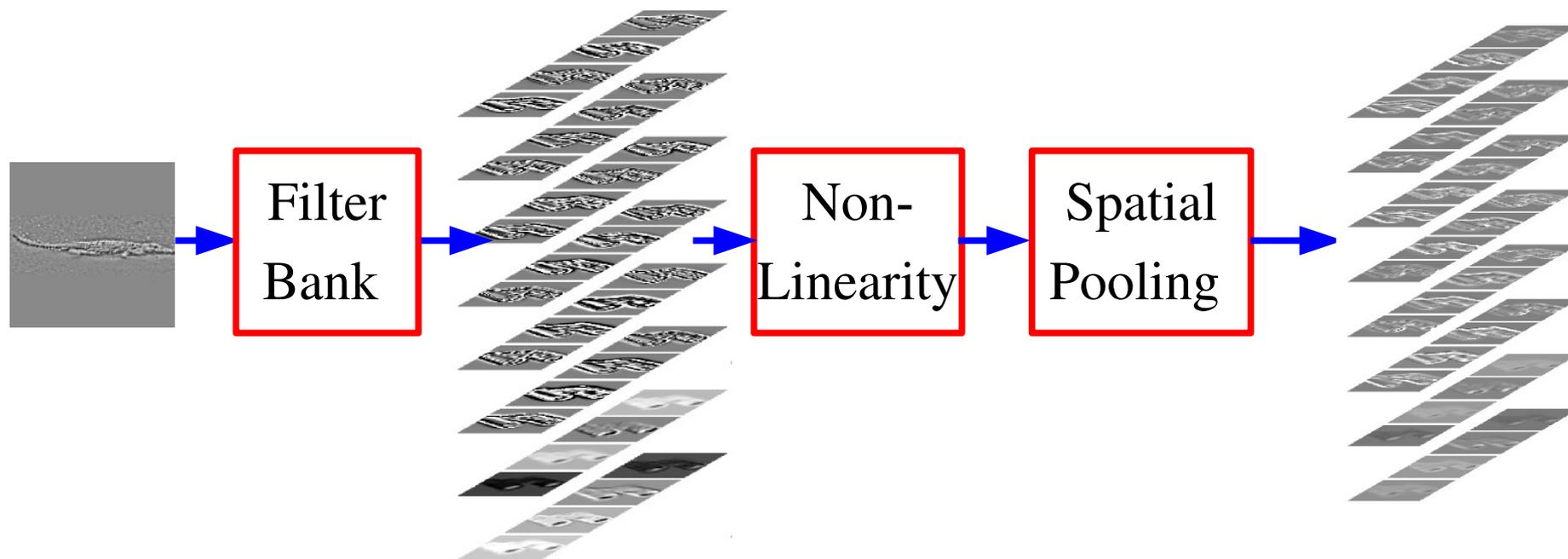
Geometric Blurr

Example:

- ▶ Edges + Rectification + Histograms + SVM [Dalal & Triggs 2005]
- ▶ SIFT + classification

Fixed Features + “shallow” classifier

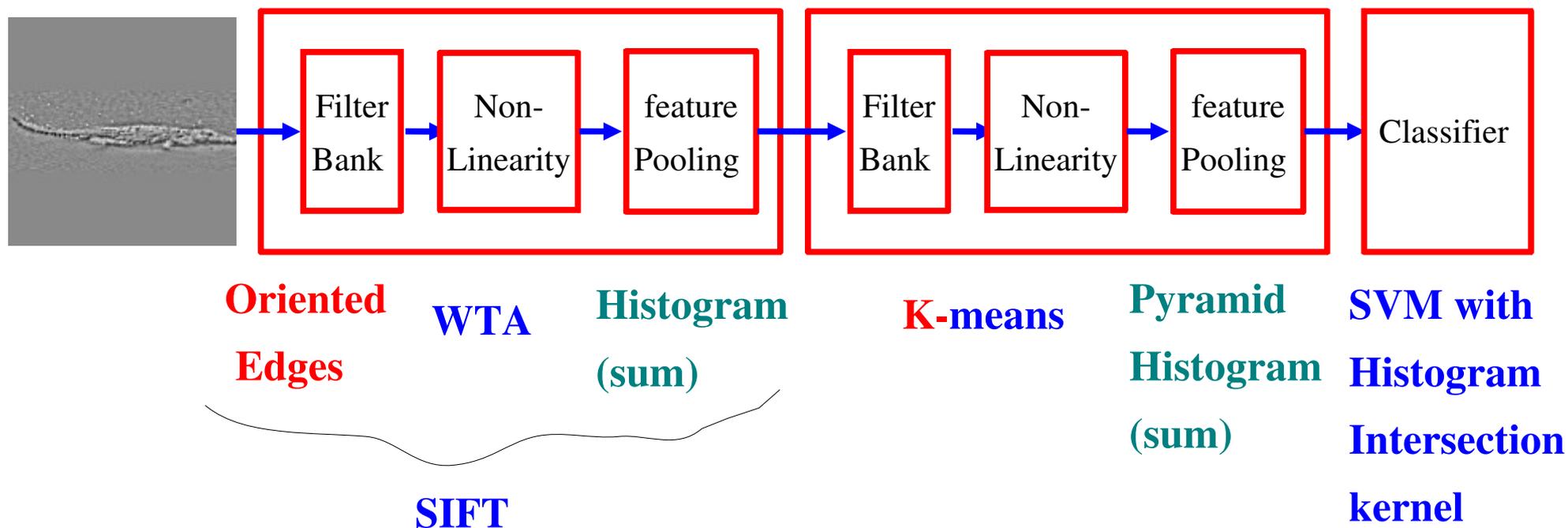
Feature Extraction by Filtering and Pooling



Biologically-inspired models of low-level feature extraction

- ▶ Inspired by [Hubel and Wiesel 1962]
- ▶ Many feature extraction methods are based on this
- ▶ SIFT, GIST, HoG, Convolutional networks.....

“State of the Art” architecture for object recognition

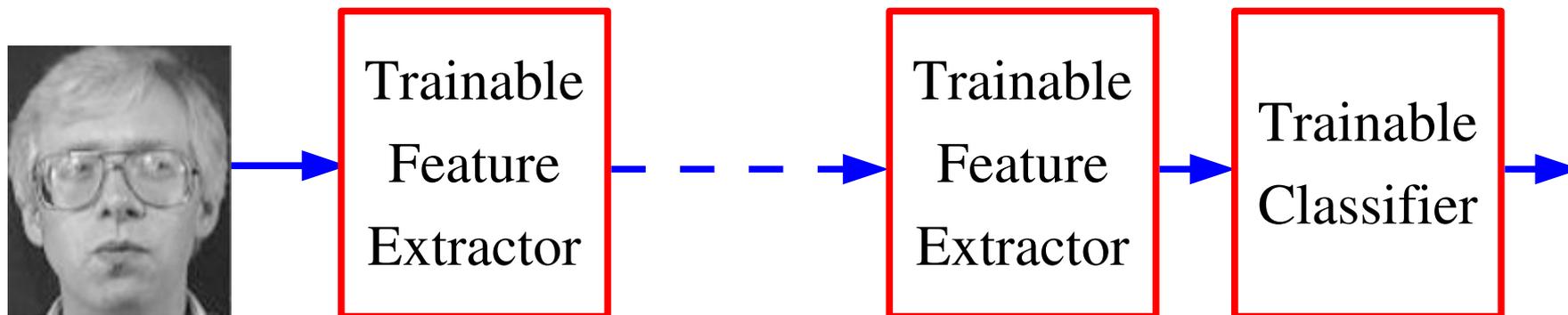


Example:

- ▶ SIFT features with Spatial Pyramid Match Kernel SVM [Lazebnik et al. 2006]

Fixed Features + unsupervised features + “shallow” classifier

Good Representations are Hierarchical



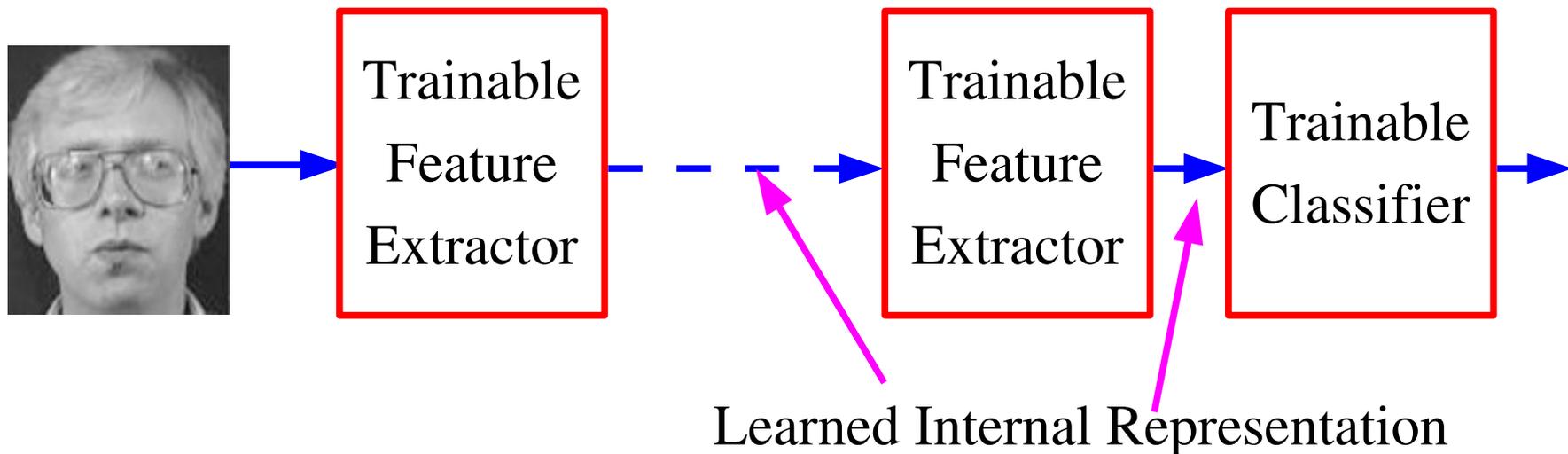
● In Language: hierarchy in syntax and semantics

- ▶ Words->Parts of Speech->Sentences->Text
- ▶ Objects,Actions,Attributes...-> Phrases -> Statements -> Stories

● In Vision: part-whole hierarchy

- ▶ Pixels->Edges->Textons->Parts->Objects->Scenes

“Deep” Learning: Learning Hierarchical Representations



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

Plan of the Tutorial

• Simple methods for supervised learning

- ▶ Energy-based learning
- ▶ Perceptron, logistic regression, SVM

• Deep Supervised Learning

- ▶ Backpropagation

• Architectures for Image Recognition

- ▶ Local feature extractors, SIFT, HoG
- ▶ Vector quantization and feature pooling

• Trainable Architectures for Image Recognition: Feature Learning

- ▶ Supervised Convolutional Networks

• Unsupervised Deep Learning, Energy-Based Models

- ▶ Predictive Sparse Decomposition

• Applications

- ▶ Face/pedestrian detection, object recognition, image segmentation, obstacle detection for robots.