Deep Learning and Application in Neural Networks

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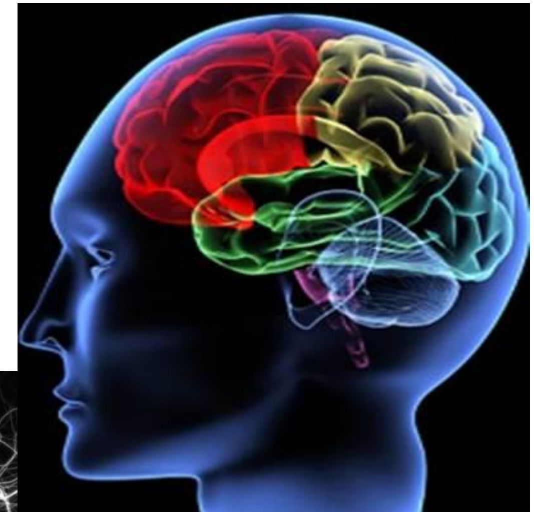
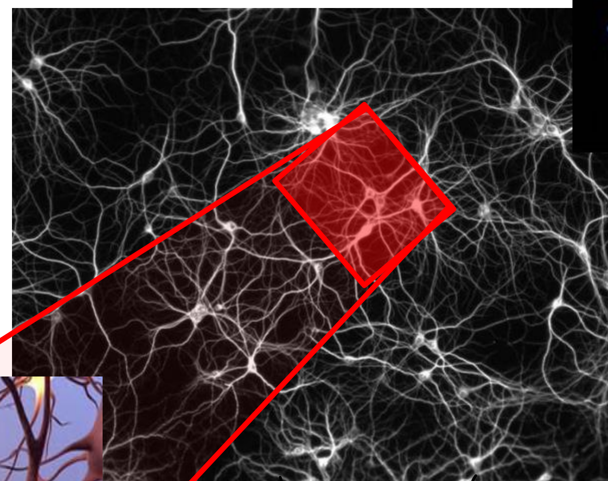
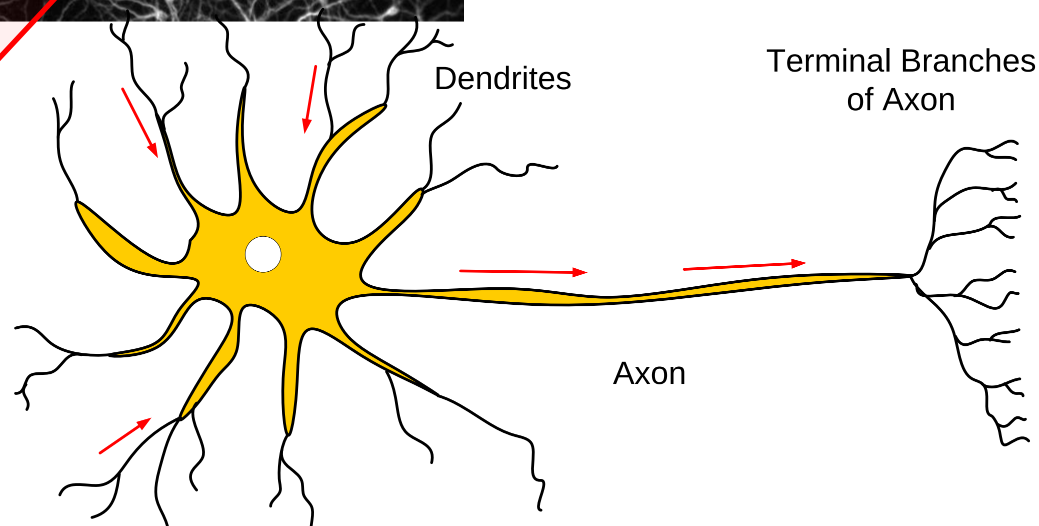
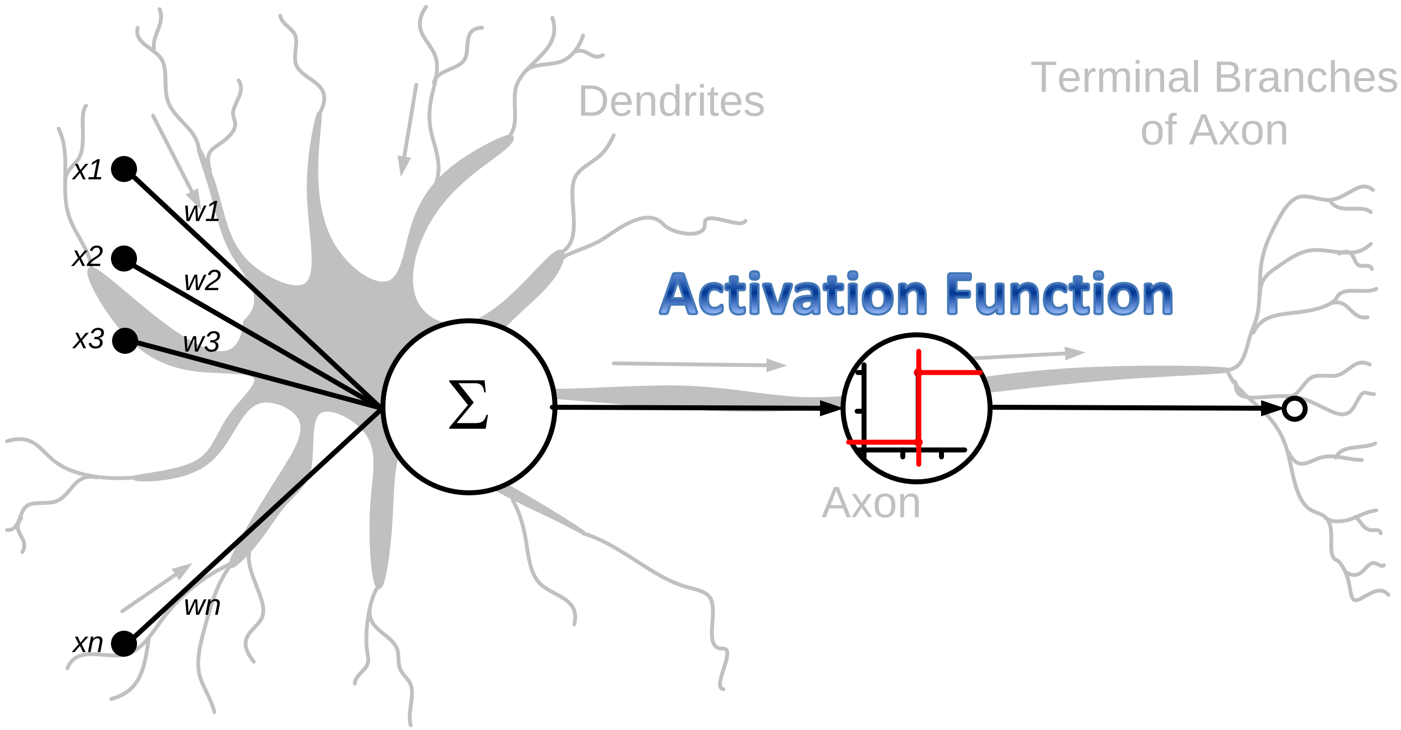
Biological Neurons





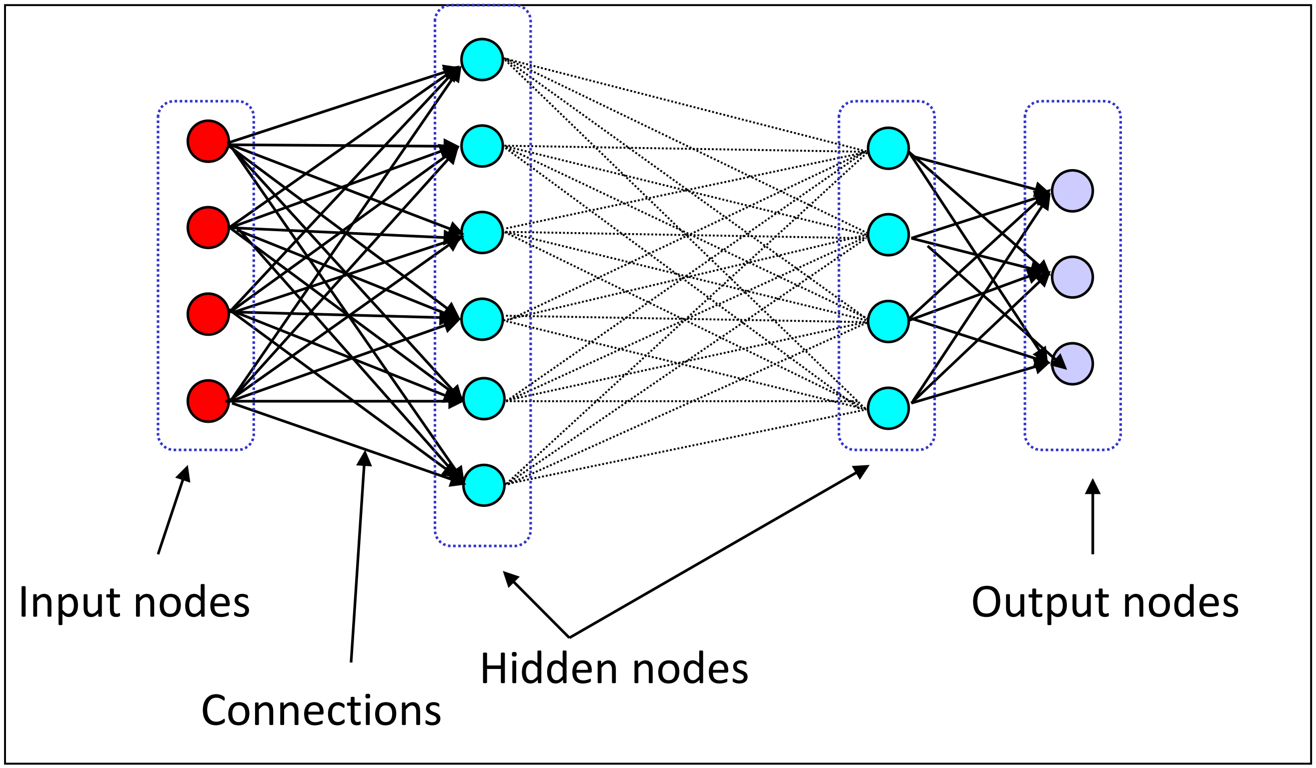


Artificial Neural Networks (ANN)



Slide credit : Andrew L. Nelson

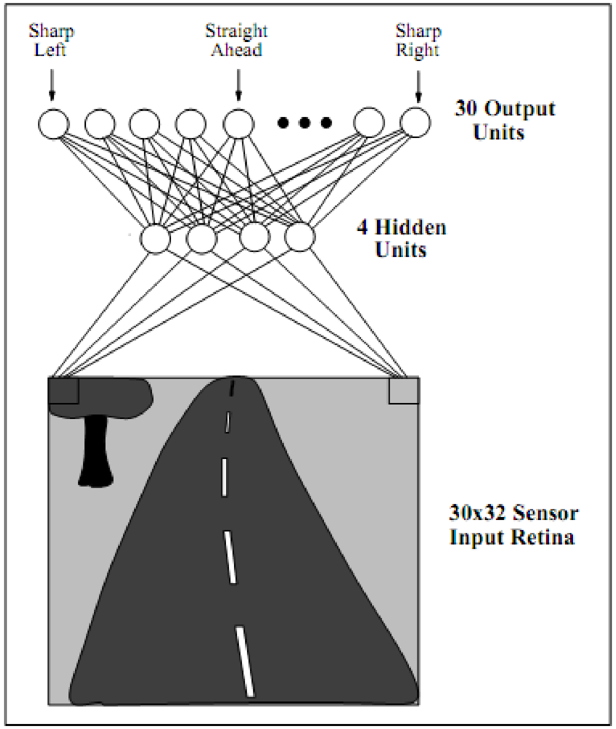
Layered Networks



$$Output: \quad y_i = f(w_i^1 x_1 + w_i^2 x_2 + w_i^3 x_3 + \cdots + w_i^m x_m)$$
$$= f(\sum_j w_i^j x_j)$$

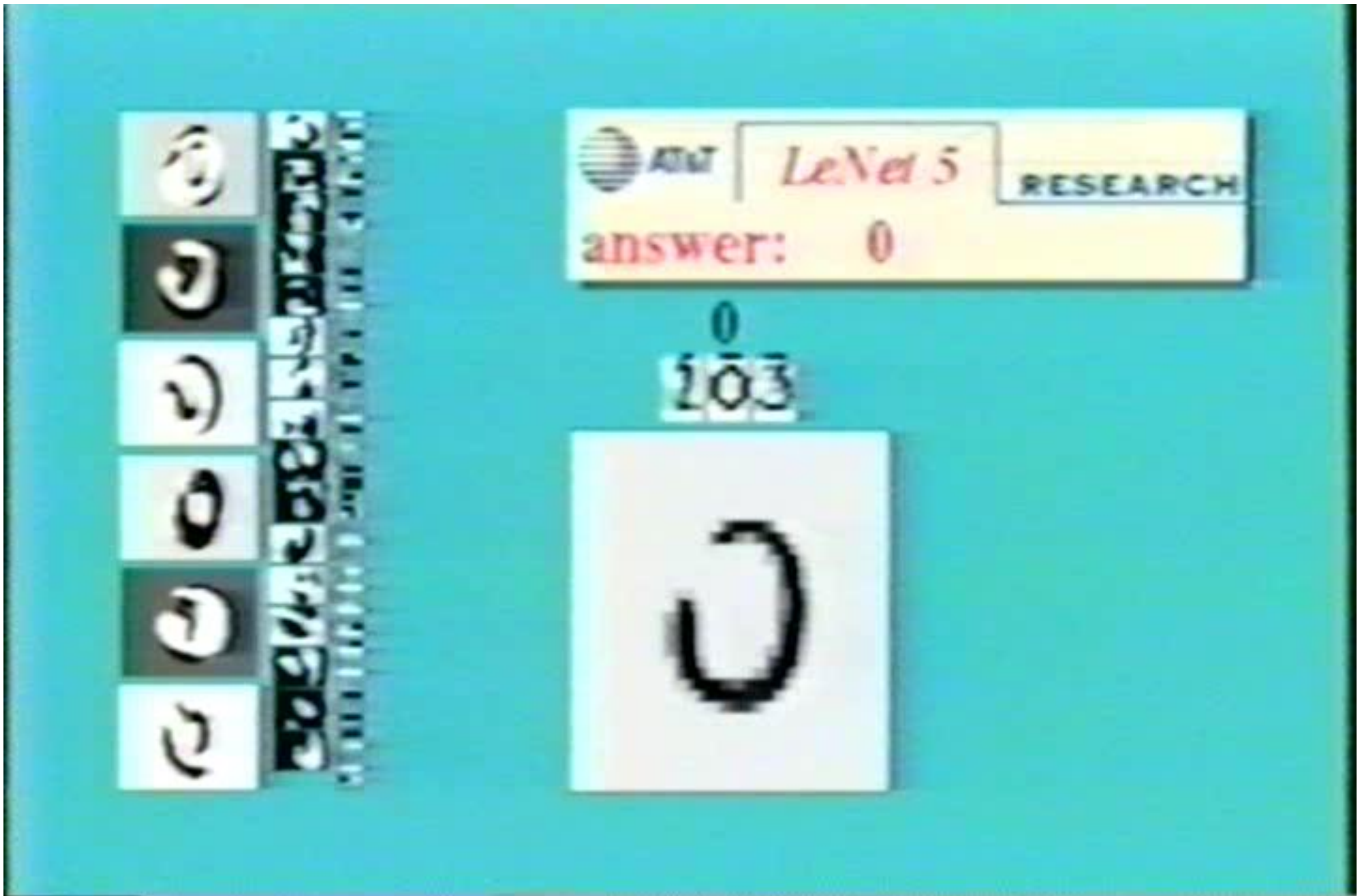
Neural network application

- ALVINN drives 70 mph on highways



Slide credit : T.Michell

Neural network application

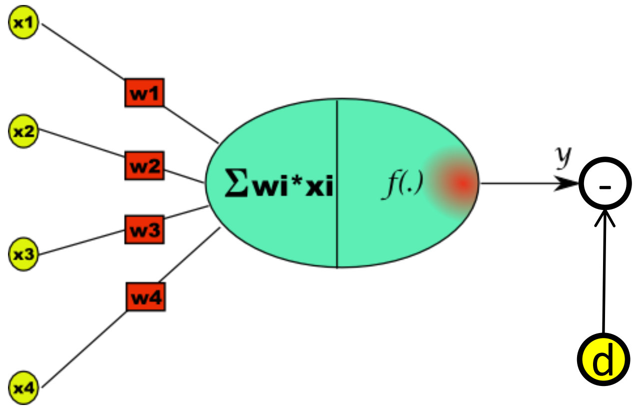


Slide credit : Andraw Ng.

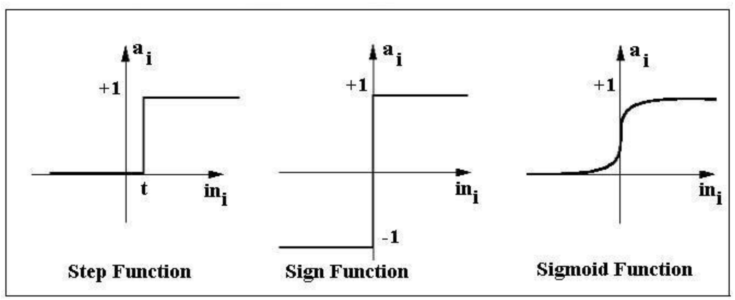
The simplest model- the Perceptron

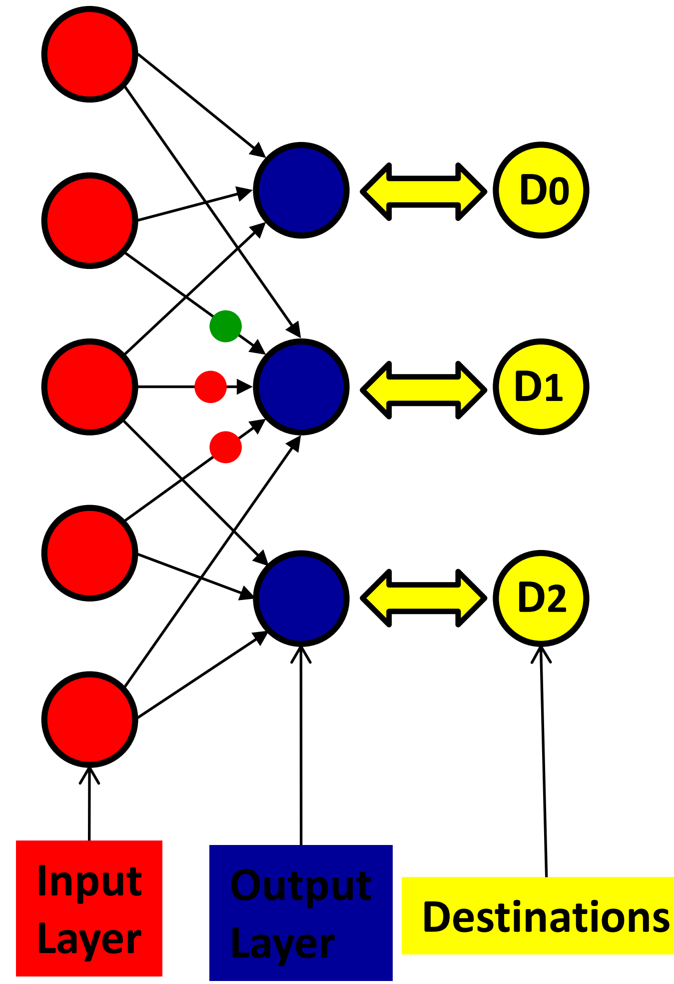
- The Perceptron was introduced in 1957 by Frank Rosenblatt.

Perceptron:



Activation functions:





Learning:

$$y^{(t)} = f\left\{\sum_i w_i^{(t)} x_i^{(t)}\right\}$$

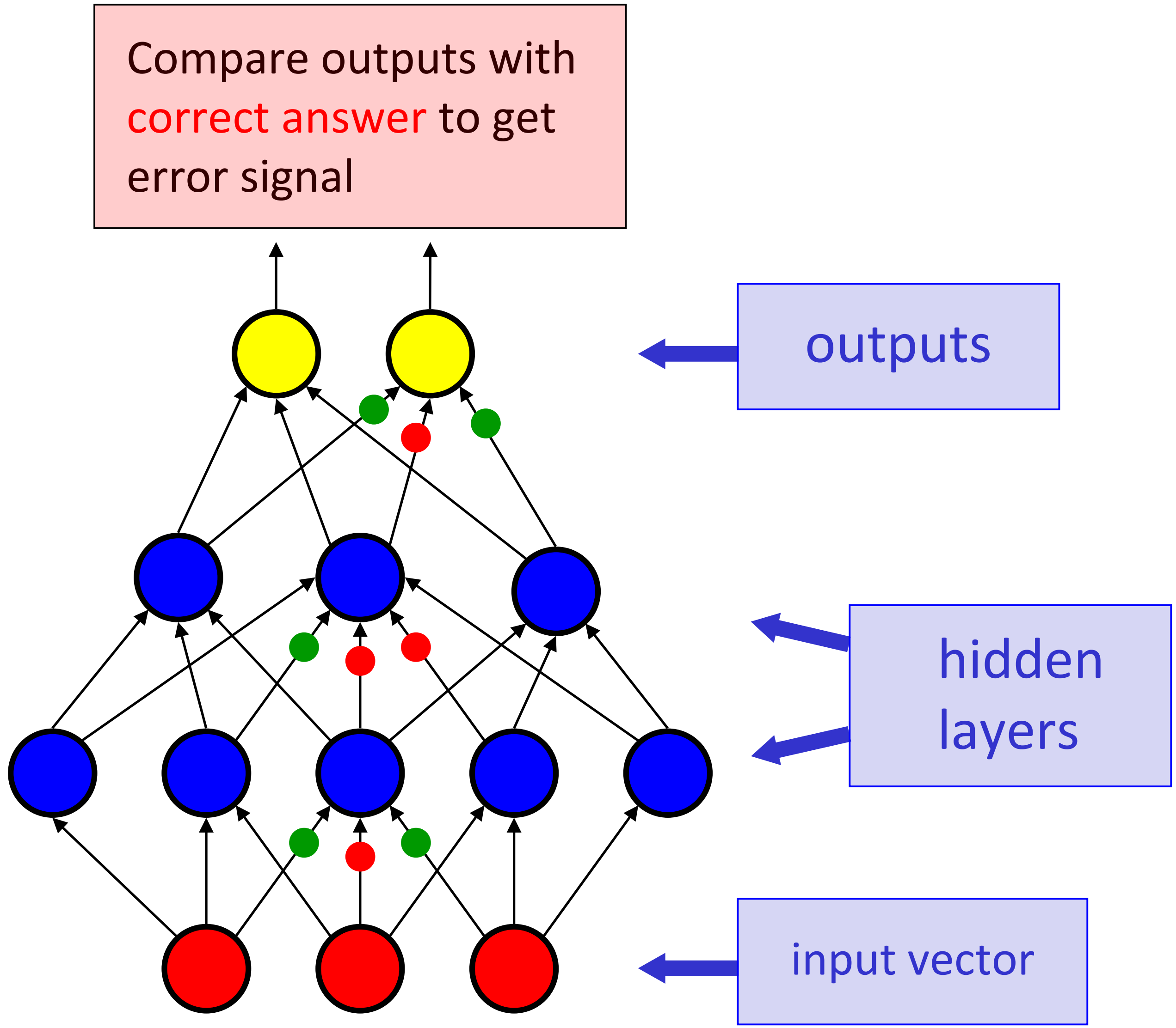
Update

$$\begin{cases} \Delta w_i^{(t)} = \varepsilon\left(d^{(t)} - y^{(t)}\right) x_i^{(t)} \\ w_i^{(t+1)} = w_i^{(t)} + \Delta w_i^{(t)} \end{cases}$$

Slide credit : Geoffrey Hinton

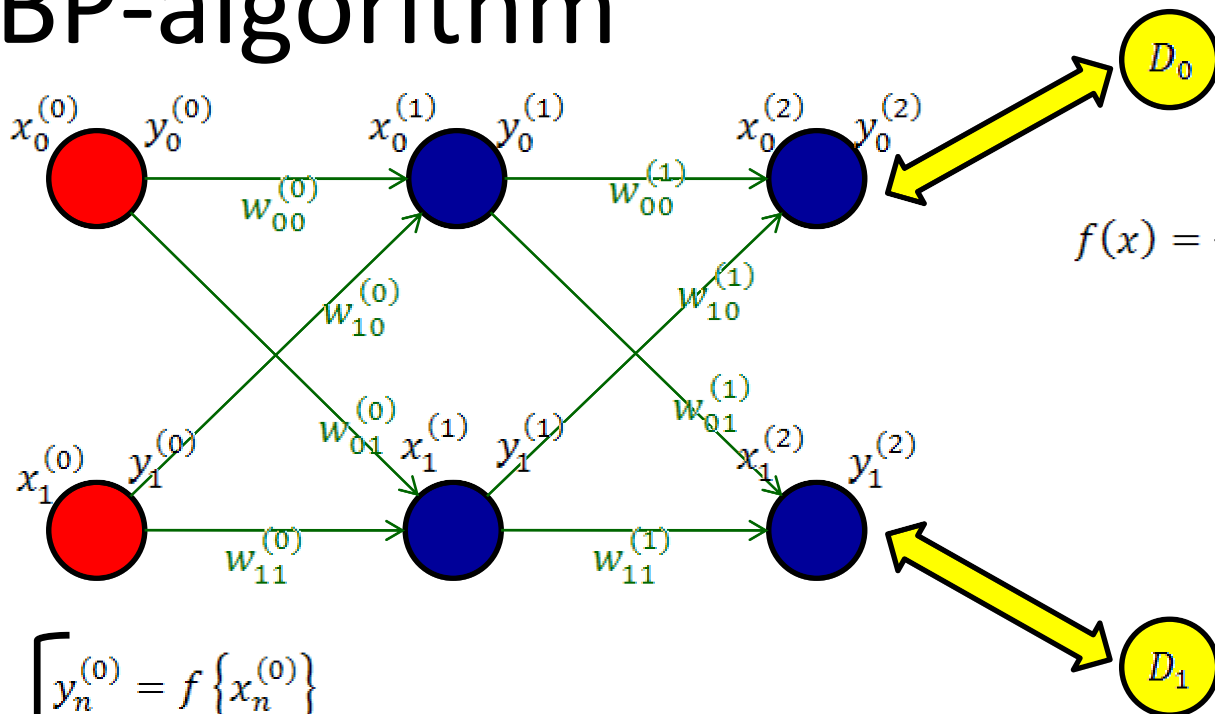
Second generation neural networks (~1985)

Back-propagate error signal to get derivatives for learning

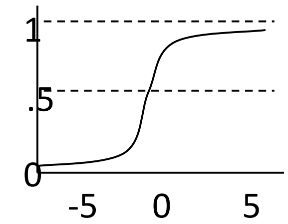


Slide credit : Geoffrey Hinton

BP-algorithm



$$f(x) = \frac{1}{1+e^{-x}}$$



Activations

$$y_n^{(0)} = f\left\{x_n^{(0)}\right\}$$

$$y_n^{(1)} = f\left\{\sum_{i=0}^{1} y_i^{(0)} w_{in}^{(0)}\right\}$$

$$y_n^{(2)} = f\left\{\sum_{i=0}^{1} y_i^{(1)} w_{in}^{(1)}\right\}$$

errors

$$\frac{\partial E}{\partial w_{ij}^{(1)}} = -2\left(D_j - y_j^{(2)}\right) f\left\{x_j^{(2)}\right\}\left(1 - f\left\{x_j^{(2)}\right\}\right) y_i^{(1)} \stackrel{\text{def}}{=} \delta_j^{(1)} y_i^{(1)}$$

$$\frac{\partial E}{\partial w_{ij}^{(0)}} = f\left\{x_j^{(1)}\right\}\left(1 - f\left\{x_j^{(1)}\right\}\right) \sum_{n=0}^{1} \delta_n^{(1)} w_{jn}^{(1)} x_i^{(0)} \stackrel{\text{def}}{=} \delta_j^{(0)} x_i^{(0)}$$

The error: $E = \sum_{n=0}^{1} \left(D_n - y_n^{(2)}\right)^2$

Update Weights: $w_{ij}^{(k)} = w_{ij}^{(k)} + \varepsilon \frac{\partial E}{\partial w_{ij}^{(k)}}$

Update

$$w_{ij}^{(1)} = w_{ij}^{(1)} + \varepsilon \delta_j^{(1)} y_i^{(1)}$$

$$w_{ij}^{(0)} = w_{ij}^{(0)} + \varepsilon \delta_j^{(0)} x_i^{(0)}$$

Slide credit : Geoffrey Hinton

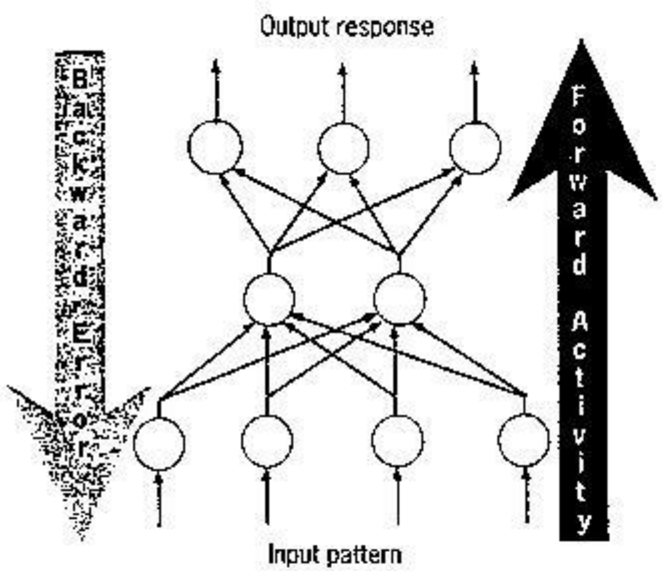
Back Propagation

Advantages

• Multi layer Perceptron network can be trained by the back propagation algorithm to perform any mapping between the input and the output.

What is wrong with back-propagation?

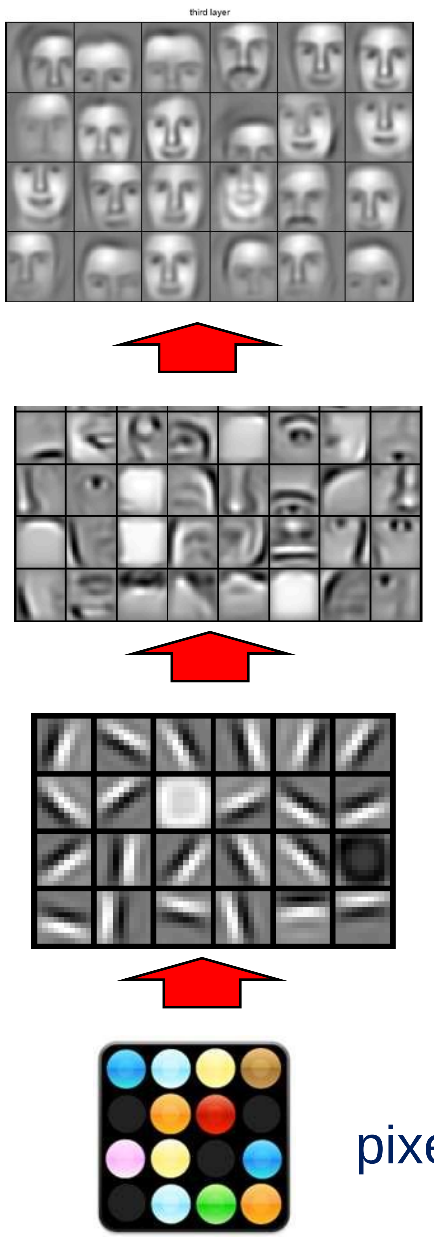
- It requires labeled training data.
  - Almost all data is unlabeled.
- The learning time does not scale well
  - It is very slow in networks with multiple hidden layers.
- It can get stuck in poor local optima.



A backpropagation network trains with a two-step procedure. The activity from the input pattern flows forward through the network, and the error signal flows backward to adjust the weights.

Slide credit : Geoffrey Hinton

Why Deep multi-layered neural network

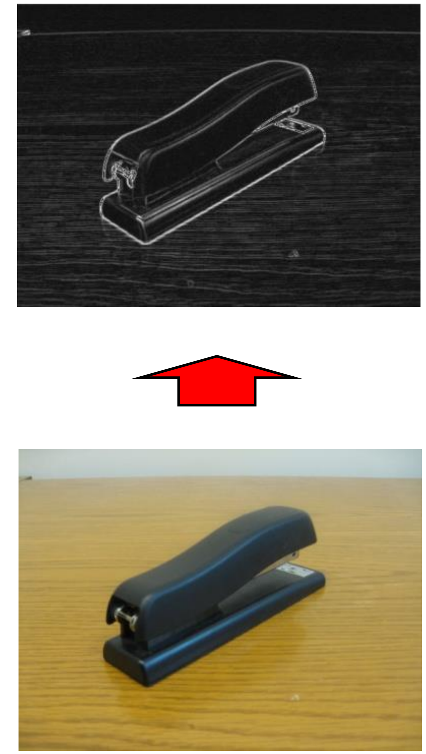


object models

object parts
(combination
of edges)

edges

pixels



Before 2006

Failing to train deep architectures

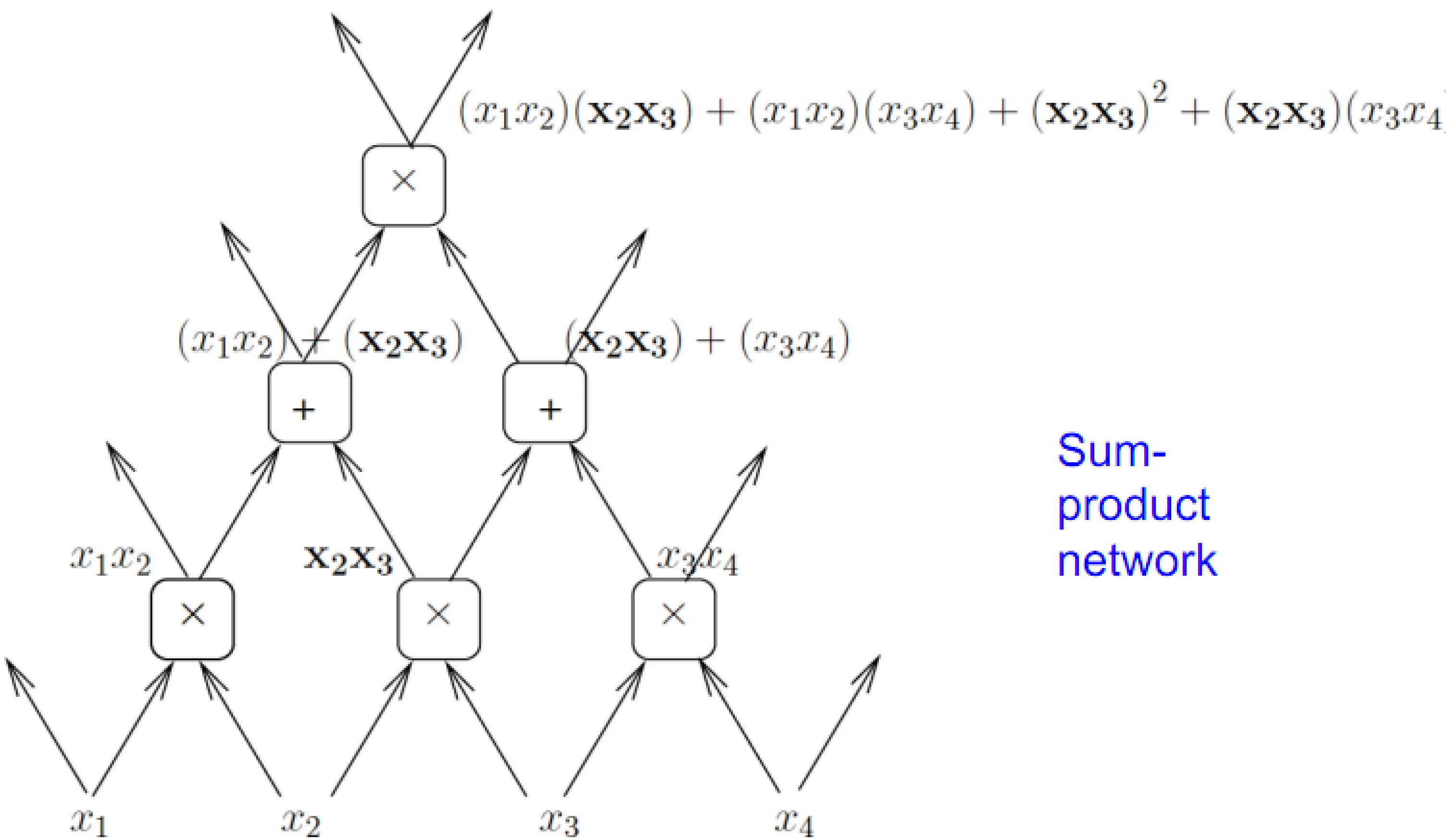
Deep Neural Networks

- Standard learning strategy
  - Randomly initializing the weights of the network
  - Applying gradient descent using backpropagation
- But, backpropagation does not work well (if randomly initialized)
  - Deep networks trained with back-propagation (without unsupervised pre-train) perform worse than shallow networks
  - ANN have limited to one or two layers

Sharing Components in a Deep Architecture

Polynomial expressed with shared components:

advantage of depth may grow exponentially



Sum-product network

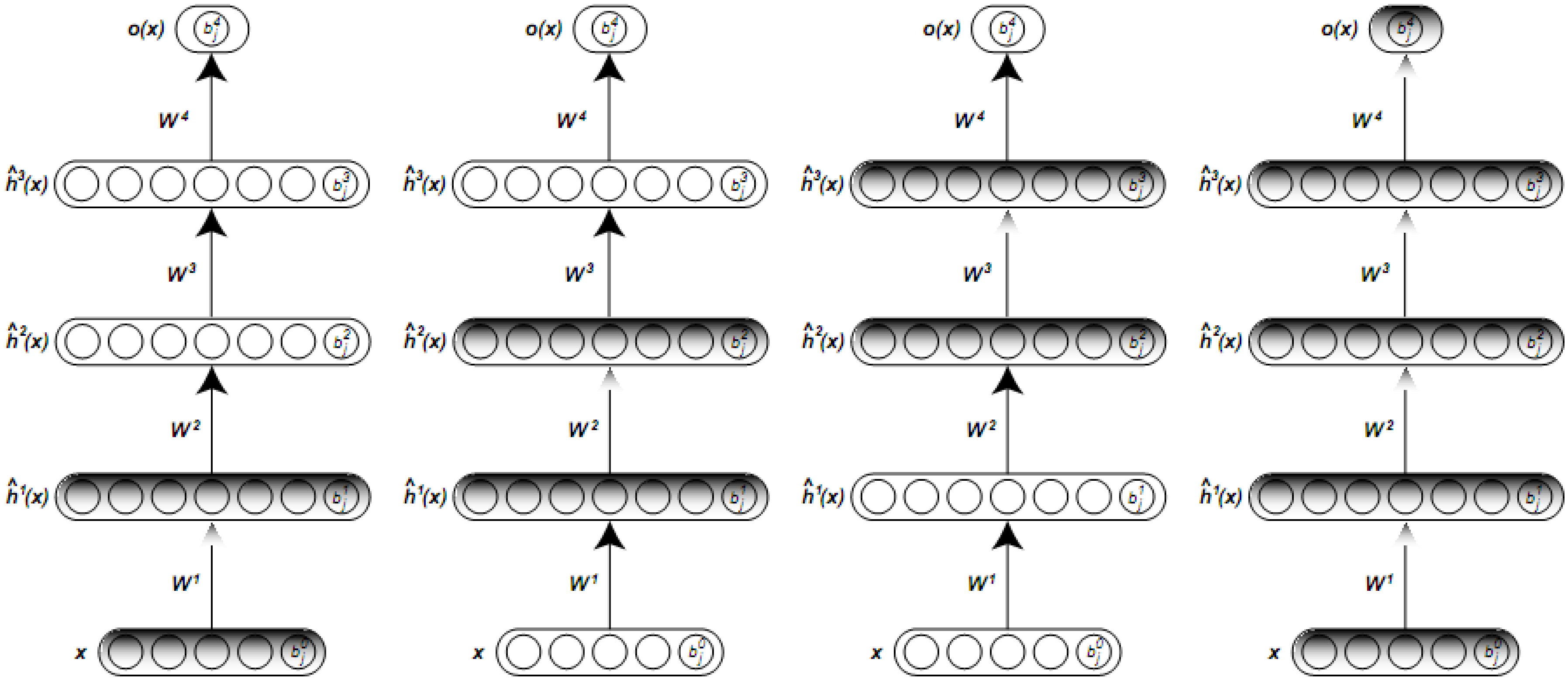
2006

Breakthrough!

2006: The Deep Breakthrough

- Hinton, Osindero & Teh « A Fast Learning Algorithm for Deep Belief Nets », *Neural Computation*, 2006
- Bengio, Lamblin, Popovici, Larochelle « Greedy Layer-Wise Training of Deep Networks », *NIPS'2006*
- Ranzato, Poultney, Chopra, LeCun « Efficient Learning of Sparse Representations with an Energy-Based Model », *NIPS'2006*

Unsupervised greedy layer-wise training procedure.



(a) First hidden layer pre-training

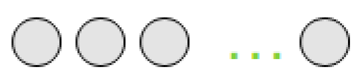
(b) Second hidden layer pre-training

(c) Third hidden layer pre-training

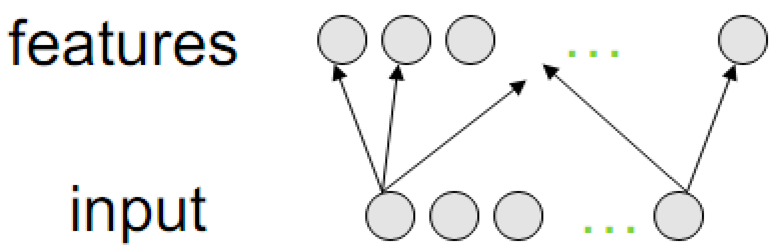
(d) Fine-tuning of whole network

Deep training

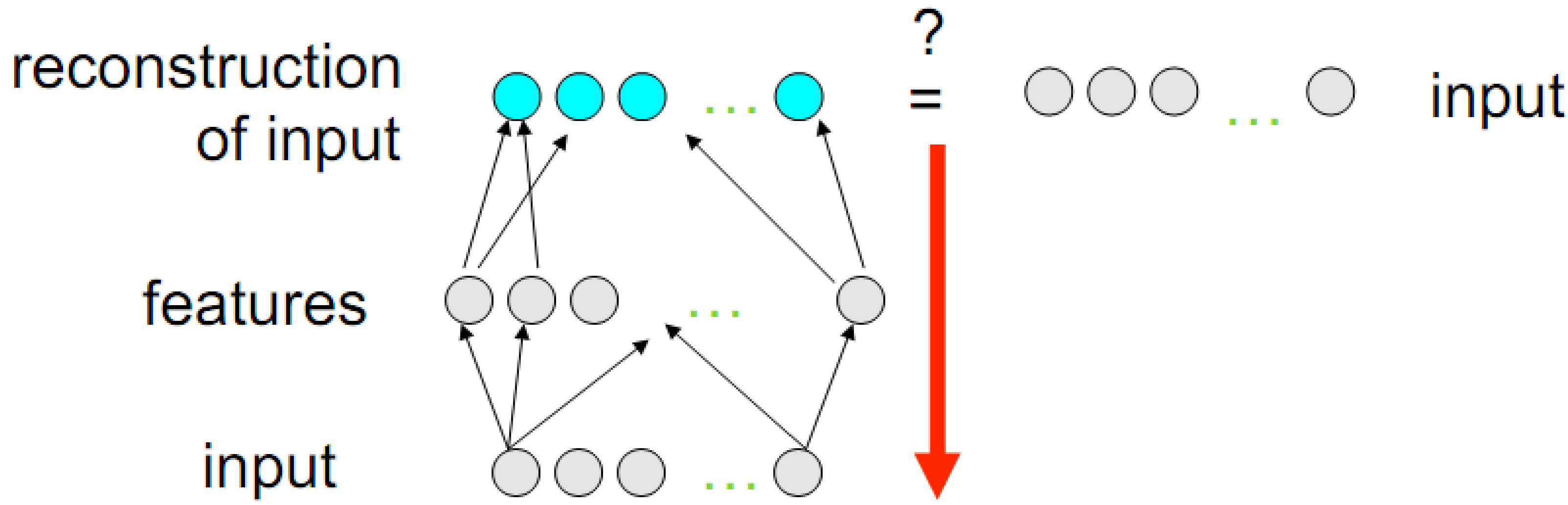
input



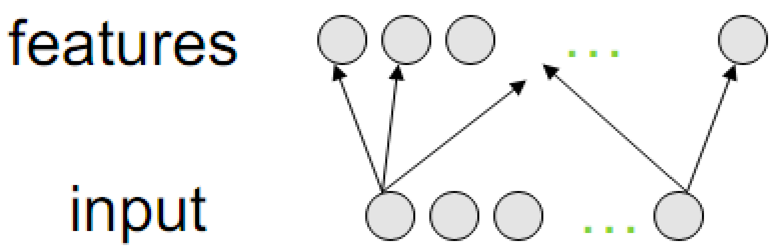
Layer-Wise Unsupervised Pre-training



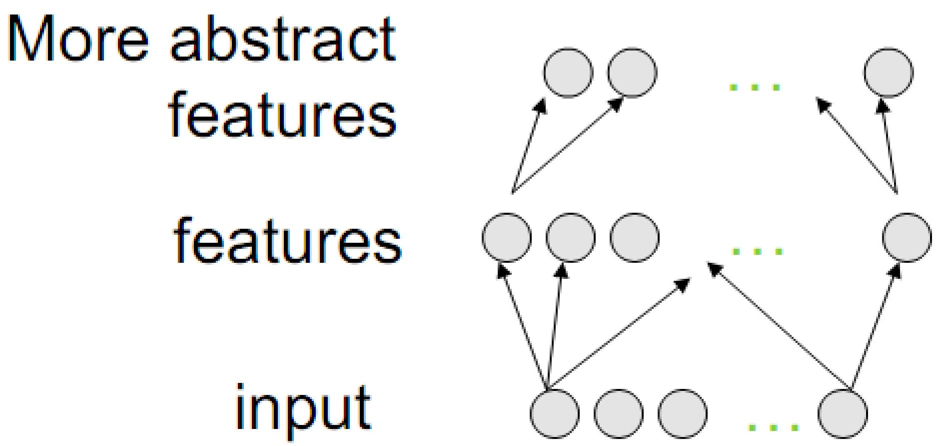
Layer-Wise Unsupervised Pre-training



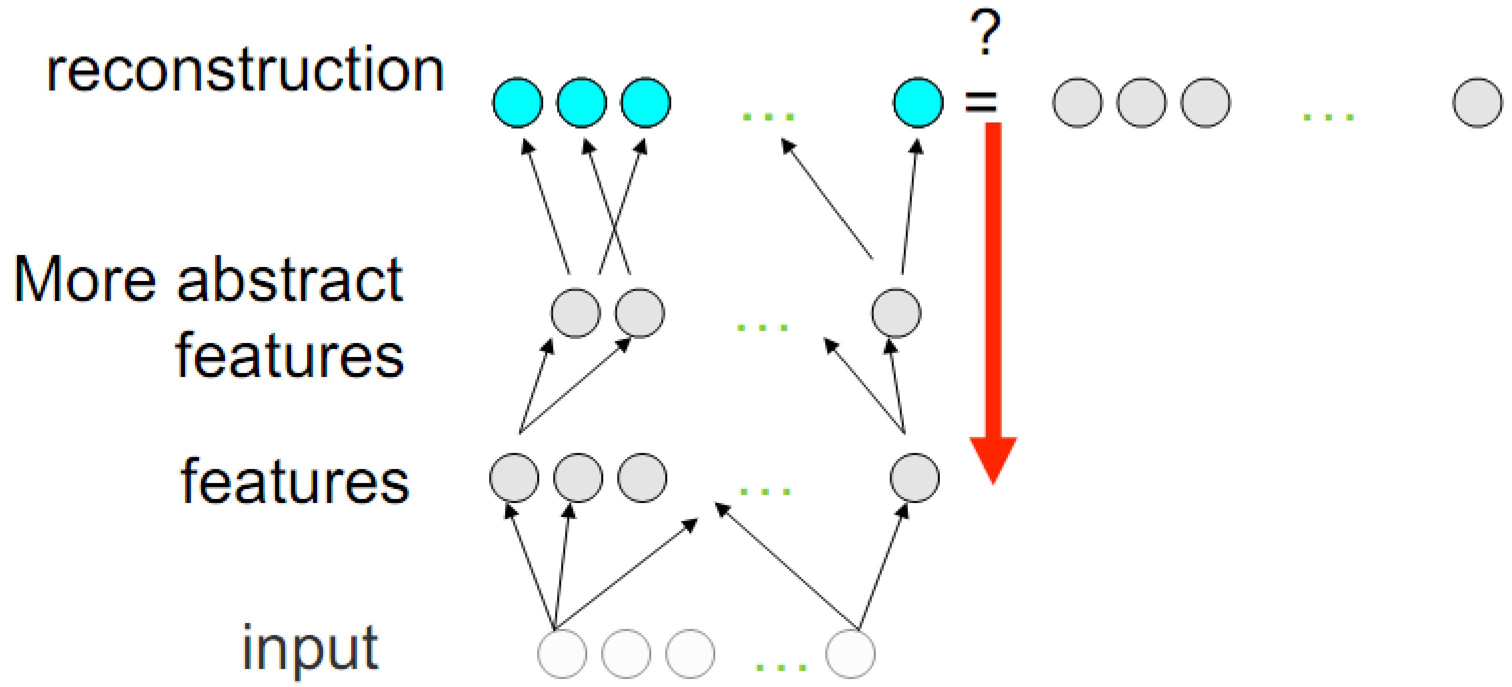
Layer-Wise Unsupervised Pre-training



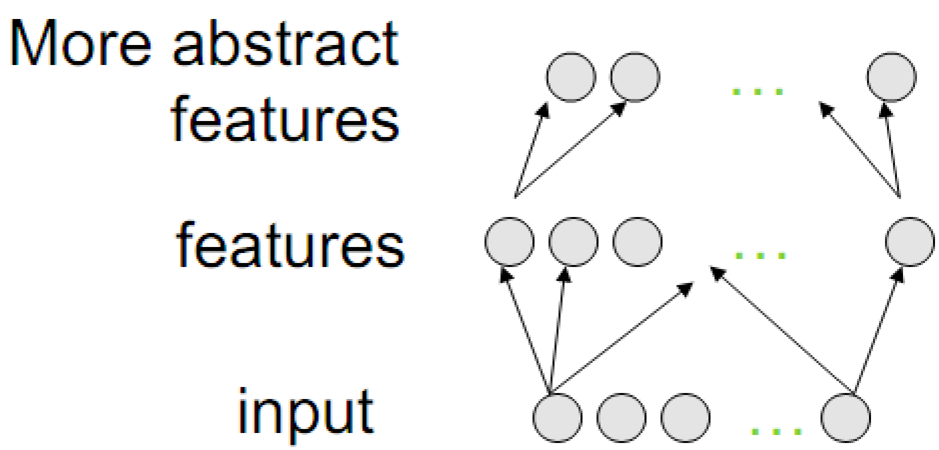
Layer-Wise Unsupervised Pre-training



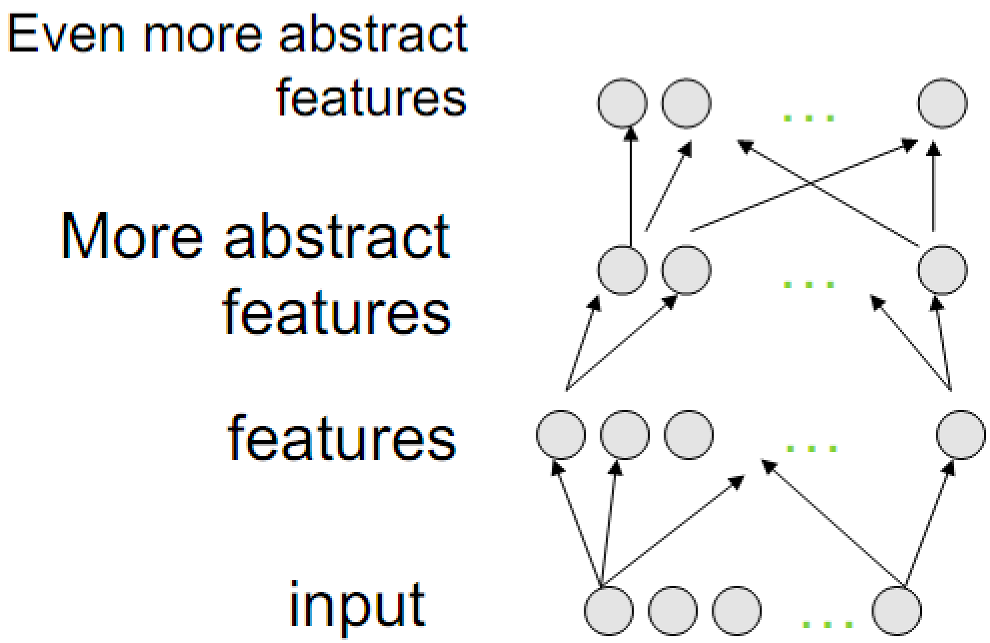
Layer-Wise Unsupervised Pre-training



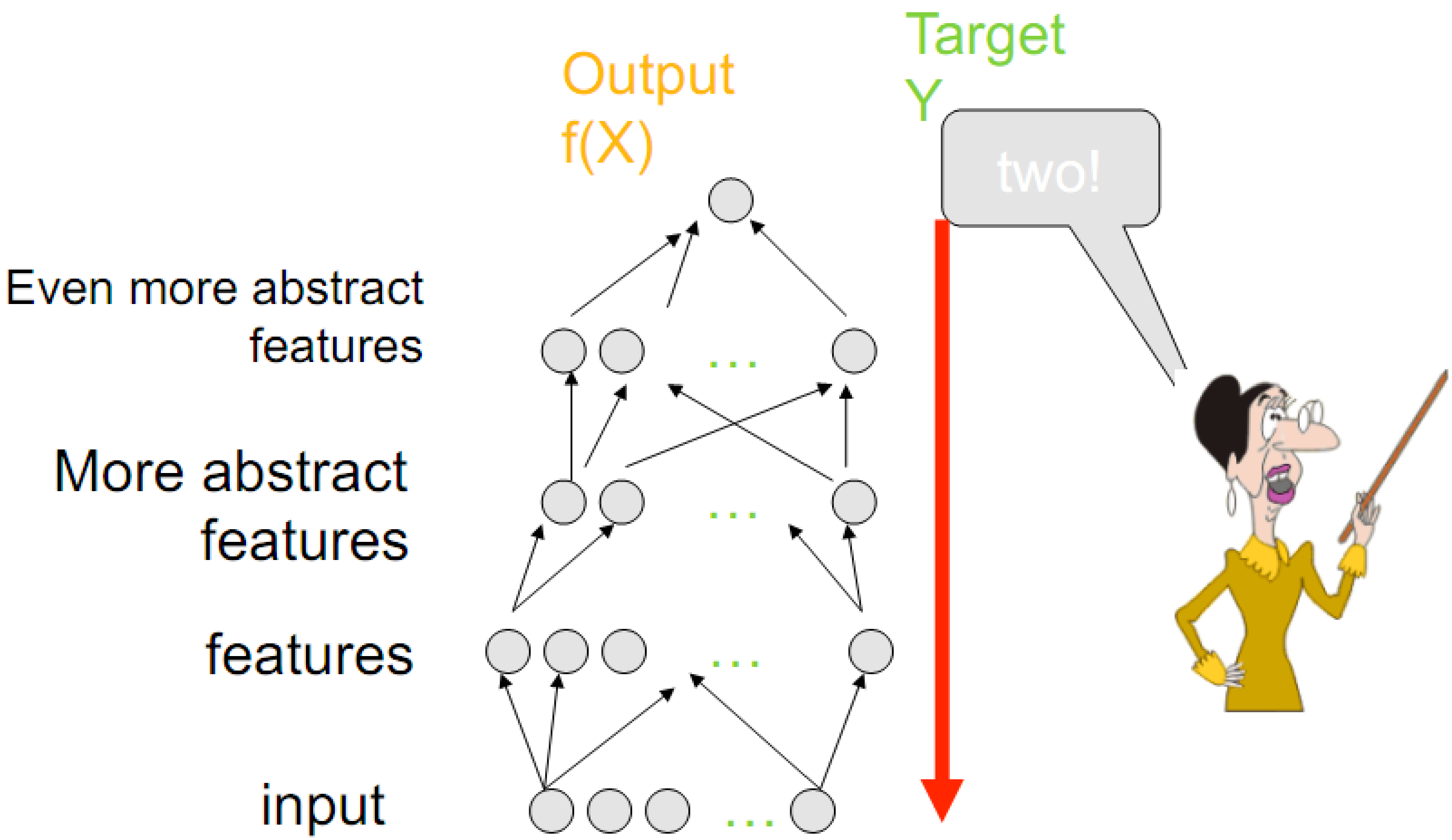
Layer-Wise Unsupervised Pre-training



Layer-Wise Unsupervised Pre-training



Supervised Fine-Tuning



Layer-Local Unsupervised Learning

- Restricted Boltzmann Machine (SRBM) *(Hinton et al, NC'2006)*
- Auto-encoders *(Bengio et al, NIPS'2006)*
- Sparse auto-encoders *(Ranzato et al, NIPS'2006)*
- Kernel PCA *(Erhan 2008)*
- Denoising auto-encoders *(Vincent et al, ICML'2008)*
- Unsupervised embedding *(Weston et al, ICML'2008)*
- Slow features *(Mohabi et al, ICML'2009, Bergstra & Bengio NIPS'2009)*

Experiments

- MNIST data set
  - A benchmark for handwritten digit recognition
  - The number of classes is 10 (corresponding to the digits from 0 to 9)
  - The inputs were scaled between 0 and 1

Exploring Strategies for Training Deep Neural Networks.
Hugo Larochelle, Yoshua Bengio, Jérôme Louradour, Pascal Lamblin; 10(Jan):1--40, 2009.

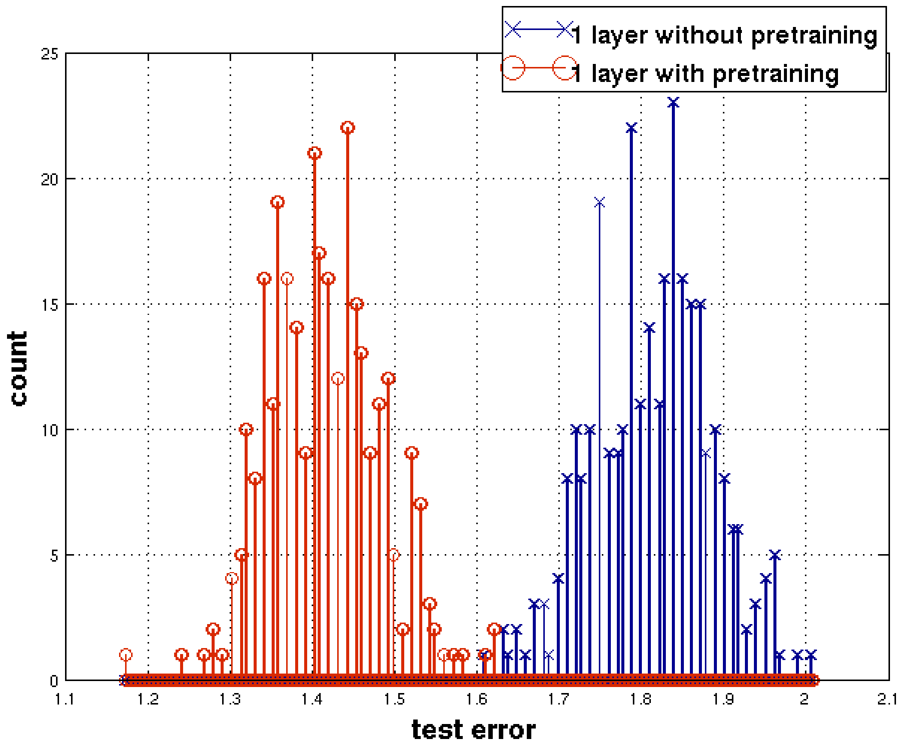
Classification error on MNIST training

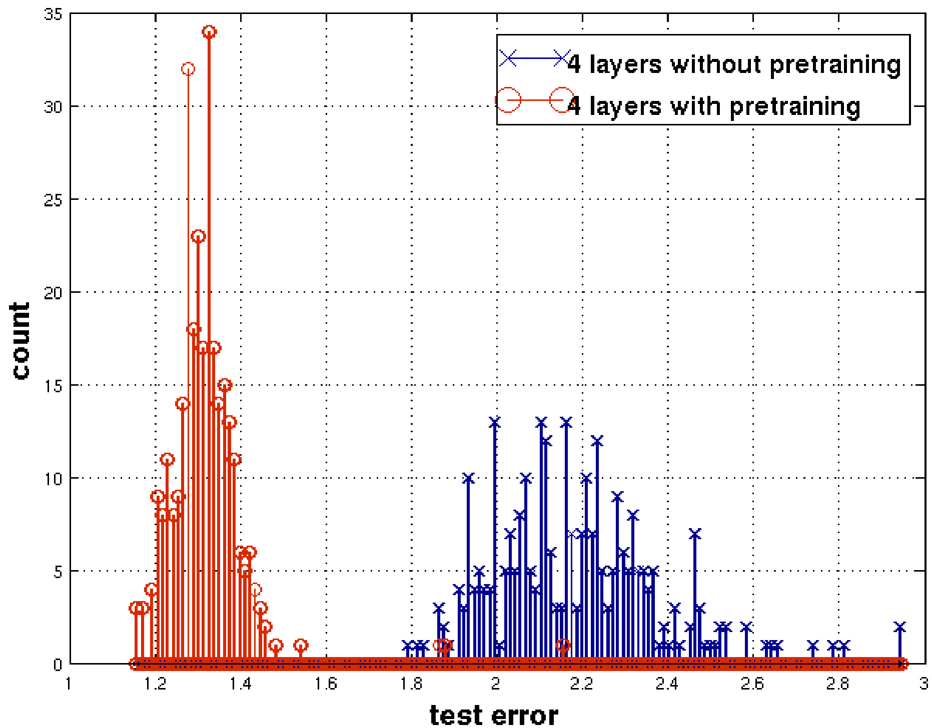
Models	Train.	Valid.	Test
SRBM (stacked restricted Boltzmann machines) network	0%	1.20%	1.20%
SAA (stacked autoassociators) network	0%	1.31%	1.41%
Stacked logistic autoregressions network	0%	1.65%	1.85%
Deep network with supervised pre-training	0%	1.74%	2.04%
Deep network, no pre-training	0.004%	2.07%	2.40%
Shallow network, no pre-training	0%	1.91%	1.93%

Table 1: Classification error on MNIST training, validation, and test sets, with the best hyperparameters according to validation error.

Experiments

- Histograms presenting the test errors obtained on MNIST using models trained with or without pre-training.

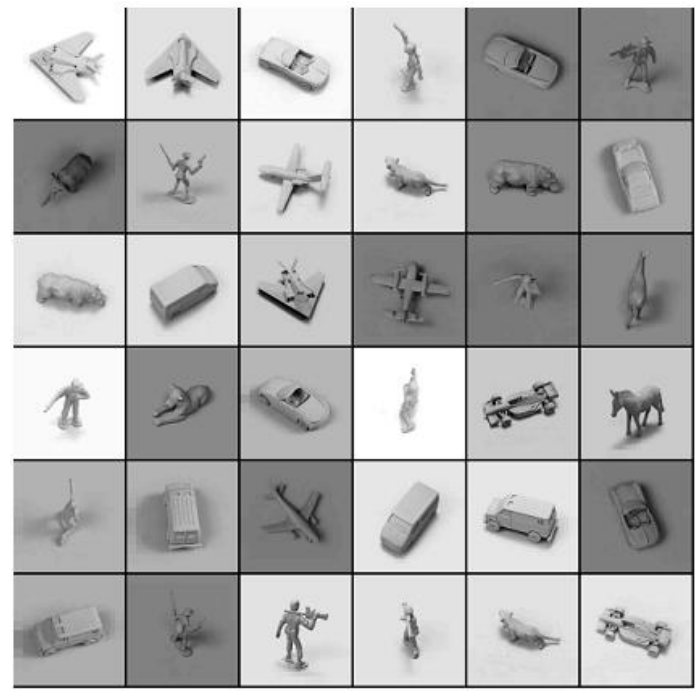




The difficulty of training deep architectures and the effect of unsupervised pre-training. Dumitru Erhan, Pierre-Antoine Manzagol, Yoshua Bengio, Samy Bengio, and Pascal Vincent; pages 153-160, 2009.

Experiments

- NORB data set
  - 5 object categories, 5 difference objects within each category.
- Classification error rate
  - DBM : 10.8 %
  - SVM : 11.6 %
  - Logistic Regression : 22.5 %
  - KNN : 18.4 %



Efficient Learning of Deep Boltzmann Machines.
Ruslan Salakhutdinov, Hugo Larochelle ;
JMLR W&CP 9:693-700, 2010.

Conclusion

- Deep Learning : powerful arguments & generalization priciples
- Unsupervised Feature Learning is crucial many new algorithms and applications in recent years
- Deep Learning suited for multi-task learning, domain adaptation and semi-learning with few labels

Application

- Classification *(Bengio et al., 2007; Ranzato et al., 2007b; Larochelle et al., 2007; Ranzato et al.,2008)*
- Regression *(Salakhutdinov and Hinton, 2008)*
- Dimensionality Reduction *(Hinton Salakhutdinov, 2006; Salakhutdinov and Hinton, 2007)*
- Modeling Textures *(Osindero and Hinton, 2008)*
- Information Retrieval *(Salakhutdinov and Hinton, 2007)*
- Robotics *(Hadsell et al., 2008)*
- Natural Language Processing *(Collobert and Weston, 2008; Weston et al., 2008)*
- Collaborative Filtering *(Salakhutdinov et al., 2007)*

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... moving beyond shallow machine learning since 2006!

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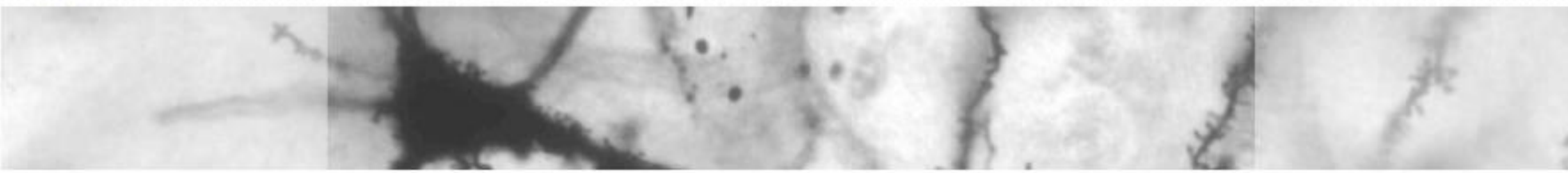

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Welcome to Deep Learning

Deep Learning is a new area of Machine Learning research, which has been introduced with the objective of moving Machine Learning closer to one of its original goals: Artificial Intelligence.

This website is intended to host a variety of resources and pointers to information about Deep Learning. In these pages you will find

- a **reading list**,
- links to **software**,
- **datasets**,
- a **discussion forum**,
- as well as **tutorials** and cool **demos**.

For the latest additions, including papers and software announcement, **be sure to visit the Blog section** of the website. **Contact us** if you have any comments or suggestions!

Last modified on April 26, 2010, at 9:45 am by ranzato

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Links

- Discussion forum

Recent Deep Learning Highlights

- Google Goggles uses ***Stacked Sparse Auto Encoders*** (Hartmut Neven @ ICML 2011)
- The monograph or review paper ***Learning Deep Architectures for AI*** (Foundations & Trends in Machine Learning, 2009).
- ***Exploring Strategies for Training Deep Neural Networks***, Hugo Larochelle, Yoshua Bengio, Jerome Louradour and Pascal Lamblin in: The Journal of Machine Learning Research, pages 1-40, 2009.
- The LISA publications database contains ***a deep architectures category***. http://www.iro.umontreal.ca/~lisa/twiki/bin/view.cgi/Public/ReadingOnDeepNetworks
- Deep Machine Learning – ***A New Frontier in Artificial Intelligence Research*** – a survey paper by Itamar Arel, Derek C. Rose, and Thomas P. Karnowski.

Thank You