

Introduction to Machine Learning

Convolution Neural Networks

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RoadMap

- 👁️ Introduction
- 👁️ Drawbacks of previous neural networks
- 👁️ Convolutional neural networks
- 👁️ LeNet 5
- 👁️ Comparison
- 👁️ Disadvantage
- 👁️ Application

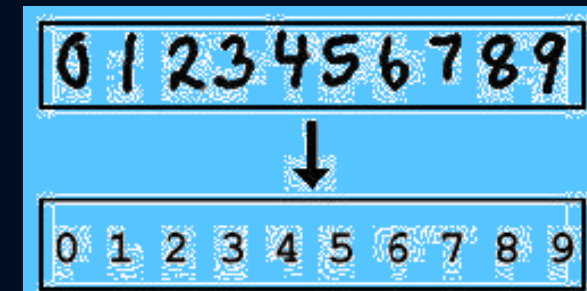
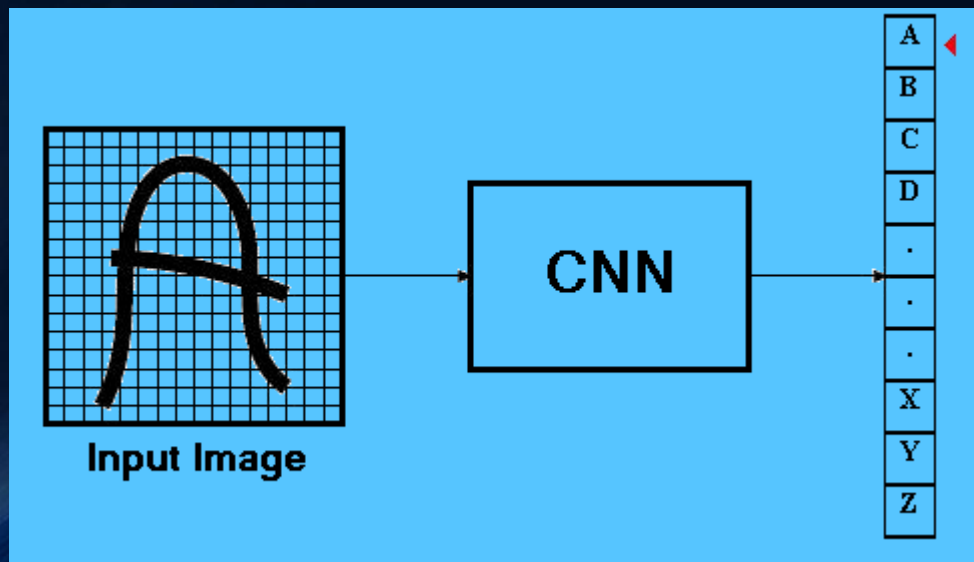
Introduction

🌀 Convolutional neural networks

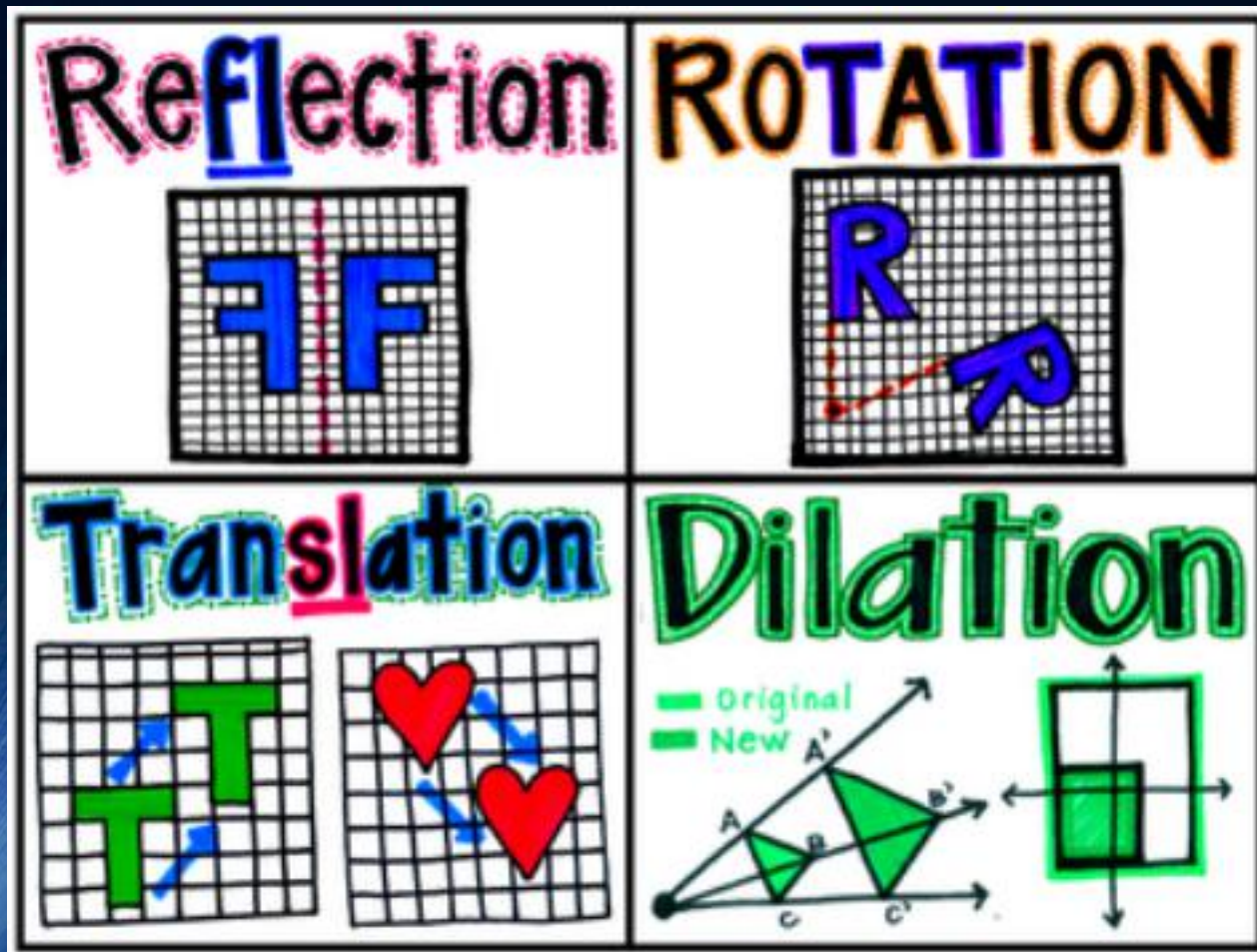
- 🌀 Signal processing, Image processing

🌀 improvement over the multilayer perceptron

- 🌀 performance, accuracy and some degree of invariance to distortions in the input images



5 Different Types of Invariant Properties




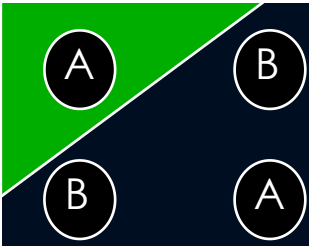
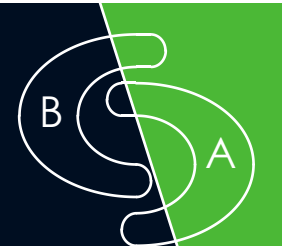


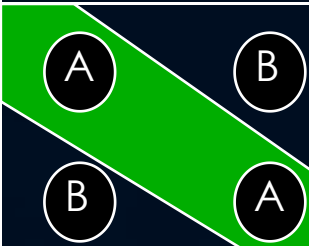

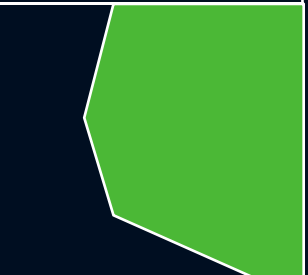



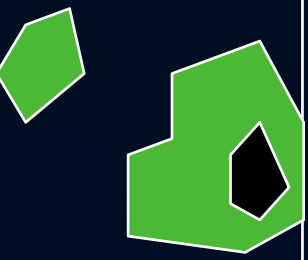
Distortion



RoadMap

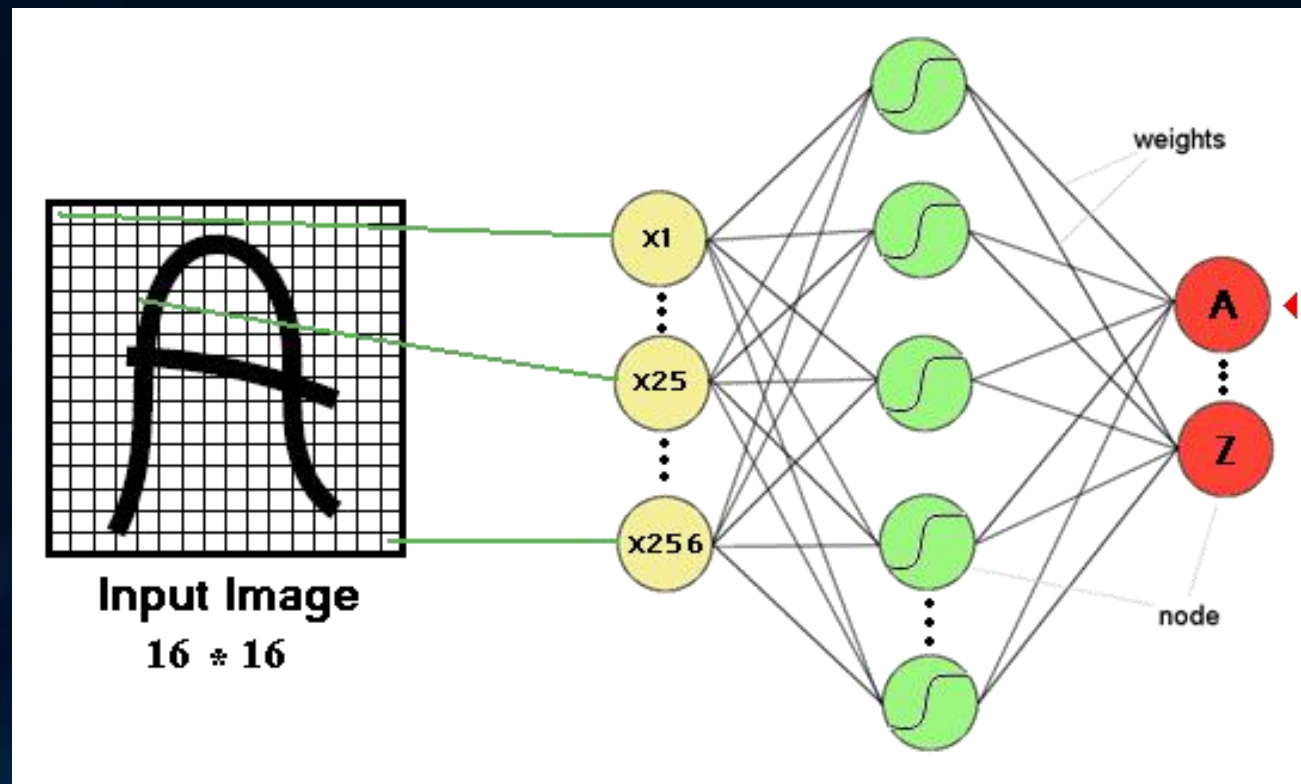
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- 👁 Application

Behavior of multilayer neural networks

Structure	Types of Decision Regions	Exclusive-OR Problem	Classes with Meshed regions	Most General Region Shapes
Single-Layer 	Half Plane Bounded By Hyper plane			
Two-Layer 	Convex Open Or Closed Regions			
Three-Layer 	Arbitrary (Complexity Limited by No. of Nodes)			

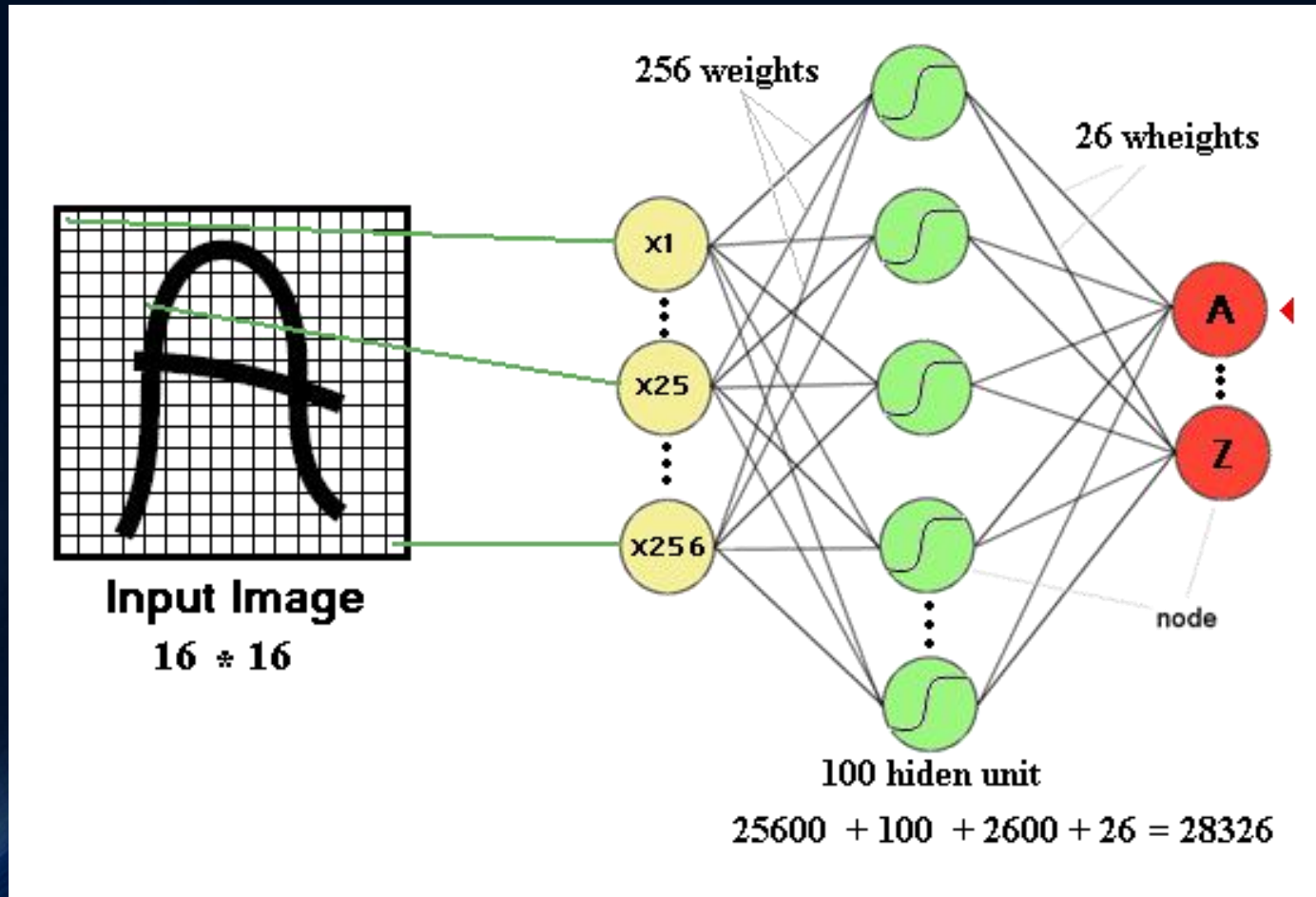
Multi-layer perceptron and image processing

- ☯ One or more hidden layers
- ☯ Sigmoid activations functions



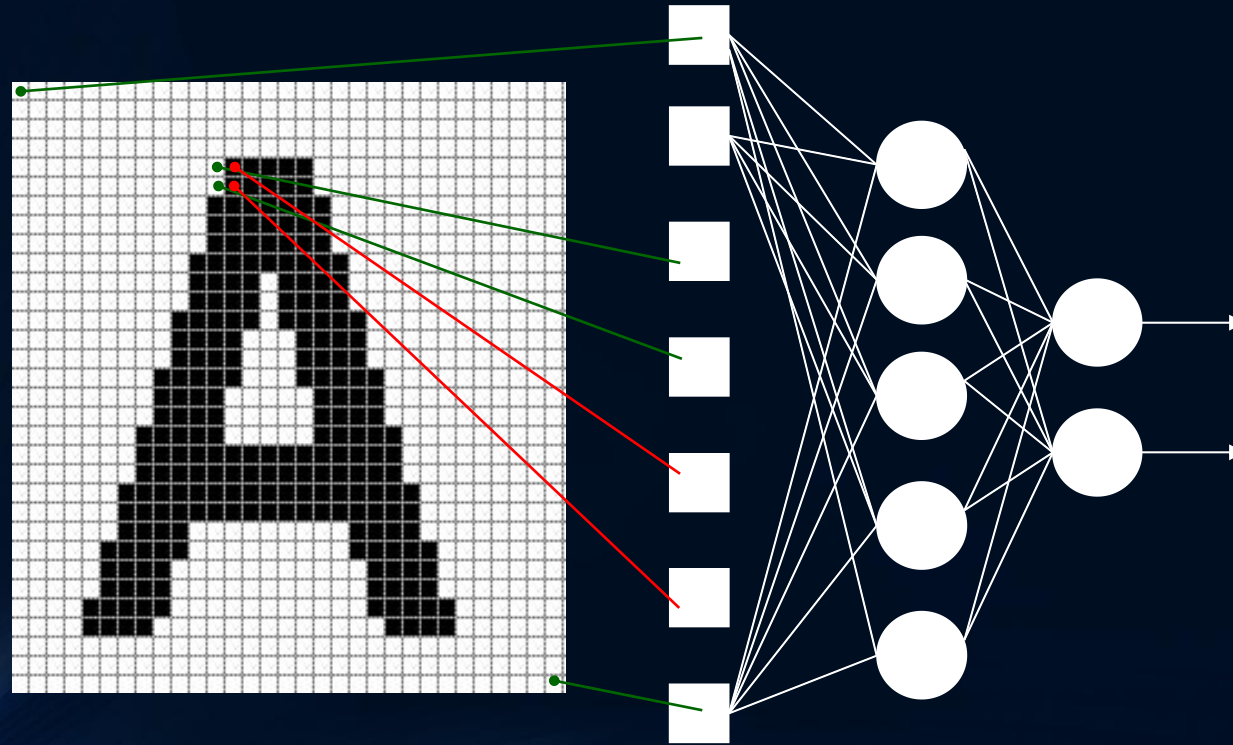
Drawbacks of previous neural networks

- ☯ the number of trainable parameters becomes extremely large



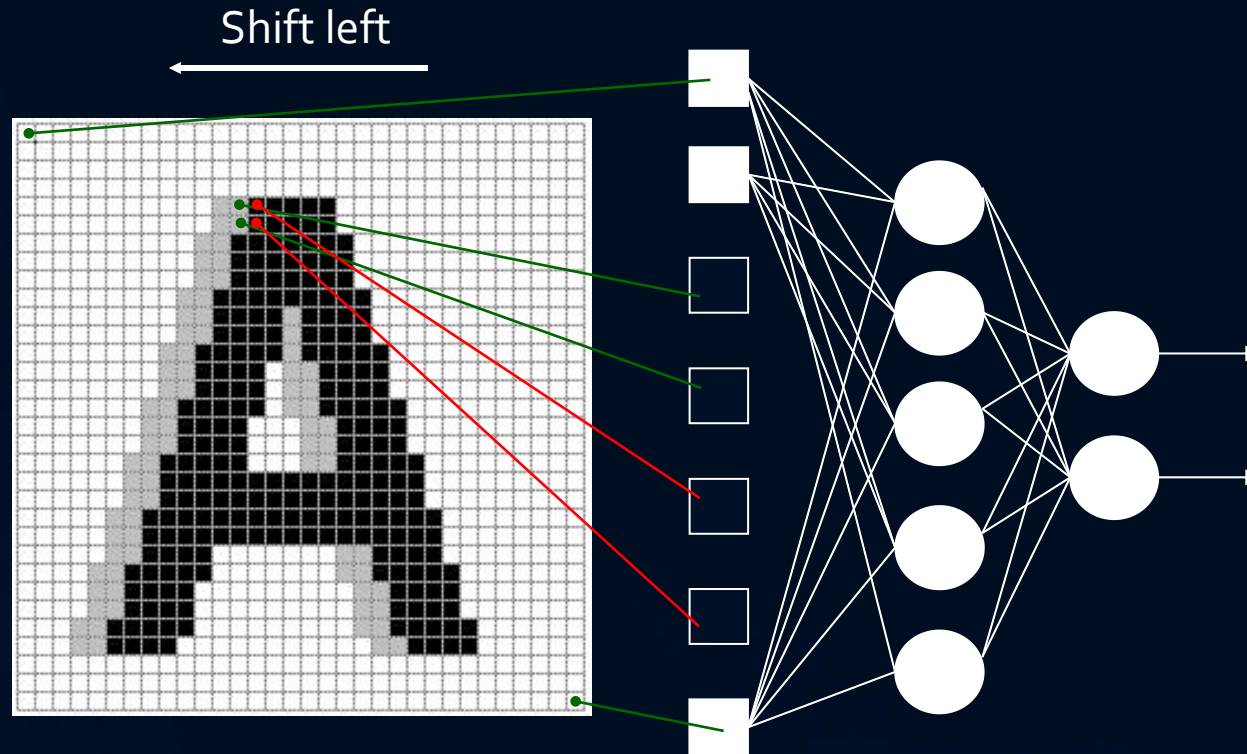
Drawbacks of previous neural networks

- ☯ Little or no invariance to shifting, scaling, and other forms of distortion

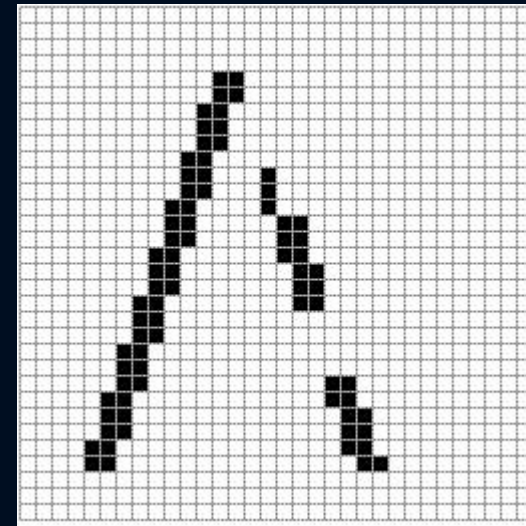
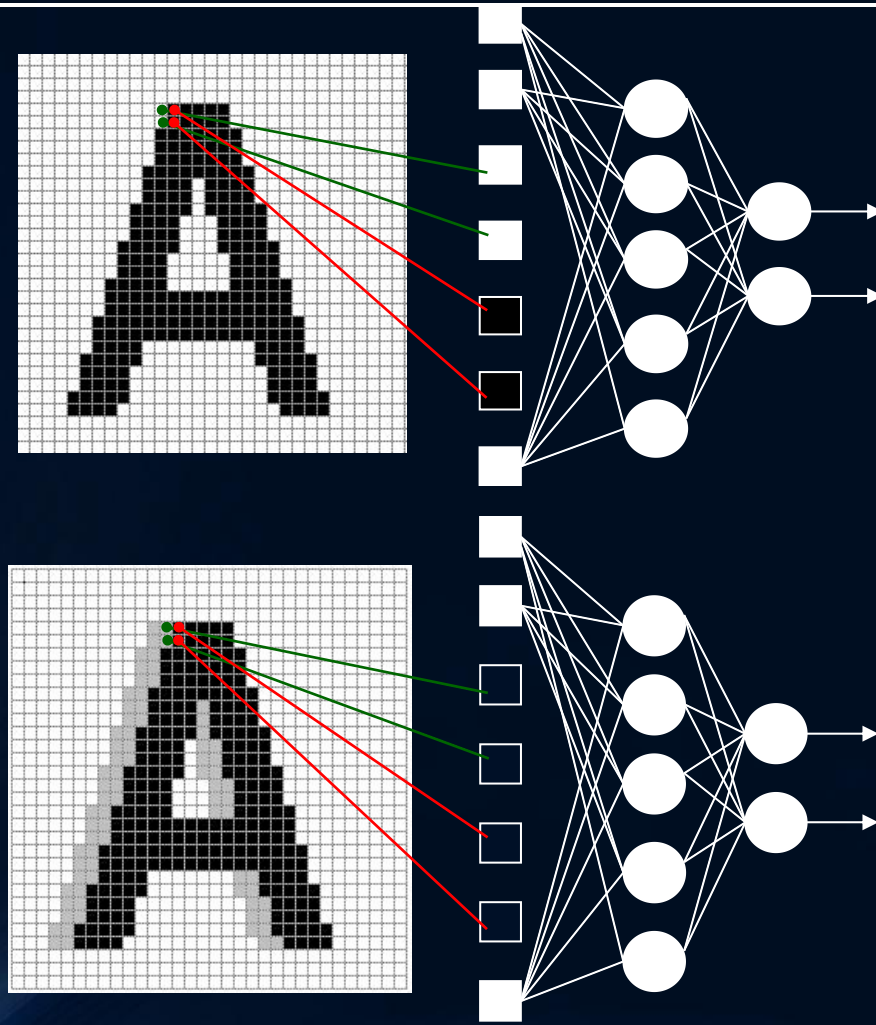


Drawbacks of previous neural networks

- ☯ Little or no invariance to shifting, scaling, and other forms of distortion



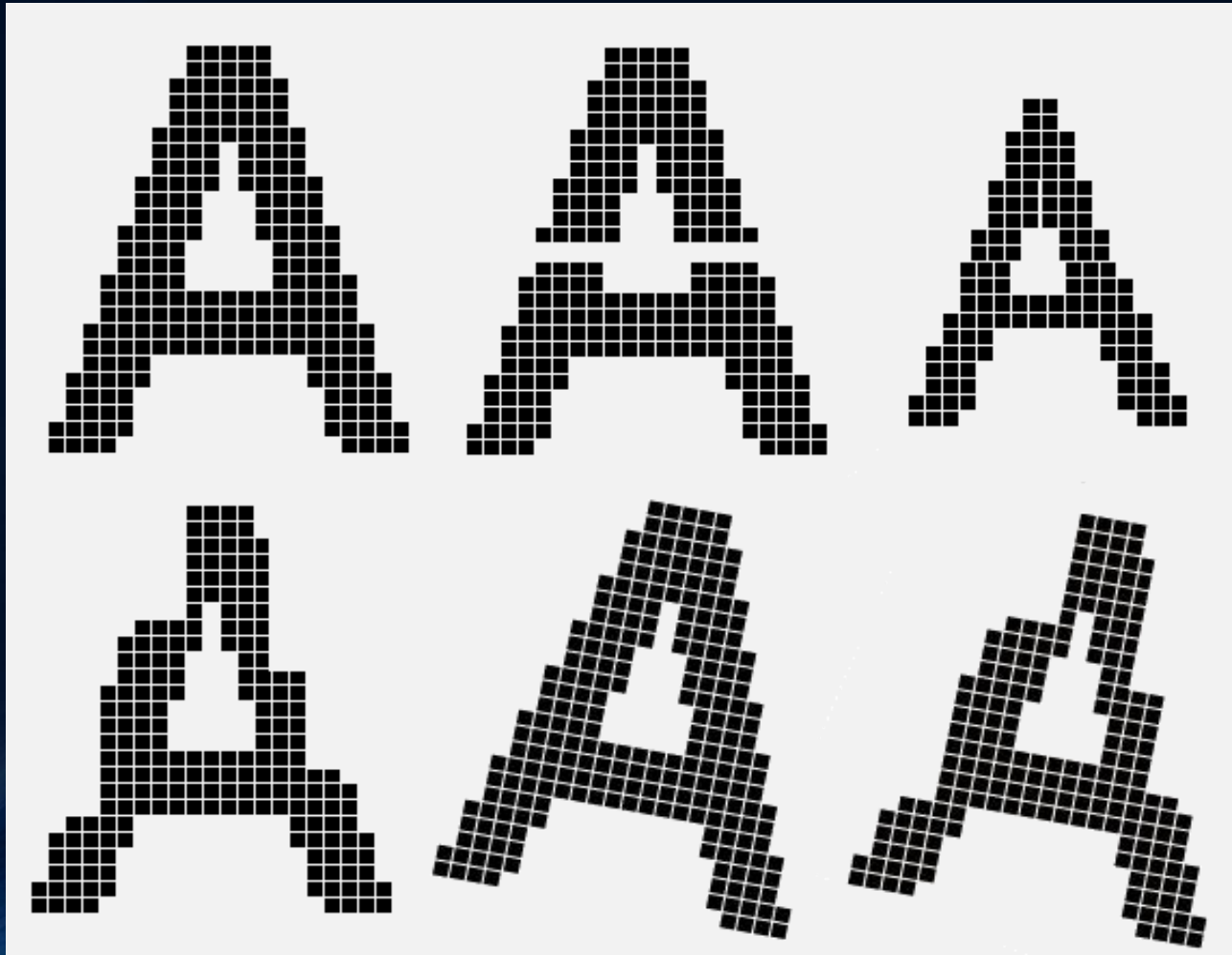
Drawbacks of previous neural networks



154 input change
from 2 shift left
77 : black to white
77 : white to black

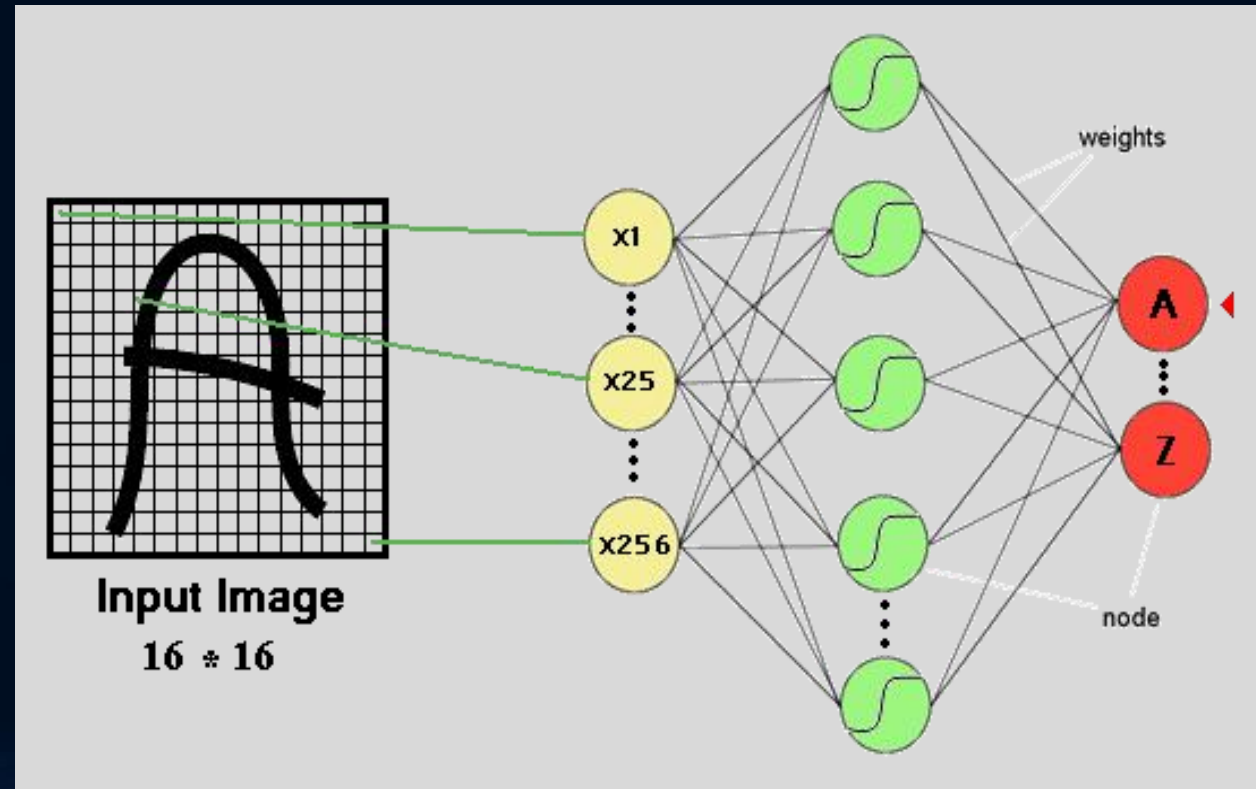
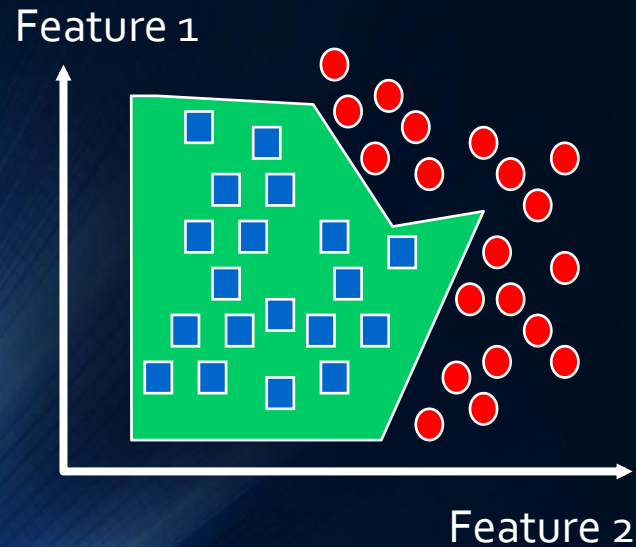
Drawbacks of previous neural networks

- ☯ scaling, and other forms of distortion



Drawbacks of previous neural networks

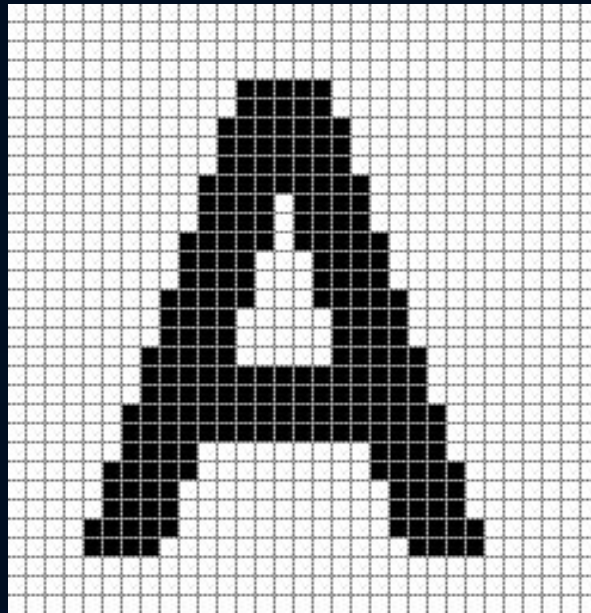
- the **topology** of the input data is completely ignored
- work with **raw data**.



Drawbacks of previous neural networks

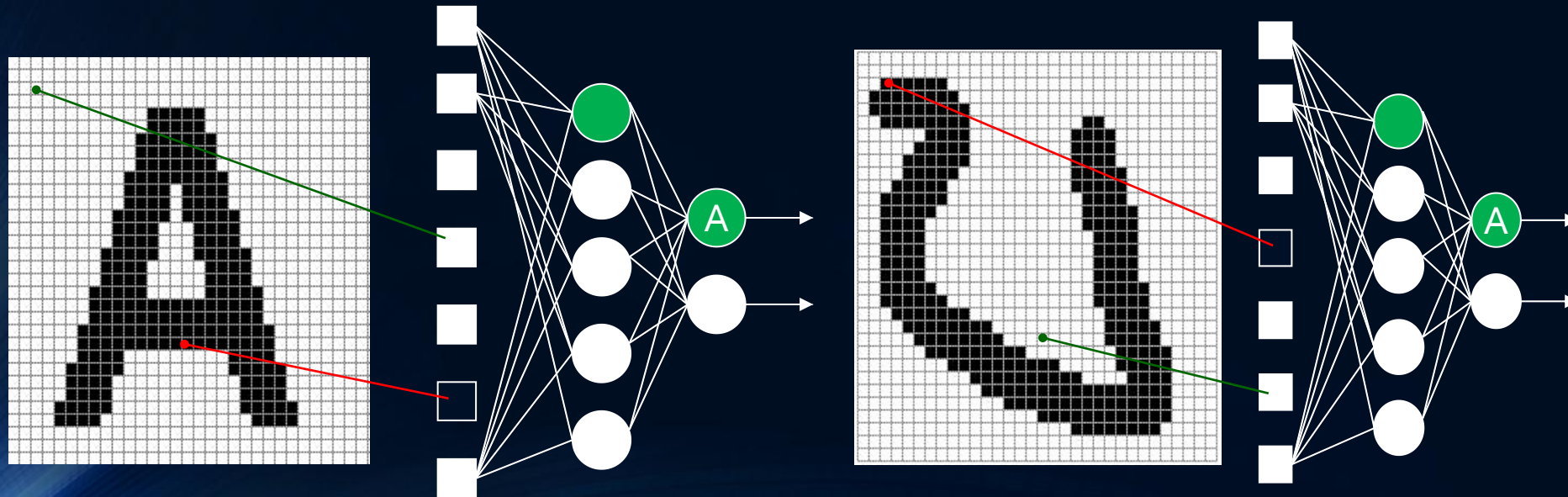
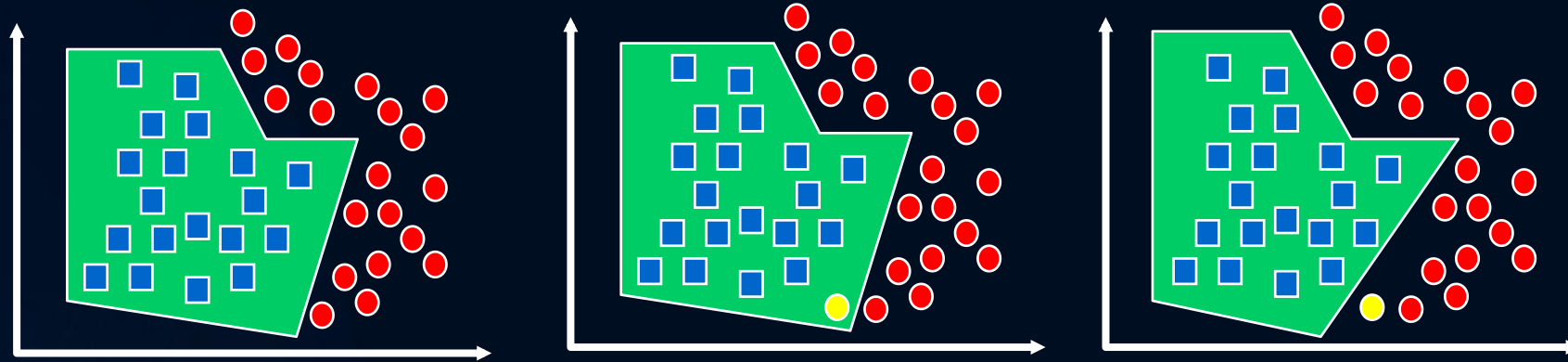
Black and white patterns: $2^{32 \times 32} = 2^{1024}$

Gray scale patterns : $256^{32 \times 32} = 256^{1024}$



32 * 32 input image

Drawbacks of previous neural networks



Improvement

- 🧠 Fully connected network of sufficient size can produce outputs that are invariant with respect to such variations.
- 🧠 **Training time**
- 🧠 **Network size**
- 🧠 **Free parameters**

RoadMap

- 👁 Introduction
- 👁 Drawbacks of previous neural networks
- 👁 Convolutional neural networks
- 👁 LeNet 5
- 👁 Comparison
- 👁 Disadvantage
- 👁 Application

History



Yann LeCun, Professor of Computer Science
The Courant Institute of Mathematical Sciences
New York University
Room 1220, 715 Broadway, New York, NY 10003, USA.
(212)998-3283 yann@cs.nyu.edu

- 🌀 In 1995, **Yann LeCun** and **Yoshua Bengio** introduced the concept of convolutional neural networks.

About CNN' s

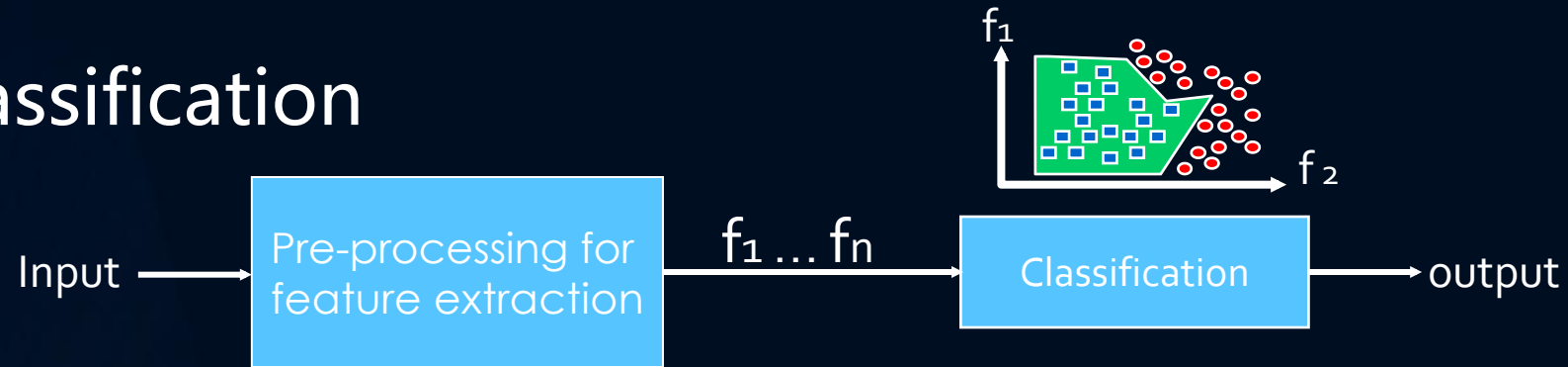
- ☯ CNN' s Were **neurobiologically** motivated by the findings of locally sensitive and orientation-selective nerve cells in the visual cortex.
- ☯ They designed a network structure that implicitly extracts relevant features.
- ☯ Convolutional Neural Networks are a special kind of **multi-layer neural networks**.

About CNN' s

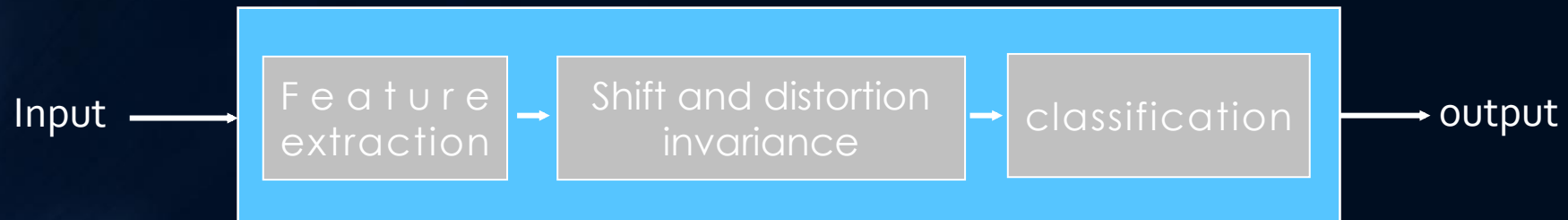
- ☯ CNN is a **feed-forward** network that can extract topological properties from an image.
- ☯ Like almost every other neural networks they **are trained** with a version of the **back-propagation algorithm**.
- ☯ Convolutional Neural Networks are designed to **recognize visual patterns** directly from pixel images with minimal preprocessing.
- ☯ They can recognize patterns with extreme variability (such as handwritten characters).

Classification

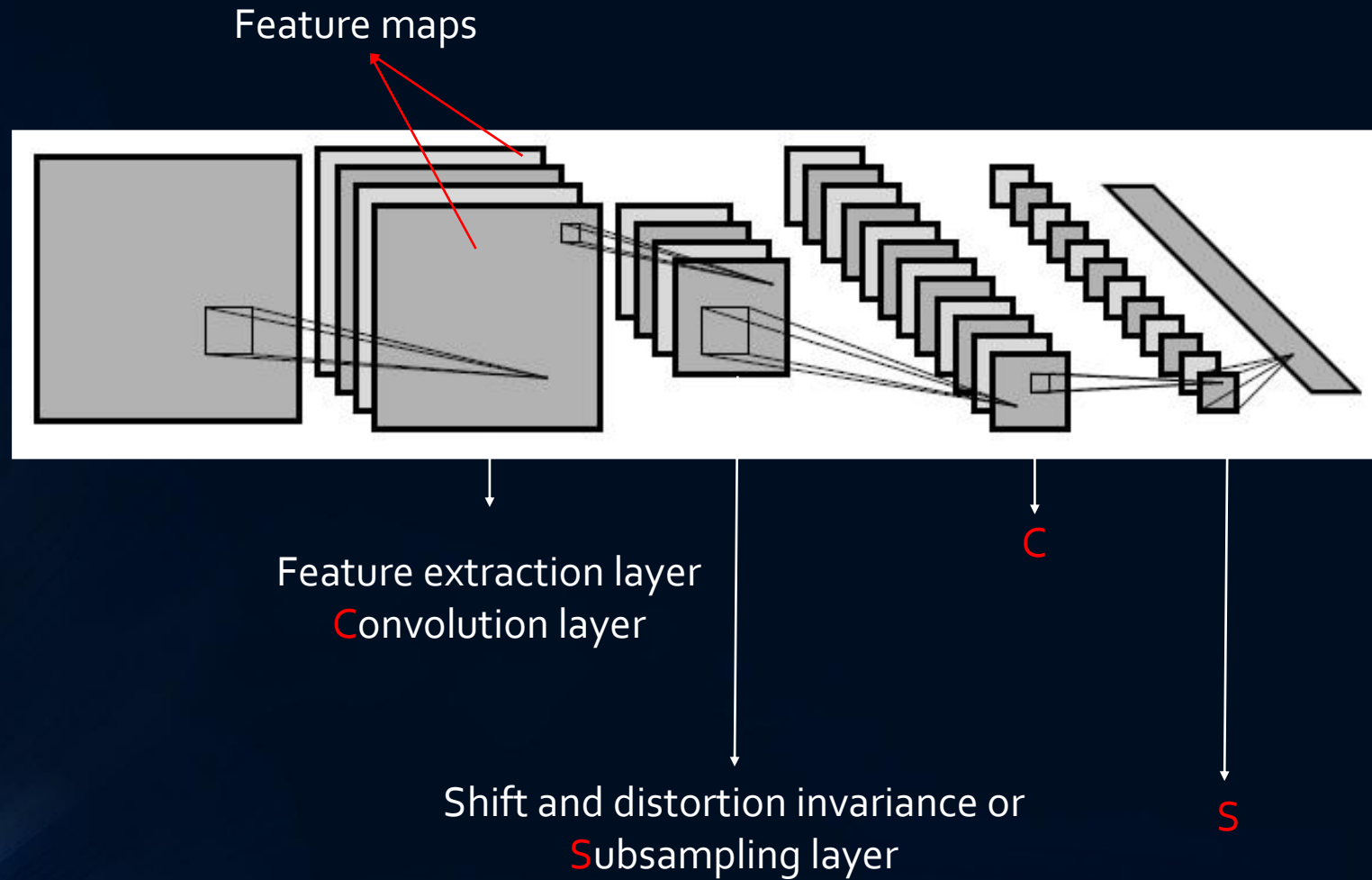
Classification



Convolutional neural network

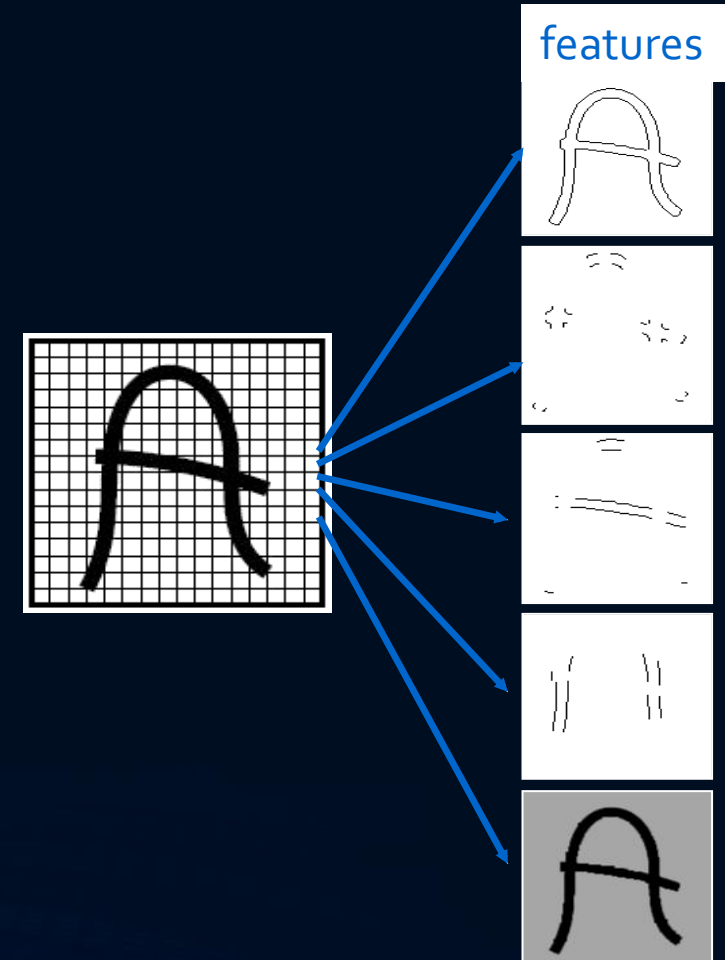
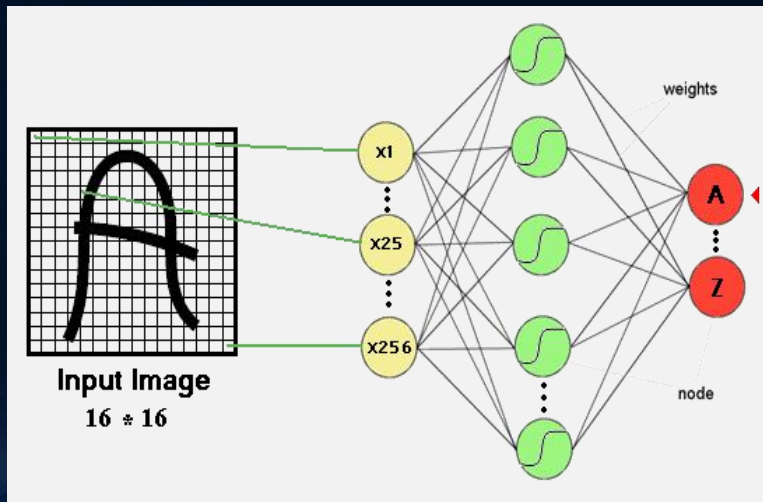
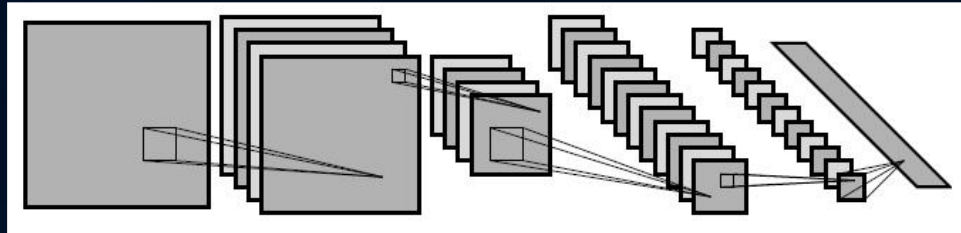


CNN' s Topology

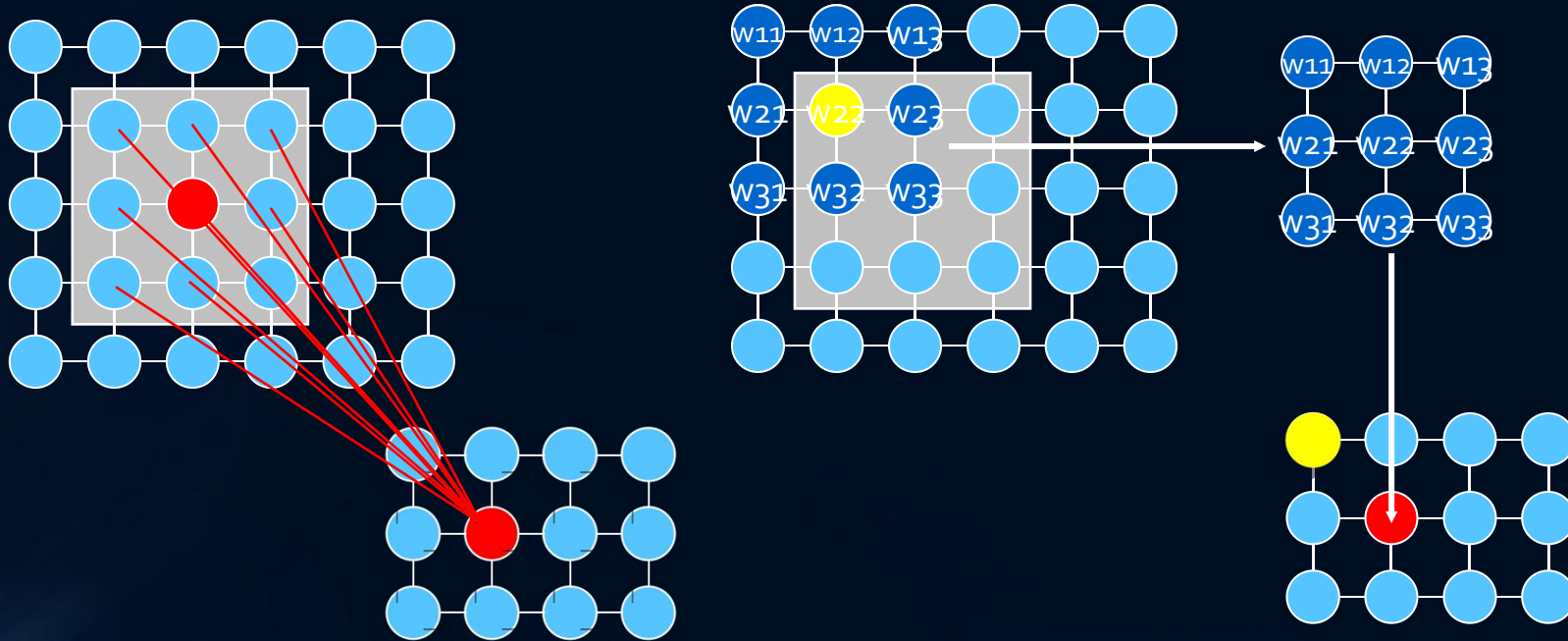
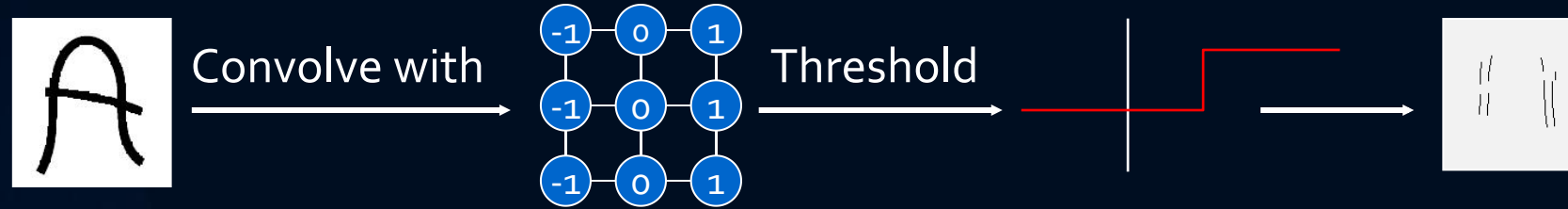


Feature extraction layer or Convolution layer

- 🌀 detect the same feature at different positions in the input image.

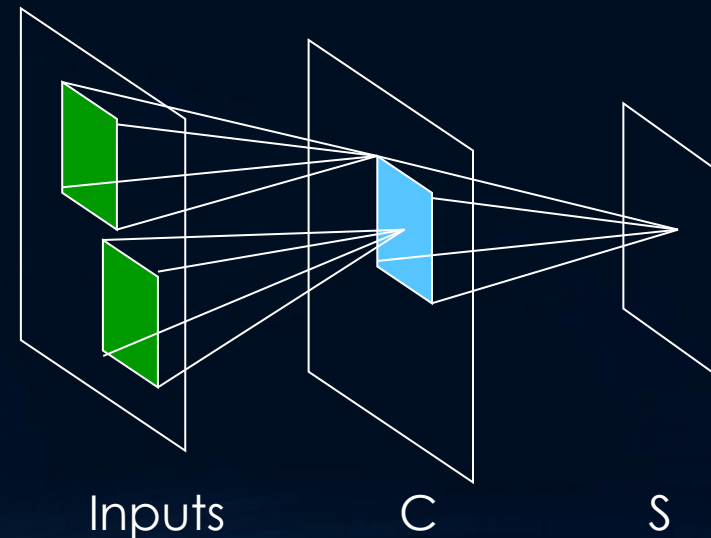


Feature extraction



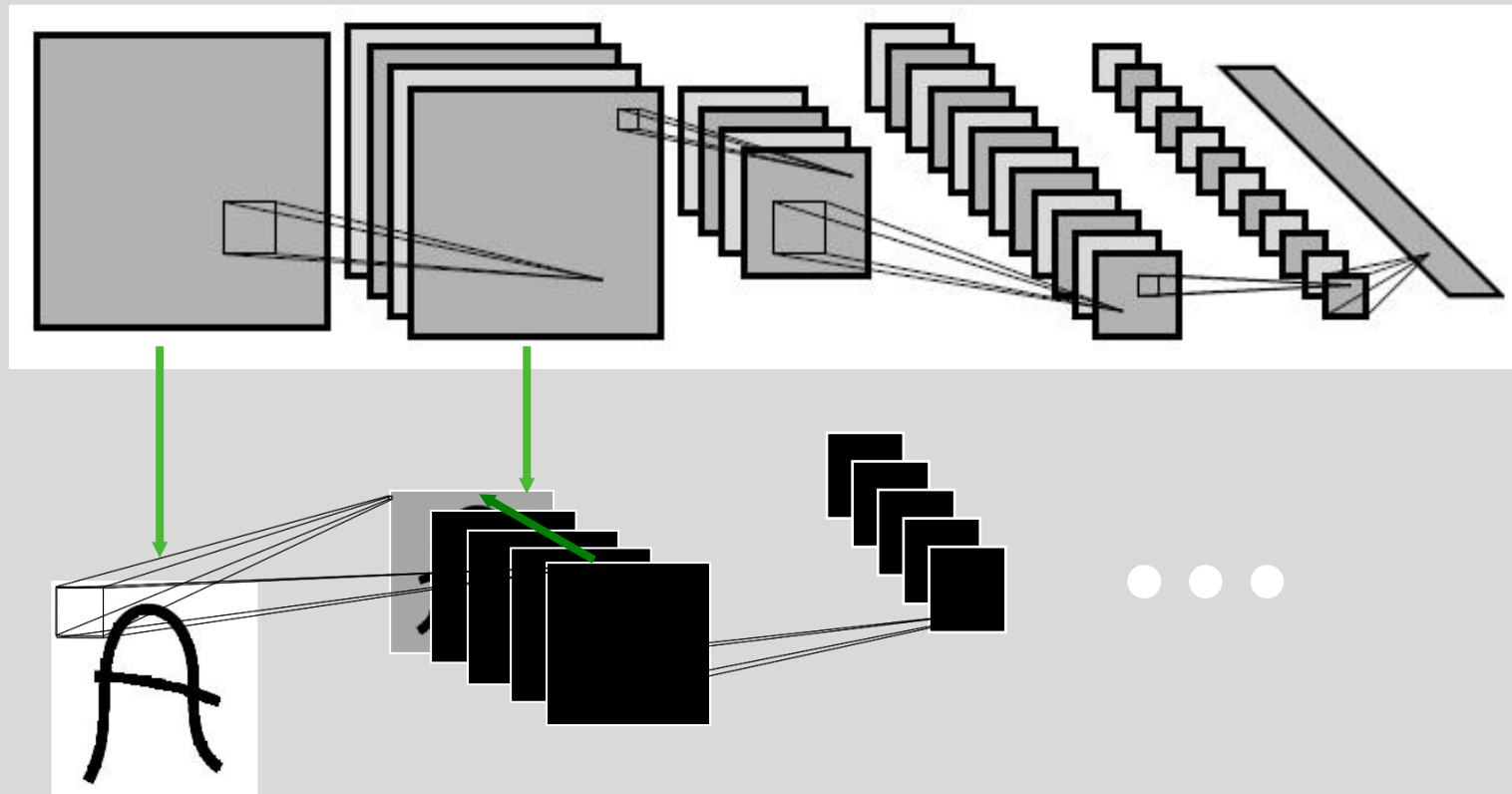
Feature extraction

- ☯ **Shared weights:** all neurons in a feature **share** the same weights (but not the biases).
- ☯ In this way all neurons detect the same feature at different positions in the input image.
- ☯ **Reduce** the number of **free parameters**.



Feature extraction

- ☯ If a neuron in the feature map fires, this corresponds to a match with the template.



Subsampling layer

- the **subsampling** layers reduce the spatial resolution of each feature map
- By reducing the **spatial resolution** of the feature map, a **certain degree** of **shift** and **distortion** invariance is achieved.

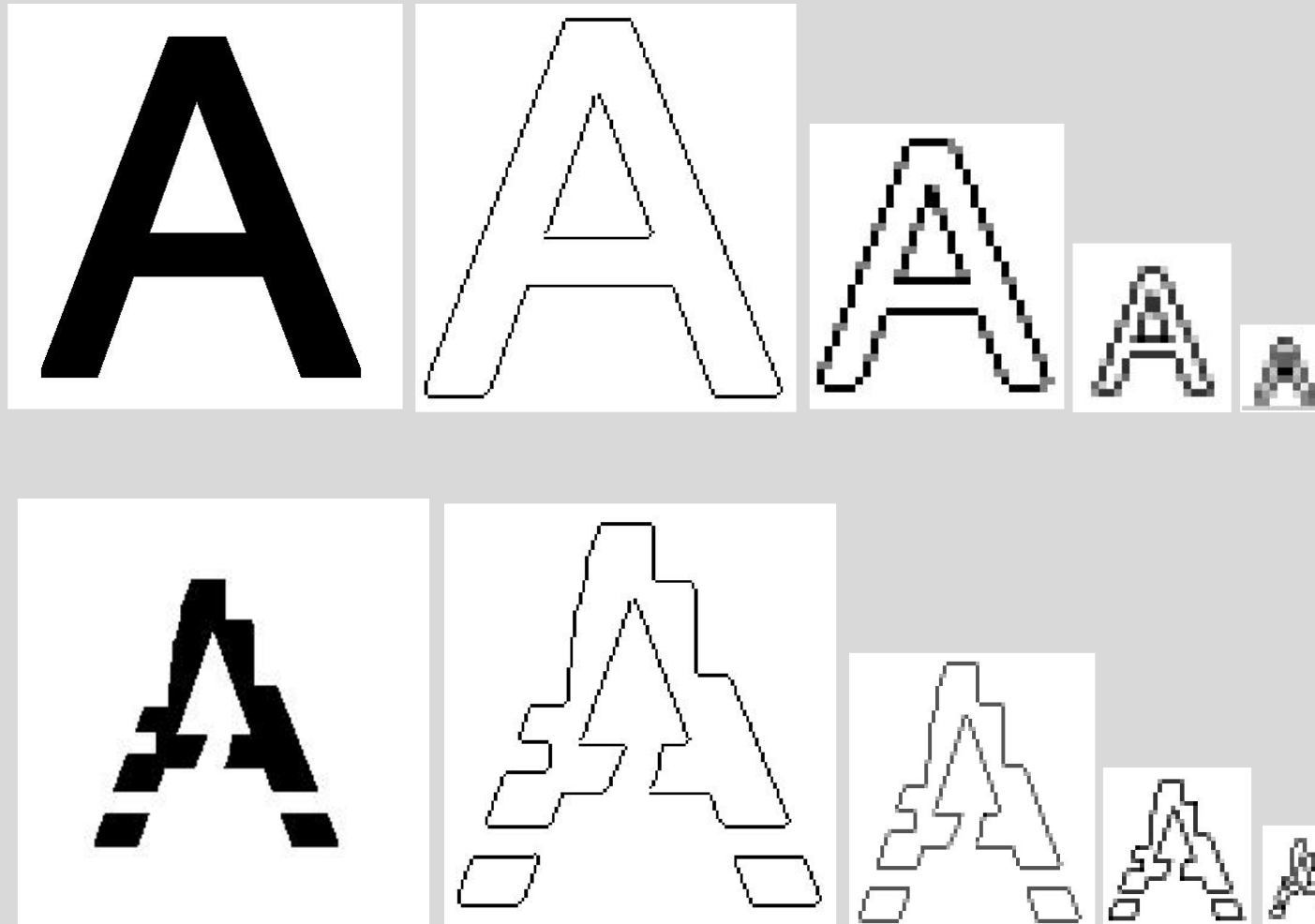


Subsampling layer

- the **subsampling** layers reduce the spatial resolution of each feature map

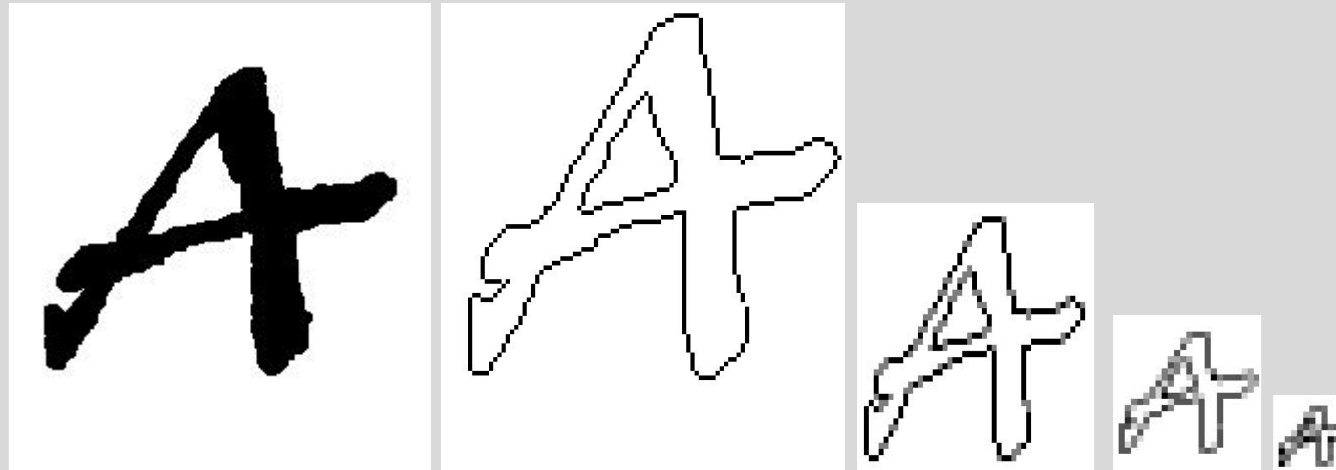


Subsampling layer



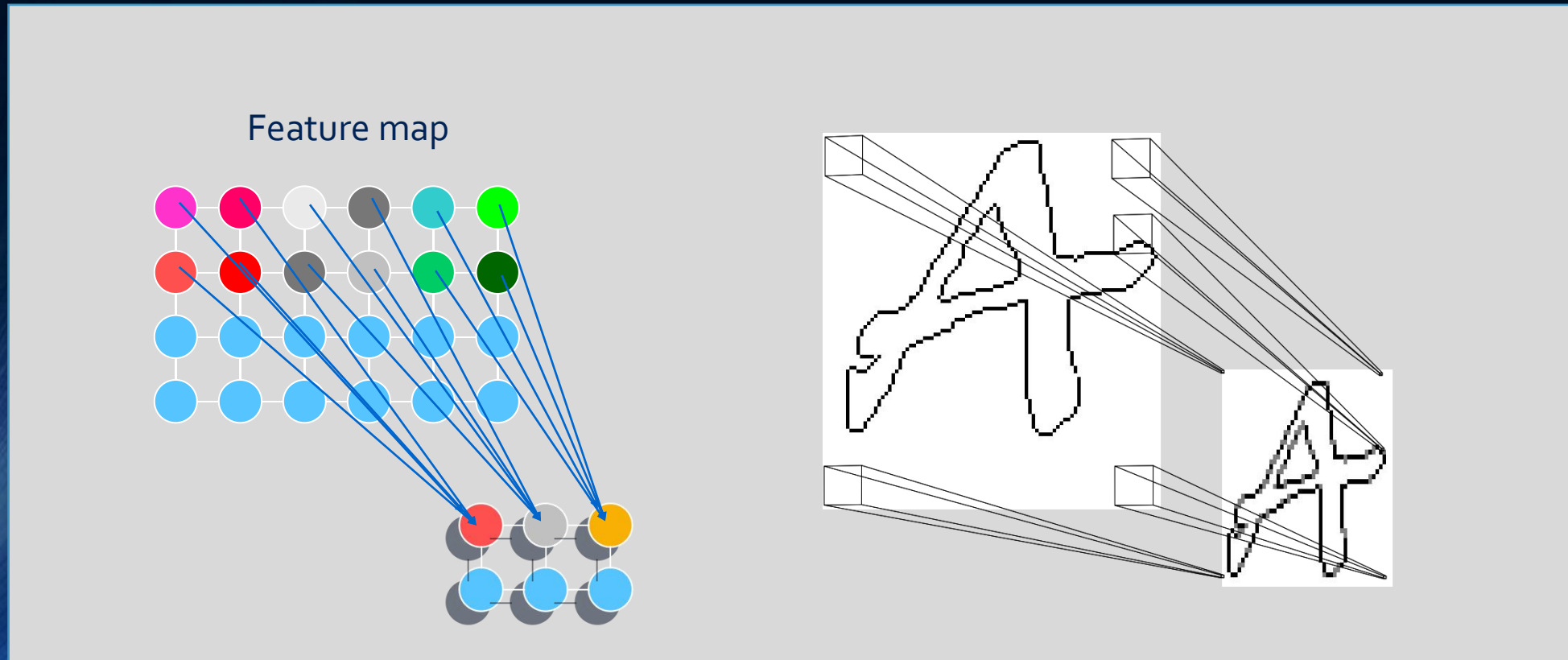
Subsampling layer

- 🌀 The **weight sharing** is also applied in subsampling layers.

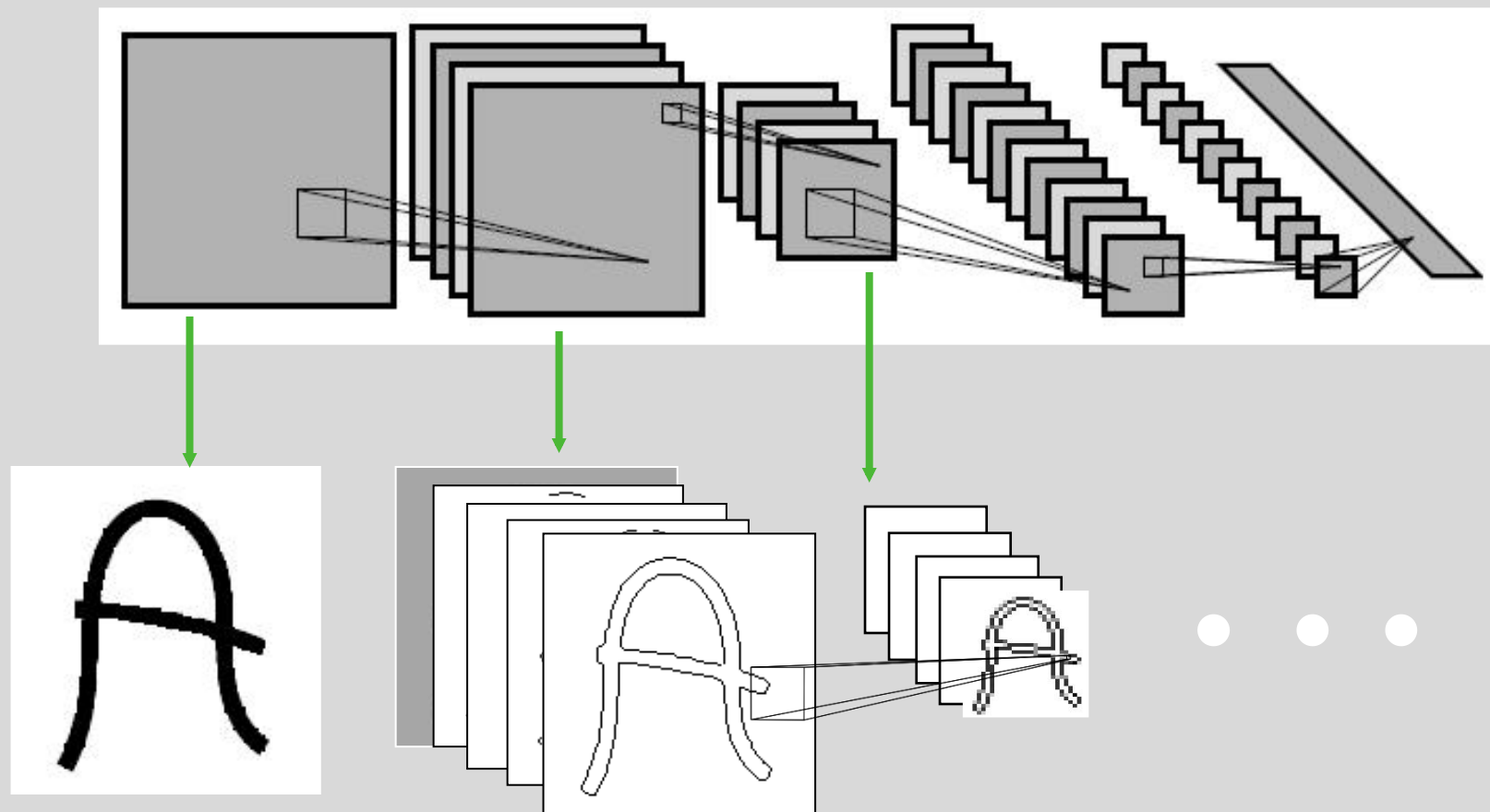


Subsampling layer

- ☯ the **weight sharing** is also applied in subsampling layers
- ☯ reduce the effect of **noises** and **shift** or **distortion**



Up to now ...

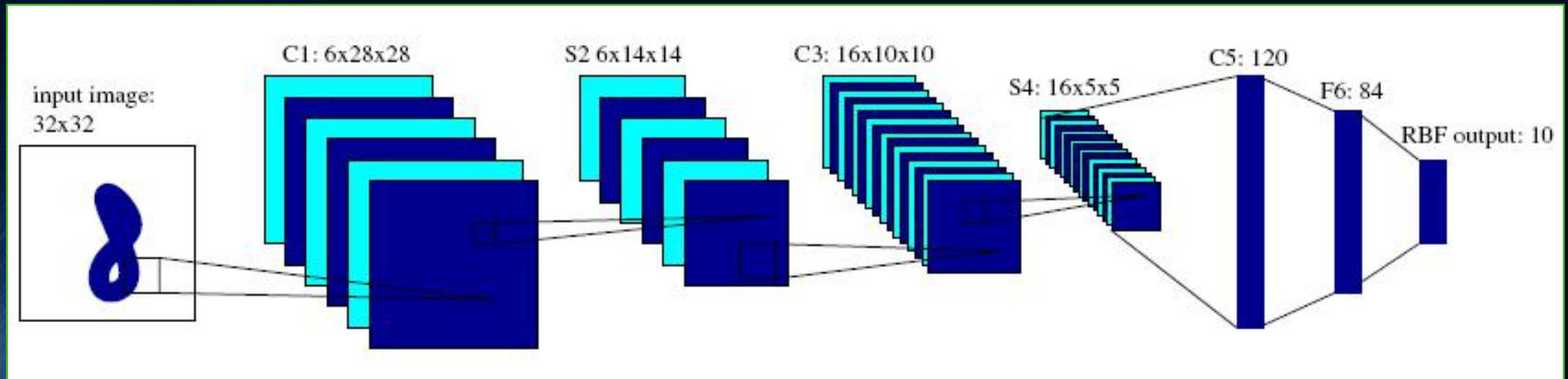


RoadMap

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- 👁 Convolutional neural networks
- 👁 **LeNet 5**
- 👁 Comparison
- 👁 Disadvantage
- 👁 Application

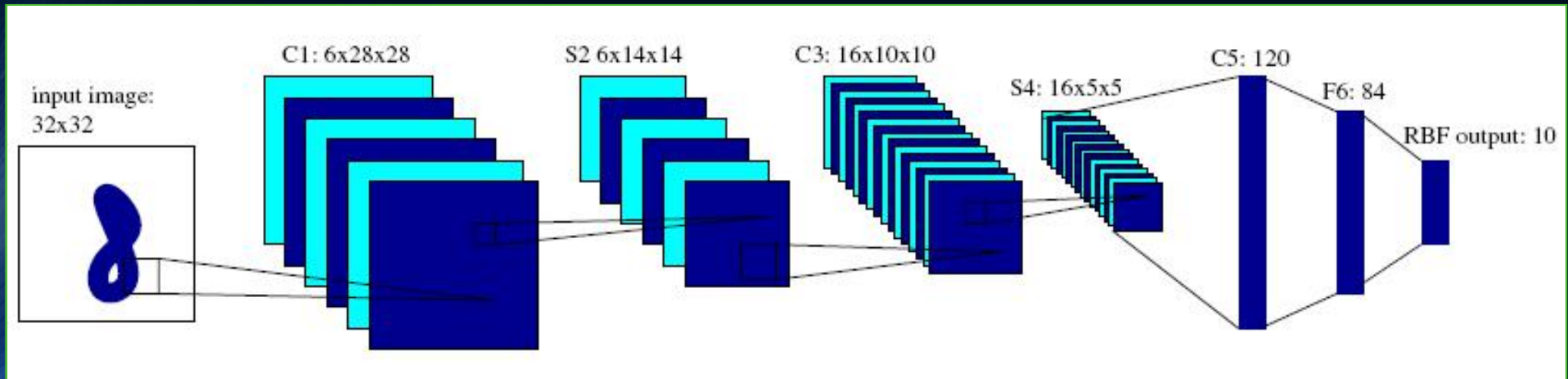
LeNet5

- ☯ Introduced by LeCun.
- ☯ raw image of 32×32 pixels as input.



LeNet5

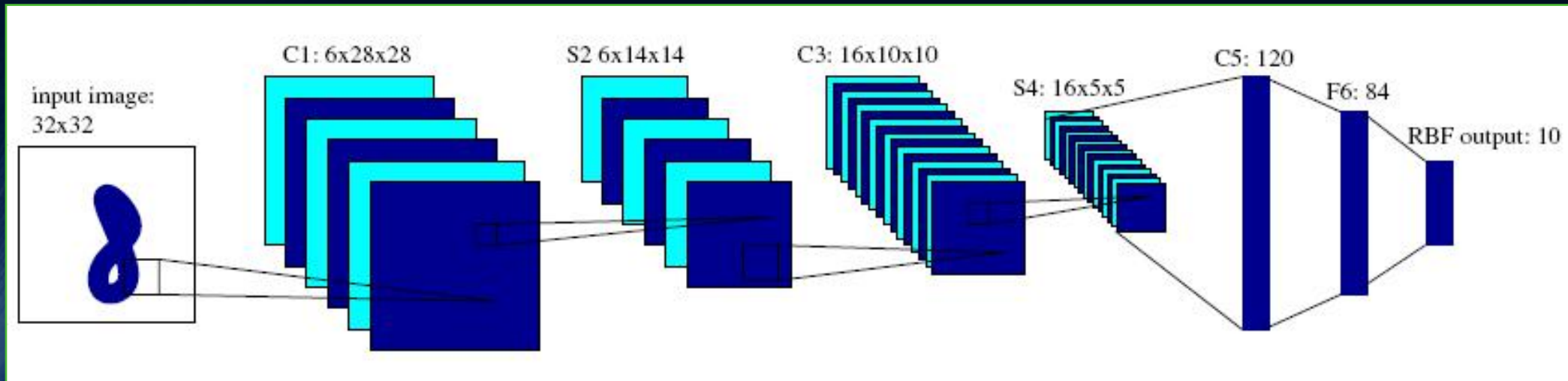
- ☯ C1,C3,C5 : Convolutional layer.
- ☯ 5×5 Convolution matrix.
- ☯ S2 , S4 : Subsampling layer.
- ☯ Subsampling by factor 2.
- ☯ F6 : Fully connected layer.



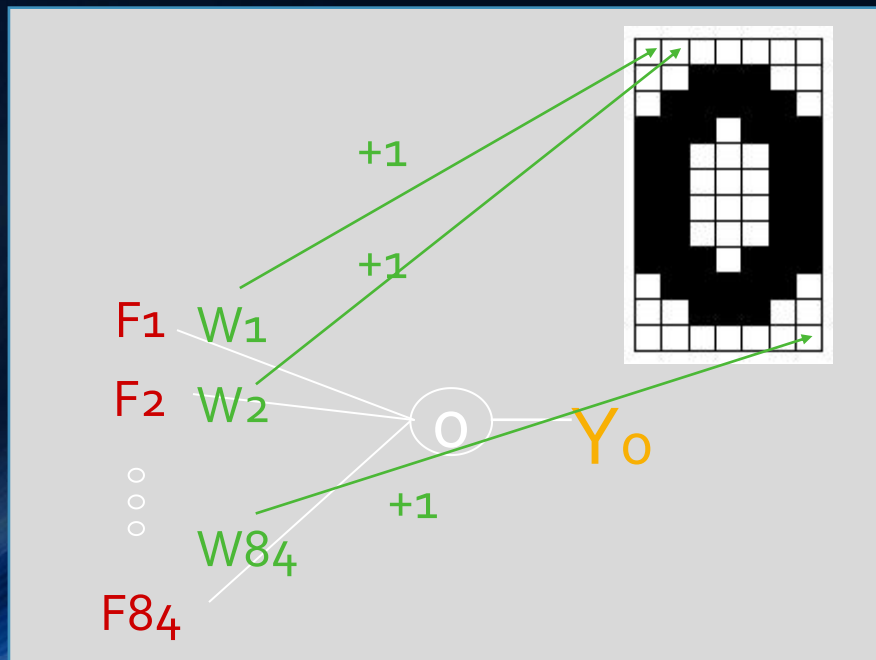
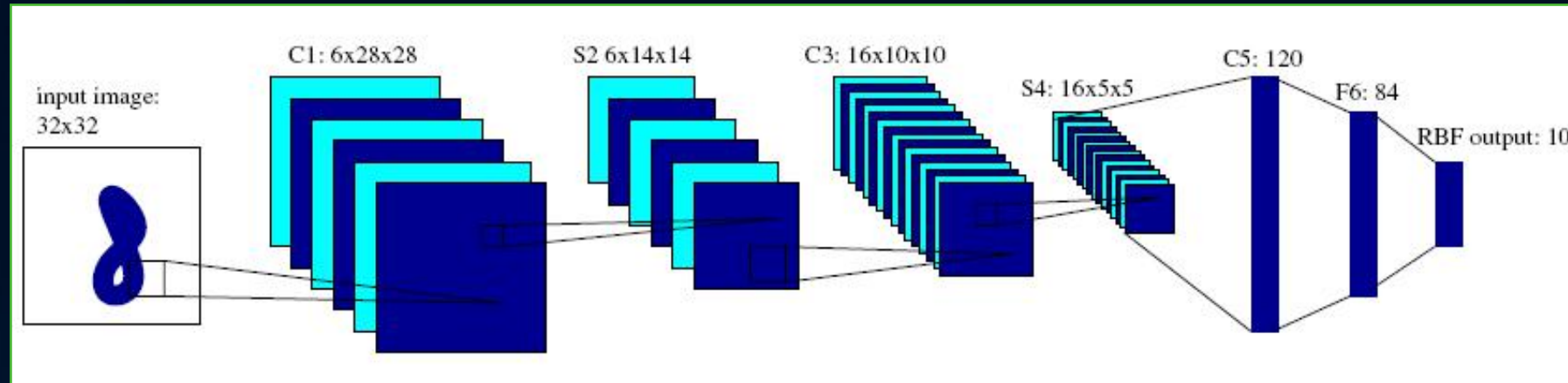
LeNet5

- ☯ All the units of the layers up to F6 have a **sigmoidal** activation function of the type:

$$y_j = \phi(v_j) = \text{Atanh}(Sv_j)$$

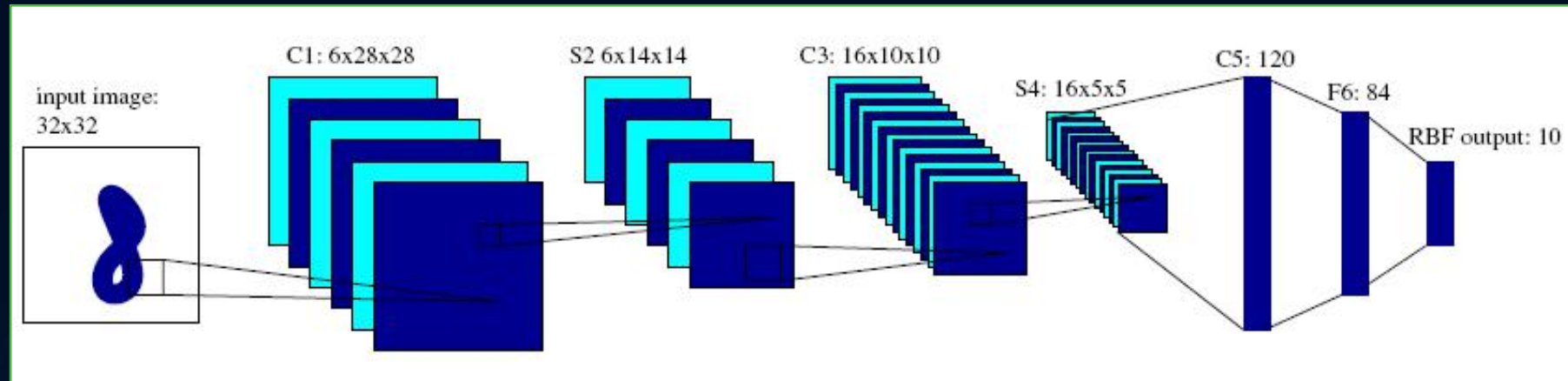


LeNet5

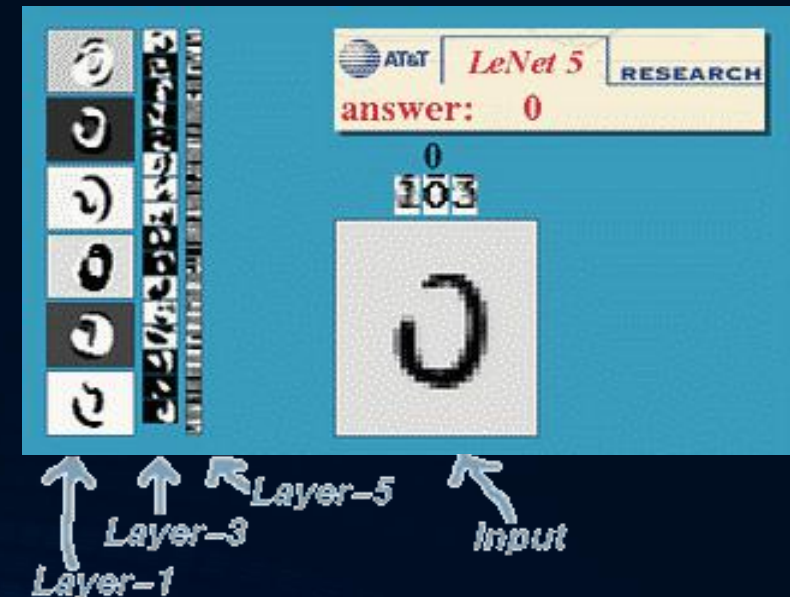


$$Y_j = \sum_{i=1}^{84} (F_i - W_{ij})^2, j = 0, \dots, 9$$

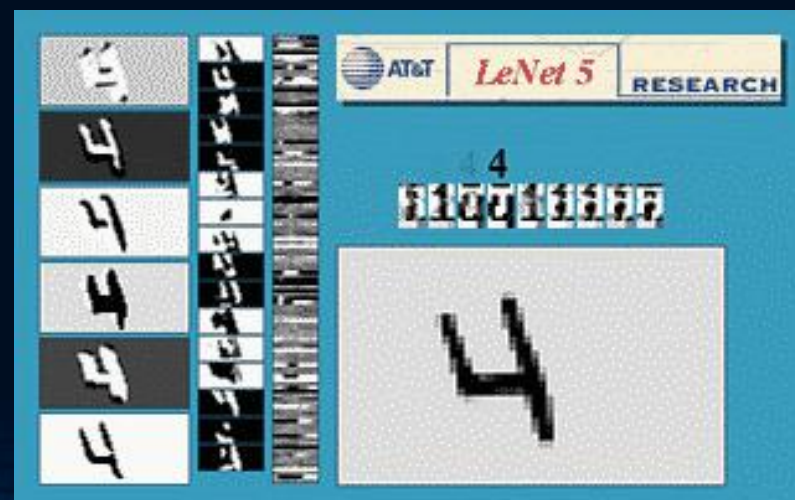
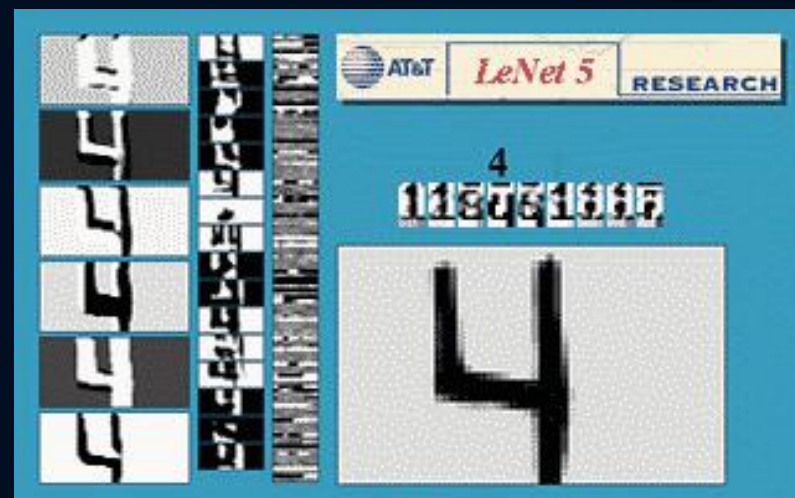
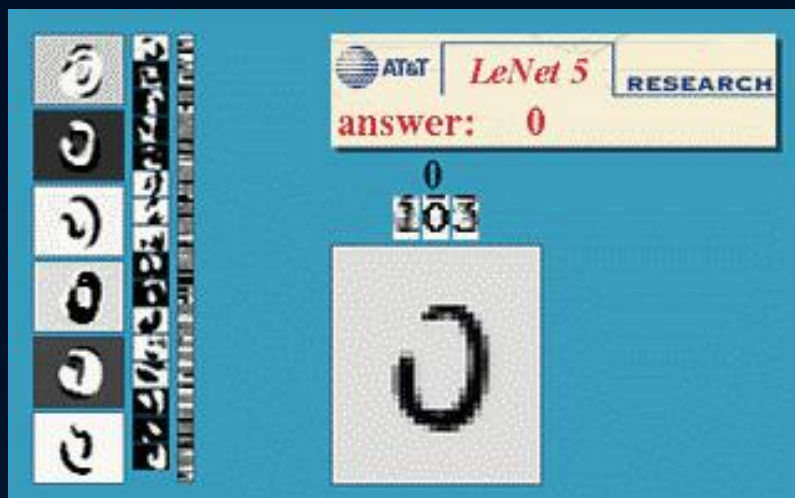
LeNet5



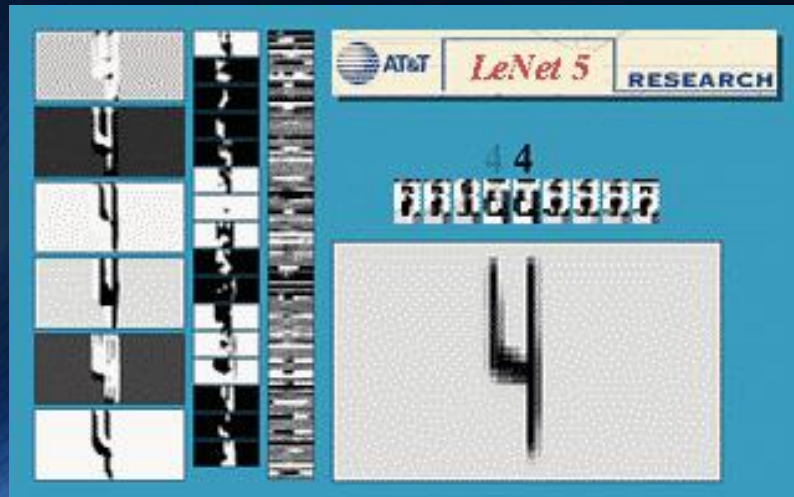
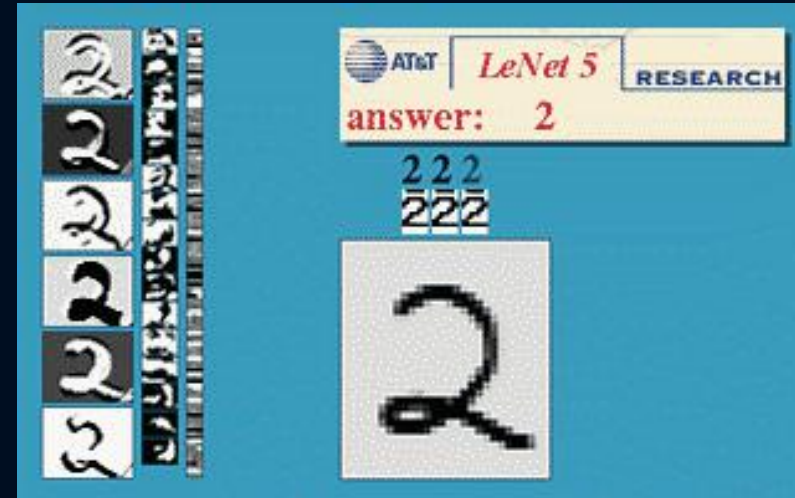
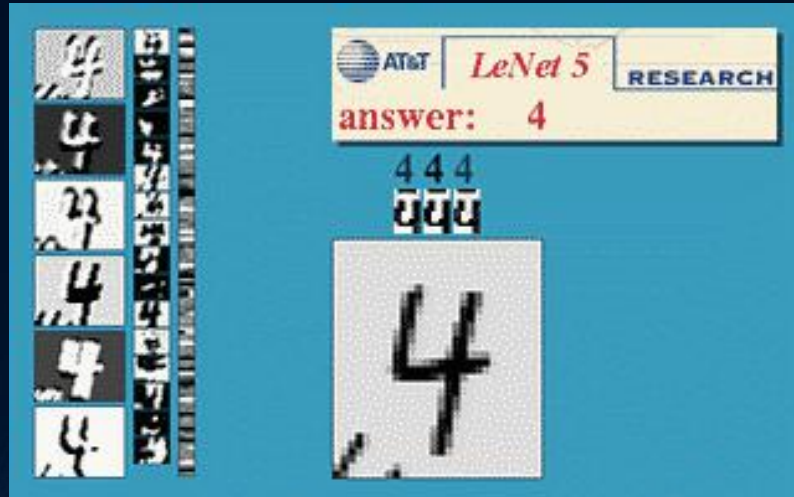
- ☯ About 187,000 connection.
- ☯ About 14,000 trainable weight.



LeNet5



LeNet5



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Comparison

- ☯ Database : MNIST (60,000 handwritten digits)
- ☯ Affine distortion : translation, rotation.
- ☯ elastic deformations : corresponding to uncontrolled oscillations of the hand muscles.
- ☯ MLP (this paper) : has 800 hidden unit.

Comparison

Algorithm	Distortion	Error	Ref.
2 layer MLP (MSE)	affine	1.6%	[3]
SVM	affine	1.4%	[9]
Tangent dist.	affine+thick	1.1%	[3]
Lenet5 (MSE)	affine	0.8%	[3]
Boost. Lenet4 MSE	affine	0.7%	[3]
Virtual SVM	affine	0.6%	[9]
2 layer MLP (CE)	none	1.6%	this paper
2 layer MLP (CE)	affine	1.1%	this paper
2 layer MLP (MSE)	elastic	0.9%	this paper
2 layer MLP (CE)	elastic	0.7%	this paper
Simple conv (CE)	affine	0.6%	this paper
Simple conv (CE)	elastic	0.4%	this paper

☯ “This paper” refer to **reference[3]** on references slide.

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Disadvantages

- ☯ From a memory and capacity standpoint the CNN is not much bigger than a regular two layer network.
- ☯ At runtime the convolution operations are **computationally expensive** and take up about **67%** of the time.
- ☯ CNN's are about **3X** slower than their fully connected equivalents (size-wise).

Disadvantages

☯ **Convolution operation**

- ☹ 4 nested loops (2 loops on input image & 2 loops on kernel)

☯ **Small kernel size**

- ☹ make the inner loops very inefficient as they frequently JMP.

☯ **Cash unfriendly memory access**

- ☹ Back-propagation require both row-wise and column-wise access to the input and kernel image.
- ☹ 2-D Images represented in a row-wise-serialized order.
- ☹ Column-wise access to data can result in a high rate of cash misses in memory subsystem.

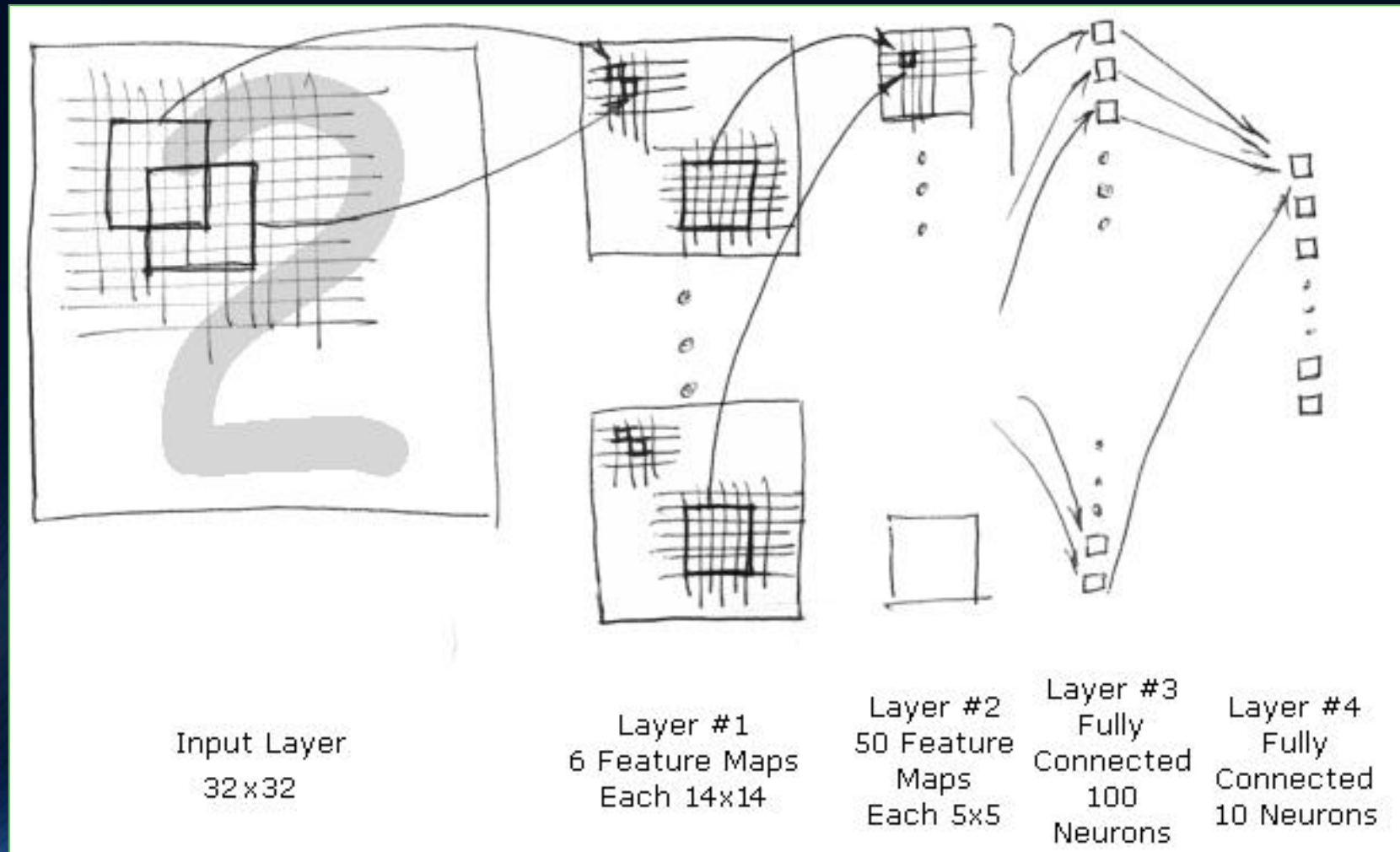
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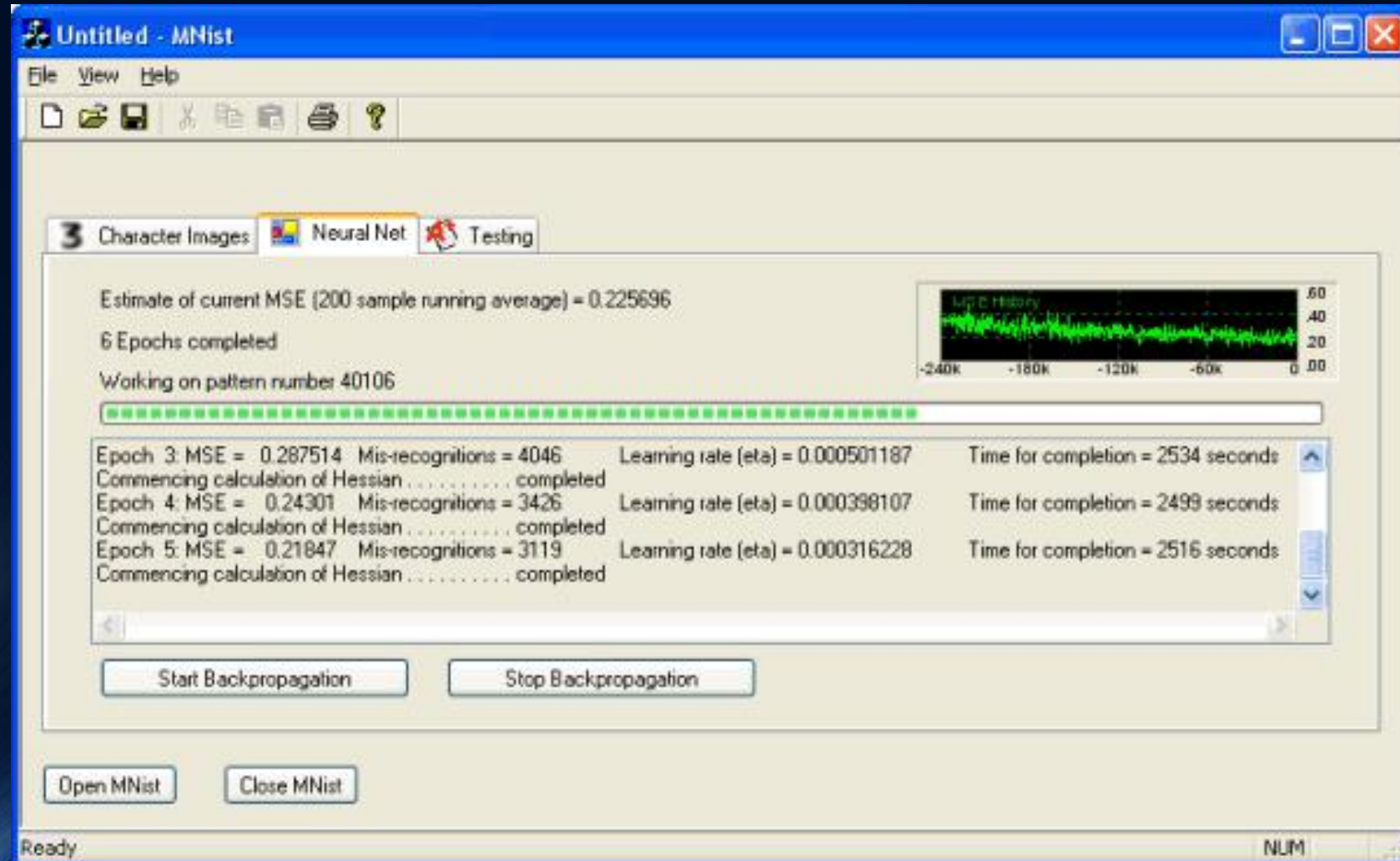
Application

- ☯ A Convolutional neural network achieves 99.26% accuracy on a modified NIST database of hand-written digits.
- ☯ MNIST database : Consist of 60,000 hand written digits uniformly distributed over 0-9.


















Application



Application



Application

				
3818	6597			
0 => 6 0 => 7				
				
2018	2182	5457		
1 => 7 1 => 3 1 => 8				
				
4176	8059	8094	9664	
2 => 7 2 => 1 2 => 8 2 => 7				
				
1681	2280	4740		
3 => 7 3 => 5 3 => 5				
				
247	2130	8520	8527	9792
4 => 6 4 => 9 4 => 9 4 => 9 4 => 9				

Application

340	674	1299	1737	2035	2040	2597	3558	4360	5937	9729	9770
5 => 3 5 => 3 5 => 3 5 => 3 5 => 3 5 => 6 5 => 3 5 => 0 5 => 3 5 => 3 5 => 6 5 => 0											
2135	2654	3365	3422	3762	4699	4838	6558	8287	9627	9679	9698
6 => 1 6 => 1 6 => 1 6 => 0 6 => 8 6 => 1 6 => 5 6 => 3 6 => 8 6 => 5 6 => 5 6 => 2											
282	1226	3225	3808	9009	9015	9024					
7 => 3 7 => 2 7 => 9 7 => 2 7 => 2 7 => 2 7 => 2											
184	582	947	1033	1068	1319	1782	1878	4497	4879	4956	6555
8 => 3 8 => 2 8 => 9 8 => 1 8 => 4 8 => 0 8 => 9 8 => 3 8 => 7 8 => 6 8 => 4 8 => 9 8 => 5											
1247	1709	1901	2582	2939	3503	3850	3869	4369	4761	6571	6632
9 => 5 9 => 5 9 => 4 9 => 7 9 => 5 9 => 1 9 => 4 9 => 4 9 => 4 9 => 8 9 => 7 9 => 8 9 => 8											

References

- [1].Y. LeCun and Y. Bengio.“Convolutional networks for images, speech, and time-series.” In M. A. Arbib, editor, *The Handbook of Brain Theory and Neural Networks*. MIT Press, 1995.
- [2].Fabien Lauer, ChingY. Suen, Gérard Bloch,“A trainable feature extractor for handwritten digit recognition”,Elsevier, october 2006.
- [3].Patrice Y. Simard, Dave Steinkraus, John Platt, "Best Practices for Convolutional Neural Networks Applied to Visual Document Analysis," International Conference on Document Analysis and Recognition (ICDAR), IEEE Computer Society, Los Alamitos, pp. 958-962, 2003.

Next

Recurrent Neural Networks