Gradient-based Learning Applied to Document Recognition

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Presenter: Lu Jiang

Outline

- Introduction
- Convolutional Neural Network
- Multiple Characters Recognition
- Conclusions

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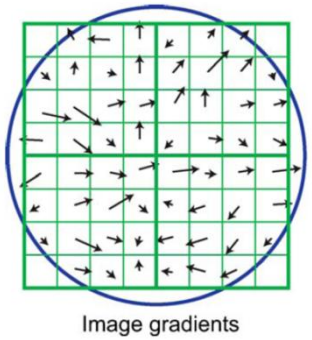
Introduction

- Key message: better pattern recognition systems can be built by relying more on automatic learning and less on hand-designed heuristics.
  - Hand-crafted features vs. learned features



Hand-crafted (SIFT)

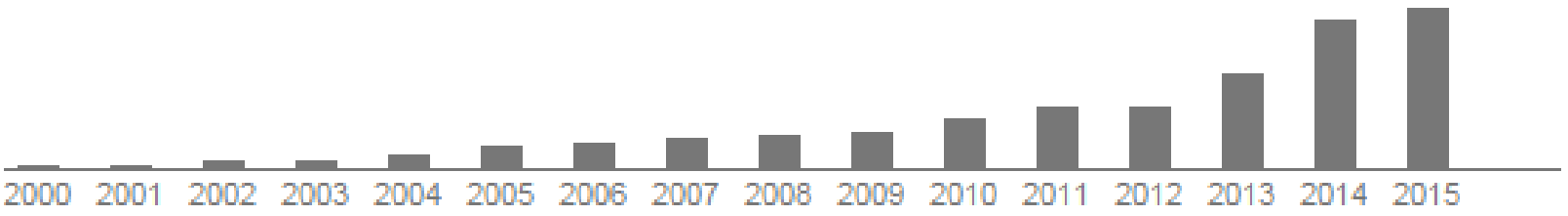
Learned filters

Why learned features:

- (a) lower dimension can be easily compared
- (b) invariant to transformations and distortions of the input patterns.

Background

- LeCun's most cited paper.
- This paper published in 1998, at that time
  - SVM (and kernel learning) are quite popular.
  - Hand-crafted features (e.g. SIFT) are dominant.
  - MNIST (58k images) is a big and challenging data.
- This paper did not become popular until 2012, when the proposed convolutional neural networks were successfully applied on ImageNet challenge (AlexNet).
- Now almost every deep learning network for visual recognition uses convolutional layers.



MNIST
(NIST handwritten digit database)

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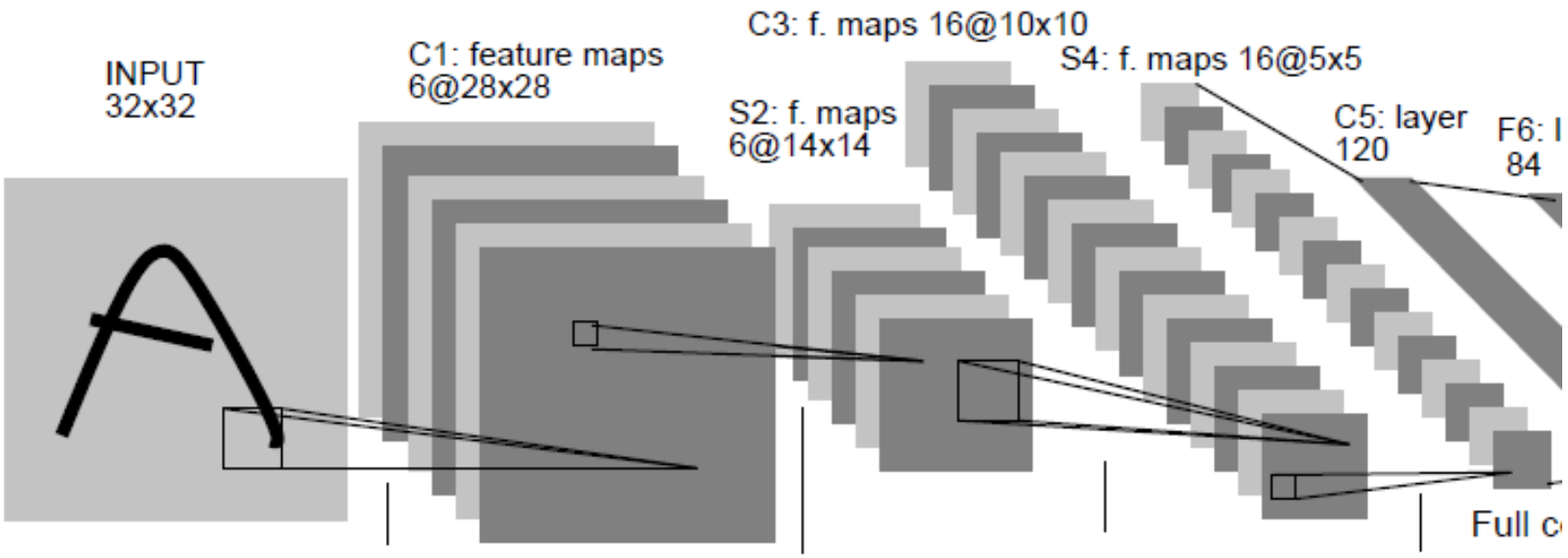
Intuitions

- A network can be fed with the pixels in raw images (fully-connected layer) but:
  - Formidable number of parameters. 256*256*3 = 196K parameters. Overfitting!
  - Sensitive to size, shift slant, position variations caused by, or example, resized images.
  - Topology in images are ignored. The fact is local nearby pixels are highly correlated. Local points can form edges, end-points, and corners.
- **Proposed approaches**: learn pattern that can be positioned at various locations; force learned pattern are from local pixels.
- **Solution**: Convolutional Neural Network
  - Convolution layer and pooling layer are inspired by “simple” and “complex” cells [Fukushima et al 1982].

Convolutional Neural Network

- Input: inputs from a set of units located in a small neighborhood in the previous layer. First conv layer receives the resized and normalized images.
- Output: a number of feature maps (holding neurons arranged in a 3D volume)



LeNet-5

Convolutional Neural Network

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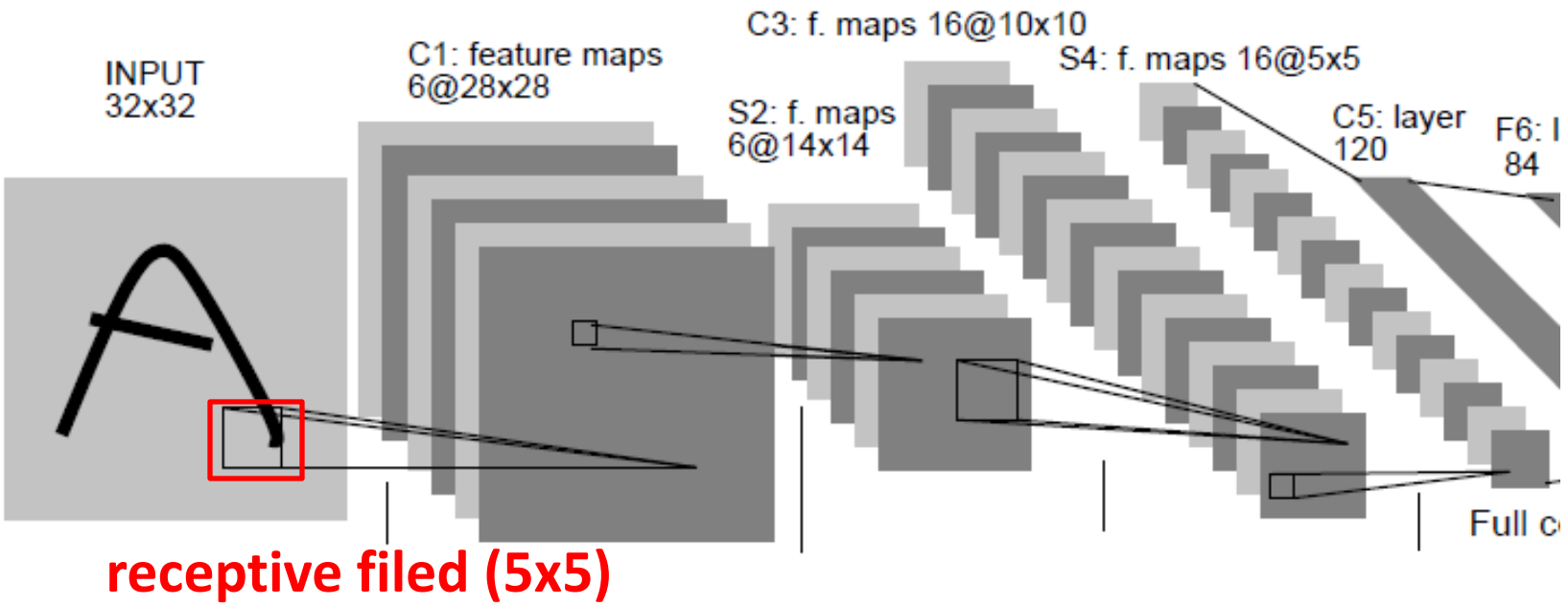

receptive filed (5x5)

slide over the input (convolution)

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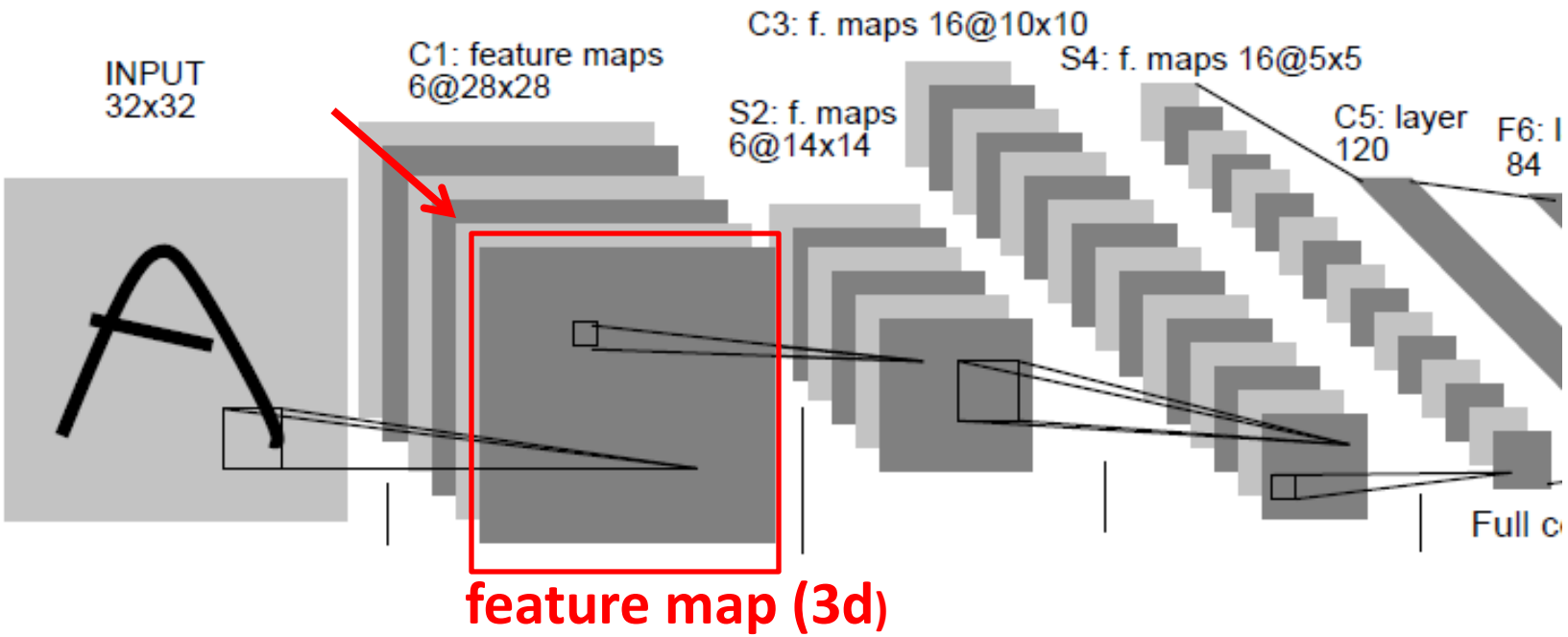

The learnable parameter in the same feature map is shared. (weight sharing)

To learn meaningful pattern at different locations.

Convolutional Neural Network

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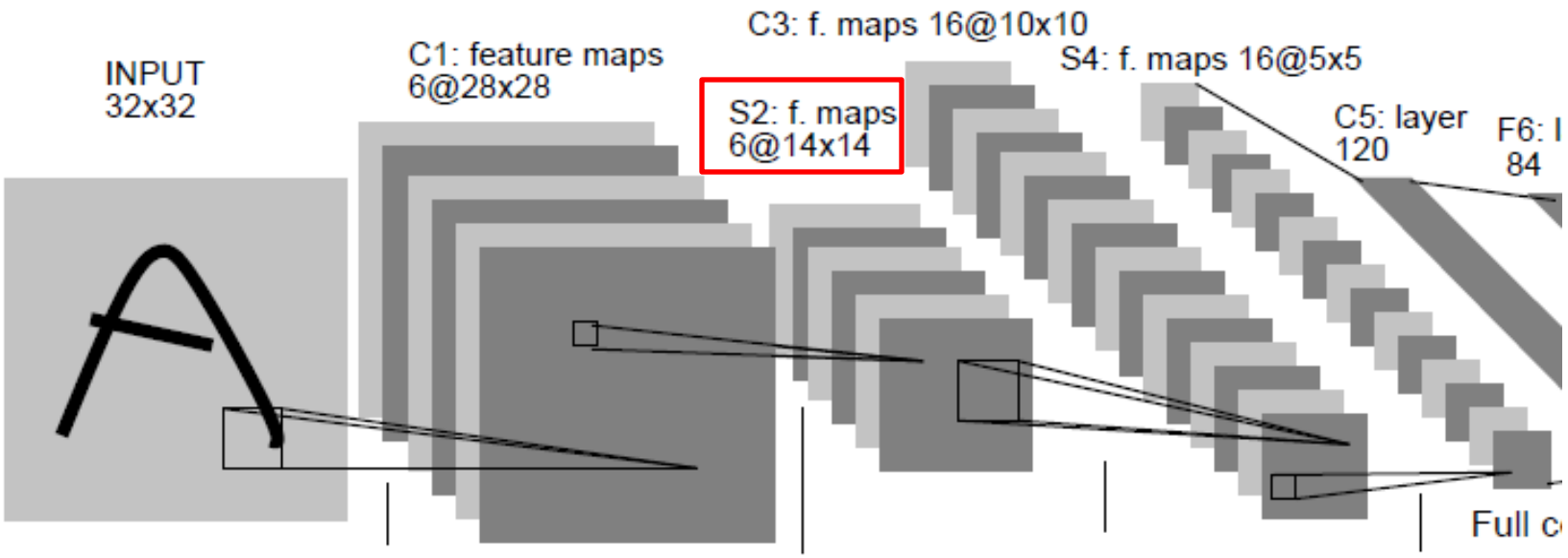

pooling (sub-sampling) layer

Down-sampling the input and preserve meaningful statistics (average or max pooling). Make learned pattern more invariant.

Convolutional Neural Network

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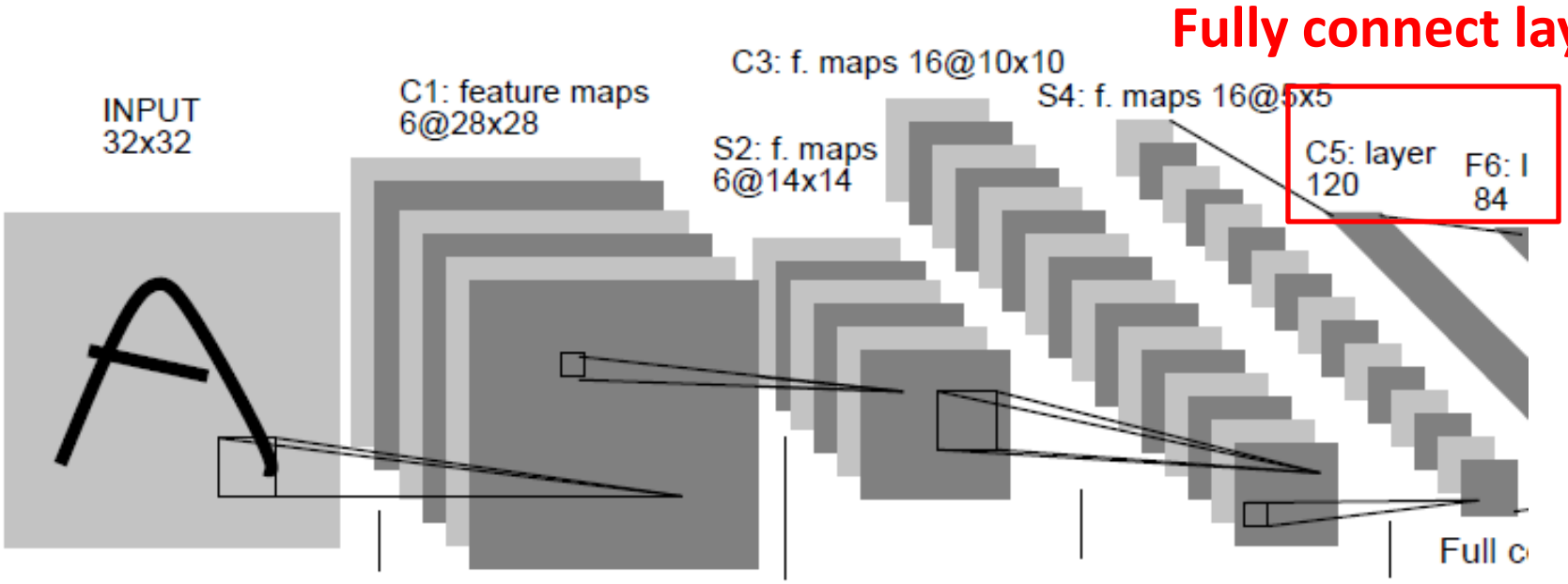
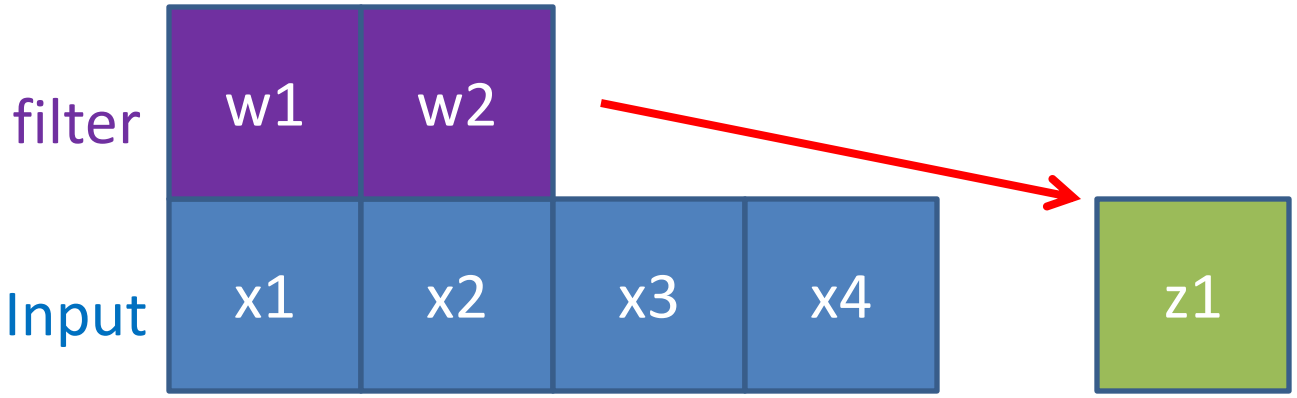
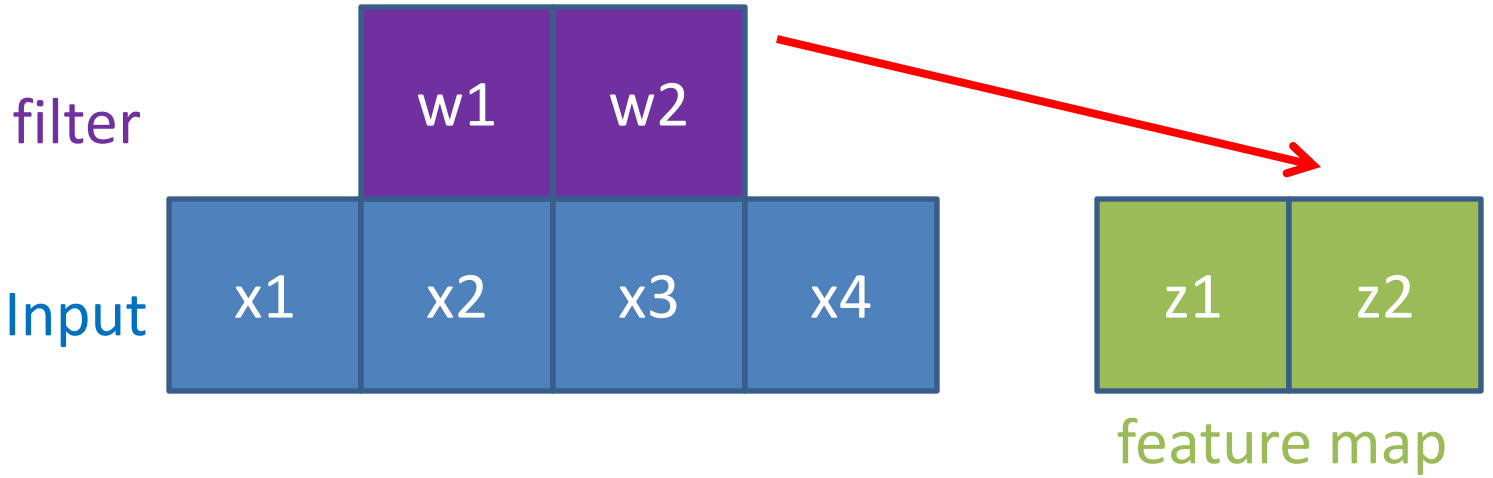


Convolutional Layer in 1D



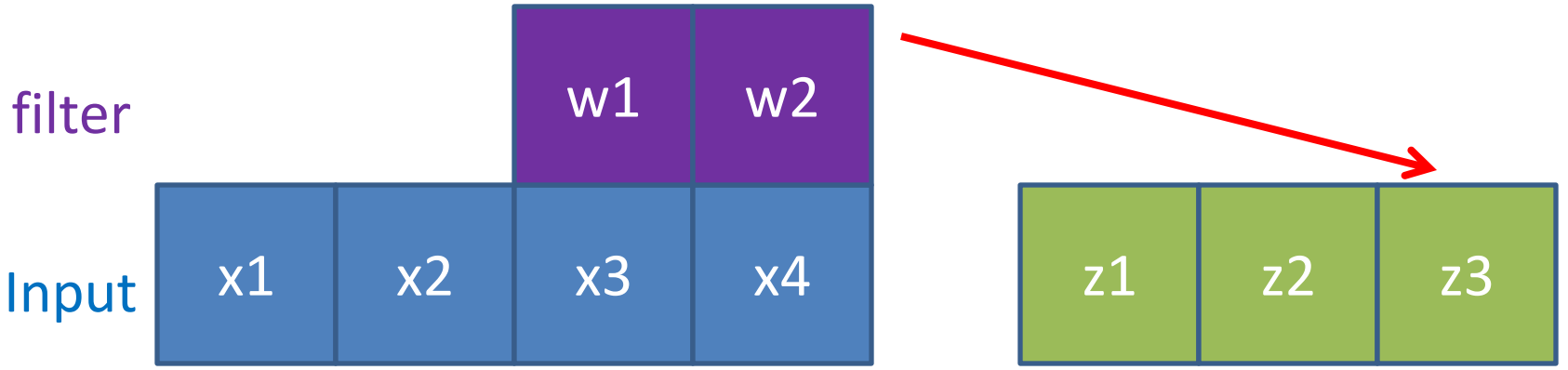
$$z_1 = w_1 x_1 + w_2 x_2 + b$$

Convolutional Layer in 1D



$$z_2 = w_1 x_2 + w_2 x_3 + b$$

Convolutional Layer in 1D



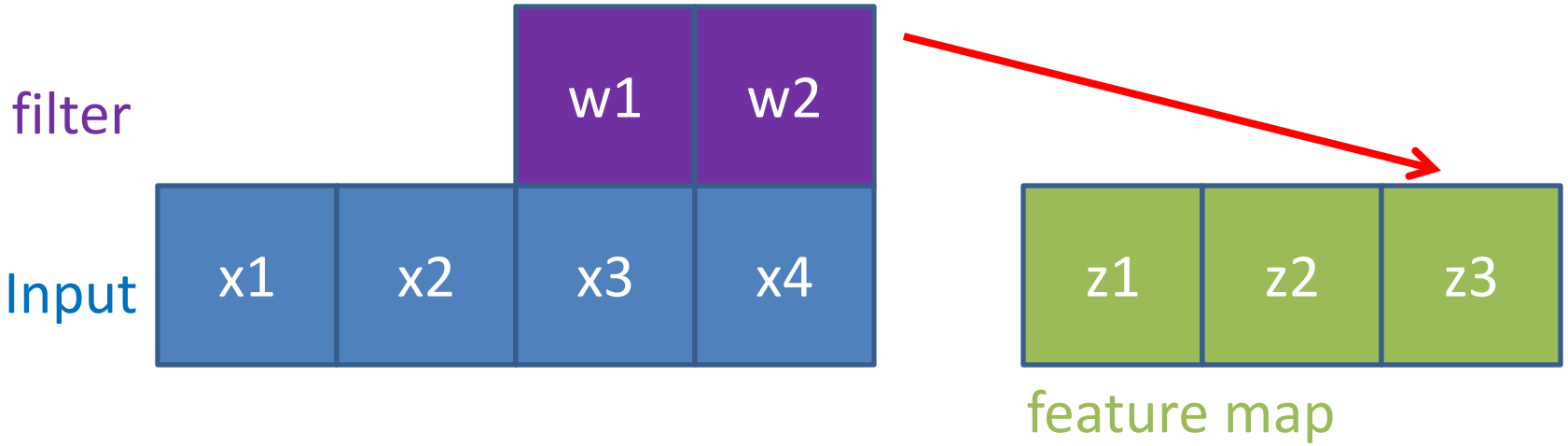
$$z_3 = w_1 x_3 + w_2 x_4 + b$$

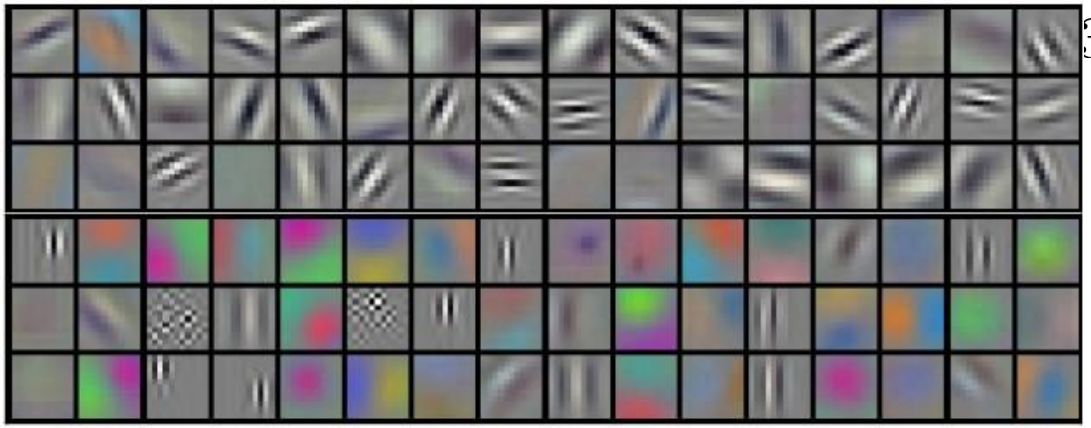
z measures the dot product similarity to the local inputs.

Our goal is to learn the parameters w

The hope is we can learn patterns frequently occurred in the inputs

Convolutional Layer in 1D





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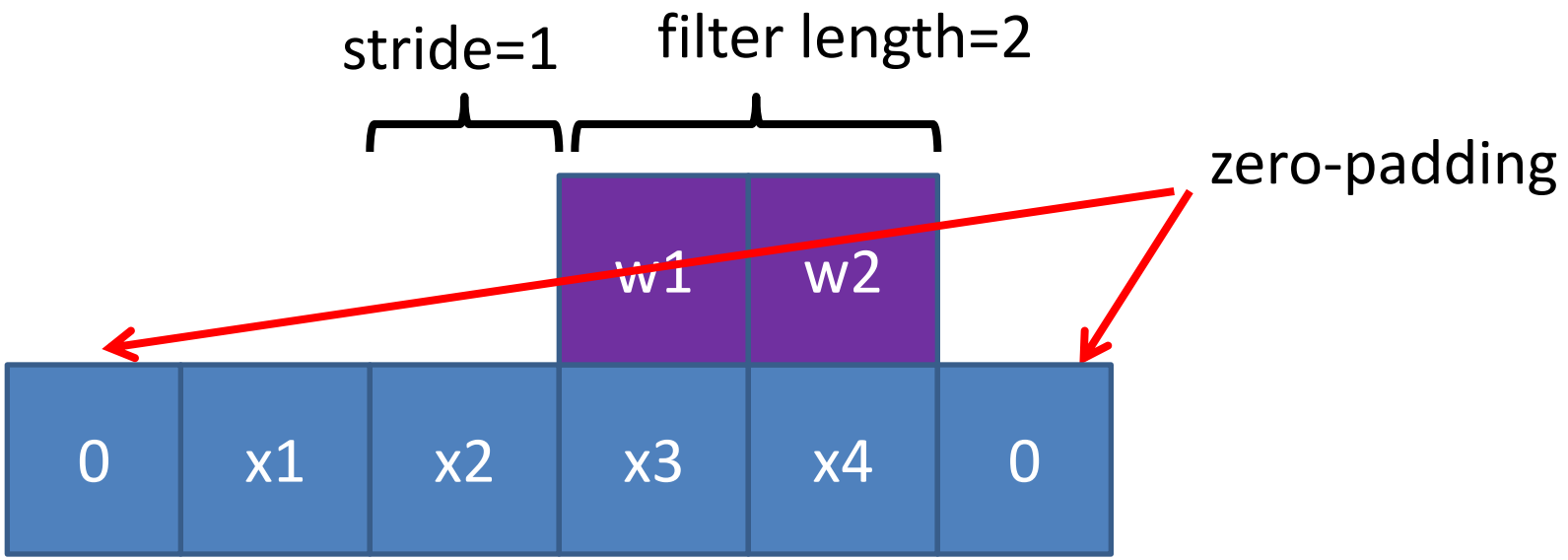
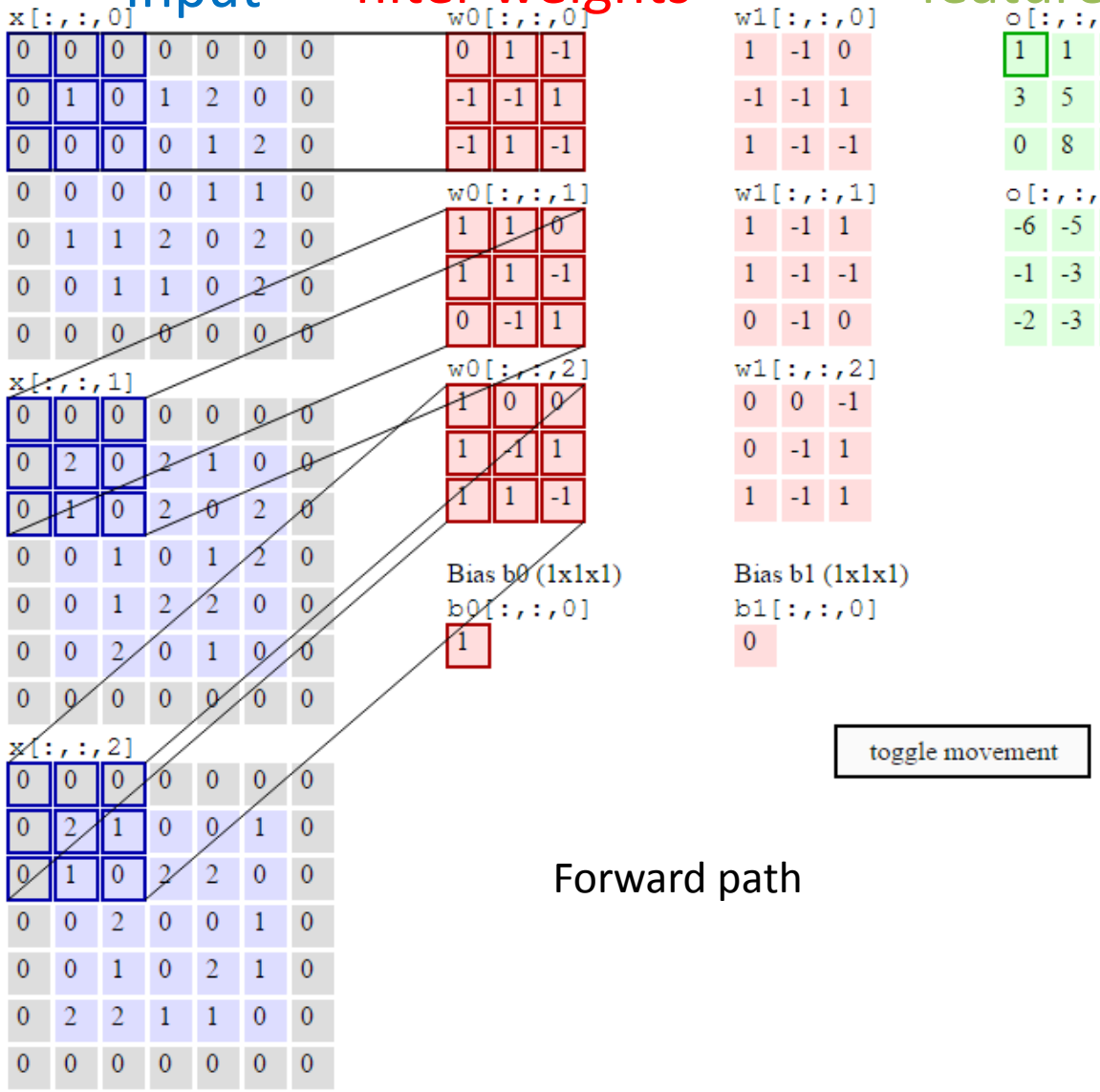
Convolutional Layer in 1D



Smaller strides work better in practice [Fei-fei Li et al. 2015].

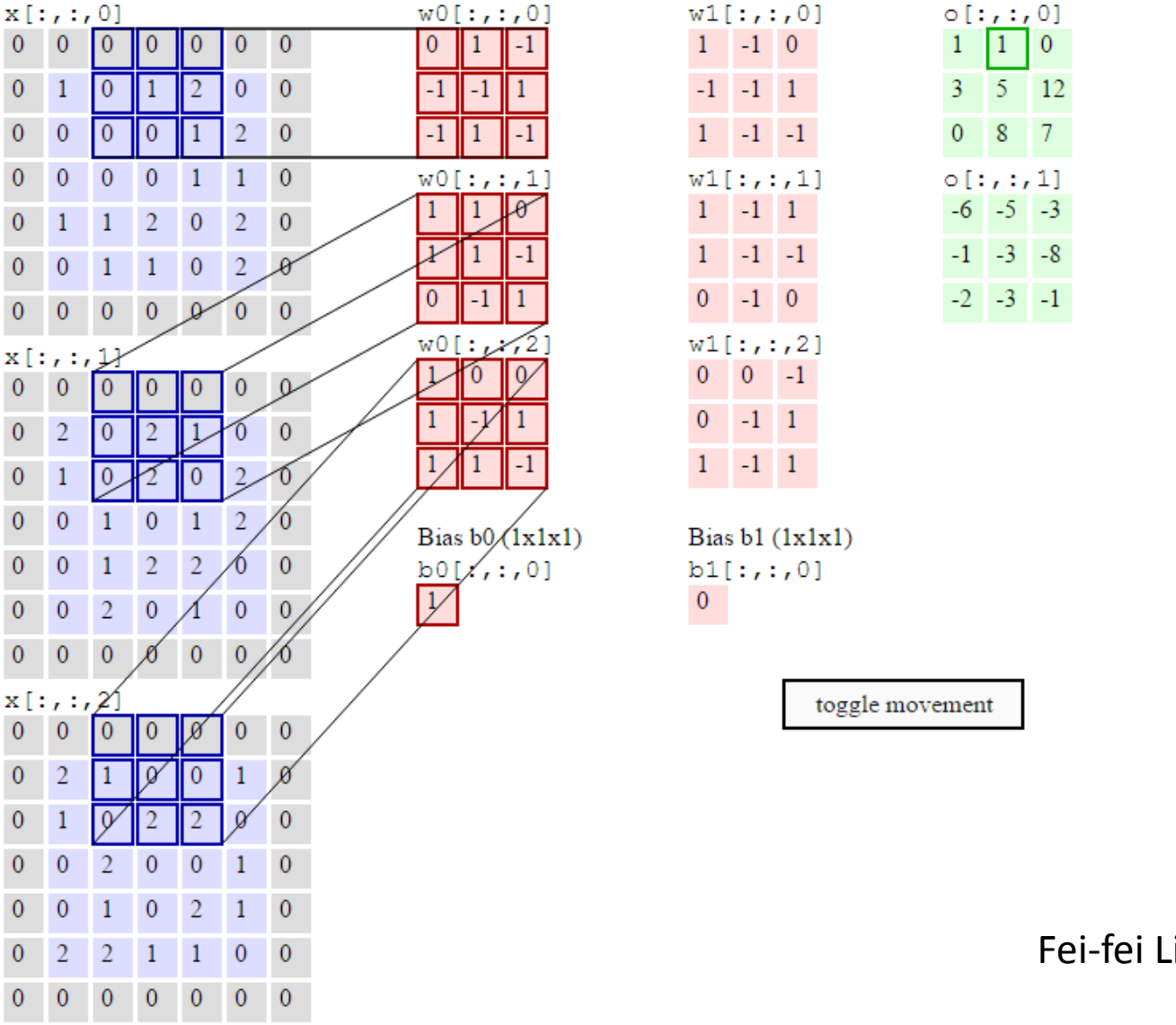
Convolutional Layer in 2D



Forward path

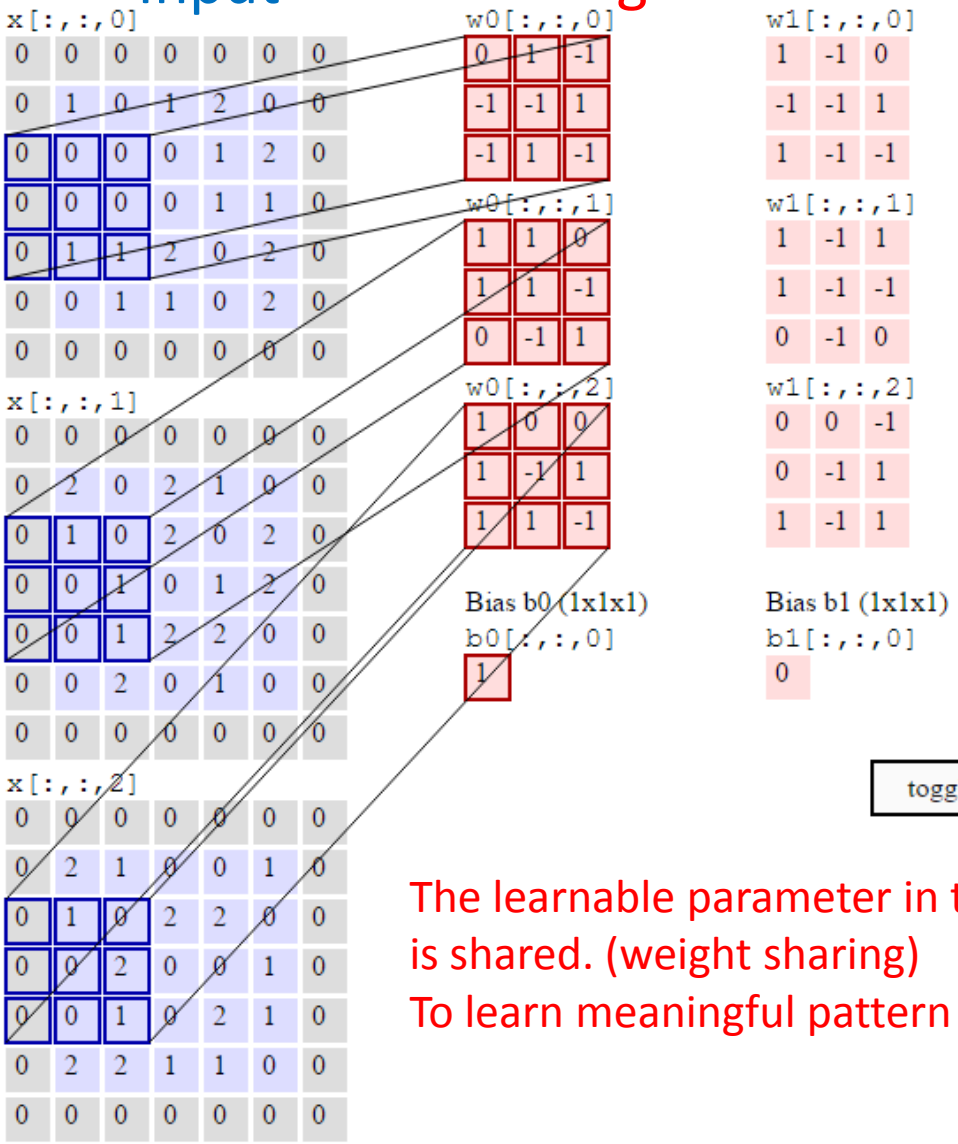
Fei-fei Li et al. 2015

Convolutional Layer in 2D



Fei-fei Li et al. 2015

Convolutional Layer in 2D



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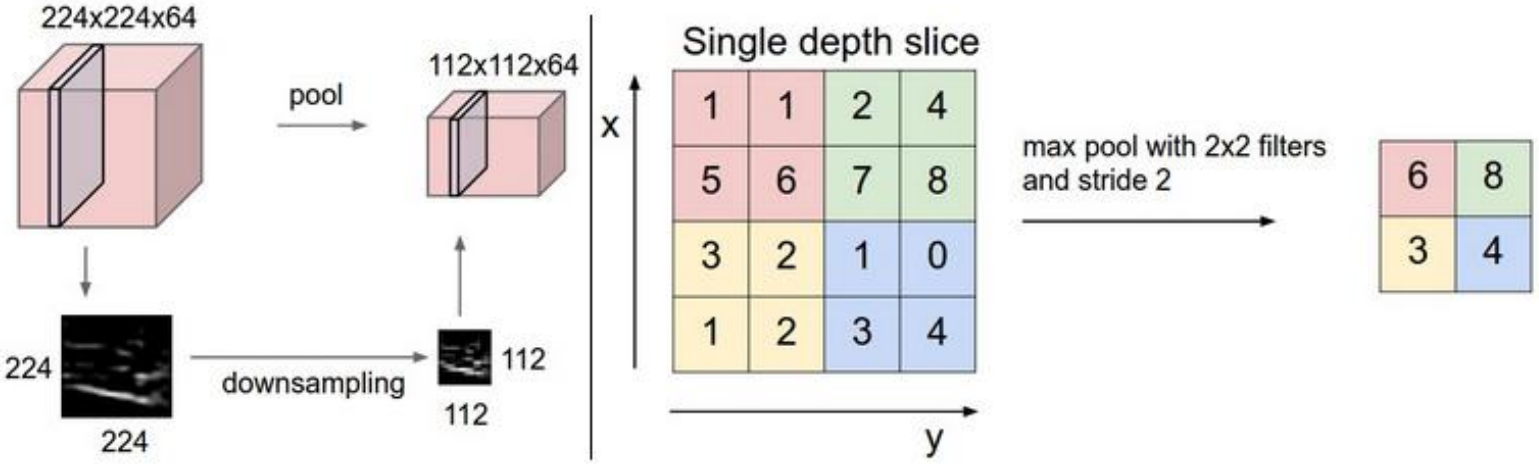
To learn meaningful pattern at different locations.

Fei-fei Li et al. 2015

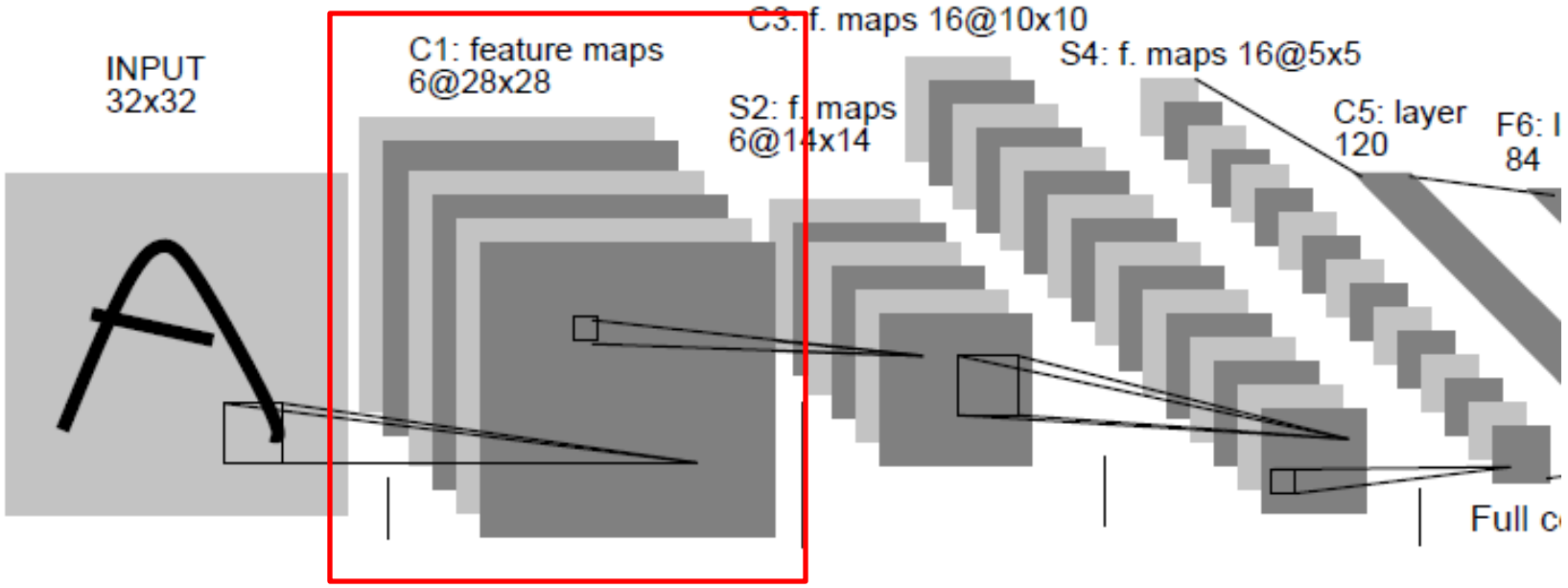
Pooling (Sub-sampling) Layer



In this paper, Lecun used a linear transformation.
Weighted sum of the inputs plus a bias term.
Max pooling becomes quite popular nowadays.

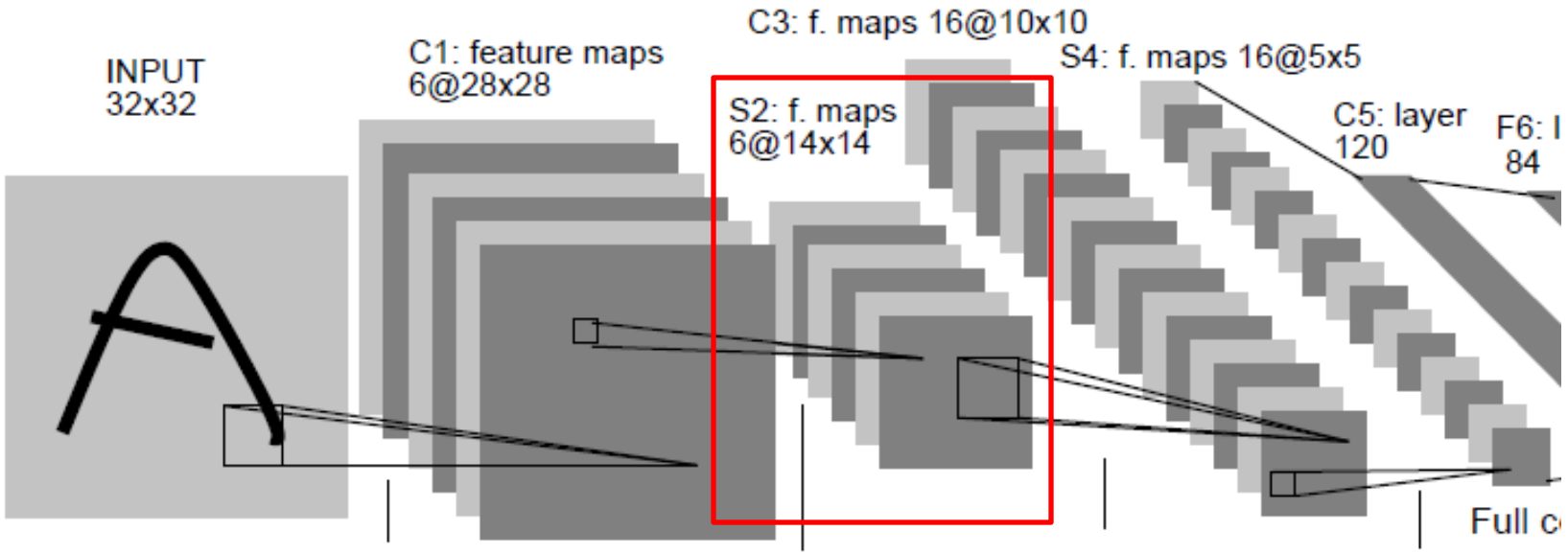
Down-sampling the input and preserve meaningful statistics (average or max pooling). Make learned pattern more invariant.

Convolutional Neural Network



- C1 layer has 6 feature maps (28x28), a 5x5 receptive filed resulting in (5*5+1)*6 = 156 learnable parameters which are from 28*28*(5*5*+1)*6 = 122,304 connections.

Convolutional Neural Network



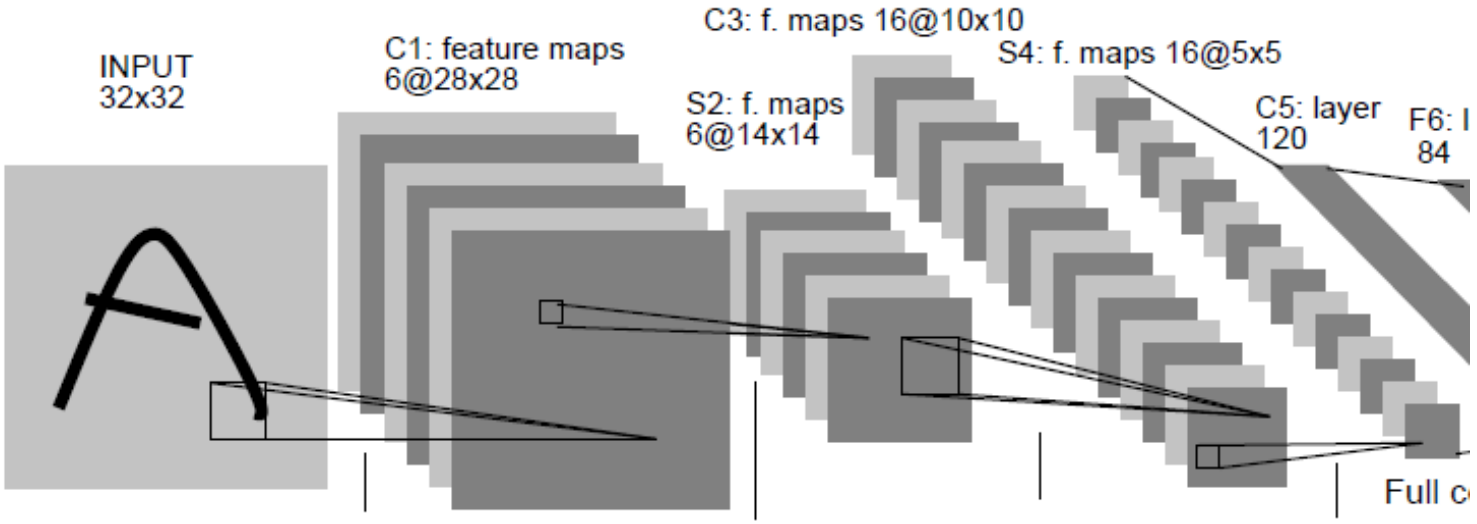
- S1 layer has 6 feature maps (14x14), a 2x2 receptive filed resulting in (1+1)*6 = 12 learnable parameters which are from 14*14*(2*2+1)*6 = 5,880 connections.

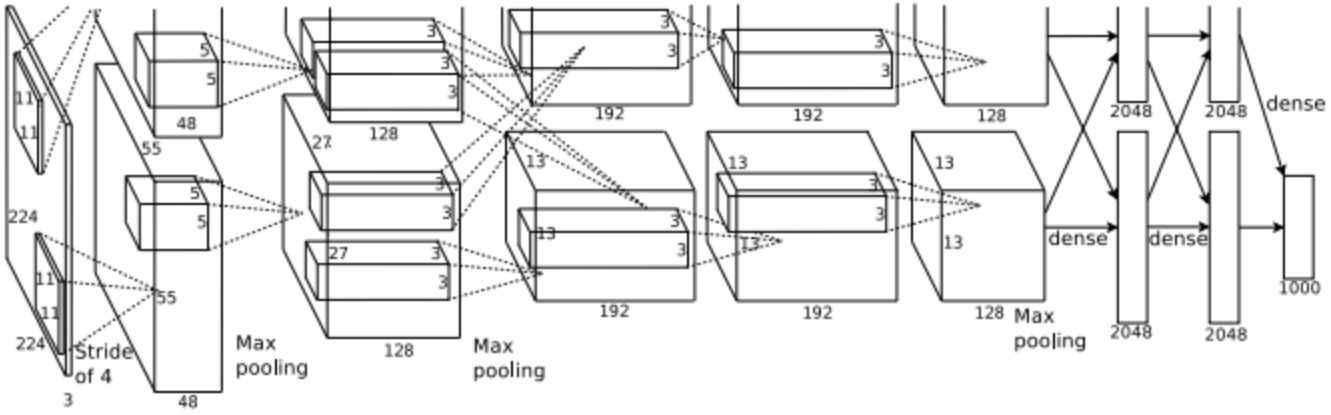
Fewer parameters but computationally intensive to compute (#connections result from convolution)

Convolutional Neural Network Training

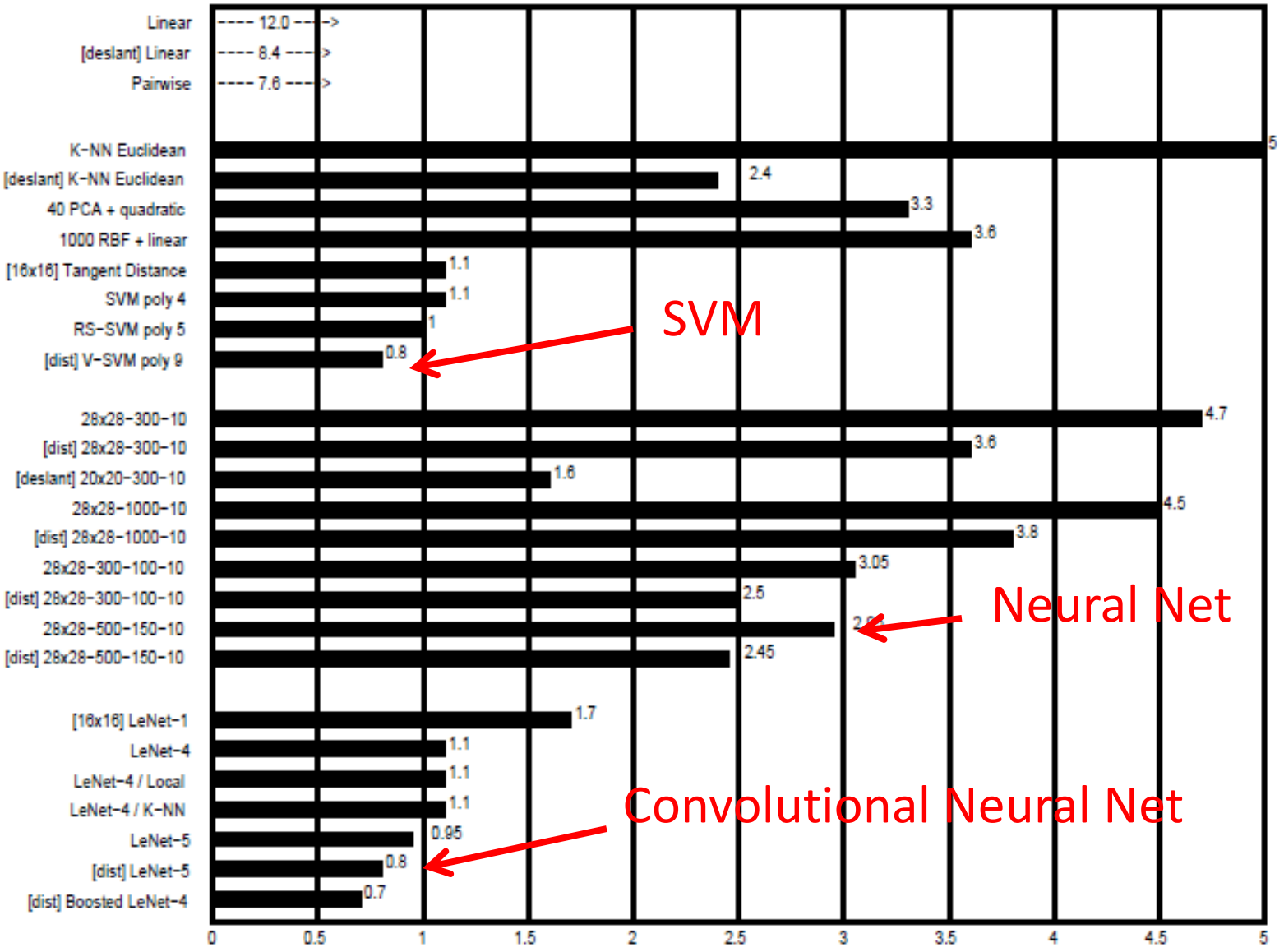
- Compute partial derivatives of the loss function with respect to each connection, as if there were no weight sharing. [via backprop]
- Aggregate the partial derivatives of all connections that share a same parameter. Update the parameter with the aggregated derivatives.

LeNet-5 to AlexNet





Results on MNIST



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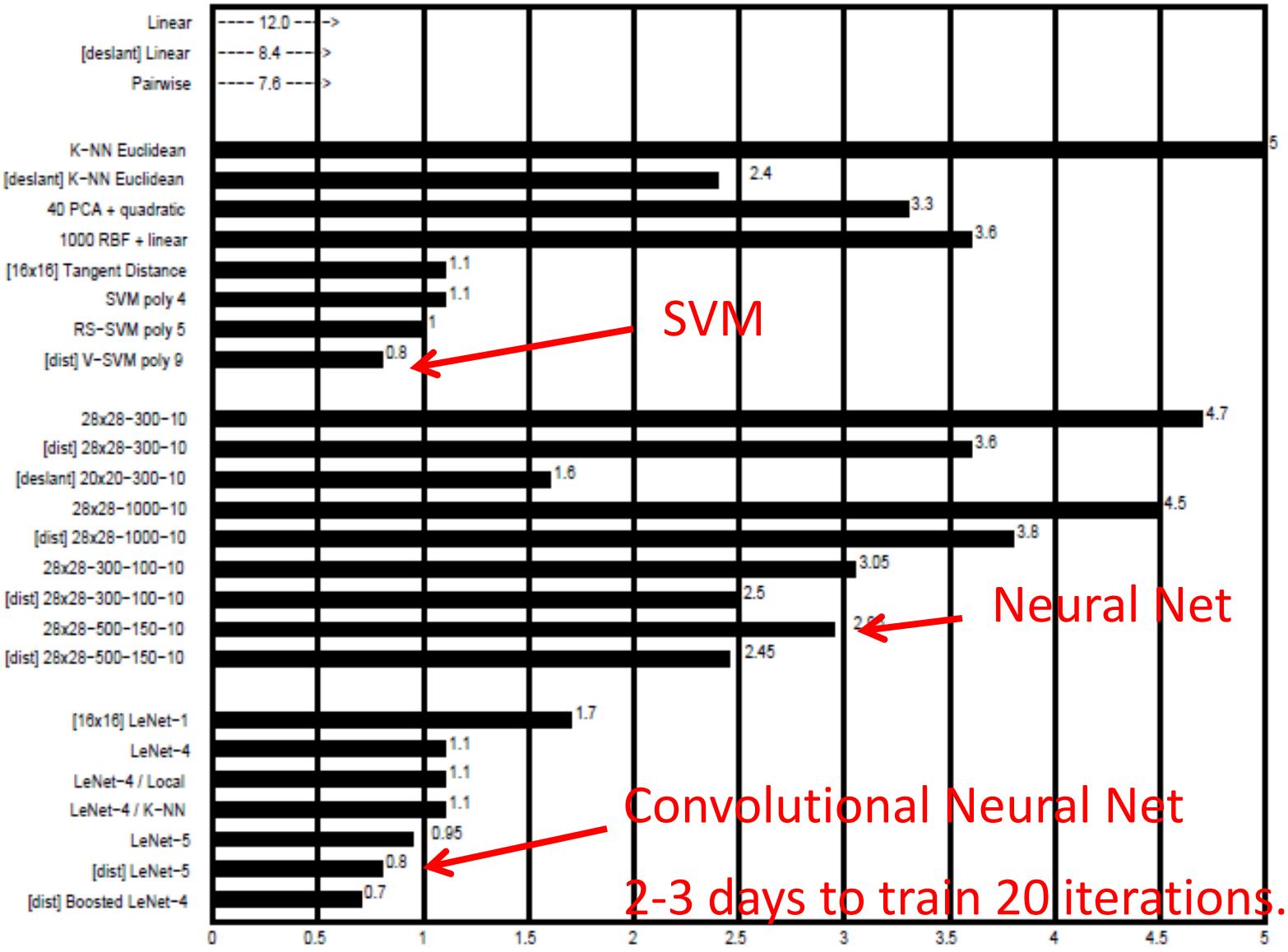

Multi-Module Recognition System

- Object-Oriented Design:
  - Every module can be a layer. For example, loss function layers, convolutional layers, and even graph transformers.
  - Every layer is an object that has functions like fprop and bprop.
  - Complex systems can be built upon those simple layers, and trained by gradient-based learning algorithms.
- Inspire the design of deep learning tools like caffe, Torch

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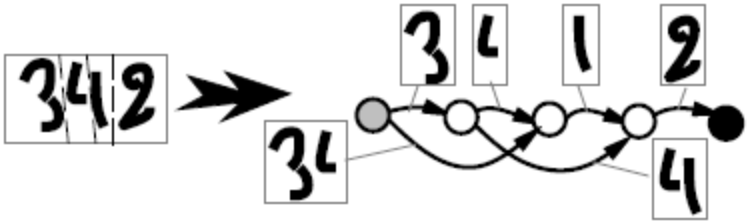
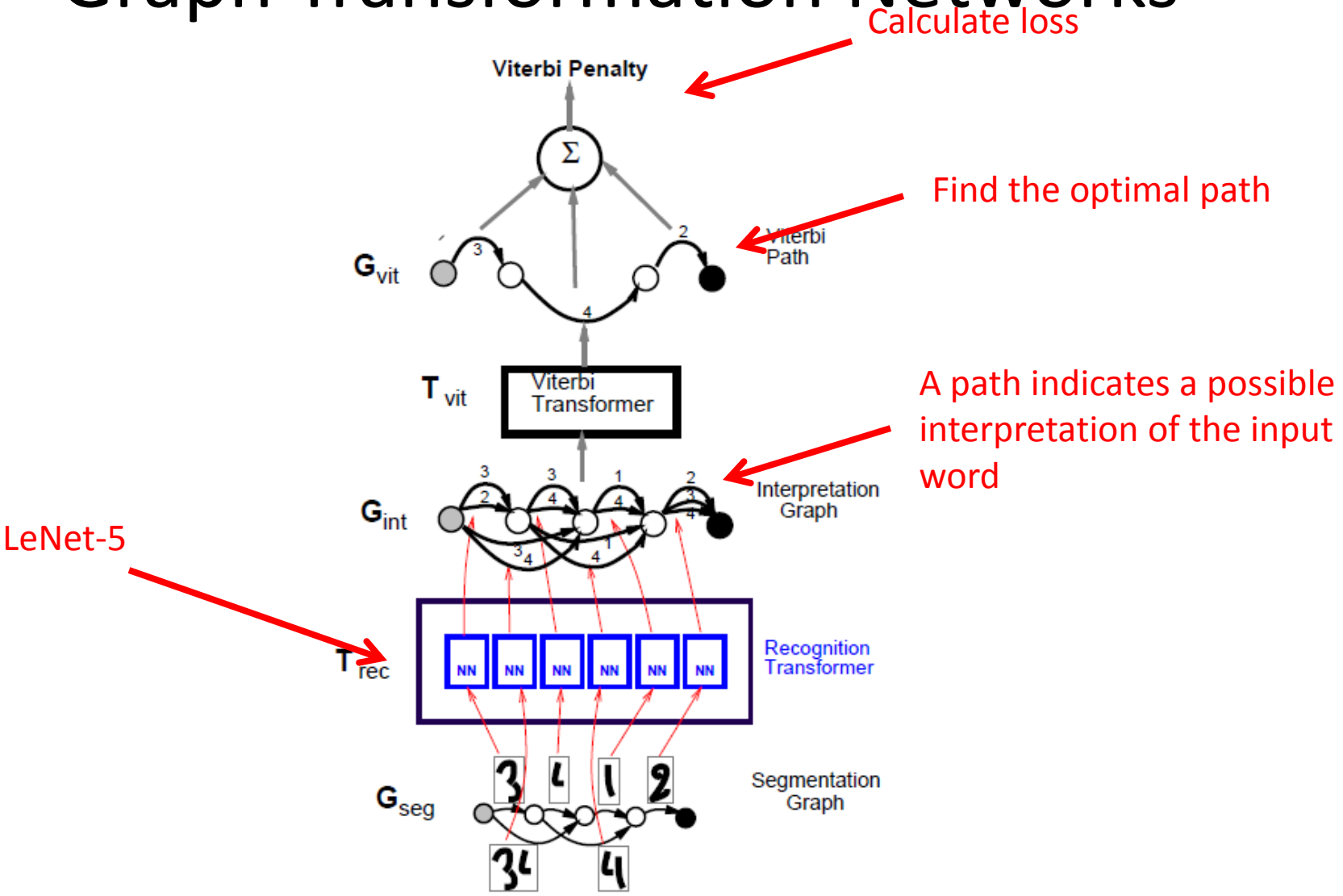
Segmentation Graph

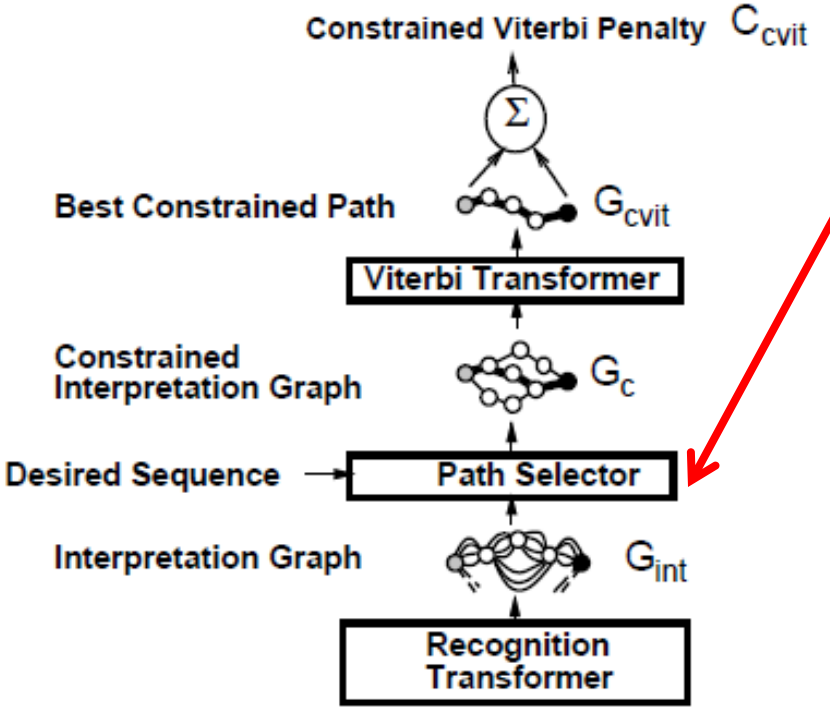


- Over-segmentation: generate a large number of different (probably incorrect) segments.
- Segmentation graph: an arc between two nodes indicate a segment result
- A complete path between start and end node contains each piece of ink once and only once

Recognizing multiple characters Graph Transformation Networks

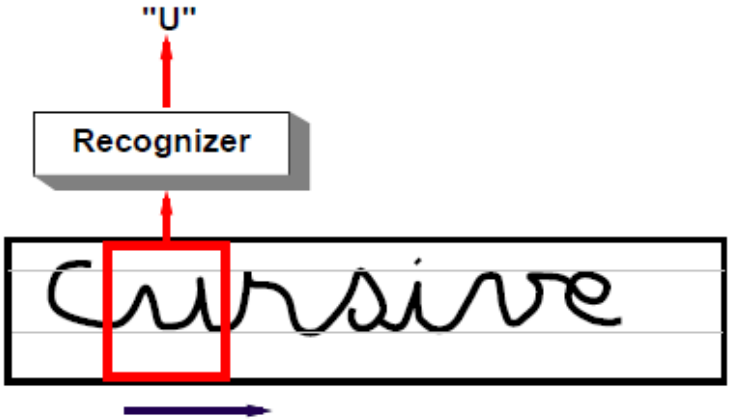


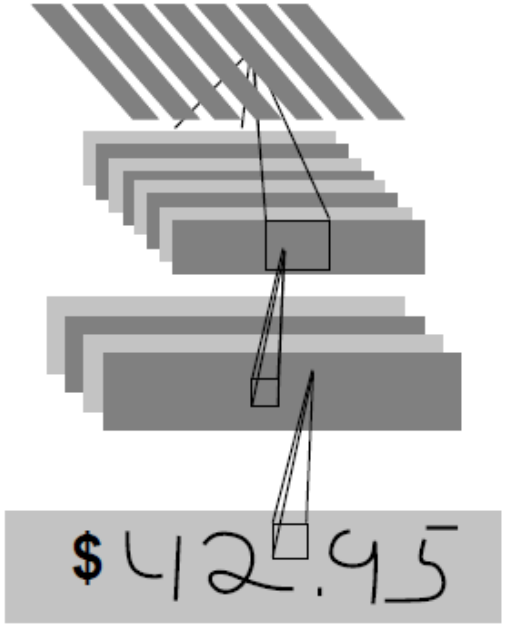
Recognizing multiple characters: Graph Transformation Networks



- To train GTN:
  - Add a layer called a path selector to select the paths with **correct label sequence** in the interpretation graph.
  - Calculate the penalty.
  - Back propagate the penalty to the neural network.
  - How to calculate the partial gradient with respect to graphs?
    - Define a binary function. Assign gradient 0 for the arcs not in the correct/optimal path. 1 otherwise.

Recognizing multiple characters: Displacement Neural Network





End-to-end convolutional neural network

Interestingly, LeCun mentioned RNN but did not use it because he said it is hard to train.

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Conclusions

- The most representative work of LeCun. A seminal on neural networks for visual recognition.
- This paper proposed several interesting notations:
  - Hand-crafted features should be replaced by learned features.
  - Large-sized systems can be learned by gradient-based method with efficient back propagation.
  - Proposed the notation of graph transformer layer that can be plugged into a network.

Thank you.

Any Questions?