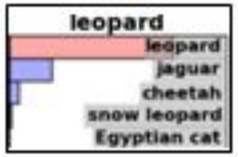
Introduction to Machine Learning

Foundations and Applications

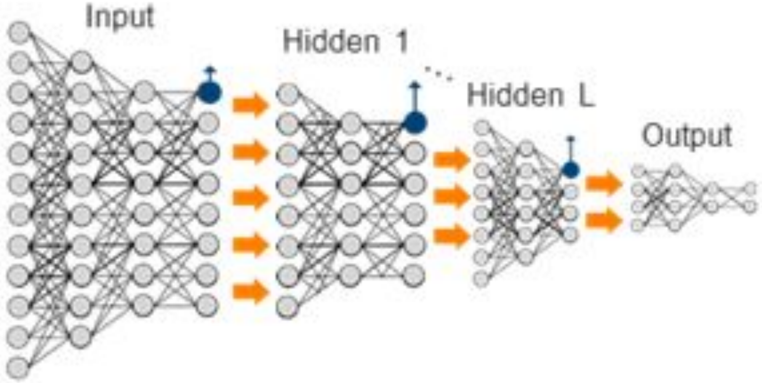
Paul J. Atzberger
University of California Santa Barbara

Image Classification with Neural Networks

Classify Image



Neural Network (NN)



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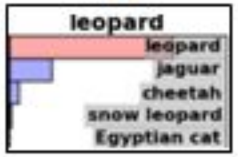

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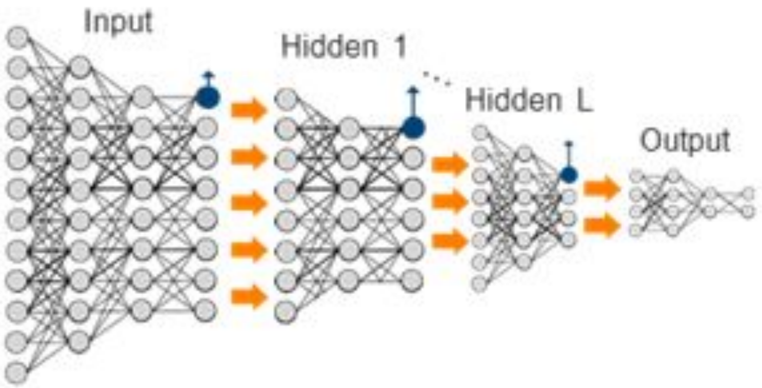

Deep neural networks are providing current state-of-the-art results.

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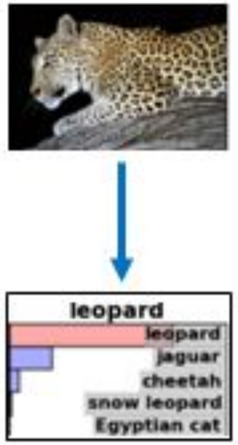
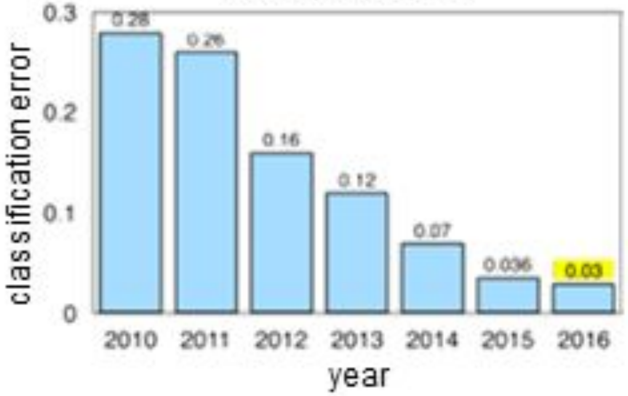


Classifier Predictions

Results: ILSVRC



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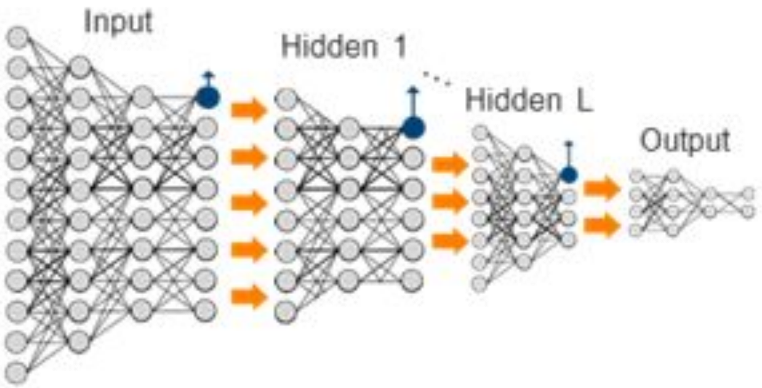

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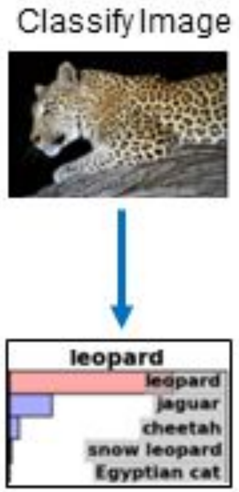

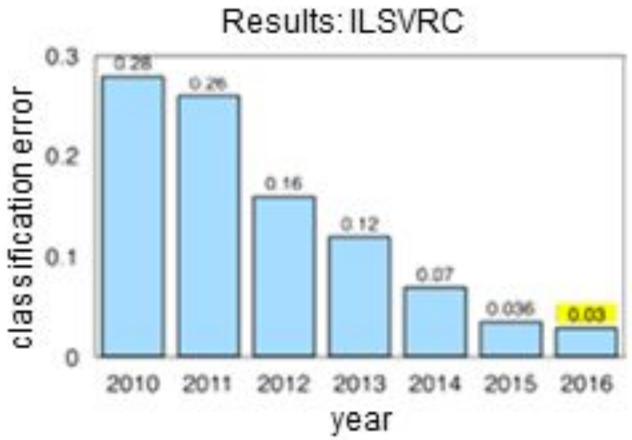

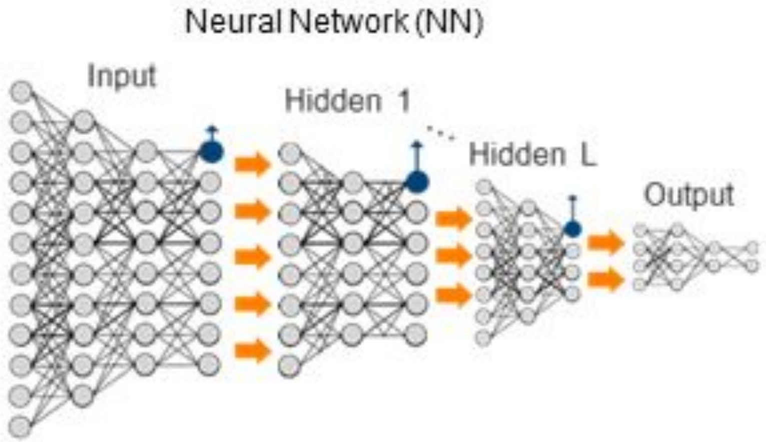

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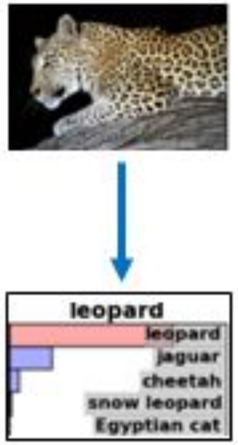

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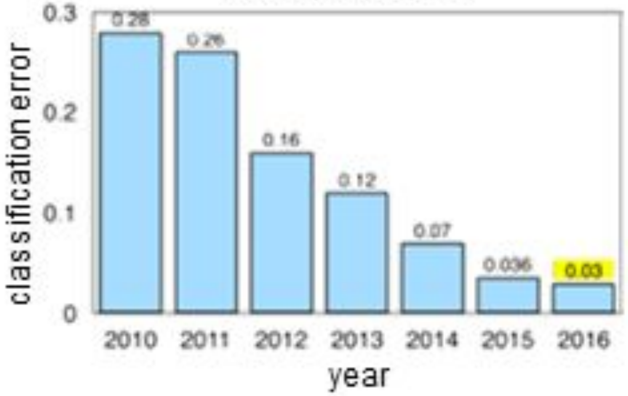

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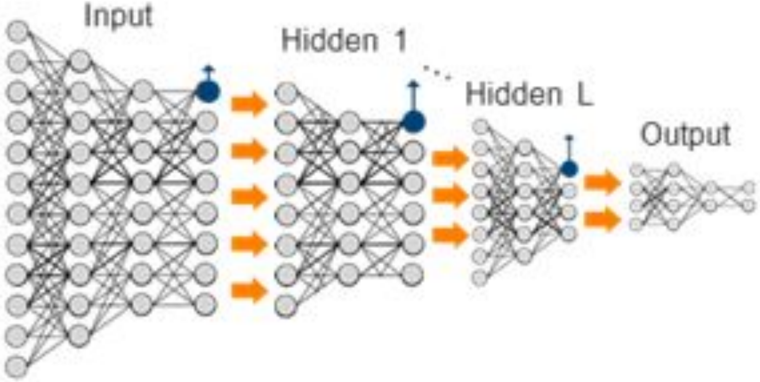

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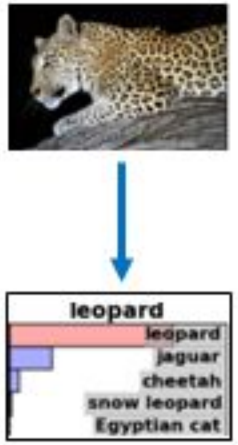

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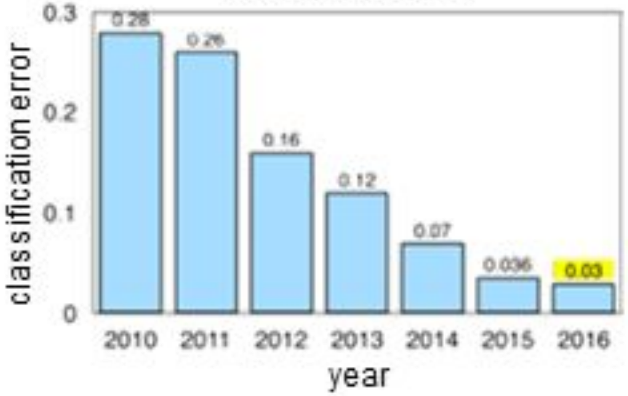

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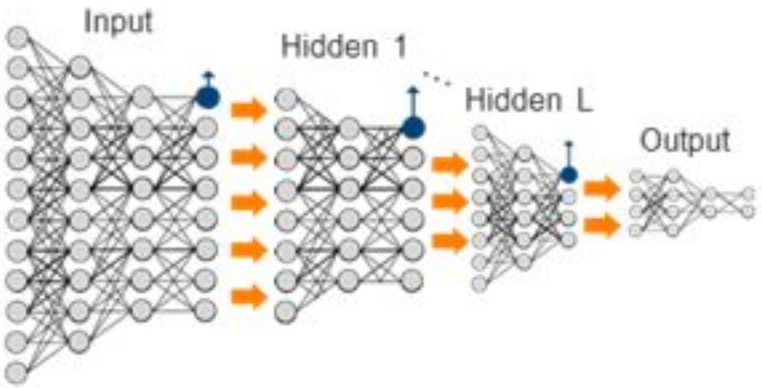

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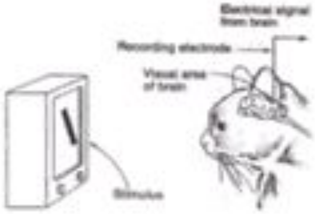
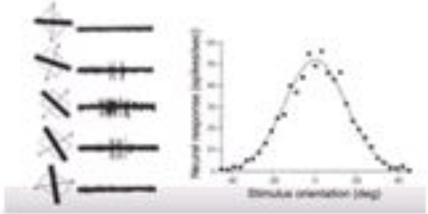


Simple Cell Neuron Response



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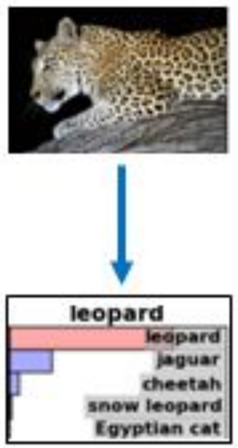

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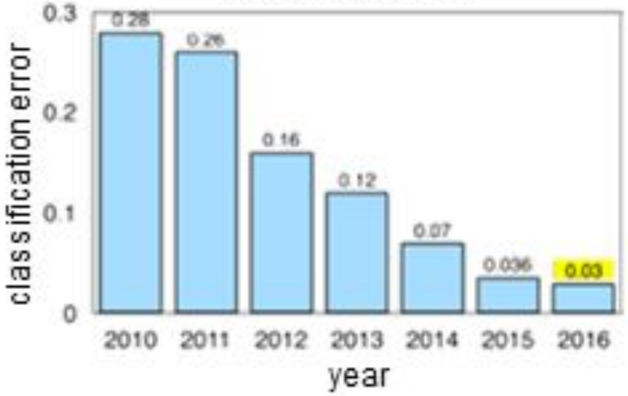

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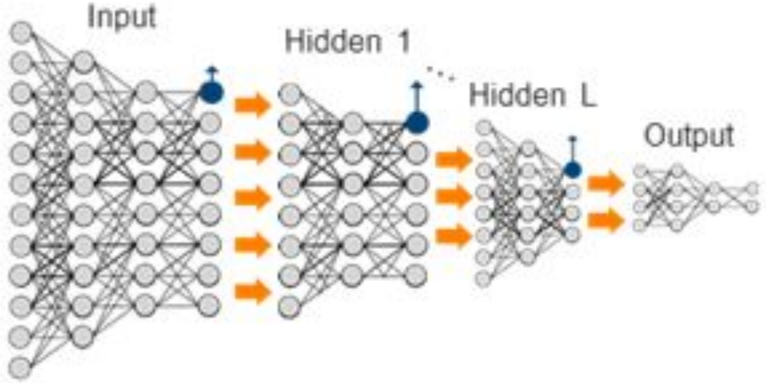

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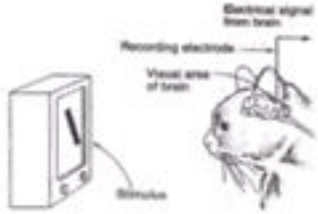

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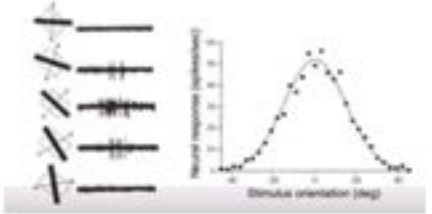
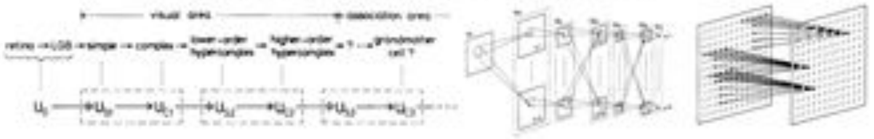
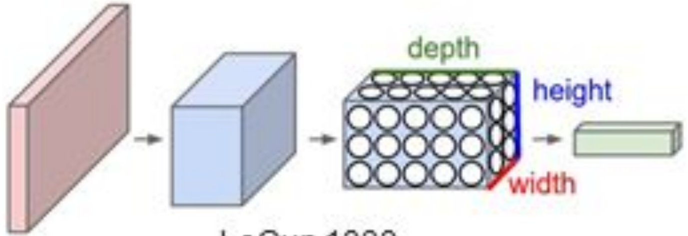


Fukashima 1980 (Neocognitron)



Convolutional Neural Network (CNN)



LeCun 1989

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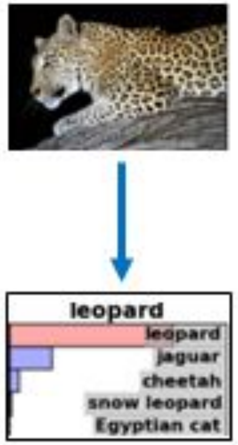

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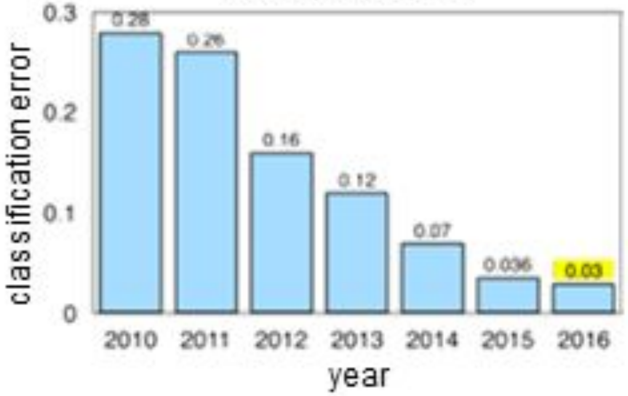

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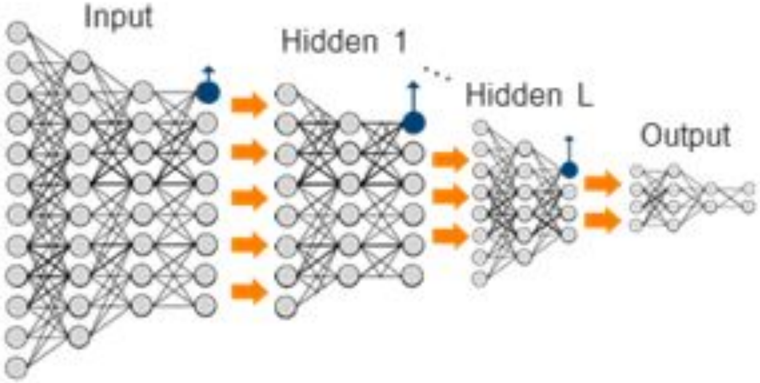

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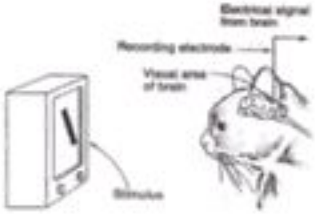

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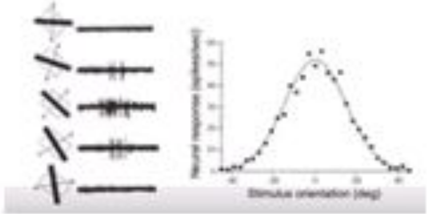

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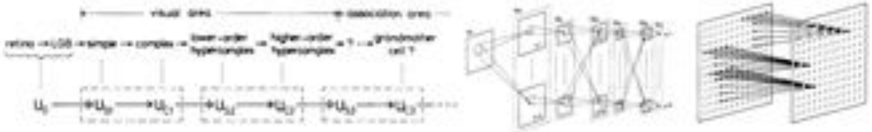

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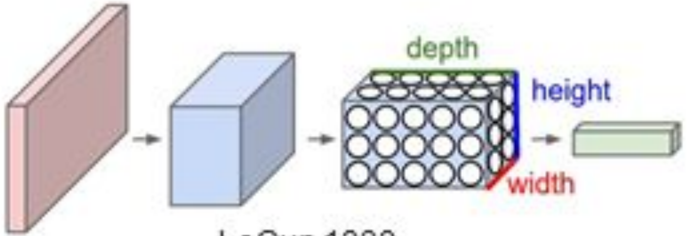

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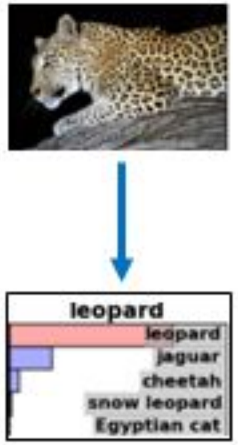

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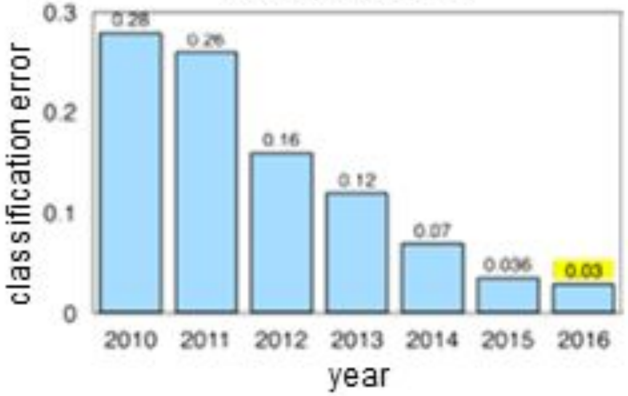

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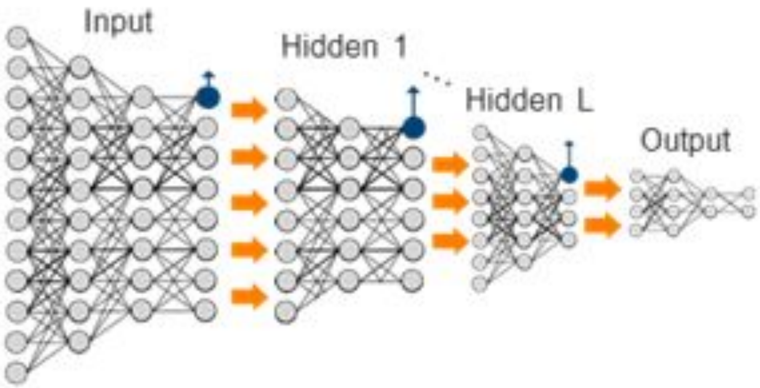

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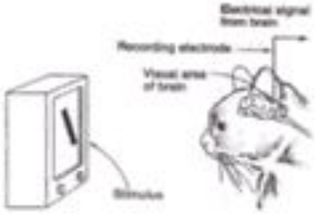

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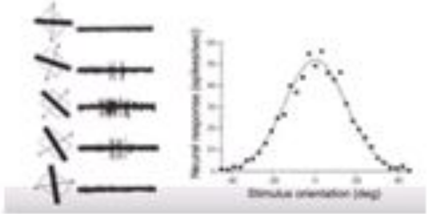

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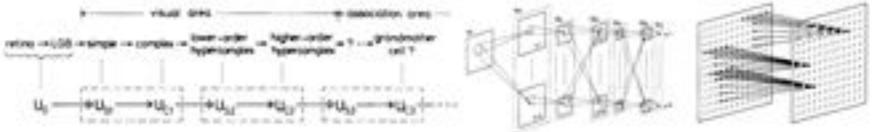

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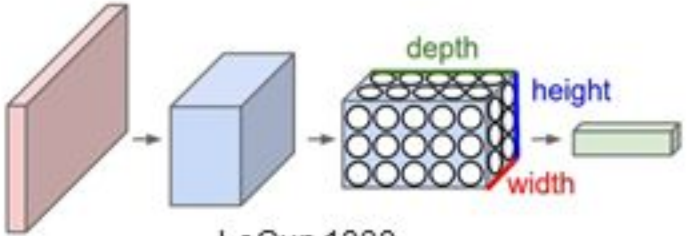

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Local connectivity of "neuron" units used with shared weights.

Deep networks → hierarchical representations "features of features."

Convolutional Neural Networks (CNNs)

Layer Operations

Hubel & Wiesel 1959: Experiments on cat visual cortex suggest some individual cells in V1 act as feature detectors (edges, orientation, intensity).

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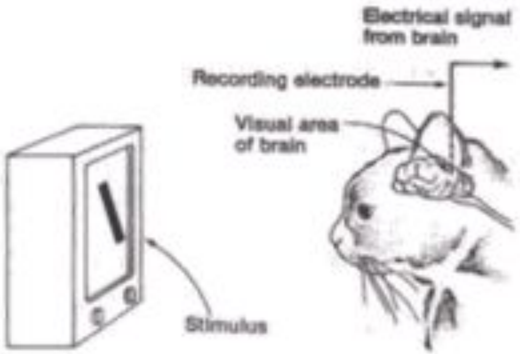
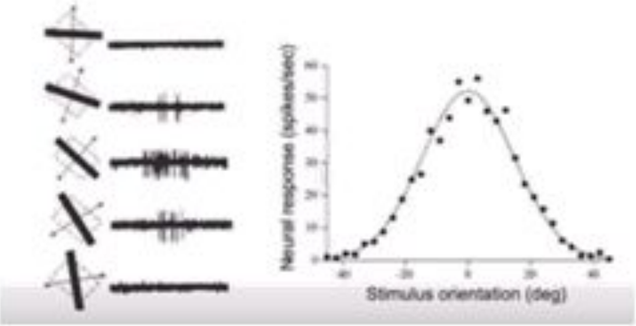


Exposure to visual stimuli



Simple Cell: Neuron Response

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Responses to localized regions in visual field, modeled by Gabor functions (hypothesis).

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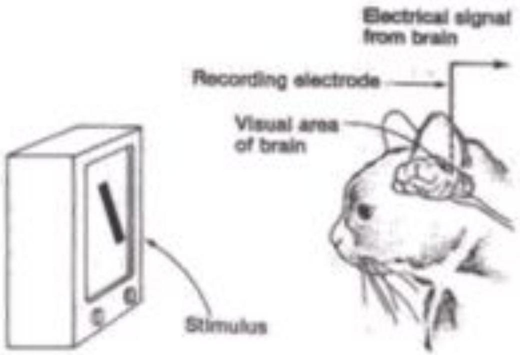

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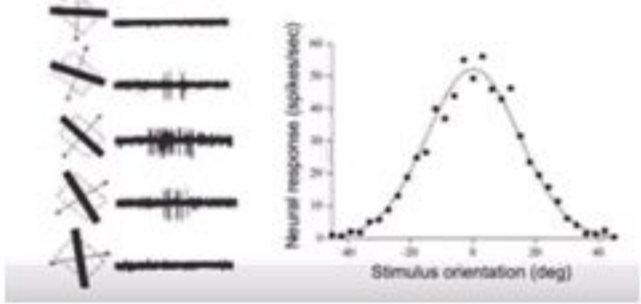

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$$s(I) = \sum_{x \in \mathbb{X}} \sum_{y \in \mathbb{Y}} w(x,y) I(x,y).$$

Gabor function:

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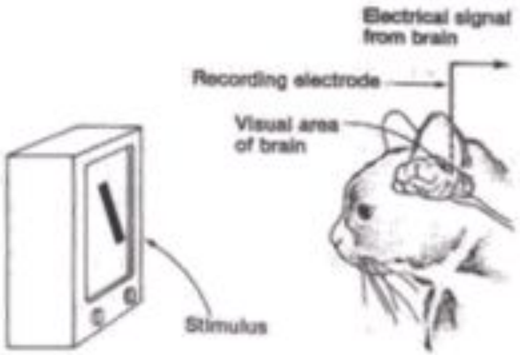

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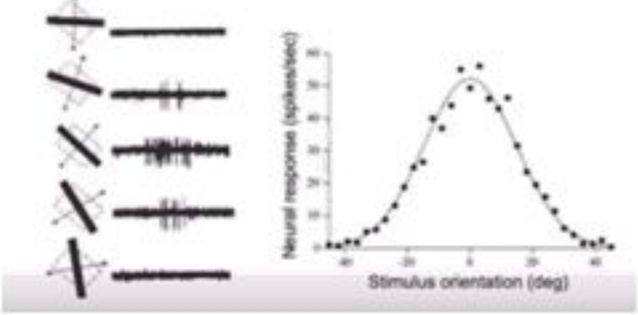

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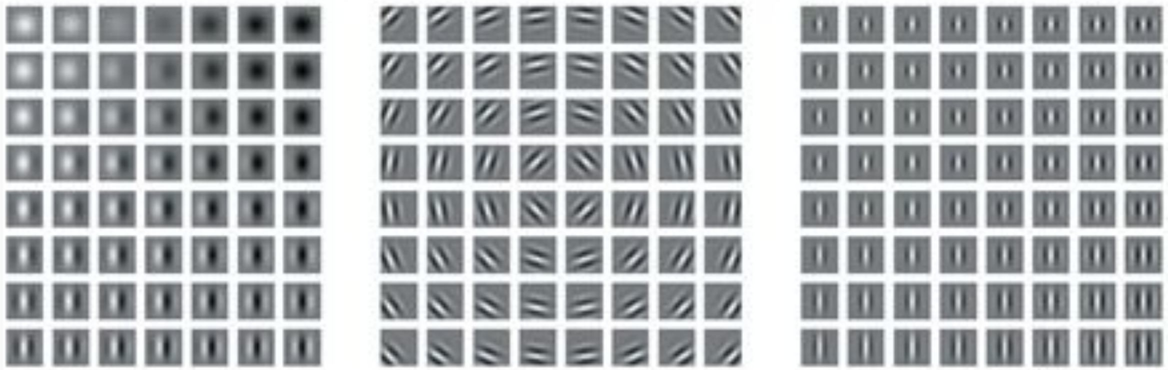

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Aim: obtain representations by learning useful "kernels" to convolve with the input image.

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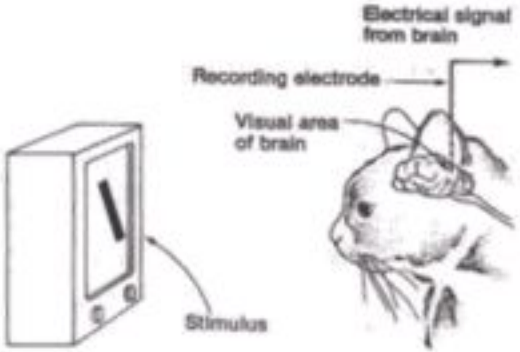

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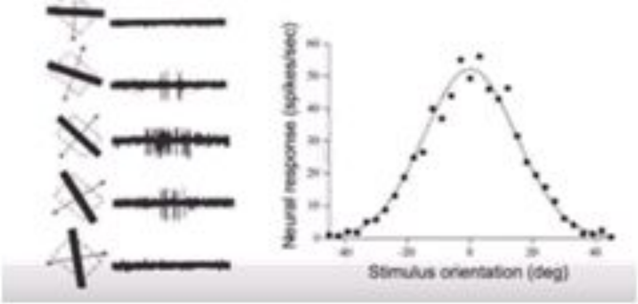

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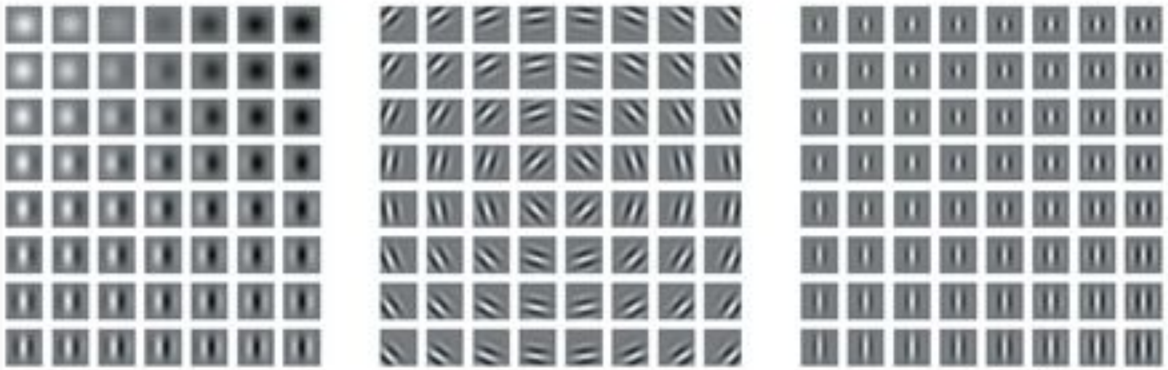

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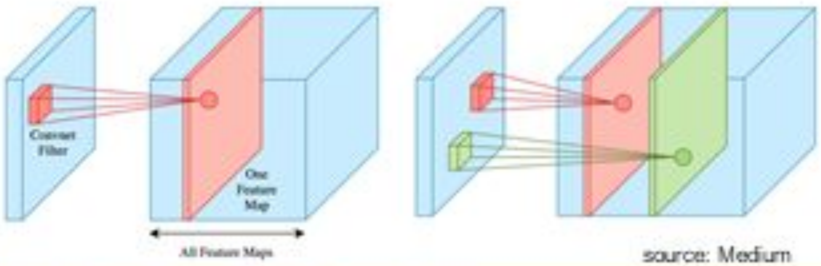

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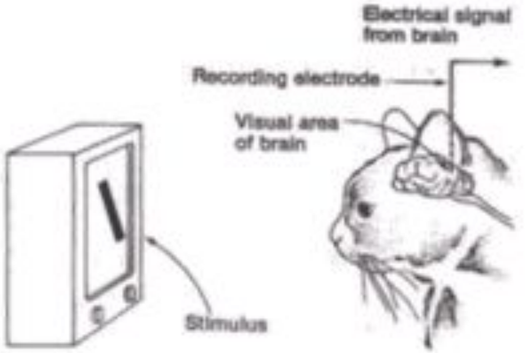

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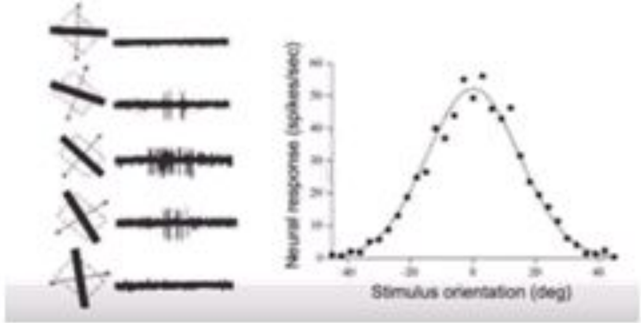

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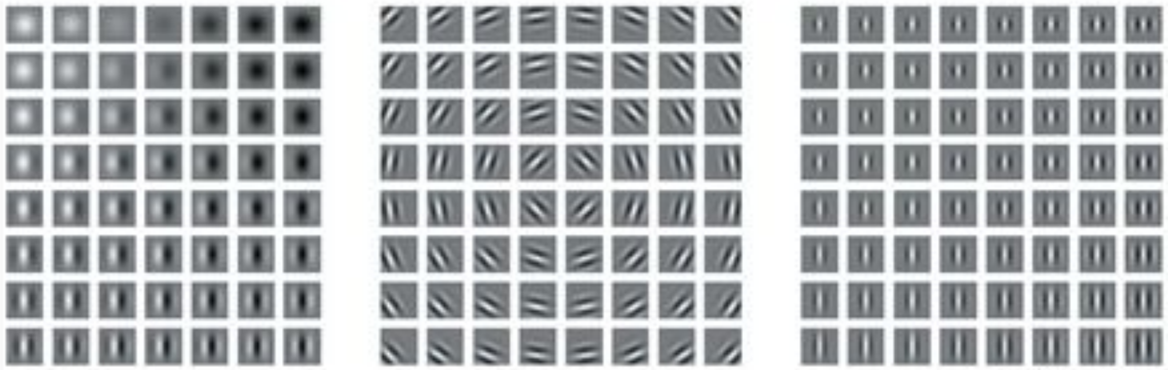

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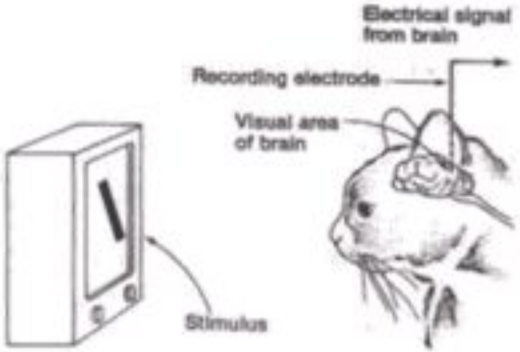

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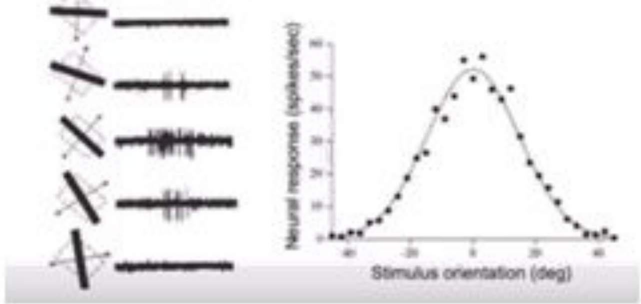

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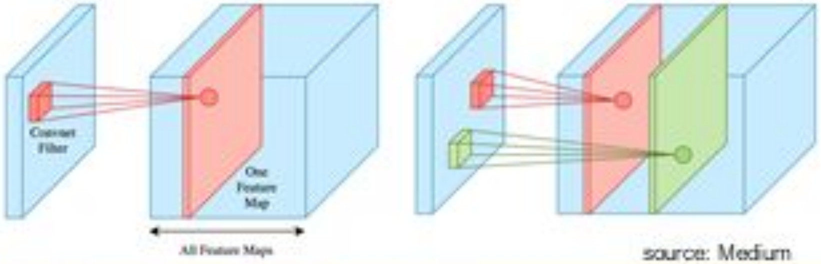
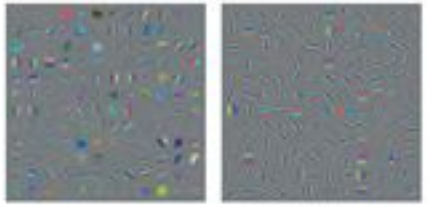
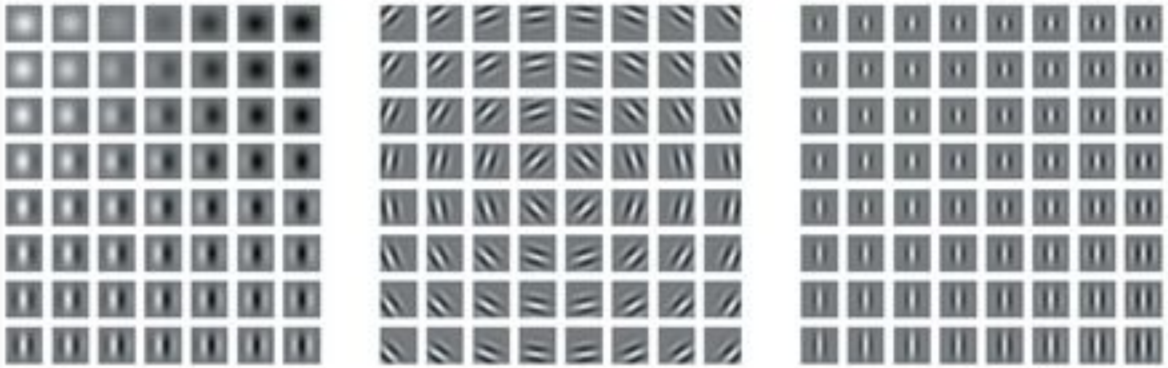


source: Medium

Kernels: trained CNN layers



source: Goodfellow 2017



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Layer Operations

Convolution (mathematical definition for 1D):

$$s(t) = (x * w)(t) = \int x(a)w(t-a)da.$$

where x(t) is the input signal, w(r) is “kernel” weight.

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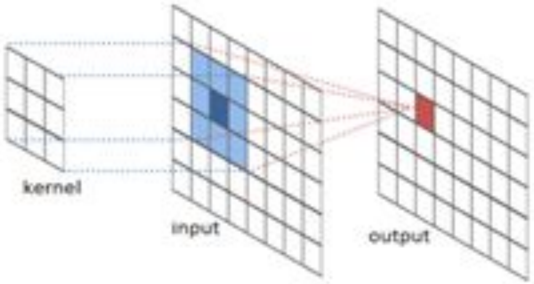

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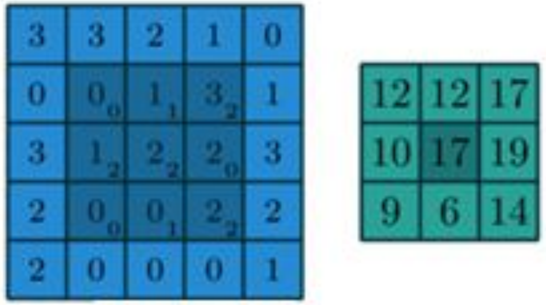

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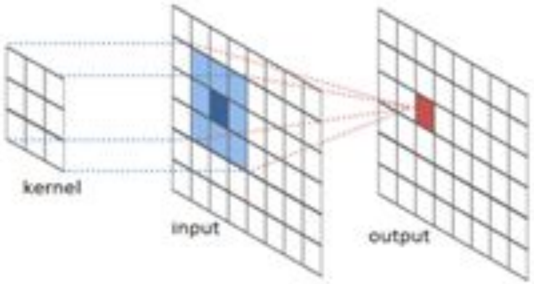

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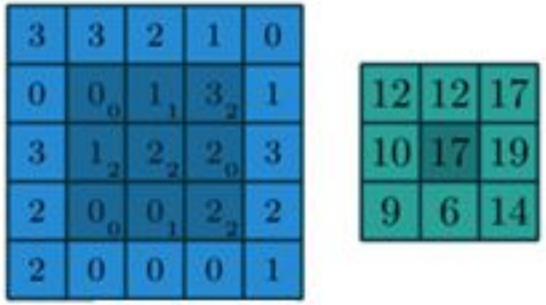

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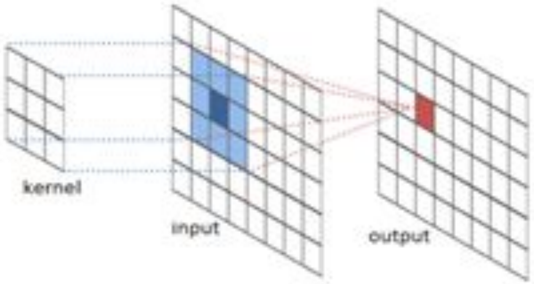

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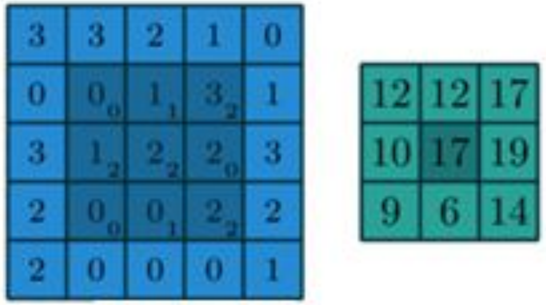

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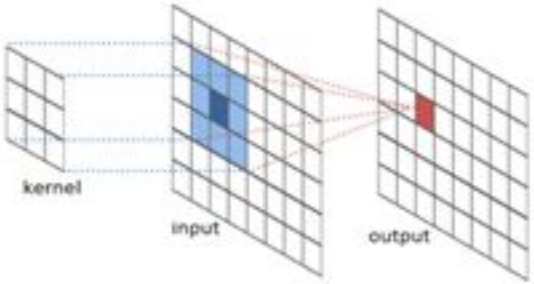

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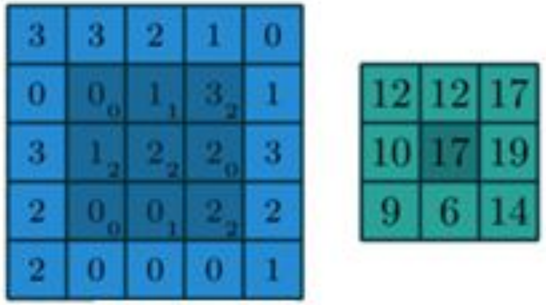

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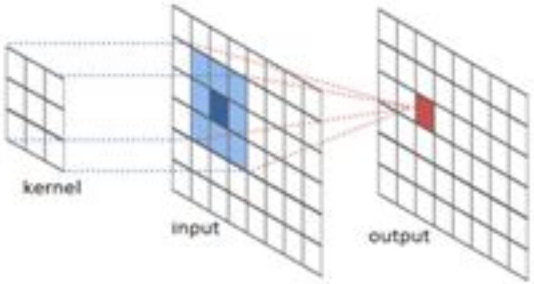

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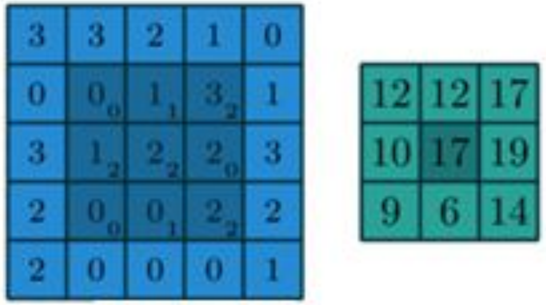

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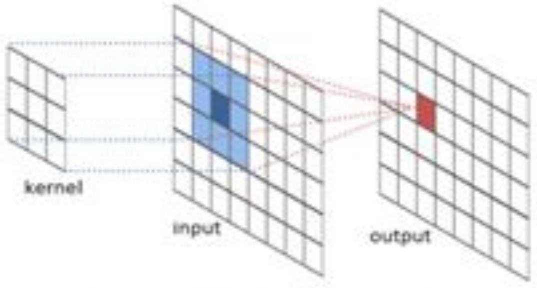

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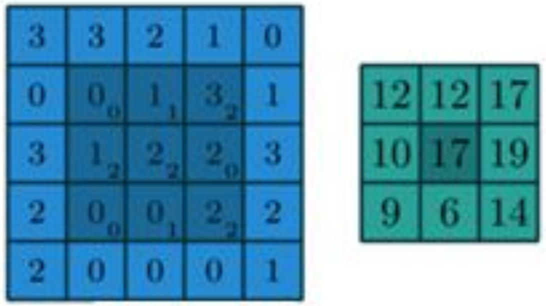

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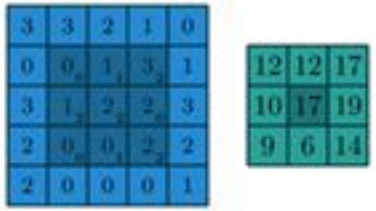
Variant of this used in practice for CNNs (not strictly a convolution).

Layer Operations

Key parameters for convolution operations:

(i) **kernel size:** NxM number of pixels with non-zero weights.

Kernel Size 3x3



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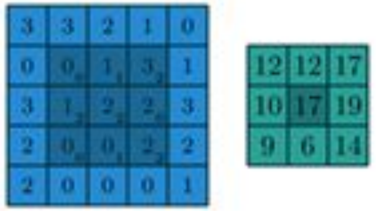

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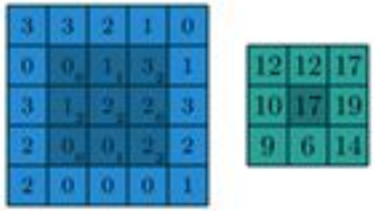

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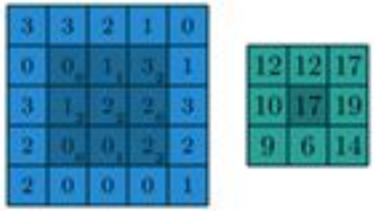
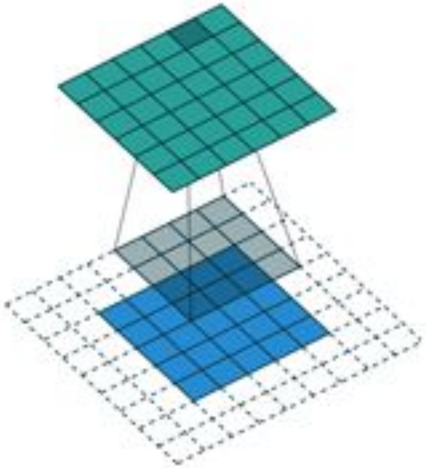
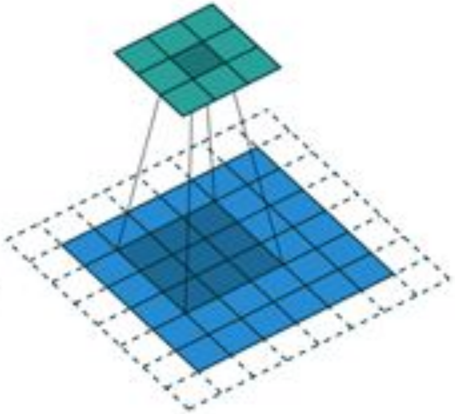


Stride 1x1



Stride 2x2



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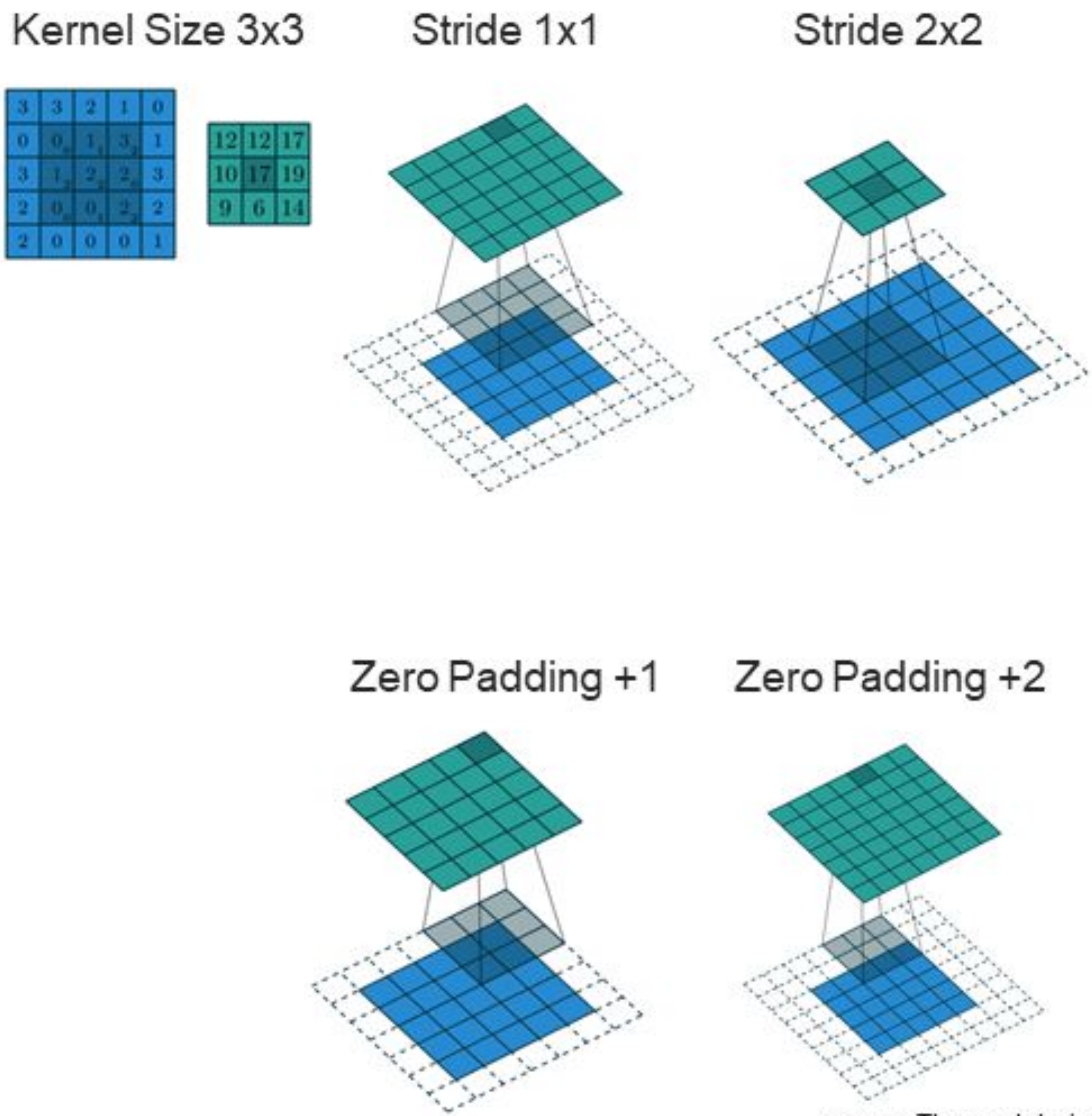

source: Theano tutorial.

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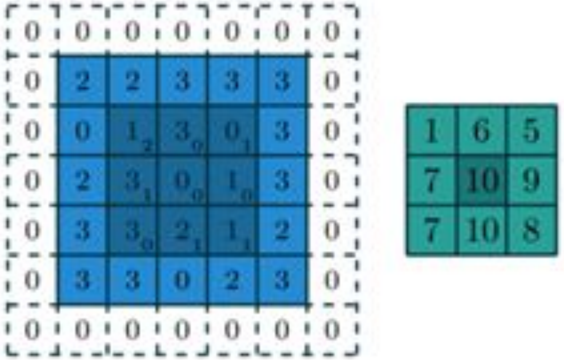
Example: Convolution with 3x3 kernel, 2x2 stride, zero padding +1.



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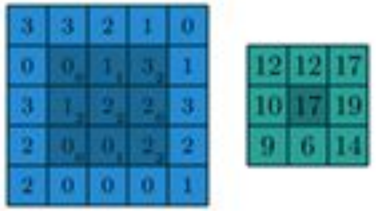

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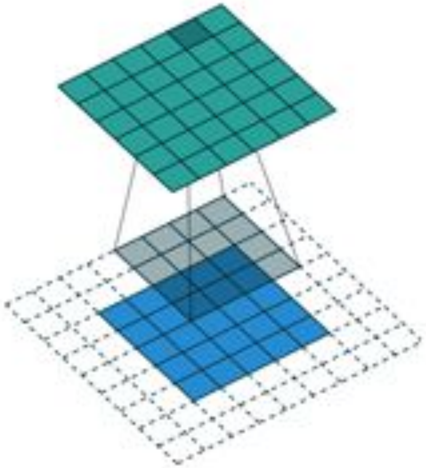

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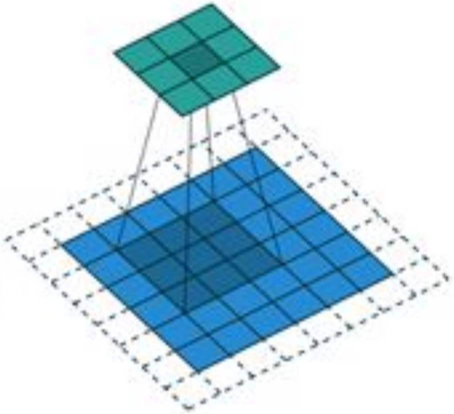
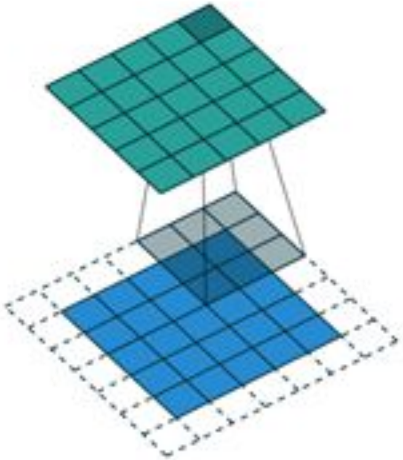
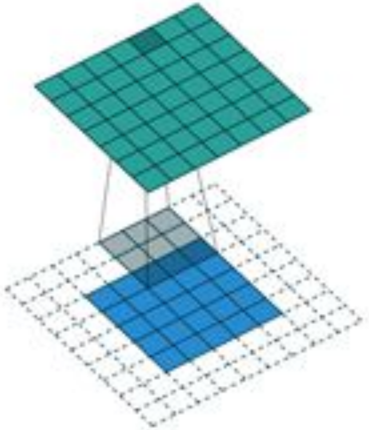


Zero Padding +1



Zero Padding +2



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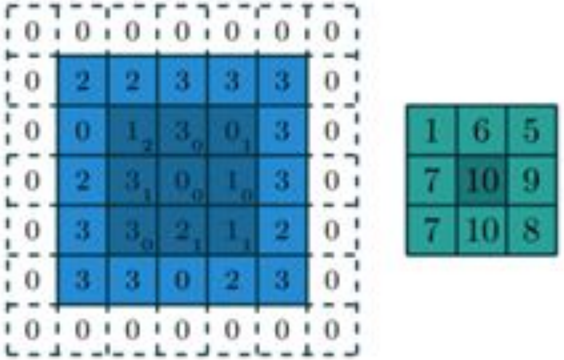
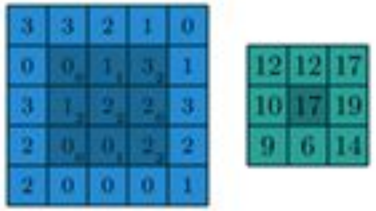


Zero-padding important to avoid shrinkage of layers in deep networks.

Kernel Size 3x3



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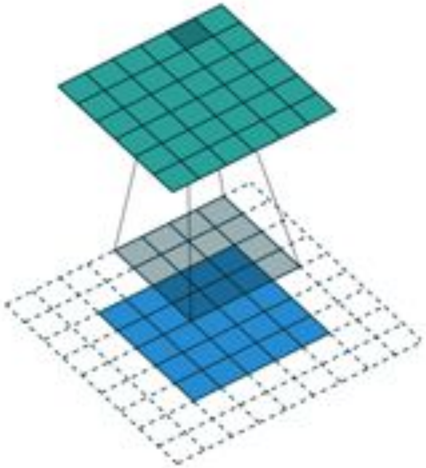

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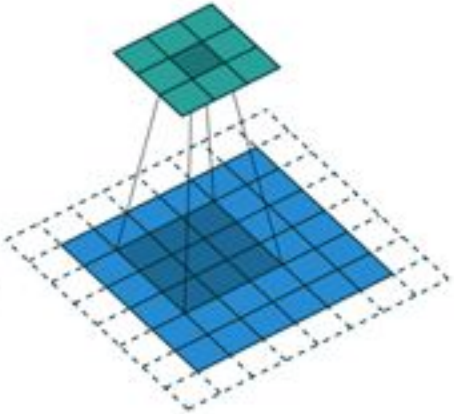

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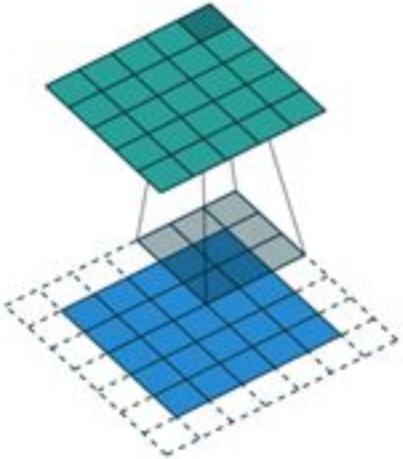
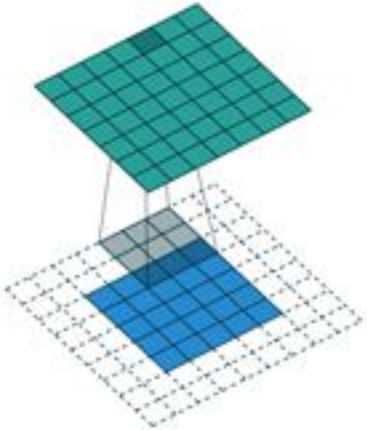


Zero Padding +2



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Detector operation: The convolution values S(i,j) are processed by a non-linearity to obtain $s(i,j) = g\big(S(i,j)\big)$. Typically, ReLU + bias used g(z) = max(z + b,0).

ReLU + bias

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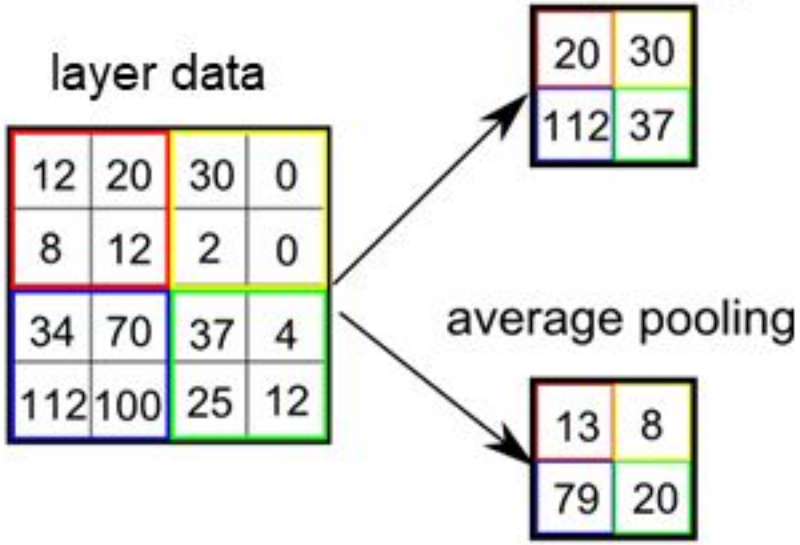
(ii) averaging

(iii) max-pooling



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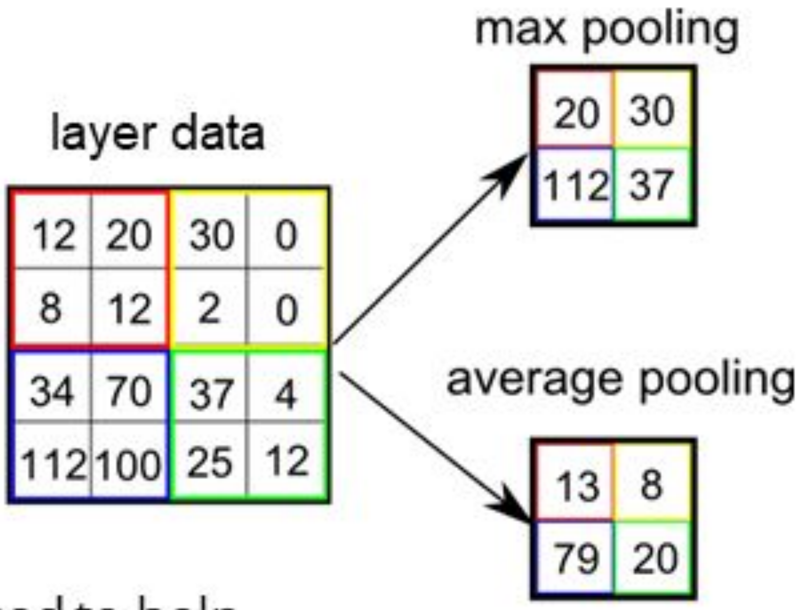

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Cross-channel pooling can be used to help learn invariances other than translation in-sensitivity.

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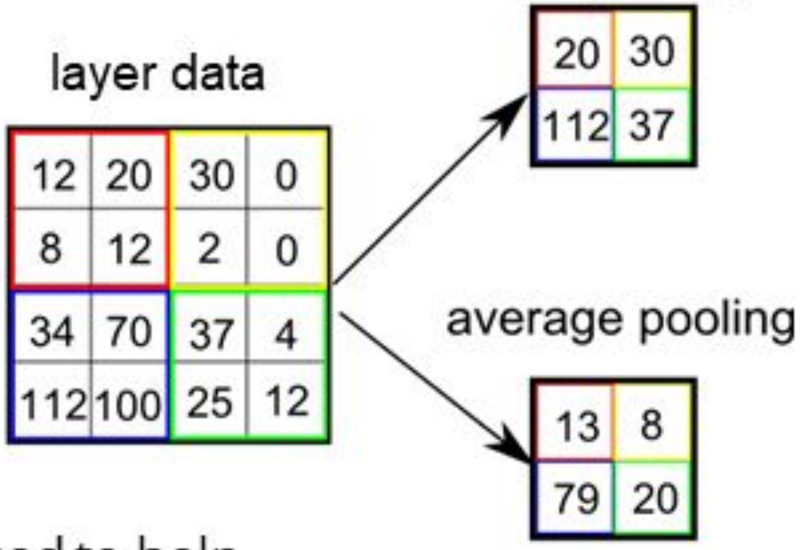

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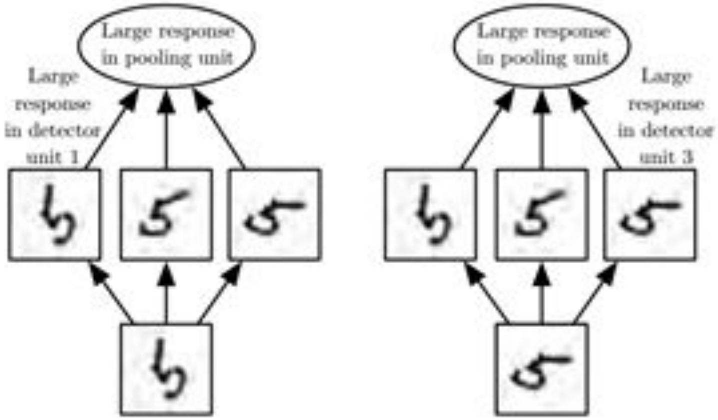
Cross-channel pooling can be used to help learn invariances other than translation in-sensitivity.

max pooling across channels



source: Goodfellow 2017

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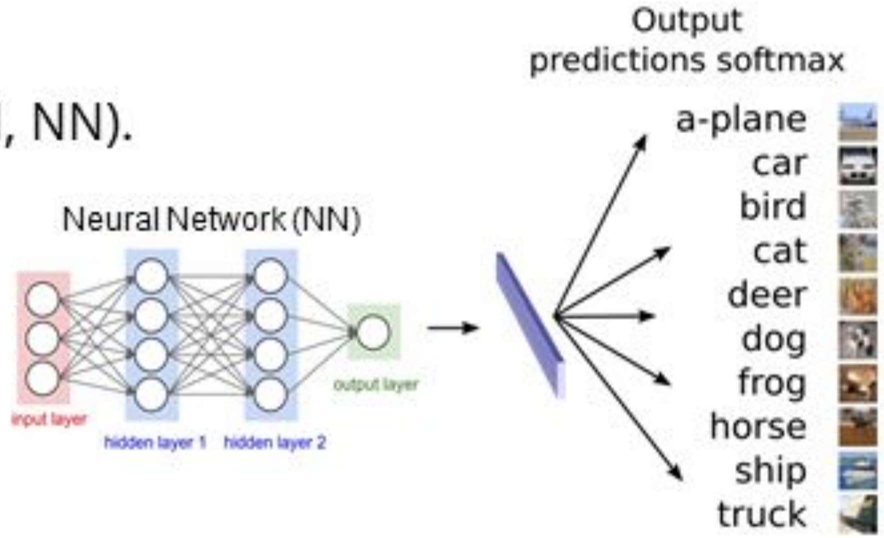
Final layer: can be any classifier for predictions (logistic, k-NN, SVM, NN).

Typically, fully connected **Feed-Forward Neural Network (FNN)**.



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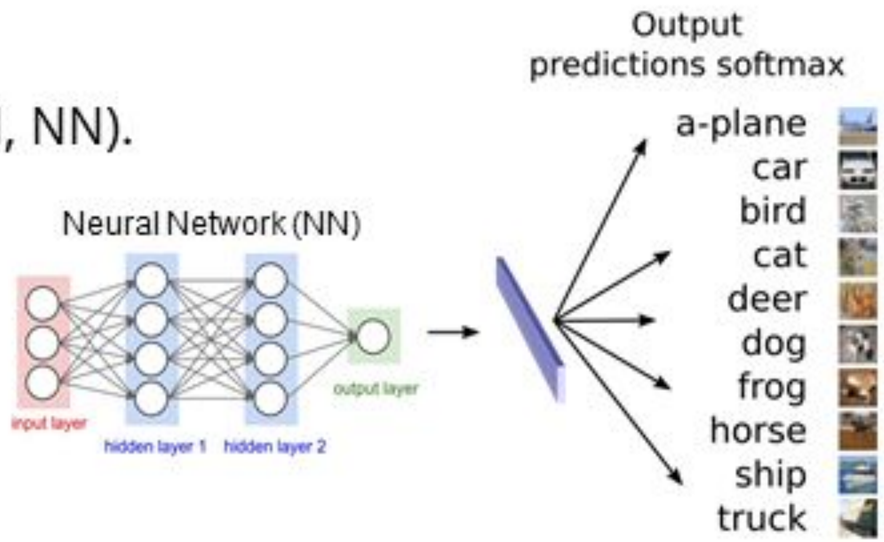

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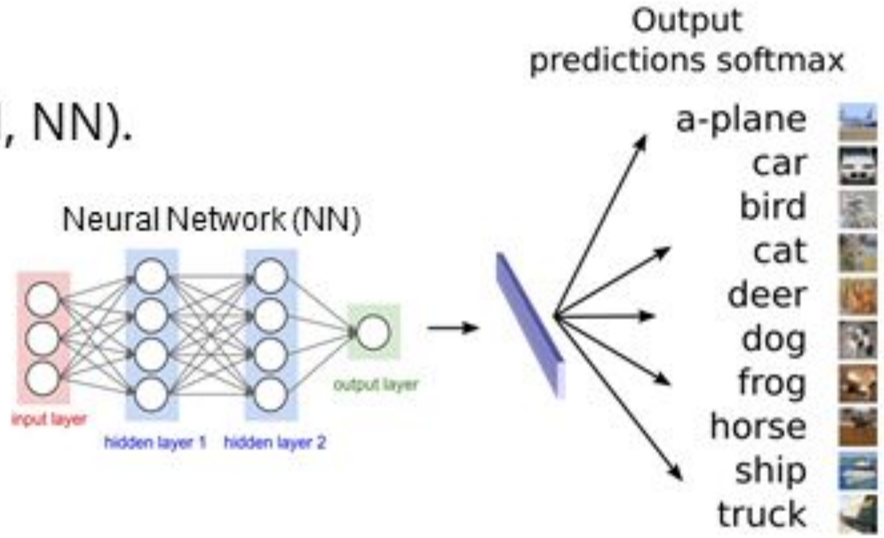

$1 - \text{hot vector}$

$$y = \left[\begin{array}{c}0\\1\\0\\0\\0\end{array}\right]\begin{array}{l}\\ \leftarrow k^{th}\text{ class}\\ \\ \\ \\ \end{array}$$

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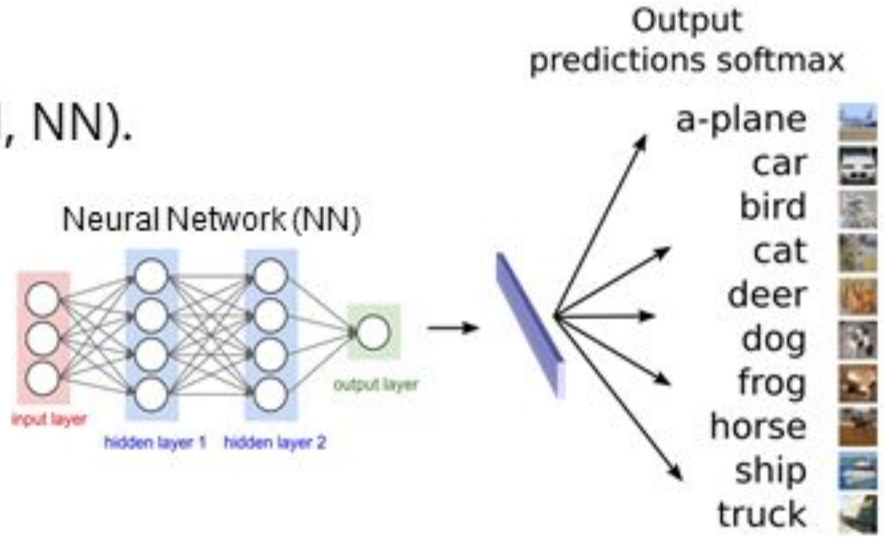

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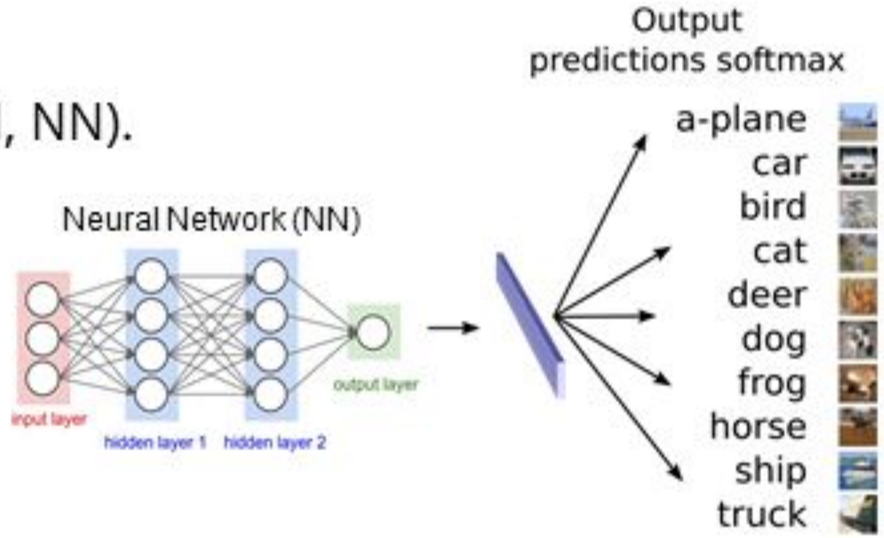

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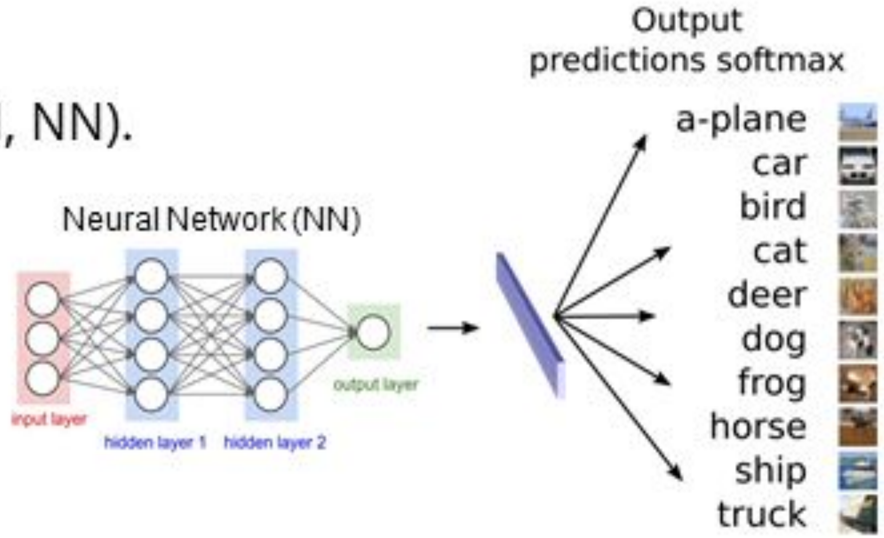
Layer Operations



Final layer: can be any classifier for predictions (logistic, k-NN, SVM, NN).

Typically, fully connected **Feed-Forward Neural Network (FNN)**.

Predictions: $\tilde{\boldsymbol{y}}$ are typically probability of class assignments $[\boldsymbol{y}]_i = y_i =$ probability image is in class i.

The output **q** ← **FFN** is turned into probability by softmax $\tilde{y}_i = \frac{\exp(q_i)}{\sum_{i=1}^{10}\exp(q_i)} \to p(\tilde{y}|x)$.

Training: back-propagation from loss $\mathrm{L}(S)$ through the FNN + conv layers.

Cross-entropy loss: $\mathrm{L}(S) = \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{10} - y_j^{(i)}\log(\tilde{y}_j^{(i)})$, where y_j is the class 1-hot vector.

$1 - \text{hot vector}$

$$y = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \leftarrow k^{th} \text{ class}$$

Layer Operations

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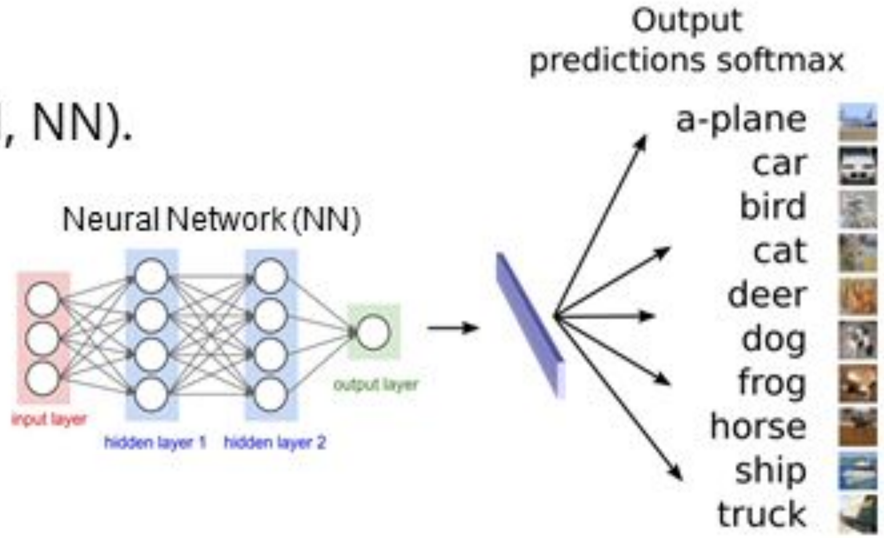

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Motivation: $\tilde{L}(\mathcal{S}) = KL(\tilde{p}(x,y)|\,\tilde{p}(x,\tilde{y})) = KL(p(y|x)\tilde{p}(x)|\,p(\tilde{y}|x)\tilde{p}(x)) = \mathrm{L}(\mathcal{S}) + \mathrm{f}(\mathrm{Y})$,
$\tilde{p}(x,y)$ is the empirical data distribution.

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$$\mathrm{y} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \begin{array}{l} \\ \leftarrow k^{th} \text{ class} \\ \\ \\ \\ \end{array}$$

Layer Operations

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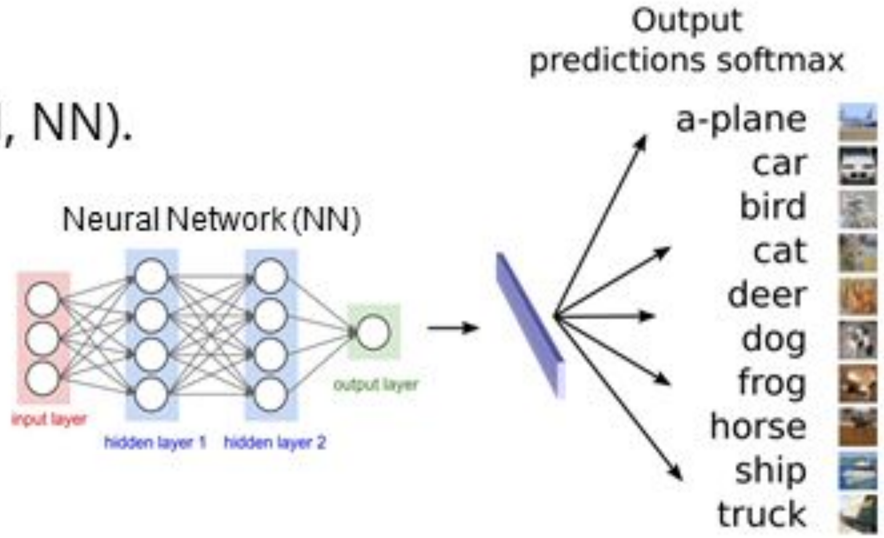

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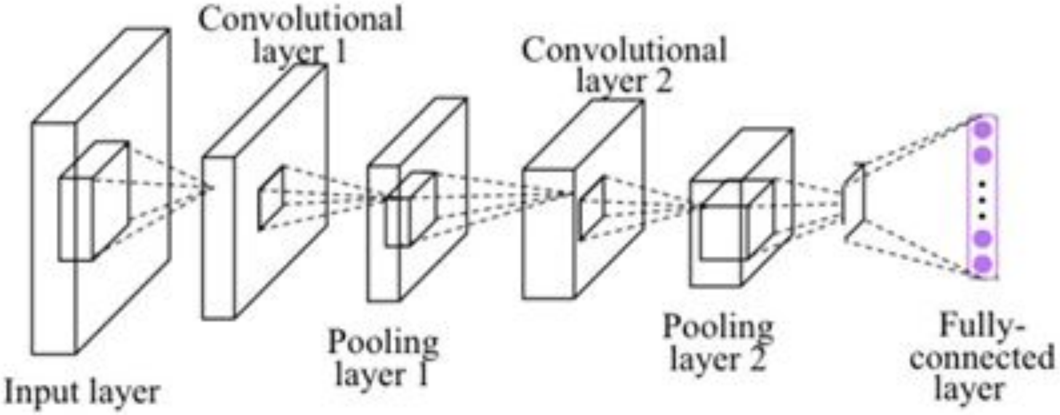
$$y = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \begin{matrix} \\ \leftarrow k^{th} \text{ class} \\ \\ \\ \\ \end{matrix}$$

Optimization only needs $\mathrm{L}(S)$ part, instead of full $\tilde{L}(S)$, to adjust the weights yielding $\tilde{y}$.

Convolutional Neural Network: Summary

Typical Architecture



Input image is split into "channels" -> RGB.

Convolution layers extract features from the image into feature channels.

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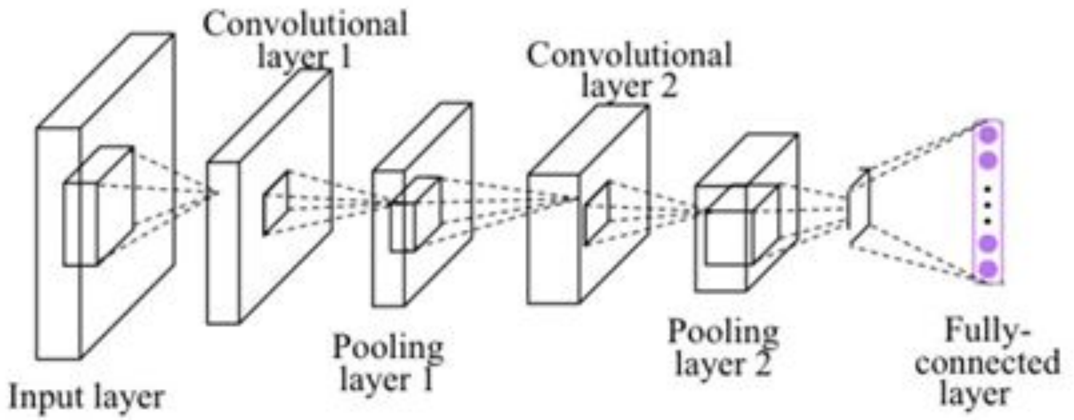

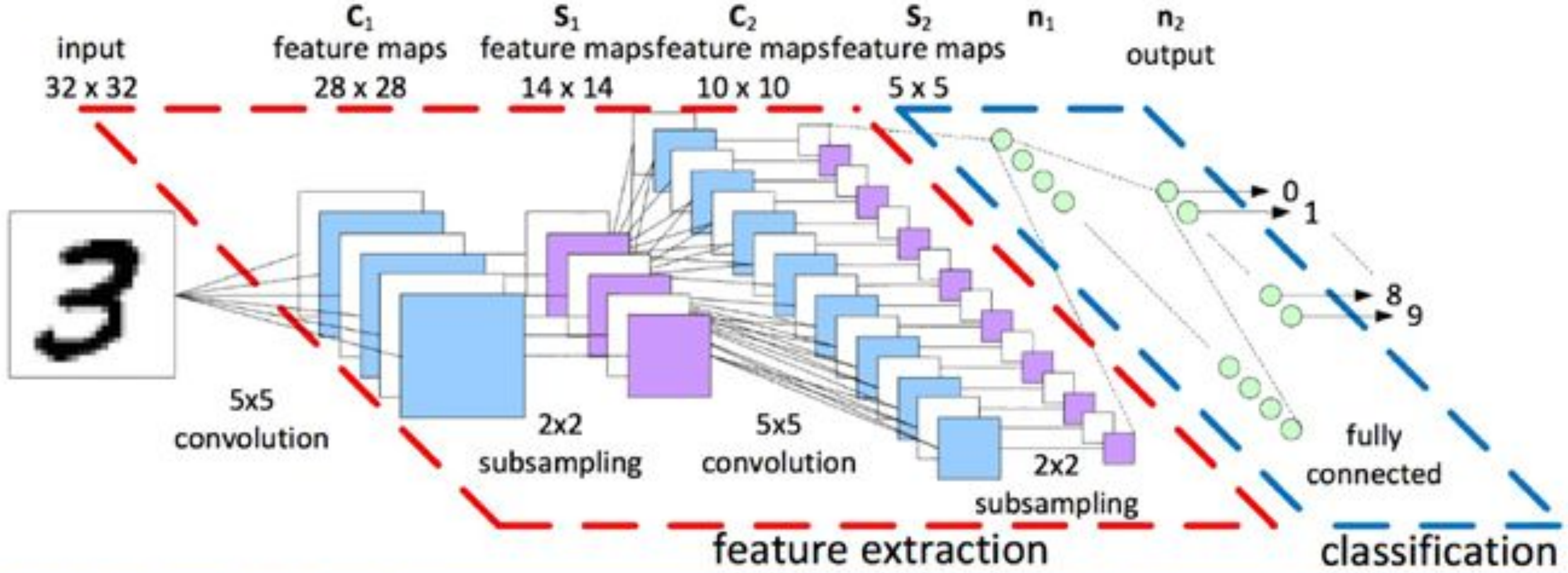

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Source: Tutorial by Chongruo Wu

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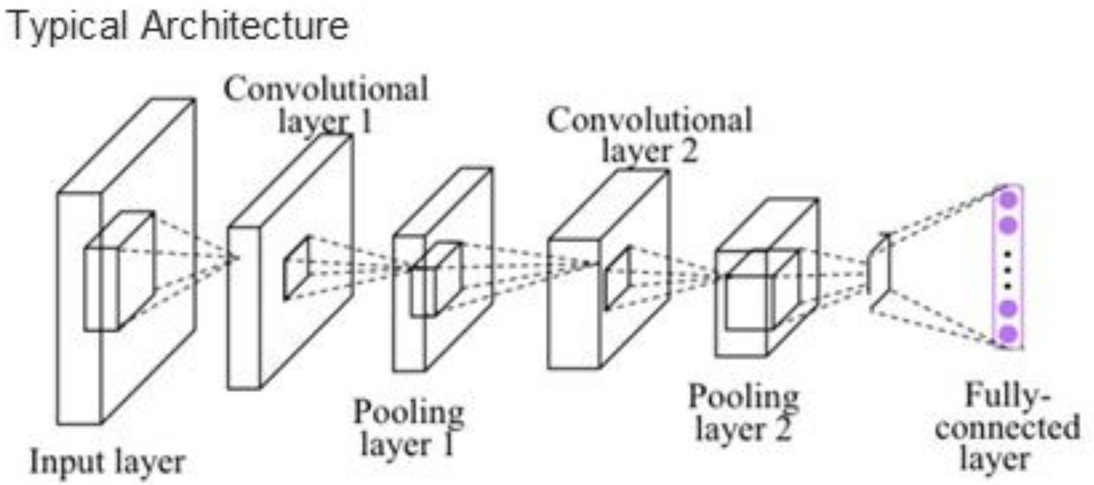

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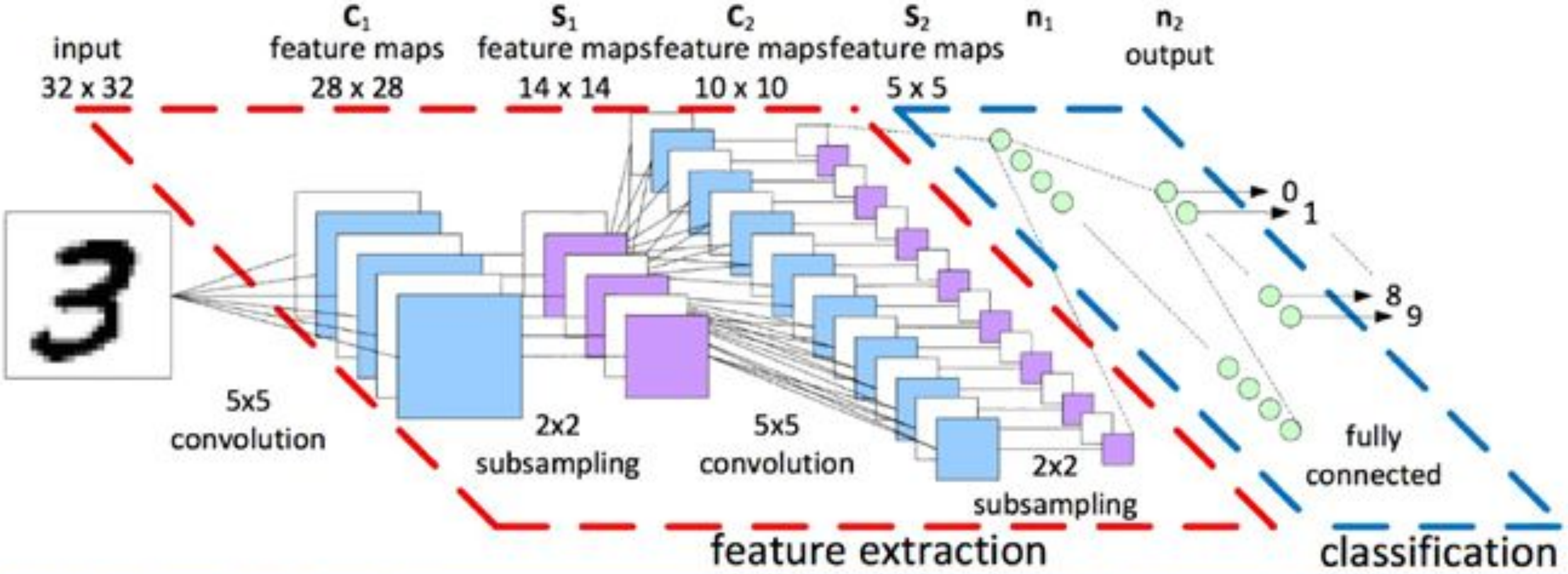
Detector operation typically ReLU + bias.

Pooling reduces entries in channel (enhances invariance to image transforms)



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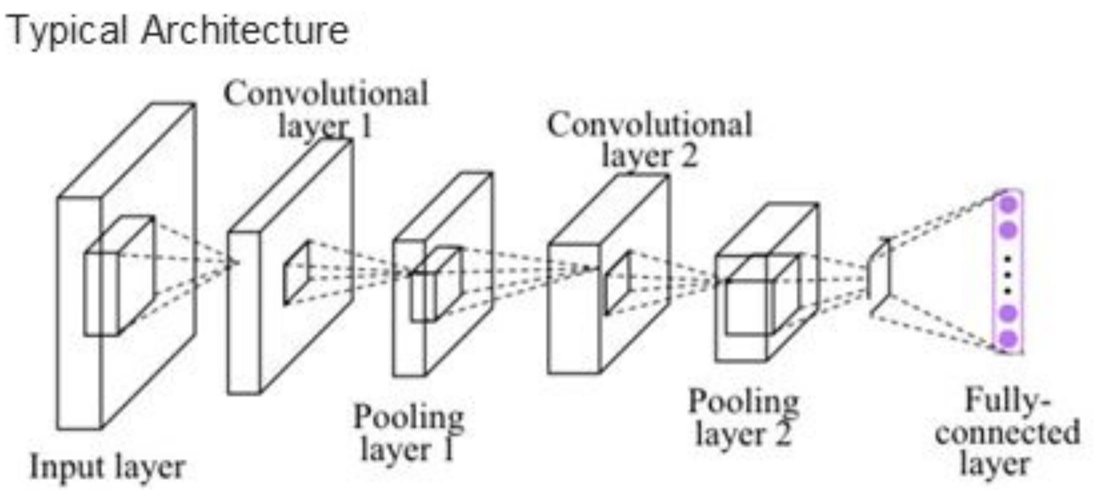

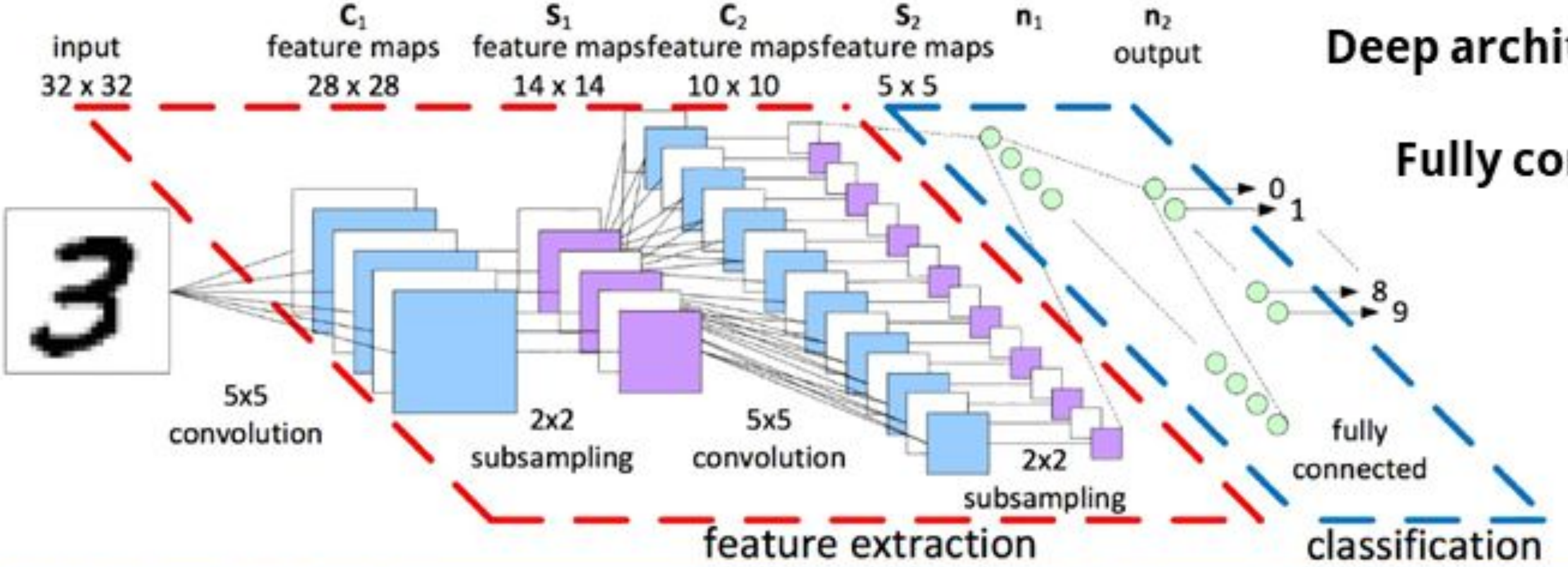

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Deep architectures stack to repeat.

Fully connected layer → predicts class.

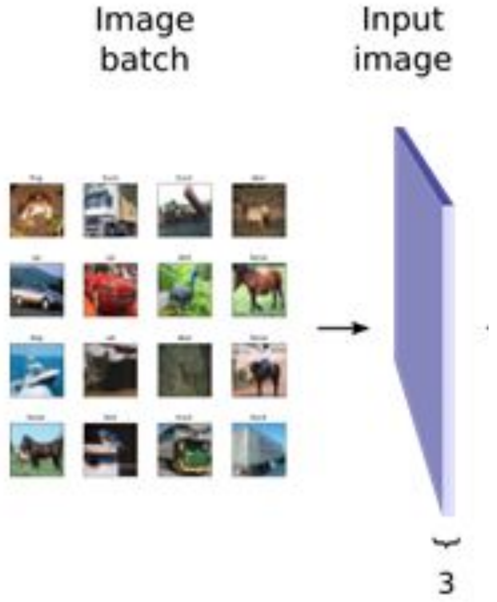
Source: Tutorial by Chongruo Wu

CIFAR10: Image Classification

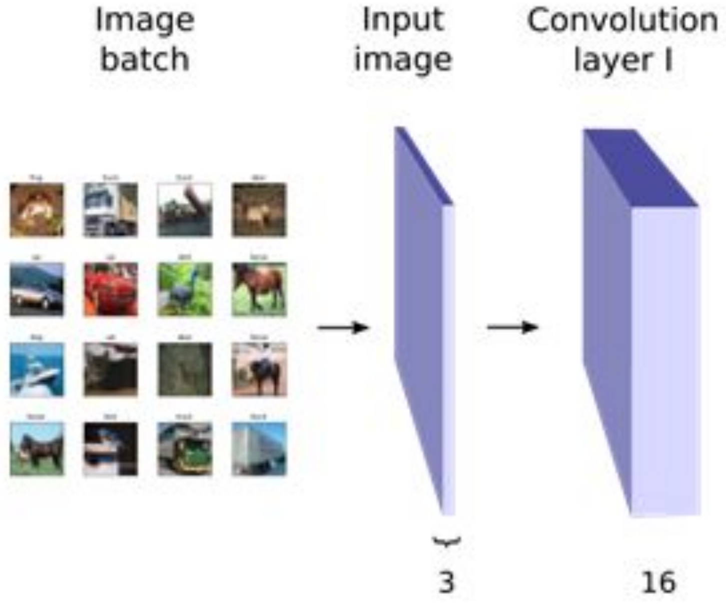
CIFAR-10: Convolutional Neural Network

Image
batch

CIFAR-10: Convolutional Neural Network



CIFAR-10: Convolutional Neural Network



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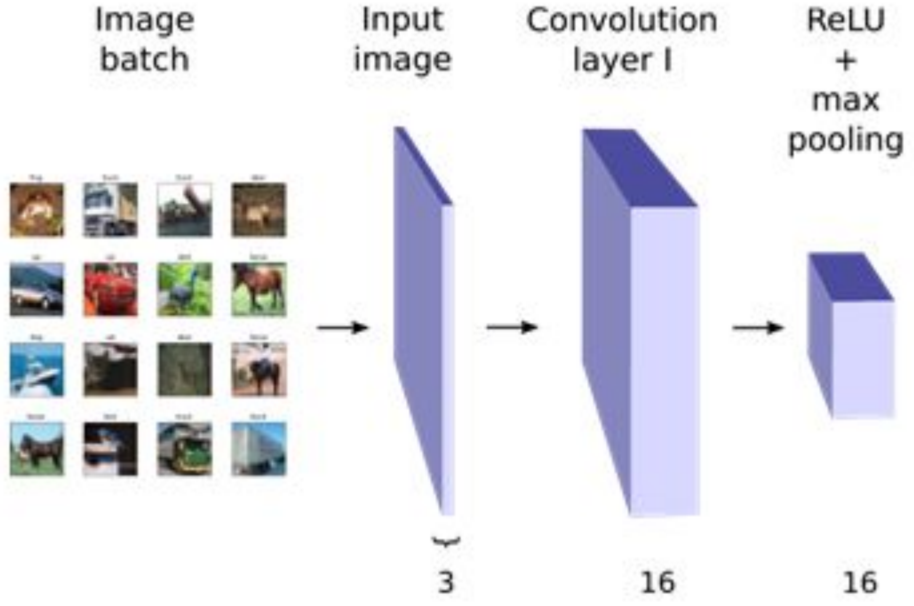

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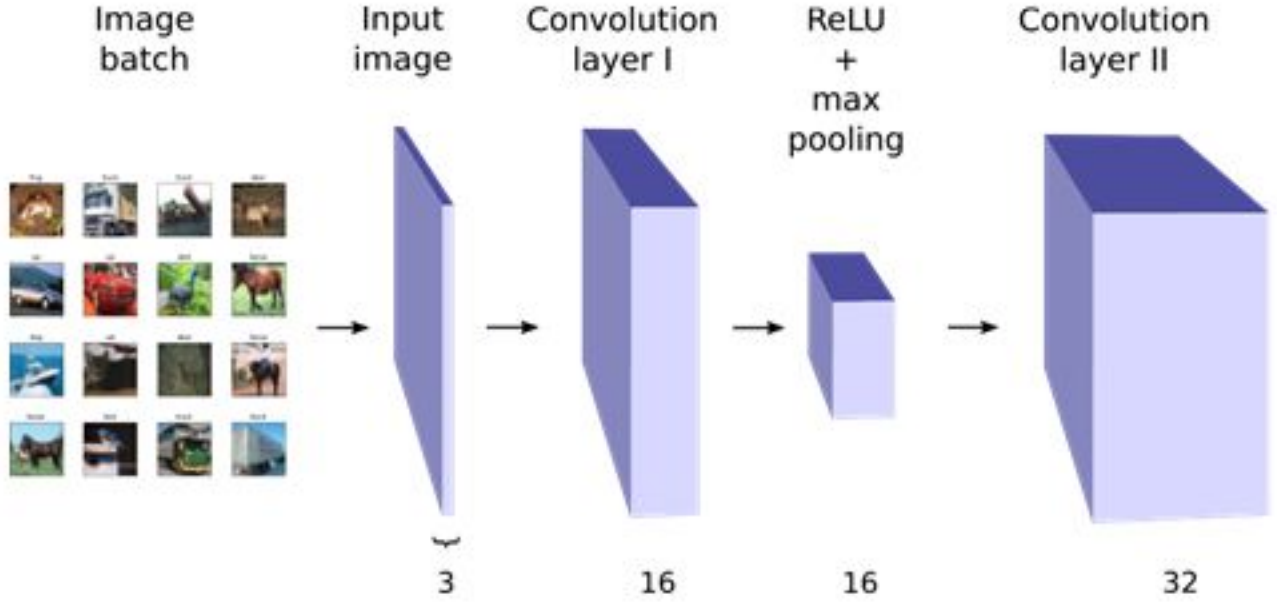

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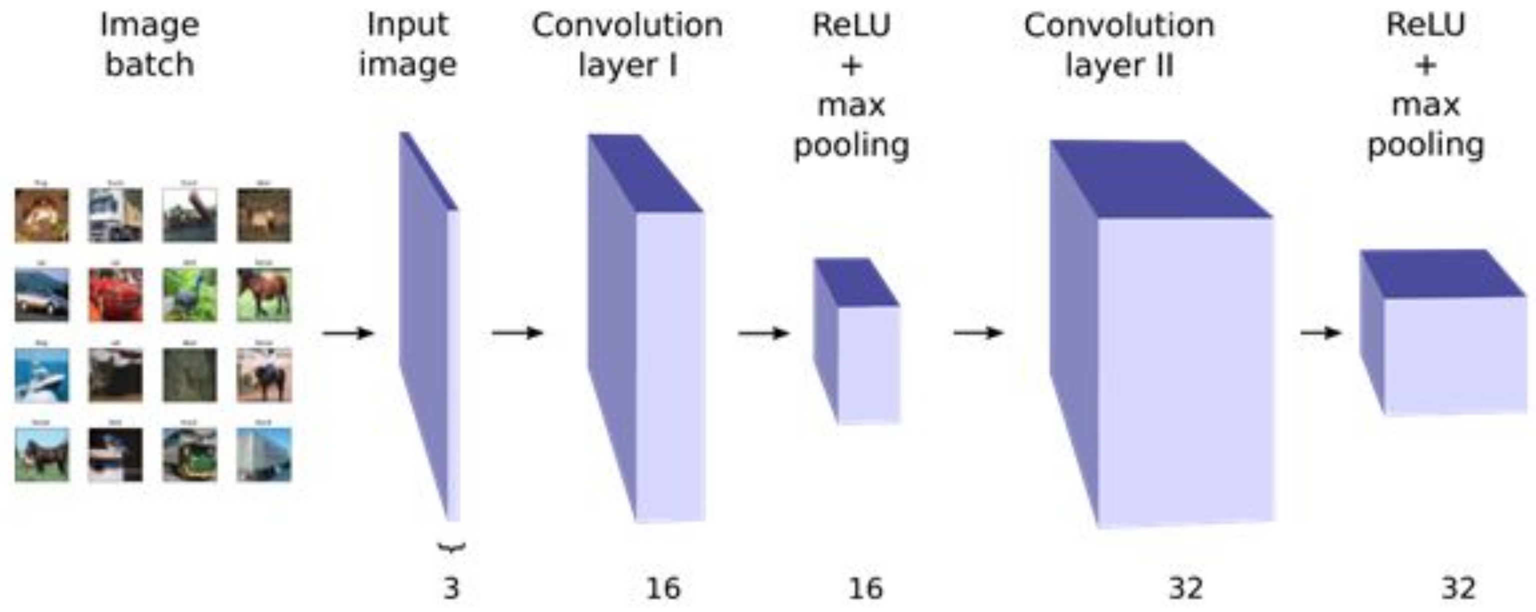

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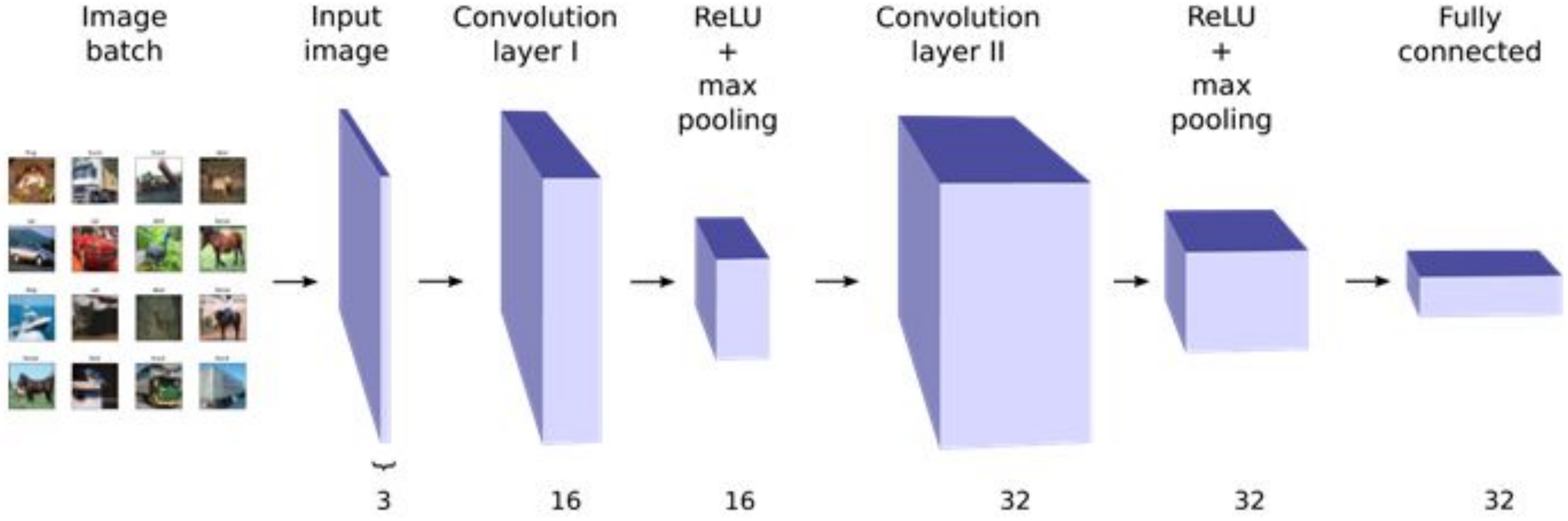

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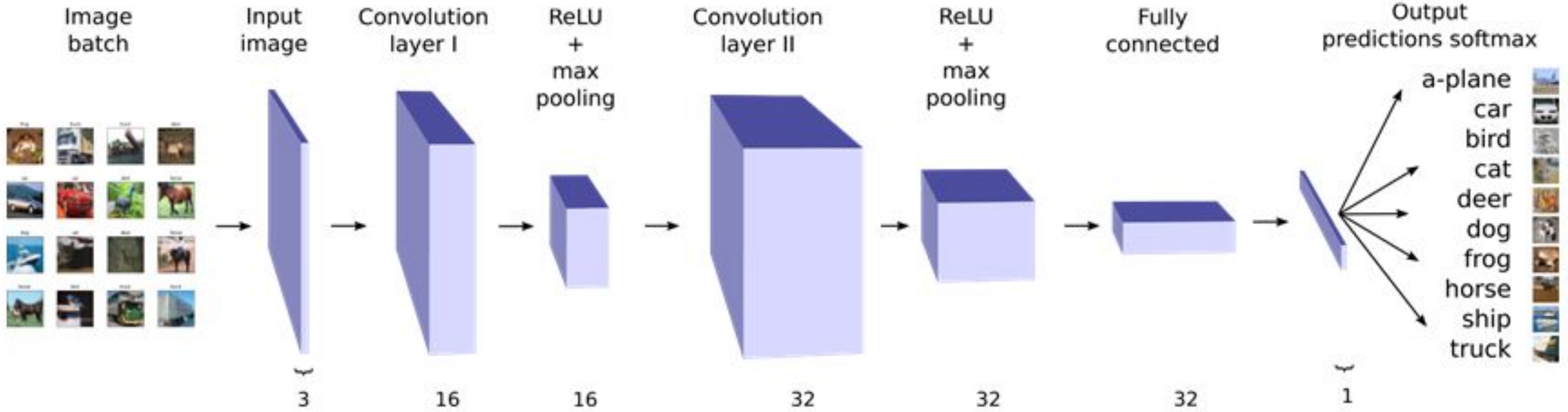

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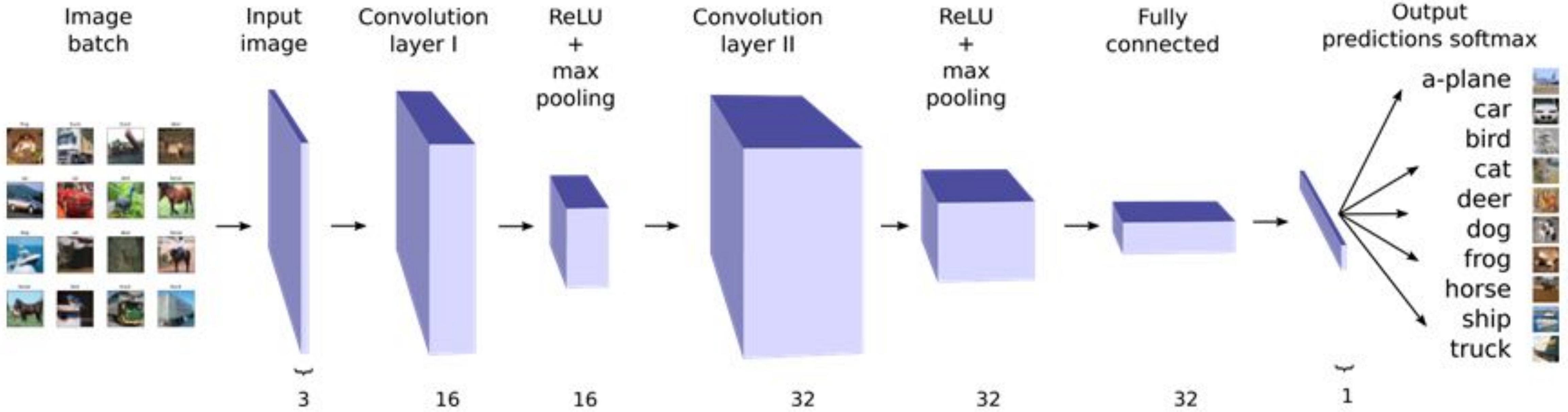
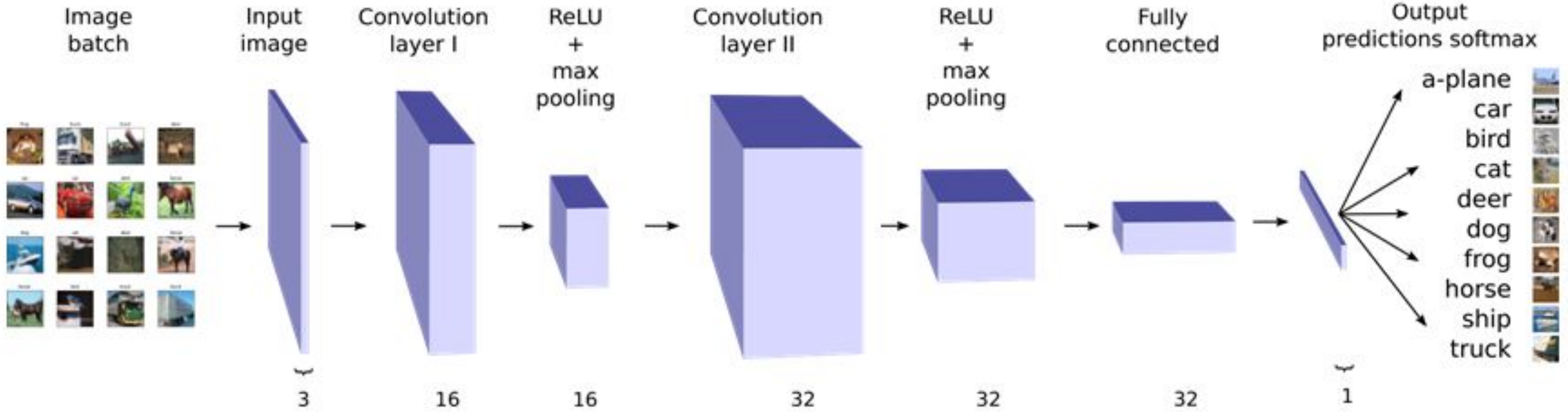


CIFAR-10 Dataset: consists of 60,000 images 32x32 pixels RGB with labels in 10 categories (plane, car, bird, cat, deer, dog, frog, horse, ship, truck).

CIFAR-10: Convolutional Neural Network



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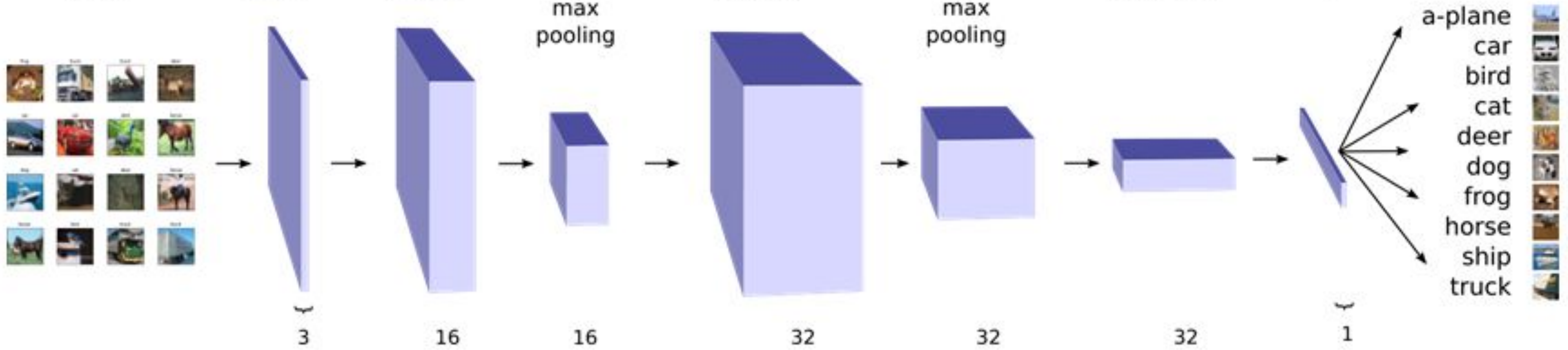

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$$y = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \leftarrow i^{th} \text{ class}$$

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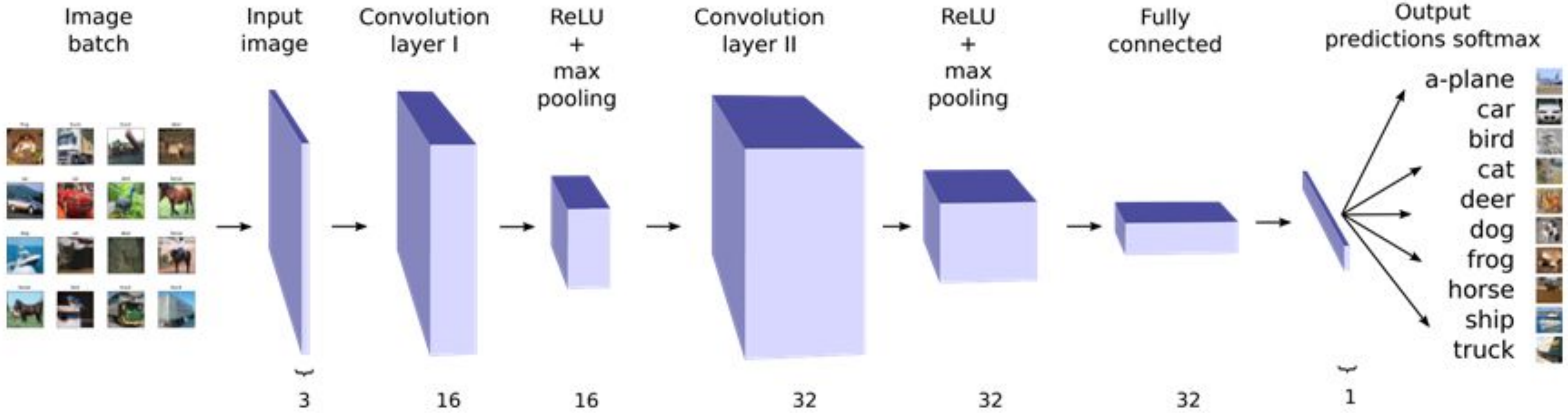

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Optimization: Stochastic Gradient Descent with batch size 100 images.

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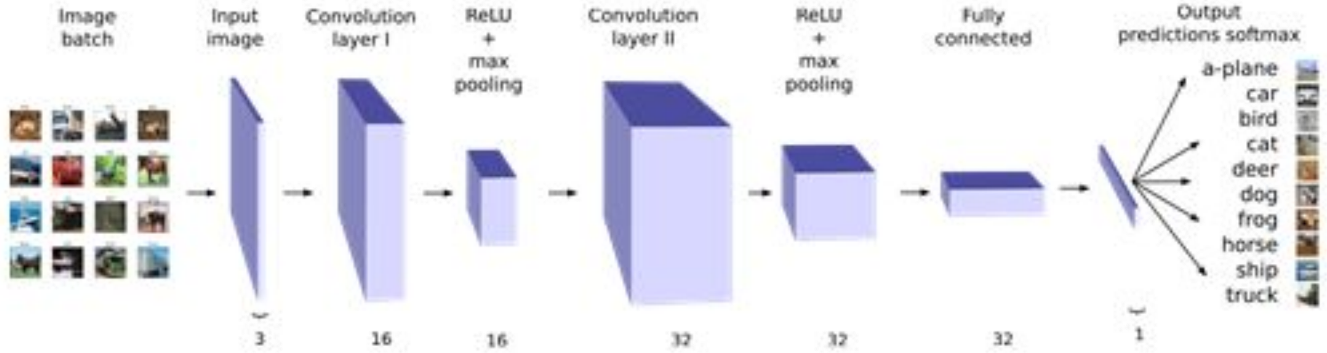
CIFAR-10: Convolutional Neural Network



Training:

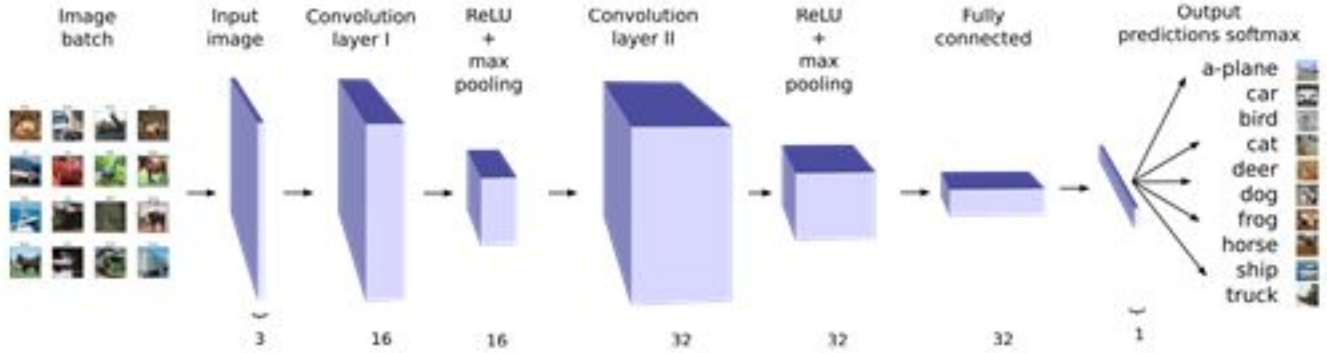
Cross-entropy loss: $L(S) = \sum_{i=1}^{m} \sum_{j=1}^{10} -y_j^{(i)} \log(\tilde{y}_j^{(i)})$.

Random initial weights.

Mini-batches of size 100.

Stochastic Gradient Descent (SGD) with learning rate 10^{-3}.

CIFAR-10: Convolutional Neural Network



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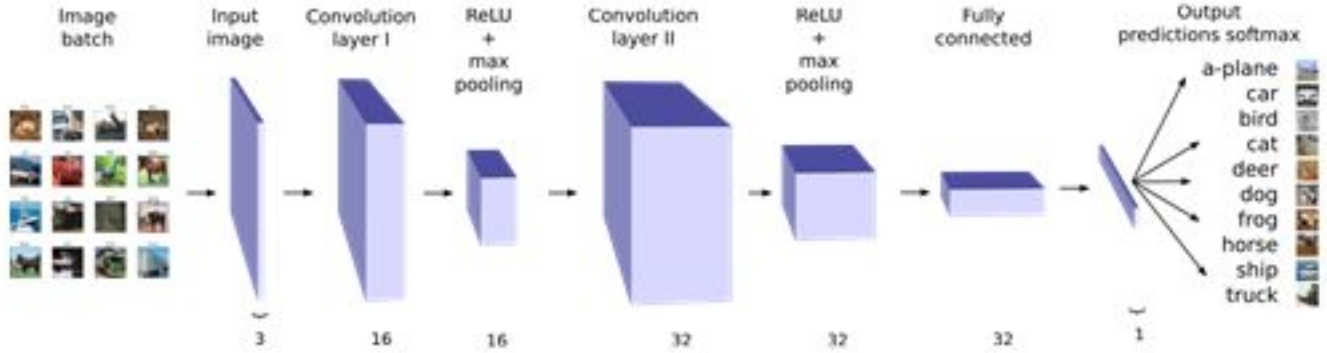
```
Training the CNN with:
numEpochs = 5
batchSize = 100

Epoch: [1/5]; batchStep = [100/500]; Loss: 1.4402.
Epoch: [1/5]; batchStep = [200/500]; Loss: 1.2206.
Epoch: [1/5]; batchStep = [300/500]; Loss: 1.2734.
Epoch: [1/5]; batchStep = [400/500]; Loss: 1.1563.
Epoch: [1/5]; batchStep = [500/500]; Loss: 1.1195.
Epoch: [2/5]; batchStep = [100/500]; Loss: 0.9954.
Epoch: [2/5]; batchStep = [200/500]; Loss: 1.1832.
Epoch: [2/5]; batchStep = [300/500]; Loss: 1.2185.
Epoch: [2/5]; batchStep = [400/500]; Loss: 0.9191.
Epoch: [2/5]; batchStep = [500/500]; Loss: 0.9215.
Epoch: [3/5]; batchStep = [100/500]; Loss: 1.0034.
Epoch: [3/5]; batchStep = [200/500]; Loss: 0.9616.
Epoch: [3/5]; batchStep = [300/500]; Loss: 0.8275.
Epoch: [3/5]; batchStep = [400/500]; Loss: 0.9199.
Epoch: [3/5]; batchStep = [500/500]; Loss: 0.9362.
Epoch: [4/5]; batchStep = [100/500]; Loss: 0.7794.
Epoch: [4/5]; batchStep = [200/500]; Loss: 0.9632.
Epoch: [4/5]; batchStep = [300/500]; Loss: 0.7169.
Epoch: [4/5]; batchStep = [400/500]; Loss: 0.6411.
Epoch: [4/5]; batchStep = [500/500]; Loss: 0.8790.
Epoch: [5/5]; batchStep = [100/500]; Loss: 0.7935.
Epoch: [5/5]; batchStep = [200/500]; Loss: 0.8741.
Epoch: [5/5]; batchStep = [300/500]; Loss: 0.7293.
Epoch: [5/5]; batchStep = [400/500]; Loss: 0.7524.
Epoch: [5/5]; batchStep = [500/500]; Loss: 0.7942.
```

CIFAR-10: Convolutional Neural Network

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Random initial weights.

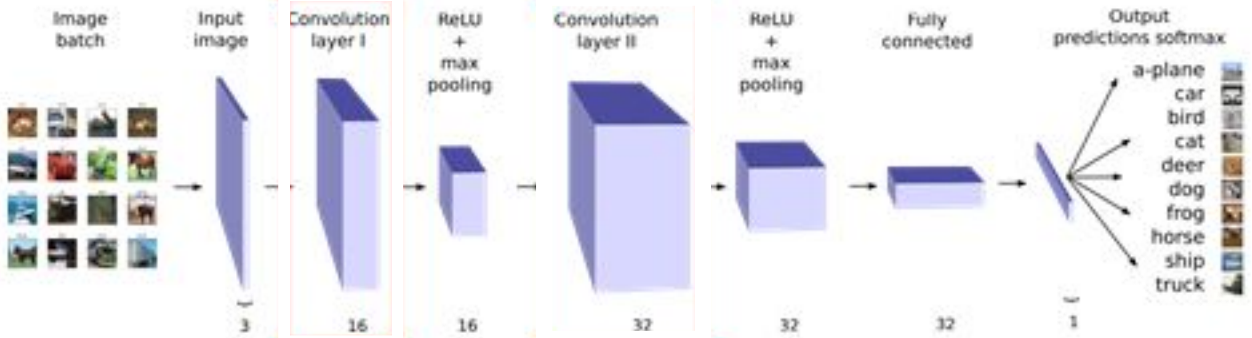
Mini-batches of size 100.

Stochastic Gradient Descent (SGD) with learning rate 10^{-3}.

Final training loss of $7.8x10^{-1}$.

CIFAR-10: Convolutional Neural Network

Hidden Layers



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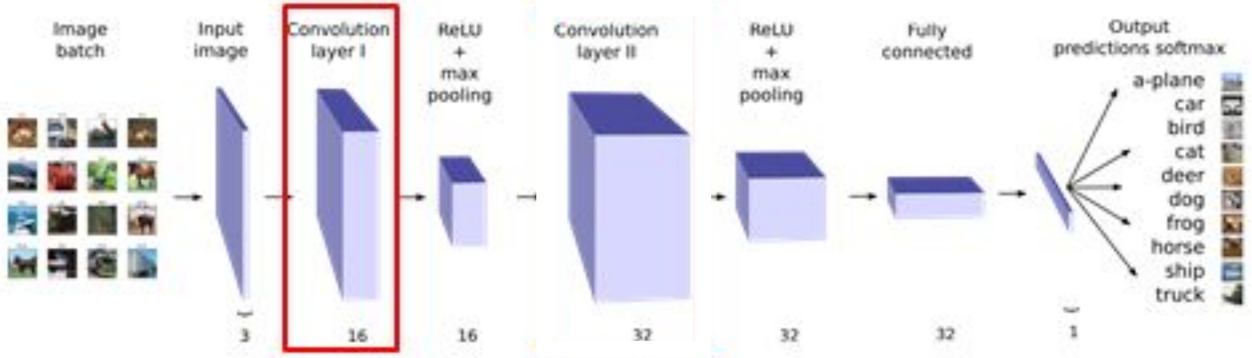

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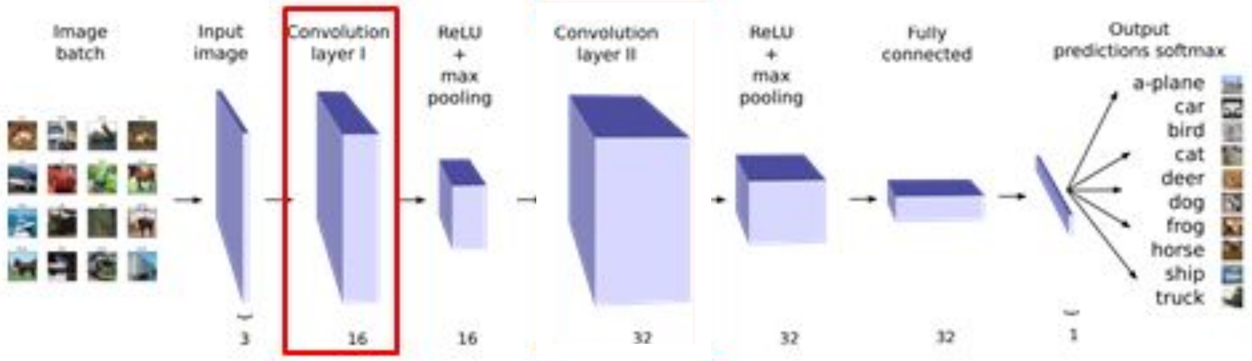

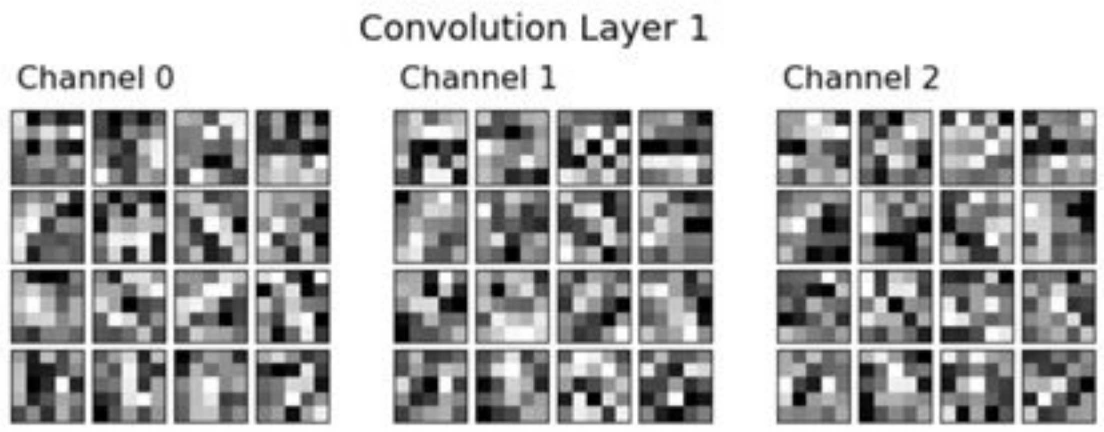

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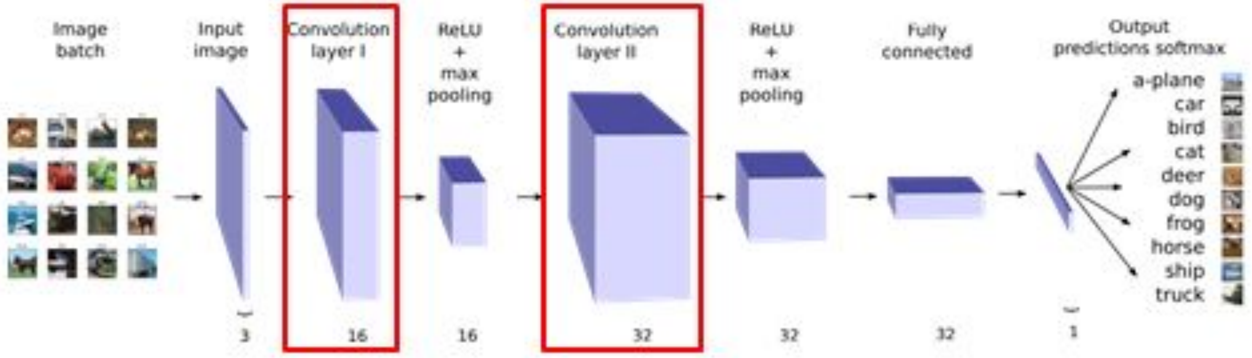

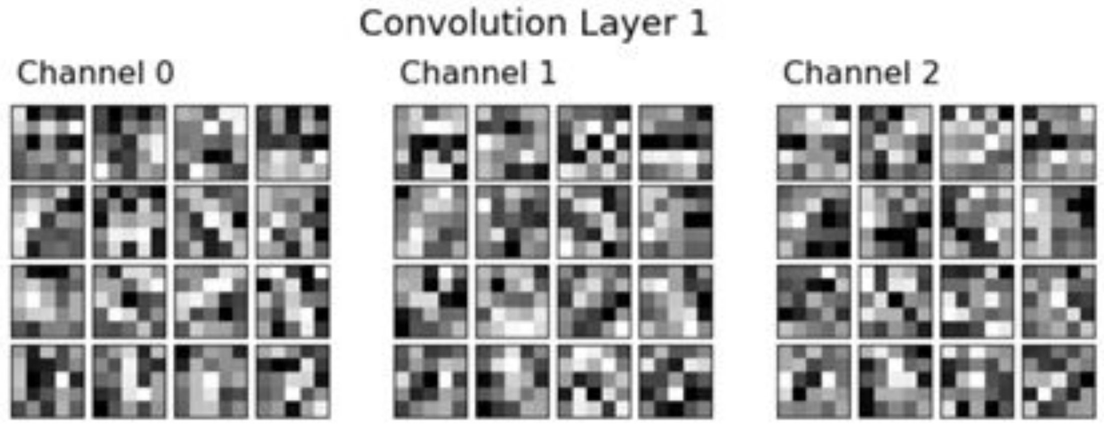

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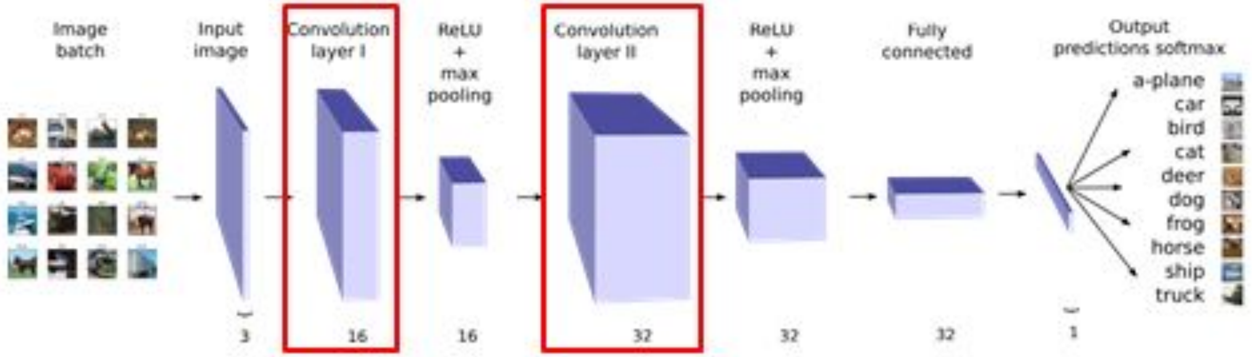

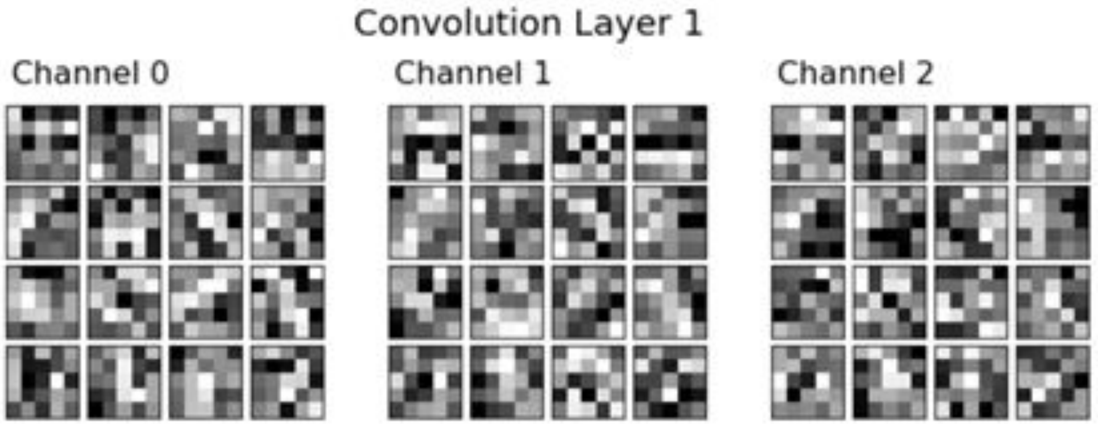

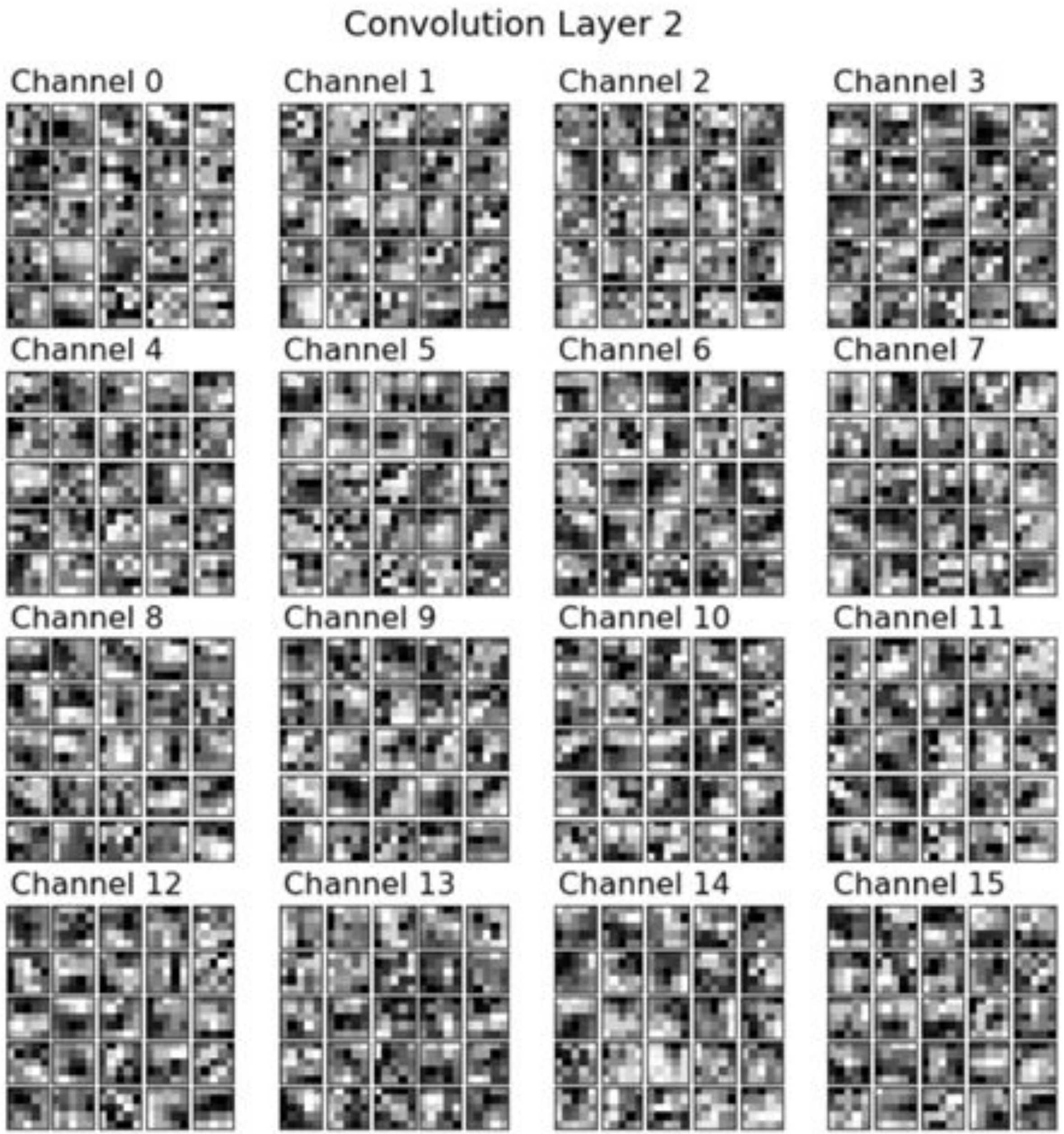

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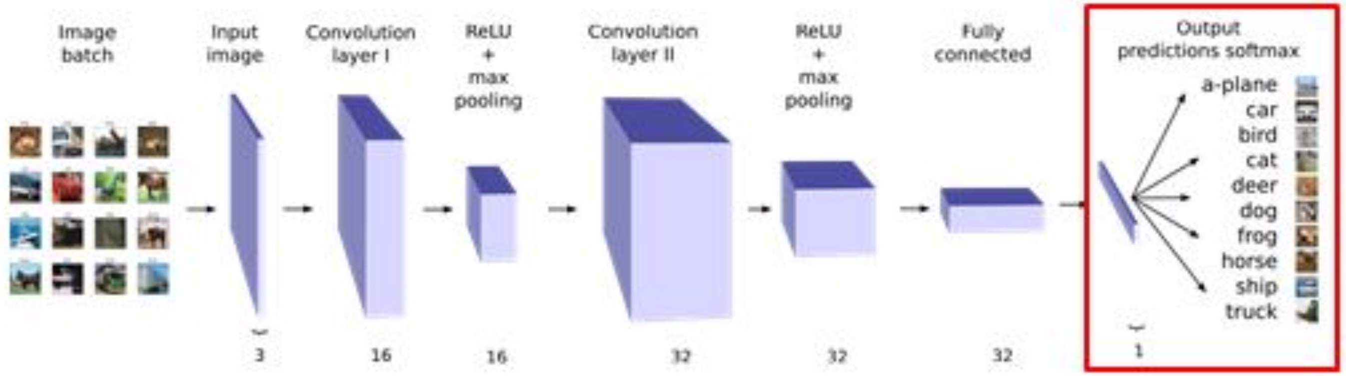

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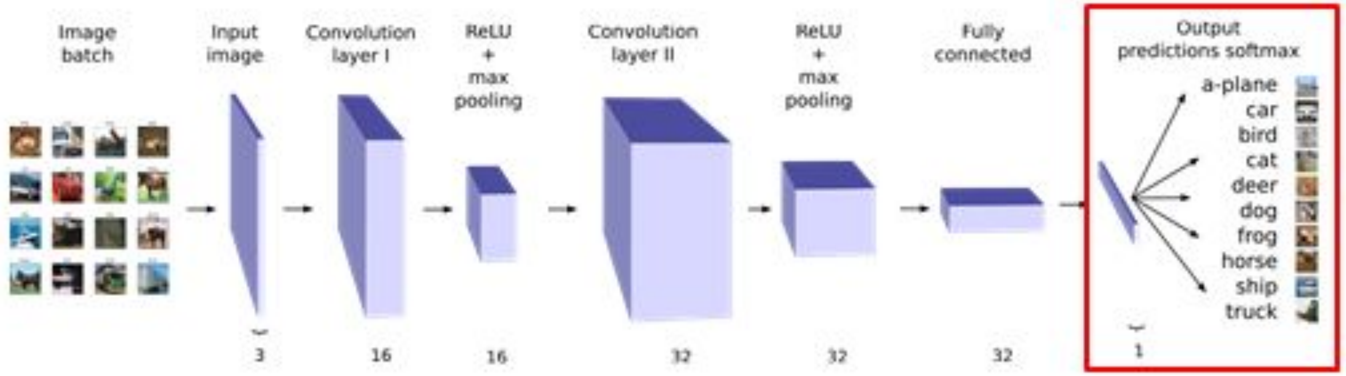

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Testing predictions of the neural network:

tested on 1000 images
tested on 2000 images
tested on 3000 images
tested on 4000 images
tested on 5000 images
tested on 6000 images
tested on 7000 images
tested on 8000 images
tested on 9000 images

Tested on a total of 10000 images.

The neural network has an accurary of 69.39%
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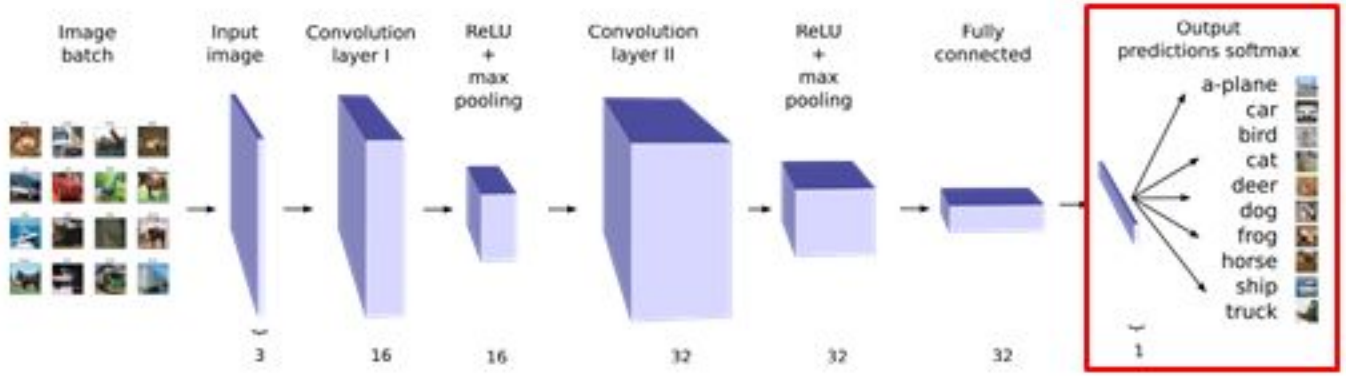
CIFAR-10: Convolutional Neural Network



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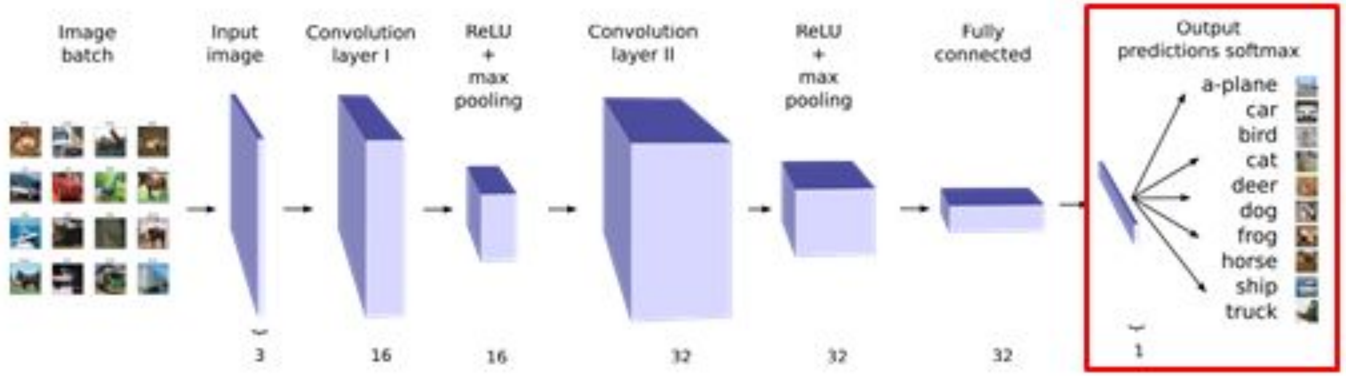


Results:

Cross-Entropy Loss: $L(S) = \sum_{i=1}^{m}\sum_{j=1}^{10} -y_j^{(i)} \log(\tilde{y}_j^{(i)})$.

Achieves a test accuracy of 69%.

This could be improved by further adjustments of hyper-parameters, tuning of architecture, additional layers, training protocols, among other strategies.

```
Testing predictions of the neural network:

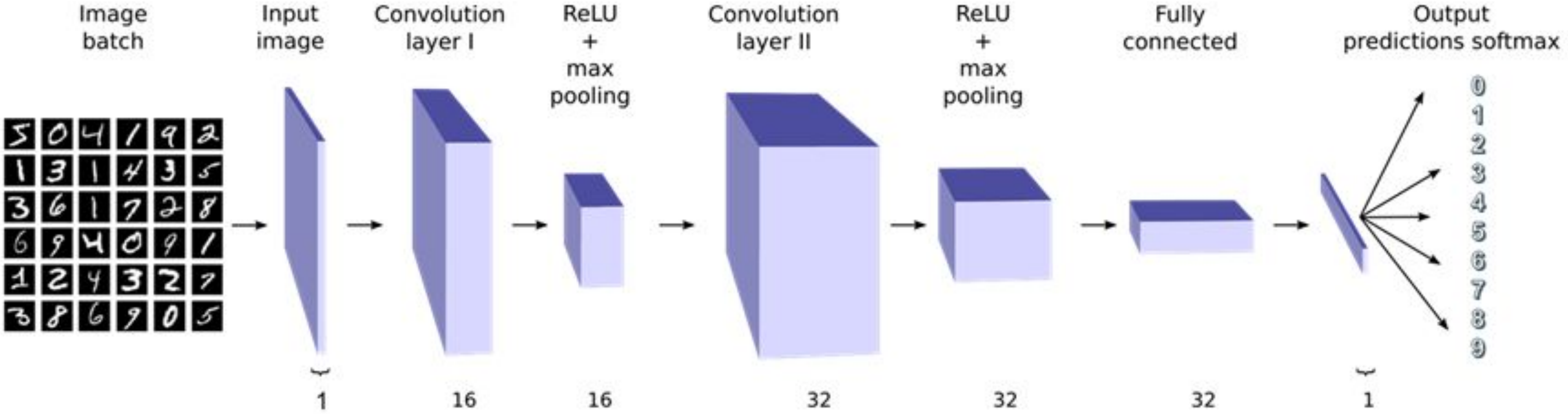
tested on 1000 images
tested on 2000 images
tested on 3000 images
tested on 4000 images
tested on 5000 images
tested on 6000 images
tested on 7000 images
tested on 8000 images
tested on 9000 images

Tested on a total of 10000 images.

The neural network has an accurary of 69.39%
```

MNIST: Digit Classification

MNIST: Convolutional Neural Network



MNIST Dataset: consists of 60,000 images 28x28 pixels grayscale with labels in 10 categories (digits).

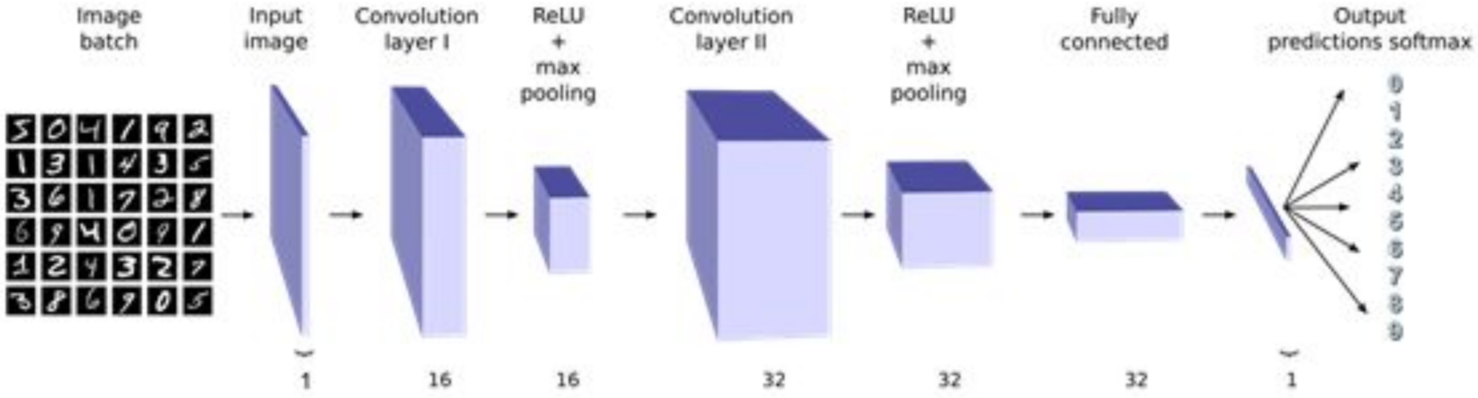
2 convolution layers + fully connected layer → q_i predicts probability of class via softmax: $\tilde{y}_i = \frac{\exp(q_i)}{\sum_{i=1}^{10} \exp(q_i)}$.

Cross-entropy loss: $\mathrm{L}(S) = \sum_{i=1}^{m}\sum_{j=1}^{10} - y_j^{(i)} \log(\tilde{y}_j^{(i)})$, y_j is the class 1-hot vector.

$$y = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \leftarrow i^{th} \text{ class}$$

Optimization: Stochastic Gradient Descent with batch size 100 images.

MNIST: Convolutional Neural Network




```
Training the CNN with:
numEpochs = 5
batchSize = 100

Epoch: [1/5]; batchStep = [100/600]; Loss: 0.1506.
Epoch: [1/5]; batchStep = [200/600]; Loss: 0.0758.
Epoch: [1/5]; batchStep = [300/600]; Loss: 0.1095.
Epoch: [1/5]; batchStep = [400/600]; Loss: 0.0388.
Epoch: [1/5]; batchStep = [500/600]; Loss: 0.0507.
Epoch: [1/5]; batchStep = [600/600]; Loss: 0.1308.
Epoch: [2/5]; batchStep = [100/600]; Loss: 0.0737.
Epoch: [2/5]; batchStep = [200/600]; Loss: 0.0230.
Epoch: [2/5]; batchStep = [300/600]; Loss: 0.0317.
Epoch: [2/5]; batchStep = [400/600]; Loss: 0.0785.
Epoch: [2/5]; batchStep = [500/600]; Loss: 0.0212.
Epoch: [2/5]; batchStep = [600/600]; Loss: 0.0645.
Epoch: [3/5]; batchStep = [100/600]; Loss: 0.0196.
Epoch: [3/5]; batchStep = [200/600]; Loss: 0.1008.
Epoch: [3/5]; batchStep = [300/600]; Loss: 0.0190.
Epoch: [3/5]; batchStep = [400/600]; Loss: 0.0265.
Epoch: [3/5]; batchStep = [500/600]; Loss: 0.0208.
Epoch: [3/5]; batchStep = [600/600]; Loss: 0.0146.
Epoch: [4/5]; batchStep = [100/600]; Loss: 0.0591.
Epoch: [4/5]; batchStep = [200/600]; Loss: 0.0080.
Epoch: [4/5]; batchStep = [300/600]; Loss: 0.0132.
Epoch: [4/5]; batchStep = [400/600]; Loss: 0.0725.
Epoch: [4/5]; batchStep = [500/600]; Loss: 0.0169.
Epoch: [4/5]; batchStep = [600/600]; Loss: 0.0063.
Epoch: [5/5]; batchStep = [100/600]; Loss: 0.0055.
Epoch: [5/5]; batchStep = [200/600]; Loss: 0.0065.
Epoch: [5/5]; batchStep = [300/600]; Loss: 0.0647.
Epoch: [5/5]; batchStep = [400/600]; Loss: 0.0081.
Epoch: [5/5]; batchStep = [500/600]; Loss: 0.0024.
Epoch: [5/5]; batchStep = [600/600]; Loss: 0.0075.
```

Training:

Cross-Entropy Loss: $\mathrm{L}(S) = \sum_{i=1}^{m}\sum_{j=1}^{10} - y_j^{(i)}\log(\tilde{y}_j^{(i)})$.

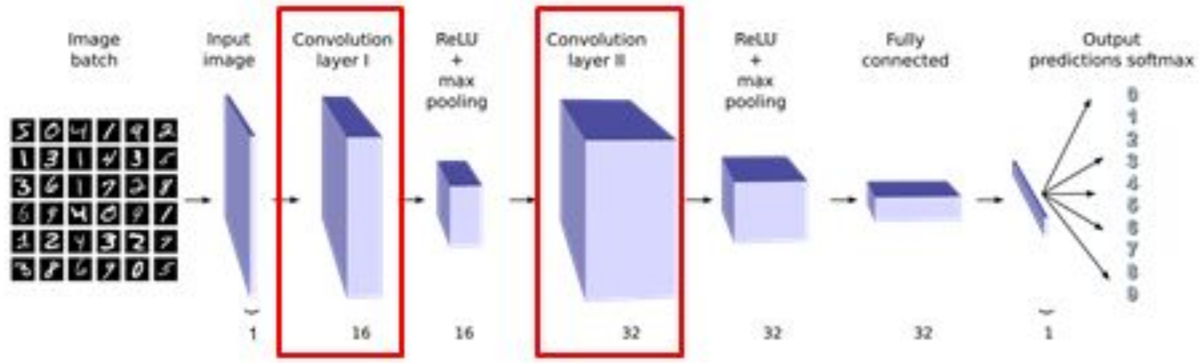
Random initial weights, mini-batches of size 100.

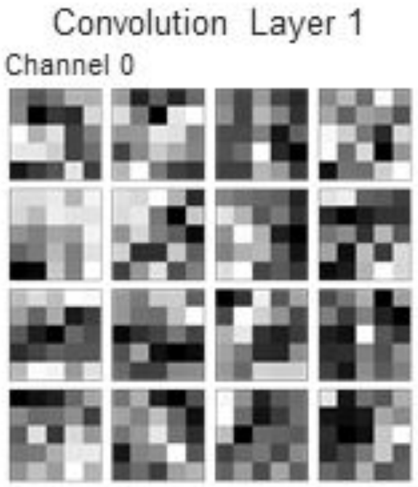
Stochastic Gradient Descent (SGD) with learning rate 10^{-3}.

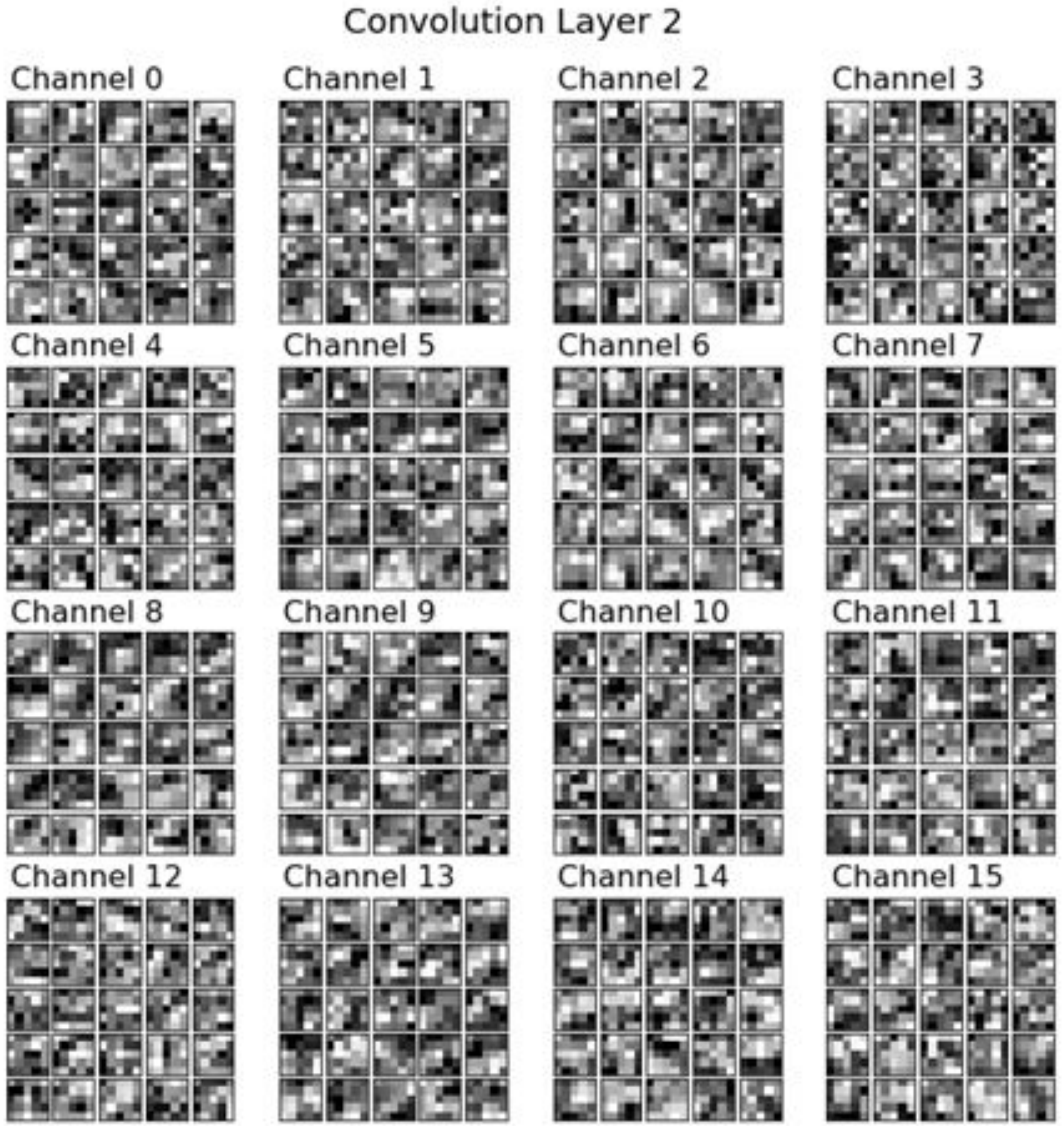
Final training loss of $7.5x10^{-3}$.

MNIST: Convolutional Neural Network

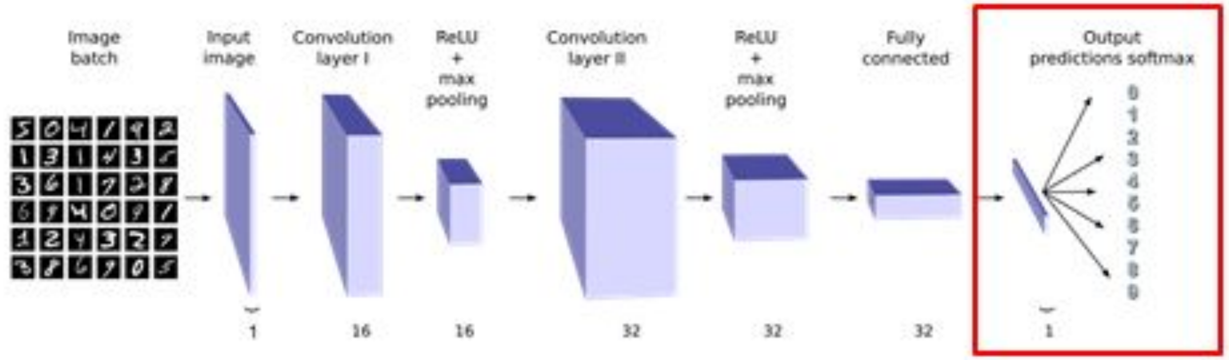
Hidden Layers







MNIST: Convolutional Neural Network



Results:

Cross-Entropy Loss $\mathrm{L}(\mathcal{S}) = \sum_{i=1}^{m}\sum_{j=1}^{10} - y_j^{(i)} \log(\tilde{y}_j^{(i)})$

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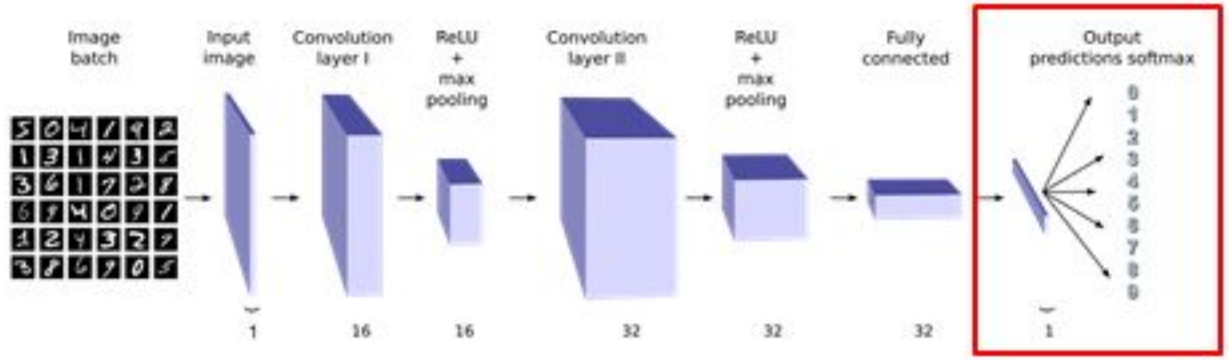

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Tested on a total of 10000 images.

The neural network has an accuracy of 99.12%
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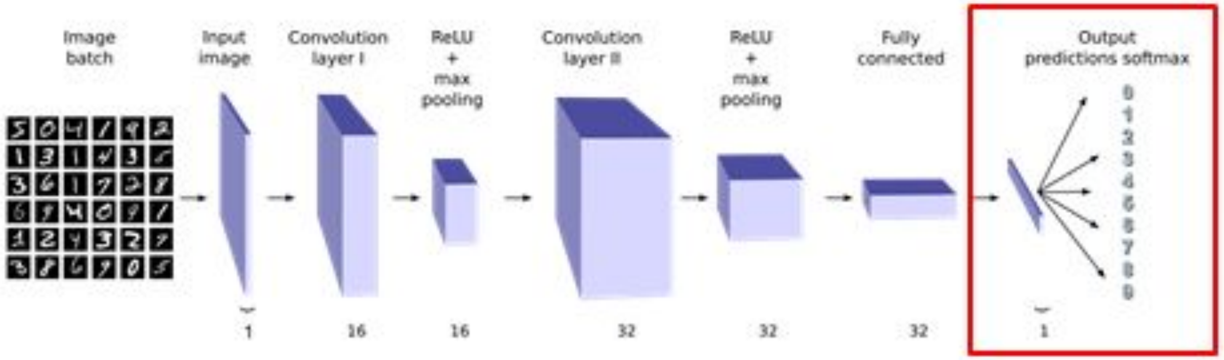
MNIST: Convolutional Neural Network



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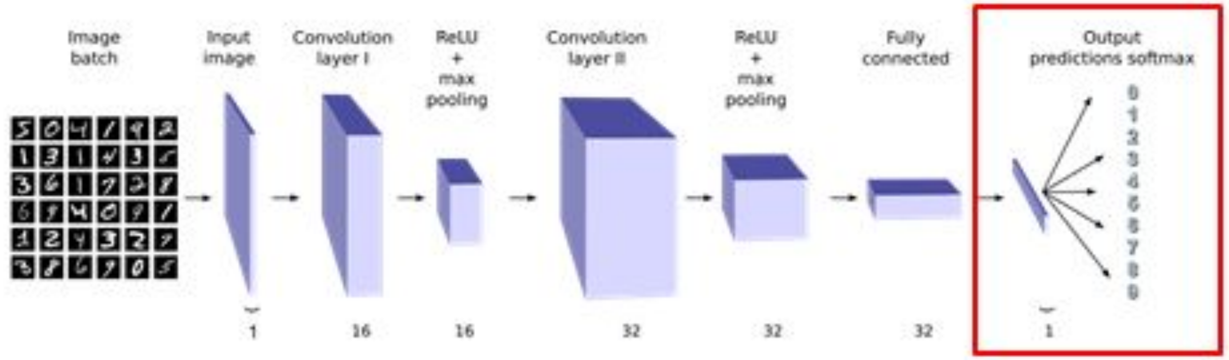

Results:

Cross-Entropy Loss $L(S) = \sum_{i=1}^{m} \sum_{j=1}^{10} - y_j^{(i)} \log(\tilde{y}_j^{(i)})$

Achieves a test accuracy of 99.12%.

Without much tuning of the CNN, we were able to obtain very good accuracy for the MNIST dataset!

```
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Tested on a total of 10000 images.

The neural network has an accuracy of 99.12%
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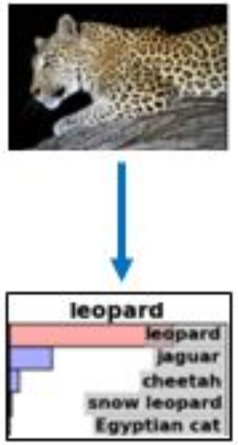
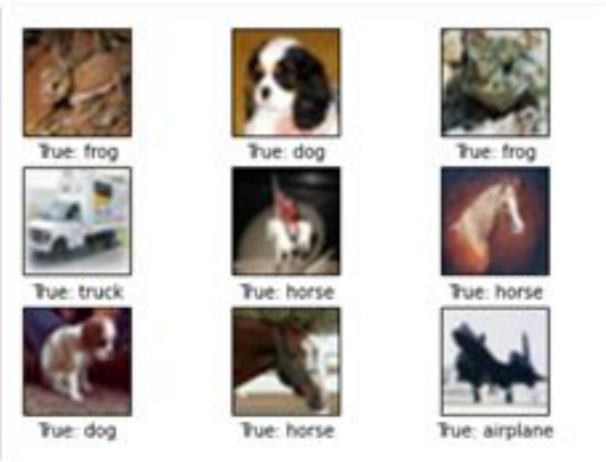
Summary

Convolutional Neural Networks (CNNs): Summary

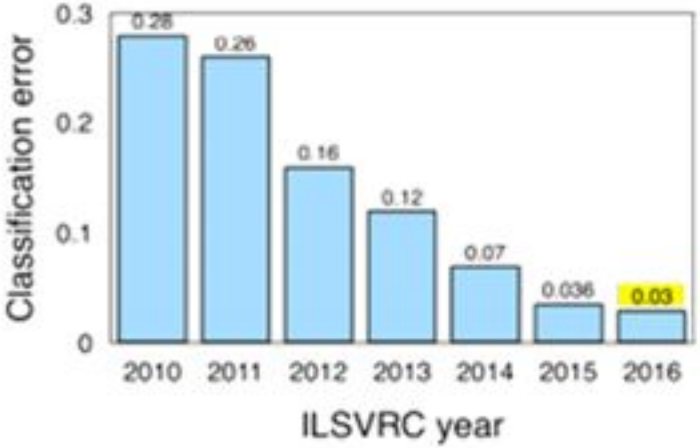
Task: Classify



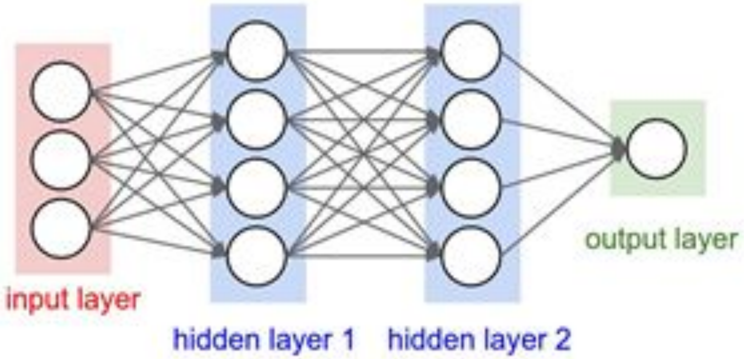
Predictions



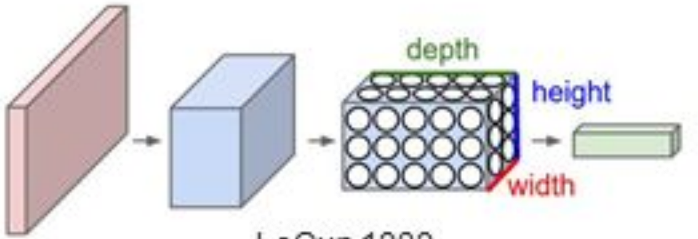
Results: ILSVRC



Neural Network (NN)

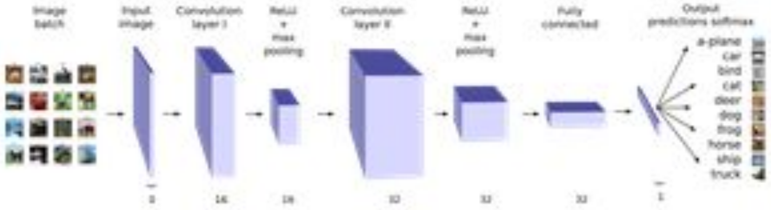


Convolutional Neural Network (CNN)



LeCun 1989

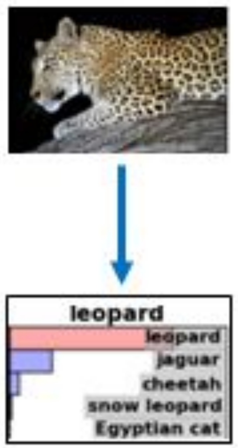
Image Classifier CNN



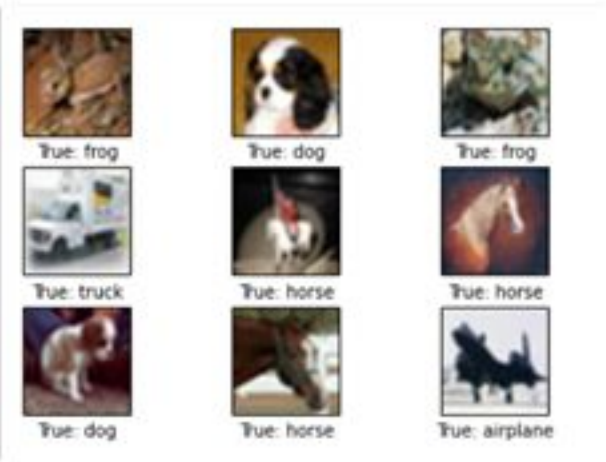
Deep neural networks are providing current state-of-the-art results.

Convolutional Neural Networks (CNNs): Summary

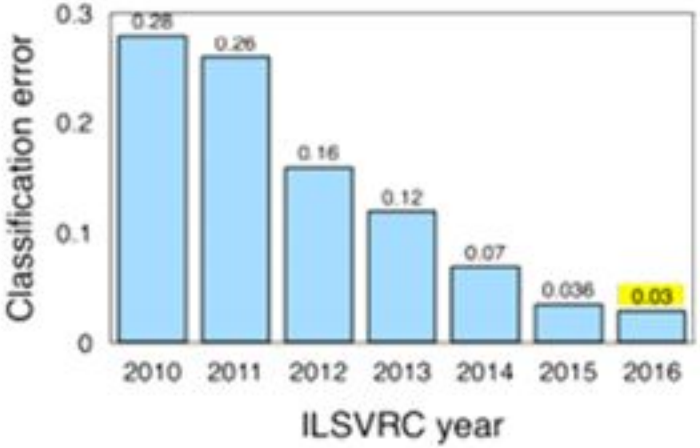
Task: Classify



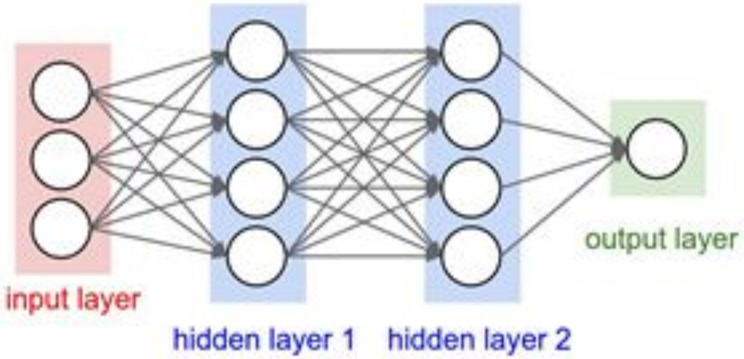
Predictions



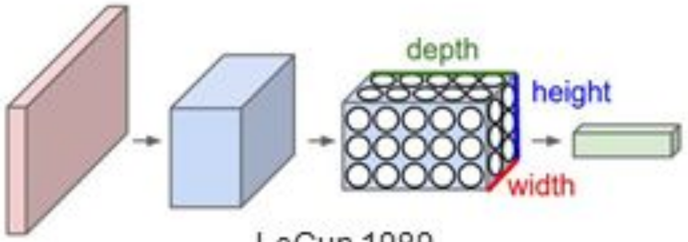
Results: ILSVRC



Neural Network (NN)



Convolutional Neural Network (CNN)

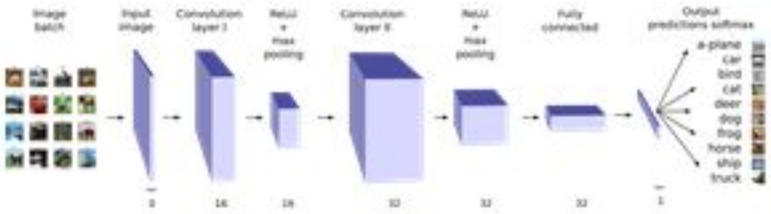


LeCun 1989

Deep neural networks are providing current state-of-the-art results.

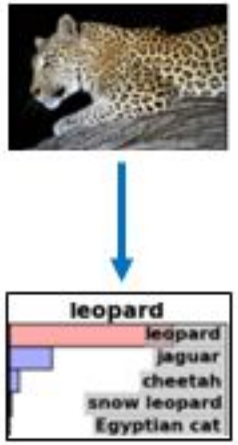
Use of shared weights provides statistical efficiency, computationally less expensive training, and possible insights into structure in data.

Image Classifier CNN



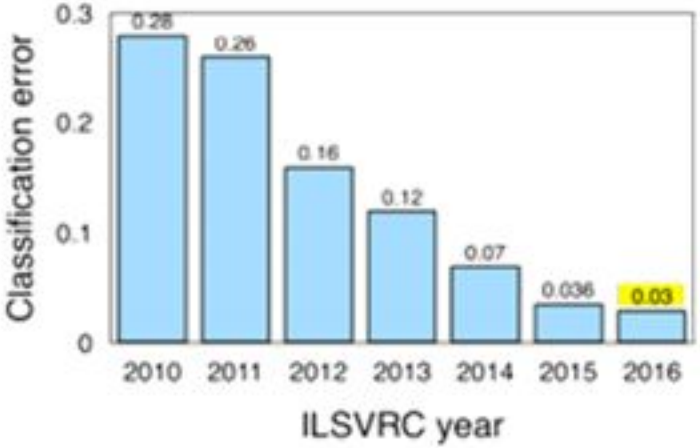
Convolutional Neural Networks (CNNs): Summary

Task: Classify

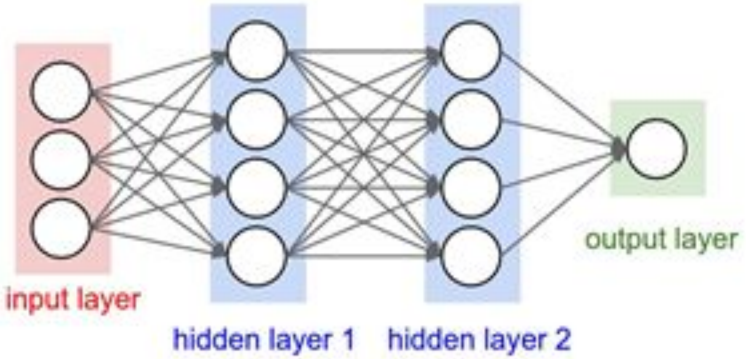


Predictions

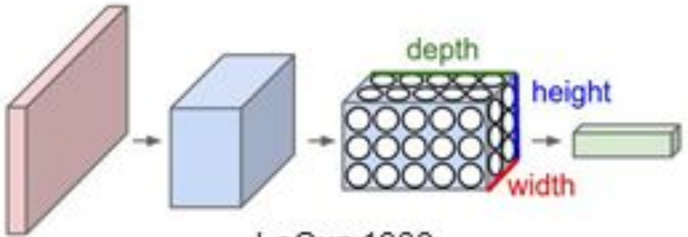
Results: ILSVRC



Neural Network (NN)

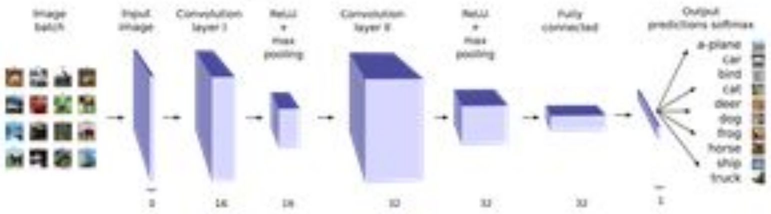


Convolutional Neural Network (CNN)



LeCun 1989

Image Classifier CNN



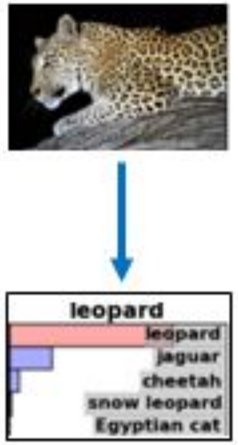
Deep neural networks are providing current state-of-the-art results.

Use of shared weights provides statistical efficiency, computationally less expensive training, and possible insights into structure in data.

Deep networks → hierarchical representations "features of features."

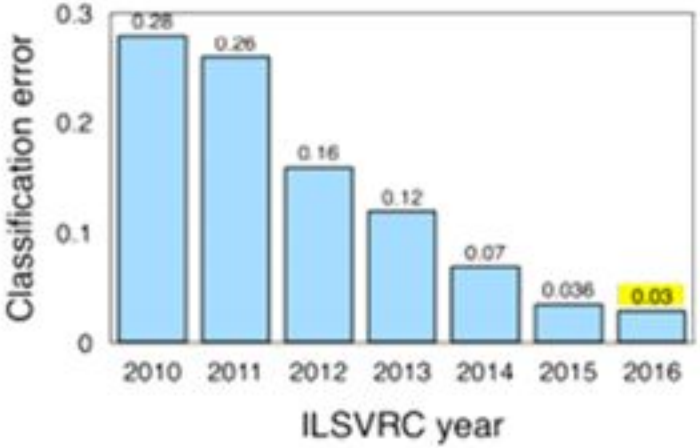
Convolutional Neural Networks (CNNs): Summary

Task: Classify

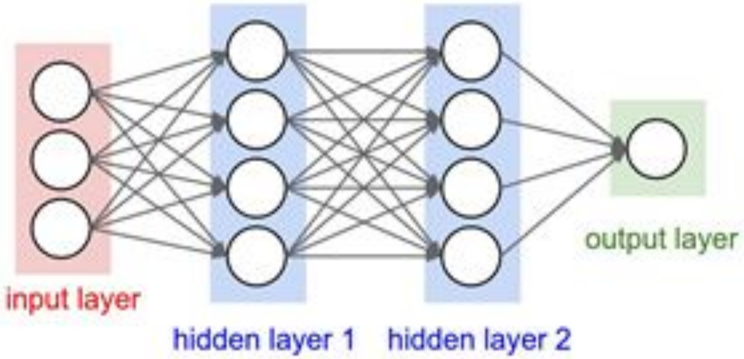


Predictions

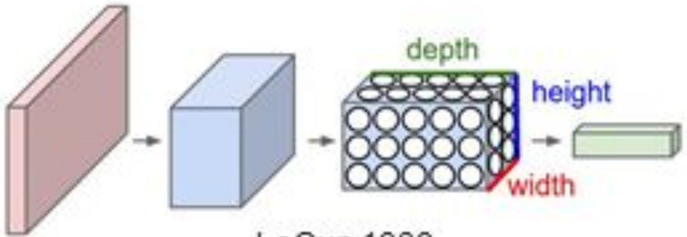
Results: ILSVRC



Neural Network (NN)

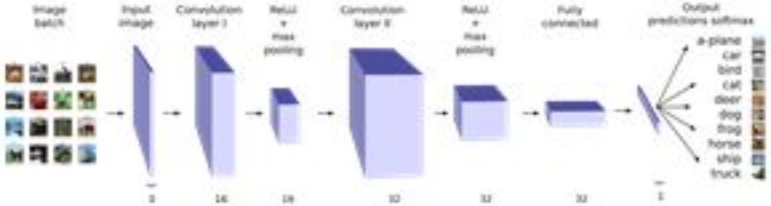


Convolutional Neural Network (CNN)



LeCun 1989

Image Classifier CNN



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Deep networks → hierarchical representations "features of features."

Many applications of these ideas beyond image classification: language processing, reinforcement learning, data generation.