Lecture 5.
Convolutional Neural Network

Review

1. Limitation of Linear Classifier
    - XOR Gate
2. Perceptron
    - Perceptron = Linear Classifier
    - Analogy to Neurons
    - Building Block of the Neural Network
3. MLP
    - MLP and the Neural Network
    - The Universal Approximation Theorem
    - Where Backpropagation becomes Important
4. Limitations of MLP

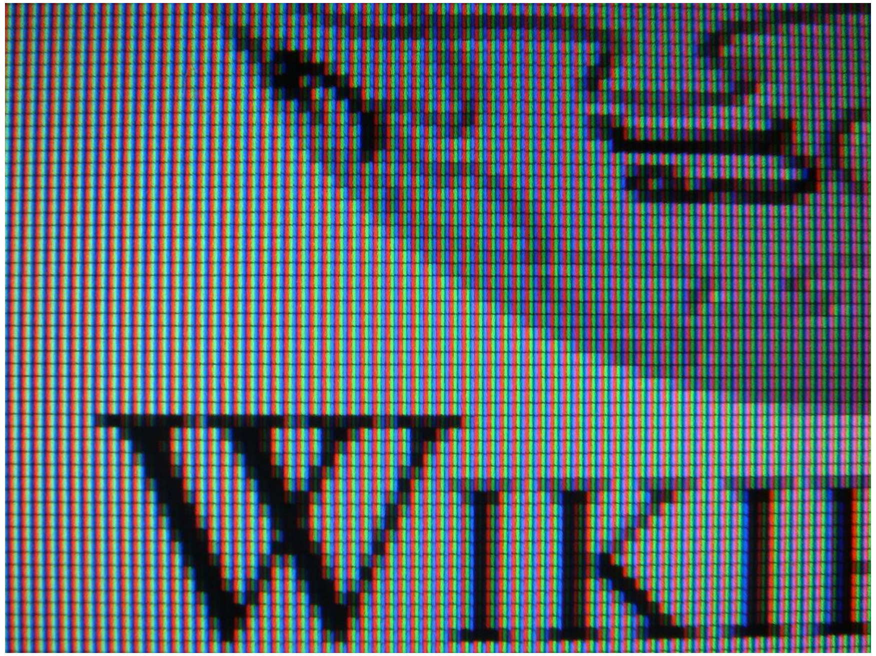
Today's Contents

1. Back to Image Classification

2. Convolutional Neural Network

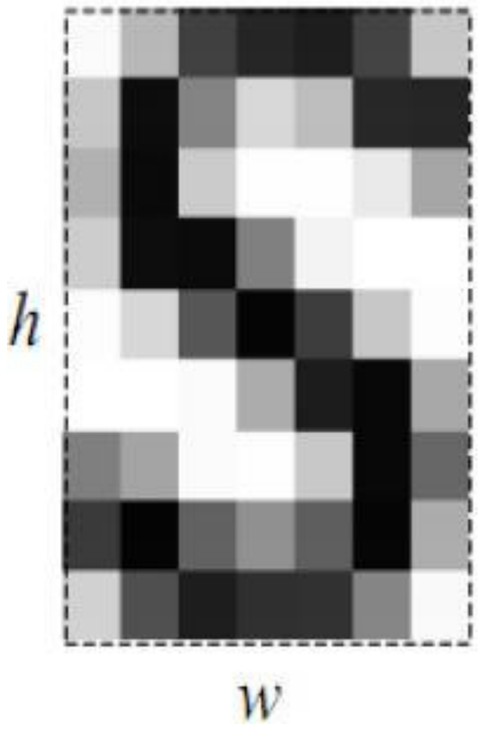
Back to Image Classification : Pixels

Image = Matrix of Pixels



Back to Image Classification : Pixels

What we see



What computer sees (grayscale)

$$\mathbf{x} = \begin{pmatrix} 251, 181, 068, 041, 032, 071, 197, \\ 196, 014, 132, 213, 187, 043, 041, \\ 174, 011, 200, 254, 254, 232, 164, \\ 202, 014, 012, 128, 242, 255, 255, \\ 253, 212, 089, 005, 064, 196, 253, \\ 255, 255, 251, 196, 030, 009, 165, \\ 127, 162, 251, 254, 197, 009, 105, \\ 062, 005, 100, 144, 097, 006, 170, \\ 207, 083, 032, 051, 053, 134, 250 \end{pmatrix}$$

Image from researchgate.net

Back to Image Classification : Pixels

RGB

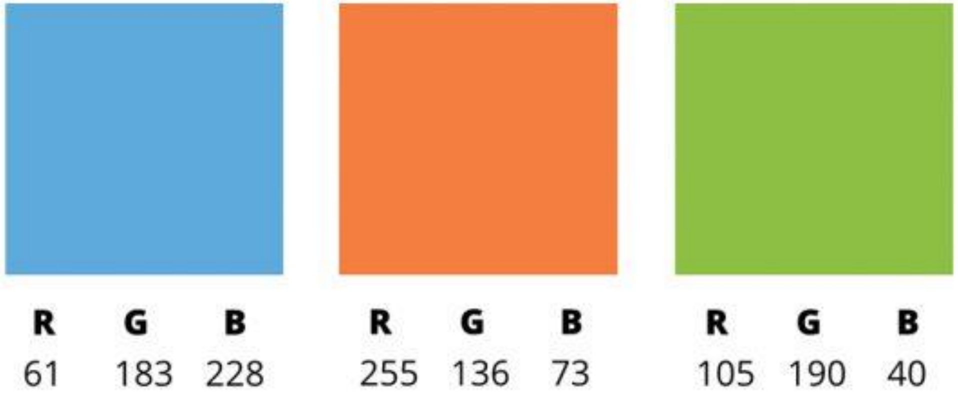


Image from https://negliadesign.com/

CIFAR-10

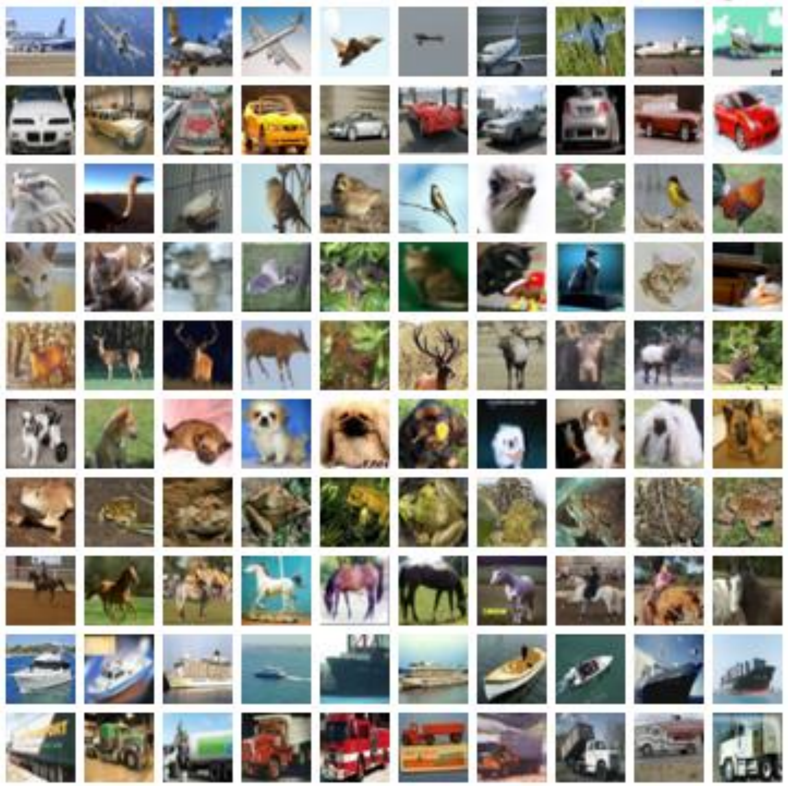
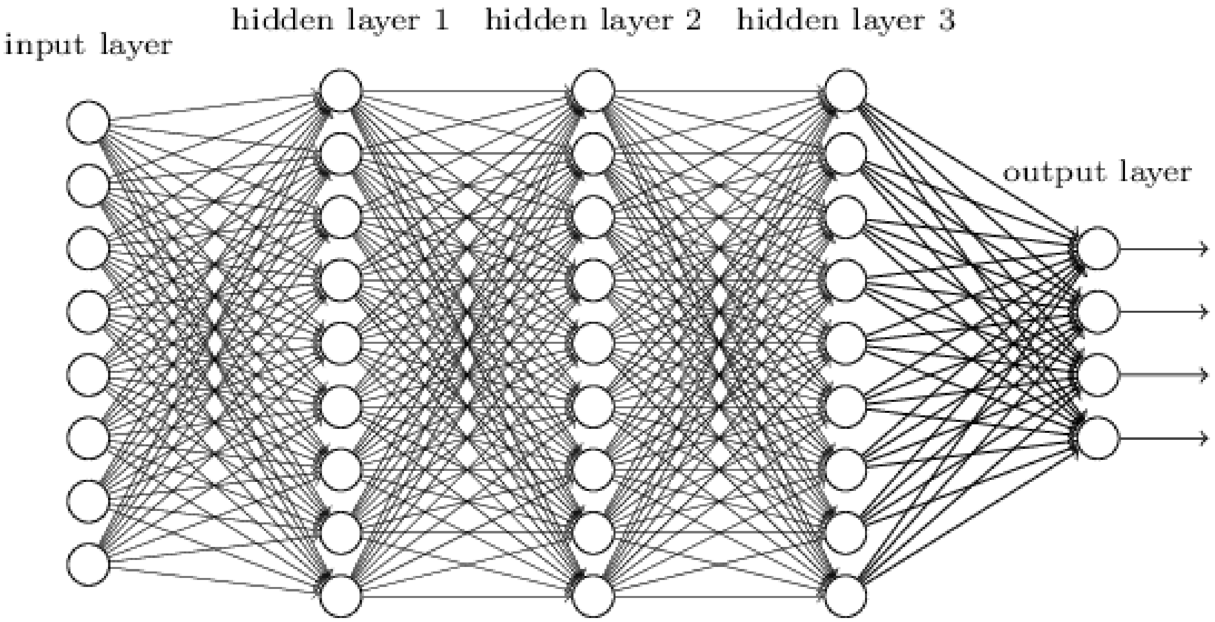


Image from https://www.kaggle.com/

Back to Image Classification : MLP

MLP



Back to Image Classification : MLP

Must Stretch Out Tensor into Vector

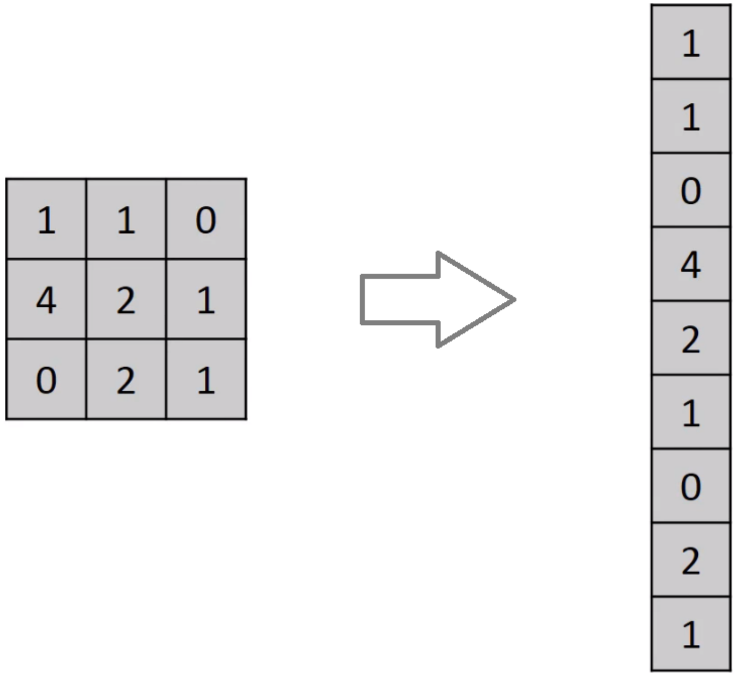


Image from https://towardsdatascience.com

Back to Image Classification : MLP

Worked well on MNIST

What about on CIFAR-10?

Back to Image Classification : MLP

However, MLPs are not appropriate for Image Classification…

1. Too many parameters required

2. Spatial structure is lost

Back to Image Classification : MLP

We want a model that,

1. Uses fewer parameters than MLPs

2. Preserves the spatial structure

Back to Image Classification : MLP

Recall The Universal Approximation Theorem…

"1개의 Hidden Layer를 가진 MLP로 어떤 함수도 근사할 수 있다."

However,

"A feedforward network with a single layer is sufficient to represent any function,
But the layer may be infeasibly large and may fail to learn and generalize correctly."

CNN : Idea

We want a model that,

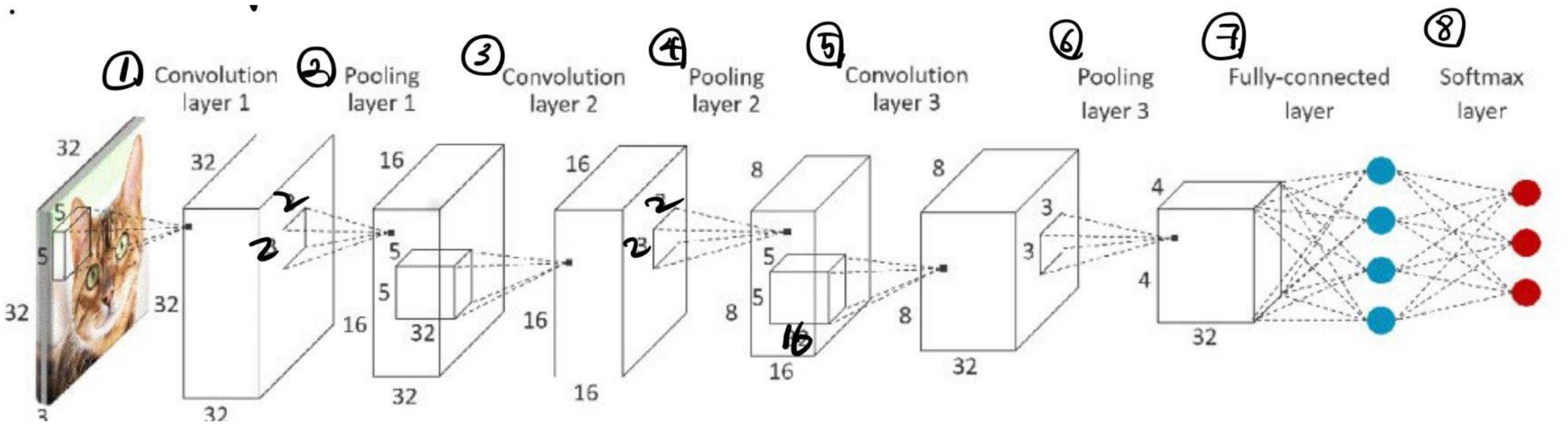
1. Uses fewer parameters than MLPs

2. Preserves the spatial structure

Convolutional Neural Network to the rescue!!!

CNN : Idea

Image from https://community.arm.com/



What happened?!?!?!

CNN : Idea

What happens during Tensor → Tensor Mapping?

What are Convolution, Pooling, Fully-Connected Layers?

How does this Model extract features from spatial structure?

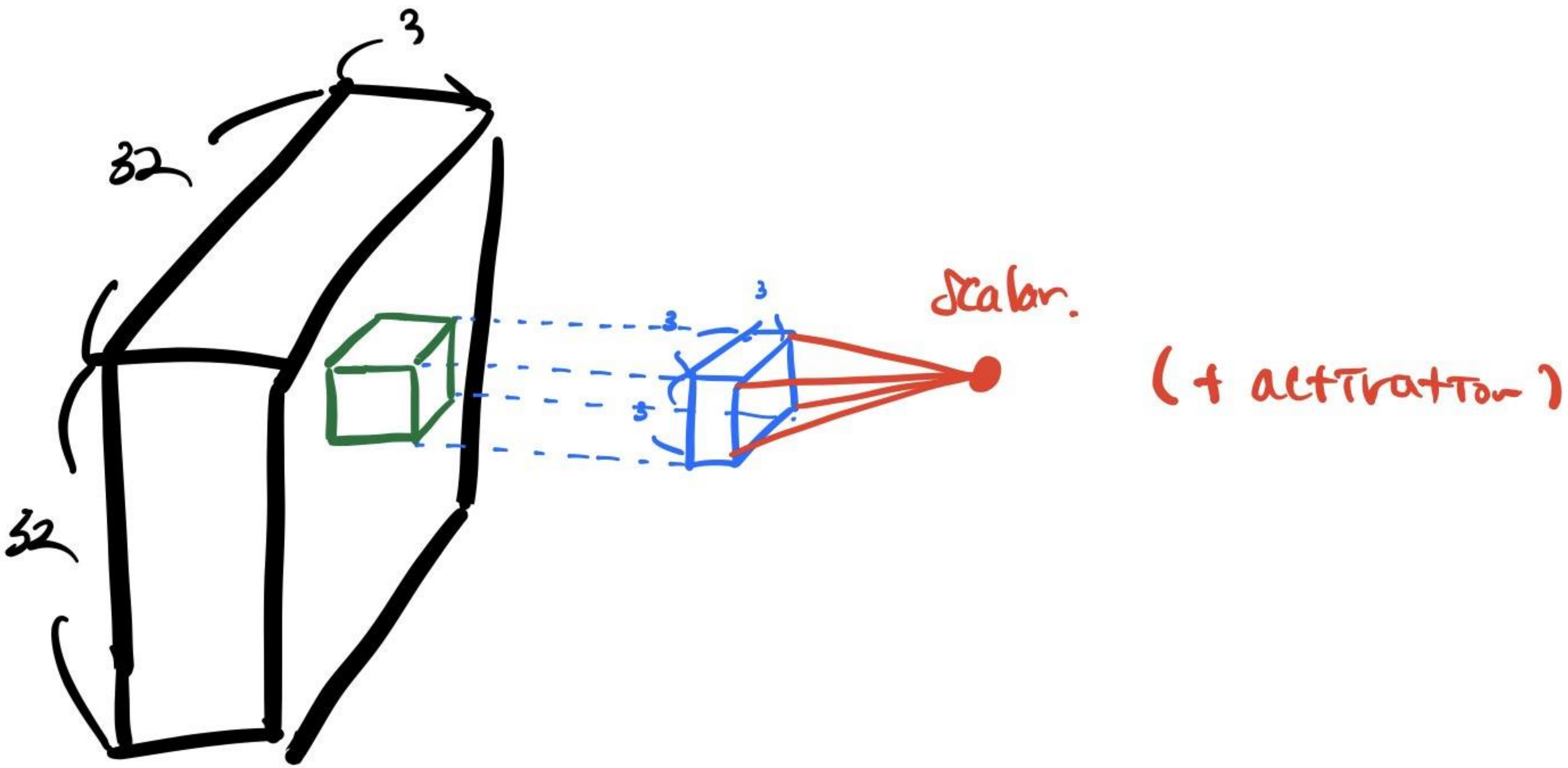
Does it use less parameters than the MLP?

CNN : Convolution

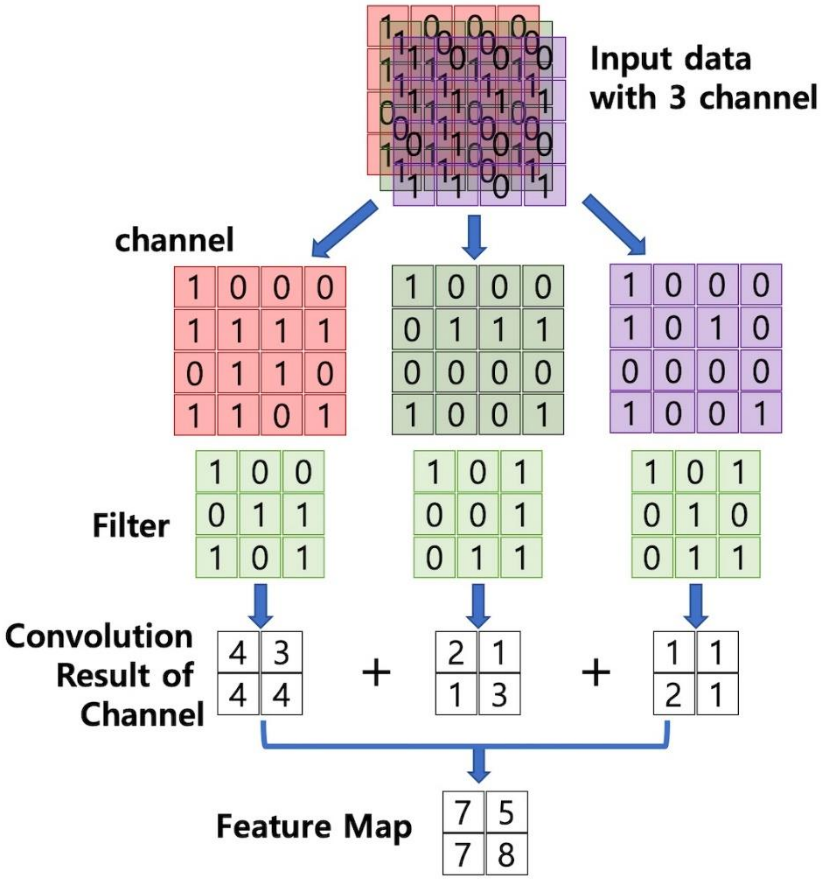
How do we map Tensor to Tensor, while preserving the spatial structure?

Apply **Filter** to small regions in the Tensor (Image)

CNN : Convolution



CNN : Convolution



While sliding over the tensor,

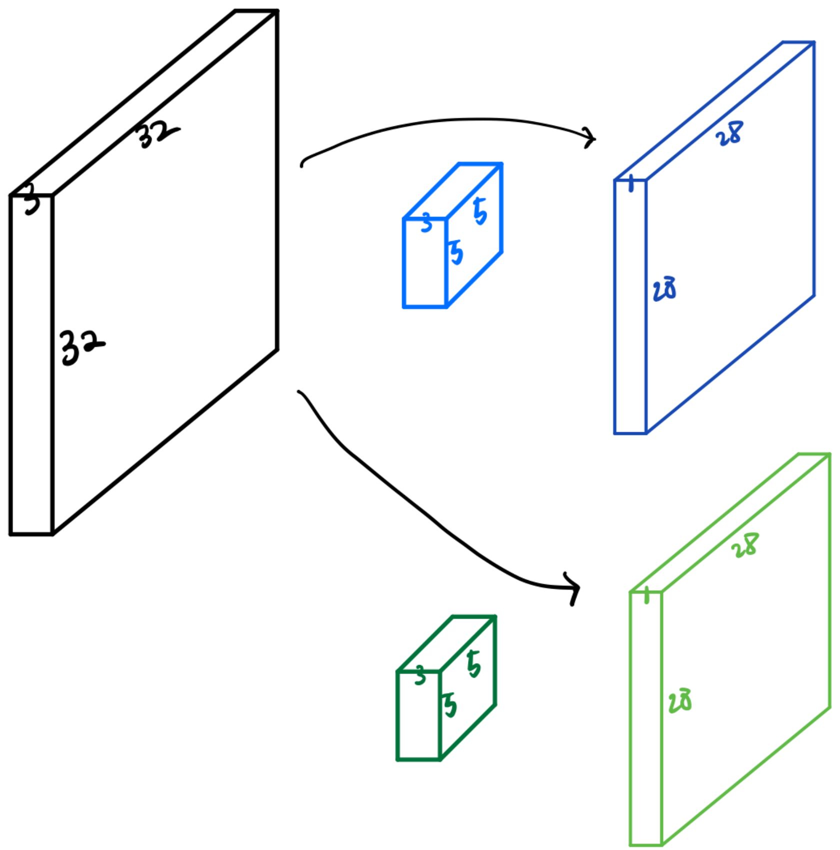
calculate the

sum of elementwise multiplication

This is called, **Convolution**

Image from taewan.kim/ppst/cnn

CNN : Convolution



1 Filter = 1 Activation Map

CNN : Convolution

Then, how do filters extract features from the image,

while preserving the spatial structure?

CNN : Convolution

For simplicity, assume White = 0 , Black = 1, and activation = RELU

filter $\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

1)

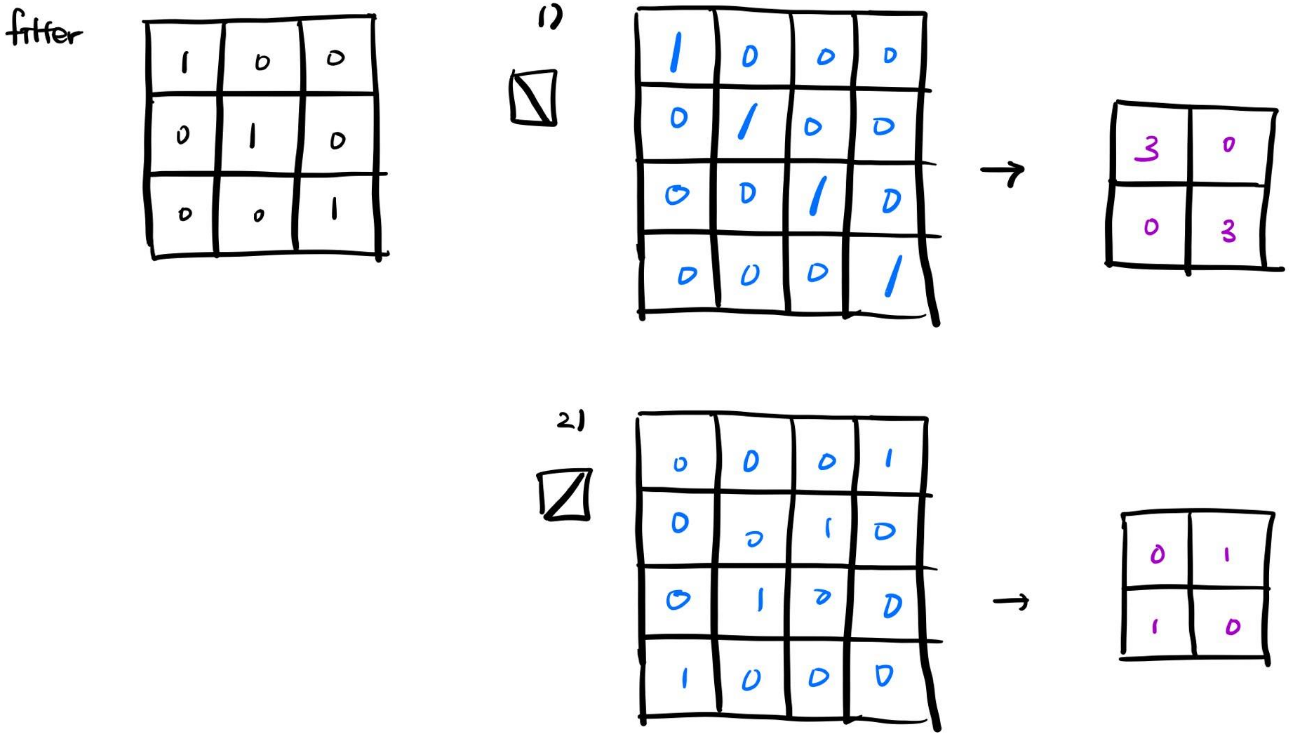
$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} 3 & 0 \\ 0 & 3 \end{bmatrix}$$

2)

$$\begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

CNN : Convolution

This filter focuses on the major diagonal… Other filters will focus on other features!



CNN : Convolution

Filters extract features from the spatial structure of the tensor

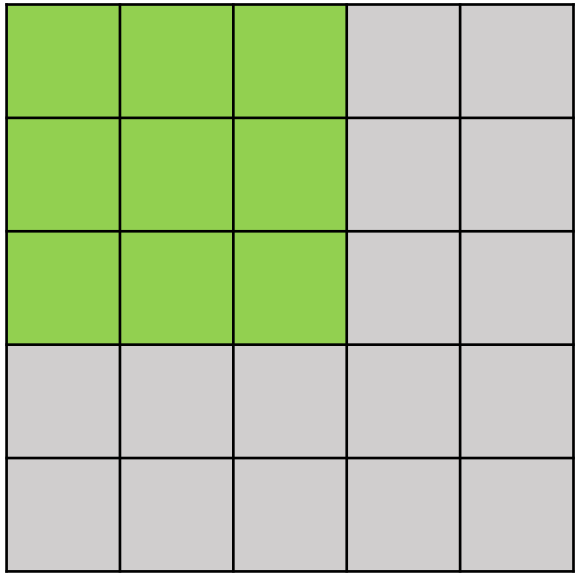
They are Parameters!!!

** So, they must be Updated via Backpropagation.

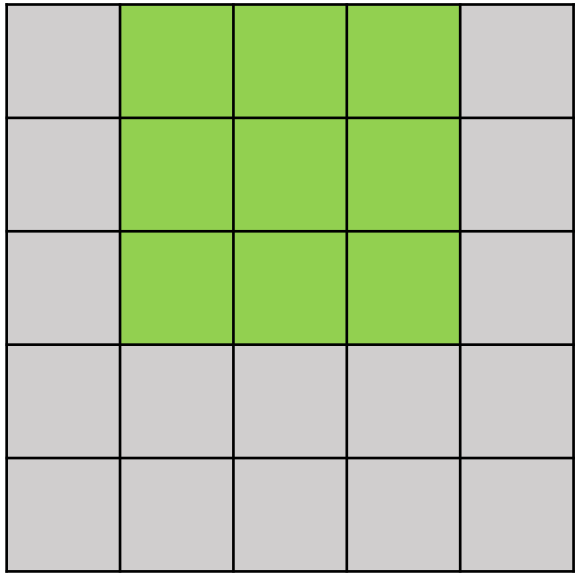
For more detail, read https://becominghuman.ai/back-propagation-in-convolutional-neural-networks-intuition-and-code-714ef1c38199

CNN : Convolution

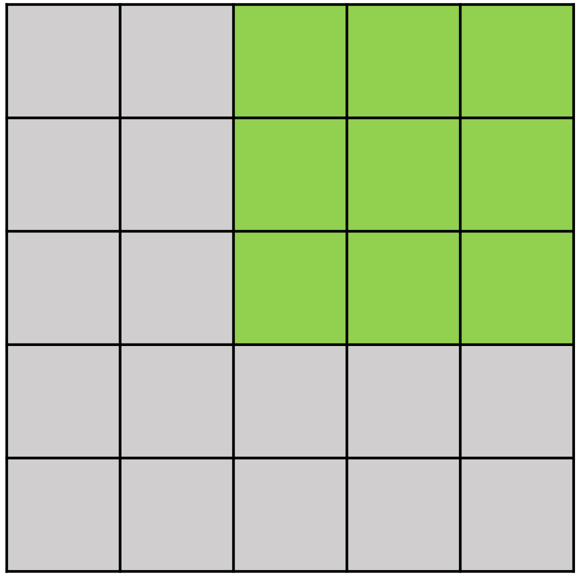
How much does a filter move per slide? **Stride**



Stride 1



Stride 2



CNN : Filters

$$O = \frac{I - F}{S} + 1$$

O = output size N = input size F = filter size S = stride

CNN : Filters

After applying filters, the dimension is reduced…!

$$O = \frac{I - F}{S} + 1 < I - F + 1 < I$$

CNN : Filters

Add **Padding** to the Tensor to remedy the problem..! But there is a tradeoff!

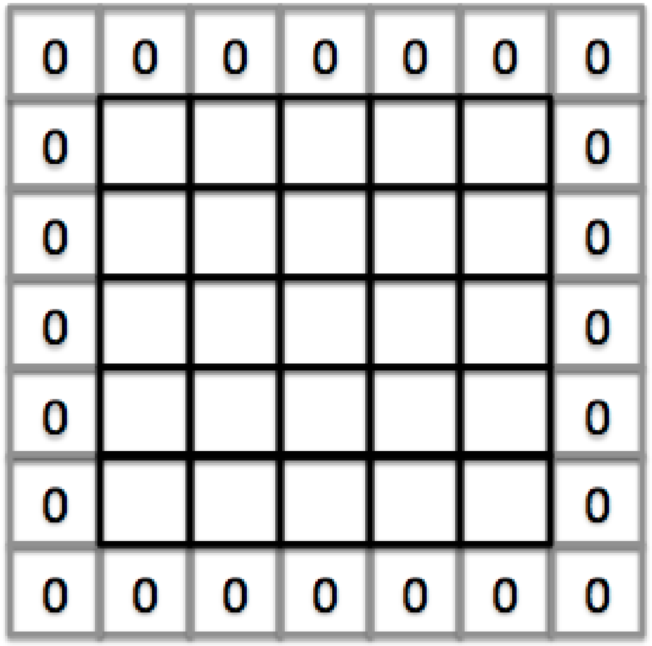


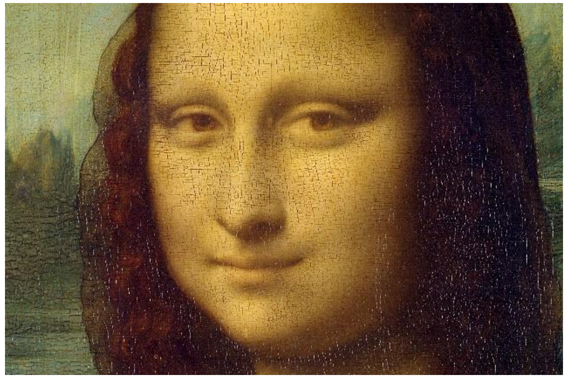
Image from medium.com

CNN : Convolution

$$O = \frac{I + 2Pa - F}{S} + 1$$

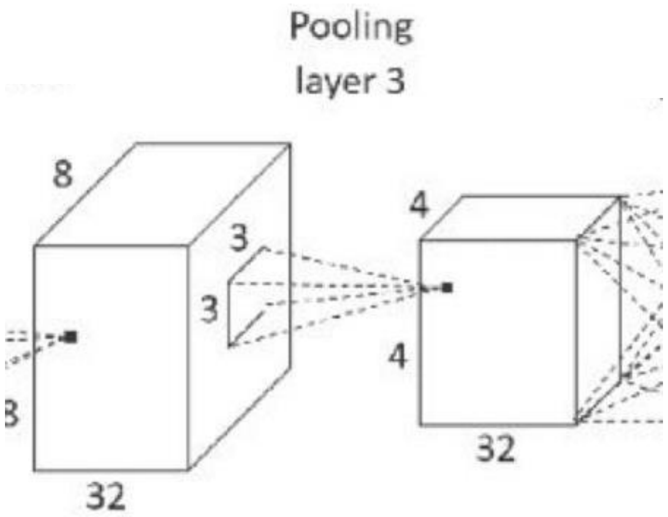
O = output size N = input size F = filter size S = stride Pa = padding size

CNN : Pooling



We want to reduce the dimension of the feature,

via **Pooling**



CNN : Pooling

Extract the representative value over a region...! No parameter involved!!!

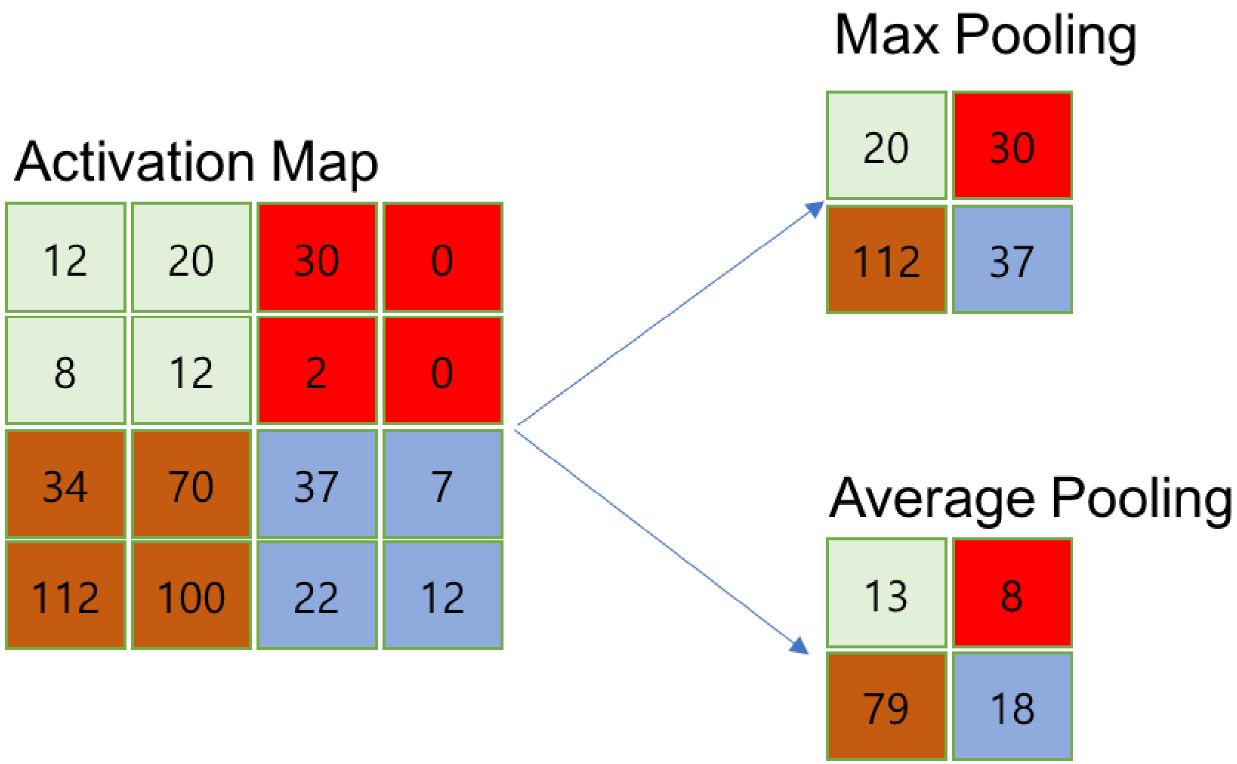


Image from taewan.kim/ppst/cnn

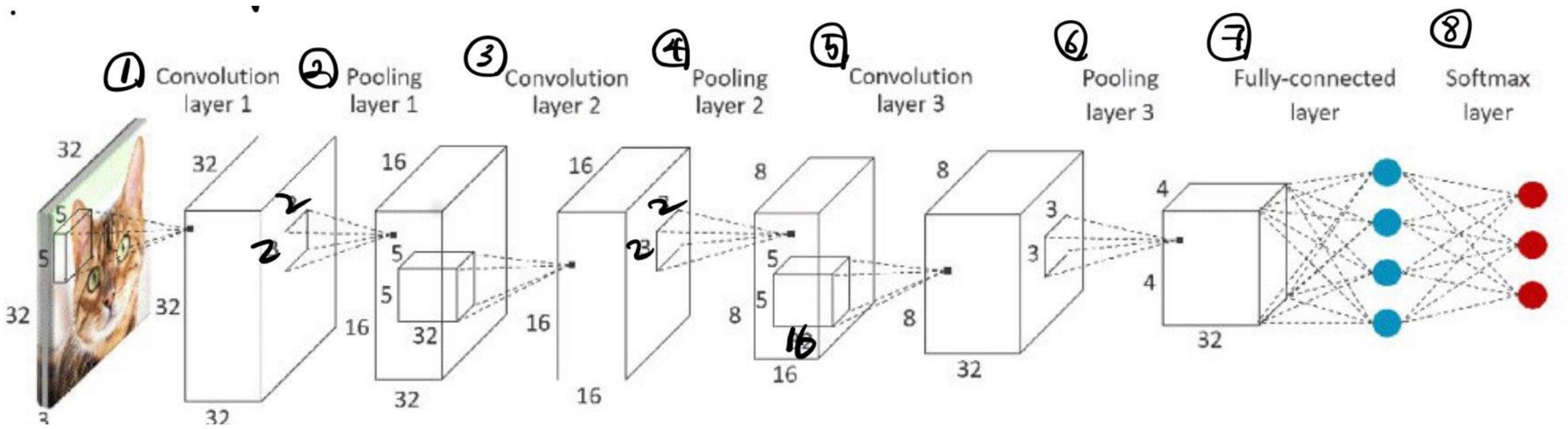
CNN : Pooling

$$O = \frac{I}{Po}$$

O = output size　　I = input size　　Po = pool size

** Generally, Pool Size = Pooling Stride

CNN : Fully-Connected Layer

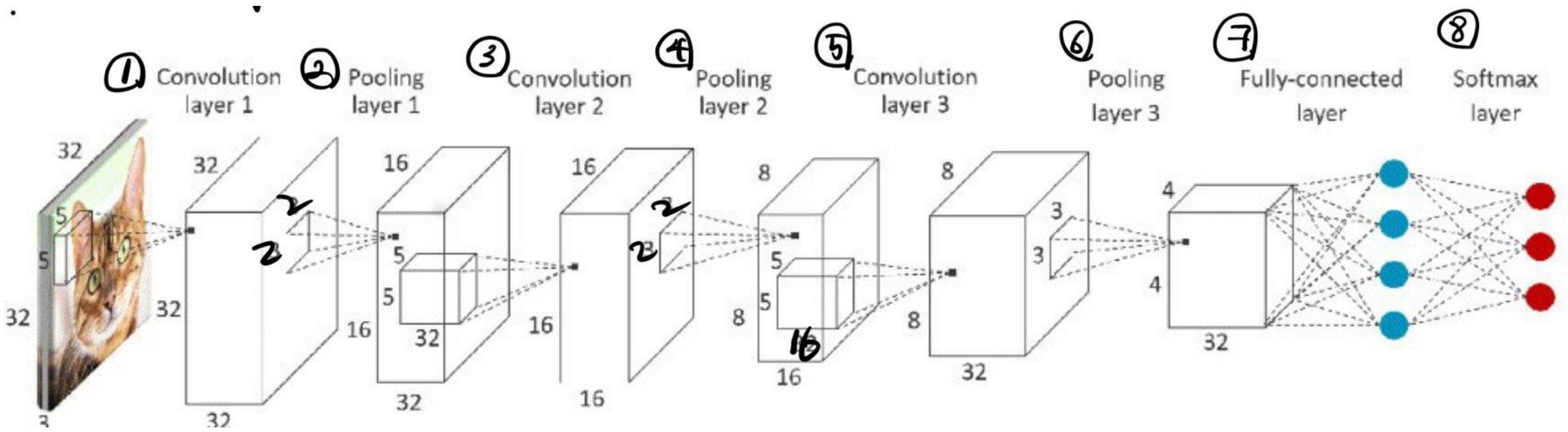


Extract features with **CONV Layers**

Then, reduce dimension with **POOL Layers**

Finally, flatten data and make classification via **FC(Fully-Connected) Layer**

CNN : Architecture



Extract features with **CONV Layers**

Then, reduce dimension with **POOL Layers**

Finally, flatten data and make classification via **FC(Fully-Connected) Layer**

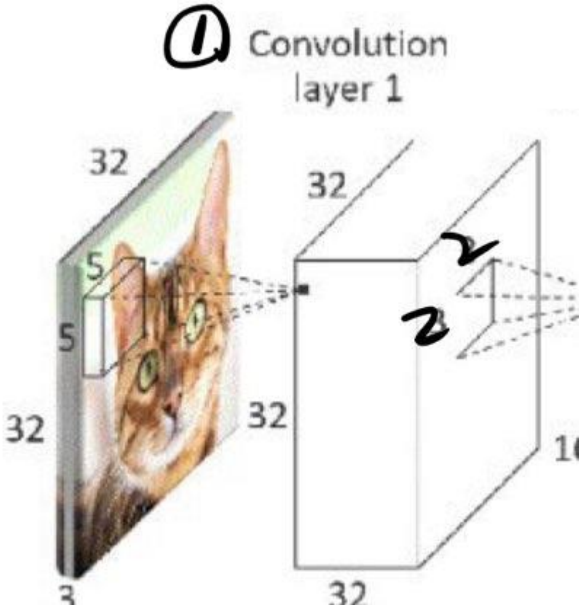
CNN : Architecture

Does it use less parameters than the MLP?

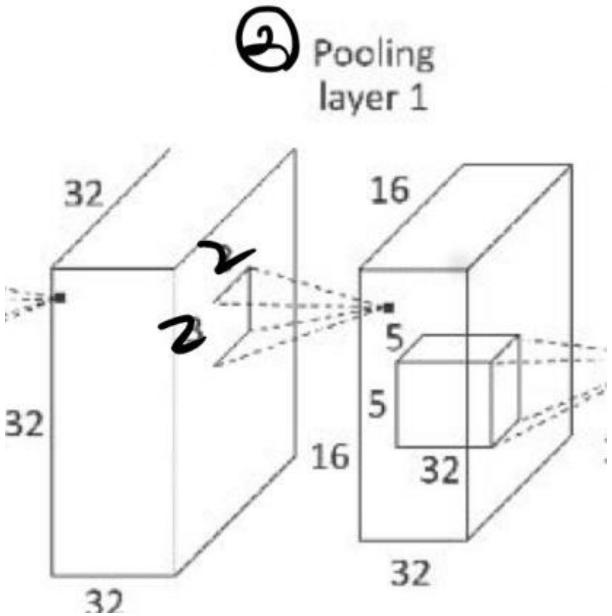
Let’s follow the CNN Architecture and figure it out!!!

CNN : Architecture

CONV1

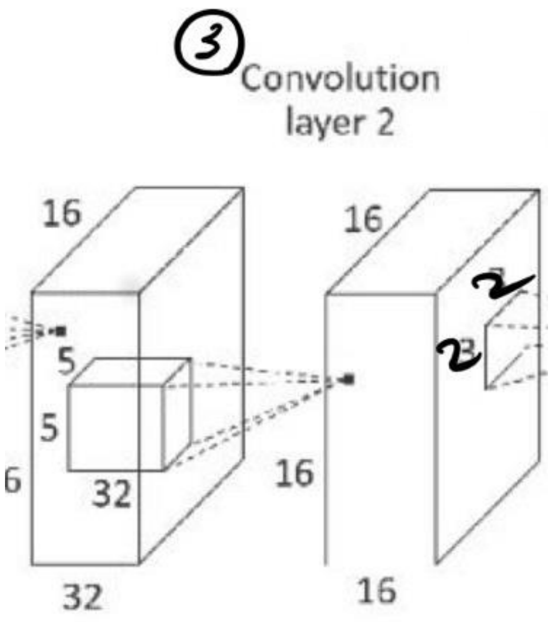


POOL1

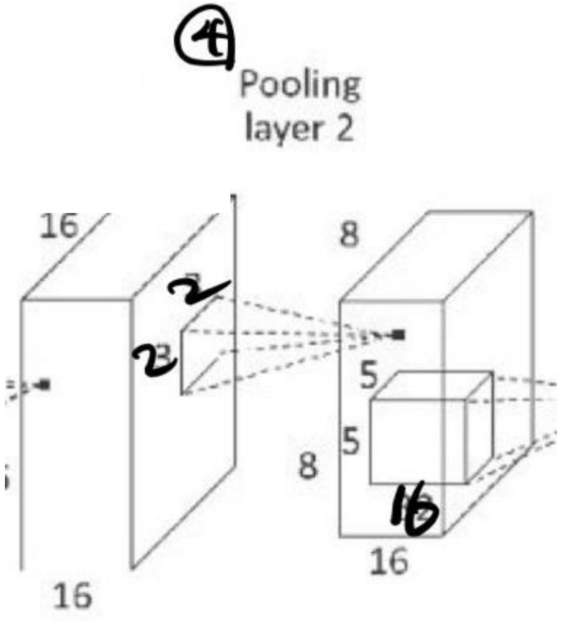


CNN : Architecture

CONV2

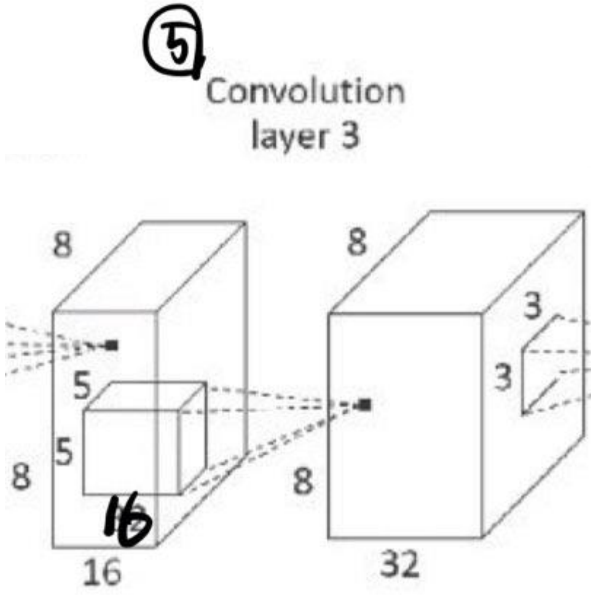


POOL2

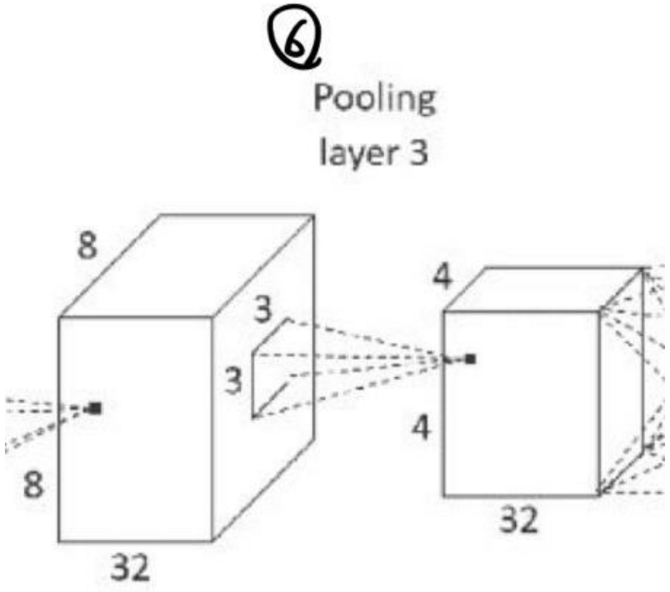


CNN : Architecture

CONV3

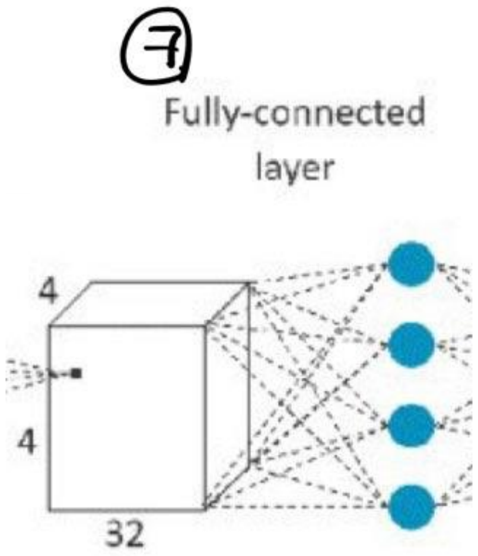


POOL3

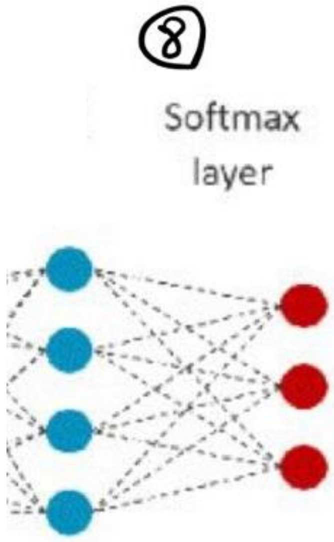


CNN : Architecture

FC



Softmax



CNN : Architecture

Total 33120 Parameters were Used!

CNN : Architecture

However, if we used MLP instead, assuming CONV + POOL as one Hidden Layer,

32 * 32 * 3 → 16 * 16 * 32 → 8 * 8 * 16 → 4 * 4 * 32 → 10

Total 35107840 Parameters were Used!

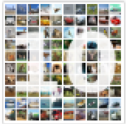
CNN : Architecture

CNN uses much less Parameters than the MLP!!!

CNN : Performance

CIFAR-10

who is the best in CIFAR-10 ?



CIFAR-10 49 results collected

Units: accuracy %

Classify 32x32 colour images.

Result	Method	Venue	Details
96.53 %	Fractional Max-Pooling	arXiv 2015	Details
95.59 %	Striving for Simplicity: The All Convolutional Net	ICLR 2015	Details
94.16 %	All you need is a good init	ICLR 2016	Details
94%	Lessons learned from manually classifying CIFAR-10	unpublished 2011	Details
93.95 %	Generalizing Pooling Functions in Convolutional Neural Networks: Mixed, Gated, and Tree	AISTATS 2016	Details
93.72 %	Spatially-sparse convolutional neural networks	arXiv 2014	
93.63 %	Scalable Bayesian Optimization Using Deep Neural Networks	ICML 2015	
93.57 %	Deep Residual Learning for Image Recognition	arXiv 2015	Details
93.45 %	Fast and Accurate Deep Network Learning by Exponential Linear Units	arXiv 2015	Details
93.34 %	Universum Prescription: Regularization using Unlabeled Data	arXiv 2015	
93.25 %	Batch-normalized Maxout Network in Network	arXiv 2015	Details
93.13 %	Competitive Multi-scale Convolution	arXiv 2015	
92.91 %	Recurrent Convolutional Neural Network for Object Recognition	CVPR 2015	Details
92.49 %	Learning Activation Functions to Improve Deep Neural Networks	ICLR 2015	Details

Classification Rankings :
https://rodrigob.github.io/are_we_there_yet/build/classification_datasets_results.html

CNN : Performance

TensorFlow

Keras

Review

We want a model that,

1. Uses fewer parameters than MLPs

2. Preserves the spatial information

Convolutional Neural Network to the rescue!!!

Preview on Next Lecture(s)

Limitations of MLP

1. Needs a lot of Labeled Data
2. Vanishing Gradient
3. Overfitting
4. Gets stuck in the Local Minima / Saddle Point

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Preview on Next Lecture(s)

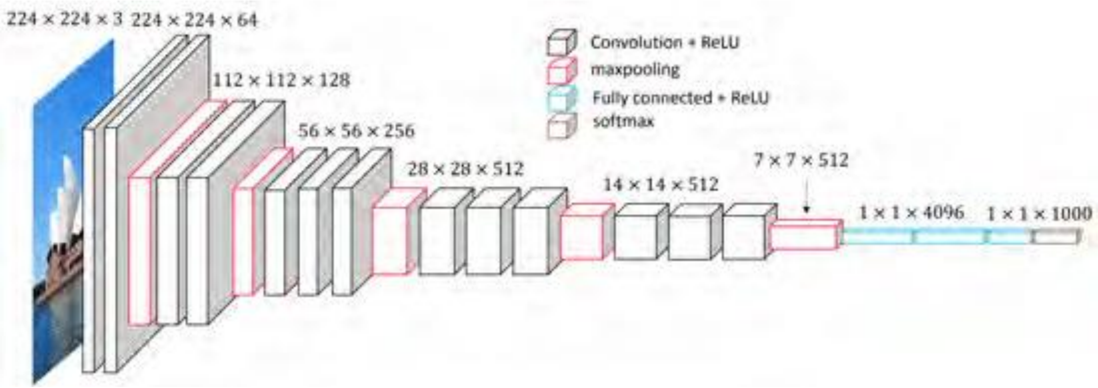

Image from researchgate.net

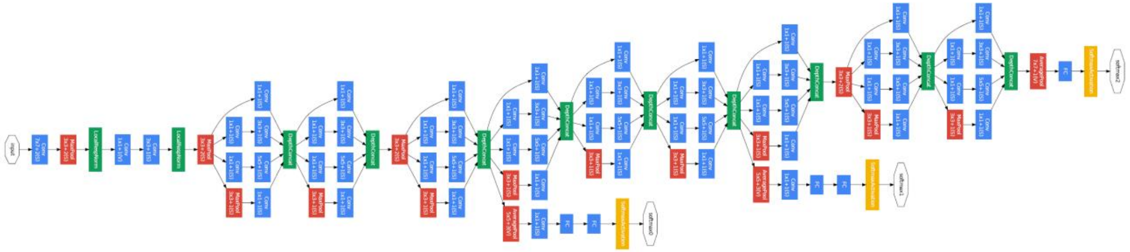

Image from medium.com