Convolutional NN

Introduction

PSIML 8 PRACTICAL SEMINAR IN MACHINE LEARNING 8

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Description

- Process & analyze visual signal
- Extract information from visual signal
- Perform on raw signal (pixel intensities values)

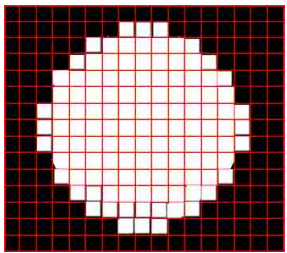
Enhance Intuition

Computer Graphics

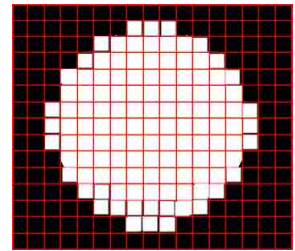
$(x_0, y_0) = (9, 8)$

$r = 7$

$\downarrow$



Computer Vision



$\downarrow$

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Tasks in Computer Vision

- Object Recognition
- Image Retrieval
- Object Detection
- OCR
- Pose Estimation
- ...

- Tracking
- Scene Reconstruction
- Optical Flow
- Semantic Segmentation
- Image Reconstuction
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Convolution Operator - Definition

Let $A, B \in \mathcal{D} \subseteq \mathbb{R}^{n \times n}$. Convolution operator, denoted as $*$ maps the space $\mathcal{D} \times \mathcal{D}$ to a field of real numbers and is defined as follows:

$$A * B = \sum_{i=1}^{n} \sum_{j=1}^{n} A_{ij} B_{ij}$$

Convolution Operator - Example

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} * \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

Convolution Operator - Example

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} * \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} = 2 * 1 + 4 * 1 + 6 * 1 + 8 * 1 = 20$$

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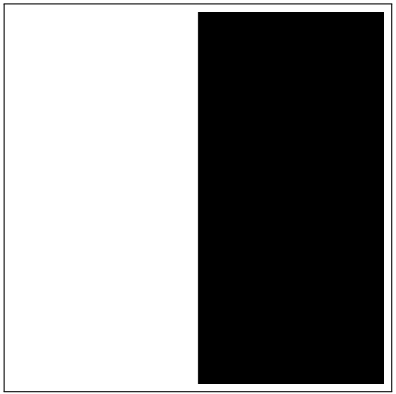
Filters

$$\begin{bmatrix} 211 & 39 & 200 & 102 & 174 & 25 & 90 & 144 \\ 138 & 44 & 184 & 110 & 193 & 30 & 92 & 136 \\ 151 & 73 & 190 & 114 & 189 & 41 & 105 & 128 \\ 129 & 101 & 123 & 181 & 201 & 169 & 117 & 191 \\ 140 & 122 & 153 & 231 & 209 & 157 & 124 & 113 \\ 221 & 115 & 77 & 244 & 198 & 149 & 156 & 247 \end{bmatrix} * \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

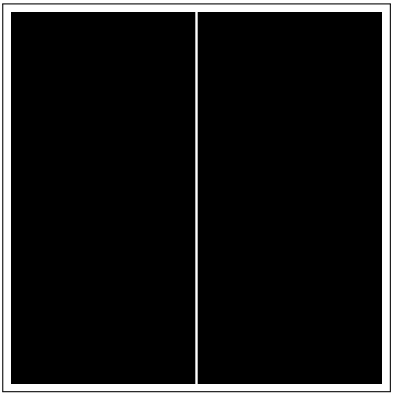
Filters - Examples

- Vertical Edge Extractor
- Horizontal Edge Extractor
- Sobel filter
- Sharpen
- Gaussian Blur

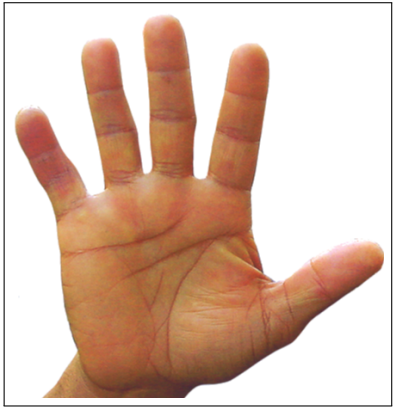
Filters - Edge Extractor



$$* \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} =$$

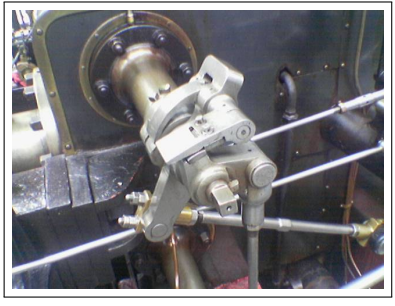


Filters - Edge Extractor

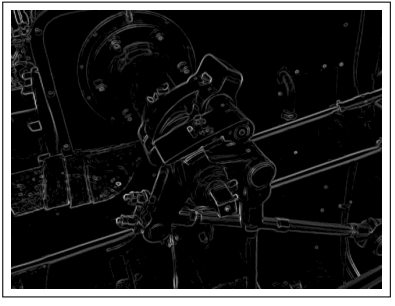


$$* \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix} =$$

Filters - Sobel



$$* \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} =$$



Filters - Gaussian Blur

$$* \frac{1}{256} \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix} =$$

Multiple Input Channels

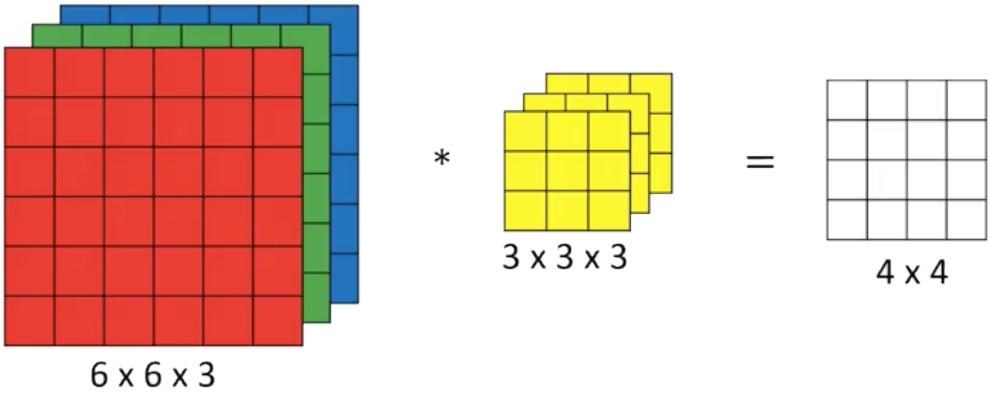
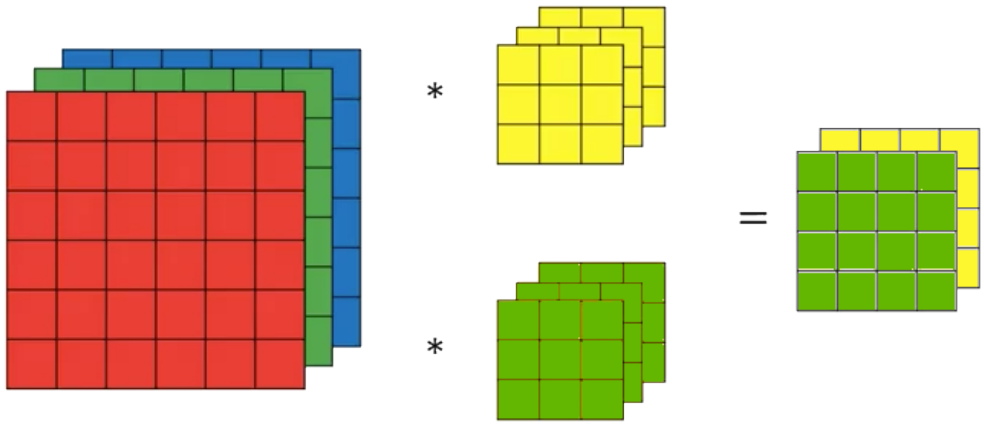


Figure: Convolution of multichannel image

Multiple Filters



Basic Concepts

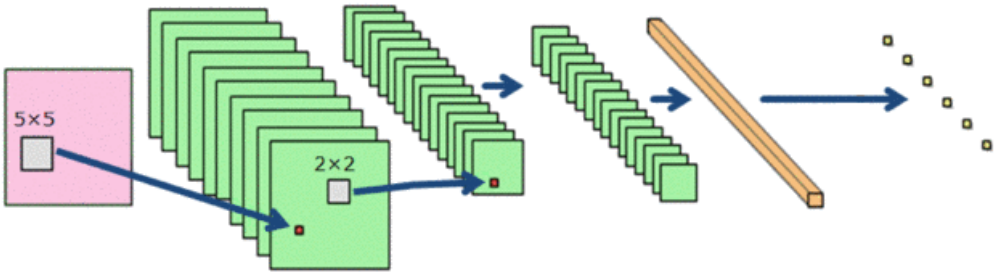


Figure: Convolutional layers stacked

Basic Concepts - Takeaway

- Image Classification
- Parameters (filters) Learning [LBD+89]
- Weight Sharing
- Feature Extraction
- Translation invariant

Basic Concepts - Feature Abstractions

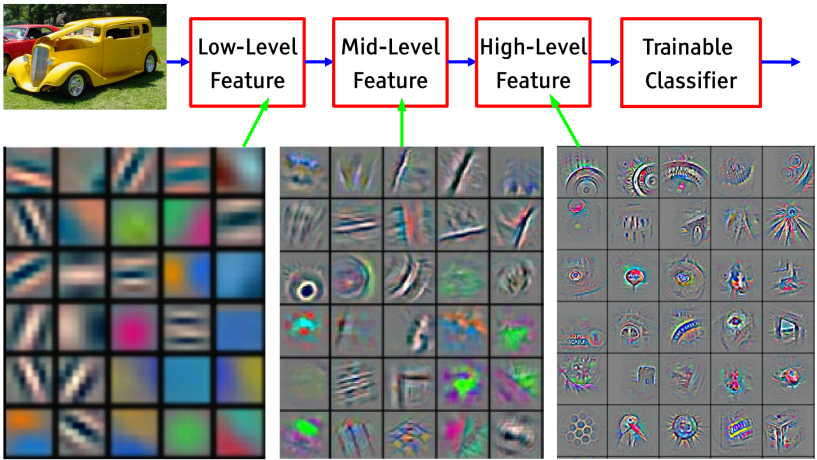


Figure: Feature Visualization [ZF13]

Basic Concepts - Pooling Layers

- Sampling important Features
- Reduce Computation Time
- Make Features Robust

Basic Concepts - Pooling Layers (Example)

Pooling Layer - Max Pooling

$$\begin{bmatrix} 9 & 2 & 4 & 1 \\ 3 & 1 & 8 & 2 \\ 4 & 5 & 9 & 2 \\ 5 & 6 & 0 & 1 \end{bmatrix} \longrightarrow \begin{bmatrix} 9 & 8 \\ 6 & 9 \end{bmatrix}$$

Basic Concepts - Architecture

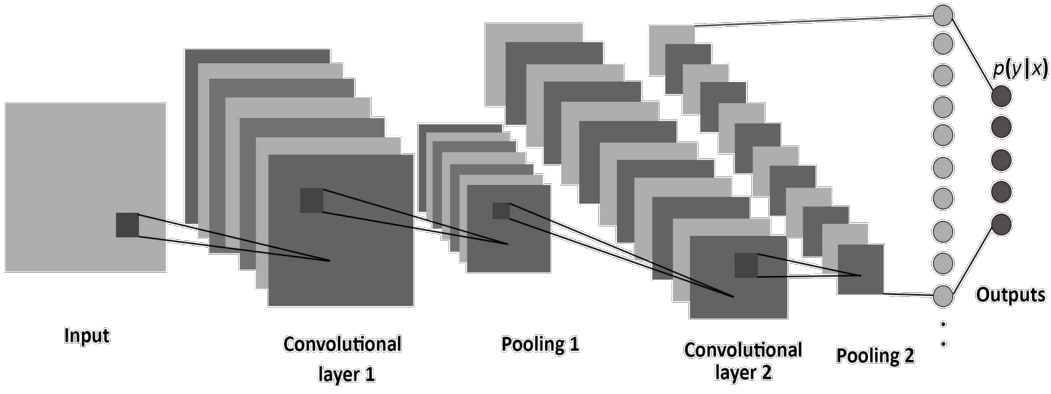


Figure: Convolutional Neural Network - Example

CNN Architecture - Lenet-5

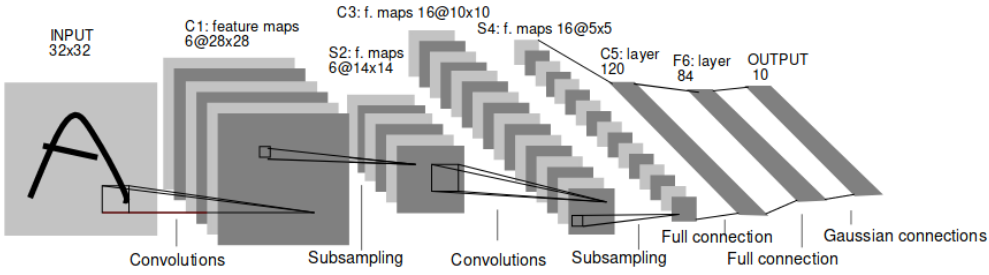


Figure: Lenet-5 Architecture [LBBH98]

CNN Architecture - AlexNet

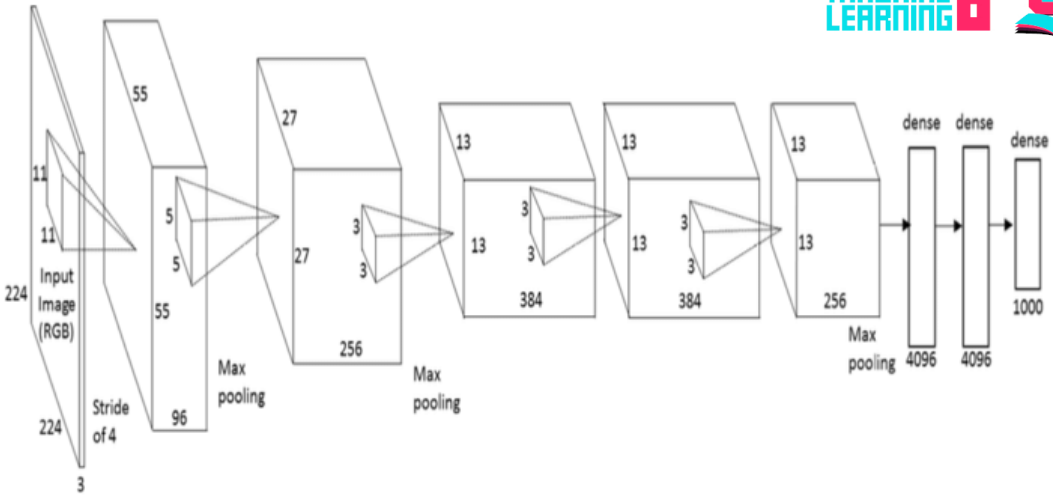


Figure: AlexNet Architecture [KSH12]

CNN Architecture - VGG

Figure: VGG Architecture

CNN - Problems

- Vanishing Gradient
- Exploding Gradient
- Computational Complexity

Residual Block

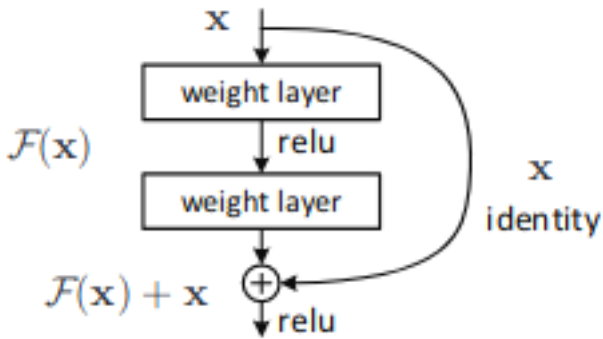


Figure: Residual Block (Skip Connection) [HZRS15]

Residual Network

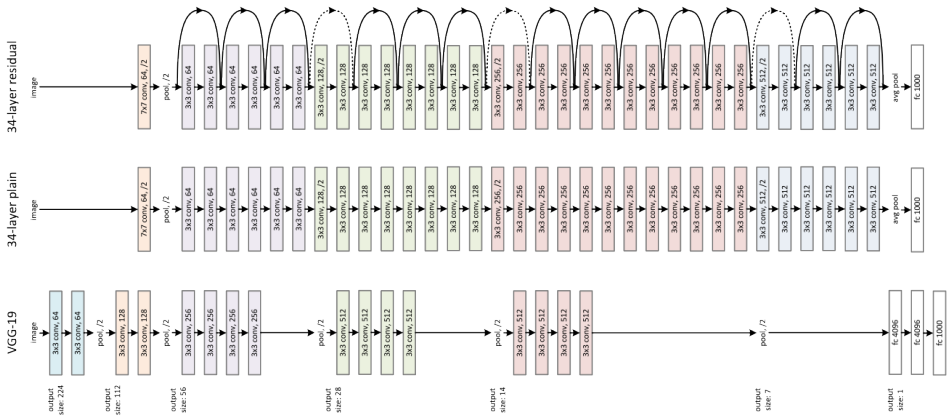


Figure: CNN Architecture - ResNet-34 [HZRS15]

1x1 Convolution

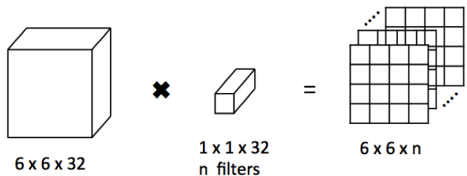


Figure: 1x1 Convolution [LCY13]

Inception Module - Idea

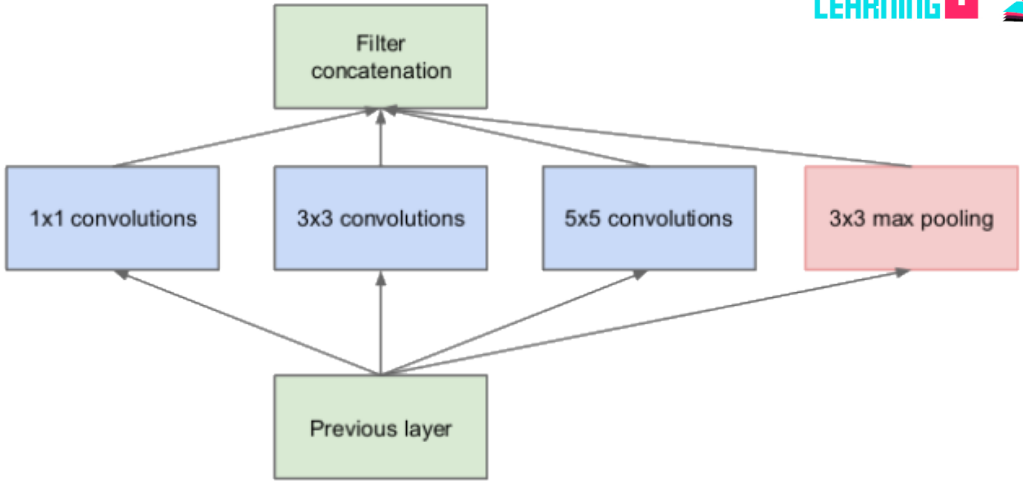


Figure: Inception Module Naive Version [SLJ+14]

Inception Module - Redone

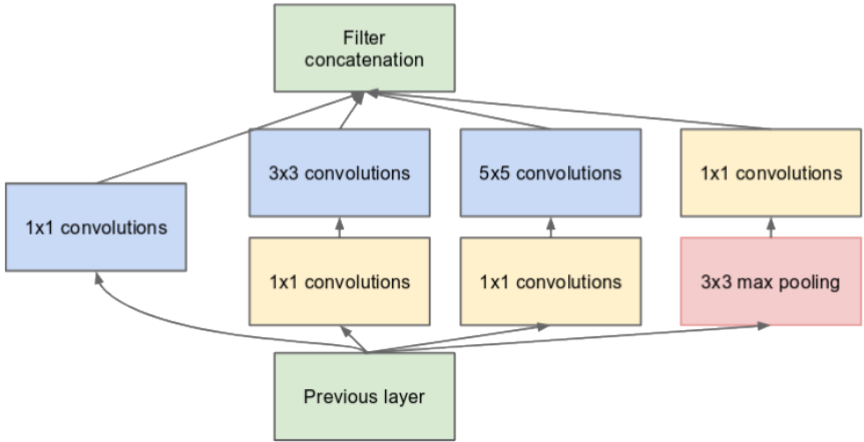


Figure: Inception Module With Dimension Reduction [SLJ+14]

Inception Network

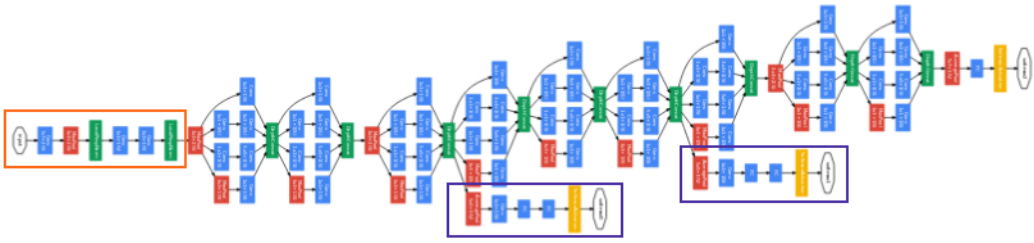


Figure: Inception Network (GoogLeNet) [SLJ+14]

CONVERGENCE

References I

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References II

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