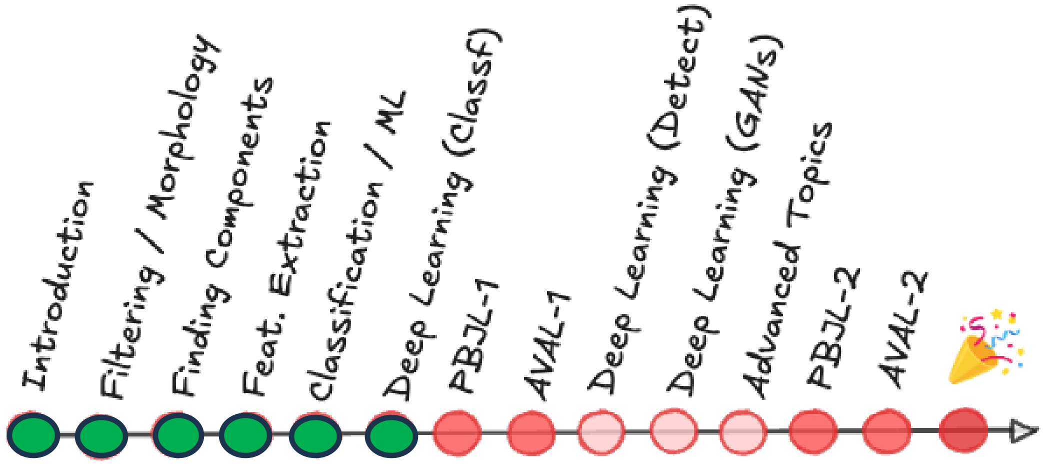
Lecture 06 – Deep Learning and CNNs

Prof. André Gustavo Hochuli

gustavo.hochuli@pucpr.br
aghochuli@ppgia.pucpr.br

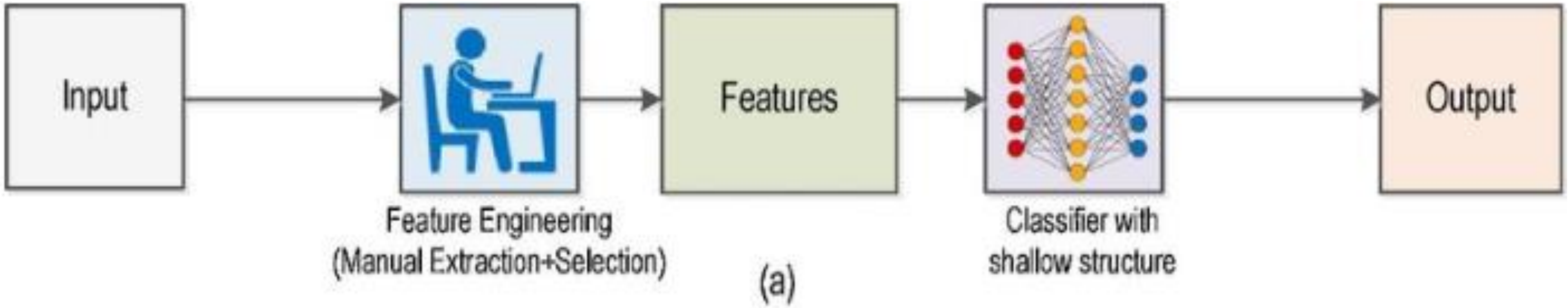
Topics

- Traditional vs Deep Learning Neural Network
  - Feature Engineering, The Curse of Dimensionality
  - Multi-Layer Perceptron & Kernel-Based Descriptors
- Deep Learning
  - Introduction to Convolutional Neural Networks
- Coding

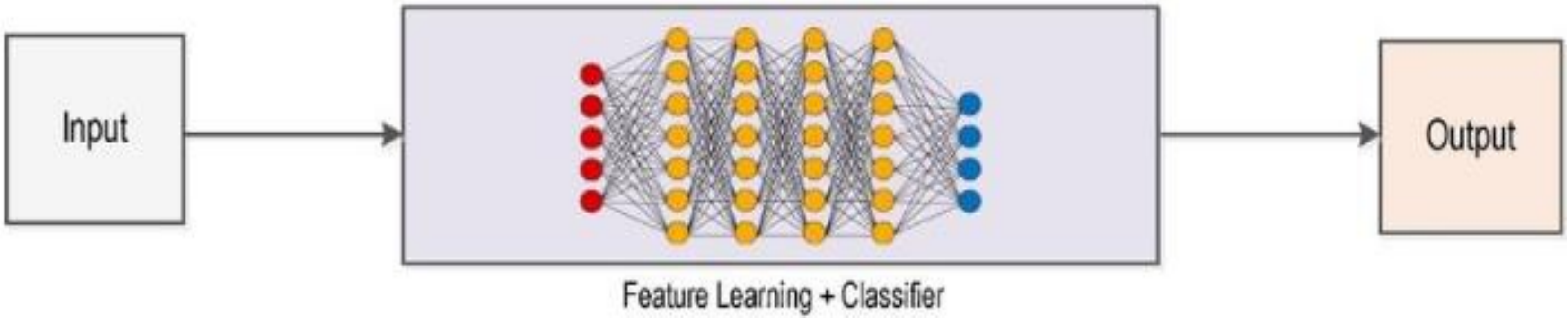


Traditional and Deep Learning

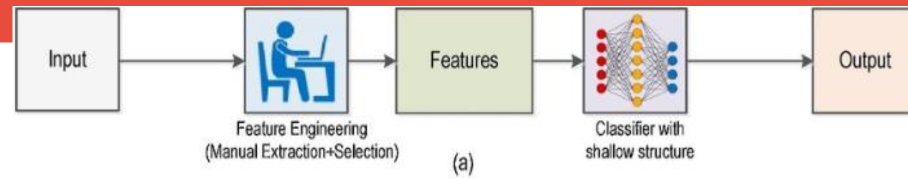
- Traditional (“Shallow”)

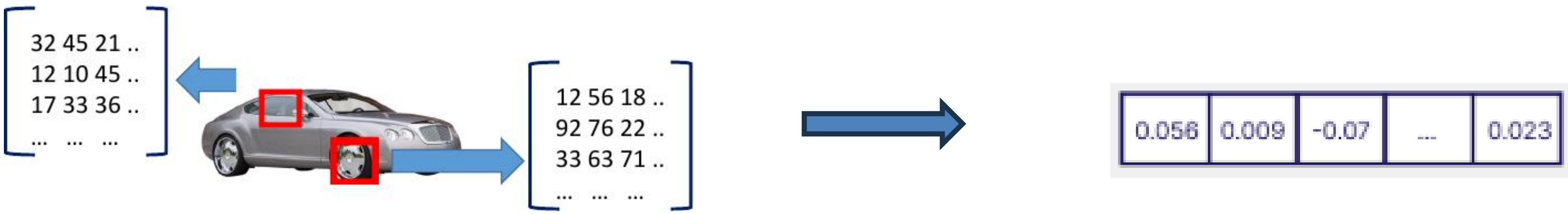


- Deep

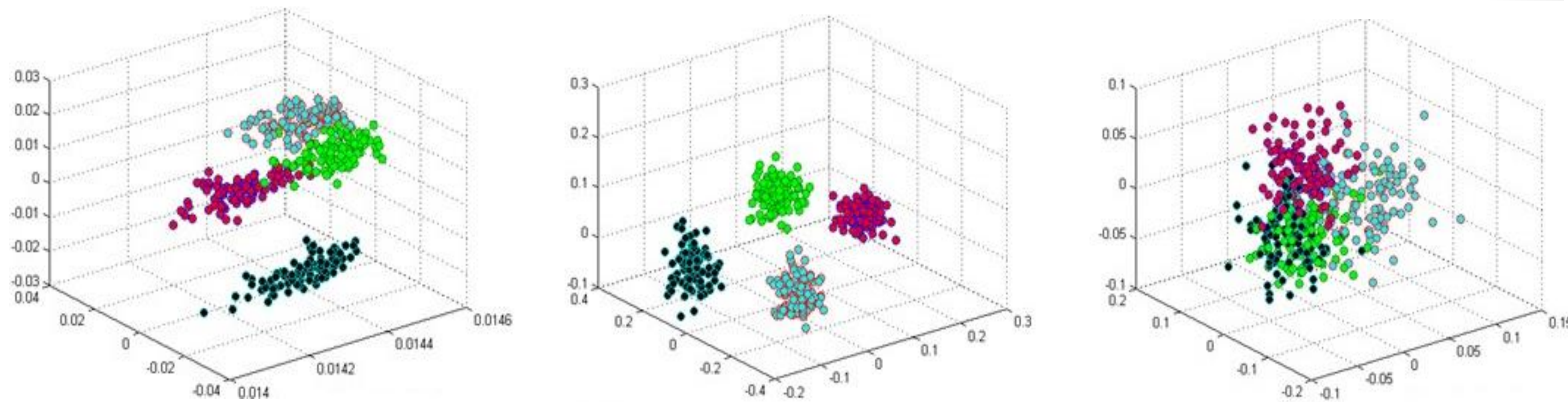


“Shallow” Learning



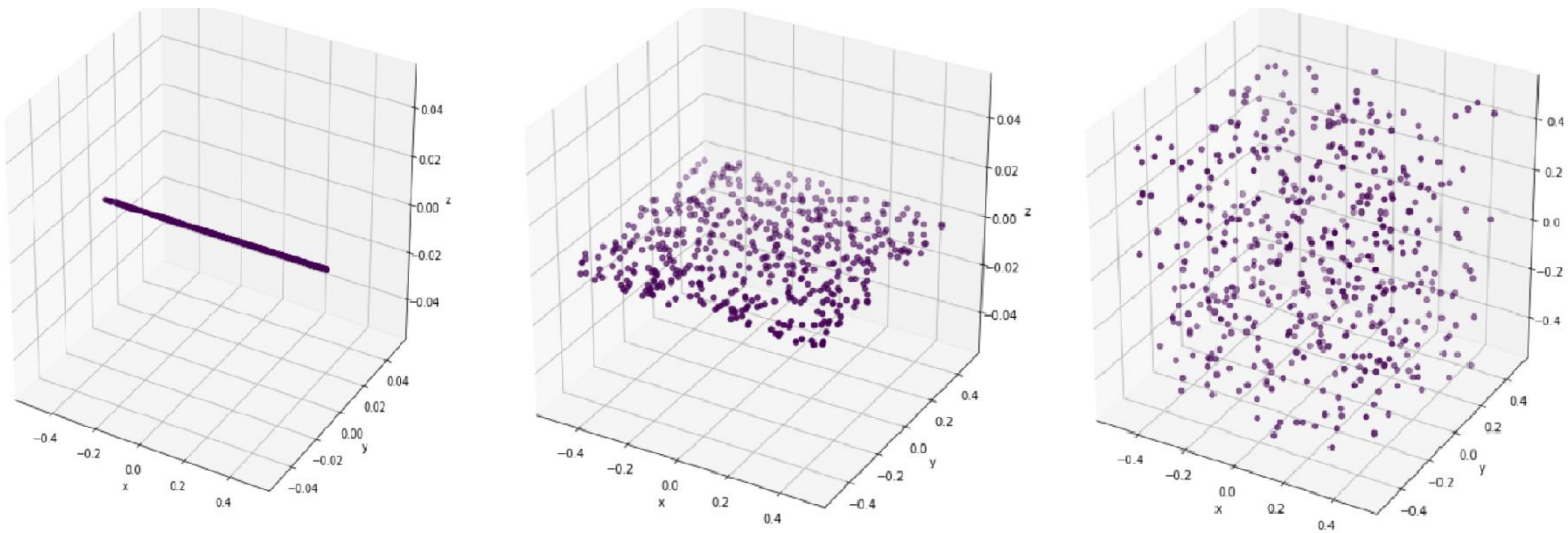


How to effectively capture discriminative features from images?



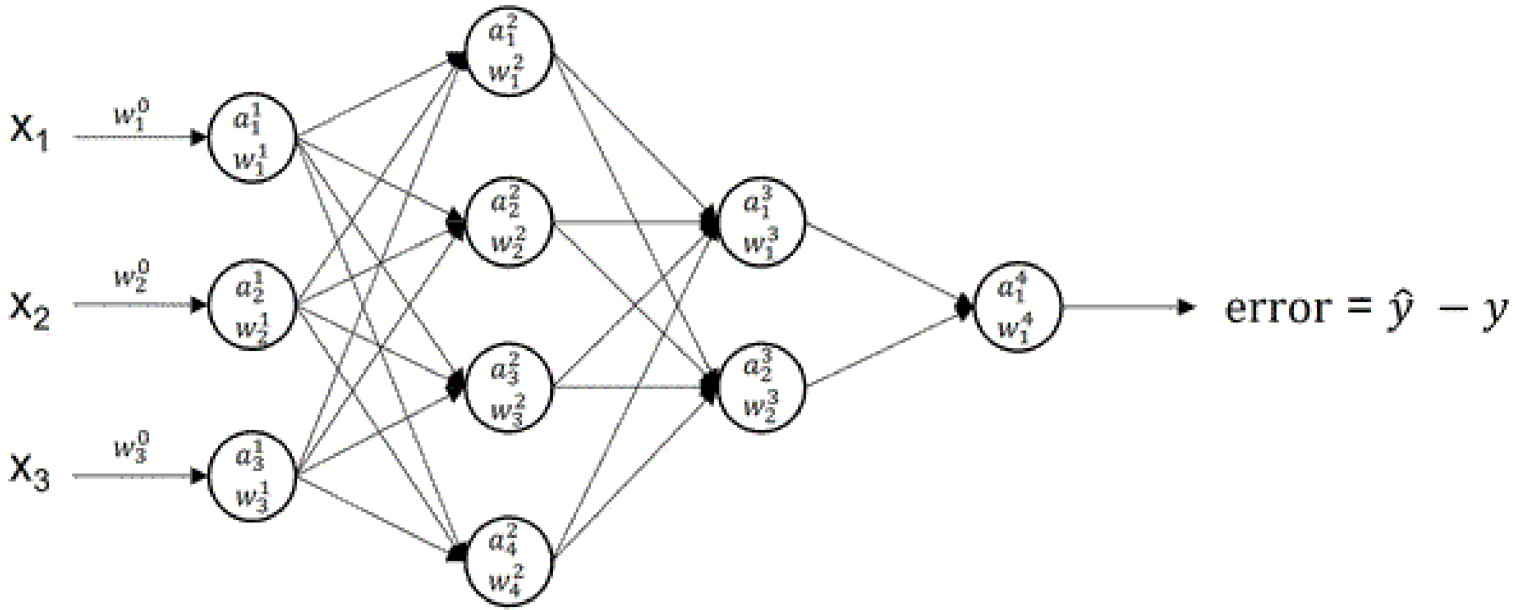
The Curse of Dimensionality

- Most of us have very reasonable intuition that more information in terms of features (dimensions) is always better. **<u>Is this always true?</u>**
  - **Exponential Growth of Feature Space** → sparsity increases
  - **Distance Metrics Lose Meaning** → similarity becomes unreliable
  - **More Data Needed** → exponential increase in samples
  - **Risk of Overfitting** → noise dominates patterns
  - **Mitigation** → feature selection, PCA, autoencoders



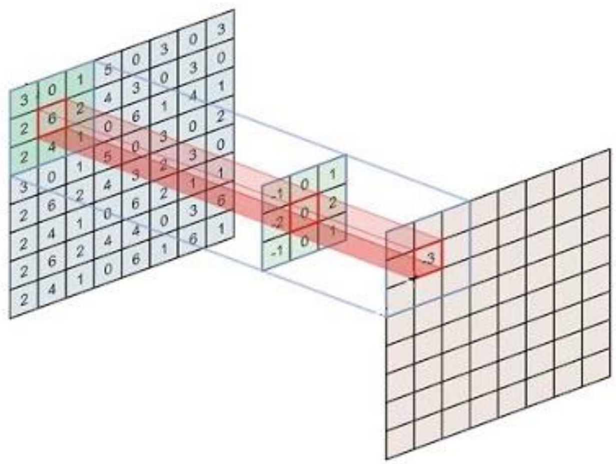
Multi-Layer Perceptron: Recap

- Features
- Weights
- Feedforward
- Error Backpropagation

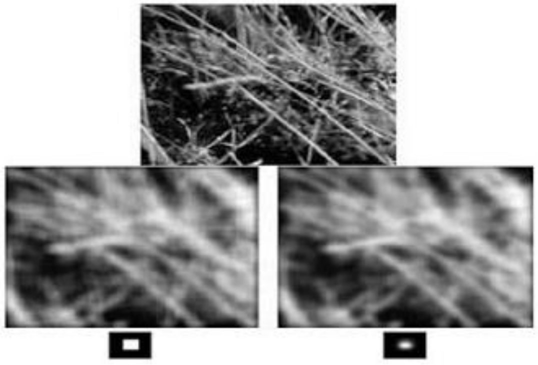


Kernel-based Descriptors: Recap

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9



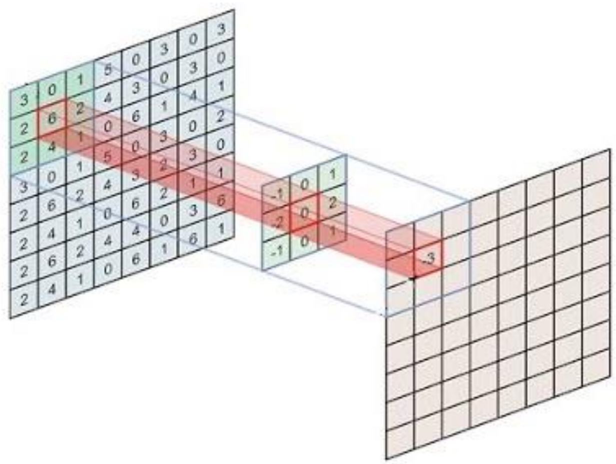
$$x * y = \sum_{i=1}^{m}\sum_{j=1}^{n} x_{(m-i)(n-j)}\, y_{(i)(j)}$$



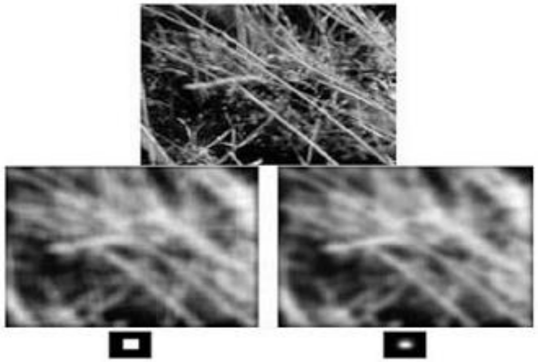
Kernel-based Descriptors: Recap

- Why not extend weight optimization to learning kernels (features)?

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

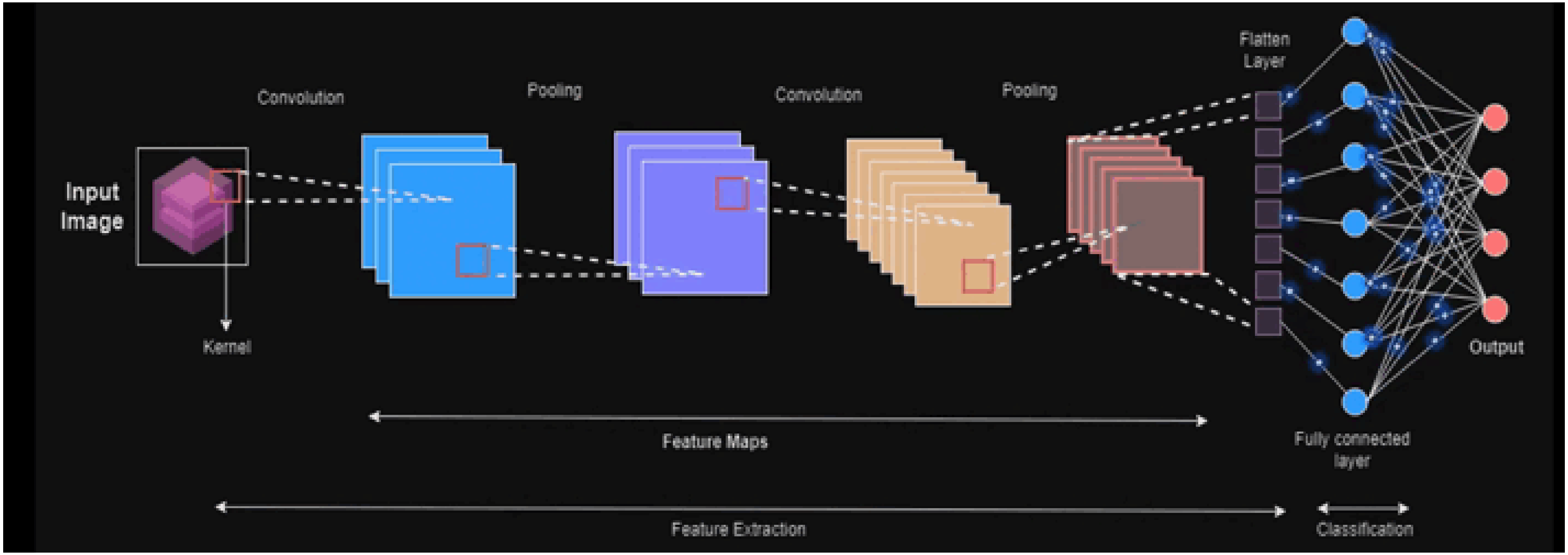


$$x * y = \sum_{i=1}^{m} \sum_{j=1}^{n} x_{(m-i)(n-j)} y_{(i)(j)}$$



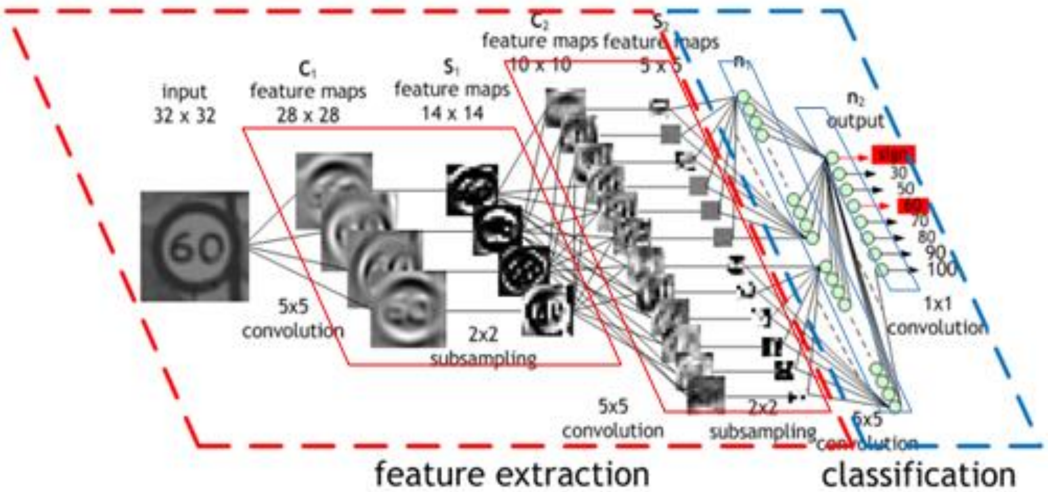
Deep Learning

- <u>Why not extend weight optimization to learning kernels (features)?</u>

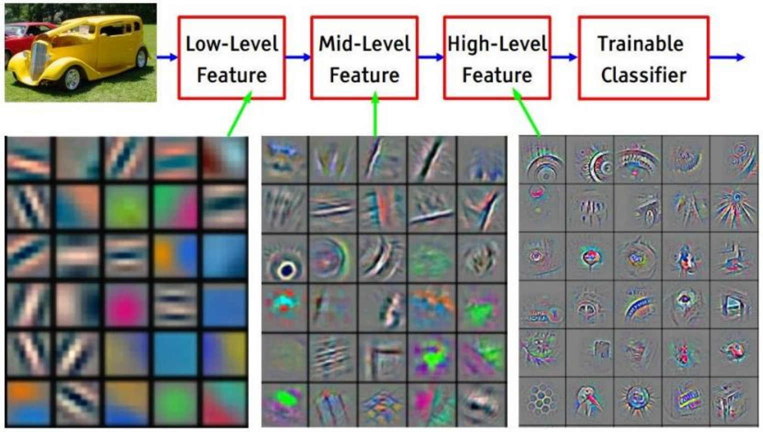


Convolutional Neural Networks

- Feature Extraction
  - Sequential Convolutional Layers
  - Learnable Descriptors (Kernels)
  - Activation Functions (ReLU)
  - Pooling Layers

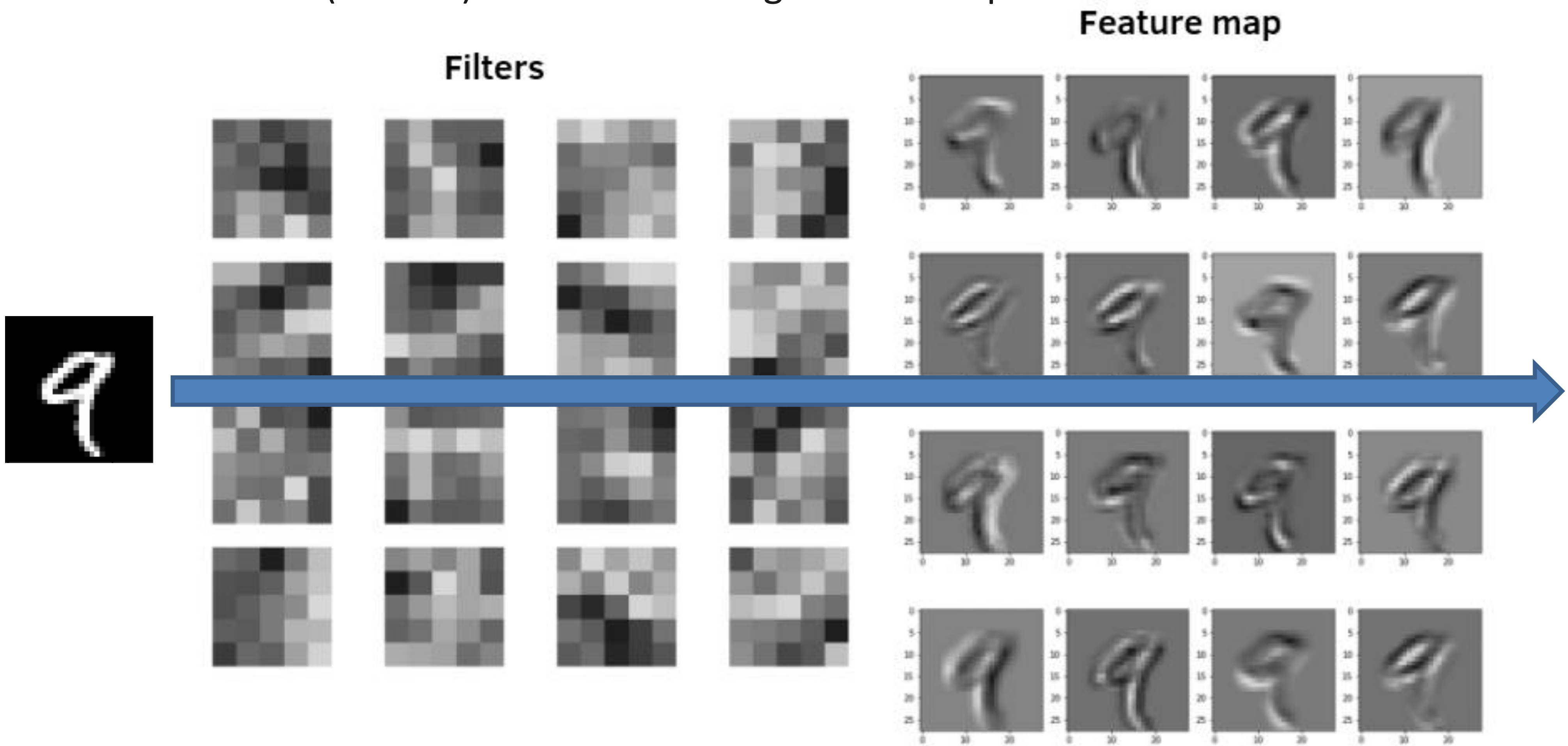


- Classification
  - Fully-Connected Layers
  - SVM
  - ....



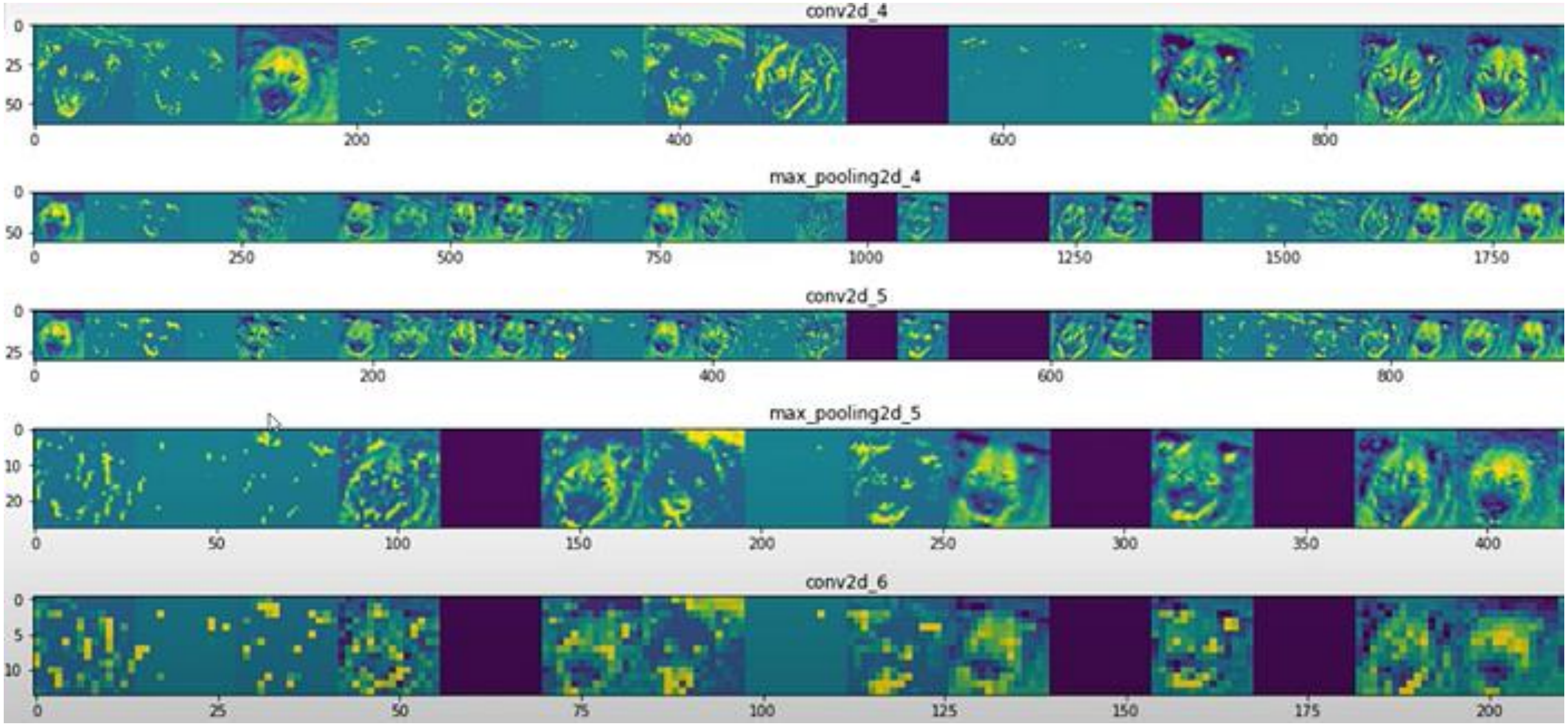
Convolutional Neural Networks

- Learned Filters (Kernels) and The Resulting Feature Map



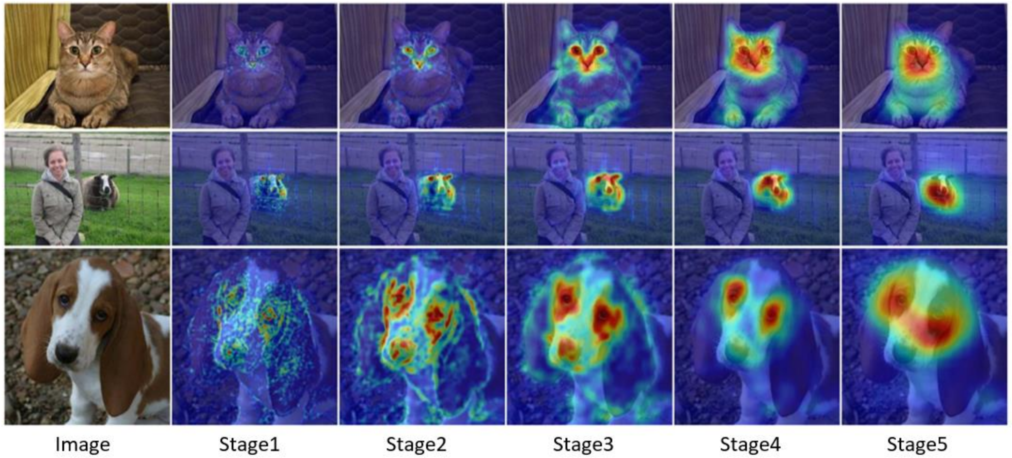
Convolutional Neural Networks

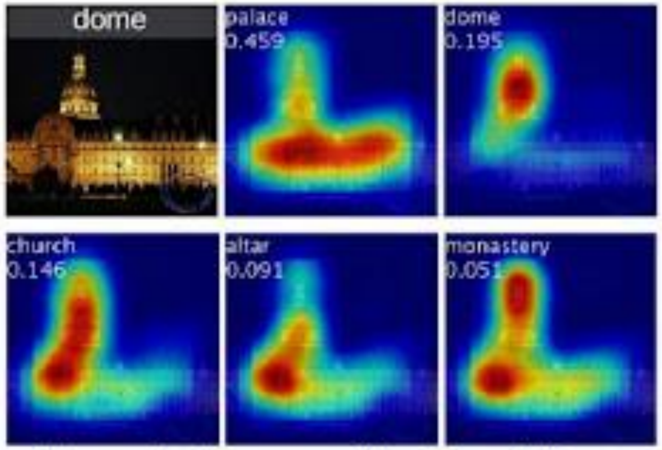
- Feature Maps



Convolutional Neural Networks

- Activations Maps



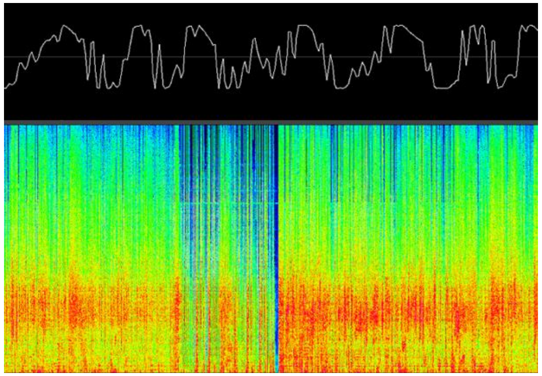


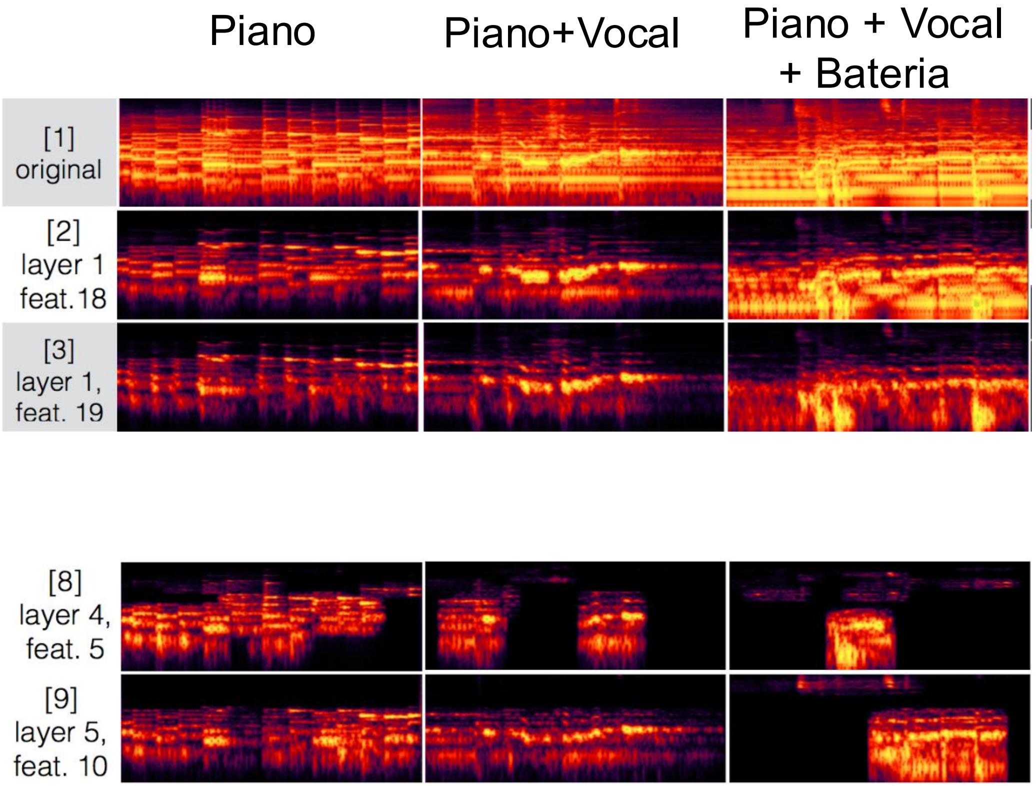
Class activation maps of top 5 predictions

Class activation maps for one object class

Convolutional Neural Networks

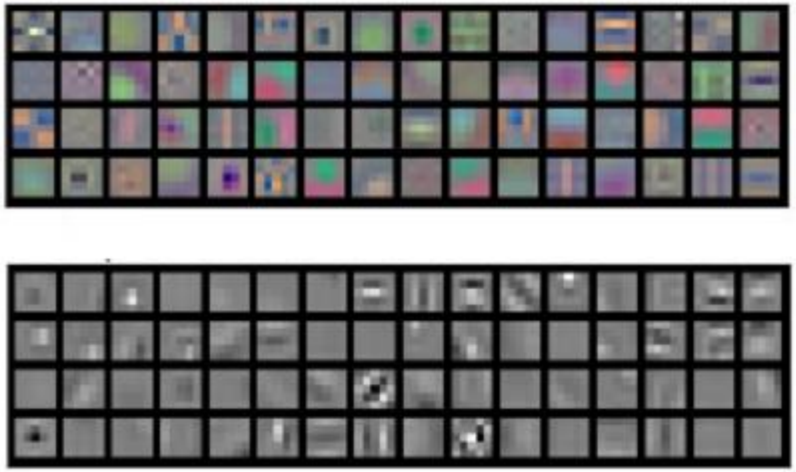
- Wide applied in the Computer Vision area (audio, images, video processing, etc.).





Convolutional Neural Networks

- Tissue Classification
- Medical Images



Convolutional Neural Networks

- Face

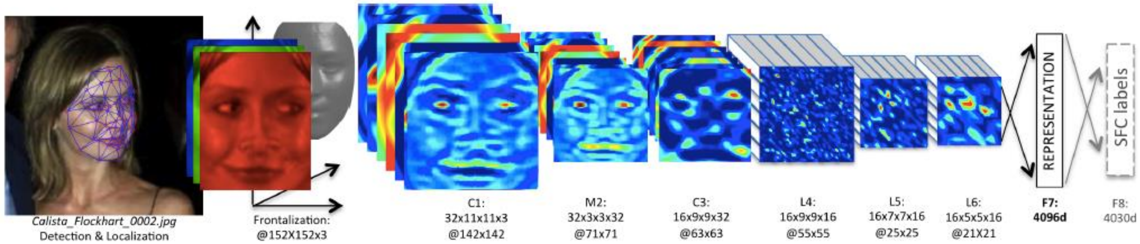
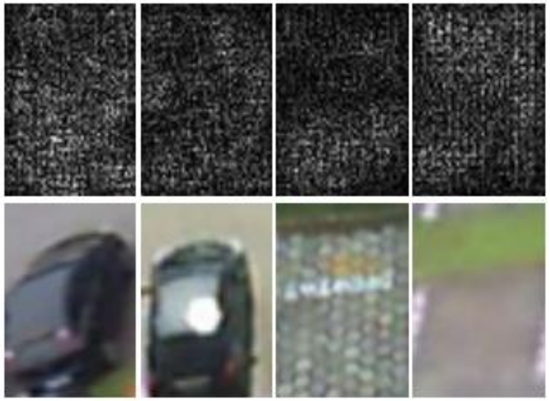


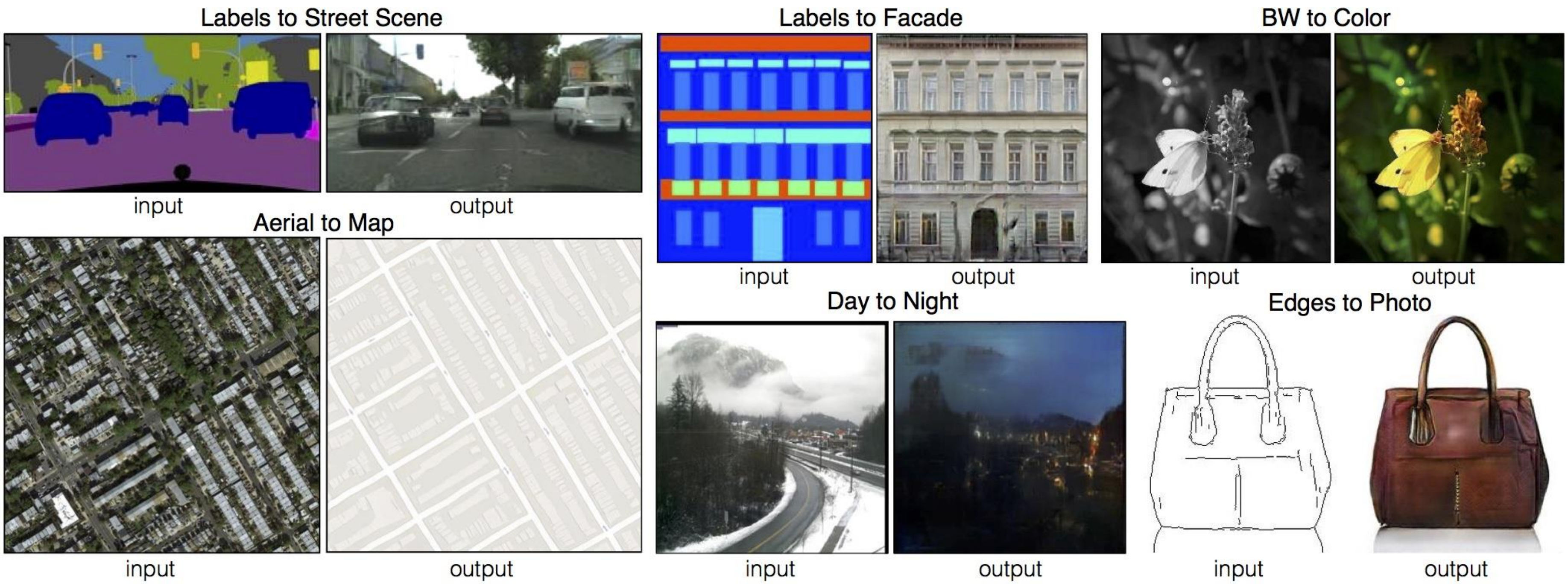
Figure 2. **Outline of the *DeepFace* architecture.** A front-end of a single convolution-pooling-convolution filtering on the rectified input, followed by three locally-connected layers and two fully-connected layers. Colors illustrate outputs for each layer. The net includes more than 120 million parameters, where more than 95% come from the local and fully connected layers.

- PKLot



Convolutional Neural Networks

- Image Translation



Convolutional Neural Networks

- Deep Fakes

https://www.youtube.com/watch?v=mUfJOQKdtAk

Convolutional Neural Networks

Pros

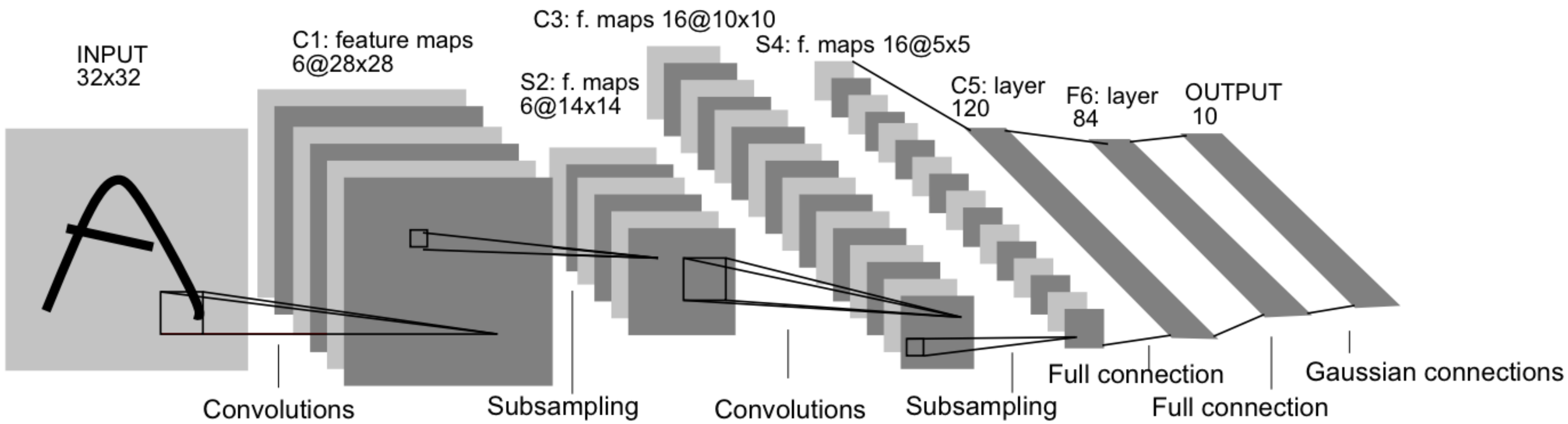
- Enables learning of features rather than hand tuning
- Impressive performance gains on
  - Computer vision
  - Speech recognition
  - Some text analysis
- Potential for much more impact

Cons

- Computationally really expensive
- Requires a lot of data for high accuracy
- Extremely hard to tune
  - Choice of architecture
  - Parameter types
  - Hyperparameters
  - Learning algorithm
  - …
- Computational + so many choices = incredibly hard to tune

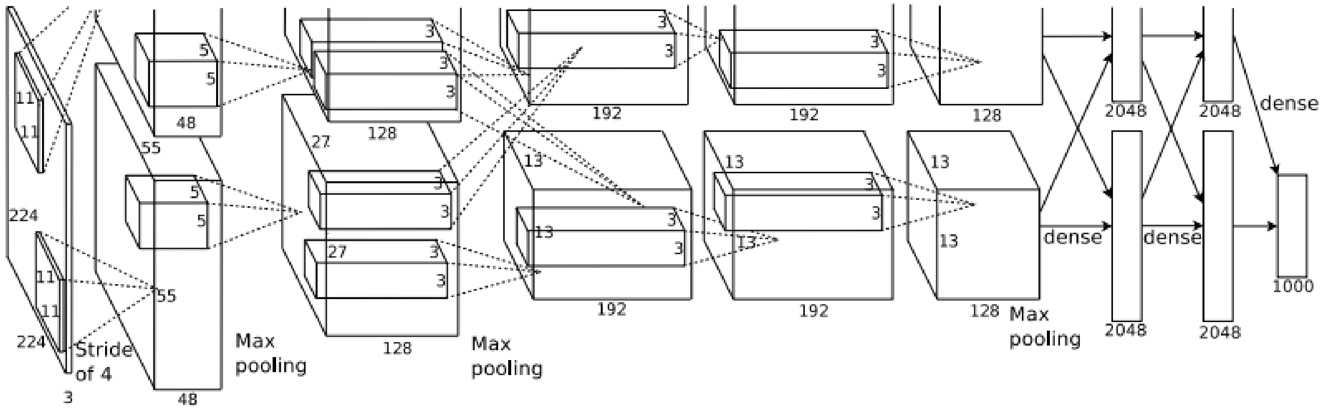
Convolutional Neural Networks

- Lenet
  - Yan Lecun – 90´s (Bell Labs / IBM / FACEBOOK)
  - Handwritten Digits
  - ~60 **K** Parameters
  - ~345 **K** Connections



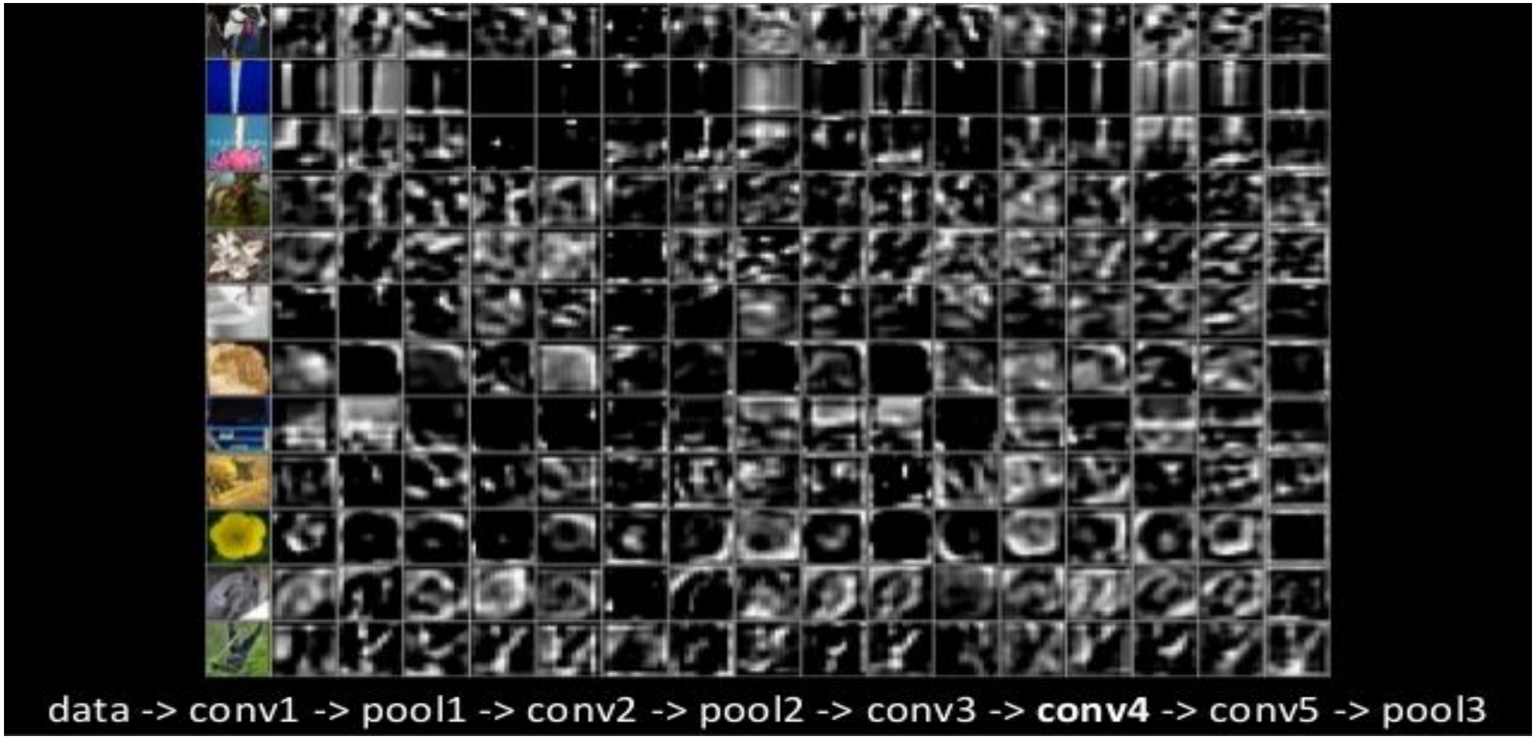
Convolutional Neural Networks

- AlexNet
  - Alex Krizhevsky – 2012 (Krizhevsky Net)
  - Imagenet 2012 Challenge (1000 classes)
    → 1.2 M Train, 50K Val, 150K Test
  - 2012 Winner (15.3% Error - Top 5)
    → 2° SIFT Based (26.2%)



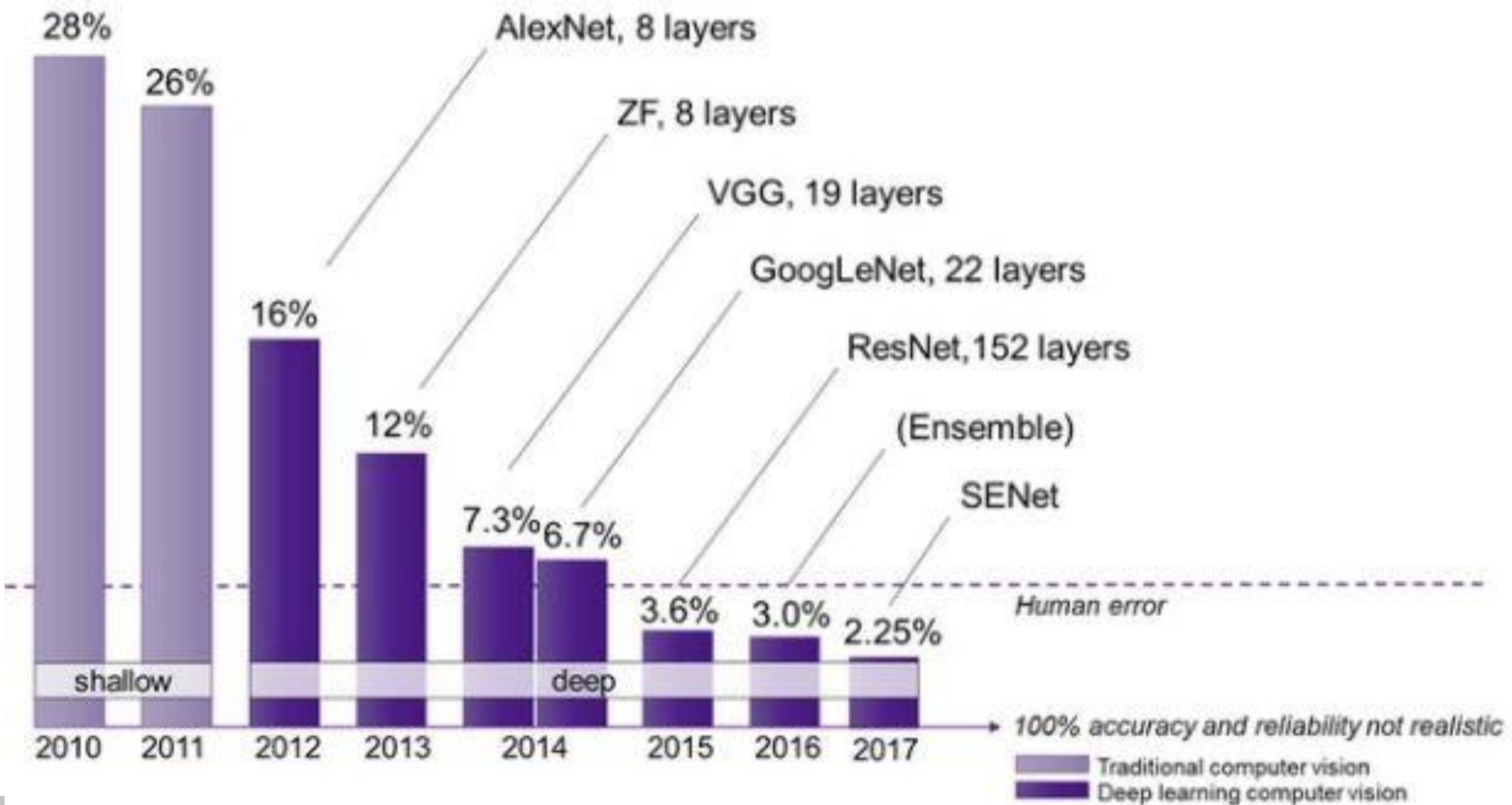
Convolutional Neural Networks

- Alexnet



Imagenet Challenge

- Imagenet Challenge (Classification)
  - 1000 classes
  - 1.2 M Train
  - 50K Val
  - 150K Test



Let's Code

- [LINK]