Lecture 06 – Deep Learning and CNNs

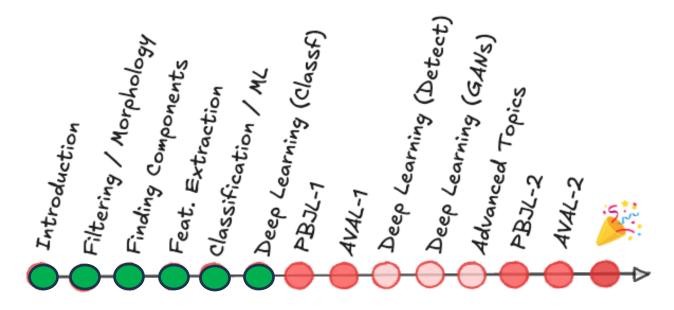
Prof. André Gustavo Hochuli

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Topics

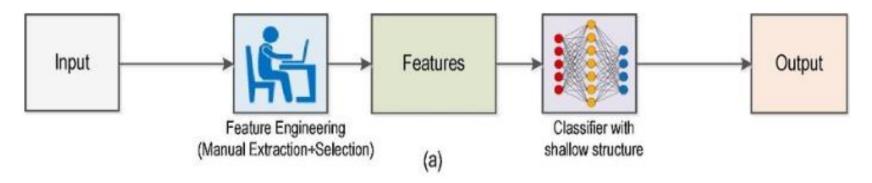
Deep Learning

- TradicConvolutional Neural Network
 - Lenet
 - Imagenet
 - Deep Networks
- Practice

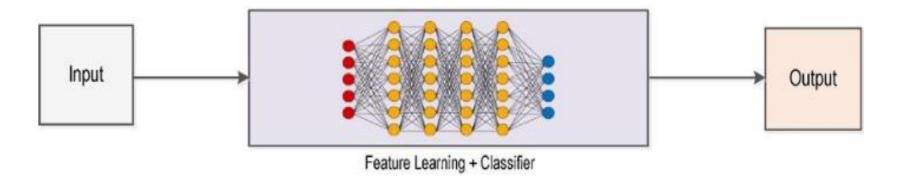


Traditional and Deep Learning

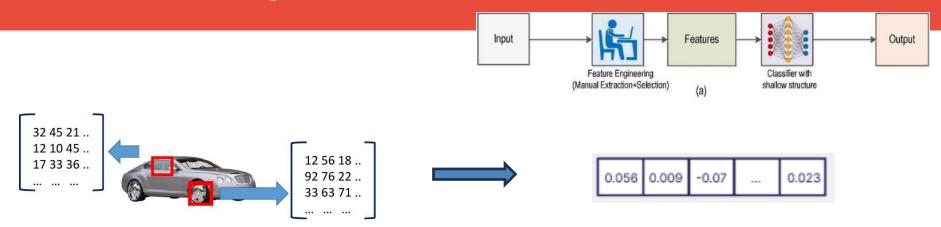
Traditional ("Shallow")



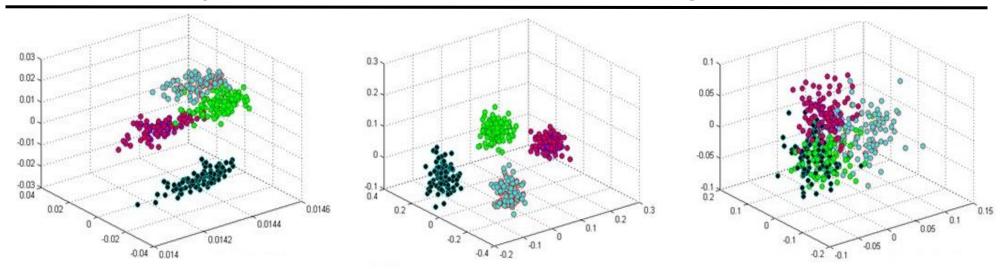
Deep



"Shallow" Learning

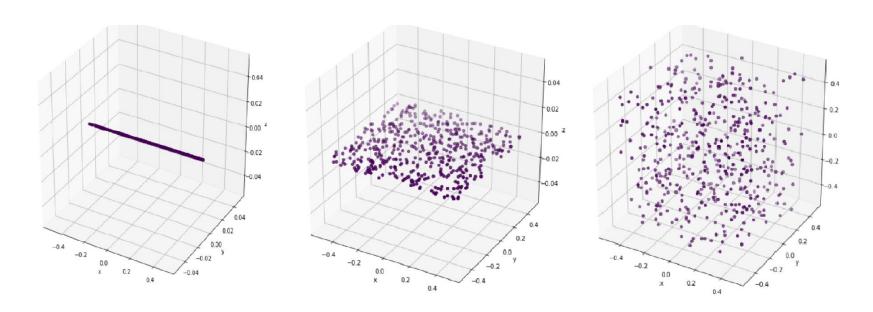


How to effectively capture discriminative features from images?



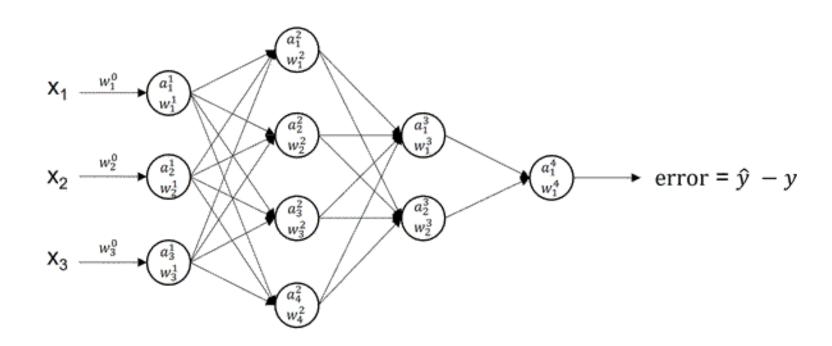
The Curse of Dimensionality

- 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



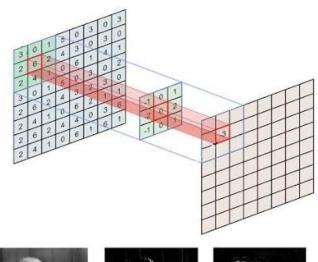
Multi-Layer Perceptron: Recap

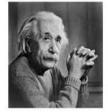
- Features
- Weigths
- FeedForward
- Error and BackPropagation



Kernel-based Descriptors: Recap

w_1	w_2	w_3
w_4	w_5	w ₆
w ₇	w ₈	w ₉

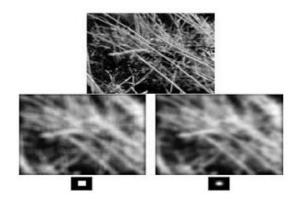








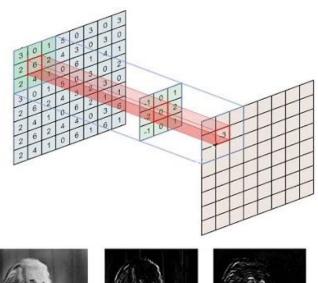
$$x * y = \sum_{i=1}^{m} \sum_{j=1}^{n} x_{(m-i)(n-j)} y_{(i)(j)}$$



Kernel-based Descriptors: Recap

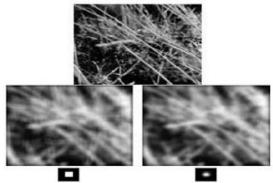
Why not extend weight optimization to learning kernels (features)?

w_1	w_2	<i>w</i> ₃
w_4	w_5	w ₆
w_7	w ₈	w ₉



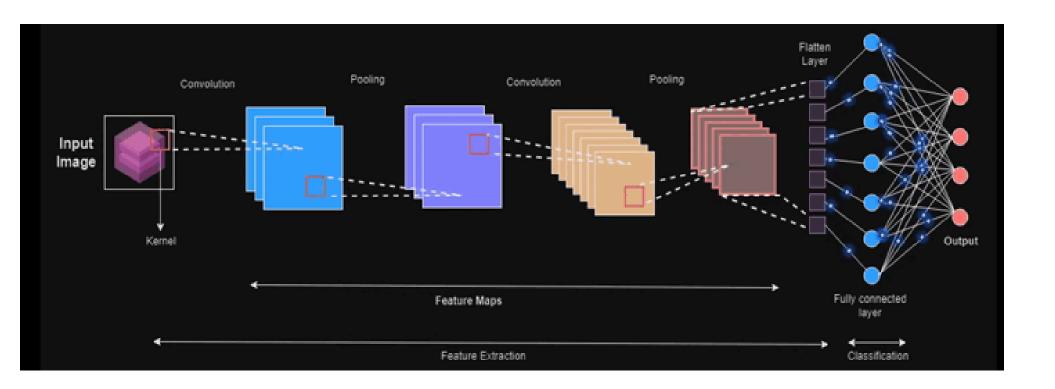


$$x * y = \sum_{i=1}^{m} \sum_{j=1}^{n} x_{(m-i)(n-j)} y_{(i)(j)}$$

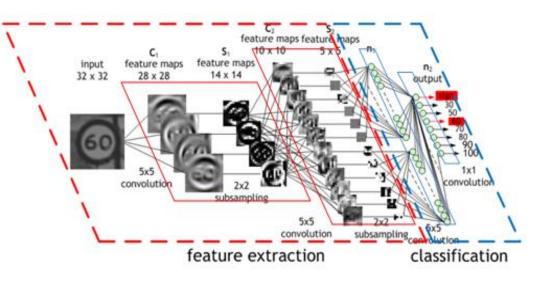


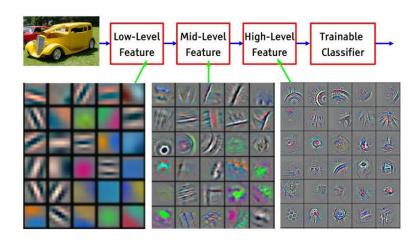
Deep Learning

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

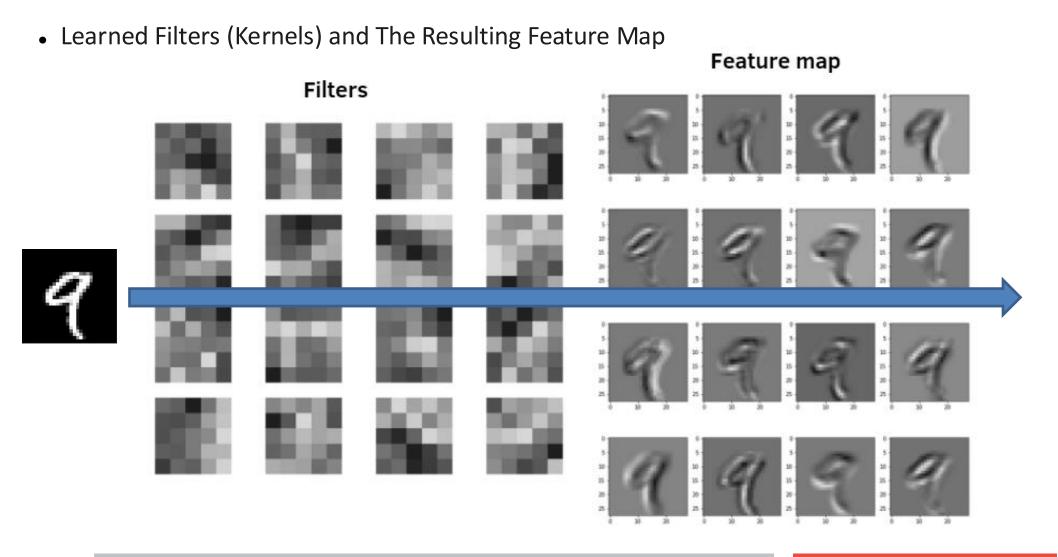


- Feature Extraction
 - Sequential Convolutional Layers
 - Learnable Filters (Kernels)
 - Activation Functions(ReLU)
 - Pooling Layers
- Classification
 - Fully-Connected Layers
 - SVM
 -





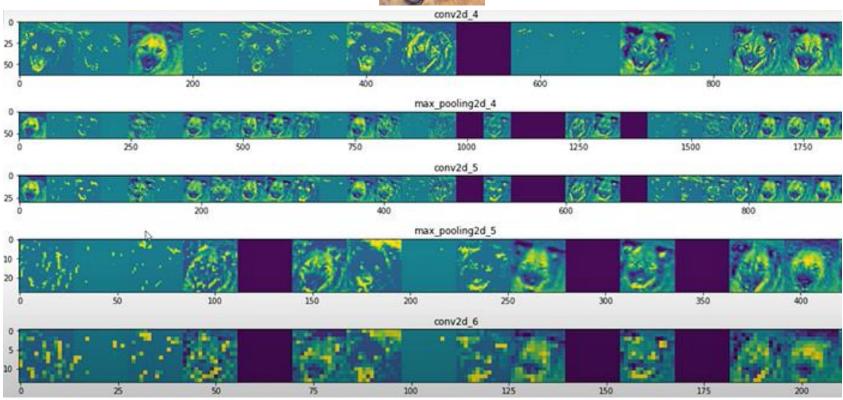
Computer Vision - Prof. André Hochuli



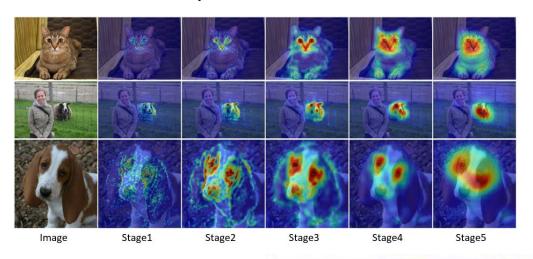
Lecture 06

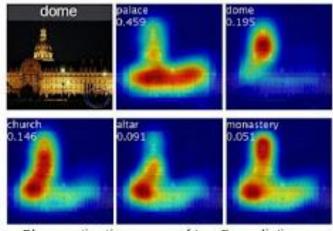
Feature Maps





Activations Maps



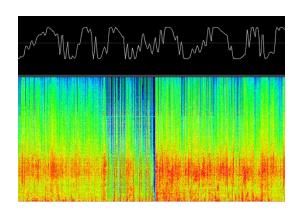


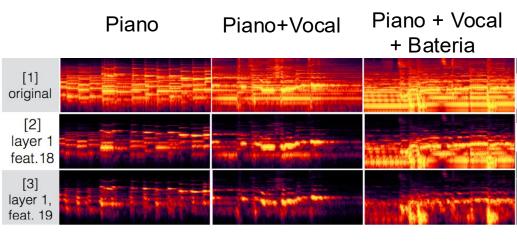
Class activation maps of top 5 predictions

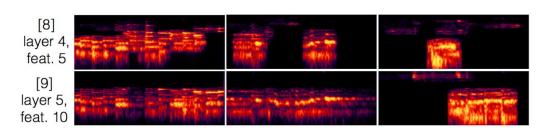


Class activation maps for one object class

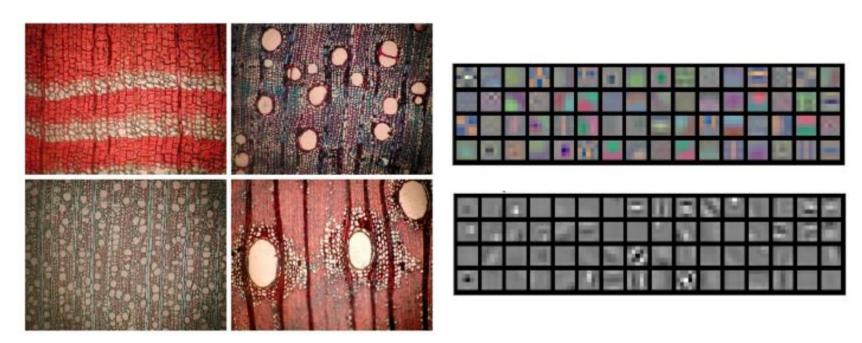
Wide applied in the Computer Vision area (audio, images, video processing, etc.).







- Tissue Classification
- Medical Images



Face

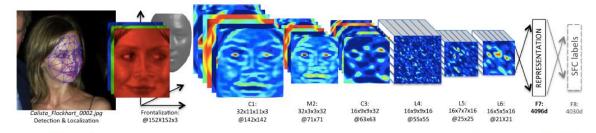


Figure 2. Outline of the *DeepFace* architecture. A front-end of a single convolution-pooling-convolution filtering on the rectified input, followed by three locally-connected layers and two fully-connected layers. Colors illustrate outputs for each layer. The net includes more than 120 million parameters,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

PKLot



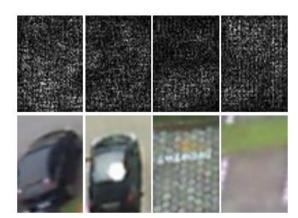
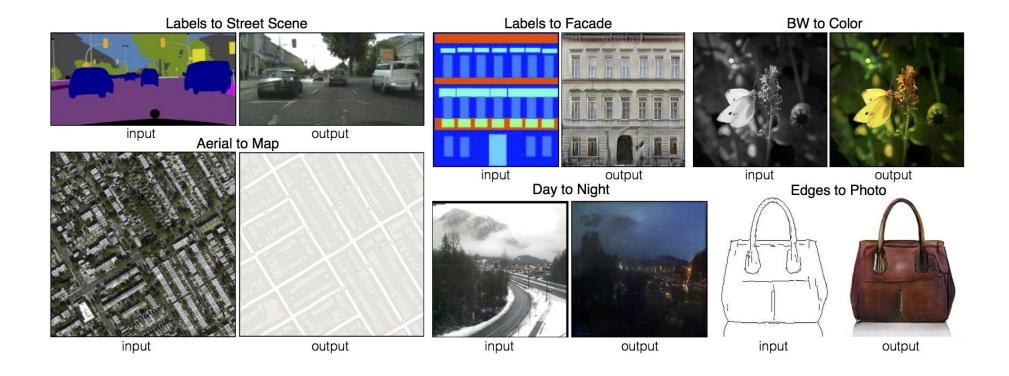


Image Translation



Deep Fakes

Animating Faces

A single model animates all images given only a single source image



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

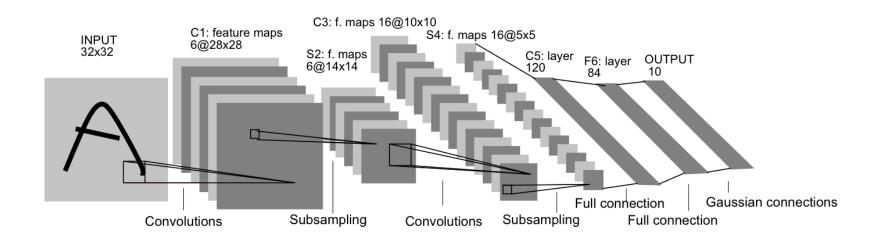
Pros

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

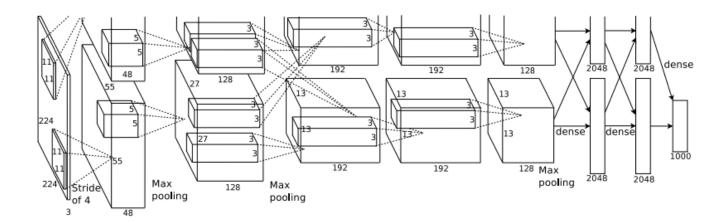
Cons

- 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

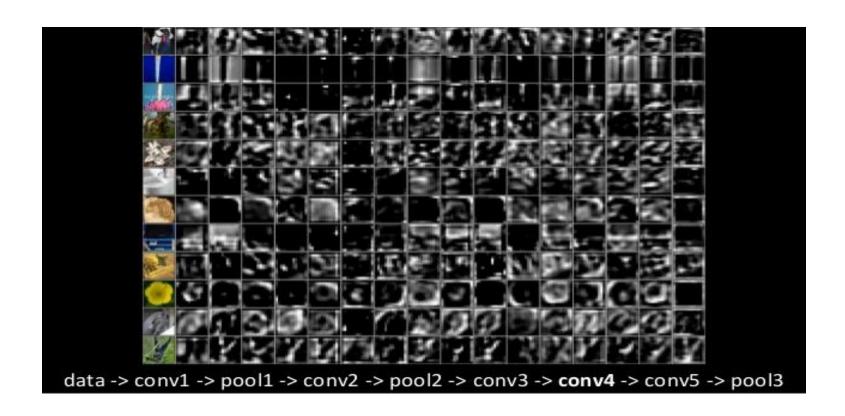
- Lenet
 - Yan Lecun 90 's (Bell Labs / IBM / FACEBOOK)
 - Handwritten Digits
 - ~60 **K** Parameters
 - ~345 K Connections



- 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%)



Alexnet

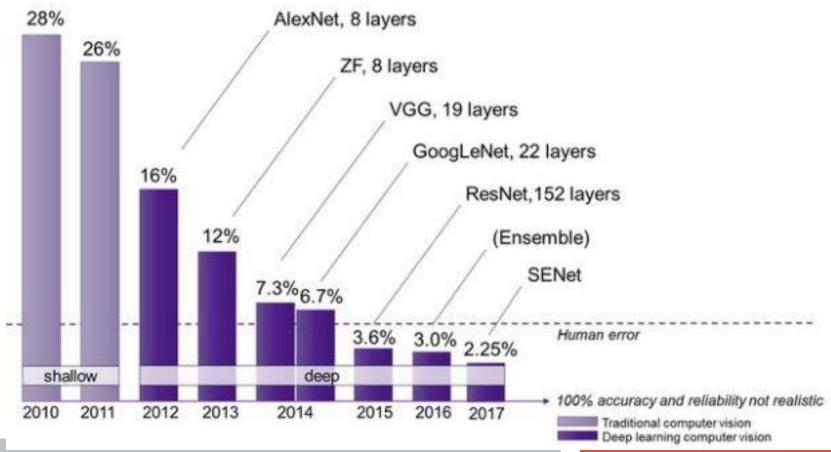


Imagenet Challenge

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







Let's Code

• [LINK]