Computer Vision Systems Programming VO

Object Recognition – Deep Learning

Christopher Pramerdorfer

Computer Vision Lab, Vienna University of Technology

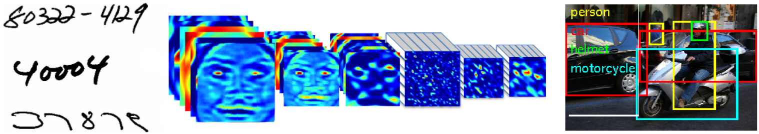
Topics

Deep learning motivation

Multilayer perceptrons

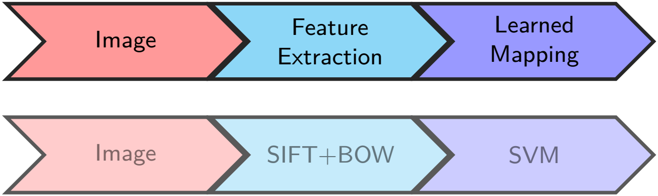
Convolutional neural networks

Deep learning applications



Images from LeCun et al. 1989, Taigman et al. 2013, `image-net.org`

Object Recognition
Traditional Approach



Object Recognition
Traditional Approach

Problem: how to choose the representation/features?

"General" features not optimal

- Not tuned to task at hand, low-level

Designing task-specific features is complex

- Virtually impossible to do optimally

Solution: learn representation as well

Learning high-level representations directly is difficult

Deep Learning (DL) solves this

- By learning a hierarchy of representations
- Layers in hierarchy build upon each other

Object Recognition
Deep Learning

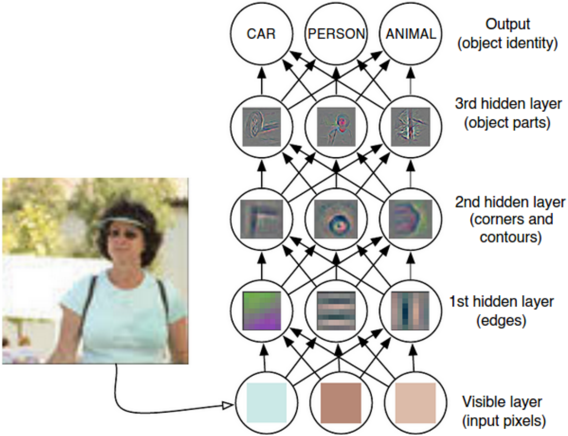
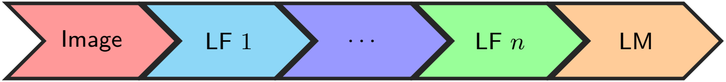


Image from Bengio, Goodfellow, and Courville 2014

n levels of features/representations

Learned jointly with the output mapping



Methods based on DL are state of the art

- For almost all recognition-related CV tasks

> "From now on, DL has to be considered as the primary candidate in essentially any visual recognition task"
> [Razavian et al. 2014]

Multilayer Perceptrons

DL is realized using MultiLayer Perceptrons (MLPs)

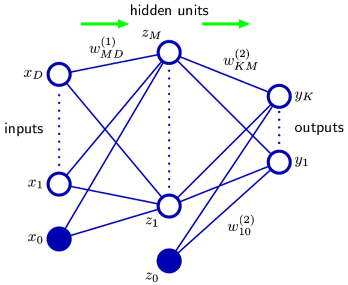


Image from Bishop 2006

Binary linear classifier

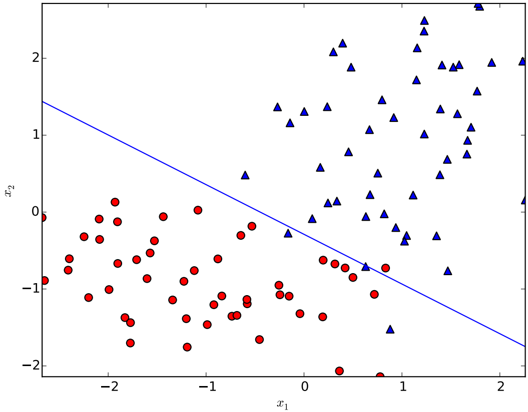
Feature vectors $\mathbf{x}$ classified as $f(\mathbf{w}^\top \mathbf{x} + b) \in \{-1, +1\}$

f is a discontinuous step function

$$f(v) = \begin{cases} +1 & \text{if } v > 0 \\ -1 & \text{otherwise} \end{cases}$$

$\mathbf{w}, b$ learned from training data

Multilayer Perceptrons
The Perceptron



Only two classes

Linear decision boundaries

Learning never converges for non-separable data

- Replace f with continuous nonlinearity (e.g. $\tanh(\cdot)$)
- Introduce layer of M such “Perceptrons” (hidden units)
- Hidden units connected to layer of K output units

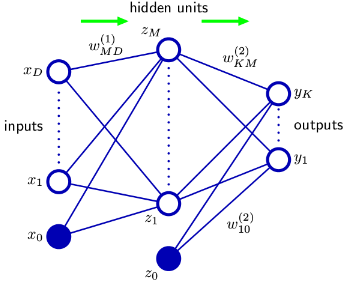


Image from Bishop 2006

Output of mth hidden unit is $z_m(\mathbf{x}) = f(\mathbf{w}_m^\top \mathbf{x})$

- Bias b included in $\mathbf{w}$ and $\mathbf{x}$, $w_0 = b$, $x_0 = 1$

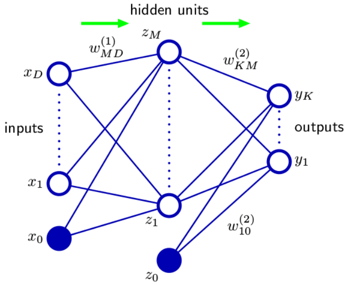


Image from Bishop 2006

Output of kth output unit is $y_k(\mathbf{z}) = g(\mathbf{w}_k^\top \mathbf{z})$

Choice of g depends on problem (regression, classification)

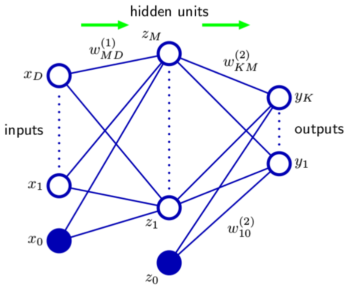


Image from Bishop 2006

Both f and g are differentiable

- Learn $\mathbf{w}$ using gradient descent
- Gradients evaluated via error backpropagation

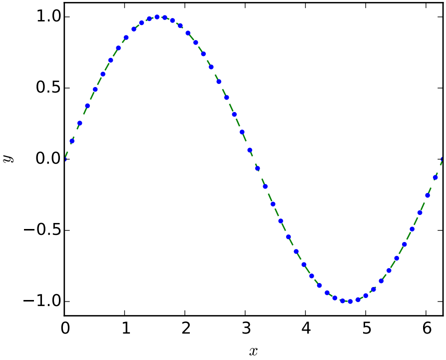
The Pylearn2 Library

Machine learning library with focus on DL

Written in Python, but interaction mostly in YAML

Open-source: `https://github.com/lisa-lab/pylearn2`

Use pylearn2 to train a MLP for regression



The Pylearn2 Library
MLP Regression Example

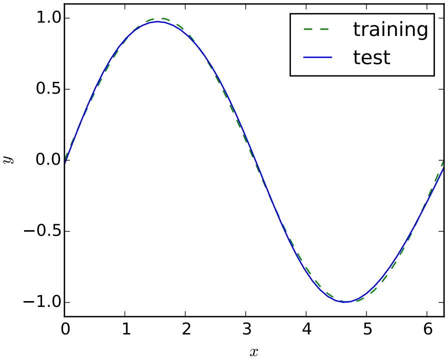
```
model: !obj:pylearn2.models.mlp.MLP {
    nvis: 1, # one input unit x
    layers: [ # two layers
        !obj:pylearn2.models.mlp.Tanh { # tanh activations for hidden units
            dim: 3, # use M=3 hidden units
            layer_name: 'hidden',
            irange: 0.1
        },
        !obj:pylearn2.models.mlp.Linear { # linear output layer for regression
            dim: 1, # one output unit, K=1
            layer_name: 'out',
            irange: 0.1
        }
    ]
}
```

The Pylearn2 Library
MLP Regression Example

```
# dataset contains the (x,y) pairs from the previous figure
dataset: &train !pkl: 'mlp_data_regression.pkl',
# train using batch gradient descent
algorithm: !obj:pylearn2.training_algorithms.bgd.BGD {
    conjugate: 1,
    batch_size: 50,
    line_search_mode: 'exhaustive',
    termination_criterion: !obj:pylearn2.termination_criteria.EpochCounter {
        max_epochs: 100 # train for 100 epochs
    }
}
```

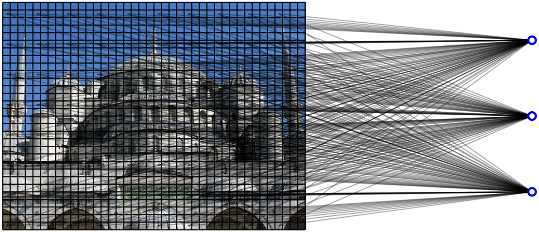
The Pylearn2 Library
MLP Regression Example

Full example: `https://github.com/cpra/cvsp-vo-slides`



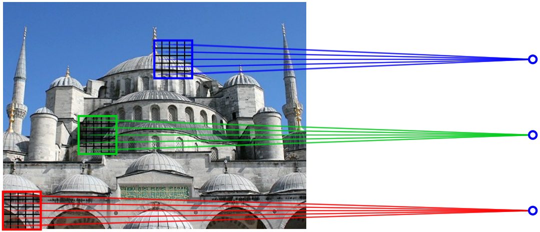
Above MLP architecture does not scale to images

- VGA resolution, $M = 1000$: ~ 300 million params



Nearby pixels are closely correlated

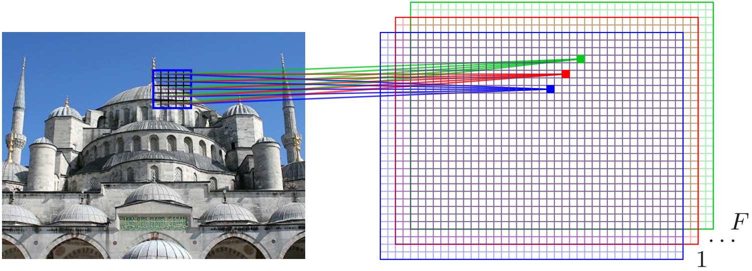
Exploit topology through locally connected layers



Convolutional layer consists of F feature maps

Each map consists of M hidden units with **shared** weights

Hidden units have a local receptive field



Number of params independent of image resolution and M

$F = 100$, 15×15 receptive field: $\sim 23,000$ params

Feature map evaluation equals

- Convolution with kernel $\mathbf{w}_f$ (hence the name)
- Followed by nonlinearity $f(\cdot) = \max(0, \cdot)$ (ReLU)

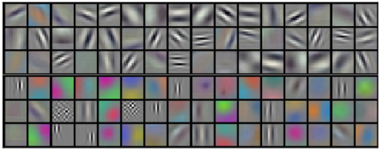
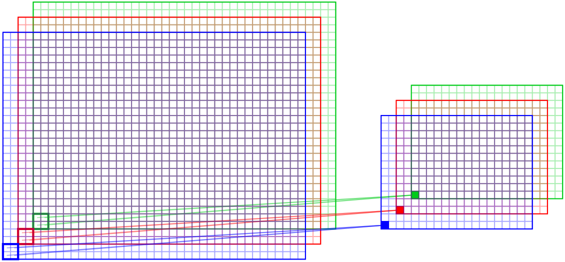


Image from Krizhevsky, Sutskever, and Hinton 2012

After convolutional layer

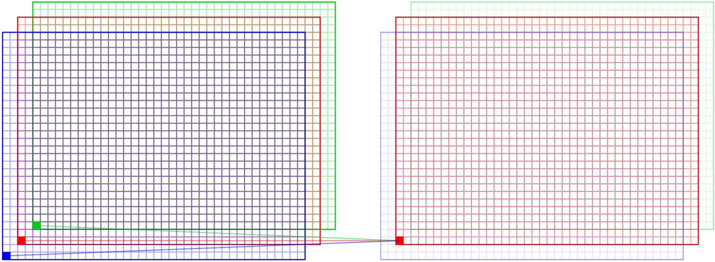
Hidden units pool information locally (e.g. max, avg)

Data reduction, robustness to small translations



Convolutional Neural Networks
Local Contrast Normalization Layers

- Between convolution and pooling layers
- Normalize responses spatially or over adjacent feature maps
- Produce more expressive, robust features



Convolutional Neural Networks

Architecture

MLPs with above layers are Convolutional Neural Networks (CNNs)

Usually several Conv $\Rightarrow$ Norm $\Rightarrow$ Pooling blocks

Later Conv layers operate on multiple feature maps

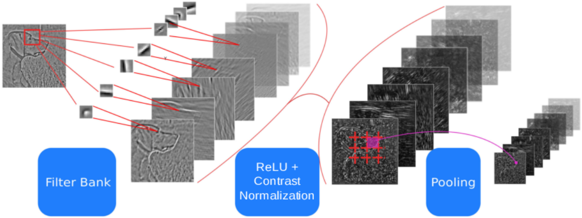


Image adapted from Kavukcuoglu 2011

Blocks followed by a traditional MLP

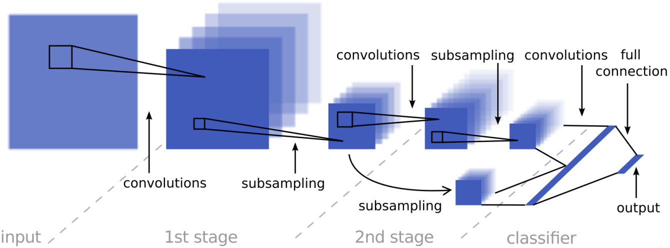


Image adapted from Sermanet et al. 2012

Deep Learning Applications
Zip Code Recognition

Zip code recognition from images

Among first applications of CNNs (1989!)

- DL and CNNs are "old" concepts
- Now successful due to available data & processing power

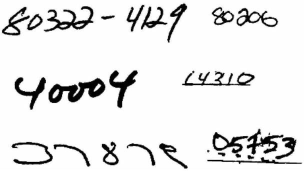


Image from LeCun et al. 1989

Deep Learning Applications
Zip Code Recognition

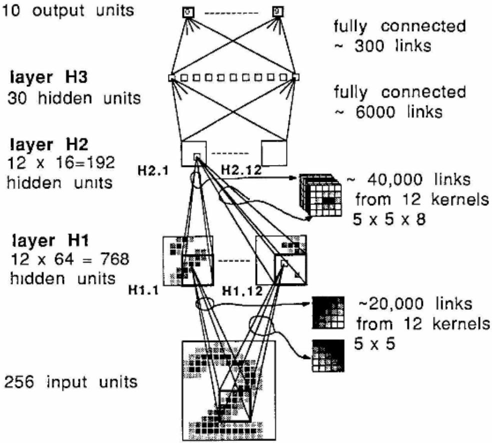


Image from LeCun et al. 1989

Let's try this ourselves

`http://cs.stanford.edu/people/karpathy/convnetjs/demo/mnist.html`

ConvNetJS

Deep Learning in your browser

Image from `convnetjs.com`

Deep Learning Applications
Face Recognition

Large market (expected $\$6.5$B by 2018)

- Security, law enforcement, HCI, ...

Complicated task

- Pose, occlusions, aging, expressions, accessories

Image adapted from http://vis-www.cs.umass.edu/lfw/

Face recognition via 3D face frontalization and DL

- Conv ⇒ Pooling ⇒ Conv for low-level features
- Locally connected layers for high-level features
- ~ 120 million parameters, ~ 4 million training images

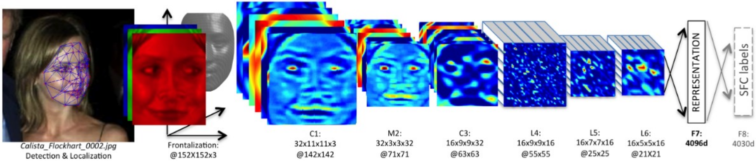


Image from Taigman et al. 2013

Human-level face verification performance

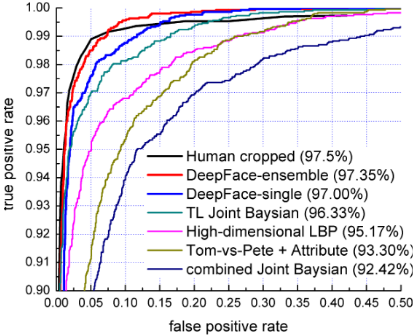
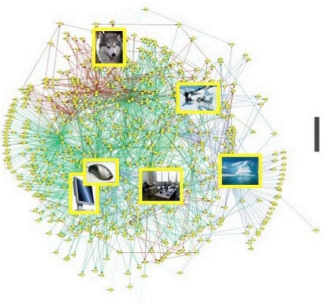


Image from Taigman et al. 2013

Object recognition on the ImageNet database

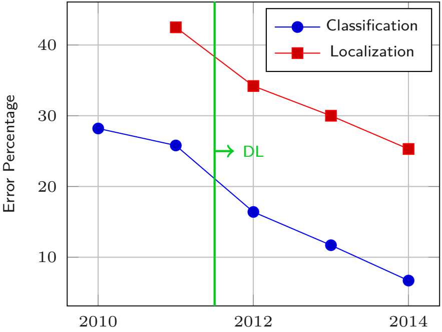
- ~ 14 million images categorized hierarchically
- Annual object recognition challenges



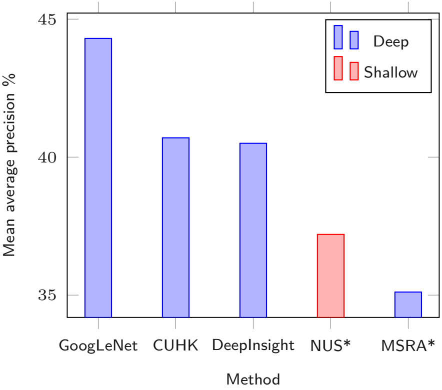
IMAGENET

Image from http://web.eecs.umich.edu/~jiadeng/

DL has lead to significant performance gains on ImageNet



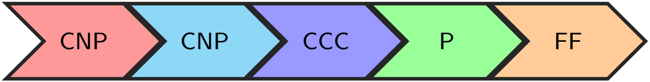
Results of 2014 ImageNet object detection challenge (excerpt)



Object classification and localization via DL

Won the 2012 challenge by a large margin

~ 60 million parameters, ~ 1.2 million training images



Implemented using cuda-convnet

- `https://code.google.com/p/cuda-convnet/`
- Open-source C++/CUDA implementation of CNNs
- Network structure definitions available on the webpage

Online demo of 2013 winner of classification challenge

`http://www.clarifai.com/`

- Scene labeling
- Action recognition
- Speech recognition
- ...

Remarks

DL and CNNs are very powerful concepts

- State of the art results in many areas of application

Training CNNs is complex

- Some CNNs are trained on GPUs for weeks
- Large training datasets required
- Reason why DL became popular only recently

Several free implementations available

- pylearn2, convnetjs, cuda-convnet, caffe, torch7, ...

Bibliography I

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Sermanet, Pierre et al. (2012). **Pedestrian Detection with Unsupervised Multi-Stage Feature Learning**.

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