Computer Vision Systems Programming VO

Deep Learning

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Topics

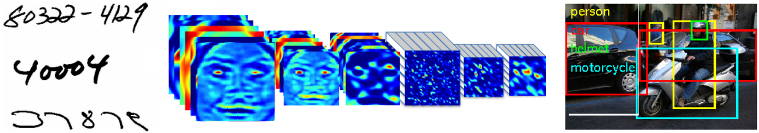
Deep learning motivation

Multilayer perceptrons

Pylearn2 library

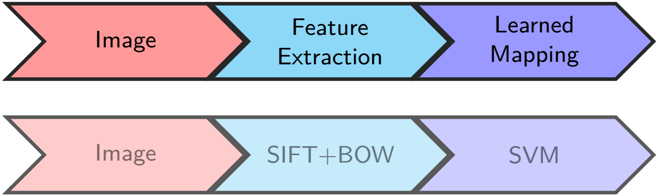
Convolutional neural networks

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

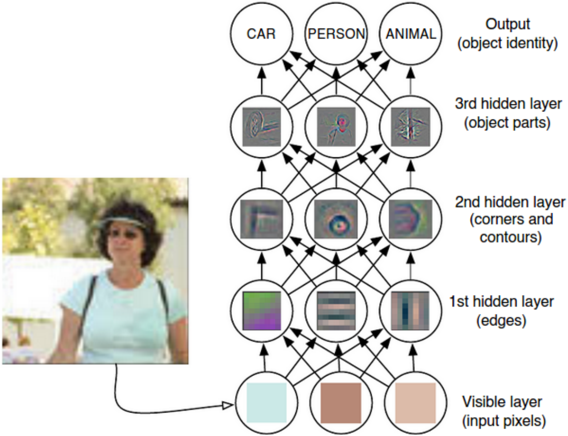
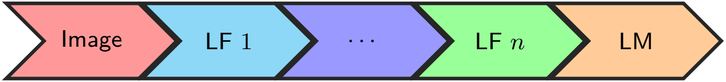


Image from Bengio, Goodfellow, and Courville 2014

Object Recognition
Deep Learning

n levels of features/representations

Learned jointly with the output mapping



Multilayer Perceptrons

DL is usually realized using MultiLayer Perceptrons (MLPs)

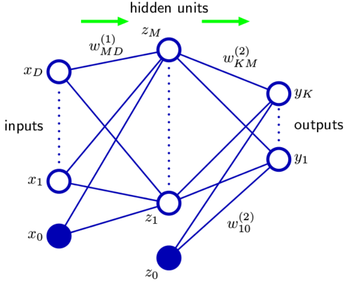


Image from Bishop 2006

Binary linear classifier

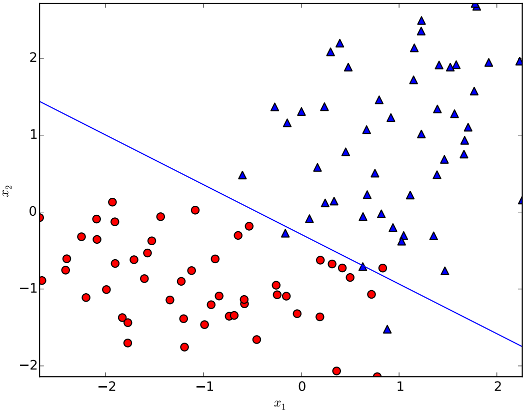
Feature vectors $\mathbf{x}$ classified as $f(\mathbf{w}^\top \mathbf{x} + b) \in \{-1, +1\}$

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

Multilayer Perceptrons

Two-Layer Architecture

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

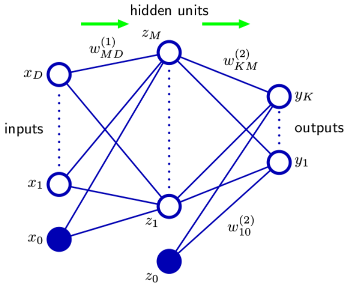


Image from Bishop 2006

Multilayer Perceptrons
Two-Layer Architecture

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

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

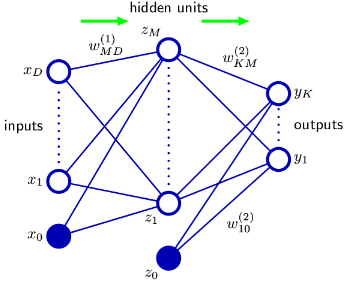


Image from Bishop 2006

Multilayer Perceptrons
Two-Layer Architecture

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)

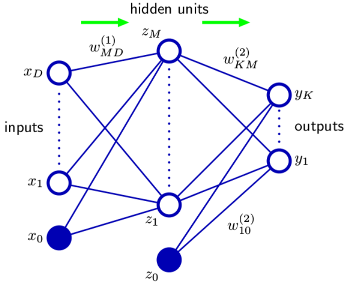


Image from Bishop 2006

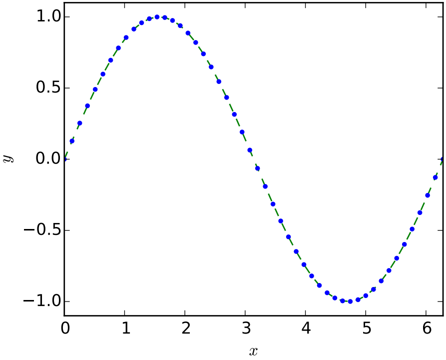
Both f and g are differentiable

- 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`

We will use pylearn2 to train a MLP for regression

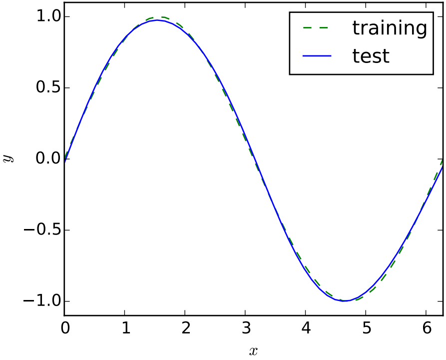


```
model: !obj:pylearn2.models.mlp.MLP {
    nvis: 1, # one input unit x
    layers: [ # two layers
        !obj:pylearn2.models.mlp.Tanh { # tanh activations for hidden units
            dim: 3, # use M=3 hidden units
            layer_name: 'hidden',
            irange: 1
        },
        !obj:pylearn2.models.mlp.Linear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

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



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