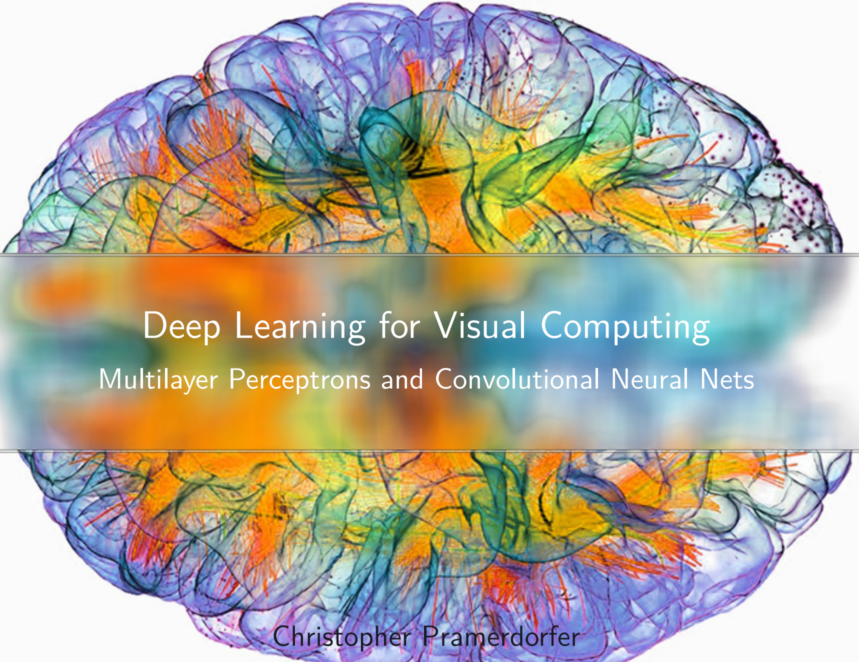

Deep Learning for Visual Computing

Multilayer Perceptrons and Convolutional Neural Nets

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Image by Neuroscape Lab

Topics

Image classification recap

Multilayer perceptrons

Representation learning and deep learning

Convolutional neural networks

Image Classification Recap

We are concerned with image classification

Image from youtube.com

$\Rightarrow$ cat

Image Classification Recap

We've covered the family of parametric models

How they can be used for classification

- Predict vector $\mathbf{w}$ of class scores

How they can be trained

- Optimize cross-entropy loss using SGD
- Using regularization strategies

Image Classification Recap

Performance has been lackluster so far

Test accuracies using HOG features and softmax classifier

- About 42% on `TinyCifar10Dataset`
- About 48% on `Cifar10Dataset`

Two directions for improvements

- Better classifier
- Better features

Multilayer Perceptrons
Motivation

Recall that softmax classifier is linear

- Restricted to linear decision boundaries

But classes not linearly separable in HOG feature space

- Unable to reach low training error

Multilayer Perceptrons (MLPs) are a powerful alternative

MLPs are universal approximators

- Can approximate any function to any degree (regression)
- Can represent arbitrary decision boundaries (classification)

Trained in the same SGD & loss function framework

A (artificial) neural network

- Is a directed computational graph
- Vertices (neurons) are scalar functions of input
- Edges define data flow

And thus a function $f : \mathbf{x} \in \mathbb{R}^D \mapsto \mathbf{w} \in \mathbb{R}^T$

- That is composed of other functions (neurons)
- Neurons operate on (subset of) $\mathbf{x}$ and/or neuron output

Multilayer Perceptrons
Feedforward Neural Networks

In feedforward neural networks this graph is acyclic

Neurons at same level in hierarchy form a layer

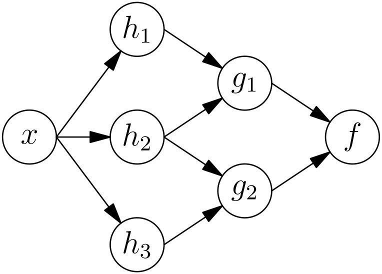
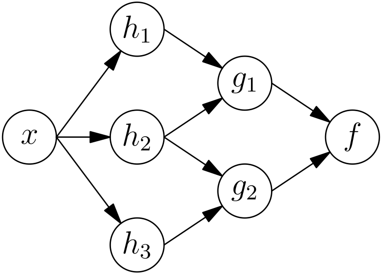


Image from wikipedia

Multilayer Perceptrons
Feedforward Neural Networks

D input units (x) and T output units (f)

Flexible number of hidden units (h,g)



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Multilayer Perceptrons

Feedforward Neural Networks

Input units only provide data (no computations)

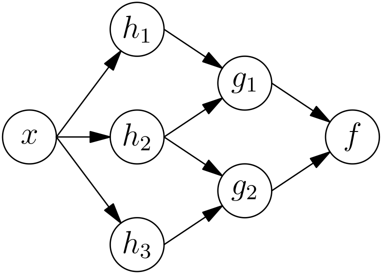


Image from wikipedia

MLPs are feedforward neural networks

- With one input layer and one output layer
- Neurons in layer l connected to all neurons in layer $l-1$

Every (non-input) neuron i computes $n_i(\mathbf{a}_i^\top \mathbf{x}_l + b_i)$

- Linear transformation of input $\mathbf{x}_l$ (varies per layer)
- Followed by some activation function n_i

Multilayer Perceptrons
Activation Functions

Activation function of output units depends on problem

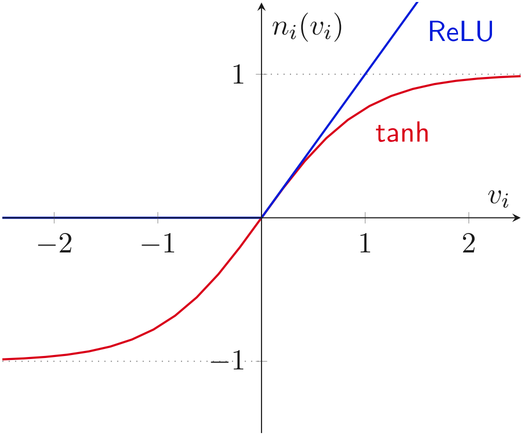
- Identity for regression
- Softmax for classification unless $L(\boldsymbol{\theta})$ includes it

Common hidden layer activation functions (non-linearities)

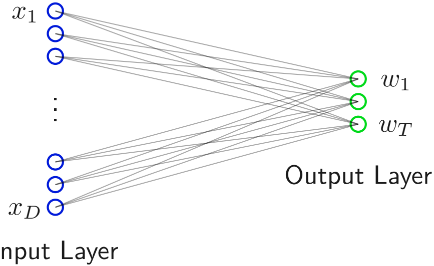
- $n_i(v_i) = \tanh(v_i)$
- $n_i(v_i) = \max(0, v_i)$ (Rectified Linear Unit, ReLU)

Multilayer Perceptrons

Activation Functions

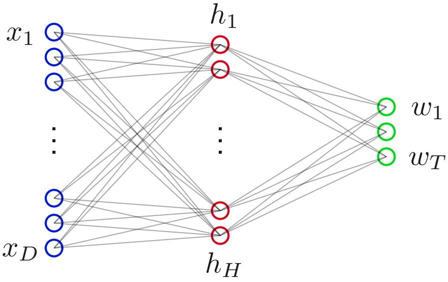


MLPs without hidden units are linear models



Most MLPs have single hidden layer with H neurons

- Depth of 2 (two layers with parameters)



Representational capacity depends on (hyperparameters)

- Number of hidden units H
- Type of non-linearities (usually ReLU)

Neural networks (including MLPs and CNNs) work best if

- They have enough capacity to overfit
- Are regularized properly to avoid this

Networks with higher capacity perform better

- Because larger networks are easier to train

Recall what we learned about gradient descent limitations

- Applies only for sufficiently large networks
- Particularly, smaller networks have bad local minima

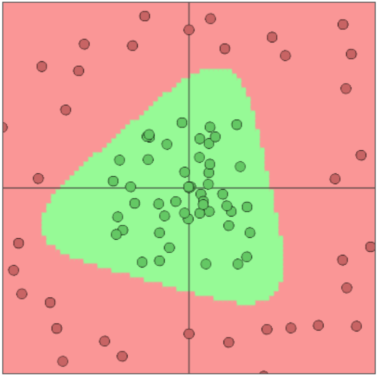


Image from cs.stanford.edu

CIFAR10 dataset, HOG features, MLP : $\approx 60\%$ test accuracy

- Much better than before
- But still far from state of the art (90% and more)

HOG features are limiting factor

Representation Learning
Motivation

Could extract additional features

- Features that retain color information
- HOG features obtained using different extractor settings
- Other features (SIFT, LBP, ...)

Standard approach until breakthrough of deep learning

- Limitations of features remain limiting factor
- Works only to some extent

Representation Learning
Motivation

Recall that manually designed features are low-level

- Capture basic properties of image
- Such as contrast changes, dominant colors

We want task-specific high-level features

- Features with semantic meaning
- E.g. presence of wheel for car classification

Representation Learning
Motivation

We cannot design reliable high-level feature extractors

- But we can try to learn them
- This task is called representation learning

Representation is feature vector used for classification

- Representation learning = learning to extract features

In our applications, input are images after preprocessing

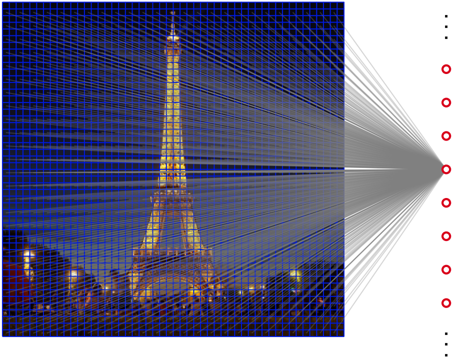
MLPs are not suited for this task

- Not designed for images

Number of parameters increases quickly with D and H

- $D \cdot H$ weights in first hidden layer
- 224 by 224 RGB image and $H = 500:\ 75$ million

Representation Learning
Challenges



Representation Learning
Challenges

Can think of a two-layer MLP as

- A stage that learns to extract H features from $\mathbf{x}$
- A stage that trains a linear classifier on these features

Must learn high-level features in single step

- This does not work in general
- Similar difficulty as solving original problem

Deep learning solves this problem using divide and conquer

- Learn to extract features in hierarchical way
- Later features build upon earlier (simpler) ones

Hierarchy has many levels, hence the name deep learning

Representation Learning
Deep Learning

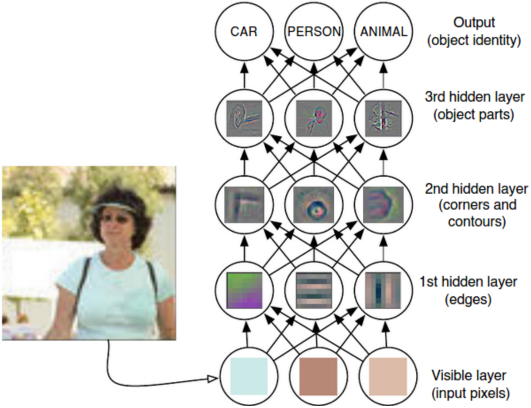


Image from [1]

Cannot just use MLPs with several hidden layers

- Usually no improvements as depth exceeds 3

MLPs are unable to learn good image features either way

- Not surprising since no understanding of images

We'll now switch to models that do

Convolutional Neural Networks

We'll now adapt above MLP architecture to images

- And other grid-like data
- Result is no longer a MLP

Should make use of spatial structure of images

- Not appropriate to flatten images to vector $\mathbf{x}$

Retain structure by arranging input neurons accordingly

- If input images have size $W_0 \times H_0$ and C_0 channels
- Input neurons form $W_0 \times H_0 \times C_0$ grid
- W_0 is width, H_0 is height, C_0 is depth of layer

Input Image

Input Layer

Spatially close pixels are highly correlated, others are not

- Nearby pixels correspond to same object (or part)
- Want to learn features using nearby pixels

Realized by

- Arranging hidden layer neurons in $W_l \times H_l$ grid
- With each neuron having a sparse connectivity

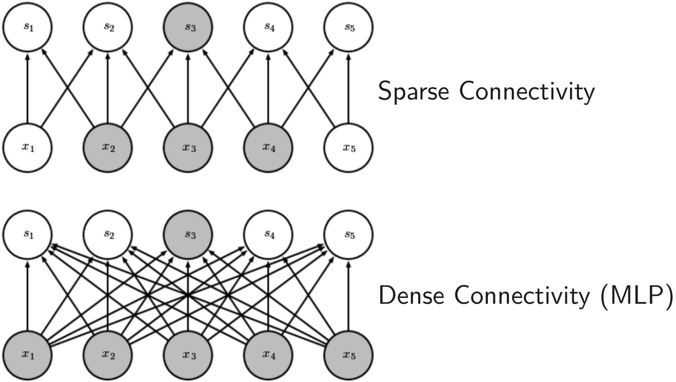


Image adapted from [1]

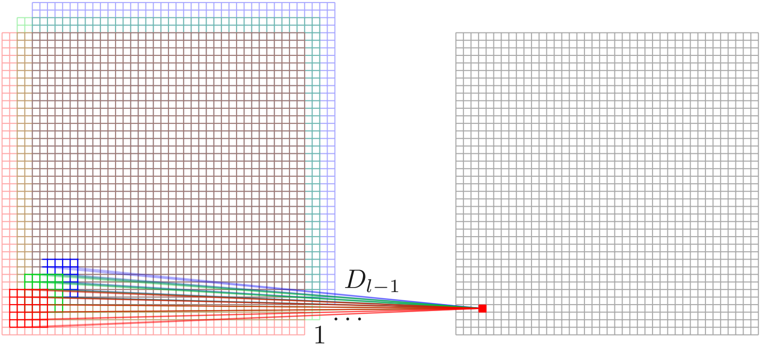
W_l and H_l depend on input width and height

- Usually $W_l = W_{l-1}$ and $H_l = H_{l-1}$

Connectivity c along with and height dimensions

- Is configurable but usually $c = 3$, that is 3×3

Connectivity along depth dimension is always D_{l-1}



Layer $l-1$

Layer l $(c \times c \times D_{l-1} = 5 \times 5 \times 3)$

Every neuron learns

- How to extract a feature
- By combining inputs in local neighborhood

Operation is same as before, $n_i(\mathbf{A}_i \cdot \mathbf{X}_i + b_i)$

- Weights and inputs are now $c \times c \times D_{l-1}$ matrices
- $\mathbf{A}_i \cdot \mathbf{X}_i$ is dot product of matrices
- Input now varies with spatial location

Such layers are called locally connected layers

Every neuron extracts different feature (different parameters)

Usually given feature is useful anywhere in image

- E.g. ability to detect car wheel anywhere in image

Enforced by weight sharing between neurons

- Neurons compute $n_i(\mathbf{A}_l \cdot \mathbf{X}_i + b_i)$
- Same weights for all neurons in layer

Now every neuron in layer

- Takes input in local neighborhood
- Computes linear combination with identical weights
- Adds bias and applies non-linearity

First two operations equal to 3D convolution operation

- Hence such layers are called convolutional layers
- Fundamental layer of convolutional neural networks

But layer can learn only single feature (not sufficient)

To overcome this problem, we replicate neurons D_l times

- Resulting in $W_l \times H_l \times D_l$ grid of neurons
- Only neurons with same depth D_l share weights
- Every 2D depth slice is called feature map

Layer with D_l feature maps can learn D_l different features

- D_l is another hyperparameter

Number of weights $\mathbf{A}_l$ depends only on c, D_{l-1}, D_l

- $c = 3, D_{l-1} = 3, D_l = 32 \implies 864$ weights
- $c = 3, D_{l-1} = 32, D_l = 64 \implies 18.5$k weights

Few parameters per layer

- Can use several convolutional layers in network
- Layer l learns to combine layer $l - 1$ features to new ones

Convolutional Neural Networks
Definition

Convolutional Neural Networks (CNNs, convnets)

- Are feedforward neural networks
- That include convolutional layers

CNNs are optimized for data with grid-like structure

- Most important models for image analysis

Receptive field increases with depth

- Input region the neuron "sees" (indirect connection)

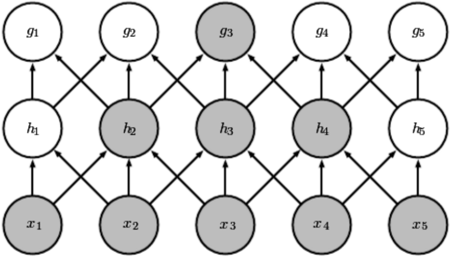


Image from [1]

So in CNNs

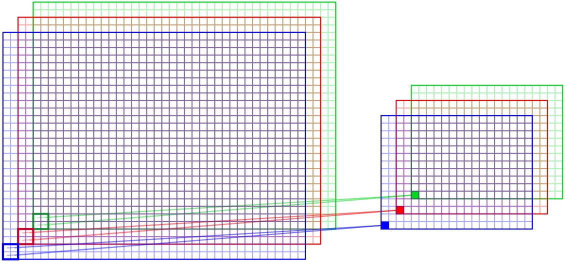
- Direct connections are sparse
- But receptive field can span most/all of image

Feature extraction approach is essentially part-based

- Earlier layers learn more local features
- Learn local features (e.g. presence of eye or nose)
- Learn global features (e.g. presence of face) from those

Most CNNs include pooling layers

- Reduce spatial resolution (but not depth) of input
- To reduce number of parameters and computations



Most common form is 2×2 max-pooling with stride 2

- $W_l = W_{l-1}/2$, $H_l = H_{l-1}/2$, and $c = 2$
- Output of neuron i is $\max(\mathbf{X}_i)$ with $\mathbf{X}_i \in \mathbb{R}^{2\times 2}$

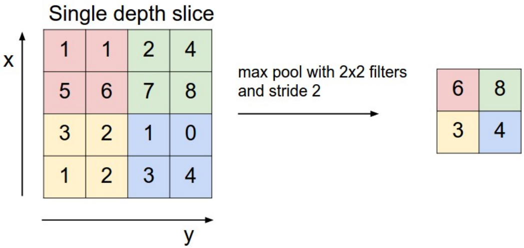


Image from cs231n.github.io

Convolutional layers are fundamental layer type in CNNs

Most CNNs also include pooling layers

Locally connected layers are used in some applications

- If features should vary with spatial location

Many other kinds of layers have been proposed

- Most are not used in current CNNs

Next lecture

- More on layer composition
- State-of-the-art CNN architectures

Bibliography

[1] *Deep learning*, 2016, [Online]. Available: http://www.deeplearningbook.org.