Introduction to Convolutional Neural Networks / Deep Learning

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https://ravika.github.io/

@vikataravi

Image Representation

157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

Image Representation

Types of Learning

- Machine Learning
  - Supervised Learning
  - Unsupervised Learning
  - Reinforcement Learning

Types of Supervised Learning

Supervised learning

Classification

Regression

"Categorical labels"
Eg: 'cat', 'dog',..

"Continuous labels"
Eg: 0.5, -1.7, …

Mapping an input to a target !

A Case Study: Fish Classification

- Problem:
  - sort incoming fish on a conveyor belt according to species
  - Assume only two classes exist:
    - Sea Bass and Salmon

Source: https://www.slideshare.net/lgustavomartins/introduction-to-pattern-recognition

Features

- Features are properties of an object:
  - Ideally representative of a specific type (i.e. class) of objects
  - Compact (memory efficient)
  - Computationally simple (CPU efficient)
  - Perceptual relevant (if trying to implement a human inspired classifier)
- **=> Should pave the way to a good discrimination of different classes of objects!**

Source: https://www.slideshare.net/lgustavomartins/introduction-to-pattern-recognition

Features

- Take a group of graphical objects
  - Possible features:
    - Shape
    - Color
    - Size
    - ...
  - Allows to group them into different classes:

Source: https://www.slideshare.net/lgustavomartins/introduction-to-pattern-recognition

Feature Vectors

- Usually a single object can be represented using several features, e.g.
  - **x1** = shape (e.g. nr of sides)
  - **x2** = size (e.g. some numeric value)
  - **x3** = color (e.g. rgb values)
  - ...
  - **xd** = some other (numeric) feature.

- **X** becomes a feature vector
  - x is a point in a d-dimensional **feature space**.

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{bmatrix}$$

Source: https://www.slideshare.net/lgustavomartins/introduction-to-pattern-recognition

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$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \mathbf{x}$$

Source: https://w

Introduction to ~~Convolutional~~ Neural Networks ~~/ Deep Learning~~

Neural Network = A function approximator

The simplest neural network

The simplest neural network

The simplest neural network

Rosenblatt's Perceptron (1953)

$x^T w = 0$

Linearly Separable

$x^T w > 0 \Rightarrow$ Class 1

$x^T w < 0 \Rightarrow$ Class 2

Why Use Only One Neuron ? Use many

Writing “code” (Keras) …

```
model = Sequential()
model.add(Dense(4,input_dim=3)
model.add(Activation('tanh'))
model.add(Dense(2))
model.compile(loss='mean_squared_error', optimizer=adam)
```

Training the model

```
# Training
# X_train : [num-train-samples x 3]
# Y_train : [num-train-samples x 2]
model.fit(X_train, y_train)
```

Model evaluation / Prediction

```
# Prediction
# X_test : [num-test-samples x 3]
# Y_test : [num-test-samples x 2]
score = model.evaluate(X_test, y_test)
```

Introduction to Convolutional Neural Networks / Deep Learning

Traditional approach: Extract features, feed to NN

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \mathbf{x}$$

{Seabass, Salmon}

Traditional approach: Extract features, feed to NN

Wouldn't it be nice if we could feed the image directly ?

… and let the “learning process” figure out which features to extract ?

MNIST Handwritten Digits Dataset

Flatten image , Feed to NN

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

For color images ?

- #Hidden Units: 120,000
- #Params: 14.4 billion
- Need huge training data to prevent over-fitting!

Do we really need full connectivity ?

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Do we really need full connectivity ?

- Head + Body + Tail + Legs = sparrow

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- Images are 2D.
- Assumption: Object image = combination of **2D image patterns**

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- Machine Learning Strategy:
  a) [Pre-final layer] Determine 2D image patterns
  b) Map 2D image patterns → Target label

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- NOTE: 2D image patterns are smaller than image

Hierarchical decomposition of input/features

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

- Images are 2D.
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- Machine Learning Strategy:
  - [All except pre-final] Determine 2D image patterns
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Efficient !

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SPOILER ALERT!
200x200x3

SPOILER ALERT!

From: mNeuron: A Matlab Plugin to Visualize Neurons from Deep Models, Donglai Wei et. al.

- Pattern detectors = Filters
- What should be the size of filters ?
- How many filters do we need at each level ?
- How many levels ?

How do filters work ?

- Determine the filter
- ‘Scan’ the filter on input image / representation
- Output = A record of all input locations that ‘match’ the filter

$$\begin{pmatrix} 0 & 1 & 2 \\ 2 & 2 & 0 \\ 0 & 1 & 2 \end{pmatrix}$$

How do filters work ?

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- ‘Scan’ the filter on input image / representation
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$$\begin{pmatrix} 0 & 1 & 2 \\ 2 & 2 & 0 \\ 0 & 1 & 2 \end{pmatrix}$$

How do filters work ?

0	0	0
0	-1	1
0	0	0

Features

Wouldn't it be nice if we could feed the image directly ?

… and let the “learning process” figure out which features to extract ?

Wouldn't it be nice if we could feed the image directly ?

… and let the “learning process” figure out which **features** to extract ?

(which filters to construct)

Convolution (in general)

3_0	3_1	2_2	1	0
0_2	0_2	1_0	3	1
3_0	1_1	2_2	2	3
2	0	0	2	2
2	0	0	0	1

12	12	17
10	17	19
9	6	14

Multiple filters, multiple ‘feature maps’

Design choices : Filter size, # of filters

3x3

1	2	1
2	4	2
1	2	1

5x5

2	7	12	7	2
7	31	52	31	7
12	52	127	52	12
7	31	52	31	7
2	7	12	7	2

7x7

1	1	2	2	2	1	1
1	3	4	5	4	3	1
2	4	7	8	7	4	2
2	5	8	10	8	5	2
2	4	7	8	7	4	2
1	3	4	5	4	3	1
1	1	2	2	2	1	1

Design choices : Filter size, # of filters

3_0	3_1	2_2	1	0
0_2	0_2	1_0	3	1
3_0	1_1	2_2	2	3
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~ Alphabets

~ Words

Pooling Layer

Pooling Layer

Pooling Layer

- **Motivation: We care about presence of features, not their exact location !**
- Dimensionality Reduction
- Prevents overfitting

Pooling Layer

- **Motivation: We care about presence of features, not their exact location !**
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- Prevents overfitting

Fully-connected layers

Fully Connected Layers

MNIST features visualized

http://blog.arimaresearch.com/wp-content/uploads/2017/01/conv_all.png

Introduction to Convolutional Neural Networks / Deep Learning

RECAP

Convolutional Neural Network

Convolutional Neural Network

Convolution Layer

Convolution Layer

Input to next layer

Convolutional Neural Network

Pooling Layer

Fully-connected Layer

ImageNet Challenge

IMAGENET

- 1,000 object classes (categories).
- Images:
  - 1.2 M train
  - 100k test.

Top-5 misclassification error rate

Case Study: AlexNet

- Winner of ImageNet LSVRC-2010.
- Trained over 1.2M images using SGD with regularization.
- Deep architecture (60M parameters.)
- Optimized GPU implementation (cuda-convnet)

Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." *NIPS* 2012.

AlexNet Architecture

AlexNet Architecture

About 57 M parameters are in the fully connected layers

									Total
Parameters :	[(11 x 11 x 3) + 1] x 96 = 35 K	[5 x 5 x 48] x 256 = 307 K	[3 x 3 x 256] x 384 = 884 K	663 K	442 K	37 M	16 M	4 M	60 M
Neurons :	253,440	27 x 27 x 256 = 186,624	13 x 13 x 384 = 64,896	13 x 13 x 384 = 64,896	13 x 13 x 256 = 43,264	4096	4096	1000	0.63 M

- Convolutional layers cumulatively contain about 90-95% of computation, only about 5% of the parameters
- Fully-connected layers contain about 95% of parameters.

Top-5 misclassification error rate

Top-5 misclassification error rate

Filters learnt by AlexNet

https://www.cc.gatech.edu/~hays/compvision/proj6/deepNetVis.png

Convolution Layer

Input to next layer

Convolution Layer

https://www.quora.com/What-is-a-1X1-convolution

1x1 (Bottleneck) Convolution Layer

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- Enable dimensionality reduction (computational savings)
- Add more non-linearity to representation space

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Committing to a single filter size at each layer seems somewhat rigid !

3x3

1	2	1
2	4	2
1	2	1

5x5

2	7	12	7	2
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2	5	8	10	8	5	2
2	4	7	8	7	4	2
1	3	4	5	4	3	1
1	1	2	2	2	1	1

Why not have multiple levels (scales) of filtering ?

Why not have multiple levels (scales) of filtering ?

Inception Module

https://i.ytimg.com/vi/_XF7N6rp9Jw/maxresdefault.jpg

GoogLeNet

12x less parameters compared to AlexNet !

9 **Inception** modules

Network in a network in a network...

Convolution
Pooling
Softmax
Other

https://www.youtube.com/watch?v=LUaRa65J_Ms

Top-5
error rate
28.2
25.8
16.4
11.7
7.3
6.7
shallow
8 layers
19 layers
22 layers
2010
2011
2012
AlexNet
2013
2014
VGG
2014
GoogleNet

How deep can the network get ?

- 50 layers ? 100 ? 1000 ?

A NN for predicting marks

NN:: FORWARD PROPAGATION

NN:: FORWARD PROPAGATION

NN:: FORWARD PROPAGATION

NN:: FORWARD PROPAGATION

NN:: GRADIENT DESCENT

NN:: GRADIENT DESCENT

NN:: GRADIENT DESCENT

NN:: GRADIENT DESCENT

NN:: BACKPROPAGATION

$$J = \sum \frac{1}{2}\left(y - f\left(f\left(XW^{(1)}\right)W^{(2)}\right)\right)^2$$

HOW DOES THIS CHANGE IF I CHANGE THESE?

$$\frac{dJ}{dW}$$

NN:: BACKPROPAGATION

NN:: BACKPROPAGATION

NN:: BACKPROPAGATION

How deep can the network get ?

- 50 layers ? 100 ? 1000 ?
- Issue: Vanishing gradients

$$\sigma(x) = \frac{1}{(1 + e^{-x})}$$

Sigmoid

Plot of Sigmoid function

https://medium.com/@deepnarainsingh/vanishing-gradients-while-training-neural-network-42d6d5d83cdf

Vanishing gradients

$$\sigma'(x) = \frac{1}{(1+e^{-x})}(1 - \frac{1}{(1+e^{-x})})$$

$$\sigma'(x) = \sigma(1-\sigma)$$

Derivative of sigmoid can be represented as

(x from −3.1 to 3.1)

https://medium.com/@deepnarainsingh/vanishing-gradients-while-training-neural-network-42d6d5d83cdf

https://medium.com/@14prakash/understanding-and-implementing-architectures-of-resnet-and-resnext-for-state-of-the-art-image-cf51669e1624

Residual Networks – A crayon analogy

https://mc.ai/explaining-resnet-with-crayons/

Residual Networks – A crayon analogy

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Residual Networks – A crayon analogy

$y = F(x) = x + R(x)$

https://mc.ai/explaining-resnet-with-crayons/

Residual Networks – A crayon analogy

Architecture of a residual block

$F(x) = x + R(x)$

https://mc.ai/explaining-resnet-with-crayons/

Residual Networks

Gradients can be supplied to shallower layers directly if needed (via skips)

28.2
25.8
16.4
11.7
7.3
6.7
3.57
shallow
8 layers
19 layers
22 layers
152 layers
year
2010
2011
2012
AlexNet
2013
2014
VGG
2014
GoogleNet
2015
ResNet

Landscape of CNNs : Applications and Architectures

Transfer Learning

Filters learnt by AlexNet

These features seem generic enough. Can we re-use them ?

https://www.cc.gatech.edu/~hays/compvision/proj6/deepNetVis.png

Transfer Learning

Transfer Learning

Examples

Pre-trained features are quite general

ImageNet pre-training

Object classification (PASCAL VOC)

- [Chatifield et al. 2014, Razavian et al. 2014, Zeiler et al. 2014]

Object detection (PASCAL VOC)

- R-CNN [Girshick et al. 2014]

Fine-grained classification (UCSD birds)

- Part-R-CNN [Zhang et al. 2014]

MIT 67 scene classification

- [Razavin et al. 2014]

…

Semantic segmentation

Input

Segmentation [9]

Semantic segmentation

Converting FC Layers to Conv Layers

1x1 (Bottleneck) Convolution Layer

- Enable dimensionality reduction (computational savings)
- Add more non-linearity to representation space

https://www.quora.com/What-is-a-1X1-convolution

Converting FC Layers to Conv Layers

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Semantic segmentation

Reinterpret classification as coarse prediction

Shelhamer, Long, Darrell, Fully Convolutional Networks for Semantic Segmentation, 2014-2016

Semantic segmentation

Reinterpret classification as coarse prediction

https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/image_segmentation.html

Semantic segmentation

http://netdissect.csail.mit.edu/thumb/slides-thumbnail.png

https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/image_segmentation.html

Semantic segmentation

Skip connections

https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/image_segmentation.html

(Extreme) Semantic segmentation

DeconvNet (2015)

https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/image_segmentation.html

(Extreme) Semantic segmentation

https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/image_segmentation.html

Siamese Network

Siamese Network

Learning Hierarchies of Invariant Features. Yann LeCun

Siamese Network

Similar Images **Dissimilar Images**

Learning Hierarchies of Invariant Features. Yann LeCun

Siamese Network

Application in Signature Verification

- The input is 8(feature) x 200(time) units.
- The cosine distance was used, (1 for genuine pairs, -1 for forgery pairs)

Bromley J, Guyon I, Lecun Y, et al. Signature Verification using a" Siamese" Time Delay Neural Network, NIPS Proc. 1994

Siamese Network (Person re-id)

http://www.fubin.org/research/Person_ReID/Person_ReID.html

Landscape of CNNs : Architectures

Image → Label

Objects

Scenes

Faces

DeepFace Architecture

Image → Number

Object Detection

CAT, DOG, DUCK

Image → Number

Age Estimation

Object detection

Image → Label Image

Scene Parsing

PSPNet

Object Parsing

Contextualized CNN

Image → Image

Depth Estimation

Crowd Counting

Marsden et al. **Fully convolutional crowd counting on highly congested scenes.** VISAPP 2017
https://arxiv.org/abs/1612.00220

Multi-channel input

NeuroRadiology (fMRI)

Multi-channel input

Solar-power plant detection from multi-spectral data

Multi-branch input

Image Colorization

https://algorithmia.com/algorithms/deeplearning/ColorfulImageColorization

Multi-branch input

Image Colorization

http://hi.cs.waseda.ac.jp/~iizuka/projects/colorization/en/

Multi-branch input

Cross-modal Scene Classification

http://projects.csail.mit.edu/cmplaces/

Multi-branch input

Activity Recognition

Recognition: Two stream

Two CNNs in paralel:

- One for RGB images
- One for Optical flow (hand-crafted features)

Fusion after the softmax layer

Simonyan, Karen, and Andrew Zisserman. "Two-stream convolutional networks for action recognition in videos." NIPS 2014.

Multi-branch output

Object Detection, Classification

Scene Parsing

http://ruder.io/multi-task/

Image CNNs for non-image data

Audio Beat Detection

http://tommymullaney.com/projects/rhythm-games-neural-networks

https://towardsdatascience.com/the-mostly-complete-chart-of-neural-networks-explained-3fb6f2367464

Resources

- Neural Networks
  - A lightweight introduction :https://www.youtube.com/playlist?list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU
  - http://www.3blue1brown.com/videos/2017/10/9/neural-network
  - Neural Networks and Deep Learning by M. Nielsen
    - http://neuralnetworksanddeeplearning.com/chap1.html
    - http://neuralnetworksanddeeplearning.com/chap2.html
    - http://neuralnetworksanddeeplearning.com/chap3.html
  - Play with Neural Networks : https://playground.tensorflow.org

- Resources for CNN and Deep Networks:
  - http://cs231n.stanford.edu/2017/syllabus.html
  - References in slides

Extra/Misc

- Determine the filter
- ‘Scan’ the filter on input image / representation
- Ouput = A record of all input locations that ‘match’ the filter

Input

Kernel Convolution

-1	-1	-1
-1	8	-1
-1	-1	-1

Feature Map

O

- Determine the filter
- ‘Scan’ the filter on input image / representation
- Ouput = A record of all input locations that ‘match’ the filter

Input

Kernel Convolution

-1	-1	-1
-1	8	-1
-1	-1	-1

Feature Map

Upper loop neuron...maybe...
784
0
1
2
3
4
5
6
7
8
9

Classification

Classification

Classification

Source: http://adilmoujahid.com/posts/2016/06/introduction-deep-learning-python-caffe/

Classification

Source: http://adilmoujahid.com/posts/2016/06/introduction-deep-learning-python-caffe/

Rosenblatt's Perceptron (1953)

Rosenblatt's Perceptron (1953)

Rosenblatt's Perceptron – Training Algorithm

```
Initialize weights w ; // Random or 0

Until [all examples correctly classified]
        For each training sample (x,y)
                Compute yt := sign(x^T w)
                 if y == yt // Correctly classified
                        continue ;
                else // Update weights
                        dw = (y - yt) * x ;
                        w   = w + dw;
                EndIf
        EndFor
EndUntil
```

7
Input image:
28x28 pixels
Input layer:
784 neurons,
one per pixel
Hidden layer:
100 neurons
Output layer:
10 neurons
7
Output:
predicted
digit value