Convolutional Neural Networks

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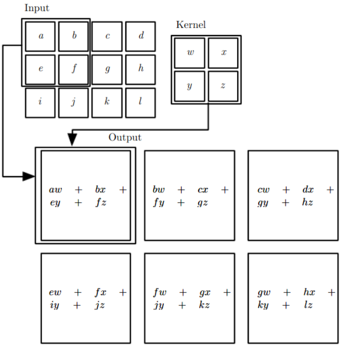
- Convolution
- Pooling
- Activation, Loss, Optimizer
- Example Networks
- Training Techniques
- Example Code

Convolution

- A type of neural network that can process known grid-structure data
  - Timeseries: 1-D grid
  - Image: 2-D grid
- "Convolution" represents a linear operation, which does not correspond precisely to the definition of convolution as used in other fields

- Three elements: grid-like data (input), kernel (filter), feature map (output)

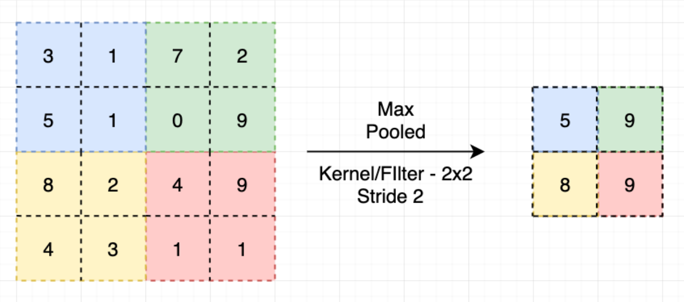


- A feature map is obtained by convolution of the input data with a kernel (image above), adding a bias term and then applying an activation function

- Convolution leverages three important ideas.
  - Sparse interactions: kernel is smaller than input
  - Parameter sharing: one set of parameters for every location
  - Equivariant representations: if the input changes, the output changes in the same way
- Convolution is dramatically more efficient than dense matrix multiplication in terms of memory requirements and statistical efficiency

Pooling

- A pooling function replaces the output of a network at a certain location with a summary statistic of the nearby outputs.
- Examples: max pooling, average pooling, L2 norm pooling



- Pooling helps to make the representation approximately invariant to small translations of the input
- Pooling layers are usually used immediately after convolutional layers

- Padding options: VALID, SAME, etc

`"VALID"` = without padding:

```
   inputs:         1  2  3  4  5  6  7  8  9  10 11 (12 13)
                  |________________|                dropped
                                 |_________________|
```

`"SAME"` = with zero padding:

```
               pad|                                      |pad
   inputs:      0 |1  2  3  4  5  6  7  8  9  10 11 12 13|0  0
               |________________|
                              |_________________|
                                             |________________|
```

Activation, Loss, Optimizer

- Keras activation function list (link)

- Regression
  - Linear: turn 1 real value to 1 real value
- Classification
  - Sigmoid: turn 1 real value to 1 real value between 0 and 1
  - Softmax: turn k real values to k real values that sum to 1

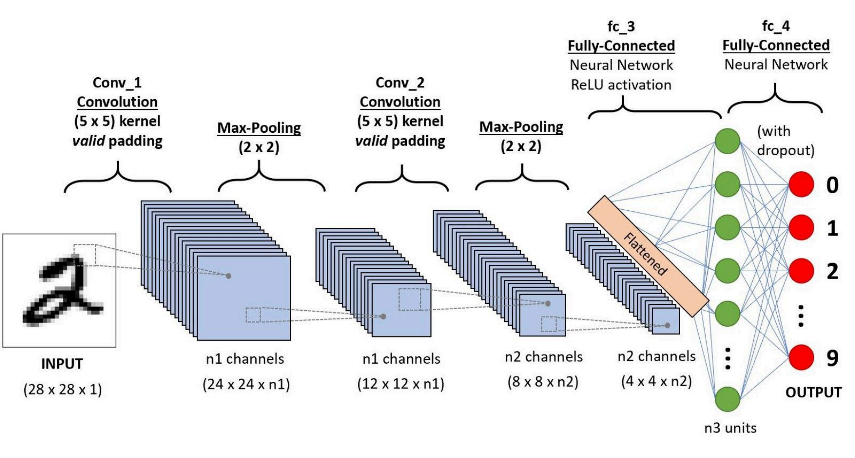
$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$$

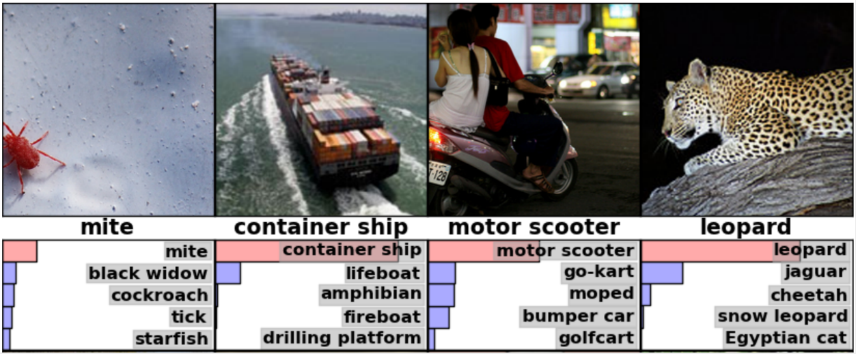
  - E.g., $\vec{z} = [8, 5, 0] \rightarrow [0.9523, 0.0474, 0.0003]$

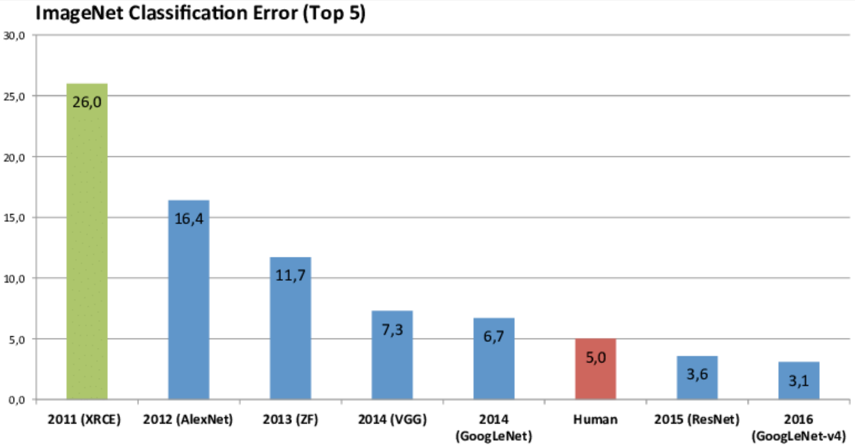
- Keras loss function list (link)

- Keras optimizer list (link)

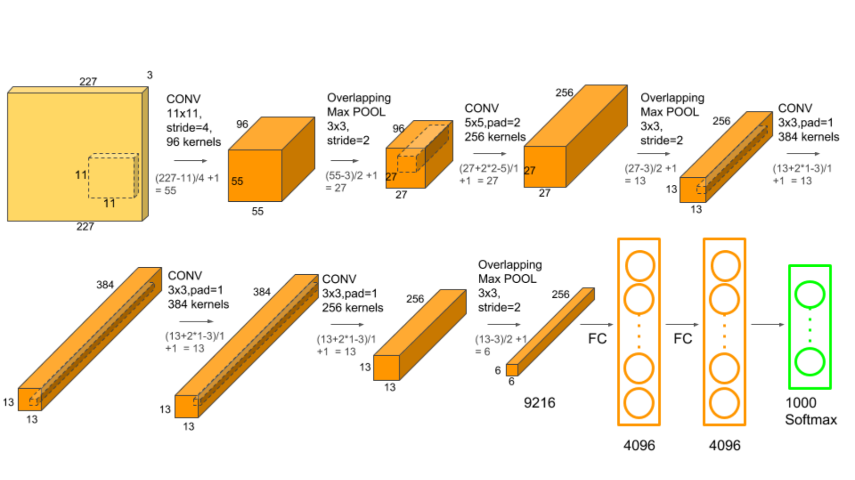
Example Networks


Conv_1
Convolution
(5 x 5) kernel
valid padding
Max-Pooling
(2 x 2)
Conv_2
Convolution
(5 x 5) kernel
valid padding
Max-Pooling
(2 x 2)
fc_3
Fully-Connected
Neural Network
ReLU activation
fc_4
Fully-Connected
Neural Network
(with
dropout)
Flattened
0
1
2
9
INPUT
(28 x 28 x 1)
n1 channels
(24 x 24 x n1)
n1 channels
(12 x 12 x n1)
n2 channels
(8 x 8 x n2)
n2 channels
(4 x 4 x n2)
n3 units
OUTPUT

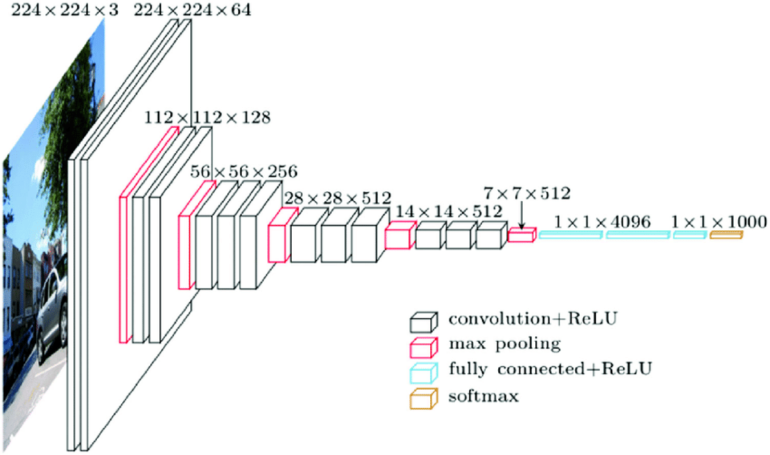

mite
container ship
motor scooter
leopard
mite
black widow
cockroach
tick
starfish
container ship
lifeboat
amphibian
fireboat
drilling platform
motor scooter
go-kart
moped
bumper car
golfcart
leopard
jaguar
cheetah
snow leopard
Egyptian cat



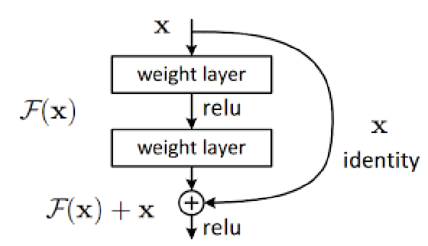
ImageNet Classification Error (Top 5)
30,0
25,0
20,0
15,0
10,0
5,0
0,0
26,0
16,4
11,7
7,3
6,7
5,0
3,6
3,1
2011 (XRCE)
2012 (AlexNet)
2013 (ZF)
2014 (VGG)
2014 (GoogLeNet)
Human
2015 (ResNet)
2016 (GoogLeNet-v4)


227
3
11
11
227
CONV
11x11,
stride=4,
96 kernels
(227-11)/4 +1
= 55
96
55
55
Overlapping
Max POOL
3x3,
stride=2
(55-3)/2 +1
= 27
96
27
27
CONV
5x5,pad=2
256 kernels
(27+2*2-5)/1
+1 = 27
256
27
27
Overlapping
Max POOL
3x3,
stride=2
(27-3)/2 +1
= 13
256
13
13
CONV
3x3,pad=1
384 kernels
(13+2*1-3)/1
+1 = 13
384
13
13
CONV
3x3,pad=1
384 kernels
(13+2*1-3)/1
+1 = 13
384
13
13
CONV
3x3,pad=1
256 kernels
(13+2*1-3)/1
+1 = 13
256
13
13
Overlapping
Max POOL
3x3,
stride=2
(13-3)/2 +1
= 6
256
6
6
9216
FC
4096
FC
4096
1000
Softmax

- 2 Conv + 2 Conv + 3 Conv + 3 Conv + 3 Conv + 3 Dense



- Original version: 152 layers (first network beat human performance)
- Many variants, e.g., ResNet-18, ResNet-50
- Residual learning (skip operation) helps train very deep networks by addressing the vanishing/exploding gradient problem



- NVIDIA's model
- Paper (link)
- Video (link)
- Blog (link)

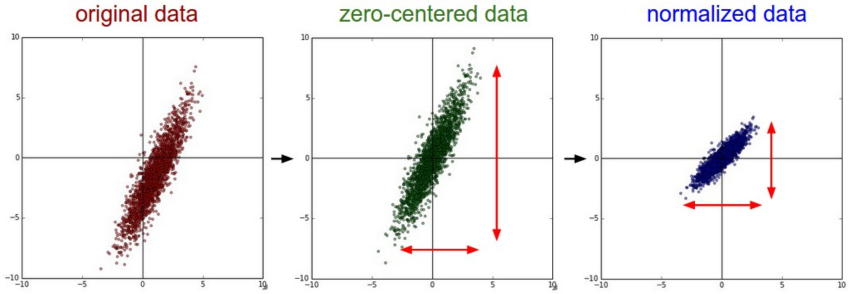
CNN Parameter Counting

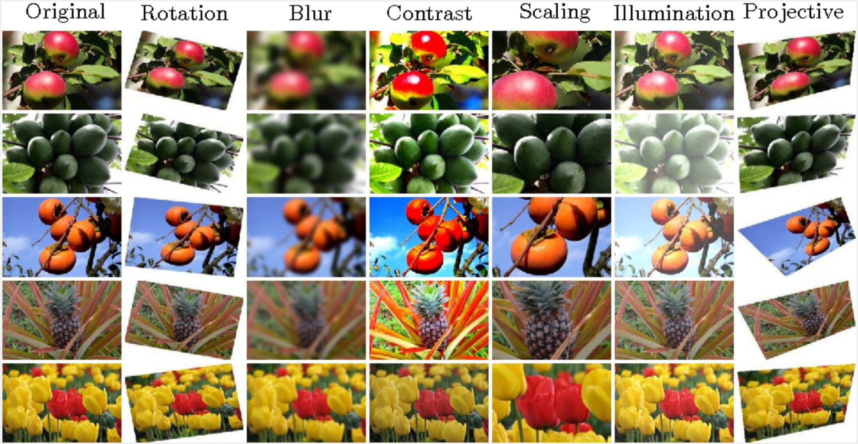
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 24, 24, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 12, 12, 64)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 12, 12, 64)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 9216)              0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               1179776
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_2 (Dense)              (None, 10)                1290
=================================================================
Total params: 1,199,882
Trainable params: 1,199,882
Non-trainable params: 0
_________________________________________________________________
```

- Input shape is 28x28x1 (this is data, not trainable parameters)
- conv2d_1: 32x3x3+32 = 320 (32 2-D kernels, each is 3x3, plus a bias term for each kernel)
- conv2d_2: 32x3x3x64+64 = 18496 (64 3-D kernels, each is 32x3x3, plus a bias term for each kernel)
- dense_1: 9216x128+128 = 1179776
- dense_2: 128x10+10 = 1290
- Total number of trainable parameters: 1,199,882

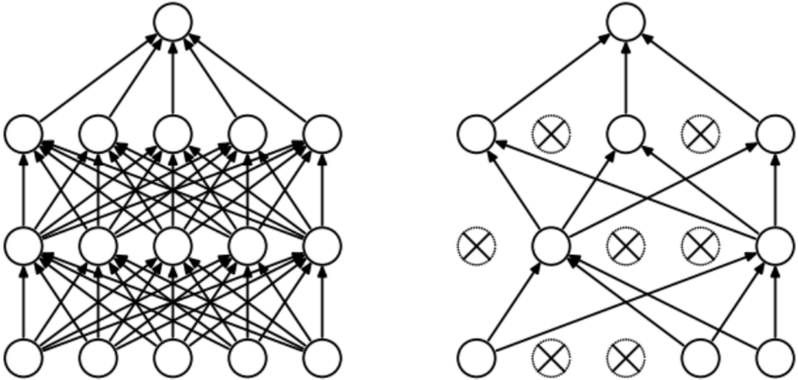
Training Techniques

- Linear normalization (know min and max): $\frac{x-min}{max-min}$, e.g., pixel values
- Z-score normalization: $\frac{x-mean(x)}{std(x)}$




Original
Rotation
Blur
Contrast
Scaling
Illumination
Projective

Dropout



(a) Standard Neural Net

(b) After applying dropout.

- grid search: simplest technique
- random search: may perform better than grid search
- coarse to fine: start with broad sweep, then zero in

Example Code

- link

- Tensorflow (link)
- Keras (link)
- Pytorch (link)