# Convolutional Neural Networks

#### Weizi Li

Department of Computer Science University of Memphis



Outline 1

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



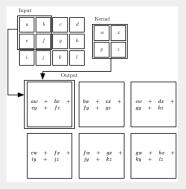
 A type of neural network that can process known grid-structure data

► 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 Convolution 3

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

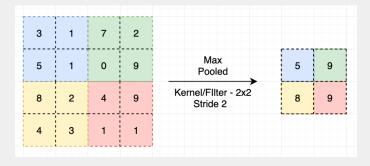


A feature map is obtained by convolution of the input data with a kernel (image above), adding a bias term and then applying an activation function Convolution 4

- 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



- 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 6

- 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

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

Losses 10

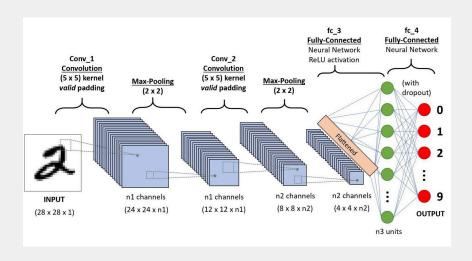
■ Keras loss function list (link)

Optimizer 11

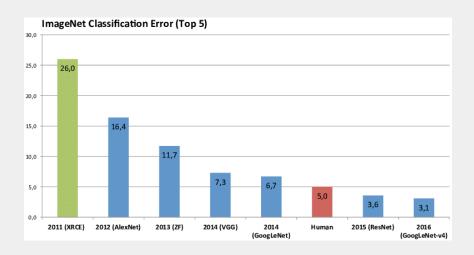
■ Keras optimizer list (link)

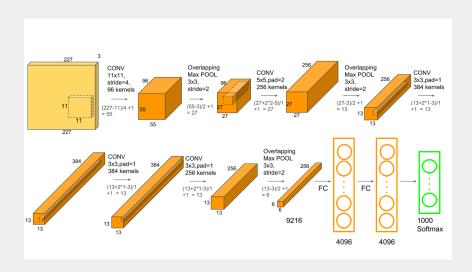
Example Networks

#### CNN Example for MNIST

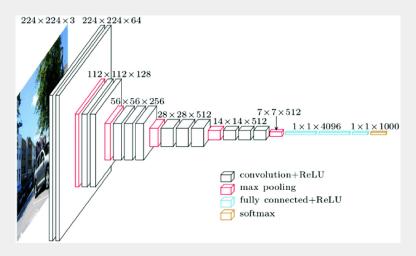




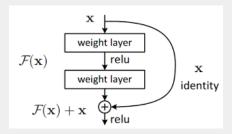




 $\blacksquare$  2 Conv + 2 Conv + 3 Conv + 3 Conv + 3 Conv + 3 Dense



- 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)

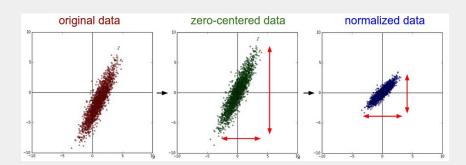
## **CNN** Parameter Counting

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 28×28×1 (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:  $32\times3\times3\times64+64 = 18496$  (64 3-D kernels, each is  $32\times3\times3$ , plus a bias term for each kernel)
- dense\_1: 9216×128+128 = 1179776
- dense\_2:  $128 \times 10 + 10 = 1290$
- Total number of trainable parameters: 1,199,882

Training Techniques

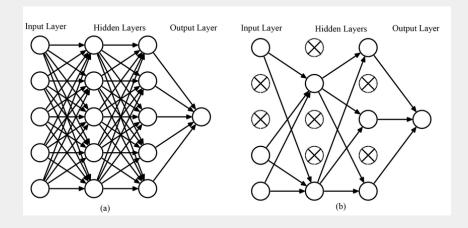
- Linear normalization (know min and max):  $\frac{x-min}{max-min}$ , e.g., pixel values
- Z-score normalization:  $\frac{x-mean(x)}{std(x)}$



### Data Augmentation



Dropout 23



- 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)