Chapter 10



- Special type of Deep Neural Network mainly used for analyzing visual data
- The network works by extracting a set of high-level features
- Multilayer Perceptrons use are fully connected networks, which makes them prone to overfitting. Here the connections between layers are regularized in a hierarchical manner
- Have at least 1 layer that uses the mathematical convolution operation
- Convolution gives us the ability to learn spatial and temporal structures in the data
- Abbreviated as CNN or ConvNet
- Huben and Wiesel found in 1962 that the Visual Cortex of the brain works in a similar way

- Types of layers in CNNs:
 - Convolutional: Abstracts the images into feature maps (also called neurons or kernels). Number of feature maps and their size are hyper parameters of the model.
 - Pooling: Reduces the dimensions of the data by combining outputs of neurons (also called downsampling). Combination can be done by taking the average or the max value of set of neurons.
 - Dropout: Randomly sets the output of neurons to zero for each training sample. This forces the network to be redundant and avoid overfitting.
 - Flatten: Flattens the higher dimensional data into a single vector.
 - **Fully connected**: A layer where all neurons connect to every neuron from previous layer. Mostly used as the last layer to connect the extracted features and output the predicted labels.

Convolutional Layer

- Creates feature maps from input data using filters
- A convolutional layer can have many filters
- Each filter strides through the entire image doing matrix multiplication to create a feature map
- Stride step size can be controlled to reduce output spatial size
- We can add zero-padding to the border around the input data to control spatial size of the convolved feature
- Output size of a filter:
 - W is the input size
 - K is the kernel size
 - P is the padding size
 - S is the stride step size

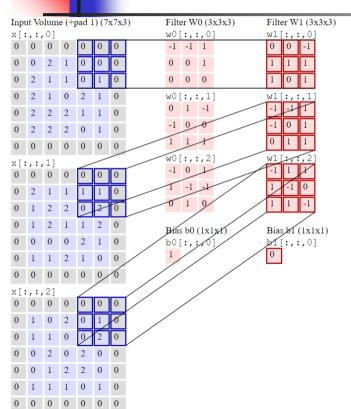
1	1	1	0	0
0	1	1	1	0
0	0	1,	1 _{×0}	1,
0	0	1,0	1,	0,0
0	1	1,	0,×0	0,

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4	3	4
2	4	3
2	3	4

Convolved Feature

Convolutional Layer



Output Volume (3x3x2)	
0[:,:,0]	

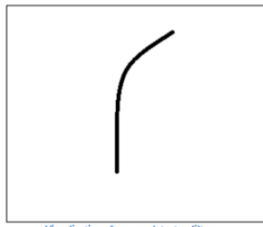
6	2	3			
-1	4	6			
2	-4	-4			
0[:,:,1]					
6	5	2			

6 5 2 8 5 8

8	5	8
3	8	-

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

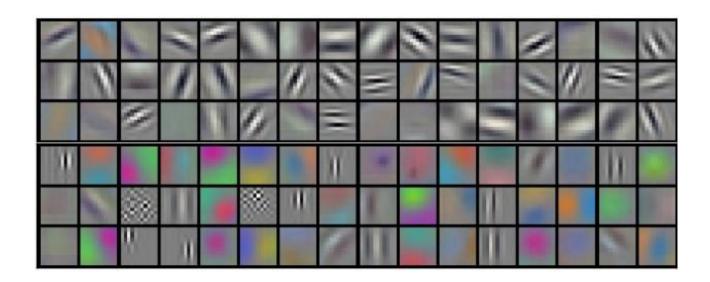
Pixel representation of filter



Visualization of a curve detector filter

Convolutional Layer

- We can visualize the learned filters
- https://youtu.be/AgkfIQ4IGaM



Pooling Layer

- Dimensionality reduction layer
 - A pooling layer also has size, stride and padding just like a convolutional layer
- Thus output size calculation is the same as with convolutional layer
- The output of the pool can be determined using maximum value of the pool or average value

3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

	_	_
3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

		200			
Sing	e	de	pth	S	ice

_			
1	1	2	4
5	6	7	8
3	2	1	0
1	2	3	4

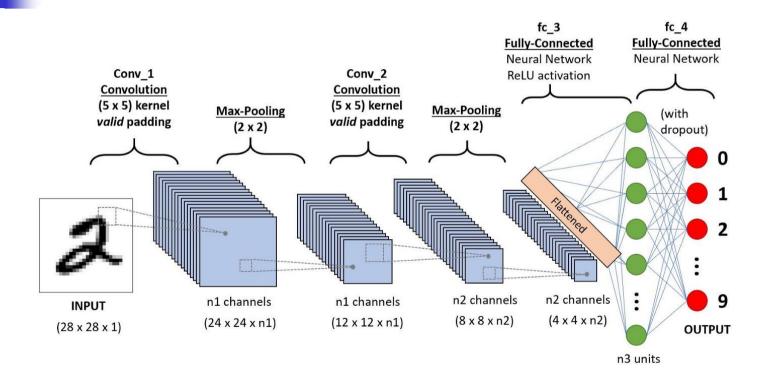
max pool with 2x2 filters and stride 2

6	8
3	4

- As with Multi-layer Perceptrons, we also use activation functions here. The most commonly used are:
 - ReLU used on convolutional layers
 - Softmax used on the output layer for single label multiclass classification tasks. Normalizes the output vector, so that the sum of probabilities add up to 1
 - Sigmoid used on the output layer for binary classification tasks and multilabel multiclass classification tasks
 - Linear used on the output layer for regression tasks
- Training is also done via backpropagation. Main steps:
 - 1. Forward pass Feeding an input sample to the CNN and getting the output
 - 2. Loss function calculate the error gradient of our output
 - 3. Backward pass Go backwards from the output through the network and update the weights according to their contribution for the error

- Many training optimizers have been created in the past years
- The main issue is trying to avoid local optimums and converge towards the global optimum in a timely manner
- Most common optimizers:
 - Stohastic Gradient Descent flat learning rate
 - Adam Adaptive learning rate
- We have various loss functions for calculating the error of the network. Most common loss functions:
 - Mean Squared Error used for regression tasks
 - Binary Cross Entropy used for binary classification tasks and multilabel multiclass classification tasks
 - Categorical Cross Entropy used for single label multiclass classification tasks

Example CNN Architecture



References, Literature, further reading

- <u>https://www.deeplearningbook.org/</u>
- https://cs231n.github.io/convolutional-networks/
- https://towardsdatascience.com/neural-network-optimization-7ca72d4db3e0
- https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-theeli5-way-3bd2b1164a53
- https://www.pyimagesearch.com/2019/01/21/regression-with-keras/
- https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/
- https://machinelearningmastery.com/how-to-choose-loss-functions-when-training-deep-learning-neural-networks/

Questions?

