Convolution Neural Networks

- Slides (./files/deep_learning_tutorial_2015.pdf) by Phillip Isola
- Slides (./files/cnn1.pdf) by Prof. Ali Ghodsi

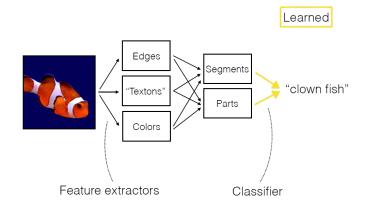
Prof. Seungchul Lee iSystems UNIST http://isystems.unist.ac.kr/

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1. Tranditional Machine Learning vs. Neural Networks

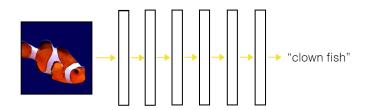
Object recognition using machine learning



Neural Network



Deep Neural Network



2. Convolution Neural Networks

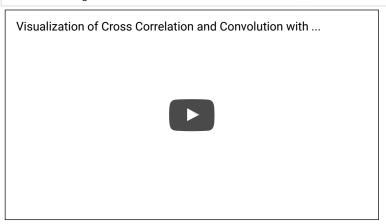
CNNs are simply neural networks that use convolution in place of general matrix multiplication in at least one of their layers

2.1. Convolution and cross-correlation

• Many machine learning libraries implement cross-correlation, but call it convolution

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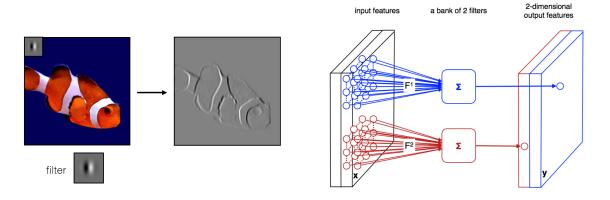
• Discrete convolution can be viewed as multiplication by a matrix

1	1	1	0	0
0	1,	1,0	1,	0
0	0,0	1,	1,0	1
0	0,,1	1,0	1,	0
0	1	1	0	0

Image

4	3	4
2	4	

Convolved Feature



Sparse interations

- CNNs, typically have sparse connectivity (sparse weights)
- This is accomplished by making the kernel (convolution mask) smaller than the input

Parameter sharing

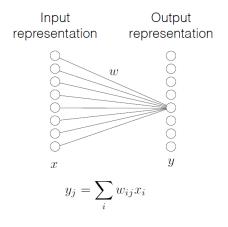
- In CNNs each number of the kernel is used at every position of the input
- Instead of learning a separate set of parameters for every location, we learn only one set

Equivariance

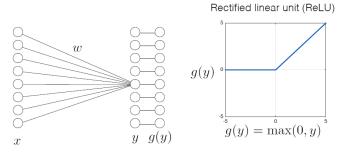
- A function f(x) is equivariant to a function g if f(g(x)) = g(f(x))
- · A convolution layer has equivariance to translation
- If we apply this translation to x, then apply convolution, the result will be the same as if we applied convolution to x, then applied the transformation to the output
- · Note that convolution is not equivariant to some other transformation, such as changes in the scale or rotation of an image

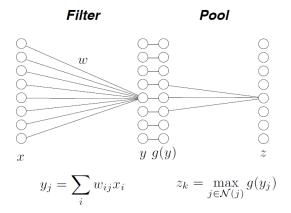
2.2. Computation in a neural net

1) Linear combination

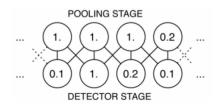


2) Nonlinear activation function

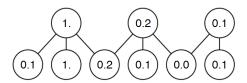




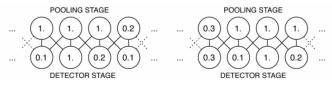
• The maximum of a rectangular neighborhood (max pooling operation)



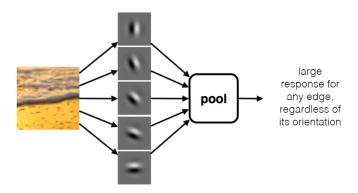
- · Other candiates
 - the average of a rectangular neighborhood
 - lacksquare the L_2 norm of a rectangular neighborhood
- Pooling with downsampling
 - reduce the representation size by a factor of 2, which reduces the computational and statistical burden on the next layer

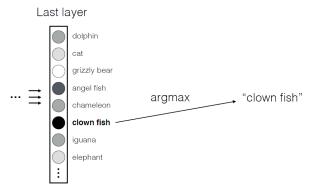


- · Pooling and translations
 - Pooling helps to make the representation become invariant to small translations of the input

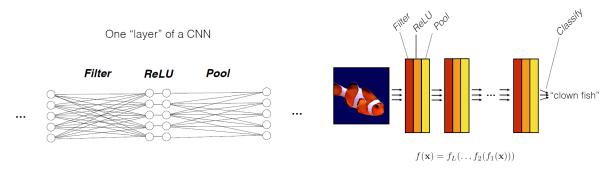


- Invariance to local translation can be a very useful property if we care more about whether some feature is present than exactly where it
- For example, we need not know the exact location of the eyes in a face



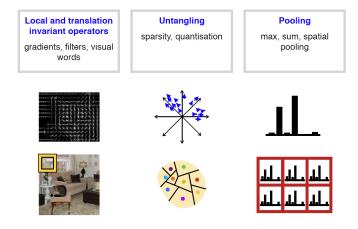


CNN summary



2.3. Ingredients

- · Select important features of the data
 - linear filters
 - pointwise nonlinearity
- Group features that all indicate the same thing
 - pooling
- Repeat to achieve greater abstraction

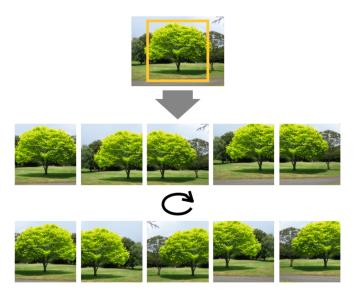


3. Learning

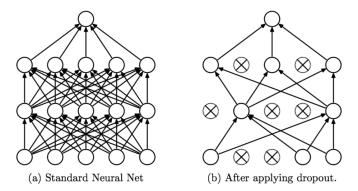
- Backpropagation and
- stochastic gradient descent

4. How to avoid overfitting?

- Convolutional nets use a prior that stuff in the world does not change identity as it translates
- Data Augmentation
 - Augment the training data by adding jittered versions of each image



- Dropout
 - Randomly choose edges not to update
 - Insensitive to local changes
 - acting as regularization



5. How do deep neural nets work?

- Hierarchy of simple, repeated computations
- Sift through data by filtering it
- Build up invariance by pooling alike features
- Can be learned with vanilla SGD

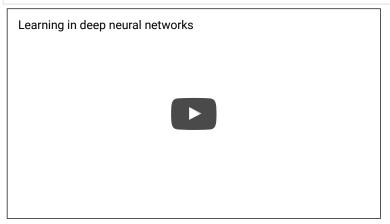
6. Software Tools

- Caffe
 - fast and popular
 - hard to use
 - C++ with linited Matlab and Python interfaces
- Theand
 - Symbolic computation and automatic differentiation python
- Torch
 - Lua

Online Video Lectures

• Slides (./files/deep_learning_tutorial_2015.pdf) by Phillip Isola





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