CSE 435

Convolutional Neural Networks

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Outline

Machine Learning

The **Task** can be expressed an unknown target function: $\mathbf{y} = f(\mathbf{x})$
ML finds a Hypothesis (model), $h(\cdot)$, from hypothesis space $\mathcal{H}$, which approximates the unknown target function.
$\hat{\mathbf{y}} = h^*(\mathbf{x}) \approx f(\mathbf{x})$

The **Experience** is typically a data set, $\mathcal{D}$, of values

The **Performance** is typically numerical measure that determines how well the hypothesis matches the experience.

Nearly all machine learning algorithms can be described with the following fairly simple recipe:

- Dataset
- Cost function (Objective, loss)
- **Model**
- Optimization procedure

Neural Network Resurgence

The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is an annual competition helped between 2010 and 2017.

The datasets comprised approximately 1 million images and 1,000 object classes.

The annual challenge focuses on multiple tasks for image classification.

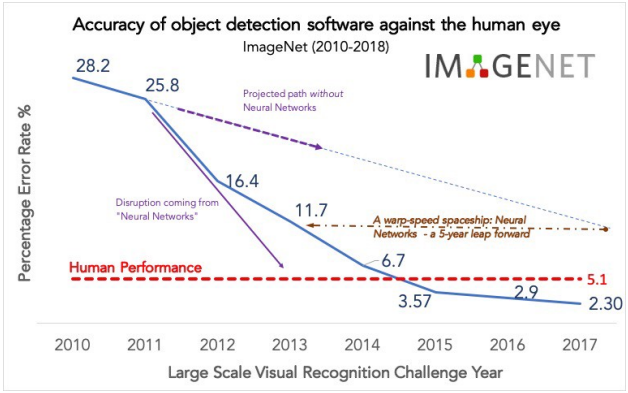


Image source: ImageNet
Alex Krizhevsky, et al. "ImageNet Classification with Deep Convolutional Neural Networks" developed a convolutional neural network that achieved top results on the ILSVRC-2010 and ILSVRC-2012 image classification tasks.

Neural Network Resurgence

AlexNET:

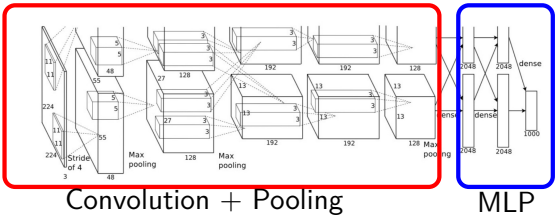


Image: ImageNet Classification with Deep Convolutional Neural Networks

Convolutions allows the network to have lots of neurons while keeping the number of actual parameters that need to be learned fairly small.

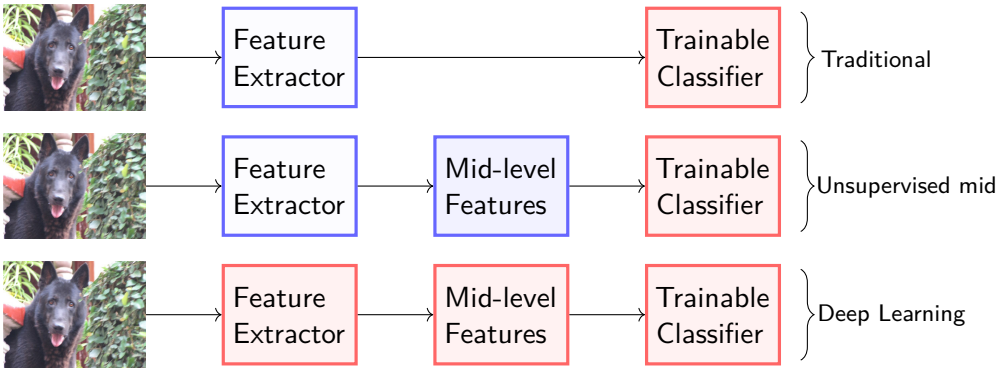
Convolutions has become very popular for verity of tasks including: Vision, NLP, Speech processing, etc.

Objective

- Understand the importance of convolutions neural networks.
- Understand variants of the basic convolution operation.

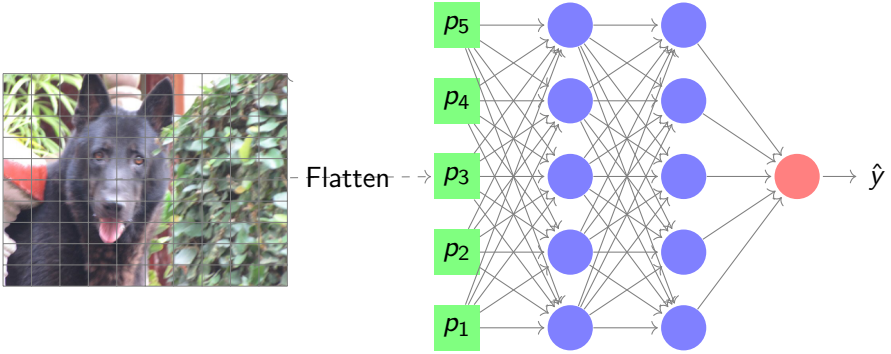
Outline

Learning Hierarchical Representations



Handcrafted features are **time consuming, brittle and not scalable** in practice. DL learn underlying features directly from data.

Apply Neural Networks to Images



Each feature in the first hidden layer has a connection to each pixel.

In computer vision features are usually **local** in space and **same operation** is applied across different locations.

Spacial Relationship

- Natural language Processing (NLP):

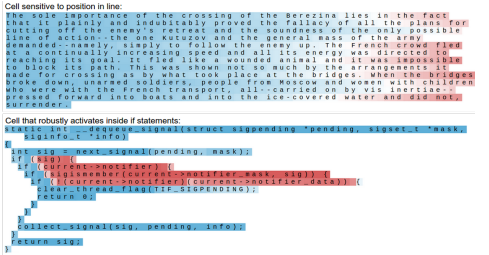


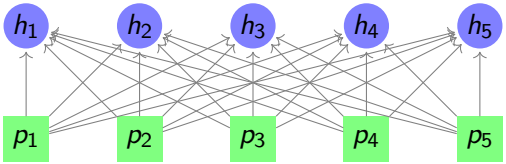
Image: The Unreasonable Effectiveness of Recurrent Neural Networks

- Speech Recognition (Voice to text):
  - “We have one **hour** before **our** appointment with the real estate agent.”
  - “There is no **right** way to **write** a great novel”
- Not all tasks have such relationships. e.g: Predicting house prices using some attributed like “number of rooms”, “suburb”, etc.

Apply Neural Networks to Images

In our ML model we would like to have these two properties.

- Feature extraction usually happens locally - sparse connectivity.
- In feature extraction the same operation is applied at different locations - parameter sharing.



Sparse Connectivity

- Feature extraction usually happens locally - **sparse connectivity**.
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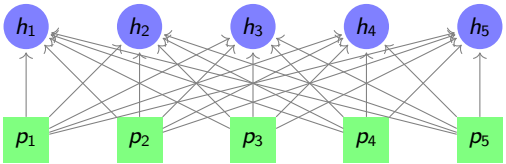

Fully Connected

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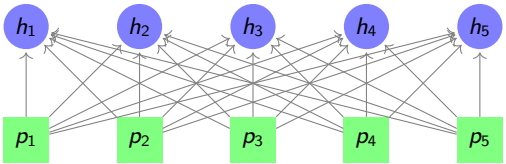
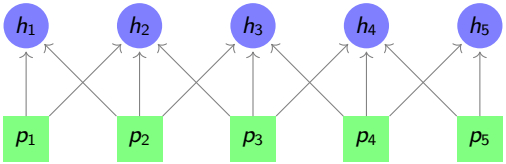


Fully Connected



Sparse connected

Parameter Sharing

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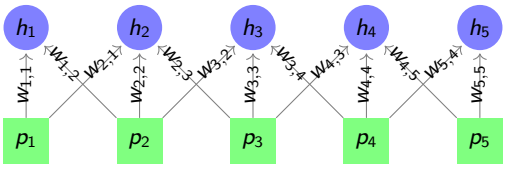
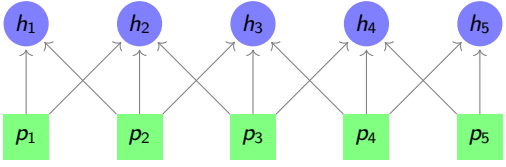


Sparse connected



Shared weights

Parameter Sharing

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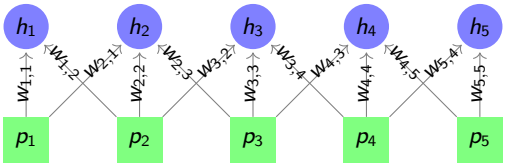

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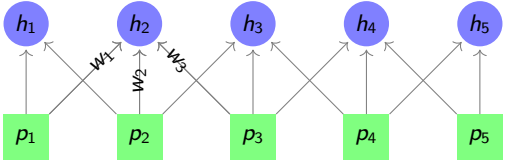

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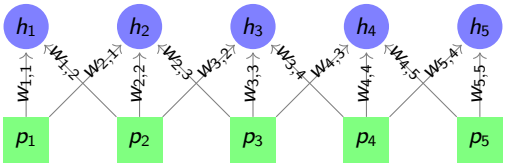
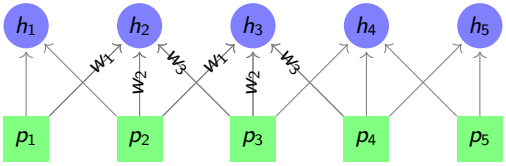


Sparse connected



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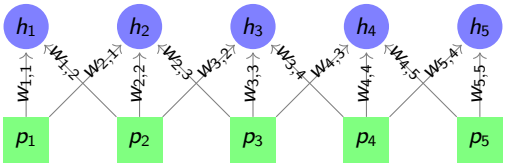

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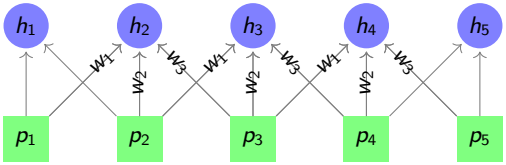
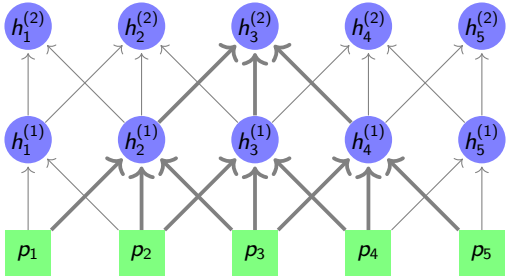


Shared weights

1D Convolution

Both ideas, **sparse connectivity** & **parameter sharing** can be achieved with convolutions.

Convolutions can also be implemented in a hierarchy, where each layer act on the features extracted by the layer below.



note that this network will have only 6 weights and 2 biases; compared to $(25+5) + (25 + 5)$ parameters in a fully connected network with the same number of neurons.

Outline

2D Convolution in Traditional Computer Vision

Feature Extractor

Trainable Classifier

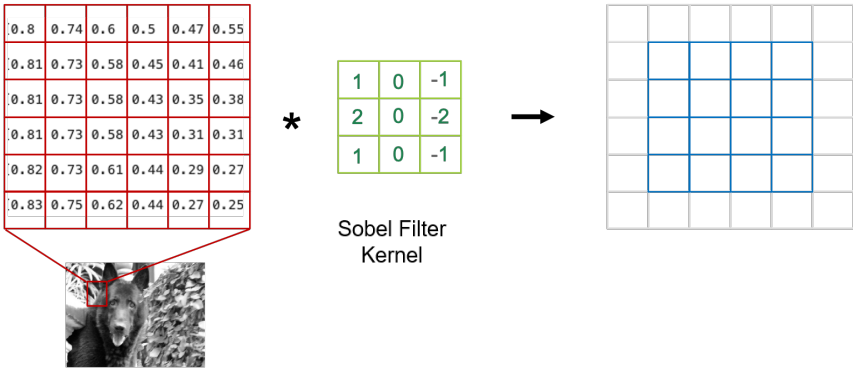
Traditional

Input Image

Edge Features

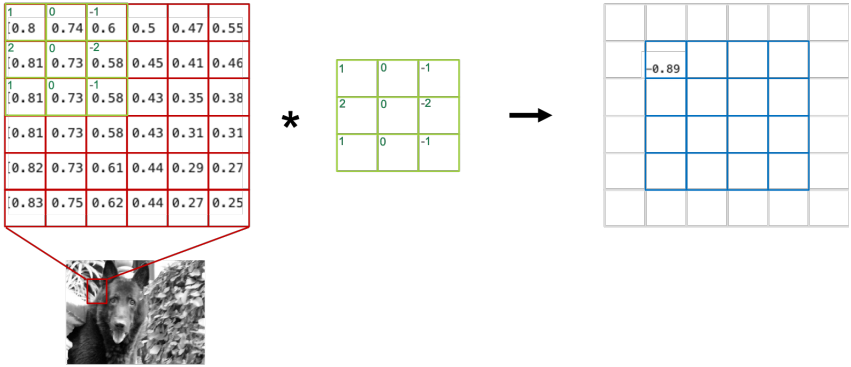
Extracting Edge Features

2D Convolution in Traditional Computer Vision



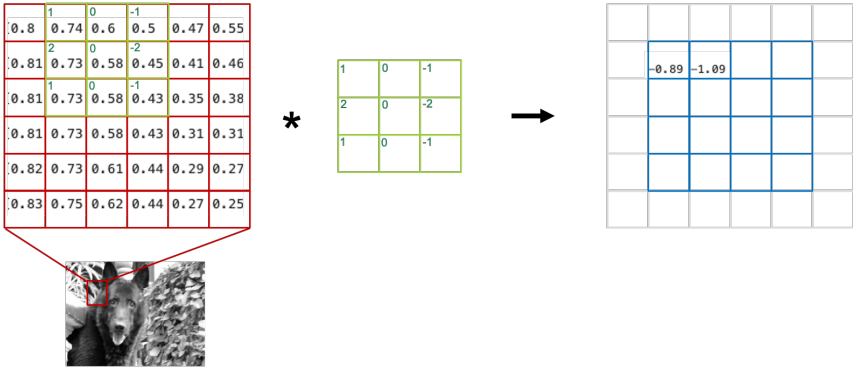
Sobel operator is human engineered

2D Convolution in Traditional Computer Vision



$$I_o(i,j) = \sum_{p=-1}^{1} \sum_{q=-1}^{1} w_{p,g} \times I_{in}(i-p, j-q)$$

2D Convolution in Traditional Computer Vision



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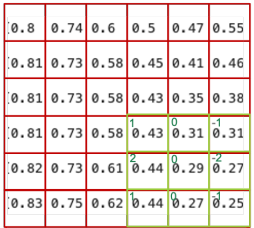

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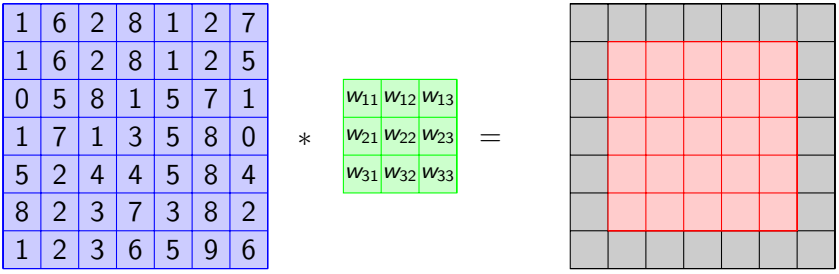
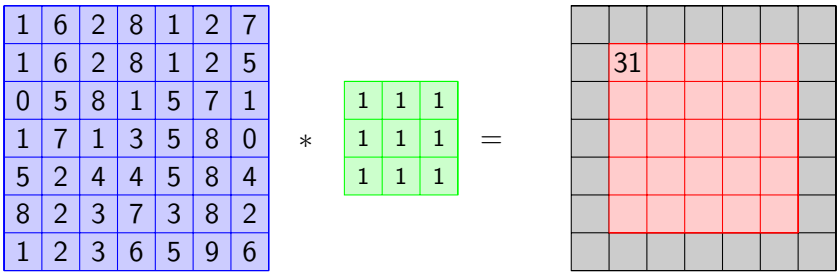
Outline

2D Convolution



The weights $[w_{11}, w_{12}, \cdots, w_{33}]$ are learned from data. For this example lets assume all weights are: $[w_{11}, w_{12}, \cdots, w_{33}] = [1, 1, \cdots, 1]$.

2D Convolution



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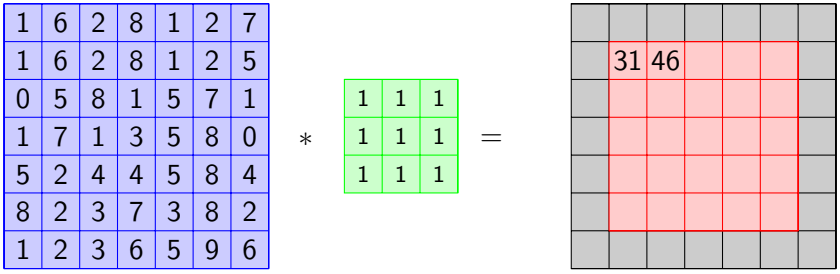

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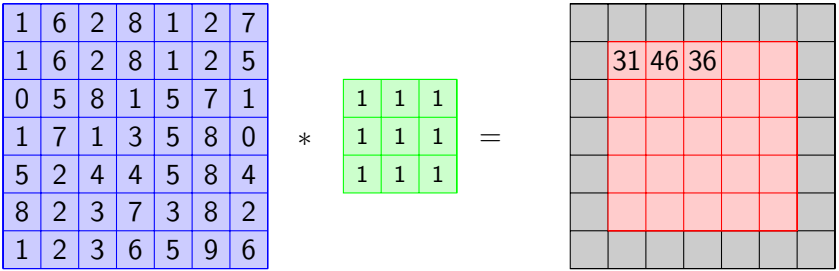

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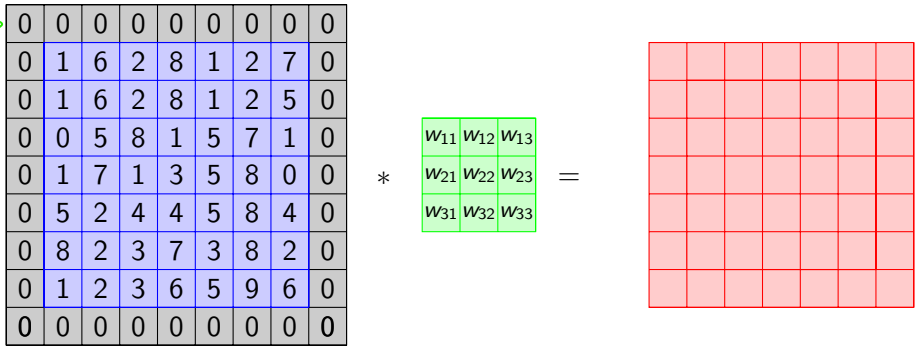
Padding



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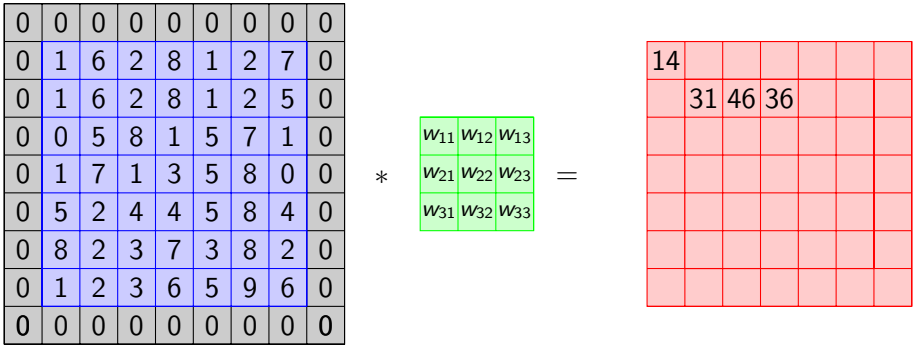
Padding will enable to get a output that is the same size of the input. the most common type of padding is zero padding.

Padding



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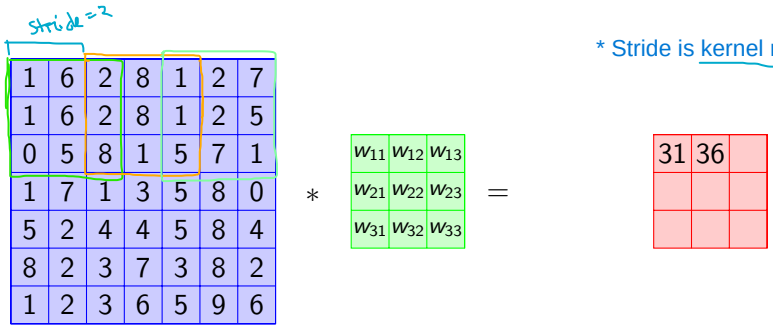
Stride

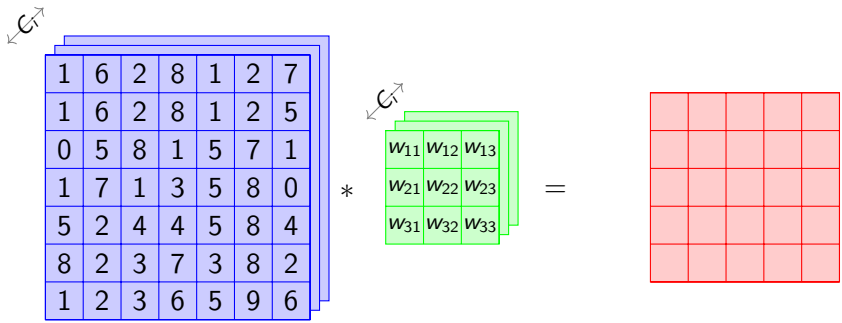


* Stride is kernel move

The weights $[w_{11}, w_{12}, \cdots, w_{33}]$ are learned from data. For this example lets assume all weights are: $[w_{11}, w_{12}, \cdots, w_{33}] = [1, 1, \cdots, 1]$. The stride of 2 will be used.

Stride will downsize the output by a factor related to the stride value.

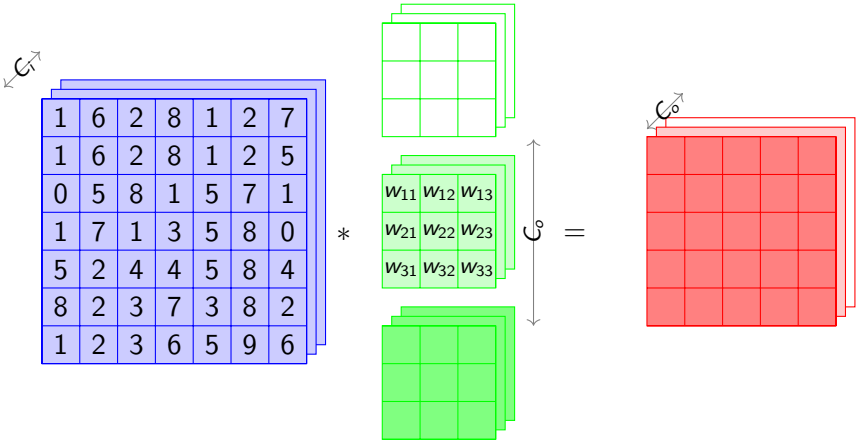
2D Convolution Multiple Input Channels



The convolution operation can be easily extended to handle multiple input channels.

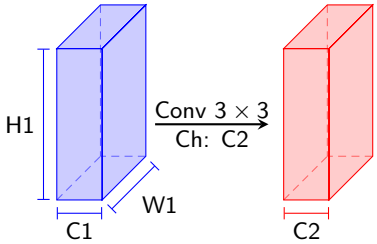
The number of channels in the weights filter *should* be equal to the number of channels in the input.

Multiple Filters



We can have multiple weights filters. The number of output channels will now be equal to the number of weight filters (C_0).

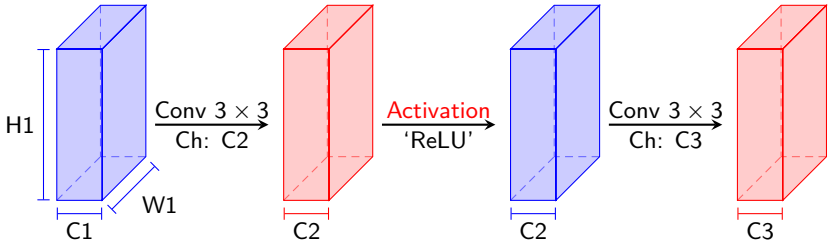
Multiple Layers



We can represent a 2D convolution in tensor representation. The input to the convolution is a tensor of size $[B, H1, W1, C1]$ and the output is tensor of size $[B, H1, W1, C2]$. B is the batch size (if padding is 'same').

```
tf.keras.layers.Conv2D(
    filters, kernel_size, strides=(1, 1), padding='valid', data_format=None,
    dilation_rate=(1, 1), groups=1, activation=None, use_bias=True,
    kernel_initializer='glorot_uniform', bias_initializer='zeros',
    kernel_regularizer=None, bias_regularizer=None, activity_regularizer=None,
    kernel_constraint=None, bias_constraint=None, **kwargs
)
```

Multiple Layers



Convolutions can be stacked one after the other.

```
tf.keras.layers.Conv2D(
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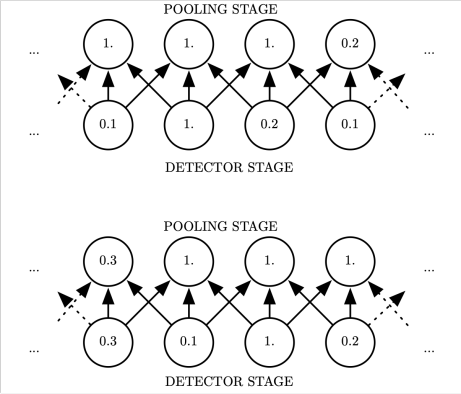
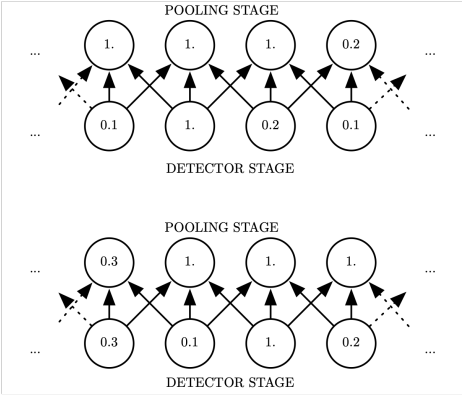
Outline

Invariance to Translation



Invariance to Translation



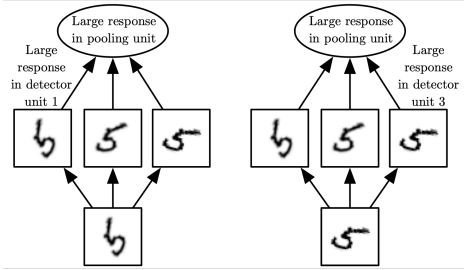


Image: Goodfellow, 2016

We would like our feature representations, not to change minimally when the input is shifted or rotated slightly.

Pooling

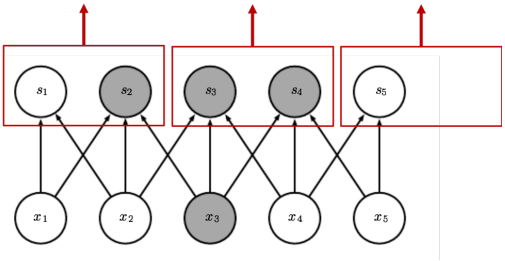


Image: Goodfellow, 2016

Pooling help reduce redundant information and provide some level of invariance to translations.

Pooling can use simple mathematical functions like max, sum , etc. "max-pooling" is the most common.

2D Pooling

1	6	2	8	1	2	7
1	6	2	8	1	2	5
0	5	8	1	5	7	1
1	7	1	3	5	8	0
5	2	4	4	5	8	4
8	2	3	7	3	8	2
1	2	3	6	5	9	6

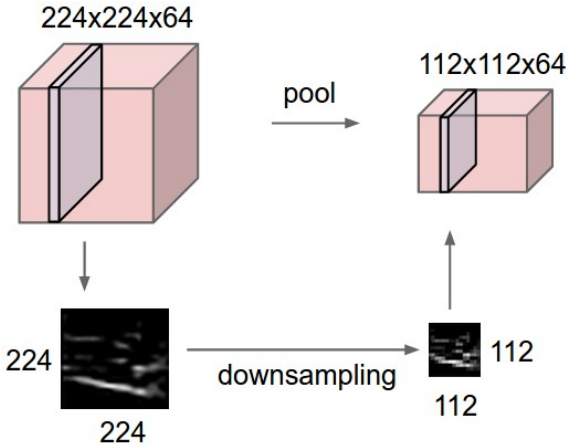
$=$

6	8	2
7		

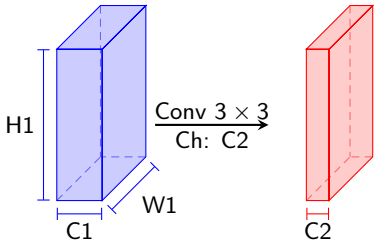
In this example we use 2D pooling with 2×2 and stride 2.

Pooling is done each channel separately.

2D Pooling



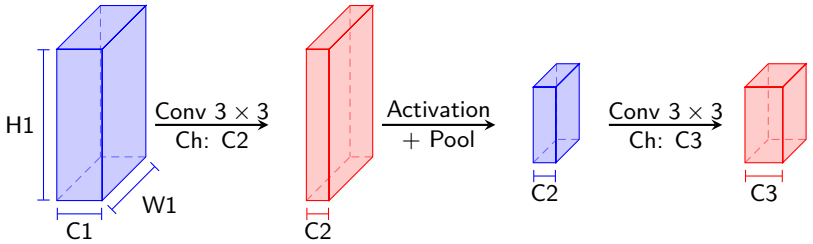
Pooling & Convolutions



Convolutions can be combined with pooling to construct a chain of layers.

```
tf.keras.layers.MaxPool2D(
    pool_size=(2, 2), strides=None, padding='valid', data_format=None, **kwargs
)
```

Pooling & Convolutions



Convolutions can be combined with pooling to construct a chain of layers.

```
tf.keras.layers.MaxPool2D(
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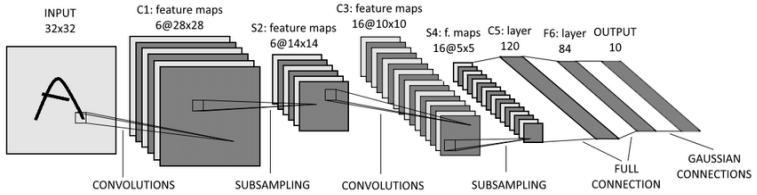
)
```

LeNet Architecture

"*LeNet is a classic example of convolutional neural network to successfully predict handwritten digits.*" [LeNet]




```
model = tf.keras.Sequential()
model.add(Conv2D(6, kernel_size=(5, 5), strides=(1, 1), activation='tanh', input_shape=input_shape, padding="valid"))
model.add(AveragePooling2D(pool_size=(2, 2), strides=(2, 2), padding='valid'))
model.add(Conv2D(16, kernel_size=(5, 5), strides=(1, 1), activation='tanh', padding='valid'))
model.add(AveragePooling2D(pool_size=(2, 2), strides=(2, 2), padding='valid'))
model.add(Flatten())
model.add(Dense(120, activation='tanh'))
model.add(Dense(84, activation='tanh'))
model.add(Dense(10, activation='softmax'))
```

Outline

Strided Convolutions

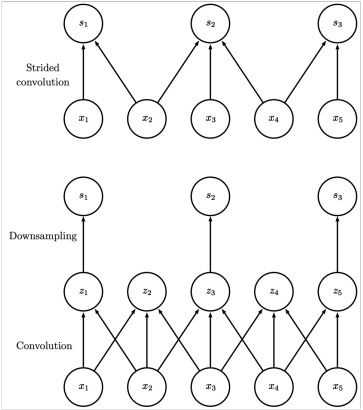
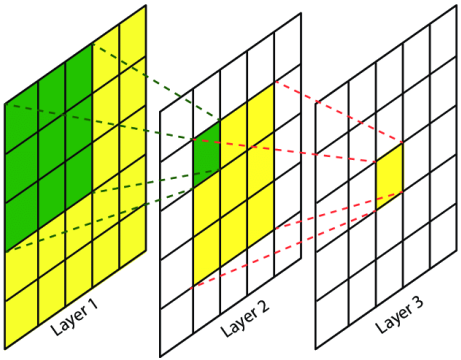


Image: Goodfellow, 2016

Can replace convolution + pooling with strided convolutions.

Receptive Field



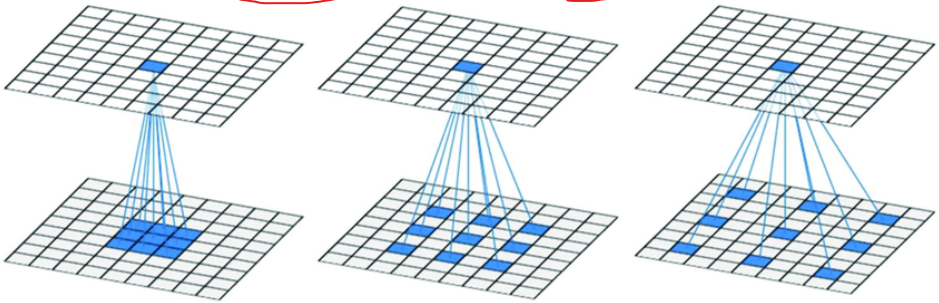
Assume 3 by 3 convolutions in each layer

Receptive field of the convolutional network, is defined as the size of the region in the input that produces the feature.

Receptive field increases with the number of layers (depth).

Dilated Convolutions

What if you want to increase the receptive field without having so many layers?

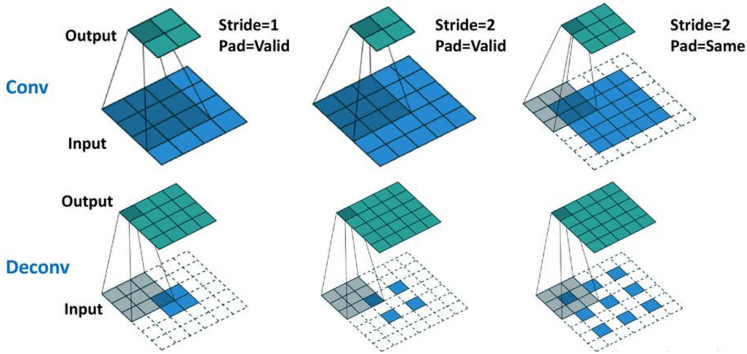


Dilated Convolutions delivers a wider field of view (receptive field) at the same computational cost. Also known as Atrous convolutions.

Transpose Convolution

Convolution + pooling (or strided convolutions) are usually used to reduce the output tensor width and height in subsequent layers of a network.

What if you want to increase the output tensor width and height? You can use transpose convolution also known as deconvolution (e.g. Image segmentation).

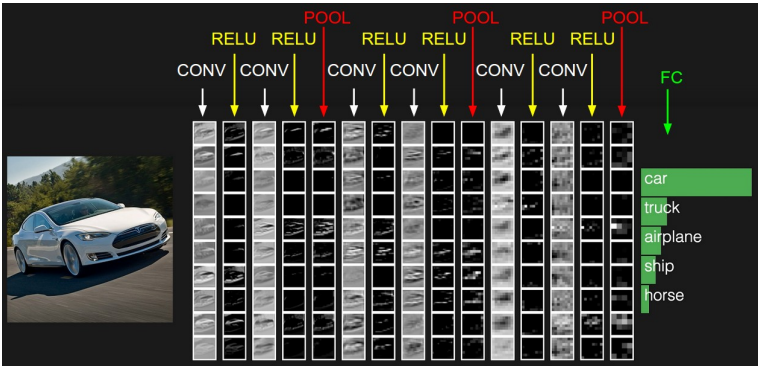


Outline

Feature Maps

Convolutional Neural Networks as a Model of the Visual System: Past, Present, and Future

Visualizing and Understanding Deep Neural Networks by Matt Zeiler



Gabor Kernels

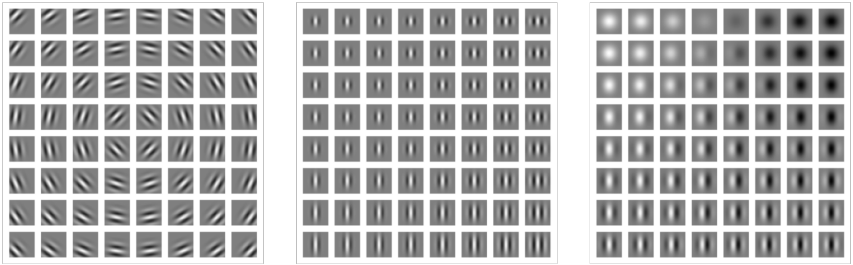


Image: Goodfellow, 2016

Gabor functions with a variety of parameter settings.

Gabor-like Learned Kernels

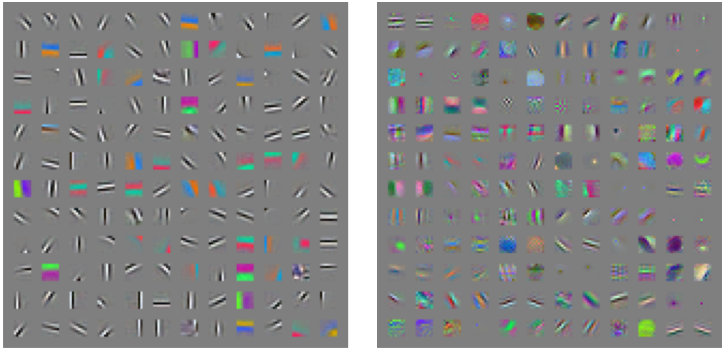


Image: Goodfellow, 2016

Many machine learning algorithms learn features that detect edges or specific colors of edges when applied to natural images. These feature detectors are reminiscent of the Gabor functions known to be present in the primary visual cortex.

Summary

1. Main components of CNN and why they work.
2. Extensions of the basic convolution operation.

Next week:

1. Popular Convolutional neural network architectures.