COMSM0045: Convolutional Neural Networks (Part 2)

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October 11, 2020

Convolutional Neural Networks

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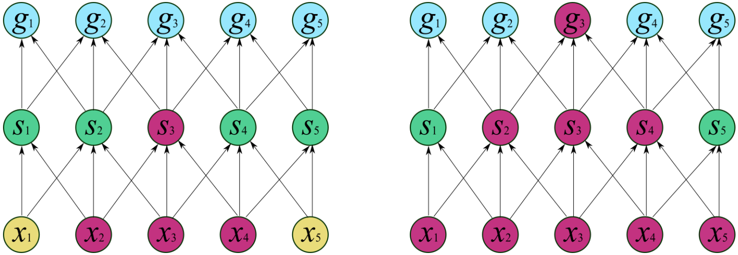
- Three primary properties distinguish fully-connected networks from convolutional neural networks:
    1. Sparse Interactions
    2. Parameter Sharing
    3. Equi-variant Representations

CNN Properties: 1- Sparse Interactions

- **The receptive field of the units in the deeper layers of a CNN is larger than the receptive field of the units in the shallow layers**



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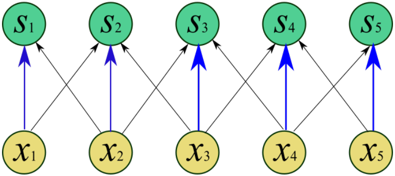
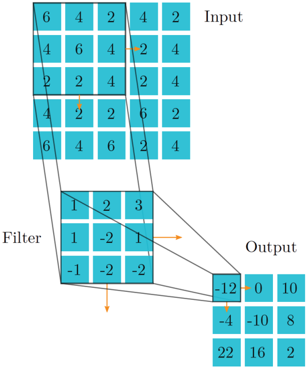
CNN Properties: 2- Parameter Sharing



CNN Properties: 2- Parameter Sharing

- And in 2-D



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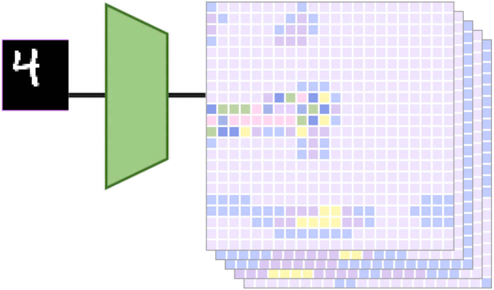
CNN Properties: 3- Equi-variant Representations

- As a result of the first two properties, CNNs exhibit some equivariance properties.
- A function is equivariant if when the input changes (or shifts) in a certain way, the output also changes in exactly the same way.
- CNNs are equi-variant to... translation

CNN Properties: 3- Equi-variant Representations

- CNNs are equi-variant to... translation
- This is of immense value in images for example.



Source: Christian Wolf Blog (2020) - What is translation equivariance, and why do we use convolutions to get it? https://link.medium.com/4u44mjdXqab

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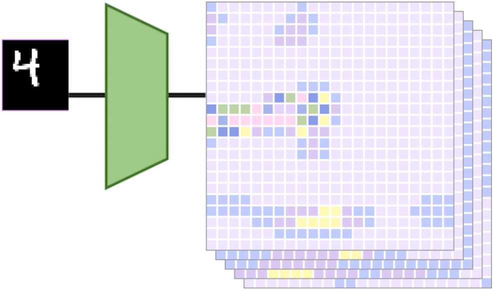

- If an object moves in the input, its representation will move in the output in the same direction.

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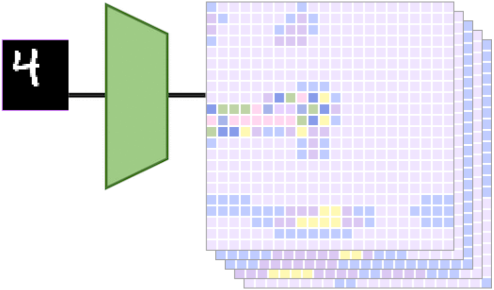

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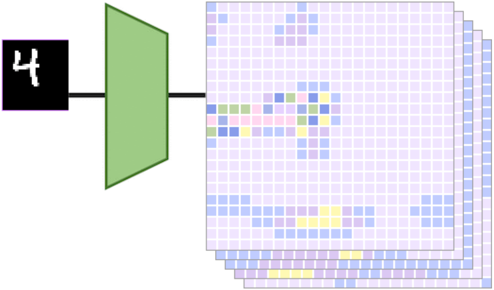

- If an object moves in the input, its representation will move in the output in the same direction.
- However CNNs are NOT equivariant to... rotation or scale

Source: Christian Wolf Blog (2020) - What is translation equivariance, and why do we use convolutions to get it? https://link.medium.com/4u44mjdXqab

Zero Padding

- However, to make the most of the input, particularly around the edges/borders, one essential feature of any CNN implementation is **zero padding** the input to make it wider
- Without zero-padding, the input shrinks by one pixel less than the kernel width at each layer
- With zero-padding, the input and output are of the same size, unlike example below

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- Without zero-padding, the input shrinks by one pixel less than the kernel width at each layer
- With zero-padding, the input and output are of the same size, unlike example below
- Without zero-padding, the number of convolutional layers that can be included in a network will be capped

CNN Architecture Considerations

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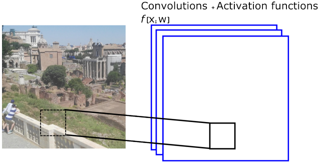
- All CNN representations omit the fourth dimension, for batch-based optimisation, for simplicity

CNN Architecture Considerations

- In the previous example, the input and output sizes of the convolution+activation layers were equal



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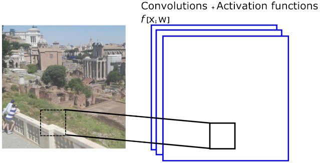

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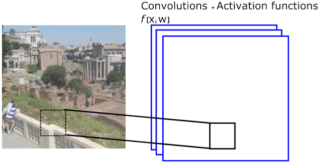

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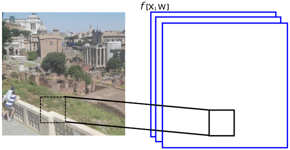
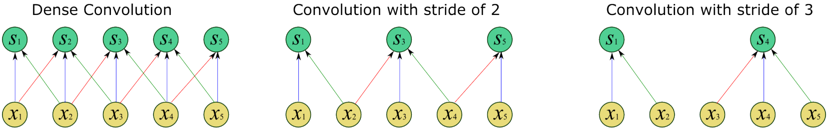


- However, practically we do not convolve densely, but instead we move the convolution skipping certain pixels.
- The number of pixels we skip, is referred to as the **stride** of the layer
- This results in downsampled convolutions
- It is possible to use separate strides for each dimension

CNN Architecture Considerations

- An example of coonvolution with a stride of two, and a stride of three, is shown below



CNN Architecture Considerations

- Care should be taken when backpropagating CNNs with zero padding or stride of more than one.

CNN Architectures - AlexNet

- When AlexNet won the most challenging computer vision task - Classifying 1000 classes by training from 10,000,000 images (The ImageNet Challenge), the new wave of CNN architectures started

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Alex Krizhevsky, Sutskever and Hinton (2012) ImageNet Classification with Deep Convolutional Neural Networks, NIPS

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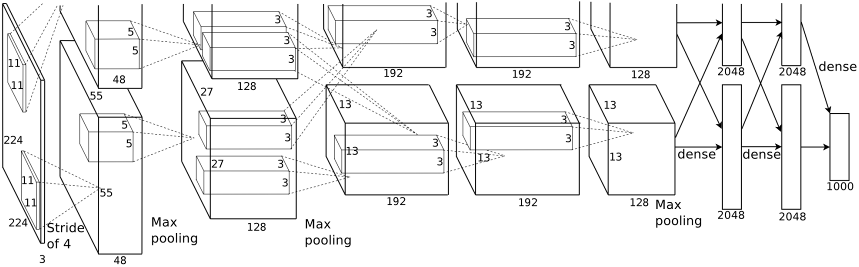

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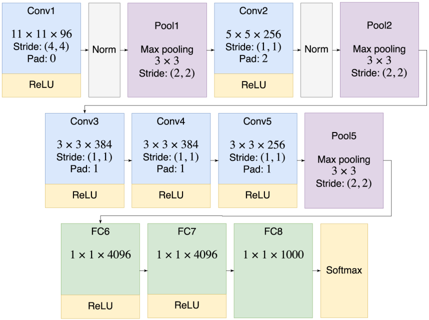
CNN Architectures - AlexNet vs VGG-16



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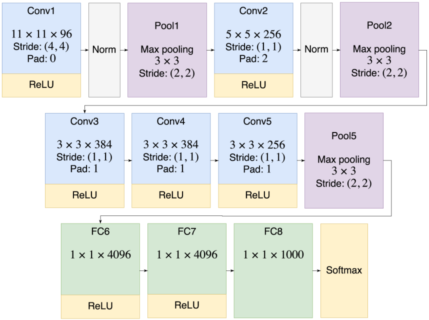
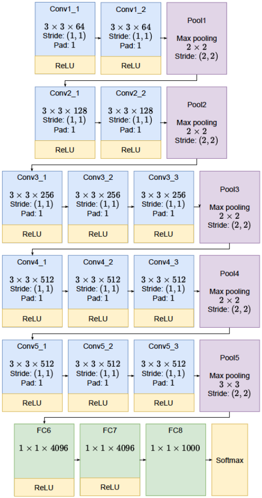
CNN Architectures - AlexNet vs VGG-16





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Training CNNs

- The most expensive part of CNN training is learning the features
- The fully-connected layers are usually relatively inexpensive to train because of the small number of features provided as input

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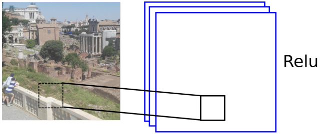
- The fully-connected layers are usually relatively inexpensive to train because of the small number of features provided as input
- When performing gradient descent, every gradient step requires a complete run of forward propagation and backward propagation through the entire network

Recent Architectures - Residual Networks (ResNet)

- Finding the right weights for a deep convolutional network is not easy.
- A trick introduced by He et al (2015) suggested adding *shortcuts* in the network architecture



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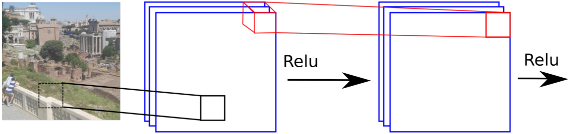

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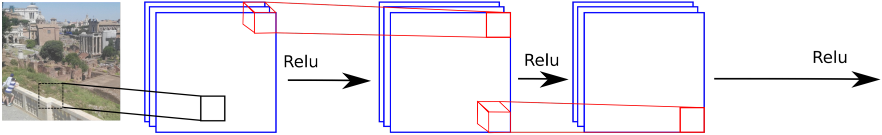

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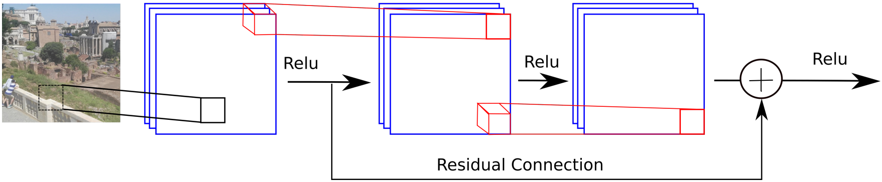

Recent Architectures - Residual Networks (ResNet)

- ResNet block

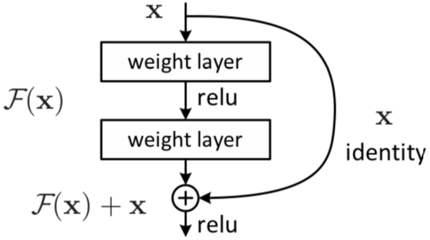

Figure 2. Residual learning: a building block.

- Allowed faster convergence - by searching for weights that deviate slightly from the identity

Source: He et al 2015. Deep Residual Learning for Image Recognition

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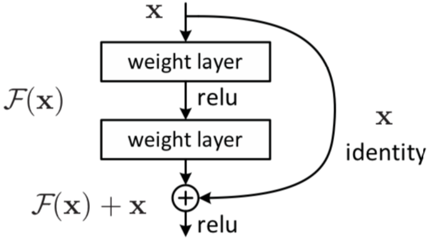

Figure 2. Residual learning: a building block.

- Allowed faster convergence - by searching for weights that deviate slightly from the identity
- Allowed training deeper networks - ResNet-50, ResNet-101

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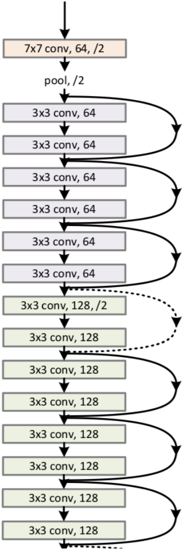
Recent Architectures - Residual Networks (ResNet)

- Part of a ResNet



Source: He et al 2015. Deep Residual Learning for Image Recognition

The latest!

- ResNext blocks

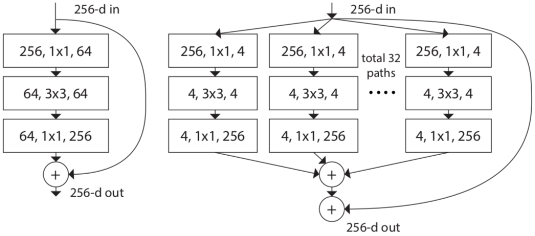


Figure 1. **Left**: A block of ResNet [14]. **Right**: A block of ResNeXt with cardinality = 32, with roughly the same complexity. A layer is shown as (# in channels, filter size, # out channels).

Source: Xie et al 2017. Aggregated Residual Transformations for Deep Neural Networks

CNN Architectures - Further architectures

- See live demos at: `http://cs231n.stanford.edu`
- Visualise recent architectures at: `http://josephpcohen.com/w/visualizing-cnn-architectures-side-by-side-with-mxnet/`

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Further Reading

- Deep Learning

  Ian Goodfellow, Yoshua Bengio, and Aaron Courville
  MIT Press, ISBN: 9780262035613.
  - Chapter 9 – Convolutional Networks