

Convolutional Neural Networks

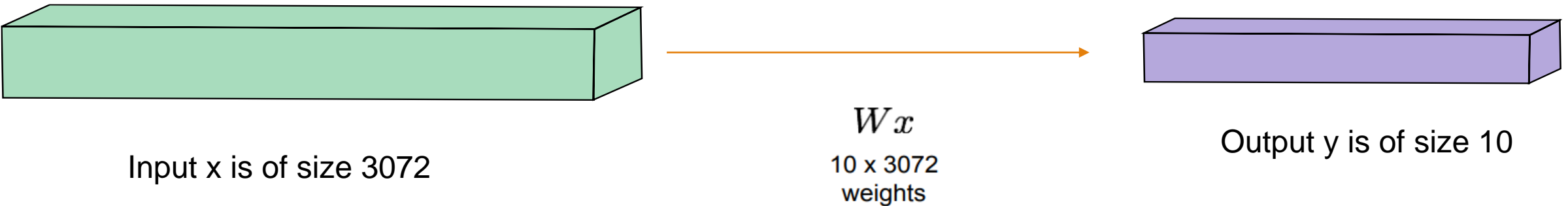
MUSTAFA HAJIJ

Purpose

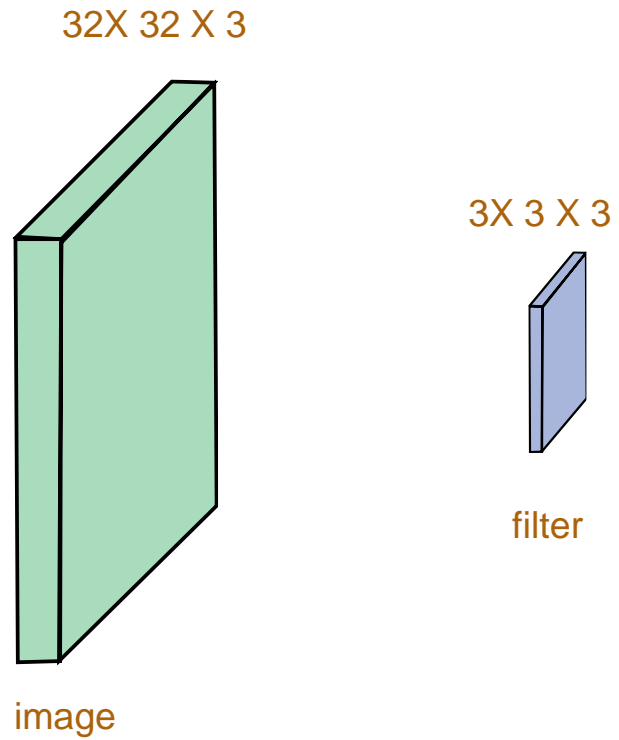
- Basics of convolution layer
- Convolutional neural networks
- Representation learning for CNNs
- End-to-end training
- Pooling
- Inductive bias
- Manifold hypothesis
- Study cases of CNNs
- Transfer learning

Convolution

Recall first the fully connected layer on image. Say that we have 32X32X3 size image. We flatten this image to a vector 3072.

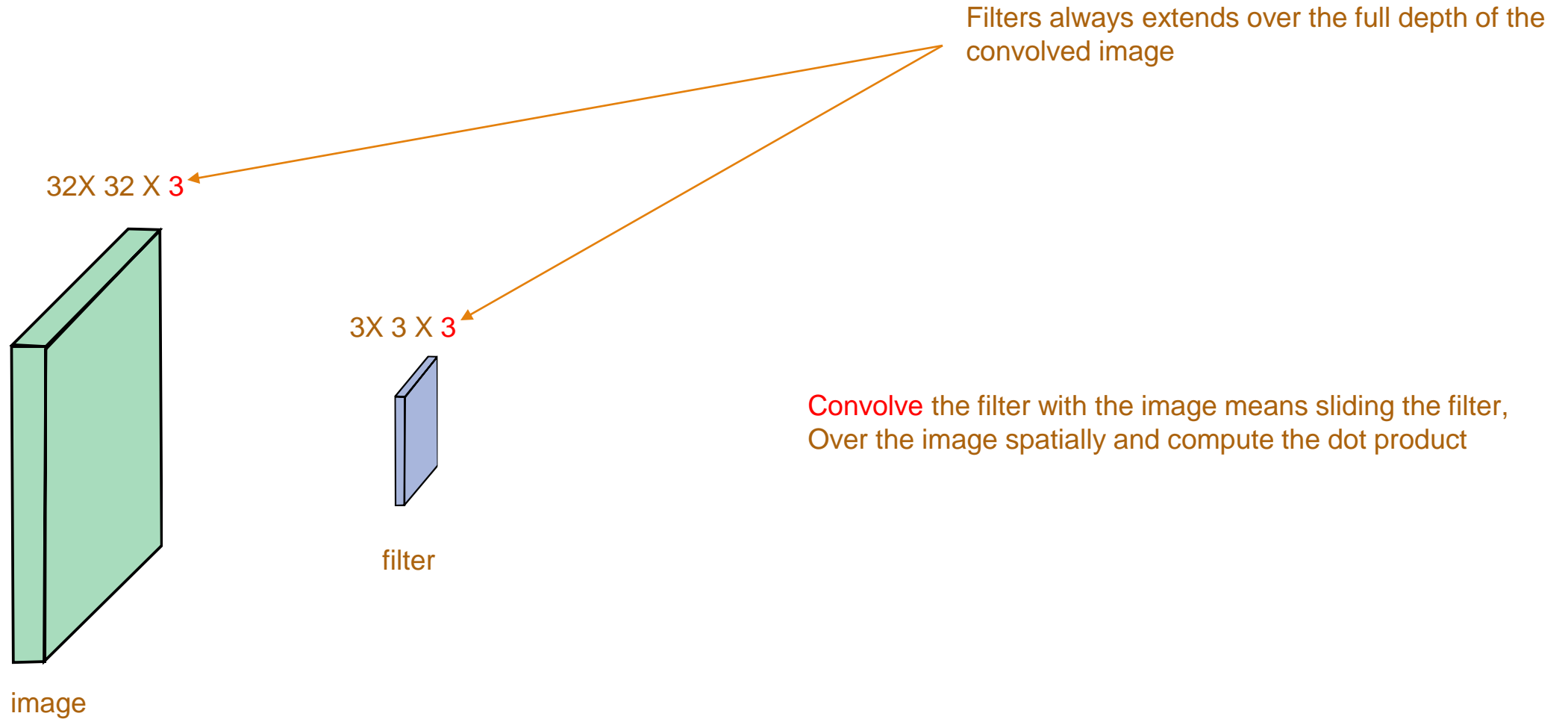


Convolution

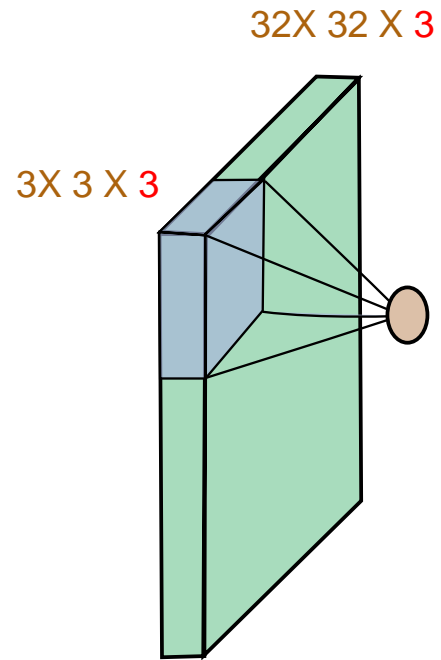


Convolve the filter with the image means sliding the filter,
Over the image spatially and compute the dot product

Convolution



Convolution

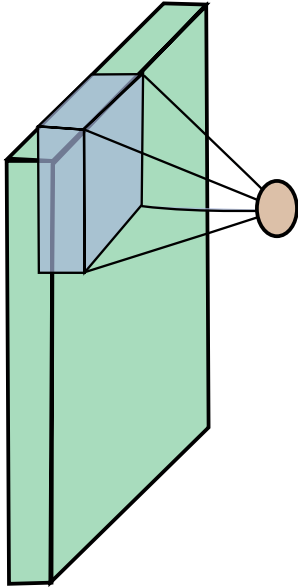


Perform dot product between the filter and the image (5X5X3 products) + bias

We can write this operation as $w^T x + b$

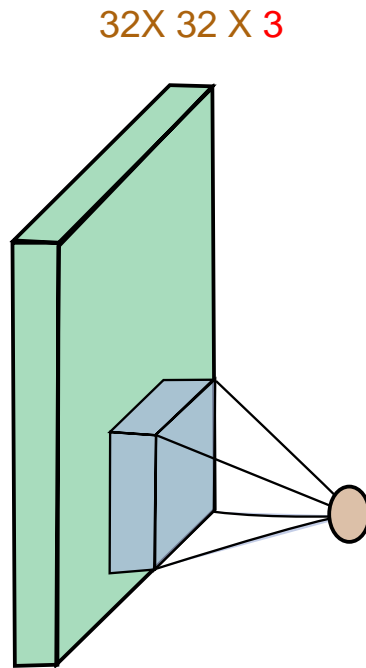
Convolution

32X 32 X 3



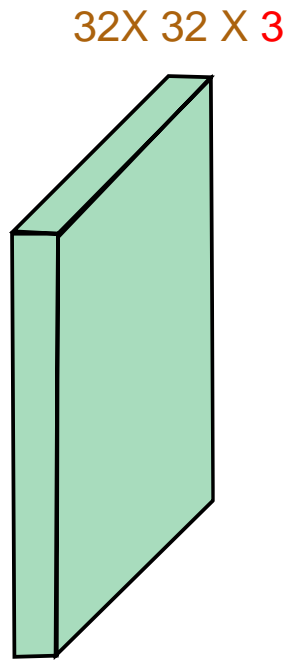
Shift and perform the dot product again

Convolution



Keep sliding spatially and compute the dot product till
You get to the other bottom right corner

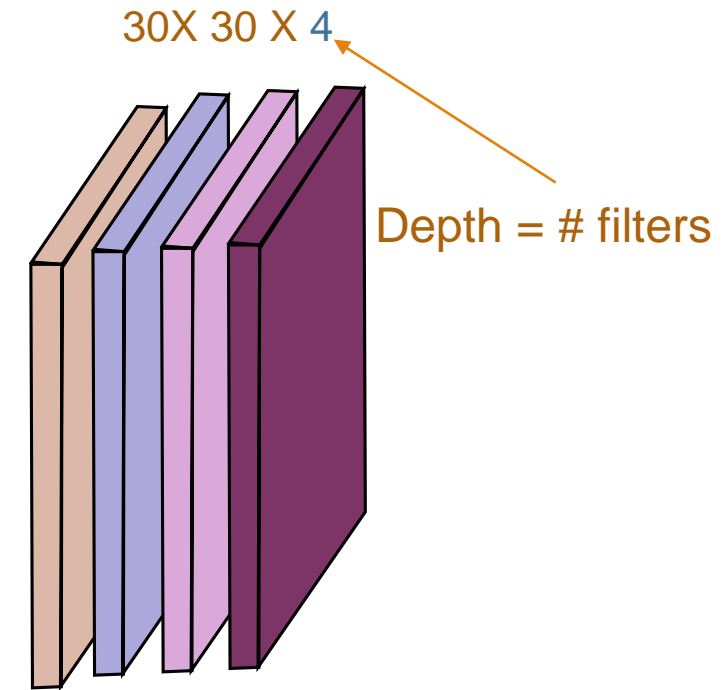
Convolution



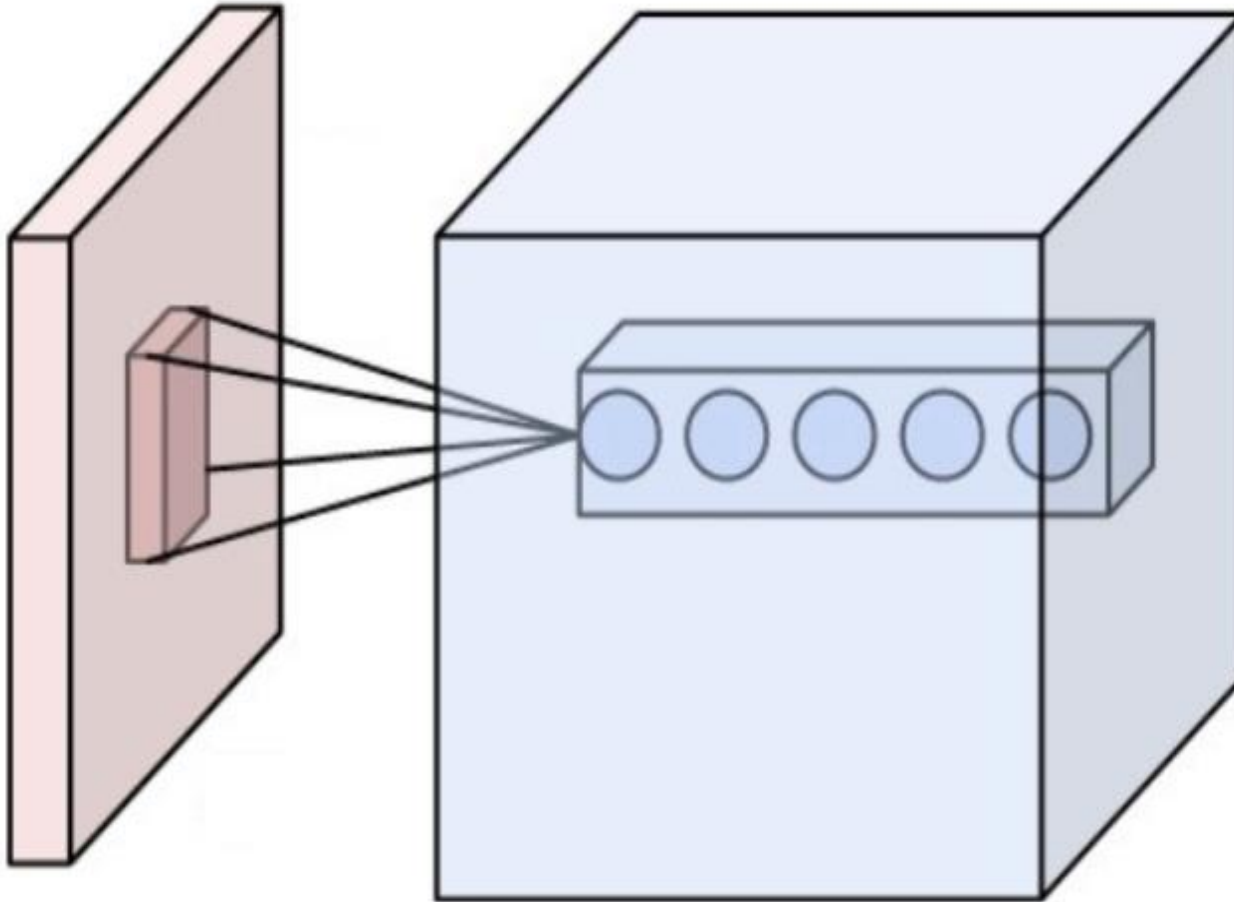
After finishing convolving with 4 filters



Activation maps

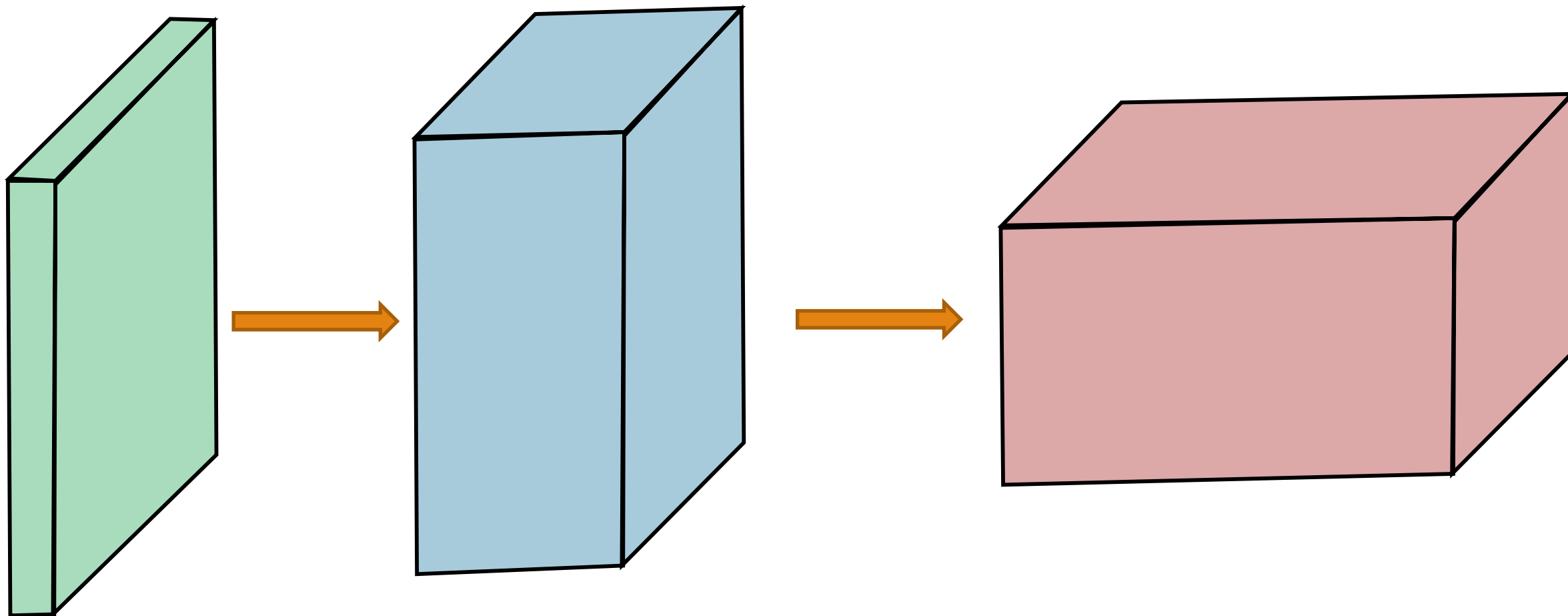


Convolution



[Image source : Convolutional neural network - Wikip](#)

Convolution



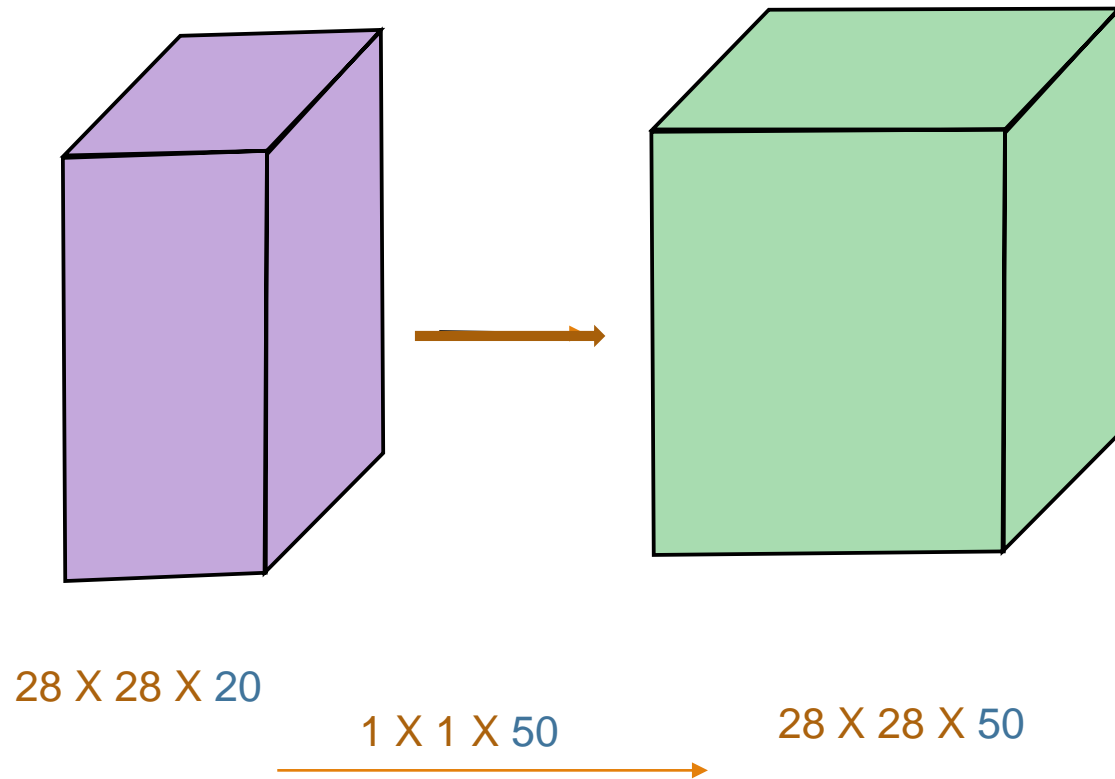
$32 \times 32 \times 3$ $\xrightarrow{5 \times 5 \times 20}$

$28 \times 28 \times 20$

$\xrightarrow{3 \times 3 \times 50}$

$26 \times 26 \times 50$

Special cases 1X1 filters



You can think about these filters are changing the volume size but keeping the width and height unchanged

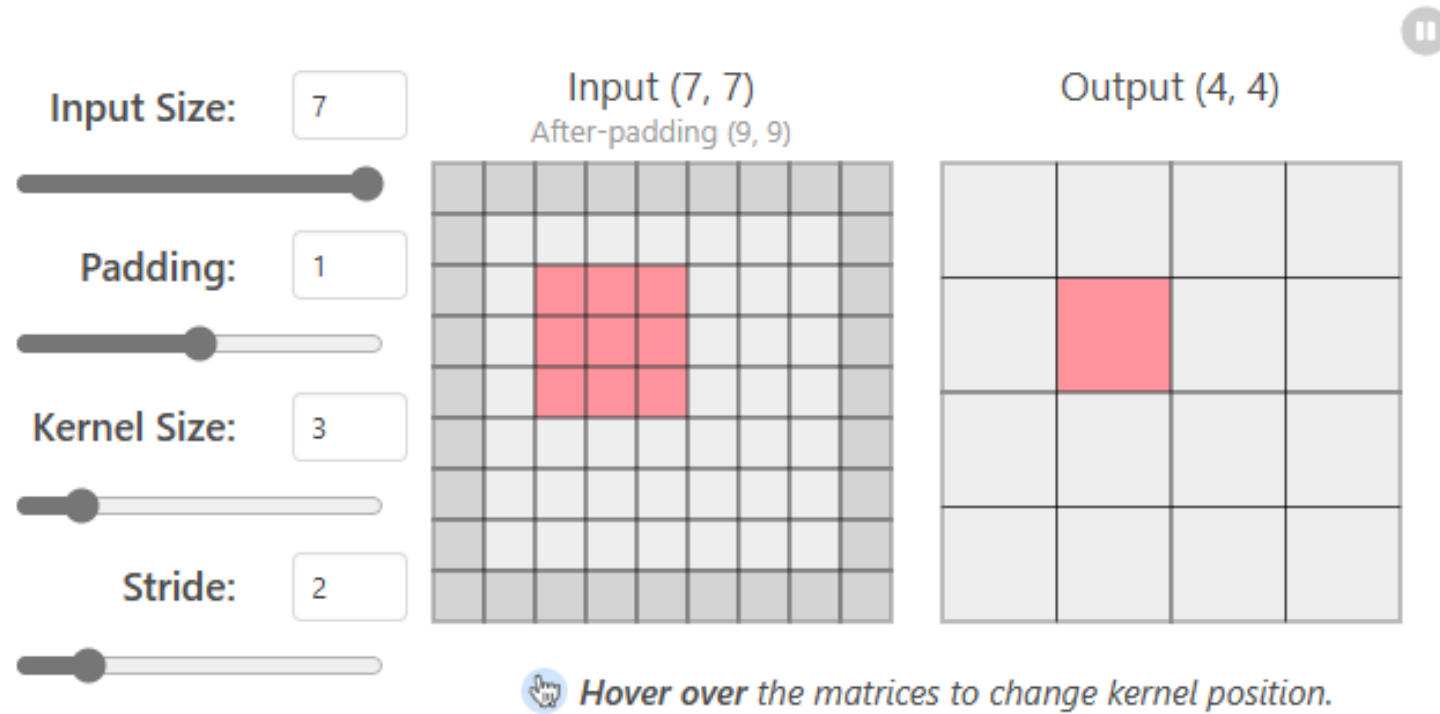
Padding and stride

Padding is a technique used to prevent the image height and width from shrinking as we apply convolution operations. It works by “padding zeros to the boundary of the image”

Stride determines how exactly do we walk when over the image as we convolve the filter With the image. Let's explore these notions interactively!

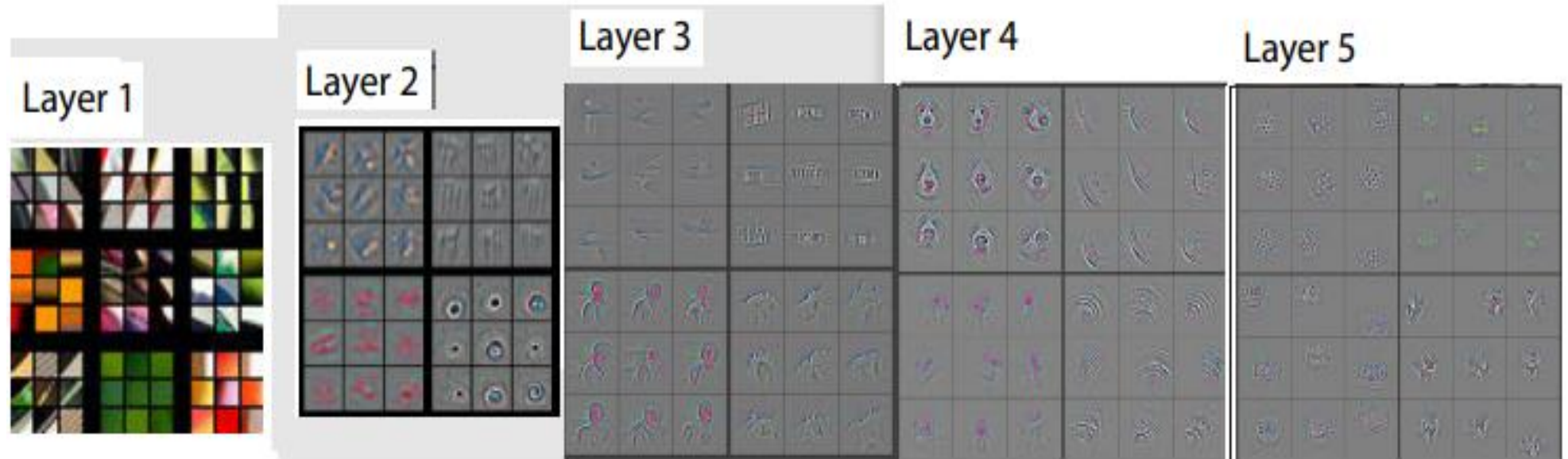
Convolution, padding and other concepts interactive tour

Lets explore this interactively!



Convolution

What do the filters learn ?

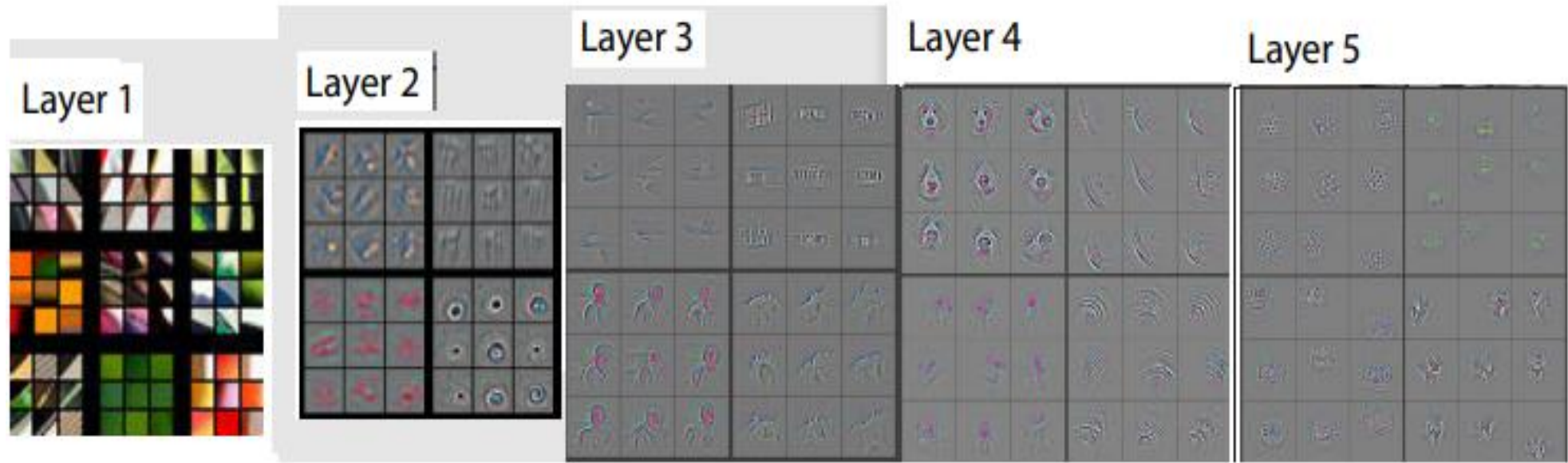


The **learned representations** refer to the hierarchical and abstract features that the network extracts from the input data during the training process. These representations are obtained by applying convolutional filters and pooling operations throughout the network's layers.

The learned representations in a CNN capture increasingly complex and abstract features from the input data. The earlier layers tend to learn low-level features, such as edges and textures, while deeper layers learn more high-level features that are specific to the task the network was trained on.

End-to-end training

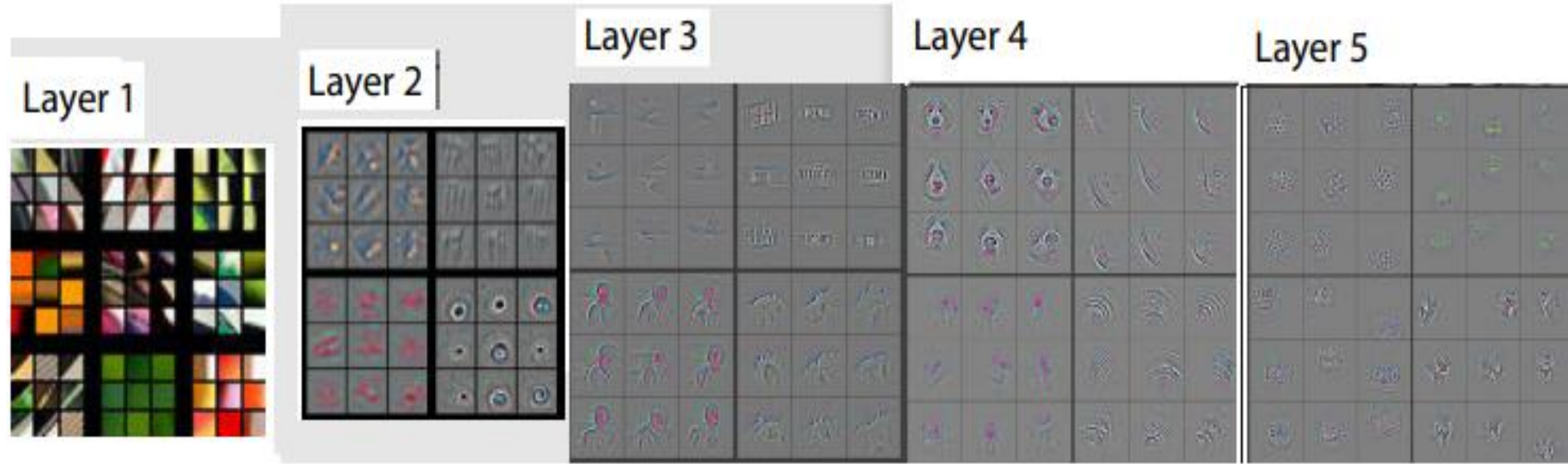
These feature are learned automatically!
In an end-to-end fashion!



- **End-to-end training** refers to a machine learning approach where a model learns to perform a task directly from raw input data to desired output, without relying on manual feature engineering or intermediate steps.
- In this process, the model learns to extract relevant features and make predictions simultaneously, effectively learning the entire process "end to end."
- This approach simplifies the development pipeline, as **it eliminates the need for designing complex feature** extraction algorithms and allows the model to automatically learn the most relevant patterns and representations from the data, leading to potentially more accurate and efficient results.

End-to-end training

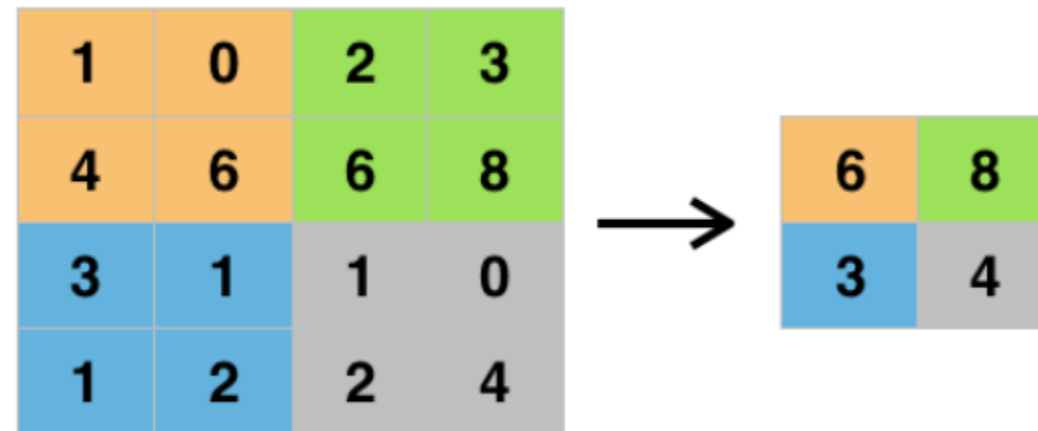
These feature are learned automatically!
In an end-to-end fashion!



- In the context of CNN it refers to training the network to directly map input images to desired outputs without explicitly designing and incorporating handcrafted features.
- In traditional approaches, engineers would manually extract features from images, such as edges or textures, and then feed these features into a separate classifier. However, with end-to-end training using CNNs, the network learns to automatically extract relevant features from raw pixel values and make predictions in a single step.
- The CNN can learn to extract hierarchical representations of the input data, enabling more efficient and accurate performance on a wide range of computer vision tasks.

Pooling

Pooling in deep learning is a technique that reduces the dimensionality of data by summarizing or **downsampling** it, aiding in capturing important features while reducing computational complexity.



Max pooling

Why CNNs work really well in practice?

Inductive bias

- Inductive bias is the set of assumptions (or biases) that a machine learning algorithm makes to generalize from limited training data and make predictions about unseen examples.
- An example of inductive bias is a machine learning algorithm assuming that simpler explanations or hypotheses are more likely to be correct than complex ones.

Inductive bias in CNNs

- In the context of Convolutional Neural Networks (CNNs), the inductive bias refers to the assumptions and design choices made in the network architecture that enable it to effectively learn and extract features from visual data.

Inductive bias in CNNs

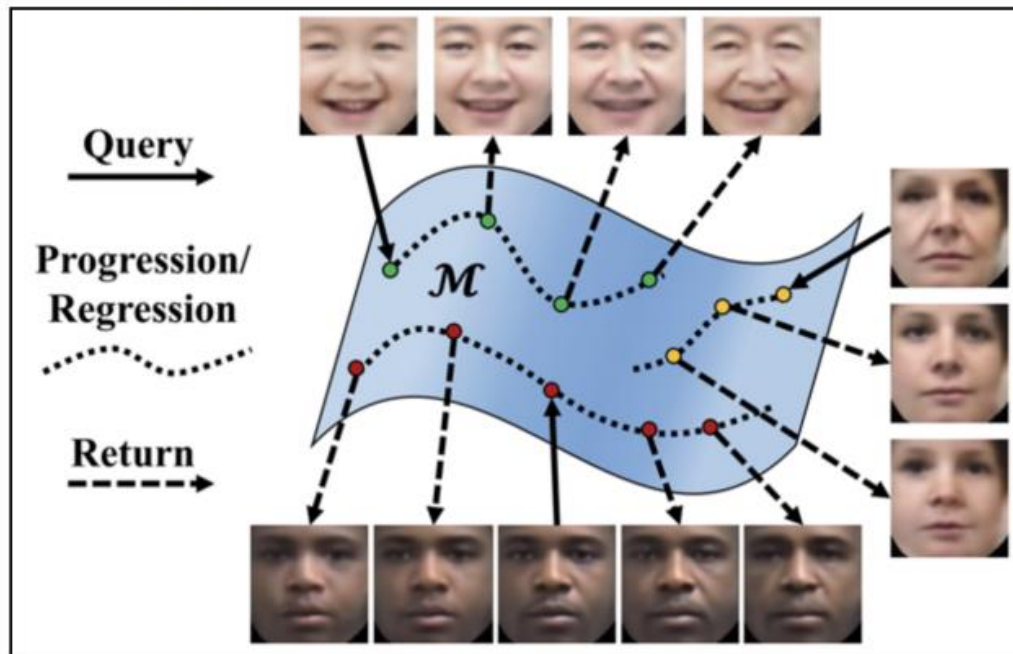
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- For example, CNNs have a built-in inductive bias that **assumes spatial locality and translation invariance**. This means that the network assumes that nearby pixels in an image are more likely to be related and that the learned features should be applicable regardless of their position in the image. By incorporating convolutional layers and pooling operations, CNNs can exploit these assumptions and efficiently capture local patterns and hierarchical representations in images.

Inductive bias in CNNs

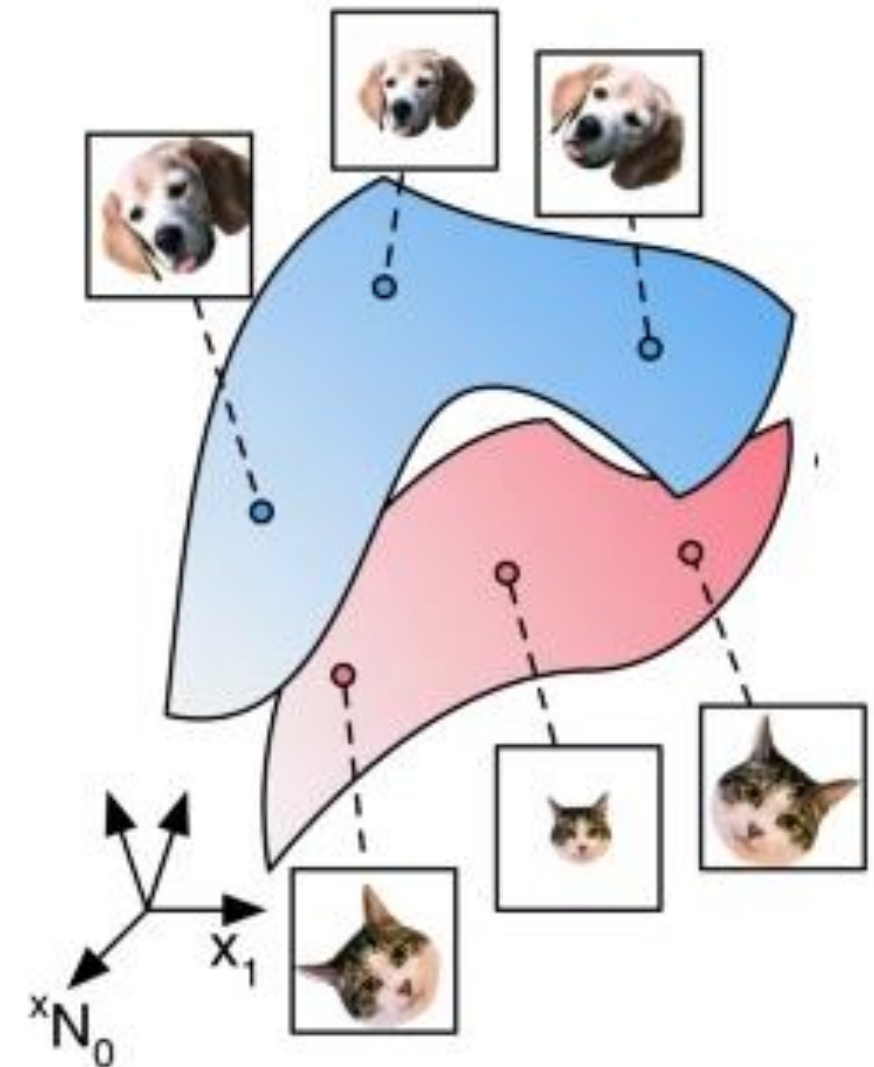
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- The inductive bias of CNNs helps them excel in tasks such as image classification, object detection, and image segmentation, where spatial relationships and local patterns play a crucial role.

The Manifold Hypothesis

The manifold hypothesis suggests that real-world data, even in high-dimensional spaces (number of pixels), often concentrates around a lower-dimensional manifold embedded within that space. NNs have the ability to learn and model complex mappings from the input space to the output space, which includes capturing the intricate relationships and patterns present in the data.



[14.3 Learning Manifolds \(buffalo.edu\)](https://buffalo.edu/)

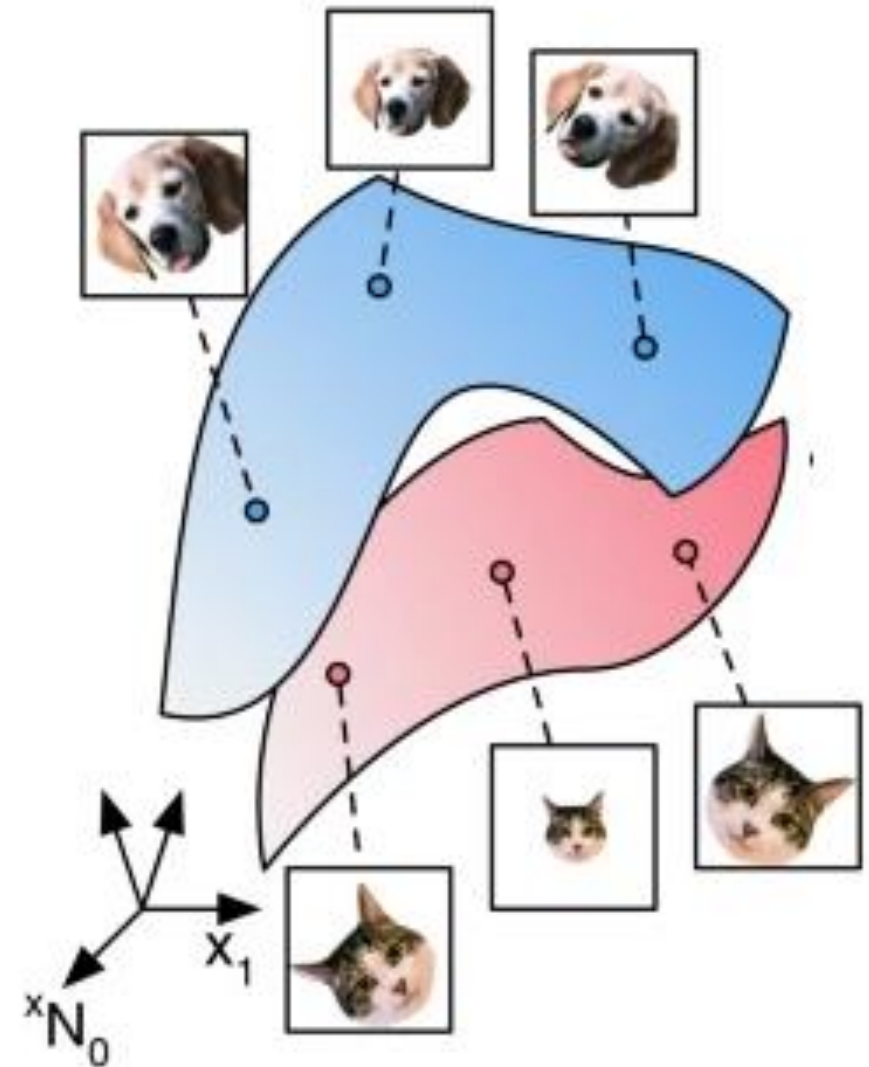


[Separability and geometry of object manifolds in deep neural networks | Nature Communications](#)

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Neural Networks work effectively because they are capable of learning and approximating the underlying structure of high-dimensional data that lies on or near a lower-dimensional manifold.



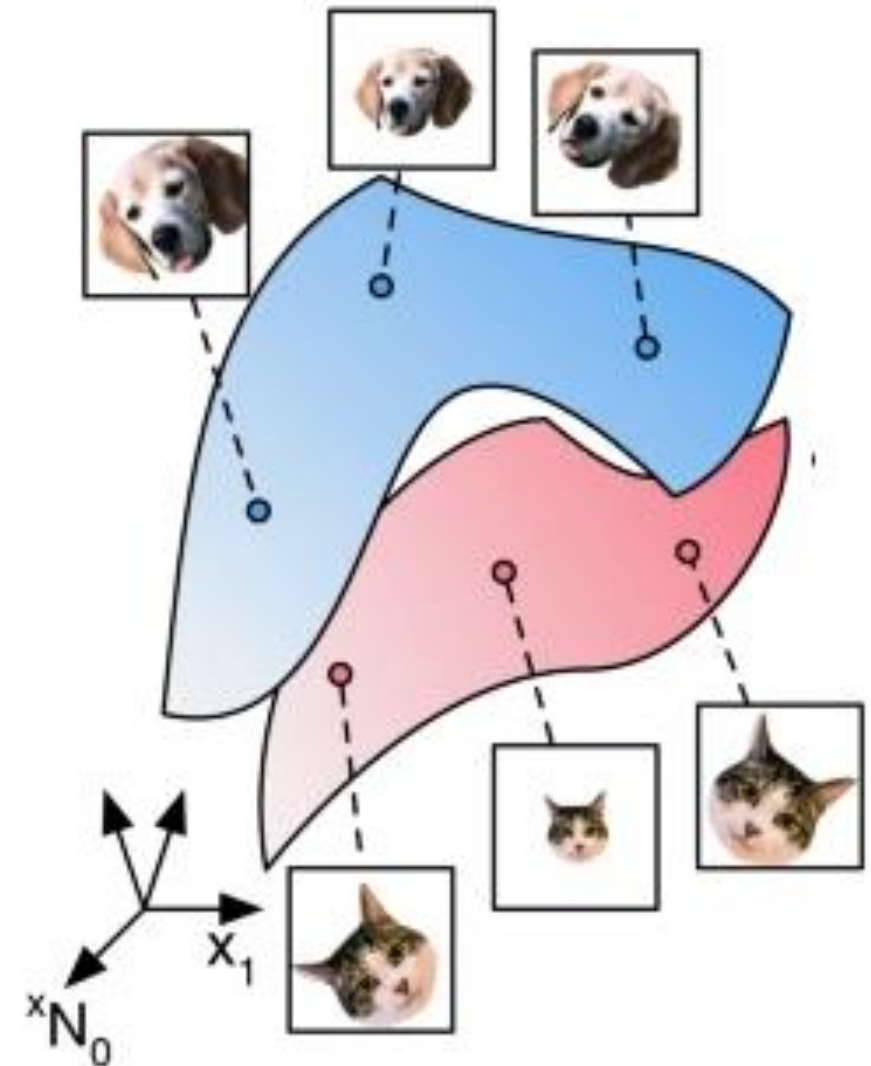
[Separability and geometry of object manifolds in deep neural networks | Nature Communications](#)

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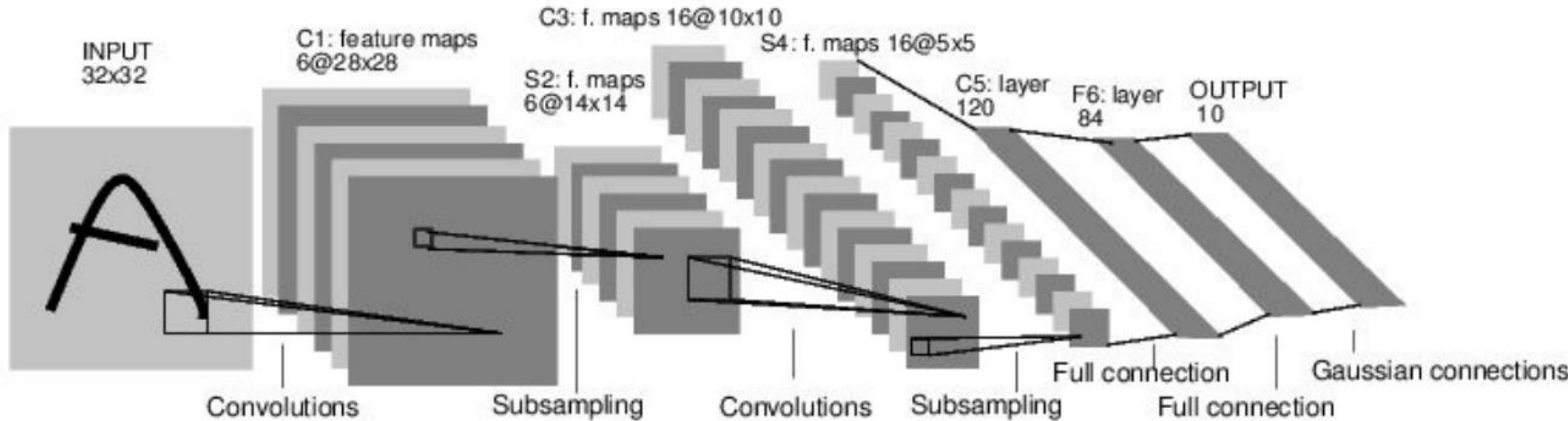
Through a process called backpropagation, NNs adjust their weights and biases during training to minimize the discrepancy between the predicted outputs and the ground truth labels. This optimization process helps the network align its learned representations with the underlying manifold, enabling it to generalize well and make accurate predictions on unseen examples.



[Separability and geometry of object manifolds in deep neural networks | Nature Communications](#)

Case study : LeNet

[LeCun et al., 1998]

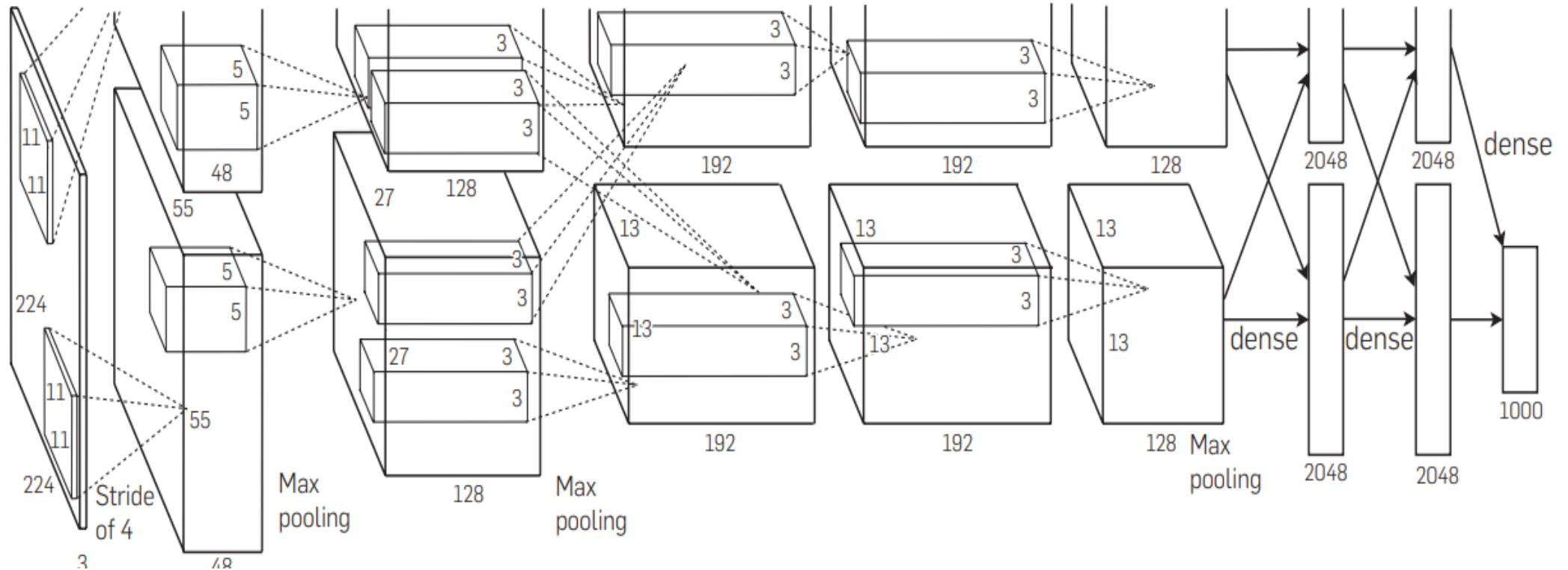


Conv filters were 5x5, applied at stride 1 Subsampling (Pooling) layers were 2x2 applied at stride

architecture is [CONV-POOL-CONV-POOL-CONV-FC] : almost standard nowadays in CNN

Case study : AlexNet

The new arrival of modern DL :



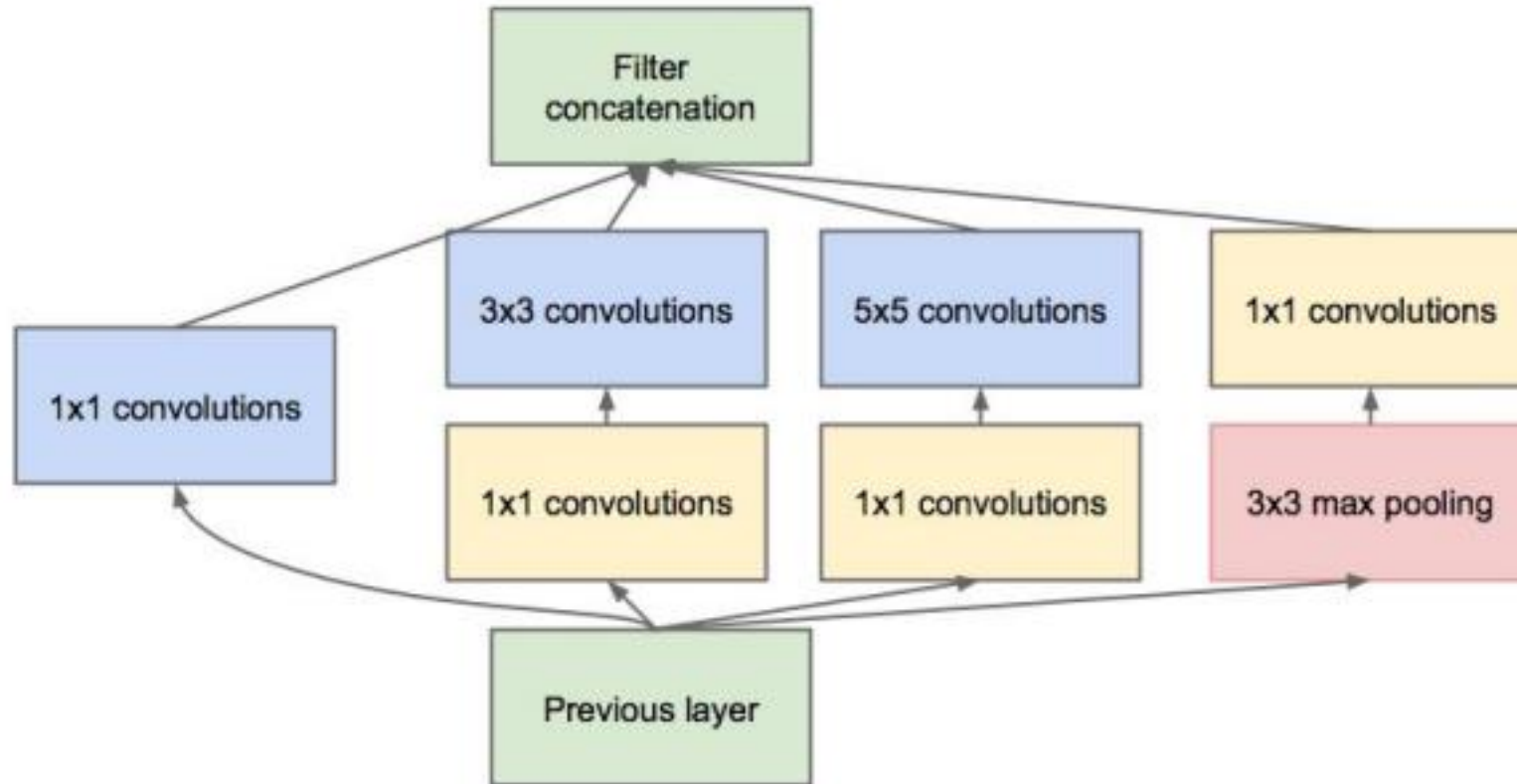
Input: 227x227x3

After CONV1: 55x55x96

After POOL1: 27x27x96

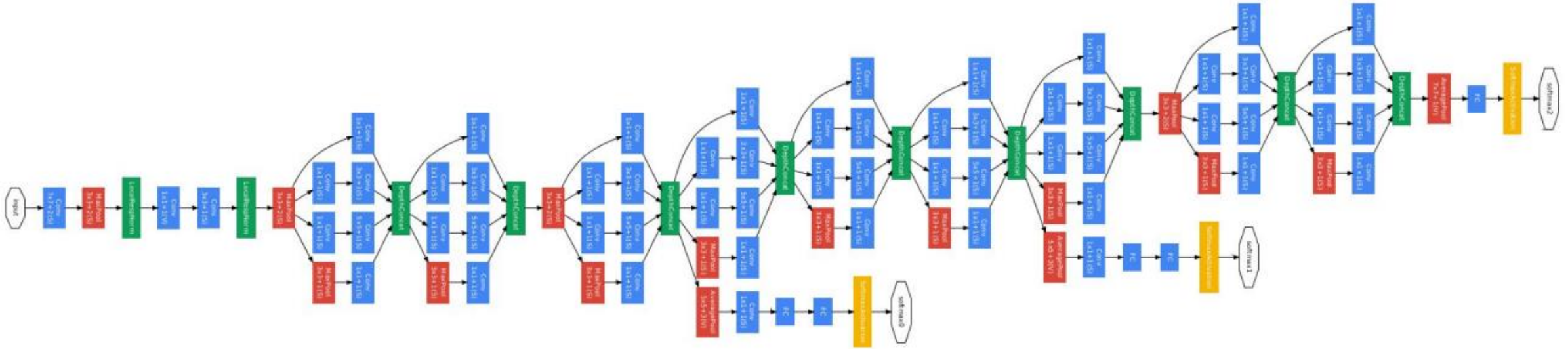
[ImageNet classification with deep convolutional neural networks \(acm.org\)](http://acm.org)

Case study : GoogleNet

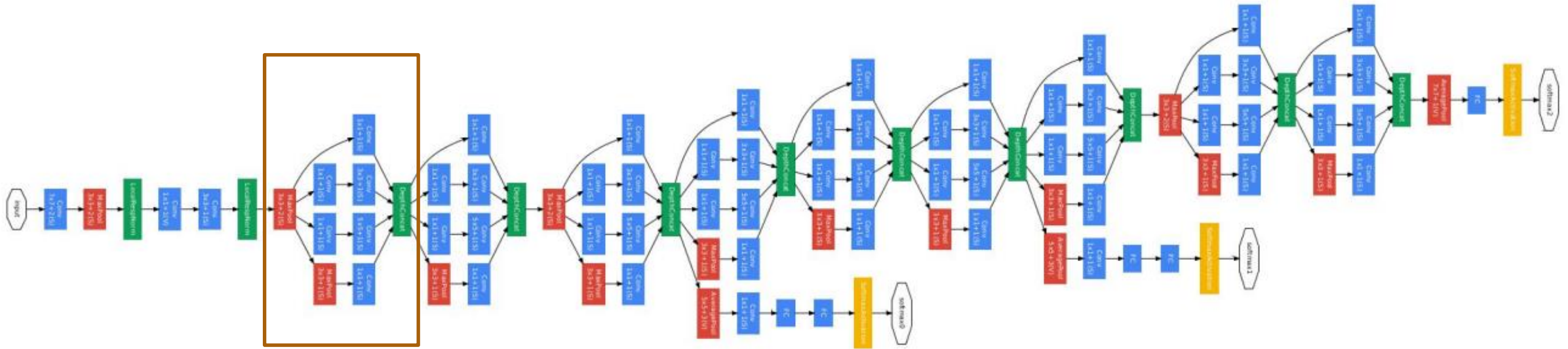


Main idea: apply filters with different size on the input image and then concatenate all of them together

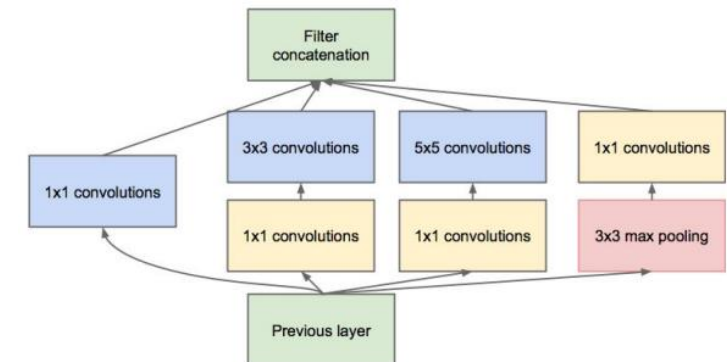
Case study : GoogleNet



Case study : GoogleNet



Although it looks complicated : it repeats the inception module multiple times



The Vanishing Gradient Problem

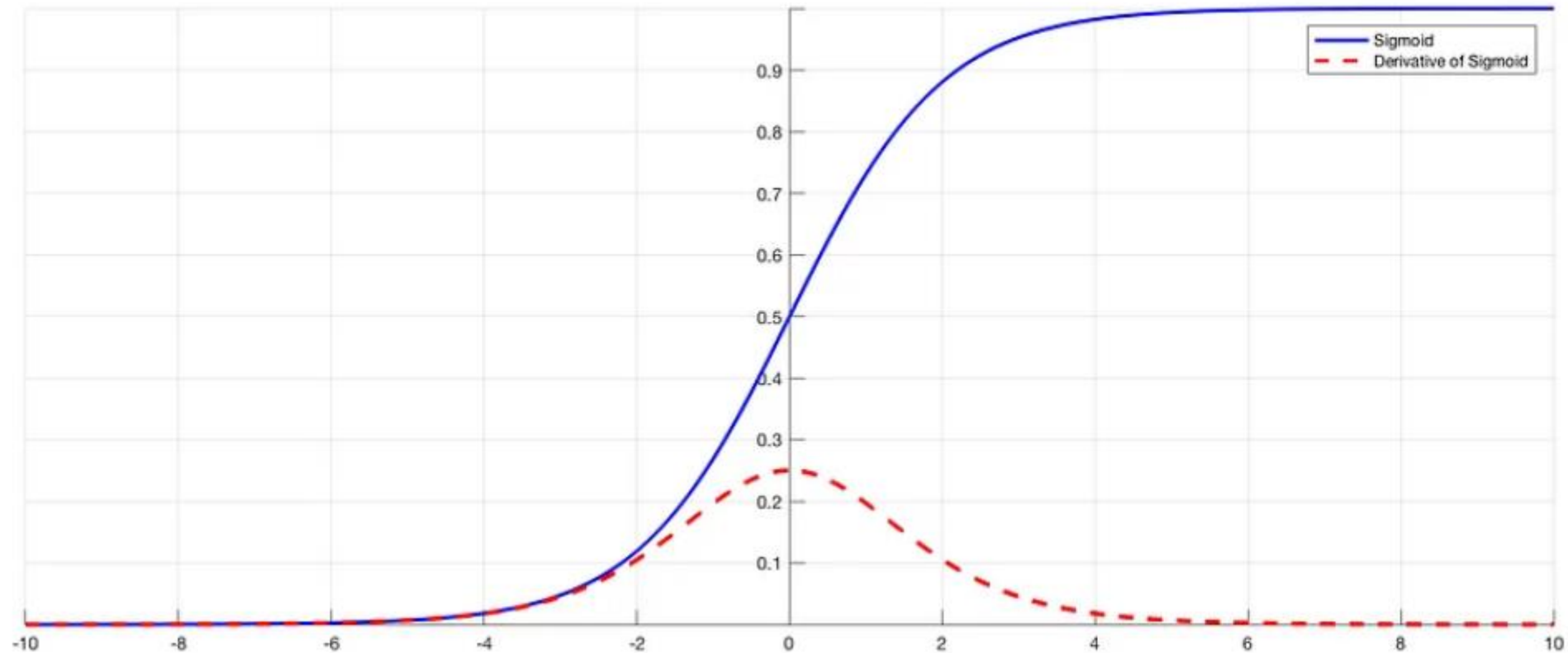


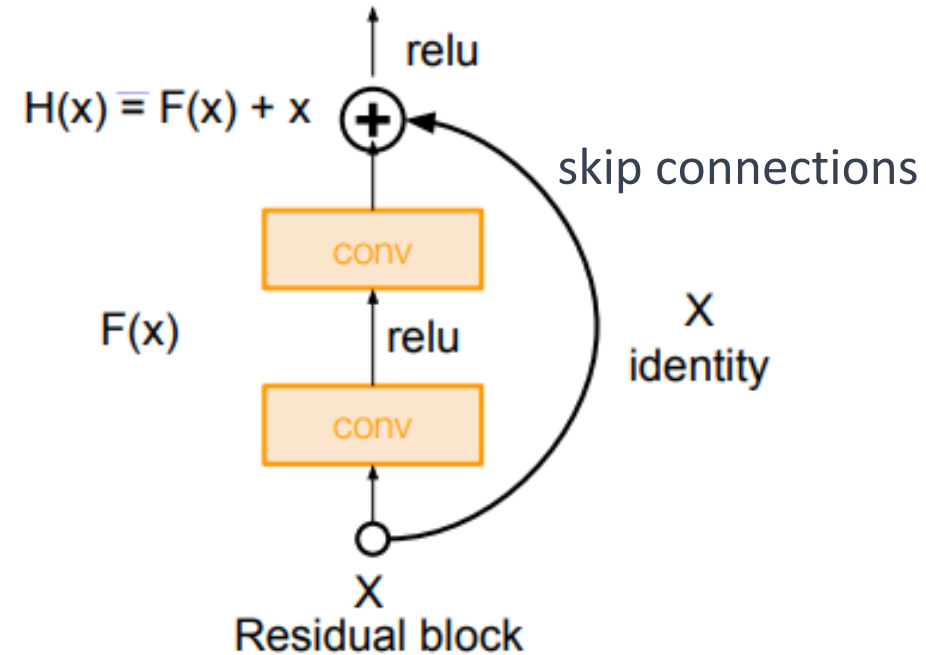
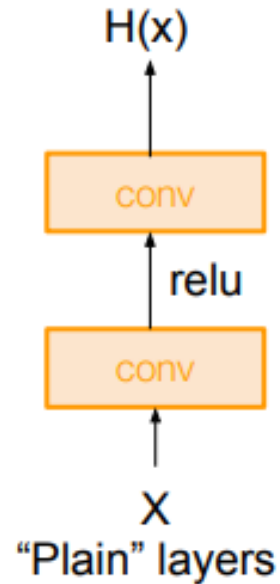
Image 1: The sigmoid function and its derivative // [Source](#)

Activation functions such as the sigmoid function compress a wide input range into a narrow output range, causing a small change in output for a large input change. As a result, the derivative becomes small.

The Vanishing Gradient Problem

- Gradients of neural networks are found using backpropagation.
- Simply put, backpropagation finds the derivatives of the network by moving layer by layer from the final layer to the initial one.
- By the chain rule, the derivatives of each layer are multiplied down the network (from the final layer to the initial) to compute the derivatives of the initial layers.
- However, when n hidden layers use an activation like the sigmoid function, n small derivatives are multiplied together. Thus, the gradient decreases exponentially as we propagate down to the initial layers.
- A small gradient means that the weights and biases of the initial layers will not be updated effectively with each training session. Since these initial layers are often crucial to recognizing the core elements of the input data, it can lead to overall inaccuracy of the whole network.

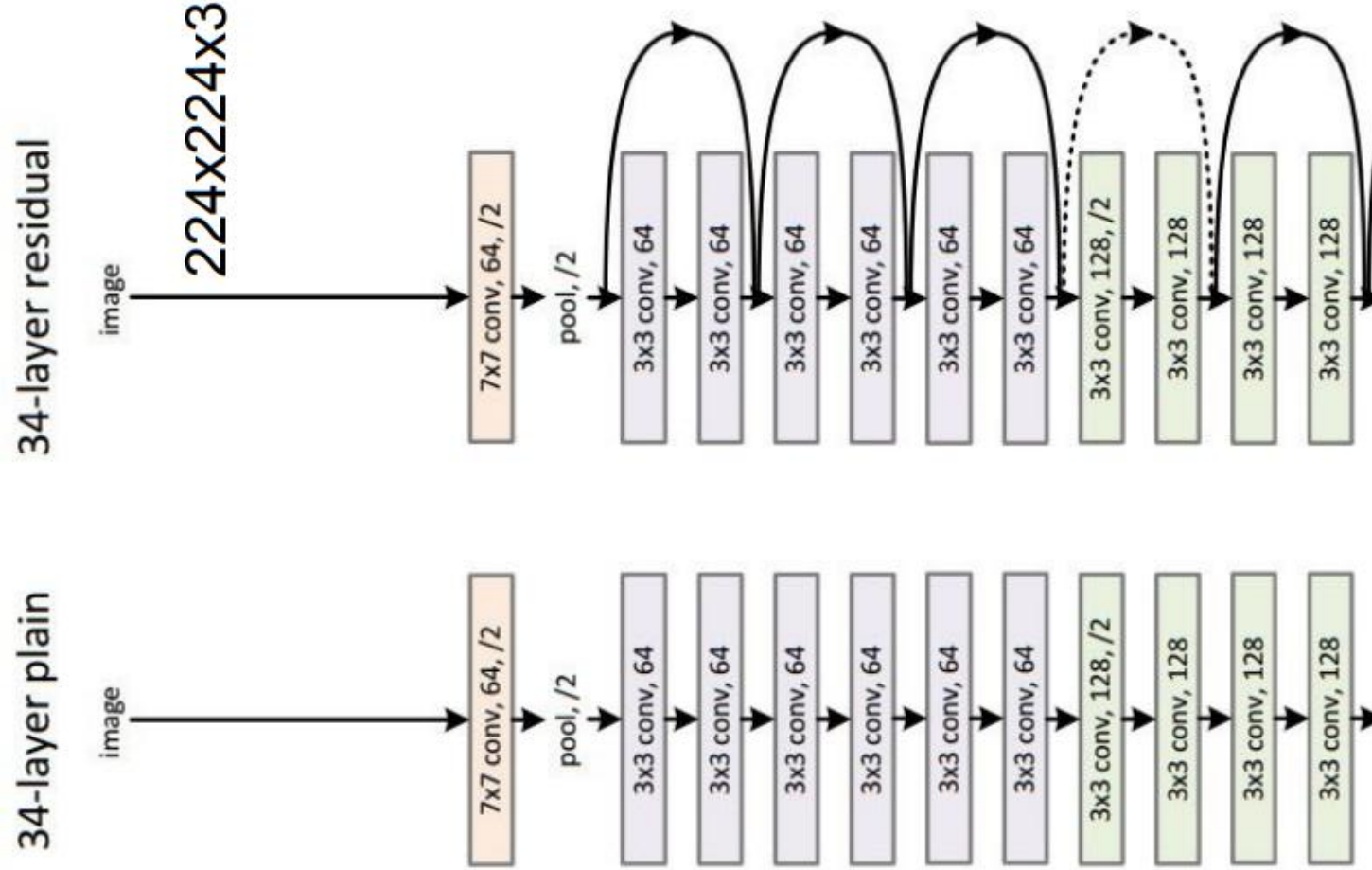
Case study : ResNet



The residual connection directly adds the value at the beginning of the block, x , to the end of the block ($F(x)+x$). This residual connection doesn't go through activation functions that "squashes" the derivatives, resulting in a higher overall derivative of the block.

Case study : ResNet

ResNets allow training
very deep neural networks

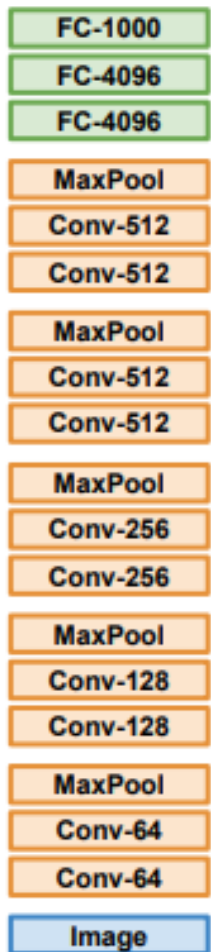


Transfer Learning

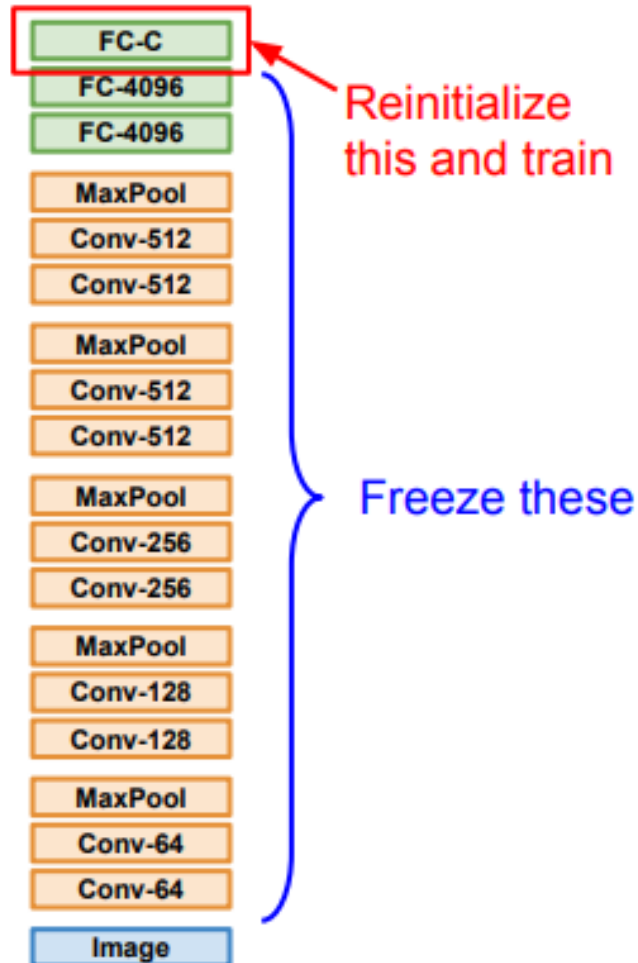
- Transfer learning is a technique in machine learning where knowledge gained from training on one task is leveraged to improve performance on a different but related task.
- It involves using pre-trained models, which are neural networks trained on large-scale datasets, as a starting point for a new task.
- By utilizing the learned representations and knowledge from the pre-trained model, transfer learning allows for faster convergence, better generalization, and improved performance, especially when the new task has limited data.

Transfer Learning

1. Train on Imagenet



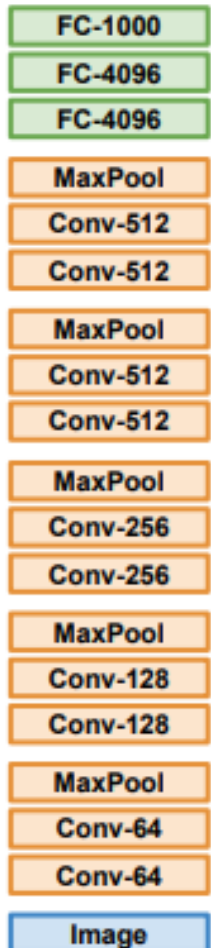
2. Small Dataset (C classes)



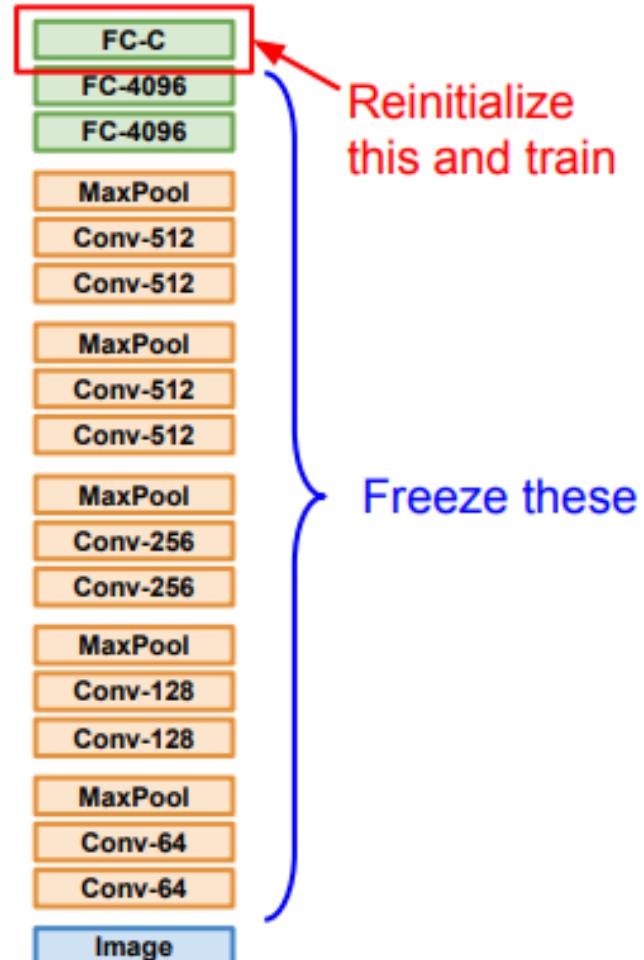
Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014 Razavian et al, "CNN Features Off-the-Shelf: An Astounding Baseline for Recognition", CVPR Workshops 2014

Transfer Learning

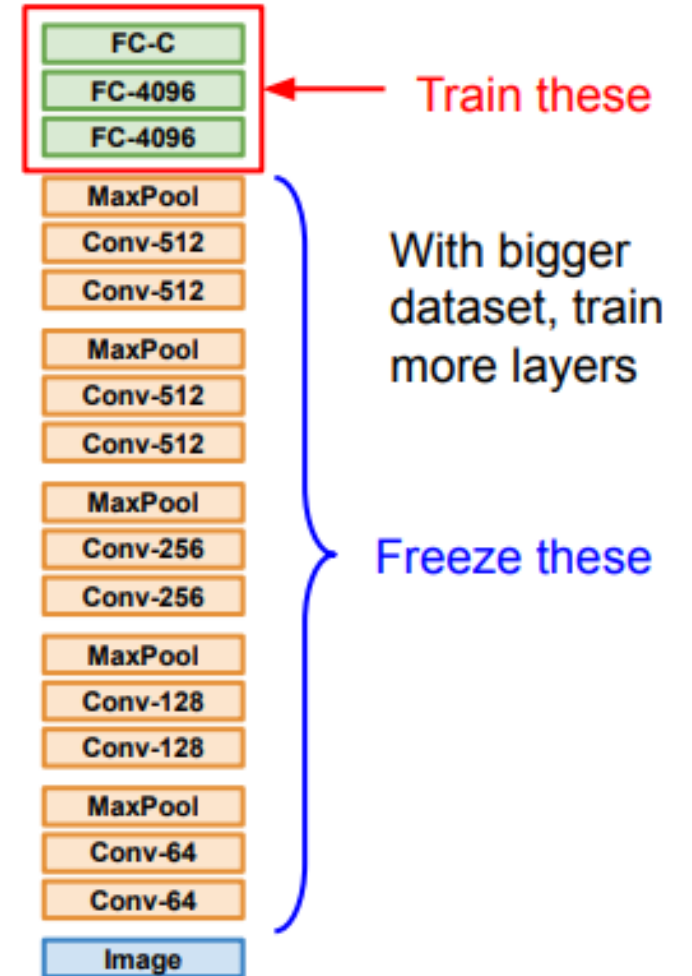
1. Train on Imagenet



2. Small Dataset (C classes)



3. Bigger dataset



Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014 Razavian et al, "CNN Features Off-the-Shelf: An Astounding Baseline for Recognition", CVPR Workshops 2014

Refs

[The Vanishing Gradient Problem. The Problem, Its Causes, Its... | by Chi-Feng Wang | Towards Data Science](#)

[Lecture 5.pptx \(stanford.edu\)](#)

[Lecture 6.pptx \(stanford.edu\)](#)

[winter1516_lecture7.pdf \(stanford.edu\)](#)

[14.3 Learning Manifolds \(buffalo.edu\)](#)

[Maximum Likelihood Estimation - how neural networks learn | Chan`s Jupyter \(goodboychan.github.io\)](#)