

Convolutional Networks

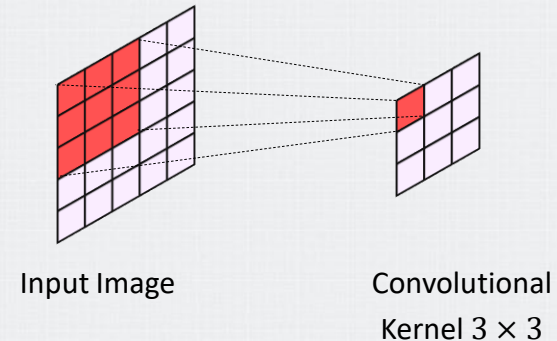
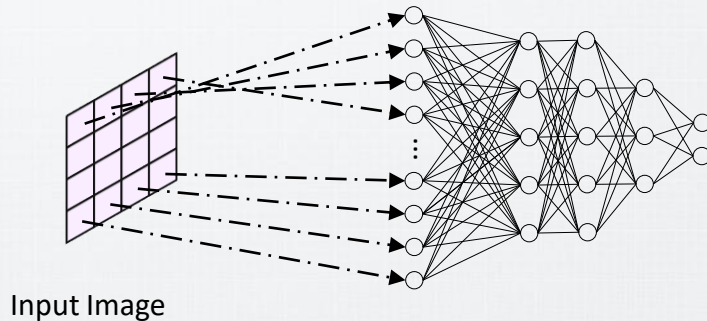
Prof. Artur Jordão

Introduction

Definition

Introduction

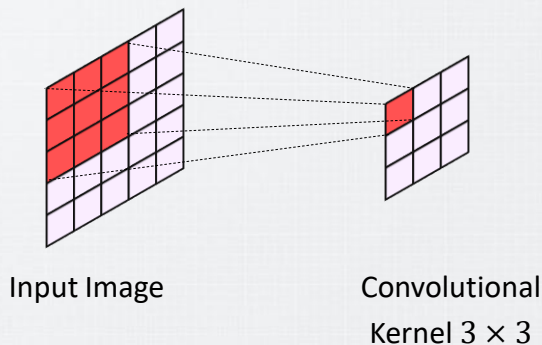
- Convolutional networks are neural networks that use **convolution** in place of general matrix multiplication in at least one of their layers
- These networks are a specialized kind of neural network for processing data with a known grid-like topology. For example:
 - Time-series data (1D grid taking samples at regular time intervals)
 - Image data (2D grid of pixels)



Motivation

Introduction

- Applying neurons directly to the image lacks the spatial location of the patterns
- Instead, we can organize neurons as elements within a window (filter/kernel)
 - Additionally, this strategy reduces the number of parameters
 - Weights are shared across “all” image locations



Architectural Details

Components

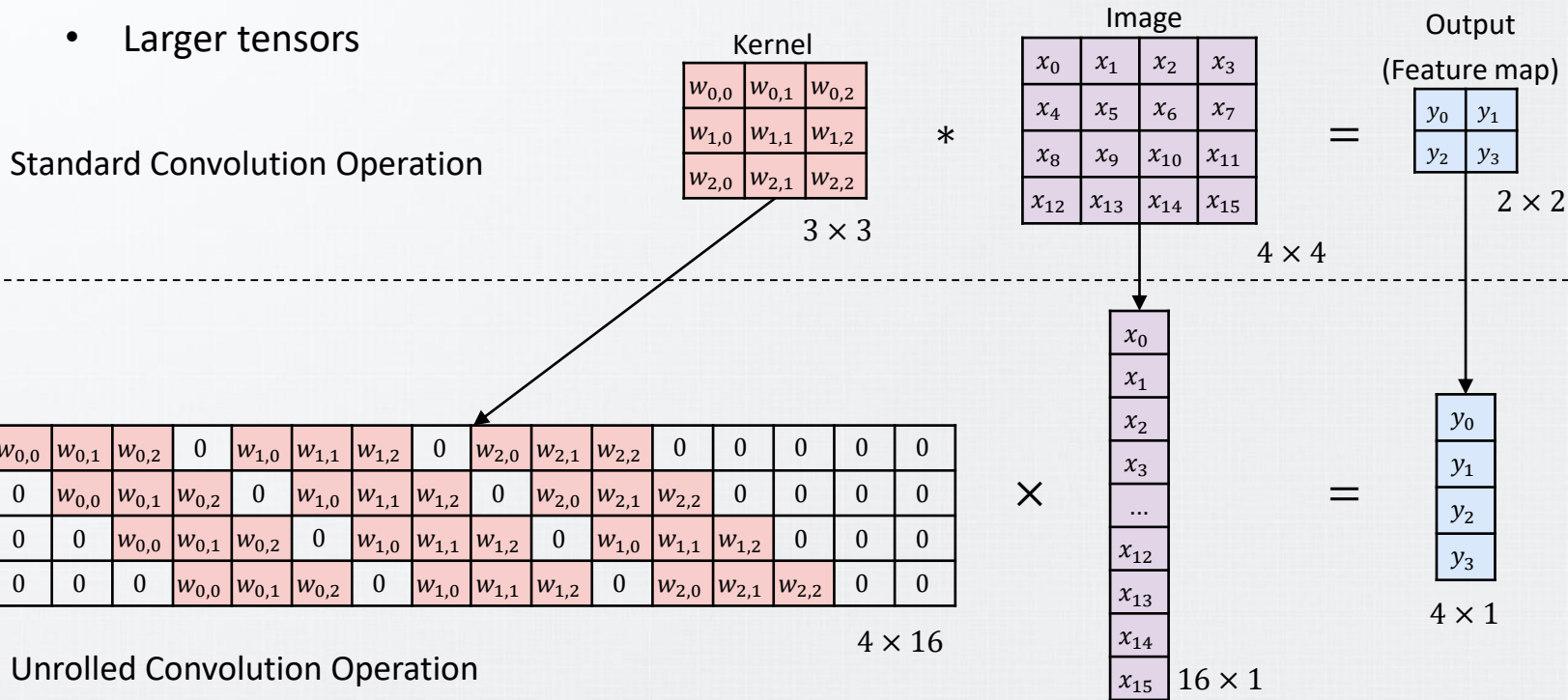
Architectural Details

- Convolutional Layers
- Downsampling Layers
 - Pooling Layers
- Classification Layers

Convolutional Layers

Introduction

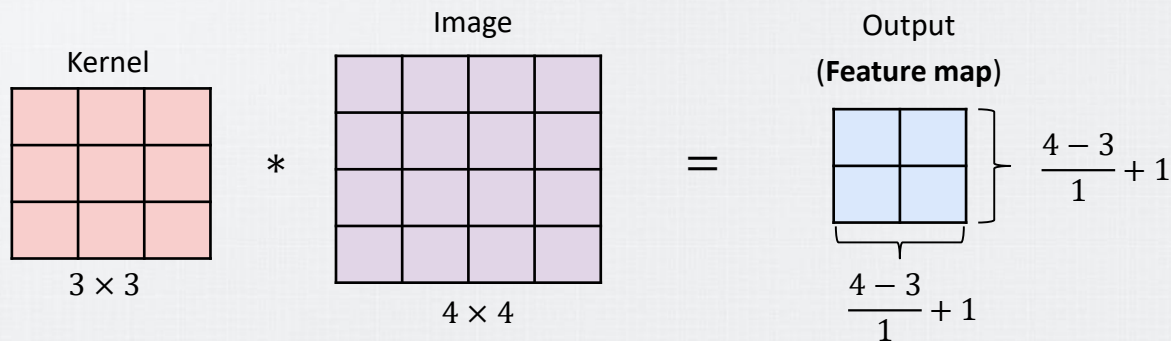
- Unrolling convolutional operation
 - Transforms the problem into a (tensor) matrix multiplication
 - Larger tensors



Convolutional Layers

Architectural Details

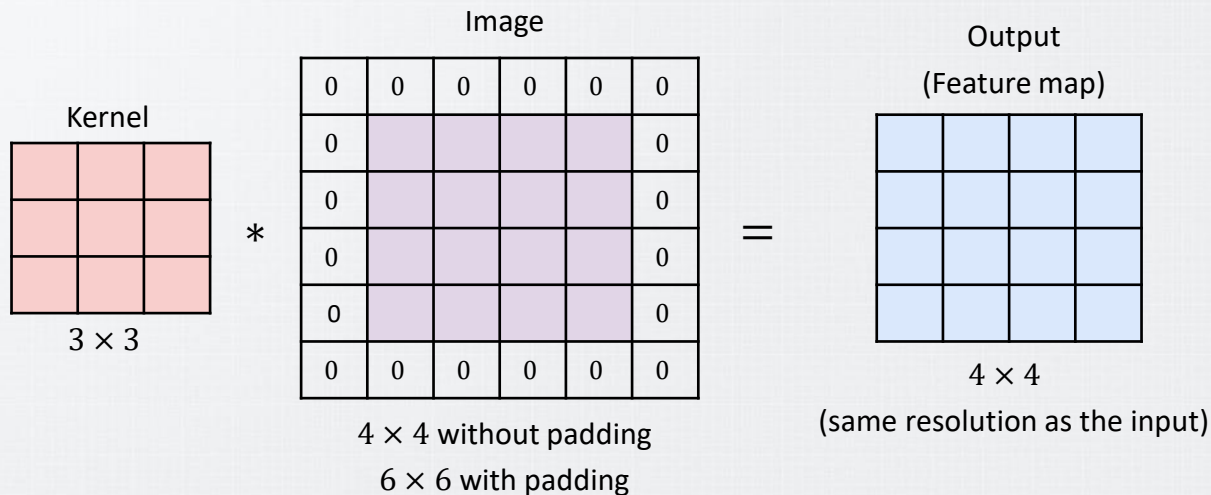
- Define W, H as the dimensions of the input image, and w, h as the dimensions of a convolutional kernel
- The convolution operation reduces the input in terms of
 - $\frac{W-w}{s_x} + 1, \frac{H-h}{s_y} + 1$, where s_i is the stride
- Most convolutional architectures employ 3×3 filters and a stride (s_x and s_y) of one



Convolutional Layers

Architectural Details

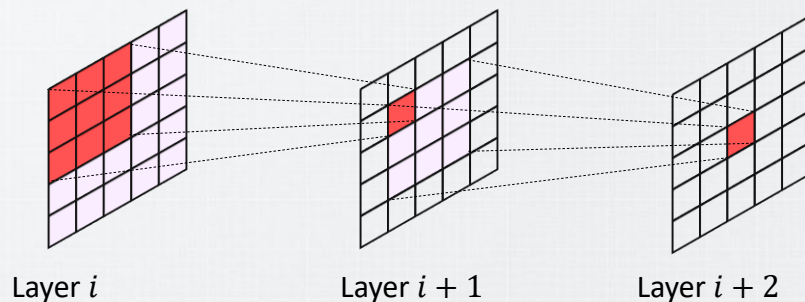
- Padding
 - It involves adding values on the input's edges to ensure that the input and output (after the convolution operation) **have the same spatial dimension**
- Most works employ **zero-padding**



Convolutional Layers

Architectural Details

- Receptive field
 - Refers to all the elements (from all the previous layers) that may affect the calculation of x (a position in the feature map) during the forward propagation
- The local operation of the convolution kernel makes the model focus too much on local representations (e.g., texture) (Geirhos et al., 2019; Guo et al., 2023)



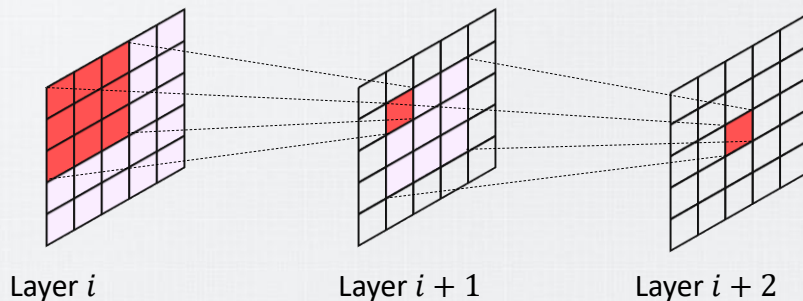
Geirhos et al. Imagenet-trained cnns are biased towards texture; increasing shape bias improves accuracy and robustness. International Conference on Learning Representations (ICLR) 2019

Guo et al. ALOFT: A Lightweight MLP-like Architecture with Dynamic Low-frequency Transform for Domain Generalization. Conference on Computer Vision and Pattern Recognition (CVPR), 2023

Downsampling Layers

Architectural Details

- An important role in learning new representations is to reduce the spatial dimensions of feature maps (Greff et al., 2017)
 - Downsampling the input increases the receptive field
- There are two distinct ways of achieving this reduction
 - Pooling operations
 - Convolutional layers with stride 2×2



Downsampling Layers

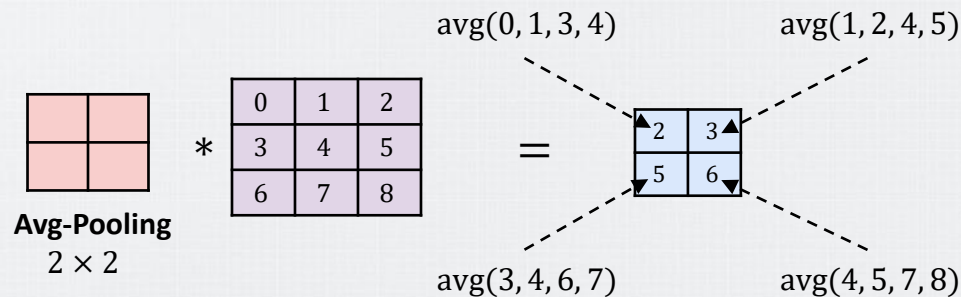
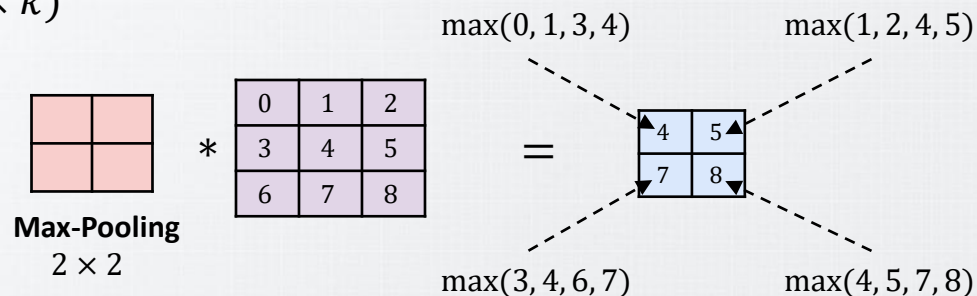
Architectural Details

- Pooling layers (also known as pooling operators or functions) are a fixed-shape window that slides over all regions in the input, computing a single output for each location traversed by the window
 - Pooling **summarizes the responses over a whole neighborhood**
- Pooling are deterministic operations
 - It contains kernel size and stride but has **no (learnable) parameters**
- Pooling helps the representation become approximately invariant to small translations of the input
 - Invariance to translation means that if we translate the input by a small amount, the values of most of the pooled outputs do not change

Downsampling Layers

Architectural Details

- Common pooling operations
 - Max-pooling ($k \times k$)
 - Average-pooling ($k \times k$)



Downsampling Layers

Architectural Details

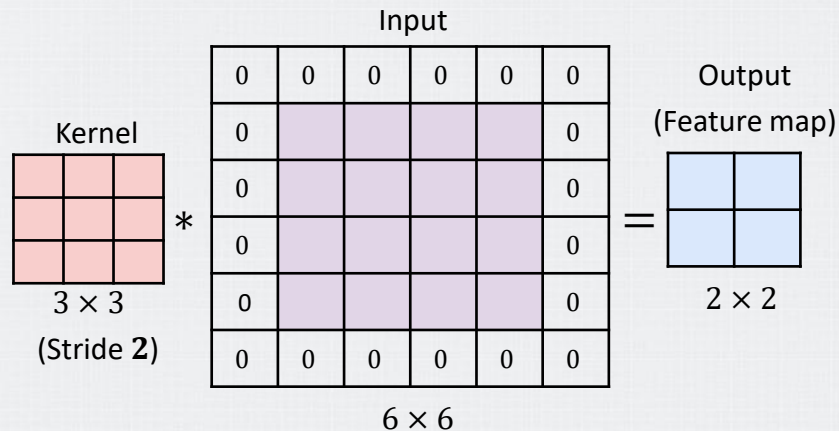
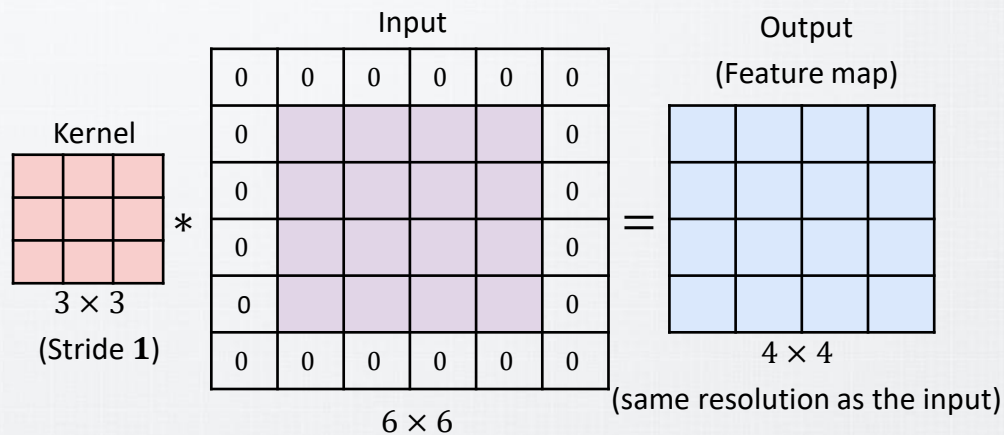
- Global-pooling operations
 - Global max-pooling
 - Global average-pooling



Downsampling Layers

Architectural Details

- Convolution with stride (s_i) = 2
 - Learnable parameters**
- Remember that the output of a convolution is $\left(\frac{W-w}{s_x} + 1, \frac{H-h}{s_y} + 1\right)$
 - By setting the stride higher than 1, we obtain downsampled feature maps

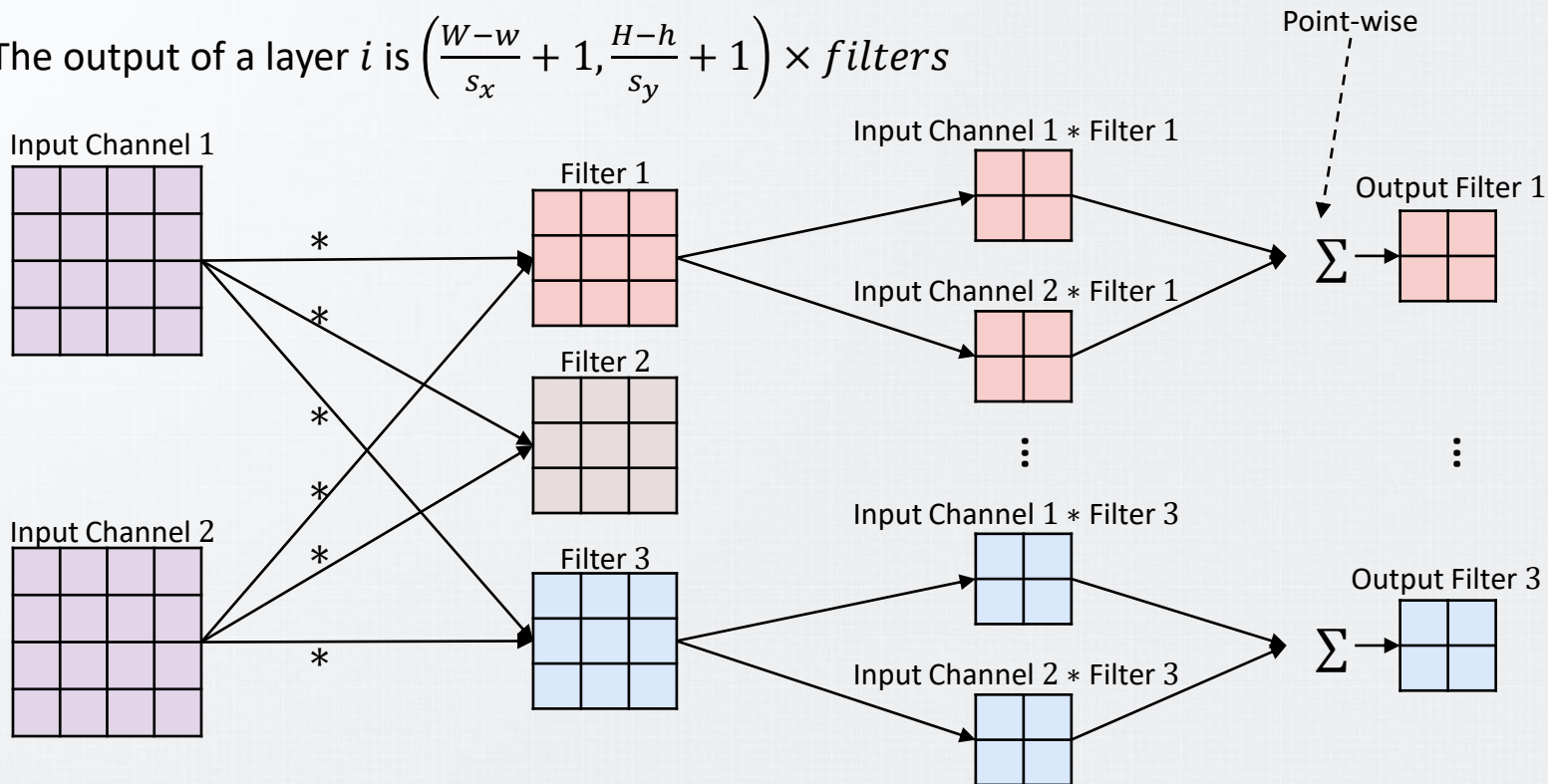


Multiple Filters

Architectural Details

- Each filter from a layer i convolves all input dimensions

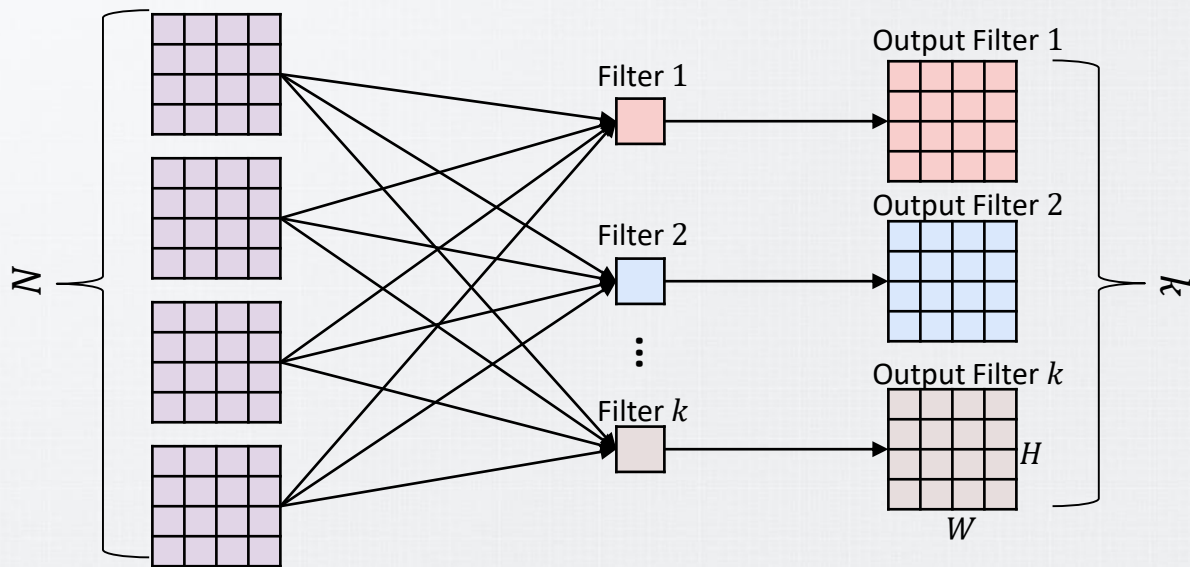
- The output of a layer i is $\left(\frac{W-w}{s_x} + 1, \frac{H-h}{s_y} + 1\right) \times \text{filters}$



1×1 Convolutional Layers

Architectural Details

- Convolutions with kernel of size 1
 - Such configuration preserves the spatial resolution of the input
 - It projects an input of size (W, H, N) into (W, H, k) , where k is the number of filters
 - Therefore, this type of convolution enables to reduce the dimension of channels

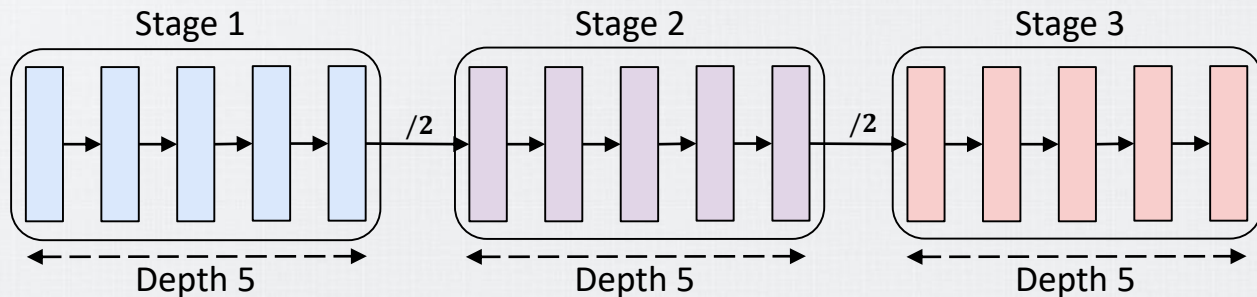


Stages

Architectural Details

- A Stage (or module) is a group of layers that operate on representations (feature maps) at the **same resolution**
 - From stage i to $i + 1$, the common strategy is to reduce the spatial resolution. For this purpose, we employ a downsampling layer ($/2$)
- The **depth (number of convolutional layers)** of these stages is defined either uniformly (e.g., ResNet20–110) or empirically (e.g., ResNet50–101)
 - A common practice is to double the number of filters as we decrease the resolution

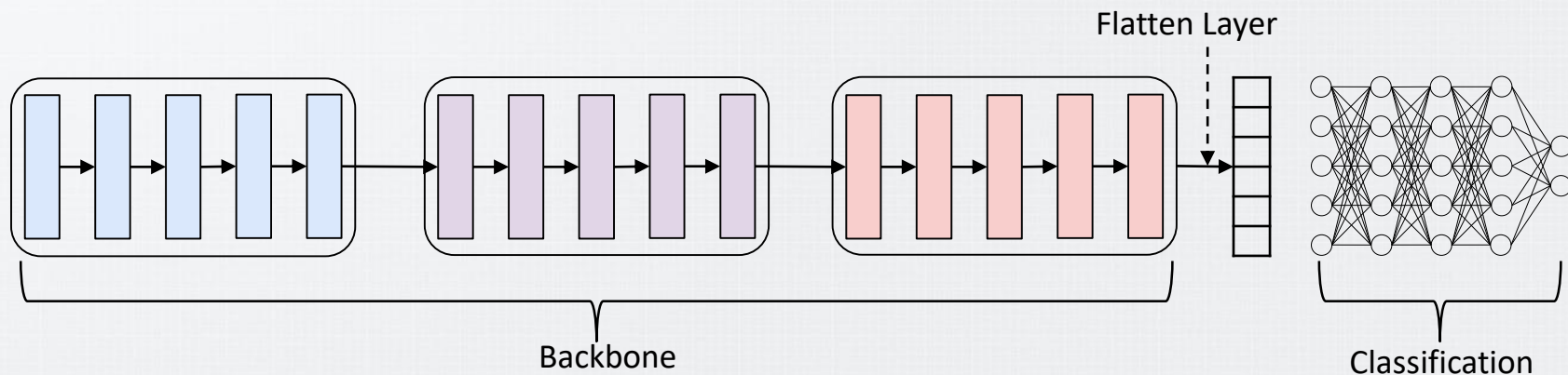
Stage	Resolution
1	32×32
2	16×16
3	8×8



Classification Layers

Architectural Details

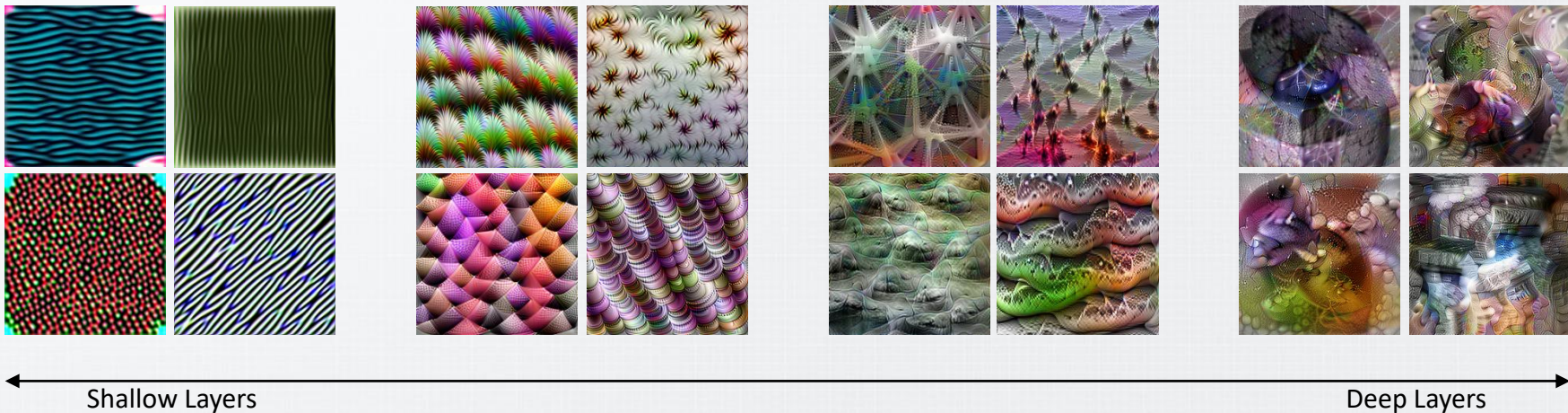
- Fully connected (FC) layers
 - MLPs
- Modern architectures often incorporate **global average pooling** before the classification layer
 - It significantly reduces the number of parameters
 - It helps to handle inputs of varying size



Representation Learned Across Layers

Architectural Details

- Neuron representations from <https://microscope.openai.com/models>
 - ResNet50



Popular Architectures

Architectural Details

- VGG (Depth 16 and 19)
- ResNet (Depth 50, 101 and 152)
- MobileNet
- NASNet
- EfficientNet
- All these architectures employ 3×3 convolutional kernels

Historical Trends

Architectural Details

- CNNs have been the de-facto standard in computer vision since the AlexNet model surpassed prevailing approaches based on hand-crafted image features (Krizhevsky et al., 2012)
- Simonyan and Zisserman (2015) demonstrated that one can train state-of-the-art models using only convolutions with small **3×3 kernels**
- He et al. (2016) introduced skip connections, which enable the training of ultra-deep neural networks and further improve performance
 - Since then, many advances in the field of deep learning have been made using skip connections

Krizhevsky et al. *ImageNet classification with deep convolutional neural networks*. Neural Information Processing Systems (NeurIPS), 2012

Simonyan and Zisserman. *Very deep convolutional networks for large-scale image recognition*. International Conference on Learning Representations (ICLR), 2015

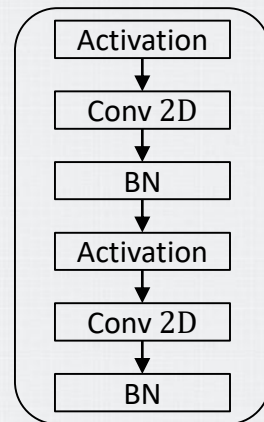
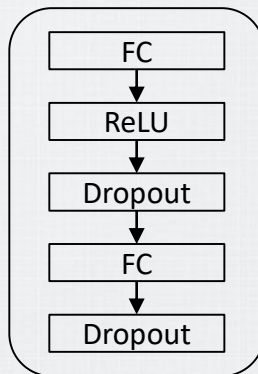
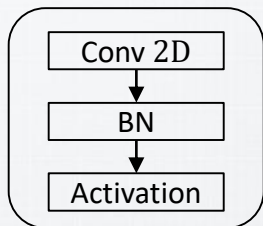
He et al. *Deep residual learning for image recognition*. Conference on Computer Vision and Pattern Recognition (CVPR), 2016

Building Blocks

Introduction

Building Blocks

- Modern neural network architectures often adopt a **modular approach**
 - Design a layer (building blocks) and replicate it to build the model
- Building blocks (or modules) are combinations of different components (sets of layers)
 - The input to the i th building block is the output of the $i - 1$ th block



Scalability and Complex Architectures

Building Blocks

- Building Blocks are fundamental for designing complex architectures
 - Once created, we can repeat the building block to compose the final architecture
- We can create **wider** models by increasing the embedding dimension or the number of channels in each block
- We can create **deeper** models by stacking more layers/blocks
- Isotropic architectures
 - Each block maintains a consistent and uniform layerwise design
- Hierarchical architectures
 - Consists of **stages** with varying scales and embedding dimensions

Scalability and Complex Architectures

Building Blocks

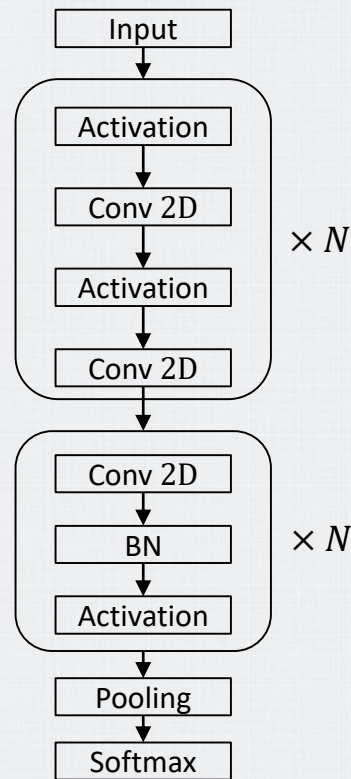
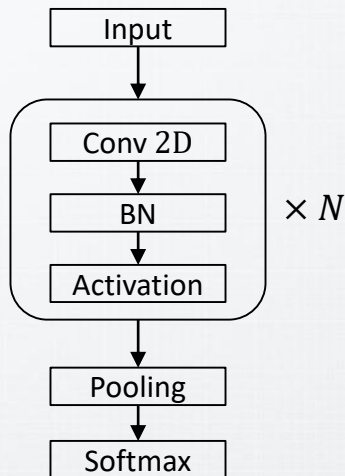
- Building blocks became popular after VGG and ResNet architectures

Layer Name	Output Size	18-Layer	50-Layer	152-Layer
Conv1	112×112	$7 \times 7, 64$, Stride 2		
Conv2_x	56×56	$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 2$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$
Conv3_x	28×28	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 2$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 8$
Conv4_x	14×14	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 2$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 36$
Conv5_x	7×7	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 2$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$
	1×1	Average Pooling, 1000 – d FC, Softmax		

Final Architecture

Building Blocks

- Building blocks facilitate the construction and representation (i.e., illustration) of modern architectures



Residual Networks (Skip Connection)

Motivation

Residual Networks

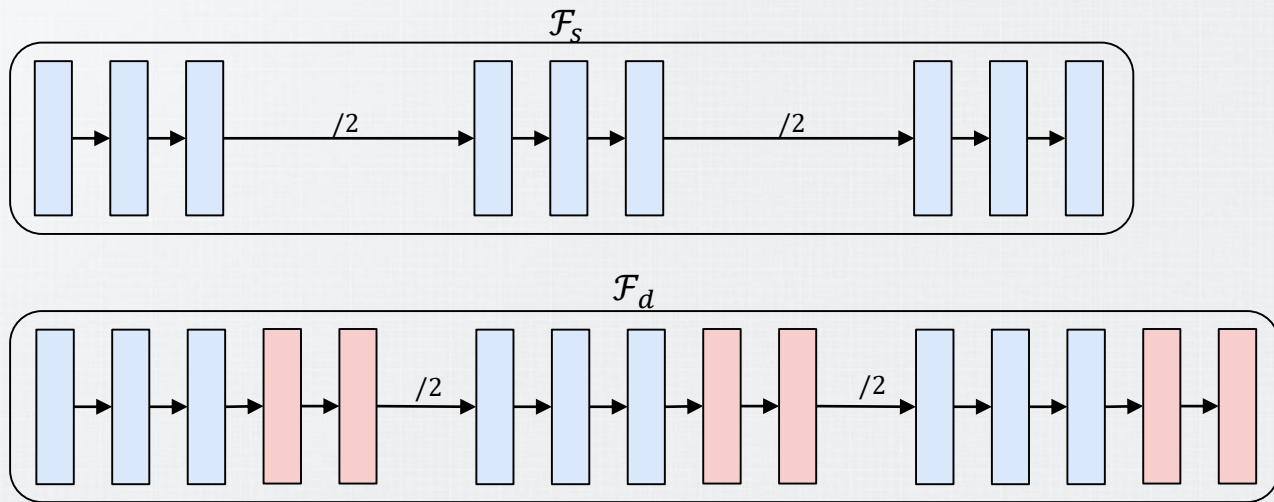
- Practical experience in deep learning suggests that deeper models can significantly improve their predictive performance
 - Unfortunately, as the network becomes **deeper**, training becomes **harder**
- The degradation problem (He et al., 2016)
 - As the network **depth increases**, **accuracy saturates** and then **rapidly degrades**
 - Unexpectedly, such degradation is not caused by **overfitting**

	Plain	Residual
18 layers	27.94	27.88
34 layers	28.54	25.03

Problem Formulation

Residual Networks

- Consider a shallow architecture \mathcal{F}_s and its deeper counterpart \mathcal{F}_d
 - \mathcal{F}_d is essentially \mathcal{F}_s with more layers (building blocks)
 - Informally: $\mathcal{F}_s \subset \mathcal{F}_d$
- The deeper model should not produce higher training error than its shallower counterpart

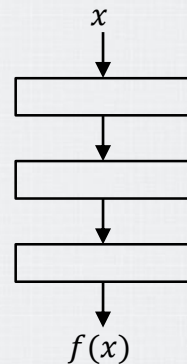


Overview

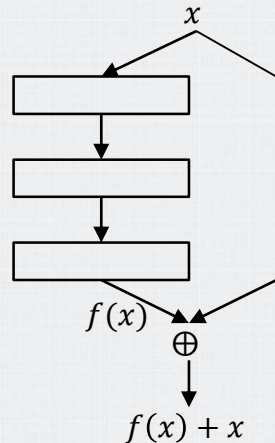
Residual Networks

- The idea consists of connecting layer i with a subsequent layer $i + j, j > 1$
 - This connection (skip-connection) is done by adding (element-wise) the feature maps of layer i and $i + j$
- Layers in Plain network
 - Receives x and outputs $f(x)$
- Layers in Residual network
 - Receives x and outputs $f(x) + x$

Plain Network



Residual Network



Theoretical Issues

Residual Networks

- Two groups of believers
 - Skip connections to avoid the vanishing gradient problem
 - Skip connections extend beyond addressing the vanishing gradient problem (I, Prof. Artur, belong to this category)

We argue that this optimization **difficulty is unlikely to be caused by vanishing gradients**. These plain networks are trained with BN [16], which ensures forward propagated signals to have non-zero variances. **We also verify that the backward propagated gradients exhibit healthy norms with BN [...]**

Source: He et al., 2016

[...] In this paper, we explore the interaction between depth and the loss geometry. We first establish that gradient explosion or **vanishing is not responsible for the slowing down of training**, as is **commonly believed**.

[...] The most prevalent explanation for why very deep networks are hard to train is that the gradient explodes or vanishes as the number of layers increase [5]; **this explanation has been infrequently challenged [...]**

[...] Firstly, **there is no exponential increase or decrease in gradient norms** (i.e., we would see vastly different gradient norm scales), as hypothesised in gradient explosion explanations. Secondly, **residual connections do not consistently increase or decrease the gradient norms**. In Figure 1, 49.4% of variables have lower gradient norm in residual networks (in comparison to a baseline of non-residual networks), making the exploding/vanishing gradient explanation untenable in this case.

Source: Ghorbani et al., 2019

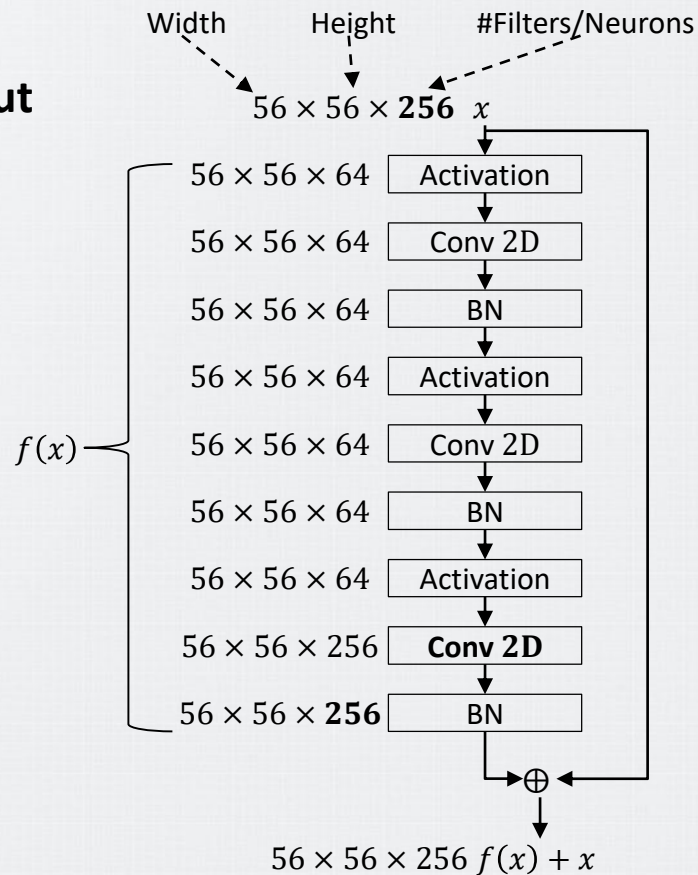
He et al. *Deep Residual Learning for Image Recognition*. Computer Vision and Pattern Recognition (CVPR), 2016

Ghorbani et al. *The Effect of Network Depth on the Optimization Landscape*. International Conference on Machine Learning (ICML), 2019

Technical Issues

Residual Networks

- Within a building block the **input and output must match**

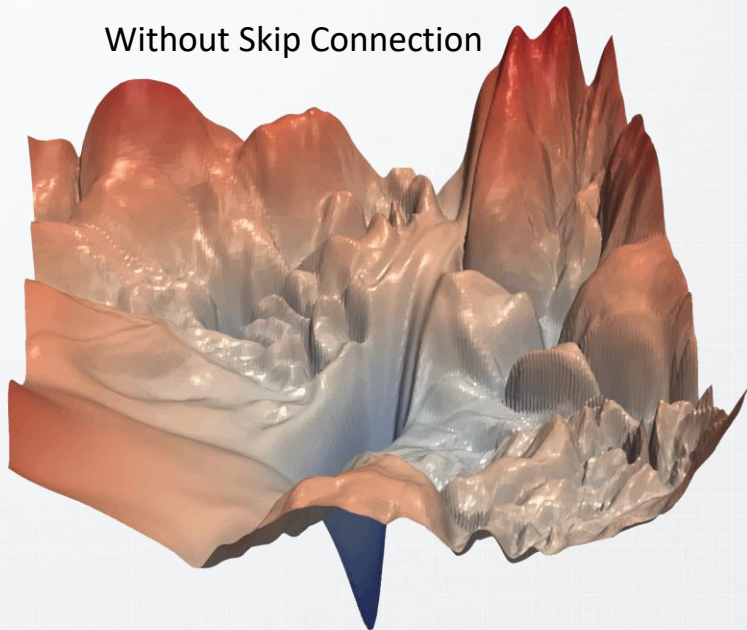


Modern Architectures

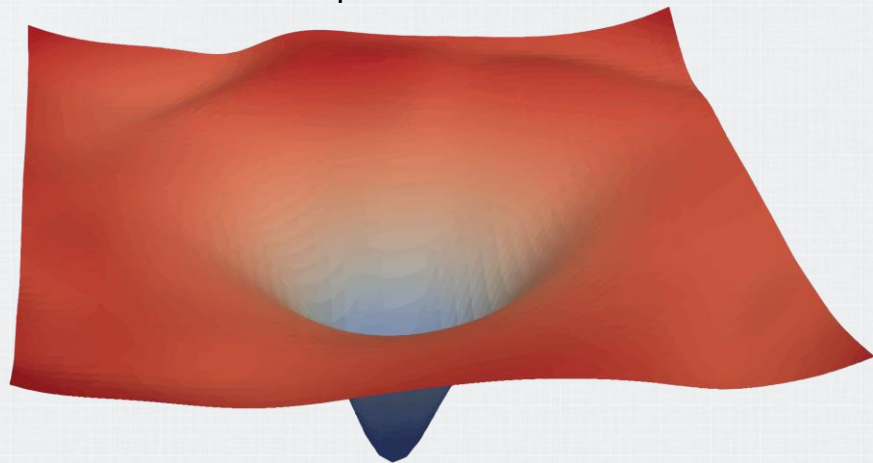
Residual Networks

- Due to the success and simplicity of residual networks, modern architectures are predominantly based on residual learning

Without Skip Connection



With Skip Connection

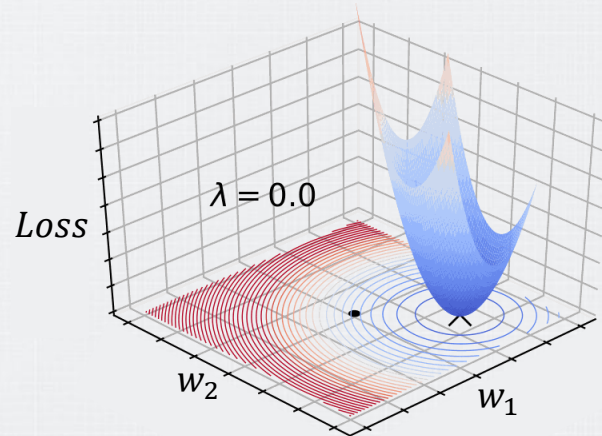
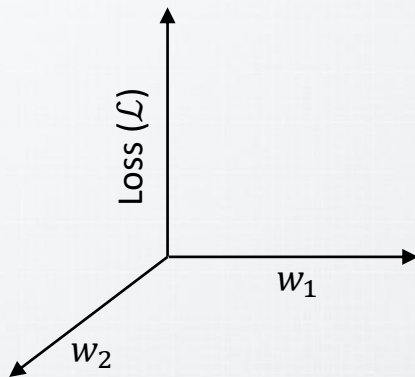


Loss LandScape

Modern Architectures

Loss LandScape

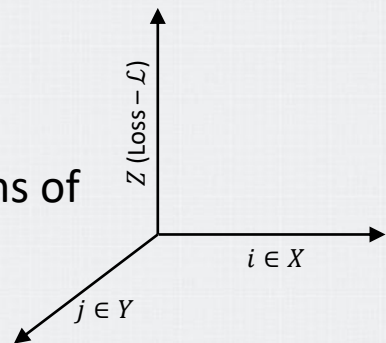
- Due to the high number of parameters (i.e., dimensions in space), visualizing the loss landscape of the parameters in overparameterized models is hard



Definitions

Loss Landscape

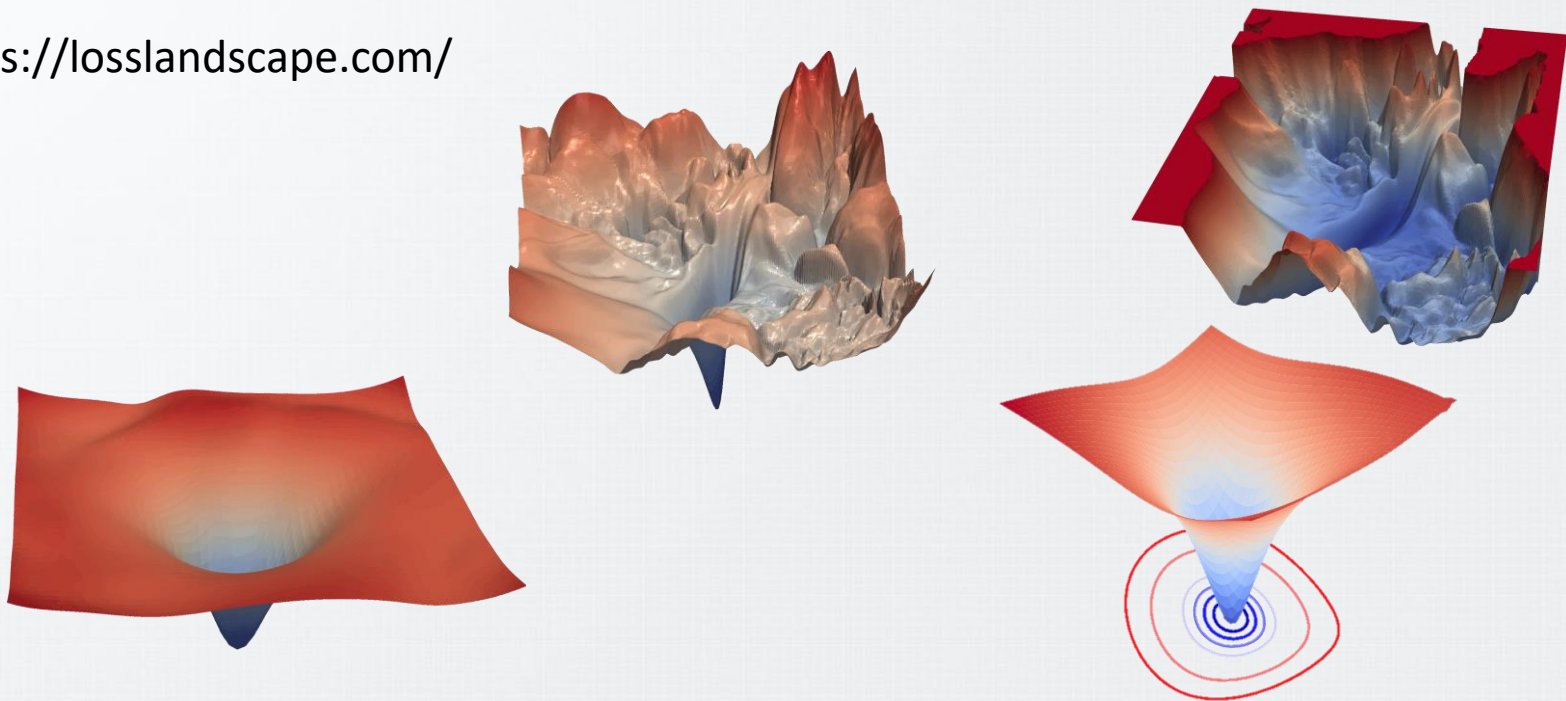
- Li et al. (2018) proposed a novel visualization scheme
 - The method samples two Gaussian random vectors (δ and β) that normalizes the filter norms in the neural network
 - Then compute the loss across different combinations of the two filter-normalized Gaussian random vectors from the minimizer
- Define $\delta \sim \mathcal{N}(0, 1)$ and $\beta \sim \mathcal{N}(0, 1)$
- Consider an equally spaced 3D grid (X, Y, Z)
- The method by Li et al. (2018) estimates the loss landscape in terms of
 - $Z_{i,j} = \mathcal{L}(\theta^* + i * \delta + j * \beta)$



Loss Landscape

Loss Landscape

- <http://www.telesens.co/loss-landscape-viz/viewer.html>
- <https://losslandscape.com/>



Bibliography

Bibliography

- He et al. *Deep Residual Learning for Image Recognition*. Computer Vision and Pattern Recognition (CVPR), 2016
- Geirhos et al. *Imagenet-trained CNNs are Biased Towards Texture; Increasing Shape Bias Improves Accuracy and Robustness*. International Conference on Learning Representations (ICLR) 2019
- Veit et al. *Residual Networks Behave Like Ensembles of Relatively Shallow Networks*. In Neural Information Processing Systems (NeurIPS), 2016
- Li et al. *Visualizing the Loss Landscape of Neural Nets*. In Neural Information Processing Systems (NeurIPS), 2018