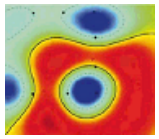
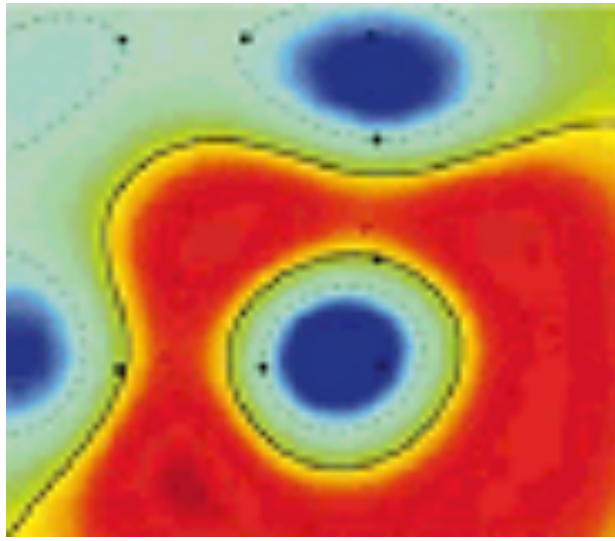


WiSe 2024/25

Deep Learning 1

Technische Universität Berlin

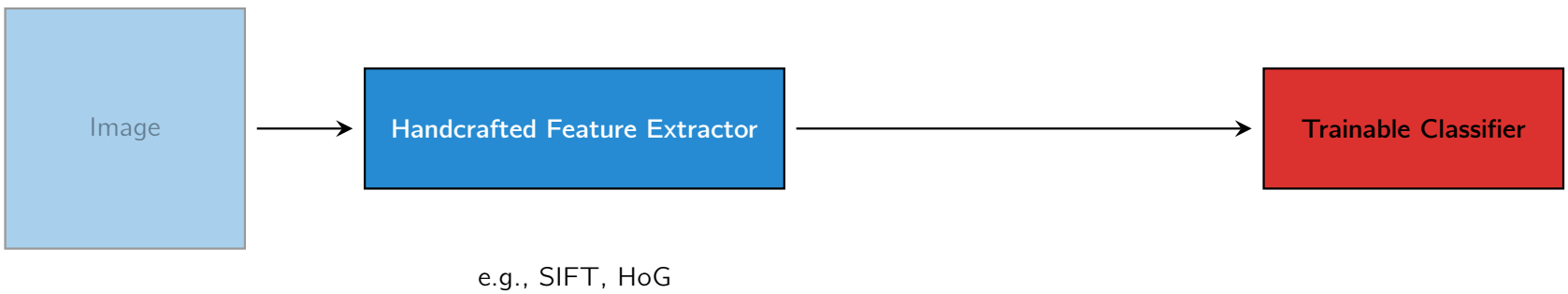


Lecture 8

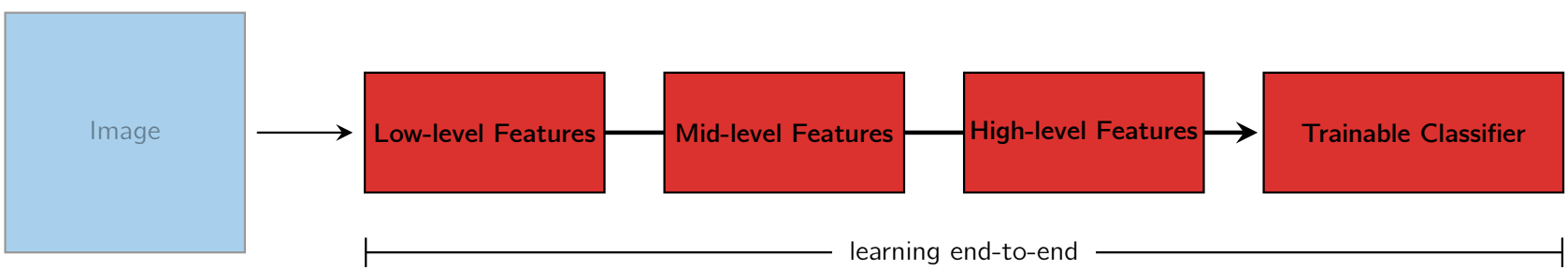
Convolution Neural Networks

Machine Learning for Computer Vision

- Traditional approach (before 2012): handcrafted features



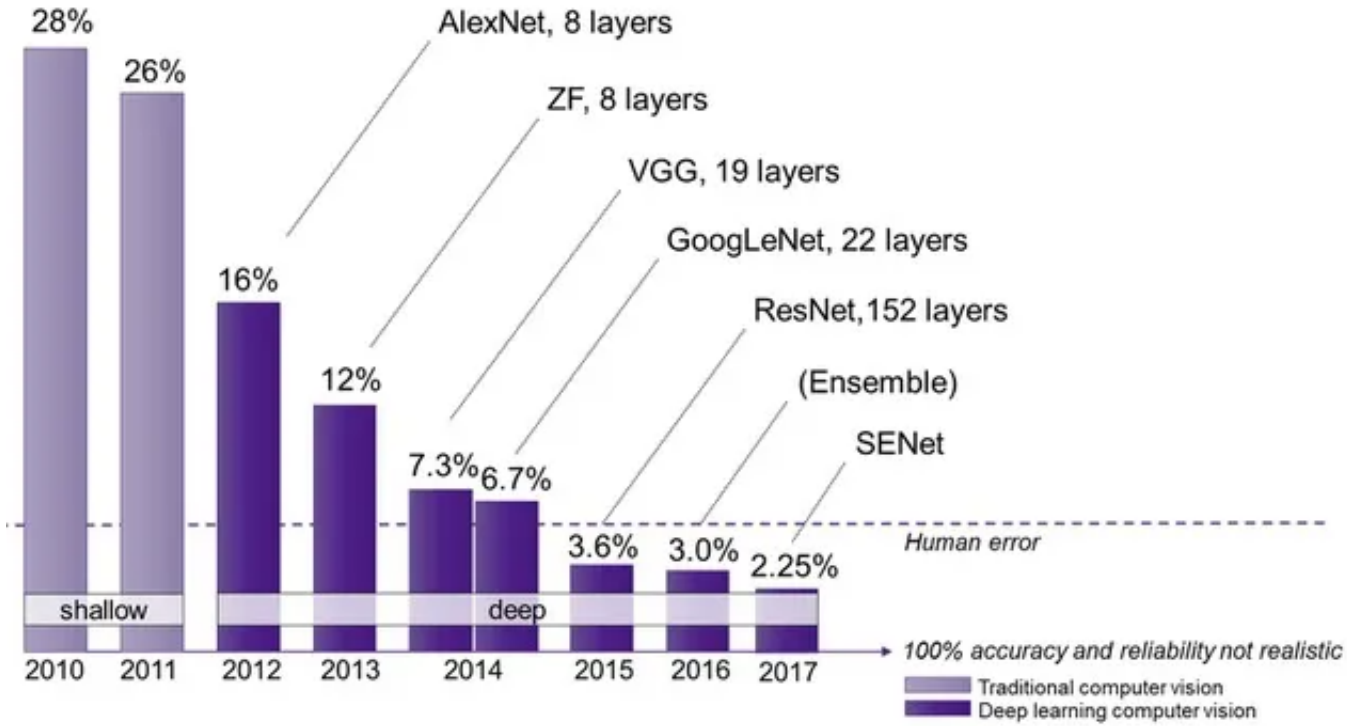
- Deep Learning (2012-...): end-to-end hierarchical feature learning



Figures are adapted from Canziani and LeCun, 2021.

ImageNet [2] Benchmark

Task: 1000-class classification (∼3M images)



ImageNet Classification Top-5 Error (%). Gordon Cooper, 2019

Remarks: 1): Another key ingredient that helped facilitate the progress on the ImageNet task is the utilization of GPUs in training large CNNs [9]; 2): More up-to-date results see `https://paperswithcode.com/sota/image-classification-on-imagenet`.

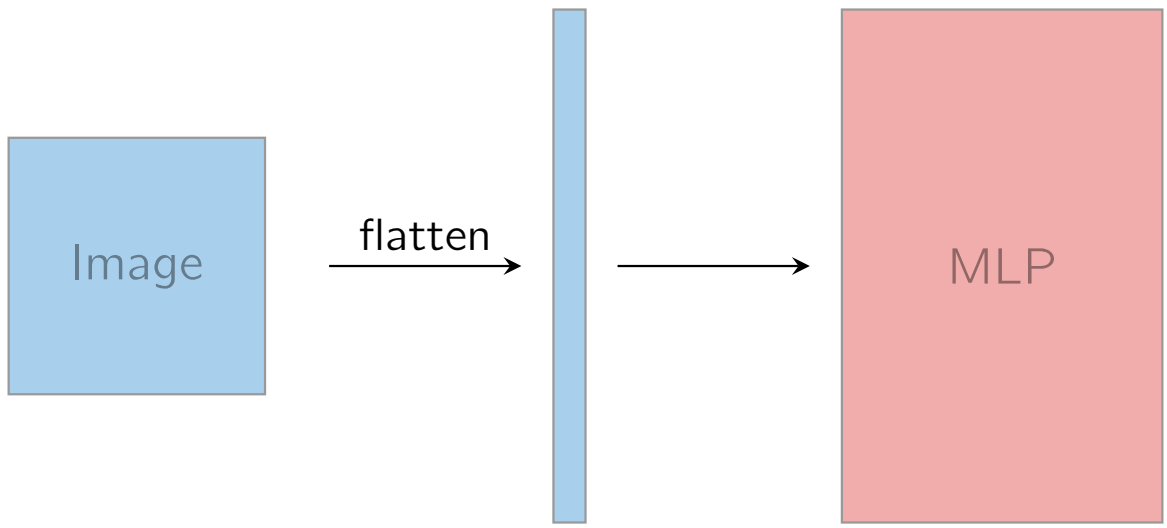
Recap: Multi-layer perceptrons

A sequence of affine and thresholding transformations:

$$
\begin{aligned}
\boldsymbol{z}^{(1)} &= W^{(1)}\boldsymbol{x} + \boldsymbol{b}^{(1)} \\
\boldsymbol{a}^{(1)} &= \sigma(\boldsymbol{z}^{(1)}) \\
&\vdots \\
\boldsymbol{a}^{(j)} &= \sigma(W^{j}\boldsymbol{a}^{(j-1)} + \boldsymbol{b}^{(j)}) \\
&\vdots
\end{aligned}
$$

Could we use MLPs for Images?

One might flatten images to be (very) tall vectors and feed these vectors as inputs to MLPs.



For example, a 3-color 32×32 image (e.g., $\mathbb{R}^{32\times32\times3}$) to a tall vector $\mathbb{R}^{3072}$

Issues

- space and algorithmic complexity
- statistical (learning) inefficiency: We do *not* exploit correlations of neighbouring pixels.

Could we use MLPs for Images? (cont.)

Issue 1: Space and Algorithmic Complexity Let m be the number of input dimensions (after flattened), e.g, $m = 3072$ and n be the number of neurons in the first layer of a MLP.

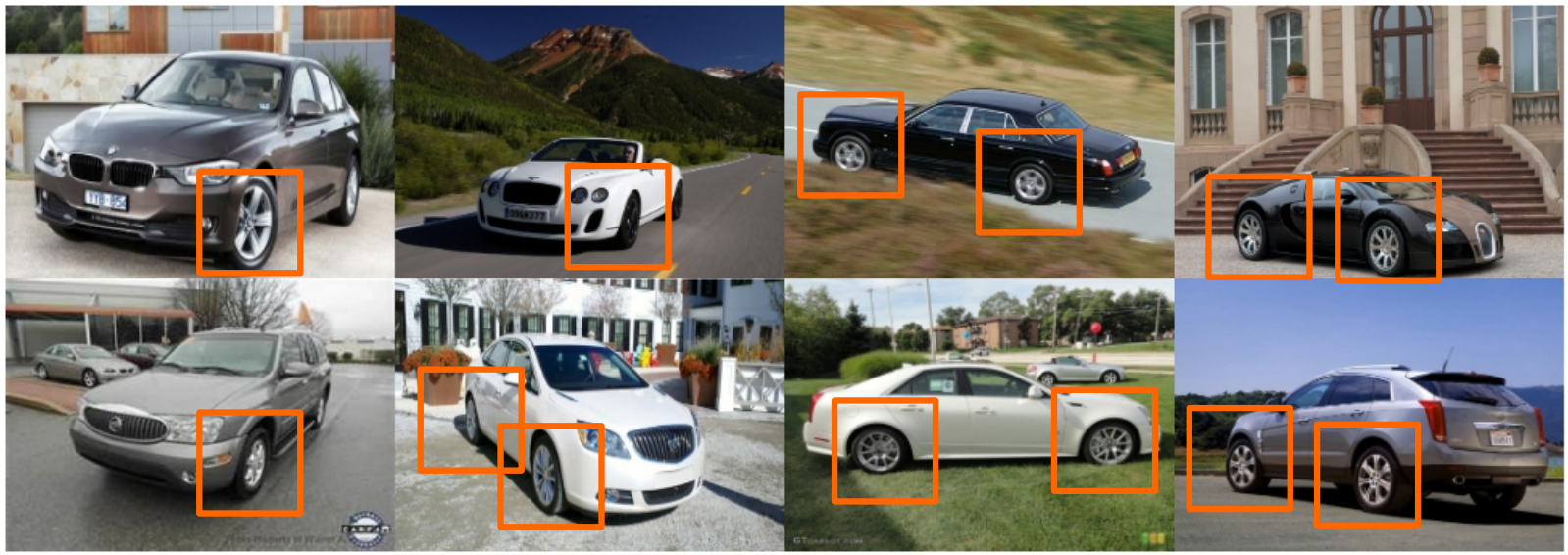
Space Complexity: We need $mn + n$ parameters.
$\rightarrow mn$ for weights $W^{(1)}$ and n for biases $\boldsymbol{b}^{(1)}$.

Algorithmic Complexity: $O(mn)$

Could we use MLPs for Images? (cont.)

Issue 2: Statistical Inefficiency

After flattening, we do not exploit local relationships between neighbouring pixels.



For example, pixels in the regions of car wheels often correlate, and the correlation might be useful for some learning tasks.

Figure is adapted from the Stanford Car dataset [12].

Overview of CNNs

CNNs = learning **hierarchical features** (from low to high level features) using **convolution** (learning correlation between neighbour pixels) and **pooling** layers (enlarging the size of neighbourhoods)[1]

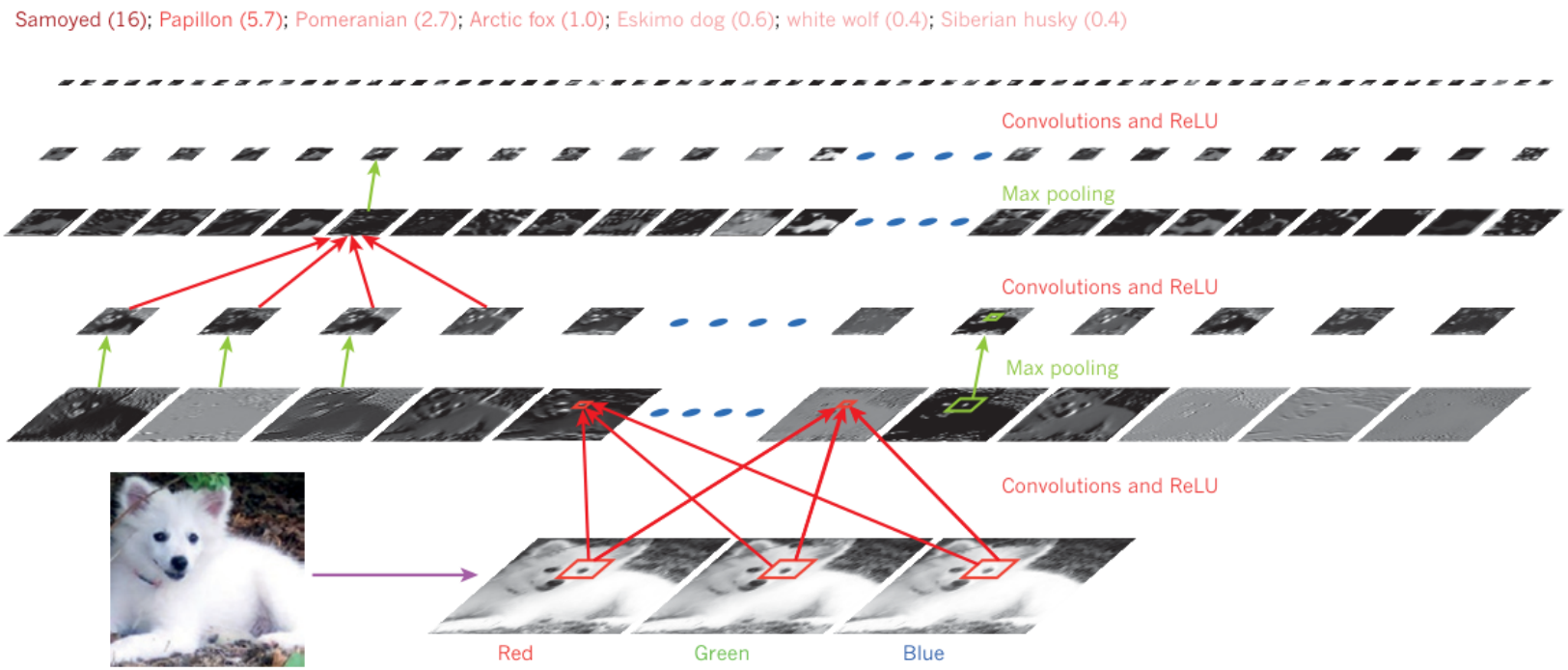


Figure 2 | Inside a convolutional network. The outputs (not the filters) of each layer (horizontally) of a typical convolutional network architecture applied to the image of a Samoyed dog (bottom left; and RGB (red, green, blue) inputs, bottom right). Each rectangular image is a feature map corresponding to the output for one of the learned features, detected at each of the image positions. Information flows bottom up, with lower-level features acting as oriented edge detectors, and a score is computed for each image class in output. ReLU, rectified linear unit.

Remarks: 1): In practice, there are other components in CNNs that help increase the performance of the models, but convolution and pooling layers are the two main important ingredients; 2) Figure is taken from LeCun et al., 2015 [15].

Convolution Operator

Let $x(t) \in \mathbb{R}$ be a one-dimensional signal at time $t \in \mathbb{R}$ and $w(\tau)$ be a weighting function. The convolution operator $*$ is

$$(x * w)(t) = \int x(\tau) w(t - \tau) \, \mathrm{d}\tau \qquad \text{(continuous setting)}$$

$$\approx \sum_{\tau=-\infty}^{\infty} x(\tau) w(t - \tau) \qquad \text{(discrete setting)}$$

We refer

- x as the **input**,
- w as the **kernel**,
- and $(x * w)(t)$ as **the feature map**, denoted with $a(t)$.

Convolution Operator (cont.)

We can see the convolution operator is **commutative**

$$
\begin{aligned}
(x * w)(t) &= \sum_{\tau} x(\tau) w(t-\tau) \\
&= \sum_{\tau'} x(t-\tau') w(\tau') && \text{(define } \tau' := t-\tau\text{)} \\
&= (w * x)(t)
\end{aligned}
$$

In deep learning, we instead use a related operator called **cross-correlation**[1], denoted with $\star$ (NOT asterisk $*$)

$$
(x \star w)(t) = \sum_{\tau'} x(t+\tau') w(\tau').
$$

Remarks: 1): the operator is generally referred and the underlying implementation of convolution layers in deep learning frameworks; therefore, we shall strict with the name *convolution* and use the symbol to indicate the actual operator; 2) The range of τ' will be made it clear in the following slides.

备注（Remarks）：

1. **该算子通常被引用**，并且在深度学习框架中 **卷积层的底层实现** 也是如此；因此，我们应当严格使用 **“卷积（convolution）”** 这一名称，并使用 **符号** 来表示实际的运算符。
2. **变量 τ' 的取值范围将在后续幻灯片中说明。**

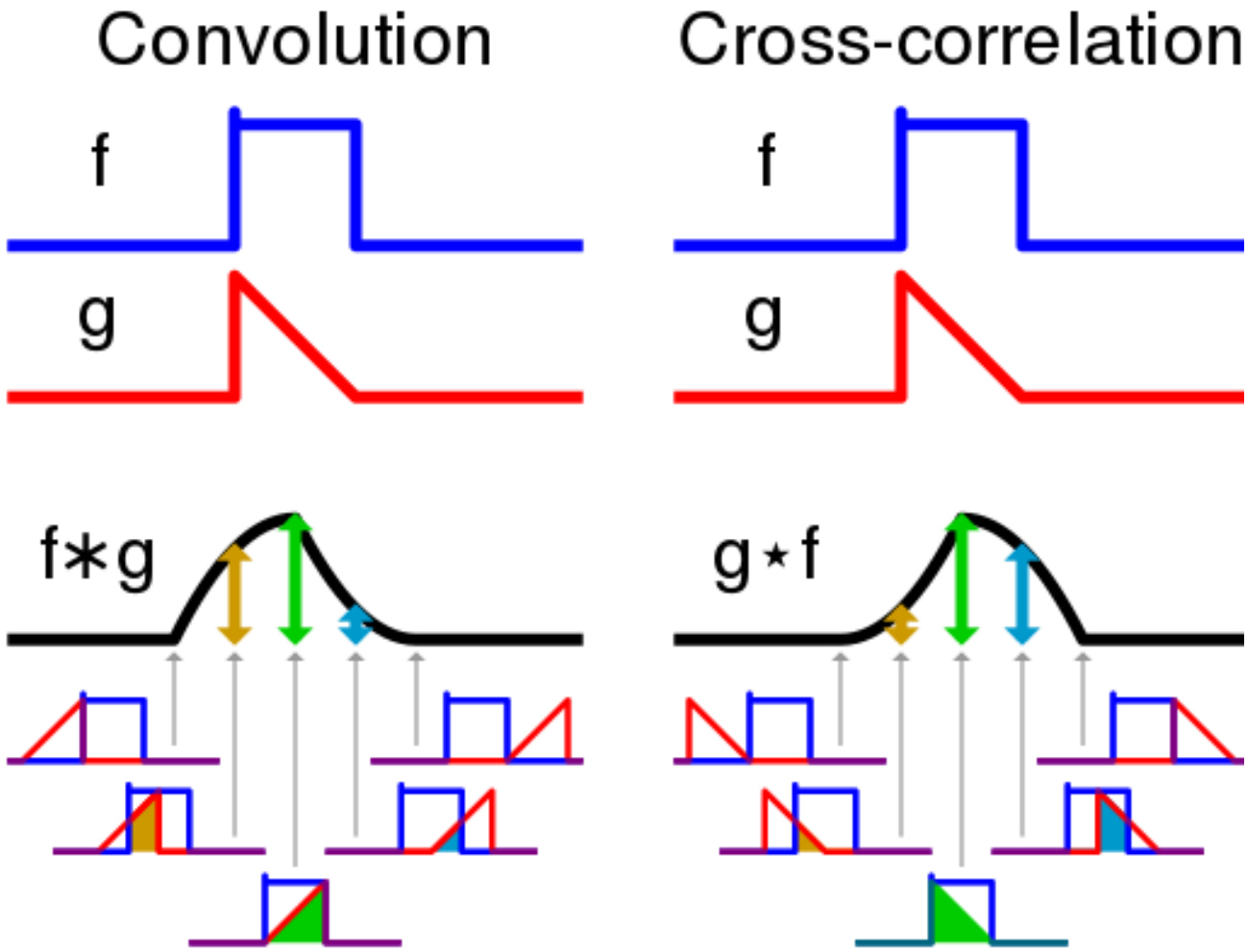
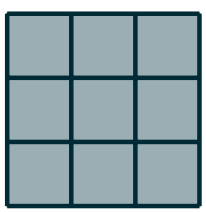


Figure from Wikipedia: `Convolution`.

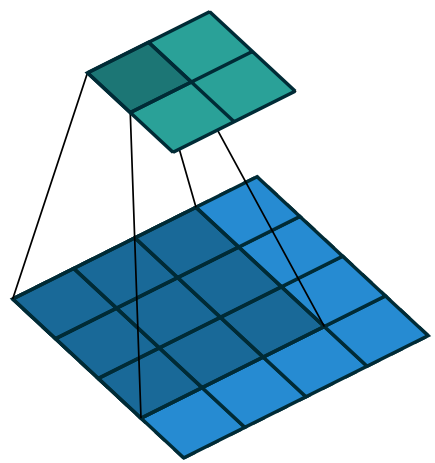
Two-Dimensional Discrete Convolution

A two-dimensional discrete convolution layer consists of

- weight ($W \in \mathbb{R}^{d_{\text{out}} \times d_{\text{in}} \times k \times k}$, or kernel) whose dimensions governed by
  - Number of input channels d_{in}, e.g., a 3-color image $d_{\text{in}} = 3$
  - Number of output channels d_{out} chosen by the user
  - Kernel size k chosen by the user
- bias ($b \in \mathbb{R}$, optional)



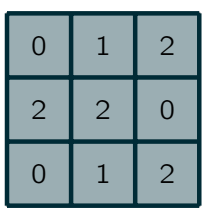
Weight W
$(k = 3, d_{\text{in}} = 1, d_{\text{out}} = 1)$



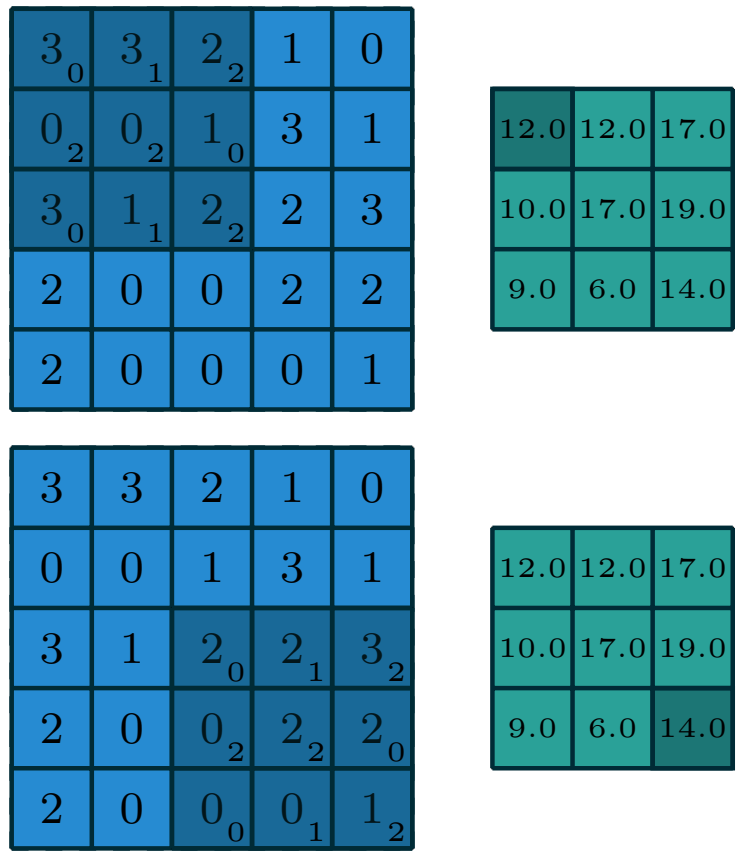
Discrete convolution using W (no bias) on an input ($d_{\text{in}} = 1$)

Figures are adapted from [3].

Numerical Example



Weight W $(k = 3)$



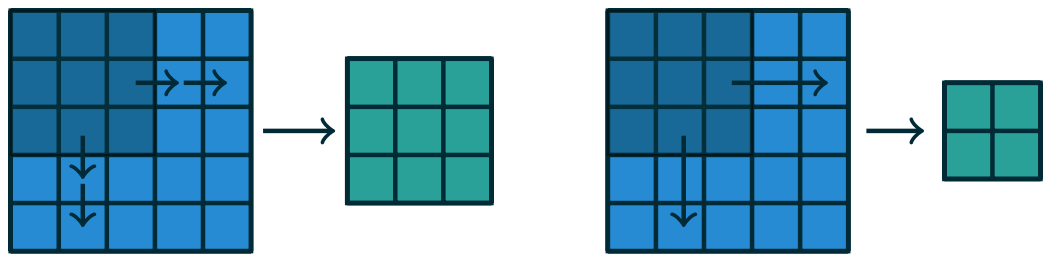
Left: Weight applied to two locations in the input;
Right: Output of the operator at the two locations (shaded entries) and other locations.

Figures are from [3].

Stride and Padding

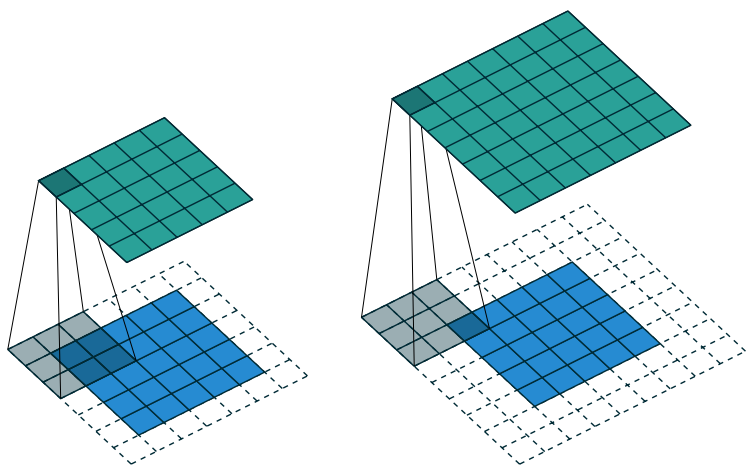
Apart from the parameters (W, b), discrete convolution also has two important hyper-parameters, namely

- Stride (amount of kernel translated)



Left: `stride` $= 1$ (previous example), **Right:** `stride` $= 2$

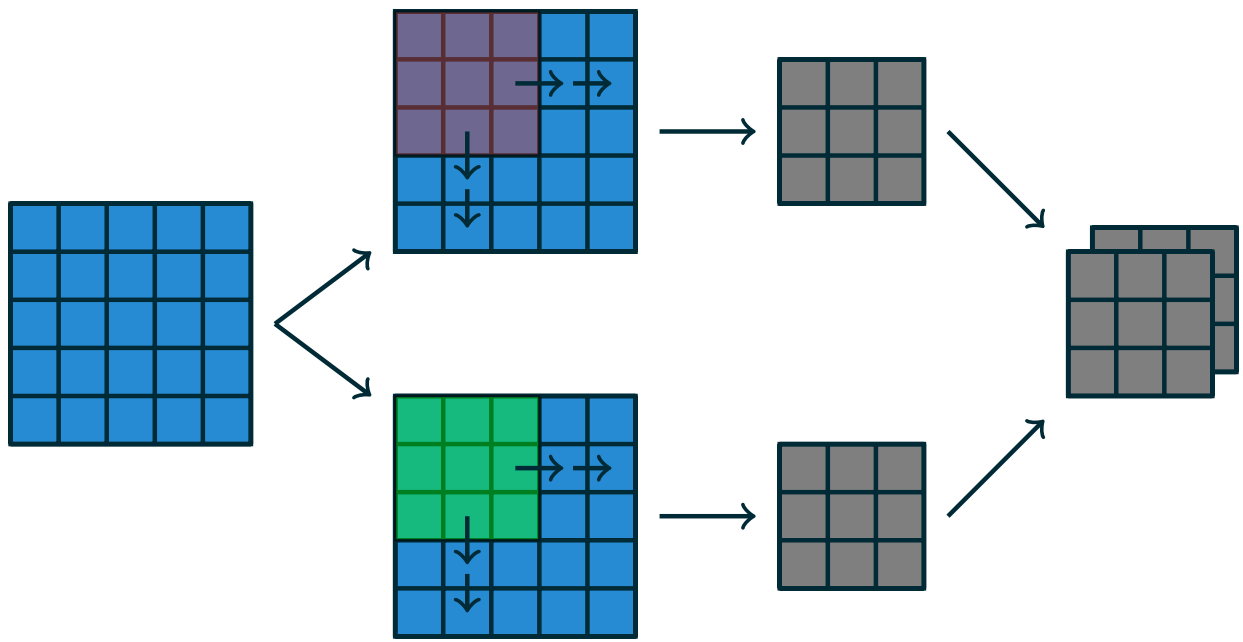
- Padding : How do we handle regions at the boundary of the input?



Padding with sizes 1 and 2 respectively.

Discrete Convolution when $d_{\text{out}} > 1$

So far, we mainly discuss the case when $d_{\text{out}} = 1$. When $d_{\text{out}} > 1$, we repeat the process d_{out} times and concatenate the output of each time together.



Example when $d_{\text{out}} = 2$ (`stride` $= 1$ and no padding)

Two-Dimensional Discrete Convolution

Denote $a \in \mathbb{R}^{d_{\text{in}} \times h_{\text{in}} \times w_{\text{in}}}$ be an input and $W \in \mathbb{R}^{d_{\text{out}} \times d_{\text{in}} \times k \times k}$ be a convolution weight. Two-dimensional discrete convolution can be expressed as

$$z_{c',m,n} = (a \star W)_{i,j} = \sum_{\tau_1=1}^{k} \sum_{\tau_2=1}^{k} \left[\sum_{c \in 1}^{d_{\text{in}}} a_{c,m+(\tau_1-1),n+(\tau_2-1)} W_{c',c,\tau_1,\tau_2} \right],$$

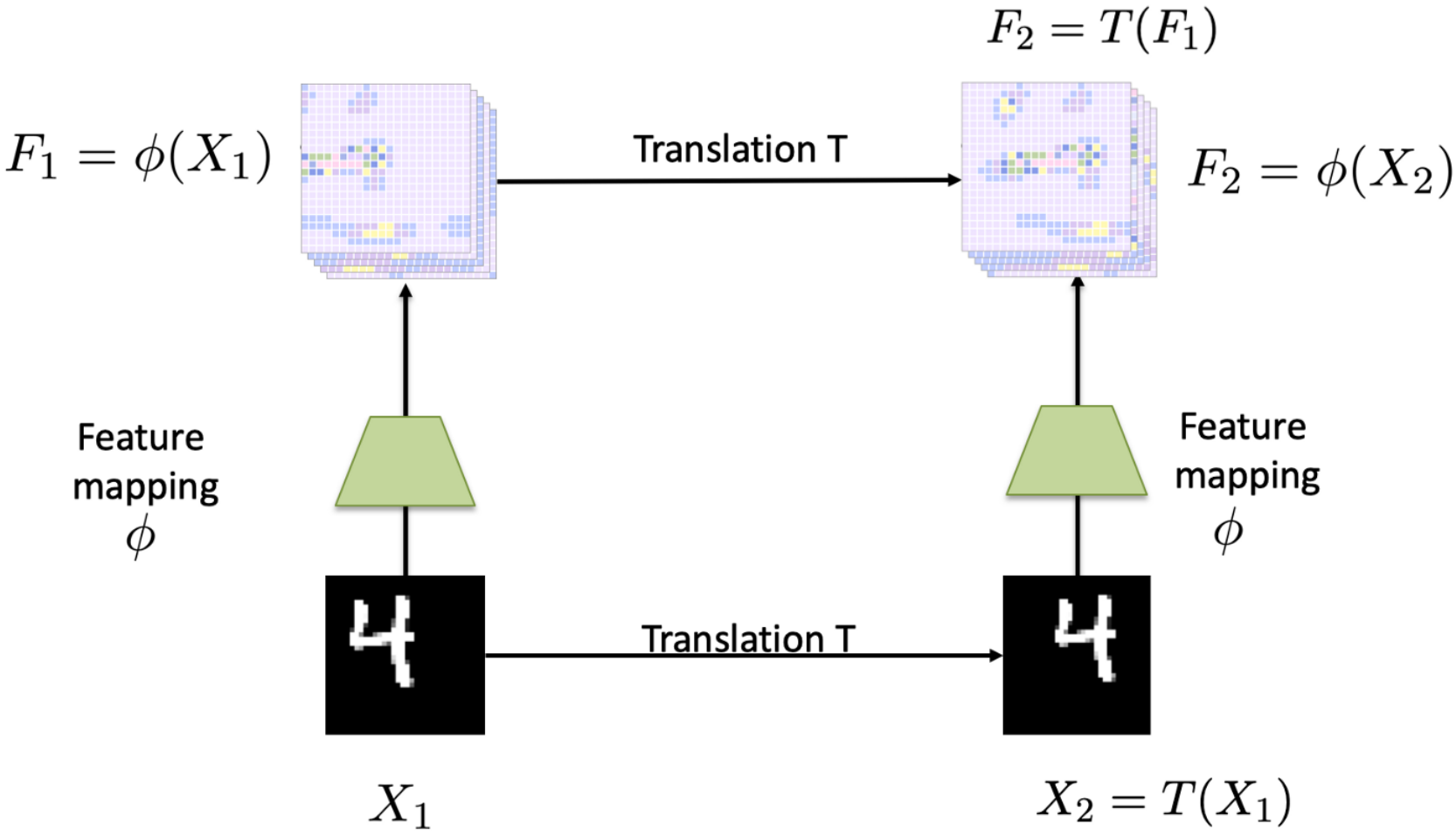
where $\forall c' \in \{1, \ldots, d_{\text{out}}\}$, $\forall m \in \{1, \ldots, h_{\text{out}}\}$, and $\forall n \in \{1, \ldots, w_{\text{out}}\}$.

The exact value of h_{out} and w_{out} depends on the kernel size, stride, and padding.
Suppose we have a square input $h_{\text{in}} = w_{\text{in}}$ and using stride=1 and no padding. We have

$$h_{\text{out}} = w_{\text{out}} = h_{\text{in}} - k + 1 \qquad \text{(Relationship 2 in [3])}$$

See [3] for the relationship between input and output size in other settings.

Translation Equivariance

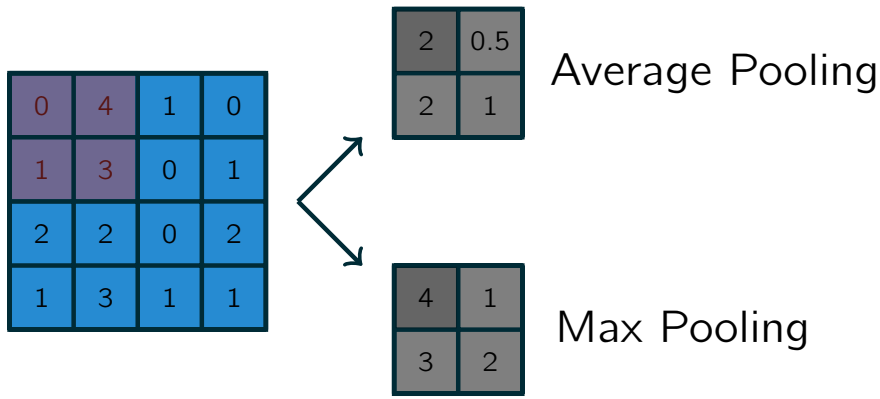


Credit: Christian Wolf

Pooling Layer

Convolution can detect patterns that are not larger than the kernel size k
A stack of convolutions can be used to increase this pattern-respond region, commonly referred to as **Receptive Field**.

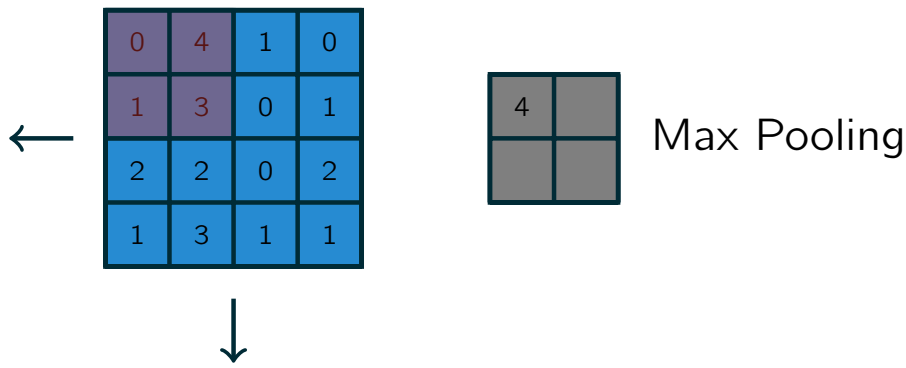
Practically, it is more effective to increase the receptive field by **subsampling** the input, or **Pooling**.
Commonly used pooling layers are average[1] and max pooling.



Average and max pooling with $k = \texttt{stride} = 2$.

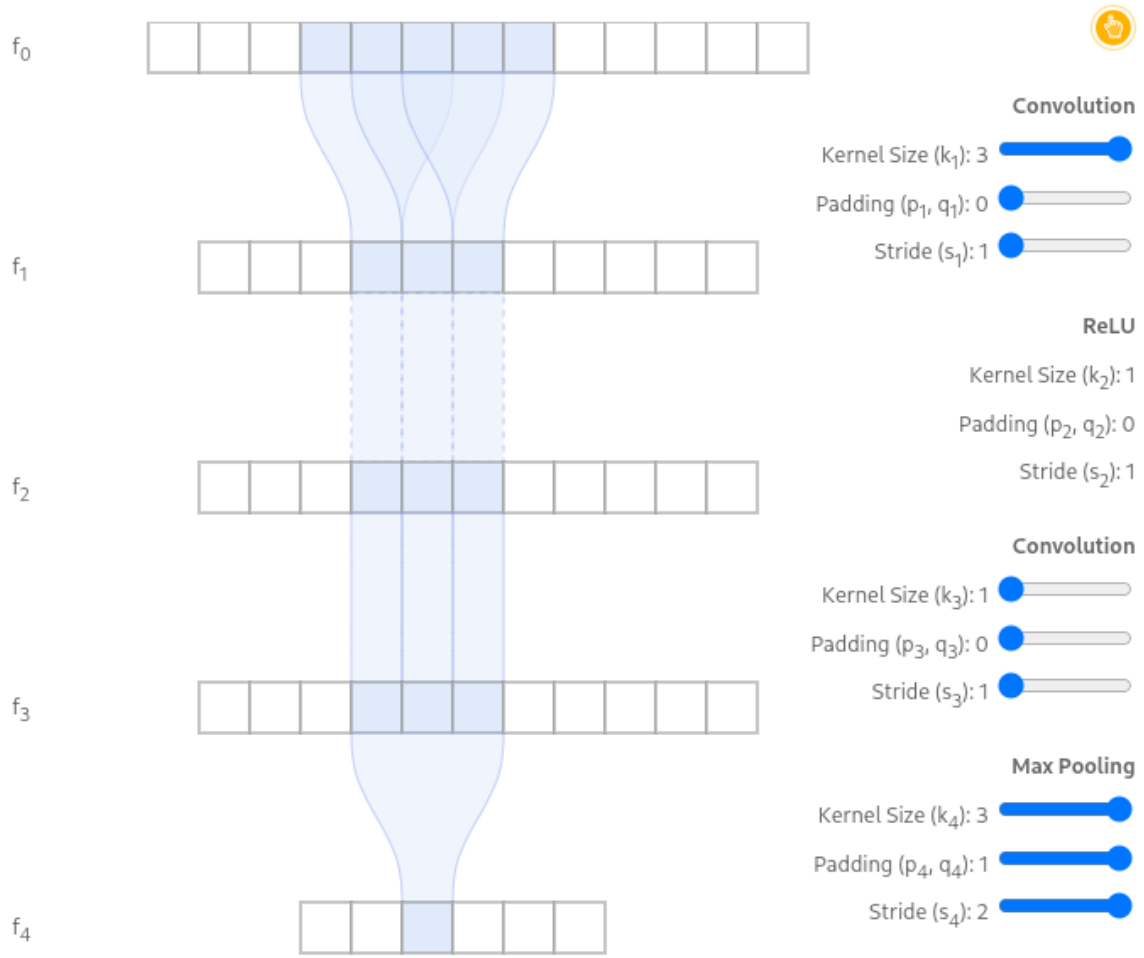
1): One can express the average pooling using convolution with constant weight $W_{\tau_1,\tau_2} = 1/k^2$ and no bias.

(Local) Translation Invariance of Max Pooling



For this example, the top-left output entry of the max pooling remains the same if the input is shifted left and down one step.

How the Size of Receptive Field Evolves



Screenshot from [1]. What happens to the receptive field if we change some of these parameters? Try it at `https://distill.pub/2019/computing-receptive-fields/`.

Blueprint of CNNs for Classification

$$\overbrace{[\text{Conv.} \rightarrow \text{Act.} \rightarrow \text{Pooling}]_{\times L} \rightarrow \text{Global Average Pooling}}^{\text{Feature Extractor}} \rightarrow \underbrace{\text{MLP}}_{\text{Classifier}}$$

Case Study: LeNet-5 [17]

Key Contribution: Pioneer work on using modern CNNs for handwritten character recognition using gradient-based learning.

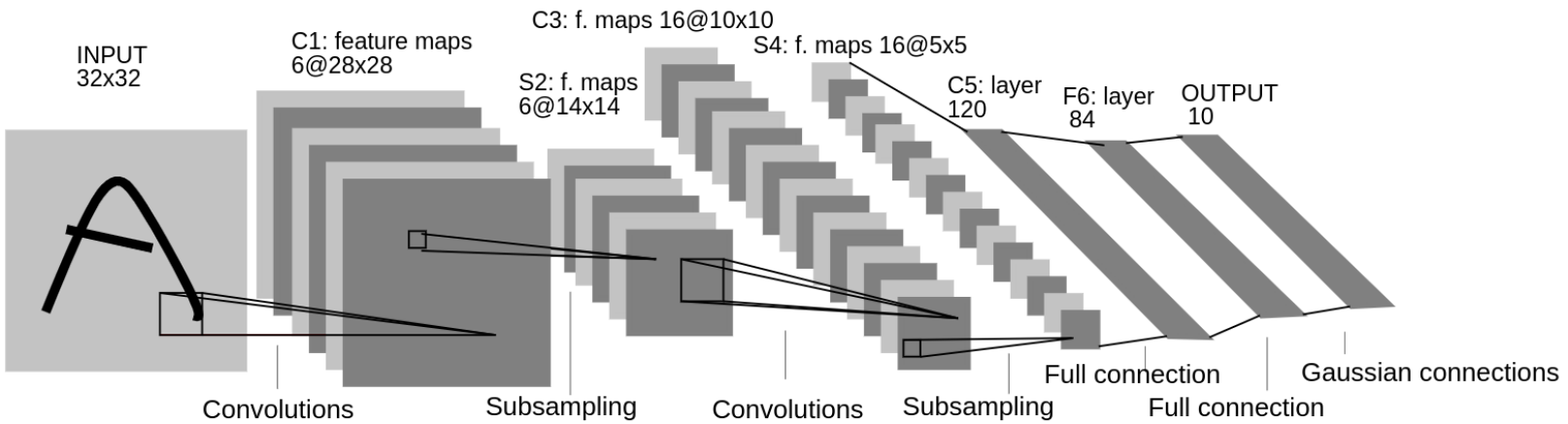


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

Building on earlier work on CNNs by LeCun [16] which was inspired by the Neocognitron by Fukushima[5].

Case Study: AlexNet [13]

Key Contributions: First CNN winning ImageNet Challenge (2012); Making use of GPUs in training

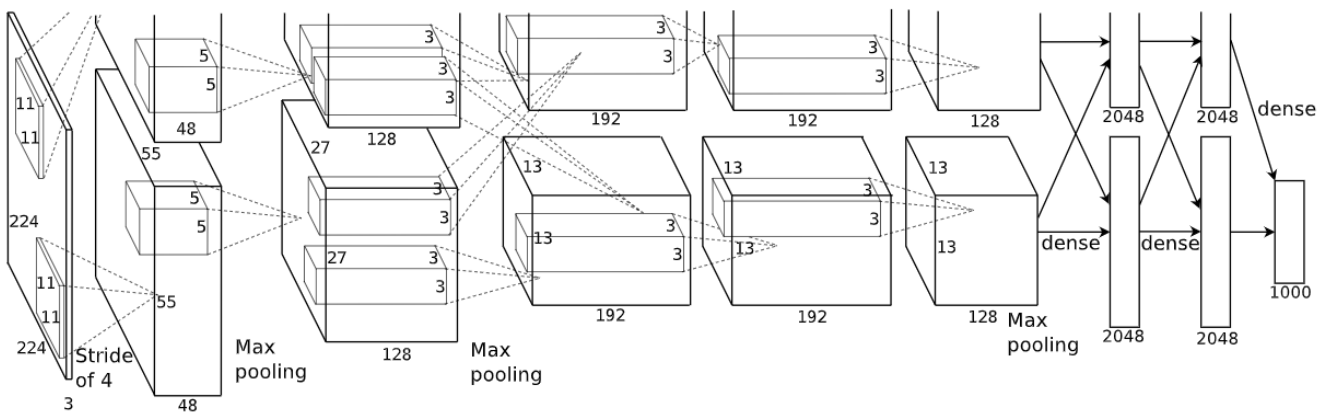


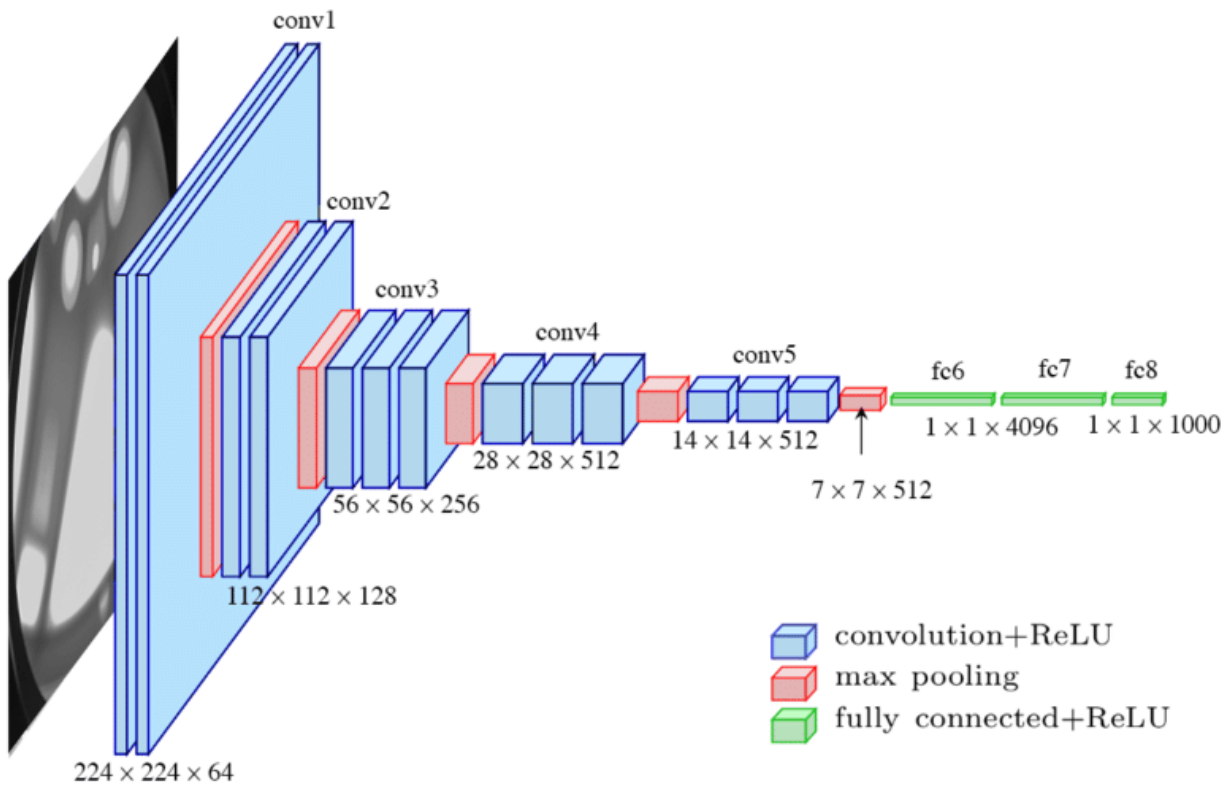
Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

该图展示了我们 CNN 的架构，并明确显示了 **两个 GPU 之间的责任分工**。

- **一个 GPU** 运行图中**顶部**的层，**另一个 GPU** 运行**底部**的层。
- GPU 仅在某些特定层进行通信。
- **网络的输入维度为 150,528**，其余层中的**神经元数量**依次为： **253,440 → 186,624 → 64,896 → 64,896 → 43,264 → 4096 → 4096 → 1000**。

Case Study: VGG [20]

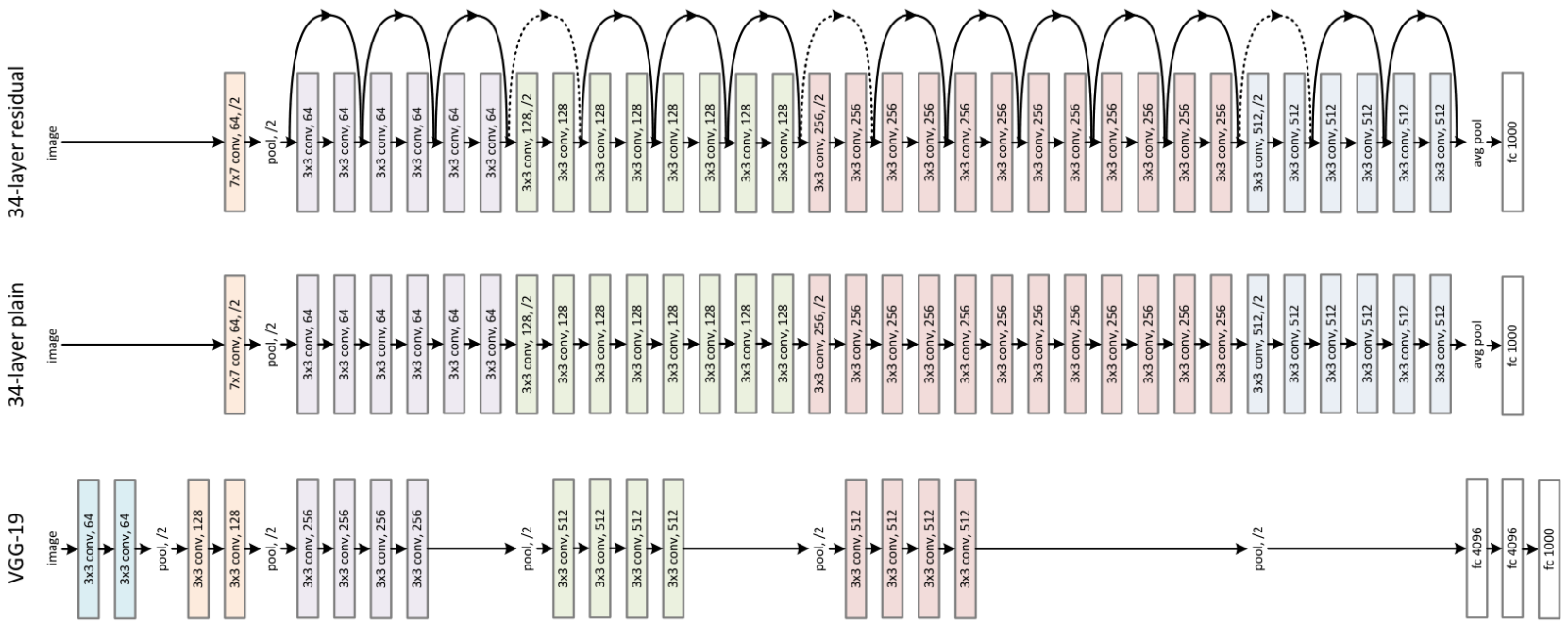
Key Contributions: Winner* of ImageNet Challenge (2014); Demonstrating the benefit of the depth.



: $\star$ 1st and 2nd places on the location and classification tracks.

Case Study: ResNets [8]

Key Contributions: Winner of ImageNet Challenge (2015) and many other challenges; Inventing the residue connection that allow training CNNs with many more layers (e.g., 8× deeper than VGG).



Case Study: ResNets [8] (cont.)

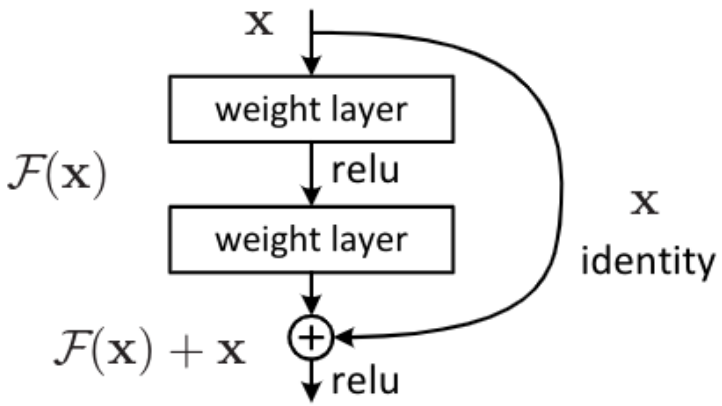


Figure 2. Residual learning: a building block.

	plain	ResNet
18 layers	27.94	27.88
34 layers	28.54	**25.03**

Table 2. Top-1 error (%, 10-crop testing) on ImageNet validation. Here the ResNets have no extra parameter compared to their plain counterparts. Fig. 4 shows the training procedures.

Residual Connections

- Core idea of ResNet by He et al.
- For layer l and intermediate representation x_l with layers NN_l

$$
\begin{aligned}
x_{l+1} &= x_l + \mathsf{NN}_l(x_l; \theta_l) \\
x_{l+2} &= x_l + \mathsf{NN}_l(x_l; \theta_l) + \mathsf{NN}_{l+1}(x_{l+1}; \theta_{l+1}) \\
&\dots
\end{aligned}
$$

- Better gradient flow by 'shortcutting' over high number of intermediate layers between loss and layer NN_l

$$
\begin{aligned}
\partial_{\theta_l} x_{l+1} &= x_l + \partial_{\theta_l} \mathsf{NN}_l(x_l; \theta_l) \\
\partial_{\theta_{l+1}} x_{l+2} &= x_l + \mathsf{NN}_l(x_l; \theta_l) + \partial_{\theta_{l+1}} \mathsf{NN}_{l+1}(x_{l+1}; \theta_{l+1}) \\
&\dots
\end{aligned}
$$

- Allows training far deeper networks with more parameters which result in better performance

What features do CNNs learn? [23]

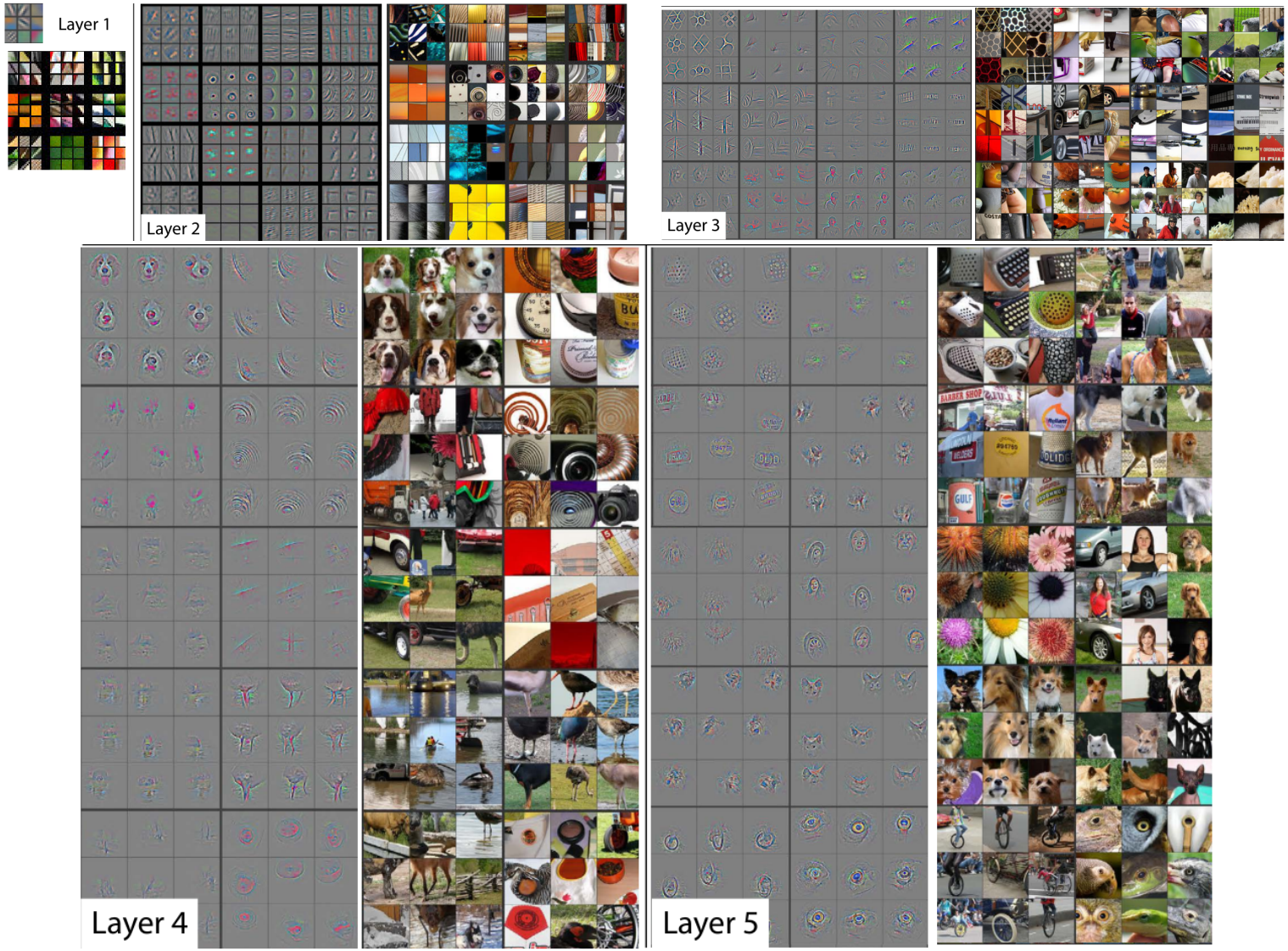


Figure 2. Visualization of features in a fully trained model. For layers 2-5 we show the top 9 activations in a random subset of feature maps across the validation data, projected down to pixel space using our deconvolutional network approach. Our reconstructions are *not* samples from the model: they are reconstructed patterns from the validation set that cause high activations in a given feature map. For each feature map we also show the corresponding image patches. Note: (i) the the strong grouping within each feature map, (ii) greater invariance at higher layers and (iii) exaggeration of discriminative parts of the image, e.g. eyes and noses of dogs (layer 4, row 1, cols 1). Best viewed in electronic form.

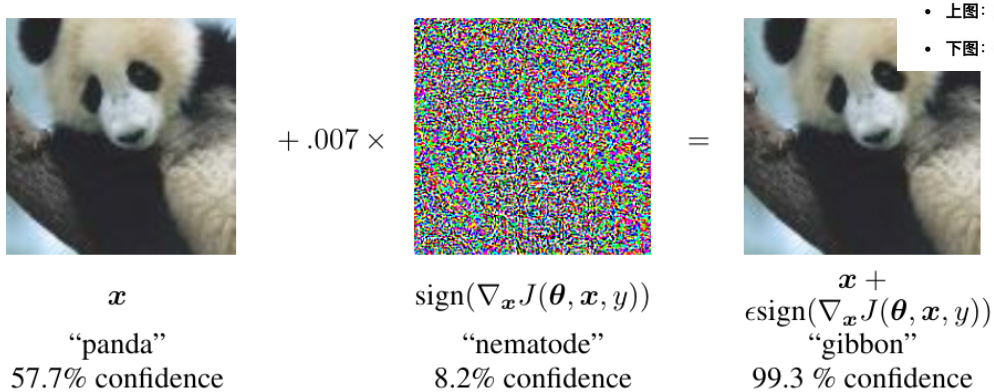
Shortcoming of CNNs: Vulnerable to Noise in Input

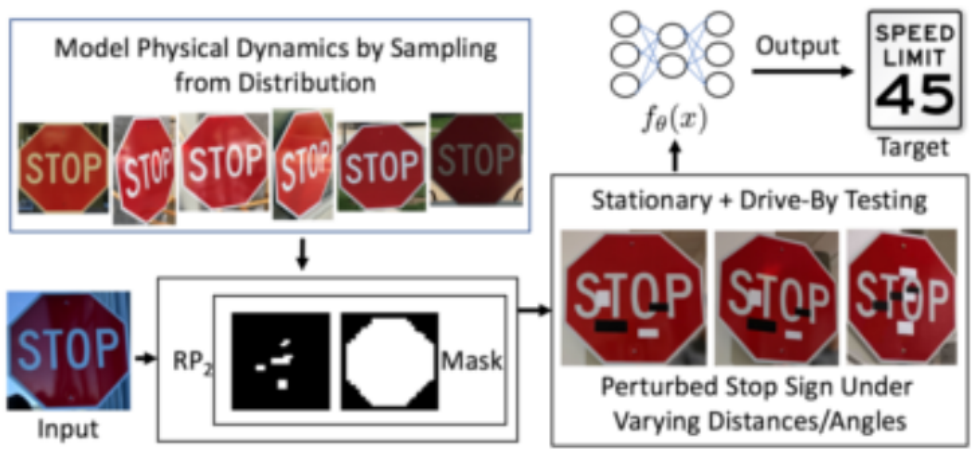
If the input is slightly (adversarially) perturbed, the prediction of CNNs can dramatically change.

CNN 的缺陷：对输入噪声的脆弱性（Shortcoming of Vulnerable to Noise in Input）

如果输入受到 **轻微（对抗性）扰动**，CNN 的预测可能会发生 **剧烈变化**。

- **上图**：对抗性噪声使 CNN 误将 **熊猫（Panda）** 识别为 **长臂猿（Gibbon）**。
- **下图**：物理对抗性贴纸使得停车标志（Stop Sign）被误识别为限速标志（Spe





Top: Adversarial noise causes the prediction of a CNN to change from "Panda" to "Gibbon"; **Bottom:** Physical adversarial sticker causes stop signs to detected as a target speed limit sign; Figures are from [7, 4] respectively.

Shortcoming of CNNs: Texture Bias [6]

Unlike humans that often rely on shape information in visual processing [14], CNNs rely heavily on textural features.

(a) Texture image

81.4%	**Indian elephant**
10.3%	indri
8.2%	black swan

(b) Content image

71.1%	**tabby cat**
17.3%	grey fox
3.3%	Siamese cat

(c) Texture-shape cue conflict

63.9%	**Indian elephant**
26.4%	indri
9.6%	black swan

Figure 1: Classification of a standard ResNet-50 of **(a)** a texture image (elephant skin: only texture cues); **(b)** a normal image of a cat (with both shape and texture cues), and **(c)** an image with a texture-shape cue conflict, generated by style transfer between the first two images.

CNN 的缺陷：纹理偏差（Shortcoming of CNNs: Texture Bias）

与人类在视觉处理中主要依赖**形状信息**不同，CNN **高度依赖纹理特征**。

- **(a) 仅包含纹理的图片（象皮）**：81.4% 置信度被 CNN 识别为 **印度象（Indian elephant）**。
- **(b) 一张正常的猫图片（同时包含形状和纹理）**：71.1% 置信度被 CNN 识别为 **虎斑猫（Tabby Cat）**。
- **(c) 纹理-形状冲突图像（通过风格迁移生成）**：CNN 仍然以 **63.9% 置信度** 将其识别为 **印度象（Indian elephant）**，尽管它的形状是猫。

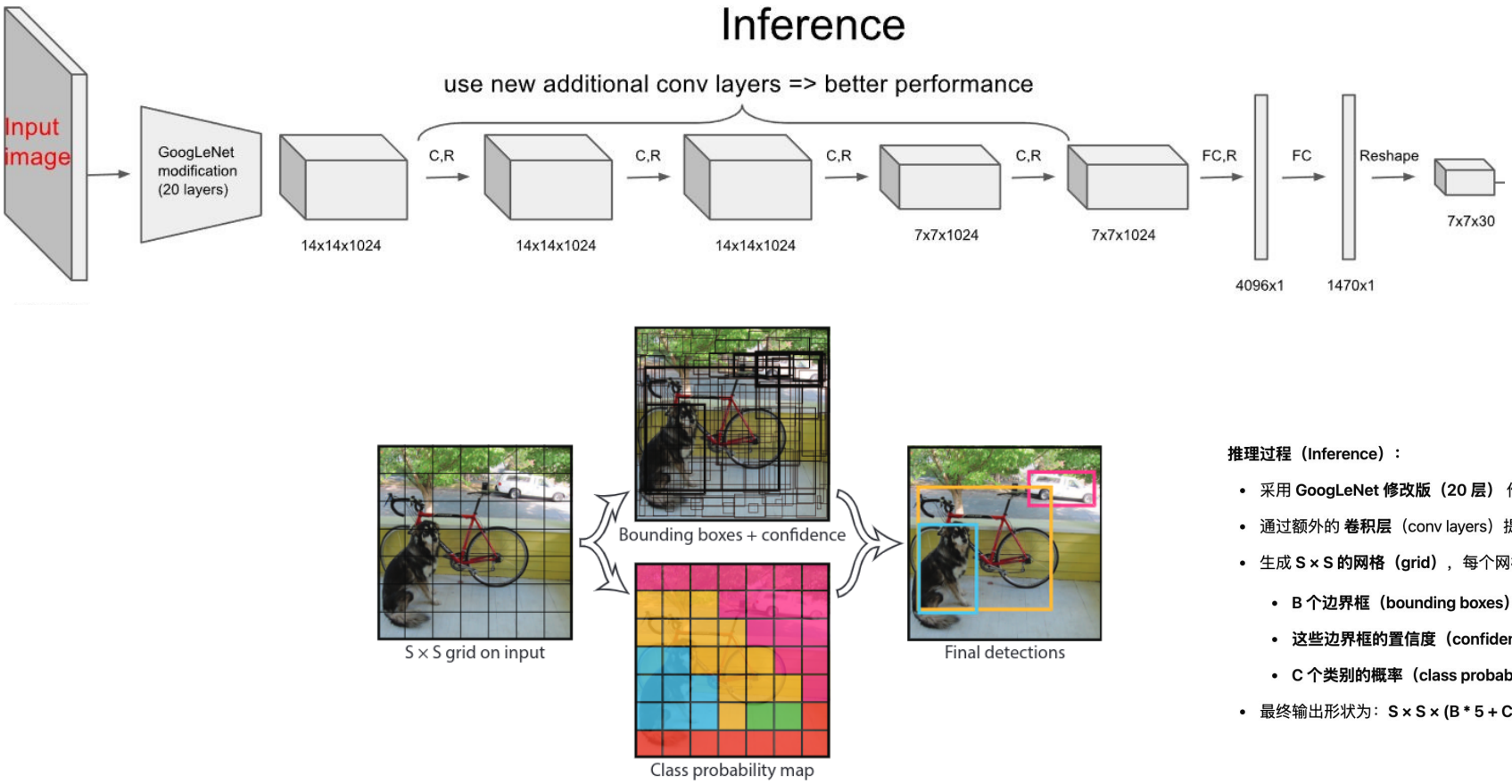
图 1 说明：CNN 主要依赖于 **纹理信息** 进行分类，而**对形状信息的依赖较弱**，导致其在某些任务上的泛化能力受限。

Applications of CNNs

Apart from image classification, CNNs are often used as feature extractors in image-based learning tasks, and the concept of CNNs can be generalized to input from other modalities

- Different Tasks: Object Detection, Image Segmentation, Image Captioning, ...
- Other Modalities: Text Classification, Text-to-Speech, ...

Object Detection: You Only Look Once (YOLO) [18]



推理过程（Inference）：

- 采用 **GoogLeNet 修改版（20 层）** 作为基础网络。
- 通过额外的 **卷积层**（conv layers）提升性能。
- 生成 **S × S 的网格（grid）**，每个网格预测：
  - **B 个边界框（bounding boxes）**。
  - **这些边界框的置信度（confidence）**。
  - **C 个类别的概率（class probabilities）**。
- 最终输出形状为：**S × S × (B * 5 + C) 的张量。**

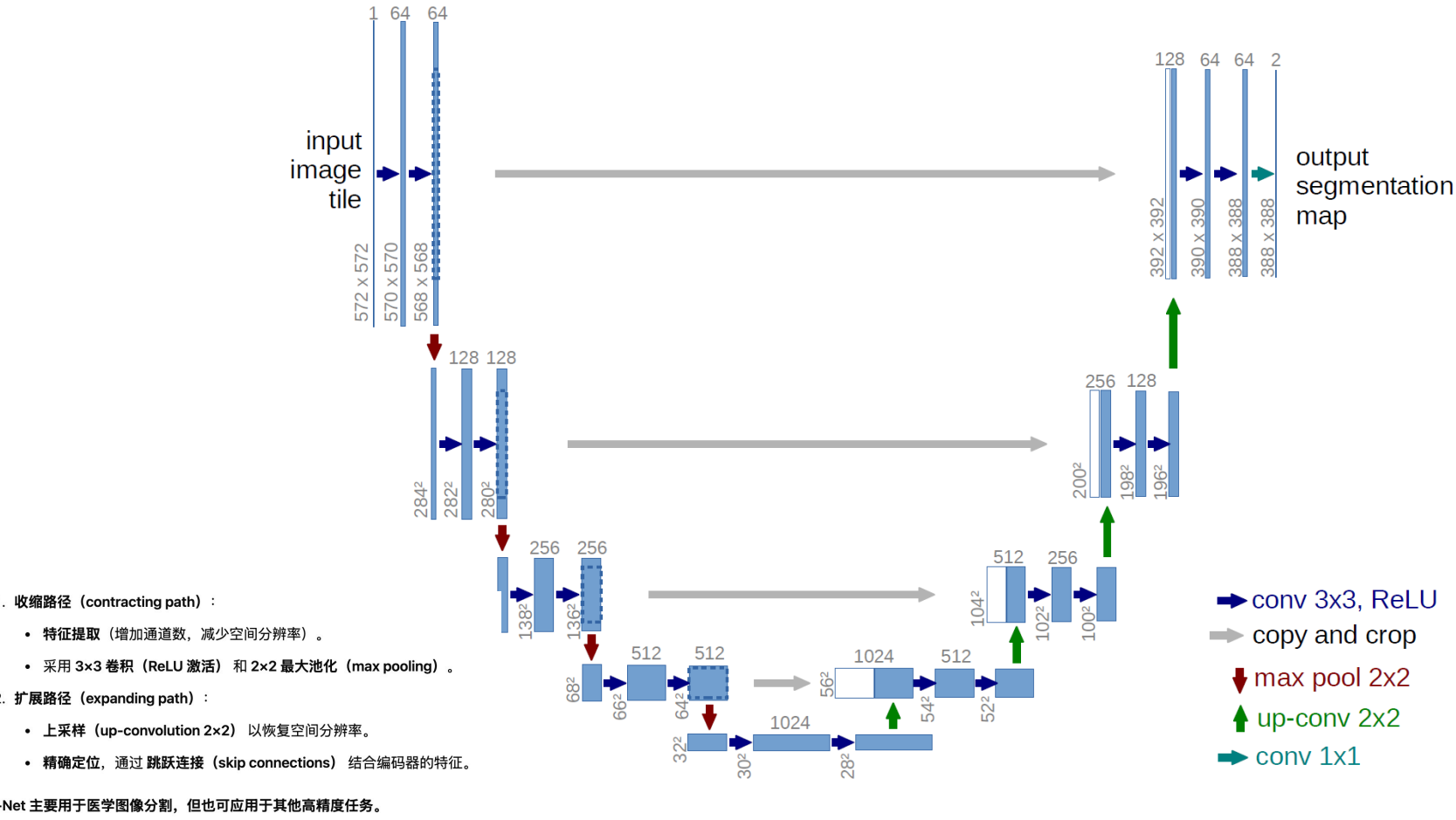
Figure 2: The Model. Our system models detection as a regression problem. It divides the image into an $S \times S$ grid and for each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities. These predictions are encoded as an $S \times S \times (B * 5 + C)$ tensor.

- YOLO 将检测任务建模为 **回归问题（regression problem）**，将输入图像划分为 **S × S 网格。**
- **每个网格单元预测 B 个边界框及其置信度，以及 C 类的类别概率。**
- **YOLO 的特点是速度快，且可以实时检测多个目标。**

The architecture image is from `https://dinghow.site/2019/08/24/object-detection-part1`.

Image Segmentation: U-net [19]

Key Contributions: Fast architecture for precise (biological) image segmentation.



1. **收缩路径（contracting path）**：
   - **特征提取**（增加通道数，减少空间分辨率）。
   - 采用 **3×3 卷积（ReLU 激活）** 和 **2×2 最大池化（max pooling）**。
2. **扩展路径（expanding path）**：
   - **上采样（up-convolution 2×2）** 以恢复空间分辨率。
   - **精确定位**，通过 **跳跃连接（skip connections）** 结合编码器的特征。

U-Net 主要用于医学图像分割，但也可应用于其他高精度任务。

Key concepts: contraction (increase what, reduce where) and expanding paths (precise localization).

Image Segmentation: U-net [19] (cont.)

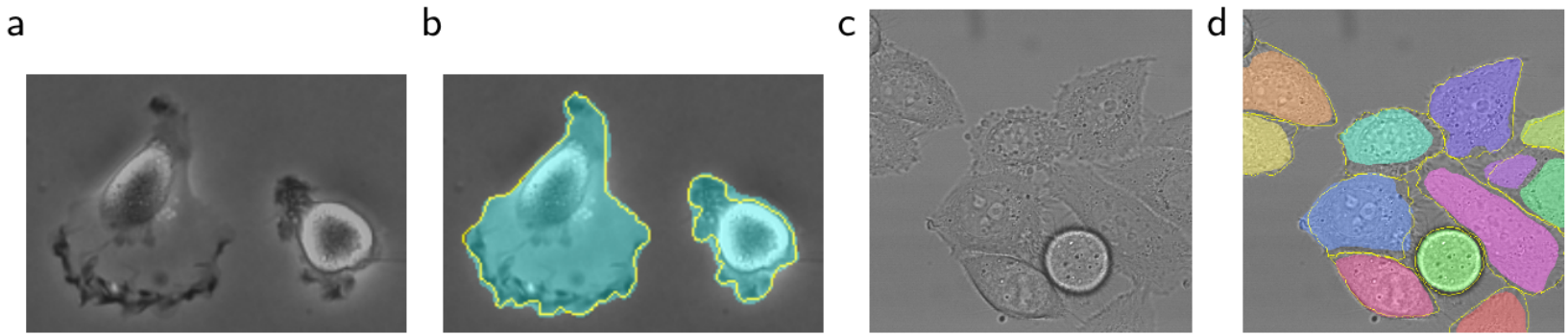
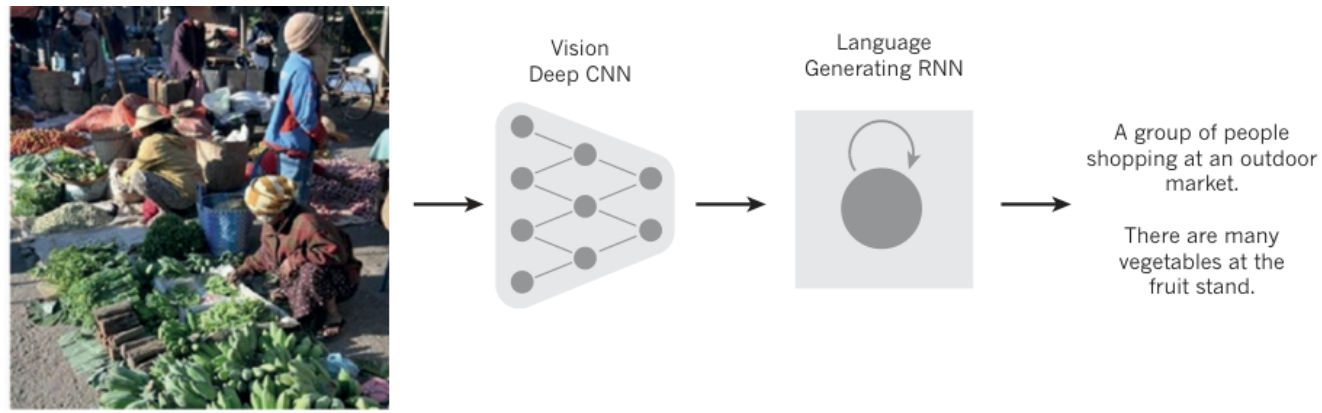


Fig. 4. Result on the ISBI cell tracking challenge. (**a**) part of an input image of the "PhC-U373" data set. (**b**) Segmentation result (cyan mask) with manual ground truth (yellow border) (**c**) input image of the "DIC-HeLa" data set. (**d**) Segmentation result (random colored masks) with manual ground truth (yellow border).

Image Captioning [21, 10, 22]



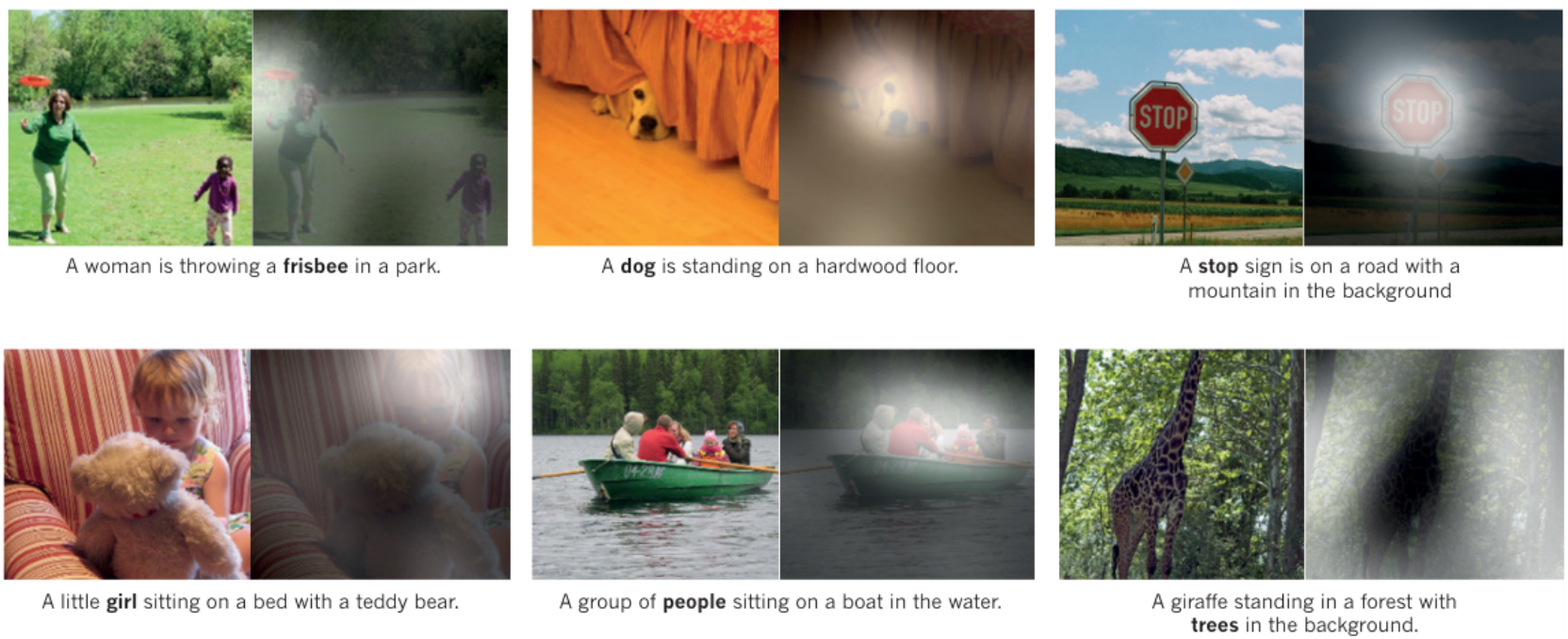


Figure from [22].

Convolution and Pooling for Text Classification [11]

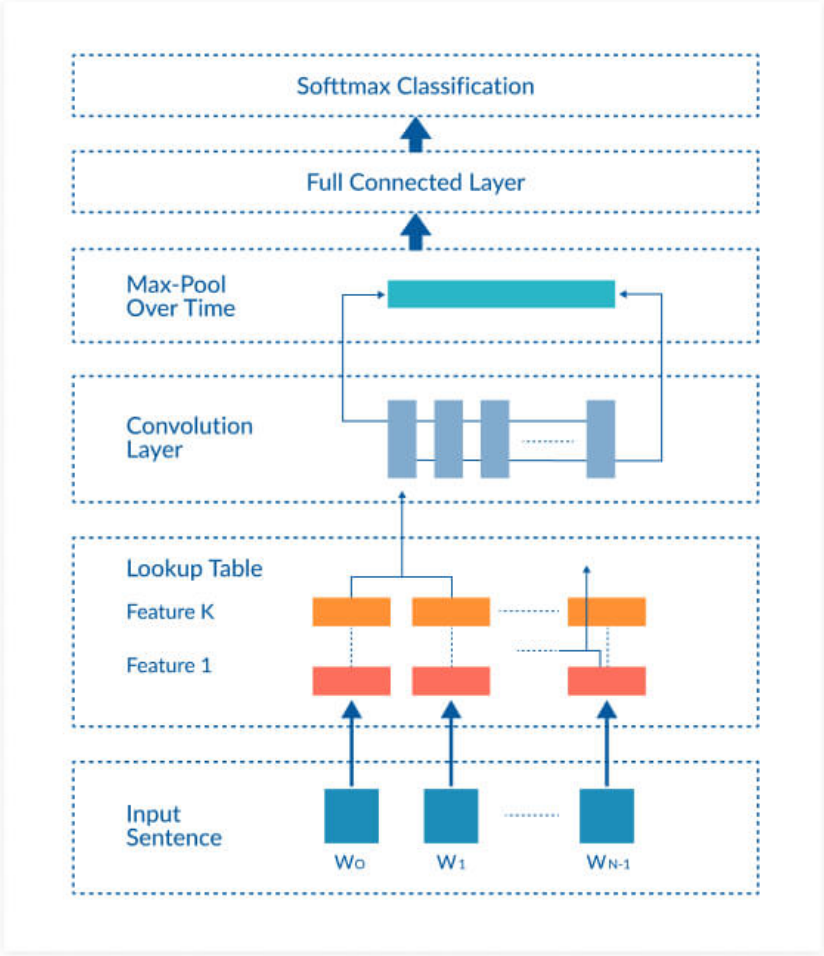


Figure is from `https://indiantechwarrior.com/sentence-classification-using-convolutional-neural-networks/`

Transformers: Attention Mechanism

- Idea: find global interactions within an input sequence or between two input sequences.
- In our case: $K = V = x \in \mathbb{R}^T$ and $Q = y \in \mathbb{R}^{T'}$
- "Query with target $y_{t'}$ all source keys x_t on how much attention to pay to source value x_t at each target timestep t'"

- Compute pairwise product $QK^T \in \mathbb{R}^{T \times T'}$ to obtain similarities
- Normalize over source dimension with softmax probability
- Scale source values $V = x$

$$\underbrace{\text{Attention(Q,K,V)}}_{T' \times T} = \underbrace{\text{Softmax}_T(QK^T)}_{T' \times T} V \tag{1}$$

核心思想（Idea）

- **在输入序列内部或两个输入序列之间** 找到全局交互关系。

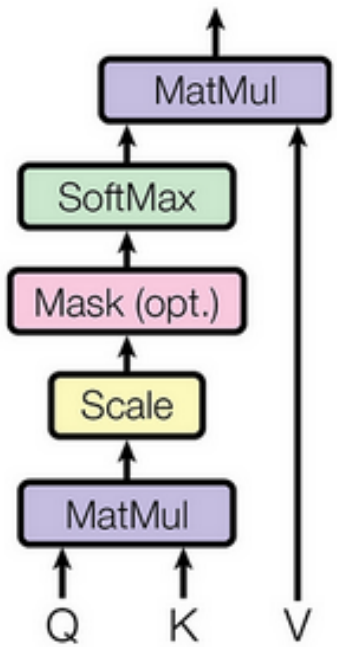
数学公式

- **在本例中**：

$$K = V = x \in \mathbb{R}^T$$

$$Q = y \in \mathbb{R}^{T'}$$

- 查询（Query）目标 $y_{t'}$ 需要从 **所有源键（keys）** x_t 计算 **应关注的程度**，以决定在 **目标时间步** t' 上关注哪个源值 x_t。



- **Query（Q）**：当前要处理的输入
- **Key（K）**：所有可能的参考信息
- **Value（V）**：与 Key 关联的信息
- Attention 通过计算 **Q 与 K 的相似性**（通常用点积）来决定 V 的重要性，最终加权求和。

Transformers: Attention Mechanism

- Original attention mechanism in Bahdanau et al used MLP as scalar projector
- QK^T is a dot product, so we can use arbitrary dimensions
- $x \in \mathbb{R}^{T \times F}$ and $y \in \mathbb{R}^{T' \times F}$, $QK^T \in \mathbb{R}^{T \times T'}$

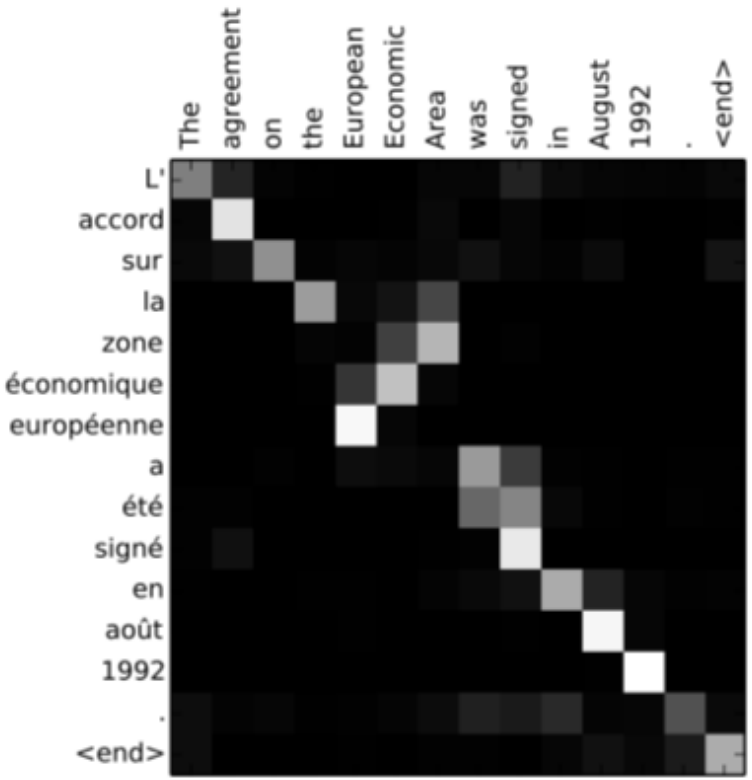


Figure: "Neural Machine Translation by Jointly Learning to Align and Translate" by Bahndanau et al.

按照 Attention 机制的计算流程，正确的顺序如下：

1. **Tokenize the input sequence and embed the tokens into a feature space.**
   - 先对文本进行**分词（tokenization）**，然后将其映射到一个**向量空间**（Embedding）。
2. **Transform the input in order to obtain the corresponding key, value and query embeddings.**
   - 通过一个**线性变换（如矩阵乘法）**从输入嵌入（embedding）中计算出 **Key (K)**、**Query (Q)** 和 **Value (V)**。
3. **Calculate the attention weights by measuring the similarity between the keys and queries.**
   - 计算**注意力分数（Attention Scores）**，通常使用**点积（dot-product）**来度量 Query 和 Key 之间的相似性：

$$\text{Score} = QK^T$$

4. **Apply softplus to the attention weights in order to ensure that the weights sum up to one.**
   - 这里的 **softplus 可能是 softmax 的笔误**，通常**softmax** 被用来归一化注意力分数，使其变成概率分布：

$$\text{Attention Weights} = \text{softmax}(Score)$$

5. **Use the attention weights to compute a weighted sum of the values to form the context vector.**
   - 使用**注意力权重**对 **Value (V)** 进行加权求和，得到**上下文向量（context vector）**：

$$\text{Context Vector} = \sum(\text{Attention Weights} \times V)$$

6. **Incorporate the attended context vector into further neural networks layers that will be used for the downstream task.**
   - 生成的 **context vector** 作为输入传递到后续神经网络层（如 Transformer 的后续层）用于 NLP 任务，如文本分类、机器翻译等。

Summary

✅ CNNs 利用局部结构（二维）并学习层次化表示，以完成特定任务。
✅ CNNs 在空间位置之间共享参数，因此适用于从信号中学习，其中特征可能出现在任意位置。
✅ CNNs 的核心组成部分：卷积层（Convolution layers）和池化层（Pooling layers）。
✅ CNNs 被广泛应用于多个领域和任务（不仅限于图像数据）。
✅ CNNs 在前几层强制进行局部交互，对于某些任务，捕获全局交互是有益的（这可以通过注意力机制层实现）。

- CNNs exploit local structure of (2d) and learn hierarchical representation for a given task.
- CNNs share parameters between spatial locations, and they are thus suitable to learn from signal where features potentially appear in any location.
- Main ingredients of CNNs: Convolution and Pooling layers.
- CNNs are widely used in many applications and domains (beyond image data).
- CNNs force local interactions in the first layers. For some tasks, it is beneficial to capture global interactions (this can be achieved with attention layers).

Bibliography I

[1] A. Araujo, W. Norris, and J. Sim.
Computing receptive fields of convolutional neural networks.
Distill, 2019.
https://distill.pub/2019/computing-receptive-fields.

[2] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei.
ImageNet: A Large-Scale Hierarchical Image Database.
In *CVPR09*, 2009.

[3] V. Dumoulin and F. Visin.
A guide to convolution arithmetic for deep learning.
arXiv preprint arXiv:1603.07285, 2016.

[4] K. Eykholt, I. Evtimov, E. Fernandes, B. Li, A. Rahmati, C. Xiao, A. Prakash, T. Kohno, and D. Song.
Robust physical-world attacks on deep learning visual classification.
In *2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018, Salt Lake City, UT, USA, June 18-22, 2018*, pages 1625–1634. Computer Vision Foundation / IEEE Computer Society, 2018.

[5] K. Fukushima.
A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position.
Biol, Cybern, 36:193–202, 1980.

[6] R. Geirhos, P. Rubisch, C. Michaelis, M. Bethge, F. A. Wichmann, and W. Brendel.
Imagenet-trained cnns are biased towards texture; increasing shape bias improves accuracy and robustness.
In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019*. OpenReview.net, 2019.

[7] I. J. Goodfellow, J. Shlens, and C. Szegedy.
Explaining and harnessing adversarial examples.
In Y. Bengio and Y. LeCun, editors, *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*, 2015.

Bibliography II

[8] K. He, X. Zhang, S. Ren, and J. Sun.
Deep residual learning for image recognition.
In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2016.

[9] S. Hooker.
The hardware lottery.
Communications of the ACM, 64(12):58–65, 2021.

[10] A. Karpathy and L. Fei-Fei.
Deep visual-semantic alignments for generating image descriptions.
In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3128–3137, 2015.

[11] Y. Kim.
Convolutional neural networks for sentence classification.
In A. Moschitti, B. Pang, and W. Daelemans, editors, *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing, EMNLP 2014, October 25-29, 2014, Doha, Qatar, A meeting of SIGDAT, a Special Interest Group of the ACL*, pages 1746–1751. ACL, 2014.

[12] J. Krause, M. Stark, J. Deng, and L. Fei-Fei.
3d object representations for fine-grained categorization.
In *4th International IEEE Workshop on 3D Representation and Recognition (3dRR-13)*, Sydney, Australia, 2013.

[13] A. Krizhevsky, I. Sutskever, and G. E. Hinton.
Imagenet classification with deep convolutional neural networks.
In P. L. Bartlett, F. C. N. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 25: 26th Annual Conference on Neural Information Processing Systems 2012. Proceedings of a meeting held December 3-6, 2012, Lake Tahoe, Nevada, United States*, pages 1106–1114, 2012.

[14] B. Landau, L. B. Smith, and S. S. Jones.
The importance of shape in early lexical learning.
Cognitive development, 3(3):299–321, 1988.

Bibliography III

[15] Y. LeCun, Y. Bengio, and G. Hinton.
Deep learning.
nature, 521(7553):436–444, 2015.

[16] Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, and L. D. Jackel.
Backpropagation applied to handwritten zip code recognition.
Neural computation, 1(4):541–551, 1989.

[17] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner.
Gradient-based learning applied to document recognition.
Proceedings of the IEEE, 86(11):2278–2324, 1998.

[18] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi.
You only look once: Unified, real-time object detection.
In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 779–788, 2016.

[19] O. Ronneberger, P. Fischer, and T. Brox.
U-net: Convolutional networks for biomedical image segmentation.
In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.

[20] K. Simonyan and A. Zisserman.
Very deep convolutional networks for large-scale image recognition.
In Y. Bengio and Y. LeCun, editors, *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*, 2015.

[21] O. Vinyals, A. Toshev, S. Bengio, and D. Erhan.
Show and tell: A neural image caption generator.
In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3156–3164, 2015.

[22] K. Xu, J. Ba, R. Kiros, K. Cho, A. Courville, R. Salakhudinov, R. Zemel, and Y. Bengio.
Show, attend and tell: Neural image caption generation with visual attention.
In *International conference on machine learning*, pages 2048–2057. PMLR, 2015.

Bibliography IV

[23] M. D. Zeiler and R. Fergus.
Visualizing and understanding convolutional networks.
In D. J. Fleet, T. Pajdla, B. Schiele, and T. Tuytelaars, editors, *Computer Vision - ECCV 2014 - 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part I*, volume 8689 of *Lecture Notes in Computer Science*, pages 818–833. Springer, 2014.