2023秋

模式识别与机器学习 (12)

卷积神经网络-1

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卷积神经网络

- **历史和动机**
- 基本操作
  - 卷积、池化、归一化、卷积神经网络
- 新进展
  - 3x3、Dilated Convolution
- 典型网络架构
  - LeNet、AlexNet、VGGNet、Inception
  - ResNet、SENet、DenseNet、Attention

Why Deep CNNs

"在使用RNN之前，一定要先尝试CNN。你会惊讶于你能走多远"。——Andrej Karpathy （特斯拉人工智能主管-> OpenAI ）

Why Deep CNNs （vs RNN）

- Facebook: A novel convolutional neural network (CNN) approach for language translation that achieves state-of-the-art accuracy at nine times the speed of recurrent neural systems.

- https://code.fb.com/ml-applications/a-novel-approach-to-neural-machine-translation/

Jonas Gehring, Michael Auli, David Grangier, Denis Yarats, Yann N. Dauphin. Convolutional Sequence to Sequence Learning. ArXiv, 2017

Why Deep CNNs （vs Transformer）

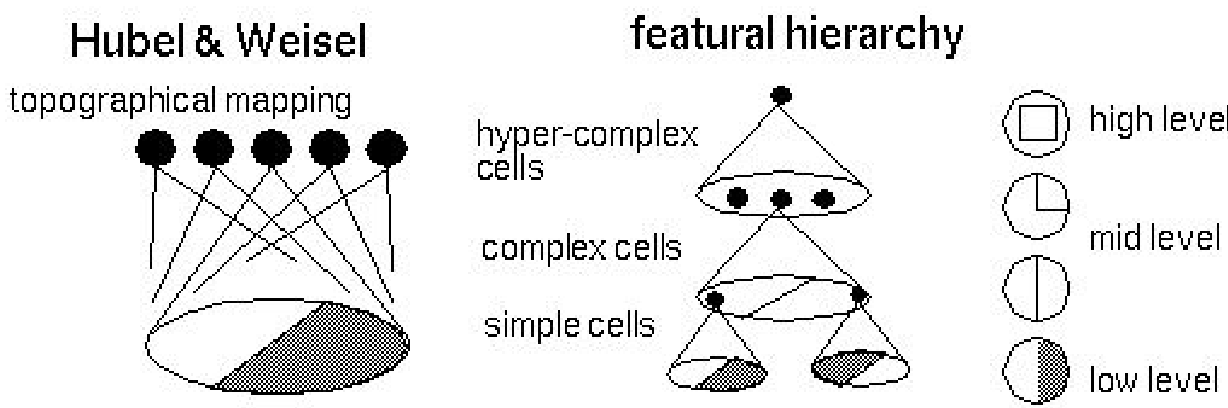
- Large Kernel
- Layer Norm
- Nonlinear Activations
- Optimization: AdamW、LAMB

- ConvNeXts compete favorably with Transformers in terms of accuracy and scalability

Simple Baselines for Image Restoration, Arxiv 2022
A ConvNet for the 2020s, Arxiv 2022
Scaling Up Your Kernels to 31x31: Revisiting Large Kernel Design in CNNs , Arxiv 2022

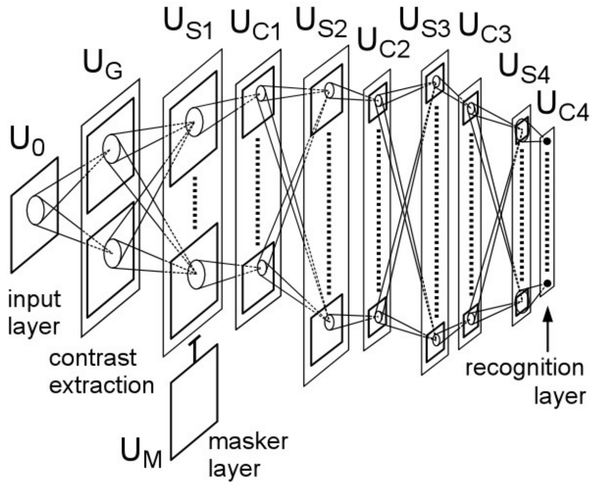
Hubel/Wiesel架构

- D. Hubel and T. Wiesel (1959, 1962, Nobel Prize 1981)
  - 视觉皮层：包括 *simple*, *complex*, and *hyper-complex* 细胞

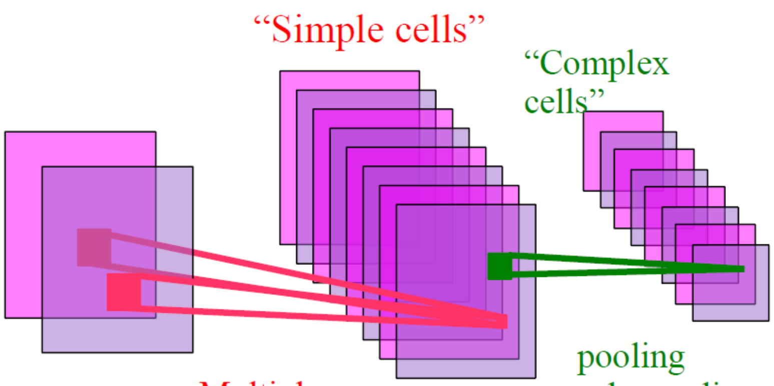


Neocognitron

- **[Hubel & Wiesel 1962]:**
  - 简单细胞：局部特征检测
  - 复杂细胞：简单特征输出的聚合



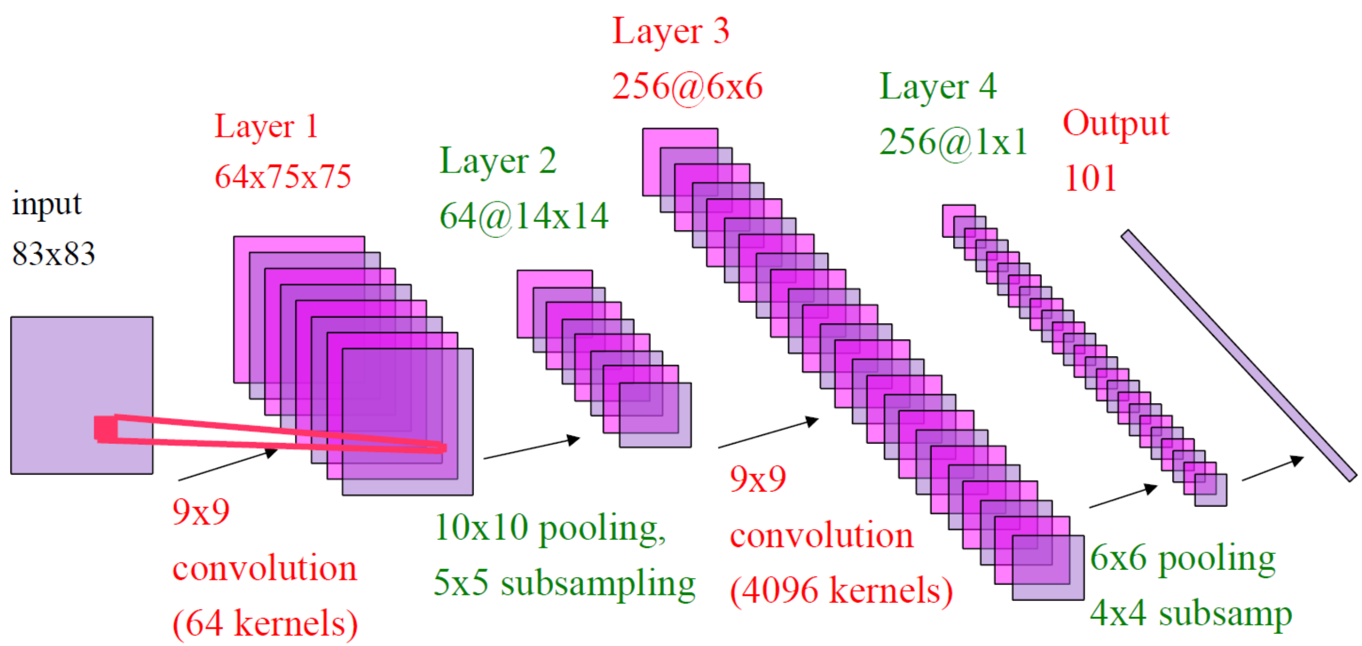
Cognitron & Neocognitron
[Fukushima 1974-1982]



卷积神经网络

卷积神经网络（上半场）

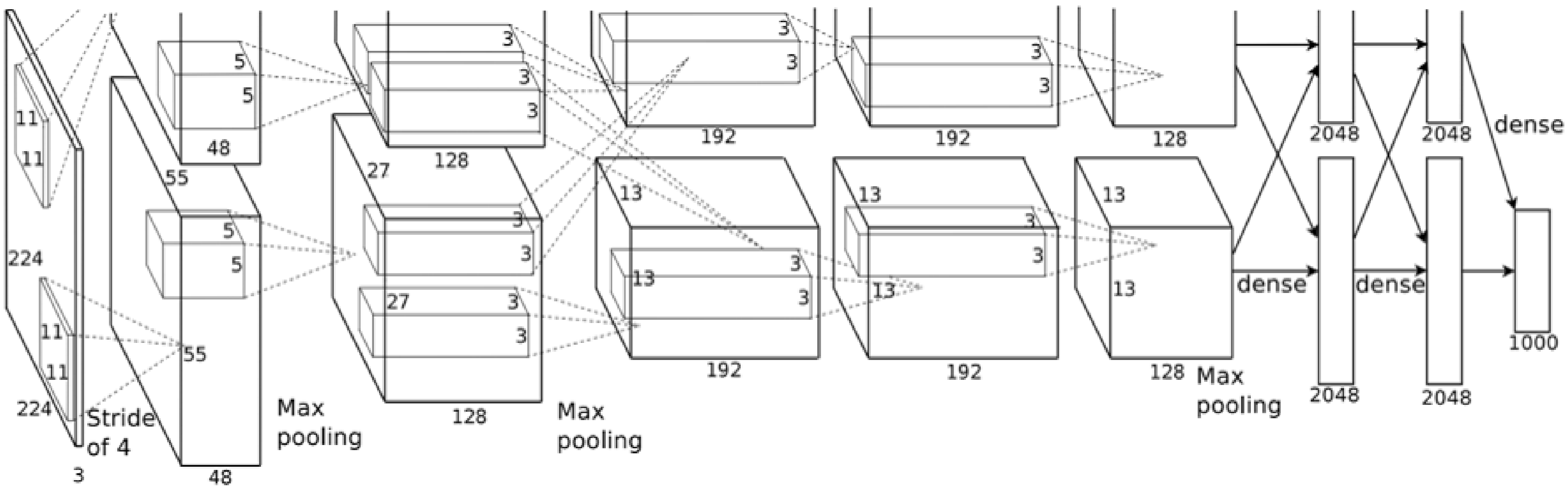
- LeCun et al., NIPS 1989



- 2个卷积层一个全连接层

深度卷积神经网络（下半场）

- Krizhevsky et al. NIPS 2012

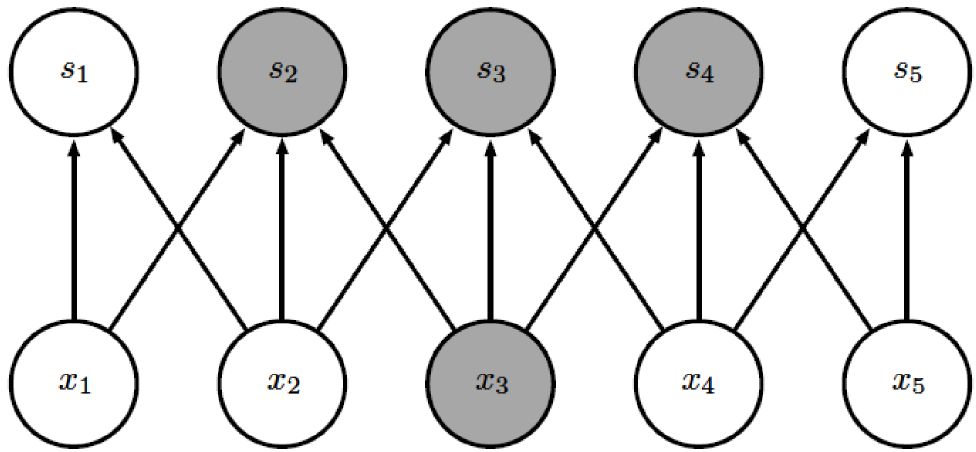


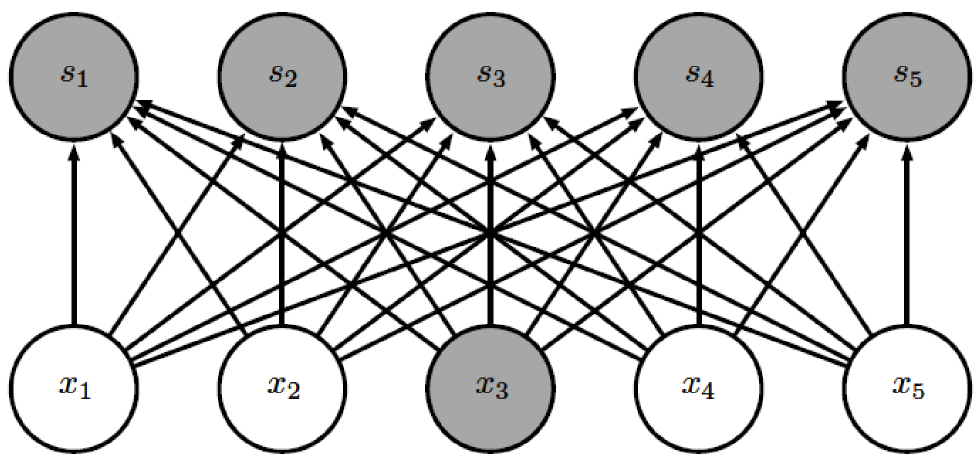
- 5个卷积层、3个全连接层

动机：

- 稀疏交互（sparse interactions）
- 参数共享（parameter sharing）
- 等变表示（equivariant representation）
  - 不变表示（invariant representation）

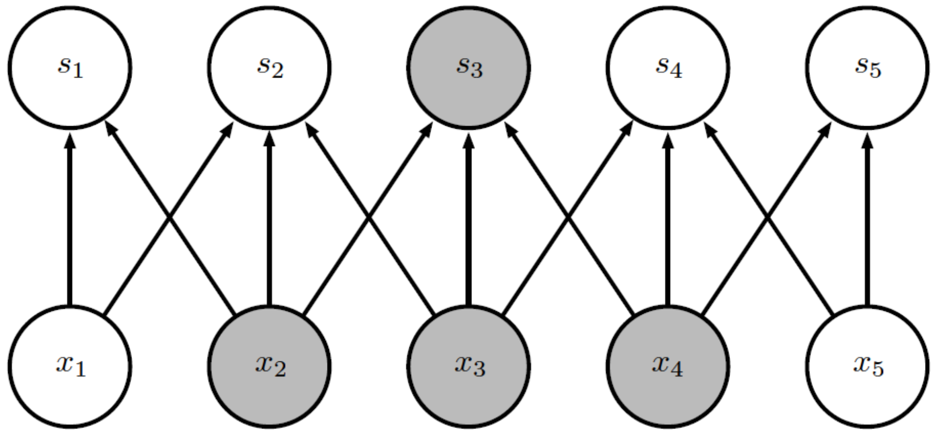
稀疏交互（稀疏连接）



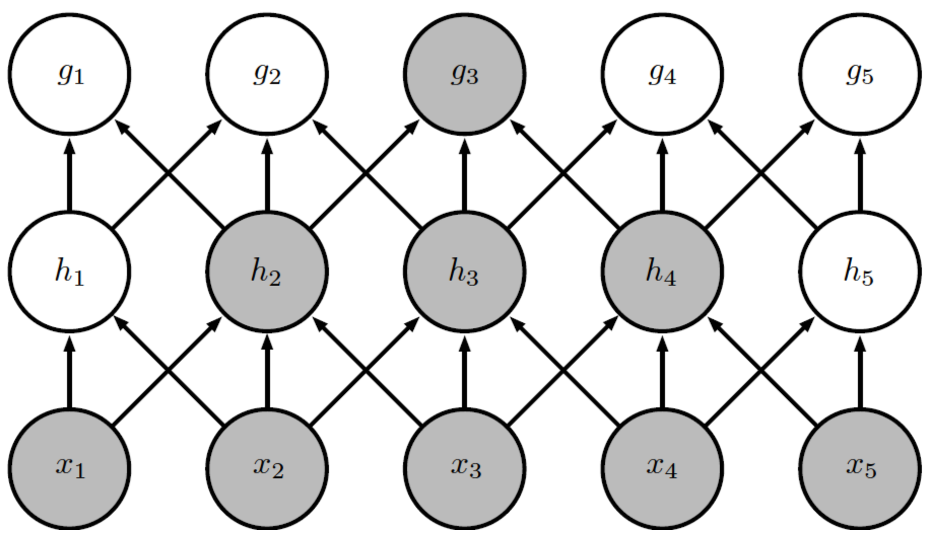


感受野（Receptive Field）

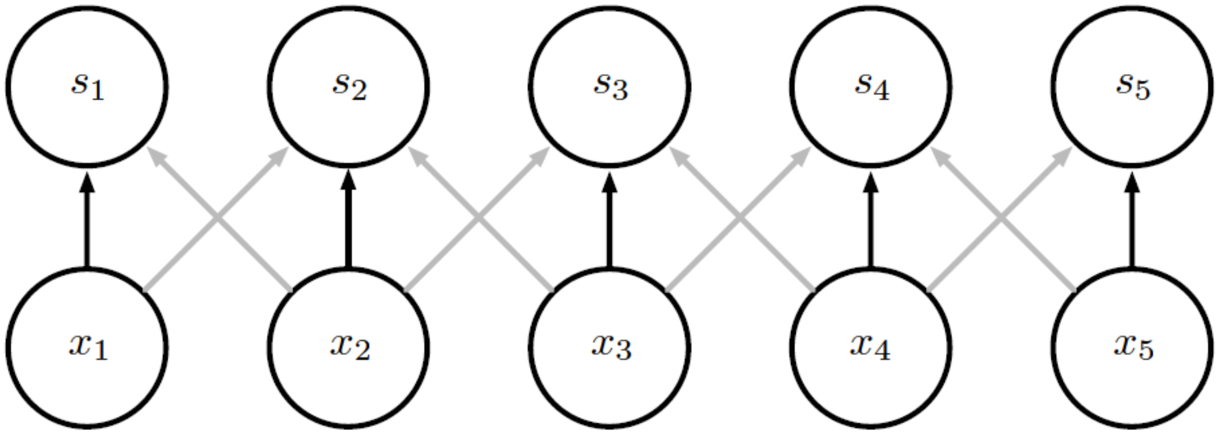
- 层1：

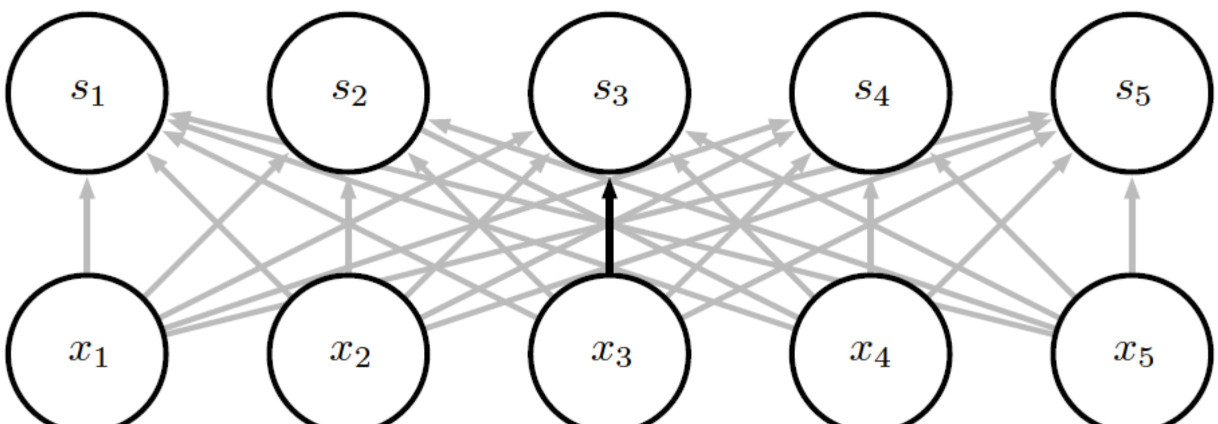


- 层2：



参数共享

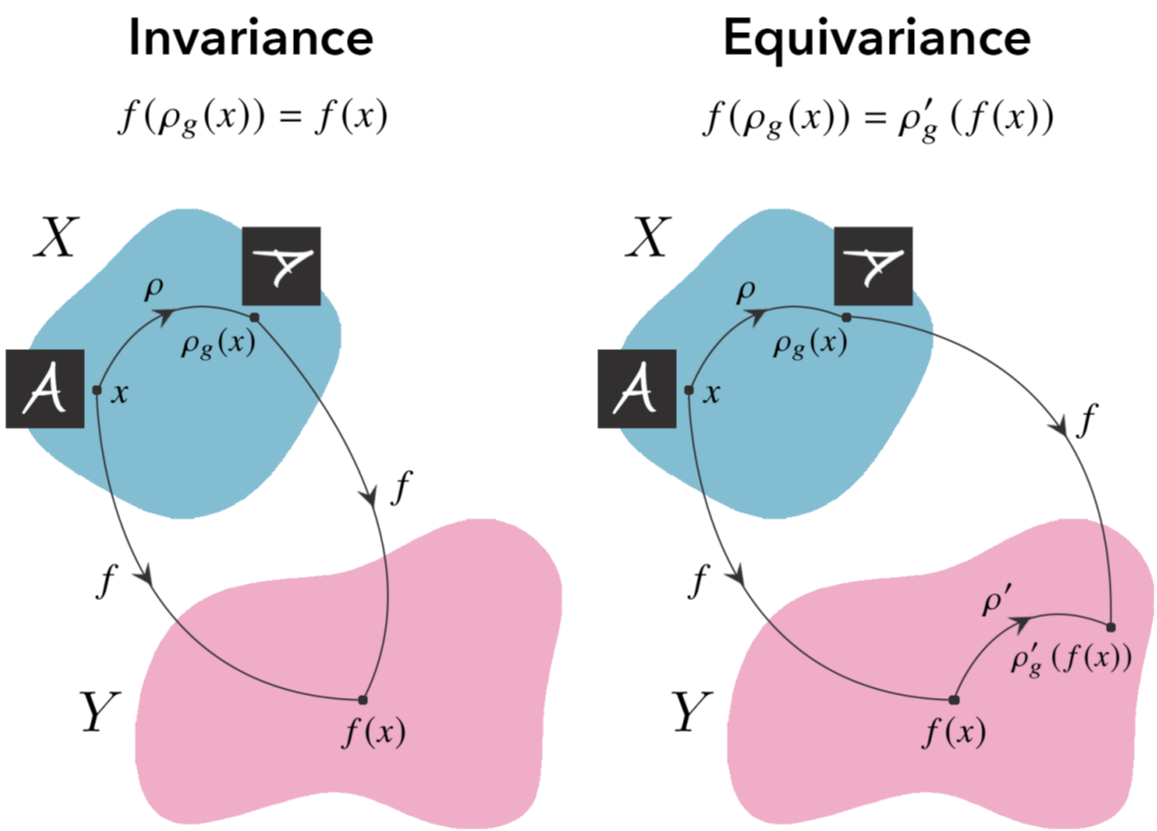




等变表示 (Equivariant Representation)

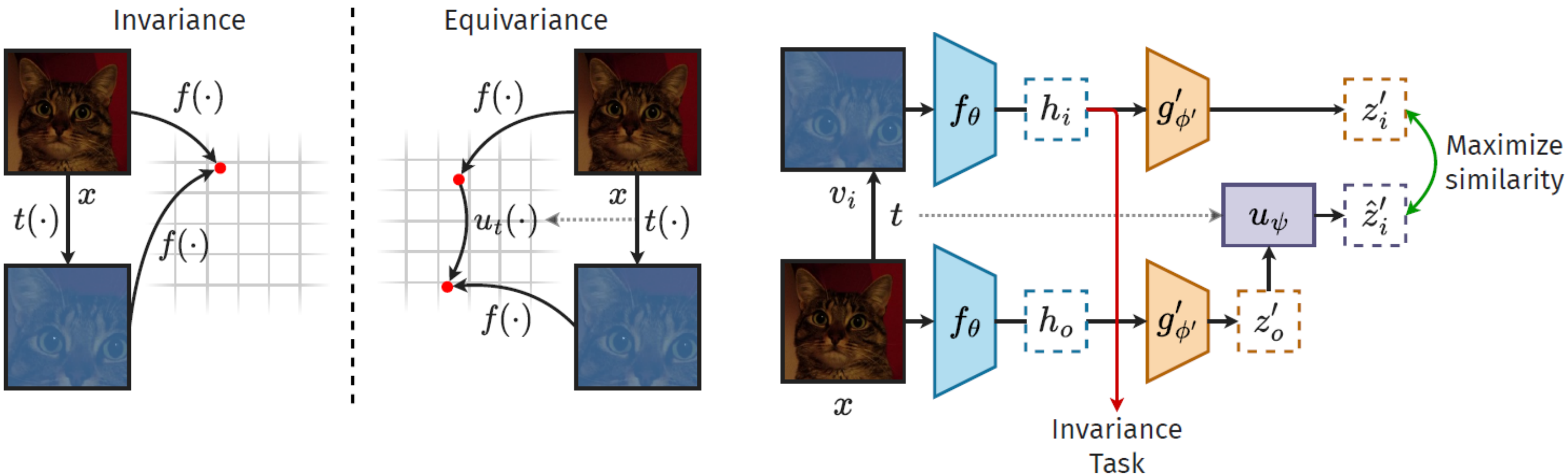
- 如果一个函数满足输入改变，输出也以同样方式进行改变的话，我们称它是**等变**的
- 卷积：平移等变
- 不变表示（Transform-invariant）

等变与不变表示 (Equivariant/Invariant)



等变性与不变性的结合

特征提取　投影头



$$\mathcal{L} = \mathcal{L}_{Invariance} + \lambda \mathcal{L}_{EquiMod}$$

- 尽可能保持不变性，但差别仍可以利用等性进一步建模

EquiMod: An Equivariance Module to Improve Visual Instance Discrimination, ICLR 2023.

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卷积：参数共享和稀疏连接

- 连续卷积

$$s(t)=\int x(a)w(t-a)da$$

$$s(t)=(x*w)(t).$$

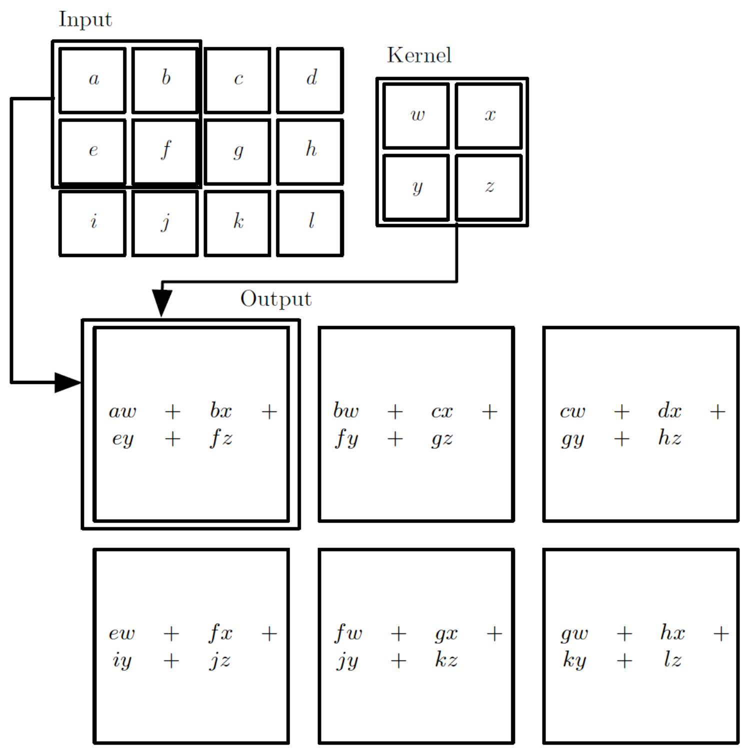
  - 输入、核函数
- 离散卷积

$$s(t)=(x*w)(t)=\sum_{a=-\infty}^{\infty}x(a)w(t-a)$$

二维卷积

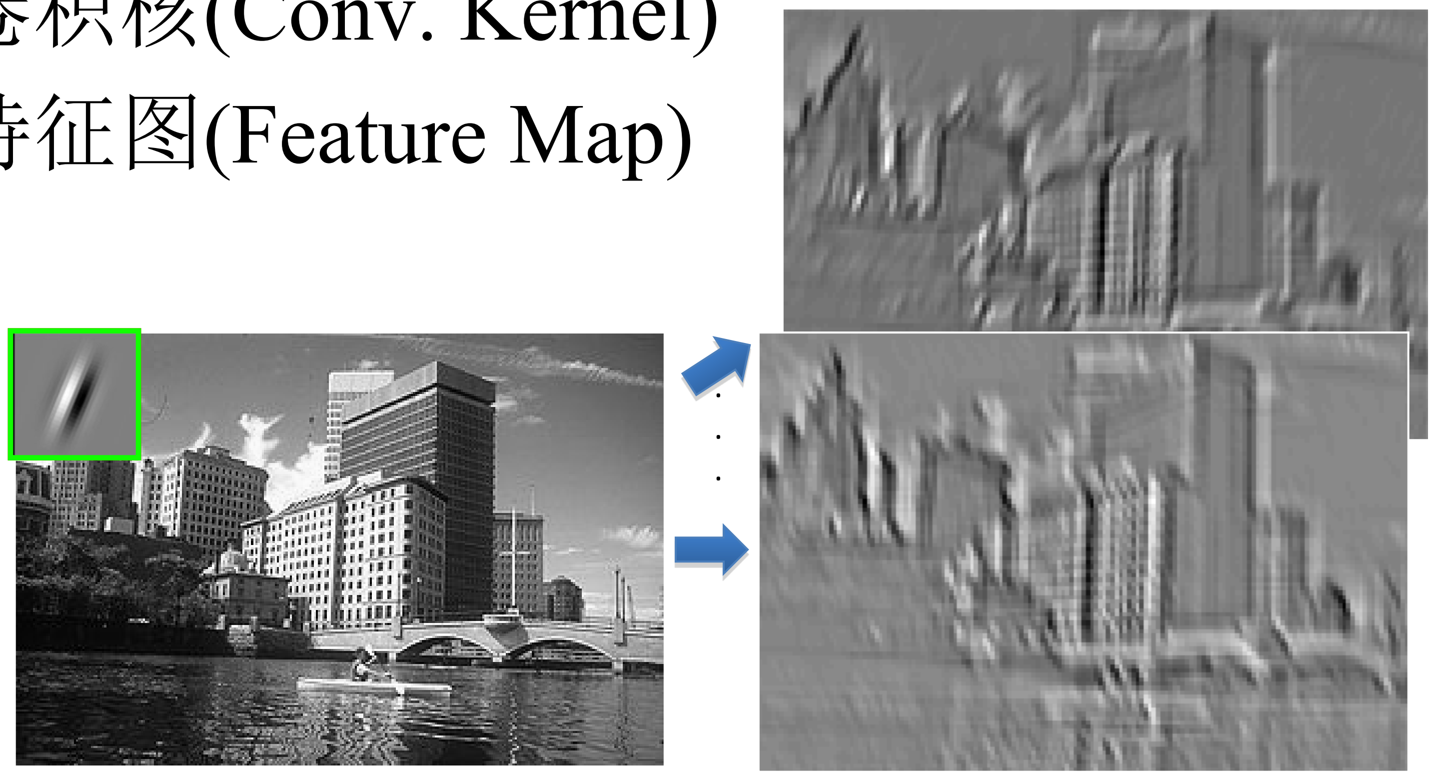
- 二维卷积

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(m,n)K(i-m, j-n)$$



直观展示

- 卷积核(Conv. Kernel)
- 特征图(Feature Map)

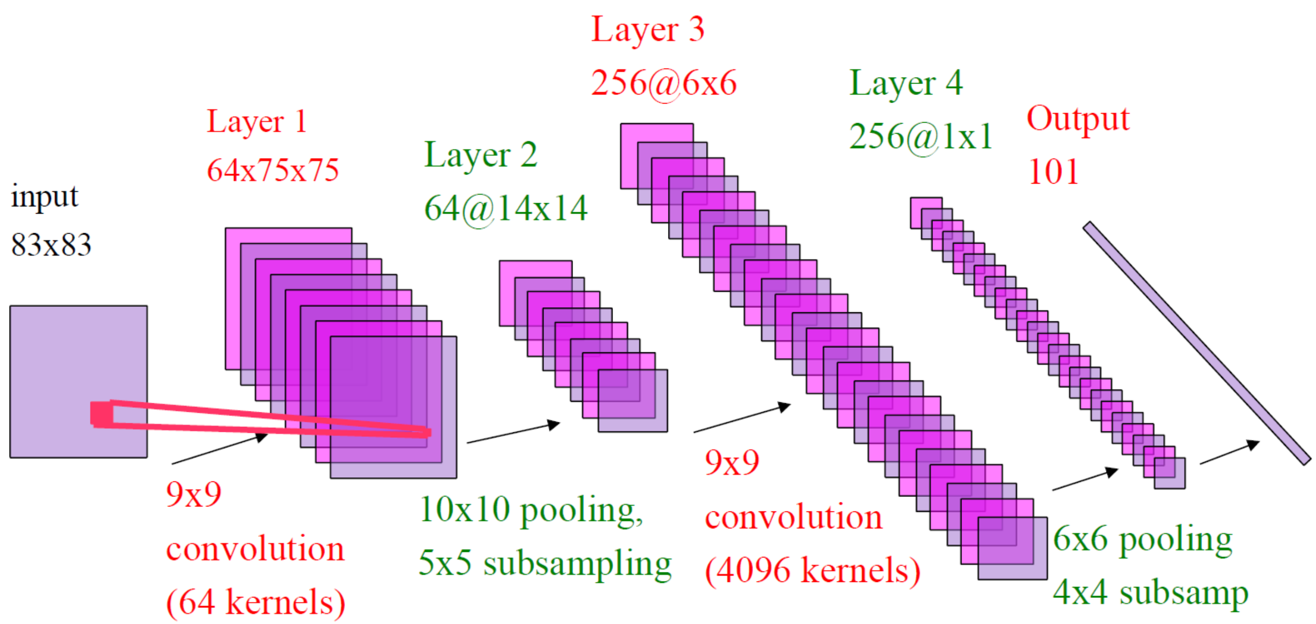


Input　　　　Feature Map

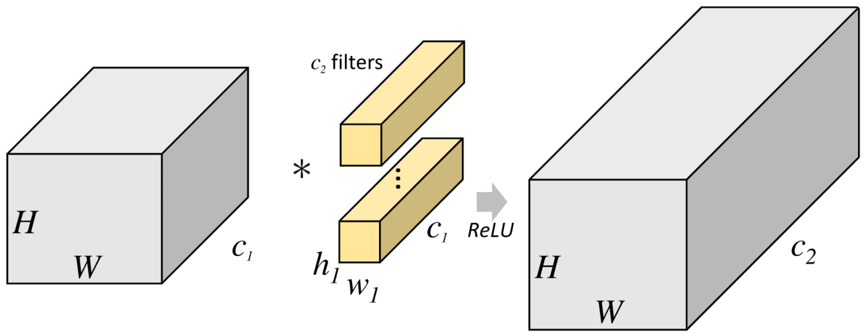
拓展：多通道卷积

- 多通道卷积

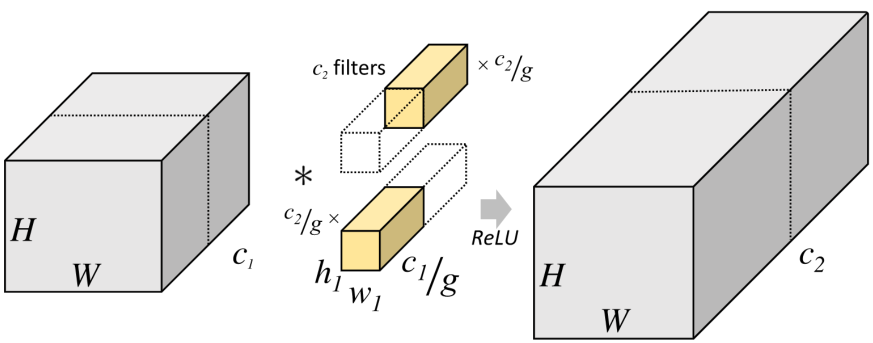
$$\boldsymbol{F}_i = \sum_{j=1}^{C} \boldsymbol{w}_{j,i} * \boldsymbol{x}_j$$



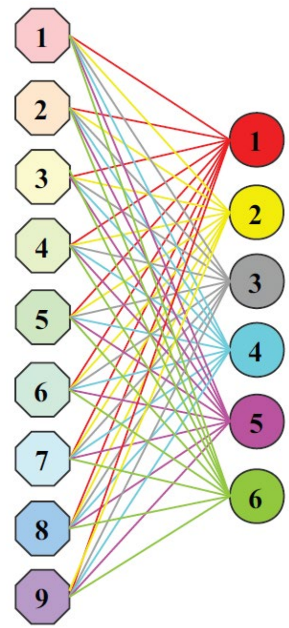
拓展：Grouped Convolution



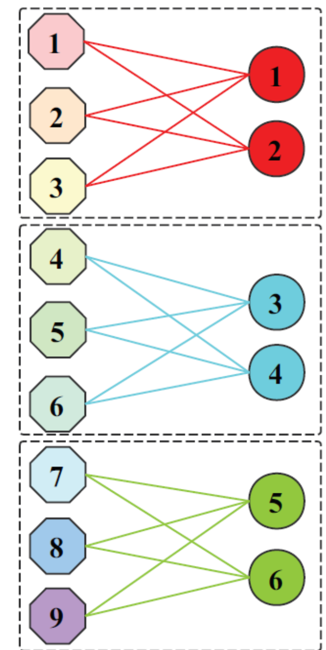
标准卷积



Grouped Convolution



标准卷积



Grouped Convolution

Fully Learnable Group Convolution for Acceleration of Deep Neural Networks, CVPR 2019.

拓展：步幅（ Stride ）

- 步幅为1

$$\underset{I}{\begin{array}{|c|c|c|c|c|}\hline a_{11} & a_{12} & a_{13} & a_{14} & \\ \hline a_{21} & a_{22} & a_{23} & a_{24} & \\ \hline a_{31} & a_{32} & a_{33} & a_{34} & \\ \hline a_{41} & a_{42} & a_{43} & a_{44} & \\ \hline & & & & \\ \hline\end{array}} * \underset{K}{\begin{array}{|c|c|c|}\hline k_{11} & k_{12} & k_{13} \\ \hline k_{21} & k_{22} & k_{23} \\ \hline k_{31} & k_{32} & k_{33} \\ \hline\end{array}} = \underset{S}{\begin{array}{|c|c|c}\hline \begin{matrix} a_{11}k_{11}+a_{12}k_{12}+a_{13}k_{13} \\ + \\ a_{21}k_{21}+a_{22}k_{22}+a_{23}k_{23} \\ + \\ a_{31}k_{31}+a_{32}k_{32}+a_{33}k_{33} \end{matrix} & \begin{matrix} a_{12}k_{11}+a_{13}k_{12}+a_{14}k_{13} \\ + \\ a_{22}k_{21}+a_{23}k_{22}+a_{24}k_{23} \\ + \\ a_{32}k_{31}+a_{33}k_{32}+a_{34}k_{33} \end{matrix} & \cdots \\ \hline \cdots & & \end{array}}$$

- 步幅为2

$$\underset{I}{\begin{array}{|c|c|c|c|c|}\hline a_{11} & a_{12} & a_{13} & a_{14} & a_{15} \\ \hline a_{21} & a_{22} & a_{23} & a_{24} & a_{25} \\ \hline a_{31} & a_{32} & a_{33} & a_{34} & a_{35} \\ \hline a_{41} & a_{42} & a_{43} & a_{44} & \\ \hline & & & & \\ \hline\end{array}} * \underset{K}{\begin{array}{|c|c|c|}\hline k_{11} & k_{12} & k_{13} \\ \hline k_{21} & k_{22} & k_{23} \\ \hline k_{31} & k_{32} & k_{33} \\ \hline\end{array}} = \underset{S}{\begin{array}{|c|c|}\hline \begin{matrix} a_{11}k_{11}+a_{12}k_{12}+a_{13}k_{13} \\ + \\ a_{21}k_{21}+a_{22}k_{22}+a_{23}k_{23} \\ + \\ a_{31}k_{31}+a_{32}k_{32}+a_{33}k_{33} \end{matrix} & \begin{matrix} a_{13}k_{11}+a_{14}k_{12}+a_{15}k_{13} \\ + \\ a_{23}k_{21}+a_{24}k_{22}+a_{25}k_{23} \\ + \\ a_{33}k_{31}+a_{34}k_{32}+a_{35}k_{33} \end{matrix} \\ \hline \cdots & \end{array}}$$

滑动2

拓展：边界条件

- 特征图尺寸逐渐减小
- 零填充（Zero Padding）、镜像填充
- 其他方式：Partial Conv.

Guilin Liu, Kevin J. Shih, Ting-Chun Wang, Fitsum A. Reda, Karan Sapra, Zhiding Yu, Andrew Tao, Bryan Catanzaro, Partial Convolution based Padding, arXiv:1811.11718 .

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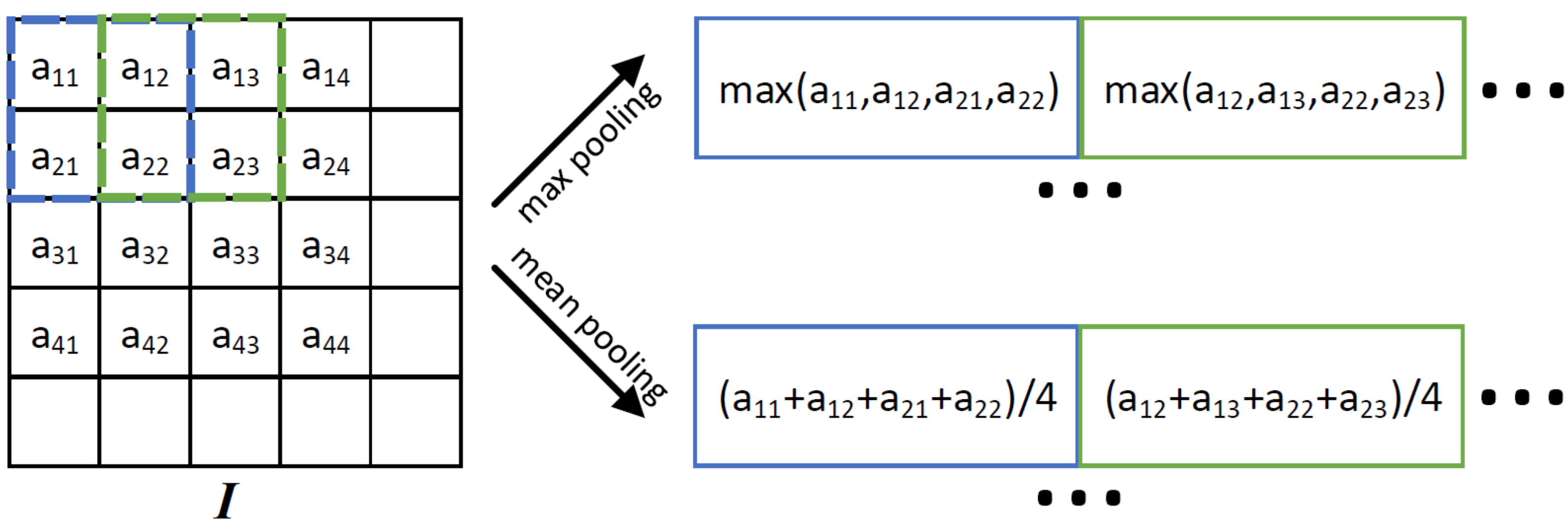
池化：形变不敏感

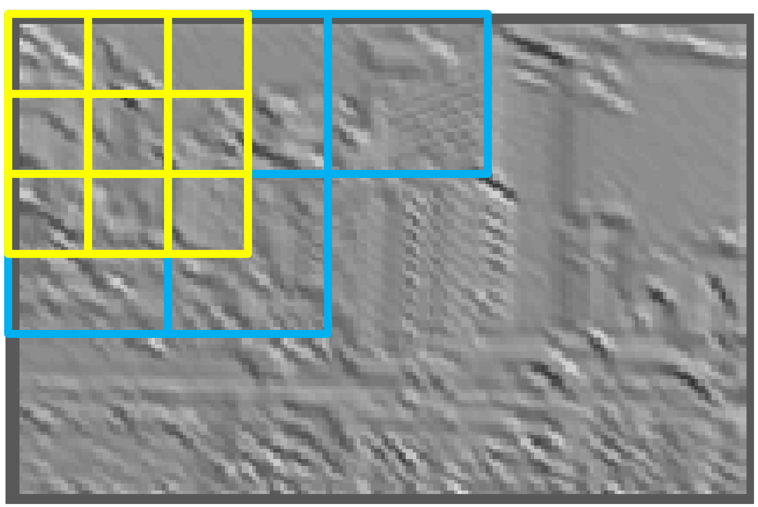
- 池化



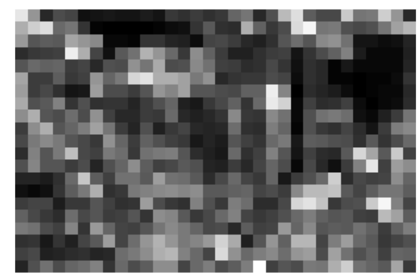
- 下采样

直观展示

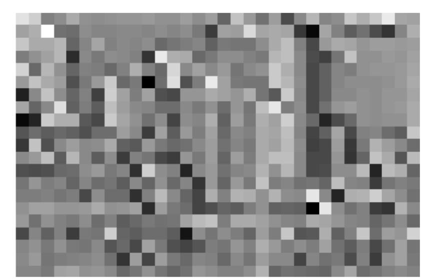
- Max Pooling
- Average Pooling



Max



Sum

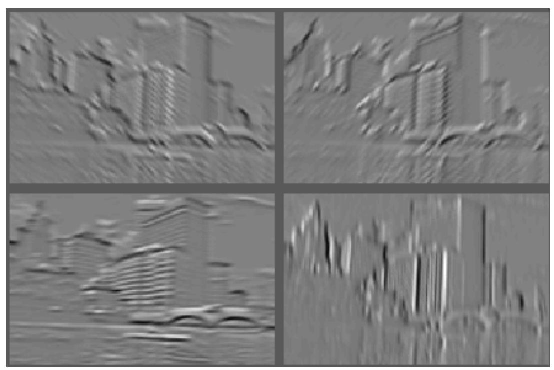


池化：Comment

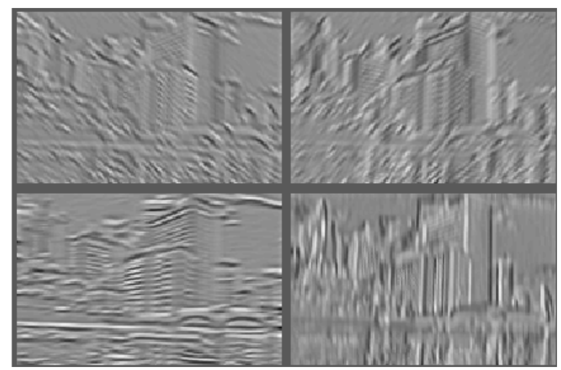
- 作用：增大感受野、形变不敏感
- Hinton (reddit, 2014): The pooling operation used in convolutional neural networks is a big mistake and the fact that it works so well is a disaster.
- https://mirror2image.wordpress.com/2014/11/11/geoffrey-hinton-on-max-pooling-reddit-ama/
- 思考：如何去掉池化但仍保持感受野和不敏感性特性？
  - Pooling / Downsampling / Conv with Larger Stride

归一化：光照不敏感

- 每个channel或所有channel归一化
- 池化前或池化后归一化



Feature Maps

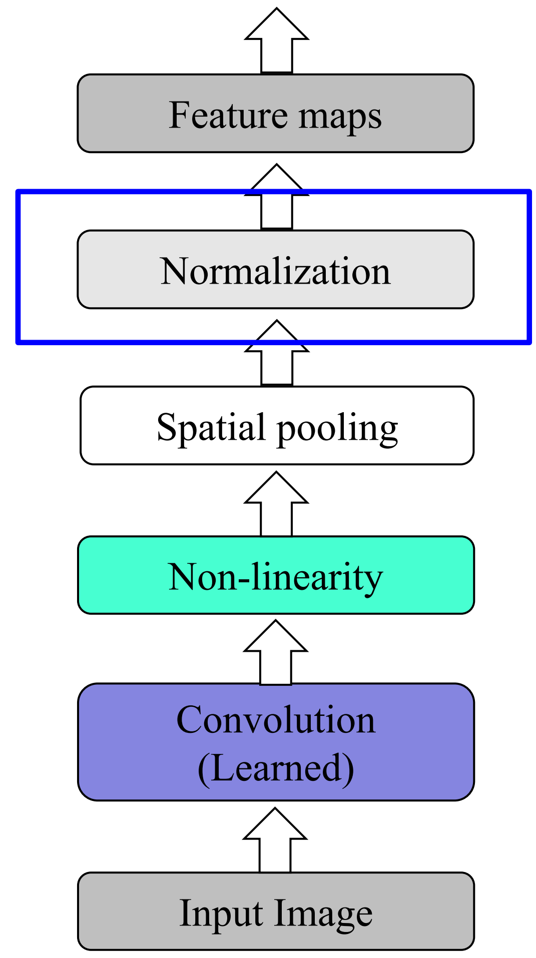


Feature Maps
After Contrast Normalization

- 已不太常用或结合Batch Normalization

总结：CNN网络层

1. 卷积
2. 非线性激活函数
3. 池化
4. 归一化



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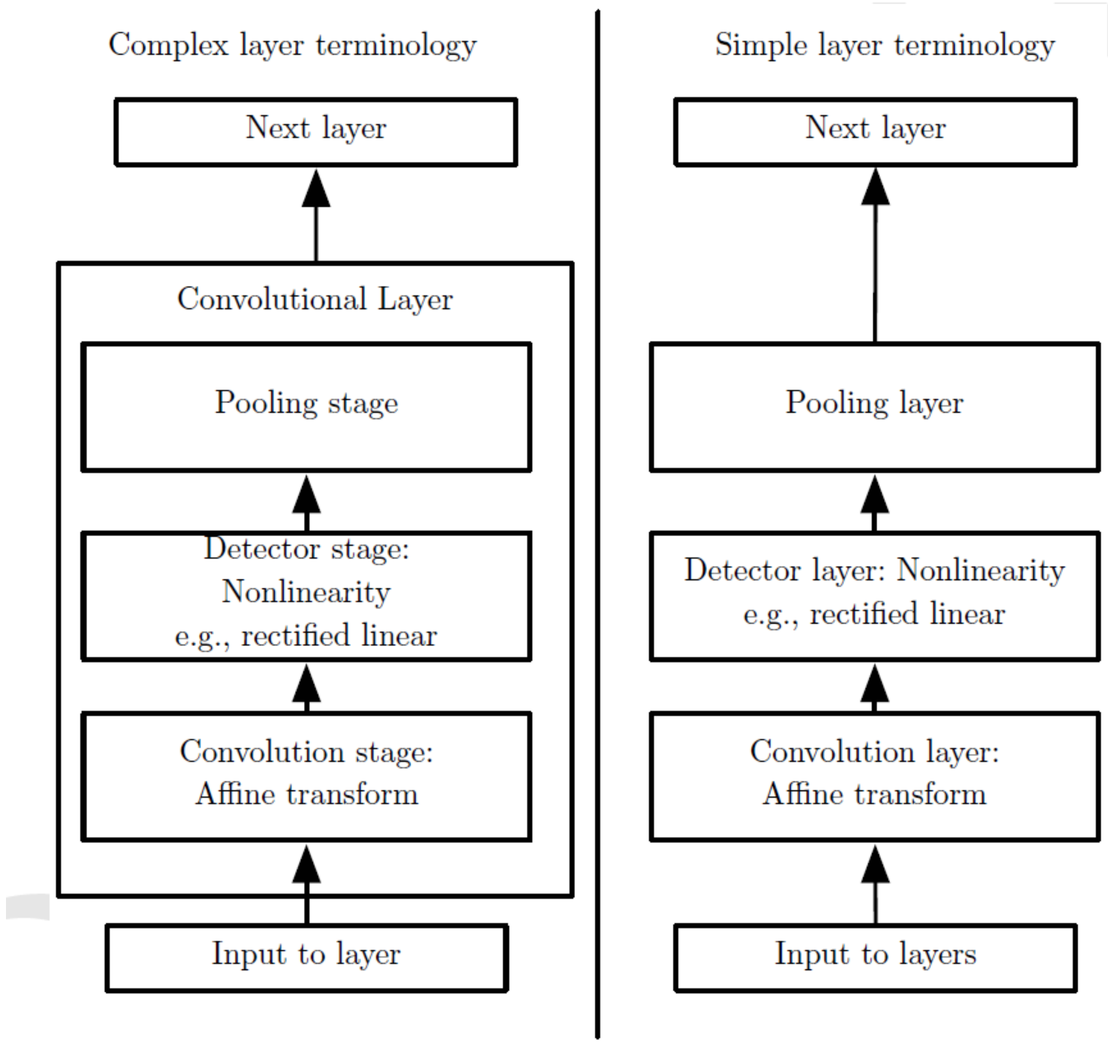
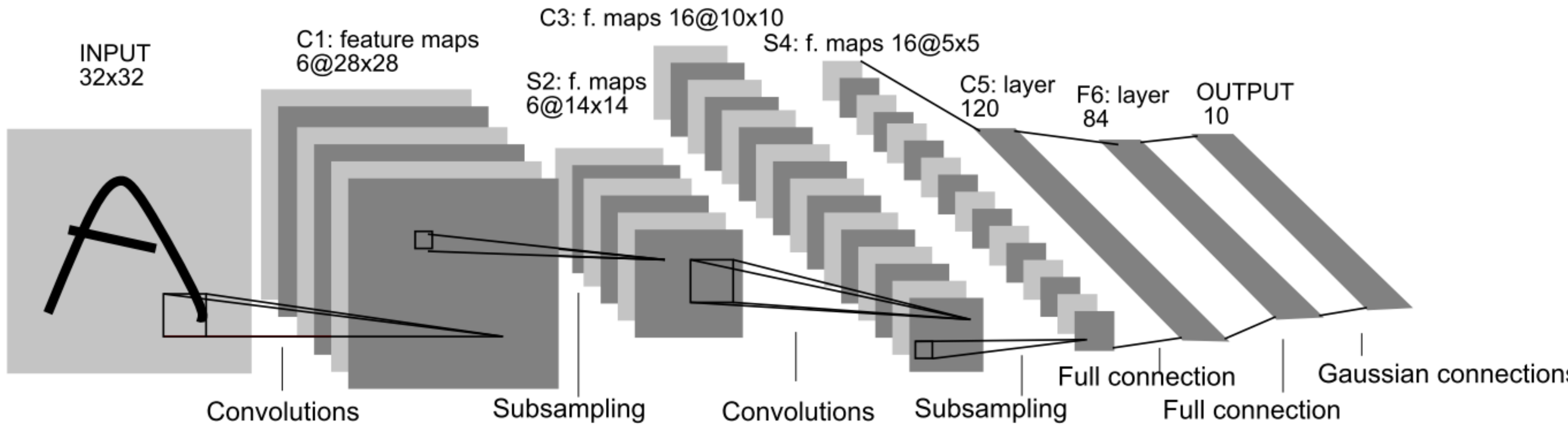
典型的卷积神经网络层

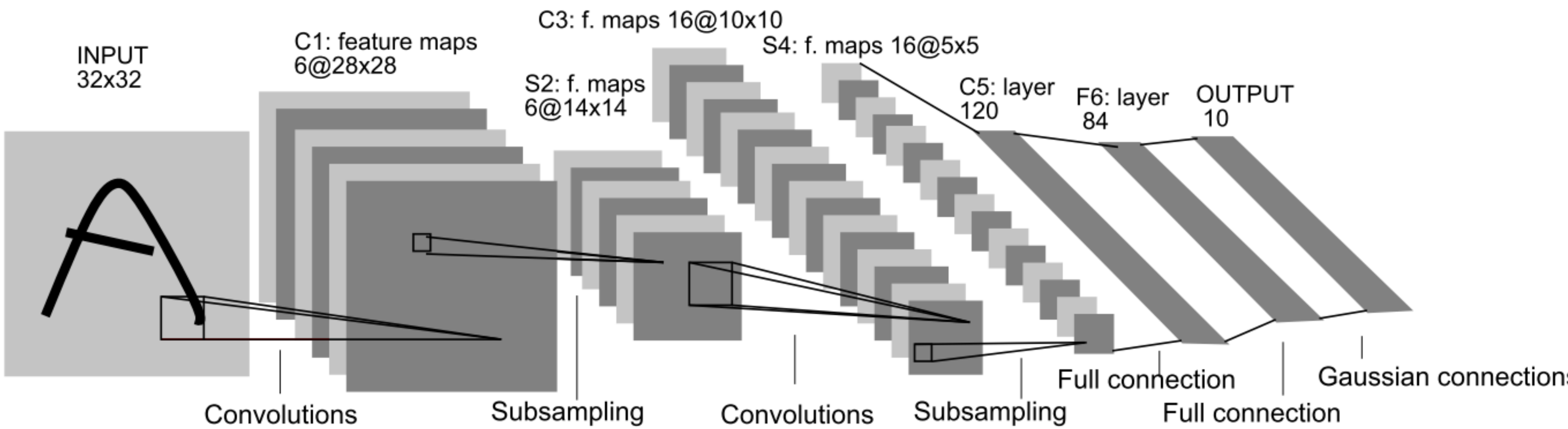

Complex layer terminology
Next layer
Convolutional Layer
Pooling stage
Detector stage:
Nonlinearity
e.g., rectified linear
Convolution stage:
Affine transform
Input to layer
Simple layer terminology
Next layer
Pooling layer
Detector layer: Nonlinearity
e.g., rectified linear
Convolution layer:
Affine transform
Input to layers

卷积神经网络示例：LeNet5（1998）



- 输入: 32x32图像
- Cx: 卷积层
- Sx: 下采样层
- Fx: 全连接层

LeNet 5, Layer C1

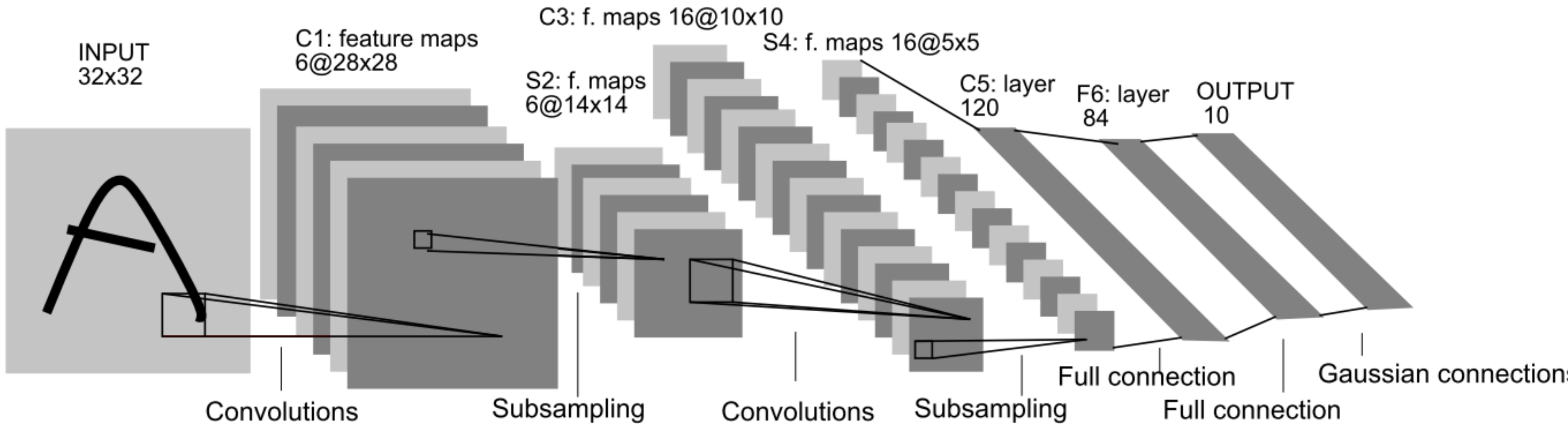


- C1: 卷积层，通道数为6，特征图大小 28x28. 卷积核 5x5.
  - 稀疏连接
  - 参数共享：参数量：(5*5+1)*6=156

    非参数共享: 28*28*(5*5+1)*6=122304

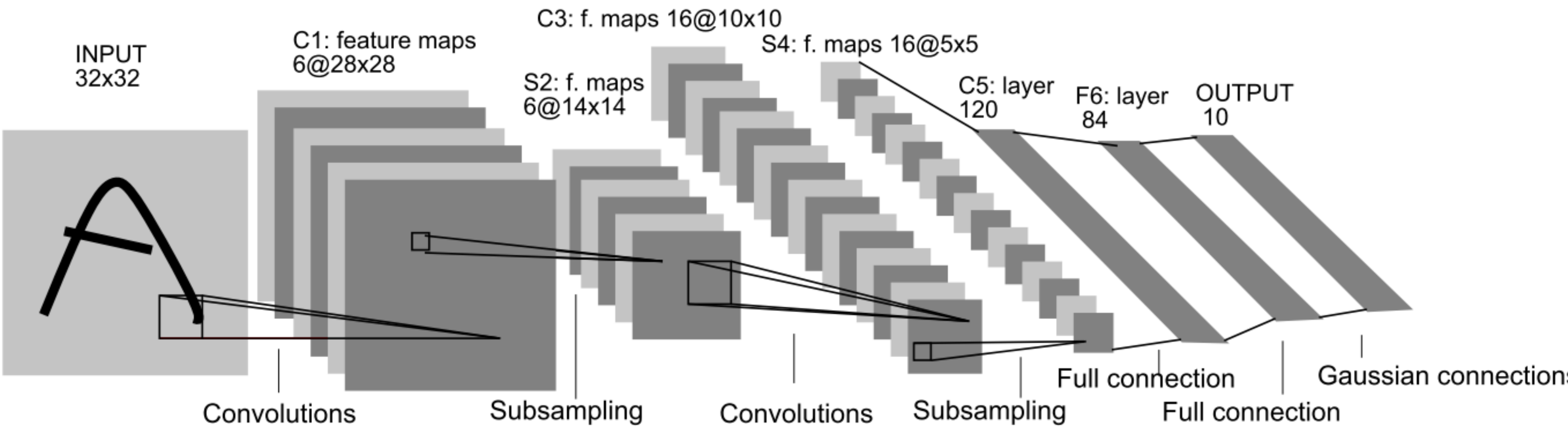
    全连接: (32*32+1)*(28*28)*6 parameters

LeNet 5, Layer S2



- S2: 下采样层，6通道，特征图大小14x14
- 2x2 感受野
- 学习参数: 6 * 2 = 12.
- 全连接: 14*14*(2*2+1)*6=5880

LeNet 5, Layer C3



- C3: 卷积层，通道数16，特征图大小 10x10
- Each unit in C3 is connected to several! 5x5 receptive fields at identical locations in S2

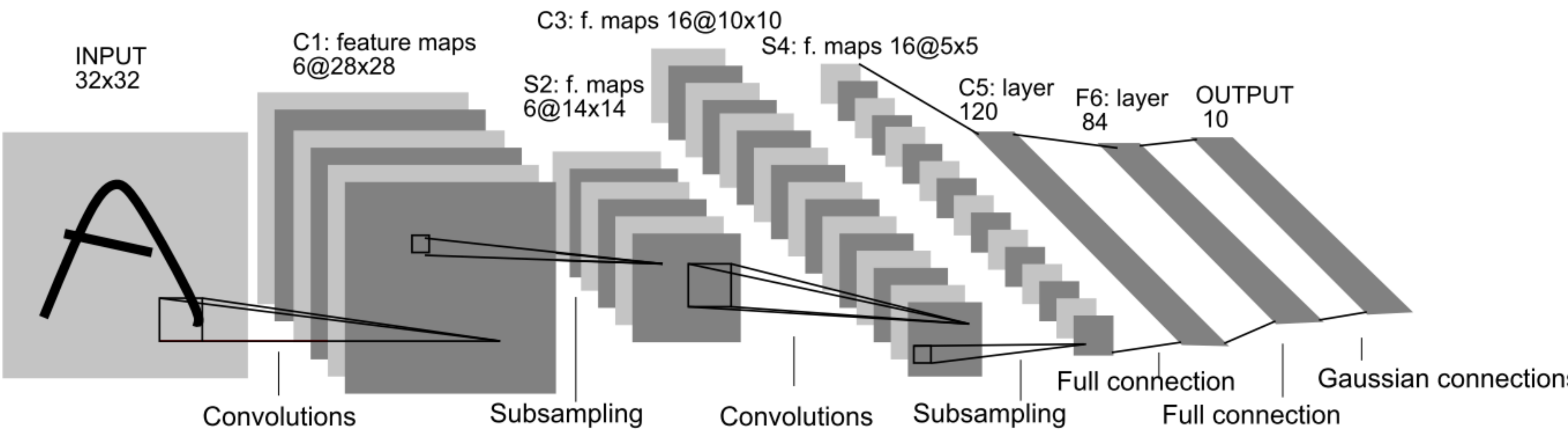
- 参数量：1516.
- 全连接: 151600

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	X				X	X	X			X	X	X	X		X	X
1	X	X				X	X	X			X	X	X	X		X
2	X	X	X				X	X	X			X		X	X	X
3		X	X	X			X	X	X	X			X		X	X
4			X	X	X			X	X	X	X		X	X		X
5				X	X	X			X	X	X	X		X	X	X

TABLE I

Each column indicates which feature map in S2 are combined by the units in a particular feature map of C3.

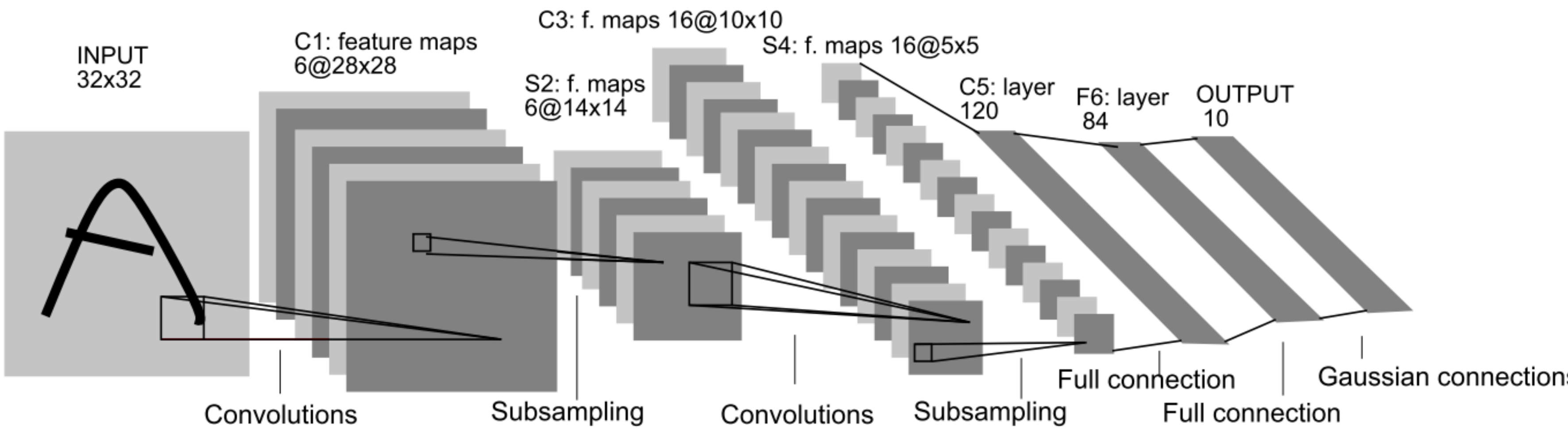
LeNet 5, Layer S4



- S4: 下采样层，with 16 feature maps of size 5x5
- 感受野：2x2

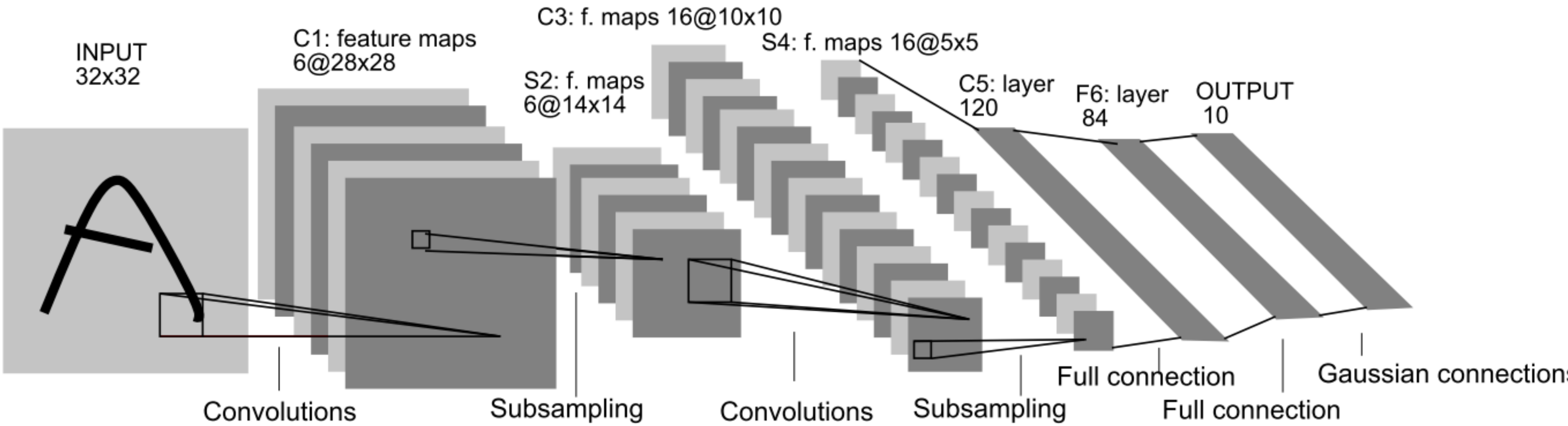
- 参数量: 16*2=32.
- 全连接: 5*5*(2*2+1)*16=2000

LeNet 5, Layer C5



- C5: 卷积层，通道数120，特征图大小1x1
- 感受野 5x5
- 参数量：120*(16*25+1) = 48120

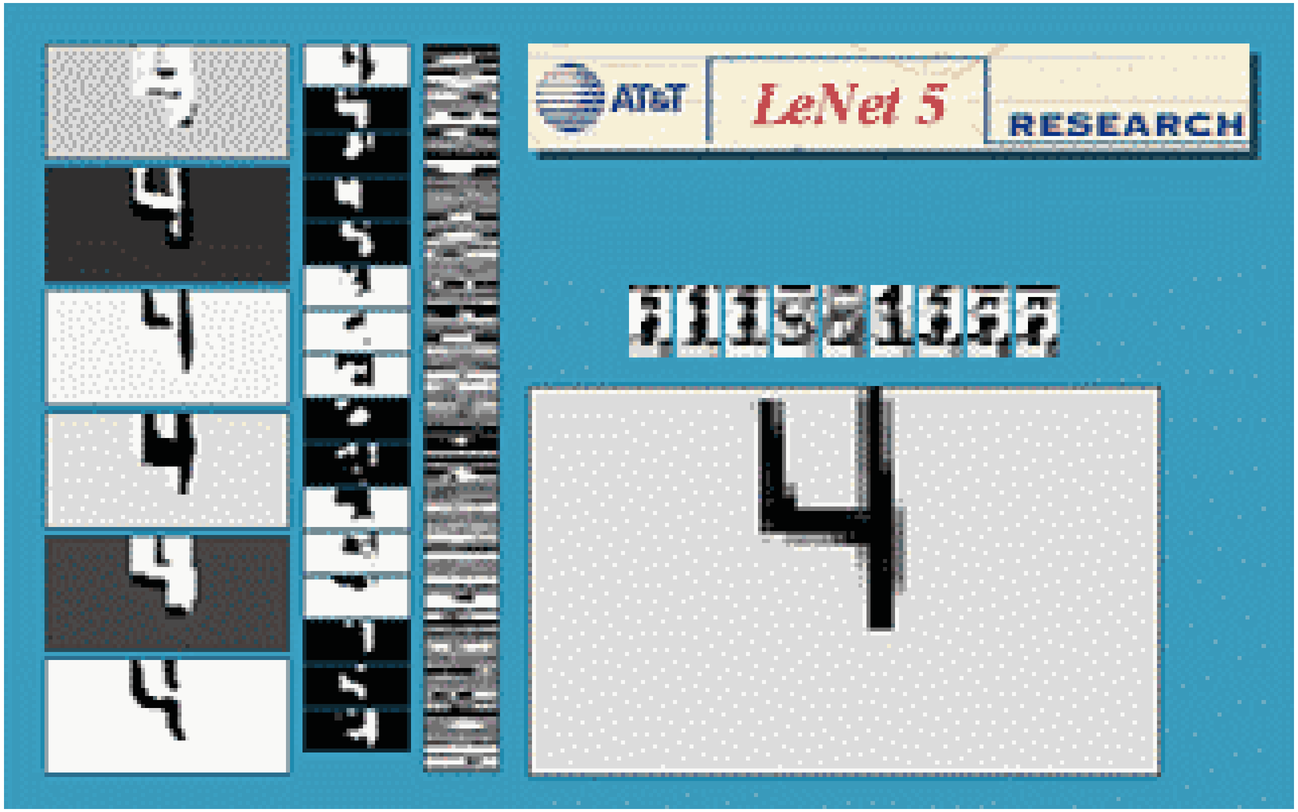
LeNet 5, Layer F6



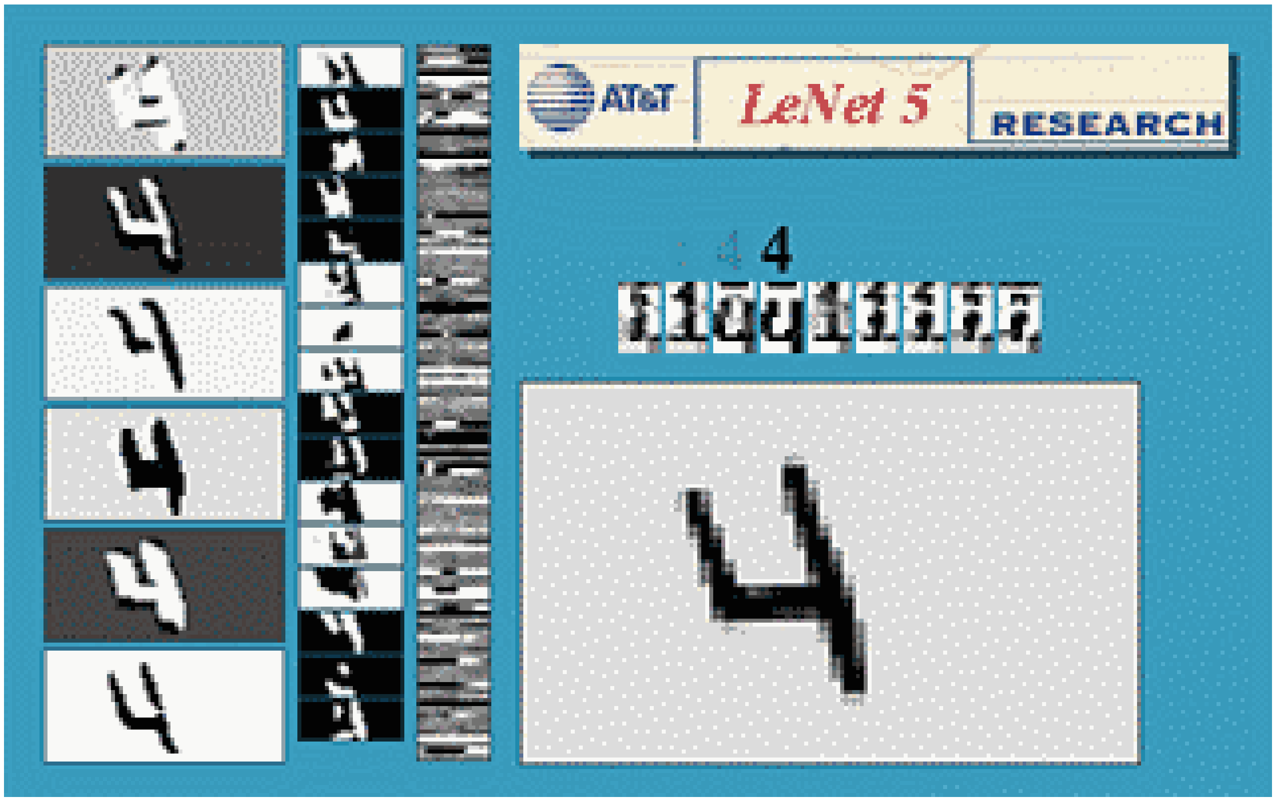
- Layer F6: 全连接层，特征位数84
- 参数量：84*(120+1)=10164.
- 输出: 10 RBF (One for each digit)

- 学习算法: BP

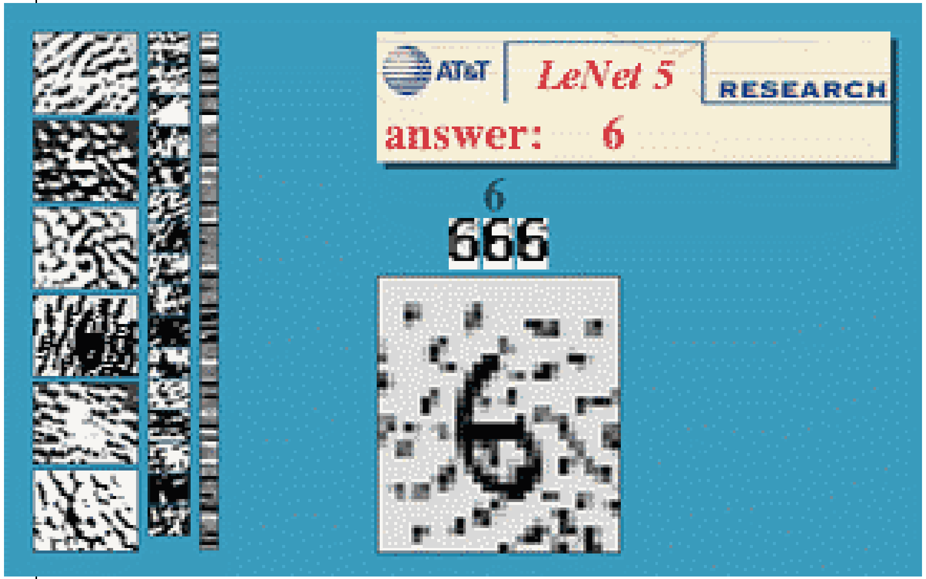
LeNet 5, Shift invariance

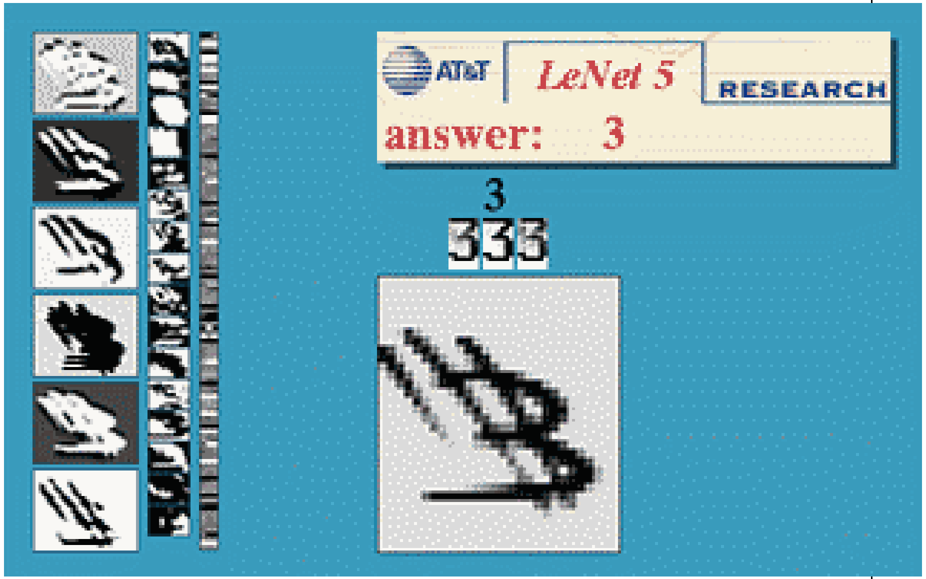


LeNet 5, Rotation invariance

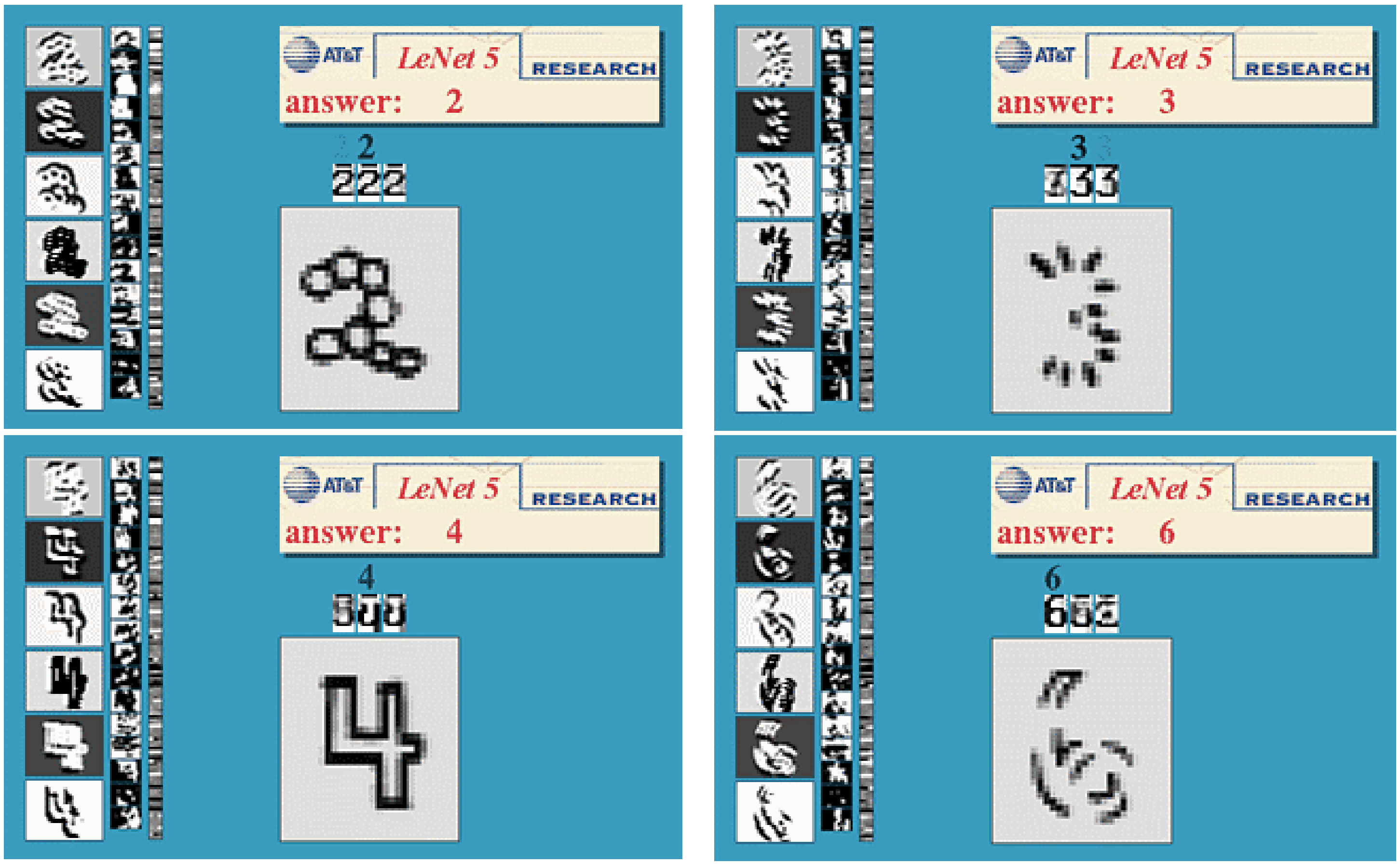


LeNet 5, Nosie resistance





LeNet 5, Unusual Patterns



卷积神经网络

- 历史和动机
- 基本操作
  - 卷积、池化、归一化、卷积神经网络
- **新进展：操作**
  - 3x3、dilated convolution
- **典型网络架构：思想和网络结构**
  - LeNet、AlexNet、VGGNet、Inception
  - ResNet、SENet、DenseNet、Attention