2019春

模式识别与深度学习 (15)

卷积神经网络-1

左旺孟

综合楼309
视觉感知与认知组
哈尔滨工业大学计算机学院
cswmzuo@gmail.com
13134506692

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”。——特斯拉人工智能主管Andrej Karpathy

Why Deep CNNs

- 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/

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

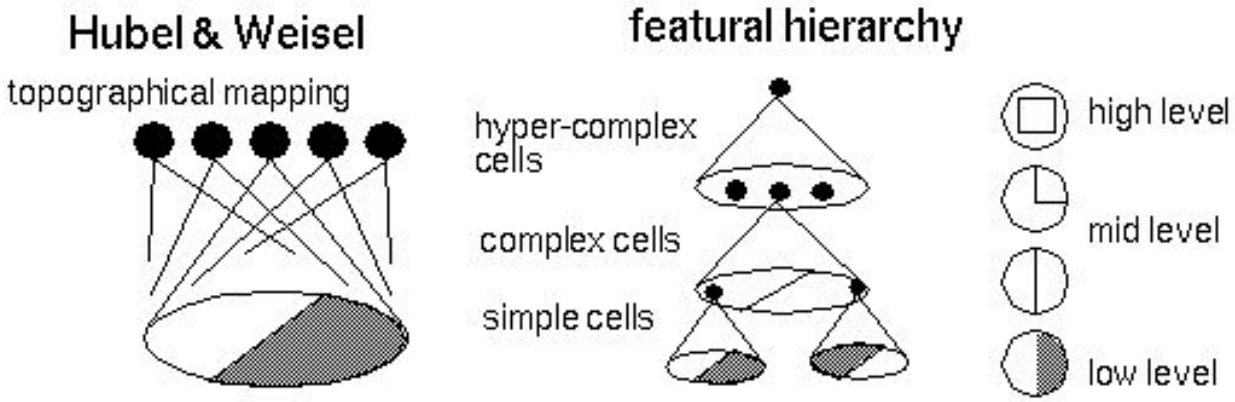
- 有一个漆黑的夜里，有一路人在路灯下反复翻找东西。
- 旁人问他:找什么?
- 路人说:丢了钥匙。

- 旁人问:在这里丢的钥匙吗?
- 路人说:不是!

- 旁人问:那为什么只在这里找呢？不去其它地方看看吗？
- 路人说：因为这里有路灯，亮，看得见。

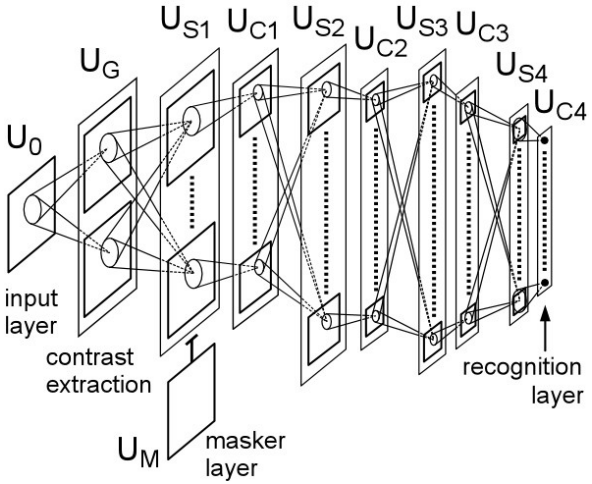
Hubel/Wiesel架构

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

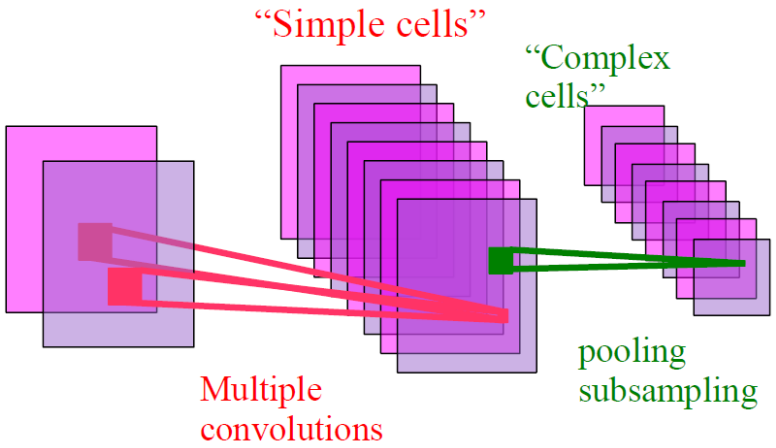


Neocognitron

- **[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



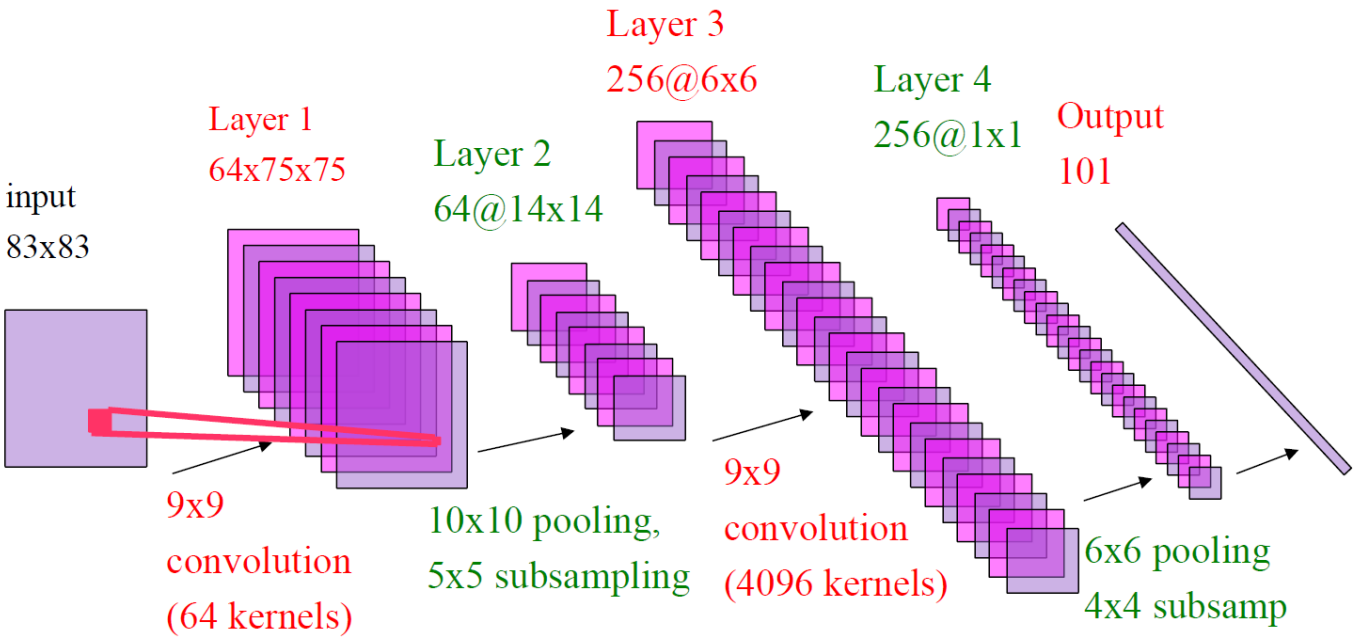
Cognitron & Neocognitron
[Fukushima 1974-1982]



卷积神经网络

卷积神经网络（上半场）

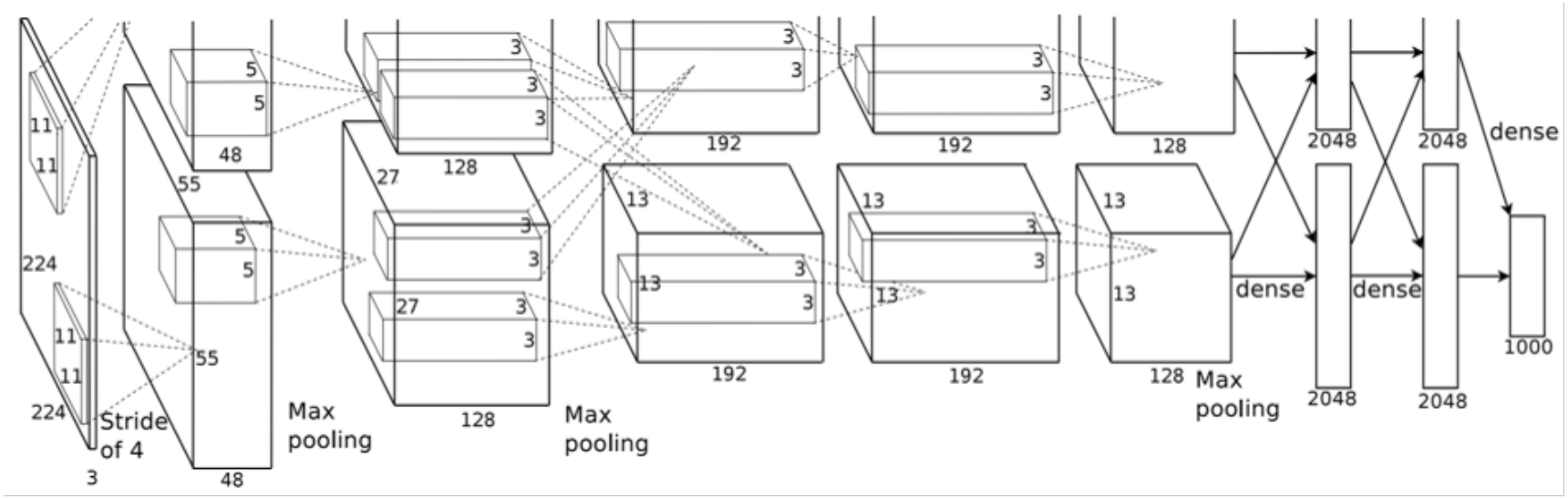
- LeCun et al., NIPS 1989



- 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

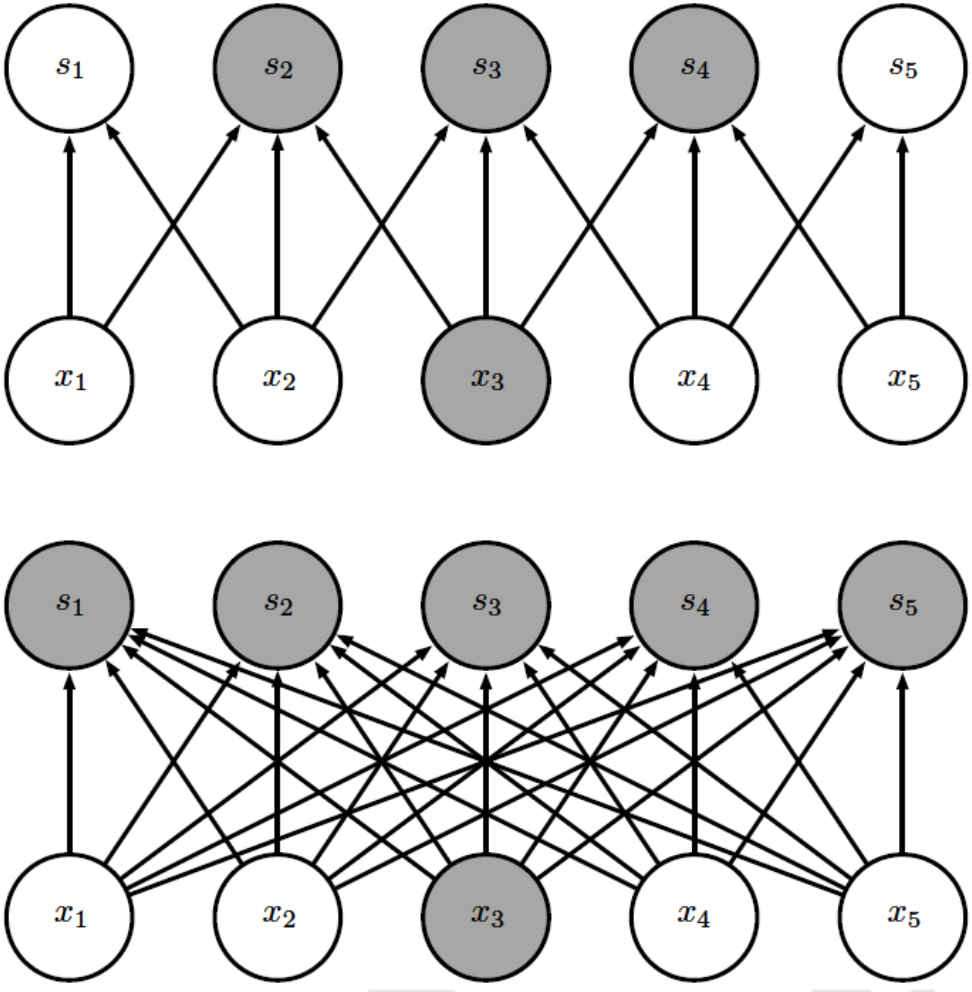


- 5个卷积层、3个全连接层

动机

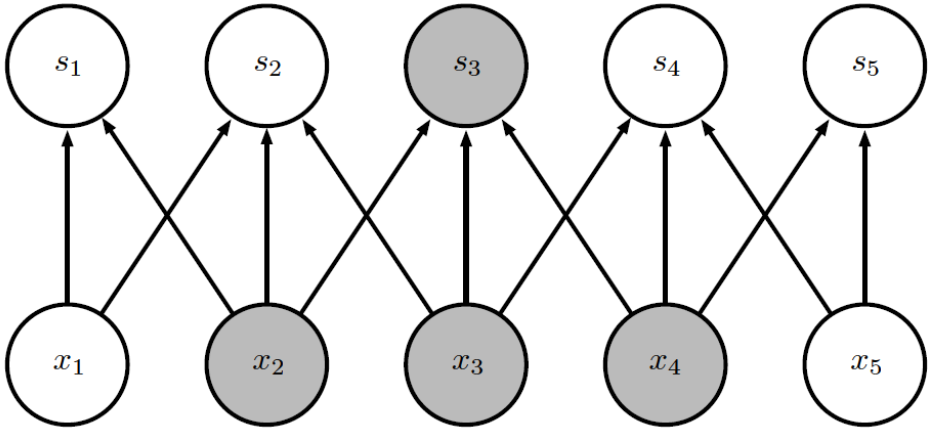
- 稀疏交互（sparse interactions）
- 参数共享（parameter sharing）
- 等变表示（equivariant representation）

稀疏交互（稀疏连接）

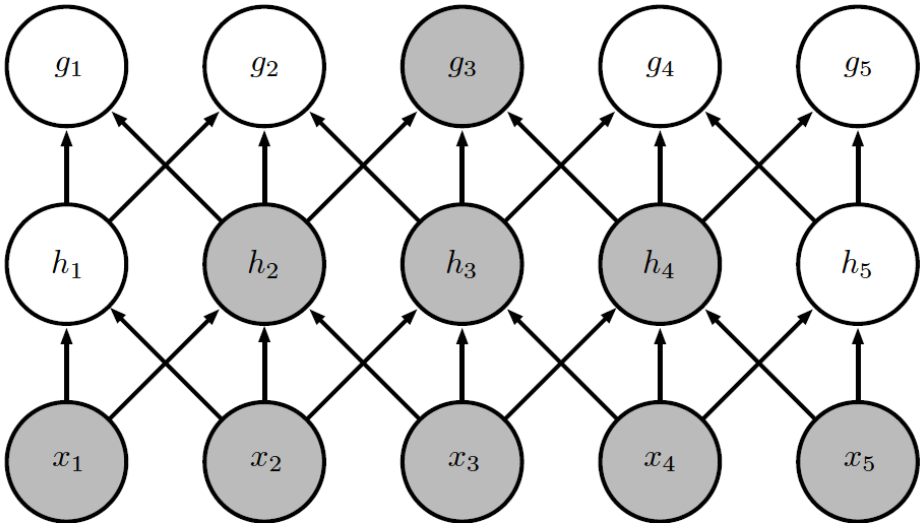


感受野（Receptive Field）

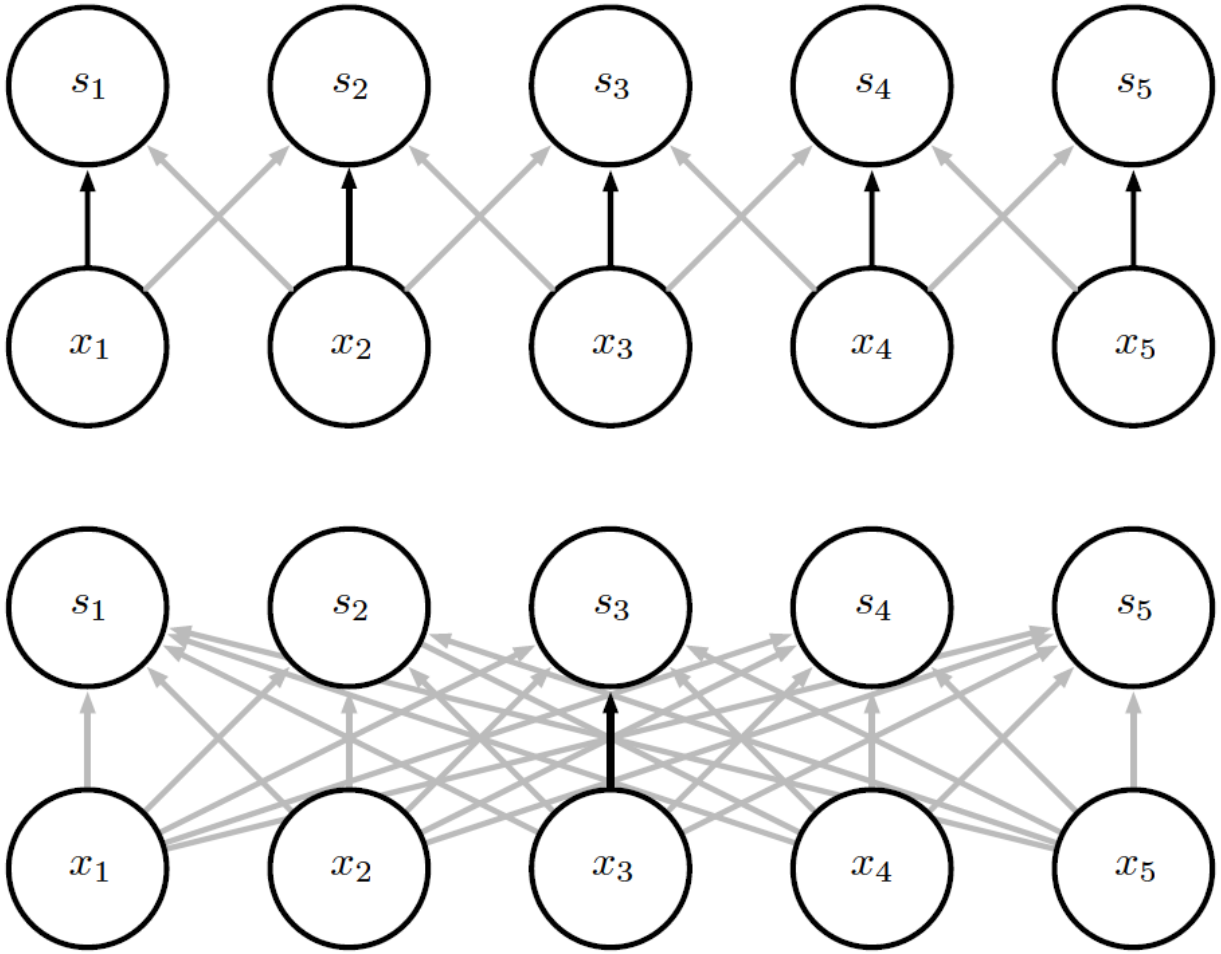
- 层1:



- 层2:



参数共享



等变表示

- 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
- 变换不敏感

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、空洞卷积（ dilated convolution ）
- 典型网络架构
  - LeNet、AlexNet、VGGNet、Inception
  - ResNet、SENet、DenseNet、Attention

卷积：参数共享和稀疏连接

- 连续卷积

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

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

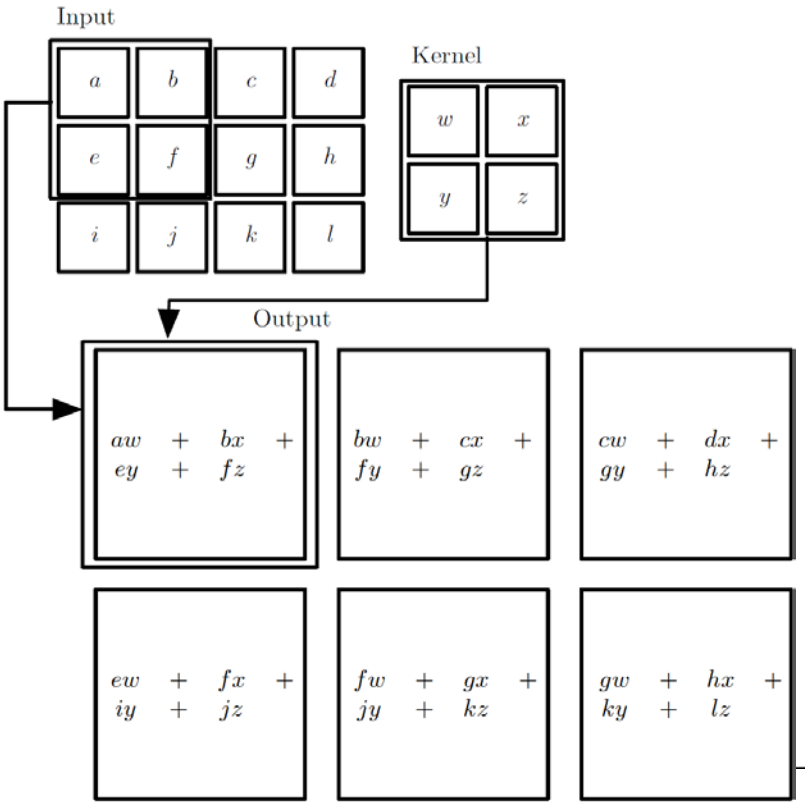
  - 输入、核函数
- 离散卷积

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

二维卷积

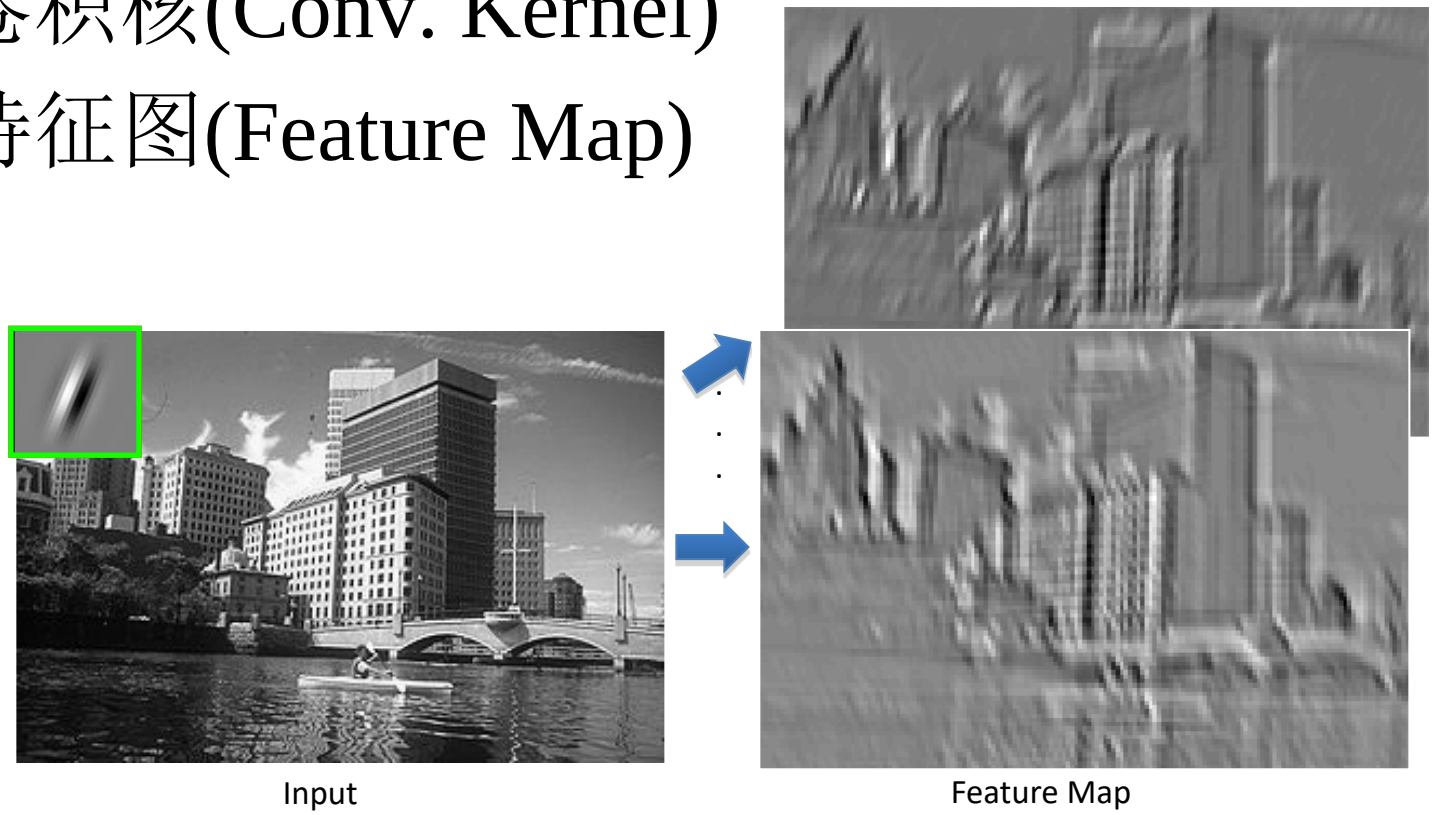
- 二维卷积

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



直观展示

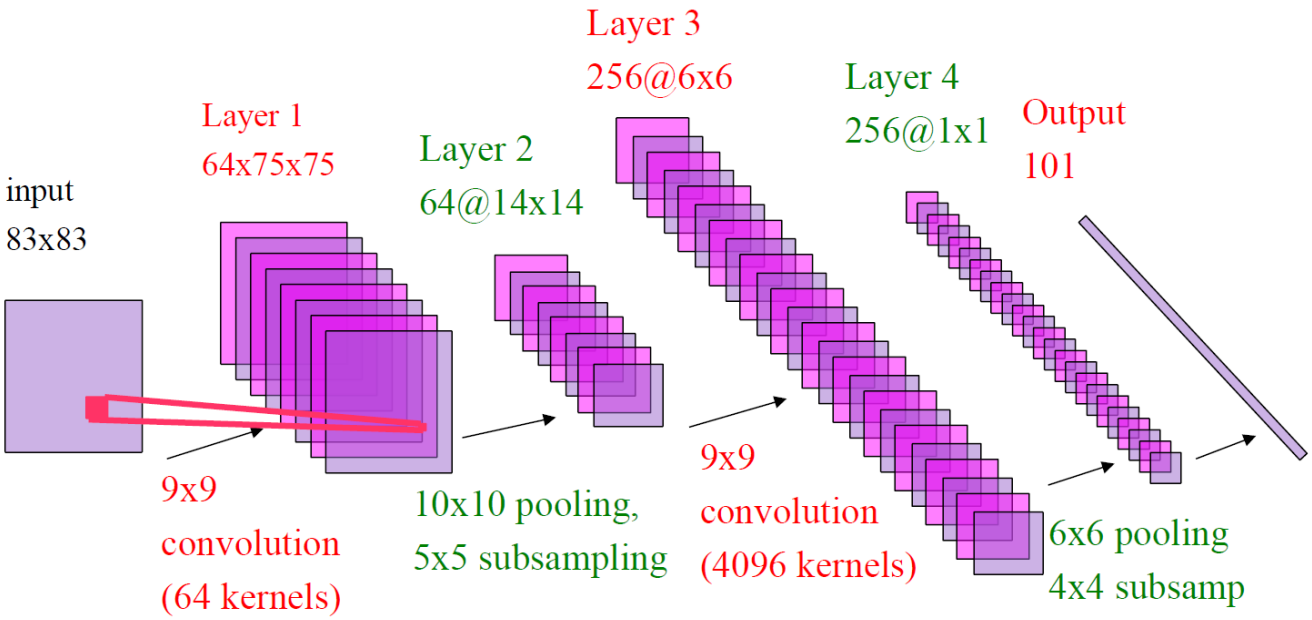
- 卷积核(Conv. Kernel)
- 特征图(Feature Map)



拓展：多通道卷积

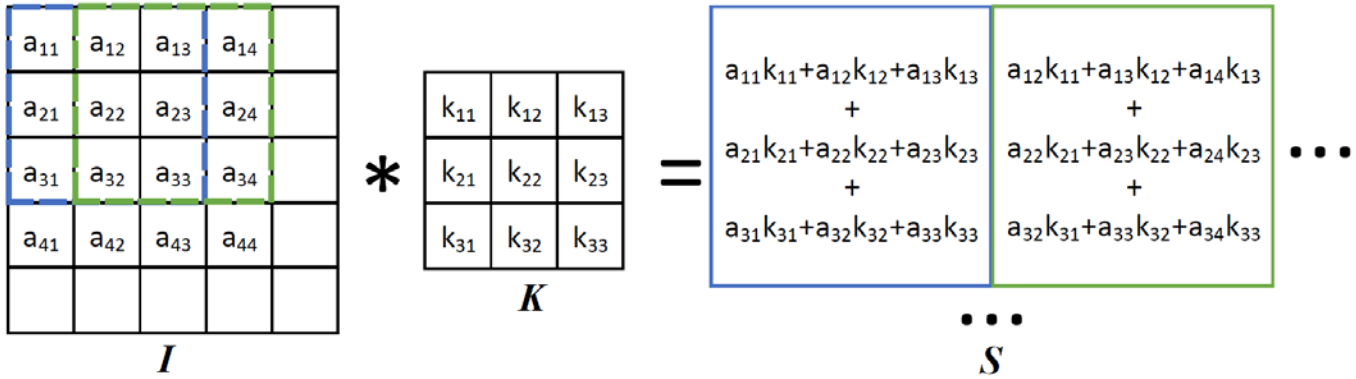
- 多通道卷积

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

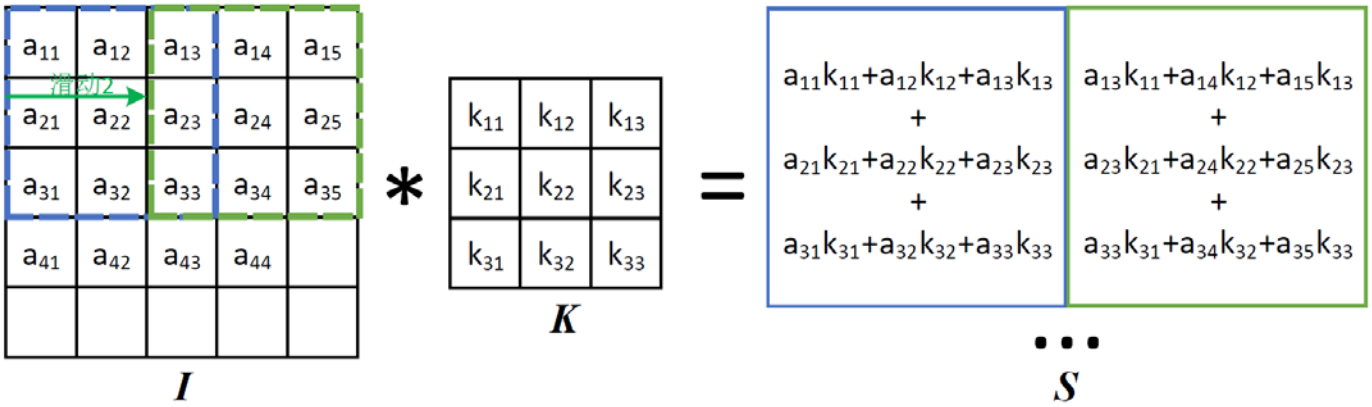


拓展：步长（ Stride ）

- 步长为1



- 步长为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.

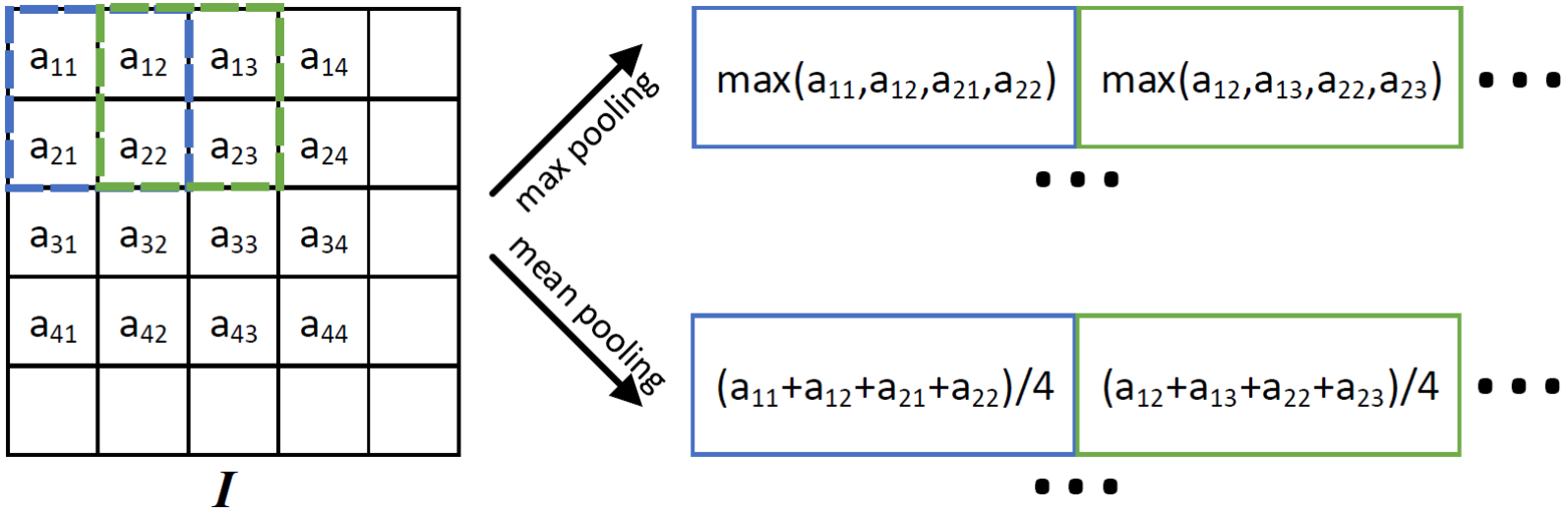
Guilin Liu, Kevin J. Shih, Ting-Chun Wang, Fitsum A. Reda, Karan Sapra, Zhiding Yu, Andrew Tao, Bryan Catanzaro, Partial Convolution based Padding, arXiv:1811.11718 .

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、空洞卷积（ dilated convolution ）
- 典型网络架构
  - LeNet、AlexNet、VGGNet、Inception
  - ResNet、SENet、DenseNet、Attention

池化：形变不敏感

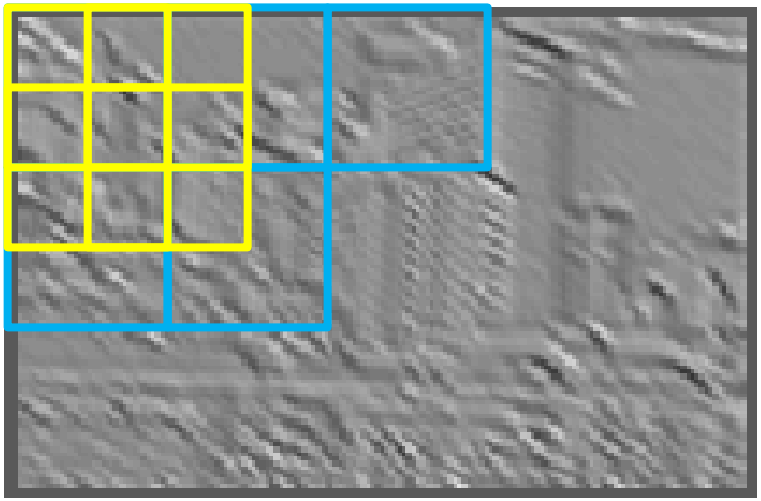
- 池化



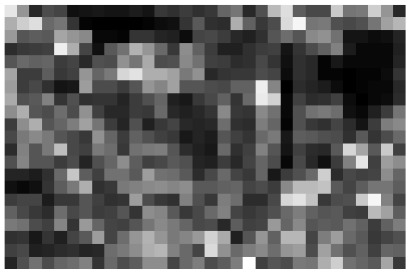
- 下采样

直观展示

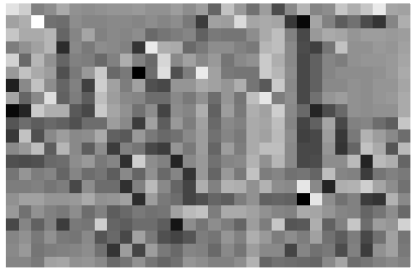
- Max Pooling
- Average Pooling



Max



Sum



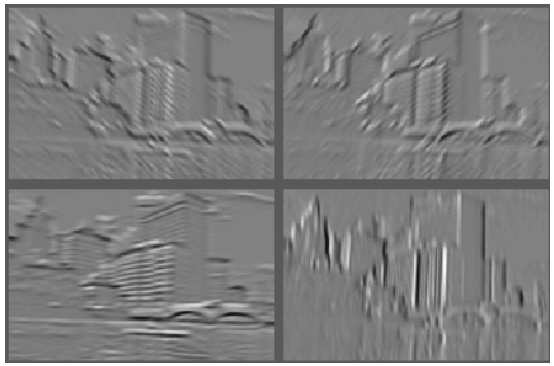
池化：Comment

- Hinton (reddit): The pooling operation used in convolutional neural networks is a big mistake and the fact that it works so well is a disaster.

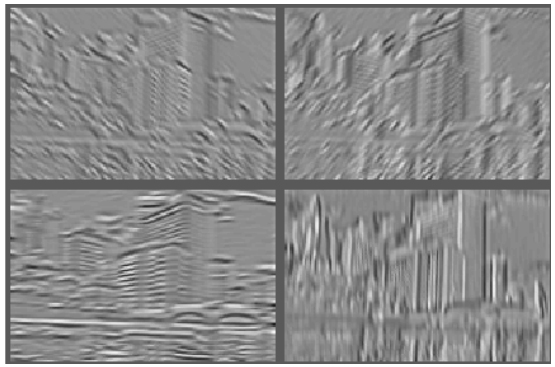
- https://mirror2image.wordpress.com/2014/11/11/geoffrey-hinton-on-max-pooling-reddit-ama/

归一化：光照不敏感

- 每个channel或跨channel归一化
- 池化前或池化后归一化



Feature Maps



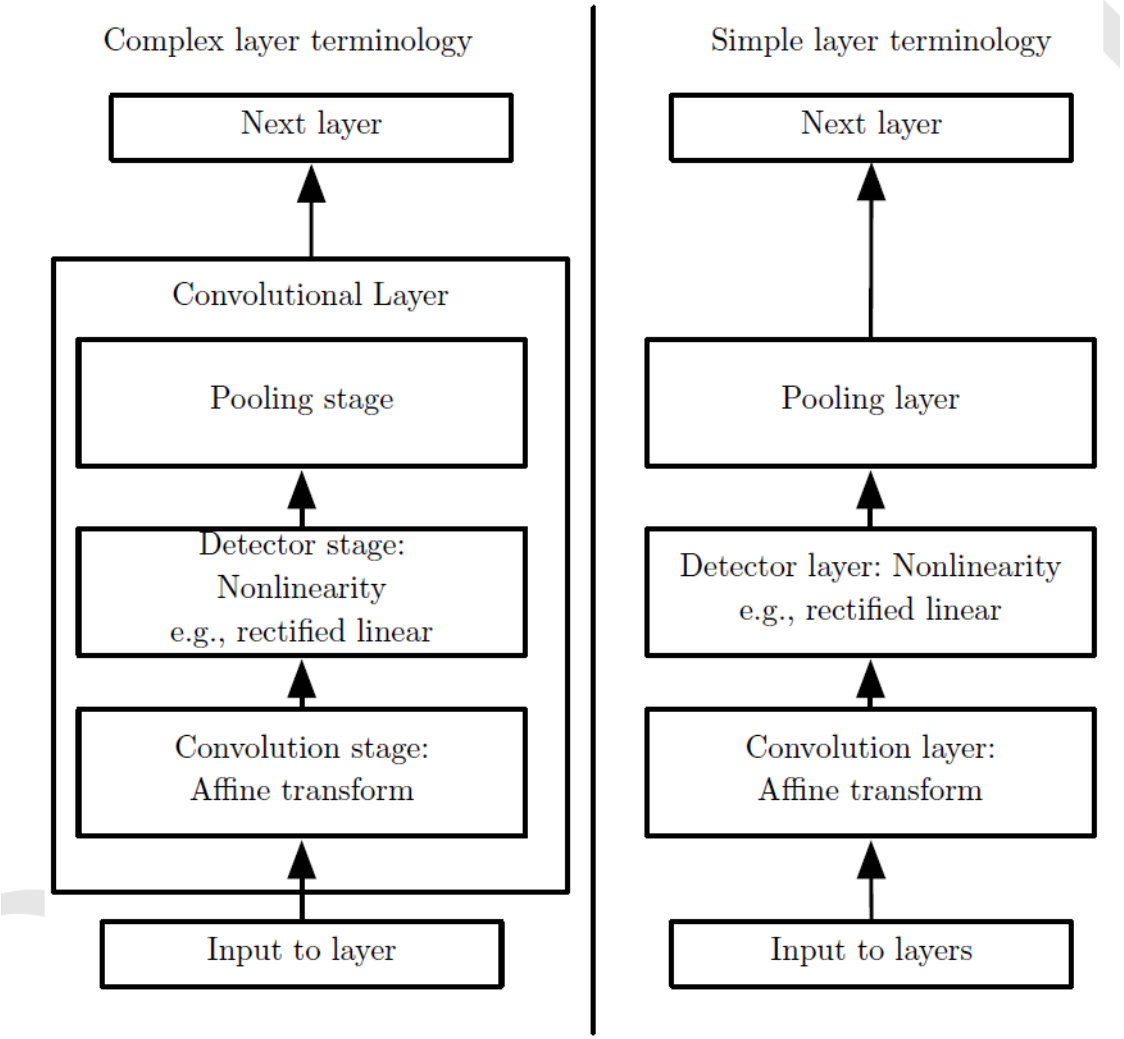
Feature Maps
After Contrast Normalization

- 不太常用或结合Batch Normalization

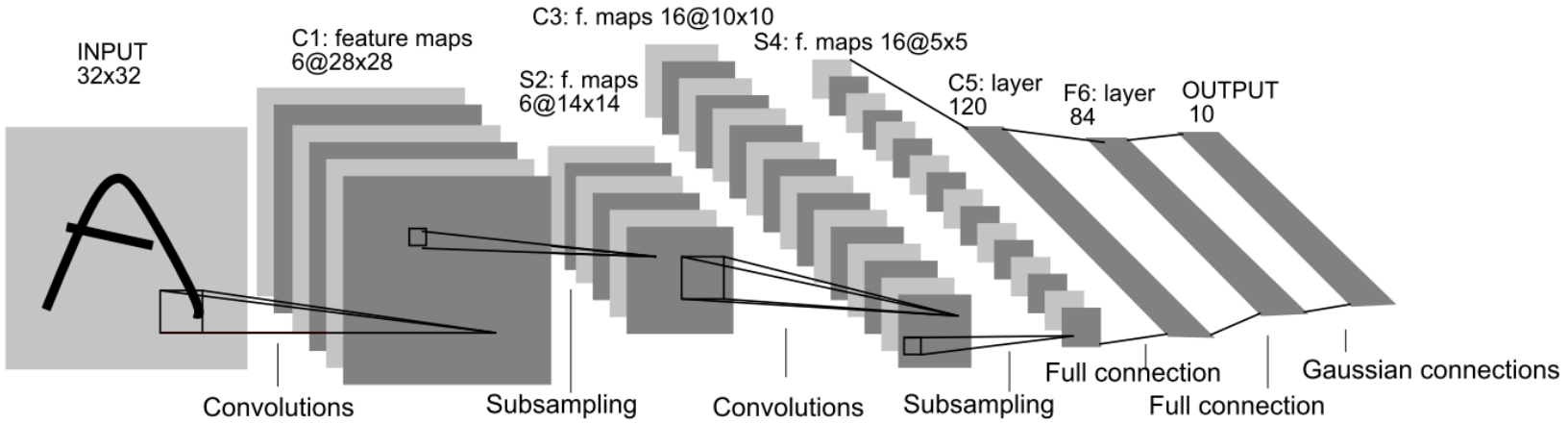
卷积神经网络

- 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、空洞卷积（ dilated convolution ）
- 典型网络架构
  - LeNet、AlexNet、VGGNet、Inception
  - ResNet、SENet、DenseNet、Attention

典型的卷积神经网络层

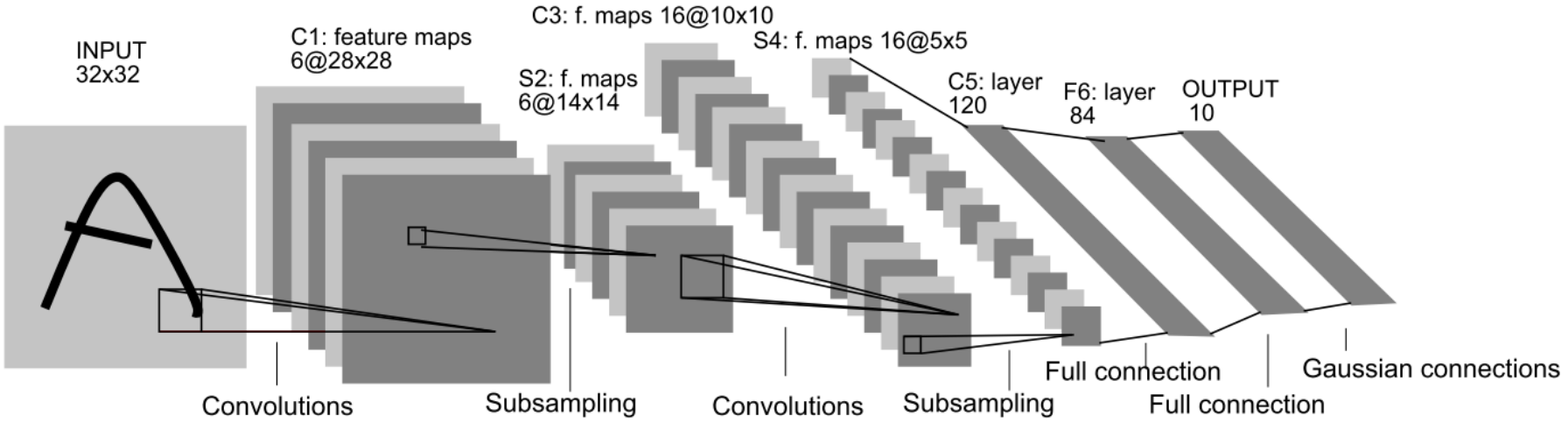

Complex layer terminology
Next layer
Convolutional Layer
Pooling stage
Detector stage:
Nonlinearity
e.g., rectified linear
Convolution stage:
Affine transform
Input to layer
Simple layer terminology
Next layer
Pooling layer
Detector layer: Nonlinearity
e.g., rectified linear
Convolution layer:
Affine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

卷积神经网络示例：LeNet5（1998）



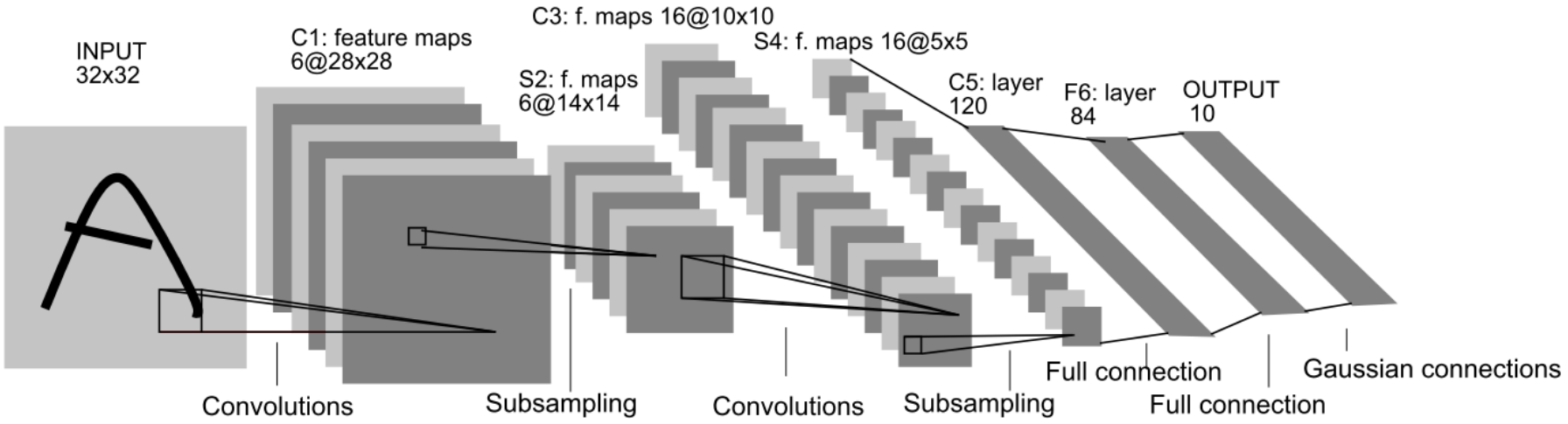
- 输入: 32x32图像
- Cx: 卷积层
- Sx: 下采样层
- Fx: 全连接层

LeNet 5, Layer C1



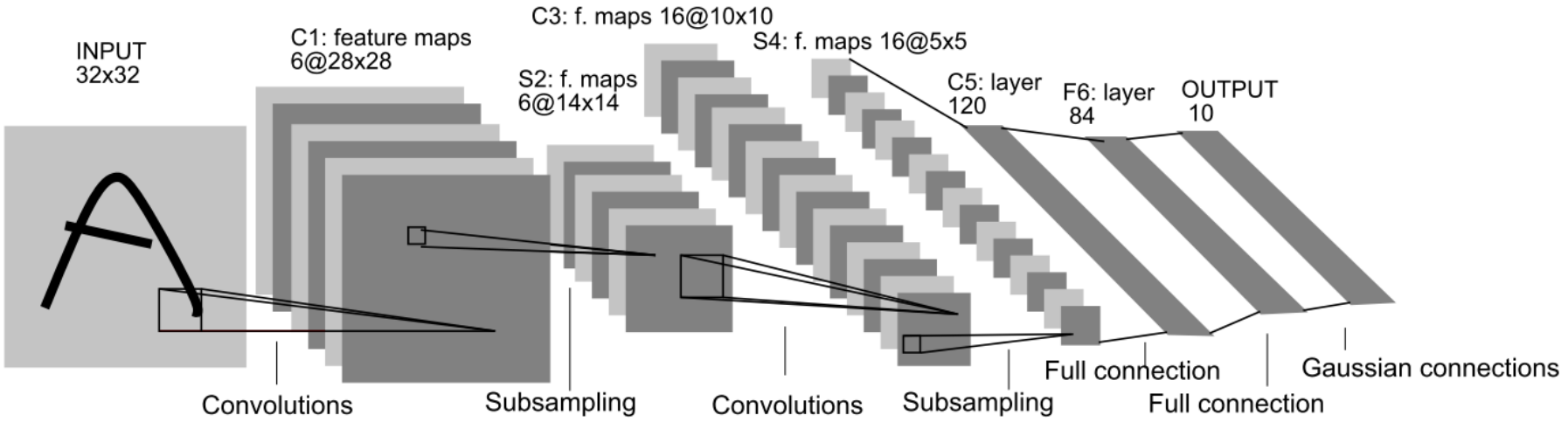
- C1: Convolutional layer with 6 feature maps of size 28x28. C1k (k=1…6) Each unit of C1 has a 5x5 receptive field in the input layer.
  - Topological structure
  - 稀疏连接
  - 参数共享： (5*5+1)*6=156 parameters to learn Connections: 28*28*(5*5+1)*6=122304 If it was fully connected we had (32*32+1)*(28*28)*6 parameters

LeNet 5, Layer S2



- S2: Subsampling layer with 6 feature maps of size 14x14
- 2x2 nonoverlapping receptive fields in C1
- Layer S2: 6*2=12 trainable parameters.
- Connections: 14*14*(2*2+1)*6=5880

LeNet 5, Layer C3



- C3: Convolutional layer with 16 feature maps of size 10x10
- Each unit in C3 is connected to several! 5x5 receptive fields at identical locations in S2

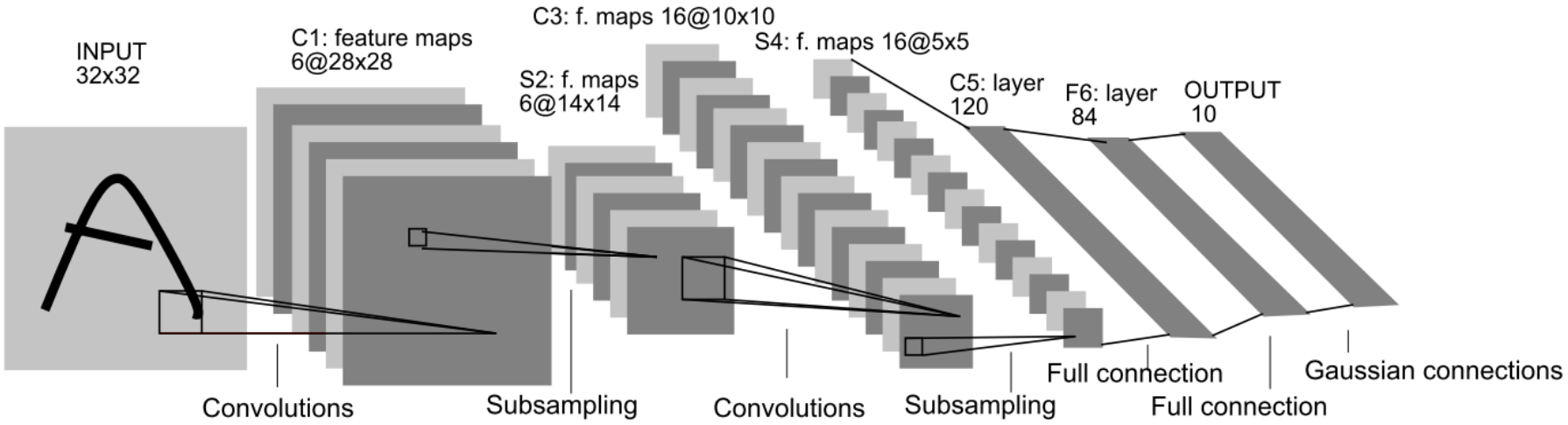
- Layer C3: 1516 trainable parameters.
- Connections: 151600

	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.

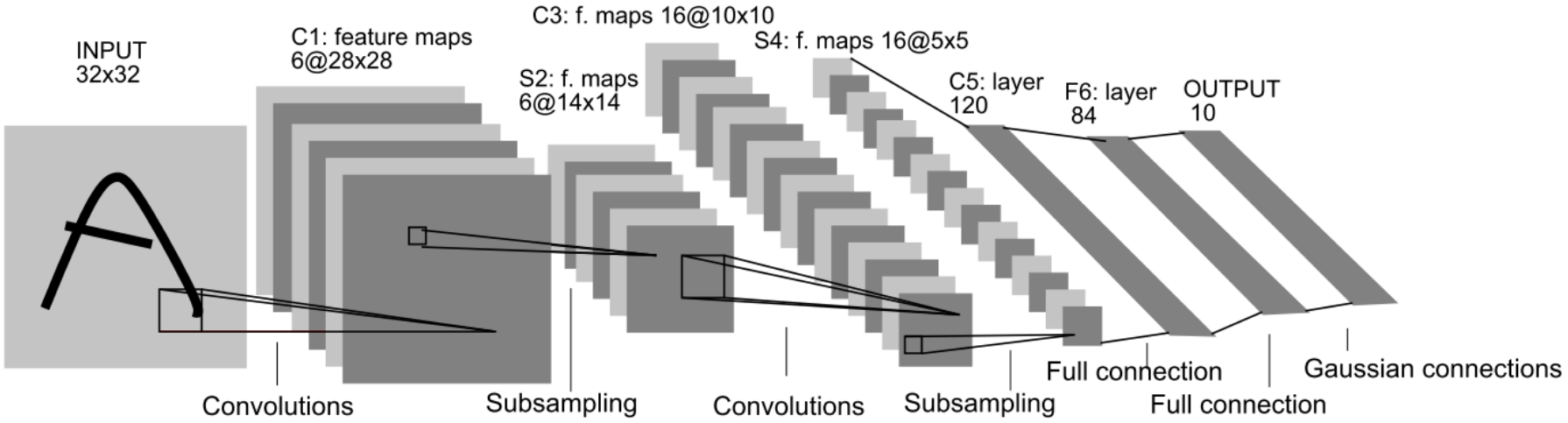
LeNet 5, Layer S4



- S4: Subsampling layer with 16 feature maps of size 5x5
- Each unit in S4 is connected to the corresponding 2x2 receptive field at C3

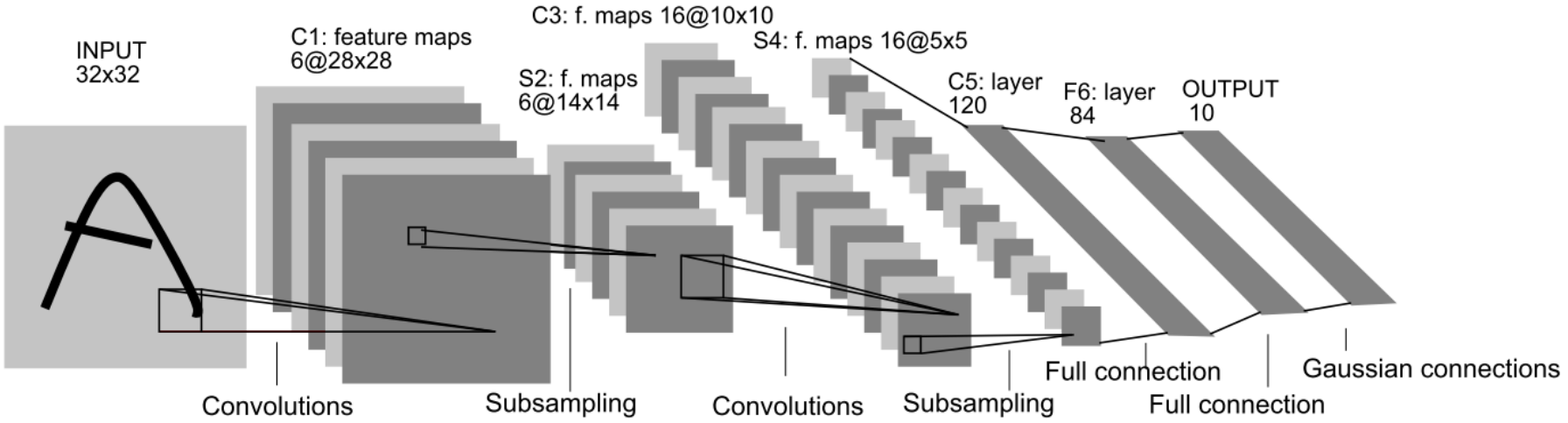
- Layer S4: 16*2=32 trainable parameters.
- Connections: 5*5*(2*2+1)*16=2000

LeNet 5, Layer C5



- C5: Convolutional layer with 120 feature maps of size 1x1
- Each unit in C5 is connected to all 16 5x5 receptive fields in S4
- Layer C5: 120*(16*25+1) = 48120 trainable parameters and connections (Fully connected)

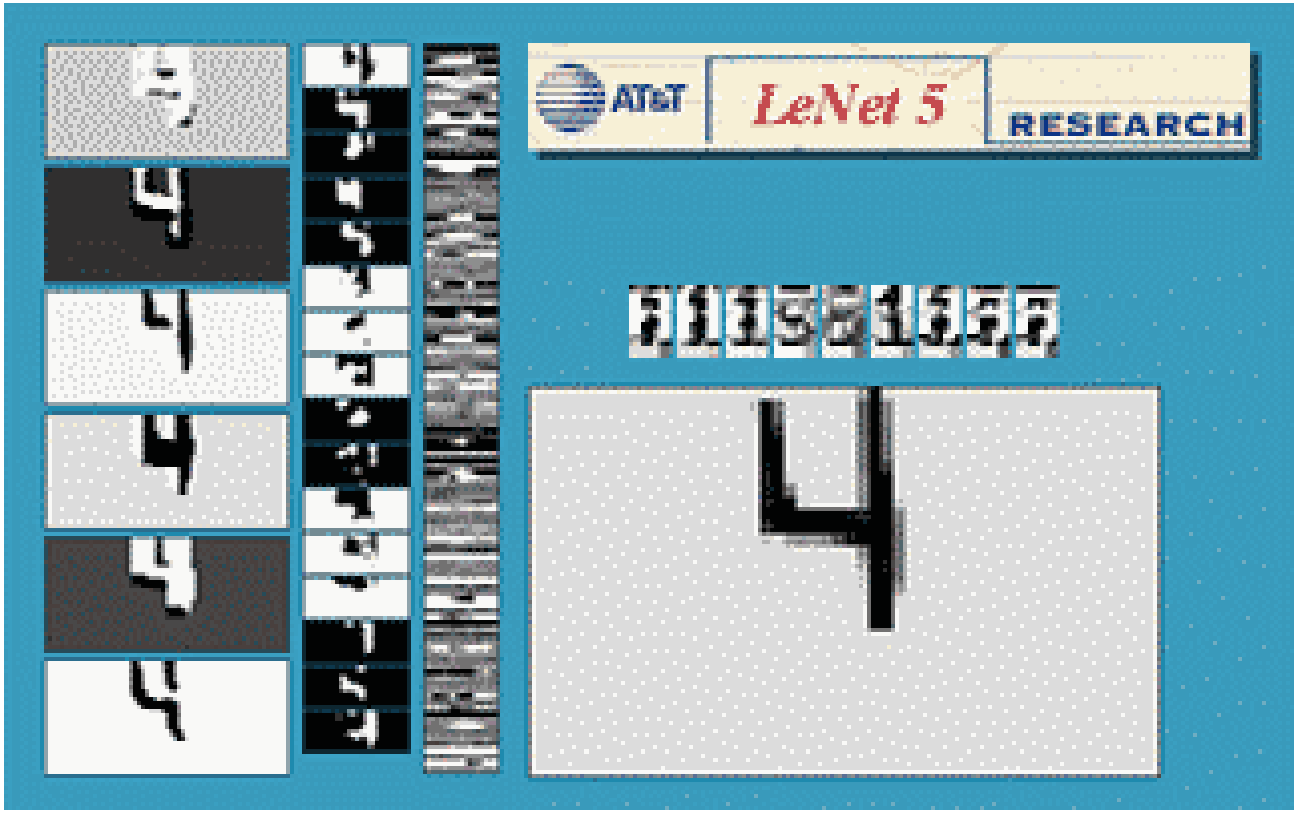
LeNet 5, Layer F6



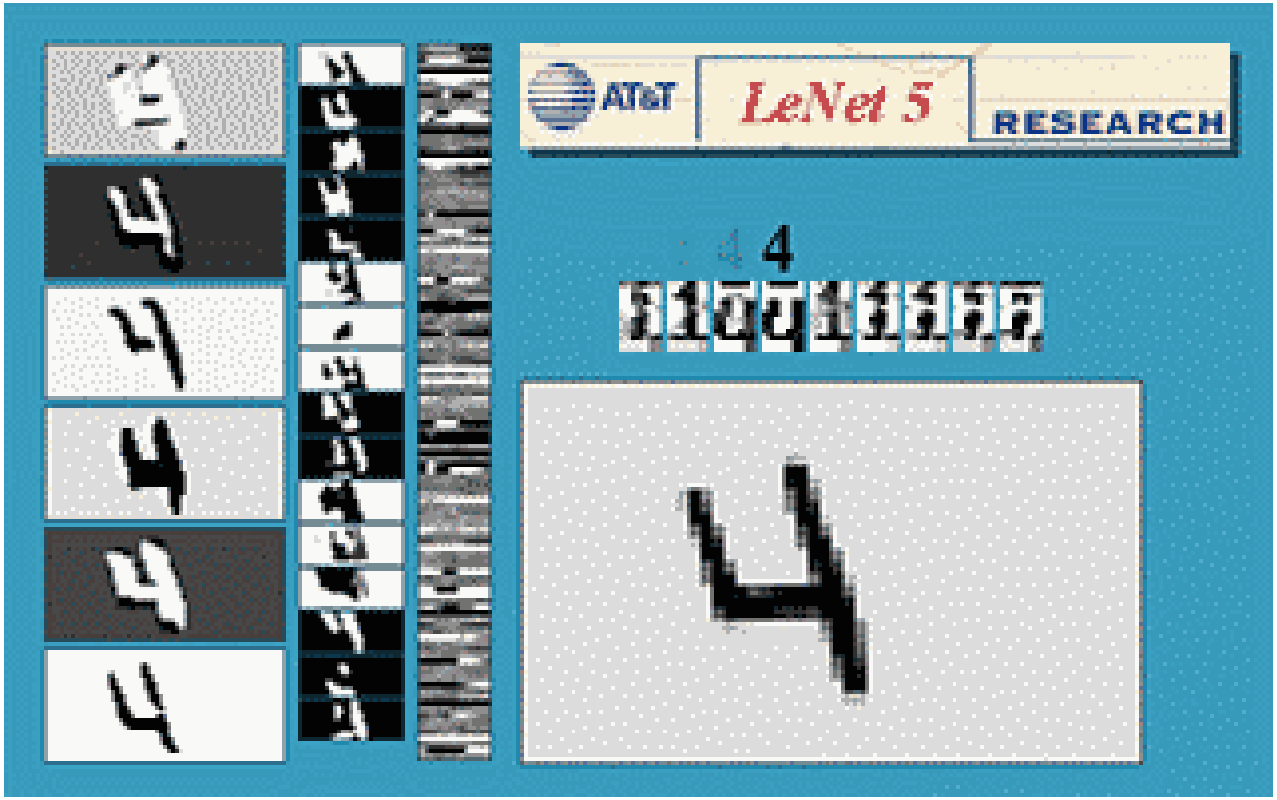
- Layer F6: 84 fully connected units. 84*(120+1)=10164 trainable parameters and connections.
- Output layer: 10RBF (One for each digit)

- 84=7x12, stylized image
- Weight update: Backpropagation

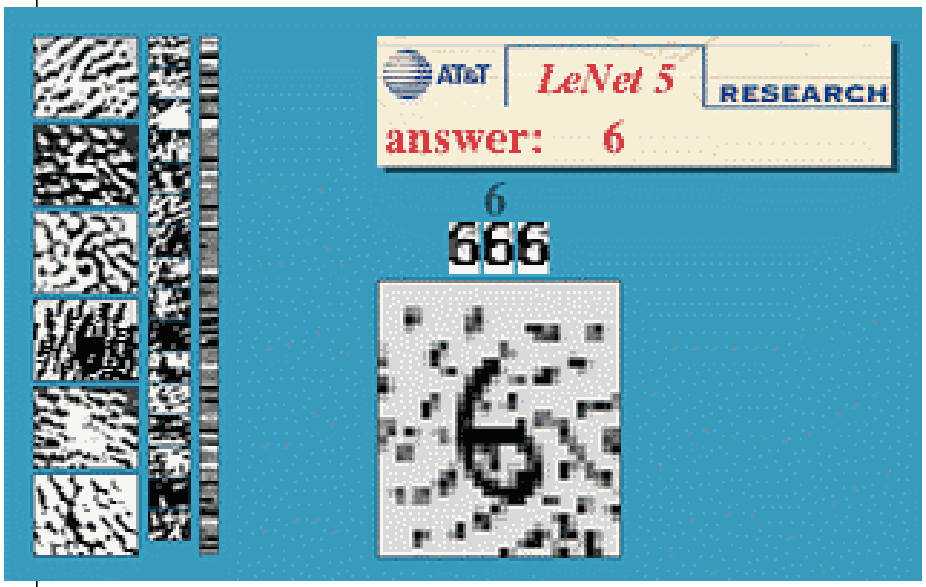
LeNet 5, Shift invariance

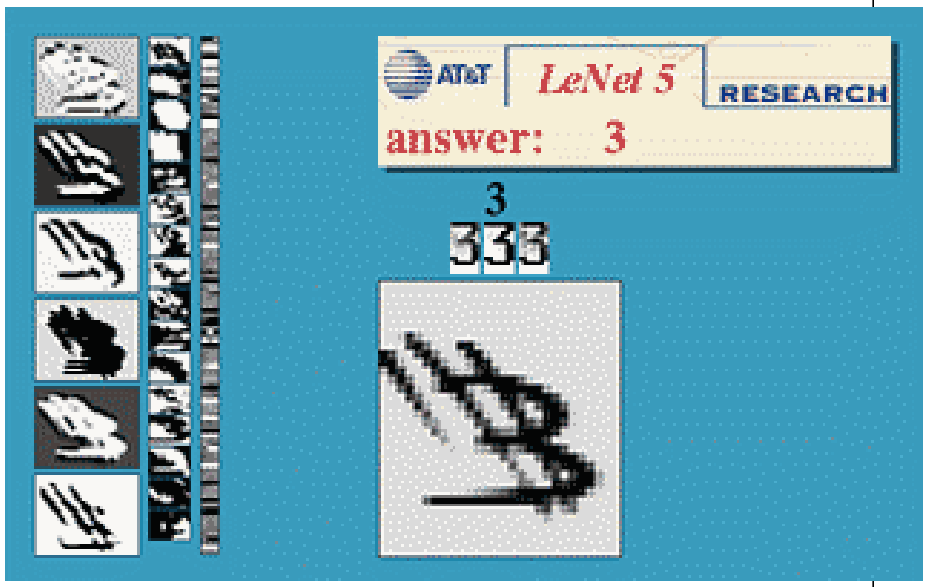


LeNet 5, Rotation invariance

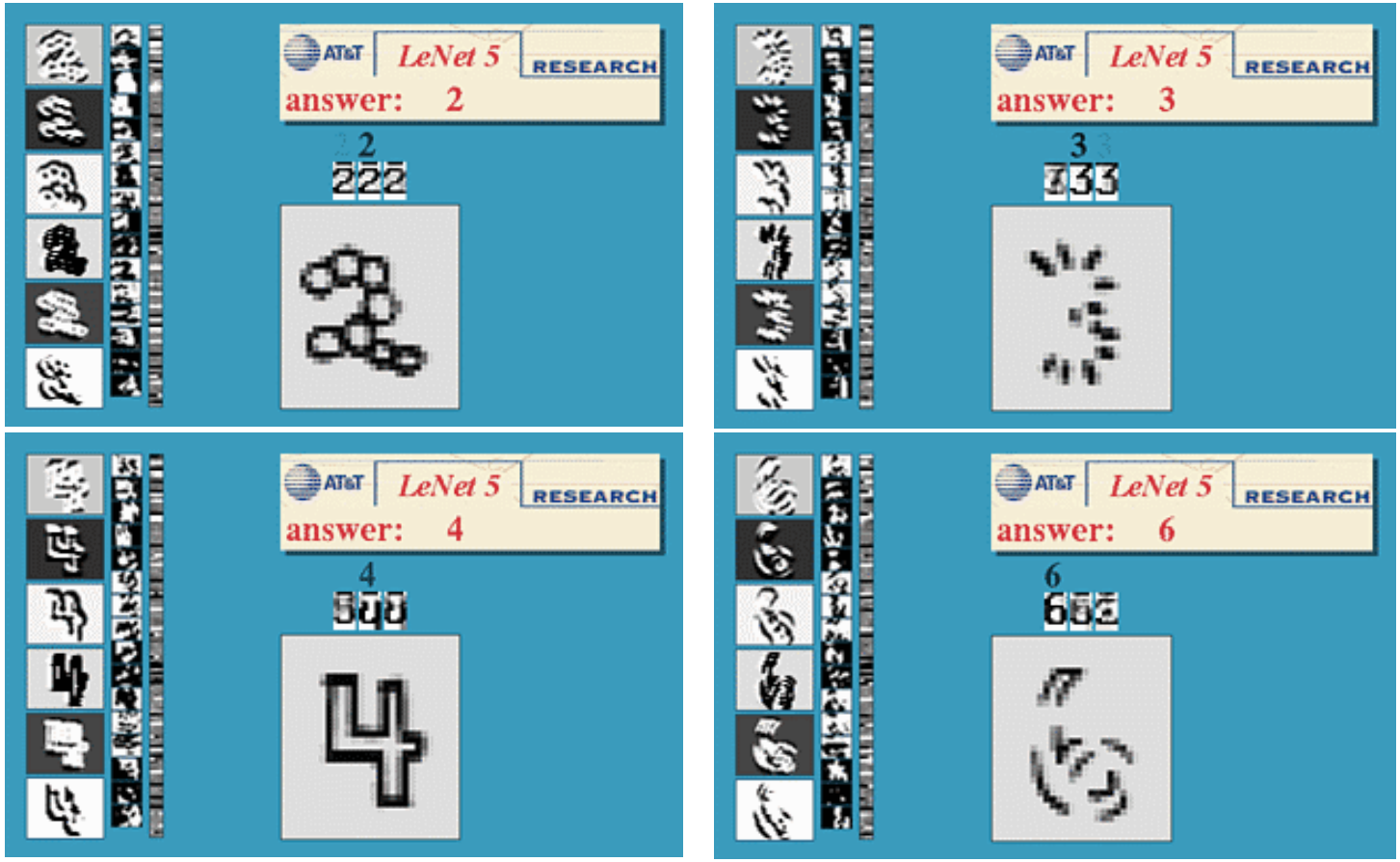


LeNet 5, Nosie resistance





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