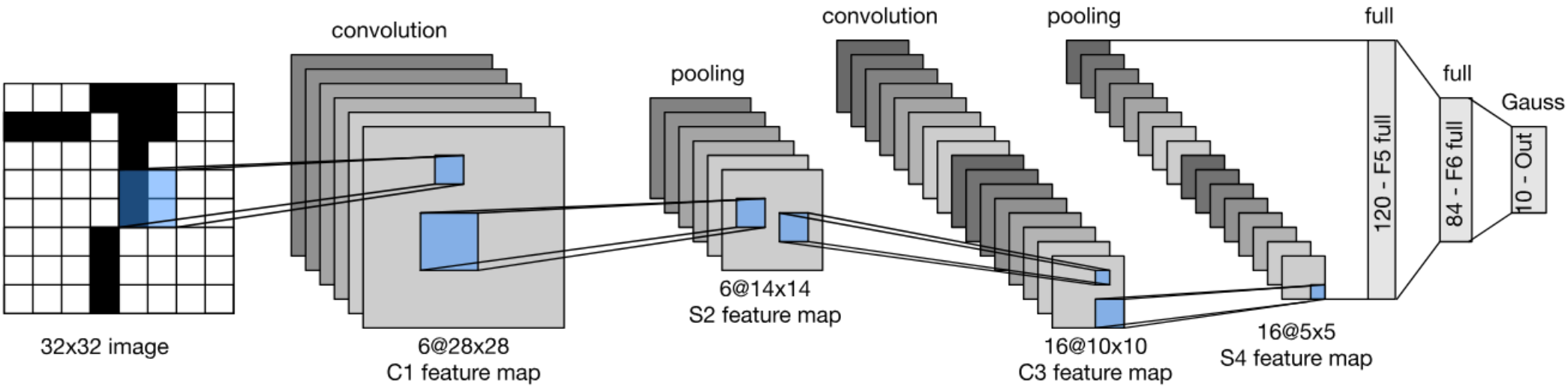
Introduction to Deep Learning

Chapter 8 LeNet, AlexNet, VGG and NiN

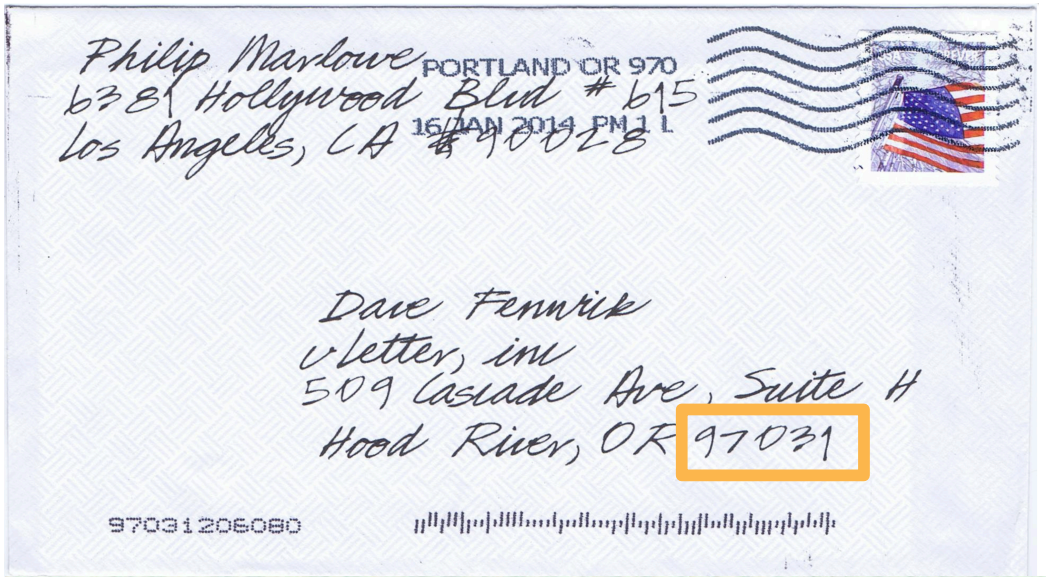
Slides From Alex Smola and Mu Li

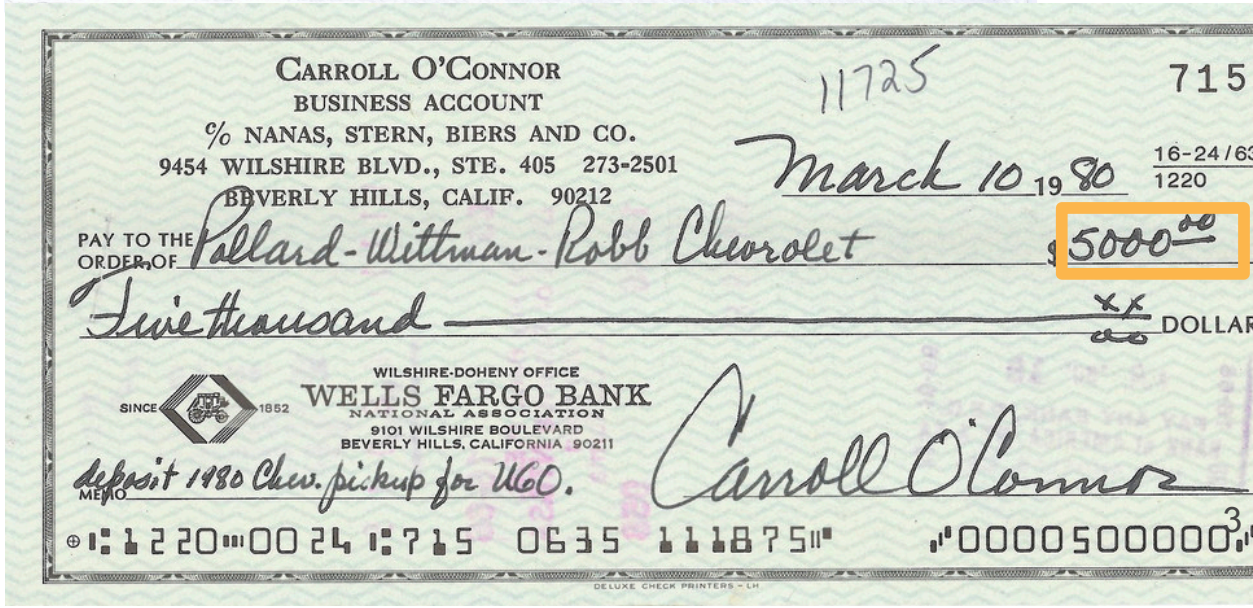
courses.d2l.ai/berkeley-stat-157

LeNet Architecture



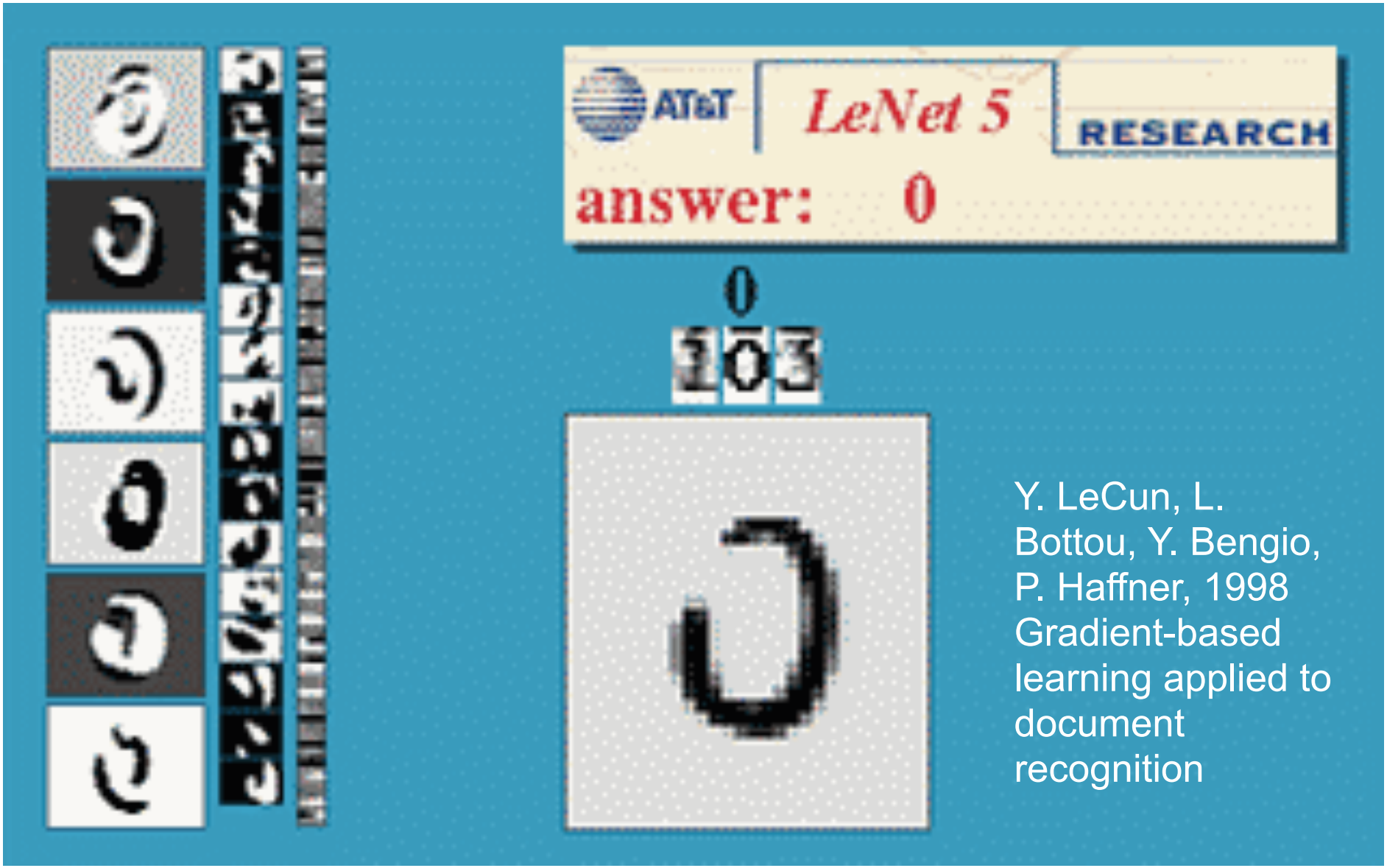
Handwritten Digit Recognition



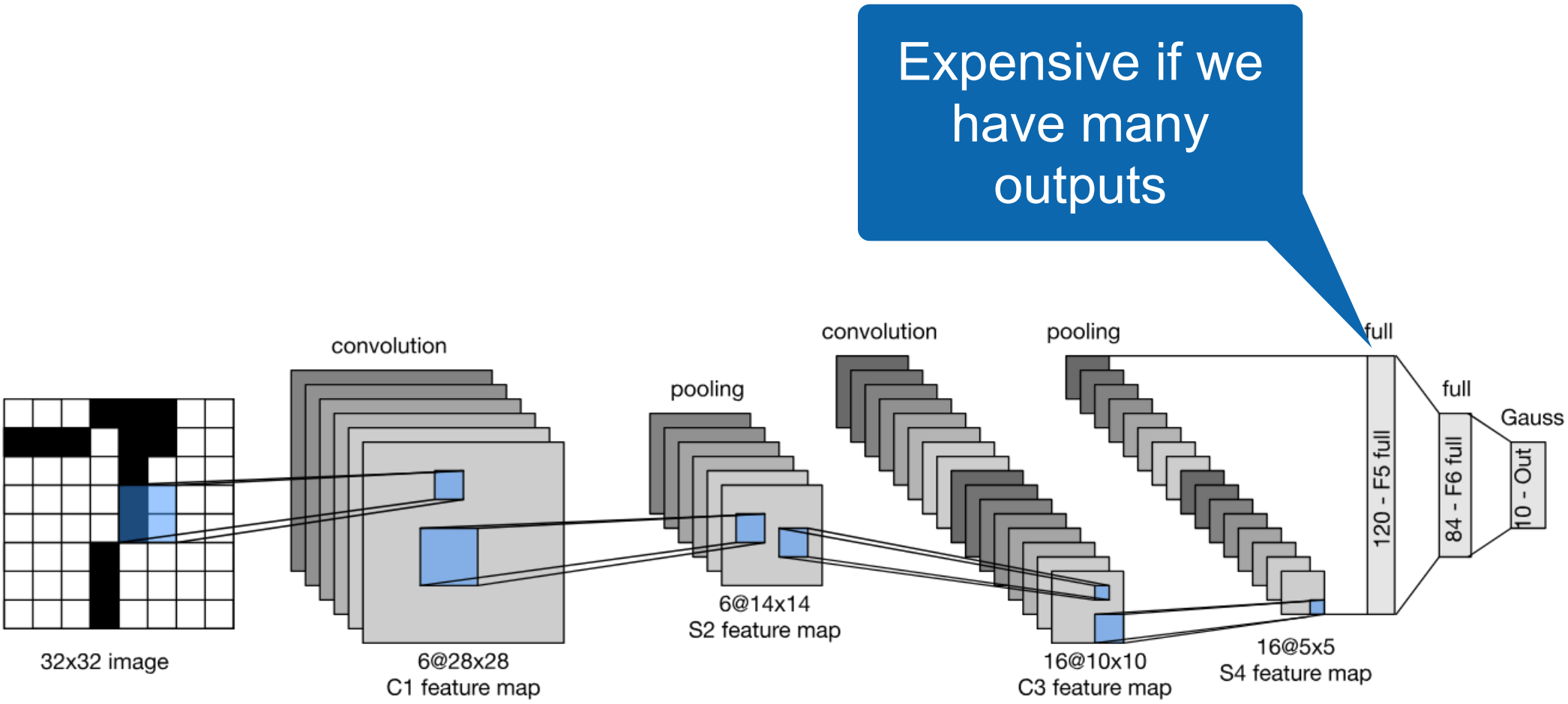


MNIST

- Centered and scaled
- 60,000 training data
- 10,000 test data
- 28 x 28 images
- 10 classes



Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, 1998 Gradient-based learning applied to document recognition


Expensive if we have many outputs
convolution
pooling
convolution
pooling
full
full
Gauss
120 - F5 full
84 - F6 full
10 - Out
32x32 image
6@28x28
C1 feature map
6@14x14
S2 feature map
16@10x10
C3 feature map
16@5x5
S4 feature map

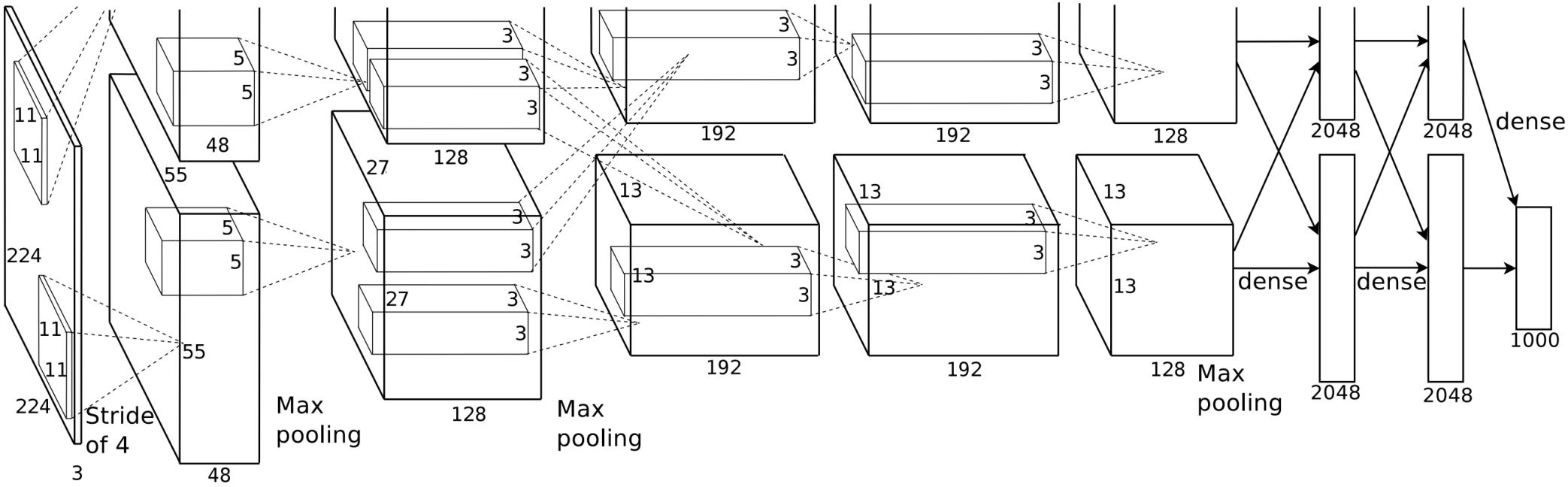
LeNet in MXNet

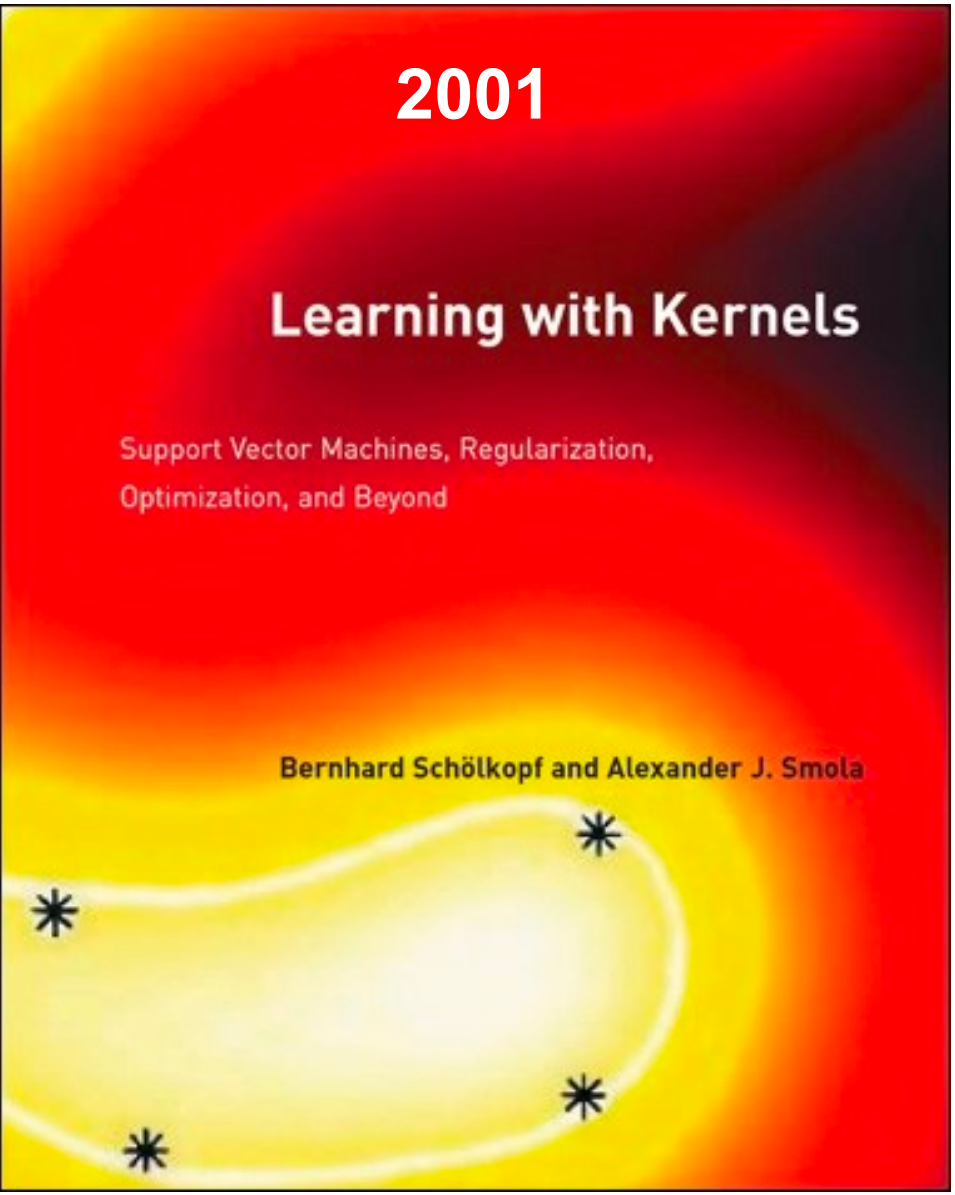
```
net = nn.Sequential()
net.add(nn.Conv2D(channels=6, kernel_size=5, activation='sigmoid'),
        nn.AvgPool2D(pool_size=2),
        nn.Conv2D(channels=16, kernel_size=5, activation='sigmoid'),
        nn.AvgPool2D(pool_size=2),
        nn.Dense(120, activation='sigmoid'),
        nn.Dense(84, activation='sigmoid'),
        nn.Dense(10))

loss = gluon.loss.SoftmaxCrossEntropyLoss()

(size and shape inference is automatic)
```

AlexNet

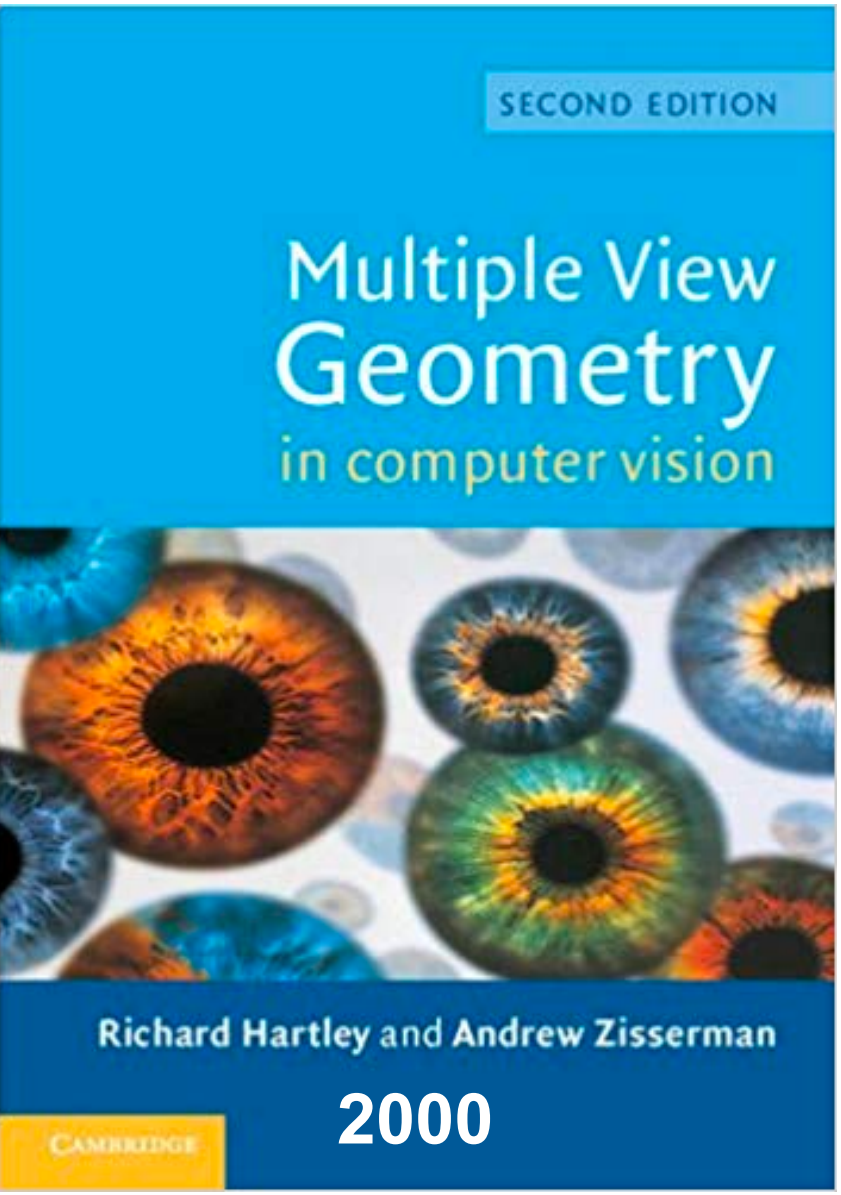

11
11
224
224
3
Stride
of 4
5
5
48
55
48
55
Max
pooling
3
3
3
128
27
128
3
3
3
27
3
3
128
Max
pooling
3
3
192
3
3
192
128
13
13
3
3
192
13
13
3
3
192
13
13
128
Max
pooling
dense
dense
2048
2048
2048
2048
dense
1000



Function Classes

In the 1990s, a new type of learning algorithm was developed, based on results from statistical learning theory: the Support Vector Machine (SVM). This gave rise to a new class of theoretically elegant learning machines that use a central concept of SVMs – -kernels – for a number of

- Extract features
- Pick kernel for similarity
- **Convex** optimization problem
- Many beautiful theorems …



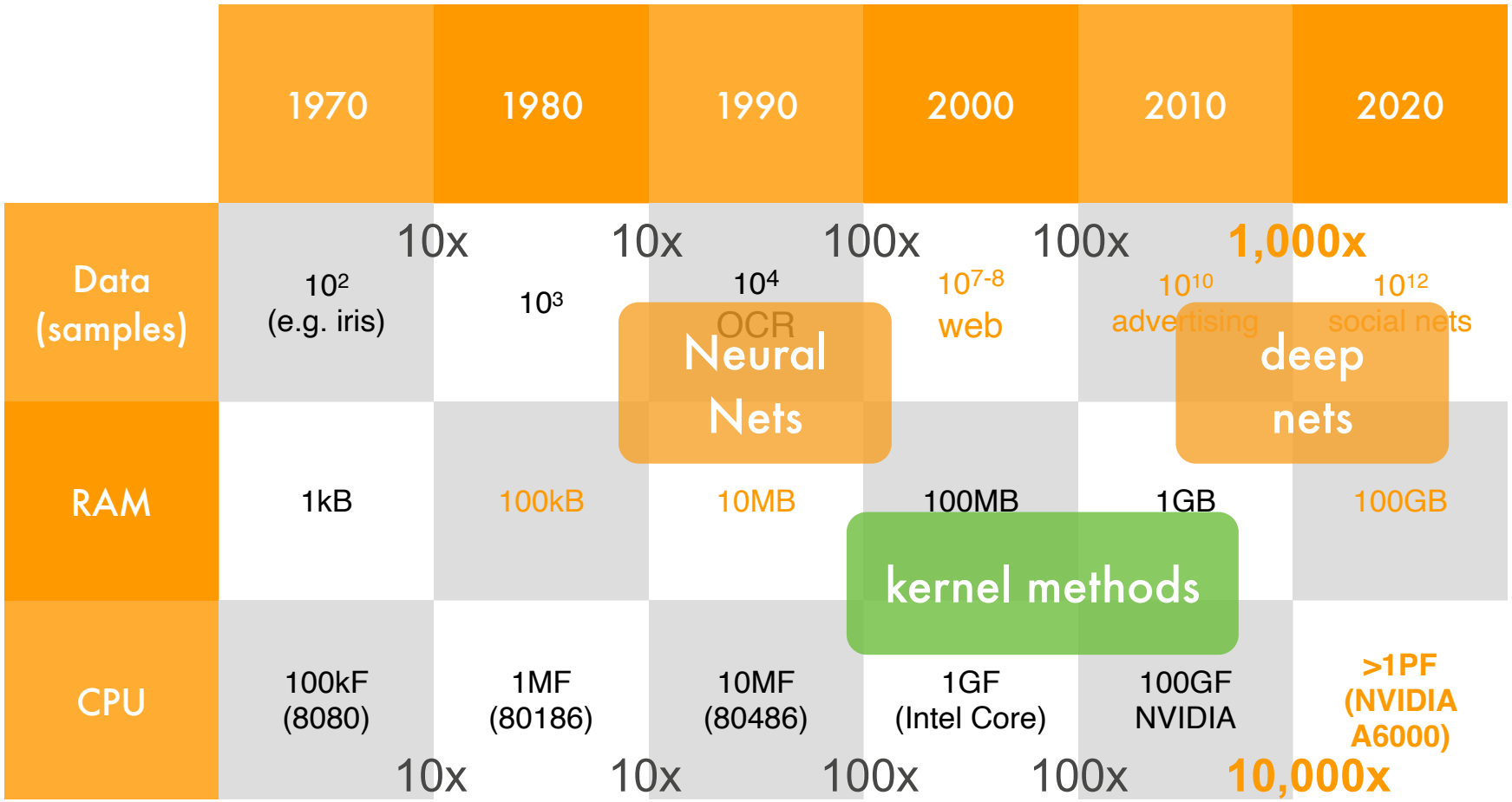
Geometry

- Kernel ideas are used to solve PDE-heat equation ($\frac{\partial u(x,t)}{\partial t} = -\Delta_M u(x,t) = -L_{XXX} u(x,t)$)
- Extract features
- Describe geometry (e.g. multiple cameras) analytically
- **(Non)Convex** optimization problems
- Many beautiful theorems …
- Works very well in theory when the assumptions are satisfied

Feature Engineering

- Feature engineering is crucial
- Feature descriptors, e.g. SIFT (Scale-invariant feature transform), SURF
- Bag of visual words (clustering)
- Then apply SVM …

Hardware

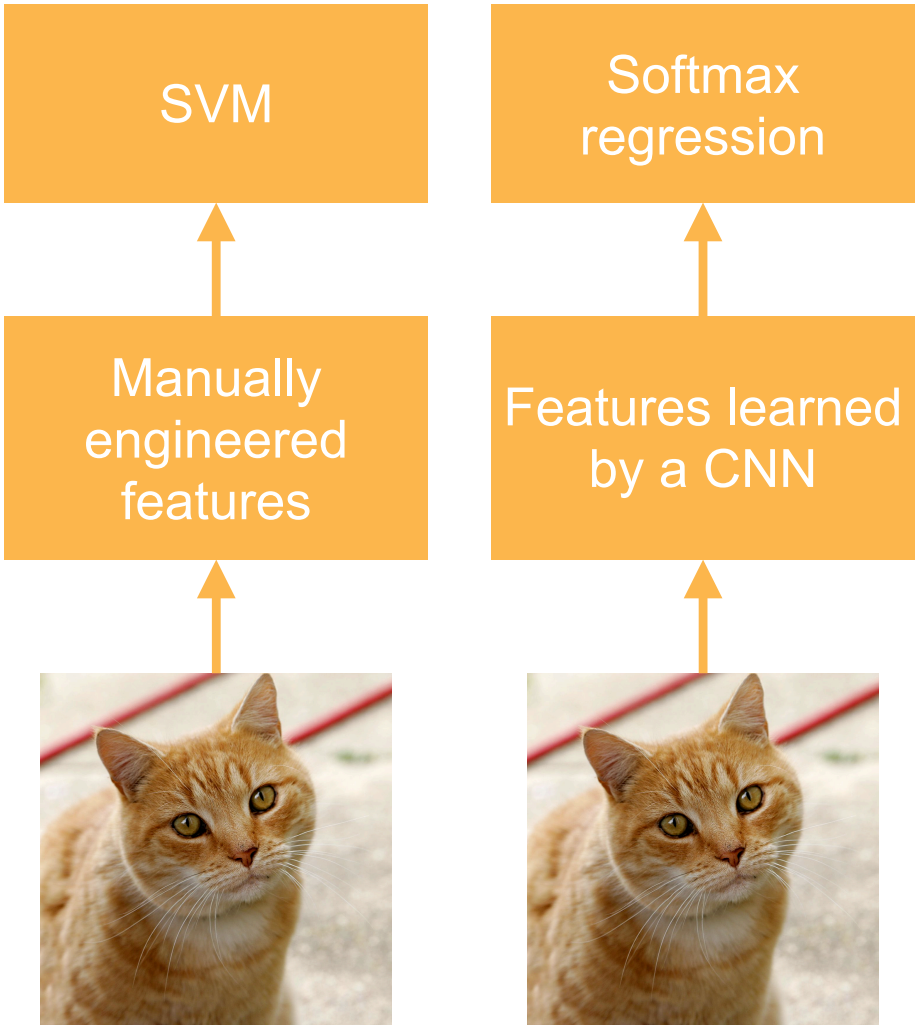

1970
1980
1990
2000
2010
2020
Data (samples)
RAM
CPU
10x
10x
100x
100x
1,000x
10^2 (e.g. iris)
10^3
10^4
OCR
10^{7-8} web
10^{10} advertising
10^{12} social nets
Neural Nets
deep nets
kernel methods
1kB
100kB
10MB
100MB
1GB
100GB
100kF (8080)
1MF (80186)
10MF (80486)
1GF (Intel Core)
100GF NVIDIA
>1PF (NVIDIA A6000)
10x
10x
100x
100x
10,000x

ImageNet (2010)

Images	Color images with nature objects	Gray image for hand-written digits
Size	469 x 387	28 x 28
# examples	1.2 M	60 K
# classes	1,000	10

AlexNet

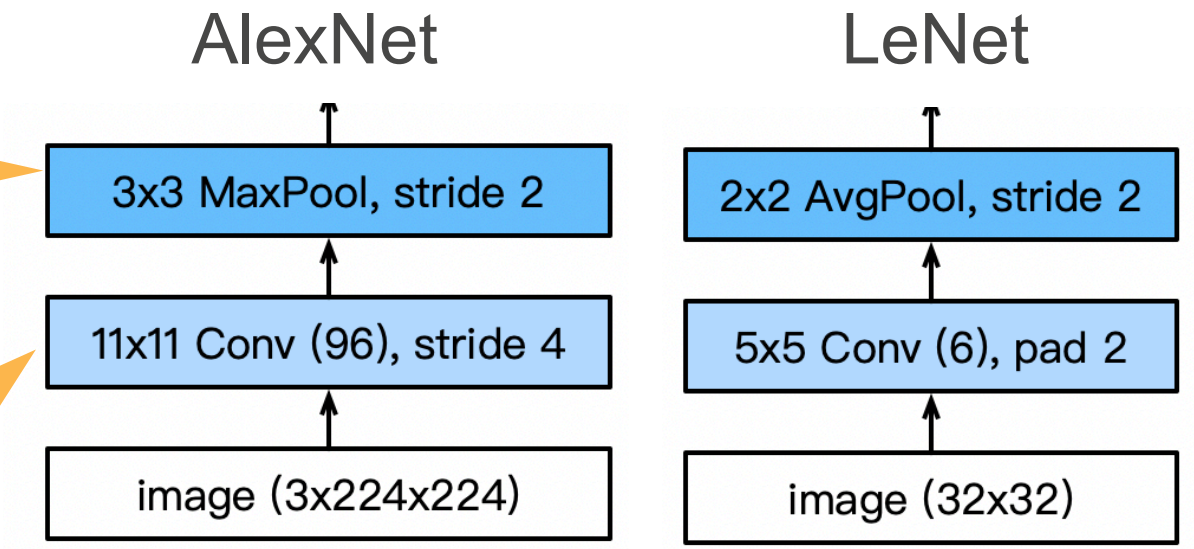
- AlexNet won ImageNet competition in 2012
- Deeper and bigger LeNet
- Key modifications
  - Dropout (regularization)
  - ReLu (training)
  - MaxPooling
- Paradigm shift for computer vision



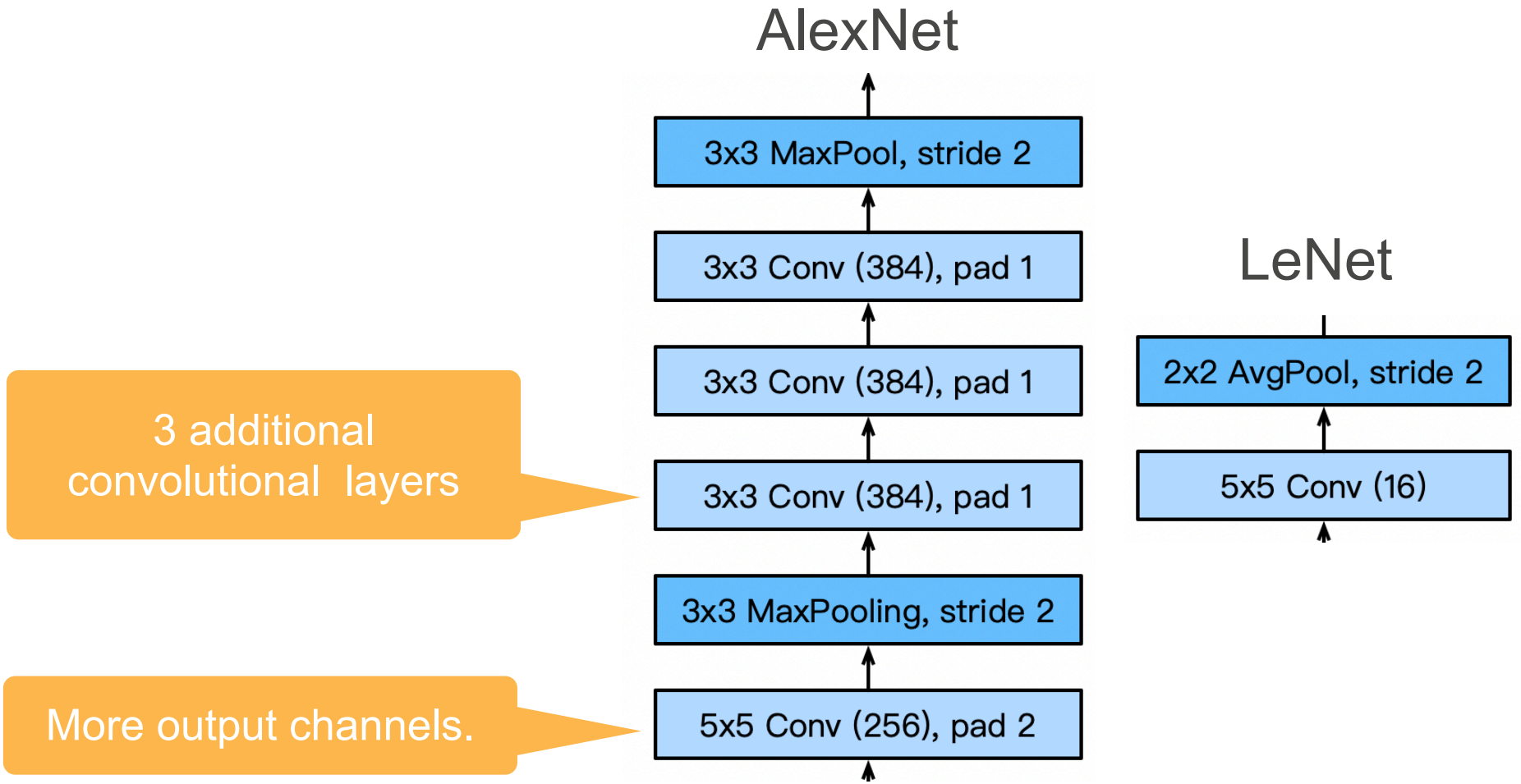
AlexNet Architecture

Larger pool size, change to max pooling

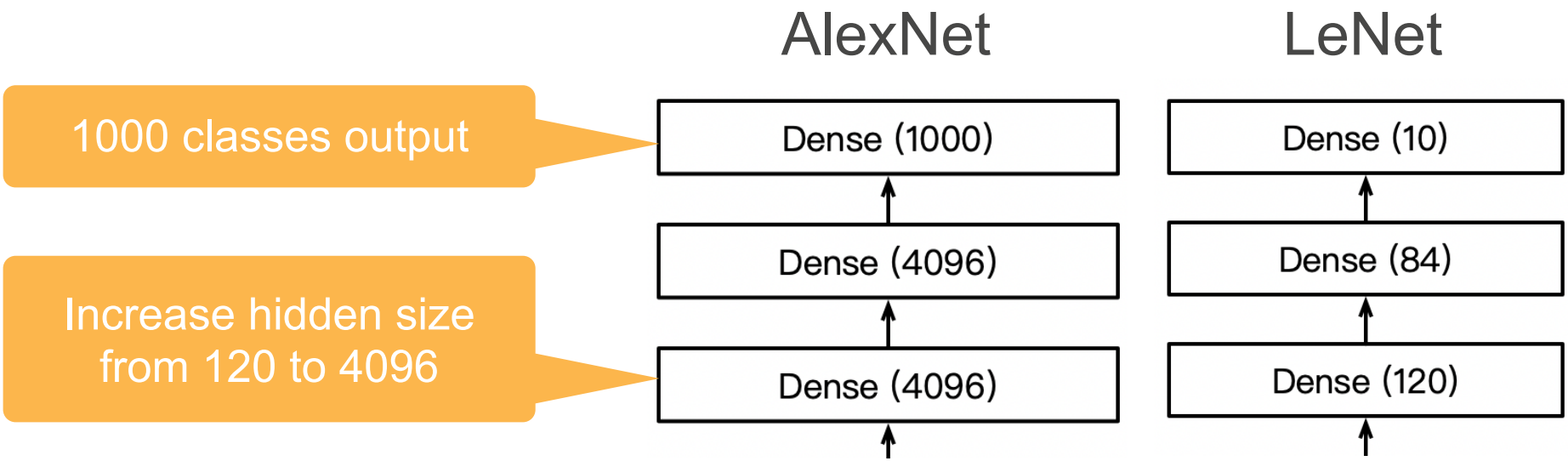
Larger kernel size, stride because of the increased image size, and more output channels.



AlexNet Architecture

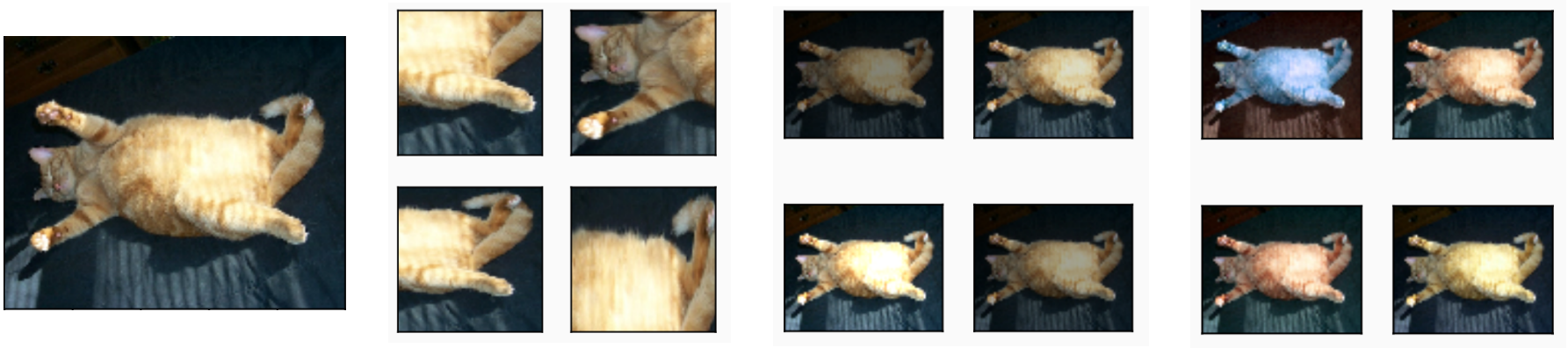


AlexNet Architecture



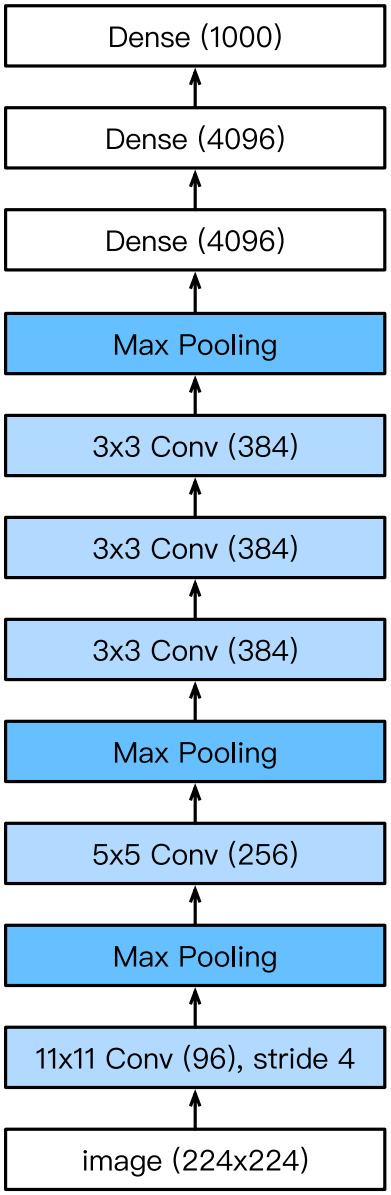
More Tricks

- Change activation function from sigmoid to ReLu (no more vanishing gradient)
- Add a dropout layer after two hidden dense layers (better robustness / regularization)
- Data augmentation

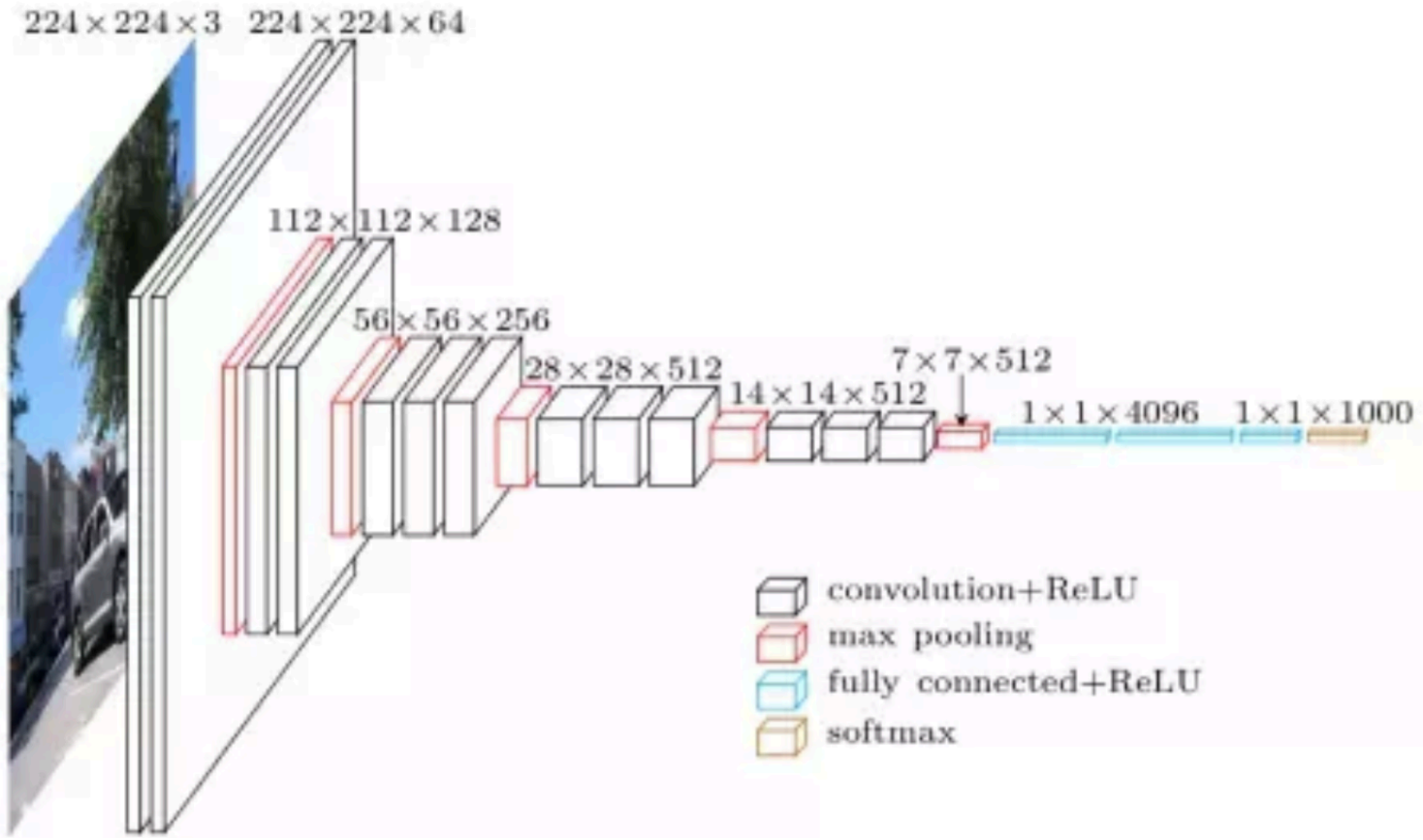


Complexity

	#parameters		FLOP	
	AlexNet	**LeNet**	**AlexNet**	**LeNet**
Conv1	35K	150	101M	1.2M
Conv2	614K	2.4K	415M	2.4M
Conv3-5	3M		445M	
Dense1	26M	0.48M	26M	0.48M
Dense2	16M	0.1M	16M	0.1M
Total	46M	0.6M	1G	4M
Increase	11x	1x	250x	1x



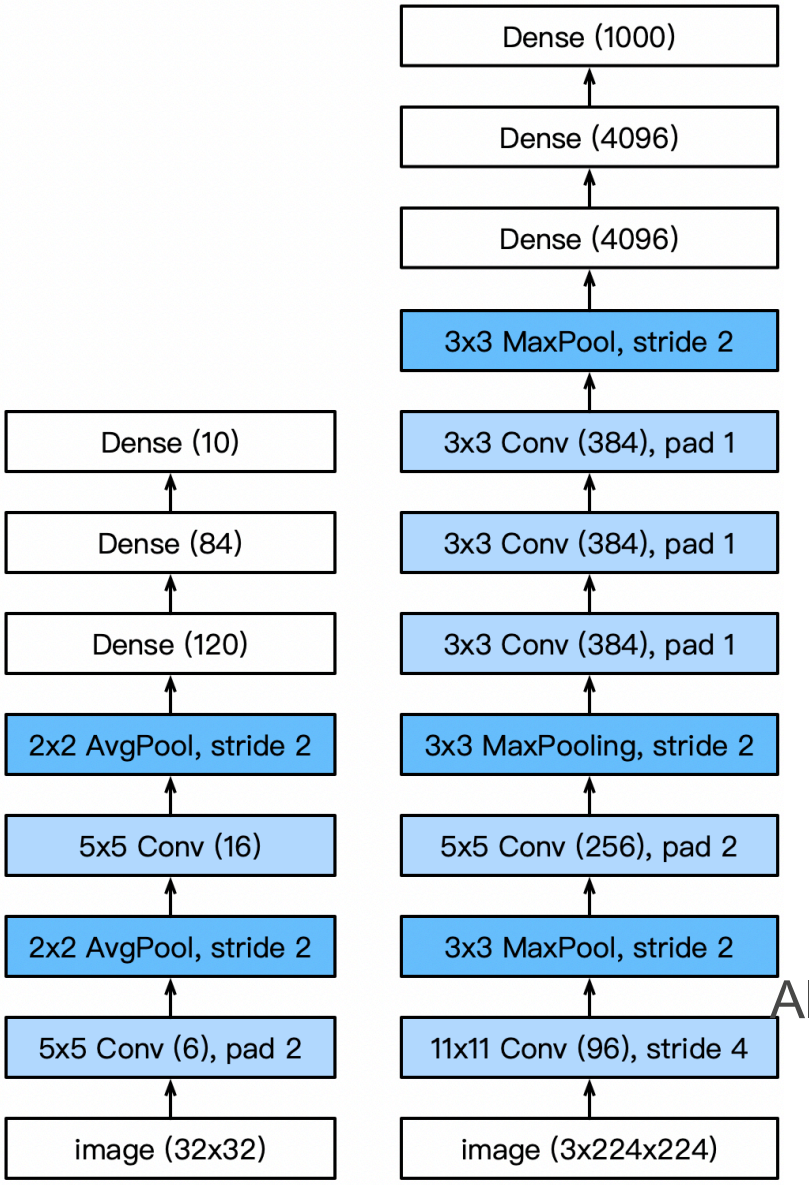
VGG



Visual Geometry Group

VGG

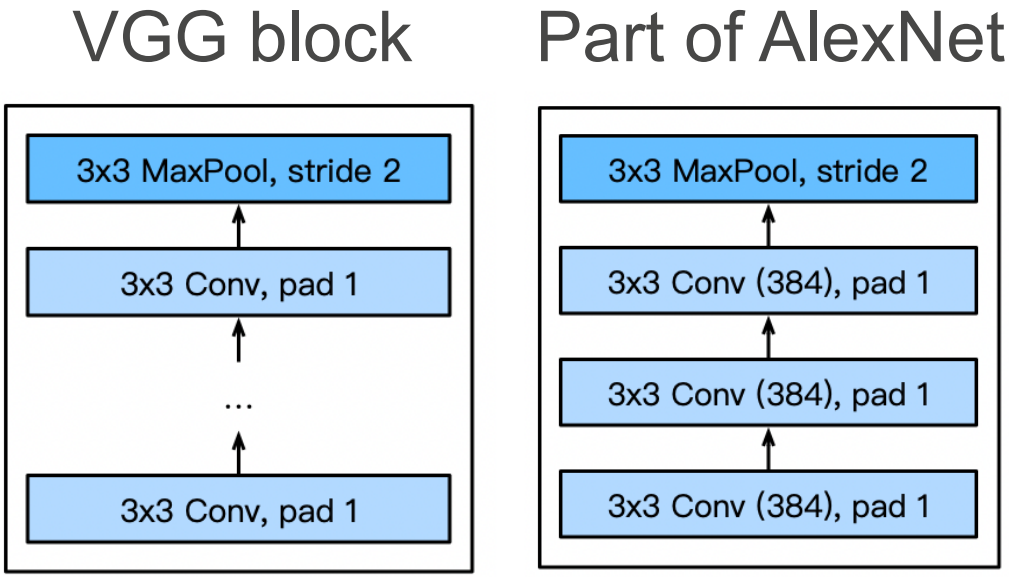
- AlexNet is deeper and bigger than LeNet to get performance
- Go even bigger & deeper?
- Options
  - More dense layers (too expensive)
  - **More** convolutions
  - Group into **blocks**



AlexNet

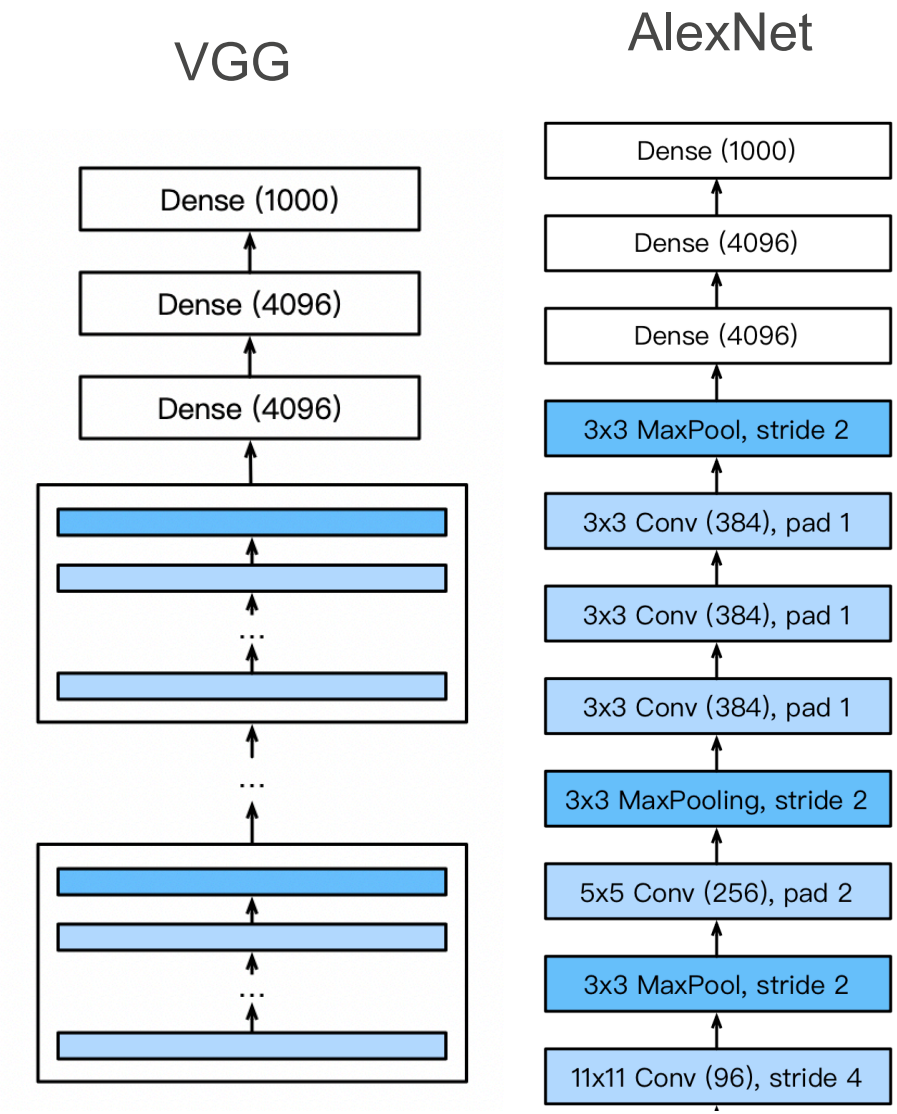
VGG Blocks

- Deeper vs. wider?
  - 5x5 convolutions
  - 3x3 convolutions (more)
  - **Deep & narrow better**
- VGG block
  - *3x3* convolutions (pad 1) **(n layers, m channels)**
  - 2x2 max-pooling (stride 2)



VGG Architecture

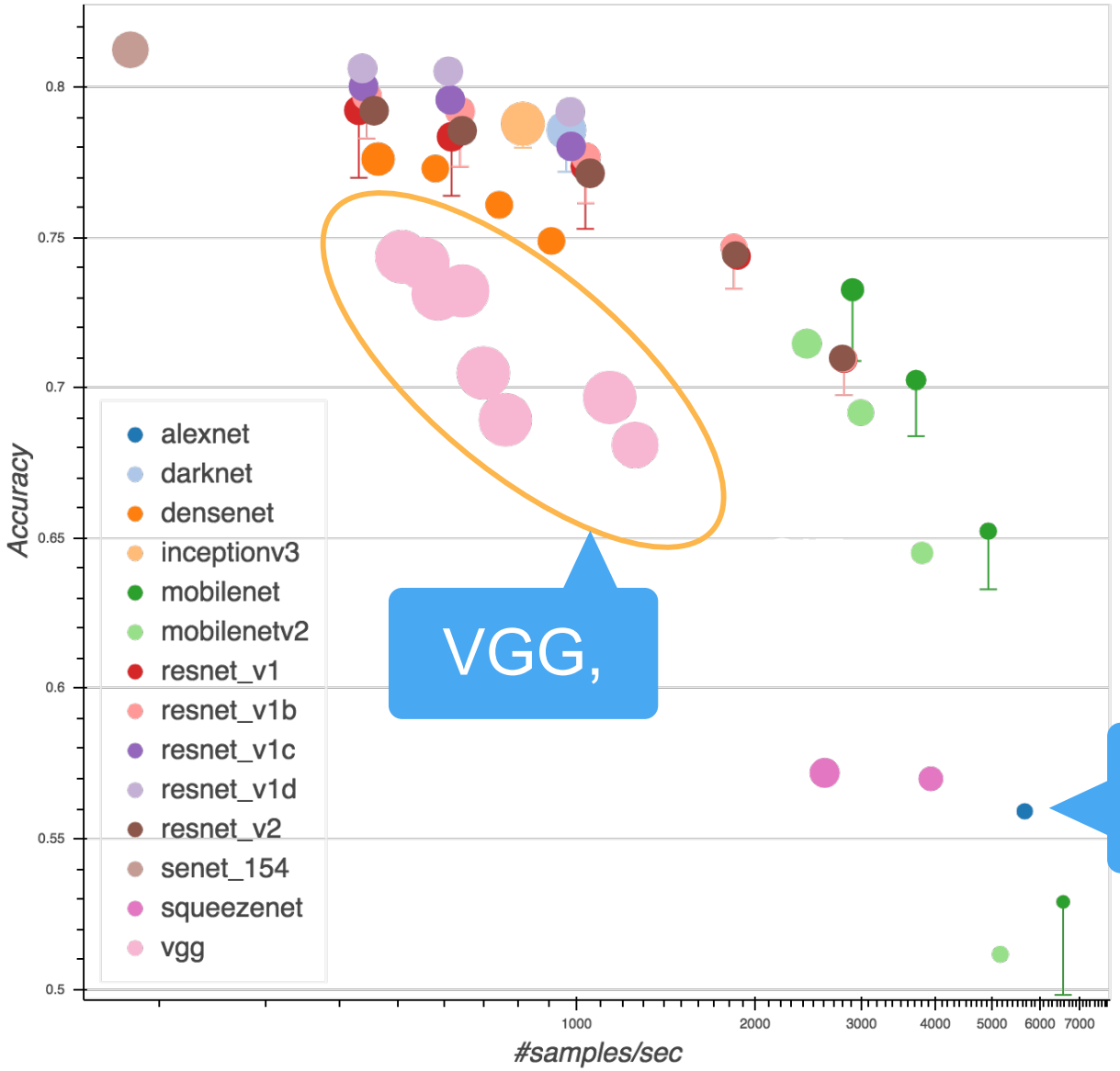
- Multiple VGG blocks followed by dense layers
- Vary the repeating number to get different architectures, such as VGG-16, VGG-19, …



Progress

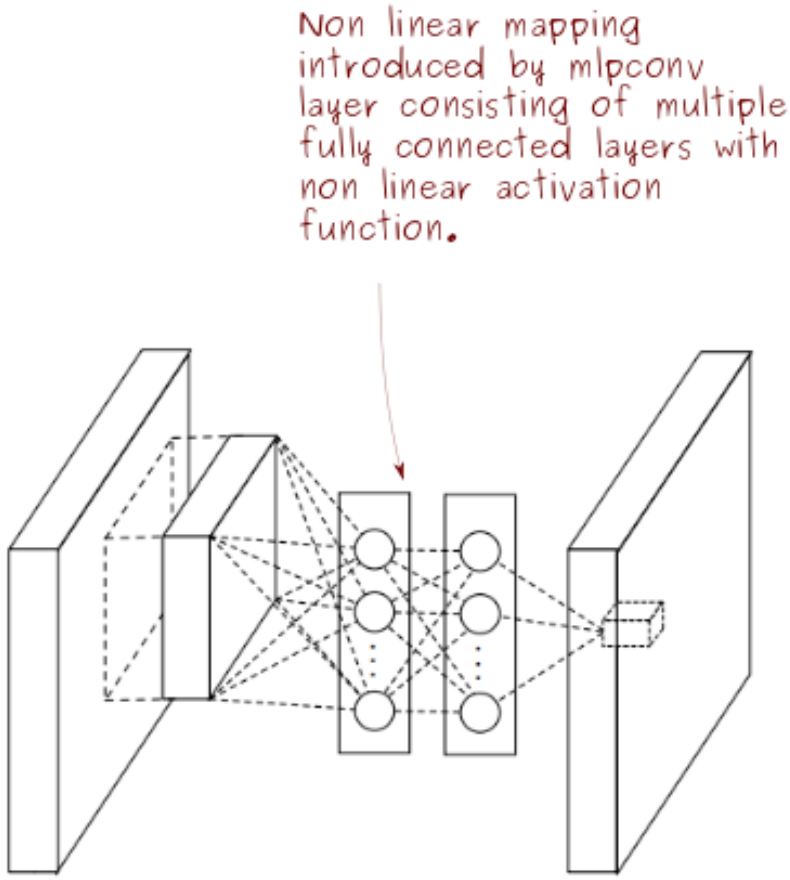
- LeNet (1995)
  - 2 convolution + pooling layers
  - 2 hidden dense layers
- AlexNet
  - Bigger and deeper LeNet
  - ReLu, Dropout, preprocessing
- VGG
  - Bigger and deeper AlexNet (repeated VGG blocks)

Model Zoo

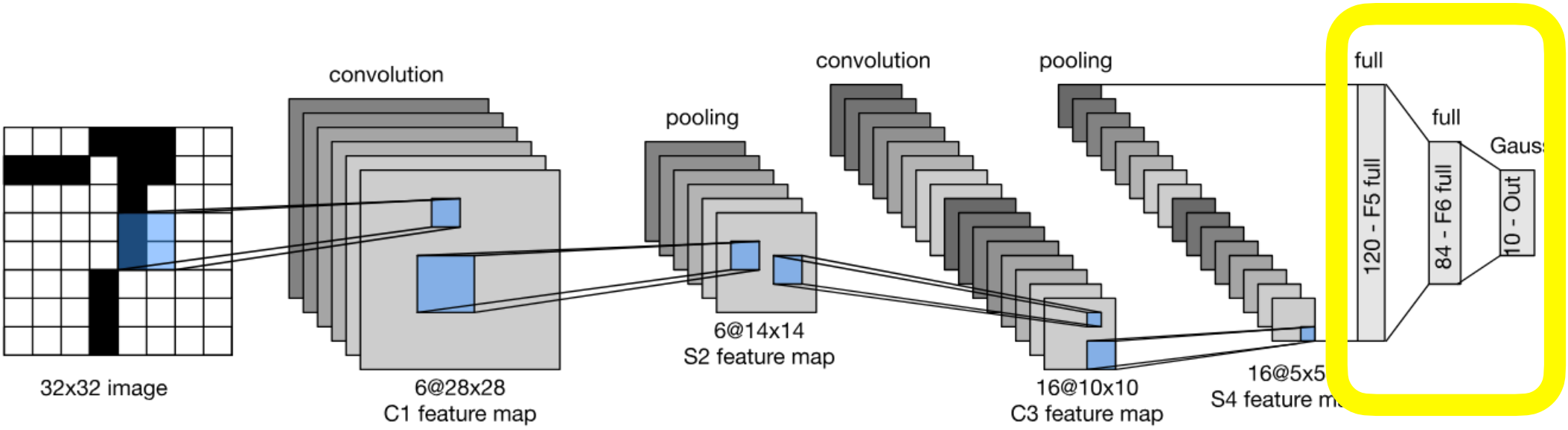


Size of circles for memory footprint

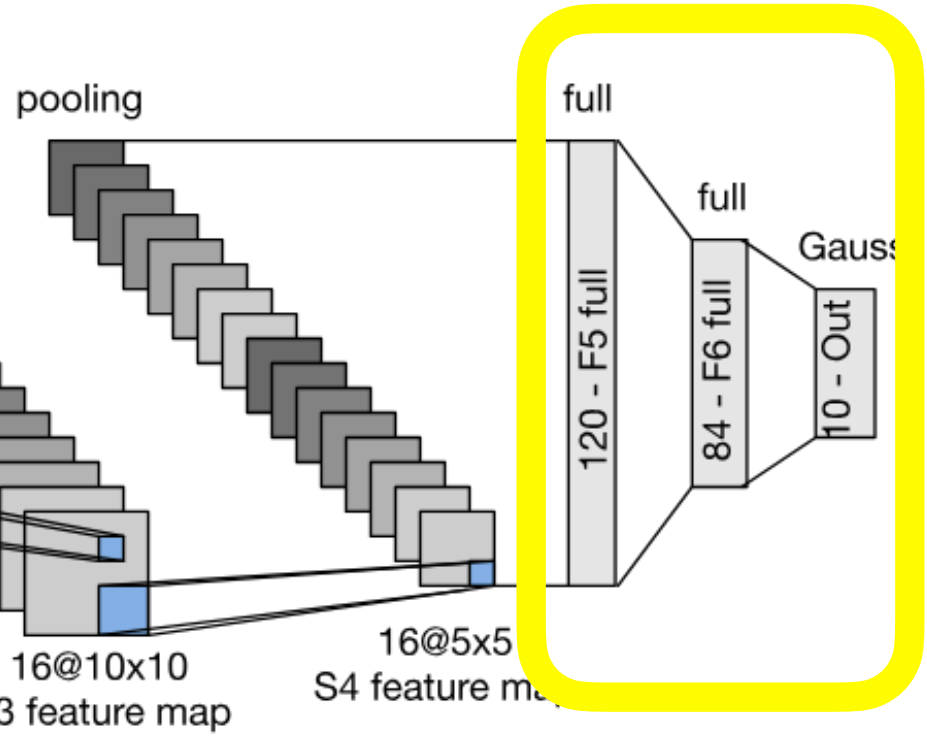
Network in Network



The Curse of the Last Layer(s)



The Last Layer(s). They are too large.



- Convolution layers need relatively few parameters

$$c_i \times c_o \times k^2$$

- Last layer needs many parameters for n classes

$$c \times m_w \times m_h \times n$$

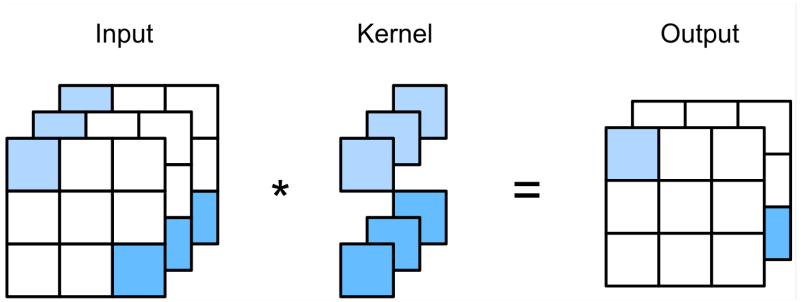
- LeNet 16x5x5x120 = 48k
- AlexNet 256x5x5x4096 = 26M
- VGG 512x7x7x4096 = 102M

VGG parameters

```
sequential1 output shape: (1, 64, 112, 112)
sequential2 output shape: (1, 128, 56, 56)
sequential3 output shape: (1, 256, 28, 28)
sequential4 output shape: (1, 512, 14, 14)
sequential5 output shape: (1, 512, 7, 7)
dense0 output shape:      (1, 4096)
dropout0 output shape:    (1, 4096)
dense1 output shape:      (1, 4096)
dropout1 output shape:    (1, 4096)
dense2 output shape:      (1, 10)
```

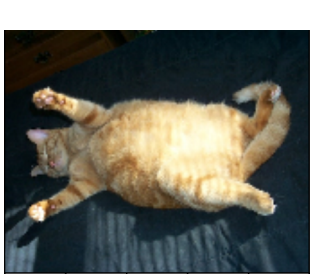
Breaking the Curse of the Last Layer

- Key Idea
  - **Get rid of the fully connected last layer(s)**
  - Convolutions and pooling reduce resolution (e.g. stride of 2 reduces resolution 4x)
- Implementation details (MLP on pixel level
  - Reduce resolution progressively
  - Increase number of channels
  - Use **1x1 convolutions**
  - (they only act per pixel)
- **Global average pooling in the end**

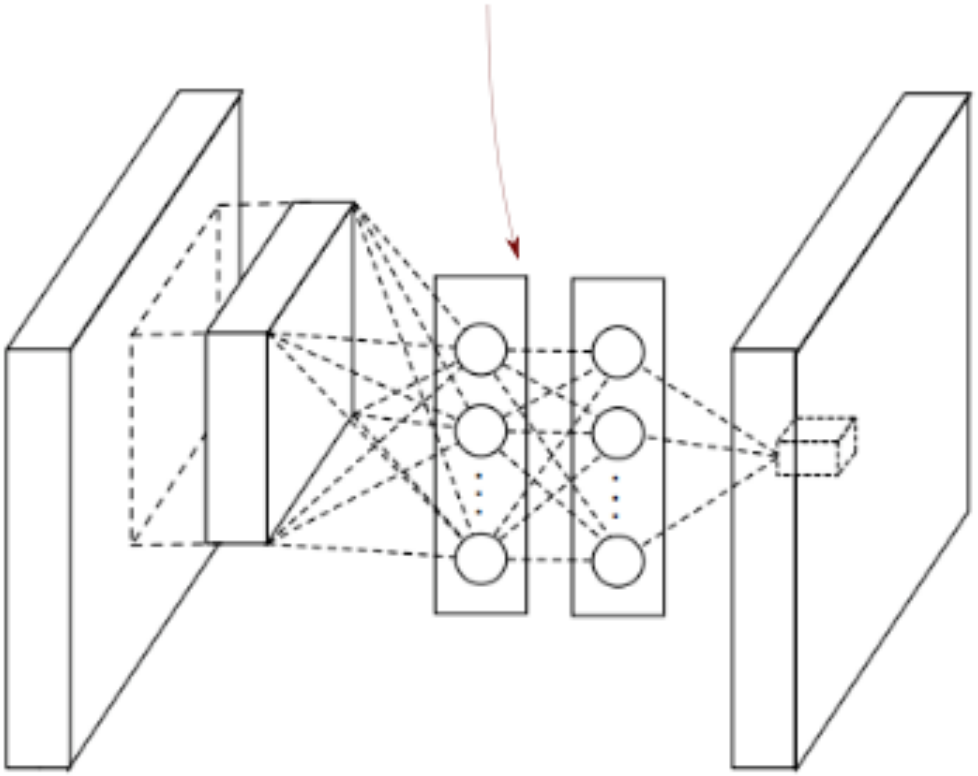


What's a 1x1 convolution anyway?

- Extreme case
  1x1 image with n channels
- Equivalent to MLP
- Pooling allows for translation invariance of detection (e.g. 5x5)

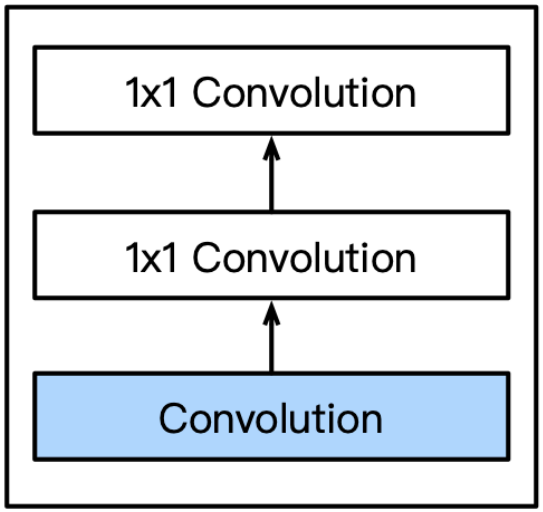


Non linear mapping introduced by mlpconv layer consisting of multiple fully connected layers with non linear activation function.

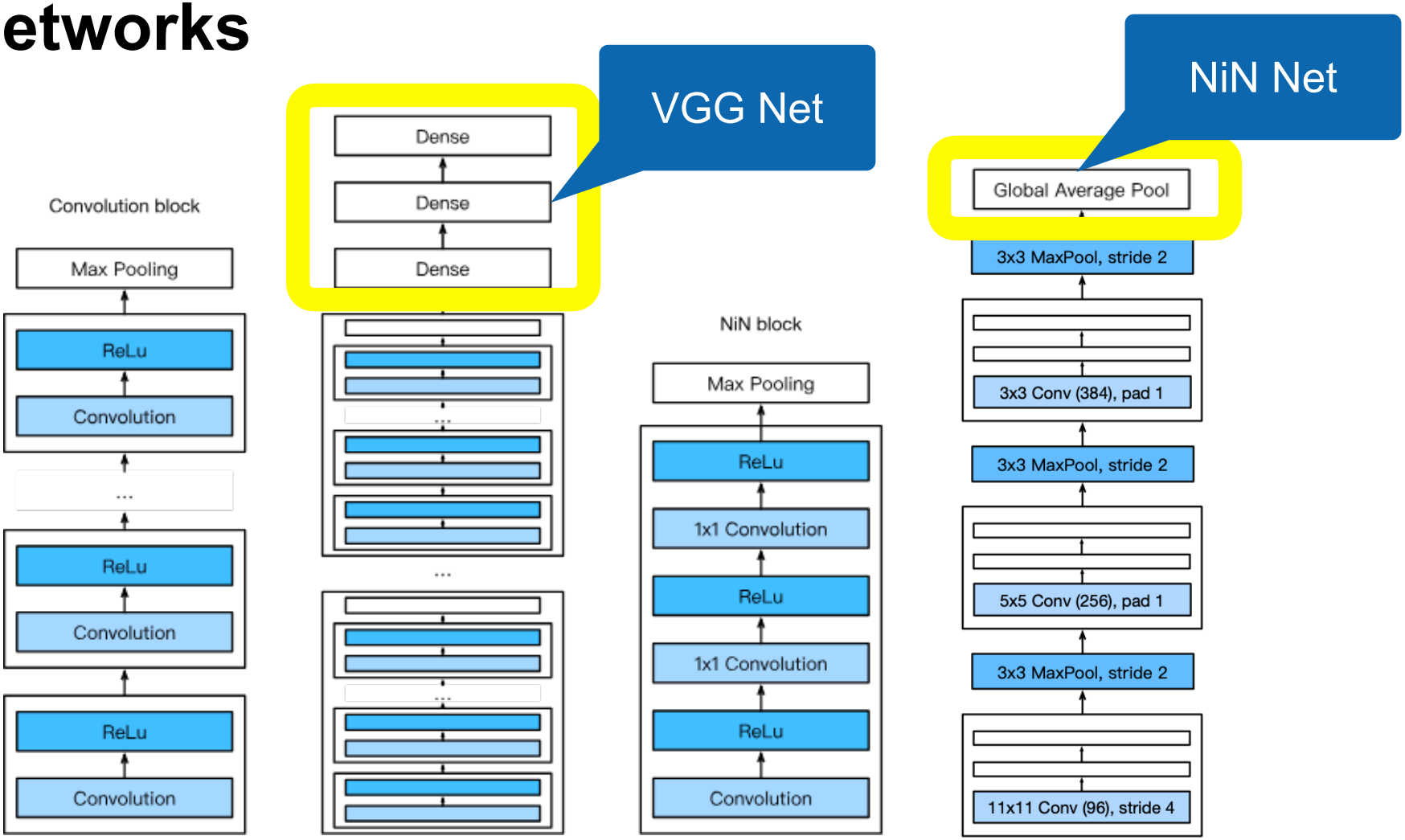


NiN Block

- A convolutional layer
  - kernel size, stride, and padding are hyper-parameters
- Following by two 1x1 convolutions
  - 1 stride and no padding, share the same output channels as first layer
  - Act as dense layers

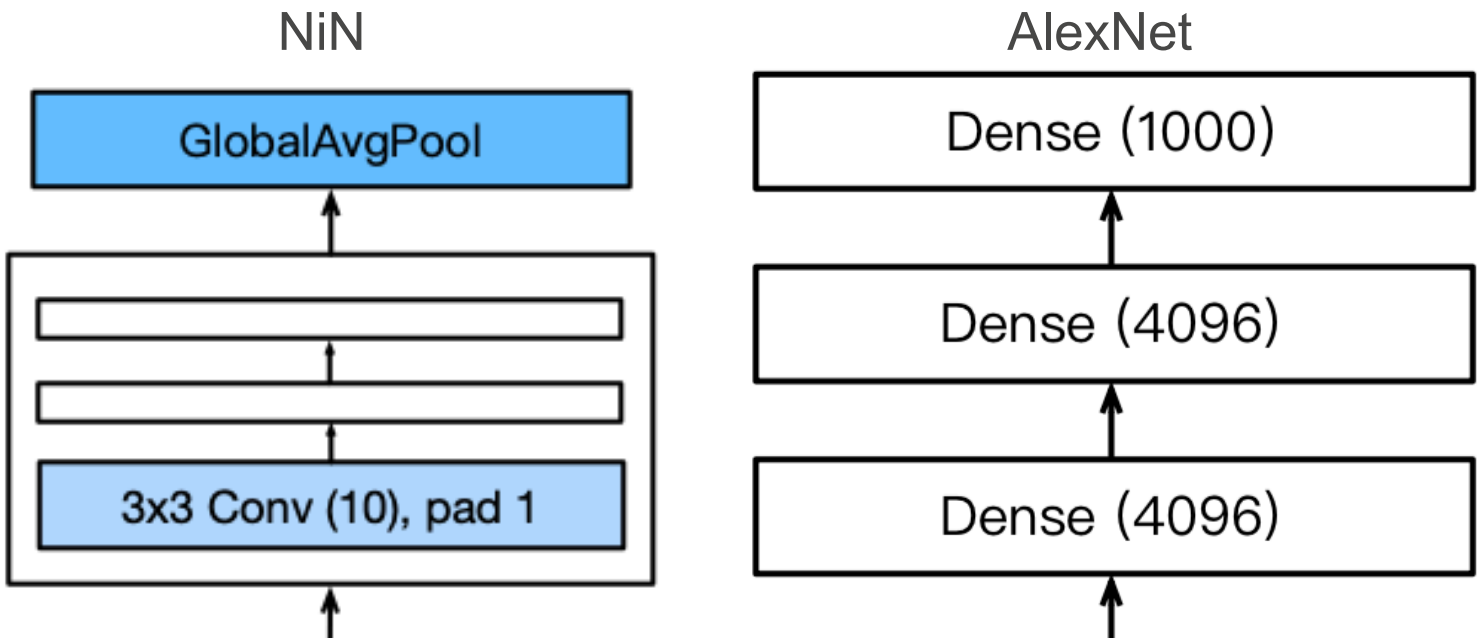


NiN Networks



NiN Last Layers

- Replaced AlexNet's dense layers with a NiN block
- Global average pooling layer to combine outputs



Summary

- Reduce image resolution progressively
- Increase number of channels
- Global average pooling for given number of classes

```
sequential1 output shape: (96, 54, 54)
pool0 output shape:       (96, 26, 26)
sequential2 output shape: (256, 26, 26)
pool1 output shape:       (256, 12, 12)
sequential3 output shape: (384, 12, 12)
pool2 output shape:       (384, 5, 5)
dropout0 output shape:    (384, 5, 5)
sequential4 output shape: (10, 5, 5)
pool3 output shape:       (10, 1, 1)
flatten0 output shape:    (10)
```

NIN dimension reduction

Summary

- **LeNet** (the first convolutional neural network)
- **AlexNet**
  - More of everything
  - ReLu, Dropout, Invariances
- **VGG**
  - Even more of everything (narrower and deeper)
  - Repeated blocks
- **NiN**
  - 1x1 convolutions + global pooling instead of dense