

Introduction to Deep Learning

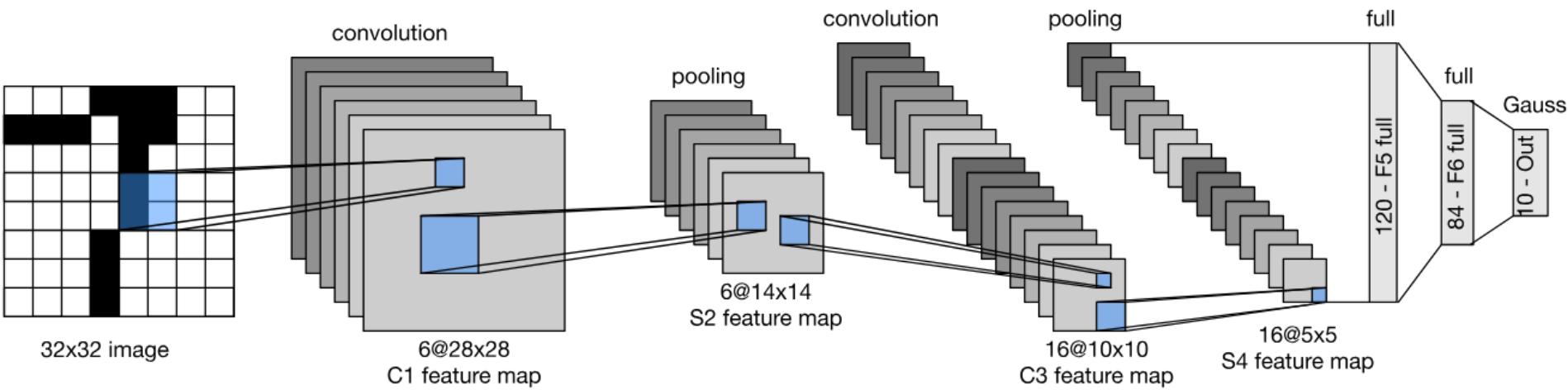
12. LeNet, AlexNet, VGG and NiN

STAT 157, Spring 2019, UC Berkeley

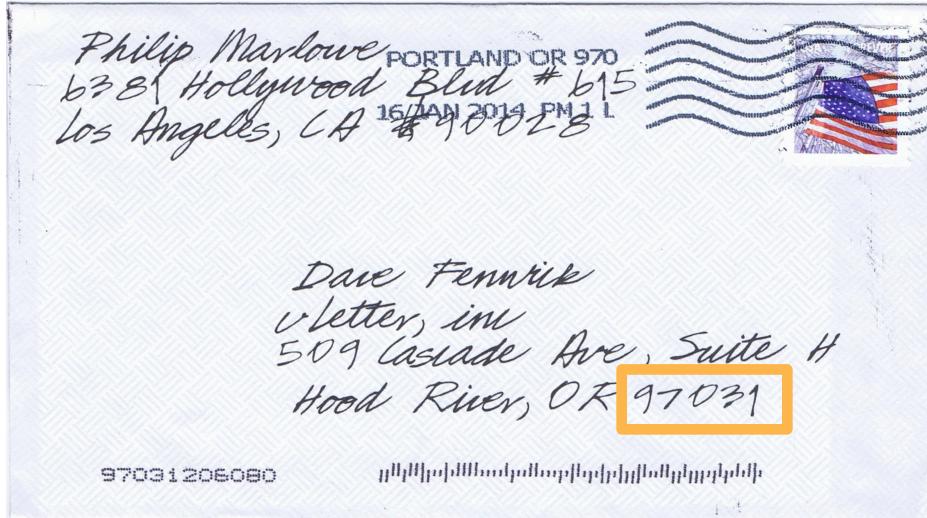
Alex Smola and Mu Li

courses.d2l.ai/berkeley-stat-157

LeNet Architecture



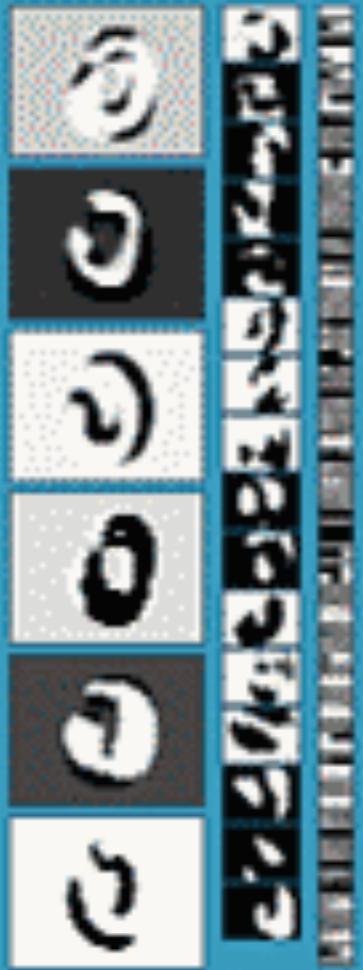
Handwritten Digit Recognition



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





AT&T *LeNet 5* RESEARCH

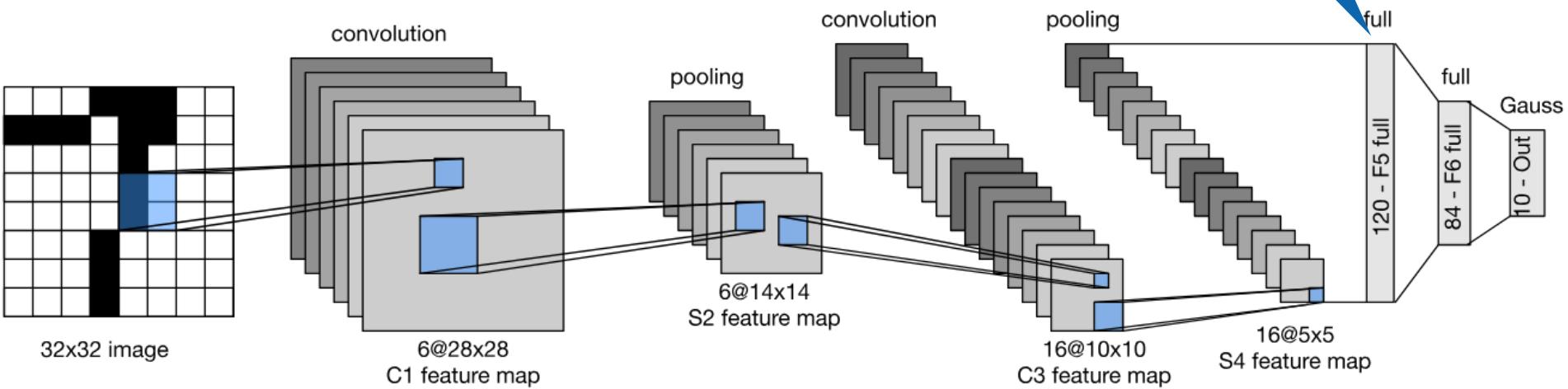
answer: 0

0
103

A 28x28 pixel grayscale image of a handwritten digit '0'. The digit is dark gray and has a slightly irregular shape. It is centered on a white background with a subtle dotted grid pattern.

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

Expensive if we
have many
outputs



LeNet in MXNet

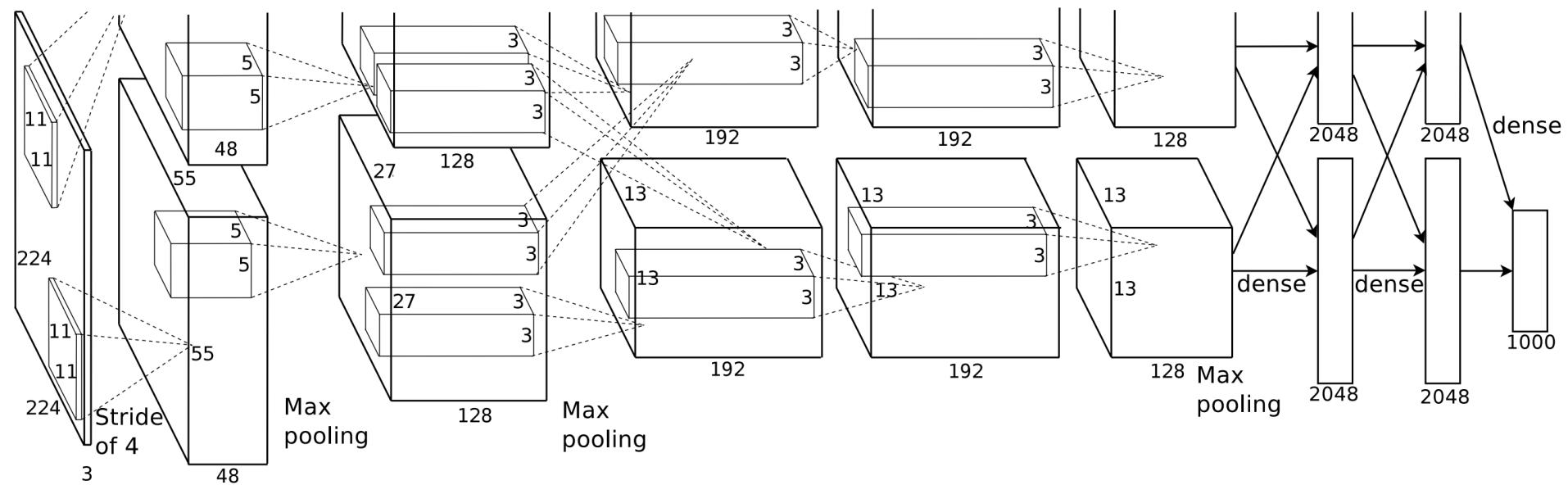
```
net = nn.Sequential()
net.add(nn.Conv2D(channels=6, kernel_size=5, activation='sigmoid'),
        nn.AvgPool2D(pool_size=2),
        nn.Conv2D(channels=16, kernel_size=5, activation='sigmoid'),
        nn.AvgPool2D(pool_size=2),
        nn.Dense(120, activation='sigmoid'),
        nn.Dense(84, activation='sigmoid'),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

loss = gluon.loss.SoftmaxCrossEntropyLoss()

(size and shape inference is automatic)
```



AlexNet



2001

Learning with Kernels

Support Vector Machines, Regularization,
Optimization, and Beyond

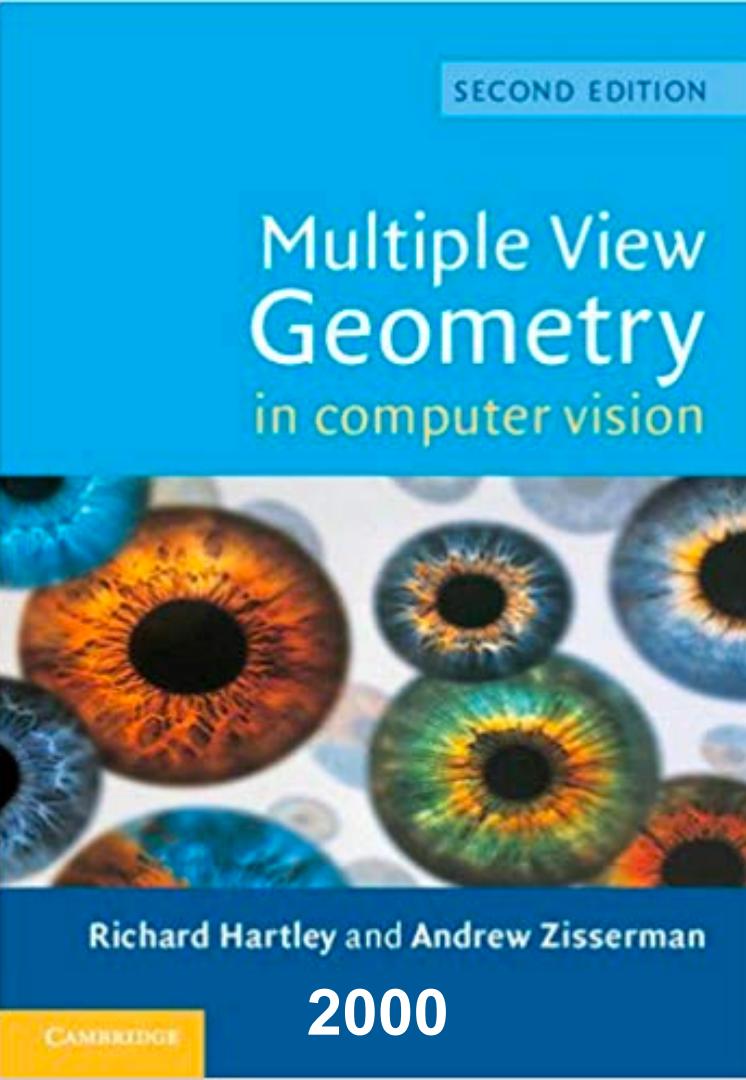
Bernhard Schölkopf and Alexander J. Smola



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

- 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)	10^2 (e.g. iris)	10^3	10^4 OCR	10^{7-8} web	10^{10} advertising	10^{12} social nets
RAM	1kB	100kB	10MB	100MB	1GB	100GB
CPU	100kF (8080)	1MF (80186)	10MF (80486)	1GF (Intel Core)	100GF NVIDIA	$>1PF$ (8xP3 Volta)



Hardware

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Data (samples)	10^2 (e.g. iris)	$10x$ 10^3	$10x$ 10^4 OCR	$100x$ 10^{7-8} web	$100x$ 10^{10} advertising	$1,000x$ 10^{12} social nets
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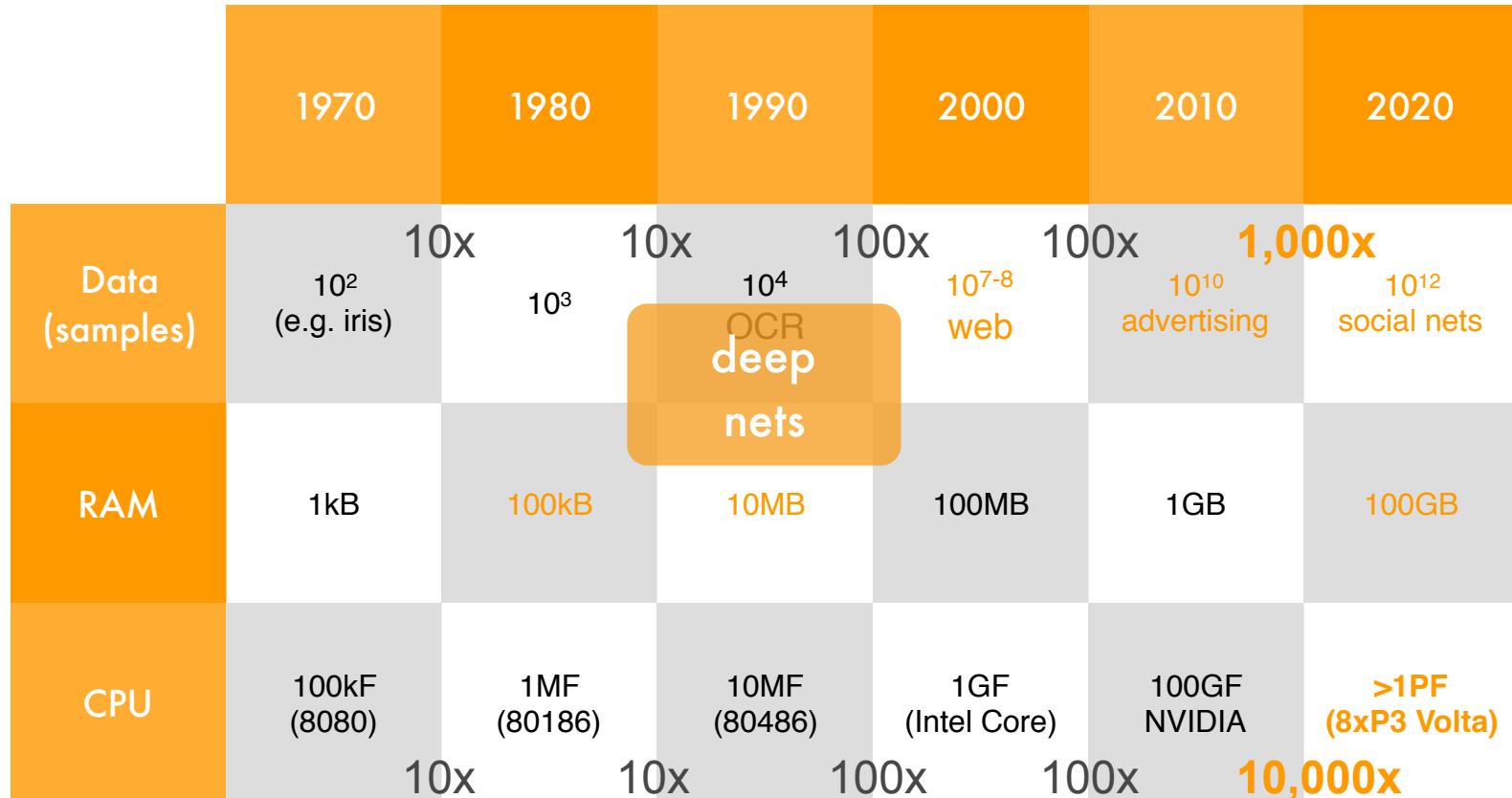


Hardware

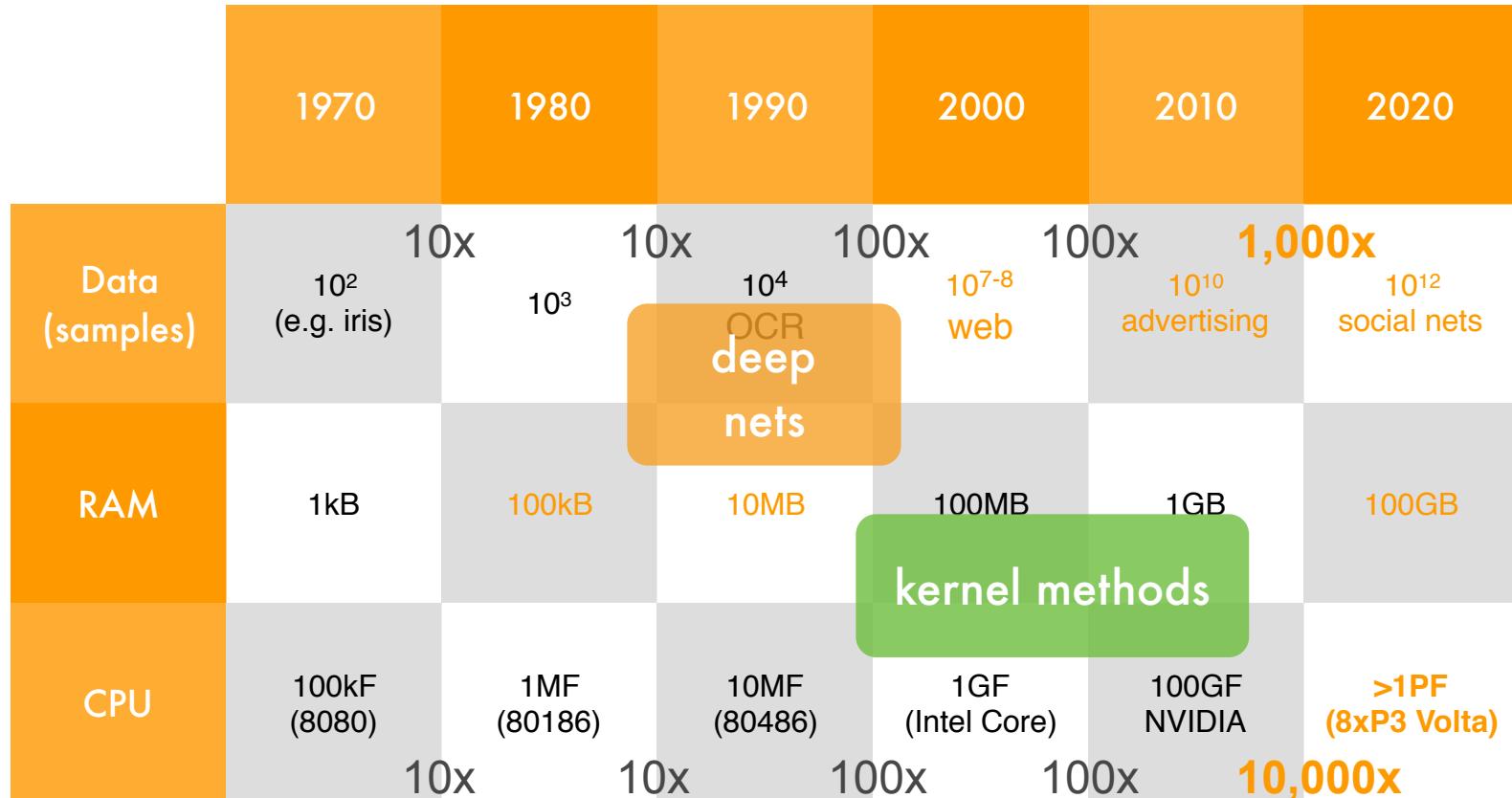
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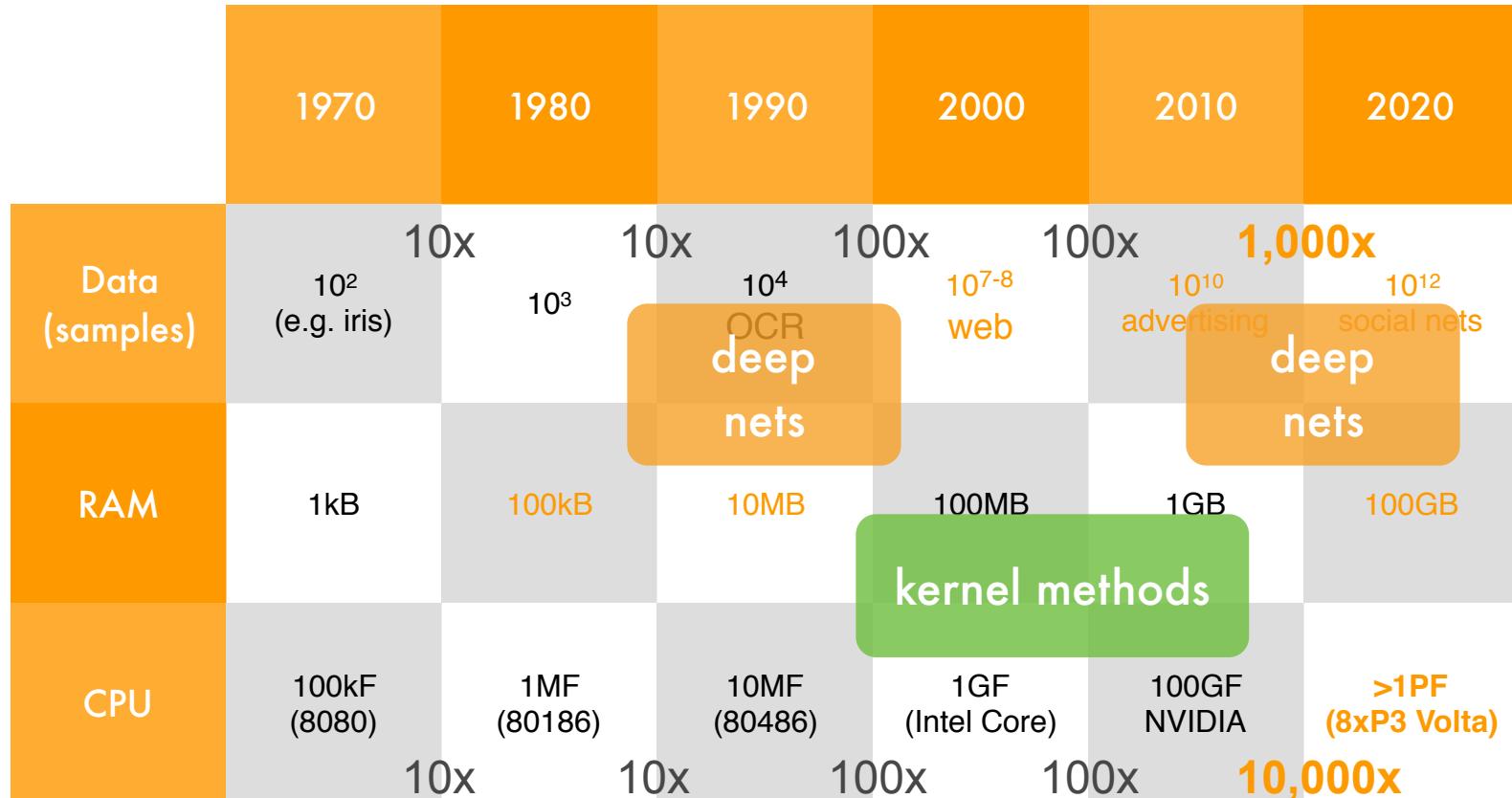
Hardware



Hardware



Hardware



ImageNet (2010)

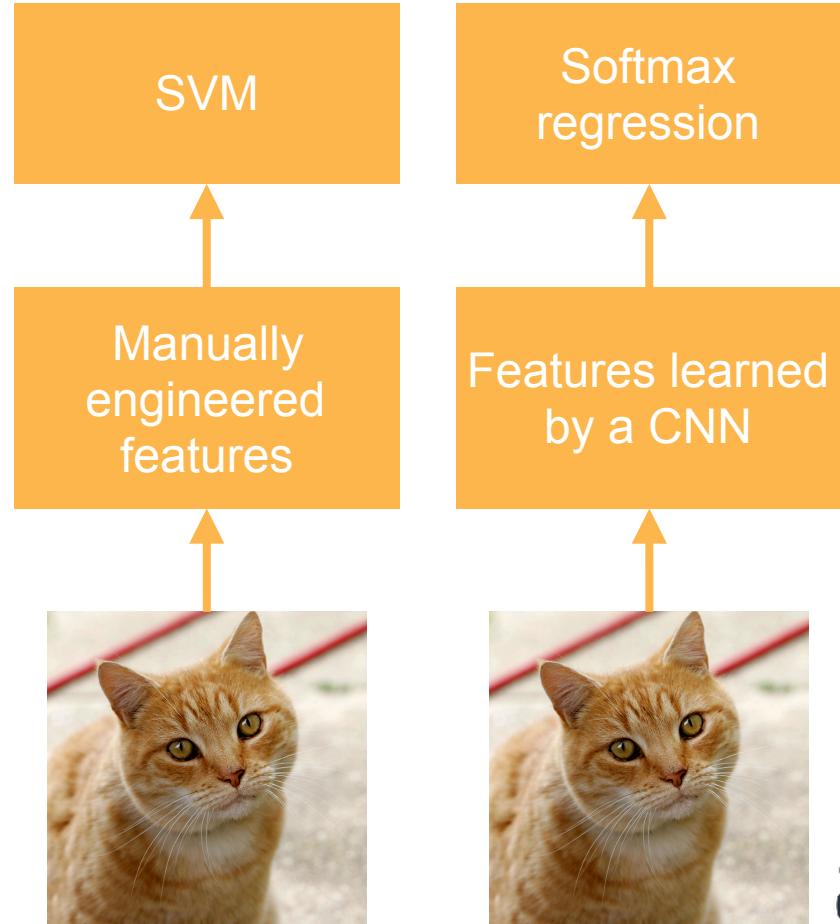


2 2 2 2 2 2 2 2 2 2
3 3 3 3 3 3 3 3 3 3
4 4 4 4 4 4 4 4 4 4
5 5 5 5 5 5 5 5 5 5
6 6 6 6 6 6 6 6 6 6

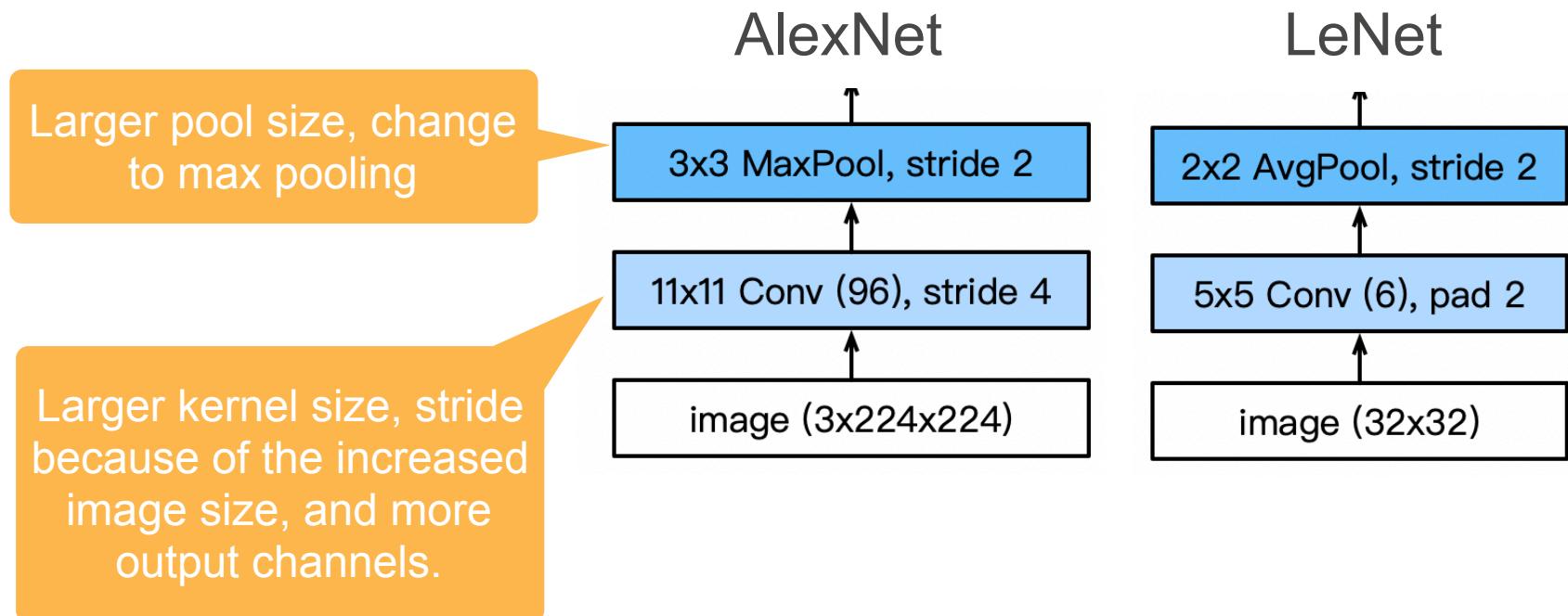
Images	Color images with nature objects	Gray image for handwritten digits
Size	469 x 387	28 x 28
# examples	1.2 M	60 K
# classes	1,000	10

AlexNet

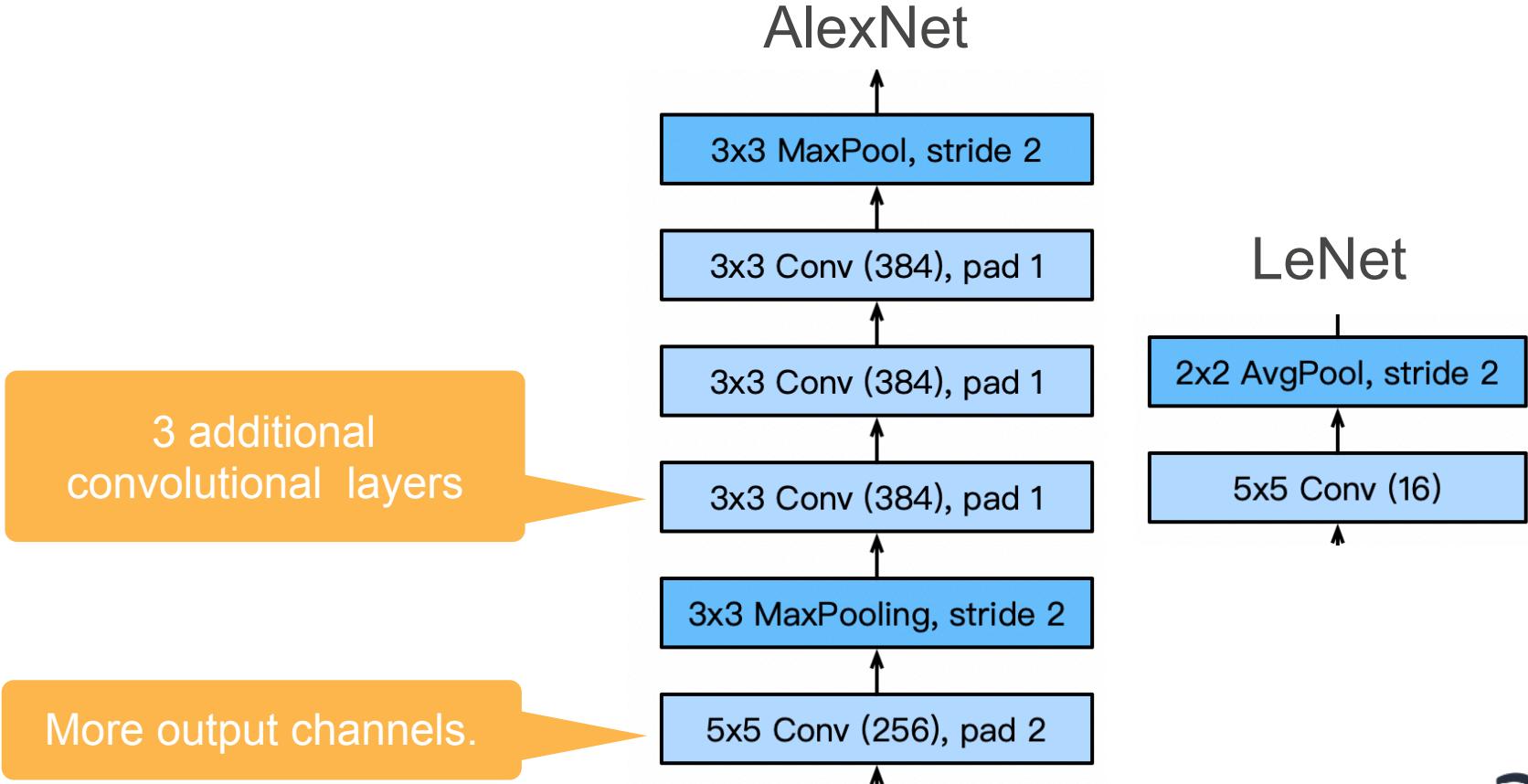
- AlexNet won ImageNet competition in 2012
- Deeper and bigger LeNet
- Key modifications
 - Dropout (regularization)
 - ReLu (training)
 - MaxPooling
- Paradigm shift for computer vision



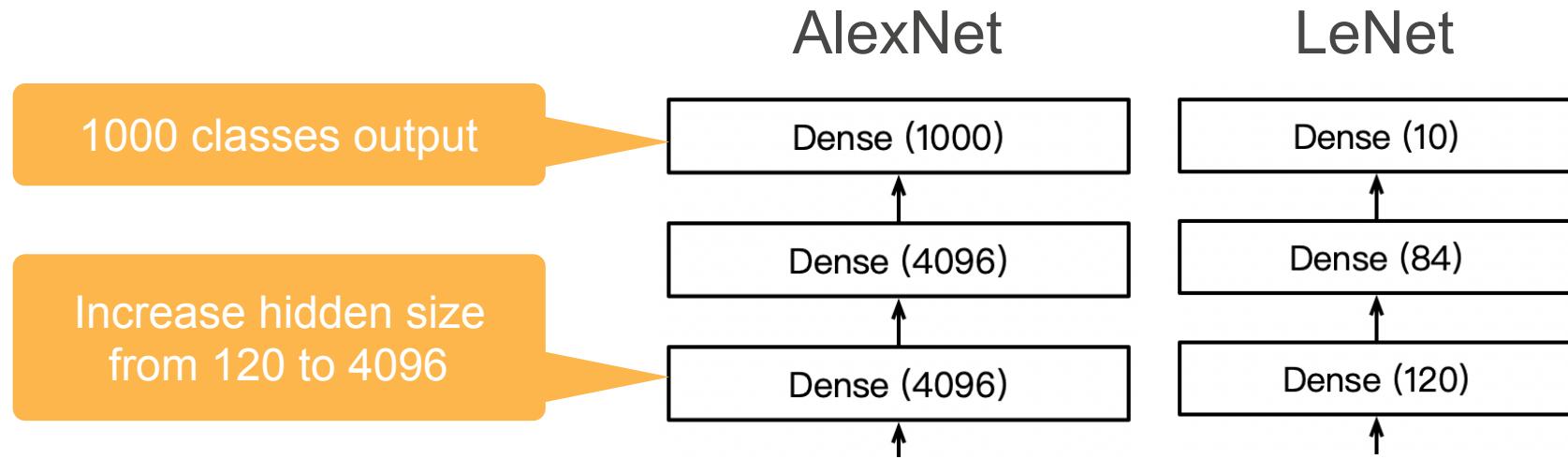
AlexNet Architecture



AlexNet Architecture



AlexNet Architecture



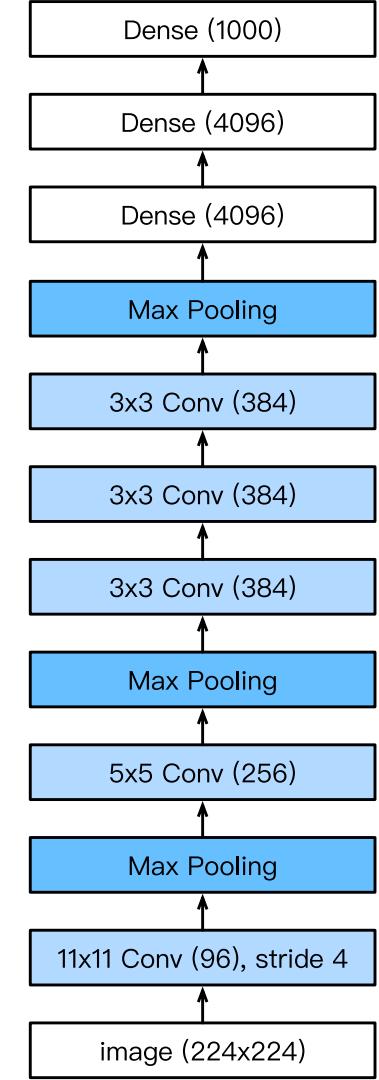
More Tricks

- 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

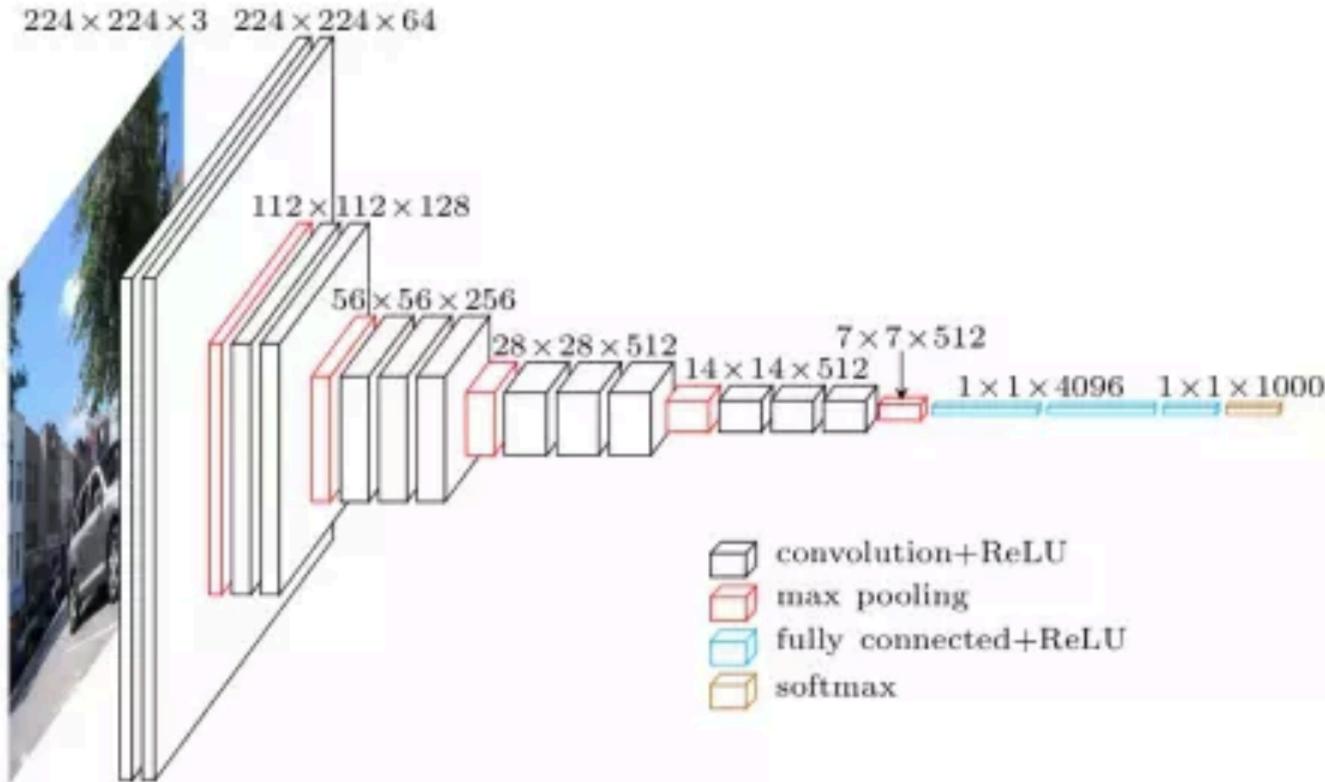


Complexity

	#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

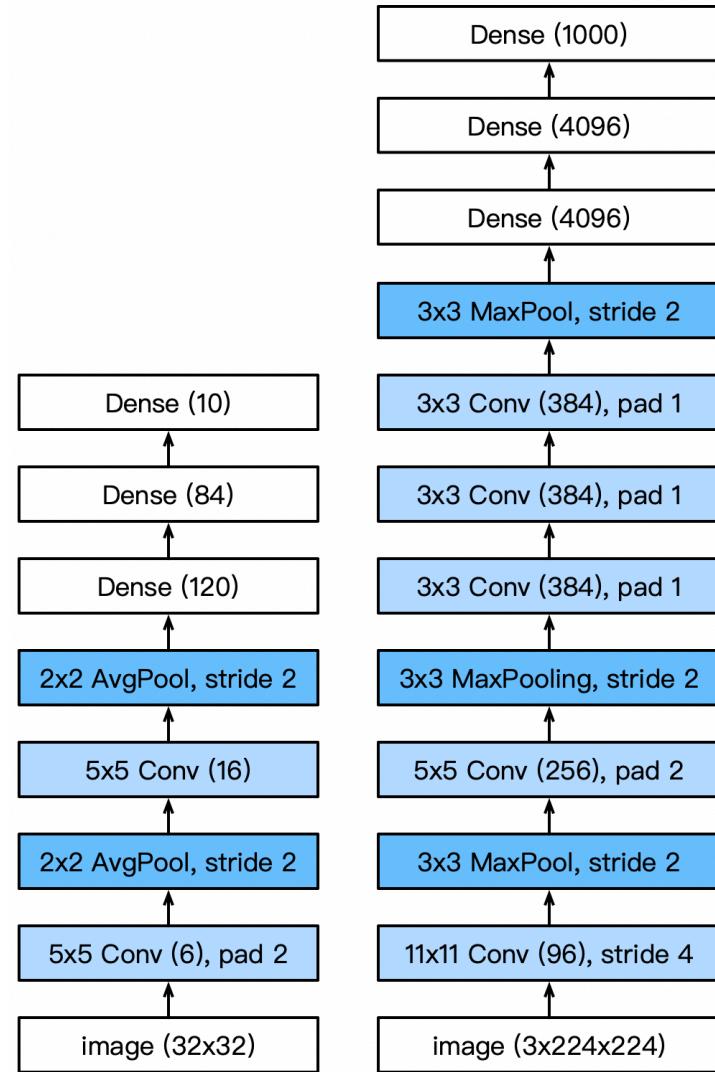


VGG



VGG

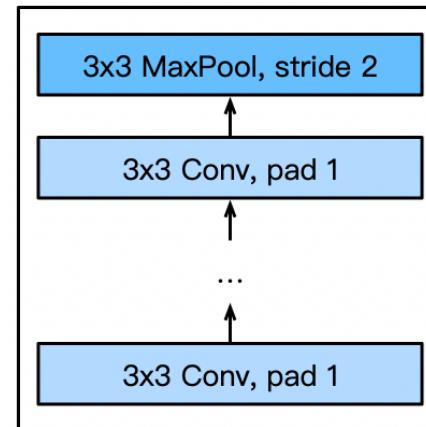
- AlexNet is deeper and bigger than LeNet to get performance
- Go even bigger & deeper?
- Options
 - More dense layers (too expensive)
 - **More convolutions**
 - Group into **blocks**



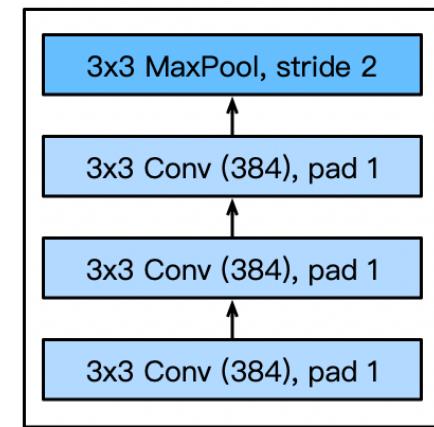
VGG Blocks

- 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 block

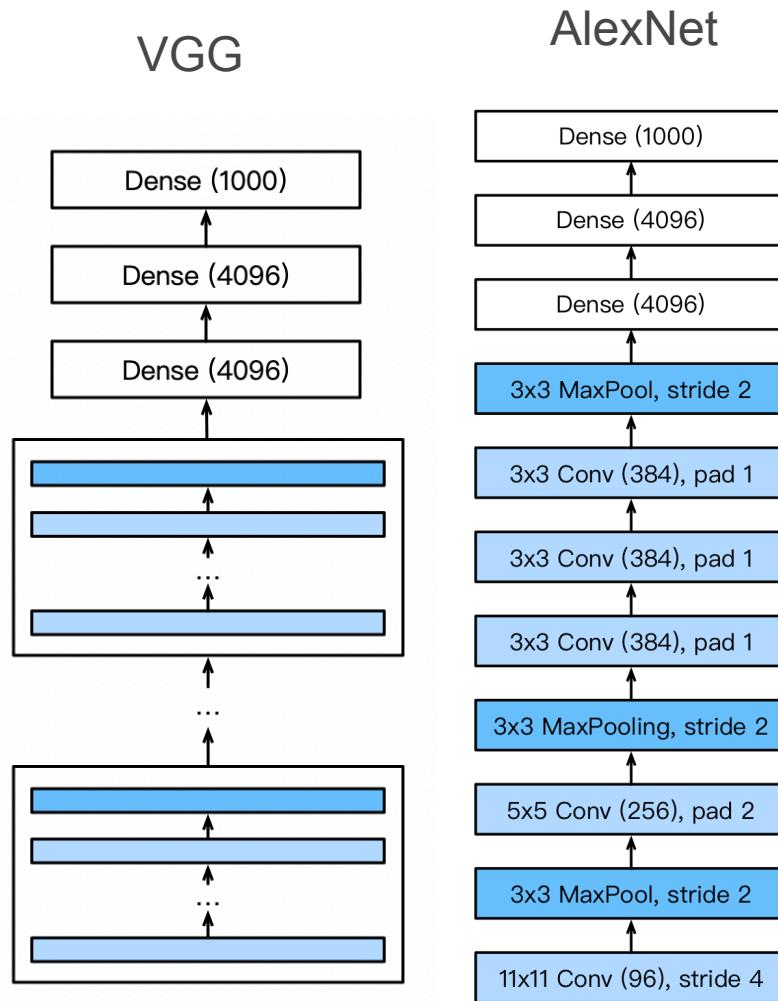


Part of AlexNet



VGG Architecture

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



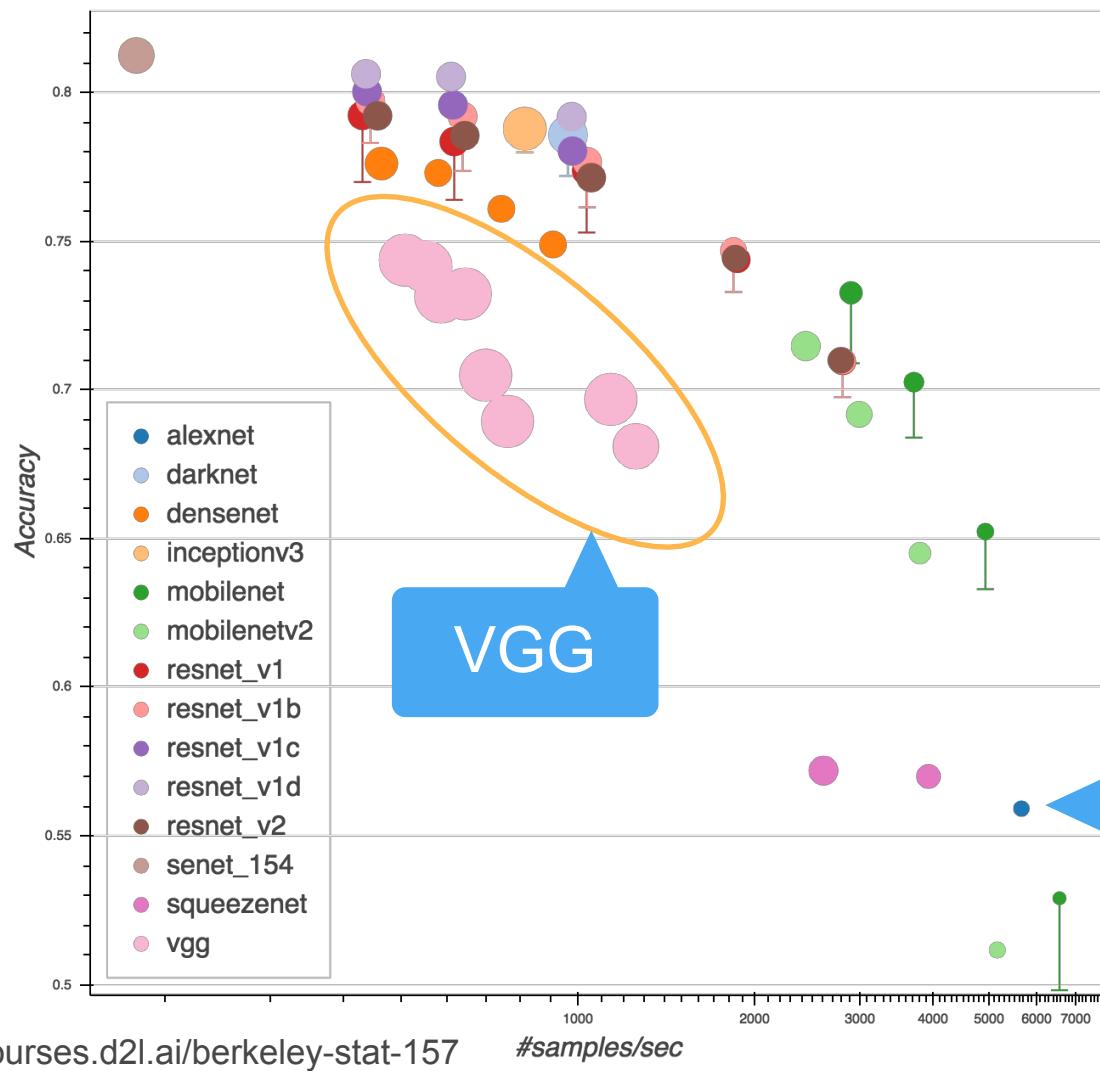
Progress

- 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)



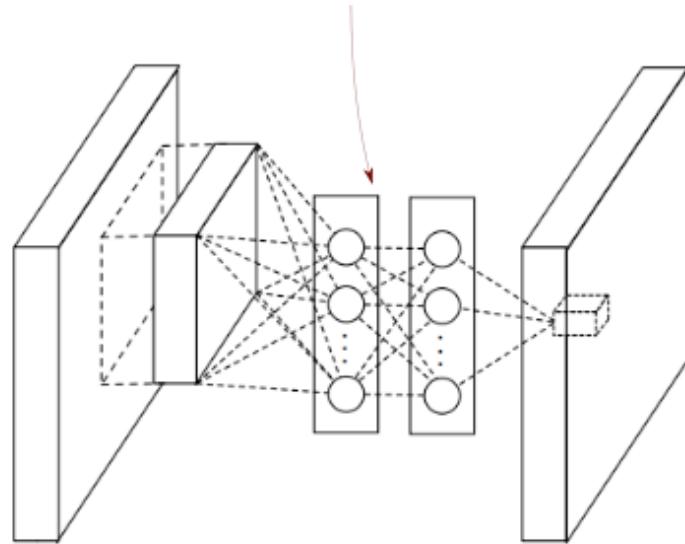
GluonCV Model Zoo

[gluon-cv.mxnet.io/
model_zoo/
classification.html](http://gluon-cv.mxnet.io/model_zoo/classification.html)

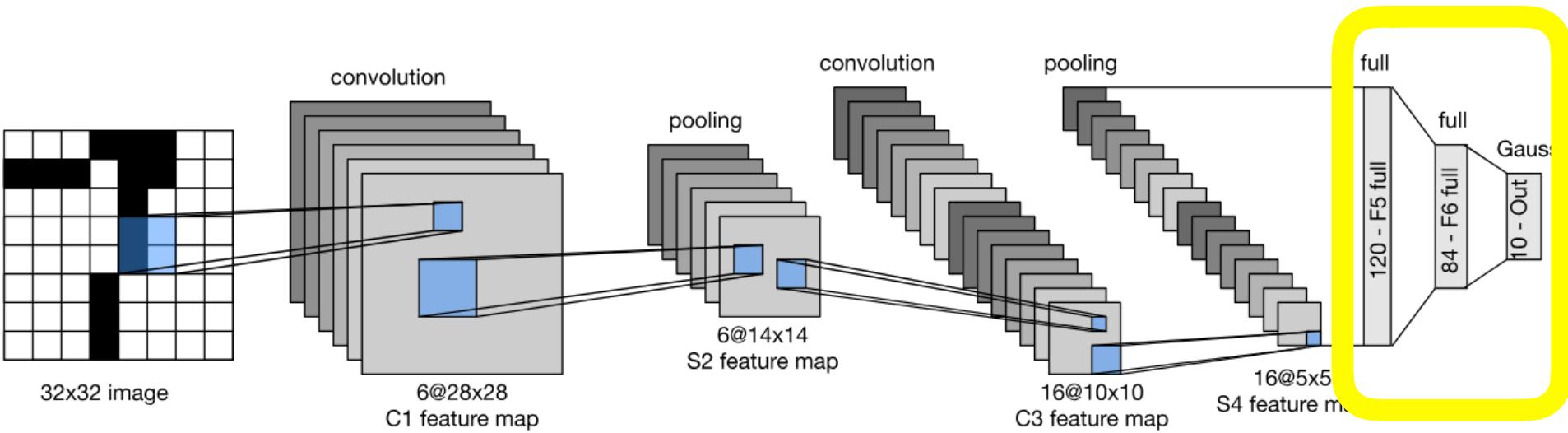


Network in Network

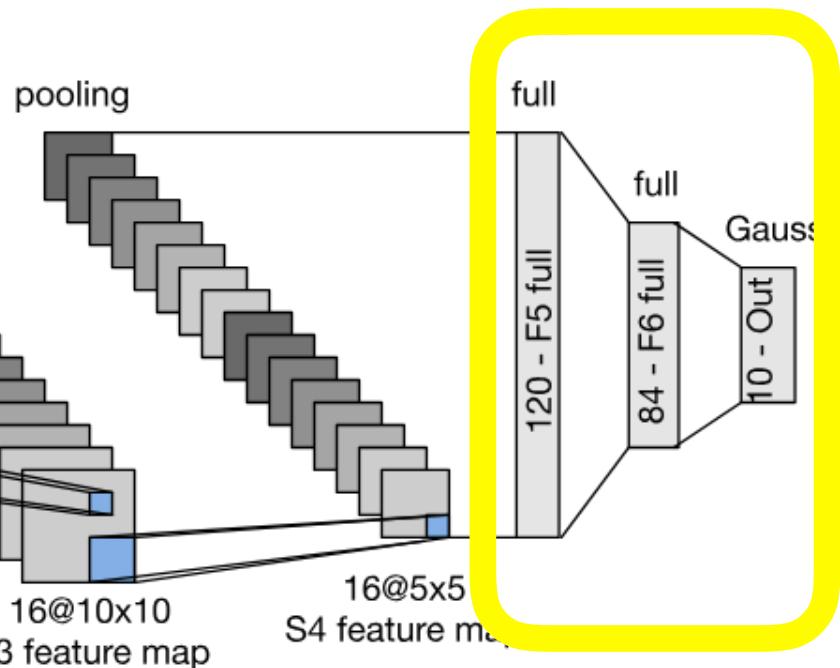
Non linear mapping introduced by mlpconv layer consisting of multiple fully connected layers with non linear activation function.



The Curse of the Last Layer(s)



The Last Layer(s)



- Convolution layers need relatively few parameters

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

- Last layer needs many parameters for n classes

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

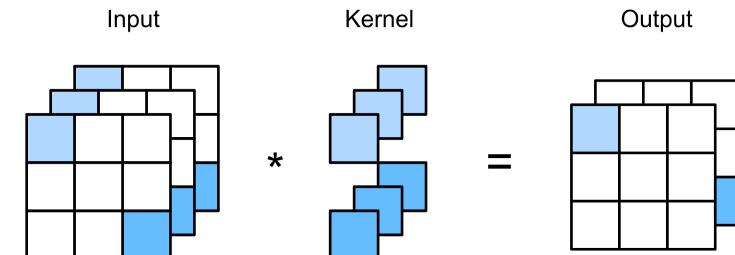
- LeNet $16 \times 5 \times 5 \times 120 = 48k$
- AlexNet $256 \times 5 \times 5 \times 4096 = 26M$
- VGG $512 \times 7 \times 7 \times 4096 = 102M$

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)

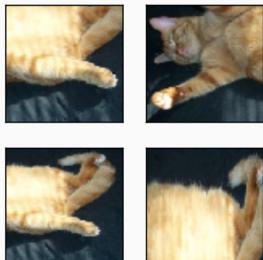
Breaking the Curse of the Last Layer

- 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
 - Reduce resolution progressively
 - Increase number of channels
 - Use **1x1 convolutions** (they only act per pixel)
- **Global average pooling in the end**

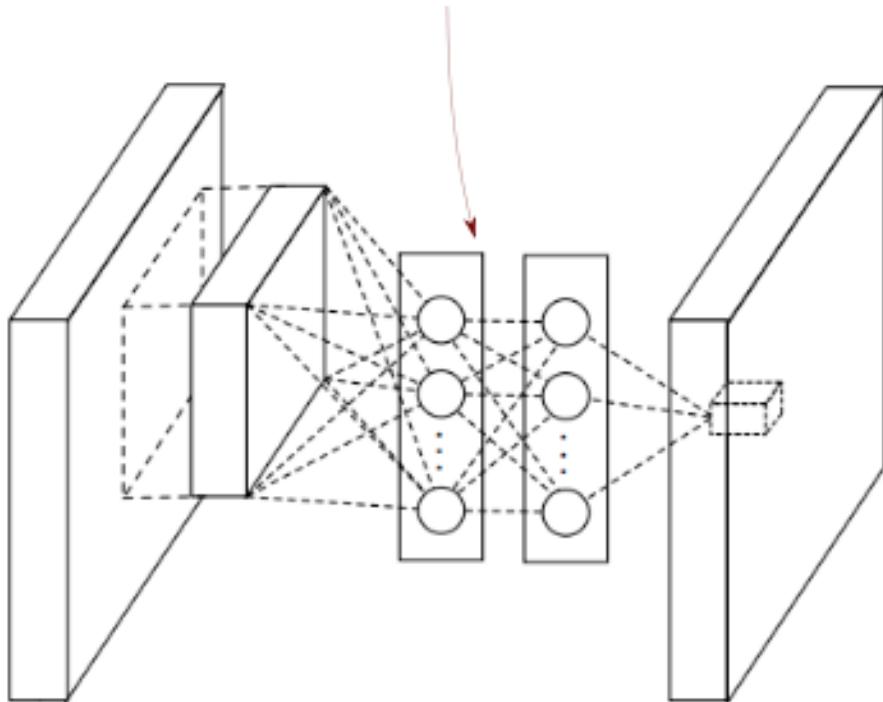


What's a 1x1 convolution anyway?

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

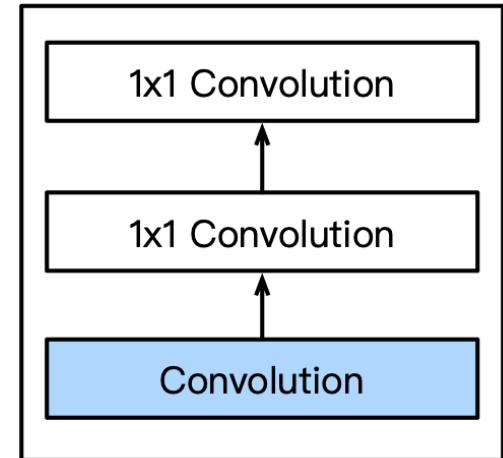


Non linear mapping introduced by mlpconv layer consisting of multiple fully connected layers with non linear activation function.

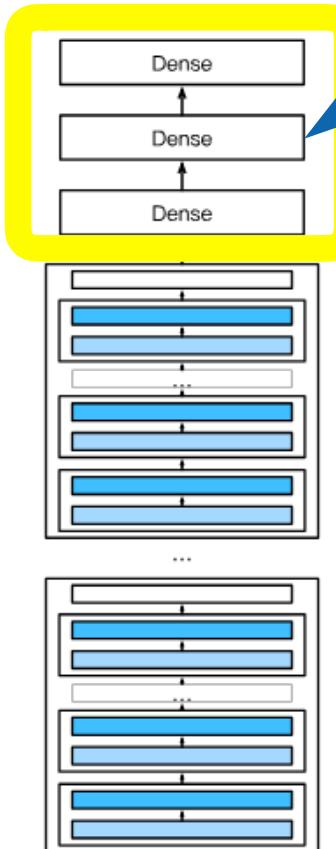
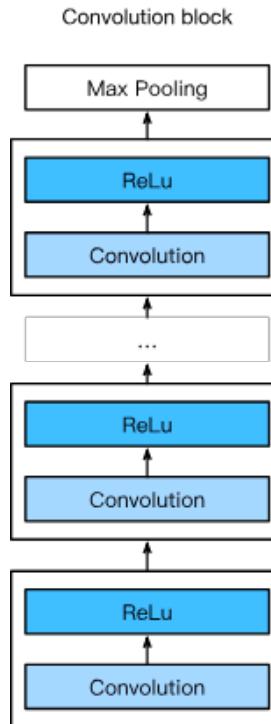


NiN Block

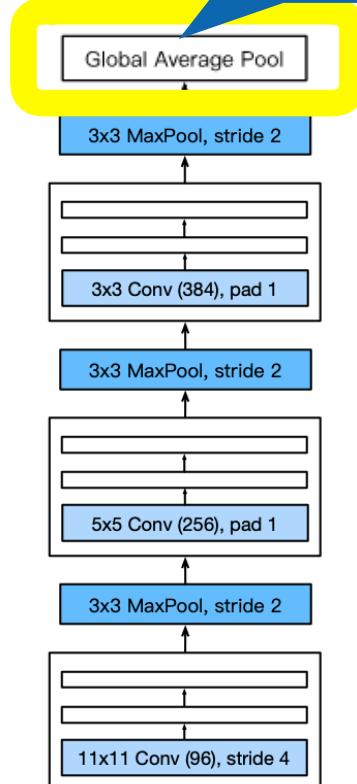
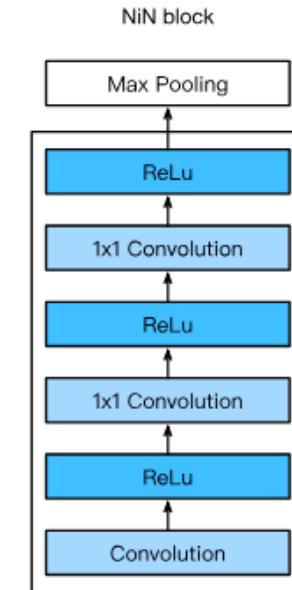
- A convolutional layer
 - kernel size, stride, and padding are hyper-parameters
- Following by two 1×1 convolutions
 - 1 stride and no padding, share the same output channels as first layer
 - Act as dense layers



NiN Networks



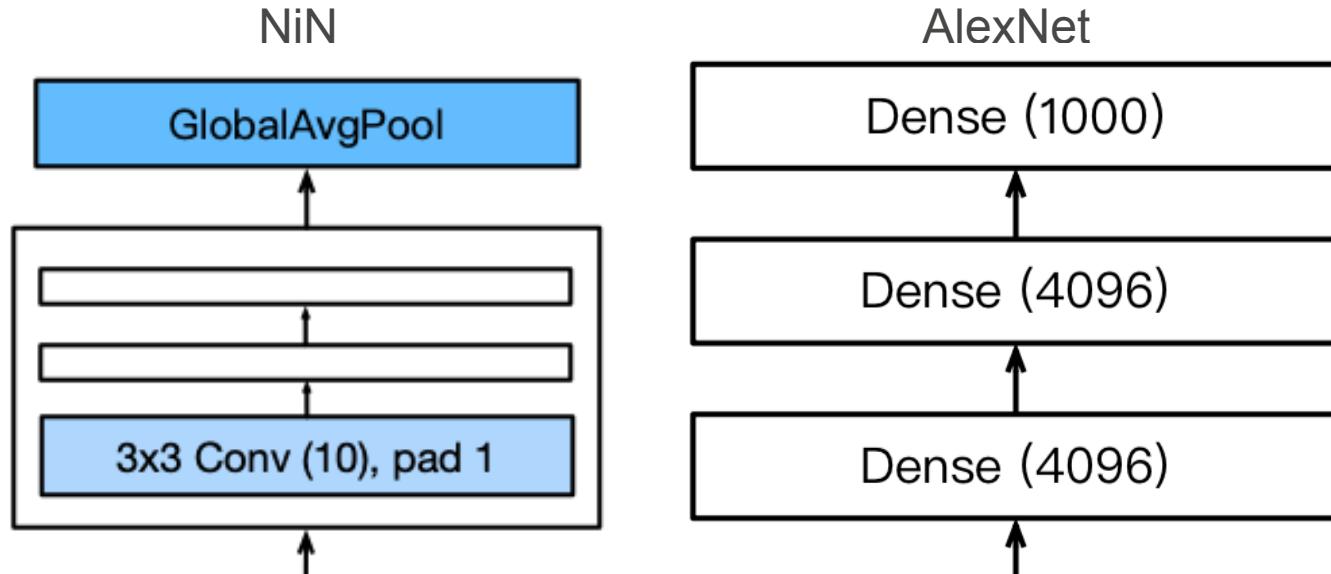
VGG Net



NiN Net

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