Introduction to Deep Learning

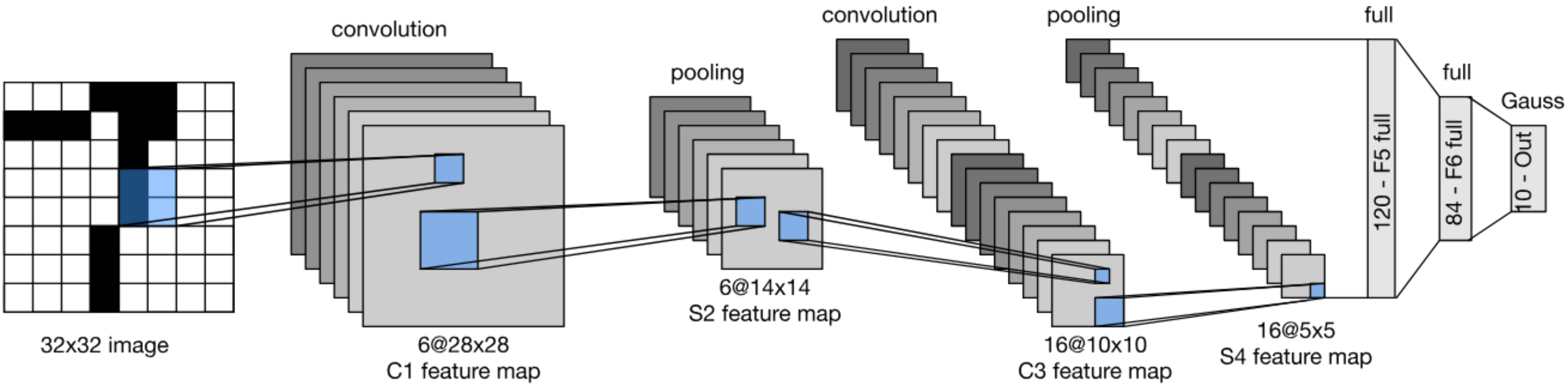
12. AlexNet, VGG and Blocks

STAT 157, Spring 2019, UC Berkeley

Alex Smola and Mu Li

courses.d2l.ai/berkeley-stat-157

LeNet Architecture



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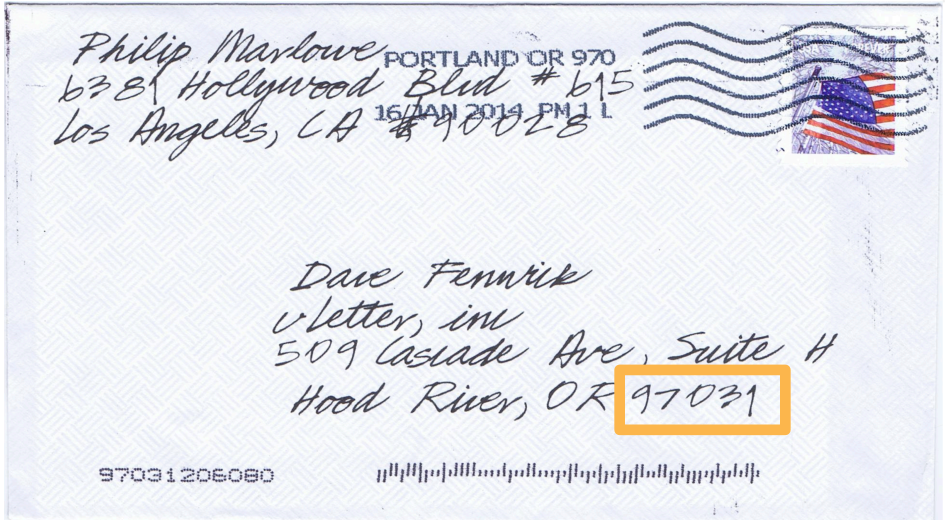
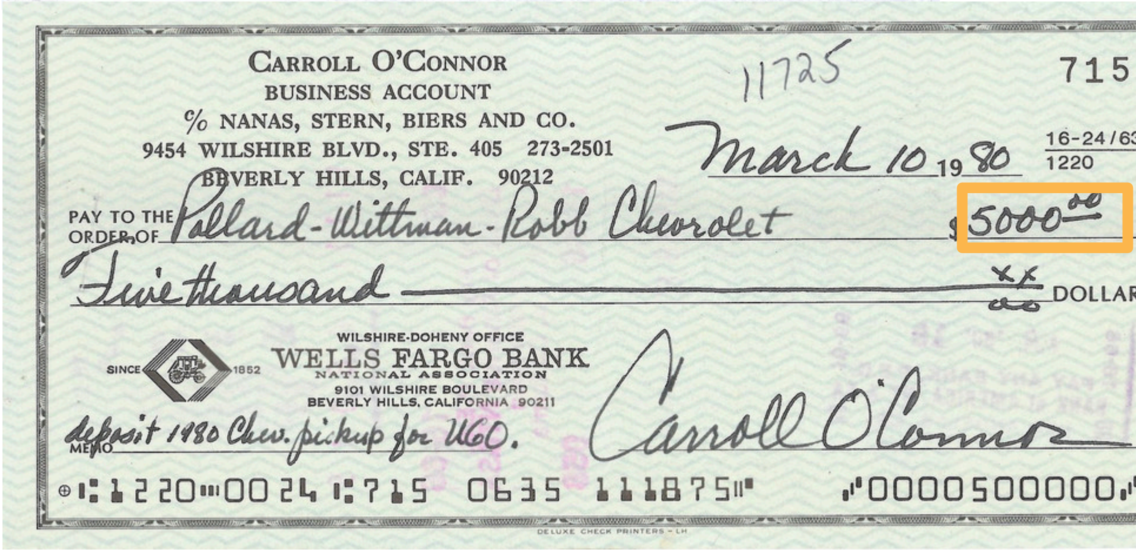
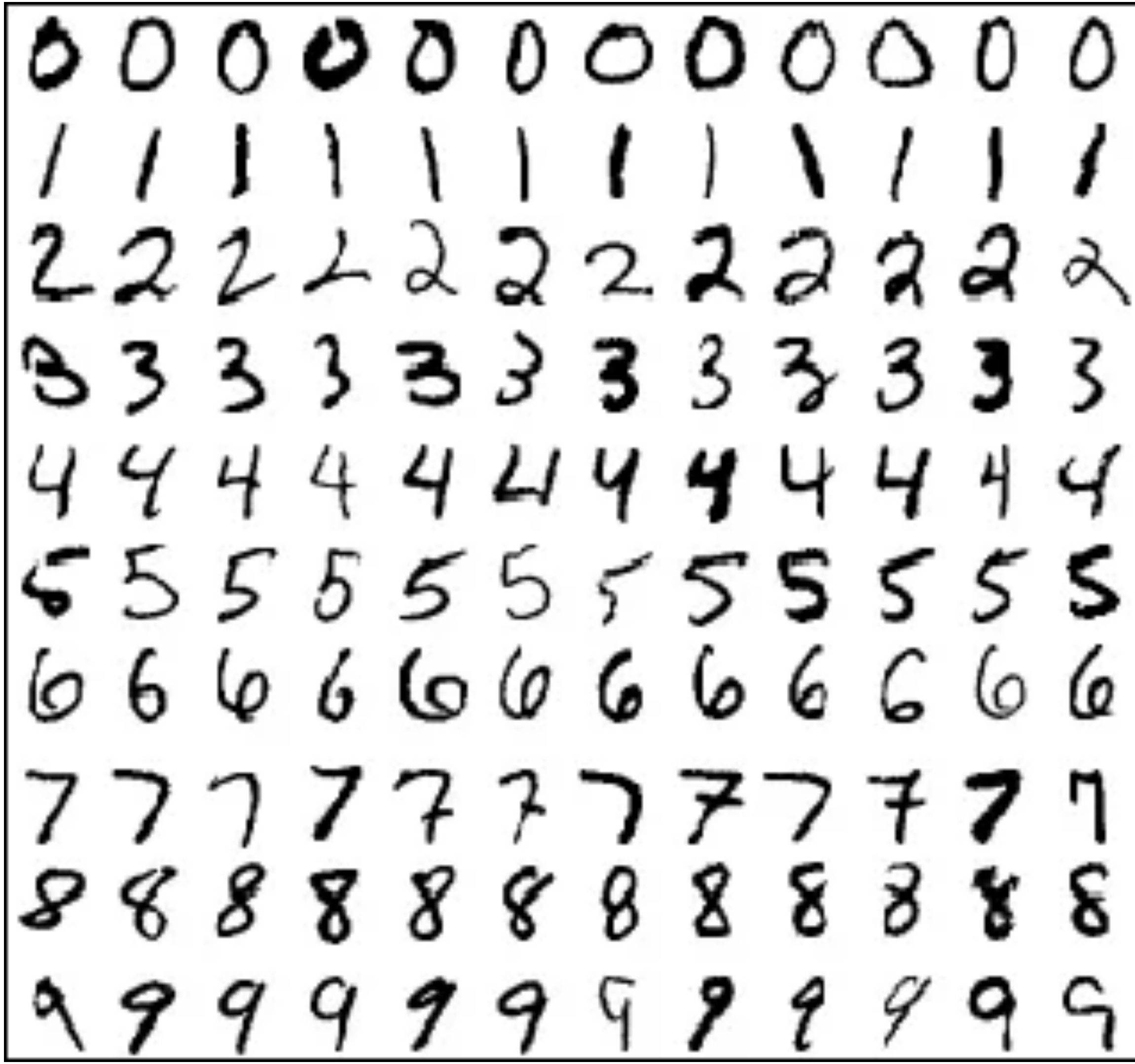
Handwritten Digit Recognition

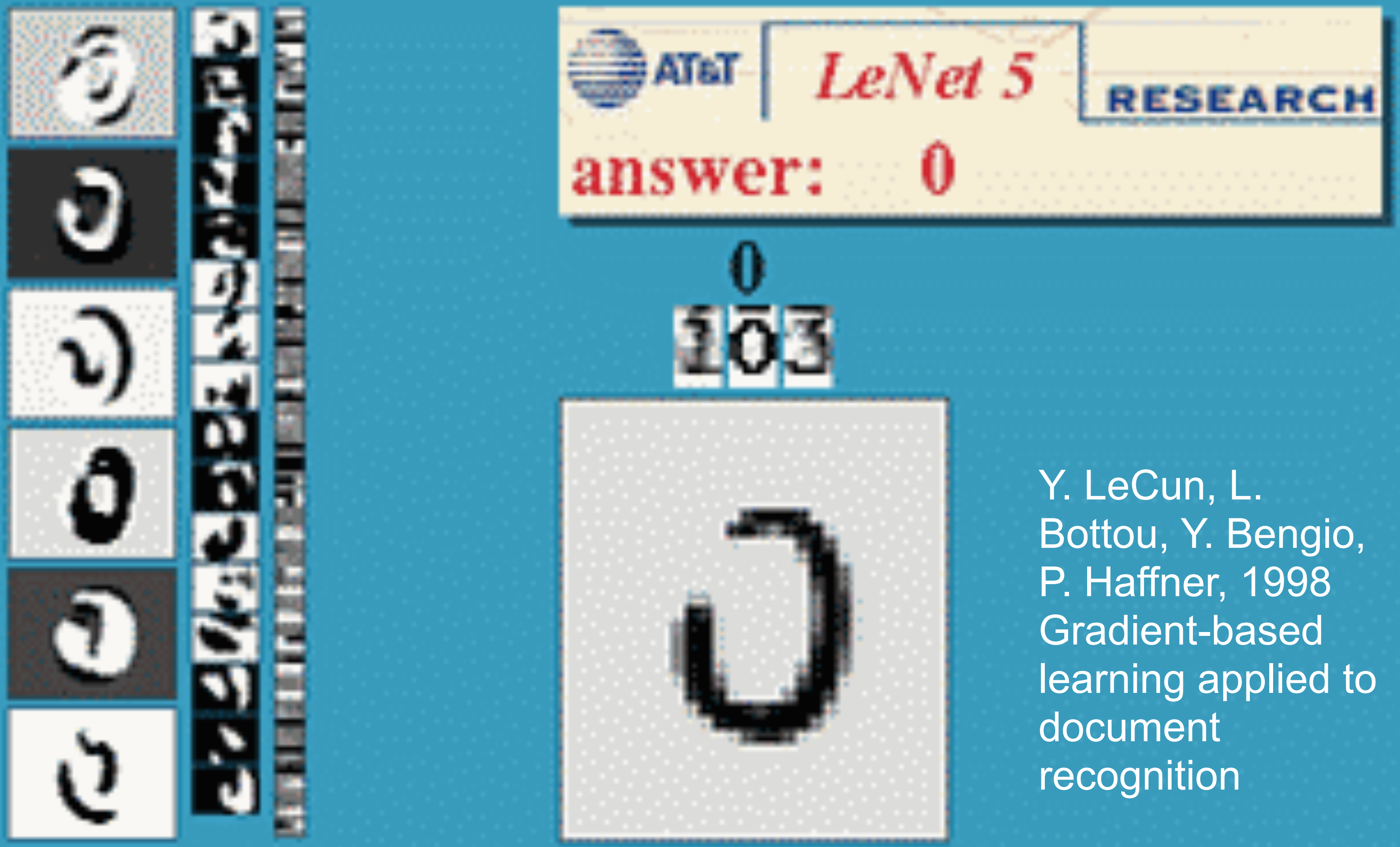




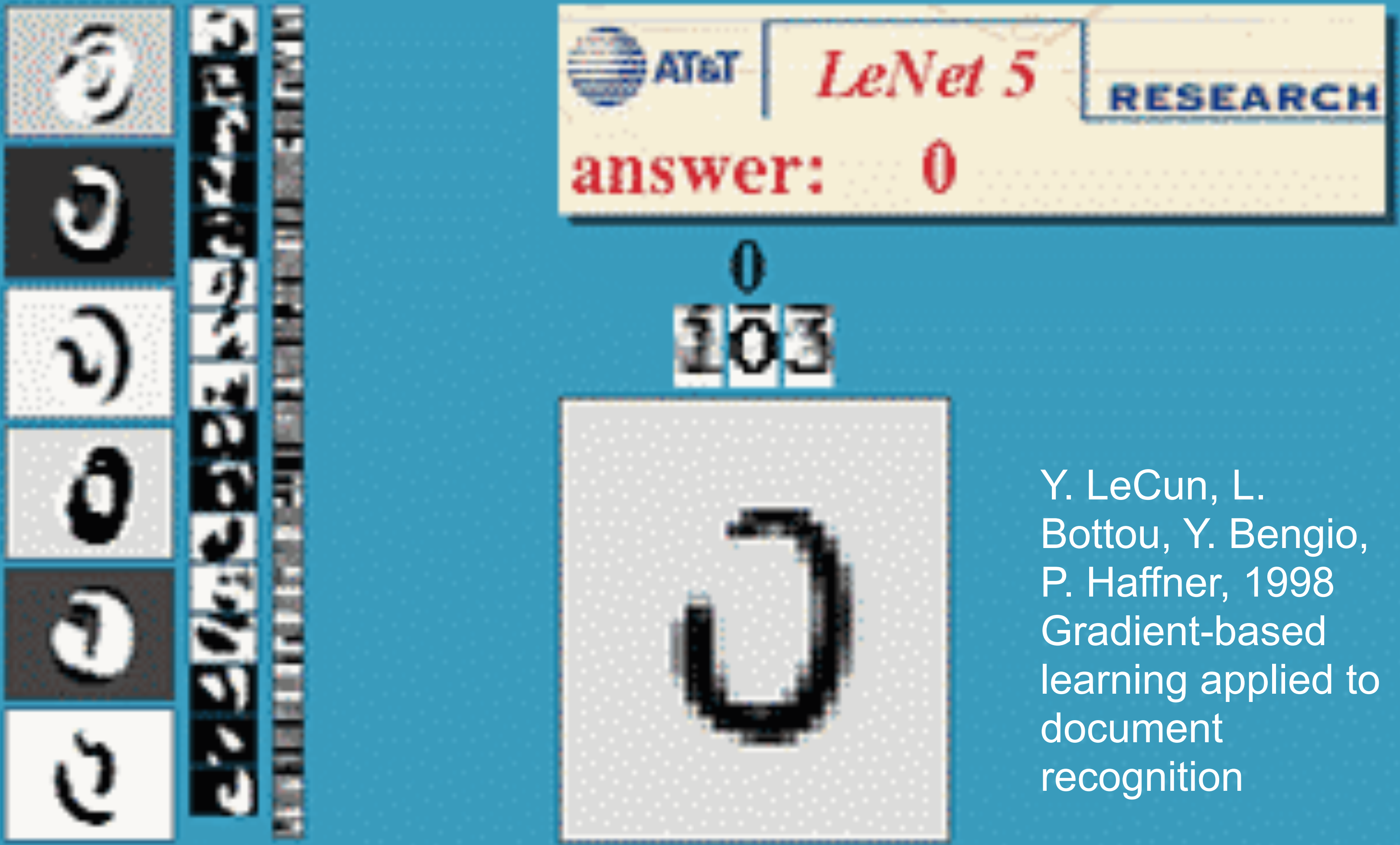
MNIST

- Centered and scaled
- 50,000 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



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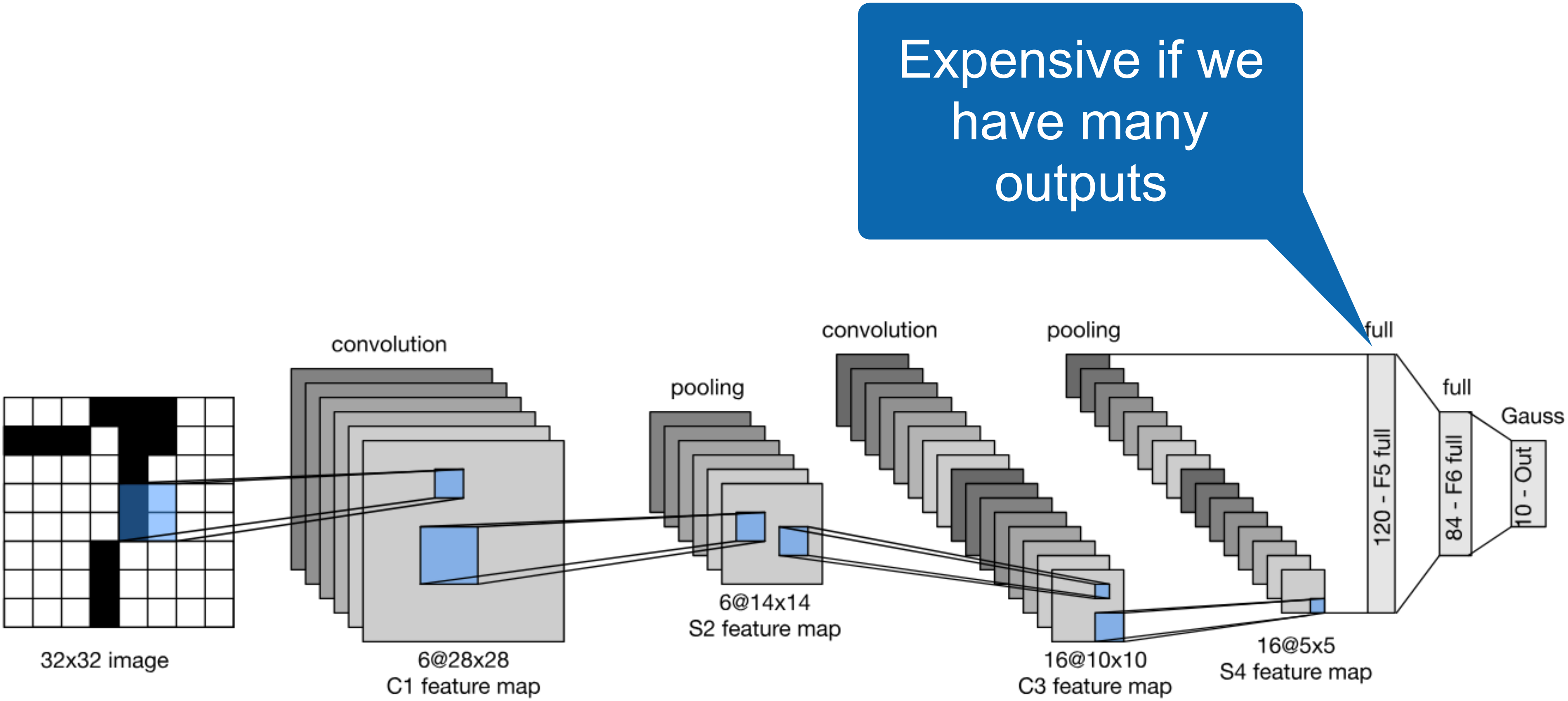

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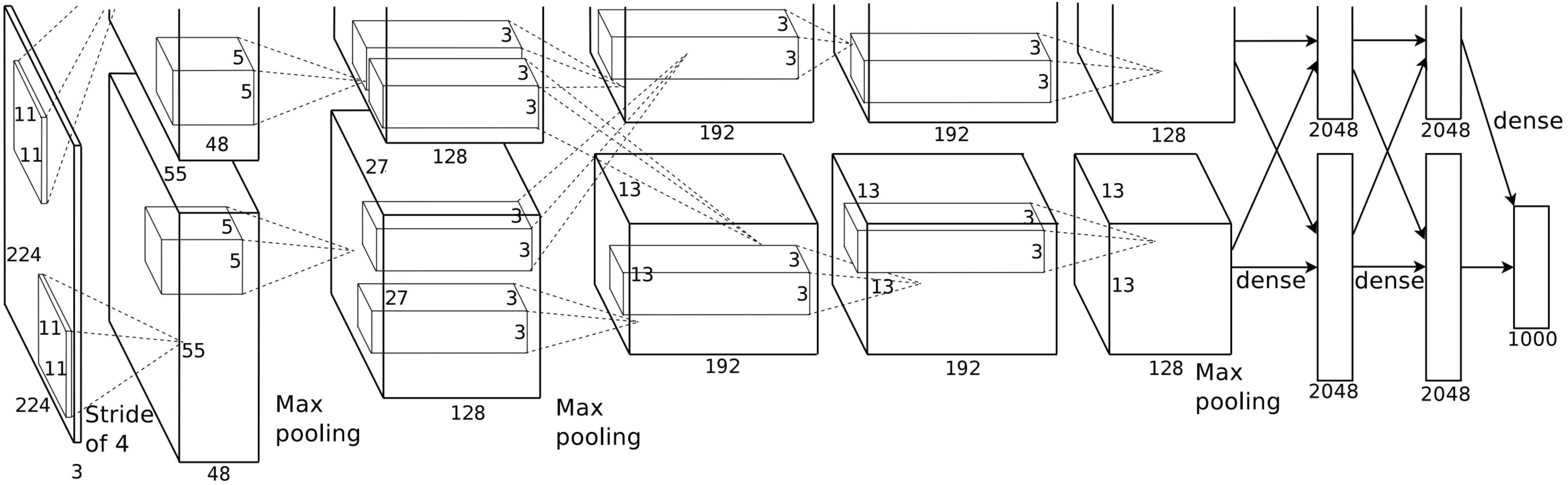
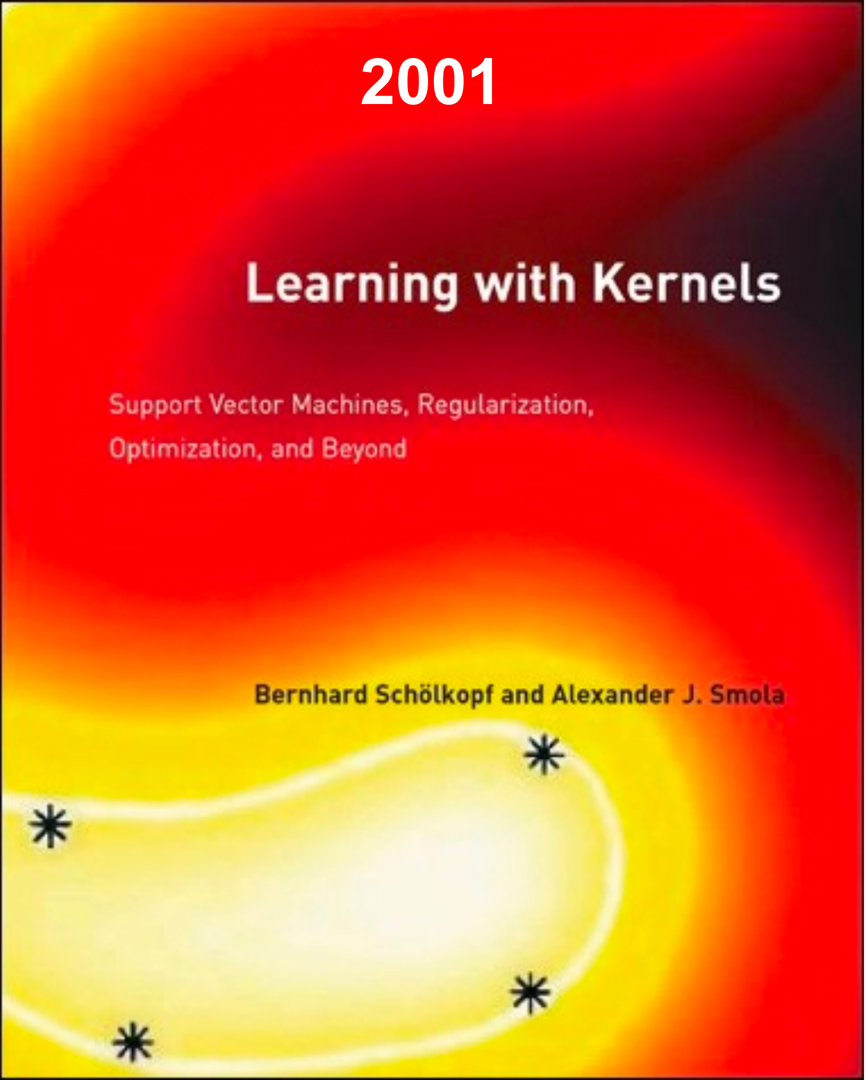
LeNet in MXNet

```
net = gluon.nn.Sequential()
with net.name_scope():
    net.add(gluon.nn.Conv2D(channels=20, kernel_size=5, activation='tanh'))
    net.add(gluon.nn.AvgPool2D(pool_size=2))
    net.add(gluon.nn.Conv2D(channels=50, kernel_size=5, activation='tanh'))
    net.add(gluon.nn.AvgPool2D(pool_size=2))
    net.add(gluon.nn.Flatten())
    net.add(gluon.nn.Dense(500, activation='tanh'))
    net.add(gluon.nn.Dense(10))

loss = gluon.loss.SoftmaxCrossEntropyLoss()

(size and shape inference is automatic)
```

AlexNet



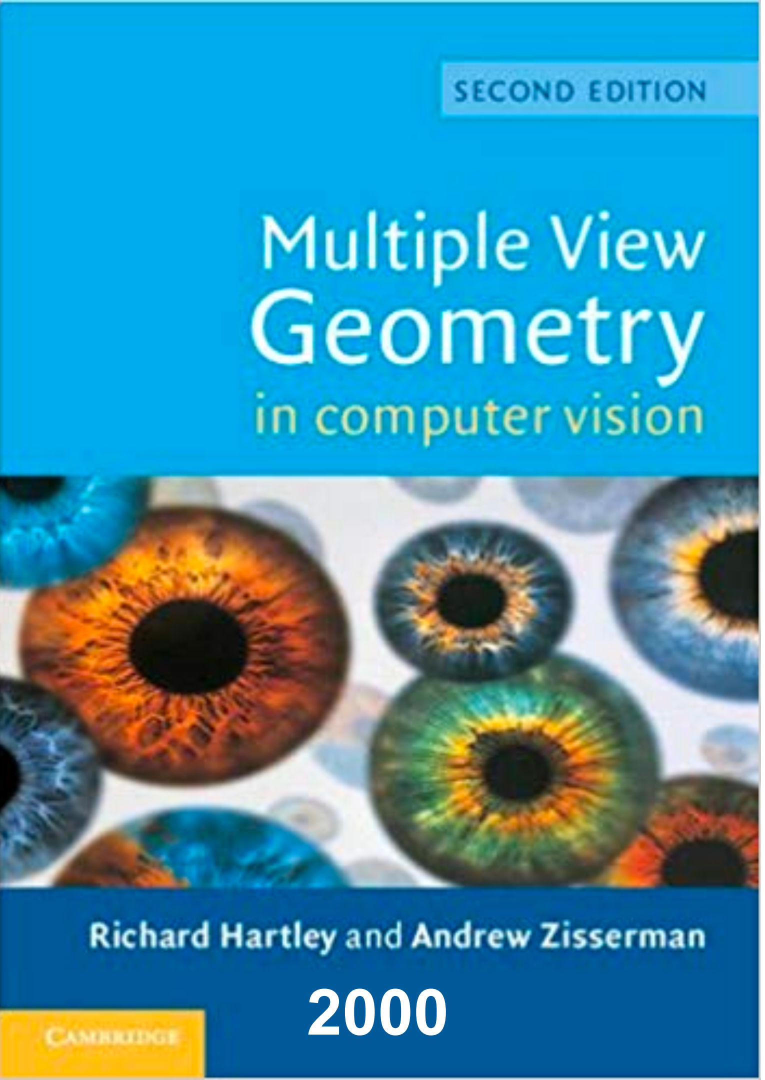
11
11
224
224
11
11
3
Stride of 4
55
55
5
5
5
5
48
48
Max pooling
27
27
3
3
3
3
3
3
3
3
128
128
Max pooling
3
3
13
13
3
3
192
192
3
3
13
13
3
3
192
192
13
13
128
128
Max pooling
dense
dense
dense
2048
2048
2048
2048
1000



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

- 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

	1970	1980	1990	2000	2010	2020
		10x	10x	100x	100x	**1,000x**
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Data growth between decades: 10x, 10x, 100x, 100x, **1,000x**

CPU growth between decades: 10x, 10x, 100x, 100x, **10,000x**

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Data: 10x 10x 100x 100x **1,000x**

CPU: 10x 10x 100x 100x **10,000x**

deep nets

Hardware

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deep nets

kernel methods

aws

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Data: 10x, 10x, 100x, 100x, **1,000x**

CPU: 10x, 10x, 100x, 100x, **10,000x**

deep nets

kernel methods

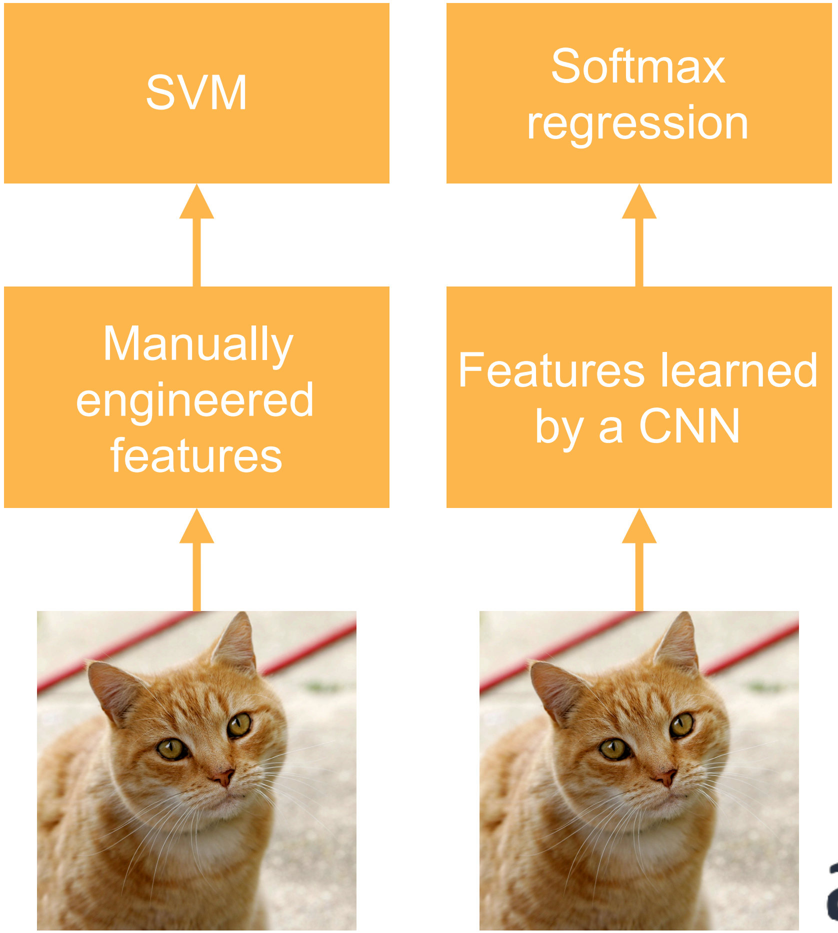
deep nets

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

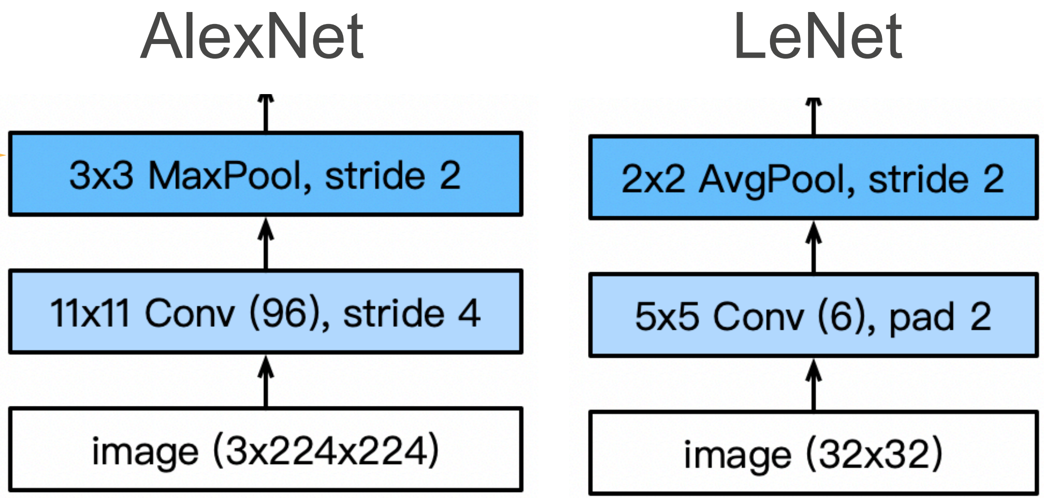
- AlexNet won ImageNet competition in 2012
- Deeper and bigger LeNet
- Key modifications
  - Dropout (regularization)
  - ReLu (training)
  - MaxPooling
- Paradigm shift for computer vision



AlexNet Architecture

Larger pool size, change to max pooling

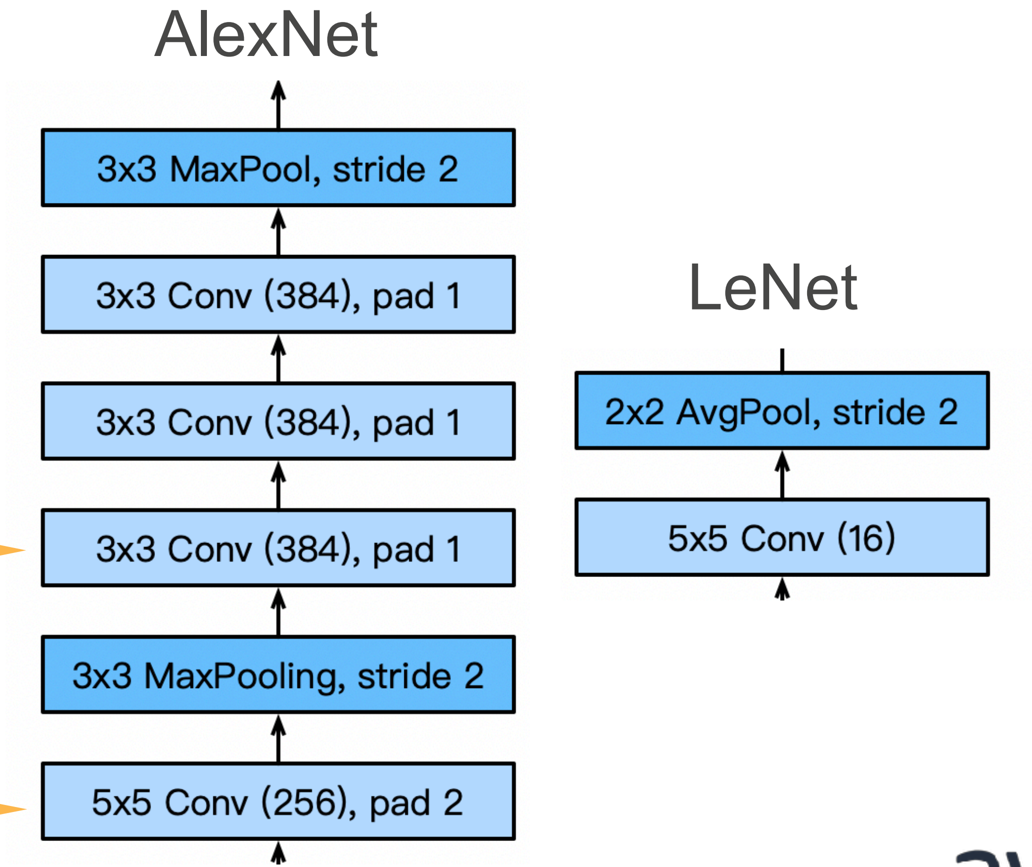
Larger kernel size, stride because of the increased image size, and more output channels.



AlexNet Architecture

3 additional convolutional layers

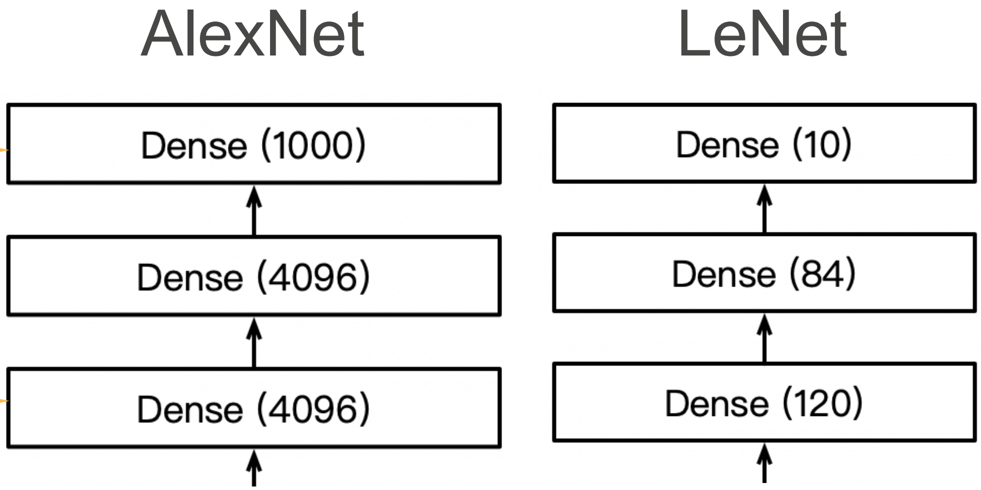
More output channels.



AlexNet Architecture

1000 classes output

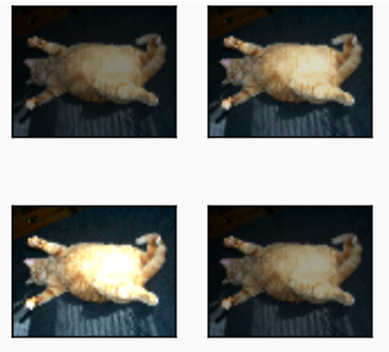
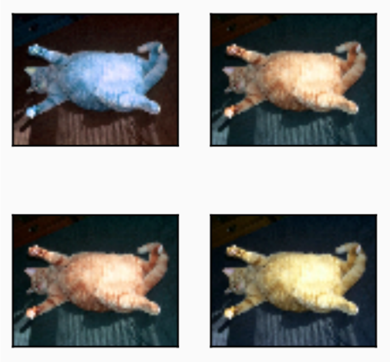
Increase hidden size from 120 to 4096



More Tricks

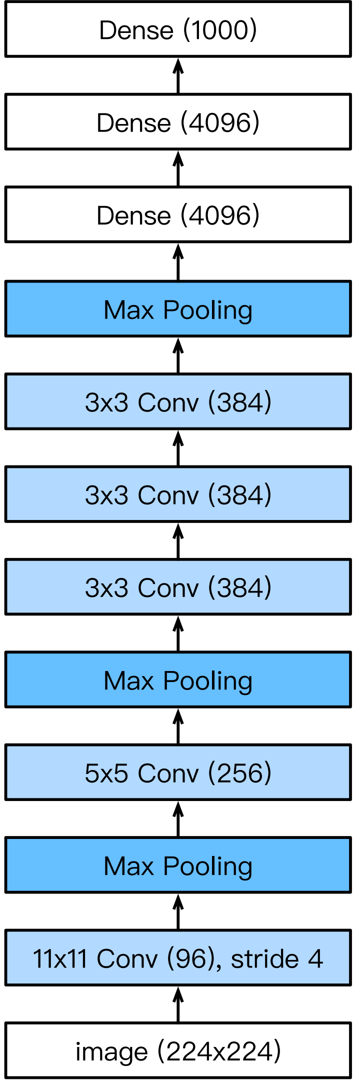
- Change activation function from sigmoid to ReLu (no more vanishing gradient)
- Add a dropout layer after two hidden dense layers (better robustness / regularization)
- Data augmentation



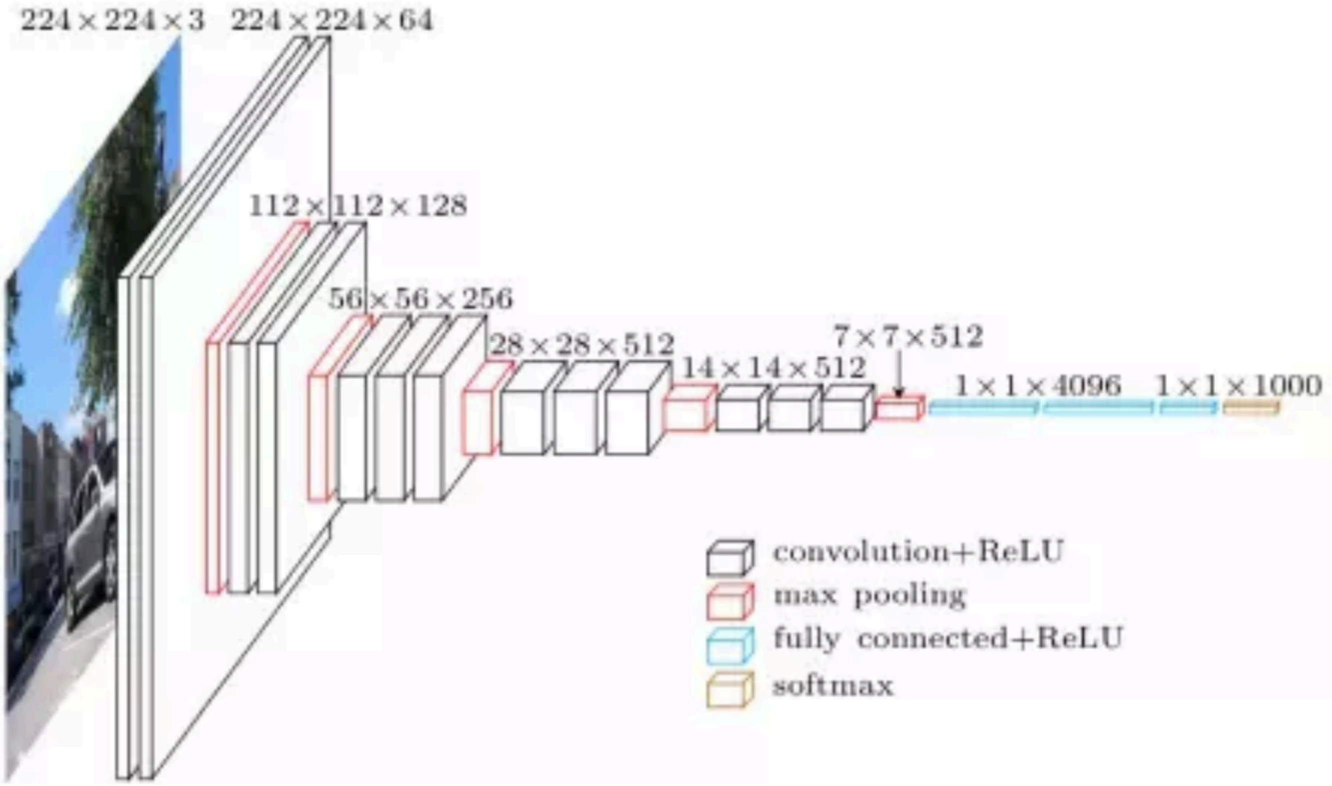



Complexity

	#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

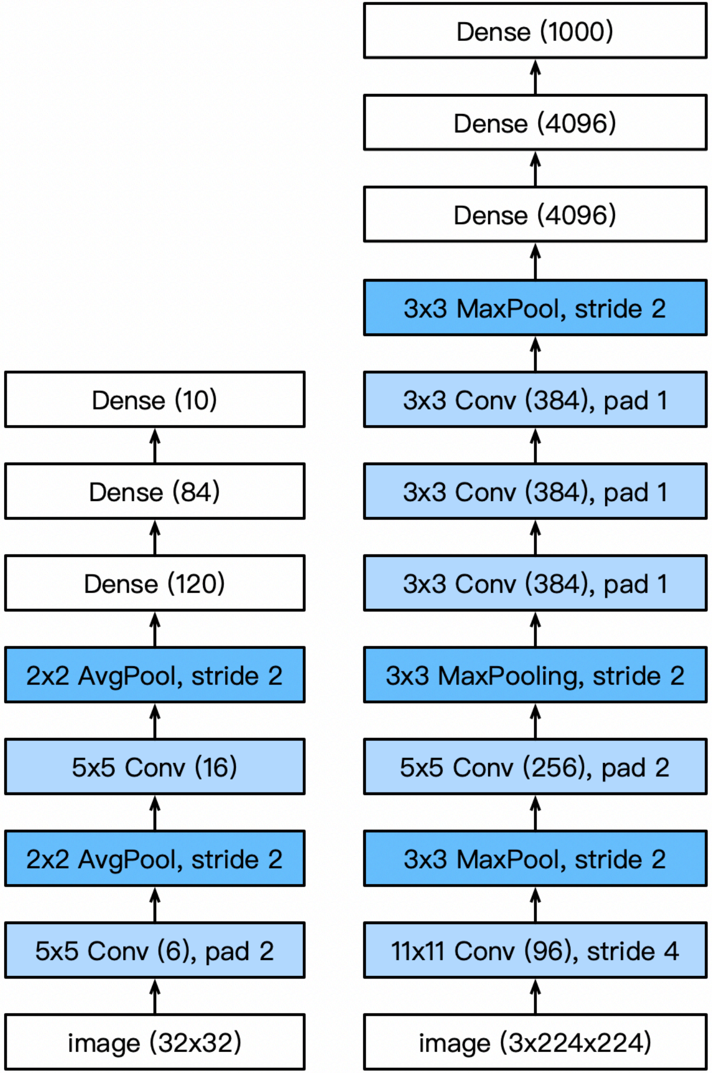


VGG


224 × 224 × 3
224 × 224 × 64
112 × 112 × 128
56 × 56 × 256
28 × 28 × 512
14 × 14 × 512
7 × 7 × 512
1 × 1 × 4096
1 × 1 × 1000
convolution+ReLU
max pooling
fully connected+ReLU
softmax

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**

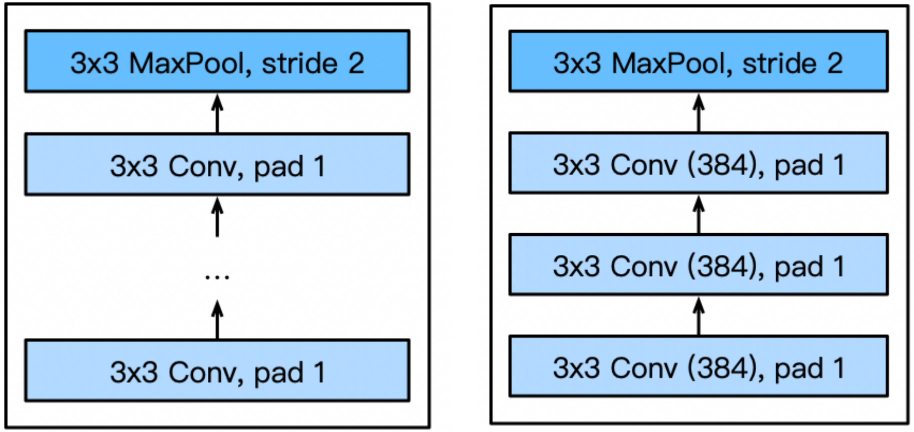


VGG Blocks

- 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)

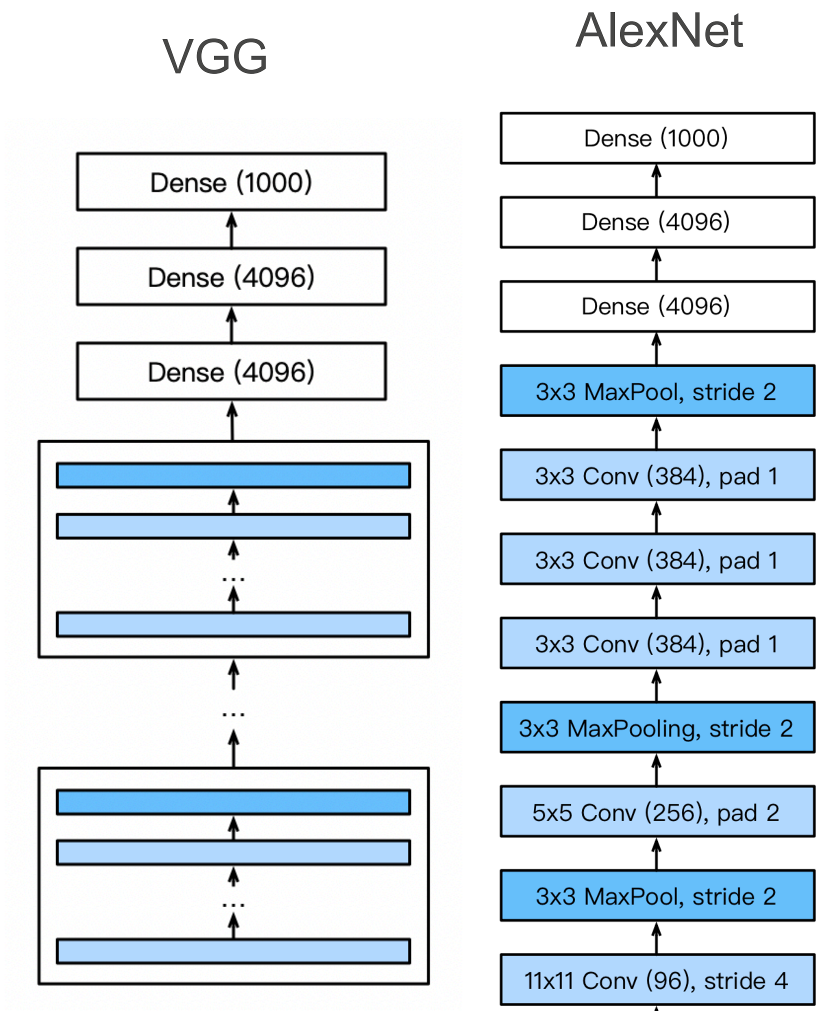
VGG block

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, ...

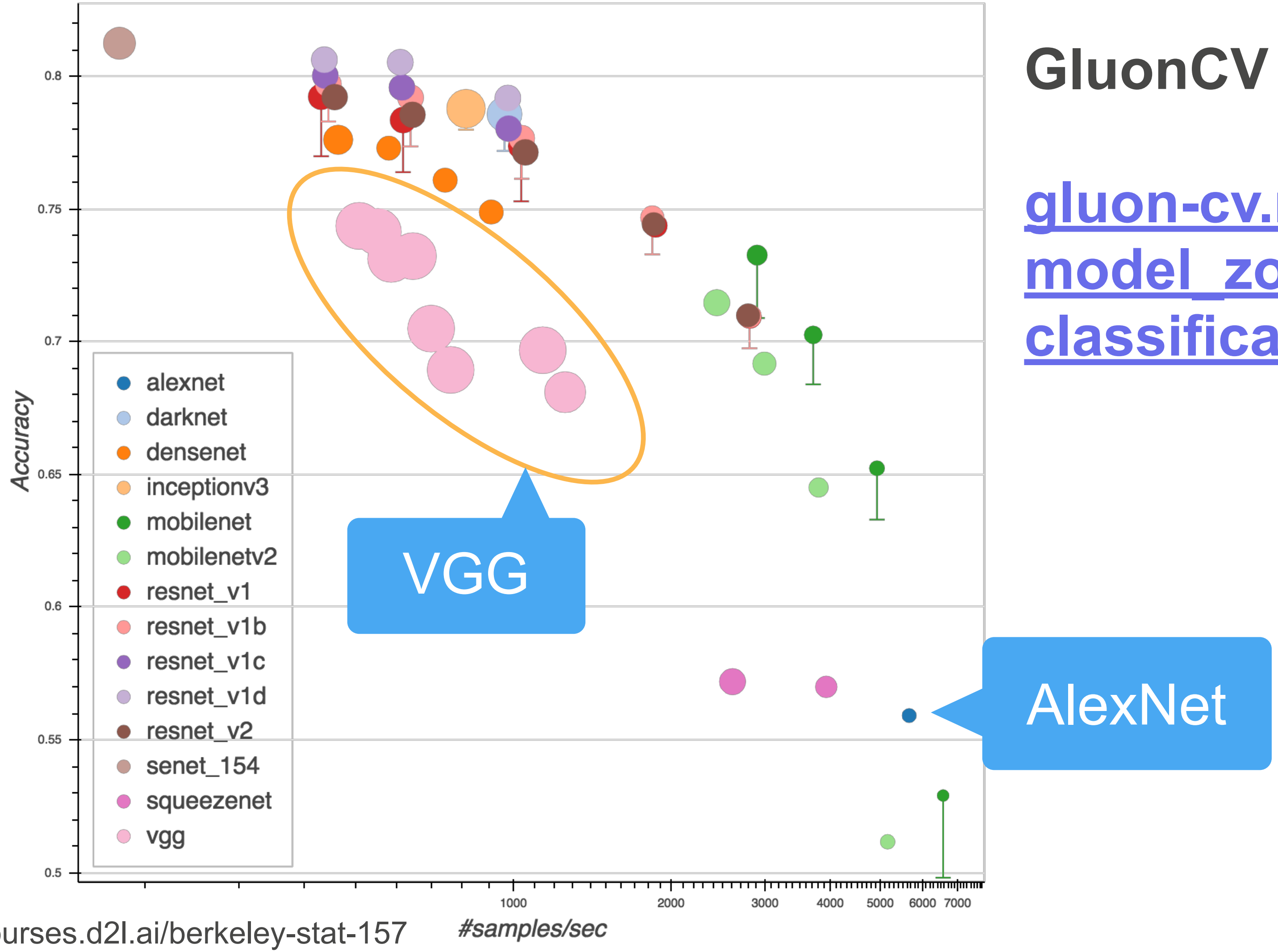


Progress

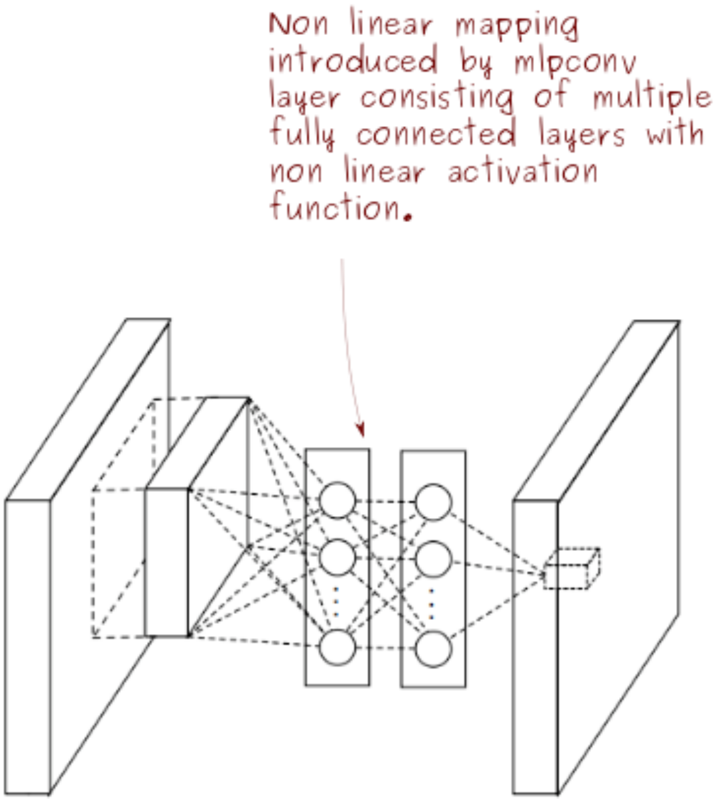
- LeNet (1995)
  - 2 convolution + pooling layers
  - 2 hidden dense layers
- AlexNet
  - Bigger and deeper LeNet
  - ReLu, Dropout, preprocessing
- VGG
  - Bigger and deeper AlexNet (repeated VGG blocks)

GluonCV Model Zoo

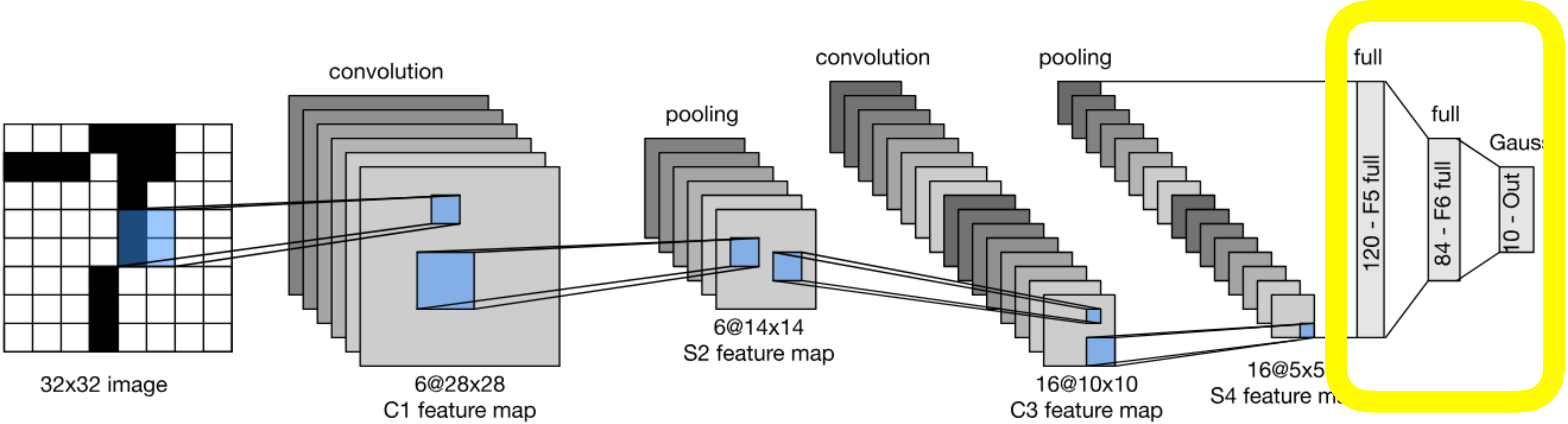
gluon-cv.mxnet.io/model_zoo/classification.html



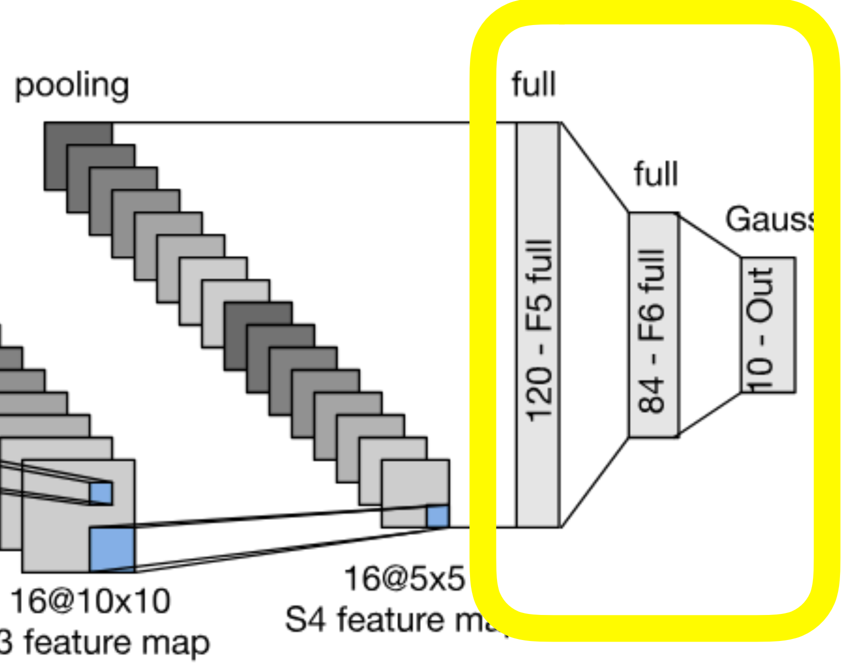
Network in Network



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

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

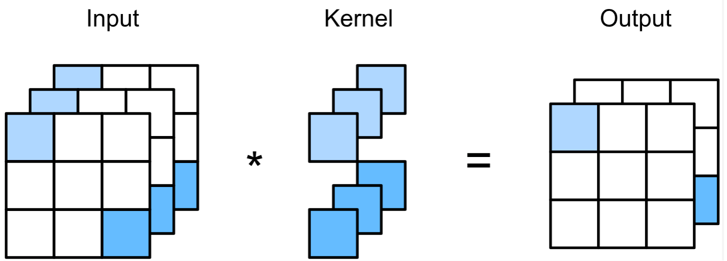
- LeNet 16x5x5x120 = 48k
- AlexNet 256x5x5x4096 = 26M
- VGG 512x7x7x4096 = 102M

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)
```

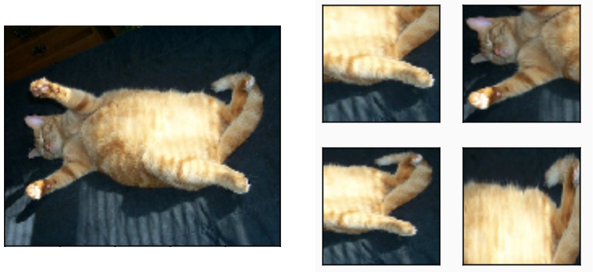
Breaking the Curse of the Last Layer

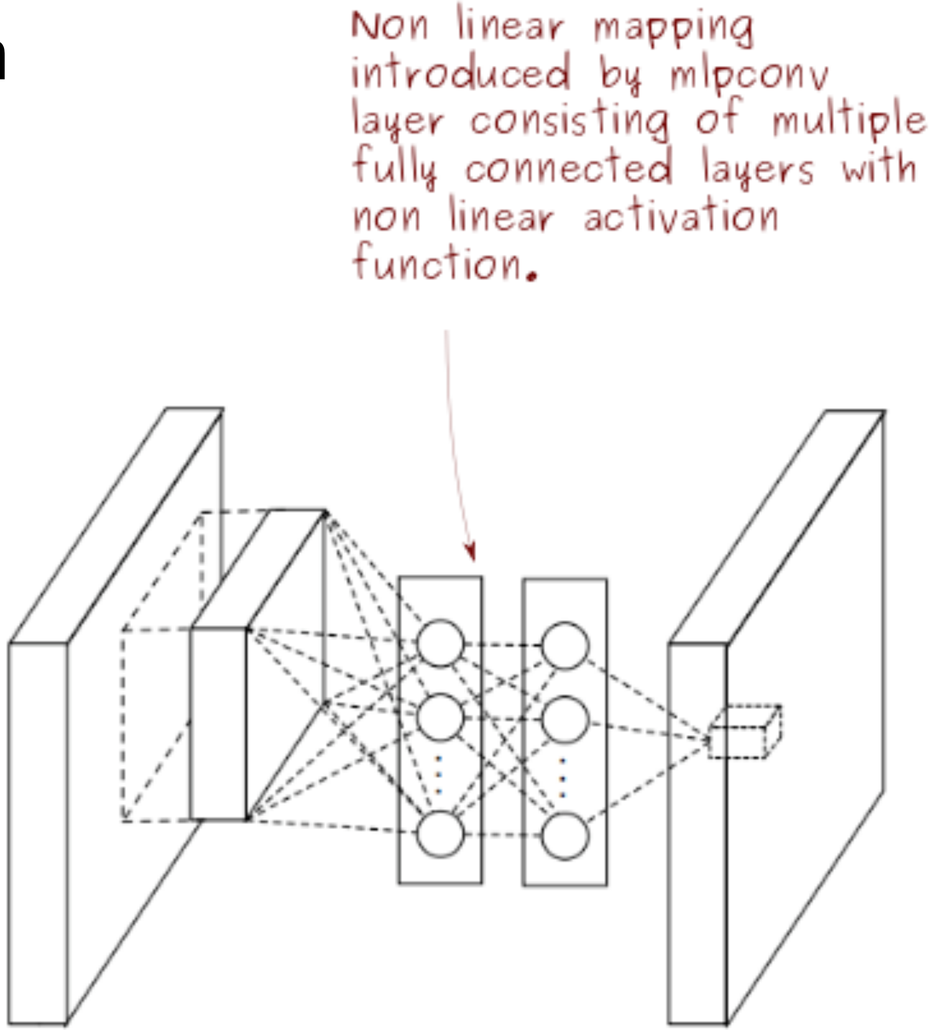
- Key Idea
  - **Get rid of the fully connected last layer(s)**
  - Convolutions and pooling reduce resolution (e.g. stride of 2 reduces resolution 4x)
- Implementation details
  - Reduce resolution progressively
  - Increase number of channels
  - Use **1x1 convolutions** (they only act per pixel)
-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



What’s a 1x1 convolution anyway?

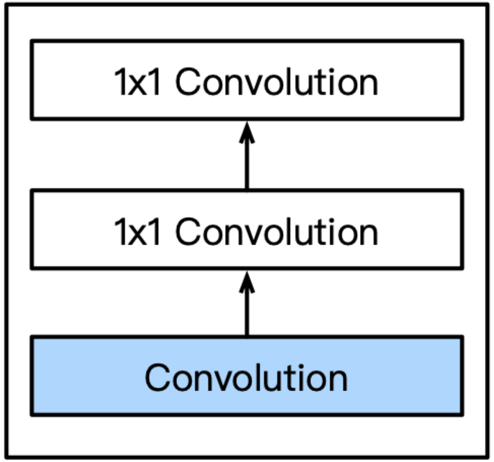
- Extreme case
  1x1 image with n channels
- Equivalent to MLP
- Pooling allows for translation invariance of detection (e.g. 5x5)



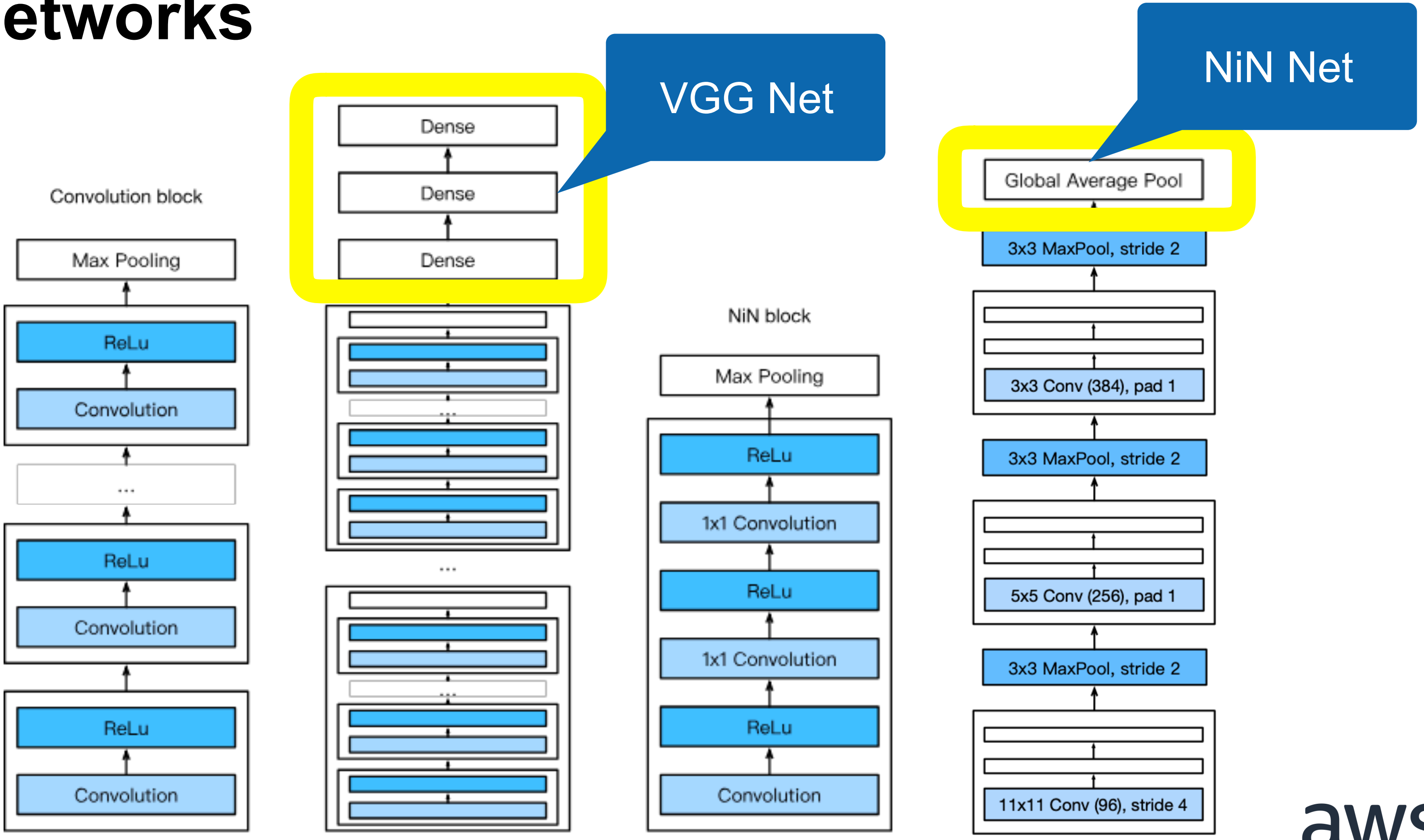


NiN Block

- 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



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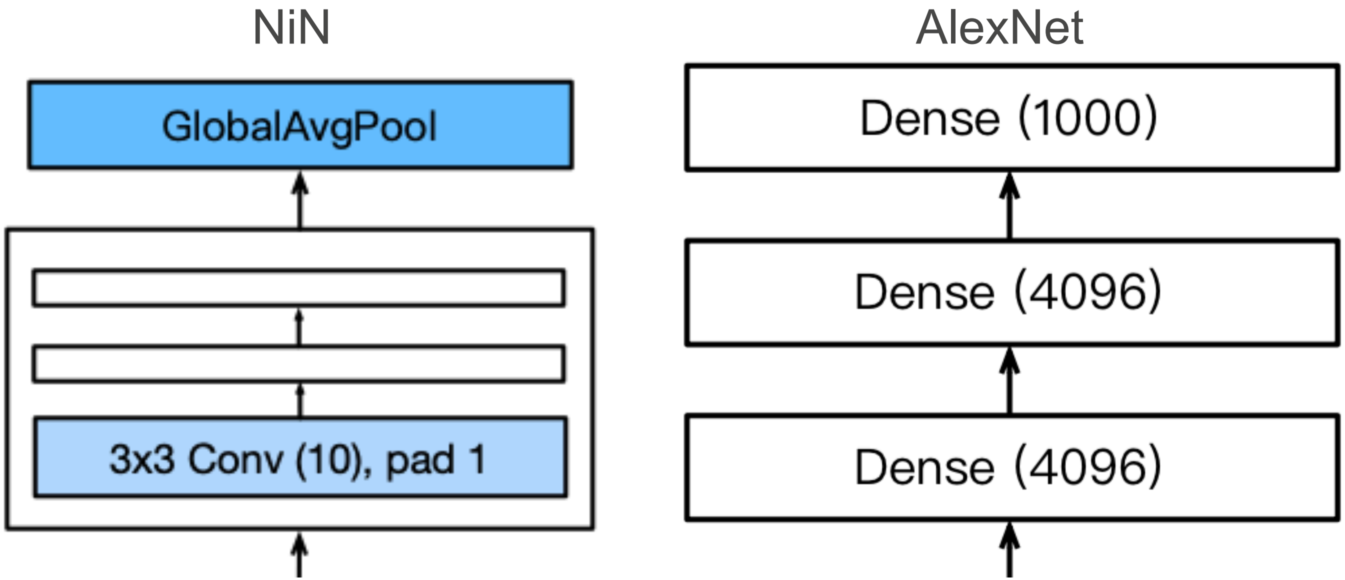
NiN Last Layers

- 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

- **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