CSCI567 Machine Learning (Fall 2024)

Prof. Dani Yogatama

University of Southern California

September 20, 2024

Outline

Acknowledgements

Not much math, a lot of empirical intuitions

Acknowledgements

Not much math, a lot of empirical intuitions

The materials borrow heavily from the following sources:

- Stanford Course CS231n: `http://cs231n.stanford.edu/`
- Dr. Ian Goodfellow's lectures on deep learning: `http://deeplearningbook.org`

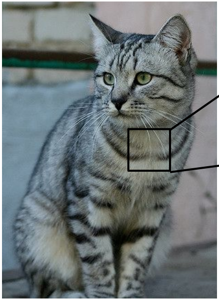
Both website provides tons of useful resources: notes, demos, videos, etc.

Image Classification: A core task in Computer Vision

(assume given set of discrete labels)
{dog, cat, truck, plane, ...}

→ cat

The Problem: Semantic Gap



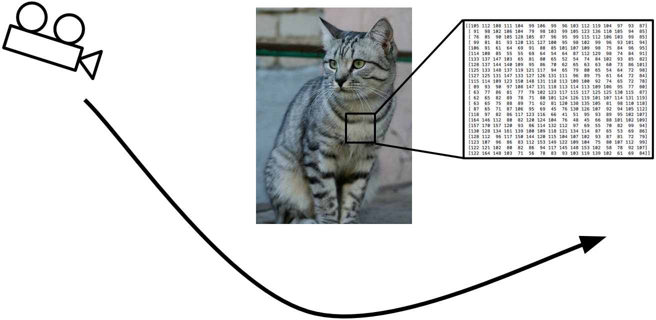

```
[[105 112 108 111 104  99 106  99  96 103 112 119 104  97  93  87]
 [ 91  98 102 106 104  79  98 103  99 105 123 136 110 105  94  85]
 [ 76  85  90 105 128 105  87  96  95  99 115 112 106 103  99  85]
 [ 99  81  81  93 120 131 127 100  95  98 102  99  96  93 101  94]
 [106  91  61  64  69  91  88  85 101 107 109  98  75  84  96  95]
 [114 108  85  55  55  69  64  54  64  87 112 129  98  74  84  91]
 [133 137 147 103  65  81  80  65  52  54  74  84 102  93  85  82]
 [128 137 144 140 109  95  86  70  62  65  63  63  60  73  86 101]
 [125 133 148 137 119 121 117  94  65  79  80  65  54  64  72  98]
 [127 125 131 147 133 127 126 131 111  96  89  75  61  64  72  84]
 [115 114 109 123 150 148 131 118 113 109 100  92  74  65  72  78]
 [ 89  93  90  97 108 147 131 118 113 114 113 109 106  95  77  80]
 [ 63  77  86  81  77  79 102 123 117 115 117 125 125 130 115  87]
 [ 62  65  82  89  78  71  80 101 124 126 119 101 107 114 131 119]
 [ 63  65  75  88  89  71  62  81 120 138 135 105  81  98 110 118]
 [ 87  65  71  87 106  95  69  45  76 130 126 107  92  94 105 112]
 [118  97  82  86 117 123 116  66  41  51  95  93  89  95 102 107]
 [164 146 112  80  82 120 124 104  76  48  45  66  88 101 102 109]
 [157 170 157 120  93  86 114 132 112  97  69  55  70  82  99  94]
 [130 128 134 161 139 100 109 118 121 134 114  87  65  53  69  86]
 [128 112  96 117 150 144 120 115 104 107 102  93  87  81  72  79]
 [123 107  96  86  83 112 153 149 122 109 104  75  80 107 112  99]
 [122 121 102  80  82  86  94 117 145 148 153 102  58  78  92 107]
 [122 164 148 103  71  56  78  83  93 103 119 139 102  61  69  84]]
```

What the computer sees

An image is just a big grid of numbers between [0, 255]:

e.g. 800 x 600 x 3
(3 channels RGB)

Challenges: Viewpoint variation



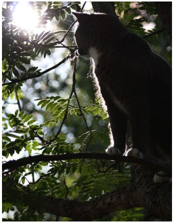
All pixels change when
the camera moves!

Challenges: Illumination

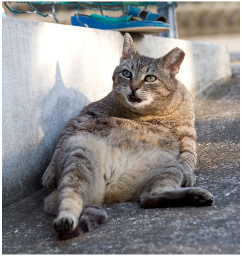

This image is CC0 1.0 public domain


This image is CC0 1.0 public domain


This image is CC0 1.0 public domain


This image is CC0 1.0 public domain

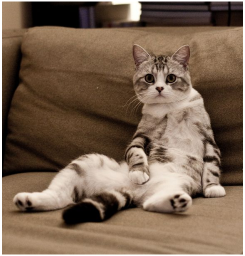
Challenges: Deformation



This image by Umberto Salvagnin is licensed under CC-BY 2.0

This image by Umberto Salvagnin is licensed under CC-BY 2.0

This image by sare bear is licensed under CC-BY 2.0



This image by Tom Thai is licensed under CC-BY 2.0

Challenges: Occlusion

Challenges: Background Clutter

This image is CC0 1.0 public domain

This image is CC0 1.0 public domain

Challenges: Intraclass variation

This image is CC0 1.0 public domain

Fundamental problems in vision

The key challenge

How to train a model that can tolerate all those variations?

Fundamental problems in vision

The key challenge

How to train a model that can tolerate all those variations?

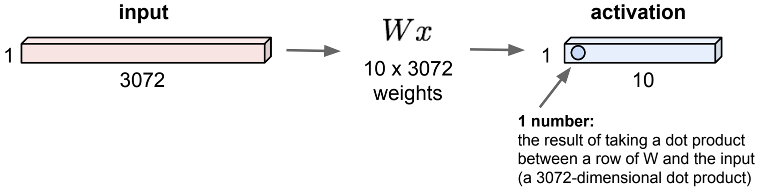
Main ideas

- need a lot of data that exhibits those variations
- need more specialized models to capture the invariance

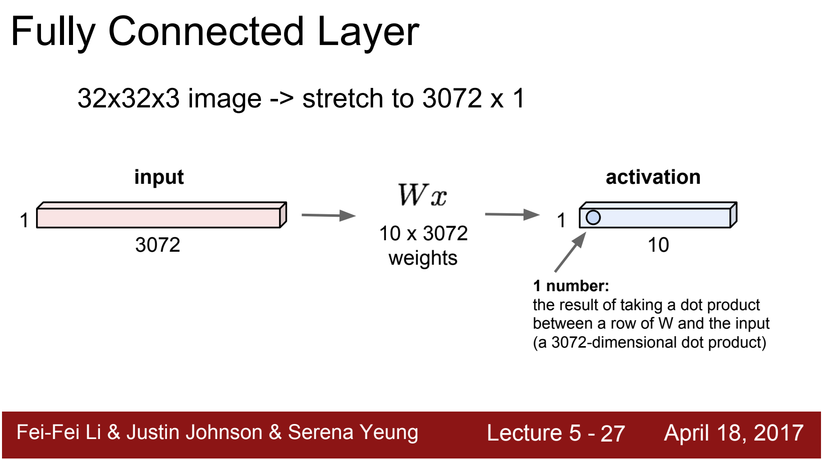
Issues of standard NN for image inputs

Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1



Issues of standard NN for image inputs



Spatial structure is lost!

Solution: Convolutional Neural Net (ConvNet/CNN)

A special case of fully connected neural nets

Solution: Convolutional Neural Net (ConvNet/CNN)

A special case of fully connected neural nets

- usually consist of **convolution layers**, ReLU layers, **pooling layers**, and regular fully connected layers

Solution: Convolutional Neural Net (ConvNet/CNN)

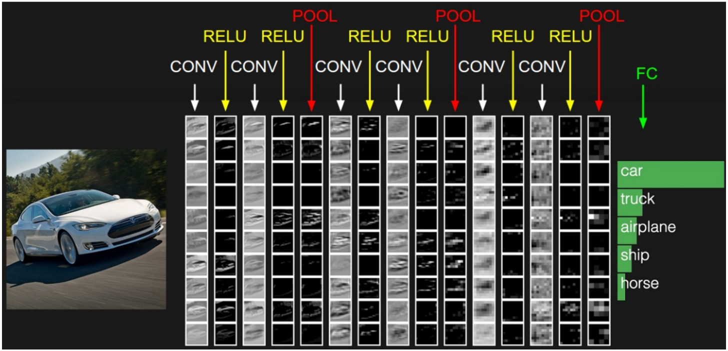
A special case of fully connected neural nets

- usually consist of **convolution layers**, ReLU layers, **pooling layers**, and regular fully connected layers
- key idea: *learning from low-level to high-level features*

Solution: Convolutional Neural Net (ConvNet/CNN)

A special case of fully connected neural nets

- usually consist of **convolution layers**, ReLU layers, **pooling layers**, and regular fully connected layers
- key idea: *learning from low-level to high-level features*

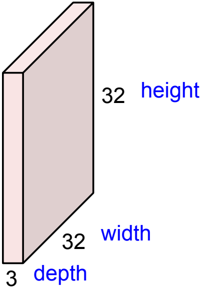


Convolution layer

Arrange neurons as a **3D volume** naturally

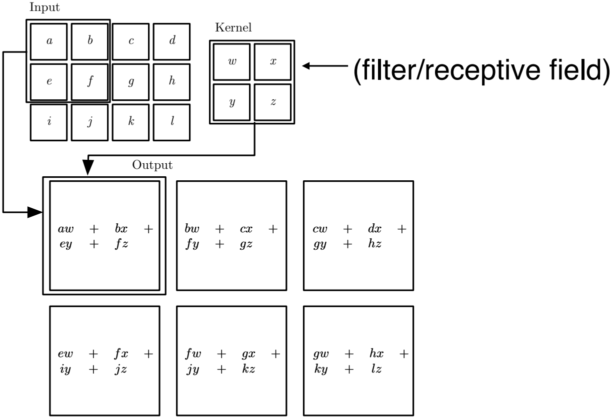
Convolution Layer

32x32x3 image -> preserve spatial structure



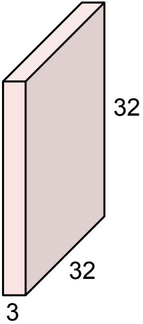
Convolution

2D Convolution

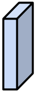


Convolution Layer

32x32x3 image



5x5x3 filter

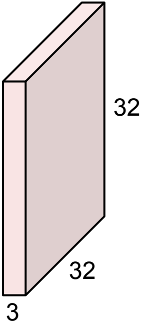


Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

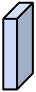
Convolution Layer

Filters always extend the full depth of the input volume

32x32x3 image

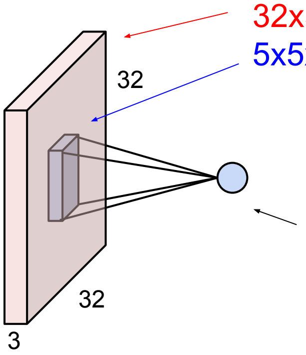


5x5x3 filter



Convolve the filter with the image i.e. “slide over the image spatially, computing dot products”

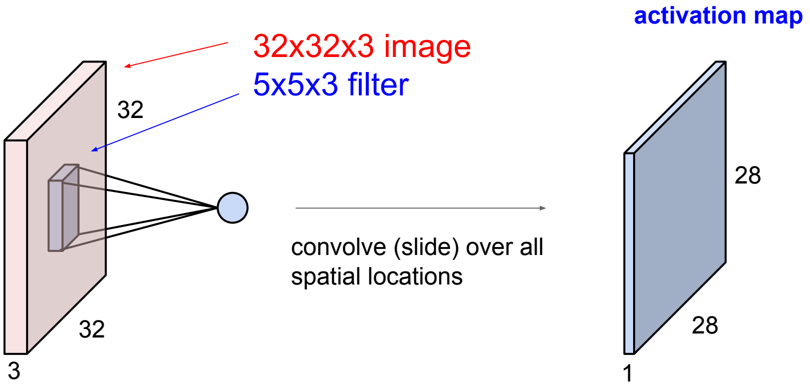
Convolution Layer



1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

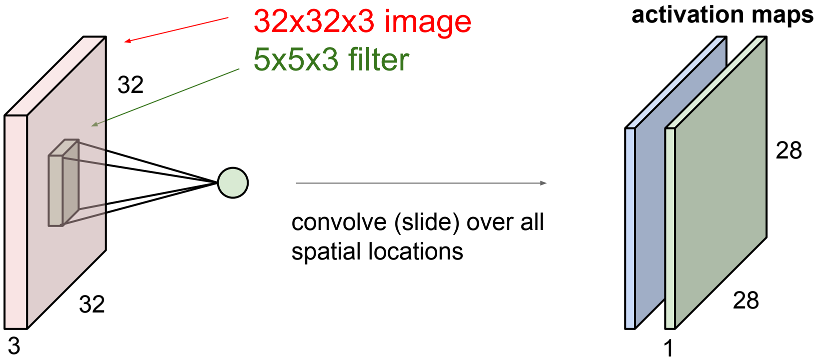
$$w^T x + b$$

Convolution Layer

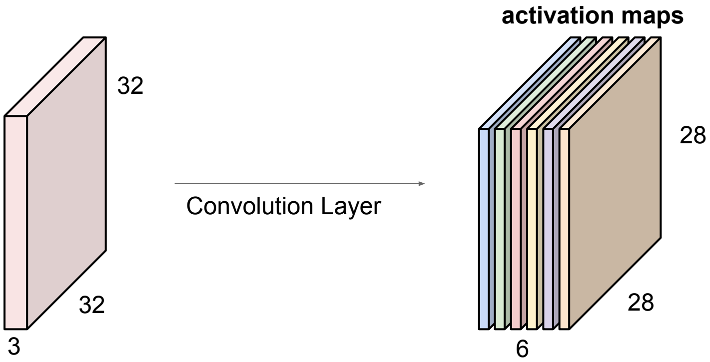


Convolution Layer

consider a second, green filter

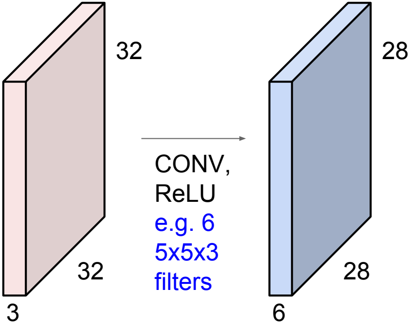


For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:

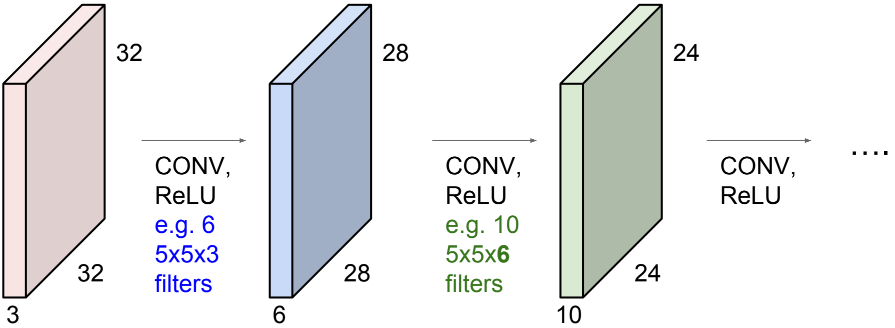


We stack these up to get a "new image" of size 28x28x6!

Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions



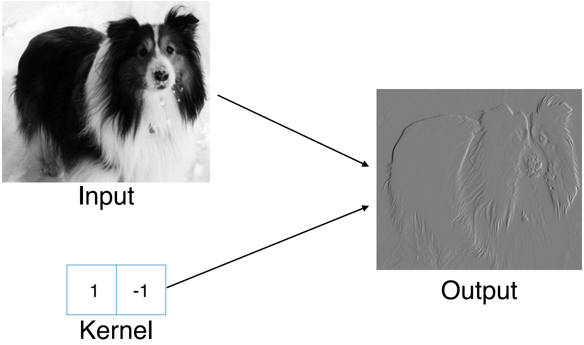
Why convolution makes sense?

Main idea: **if a filter is useful at one location, it should be useful at other locations.**

Why convolution makes sense?

Main idea: **if a filter is useful at one location, it should be useful at other locations.**

A simple example why filtering is useful



Connection to fully connected NNs

A convolution layer is a special case of a fully connected layer:

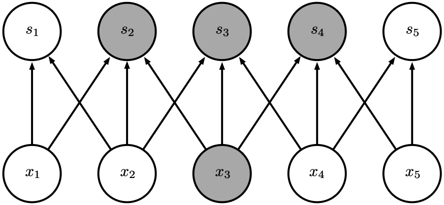
Connection to fully connected NNs

A convolution layer is a special case of a fully connected layer:

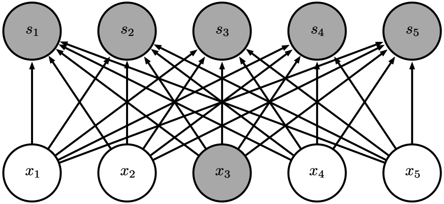
- filter = weights with **sparse connection**

Local Receptive Field Leads to Sparse Connectivity (affects less)

Sparse connections due to small convolution kernel



Dense connections



(Goodfellow 2016)

Sparse connectivity: being affected by less

Sparse connections due to small convolution kernel

Dense connections

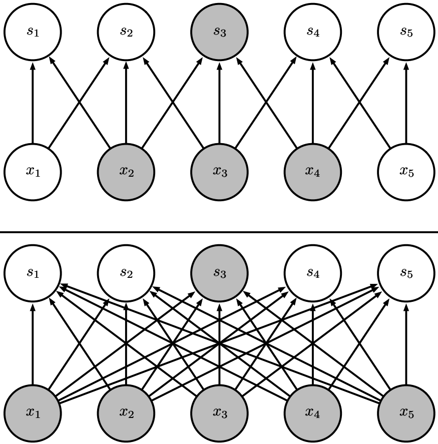


Figure 9.3

(Goodfellow 2016)

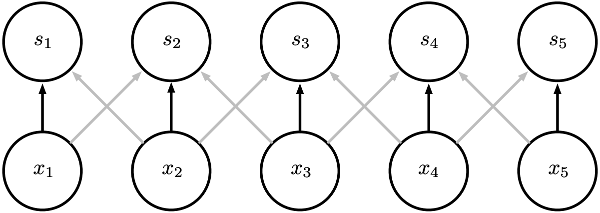
Connection to fully connected NNs

A convolution layer is a special case of a fully connected layer:

- filter = weights with **sparse connection**
- **parameters sharing**

Parameter Sharing

Convolution shares the same parameters across all spatial locations



Traditional matrix multiplication does not share any parameters

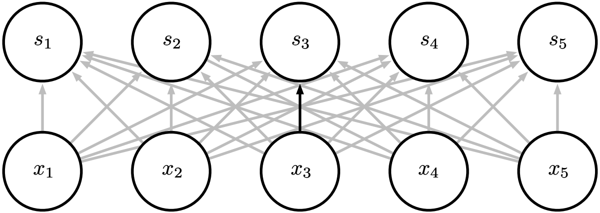


Figure 9.5

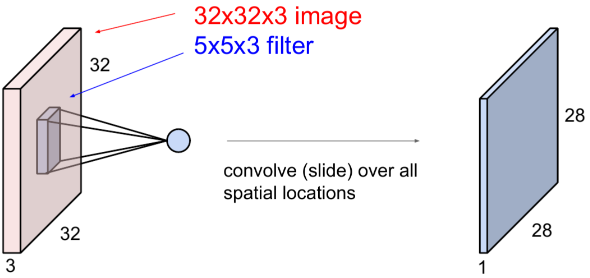
Connection to fully connected NNs

A convolution layer is a special case of a fully connected layer:

- filter = weights with **sparse connection**
- **parameters sharing**

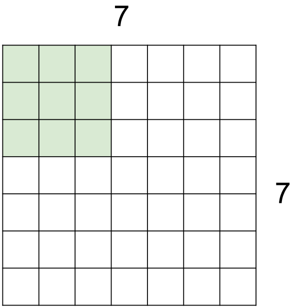
Much fewer parameters! Example (ignore bias terms):

- FC: $(32 \times 32 \times 3) \times (28 \times 28) \approx 2.4M$
- CNN: $5 \times 5 \times 3 = 75$



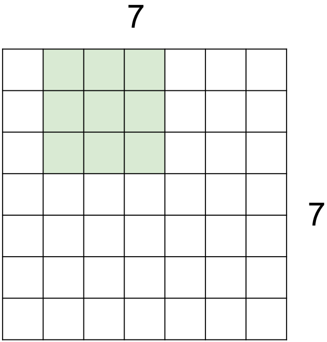
Spatial arrangement: stride and padding

A closer look at spatial dimensions:



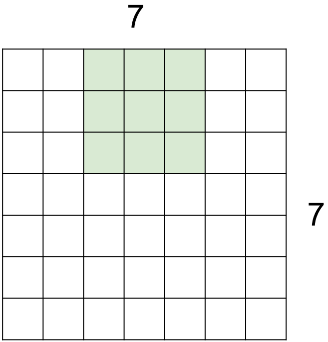
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



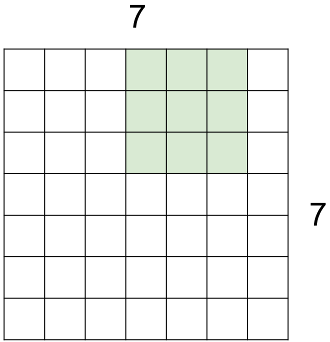
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



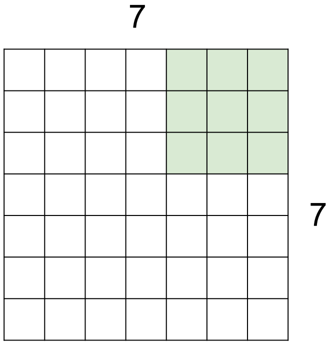
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

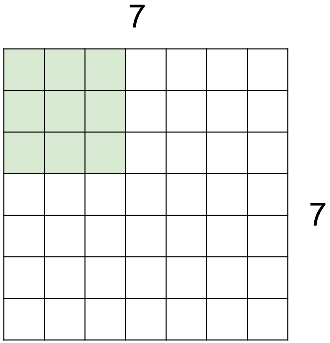
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

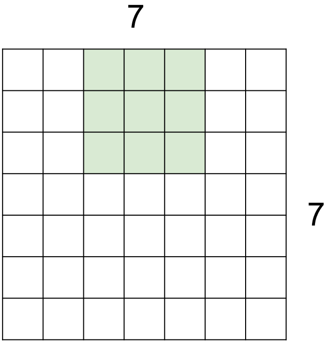
=> 5x5 output

A closer look at spatial dimensions:



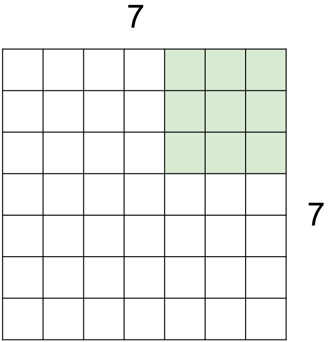
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:



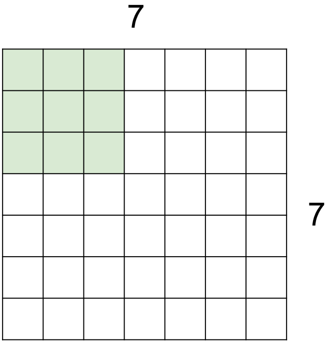
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:



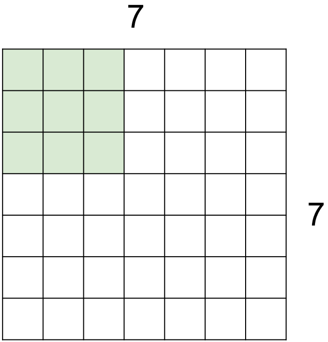
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
=> 3x3 output!

A closer look at spatial dimensions:



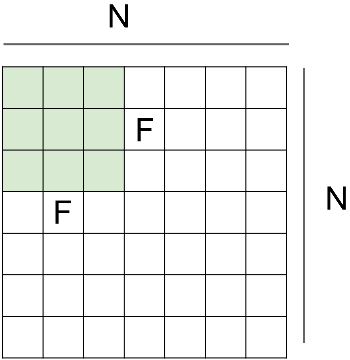
7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

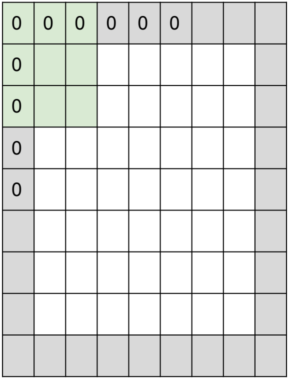
doesn't fit!
cannot apply 3x3 filter on
7x7 input with stride 3.



Output size:
(N - F) / stride + 1

e.g. N = 7, F = 3:
stride 1 => (7 - 3)/1 + 1 = 5
stride 2 => (7 - 3)/2 + 1 = 3
stride 3 => (7 - 3)/3 + 1 = 2.33 :\

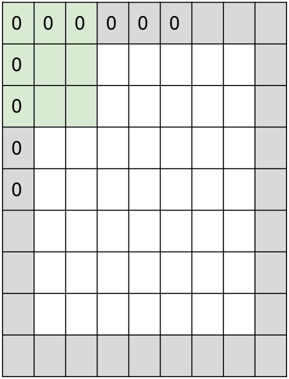
In practice: Common to zero pad the border



e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

(recall:)
(N - F) / stride + 1

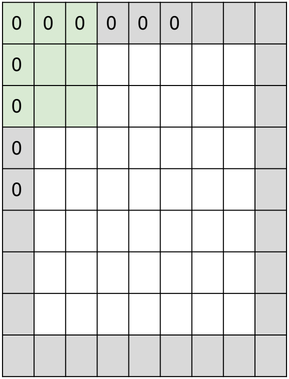
In practice: Common to zero pad the border



e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

7x7 output!

In practice: Common to zero pad the border

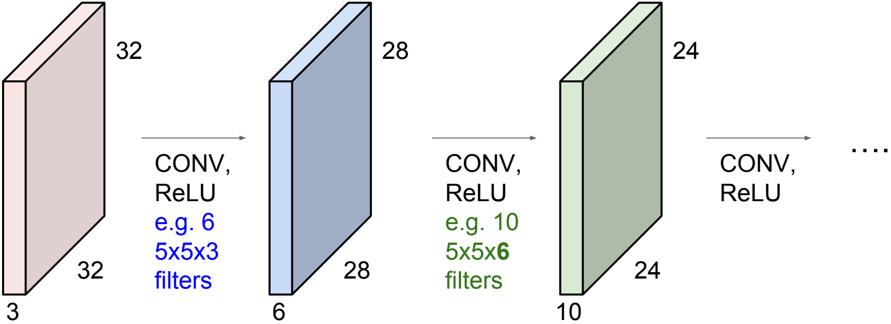


e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

7x7 output!
in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

Remember back to…

E.g. 32x32 input convolved repeatedly with 5x5 filters shrinks volumes spatially! (32 -> 28 -> 24 ...). Shrinking too fast is not good, doesn’t work well.



Summary for convolution layer

Input: a volume of size $W_1 \times H_1 \times D_1$

Summary for convolution layer

Input: a volume of size $W_1 \times H_1 \times D_1$

Hyperparameters:

- K filters of size $F \times F$
- stride S
- amount of zero padding P (for one side)

Summary for convolution layer

Input: a volume of size $W_1 \times H_1 \times D_1$

Hyperparameters:

- K filters of size $F \times F$
- stride S
- amount of zero padding P (for one side)

Output: a volume of size $W_2 \times H_2 \times D_2$ where

- $W_2 =$
- $H_2 =$
- $D_2 =$

Summary for convolution layer

Input: a volume of size $W_1 \times H_1 \times D_1$

Hyperparameters:

- K filters of size $F \times F$
- stride S
- amount of zero padding P (for one side)

Output: a volume of size $W_2 \times H_2 \times D_2$ where

- $W_2 = (W_1 + 2P - F)/S + 1$
- $H_2 =$
- $D_2 =$

Summary for convolution layer

Input: a volume of size $W_1 \times H_1 \times D_1$

Hyperparameters:

- K filters of size $F \times F$
- stride S
- amount of zero padding P (for one side)

Output: a volume of size $W_2 \times H_2 \times D_2$ where

- $W_2 = (W_1 + 2P - F)/S + 1$
- $H_2 = (H_1 + 2P - F)/S + 1$
- $D_2 =$

Summary for convolution layer

Input: a volume of size $W_1 \times H_1 \times D_1$

Hyperparameters:

- K filters of size $F \times F$
- stride S
- amount of zero padding P (for one side)

Output: a volume of size $W_2 \times H_2 \times D_2$ where

- $W_2 = (W_1 + 2P - F)/S + 1$
- $H_2 = (H_1 + 2P - F)/S + 1$
- $D_2 = K$

Summary for convolution layer

Input: a volume of size $W_1 \times H_1 \times D_1$

Hyperparameters:

- K filters of size $F \times F$
- stride S
- amount of zero padding P (for one side)

Output: a volume of size $W_2 \times H_2 \times D_2$ where

- $W_2 = (W_1 + 2P - F)/S + 1$
- $H_2 = (H_1 + 2P - F)/S + 1$
- $D_2 = K$

#parameters: $(F \times F \times D_1 + 1) \times K$ weights

Summary for convolution layer

Input: a volume of size $W_1 \times H_1 \times D_1$

Hyperparameters:

- K filters of size $F \times F$
- stride S
- amount of zero padding P (for one side)

Output: a volume of size $W_2 \times H_2 \times D_2$ where

- $W_2 = (W_1 + 2P - F)/S + 1$
- $H_2 = (H_1 + 2P - F)/S + 1$
- $D_2 = K$

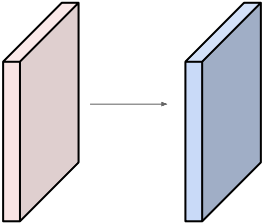
#parameters: $(F \times F \times D_1 + 1) \times K$ weights

Common setting: $F = 3, S = P = 1$

Examples time:

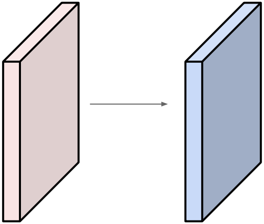
Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

Output volume size: ?



Examples time:

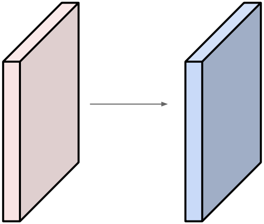
Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2



Output volume size:
(32+2*2-5)/1+1 = 32 spatially, so
32x32x10

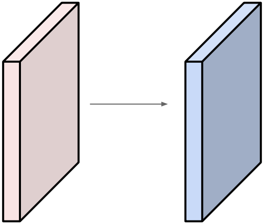
Examples time:

Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2



Number of parameters in this layer?

Examples time:



Input volume: **32x32x3**

10 5x5 filters with stride 1, pad 2

Number of parameters in this layer?

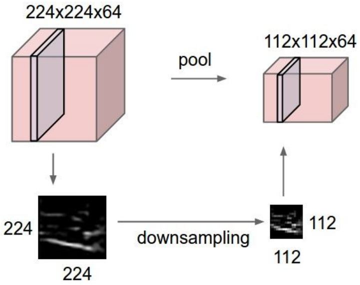
each filter has 5*5*3 + 1 = 76 params (+1 for bias)

=> 76*10 = **760**

Another element: pooling

Pooling layer

- makes the representations smaller and more manageable
- operates over each activation map independently:



Pooling

Similar to a filter, except

- depth is always 1

Pooling

Similar to a filter, except

- depth is always 1
- different operations: average, L2-norm, max

Pooling

Similar to a filter, except

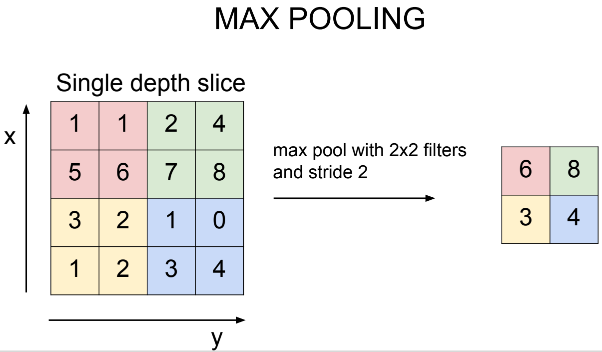
- depth is always 1
- different operations: average, L2-norm, max
- no parameters to be learned

Pooling

Similar to a filter, except

- depth is always 1
- different operations: average, L2-norm, max
- no parameters to be learned

Max pooling with 2×2 filter and stride 2 is very common



Putting everything together

Typical architecture for CNNs:

Input $\rightarrow$ [[Conv $\rightarrow$ ReLU]*N $\rightarrow$ Pool?]*M $\rightarrow$ [FC $\rightarrow$ ReLU]*Q $\rightarrow$ FC

Putting everything together

Typical architecture for CNNs:

Input $\rightarrow$ [[Conv $\rightarrow$ ReLU]*N $\rightarrow$ Pool?]*M $\rightarrow$ [FC $\rightarrow$ ReLU]*Q $\rightarrow$ FC

Common choices: $N \leq 5, Q \leq 2$, M is large

Putting everything together

Typical architecture for CNNs:

Input $\rightarrow$ [[Conv $\rightarrow$ ReLU]*N $\rightarrow$ Pool?]*M $\rightarrow$ [FC $\rightarrow$ ReLU]*Q $\rightarrow$ FC

Common choices: $N \leq 5, Q \leq 2$, M is large

Well-known CNNs: LeNet, AlexNet, ZF Net, GoogLeNet, VGGNet, etc.

All achieve excellent performance on image classification tasks.

How to train a CNN?

How do we learn the filters/weights?

How to train a CNN?

How do we learn the filters/weights?

Essentially the same as FC NNs: apply **SGD/backpropagation**