2012 : AlexNet ImageNet

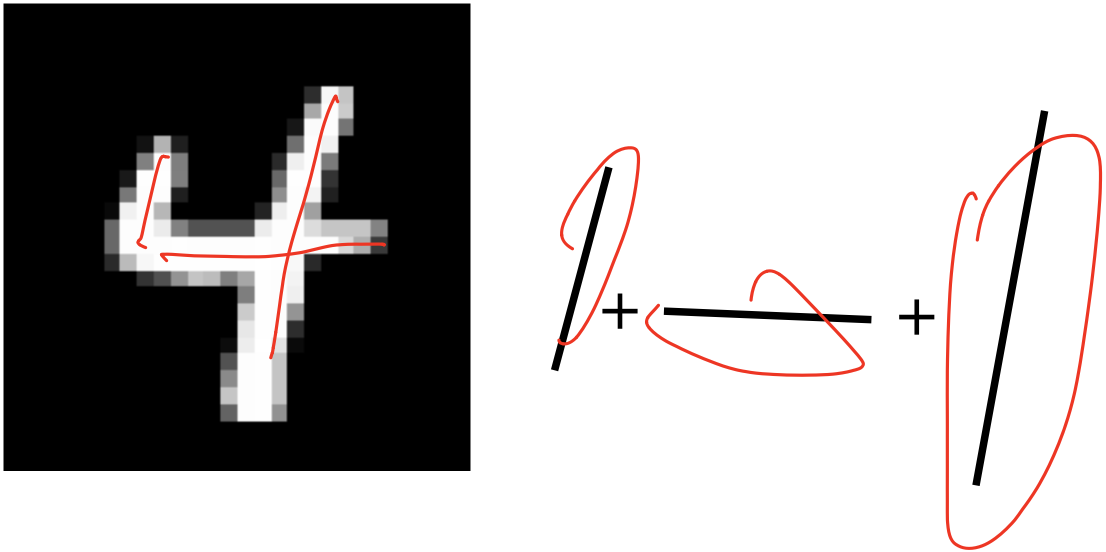
DSC 140B

Representation Learning

Lecture 23 | Part 1

Convolutions

Transformer

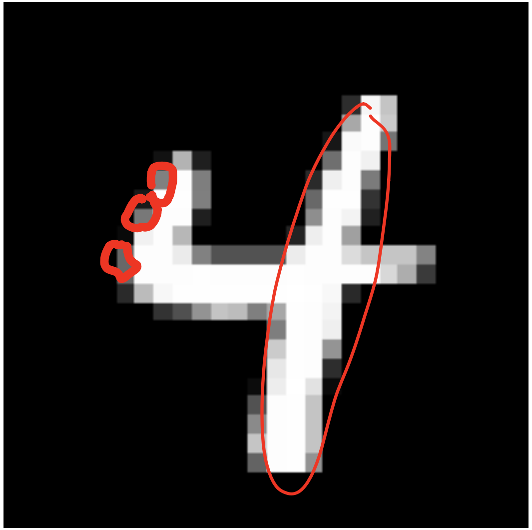


From Simple to Complex

- Complex shapes are made of simple patterns
- The human visual system uses this fact
- Line detector → shape detector → … → face detector
- Can we replicate this with a deep NN?

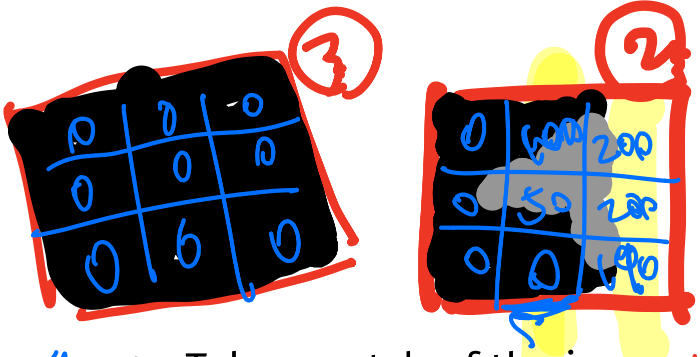
Edge Detector

- How do we find **vertical edges** in an image?
- One solution: **convolution** with an **edge filter**.

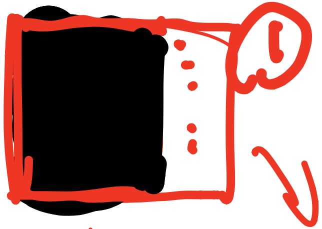


Vertical Edge Filter

0	-1	1
0	-1	1
0	-1	1



Idea



255×1+255×1
+255×1

- Take a patch of the image, same size as filter.
- Perform “dot product” between patch and filter.
- If large, this is a (vertical) edge.

(0×−1+50×−1
+200×1+200×1
+190×1 = 3

image patch:

0	0	255
0	0	255
0	0	255

filter:

0	−1	1
0	−1	1
0	−1	1

✓

Idea

- Move the filter over the entire image, repeat procedure.

0	0	0	0	0	0		
0	0	.9	0	0	.7		
0	0	.9	0	0	.8		
0	0	.8	0	0	.9		
0	0	.7	0	0	0		

8

8

$*$ 3

0	-1	1
0	-1	1
0	-1	1

3

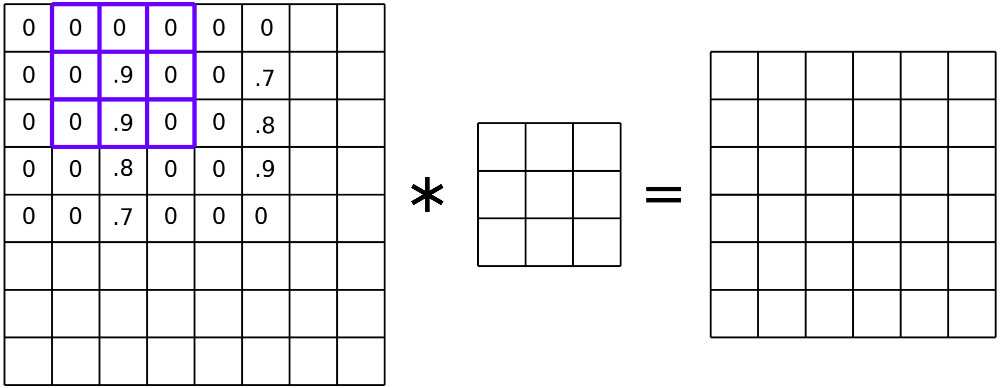
=

1.8	0	✓			

4

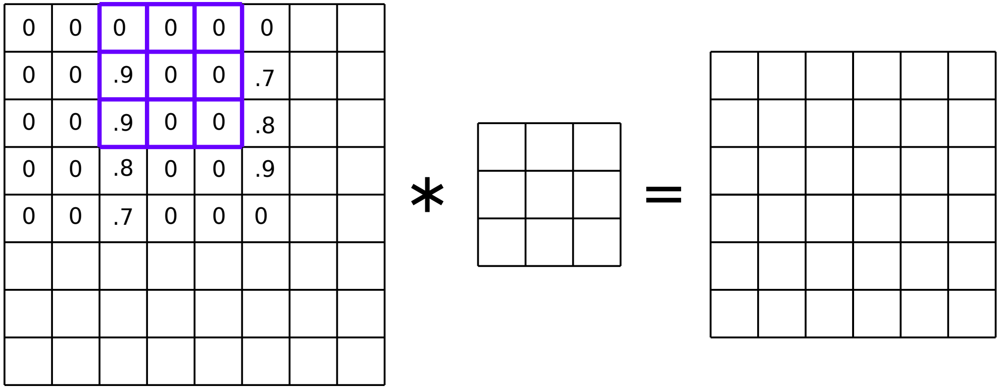
Idea

- Move the filter over the entire image, repeat procedure.



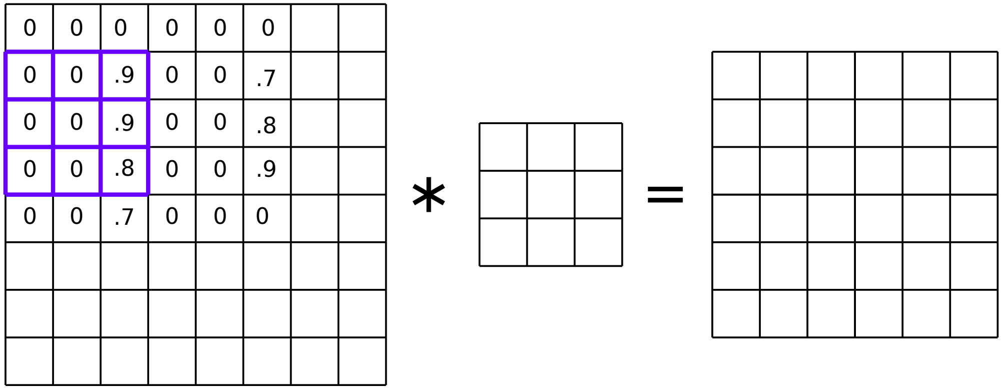
Idea

- Move the filter over the entire image, repeat procedure.



Idea

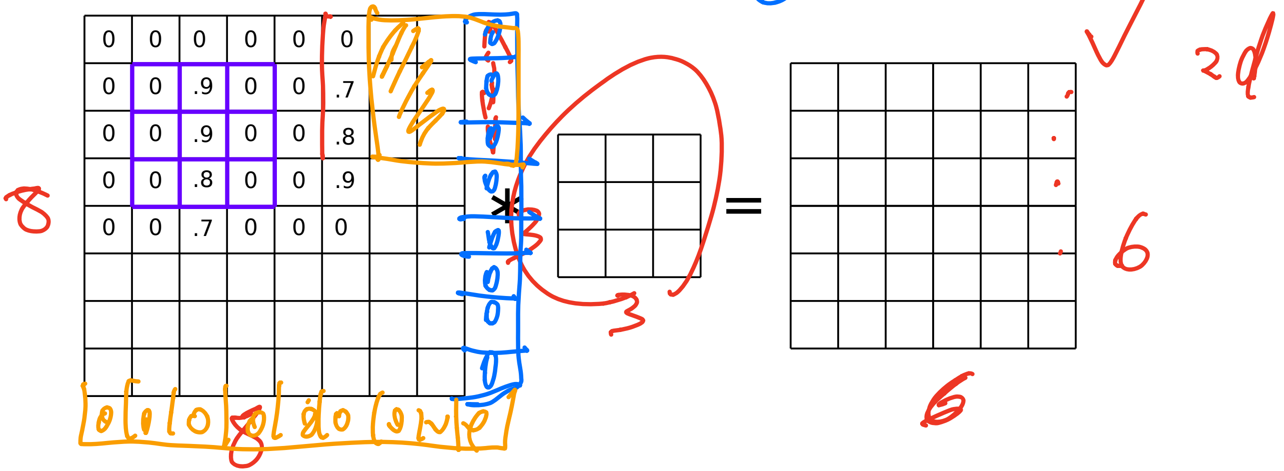
- Move the filter over the entire image, repeat procedure.



Idea

- Move the filter over the entire image, repeat procedure.

padding =1

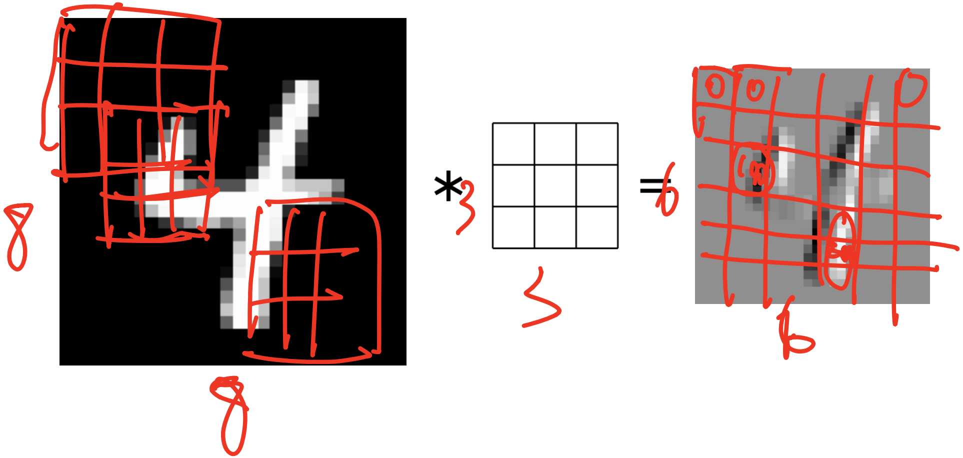


Convolution

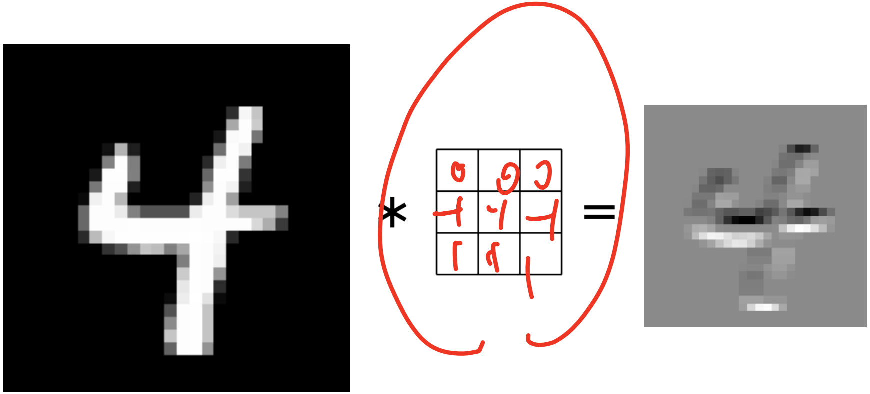
- The result is the (2d) **convolution** of the filter with the image.
- Output is also 2-dimensional array.
- Called a **response map**.

feature map

Example: Vertical Filter



Example: Horizontal Filter



More About Filters

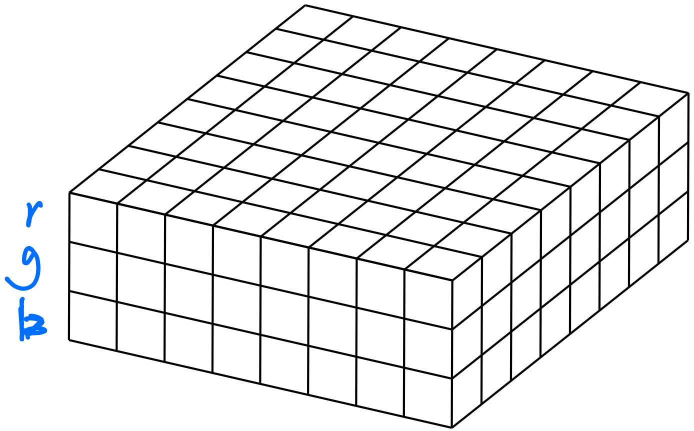
- Typically 3×3 or 5×5. 4×4
- Variations: different **stride**, image **padding**. = 2

1 2 = 4

3-d Filters

- Black and white images are 2-d arrays.
- But color images are 3-d arrays:
  - a.k.a., **tensors**
  - Three color **channels**: red, green, blue.
  - height × width × 3
- How does convolution work here?

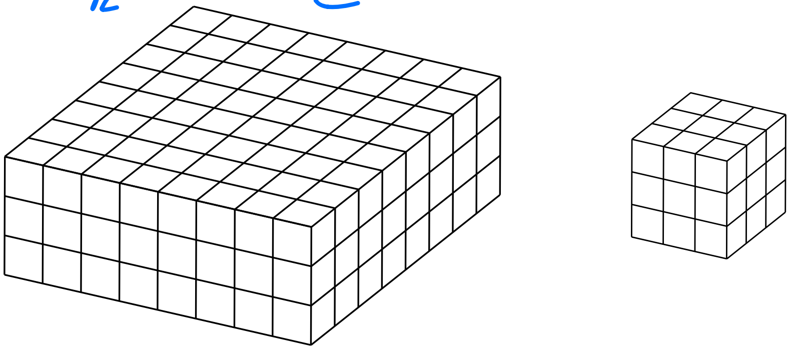
Color Image



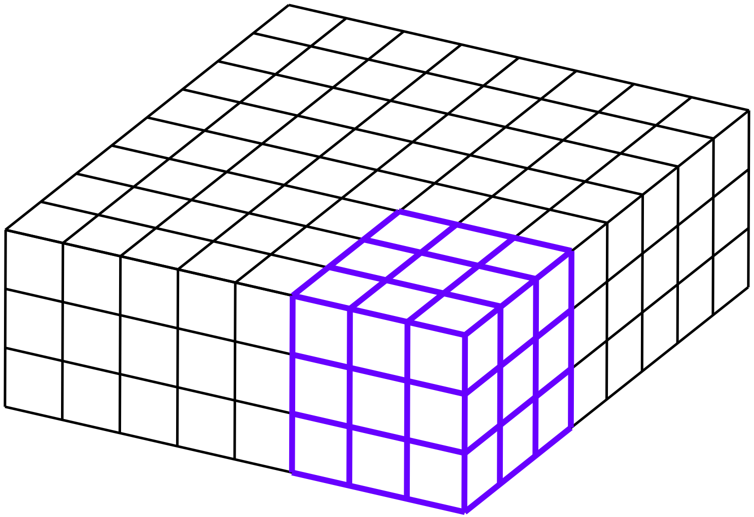
3-d Filter

- The filter must also have three channels:
  - $3 \times 3 \times 3$, $5 \times 5 \times 3$, etc.

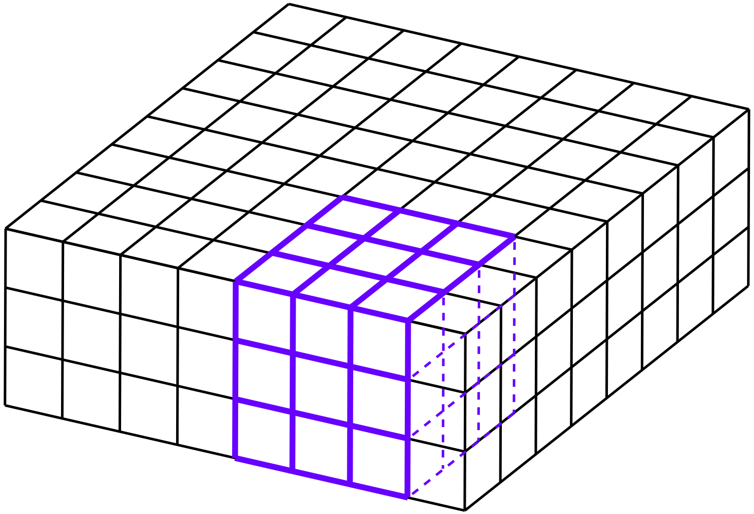
h w c



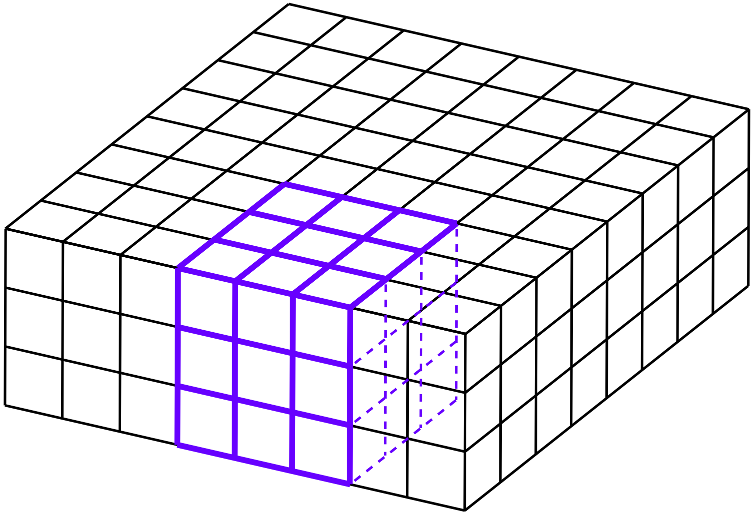
3-d Filter



3-d Filter



3-d Filter

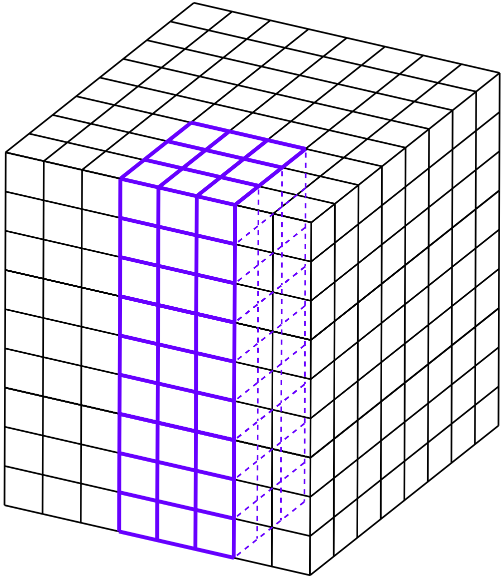


Convolution with 3-d Filter

- Filter must have same number of channels as image.
  - 3 channels if image RGB.
- Result is still a 2-d array.

General Case

- Input "image" has k channels.
- Filter must have k channels as well.
  - e.g., $3 \times 3 \times k$
- Output is still $2-d$



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Representation Learning

Lecture 23 | Part 2

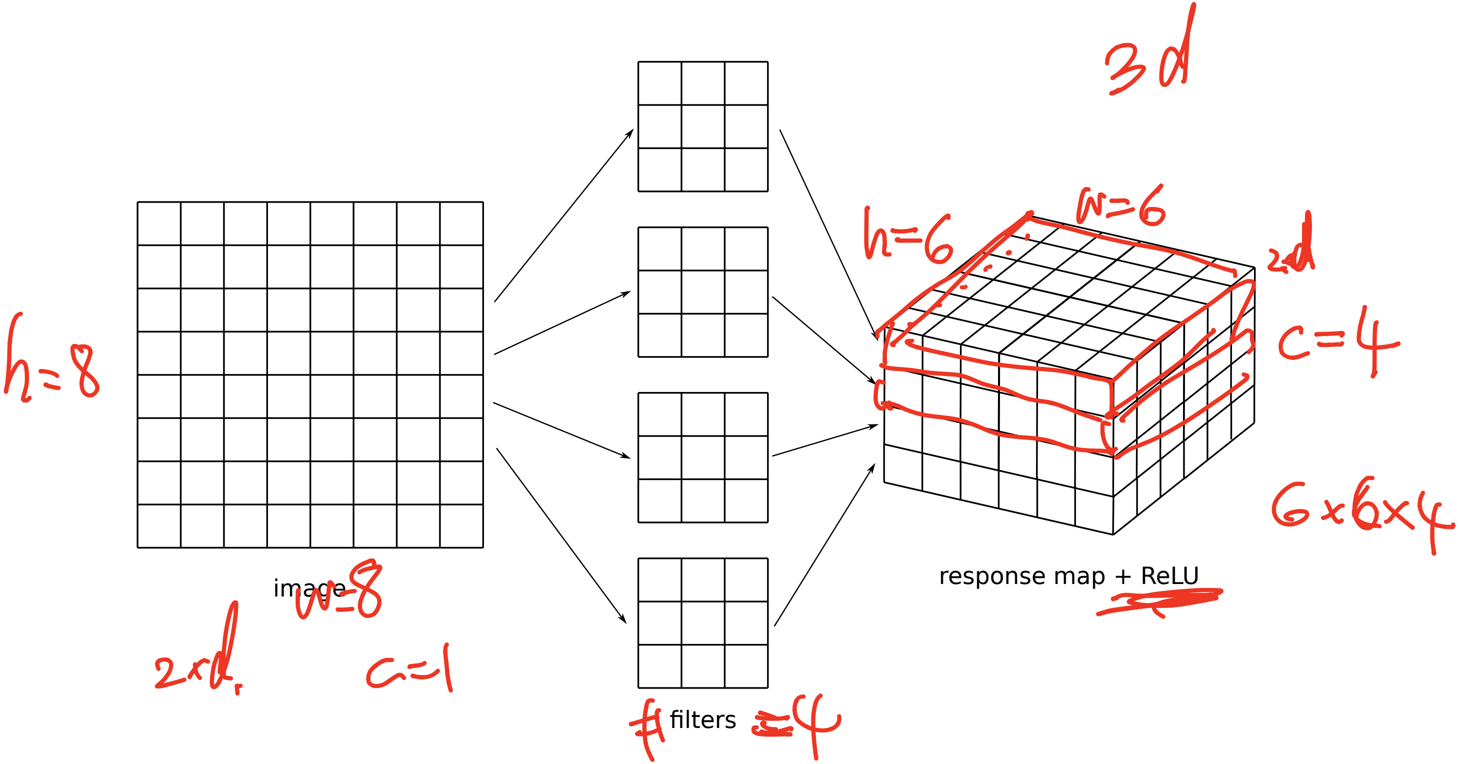
Convolutional Neural Networks

Convolutional Neural Networks

ConvNet

- **CNN**s are the state-of-the-art for many computer vision tasks
- **Idea**: use convolution in early layers to create new feature representation.
- **But!** Filters are **learned**.

Input Convolutional Layer

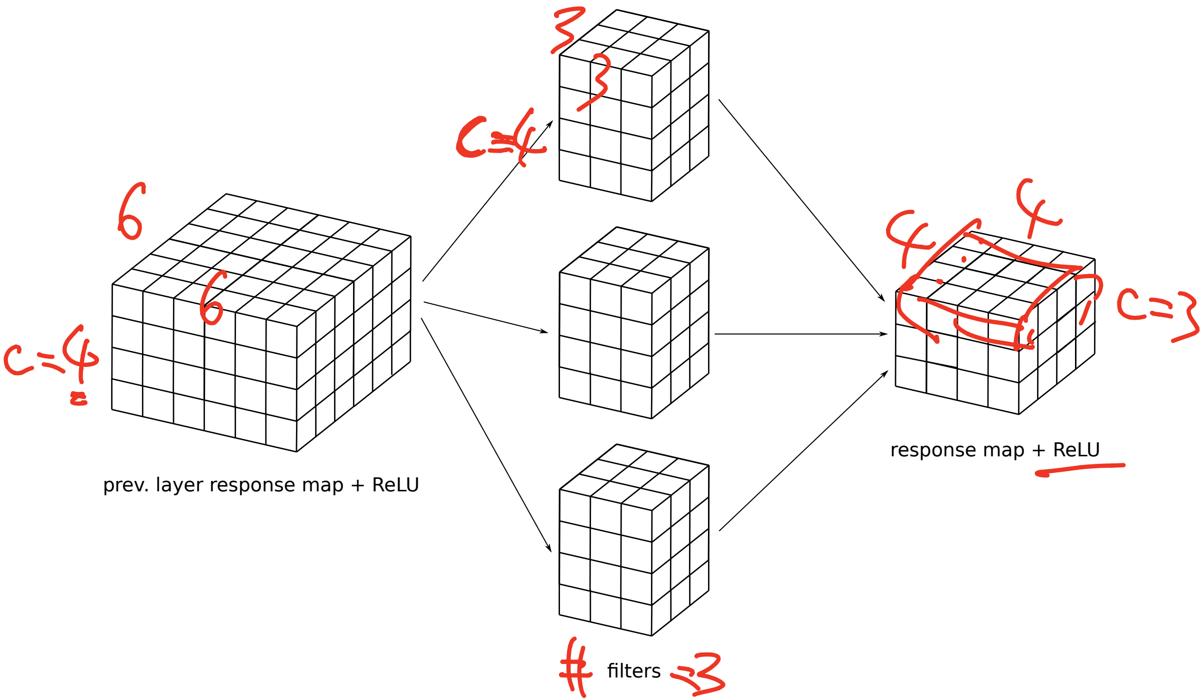


Input Convolutional Layer

- Input image with one channel (grayscale)
- k_1 filters of size $\ell \times \ell \times 1$
- Results in k_1 convolutions, stacked to make response map.

  $w \times h \times k_1$
- ReLU (or other nonlinearity) applied entrywise.

Second Convolutional Layer



Second Convolutional Layer

- Input is a 3-d **tensor**.
  - "Stack" of k_1 response maps.

- k_2 filters, each a 3-d tensor with k_1 channels.

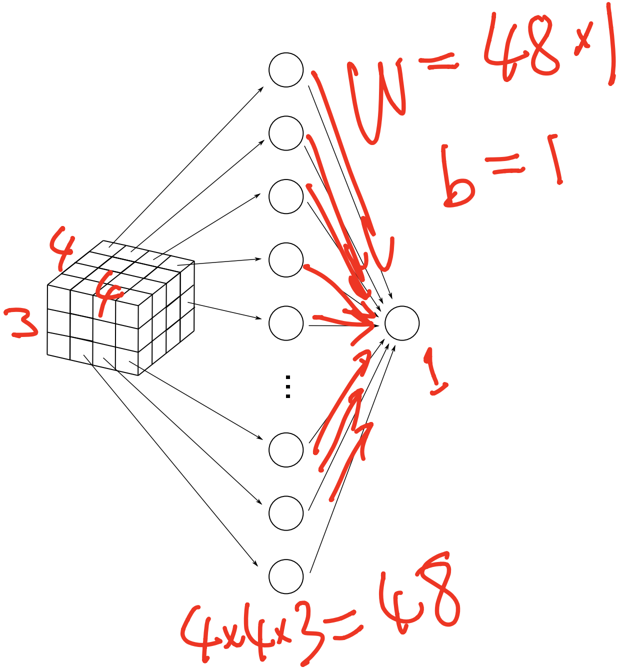
- Output is a 3-d tensor with k_2 channels.

$w \times h \times k_2$

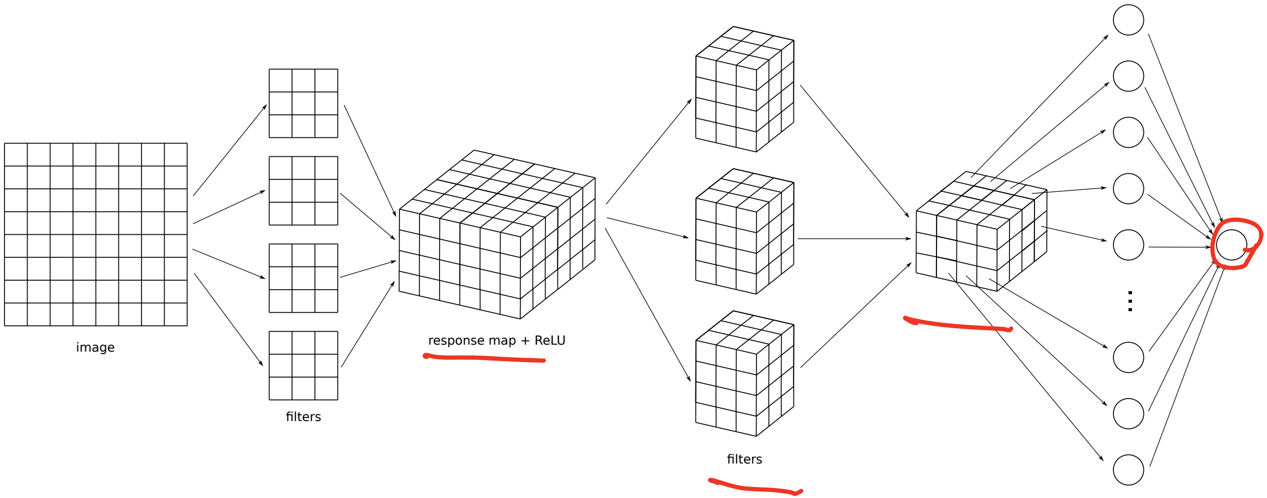
More Convolutional Layers

- May add more convolutional layers.
- Last convolutional layer used as input to a feedforward, fully-connected network.
- Need to “flatten” the output tensor.

Flattening



Full Network

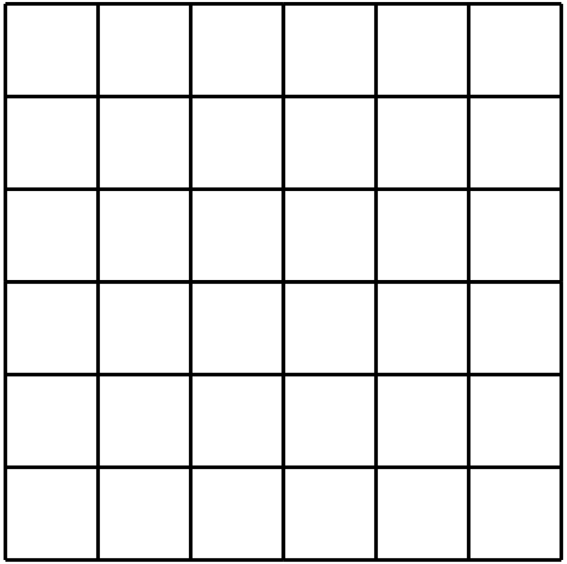


What is learned?

- The filters themselves.
- The weights in the feedforward NN used for prediction.

Max Pooling

- **Max pooling** is an important part of convolutional layers in practice.
- Reduces size of response map, number of parameters.



DSC 140B

Representation Learning

Lecture 23 | Part 3

Example: Image Classification

Problem

- Predict whether image is of a **car** or a **truck**.

Problem

- Predict whether image is of a **car** or a **truck**.

Problem

- Predict whether image is of a **car** or a **truck**.

Problem

- Predict whether image is of a **car** or a **truck**.

Problem

- Predict whether image is of a **car** or a **truck**.

Problem

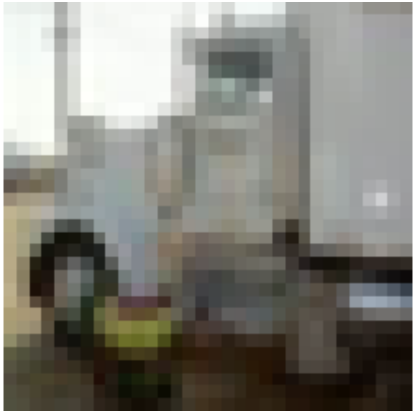
- Predict whether image is of a **car** or a **truck**.

Problem

- Predict whether image is of a **car** or a **truck**.

Problem

- Predict whether image is of a **car** or a **truck**.



Problem

- Predict whether image is of a **car** or a **truck**.

Problem

- Predict whether image is of a **car** or a **truck**.

Details

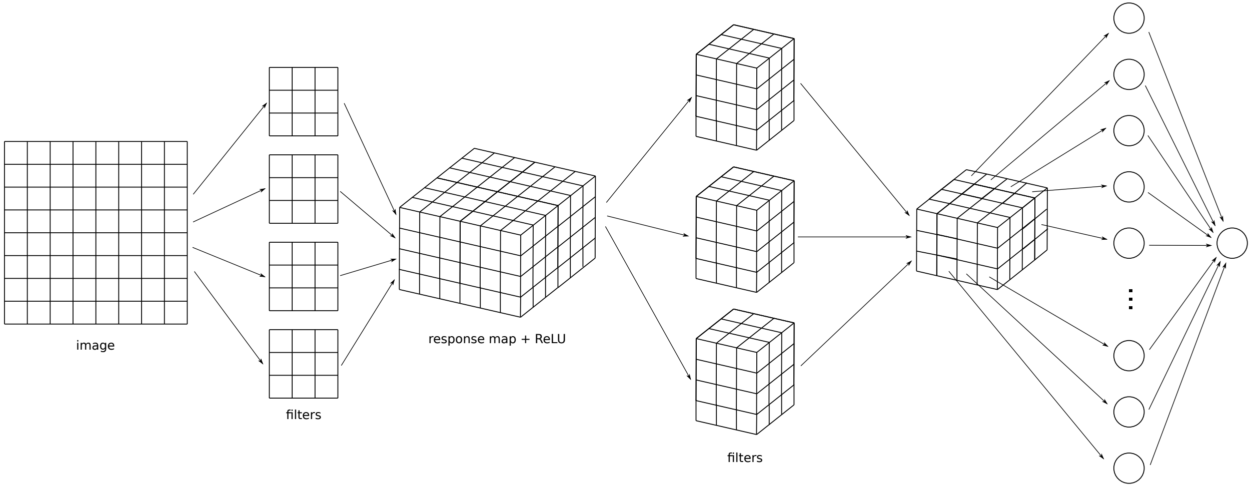
- 3-channel 32×32 color images
- 10,000 training images; 2,000 test[1]
- Cars, trucks in different orientations, scales
- Balanced: 50% cars, 50% trucks

[1] CIFAR-10

Approach #1: Least Squares Classifier

- Train directly on raw features (grayscale)
- Result: 72% train accuracy, 63% test accuracy
- Need a better feature representation

Approach #2: Convolutional Neural Network



Architecture

- 3 convolutional layers with 32, 64, 64 filters
- ReLU, max pooling after first two
- Dense layer with 64 hidden neurons, ReLU
- Output layer with sigmoid activation
- Minimize cross-entropy loss; use *dropout*

The Code

```
model = keras.models.Sequential()

model.add( keras.layers.Conv2D(32, (7, 7), activation='relu', input_shape=(32, 32, 1)))
model.add(keras.layers.MaxPooling2D((2, 2)))

model.add(keras.layers.Conv2D(64, (5, 5), activation='relu'))
model.add(keras.layers.MaxPooling2D((2, 2)))

model.add(keras.layers.Conv2D(64, (3, 3), activation='relu'))

model.add(keras.layers.Flatten())
model.add(keras.layers.Dropout(0.5))
model.add(keras.layers.Dense(64, activation='relu'))
model.add(keras.layers.Dense(1, activation='sigmoid'))
```

The Code

```
model.compile(
    optimizer=keras.optimizers.RMSprop(),
    loss=keras.losses.BinaryCrossentropy(),
    metrics=['accuracy']
)

model.fit(
    X_train,
    y_train,
    epochs=30,
    validation_data=(X_test, y_test)
)
```

Results

- 94% train accuracy, 90% test accuracy

Results

car / car

Results

truck / car

Results

truck / truck

Results

truck / truck

Results

truck / truck

Results

truck / truck

Results

truck / truck

Results

car / car

Results

truck / truck

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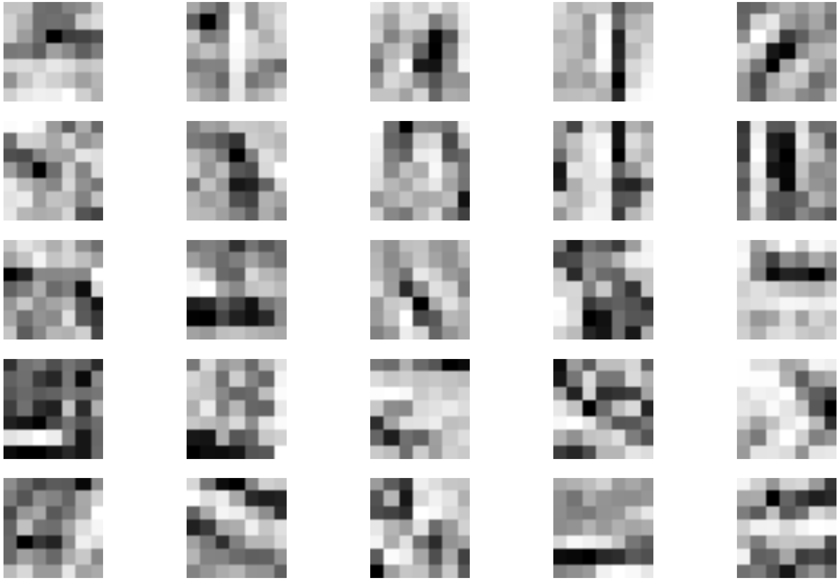
car / car

Results

car / car

Filters



Next Steps

- In practice, you might not train your own CNN
- Instead, take "pre-trained" convolutional layers from a much bigger network
- Attach untrained fully-connected layer and train
- This is **transfer learning**