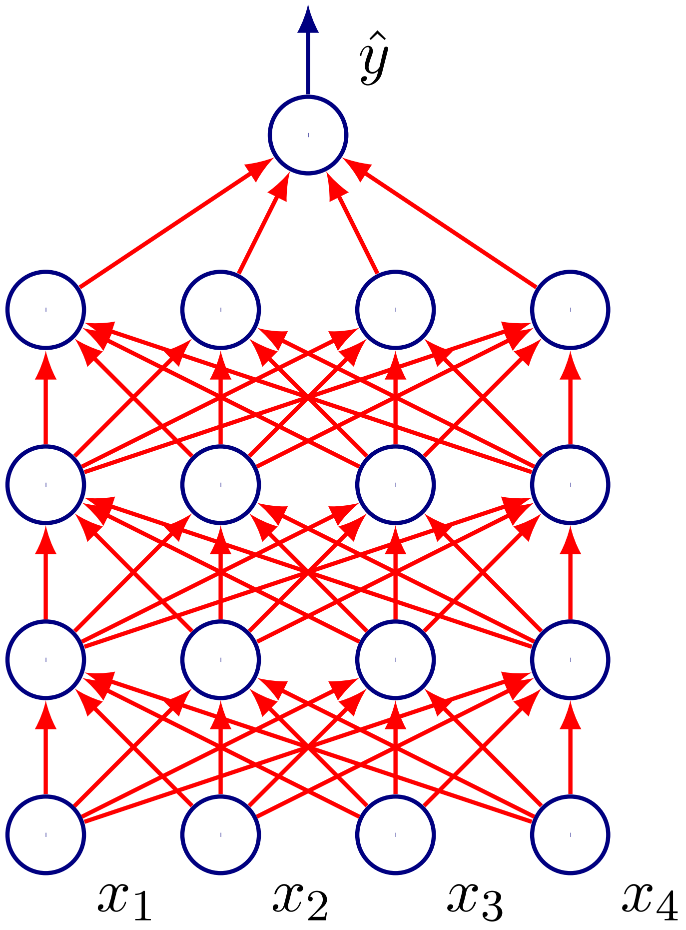
UNIVERSITÀ DELLA CALABRIA

ConvNets

Fully Connected Networks



$$a_i = \sum_{j \prec i} w_{i,j} z_j$$

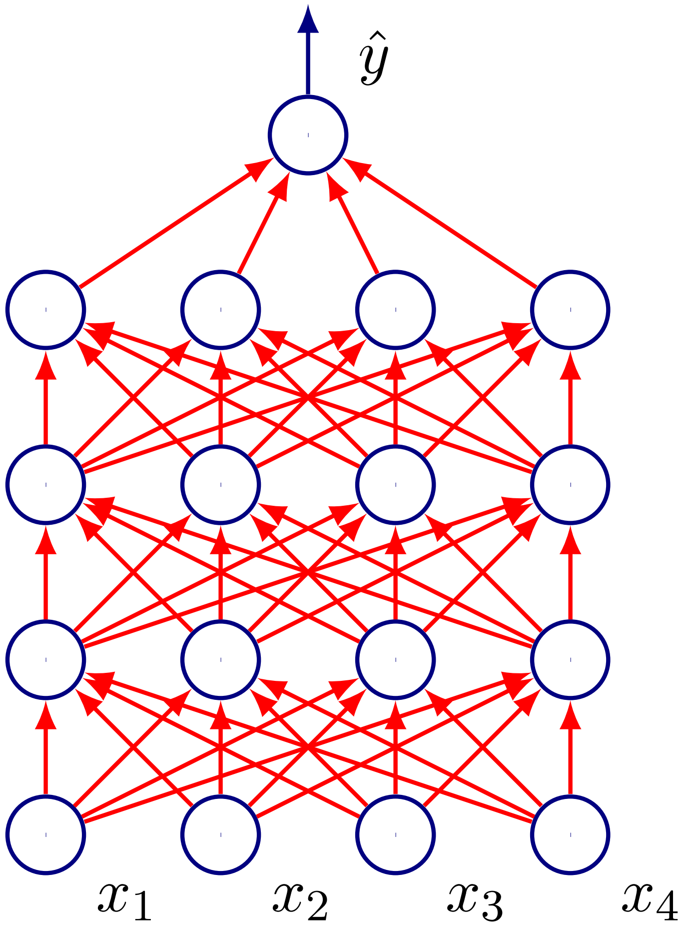
$$z_i = f(a_i)$$

$$\mathbf{a}^{(h+1)} = \mathbf{W}^{(h)} \mathbf{z}^{(h)}$$

$$\mathbf{z}^{(h+1)} = f\left(\mathbf{a}^{(h+1)}\right)$$

$$\mathbf{z}^{(0)} = \mathbf{x}$$

Fully Connected Networks



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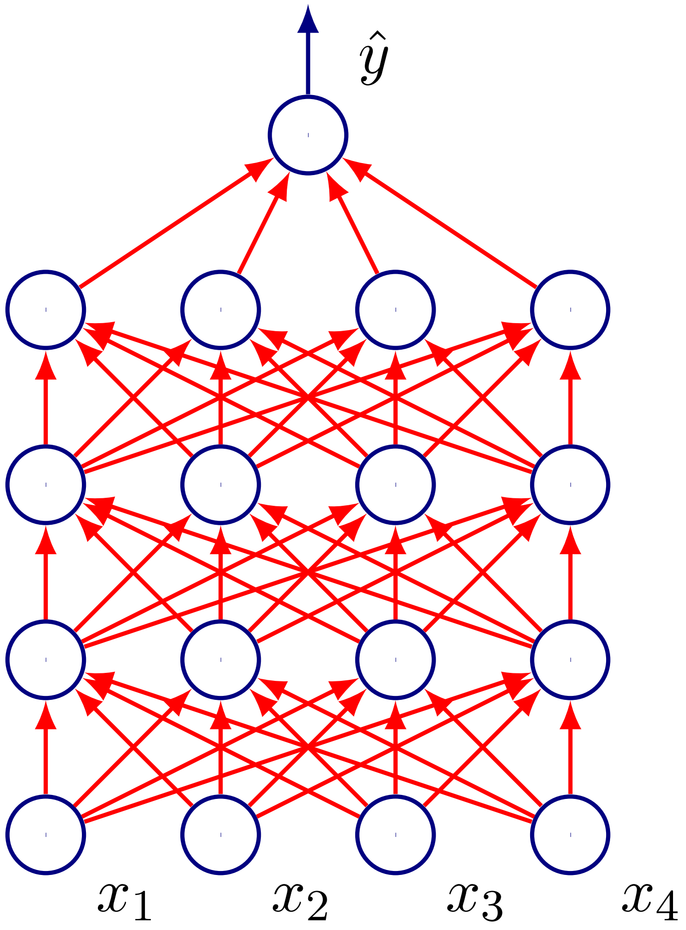
  - (5*4) + (5*4) + (5*4) + (5*4) + 5 connections

Fully Connected Networks



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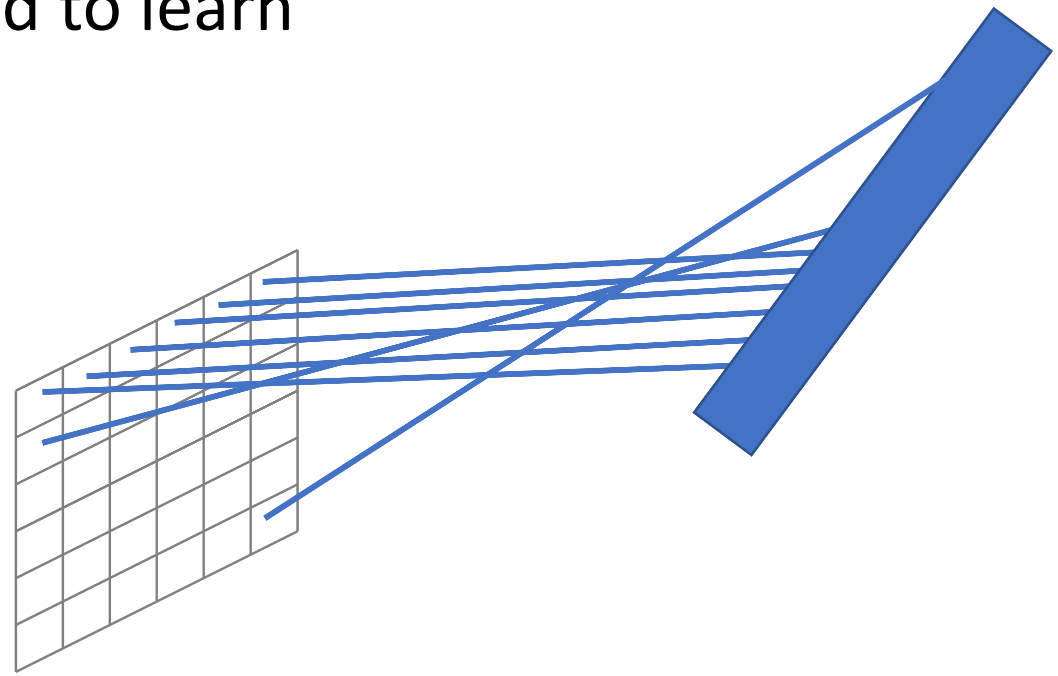
- Each element is connected to the other, so we have
  - (5*4) + (5*4) + (5*4) + (5*4) + 5 connections
- For a generic network with *k* layers and size d_h for each layer *h*, we have

$$\sum_{h=1}^{k} d_h \cdot d_{h-1}$$

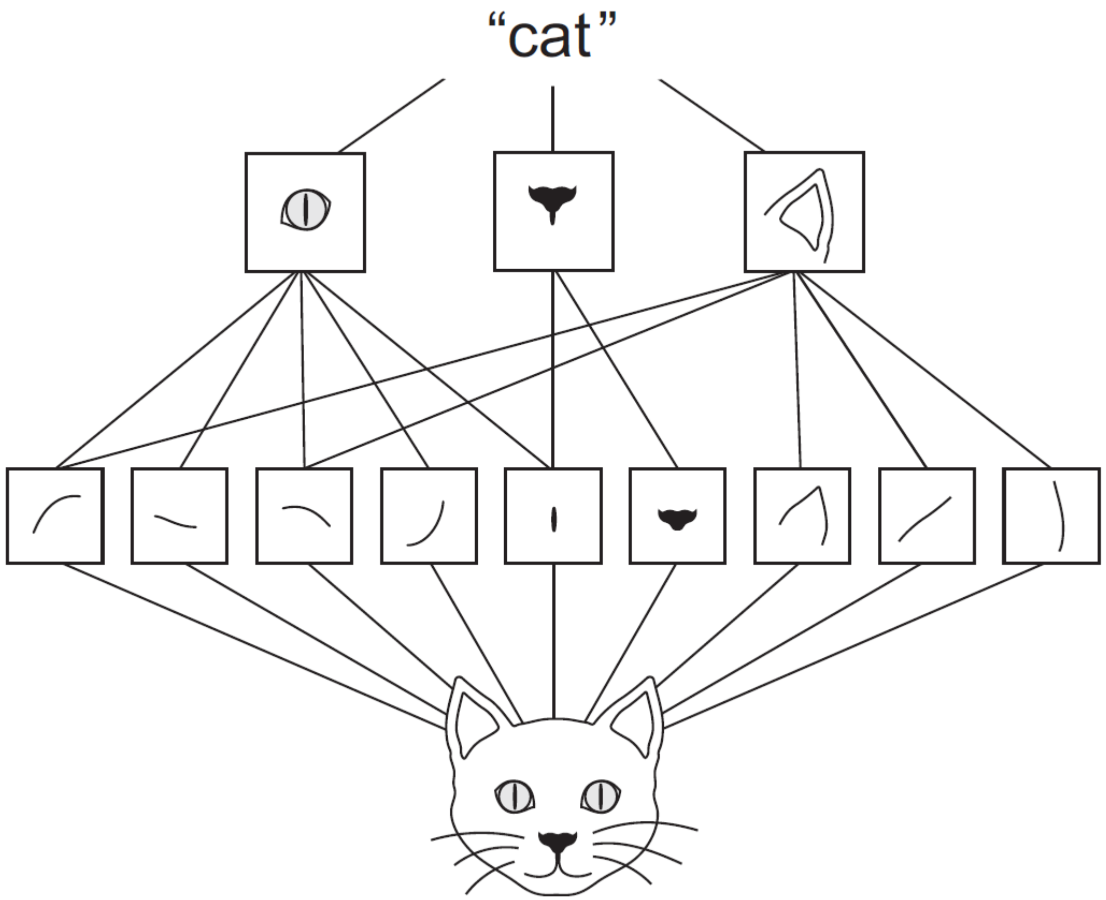
Further Issues with Images

- The «flat» approach is not suited to learn
  - Spatial patterns
  - Spatial hierarchies

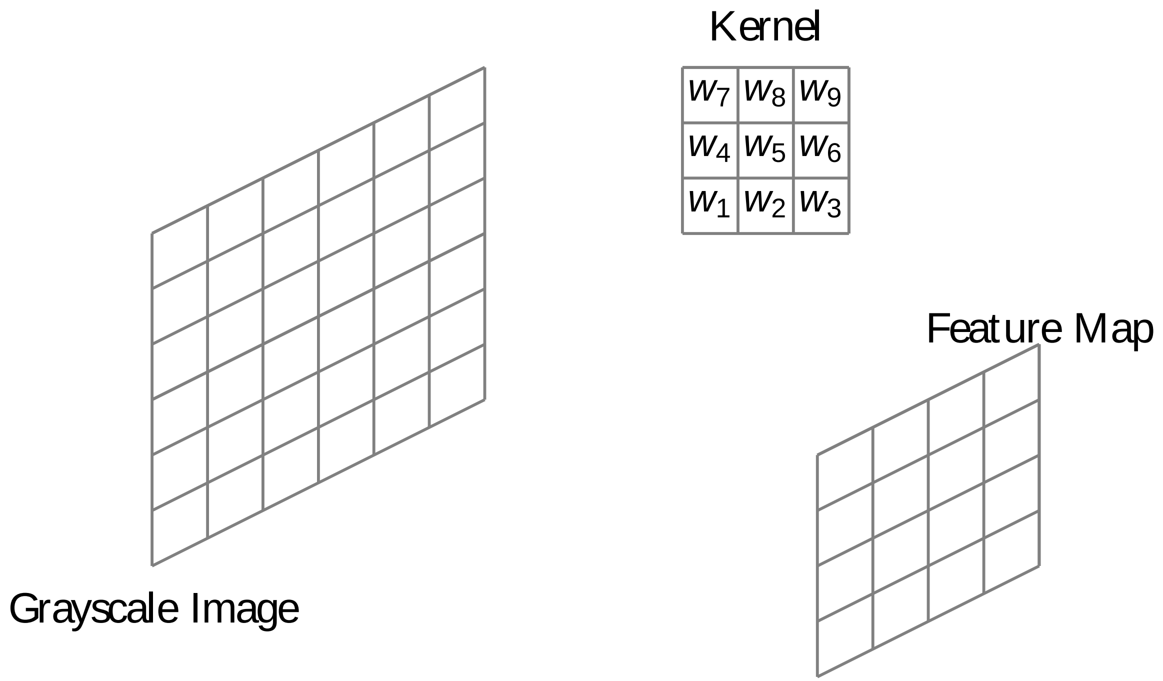


Example of patterns and hierarchies

- How to identify such patterns?
- How to generalize them?



Convolution



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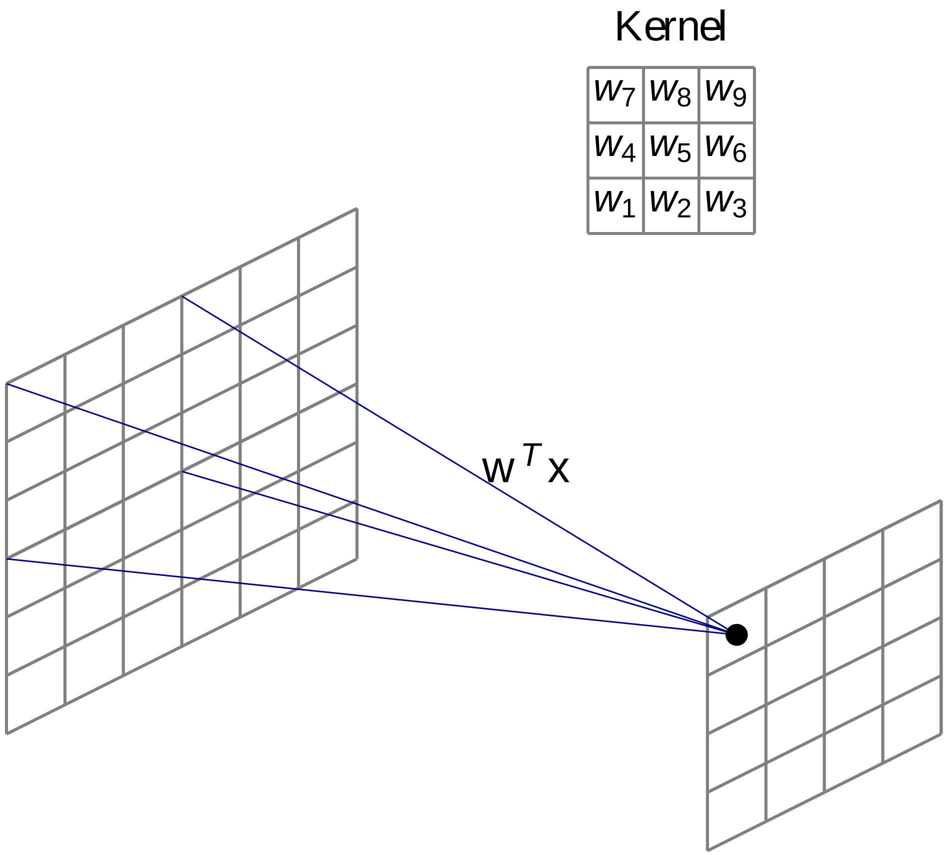
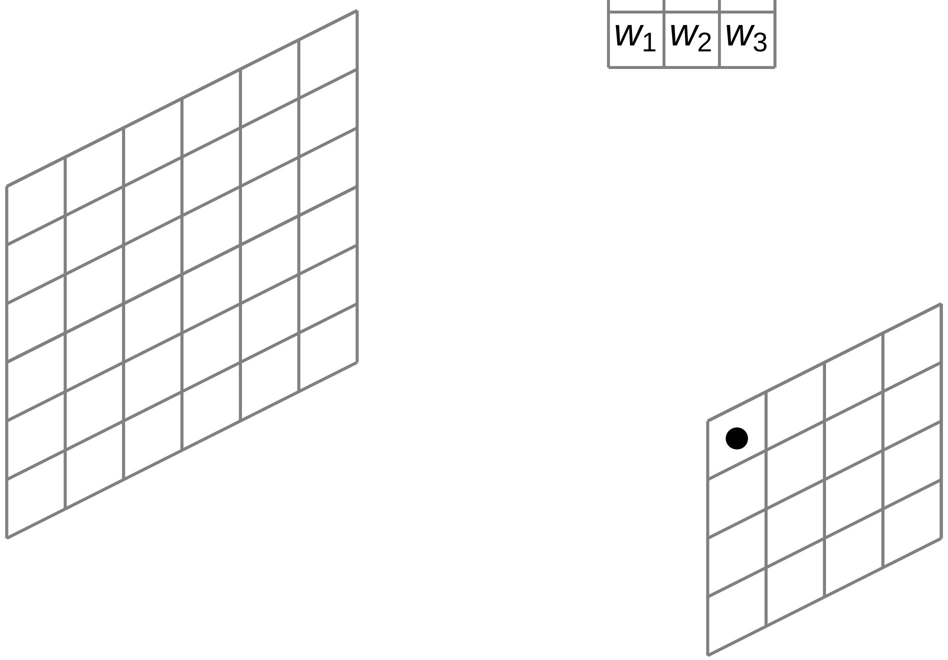


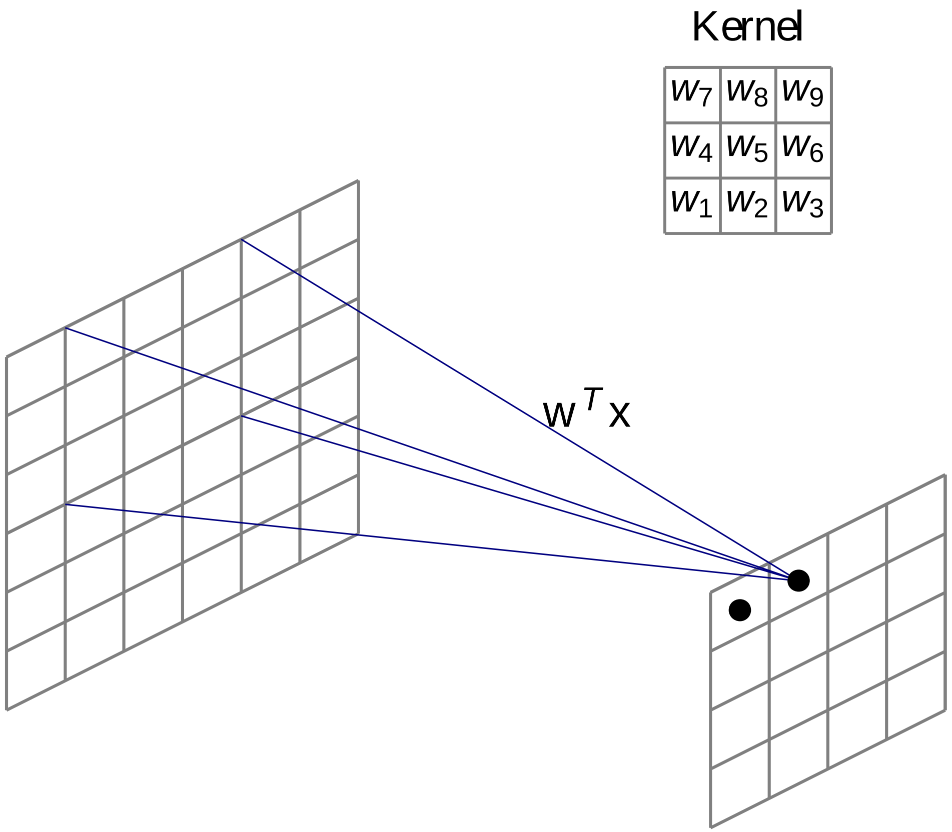
Convolution

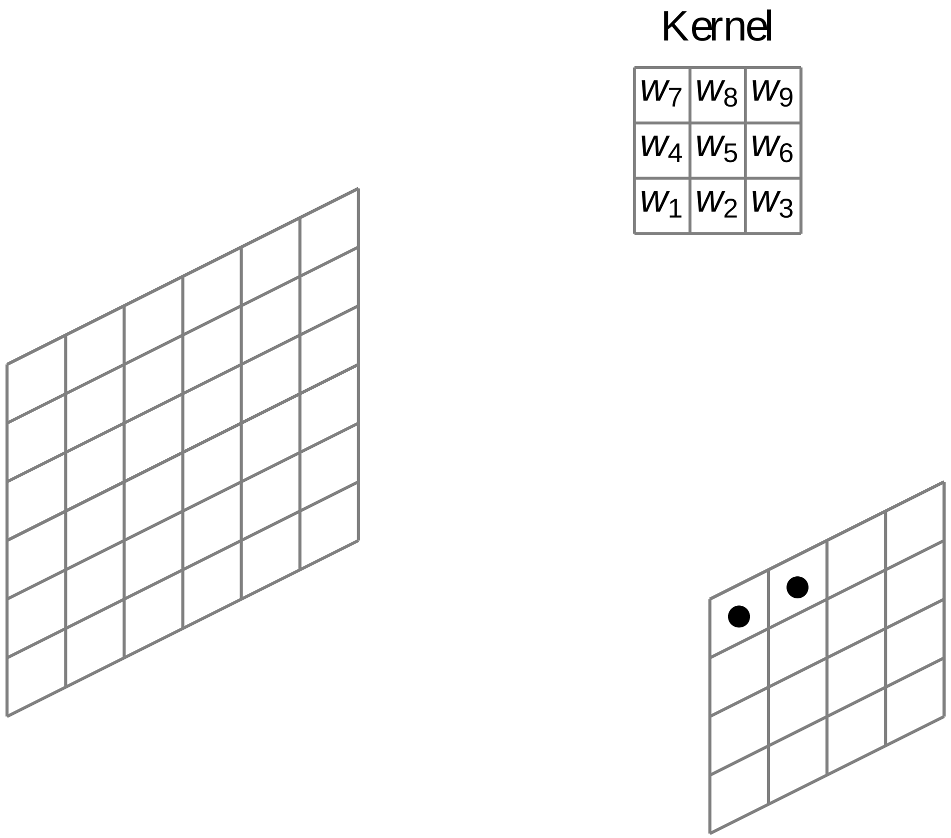
Kernel

w_7	w_8	w_9
w_4	w_5	w_6
w_1	w_2	w_3



Convolution

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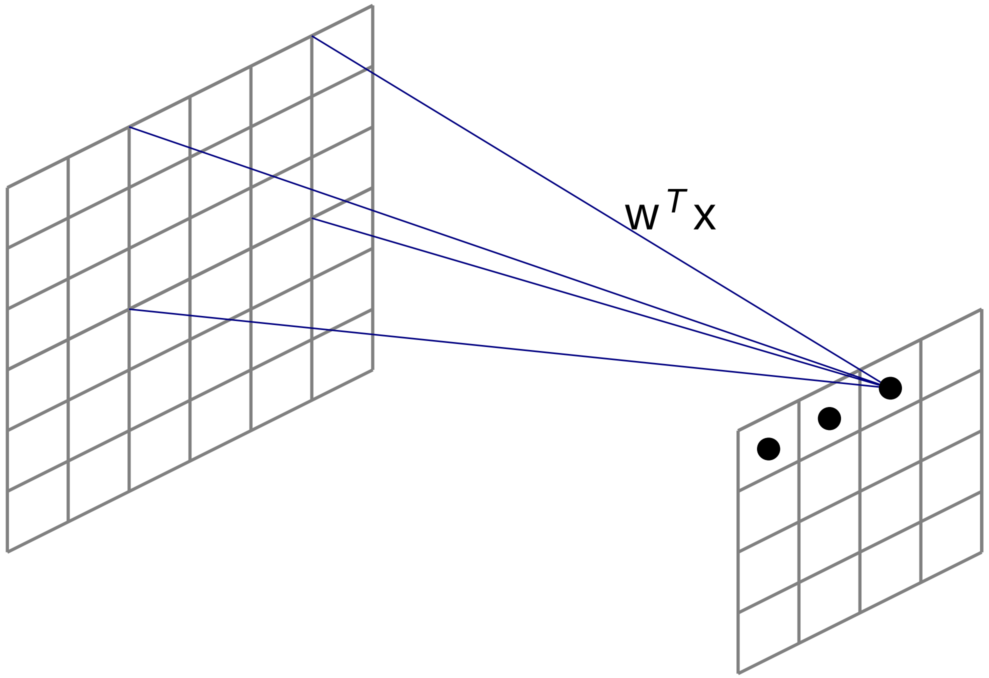
Convolution



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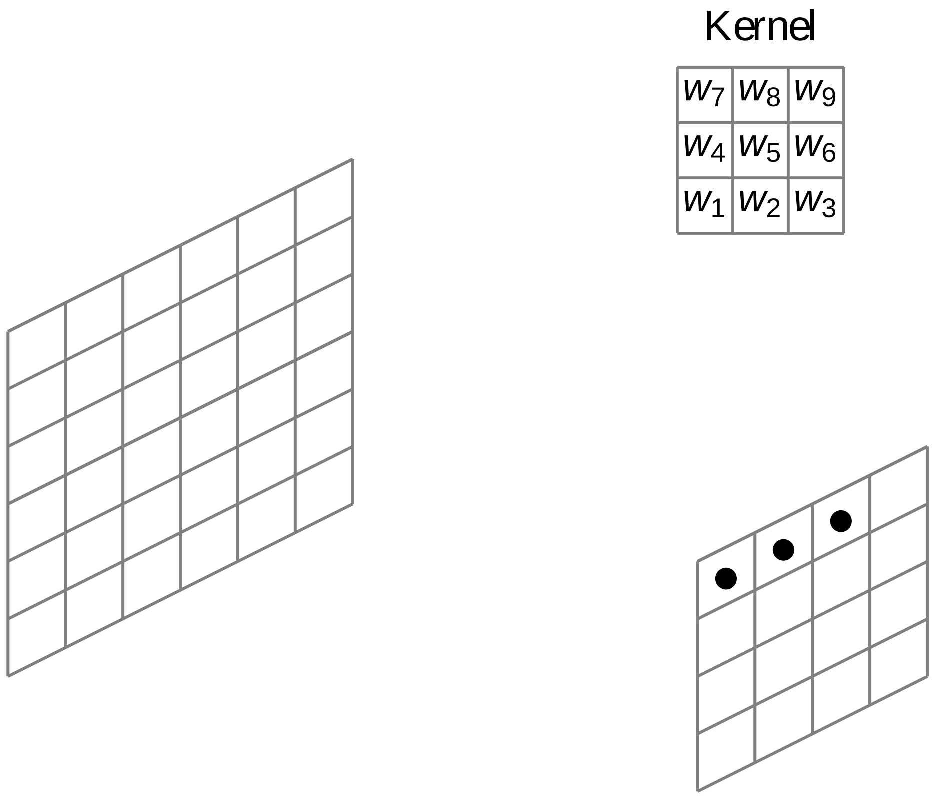

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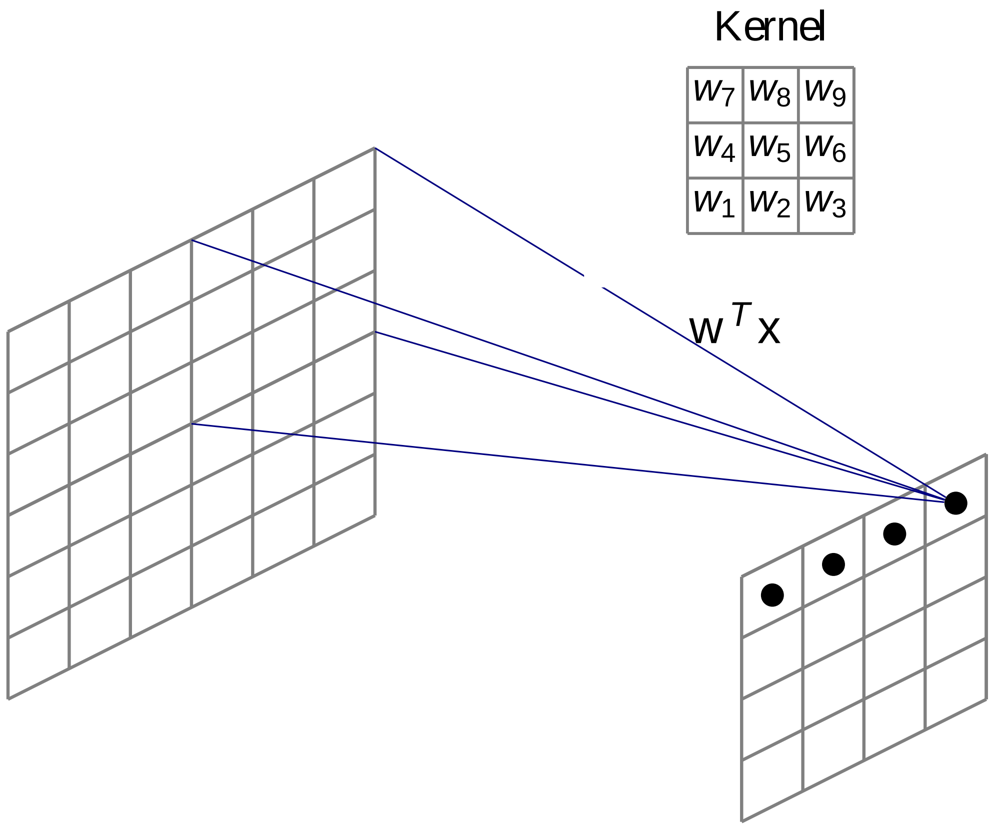

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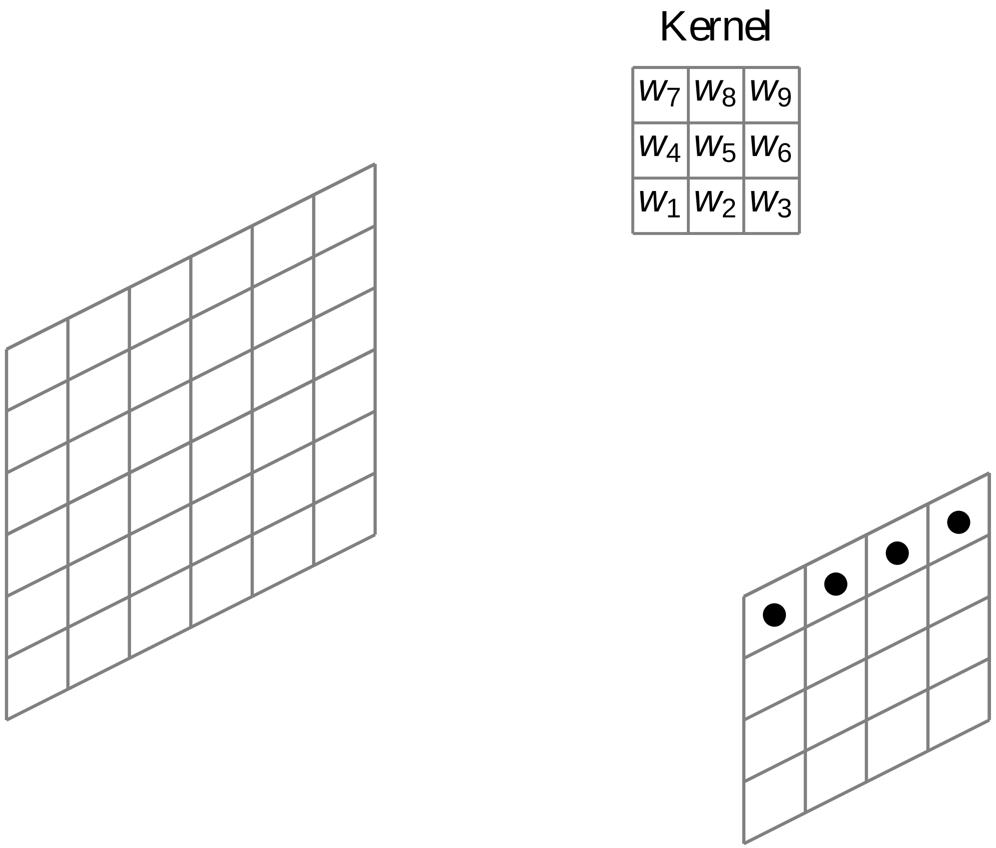
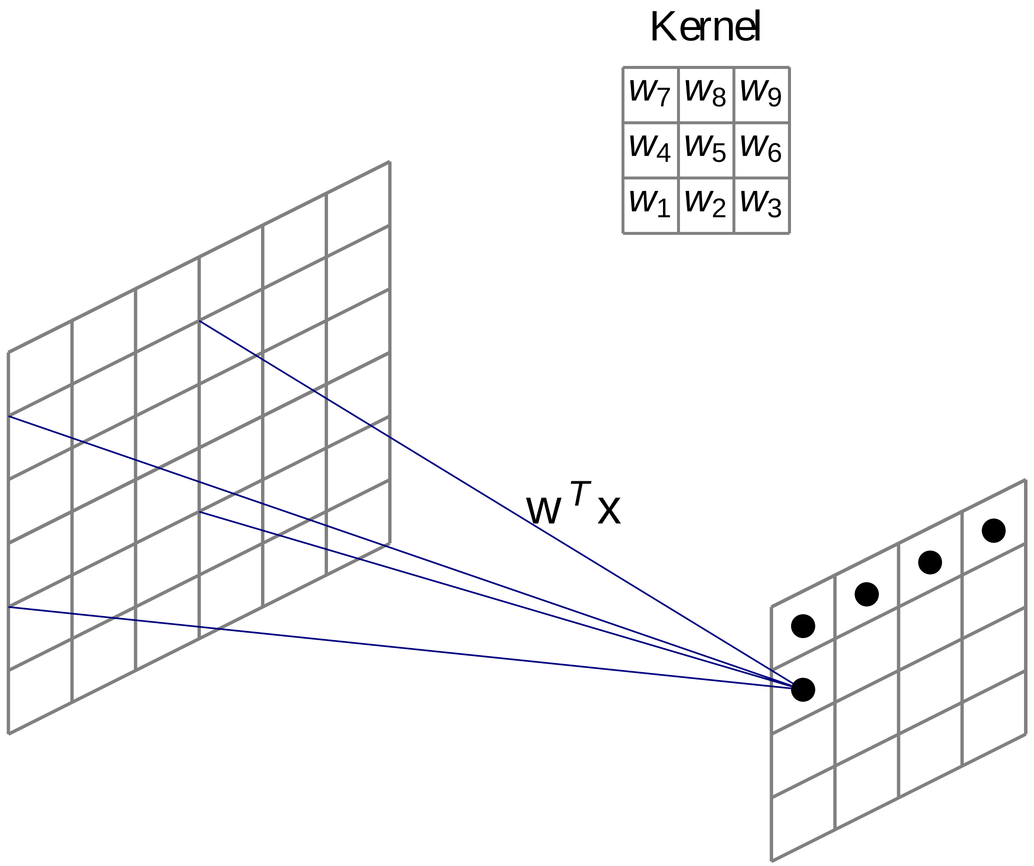
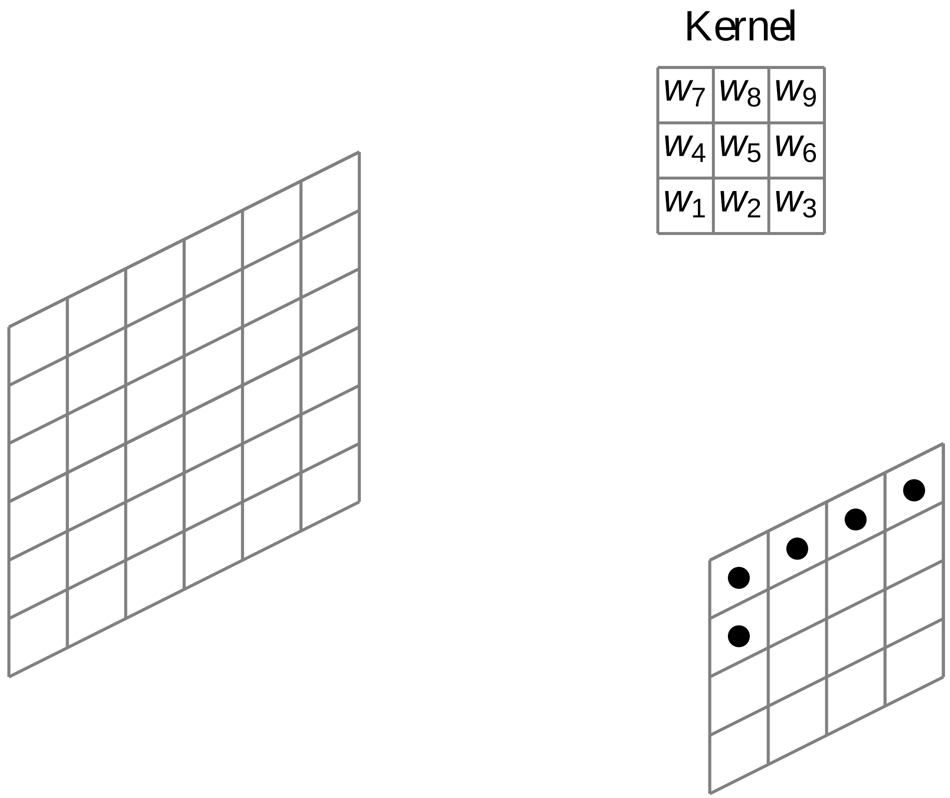


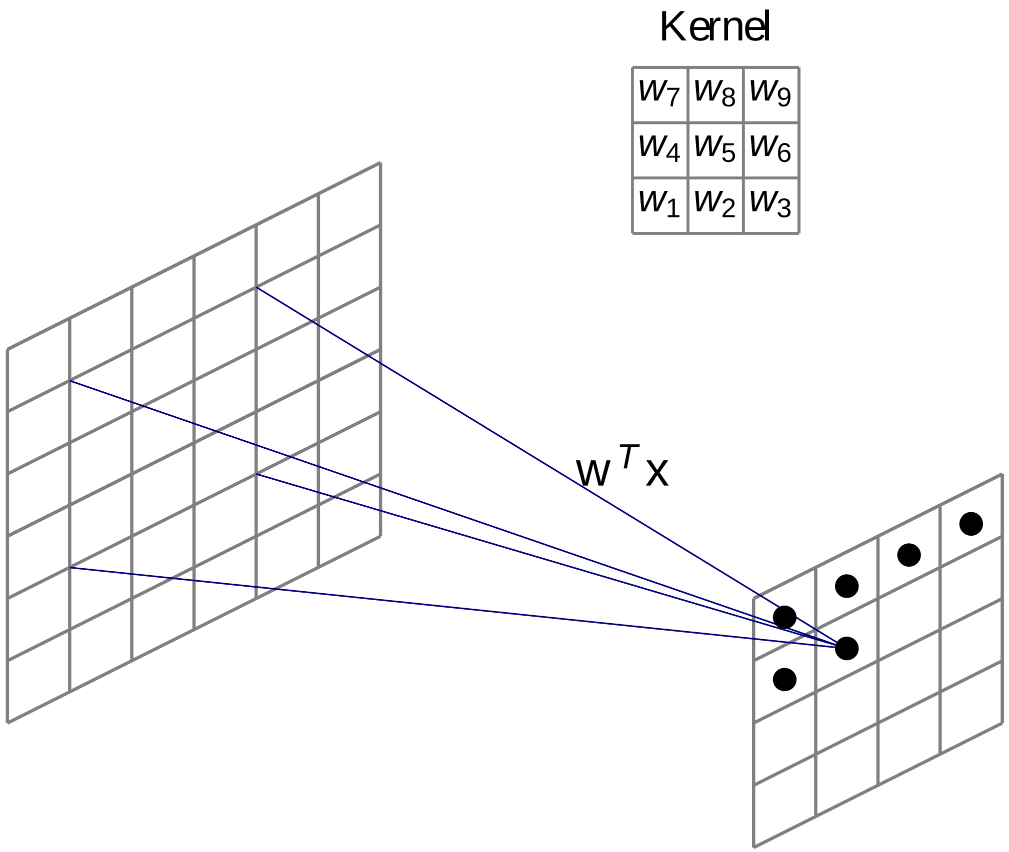
Convolution



Convolution



Convolution



Convolution

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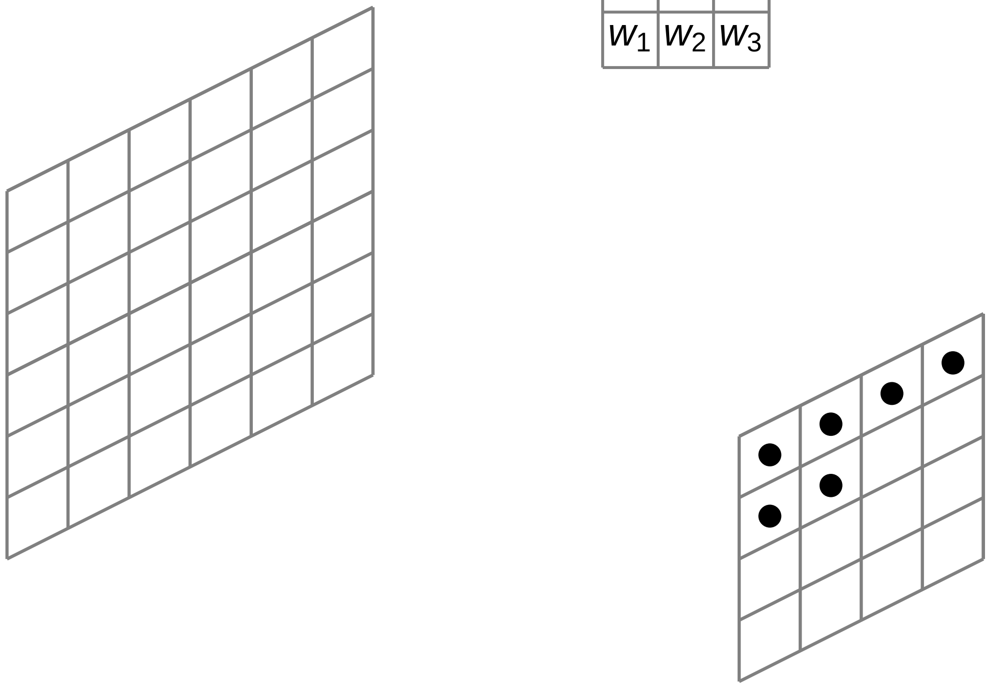
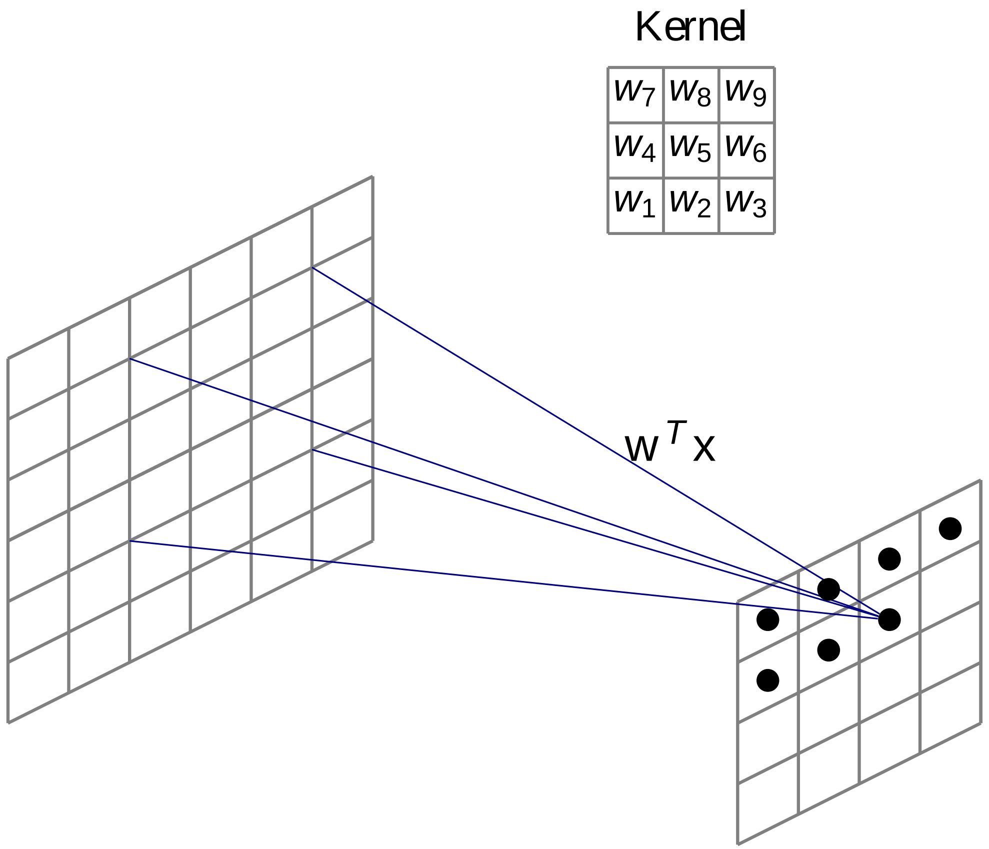
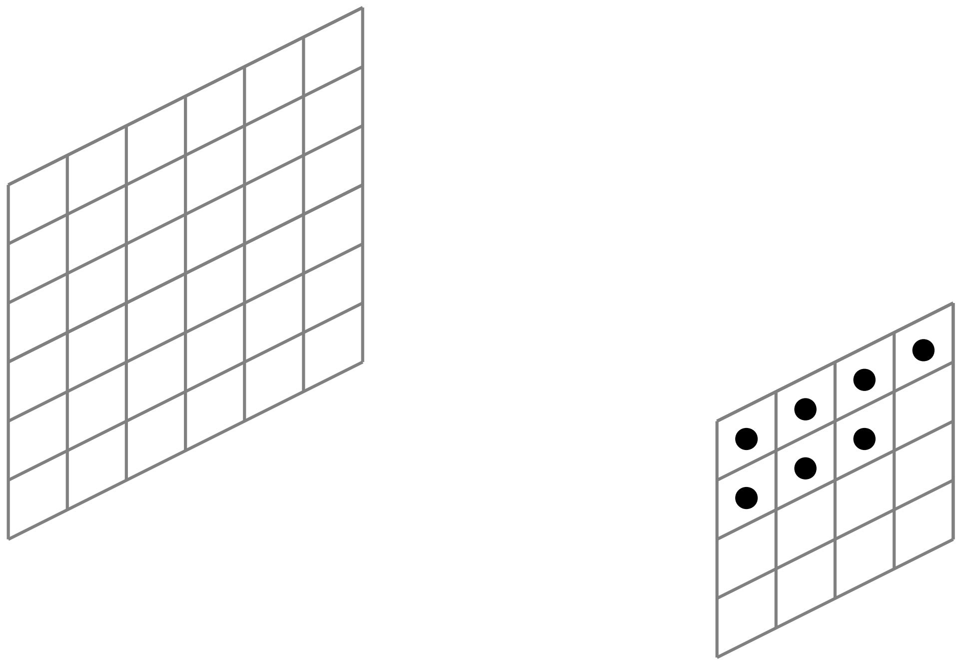


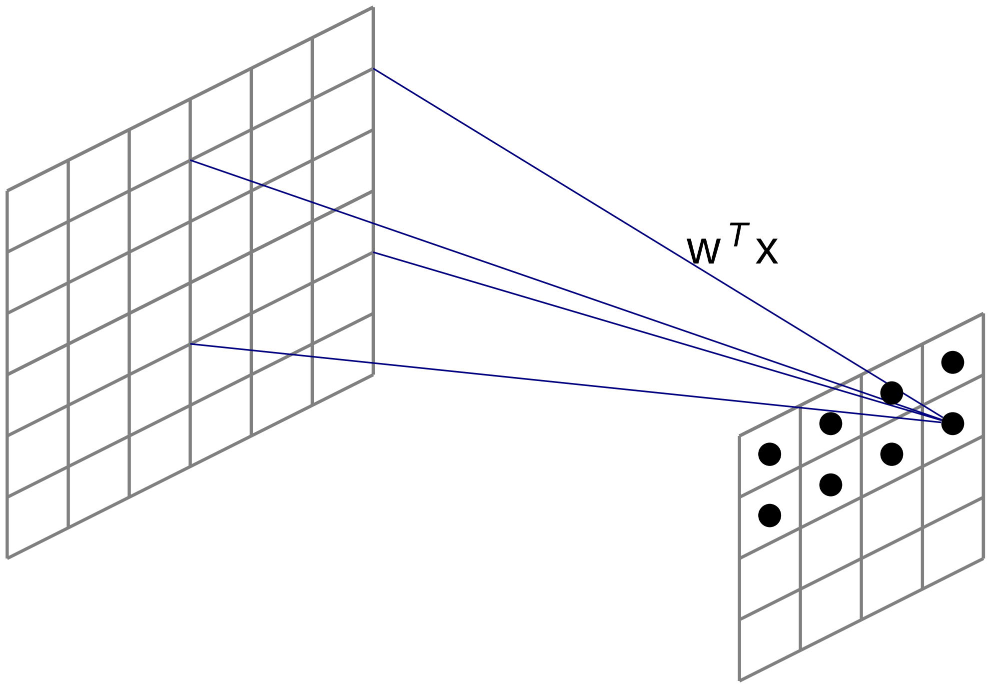
Convolution



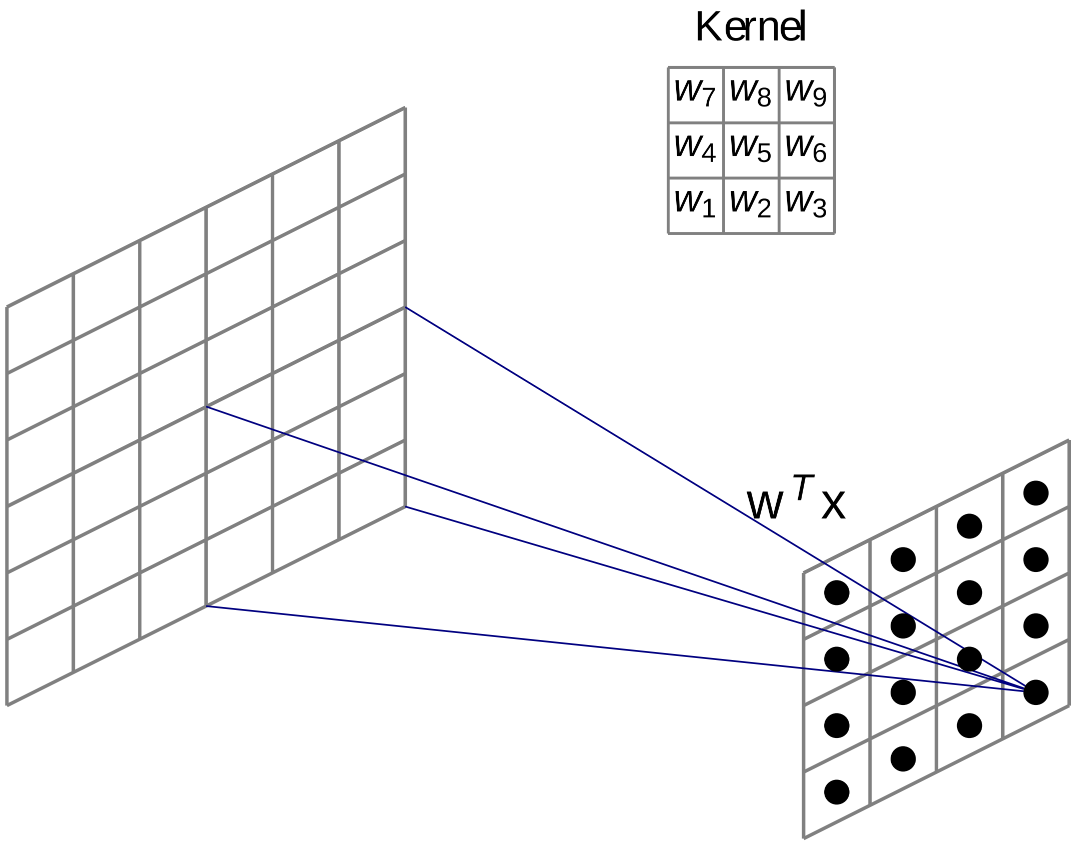
Convolution



Convolution

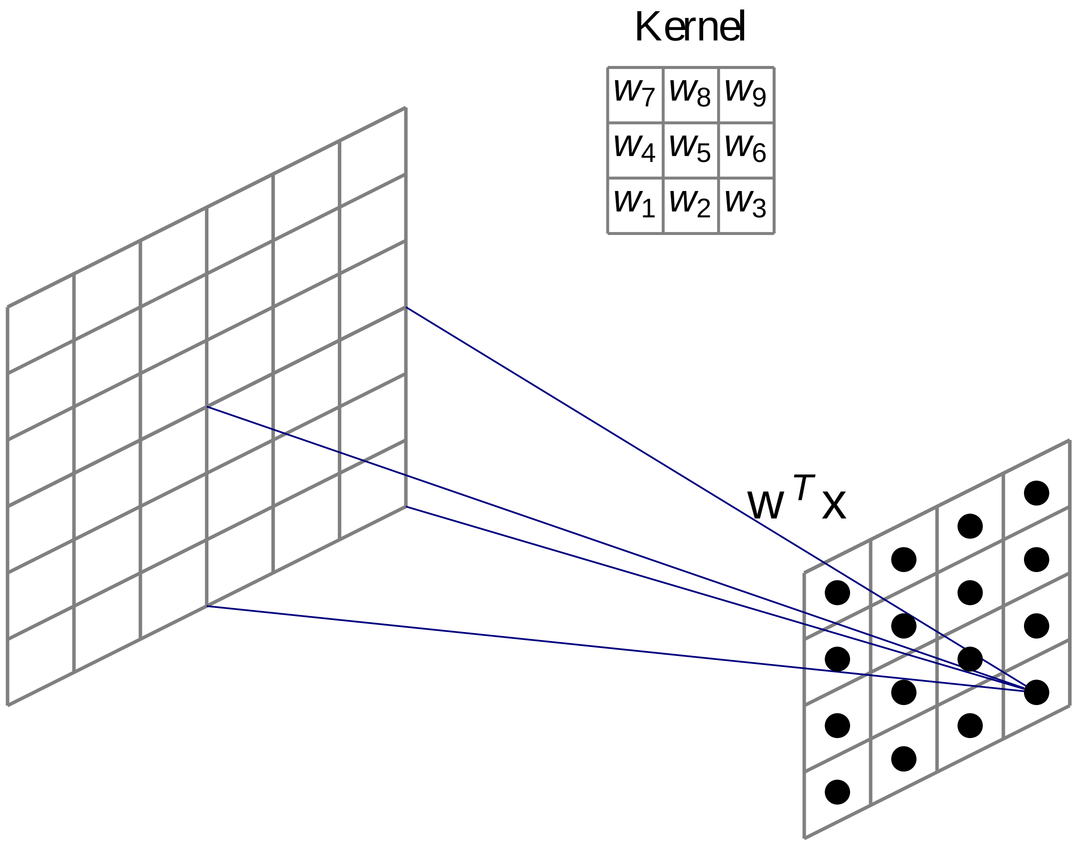


Convolution



Convolution

- What is the number of parameters?

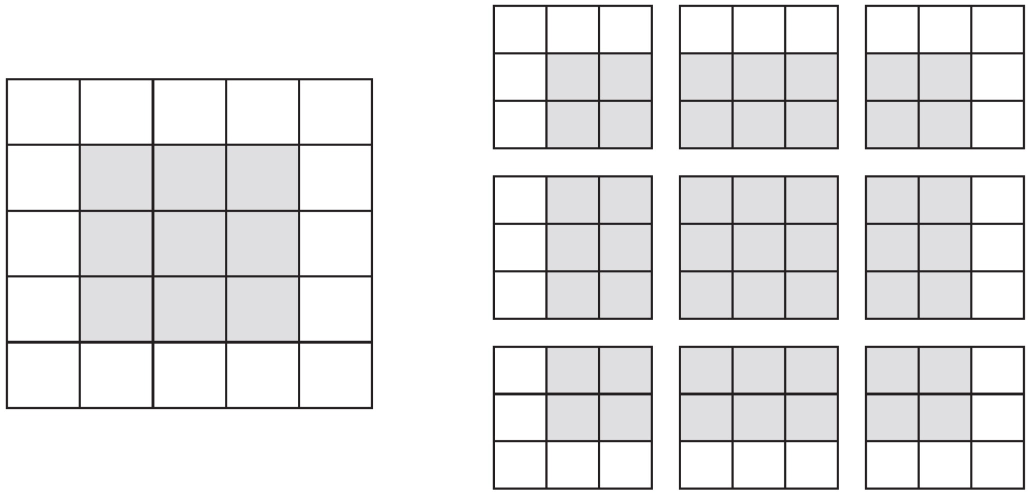


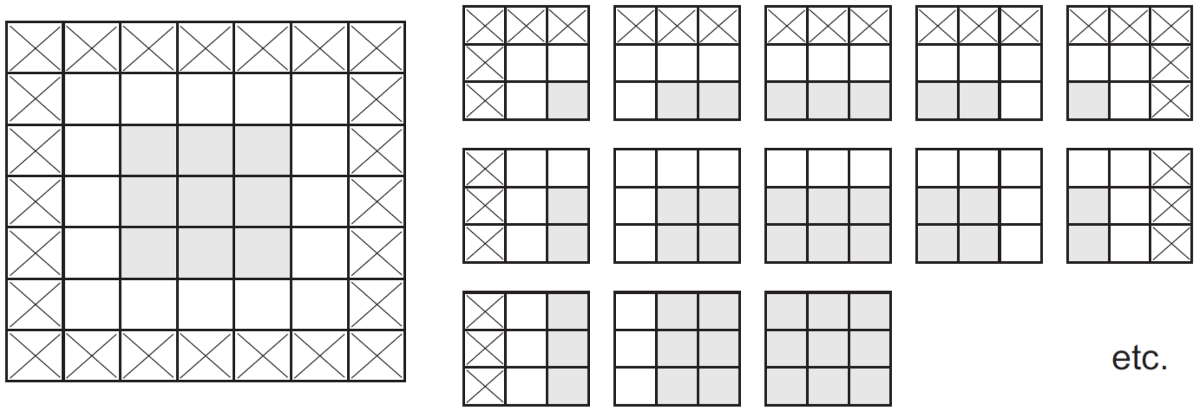
Why CNNs?

- Convolution leverages four ideas:
  - Sparse interactions
    - need to store fewer parameters, computing output needs fewer operations ($O(m \times n)$ versus $O(k \times n)$)
  - Parameter sharing
    - Same kernel is used throughout the input, so instead learning a parameter for each location, only a set of parameters is learnt
  - Equivariant representations
  - Ability to work with inputs of variable size

Padding

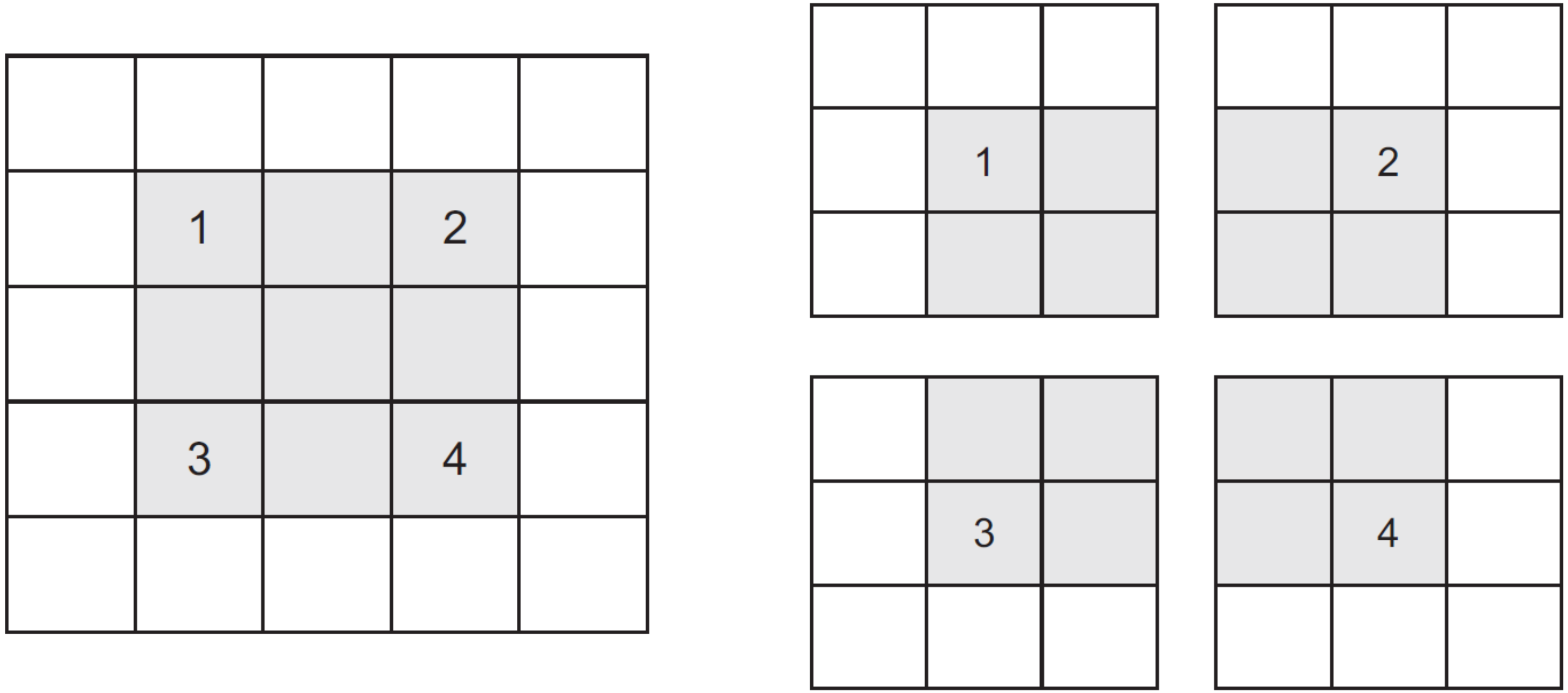
- The result of the convolution with a 3x3 feature maps shriks the images by 2 pixels along each dimension
- To avoid this effect, one might use padding, that is, add one external box of appropriate width and height.





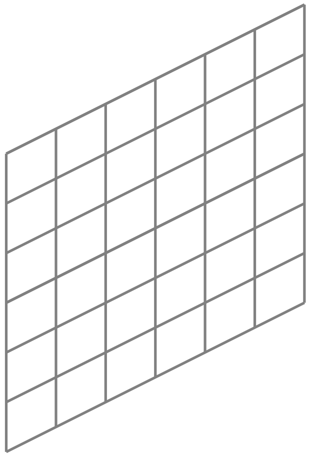
Strides

- The center of the convolution are not necessarily contiguous
- The distance between two consecutive windows is the stride



Example of 2x2 stride

Multiple Filters



Kernel

7	8	9
4	5	6
1	2	3

Kernel

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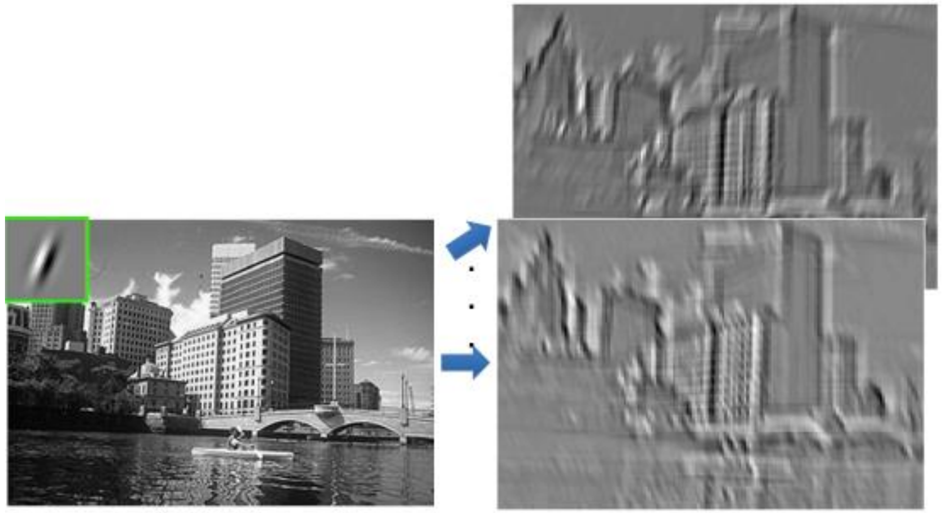
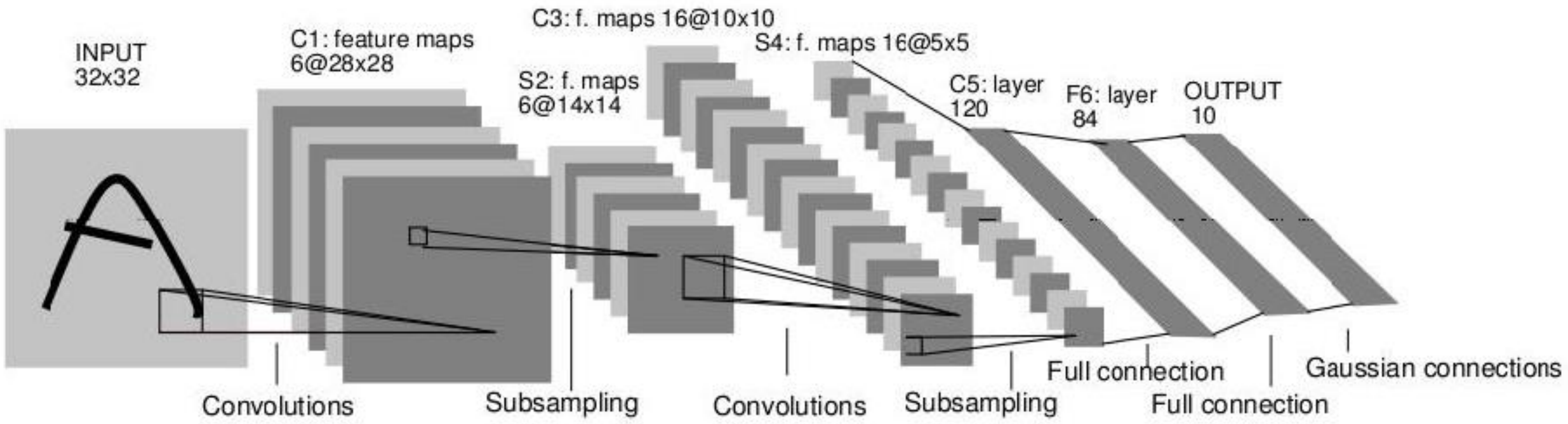


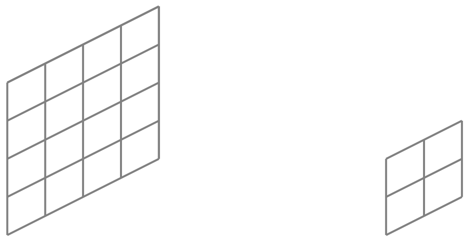
- We can use multiple kernels…
- … and each kernel identifies a feature map

Convolutional Networks

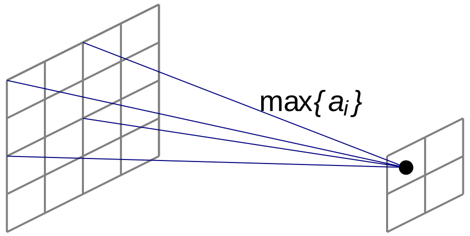
- Neural Networks that use convolution in place of general matrix multiplication in at least one layer



Pooling



Pooling



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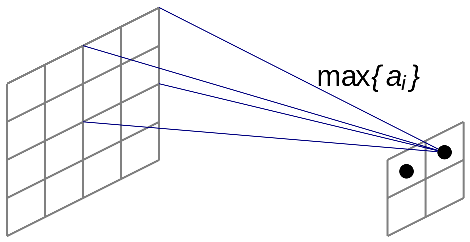

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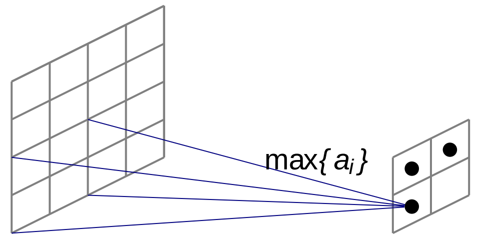

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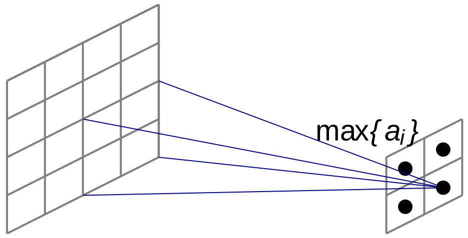
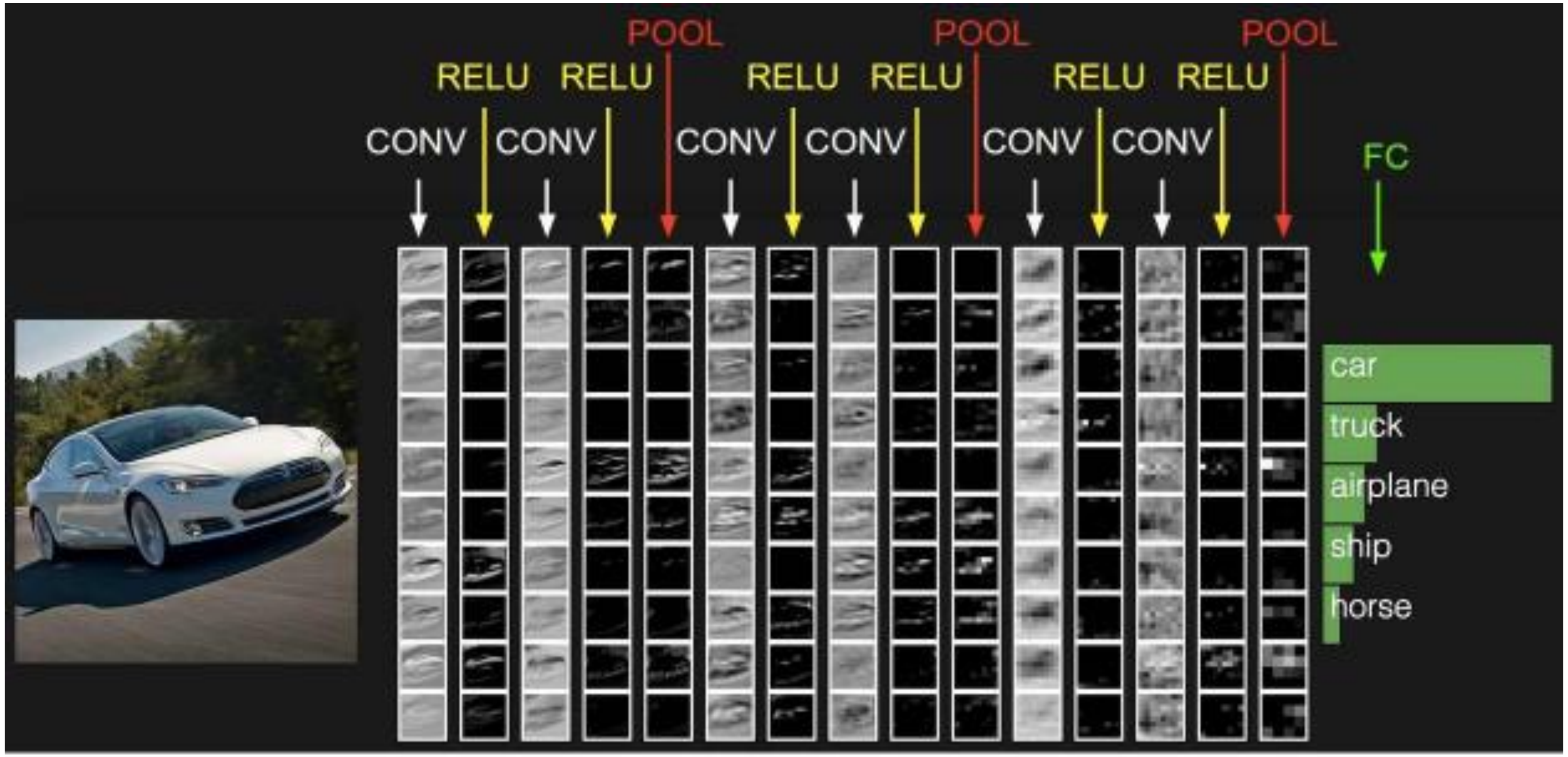
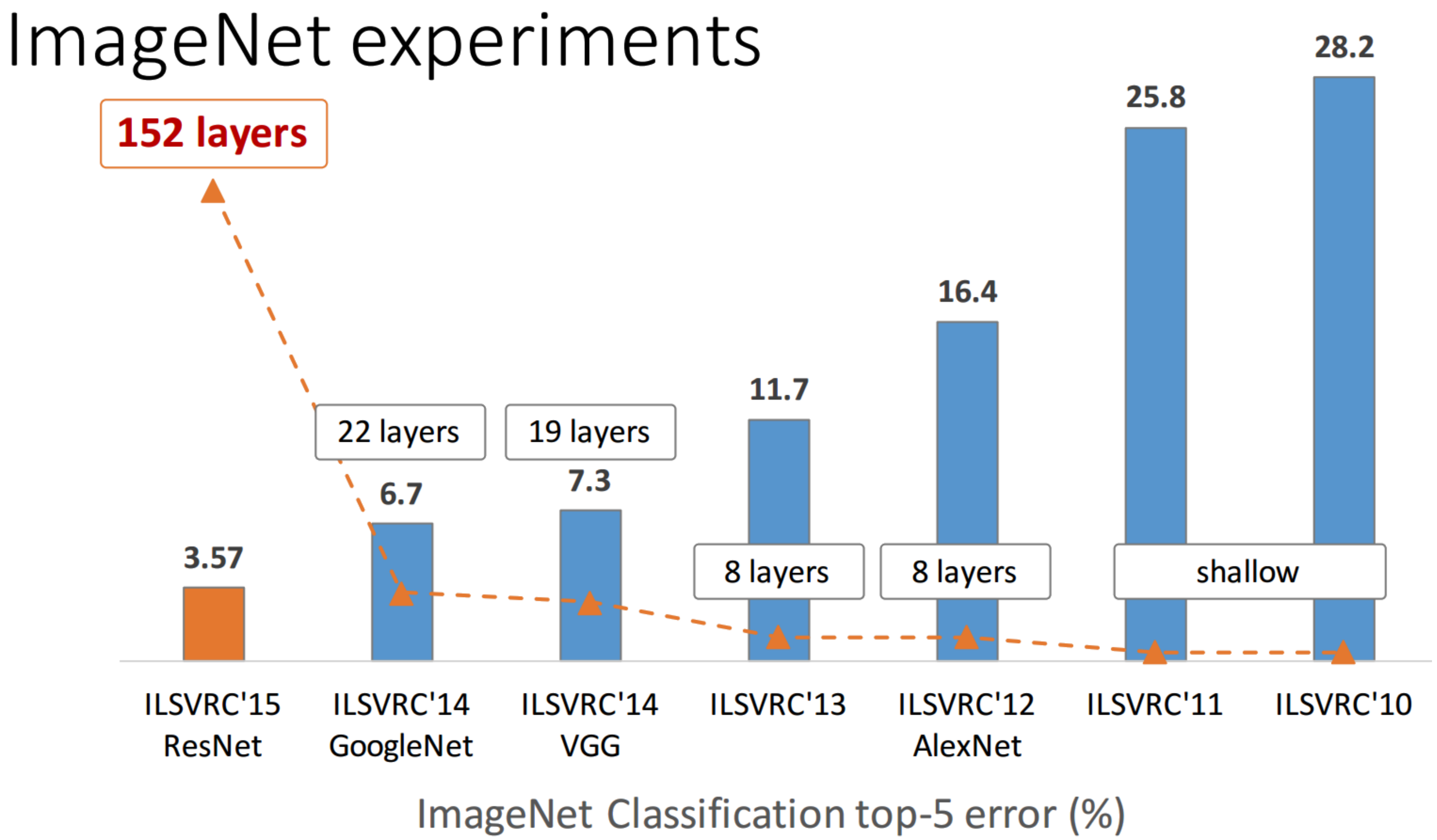


Convolutional neural networks

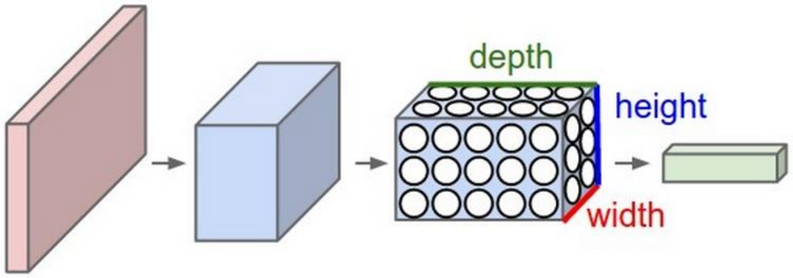


Deep Learning and Convolution



Convolution in general

- Not just 2-D image as a running example
  - Operates on volumes
    - E.g., RGB Images would be depth 3 input
  - Operates on 1-D vect



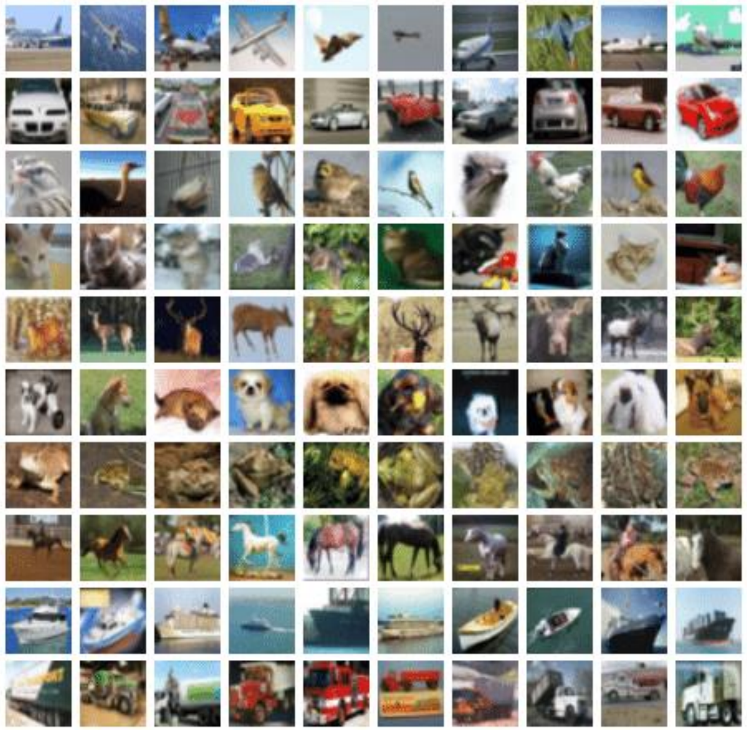
Example with RGB Images (1/4)

```
import tensorflow as tf
from tensorflow.keras import datasets, layers, models, optimizers

# CIFAR_10 is a set of 60K images 32x32 pixels on 3 channels
IMG_CHANNELS = 3
IMG_ROWS = 32
IMG_COLS = 32

#constant
BATCH_SIZE = 128
EPOCHS = 20
CLASSES = 10
VALIDATION_SPLIT = 0.2
OPTIM = tf.keras.optimizers.RMSprop()
```

Multiclass classification



Example with RGB Images (2/4)

Number of filters

Kernel size

No padding (otherwise, use 'same')

```
#define the convnet
def build(input_shape, classes):
  model = models.Sequential()
  model.add(layers.Convolution2D(32, (3, 3), activation='relu', padding='valid'
                        input_shape=input_shape))
  model.add(layers.MaxPooling2D(pool_size=(2, 2)))
  model.add(layers.Dropout(0.25))

  model.add(layers.Flatten())
  model.add(layers.Dense(512, activation='relu'))
  model.add(layers.Dropout(0.5))
  model.add(layers.Dense(classes, activation='softmax'))
  return model
```

Example with RGB Images (3/4)

```
# data: shuffled and split between train and test sets
(X_train, y_train), (X_test, y_test) = datasets.cifar10.load_data()
# normalize
X_train, X_test = X_train / 255.0, X_test / 255.0
# convert to categorical
# convert class vectors to binary class matrices
y_train = tf.keras.utils.to_categorical(y_train, CLASSES)
y_test = tf.keras.utils.to_categorical(y_test, CLASSES)

model=build((IMG_ROWS, IMG_COLS, IMG_CHANNELS), CLASSES)
model.summary()
```

Example with RGB Images (4/4)

```
# use TensorBoard,
callbacks = [
  # Write TensorBoard logs to `./logs` directory
  tf.keras.callbacks.TensorBoard(log_dir='./logs')
]

# train
model.compile(loss='categorical_crossentropy', optimizer=OPTIM, metrics=['accuracy'])

model.fit(X_train, y_train, batch_size=BATCH_SIZE,
  epochs=EPOCHS, validation_split=VALIDATION_SPLIT,
  verbose=VERBOSE, callbacks=callbacks)
score = model.evaluate(X_test, y_test,
                     batch_size=BATCH_SIZE, verbose=VERBOSE)
print("\nTest score:", score[0])
print('Test accuracy:', score[1])
```