Convolutional Neural Networks (Covnets)

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References:

- *Hands-On Machine Learning with Scikit-Learn and TensorFlow* by Aurélien Géron (O'Reilly), 2017, 978-1-491-96229-9.
- François Chollet, *Deep Learning with Python*, Manning Pub. 2018

Introduction

- YouTube Video: *Convolutional Neural Networks (CNNs) explained* from Deeplizard

https://youtu.be/YRhxdVk_sIs

Outline

1. Introduction
2. Convolutional layer
    1. Filters
    2. Stacking feature maps
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3. Pooling layer
4. CNN architectures
5. Keras example
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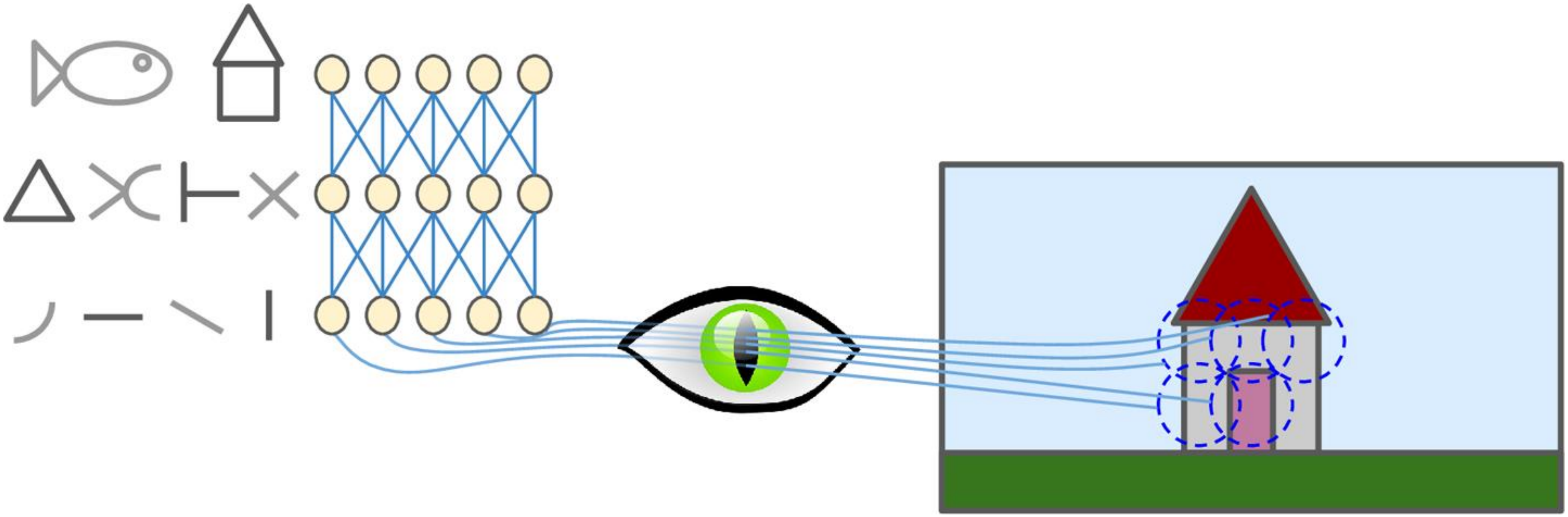
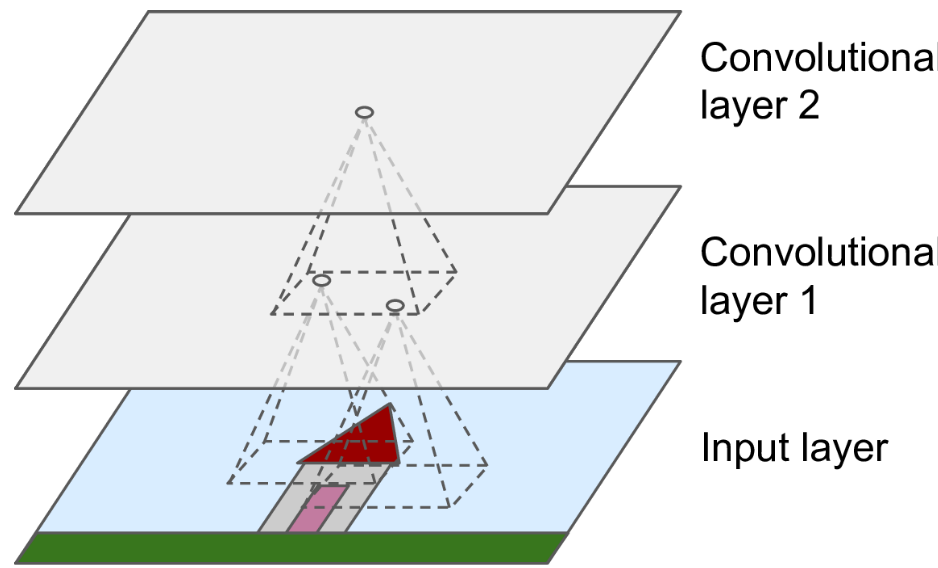
1. Introduction

- *Convolutional neural networks (CNNs)* emerged from the study of the brain's visual cortex.
- Many neurons in the visual cortex have a small *local receptive field.*



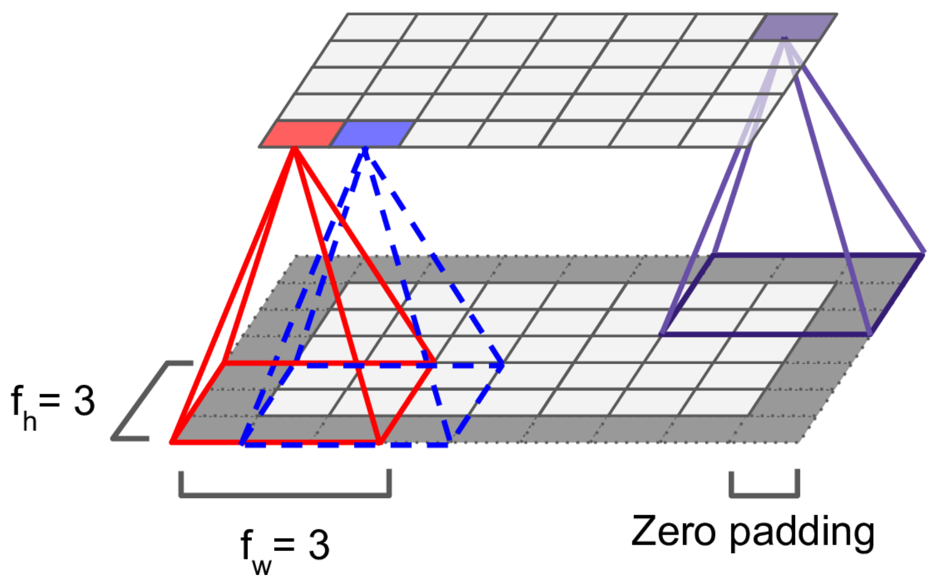
2. Convolutional Layer

- Neurons in one layer are not connected to every single pixel/neuron in the previous layer, but only to pixels/neurons in their receptive fields.
- This architecture allows the network to concentrate on low-level features in one layer, then assemble them into higher-level features in the next layer.
- Each layer is represented in 2D.



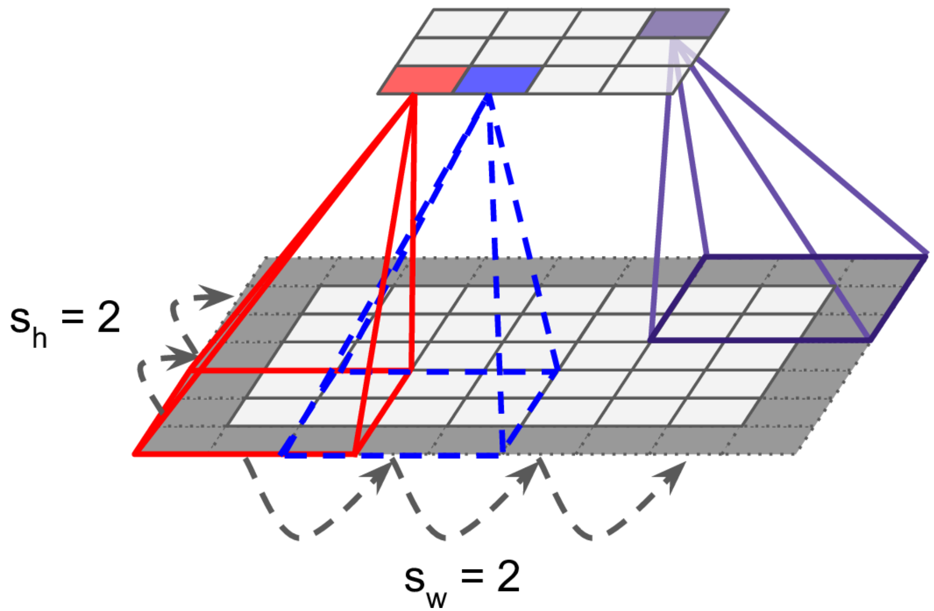
2. Convolutional Layer

- f_h and f_w are the height and width of the receptive field.
- *Zero padding:* In order for a layer to have the same height and width as the previous layer, it is common to add zeros around the inputs.
- Keras default is no padding



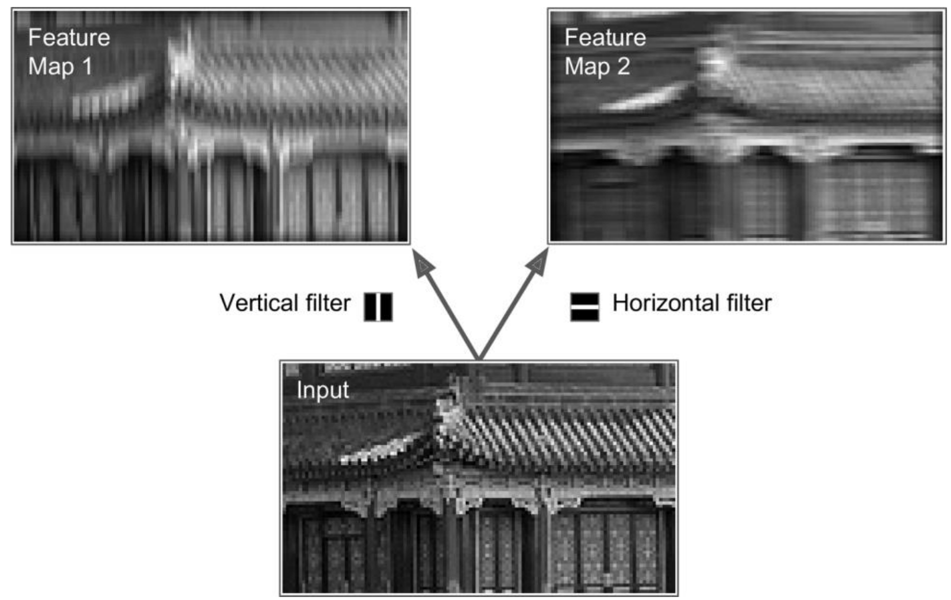
2. Convolutional Layer

- It is also possible to connect a large input layer to a smaller layer by spacing out the receptive fields.
- The distance between two consecutive receptive fields is called the *stride*.
- A neuron located in row i, column j is connected to the neurons in the previous layer located in:
  - Rows: $i \times s_h$ to $i \times s_h + f_h - 1$
  - Cols: $j \times s_w$ to $j \times s_w + f_w - 1$



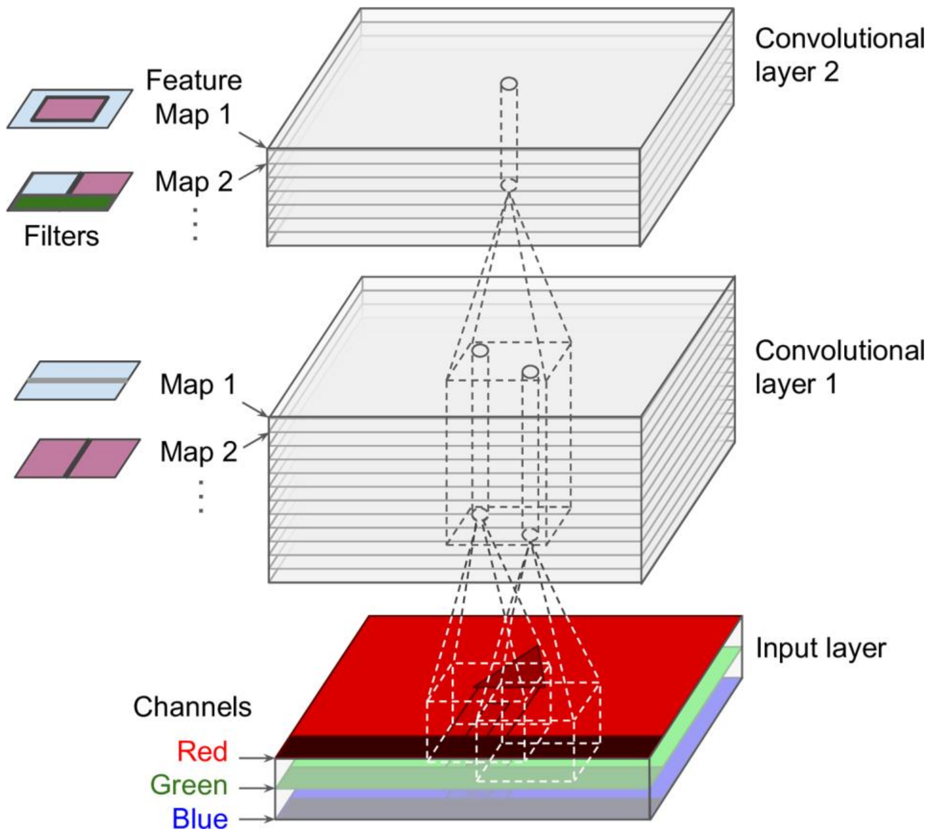
2.1. Filters

- A neuron's weights can be represented as a small image the size of the receptive field, called *filters*.
- When all neurons in a layer use the same line filters, we get the *feature maps* on the top.



2.2. Stacking Feature Maps

- In reality, each layer is *3D* composed of several feature maps of equal sizes.
- Within one feature map, all neurons share the same parameters, but different feature maps may have different parameters.
- Once the CNN has learned to recognize a pattern in one location, it can recognize it in any other location.



2.3. Mathematical Summary

Equation 13-1. Computing the output of a neuron in a convolutional layer

$$z_{i,j,k} = b_k + \sum_{u=1}^{f_h} \sum_{v=1}^{f_w} \sum_{k'=1}^{f_{n'}} x_{i',j',k'} \cdot w_{u,v,k',k} \quad \text{with} \begin{cases} i' = u \cdot s_h + f_h - 1 \\ j' = v \cdot s_w + f_w - 1 \end{cases}$$

- $z_{i,j,k}$ is the output of the neuron located in row *i*, column *j* in feature map *k*
- $f_{n'}$ is the number of feature maps in the previous layer

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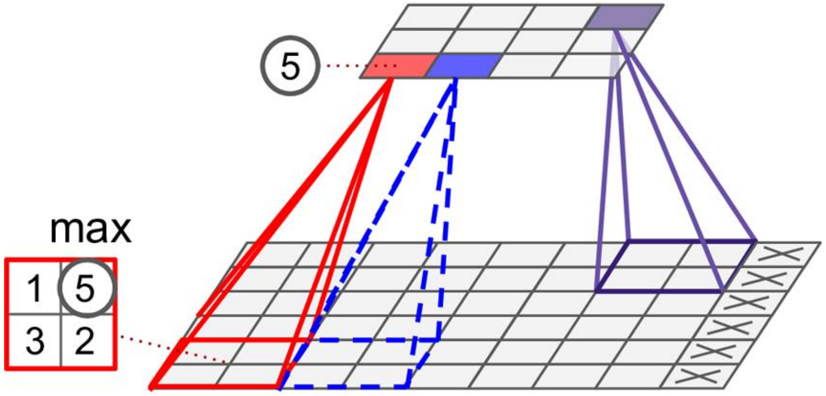
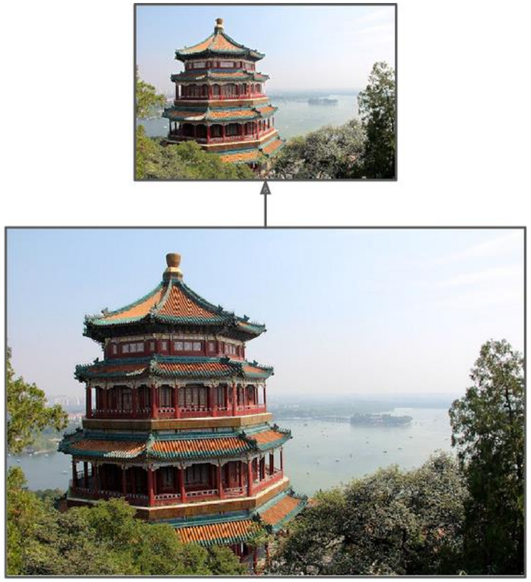
3. Pooling Layer

- Its goal is to *subsample* (i.e., shrink) the input image in order to reduce the computational load, the memory usage, and the number of parameters.
- It aggregates the inputs using max or mean.





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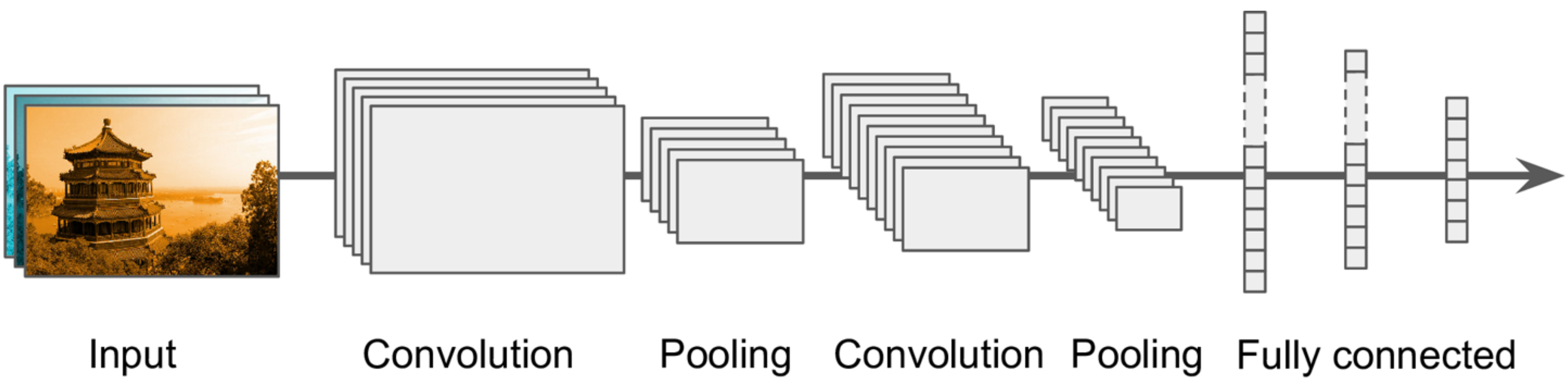
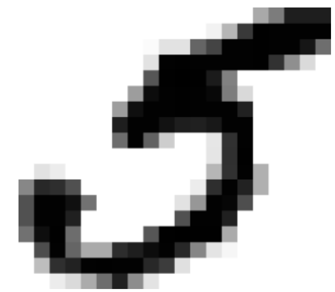
4. CNN Architectures

- Stack few convolutional layers (each one generally followed by a ReLU layer), then a pooling layer, then another few convolutional layers, then another pooling layer, and so on. The image gets smaller and smaller, but it also gets deeper and deeper. At the end, a regular NN is added.



5. Keras Example - MNIST



```python
from keras import models
from keras import layers

model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu',
        input_shape=(28, 28, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
```

32 feature maps

Filter size

2×2 window and stride 2

5. Keras Example

```
# add a classifier

model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))
```

5. Keras Example

```
>>> Model.summary()
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 13, 13, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 11, 11, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 5, 5, 64)          0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 3, 3, 64)          36928
_________________________________________________________________
flatten_1 (Flatten)          (None, 576)               0
_________________________________________________________________
dense_1 (Dense)              (None, 64)                36928
_________________________________________________________________
dense_2 (Dense)              (None, 10)                650
=================================================================
Total params: 93,322
Trainable params: 93,322
Non-trainable params: 0
```

5. Keras Example

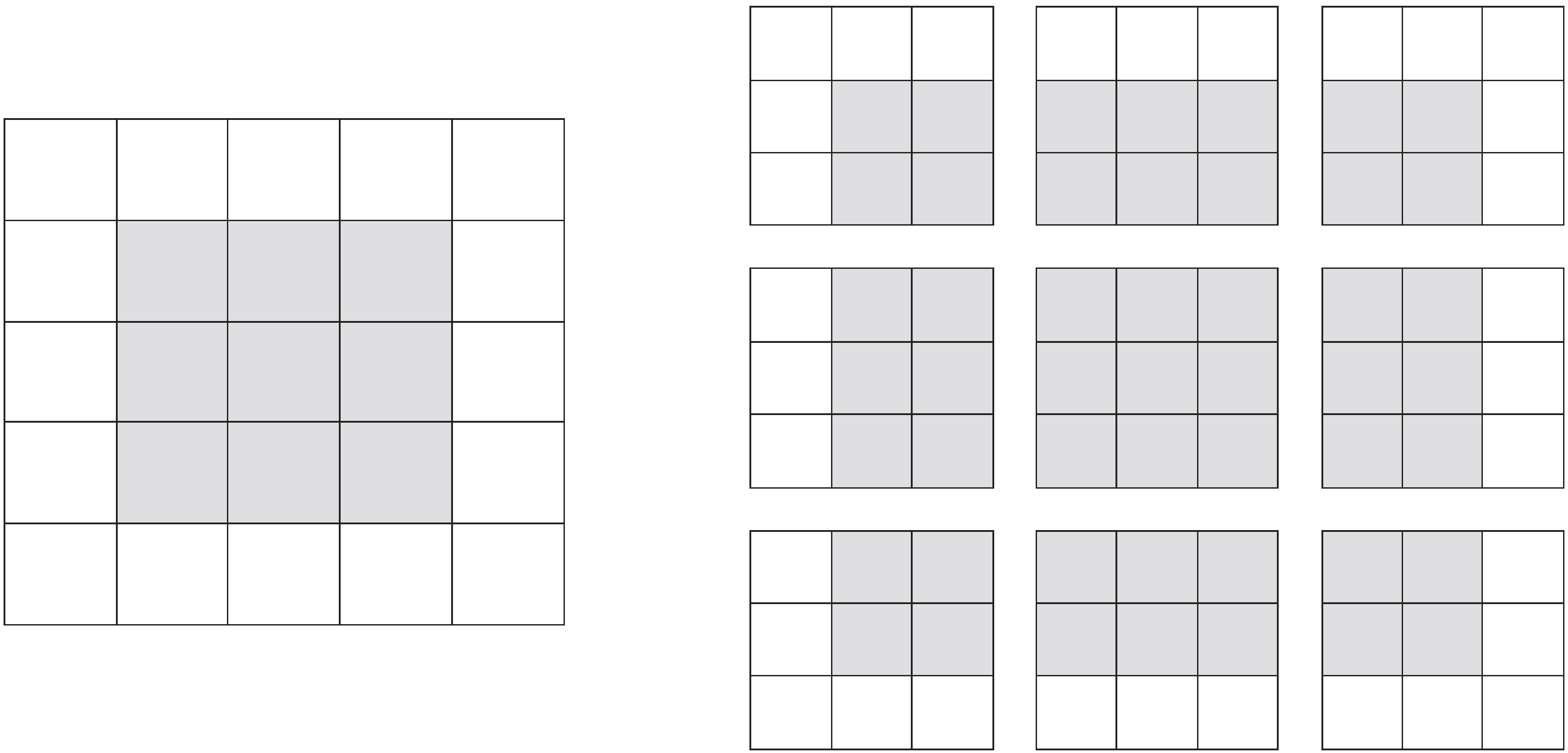


Figure 5.5 Valid locations of 3 × 3 patches in a 5 × 5 input feature map

5. Example – Prepare the data

```
from keras.datasets import mnist
(train_images, train_labels), (test_images,
      test_labels) = mnist.load_data()
#(60000, 28, 28), (6000), #(10000, 28, 28), (1000)
train_images = train_images.reshape((60000, 28 * 28))
train_images = train_images.astype('float32') / 255
test_images = test_images.reshape((10000, 28 * 28))
test_images = test_images.astype('float32') / 255

from keras.utils import to_categorical   #one hot
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)
```

5. Keras Example

```
# Compile, train and evaluate

model.compile(optimizer='rmsprop',
       loss='categorical_crossentropy',
       metrics=['accuracy'])
model.fit(train_images, train_labels, epochs=5,
       batch_size=64)
…
Epoch 5/5
60000/60000 [===] - 7s - loss: 0.0187 - acc: 0.9943

test_loss, test_acc = model.evaluate(test_images,
       test_labels)
```

0.9913

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Exercises

From Chapter 13, solve exercises:

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