Deep Computer Vision Using Convolutional Neural Networks

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References:

- *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow* by Aurélien Géron (O'Reilly). 2019, 978-1-492-03264-9.
- François Chollet, *Deep Learning with Python*, Manning Pub. 2018

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1. Introduction
2. Convolutional layer
   1. Filters
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   4. Memory requirements
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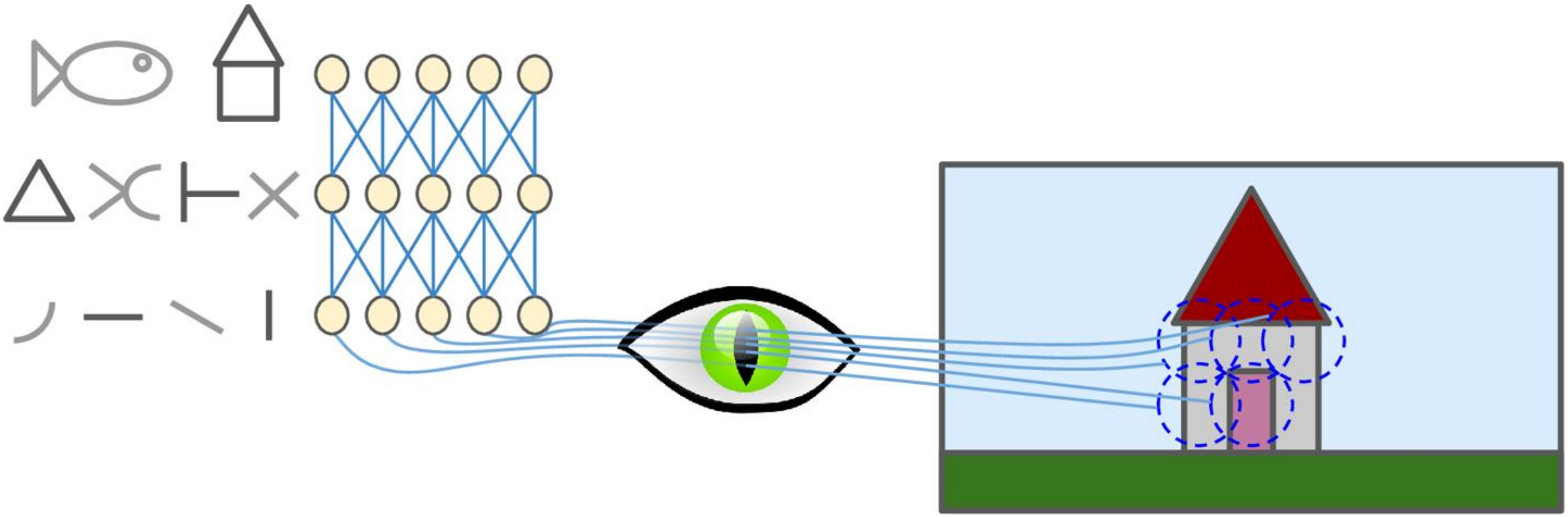
Introduction

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

https://youtu.be/YRhxdVk_sIs

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.*



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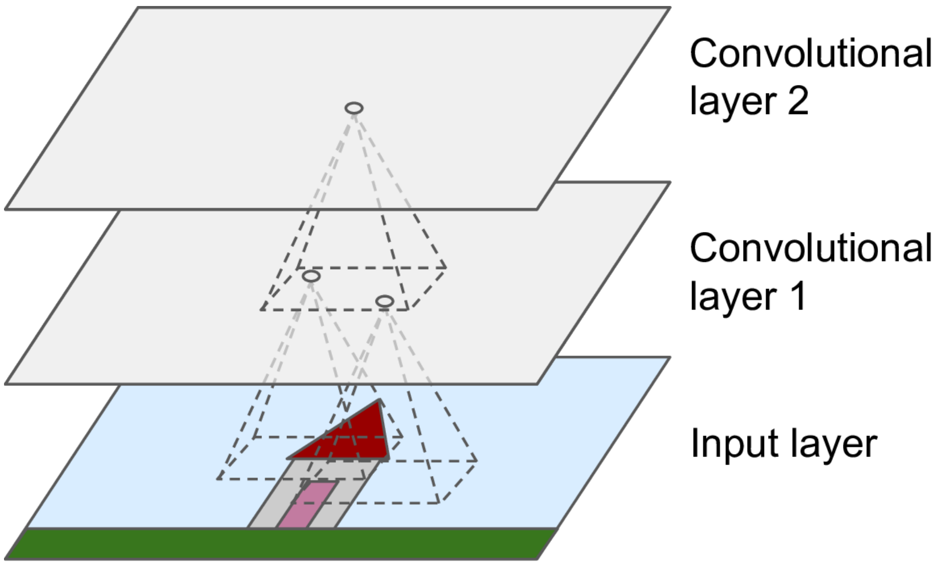
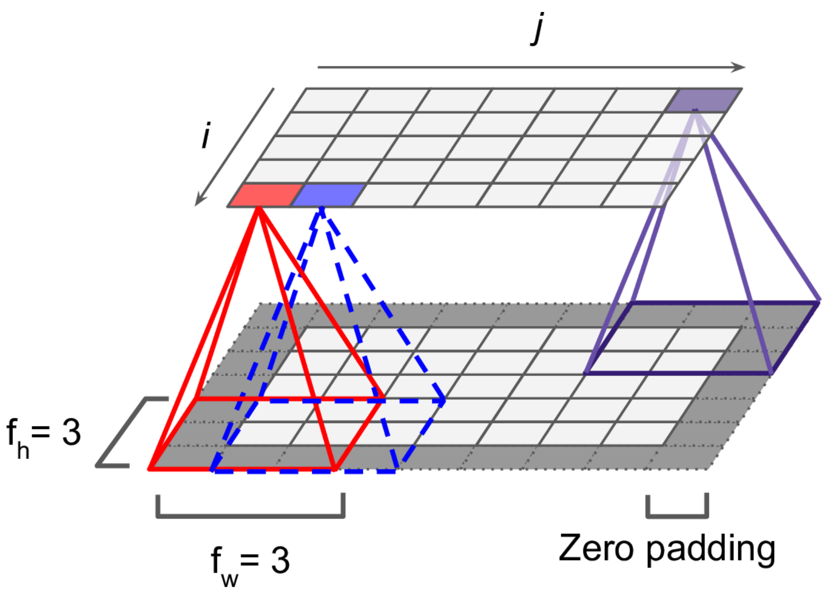
2. Convolutional Layer

- 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.



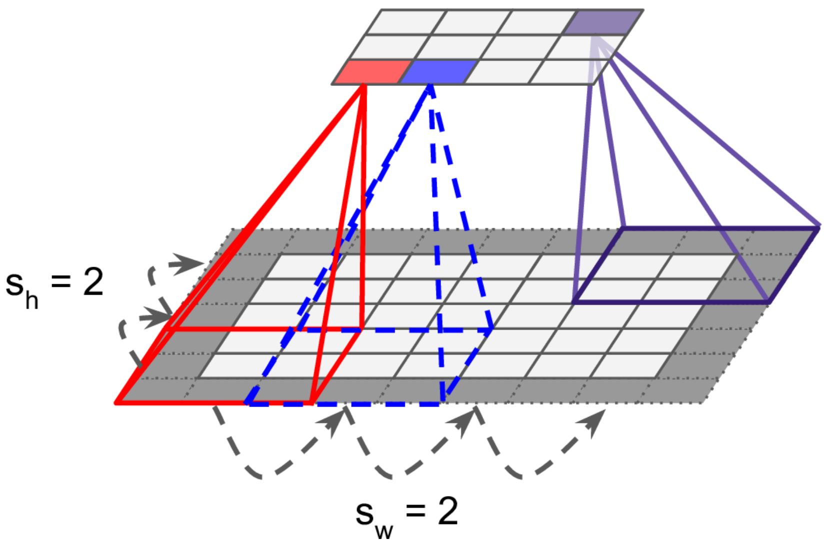
2. Convolutional Layer

- 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.



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 $j \times s_w + f_w - 1$



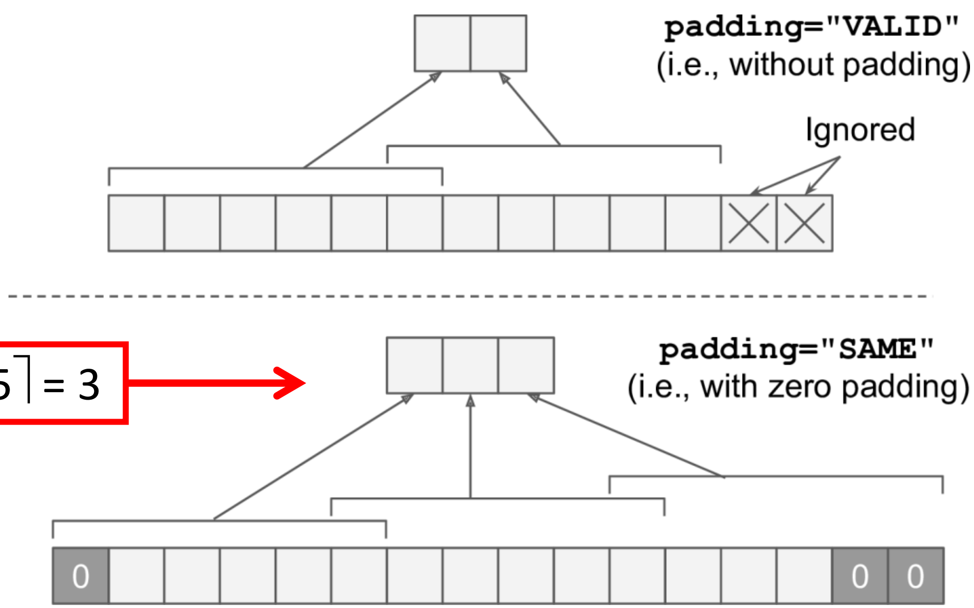
2. Convolutional Layer

- Keras supports
  - **No padding** (default)

    `padding="VALID"`
  - **Zero padding**

    `padding="SAME"`
- Example:
  - Input width: 13
  - Filter width: 6
  - Stride: 5

$\lceil 13 / 5 \rceil = 3$



2. Convolutional Layer

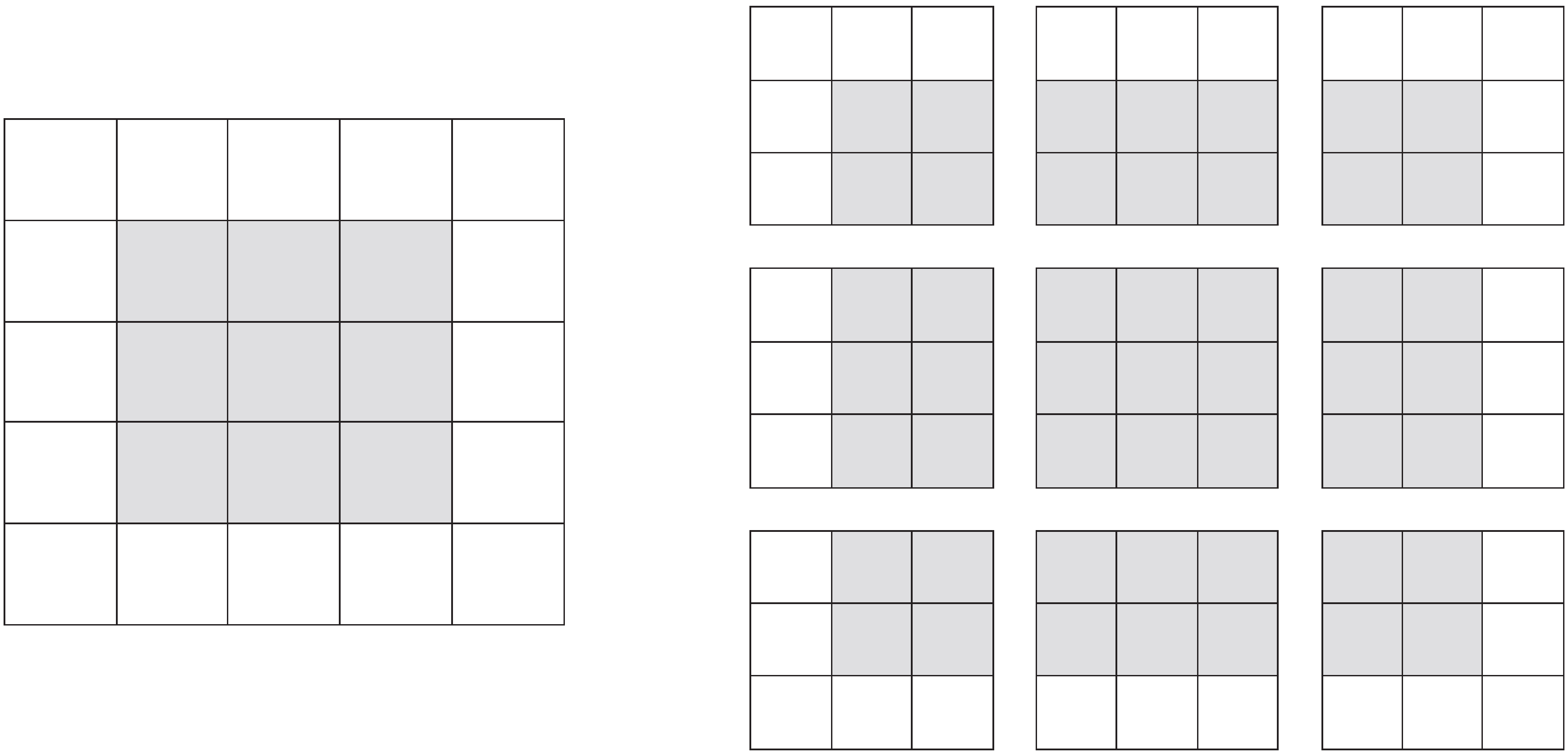
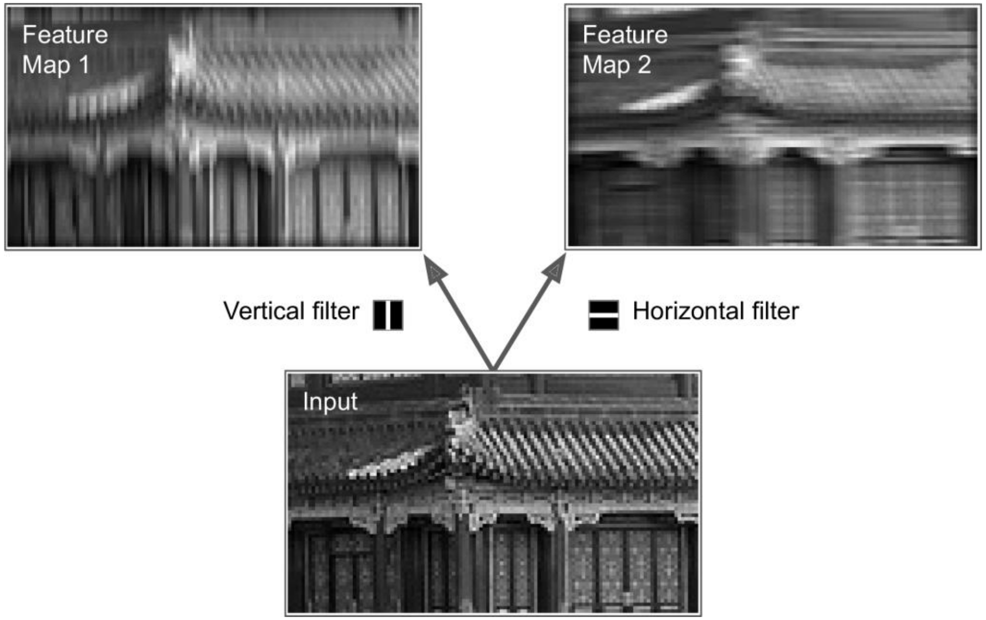


Figure 5.5 Valid locations of 3 × 3 patches in a 5 × 5 input feature map

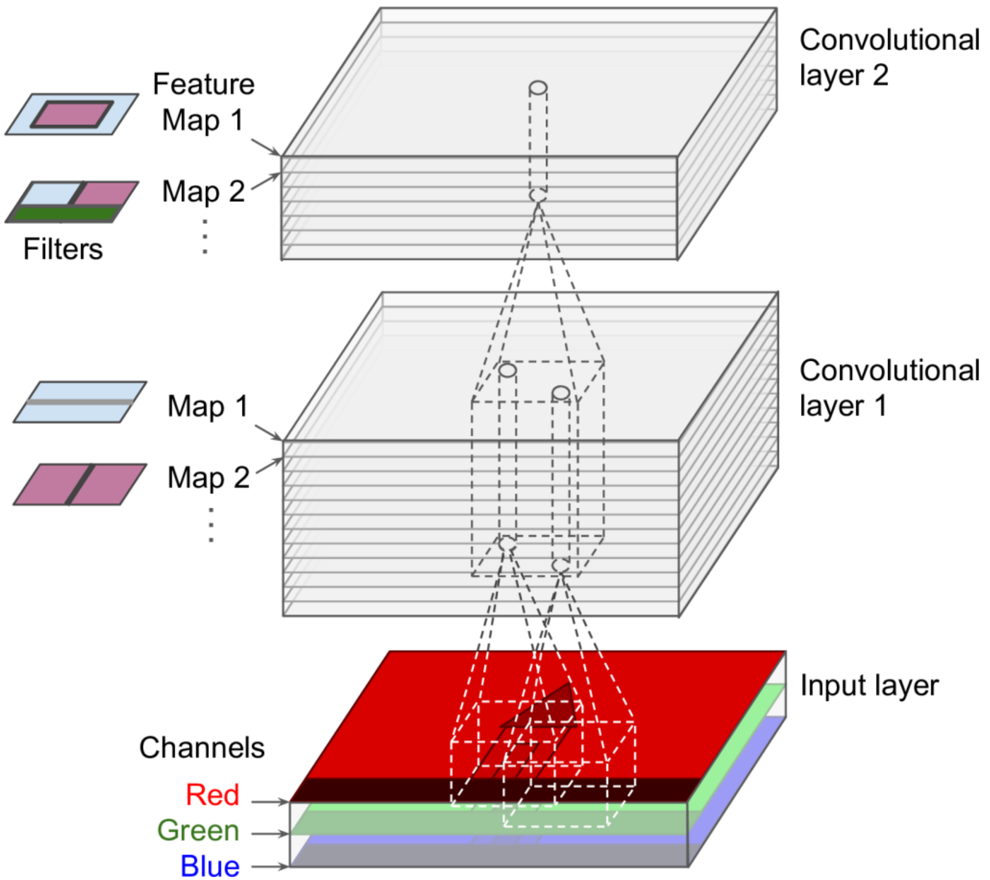
2.1 Filters

- 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 14-1. Computing the output of a neuron in a convolutional layer

$$z_{i,j,k} = b_k + \sum_{u=0}^{f_h-1} \sum_{v=0}^{f_w-1} \sum_{k'=0}^{f_{n'}-1} x_{i',j',k'} \cdot w_{u,v,k',k} \quad \text{with} \begin{cases} i' = i \times s_h + u \\ j' = j \times s_w + v \end{cases}$$

- $z_{i,j,k}$ 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

2.4 Memory Requirements

- Convolutional layers require a huge amount of RAM.
- **Example**: Convolutional layer with 5 × 5 filters, 200 feature maps of size 150 × 100, with stride 1 and `"same"` padding. Input is RGB image (three channels).
  - Parameters = (5 × 5 × 3 + 1) × 200 = 15,200
  - Size of feature maps (single precision) = 200 × 150 × 100 × 4 = 12 MB of RAM
  - 1.2 GB of RAM for a mini batch of 100 instances

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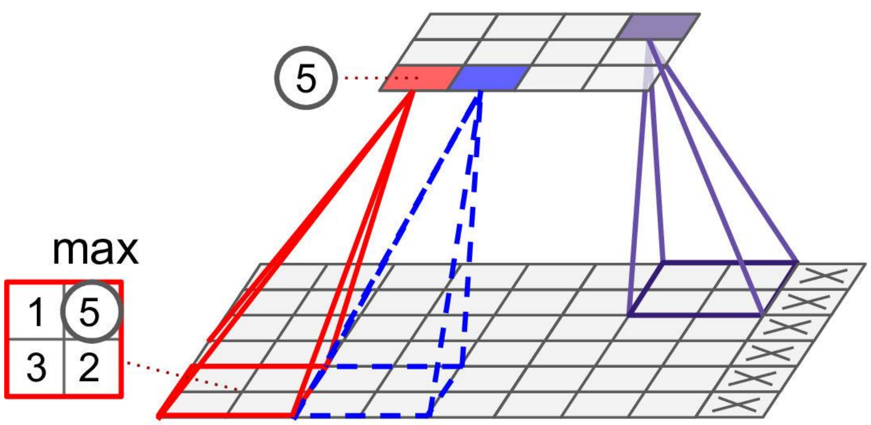
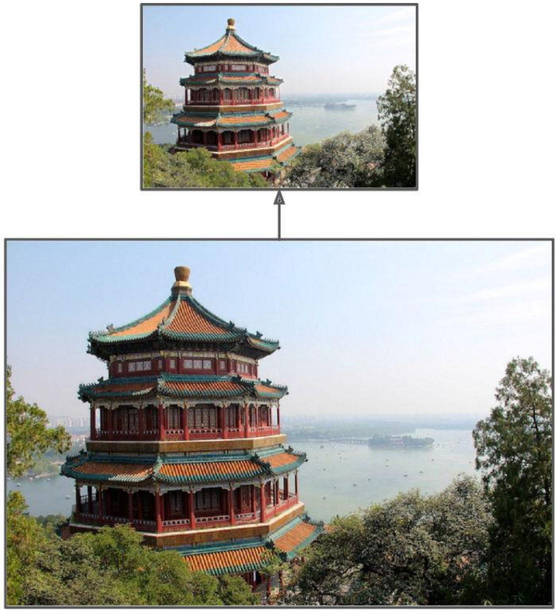
3. Pooling Layer

- 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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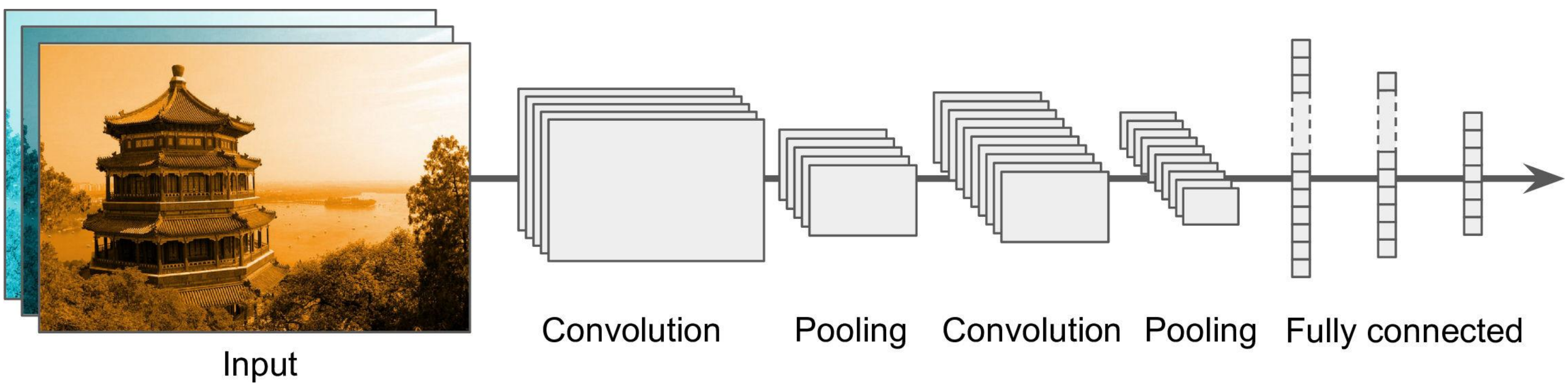
4. CNN Architectures

- 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.



4.1 Example – Fashion MNIST

Filter size

```
model = keras.models.Sequential([
    keras.layers.Conv2D(64, 7, activation="relu", padding="same",
        input_shape=[28, 28, 1]),
    keras.layers.MaxPooling2D(2),
    keras.layers.Conv2D(128, 3, activation="relu", padding="same"),
    keras.layers.Conv2D(128, 3, activation="relu", padding="same"),
    keras.layers.MaxPooling2D(2),
    keras.layers.Conv2D(256, 3, activation="relu", padding="same"),
    keras.layers.Conv2D(256, 3, activation="relu", padding="same"),
    keras.layers.MaxPooling2D(2),
    keras.layers.Flatten(),
    keras.layers.Dense(128, activation="relu"),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(64, activation="relu"),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(10, activation="softmax")
])
```

Feature maps

2×2 window and stride 2

4.1 Example – Fashion MNIST

```
model.compile(loss="sparse_categorical_crossentropy",
      optimizer="nadam", metrics=["accuracy"])

history = model.fit(X_train, y_train, epochs=10,
      validation_data=(X_valid, y_valid))
Train on 55000 samples, validate on 5000 samples
Epoch 1/10 55000/55000 [==============================] - 51s
923us/sample - loss: 0.7183 - accuracy: 0.7529 - val_loss:
0.4029 - val_accuracy: 0.8510
…
Epoch 10/10
55000/55000 [==============================] - 50s
911us/sample - loss: 0.2561 - accuracy: 0.9145 - val_loss:
0.2891 - val_accuracy: 0.9036
```

4.1 Example – Fashion MNIST

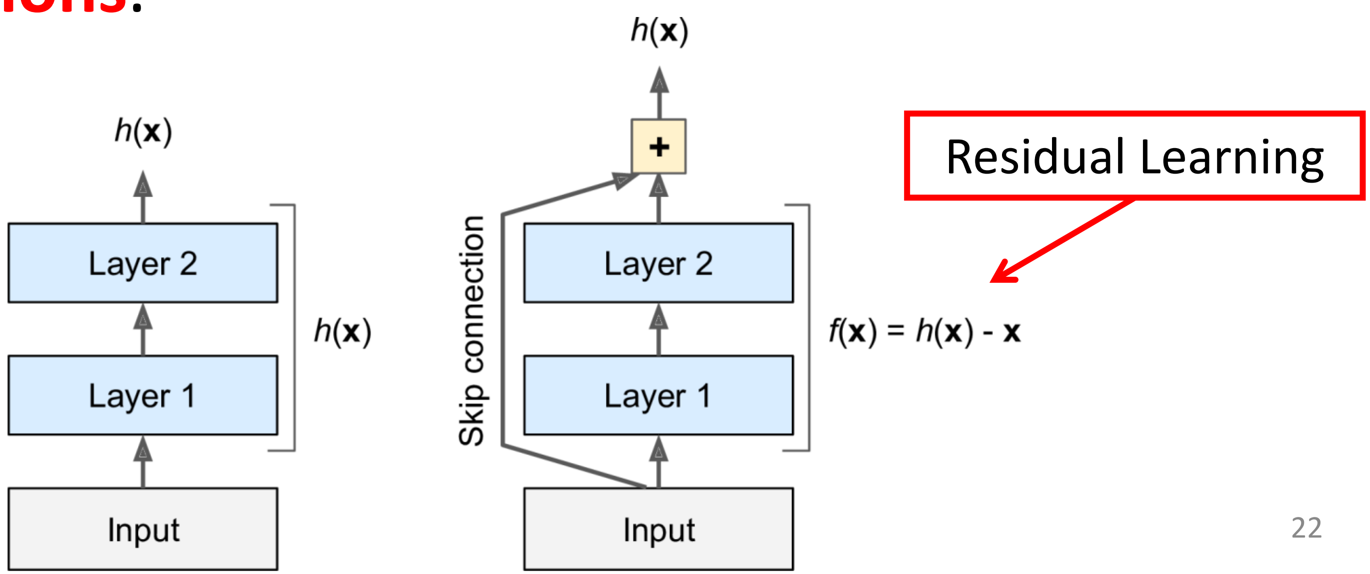
```
score = model.evaluate(X_test, y_test)
X_new = X_test[:10] # pretend we have new images
y_pred = model.predict(X_new)
```

```
10000/10000 [==============================] - 2s
239us/sample - loss: 0.2972 - accuracy: 0.8983
```

Can reach 92% with more epochs

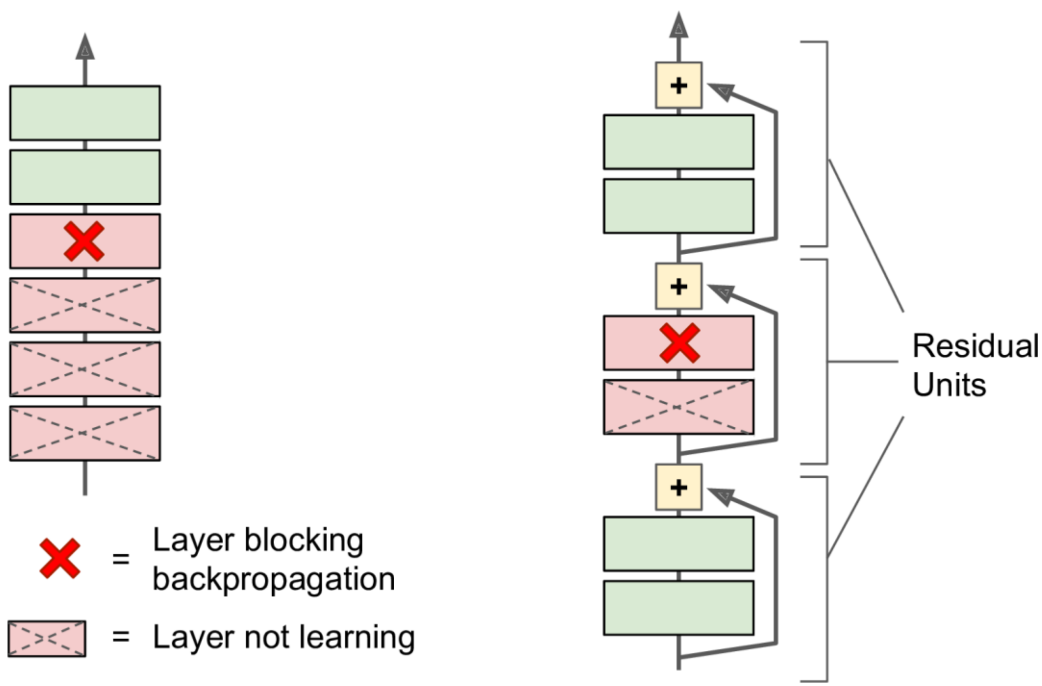
4.2 ResNet

- **Residual Network** (or ResNet) won the ILSVRC 2015 challenge.
- Top-5 error rate under 3.6%, using an extremely deep CNN composed of **152 layers**.
- To train such a deep network, it uses **skip connections**.



4.2 ResNet

- The network can start making progress even if several layers have not started learning yet.
- ResNet is a **stack** of residual units.



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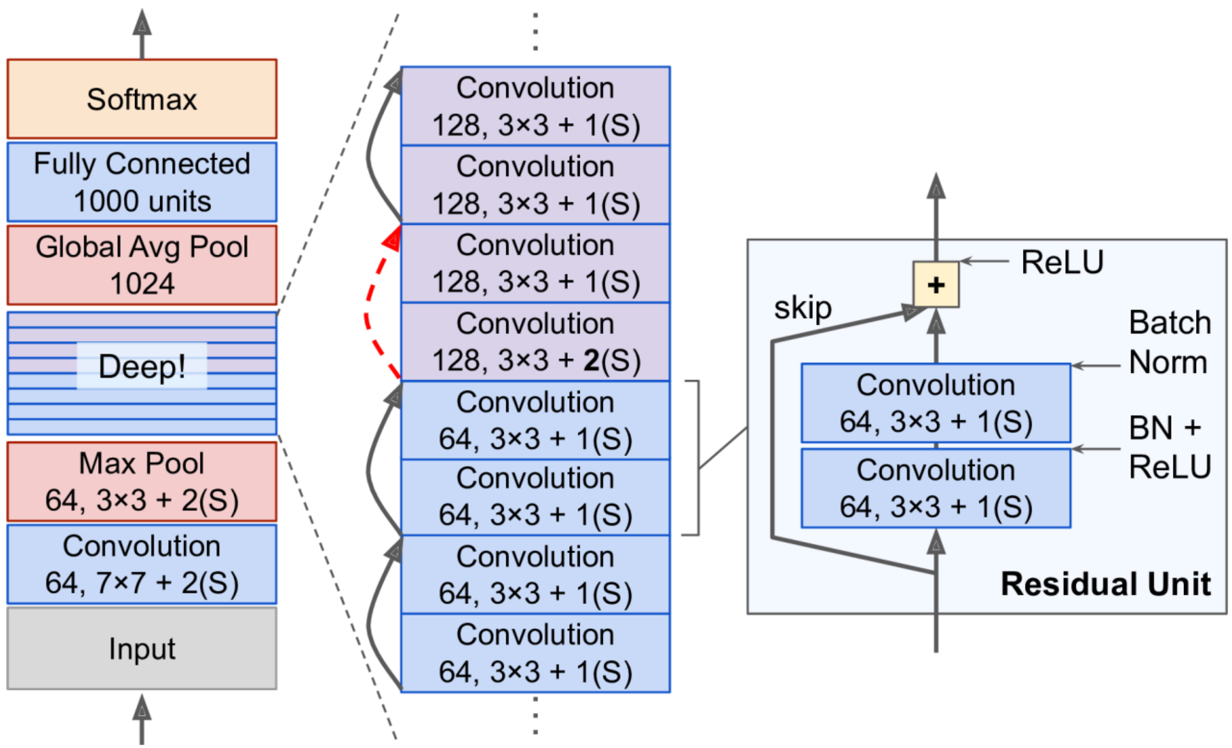

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5. Using Pretrained Models

- Pretrained networks are readily available from the **`keras.applications`** package.
- Check https://github.com/keras-team/keras-applications
- You can load the **ResNet-50** model, pretrained on ImageNet, with the following line of code:

```
model = keras.applications.resnet50.ResNet50(
    weights="imagenet")
```

5. Using Pretrained Models

```
# Input: 224 × 224-pixel images
images_resized = tf.image.resize(images, [224, 224])

# Preprocess images, should be scaled 0-255
inputs = keras.applications.resnet50.preprocess_input(
      images_resized * 255)

Y_proba = model.predict(inputs)

# Get top predictions out of the 1000-class probs.
top_K = keras.applications.resnet50.decode_predictions(
      Y_proba, top=3)
```

5. Using Pretrained Models

```
# Print results
for image_index in range(len(images)):
    print("Image #{}".format(image_index))
    for class_id, name, y_proba in top_K[image_index]:
        print("  {} - {:12s} {:.2f}%".format(
                    class_id, name, y_proba * 100))
    print()
Image #0
  n03877845 - palace       42.87%
  n02825657 - bell_cote    40.57%
  n03781244 - monastery    14.56%

Image #1
  n04522168 - vase         46.83%
  n07930864 - cup          7.78%
  n11939491 - daisy        4.87%
```

Correct Class

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6. Pretrained Models for Transfer Learning

- Training a pretrained network (**Xception**) for a dataset from TFDS (https://homl.info/tfds).
- `tf_flowers`: 3670 images, 5 classes


```
# Load the dataset
import tensorflow_datasets as tfds

dataset, info = tfds.load("tf_flowers",
      as_supervised=True, with_info=True)

dataset_size = info.splits["train"].num_examples # 3670
n_classes = info.features["label"].num_classes   # 5
class_names = info.features["label"].names
```

6. Pretrained Models for Transfer Learning

```
# Reloood the dataset with three splits tf.data.Dataset
test_set_raw, valid_set_raw, train_set_raw = tfds.load(
      "tf_flowers", split=["train[:10%]",
      "train[10%:25%]", "train[25%:]"],
      as_supervised=True)

# Define the preprocessing function
def preprocess(image, label):
    resized_image = tf.image.resize(image, [224, 224])
    final_image =
      keras.applications.xception.preprocess_input(
            resized_image)
    return final_image, label
```

6. Pretrained Models for Transfer Learning

```
# Apply this preprocessing function to the 3 datasets
# Shuffle the training set
# Add batching and prefetching to all the datasets
batch_size = 32
train_set = train_set_raw.shuffle(3000).repeat()
train_set = train_set.map(partial(preprocess,
      randomize=True)).batch(
      batch_size).prefetch(1)
valid_set = valid_set_raw.map(preprocess).batch(
      batch_size).prefetch(1)
test_set = test_set_raw.map(preprocess).batch(
      batch_size).prefetch(1)
```

6. Pretrained Models for Transfer Learning

```
# Load an Xception model, pretrained on ImageNet
#  excluding the global avg pool. and dense o/p layers
base_model = keras.applications.xception.Xception(
      weights="imagenet", include_top=False)
# Add global avg pool. layer based on model output
avg = keras.layers.GlobalAveragePooling2D()(
      base_model.output)
output = keras.layers.Dense(n_classes, # Add desnse o/p
      activation="softmax")(avg)
model = keras.models.Model(inputs=base_model.input,
      outputs=output) # Create the Keras Model
```

6. Pretrained Models for Transfer Learning

```python
# Freeze the weights of the pretrained layers
for layer in base_model.layers:
    layer.trainable = False

# Compile the model and start training
optimizer = keras.optimizers.SGD(lr=0.2, momentum=0.9,
      decay=0.01) # LR=0.2 with scheudle, k=1/0.01
model.compile(loss="sparse_categorical_crossentropy",
      optimizer=optimizer, metrics=["accuracy"])
history = model.fit(train_set, epochs=5,
      validation_data=valid_set) # Tops at 75-80% acc.
```

$$\boxed{\eta(t) = \eta_0 \,/\, (1 + t/k)}$$

6. Pretrained Models for Transfer Learning

```
# Unfreeze the weights of the pretrained layers
for layer in base_model.layers:
      layer.trainable = True

# Recompile with lower LR and decay
optimizer = keras.optimizers.SGD(lr=0.01, momentum=0.9,
       nesterov=True, decay=0.001)
model.compile(loss="sparse_categorical_crossentropy",
      optimizer=optimizer, metrics=["accuracy"])
history = model.fit(train_set, epochs=40,
      validation_data=valid_set) # Result: 95% acc.
```

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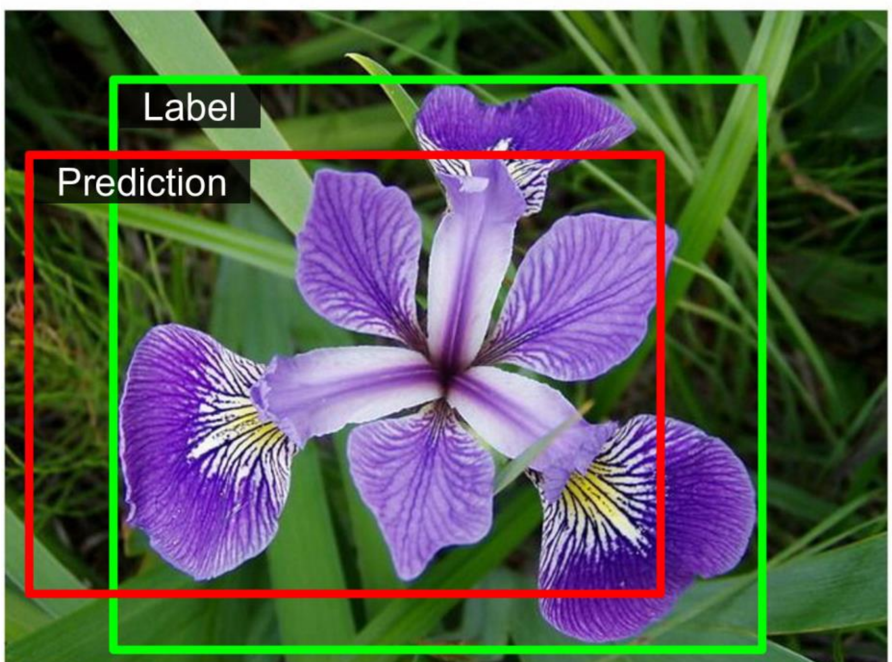
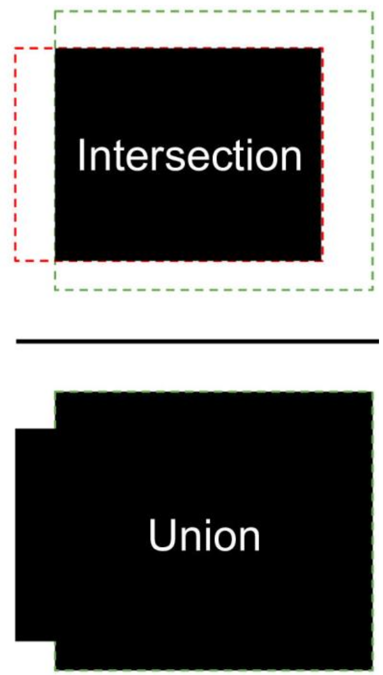
7. Classification and Localization

- Localizing an object in a picture can be expressed as a regression task.
- Predict the horizontal and vertical coordinates of the object's center and its height and width.





Common metric: the Intersection over Union (IoU)

7. Classification and Localization

```
base_model = keras.applications.xception.Xception(
      weights="imagenet", include_top=False)
avg = keras.layers.GlobalAveragePooling2D()(
      base_model.output)
class_output = keras.layers.Dense(n_classes,
      activation="softmax")(avg)
loc_output = keras.layers.Dense(4)(avg)
model = keras.Model(inputs=base_model.input,
      outputs=[class_output, loc_output])
model.compile(loss=["sparse_categorical_crossentropy",
      "mse"], loss_weights=[0.8, 0.2],
      optimizer=optimizer, metrics=["accuracy"])
```

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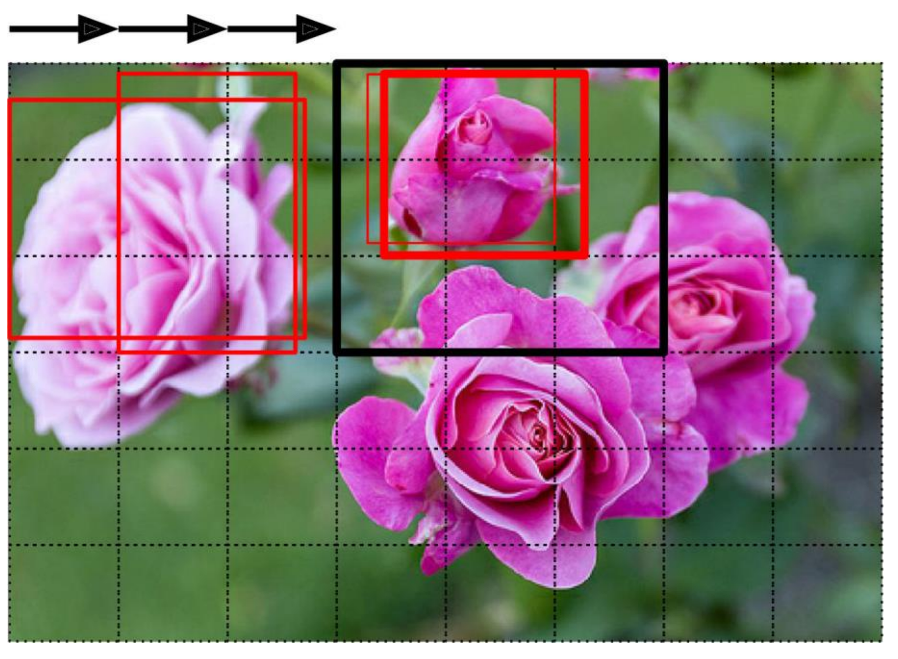
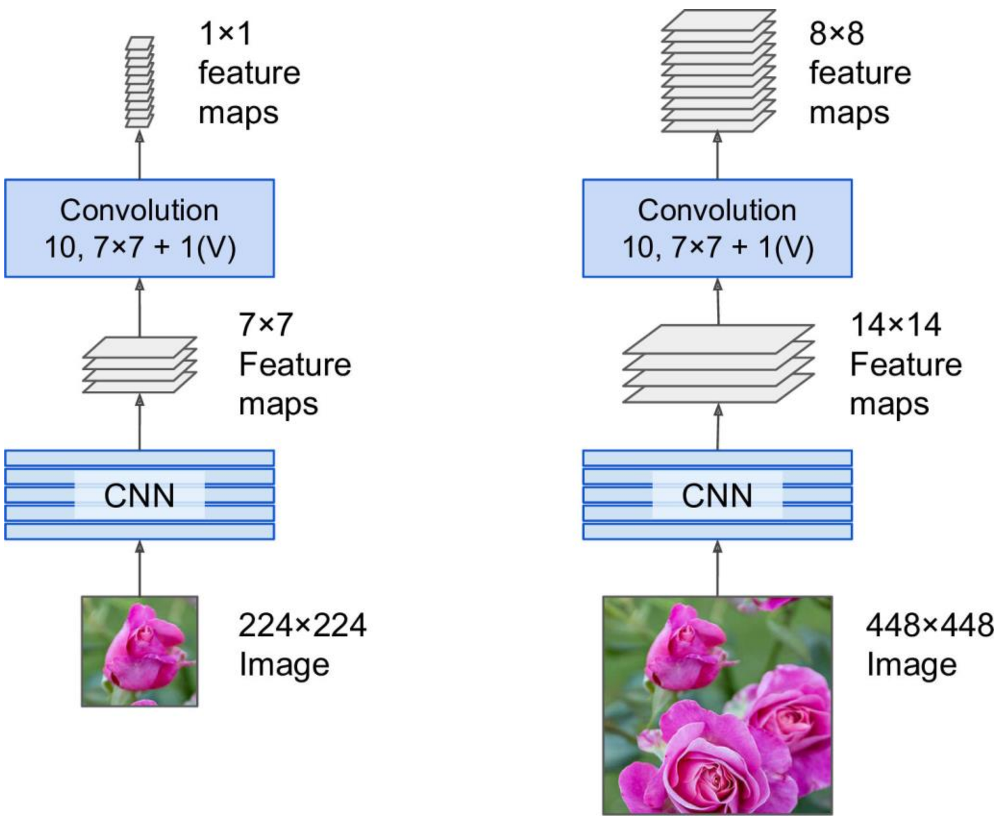
8. Object detection

- The task of classifying and localizing multiple objects in an image.
- A slow approach is use a CNN trained to classify and locate a single object, then slide it across the image.



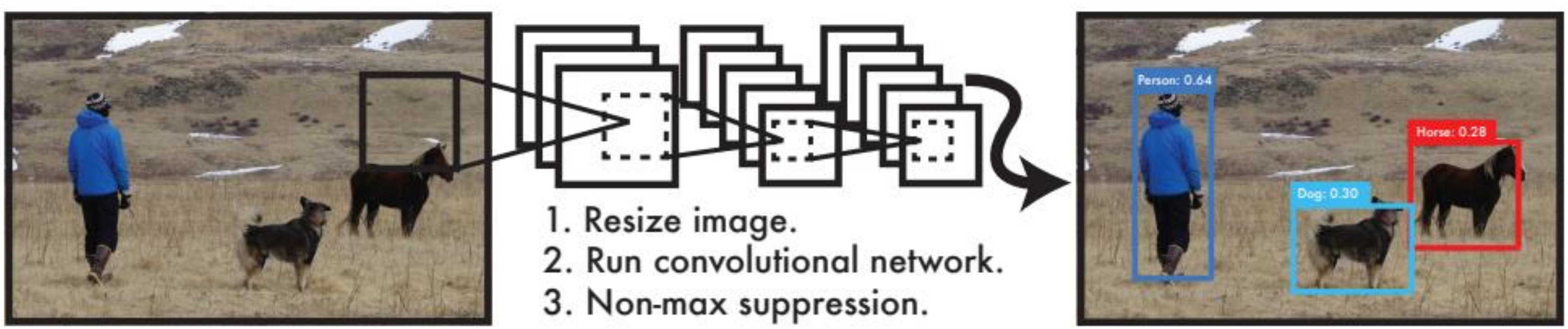
8.1 Fully Convolutional Networks

- FCN has also a convolution layer at the output with **`valid`** padding.
- FCN can process images of any size.
- Example:
  - Train the CNN for classification and localization on small images, 10 outputs.
  - For larger image, it output 8×8 grid where each cell contains 10 numbers.



8.2 You Only Look Once (YOLO)

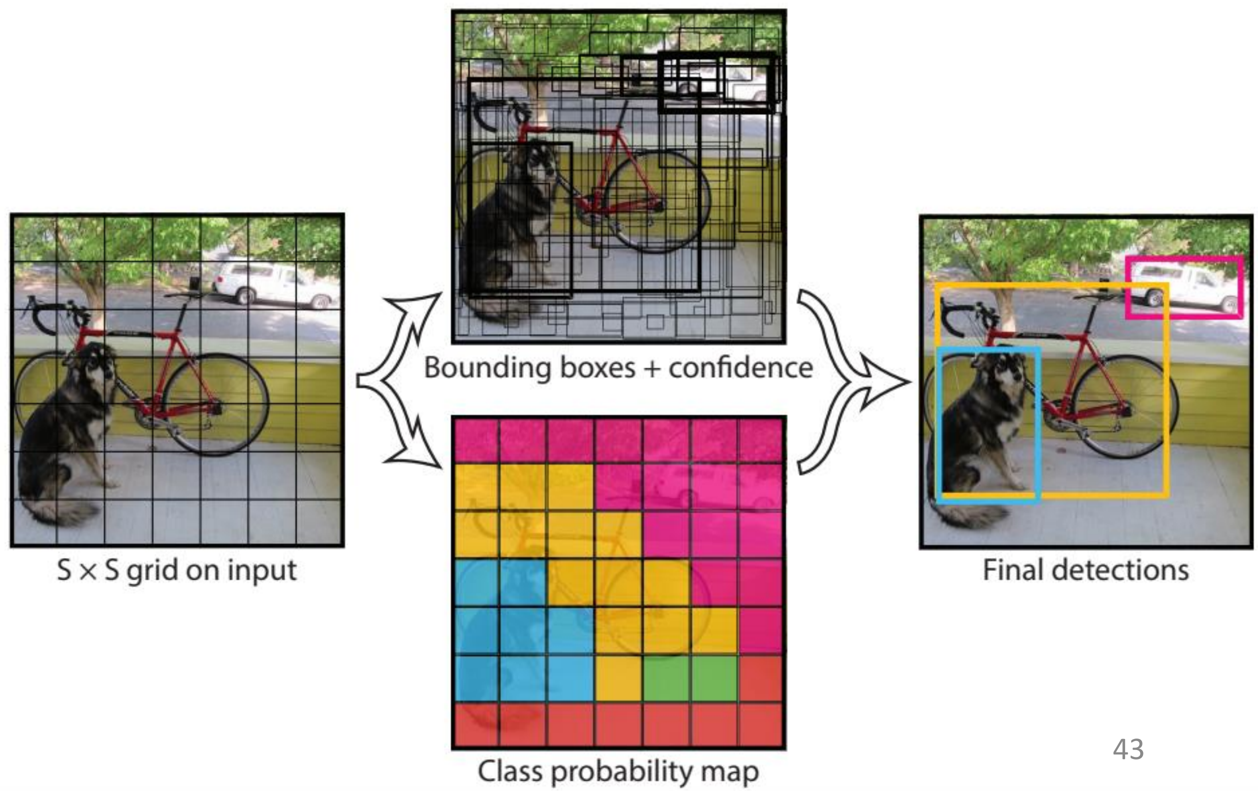
- YOLO is an extremely fast and accurate object detection architecture.
    1. Resizes the input image to 448 × 448
    2. Runs a single convolutional network on the image
    3. Thresholds the resulting detections by the model's confidence.



8.2 You Only Look Once (YOLO)

- Models detection as a regression problem. It divides the image into an $S \times S$ grid.

- For each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities.



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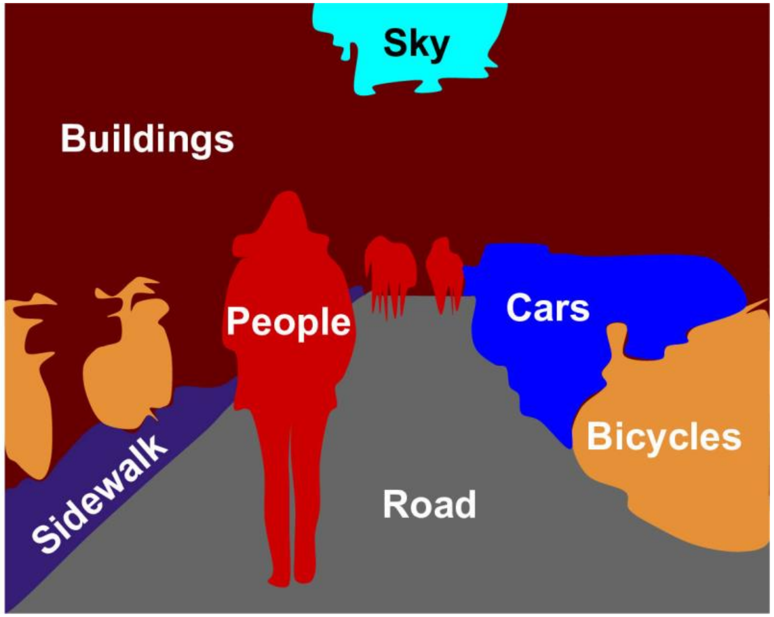
9. Semantic Segmentation

- Each pixel is classified according to the class of the object it belongs to.
- Can use **FCN** followed by up **sampling** layers.



Exercises

From Chapter 14, solve exercises:

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