Computer Vision

Output from: You only look once (YOLO;; Redmon et al. 2016)

Professor Marie Roch with major contributions from Professor Liu

Chapter 25, Russell & Norvig (we only cover highlights)

Computer vision tasks

- Detection
- Labeling
- Relationships between objects

Most vision tasks are handled as classification problems.

Output from: You only look once (YOLO;; Redmon et al. 2016)

Our focus: Single label image classification

Spanish shawl nudibranch
(*Flabellina iodinea*)

What makes this hard?

- Perspective and view point changes

mixbook.com

The same tree

Pinhole cameras & perspective

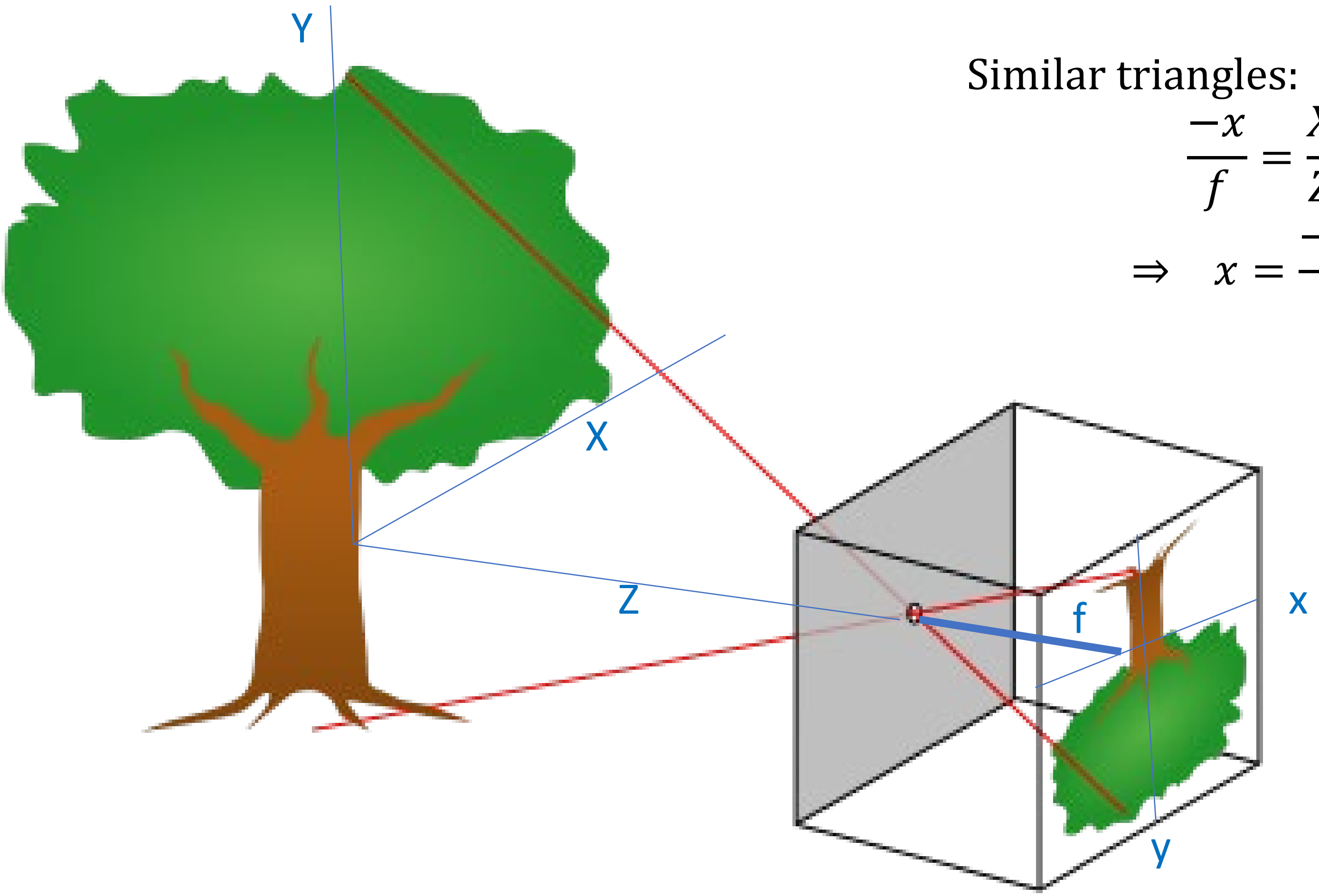


image: Wikimedia commons

Similar triangles:

$$\frac{-x}{f} = \frac{X}{Z}, \frac{-y}{f} = \frac{Y}{Z}$$

$$\Rightarrow \quad x = \frac{-fX}{Z}, y = \frac{-fY}{Z}$$

f – focal distance between pinhole & projection plane

Illumination

Each row is the same person with different lighting conditions

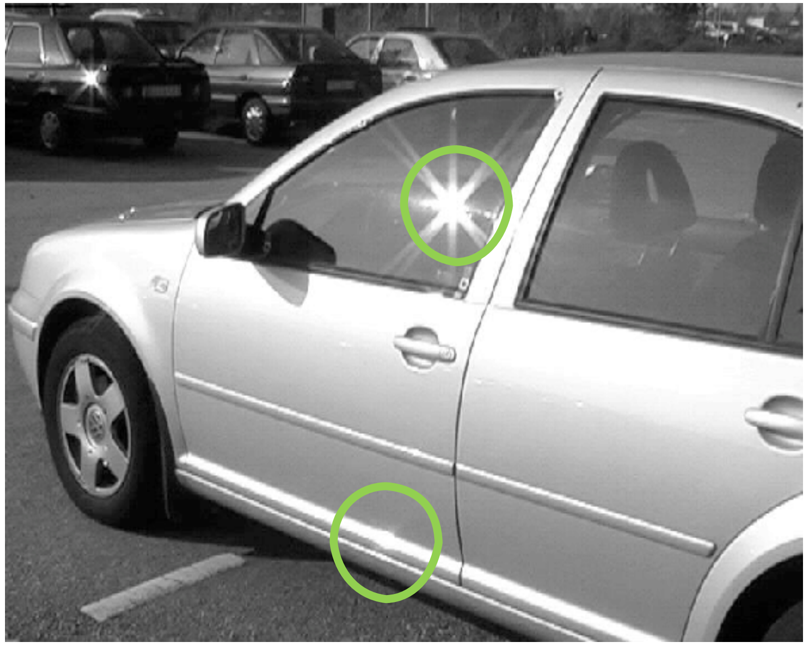


image: Aanæs 2003

Specular reflections

Deformation

Instances of the same class may be nonridgid and undergo deformation

image credit: Sarah K, Benton County 4-H, MN, https://extension.umn.edu/

Occlusion

Objects can be hidden by other objects

Clutter and noise

Background regions that are similar to the foreground

- Satantic leaf-tailed gecko
- rock wallabees

images from *Wired* and Camouflage by Steve Parker
educational fair use:

Variation

WizSmart dog pads

Images have same label (dog) although they are quite different

Summary

Computer vision must deal with a variety of complicating factors

- perspective
- illumination
- deformation
- occlusion
- clutter and noise
- variation

image credit: Nate @ http://floorsix.blogspot.com/

Like all supervised machine learning problems

- Need labeled corpus
    - Training data
    - Test data

- Simple k-nearest neighbor classifier
    - Training: Retain database of images
    - Test: Look for most similar images and use plurality class

Measuring distance between images

- Naïve method: pixel by pixel comparison (all we will be doing)

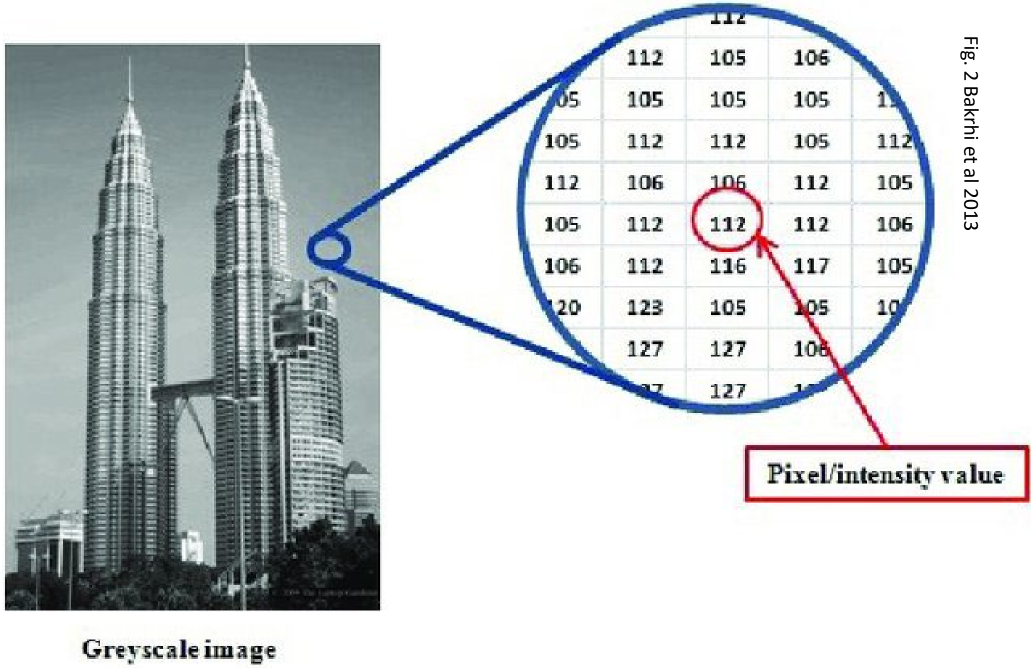
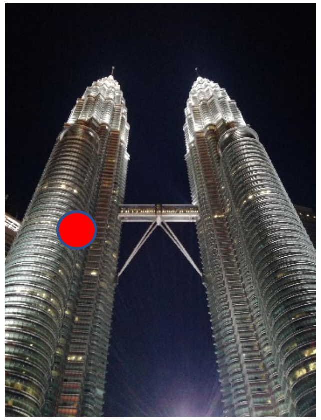


Fig. 2 Bakrhi et al 2013

- L1 or L2 distance



L_p distance: $d(I,\ J) = \sqrt[p]{\sum_{x,y} \left| I_{x,y} - J_{x,y} \right|^p}$

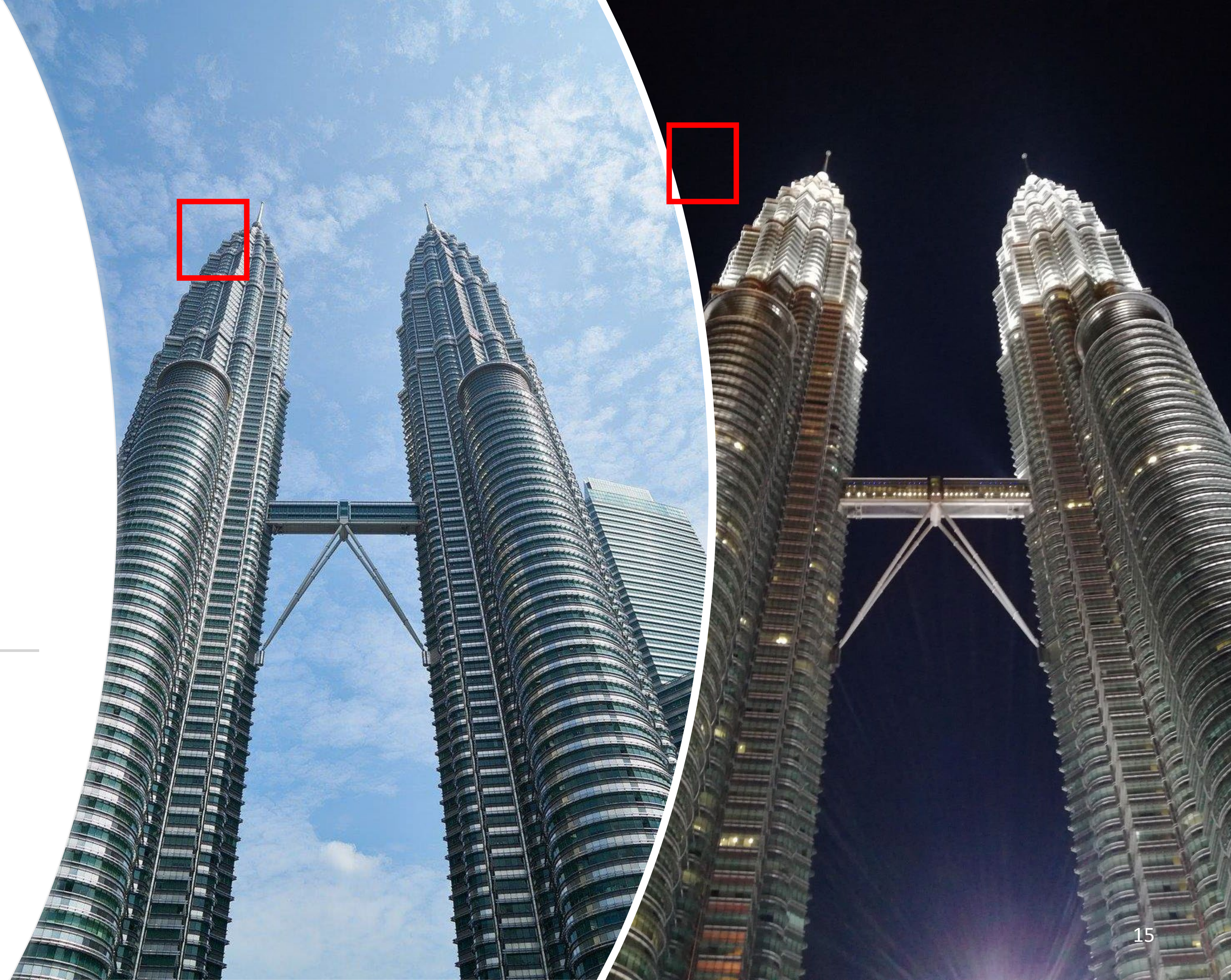
How well is our method going to do with respect to?

- perspective
- illumination
- deformation
- occlusion
- clutter and noise
- variation

images from CIFAR 100 dataset

A better way…

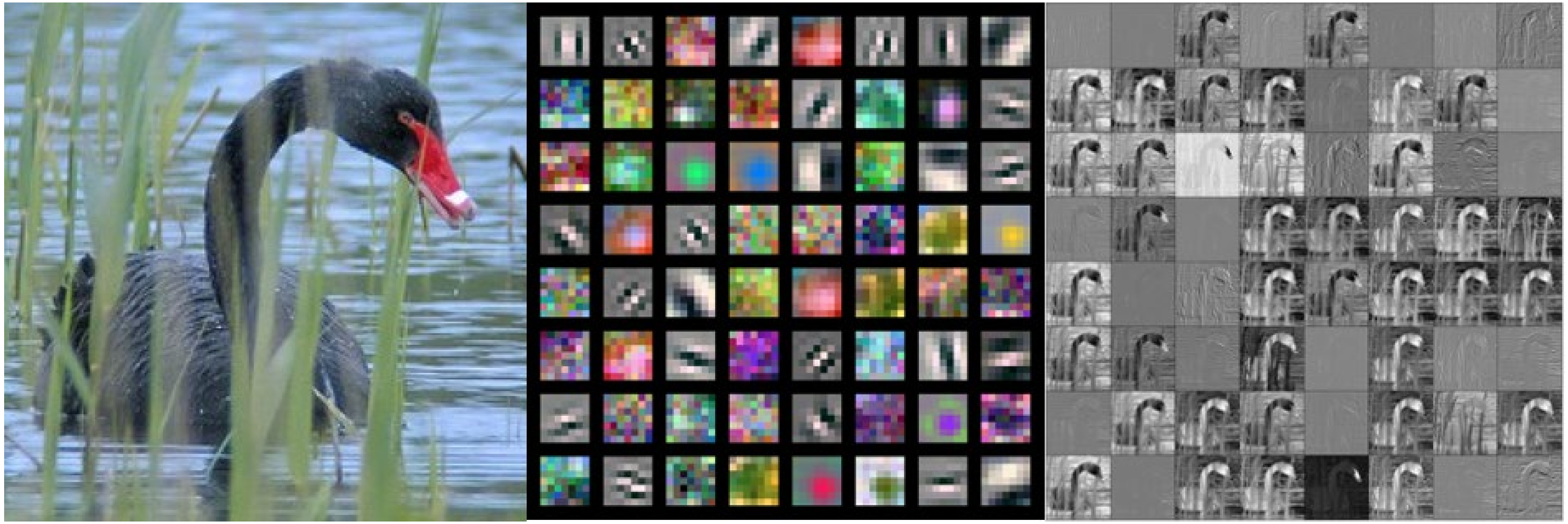
What if we compared local regions?



Convolutional neural networks

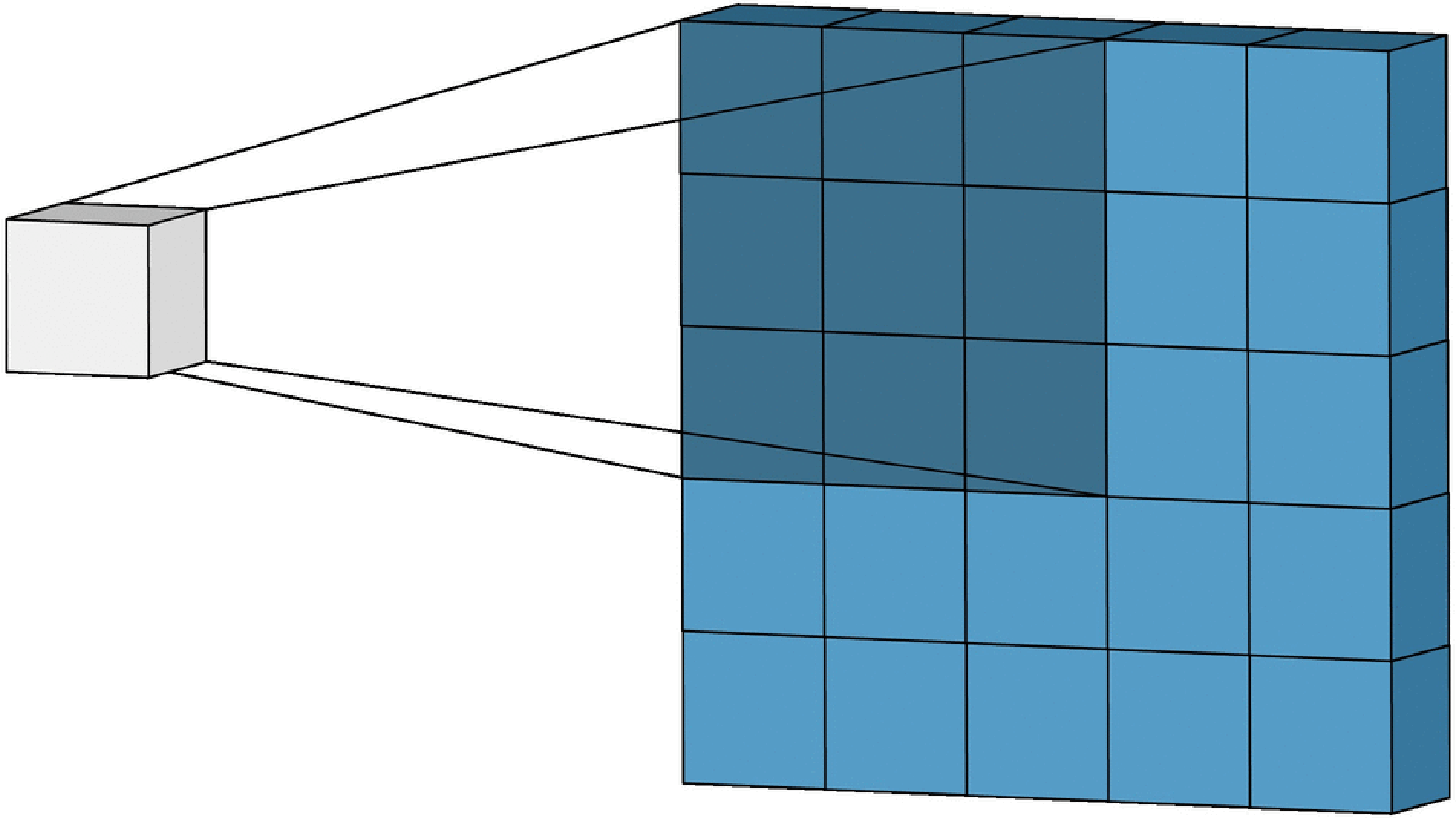
- Learn *kernels* of recurring subregions of images
- Convolve the *kernels* with a tensor (e.g. image)
- Deeper layers typically learn more complex information

image: medium.com/apache-mxnet



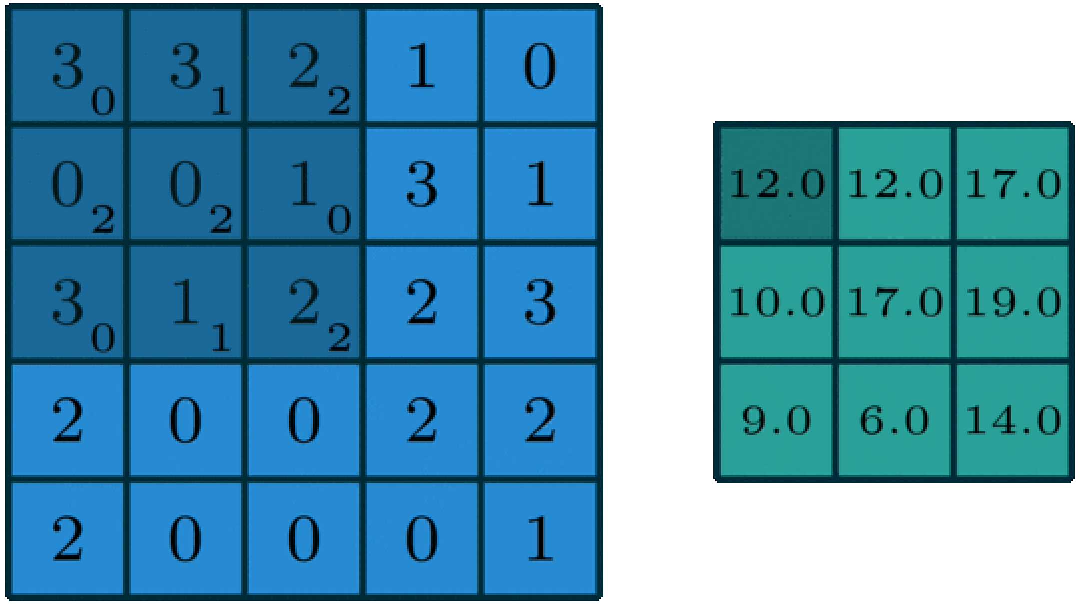
Resnet convolutional kernels

Convolution in 2D



Animation credit: [Irhum Shafkat]

Convolution in 2D



$$w = \begin{bmatrix} 0 & 1 & 2 \\ 2 & 2 & 0 \\ 0 & 1 & 2 \end{bmatrix}$$

Animation credit: Irhum Shafkat

Convolution in 2D

- Convolve (*) image I with kernel K:

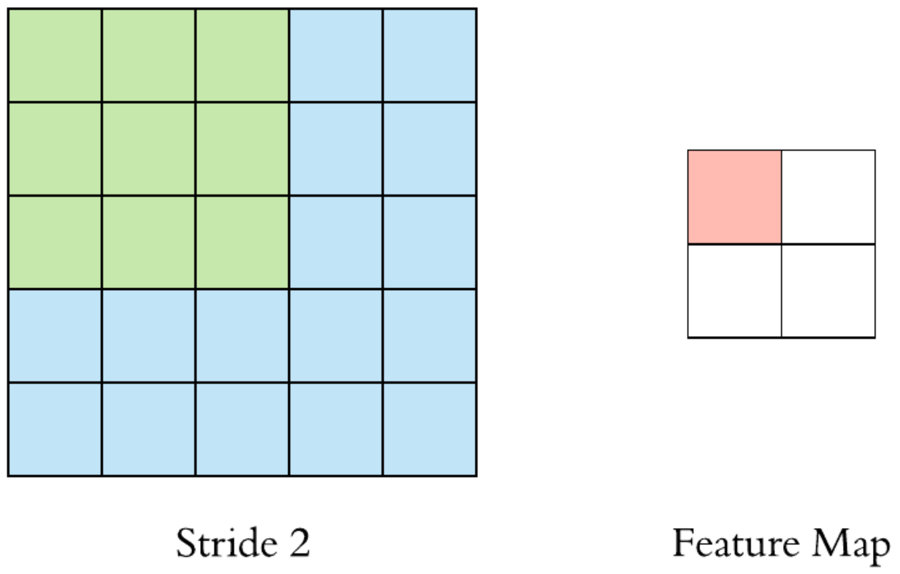
$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I[m,n]K[i-m,j-n]$$

- Many libraries implement cross-correlation instead of convolution (kernel not reversed, not important in practice):

$$\sum_m \sum_n I[i+m,j+n]K[i,j]$$

Convolutional layers

- Fixed-size kernel, e.g. (5, 5)
- Convolutional output is passed through the activation function
- Stride parameters cause skips



- Common to pool regions and take some statistic e.g., max

Basic ideas

- Convolution is an operation like any other
- Loss can be backpropagated and kernel weights adjusted
- Loss function guides what is learned
- Downsampling operations called pooling reduce size

- Going from convolut
  - Flatten last layers
  - feed-forward network

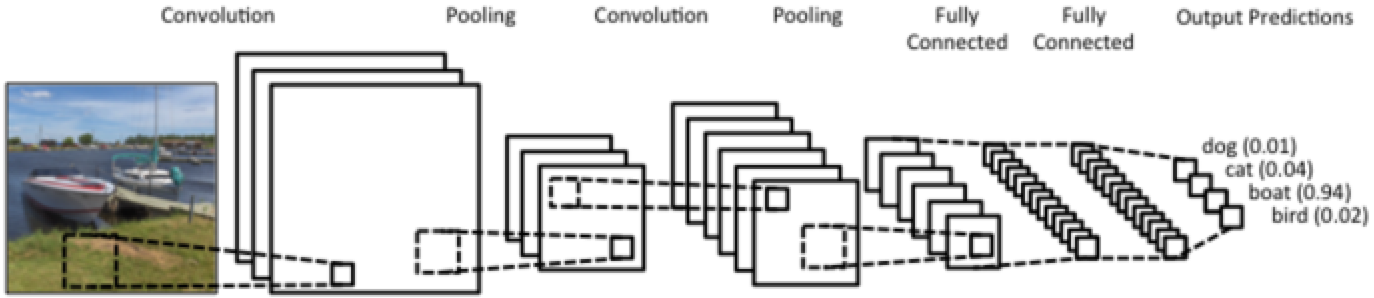


image credit: Irene Le

Keras convolutional layers

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Input, Conv2D, MaxPooling2D
model = Sequential()
model.add(Input(shape=(1000,1000,1))  # 1000x1000 grayscale
model.add(Conv2D(32, kernel_size=(5, 5), activation='relu')))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
model.add(Conv2D(64, kernel_size=(5, 5), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
# Convert to vector, then feed forward network
model.add(Flatten())
model.add(Dense(1000, activation='relu'))
model.add(Dense(NumClasses, activation='softmax'))
```