

# Multimedia Technology

## Lecture 7: Image Features

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*Autumn Semester 2022*

- We already know how the image is represented in computer
- We can process image as a matrix
- We can process image as a multi-variable function
- In this lecture, focus is turned on image features
- Why image feature?
- What are they
  - Image Local Features
  - Image Global Features
- How to extract them?

# Outline

1 Global Features

2 Scale Space

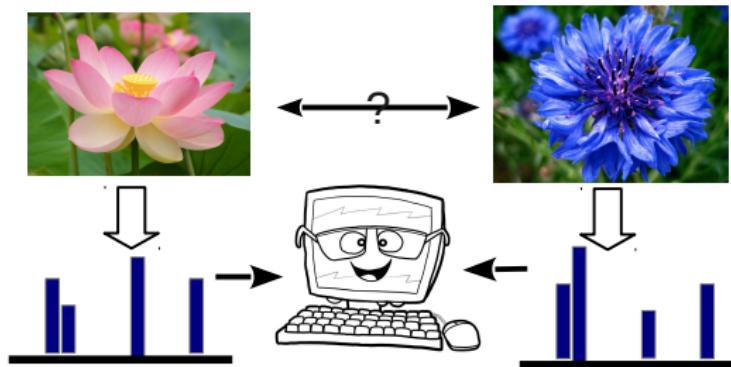
3 Local Features

4 Deep Features

5 References

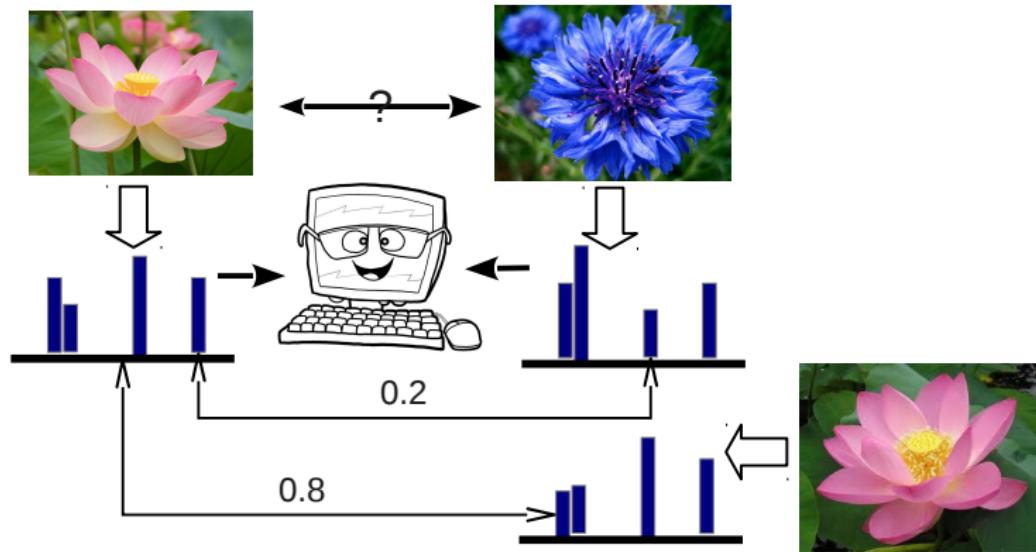
# Why image features? (1)

- Images are not directly comparable by computer
- Features are the media to represent the images



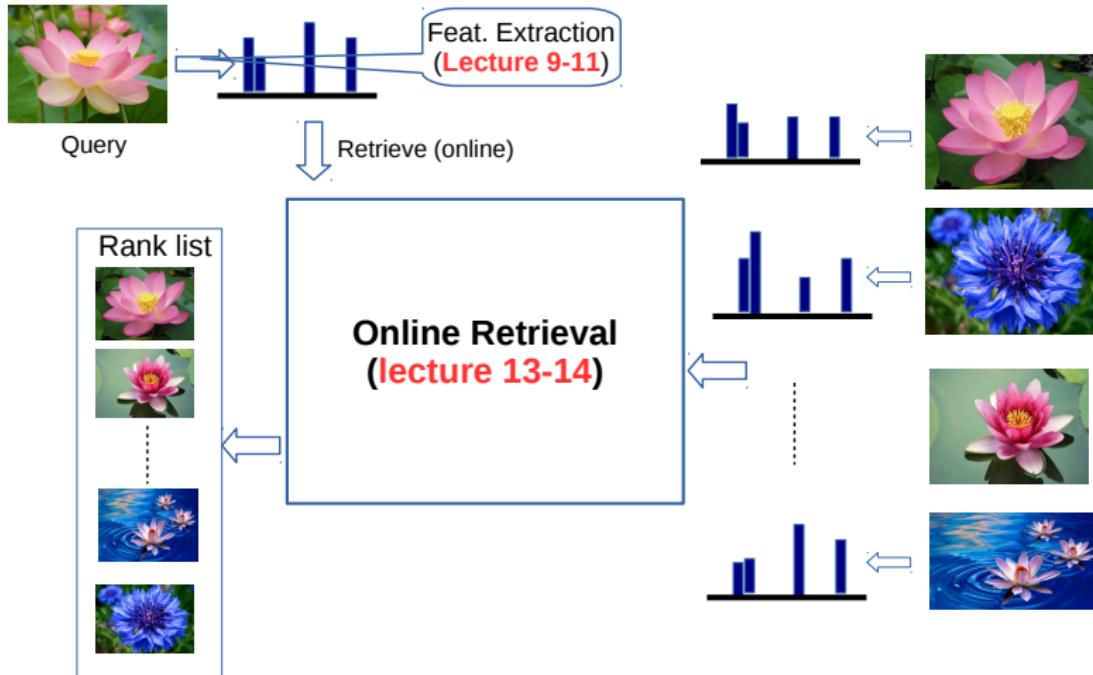
- Open issue: how the images are represented in our brain??

# Why image features? (2)



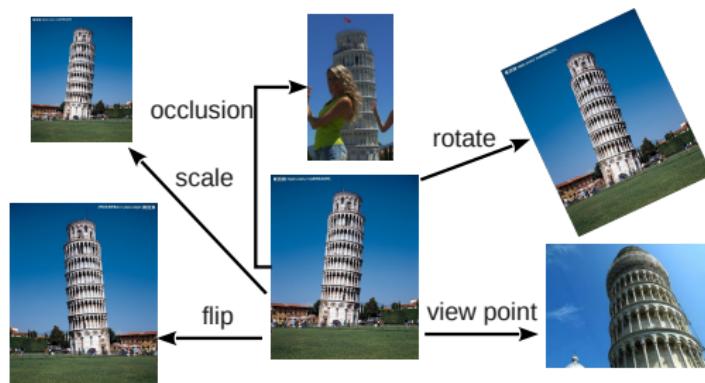
- Features should reflect the similarity as precise as possible

# Framework of content based image retrieval (CBIR)



- CBIR = image features + retrieval/comparing method

# Invariance properties of the features

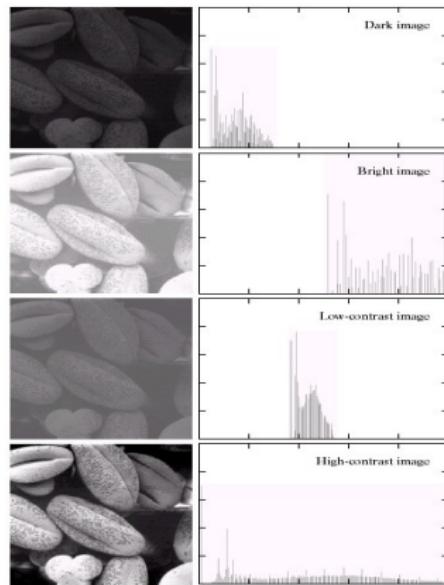
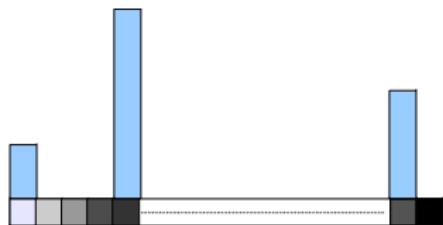


- Scale invariance is desired
- Rotation invariance is desired
- Flip invariance is desired
- Sometimes, color invariance is desired
- ...

# Image global features

- They are mostly statistical variables defined on image
- Easy to compute
- Popular global features:
  - Color Histogram
  - Color Moments
  - Histogram of Oriented Gradients
  - VLAD: globalized local feature (talk later)

# Color Histogram (1)

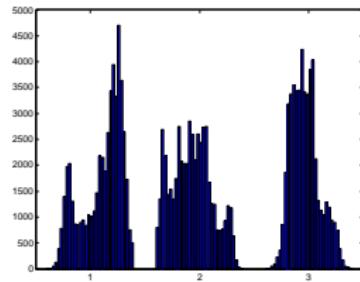


- Counting num. of pixels in each color range
- For **color** images:
  - Apply CH on each channel
  - Concatenate the vectors

# Color Histogram (2)



(a) Original image



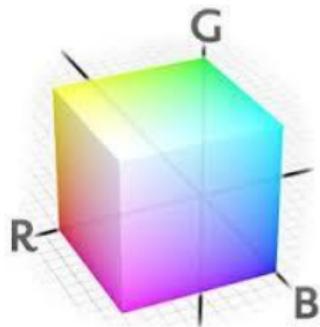
(b) Color histogram from RGB channels

# Color Histogram (3)

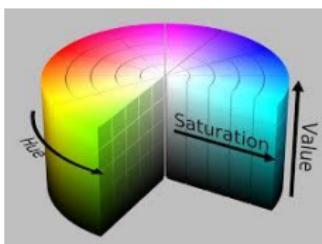
```
1 img1 = imread('lena.jpg');
2 r1 = im2double(img1(:,:,1))*256;
3 hr = hist(reshape(r1,(225*225),1),32);
4 g1 = im2double(img1(:,:,2))*256;
5 hg = hist(reshape(g1,(225*225),1),32);
6 b1 = im2double(img1(:,:,3))*256;
7 hb = hist(reshape(b1,(225*225),1),32);
8 hist = [hr;hg;hb];
9 bar(hist);
10
```

Listing 1: Code to calculate histogram of 3 channels

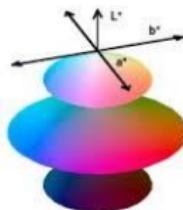
# Color Spaces



(c) RGB color space



(d) HSV color space



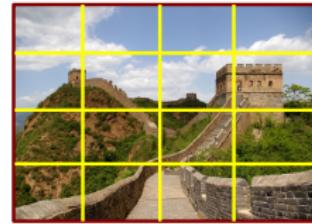
(e) Lab color space

- Image can be represented with different color spaces
- There are formulars to do the transform in between
- Color histograms on HSV and Lab are more distinctive

# Color Moment

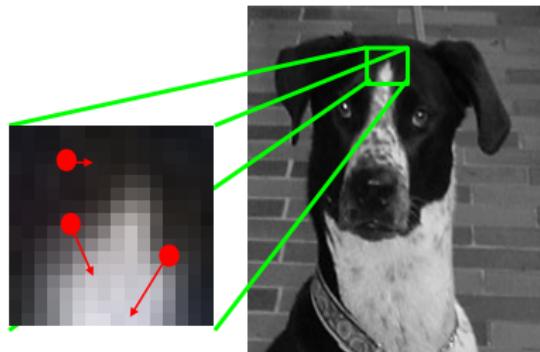
- Intensity value distribution (on one channel) is viewed as a statistical variable
- We can calculate its moments (usually referred as central moment)
- Which is given below

$$\mu_n = E[X - E[x]]^n$$



- $E[x]$  is calculated by taking the average
- $n$  is the order
- Moments are concatenated and moments from different blocks are concatenated
- It turns out to be simple but pretty successful

# HOG: Histogram of Oriented Gradients



$$\nabla I(x, y) = \left( \frac{\partial I(x, y)}{\partial x}, \frac{\partial I(x, y)}{\partial y} \right) \quad (1)$$

- $\pi$  ..... + $\pi$

- Orientation

- Magnitude

$$m = \sqrt{2} \sqrt{\frac{\partial I(x, y)^2}{\partial x} + \frac{\partial I(x, y)^2}{\partial y}} \quad (2)$$

$$\theta = \tan^{-1} \frac{\frac{\partial I(x, y)}{\partial y}}{\frac{\partial I(x, y)}{\partial x}} \quad (3)$$

# Partial Derivatives on Image

- Image is a multi-variable function  $f(x, y)$
- When taking derivatives,  $dx=dy=1$
- As a result

$$\frac{\partial I(x, y)}{\partial x} = I(x, y) - I(x - 1, y)$$

- The second order derivative is given as

$$\begin{aligned}\frac{\partial^2 I(x, y)}{\partial x^2} &= [I(x + 1, y) - I(x, y)] - [I(x, y) - I(x - 1, y)] \\ &= [I(x + 1, y) + I(x - 1, y)] - 2 \cdot I(x, y)\end{aligned}$$

# How well are the global features?



Scaling



Rotation



Affine



Flip



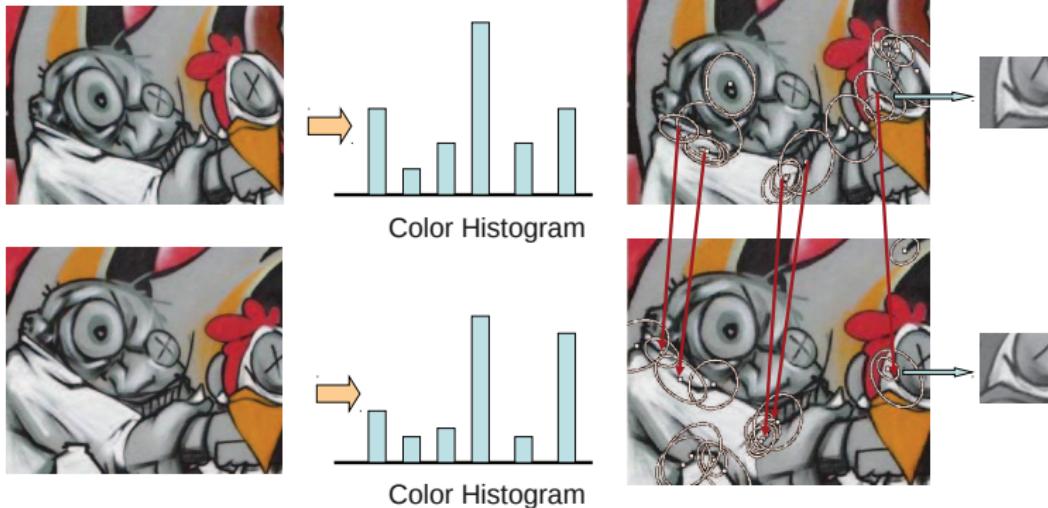
Occlusion

Transform	CH	HOG	Human vision
Scale	partially	partially	fully <sup>1</sup>
Rotation	fully	no	fully
Affine	partially	partially	fully
Flip	fully	no	fully
Occlusion	no	no	fully
Light/Color	vulnerable	vulnerable	fully
Blur	vulnerable	vulnerable	partially
View point	vulnerable	vulnerable	partially

- Homework:
  - Submit transformed images as query to Google image
  - See how well the system achieves invariances

<sup>1</sup>except for extreme cases

# Global Feature vs Local Interest Point Feature



(a) Two paradigms for evaluating similarity between two images: global feature against local feature

- Images are compared in a finer granularity

# Scale Invariance: the concept (1)

- We already mentioned this concept before
- We study how we can achieve this for image local feature



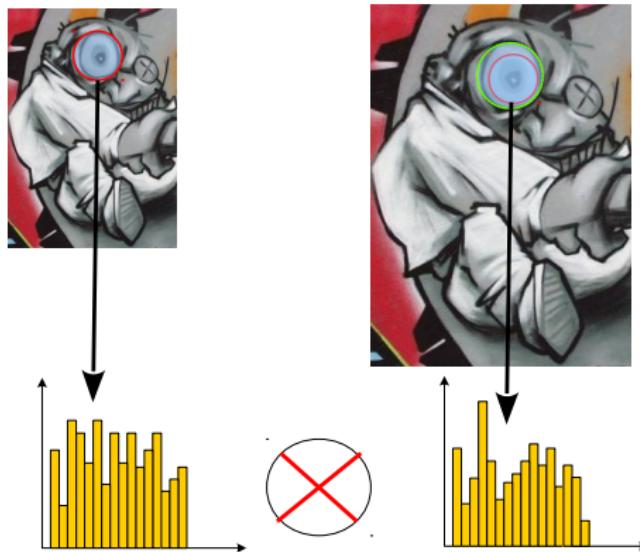
- Local feature is detected, we cannot simply compare their pixel values
- They are simply not distinctive

# Scale Invariance: the concept (2)



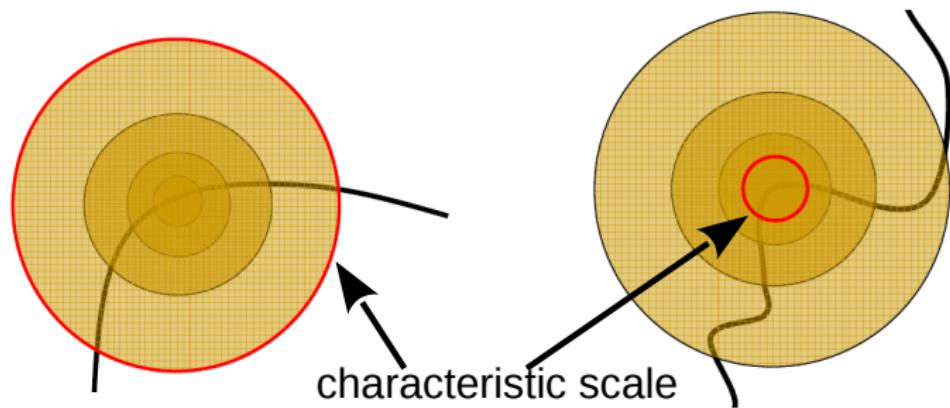
- We need to compare a local region
- But how to scope this local region?
- Fix the size for all points detected?

# Scale Invariance: the concept (3)



- It is not working!!
- Fixed size does not cover the same region in two different images
- What we expect is the region scoped by green circle

# Scale Invariance: the concept (4)



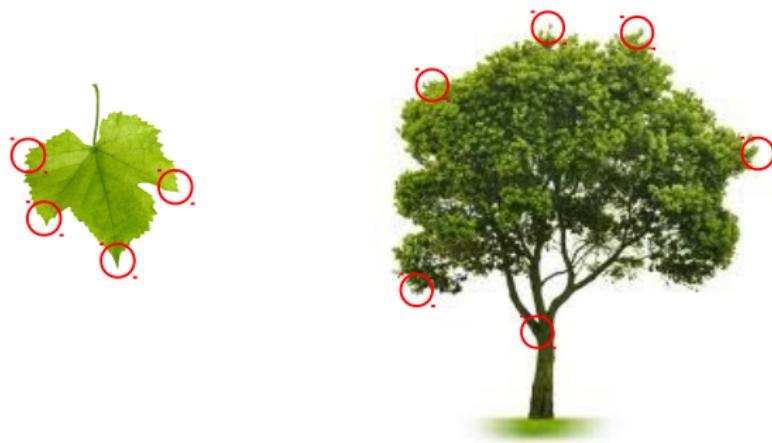
- We are looking for something like this
- The selected scale in two images cover the same local structure
- Notice that we detect corners from each image independently

# Scale Invariance: scale space (1)



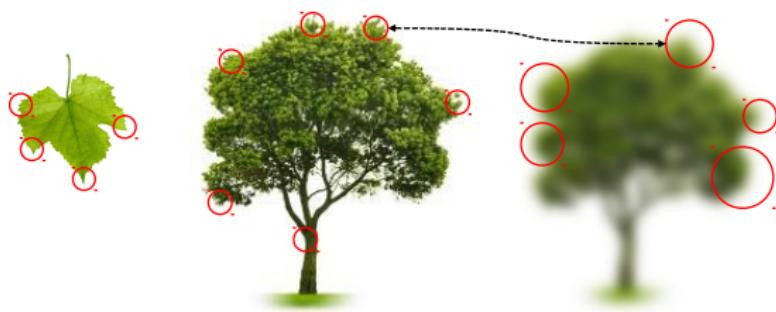
- In order to achieve scale invariance, let's look at scale space first
- What you can see you stand under tree?
- What you can see you stand 50 meters away from the tree?

# Scale Invariance: scale space (2)



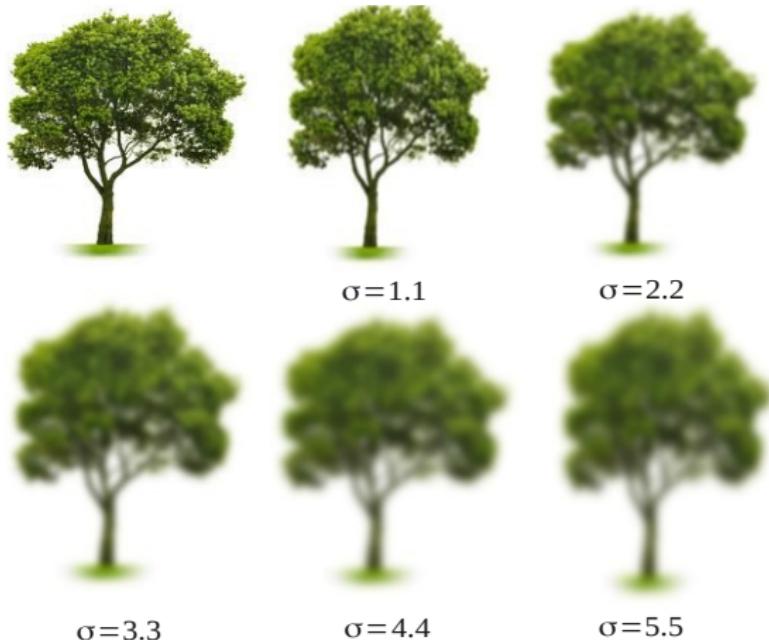
- Now you are asked to finger out corners from the leaf and from the tree
- Are you convinced?
- Can you still see the corners in one leaf when you stand 50 meters away?

# Scale Invariance: scale space (3)



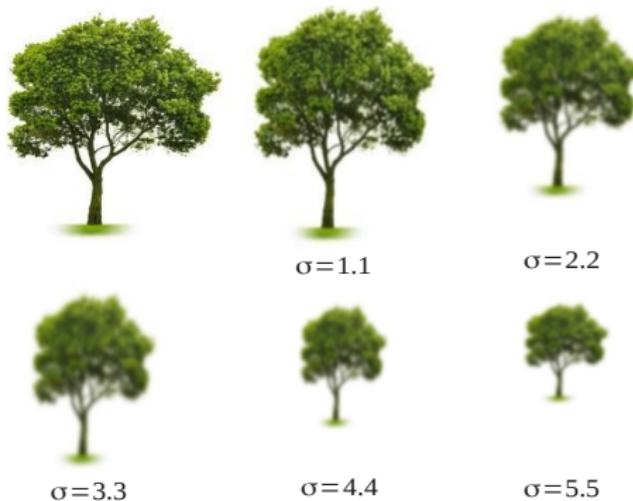
- Now let's move to 200 meters away from the tree
- What you can see??
- Conclusion: **certain corners only appear/survive in certain range of scales/watching distances**

# Scale Invariance: scale space (4)



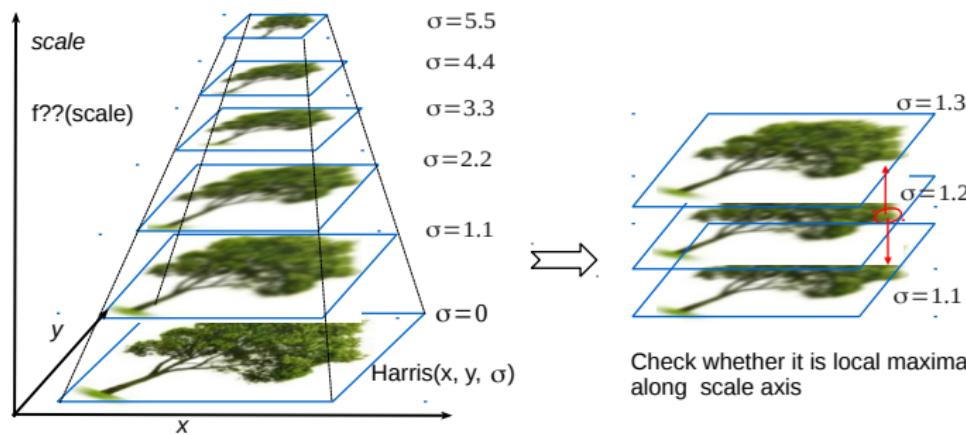
- Once the photo is taken, the distance between the tree and our watch position is fixed
- We simulate this by convolution with different  $\sigma$ s

# Scale Invariance: scale space (5)



- When the image is blurred heavily, it is no need to keep its original size
- So finally we have above blurred image series
- As mentioned before, in different distances, you see different corners
- We want to find these stable points, which are visible within certain distance range

# Scale Invariance: scale space (6)

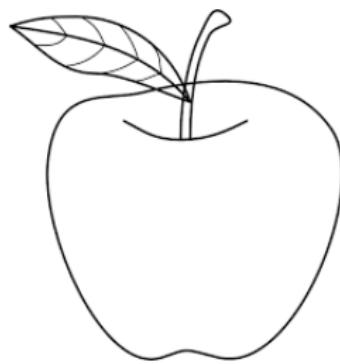


- If we stack up this series of blurred images
- We have this pyramid
- Stable points are those which attain local maximum in scale space
- Local maximum means it is '**salient**' within certain distance range





# Why edges (2)



# Why edges (3)



(a)



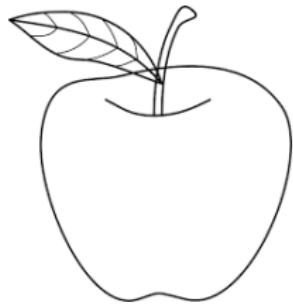
(b)



(c)

- Edges use less number of pixels than color blocks (Fig. (b)-(c)), however turn out to be more informative

# Why edges (4)



(a)



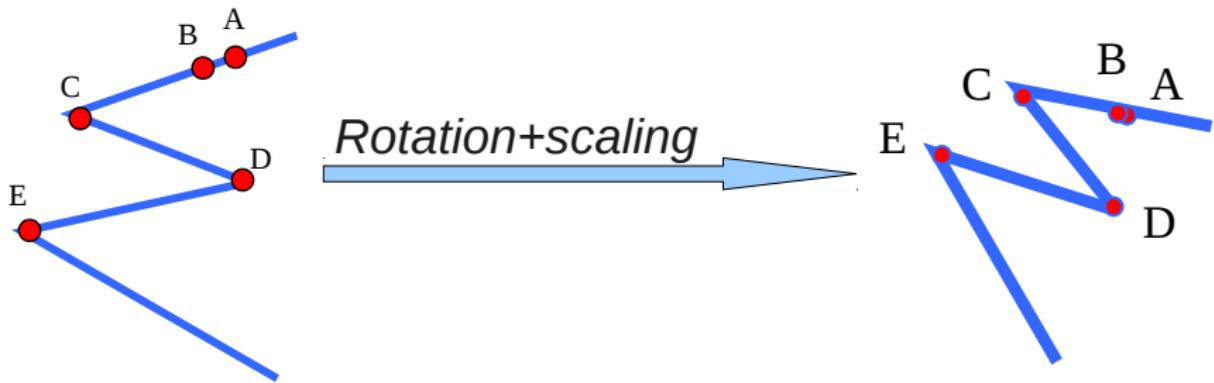
(b)



(c)

- Edges already carry most of the information to outline an object

# Why corners instead of edges (1)



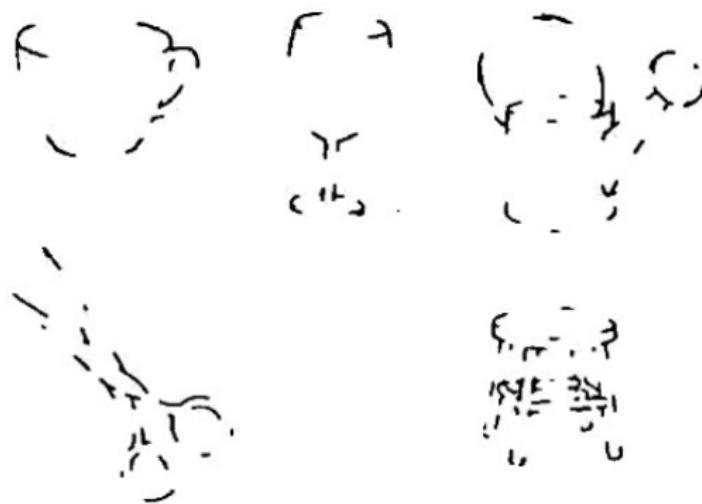
- Points (A, B) along the edges merged to each other
- The same for points in the flat region
- Corners (C, D, E) survive through scaling and rotation
- Different regions have different degree of robustness
- Corners are preferred

# Why corners instead of edges (2)



- Guess what are the objects with edges only (corners are largely removed)

# Why corners instead of edges (3)



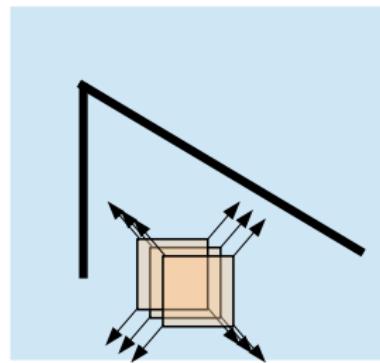
- Guess what are the objects with corners only

# Why corners instead of edges (4)

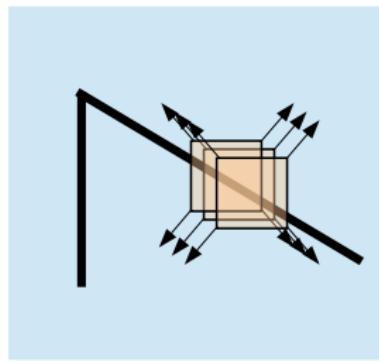


- Check your answer

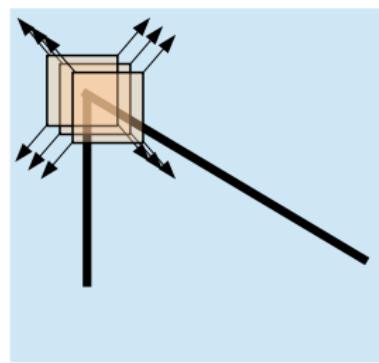
# How to detect the corners



(a)



(b)



(c)

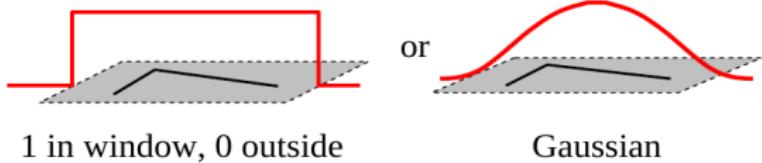
- Take an observing window, and move around
- No change in (a)
- Change happens along one direction in (b)
- Strong responses in two directions in (c)

# Formularize the probing procedure (1)

$$E(u, v) = \sum_{x, y} w(x, y) \cdot [I(x+u, y+v) - I(x, y)]^2$$

Window function  
 Shifted intensity  
 Intensity

Window function  $w(x, y) =$



- Measuring the energy changes
- $w$  is the probing window
- $u$  and  $v$  are the shifts in  $x$  and  $y$  directions

## Formularize the probing procedure (2)

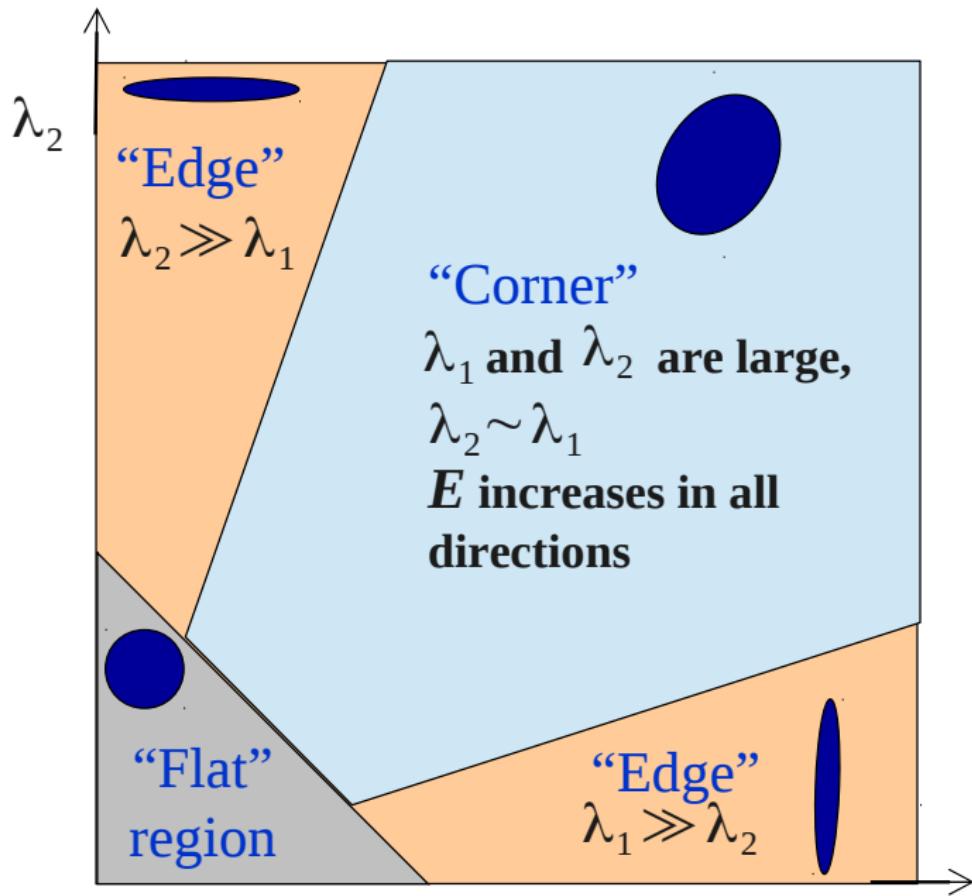
$$I(x+u, y+v) \approx I(x, y) + u \cdot I_x(x, y) + v \cdot I_y(x, y)$$

$$\begin{aligned} E(u, v) &= \sum_{x,y} w(x, y)[I(x + u, y + v) - I(x, y)]^2 \\ &= \sum_{x,y} w(x, y)[I(x, y) + uI_x(x, y) + vI_y(x, y) - I(x, y)]^2 \\ &= \sum_{x,y} w(x, y)[uI_x(x, y) + vI_y(x, y)]^2 \\ &= [u, v] \left( \sum_{x,y} w(x, y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \right) \begin{bmatrix} u \\ v \end{bmatrix} \end{aligned} \tag{4}$$

# Formularize the probing procedure (3)

$$\begin{aligned}
 E(u, v) &= \sum_{x,y} w(x, y)[I(x + u, y + v) - I(x, y)]^2 \\
 &= \sum_{x,y} w(x, y)[I(x, y) + uI_x(x, y) + vI_y(x, y) - I(x, y)]^2 \\
 &= \sum_{x,y} w(x, y)[uI_x(x, y) + vI_y(x, y)]^2 \\
 &= [u, v] \left( \sum_{x,y} w(x, y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \right) \begin{bmatrix} u \\ v \end{bmatrix}
 \end{aligned} \tag{5}$$

$$E(u, v) = [u, v] \cdot M \cdot \begin{bmatrix} u \\ v \end{bmatrix} \tag{6}$$



# Harris Detector: the results

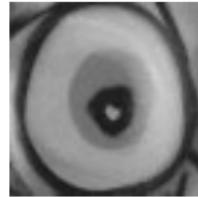
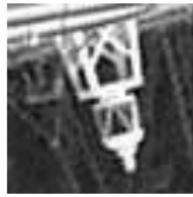
- Steps:
  - ① Compute  $\text{Harris}(x, y)$  for each pixel
  - ② Select the points that attain local maximum (**Non-maximum suppression**)
  - ③ Consider points whose  $\text{Harris}(x, y) > t_0$



- How to make use of these detected points?
- How the circle comes?

# SIFT descriptor: the motivation

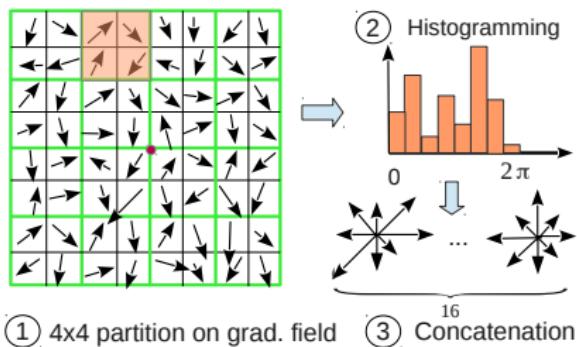
- Up to now, we are able to extract local point as a local patch
- To check whether two local patches are similar or not
- We need a feature representation for this local patch
- There are dozens of options: CH, CM or Gabor (wavelet feature)
- SIFT turns out to be the most successful one



# Overview about SIFT descriptor

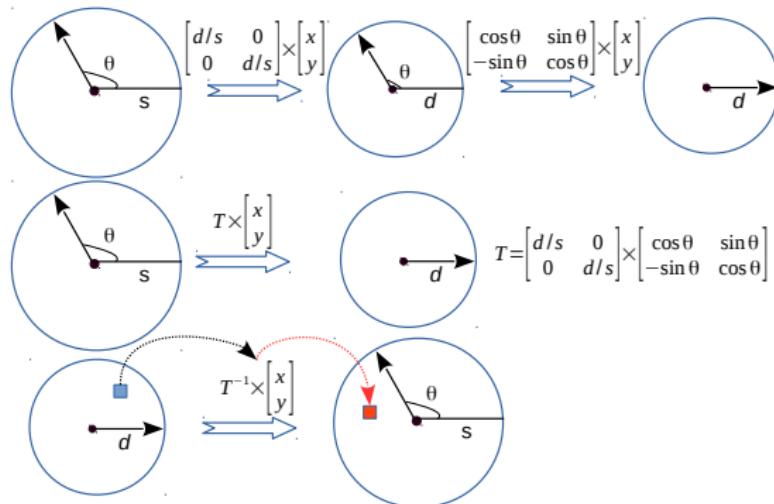
- It is known the best local interest point (keypoint) descriptor
- Num. Of citations: 31,039 (up to 14th, Aug., 2015)
- It is distinctive, but still tolerant to small errors (displacement, lighting changes, deformation) in the local patch
- When people talk about image local features, people talk on the basis of SIFT
  
- Refer to: David G. Lowe, Distinctive Image Features from Scale-Invariant Keypoints, IJCV'04, pp. 91-110.

# SIFT descriptor: the procedure



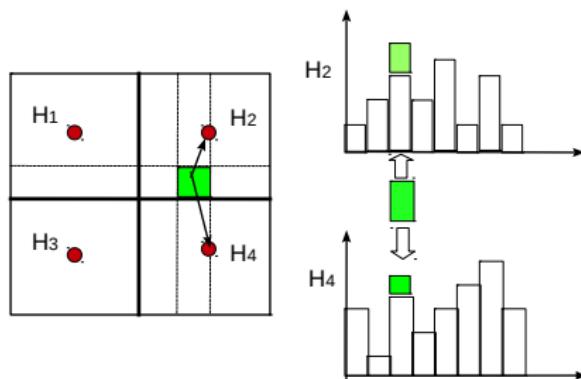
- Pre-processing steps:
- Normalize the patch to  $2d \times 2d$
- Calculate gradient field
- SIFT generation:
  - ① Partition gradient into  $4 \times 4$  grid
  - ② Compute gradient histogram on each block
  - ③ Concatenate 16 histograms as the final feature

# Three tricks in SIFT Implementation: (1)

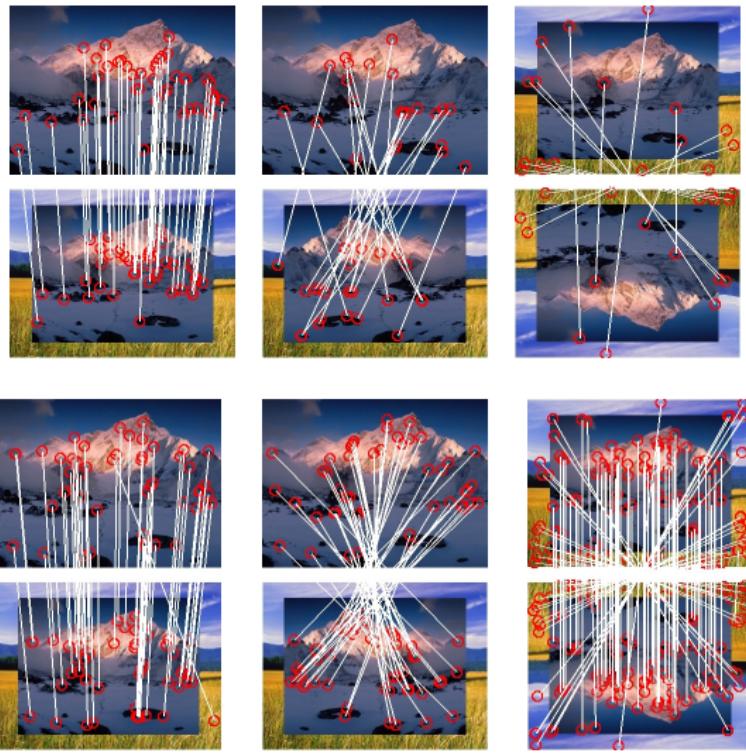


- ① Extracting hole-less Normalized Patch
- ② 2D interpolation
- ③ Removal of abnormal peaks

# Three tricks in SIFT Implementation (2)



- ① Extracting hole-less Normalized Patch
- ② 2D interpolation
- ③ Removal of abnormal peaks



(a) Scale

(b) Scale+flip

(c) Rotate+flip

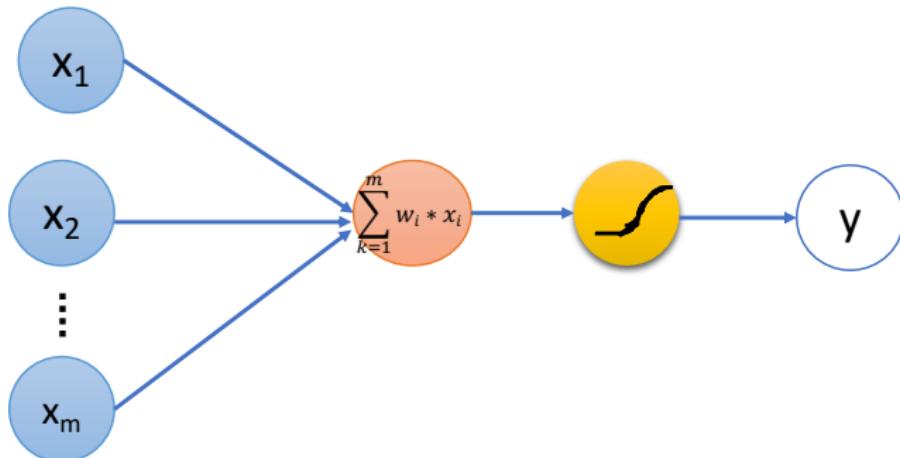
# Summary over Geometric Invariances

- Based on different schemes, we can achieve
  - ① **Scale invariance** by detecting points in scale-space
  - ② **Rotation invariance** by estimating the dominant orientation
  - ③ **Affine invariance** by adapting to local structure
  - ④ **Flip invariance** by estimating the dominant angular moment

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- 1 Global Features
- 2 Scale Space
- 3 Local Features
- 4 Deep Features
- 5 References

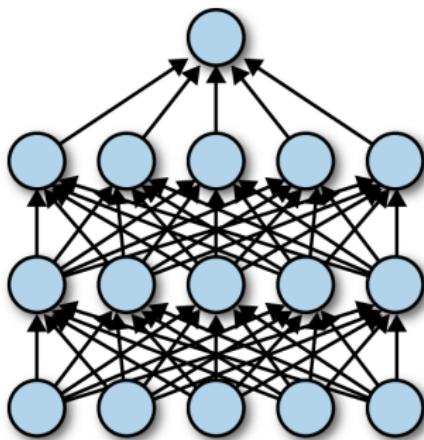
# Perceptron: a Review



$$N(x) = \eta \left( \sum_{i=1}^m w_i \cdot x_i + b \right) \quad (7)$$

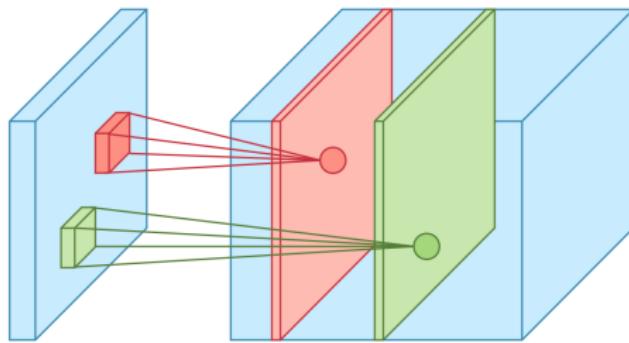
- The basic element for a neural Network is neuron
- It consists of a linear mapping with a non-linear activation

# Dense Network: a Review



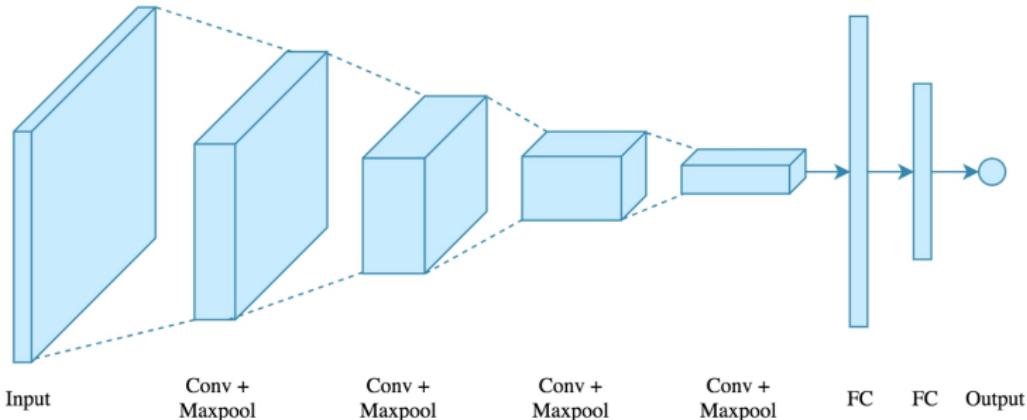
- Dense Network

# Convolution Neural Network (1)



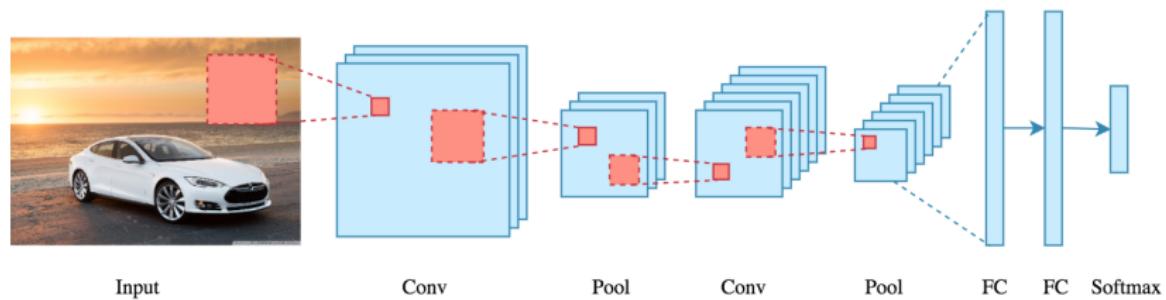
- One filter convolves over the whole image
- The resulting image is called a feature map
- One filter is trained to pick certain pattern from the image

# Convolution Neural Network (2)



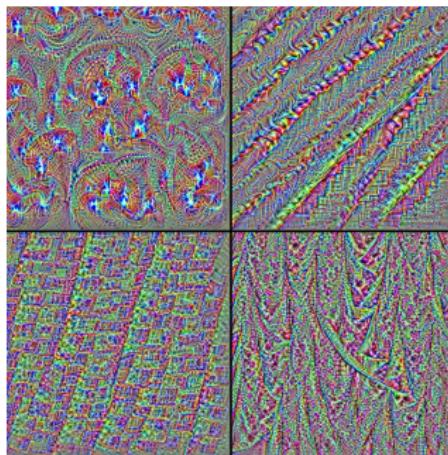
- A complete CNN is a stack-up of several CNN layers

# Convolution Neural Network (3)



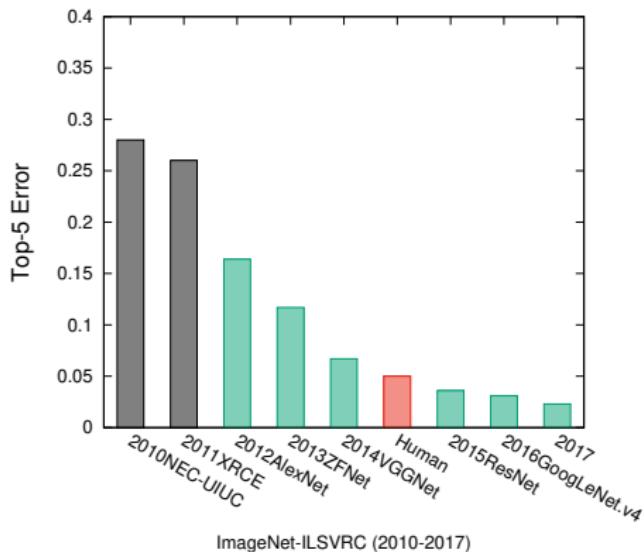
- CNN is first found to be powerful for image classification task
- The filter maintains the relative location pixels

# Convolution Neural Network (4)



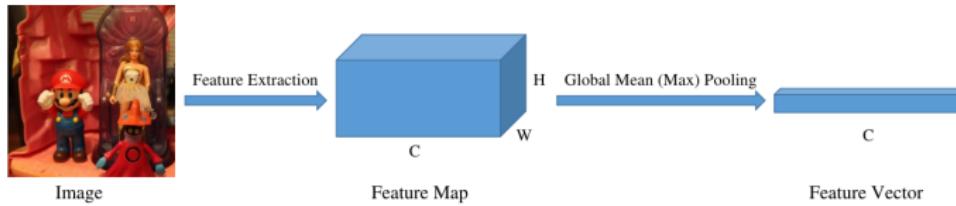
- A visualization of VGG-Block5 filters
- One filter picks a specific pattern from the feature maps of the previous layer

# CNN for Classification



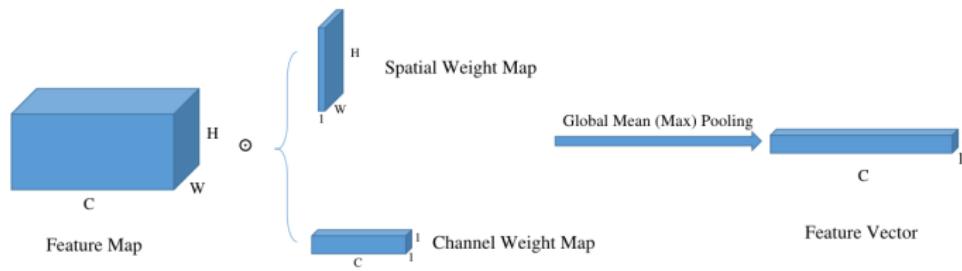
- Year 2012 is the starting year of deep learning
- Supervised image classification is no longer a problem

# Global Max Pooling



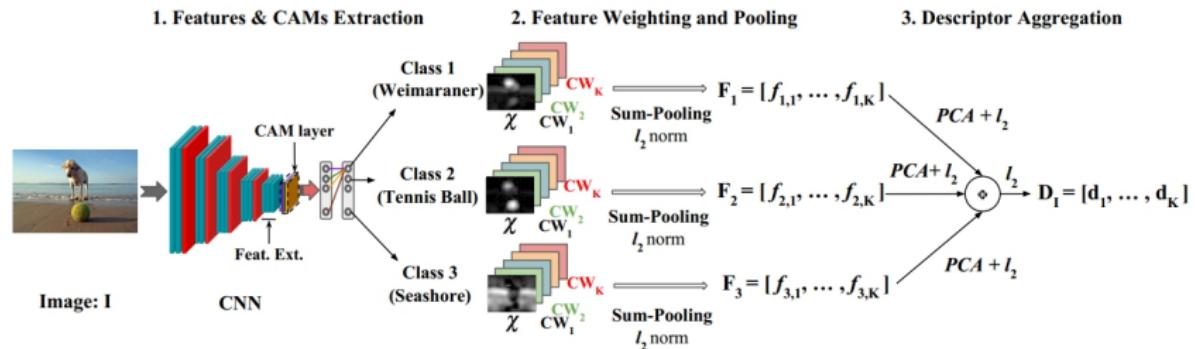
- One feature vector is produced for one image
- Max pooling is applied on one feature map
- Pooling results are concatenated into a fixed length vector

# Global Weighted Max Pooling

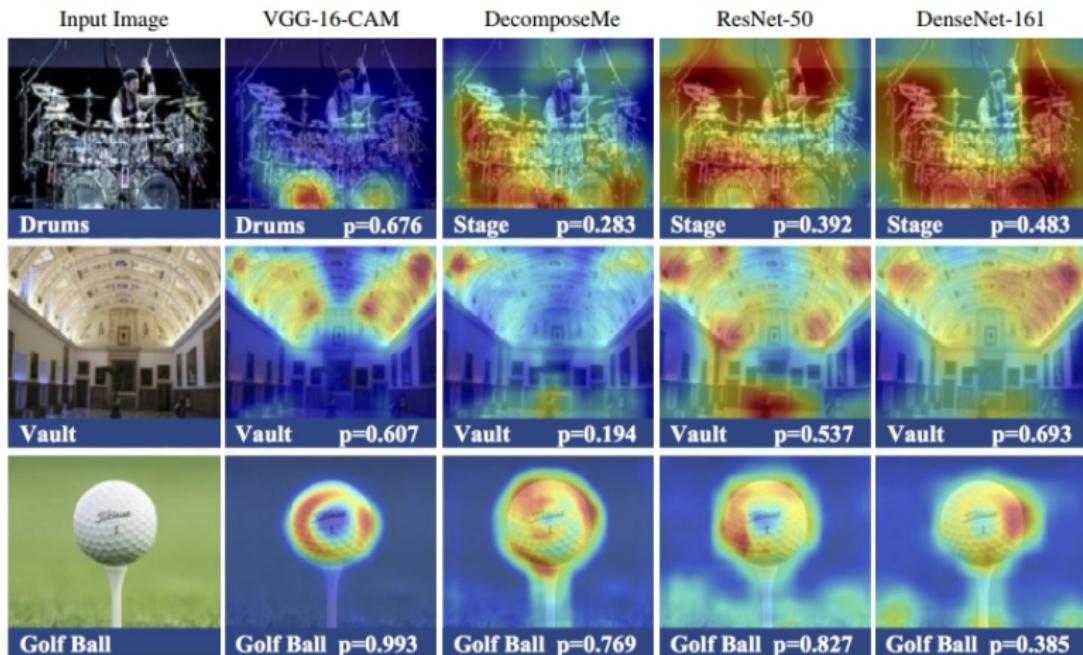


- As a variant, you can assign a weight according to the importance

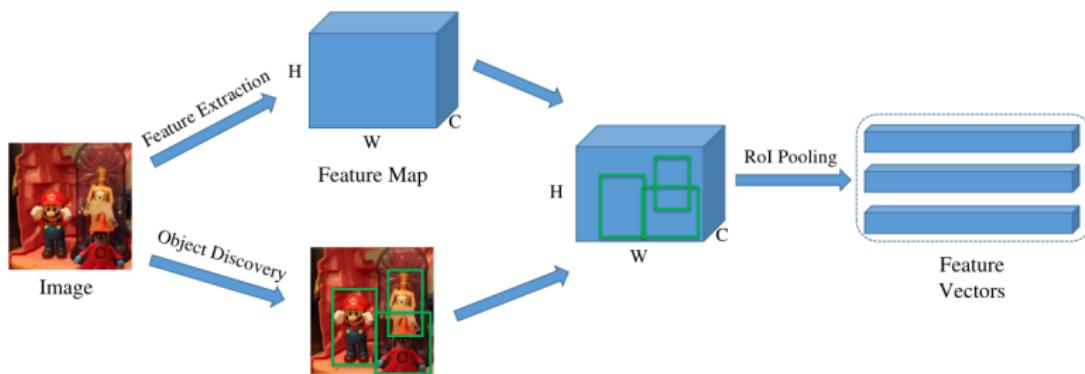
# Global Max Pooling Example (1)



# Global Max Pooling Example (2)

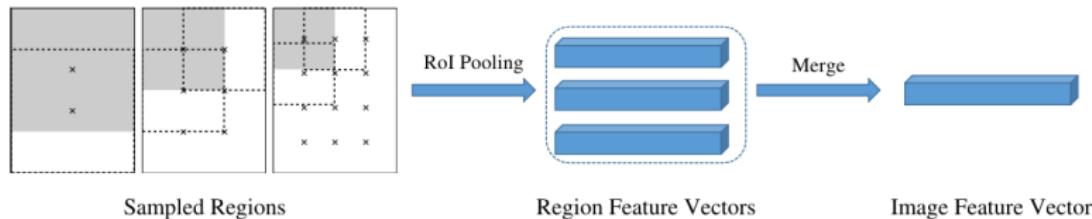


# ROI Pooling



- Given we want to build feature from a local region
- Maxpooling/average pooling is applied on a local

# ROI Pooling Example



- R-MAC extracts local features from feature maps

# References

- ① Distinctive Image Features from Scale-Invariant Keypoints, D. G. Lowe, *IJCV'10*
- ② SURF: Speeded Up Robust Features, H. Bay and et al., *ECCV'06*
- ③ Flip invariant SIFT for Video Copy and Object Detection, Wan-Lei Zhao and et al. *TIP'13*
- ④ Feature Detection with Automatic Scale Selection, Tony Lindeberg, *IJCV'98*, pp.79-116
- ⑤ Scale and affine invariant interest point detectors, Krystian Mikolajczyk and et al. *IJCV'02*, pp.63-86
- ⑥ Local Invariant Feature Detectors: A Survey, T. Tuytelaars and K. Mikolajczyk, NoW Publisher Inc. 2008
- ⑦ Class-weighted convolutional features for visual instance search, Jimenez A, Alvarez J M, Giro-i-Nieto X., 2017
- ⑧ Fast R-CNN, Girshick R., CVPR, 2015: 1440-1448
- ⑨ Particular object retrieval with integral max-pooling of CNN activations, Tolias G, Sicre R, Jégou H., 2015

# Q & A

# Thanks for your attention!