

7-9-2021

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Tuesday

week #2 lecture #2

## Image classification

a core task in Computer Vision

### The Problem:

Semantic gap

for the computer it is just a tensor of integers b/w  
[0, 255]

e.g.  $800 \times 600 \times 3$  3 channels of RGB

2 types of images

a) Gray scale images

Gray shades

0, 255

Dark pixel, White pixel

Single  
matrix

b) RGB Images  
colored images

3 matrices 2d  
or ~~3~~ 3D matrix

$$2^8 \times 2^8 \times 2^8 = 2^{24}$$

### Challenges:

① Viewpoint variations

All ~~pixels~~ pixels change when the camera moves

## ② Background Clutter

Background & foreground would have almost same numbers hence colors

## ③ Illumination

## ④ Occlusion

Some part of the object is visible only in the image

## ⑤ Deformation

Daily life objects shape isn't rigid, so shape changes we have to detect it.

## ⑥ Intra-class variation

### An Image classifier:

unlike e.g. a sorting a list of numbers.

we can't hardcode the algorithm for an object

### Attempts have been made:

Find edges

Find corners



## ML: Data Driven Approach:

- ① Collect a dataset of images & labels
- ② Use ML algo's to train a classifier.
- ③ Evaluate the classifier on new images

## Nearest Neighbor classifier:

First classifier:

Nearest Neighbor

2 steps

- ① Memorize all data & labels
- ② Predict the ~~data~~ label of most similar training image

Distance Metric

Euclidean distance

Example Dataset: CIFAR10:

10 classes

50,000 training Images

10,000 Testing Images



## Distance Metric:

To compare Images

L1 distance:

$$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$

Take Pixel wise difference absolute value & add them

minimum difference = 0

max difference =  $255 \times \text{dimensions of Pictures}$

Mostly  $X$  means data or images

$Y$  means labels

$tr$  = training set

$N$  = no. of images

$D$  = Dimensions

$$X = N \times D$$

↓

it should be

$$N \times D_1 \times D_2 \times 3$$

$$\underbrace{\quad \quad \quad}_{D} \quad \underbrace{\quad \quad \quad}_{RGB}$$

$$\text{Training} = O(1)$$

$$\text{Prediction} = O(N) \text{ for 1 image}$$

$$O(N^2) \text{ for } N \text{ images}$$

Problem - for <sup>for</sup>  $N$  images Prediction takes more time.

we want faster <sup>large</sup> Prediction & <sup>fine</sup> Slow training for Now.

## K-Nearest Neighbors:

we could have noise in data & our prediction could

be wrong so NN has extension K-NN.

Take odd  $K$  for voting in NN's and most votes have  
the label as our prediction