CS231n Lecture2

<u>*Sematic gap*</u>: width x height x RGB (complexity of tasks)

Challenges:

1. Viewpoint Variation: zoom, shift, all pattern is changed
2. Illumination: brightness value
3. Deformation: for example, strange images
4. Occlusion: hidden foreground object
5. Background clutter: how to distinguish between foreground and background
6. Intra-class variation: full species that look similar

Training example for pattern matching base on ***ImageNet*** – CIFAR-10: 10 labels and 50,000 training images [32x32], 10,000 test images.

L1 distance: $$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$

test image

56	32	10	18
90	23	128	133
24	26	178	200
2	0	255	220

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training image

10	20	24	17
8	10	89	100
12	16	178	170
4	32	233	112

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pixel-wise absolute value differences

46	12	14	1
82	13	39	33
12	10	0	30
2	32	22	108

$\xrightarrow{\text{add}}$ 456

Q. How does the classification speed depend on the size of the training data?

Linearly independently,

CNNs: despite of expensive training, it is possible to test in real time.

Q. What is the accuracy of the nearest neighbor classifier on the training data, when using the Euclidean distance?

100%: we're always find a training example exactly on top of that test which has 0 distance, according to data manifold.

Q. What if using Manhattan distance instead?

Absolute value, it will be same as well.

Q. What is the accuracy of the k-nearest neighbor classifier on the training data?

Basically, the point around you overwhelmed, the best example is of a different class.

Q. How do we set the hyper-parameters?

Very problem-dependent

Just try them all out and see what works best

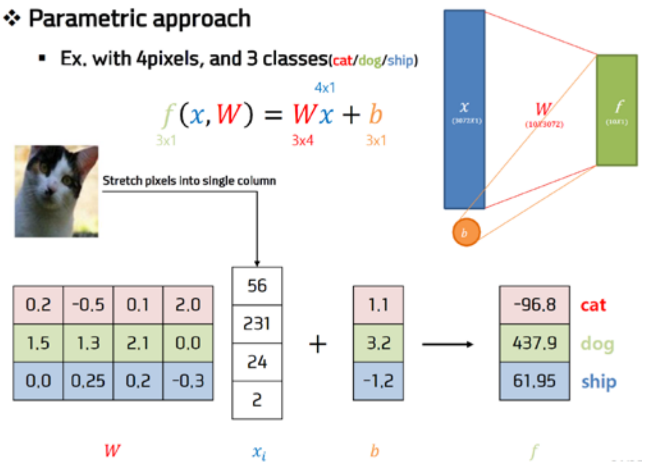
K-nearest neighbor on images never used due to shifted, messed up and darkened image

<u>Parametric approach</u>

It is going to be choose parameters(weights)

Linear classifier (w, b)

Q. What does the linear classifier do?



Q. How we could process different scales from images?

Resize the different images easily such as augmentation.

jittering and stretching : huge amount of that stuff such that is rotated.

Q. Average of pixels?

Work worse, it doesn’t want to minimize the mean of images.

<u>A feacture for images</u>

There are many label examples in images based on colors.

Q. If a class is imbalanced?

The bias for imbalanced class would be higher because this classifier is just used to spewing out large numbers ***based on the loss.***

We must find data manofold what you want to do, jittering, rotating and separating out, for example, all the cars and non-cars.

Q. What would be a very hard set of classes for a linear classifier to distinguish?

Negative Images mean to make the shape such as an edge but not exact color for the original image.

In a image, for example, there is a cat on the left side and there is also a cat next to it. It dosen't have problem, the weight would be shown on the pixels in the image.

Stacking linear classifiers

The purpose for image classification is to minimize the loss, changing weights unitl loss is almost zero, and then that is classifying all the images unless it is higher loss.