FACULTY OF MATHEMATICS,
PHYSICS AND INFORMATICS
Comenius University
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Neural Networks for Computer Vision

Lecture 2: Image Classification

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Acknowledgment

The majority of slides are directly adopted from slides for CS231n[1] course at Stanford University!

[1] *Stanford CS231n lecture slides.* http://cs231n.stanford.edu/slides/

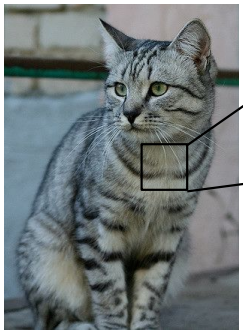
Contents

Image Classification

Image Classification

$\Rightarrow$ Cat

The Problem: Semantic Gap

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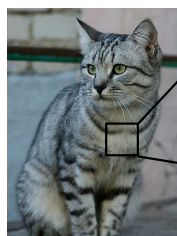
```

What the computer sees

An image is a tensor of integers between [0, 255]:

e.g. 800 x 600 x 3
(3 channels RGB)

Challenges: Viewpoint variation

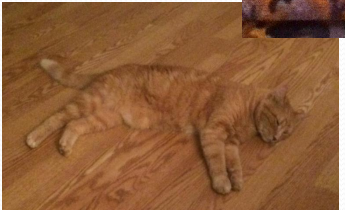


All pixels change when the camera moves!

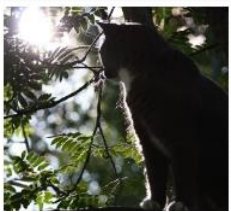
Challenges - background



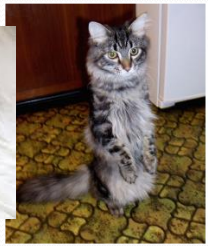
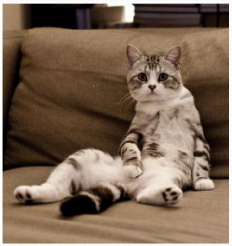




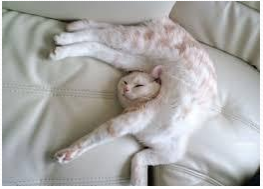
Challenges - illumination



Challenges - deformation





Challenges - occlusion





Challenges - intraclass variation

Image Classifier

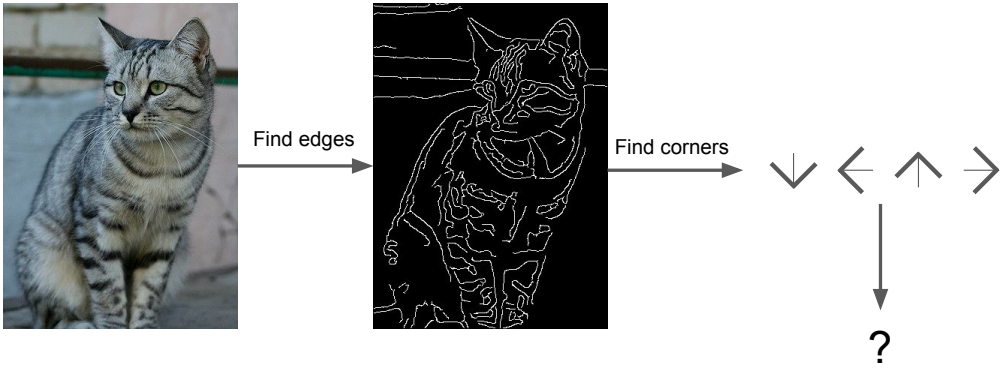
```
def classify_image(image):
    # some magic
    return class_label
```

Image Classifier

```
def classify_image(image):
    # some magic
    return class_label
```

There is no obvious way how to do this!

Classical CV



John Canny, "A Computational Approach to Edge Detection", IEEE TPAMI 1986

Machine Learning

Machine learning algorithms are algorithms which can improve their performance from experience. In case of CV experience usually means large annotated datasets.

Typical ML workflow:

1. Collect a dataset of images and corresponding labels
2. Train a classifier using ML
3. Evaluate the classifier on a new set of images

Nearest Neighbors classifier

One of the simplest classifiers is the nearest neighbor classifier:

- We train the classifier by simply remembering all of the training images and labels.
- To classify a new image we assign it the label of the image from the training set which is closest the new image.

Distance metric

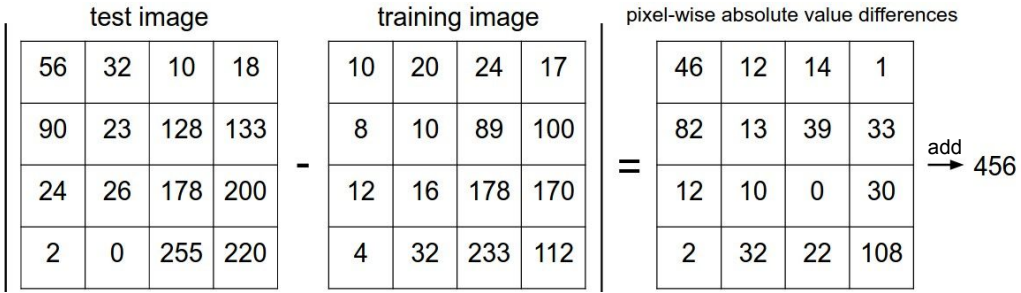
Training data with labels

query data

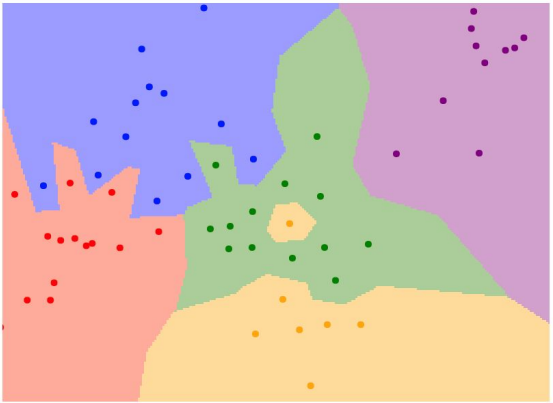
Distance Metric $\left|\right.$  ,  $\left|\right. \rightarrow \mathbb{R}$

Simple metric

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



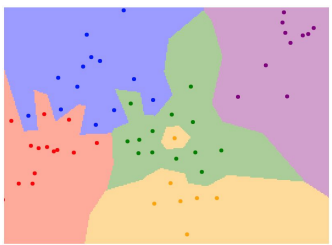
Decision boundary



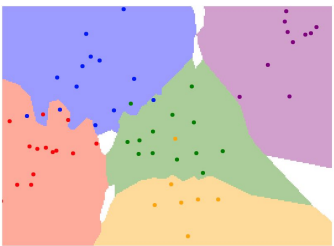
1-nearest neighbor

k-Nearest Neighbors

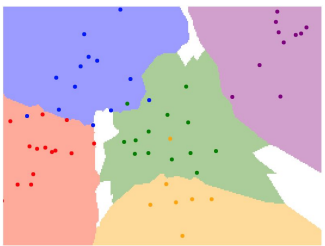
Instead of copying label from nearest neighbor,
take **majority vote** from K closest points



K = 1



K = 3



K = 5

Hyperparameters

Before using kNN we have to make few decisions:

- Which k do we use? E.g. number of neighbors.
- What kind of metric we use to calculate the distances?

Hyperparameters

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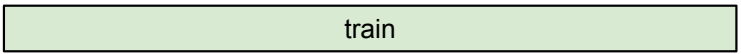
- Which k do we use? E.g. number of neighbors.
- What kind of metric we use to calculate the distances?

Both of these are **hyperparameters**. In general, hyperparameters change the algorithms themselves. We use the prefix hyper, since more sophisticated algorithms usually have parameters which are learned during training.

Setting these is difficult and dependent on the given problem! Usually you have to try and see what works best!

Setting Hyperparameters

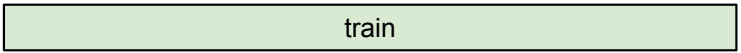
Idea #1: Choose hyperparameters
that work best on the **training data**



Setting Hyperparameters

Idea #1: Choose hyperparameters that work best on the **training data**

BAD: K = 1 always works perfectly on training data



Setting Hyperparameters

Idea #1: Choose hyperparameters that work best on the **training data**

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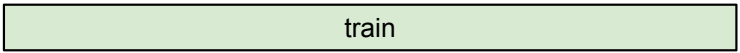
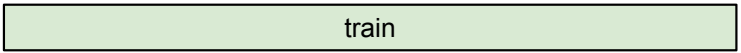


Idea #2: choose hyperparameters that work best on **test** data

Setting Hyperparameters

Idea #1: Choose hyperparameters that work best on the **training data**

BAD: K = 1 always works perfectly on training data



Idea #2: choose hyperparameters that work best on **test** data

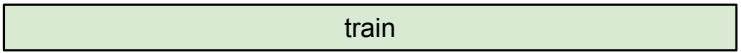
BAD: No idea how algorithm will perform on new data

Never do this!

Setting Hyperparameters

Idea #1: Choose hyperparameters that work best on the **training data**

BAD: K = 1 always works perfectly on training data



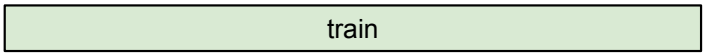
Idea #2: choose hyperparameters that work best on **test** data

BAD: No idea how algorithm will perform on new data

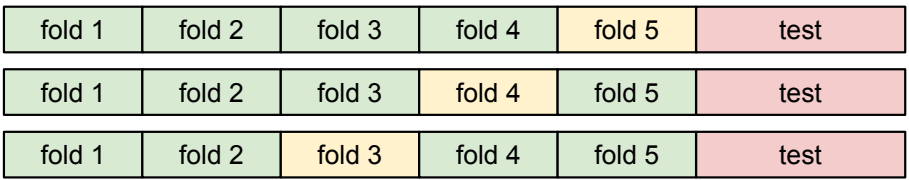
Idea #3: Split data into **train**, **val**; choose hyperparameters on val and evaluate on test

Better!

Setting Hyperparameters



Idea #4: **Cross-Validation**: Split data into **folds**,
try each fold as validation and average the results



Useful for small datasets, but not used too frequently in deep learning

Example Dataset - CIFAR10

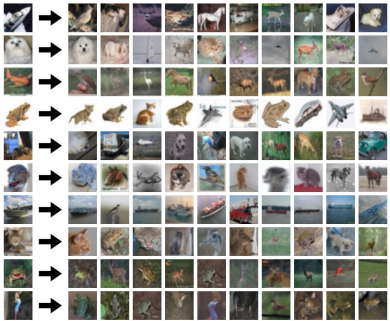
10 classes
50,000 training images
10,000 testing images

Alex Krizhevsky, “Learning Multiple Layers of Features from Tiny Images”, Technical Report, 2009.

Example Dataset - CIFAR10

10 classes
50,000 training images
10,000 testing images

Test images and nearest neighbors

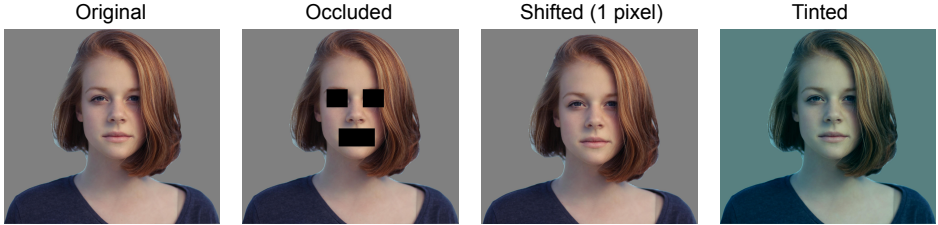


Alex Krizhevsky, "Learning Multiple Layers of Features from Tiny Images", Technical Report, 2009.

kNN - not a good choice

k-Nearest Neighbor with pixel distance **never used.**

- Distance metrics on pixels are not informative
- Very slow at test time



Original image is CC0 public domain

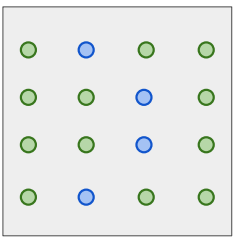
kNN - not a good choice

k-Nearest Neighbor with pixel distance **never used.**

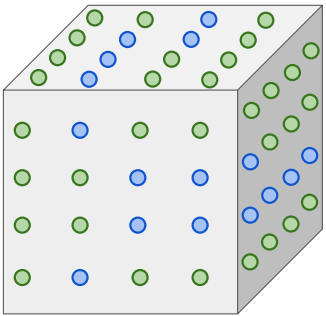
- Curse of dimensionality

Dimensions = 1
Points = 4

Dimensions = 2
Points = 4^2



Dimensions = 3
Points = 4^3



Linear Classifier

Image

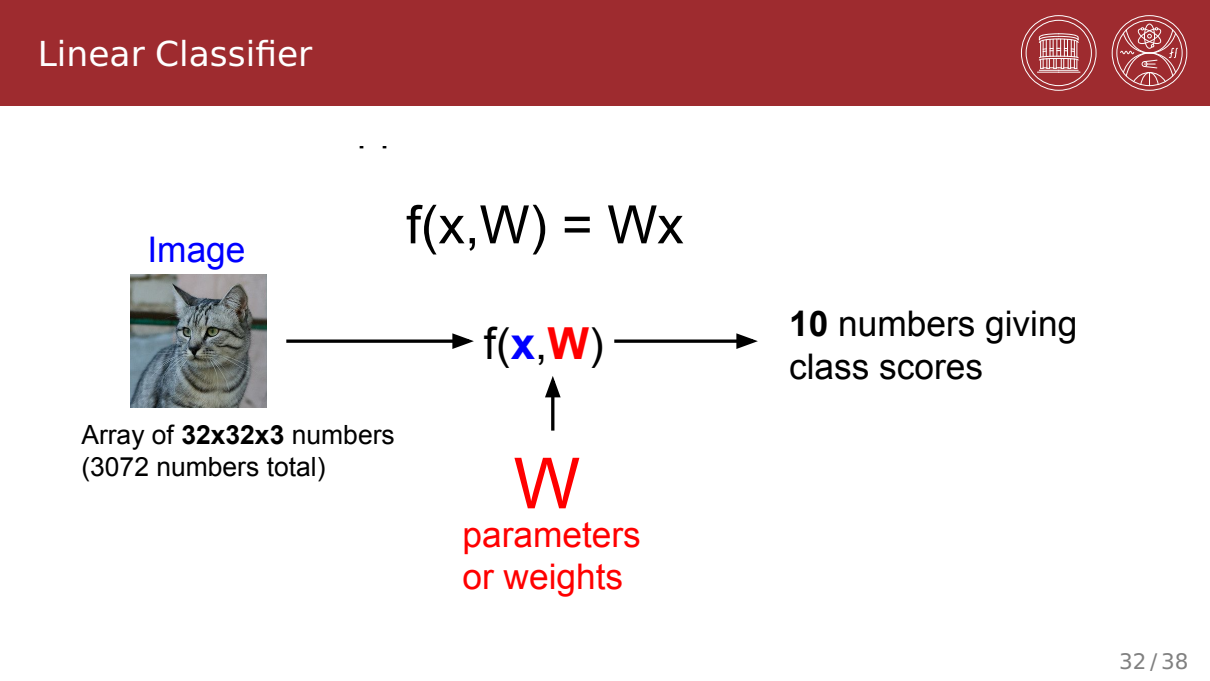
Array of **32x32x3** numbers
(3072 numbers total)

f(**x**,**W**)

10 numbers giving
class scores

W
parameters
or weights

Linear Classifier



Linear Classifier

Image

Array of **32x32x3** numbers
(3072 numbers total)

$$f(x,W) = Wx$$

3072x1

10x1 10x3072

$f(\mathbf{x},\mathbf{W})$

10 numbers giving class scores

W
parameters or weights

Linear Classifier

Image

Array of **32x32x3** numbers
(3072 numbers total)

$$f(x,W) = Wx + b$$

3072x1 (x)

10x1 (b)

10x1 (f(x,W))

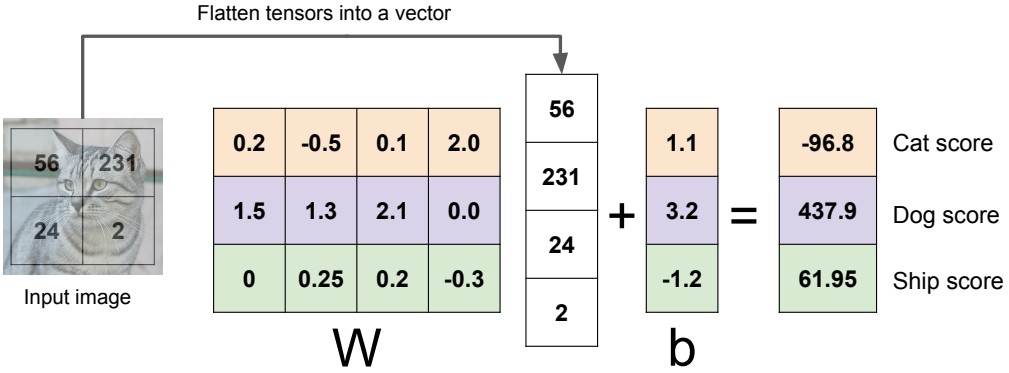
10x3072 (W)

f(**x**,**W**)

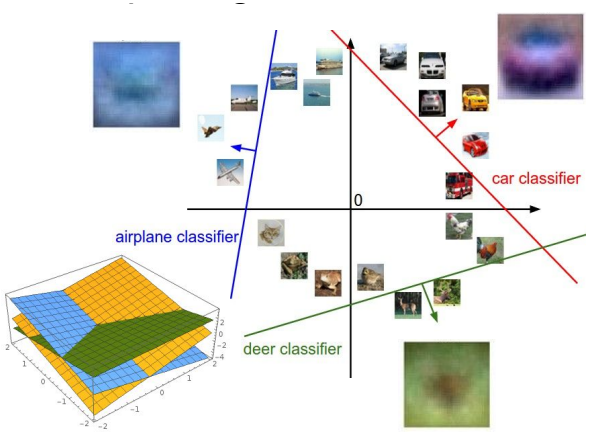
10 numbers giving class scores

W
parameters
or weights

Linear Classifier - Example



Linear Classifier - Decision Boundary



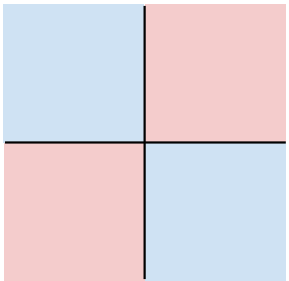
$$f(x,W) = Wx + b$$

Array of **32x32x3** numbers
(3072 numbers total)

Linear Classifier - Hard cases

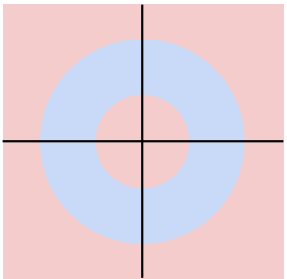
Class 1:
First and third quadrants

Class 2:
Second and fourth quadrants



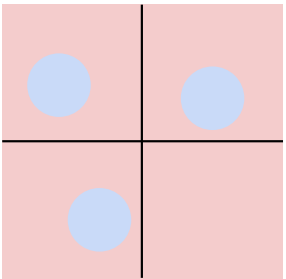
Class 1:
1 <= L2 norm <= 2

Class 2:
Everything else



Class 1:
Three modes

Class 2:
Everything else



Next week - optimization

$$f(\boldsymbol{x}, W) = W\boldsymbol{x} + \boldsymbol{b}$$

- Loss function
  - Quantifying *good* parameters
- Optimization
  - Finding optimal parameters to minimize the loss function
- Convolutional Neural Networks